2022 The 27th International Conference on Automation & Computing

Smart Systems and Manufacturing

University of the West of England, Bristol, UK
1-3 September 2022

Edited by: Chenguang Yang & Yuchun Xu

Chinese Automation & Computing Society in the UK
Preface

Welcome to the 27th International Conference on Automation and Computing (ICAC2022) held at the UWE Bristol.

The ICAC series has a long established history since its first conference in London in 1995. The conference initially aimed at providing a forum for Chinese scientists, engineers, and academics in the UK to update technical knowledge, exchange research ideas, and formulate joint research programs, especially between the UK and China for mutual benefits. Since 2007, the conference has been transforming towards a true international profile with delegates coming from all around the world. In the last decade, all papers that had been presented in this conference series have entered the IEEE Xplore digital library and EI indexed.

The scope of ICAC2022 covers a broad spectrum of multi-disciplinary fields in automation, manufacturing, computing, information systems and condition monitoring, ranging from theoretical studies to real-world applications and problem solving. We are pleased to see the continuous high quality submissions this year with the theme on Smart Systems and Manufacturing.

On behalf of the conference committee, we would like to take this opportunity to thank all those who have contributed to this conference, as well as the members of the local organising committee and the international program committee for their fantastic work. Our sincere gratitude also goes to the conference sponsors for their support, particularly to the Actuators journal for its generous sponsorship of best student paper awards. Last but not least, we want to thank all the volunteers for their diligent work and services to the conference.

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September 2022

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Best Student Paper Award

Graph Neural Networks for Interpretable Tactile Sensing

Wen Fan, Hongbo Bo, Yijiong Lin, Yifan Xing, Weiru Liu, Nathan Lepora, Dandan Zhang

Best Application Paper Award

Material Removal Rate Prediction with Phase Sensitive Variables Selection and Phase Partition

Chunpu Lv, Tao Zhang, Huangang Wang

Best Conference Paper Award

Dual Quaternion Based Finite-Time Tracking Control for Mechatronic Systems with Actuation Allocation

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Developing Data-Driven Intelligent Autonomous Systems: Information Fusion; Event Correlation; Decision Making and Planning

Abstract: Intelligent agents (and to some extent, intelligent robots) in data-driven intelligent autonomous systems, operating in large sensor networks with uncertain and dynamic environments, shall at least possess the following abilities. First, agents shall be able to perceive, analyze and combine uncertain and inconsistent information from multi-model heterogeneous sources in order to establish the true state of events that are of interest. Second, agents shall be able to model, correlate, and make inferences about dispersed events from different sources in real-time in order to achieve situation awareness. Third, agents shall be able to make decisions taking into account constraints and preferences, and to dynamically plan in order to act appropriately.

Over the past 20 years, my group, working together with UK and international collaborators, has been conducting research addressing these challenges. First, we developed numerous information fusion approaches to handle uncertain and inconsistent information under different circumstances. We have particularly established some common principles governing the fusion of both uncertain information (especially in numerical forms) and knowledge (especially in logical forms). Second, we developed several methods to correlate and reason with seemingly unrelated events to draw (high-level) conclusions that are beyond the immediate meaning of directly observed events. Third, we have been investigating how to integrate state-of-the-art planning algorithms with traditional agent architectures (such as Belief-Desire-Intension agents). Specifically, we have been looking into how to deploy First Principles Planners (FPPs), which are online planning algorithms, when an agent has no available plans to use. The ability for an agent to evolve its planning capabilities overtime has also been studied.

This talk will cover some of our major research results, with several demos (e.g., cyber-physical systems, smart grids) illustrating the potentials in real-world applications.

Biography: Weiru Liu holds Chair of Artificial Intelligence (AI) at the University of Bristol, and is Associate Dean for Temple Quarter Enterprise Campus (Research and Enterprise) since early 2020. Previously, she was the Faculty Research Director for the Engineering Faculty between 2017 to 2020. Her research interests include uncertain information fusion, event correlation and reasoning, large scale data analytics, agent systems with online planning, with a wide...
range of applications such as security, healthcare, robotics. Recently, she has been looking into approaches in explainable AI tailored to non-experts as part of an EPSRC funded project. She is also a Co-I of the £10m ESRC funded Centre for Sociodigital Futures examining social implications and the importance of social science in designing future AI technologies. She has published over 200 peer-reviewed papers, with several Best Paper Awards. She chaired a number of international conferences, and was an invited keynote speaker at several international conferences.

Prior to joining the University of Bristol in 2017, she held Chair of AI at Queen’s University Belfast, and was the Director of Research for the Knowledge and Data Engineering Cluster for 6 years. She has a sustained track record of securing peer-reviewed, highly competitive funding from a diverse range of funding bodies (over £58m as Principal Investigator or Co-Investigator), and was the PI for the £2.3m R&D grant funded by the Allstate Insurance Company (US) and Invest Northern Ireland on detecting fraudulence medical claims. In 2011, she received a Queen's Impact Award (sponsored by EPSRC) at Queen’s University Belfast.

She has been a member of the UK EPSRC ICT Strategic Advisory Team (SAT) since 2017 and a member of UK Higher Education Research Excellence Framework (REF) 2021 Institutional-level Environment Pilot Panel (ILEPP). She was a member of Independent Research Fund Denmark (DFF), and a member of Academy of Finland AI and Data Science Review Panel. She is also a Co-Director of the Centre for Doctoral Training in Future Autonomous and Robotic Systems: Towards Ubiquity (FARSCOPE-TU) at Bristol.
Abstract: In the context of Industry 4.0 technological development and digital transformation in industry and our society, this talk will first discuss the trends and challenges of shifting from product design to product-Service ecosystem (PSS) Design along the product lifecycle under the manufacturing servitisation. Secondly, it will discuss and demonstrate how digital twins and crowdsourcing technologies (e.g. Industry 4.0 technologies) are integrated for smart product service ecosystem design. To support this solution, a product design lifecycle information model (PDLIM) is then explored to potentially support data-driven design paradigm based on digital twins. Finally, it will discuss emerging directions of Human-in-the-loop machine learning or interactive machine learning for effective human-data (machine) co-decision making for digital-twin-based design approach and its challenges ahead.

Biography: Professor Shengfeng Qin is a professor of digital design and manufacturing in the school of Design, Northumbria University, UK.

Professor Qin joined Northumbria School of Design in 2014. He was 2019 Newton Prize recipient based on his collaborative research work with Professor Cuixia Ma at the Institute of Software of Chinese Academy of Sciences on Transforming Service Design and Big Data Technologies into Sustainable Urbanisation.

Prior to this appointment, he worked as a Senior/Lecturer in Department of Design at Brunel University (2001-2013), a Post-Doctoral Research Fellow (2000-2001) at University of Loughborough, a Research Assistant in the School of Product Design of Cardiff Metropolitan University (1998-1999). He was an Academic Visitor at the University of Birmingham (1996-1997) from East China Jiaotong University.

His research interest is broadly in digital design and manufacturing methods and technology for product-service systems. Early work includes design optimization, Computer Aided Design and Manufacturing (CAD/CAM), sketch-based modelling and interfacing, gesture-based modelling and interfacing, design process and team management.

At Northumbria University, Professor Qin has established the Smart Design Lab (SDL), leading design research into future smart products, services and interconnected systems design by
applying cutting edge smart technologies and smart multi-disciplinary design research methods/tools. He is also Co-director for Joint Design Innovation Lab between Northumbria University and Northwestern Polytechnical University of China.

Professor Qin is currently the Director for our MA Design Programme, teaching research principles and methods for this programme. He is the Editor-in-Chief for International Journal of Rapid manufacturing, and an Associate Editor for International Journal of Design Engineering.
Efficient Mask Attention-Based NARMAX (MAB-NARMAX) Model Identification

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Abstract—Model structure selection is crucial in system identification and data-driven modelling. Many spurious candidate variables can influence the determination of model structures due to the lack of prior knowledge of the system of interest. The commonly used method is to test as many possible models as possible and select a set of best models. This study proposes a novel mask attention-based NARMAX (MAB-NARMAX) modelling method for nonlinear dynamic system identification. The mask attention mechanism comes from the widely used neural network Transformer to reduce the dependency of the features and neurons. The performance of the proposed method is tested on three simulation datasets. Results show that the proposed MAB-NARMAX modelling framework has convincing multi-step-ahead prediction performance for nonlinear system identification in that it can produce the precious model structure. Even when the data are polluted with high noise (resulting in low SNR), the proposed method can still generate reliable system models compared with the state-of-the-art machine learning methods, e.g., LASSO and LSTM.

Keywords—model structure selection; NARMAX; mask matrix; nonlinear system identification

I. INTRODUCTION

Data-driven modelling and complex system identification has consistently been a powerful technique in analysing and investigating systems and their behaviours [1]. Sparse, interpretable, and transparent (SIT) parametric models are usually desirable and useful for understanding the inherent dynamics and interactions of the system states. An effective representation of the SIT modelling method is the famous NARMAX (nonlinear autoregressive moving average with exogenous inputs) model [1]. Moreover, a NARMAX model is usually compact and clear to explain and reveal the model structure in many applications where the primary modelling objective and task are to exploit and obtain an insightful description of how the system output explicitly depends on the system inputs [2]-[5].

In NARMAX modelling, model structure detection and selection are critical procedures for efficient and effective model identification [1][2][10]. The detection and decision of the model structure can be influenced by lots of factors of the signals from the system, like signal noise, the sampling rate of the signal, and the richness of the input signal. Other factors, which come from the modelling process, like the maximum lags in the system signals and the nonlinear degree for the polynomial model, are also crucially important for reliable system identification [2].

For convenience of description, consider the case of systems with single input and single output (SISO), denoted by $u(t)$ and, respectively, where $I$ is the sampling index (time instant). The lagged input and output variables are defined as:

$$u(t) \rightarrow u(t-d), u(t-d-1), \ldots, u(t-n_u)$$

$$y(t) \rightarrow y(t-1), y(t-2), \ldots, y(t-n_y)$$

(1)

where $d$ is a time lag between the system input and output (usually $d = 1$ but can be set to zero if the system input $u(t)$ instantly affects the system behaviour), $n_u$ and $n_y$ are the maximum time lags. These lagged variables can be used to create a model term dictionary, which can be used to build models. In doing so, a sparse learning algorithm, e.g., the orthogonal least squares with error reduction ratio (OLS-ERR) algorithm [14], the term clustering based algorithm [3], and random search approaches [4][5], can be used to determine a set of best models.

It is important to define the model settings appropriately. Taking the choice of $n_u$ and $n_y$ as an example, if these two hyper-parameters are much smaller than that of the ‘true’ system model, then many important lagged variables will not get involved in model construction, implying that the resulting model term dictionary will only contain partial information of the underlying system. Consequently, the finally identified ‘best’ model(s) may not be able sufficiently to characterise the system input-output behaviour. This is a fundamental issue in all system identification and data-driven modelling practices and applications, no matter what kind of models (e.g., NARX/NARMAX, traditional neural networks, deep neural networks) are used. Therefore, in practice, $n_u$ and $n_y$ are usually set to be large enough to ensure that the dictionary is large enough for representing the input-output behaviour of the system of study. However, large $n_u$ and $n_y$ means that larger numbers of candidate model terms are included in the dictionary, many of which are irrelevant and not useful for characterising the system dynamics but can only increase the difficulty in finding the best and most reliable models. So, it is always a challenge to properly define the model settings for transparent, interpretable, and parsimonious model identification of complex systems whose structure is completely unknown. Many methods and algorithms have been proposed for model structure determination in the literature. In [6], a novel mutual
information-based integrated forward orthogonal search algorithm was proposed. This algorithm can comprehensively measure the contributions of the model terms for NARMAX model identification. In [7], an adjustable prediction error sum of squares (APRESS) was proposed for model structure detection. In [8], the performance of APRESS was compared with the Akaike information criterion (AIC) and Bayesian information criterion (BIC), and it was shown that APRESS outperforms AIC and BIC for robust and parsimonious model structure selection. In [9], an efficient alternative model structure selection algorithm using an exhaustive-like mechanism was proposed. These methods, as well as many other methods, were designed to prevent spurious model terms from being included in the final models; this is important for obtaining a set of best models that are not only transparent and parsimonious, but also have good generalisation properties.

Recently, a novel attention-based neural network named Transformer has been widely used [10]. A particular layer, ‘mask’, in the multi-head self-attention of Transformer is utilised for specializing (rare information), syntactic (dependency syntax and significant relations) and window roles (size of the signals and relative position) [11][12]. The structure and good properties of mask layer motivate us to introduce the concept and scheme of ‘mask’ into system identification for model structure selection.

This study aims to exploit the potential of the idea of mask layer or mask matrix used in Transformer and make use of it for better model identification of nonlinear dynamic systems. The work focuses on NARMAX model identification and the use of mask operations for model input variable and term selection. The performance of the proposed mask attention-based NARMAX (MAB-NARMAX) method is evaluated via three simulation case studies, and the experimental results confirm the good properties of the new method. The main contributions of the work are summarised as follows:

- We present a 1D mask matrix and apply it for model input variable and term selection.
- We propose a novel mask attention-based NARMAX (MAB-NARMAX) method for nonlinear system modelling and identification using the proposed 1D mask operations.
- We evaluate the performance of the proposed MAB-NARMAX by three simulation examples, which confirm the good performance and properties of the proposed method.

The remaining of this paper is organised as follows. In Section 2, the mask layer of the Transformer is briefly introduced, and the proposed one-dimensional mask layer and MAB-NARMAX are explained. In Section 3, three simulation examples and a real data problem. This paper is concluded in Section 4.

II. MASK ATTENTION-BASED NARMAX

A. Mask layer

A mask matrix is such a square matrix whose entries are either zero or one, that is, $M \in \mathbb{I}^{1 \times r}$, $M_{i,j} \in \{0,1 \}$ [13]. A mask matrix can improve computational efficiency in complex neural networks [14]. Generally, mask matrices used in Transformer are defined in 2D space and use binary values to indicate which features (variables) or neurons are important and in favour of further processing in the next stage. A typical diagonal 2D mask matrix is shown in Figure 1.

![Figure 1 The diagonal two-dimensional mask matrix](image1)

The black dots in the diagonal mask matrix mean the value is 1, where $M_{i,i} = 1$, while the white circles (or disks) indicate that the value is 0, where $M_{i,j} = 0, i \neq j$.

With the definition of the mask matrix [15], the self-attention in Transformer can be redefined as the mask-attention function:

$$A_{uv}(Q,K,V) = S_{uv}(Q,K)V$$

$$S_{uv}(Q,K) = \frac{M_{i,j}\exp(Q_{i}K_{j})}{\sum_{i,j}M_{i,j}\exp(Q_{i}K_{j})}$$

where the queries $Q$, keys $K$ and values $V \in \mathbb{I}^{r \times d_{i}}$ are three separate parts transformed from the input $X^{input}$. $M \in \mathbb{I}^{r \times r}$, $M_{i,j} \in \{0,1 \}$ is the mask matrix; $S(\cdot)$ is the softmax function; $d_{i}$ is the dimension of $K$. For details about mask matrix and mask-attention function, interested readers are referred to [16][17], where several mask generation methods are presented.

Note that variable and model term selection for NARMAX can be carried out in 1D space, where the model term index can be represented as a mask vector, as shown in Figure 2.

Specifically, the mask vector is defined as:

$$M_{i,s} = \begin{cases} 1, & \text{if } l = s \\ 0, & \text{if } l = p \end{cases}$$

where $s,p=1,2,...,L$, $L$ is the total length of the mask vector; $s$ and $p$ are random indexes of the mask vector, representing the location of ‘0’ in the mask while $p$ is the position of ‘1’. In this study, a random sampling and random generation approach is used to generate mask matrices (vectors).

![Figure 2 The proposed 1D mask matrix](image2)

B. NARMAX and polynomial NARX

The nonlinear autoregressive moving average with exogenous input (NARMAX) model is defined as [1]:

$$y(t) = f(y(t-k), u(t-k), e(t-k)) + e(t)$$

where $f(\cdot)$ is a nonlinear function, $y(t)$ is the output at time $t$, $y(t-k)$ and $u(t-k)$ are the output and input at previous times $k$, $e(t)$ is the error term, and $e(t-k)$ is the error at previous times $k$. The polynomial NARX model is defined as:

$$y(t) = f(y(t-k), u(t-k), e(t-k)) + e(t)$$

where $f(\cdot)$ is a polynomial function of degree $p$, and $y(t)$, $u(t)$, and $e(t)$ are defined as above.
\[ y(k) = F[y(k-1),...,y(k-n_y)], \]
\[ u(k-d),...,u(k-d-n_u), \]
\[ e(k-1),...,e(k-n_e)] + e(k) \]

where, \( y(k) \), \( u(k) \) and \( e(k) \) are the system output, input and noise sequences, respectively; \( n_y \), \( n_u \), and \( n_e \) are the maximum lags for the system output, input, and noise; \( F[\cdot] \) is some nonlinear function, and \( d \) is a time delay, typically set to \( d = 1 \). The noise terms \( e(k) \) are normally defined as the prediction errors. In practice, there are many types of model structures that can be used to approximate the unknown mapping \( F[\cdot] \), including power-form polynomial models [18], rational models [19], neural networks [20], fuzzy logic-based models [21], and wavelet expansions [22][23][24]. The most commonly used model is the power-form polynomial representation [1].

The polynomial NARX model is the special case of the polynomial NARMAX model, which does not include the noise-dependent or noise model terms [1]. NARX model is of the form:

\[ y(k) = F[y(k-1),...,y(k-n_y)], \]
\[ u(k-d),...,u(k-d-n_u)] + e(k) \]  (5)

Equation (5) can usually be rearranged as:

\[ y(k) = \theta_0 + \sum_{i=1}^{n} f(x_i(k)) + \ldots + \sum_{i=1}^{n} f(x_i(k),x_{i1}(k),...,x_{in}(k)) + e(k) \]  (6)

where \( \ell \) is the degree of polynomial nonlinearity, \( \theta_{i_1,...,i_n} \) are model parameters, \( n = n_y + n_u + n_e \), and

\[ f_{i_1,...,i_n}(x_i(k),x_{i1}(k),...,x_{in}(k)) = \theta_{i_1,...,i_n} \prod_{i=1}^{n} x_i(k), 1 \leq m \leq \ell \]  (7)

\[ x_{i}(k) = \begin{cases} y(k-m), & 1 \leq m \leq n_y \\ u(k-m+n_y), & n_y+1 \leq m \leq n_y+n_u, \end{cases} \]  (8)

More specifically, (3) can be explicitly written as:

\[ y(k) = \theta_0 + \sum_{i=1}^{n} \theta_{i_1} x_i(k) + \ldots + \sum_{i=1}^{n} \sum_{k_{i1}}^{n} \sum_{k_{i2}}^{n} \cdots \sum_{k_{in}}^{n} \theta_{i_1,...,i_n} x_i(k) x_{i_1}(k) \ldots x_{in}(k) + e(k) \]  (9)

The degree of a multivariate polynomial is defined as the highest nonlinear order among all the model terms. Like the model \( y(k) = 0.5y(k-1) + u(k-1) + 0.25y(k-1)u(k-2) \), the degree of nonlinearity is 2, that is, \( \ell = 2 \).

C. MAB-NARMAX model

The general process of the proposed MAB-NARMAX is shown in Figure 3. On the basis of the mask vector and the polynomial NARX model defined by (3) and (9), respectively, we define a mask attention based NARX model as:

\[ \hat{y}(k) = \theta_0 + \sum_{i=1}^{n} m_i \cdot \theta_{i_1} x_i(k) + \ldots + \sum_{i=1}^{n} \sum_{k_{i1}}^{n} \sum_{k_{i2}}^{n} \cdots \sum_{k_{in}}^{n} m_{i_{1k_{i1}}...i_{nk_{in}}} \cdot \theta_{i_1,...,i_n} x_i(k) x_{i_{1}}(k) \ldots x_{in}(k) + e(k) \]  (10)

Figure 3 The structure and process of the proposed MAB-NARMAX method

Let \( m_{i_{1}...i_{n}} \in \{0,1\}^{\times v}, v \in \{i_{1},i_{2},...,i_{1},...,i_{n}\} \) be a mask matrix with binary values in each mask layer, as shown in Figure 2. Equation (10) is the description of the output of the final layer in Figure 3. For each layer in the masked NARMAX model, the NARMAX maps the discrete terms to an output as:

\[ S_m(X_i) = M_i \ell A(X_i,K_i) \]  (11)

\[ A(X_i,K_i) = X_i \times K_i \]  (12)

\[ X_{i+1} = F(S_m(X_i)) \]  (13)

where \( M_i \) is the mask matrix in the \( l \)-th layer, \( S_m(X_i) \) is the regressors selected by the mask matrix in the \( l \)-th layer, \( \ell \) means doc product between mask matrix and the model terms from former layer; \( X_i \) is the input signal of the \( l \)-th layer, \( K_i \) is the time lagged operation, \( A(X_i,K_i) \) are the lagged variables of \( X_i; \) \( X_{i_{1}} \) are the selected model terms.

Then, the current best model is compared with the target signal to evaluate the performance of the identified NARMAX model. A backward-optimization algorithm is applied to adapt the values of the mask matrix for a better NARMAX model. Once the error of the identified model is below a specified threshold (tolerance), the MAB-NARMAX modeling procedure will terminate.

III. CASE STUDIES AND NUMERICAL EXPERIMENTS

To demonstrate the performance of the proposed method, three nonlinear systems with different noise are considered. For comparison purposes, LASSO [25] and LSTM [26] are also utilized to solve the same problems. To better evaluate the these methods, multi-step-ahead (long-term) prediction [27], rather than one-step-ahead prediction is considered.

The each of the three systems, a total number of 500 input-output data points were recorded, 70% of which (consisting of the first 350 points) was for training, 20% (consisting of the next 100 points) was for validating and the remaining 10% (consisting of the final 50 data points) was for test.

Following [6], the maximum time lags for the system signals in the proposed MAB-NARMAX were chosen to be 5, and the nonlinear degree was set to be 3. For comparison purposes, the input vector for the LASSO and LSTM models had the same predictors as those for the MAB-NARMAX. In this study, the configurations of the LSTM network were as follows:
A. Example 1: A System Contaminated by White Noise

Consider a nonlinear system contaminated by white noise as below:

\[ y(t) = -0.6y(t-1) + 0.5u(t-2) - 0.2u(t-2)y(t-3) - 0.25u(t-2)u(t-3) + e(t) \]  

(14)

where the input \( u(t) \) is uniformly distributed on \([-1,1]\), while the noise \( e(t) \) is Gaussian with zero mean and standard deviation of 0.025. It was assumed that the ‘true’ system model structure was not known. With these model settings, the proposed method was applied to these 500 data points.

<table>
<thead>
<tr>
<th>Index</th>
<th>Term</th>
<th>True model</th>
<th>Model by MAB-NARMAX</th>
<th>Model by LASSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( u(t-1) )</td>
<td>( x )</td>
<td>( x )</td>
<td>-0.0064</td>
</tr>
<tr>
<td>2</td>
<td>( u(t-2) )</td>
<td>0.5</td>
<td>0.4989</td>
<td>0.4933</td>
</tr>
<tr>
<td>3</td>
<td>( u(t-3) )</td>
<td>( x )</td>
<td>( x )</td>
<td>-0.0054</td>
</tr>
<tr>
<td>4</td>
<td>( y(t-1) )</td>
<td>-0.6</td>
<td>-0.6022</td>
<td>-0.5873</td>
</tr>
<tr>
<td>5</td>
<td>( u(t-2)u(t-3) )</td>
<td>-0.25</td>
<td>-0.2476</td>
<td>-0.2373</td>
</tr>
<tr>
<td>6</td>
<td>( u(t-2)u(t-5) )</td>
<td>( x )</td>
<td>( x )</td>
<td>-0.0115</td>
</tr>
<tr>
<td>7</td>
<td>( u(t-2)y(t-3) )</td>
<td>-0.2</td>
<td>-0.2060</td>
<td>-0.1798</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Method</th>
<th>RMSE</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAB-NARMAX</td>
<td>0.0209</td>
<td>0.0173</td>
</tr>
<tr>
<td>LASSO</td>
<td>0.0224</td>
<td>0.0188</td>
</tr>
<tr>
<td>LSTM</td>
<td>0.1091</td>
<td>0.0544</td>
</tr>
</tbody>
</table>

B. Example 2: A System with both Internal and Additive Noise

Consider the following system:

\[ z(t) = -0.6z(t-1) - 0.2u(t-2)u(t-3) + e(t) \]  

(15)

\[ + 0.5u(t-2) - 0.25u(t-2)u(t-3) + e(t) \]

\[ y(t) = z(t) + \xi(t) \]  

(16)

where the input is following the uniformly distribution on \([-1,1]\), the internal noise \( e(t) \sim N(0,0.01^2) \) and the additive noise \( \xi(t) \sim N(0,0.1^2) \).

Again, the ‘real’ model structure was set to be a black box. The identified model structures by MAB-NARMAX and LASSO are listed in Table III, where the proposed method correctly identify all four ‘true’ model terms with almost the same parameters, however, Lasso selected a great number of spurious model terms. This results in that the parameters of the selected model terms by Lasso are quite different from the ‘true’ model structure. The values of RMSE and MAE of the all models by are listed in Table IV.

The predictions from the all models on the testing dataset, are shown in Figure 5. Again, a closer inspection can reveal that MAB-NARMAX shows better prediction performance.

<table>
<thead>
<tr>
<th>Index</th>
<th>Term</th>
<th>True model</th>
<th>Model by MAB-NARMAX</th>
<th>LASSO Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( u(t-2) )</td>
<td>0.5</td>
<td>0.5258</td>
<td>0.5138</td>
</tr>
<tr>
<td>…</td>
<td>…</td>
<td>( x )</td>
<td>( x )</td>
<td>…</td>
</tr>
<tr>
<td>4</td>
<td>( y(t-1) )</td>
<td>-0.6</td>
<td>-0.5407</td>
<td>-0.1549</td>
</tr>
<tr>
<td>…</td>
<td>…</td>
<td>( x )</td>
<td>( x )</td>
<td>…</td>
</tr>
<tr>
<td>7</td>
<td>( u(t-2)u(t-3) )</td>
<td>-0.25</td>
<td>-0.2277</td>
<td>-0.2241</td>
</tr>
<tr>
<td>…</td>
<td>( x )</td>
<td>( x )</td>
<td>( x )</td>
<td>…</td>
</tr>
<tr>
<td>9</td>
<td>( u(t-2)y(t-3) )</td>
<td>-0.2</td>
<td>-0.2157</td>
<td>-0.0388</td>
</tr>
<tr>
<td>…</td>
<td>( x )</td>
<td>( x )</td>
<td>( x )</td>
<td>…</td>
</tr>
<tr>
<td>15</td>
<td>( y(t-3)y(t-5) )</td>
<td>( x )</td>
<td>( x )</td>
<td>-0.0110</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Method</th>
<th>RMSE</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAB-NARMAX</td>
<td>0.1074</td>
<td>0.0840</td>
</tr>
</tbody>
</table>
C. Example 3-the input is driven by a non-white noise

Consider the following nonlinear system:

\[ w(t) = e(t) - 0.5u(t-1) \]  
\[ y(t) = -0.6y(t-1) - 0.2u(t-2)y(t-3) + 0.5u(t-2) - 0.25u(t-2)u(t-3) + w(t) \]

where the input \( u(t) \) is uniformly distributed on \([-1,1]\] and the internal noise \( e(t) \sim N(0,0.05^2) \). Model structures identified by MAB-NARMAX and LASSO methods are listed in Table V, in which the proposed method can precisely find all the four ‘true’ model terms, whereas Lasso selected many spurious model terms. The values of RMSE and MAE of the all models are listed in Table IV.

The predictions from the two models on the whole dataset are shown in Figure 6. While all models give excellent predictions, a closer inspection can show that MAB-NARMAX performs better.

TABLE V. IDENTIFIED MODEL STRUCTURE FOR EXAMPLE 3

<table>
<thead>
<tr>
<th>Index</th>
<th>Term</th>
<th>True model</th>
<th>MAB-NARMAX</th>
<th>LASSO Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( u(t-1) )</td>
<td>x</td>
<td>x</td>
<td>-0.0123</td>
</tr>
<tr>
<td>2</td>
<td>( u(t-2) )</td>
<td>0.5</td>
<td>0.5045</td>
<td>0.5019</td>
</tr>
<tr>
<td>5</td>
<td>( y(t-1) )</td>
<td>-0.6</td>
<td>-0.6150</td>
<td>-0.7023</td>
</tr>
<tr>
<td>9</td>
<td>( y(t-5) )</td>
<td>x</td>
<td>x</td>
<td>-0.0119</td>
</tr>
<tr>
<td>14</td>
<td>( u(t-2)u(t-3) )</td>
<td>-0.25</td>
<td>-0.2455</td>
<td>-0.2361</td>
</tr>
<tr>
<td>17</td>
<td>( u(t-2)y(t-3) )</td>
<td>-0.2</td>
<td>-0.2065</td>
<td>-0.1630</td>
</tr>
<tr>
<td>33</td>
<td>( y(t-4)^2 )</td>
<td>x</td>
<td>x</td>
<td>0.0148</td>
</tr>
</tbody>
</table>

TABLE VI. STATISTICAL CRITERIA PERFORMANCE

<table>
<thead>
<tr>
<th>Method</th>
<th>Testing set</th>
<th>RMSE</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAB-NARMAX</td>
<td></td>
<td>0.0489</td>
<td>0.0385</td>
</tr>
<tr>
<td>LASSO</td>
<td></td>
<td>0.0489</td>
<td>0.0402</td>
</tr>
</tbody>
</table>

IV. CONCLUSION

This study proposes a novel mask attention-based NARMAX (MAB-NARMAX) method for solving the model structure detection problem which is a fundamentally important and challenging task in most real applications. MAB-NARMAX makes use of the power and good properties of NARMAX, and the efficient computational and information processing capability of the mask matrix used in the Transformer neural network model. The mask matrix used in MAB-NARMAX is actually a mask vector; it has a simple structure but can help produce more precise, efficient and parsimonious models than the most commonly used state-of-the-art methods – LASSO and LSTM for the multi-step-ahead (long-term) prediction, as shown by the three numerical examples. The application of MAB-NARMAX model is not limited to the polynomial NARX and NARMAX models. It can also be applied to any linear-in-the-parameters modelling. Still, a further comprehensive study and investigation on the mask matrix and the backward optimization in MAB-NARMAX will be carried out in the future.

The limitations of this study lie in two aspects. First, we have only used mask matrix as feature selection. In the future, more investigations on the backward optimization scheme will be carried out. Second, our experimental studies focus on three numerical examples, but in the future, more analyses on real-world application will be investigated.

ACKNOWLEDGMENT

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[2] H. L. Wei, S. A. Billings, and J. Liu, "Term and variable selection for non-linear system


An Overview of Artificial Intelligence in Product Design for Smart Manufacturing

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Abstract—Artificial intelligence (AI) has received significant attention nearly from every part of the world because it is a critical technology approach in developing intelligent systems. The manufacturing sector utilises AI, especially in the product design stage. This paper presents an overview of how AI can enhance the product design stage for smart manufacturing. First, the paper introduces an overall understanding of smart manufacturing, its definition, importance, and characteristics. Then, it delivers a brief overview of the stages of product design. The essential concepts of AI techniques as well as various AI applications in the product design stage ranging from conceptual, embodiment, to detail design are discussed. Finally, research challenges and future directions for using AI in smart product design are provided and discussed.

Keywords - smart manufacturing; product design; artificial intelligence; machine learning; deep learning.

I. INTRODUCTION

The fourth industrial revolution is characterised by smart manufacturing, which plays an essential role in the world. The crucial features of smart manufacturing are the complete integration of the various technologies to increase flexibility through real-time responses and collaborations [1-3]. All features aim to deliver products to the customer on time with high efficiency so customer needs can be satisfied through personalisation and customisation. Each process in the manufacturing industry, especially product design and development [4], needs to significantly improve its efficiency [5] in terms of shortening operation time for high performance.

To achieve smart manufacturing, various technologies e.g., internet of things or cyber-physical systems are used in combination. Because most of the technologies depend on a data-driven strategy, a vast amount of data is created during the operation stages of a manufacturing process. Artificial Intelligence (AI) has been applied in the manufacturing operations [6] to analyse the data to make decisions for operating systems to reduce any effect that impacts cost and quality. AI systems aim to respond in real-time to process issues. More advanced AI even self-monitor and self-control in an autonomous style.

Product design is a crucial though time consuming activity [7]. A designer normally spends more than half of the time on organising data and designing knowledge [8]. To develop a smart design which meets customer needs, increases market competitiveness, and design effectively, this stage requires the employment of essential tools such as AI to support developing design, analysing data, and managing design knowledge efficiently.

This paper contributes to developing product design by using AI in smart design for smart manufacturing. In addition, this paper provides an overview of smart manufacturing characteristics, an introduction to the concept of AI, and a background into smart product design.

II. UNDERSTANDING OF SMART MANUFACTURING

A. Definition of Smart Manufacturing

The fourth industrial revolution or “Industry 4.0” is well-known in the industrial sector [9]. The main concept of Industry 4.0 is the digitalisation of manufacturing by the integration of various innovative technologies. Smart Industry 4.0-systems utilise real-time data between devices and machines, machine-to-machine and machine-to-systems [10] for real-time response, self-planning, self-control, self-monitoring [11].

Smart manufacturing as a concept has been used to describe manufacturing systems which are driven by data-driven technologies [12, 13]. Smart manufacturing implemented as a completely integrated intelligent system serves customer needs in real-time to react to changing demands and conditions in a factory [14]. Technologies that have been used in smart manufacturing are e.g. the Internet of Things (IoT), cyber-physical systems (CPS), cloud computing, data mining, robotics and artificial intelligence (AI) [15].

B. Characteristics of Smart Manufacturing

Customers and market demand require manufacturing flexibility to serve their needs quickly. Agile operation in manufacturing requires real-time response. Accordingly, conventional manufacturing requires improving its systems to be more intelligent and more flexible [5].

Smart manufacturing consists of six pillars: manufacturing technology and process, materials, data, predictive engineering, sustainability, and resource sharing and networking [2, 3]. The naming of the pillars varies depending on time, organisation, or researcher (e.g., production planning has been used instead of predictive engineering). This paper focuses on the characteristics rather than the names. The characteristics of smart manufacturing (Fig 1.) are as follows:

The Royal Thai Government Scholarship (No. 1018.2/2856) for Janjira’s PhD study (2021-2024)
• **Flexibility**: it is defined as the ability to adjust and operate due to changing requirements [3], as well as increasing market demand in terms of customisation and personalised products (e.g., changing colour, changing the part, more features added). Therefore, the manufacturers require to develop the systems, methods, and tools for more flexibility and cutting down the lead time, leading to meeting customer needs and launching the products in time and increasing market competitiveness.

• **Quick response**: when the market changes due to new trends, new innovative technology or other disruptions, it is necessary for manufacturers to improve or adjust their strategies to minimise the operation time and serve products in time, especially in product development, product design and manufacturing stages [4].

• **Communication and collaboration**: the objective is to meet the specification of the product accurately and with high efficiency in time. Thus, communication and collaboration in the respective section such as marketing, design, production, service, etc. is very important because stakeholders should be up-to-date on all information in real-time, leading to more efficient monitoring and problem prevention.

• **Integrated intelligent system**: integrating the innovative technologies such as IoT, CPS, cloud computing, AR, robotics and AI to form a smart manufacturing system that uses smart design, smart monitoring, smart machining, smart control, and smart scheduling [11] to support all the requirements mentioned above. Integration of intelligent systems causes lower cost, higher quality, shorter lead time, quick response.

![Figure 1. Characteristics of Smart Manufacturing](image)

III. PRODUCT DESIGN

A. Definitions of Product Design

Product design in this context is the process of designing a product that begins with receiving the market needs or customer needs until generating the product's overall detail before production. Moreover, product design is a crucial step because many factors need to be considered to meet requirements. Fig. 2 shows factors in product design that are affecting a product. For example, the materials selection process not only means selecting by the properties of materials but also considering aesthetic issues (texture, colour) and cost.

![Figure 2. Factors that affect product design](image)

B. Stages of Product Design

There are many activities in a product design stage, including the translation of customer needs to technical requirements, designing the shape and form, selecting materials, and considering the possibility of manufacturing and the assembly process until the overall product detailing is completed before moving on to the production stage.

Product design can be separated into three stages: conceptual design, embodiment, and detail design [16], as shown in Fig. 3.

![Figure 3. Product design stages](image)

• **Conceptual design**: in this crucial stage, an unwise decision becomes the root of complexity in the operation [7]. All the activities in this stage deal with the needs and requirements, such as analysing customer needs and design requirements, specifying the main function, and searching for principles for solving the fundamental design problem [10]. Moreover, it requires evaluating the conceptual design, an overview of the design, to finally select a feasible concept.

• **Embodiment design**: outcomes from the stage are to clarify, confirm or optimise the details in primary design functions [17], such as the form design (shape and material of part), manufacturing process, assembly, and cost, as well as provide a solution for auxiliary functions if possible. If all the activities are done, the design in this stage will become the best solution, and it is chosen for the detail design stage [17, 18].

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**Detail design**: this step determines the complete overall specification, overall cost, and other key factors in detail [4, 18], such as a method of operation, aspect of assembly, and packaging, for transfer to the production phase. At this stage, the designer should have explored all of the potential possibilities that might impact the design and complete with only one choice and manufacturable solution [17].

### C. Smart Product Design

Product design is a key part of success in the market competition in terms of cost-effective and fast-to-market operation. A broad set of information is required in this stage [15]. Therefore, transforming the traditional product design into smart product design is important.

Smart manufacturing looks at the integration of intelligent systems in order to be more flexible and agile. In addition, due to its speed and data availability, smart product design can add product personalisation to classic mass production. The main characteristics of smart product design appreciate and improve user experience through personalisation, smart and connected product ecosystems, mass customisation, and smart decision-making [19].

### IV. ARTIFICIAL INTELLIGENCE IN PRODUCT DESIGN

#### A. Artificial Intelligence

There are multiple definitions of Artificial Intelligence (AI). AI has attracted much attention from many researchers in various industries. AI has been defined in many ways. Some AI definitions are shown in [4, 20-22]. Wang, et al. [4] have provided the following high-level definition of AI: "The theories, methodologies, technologies, and tools that are intended to understand human intelligence, develop artificial systems with intelligence, empower artefacts to perform intellectual tasks, and leverage computational means to simulate intelligent behaviours".

Some terminologies are referred to a AI, such as Machine Learning (ML) and Deep Learning (DL); however, these technologies are subsets of AI [23]. Here is a brief introduction to help understand the elements:

- **Machine learning**: a branch of AI focusing on the ability of programs to perform data-driven calculations such as classification, regression, or clustering [23]. There are various ML algorithms such as neural networks (NN), K-means, Decision Trees and Random Forests [1, 24], k-nearest neighbours, multi-regression, logistic regression, and Latent Dirichlet Allocation (LDA) [22].

- **Deep learning**: a branch of ML and a subset of AI. Deep Learning (DL) uses multiple layers of neural networks [25] to process numerical data. The "deep" in DL refers to the number of layers of the neural networks [23]. In the industrial sector, DL algorithms such as multi-layer perceptron and convolutional neural networks (CNN) are used for estimating costs in the conceptual design stage [26].

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**Figure 4.** The contribution of implementing AI in product design for smart manufacturing

**B. Artificial Intelligence in Product Design**

Product design can be a time-consuming process in manufacturing. However, the product design step is crucial and can affect marketing, production, and maintenance. Furthermore, there is a multitude of factors to be considered to satisfy customer needs, such as ergonomics, function, shape, service, and price resulting to designers spend a lot of time organising the many data and design knowledge. Thus, product design should employ the best cutting-edge technologies, such as AI, to facilitate the development and analyse data to serve a smart design decision, meet customer needs on time, boost market competitiveness, and design efficiently.

1) **Conceptual Design**

This step is to determine the concept function and design of the product by considering the needs translated into the concepts. Analysing the market or customer needs should be done carefully; otherwise, it will affect to the next steps which then fail to meet the final requirements.

Many researchers focused on systematically understanding the needs of the whole product, whereas, previously, the needs were captured by focus group and interview approaches [27]. The customer needs are generally expressed in natural language. Natural Language Processing (NLP) is a powerful branch of AI. However, the analysis of spoken language is challenging because the corresponding data can be unstructured, biased and prone to human error, thus making data analysis complex [22]. Wang, et al. [28] adopt a deep learning approach to improve the efficiency of mapping the customer needs and design parameters due to a large number of review data customers using natural language. Zhou, et al. [22] applied a machine learning approach to analyse customer needs for product ecosystem, which is collected by an online product review system to cut analysing time, improve effectiveness and efficiency of the online product review system. The result improved the designer’s understanding of customer needs but fails in a part of product configurations by considering the capability of the manufacturers.
In this stage not only translating needs to concept functions but also finding alternative concept design candidates for the subsequent embodiment and detail design is required. Some research points out that in the recent year applying AI, especially DL, in Computer-Aided Design (CAD) and Computer-Aided Engineering (CAE) has increased as can be seen in [29-31]. Yoo, et al. [32] researched generating 3D model and evaluation of engineering performance of a vehicle wheel by integrating AI – in this case deep learning – into a CAD and CAE system. In this system, AI estimates the engineering performance and generates a large number of 3D model candidates, which engineers and industrial designers can review and discuss. However, some points are still challenging such as expanding the scope to consider manufacturing constraints, the generation of 3D models without using 2D images, and integrated AI to CAE simulation to optimise nonlinear problems.

Apart from the customer need for translation and concept design generation, another part of the conceptual design stage also applies AI. AI has been used to estimate cost and visualise machining features to guide the designer to reduce the manufacturing cost during the conceptual design stage [26].

2) Embodiment and Detail Design

This paper presents AI applications in embodiment and detailed design stages simultaneously. The main activities in these design stages will be shown in two main activity groups, i.e. material selection and product form design.

a) Material Selection

Materials selection is one key point of product design, especially engineering design in general [33], due to the fact that materials play an essential role during the product design and production stages. Ashby [34] studied materials and developed a diagram that helps designer select materials; this is well-known as the Ashby diagram. Some study points out that there is some gap in the method for selecting materials and several researchers point out that traditional material selection depends on designer experience. Hence, many researchers became interested in adopting AI for material selection. Merayo, et al. [24] summarised and compared the related AI tools for material selection. This study has confirmed the importance of AI for making a decision in materials selection. Liu, et al. [35] use AI to classify the microstructure of graphite. The microstructure of each type is quite similar and difficult to classify by humans, but the properties are different. In case misclassifying will impact product failure [34]. Recently, Das, et al. [36] used AI to rank the candidate material and select materials for storage tanks and flywheels by comparing the result with Multiple-attributed decision-making (MADM) framework from the previous study, which lacks of evidence in the part of geometry. It was found that, their results were competitive to the real-world practice.

b) Product form design

Mechanical design is a broader term covering the design of various parts, components, products, or systems of mechanical nature [37], and sometimes refers to the designing of machine elements. The term product form design will be used in this paper. The terms ‘Product form design’ or ‘form design’ will be used solely when referring to designing the shape, features, and form of a product.

Feng, et al. [8] point out that designers spend a lot of time organising data and gathering knowledge during the mechanical design stage. Thus, many researchers tried to implement AI for managing data to reduce the workload for the designers and increase the quality of product design.

Recently, Bermejillo Barrera, et al. [20] study AI-aided design by implementing AI and a CAD model library to predict the structure and properties of tissue engineering scaffolds to serve in different design requirements. The interesting point is that simulation and conventional design cannot be applied due to the geometry complexity and aspect ratio of tissue engineering scaffolds. The paper validated possible ways for using AI-aided design of tissue scaffolds which might lead to an automated design. In addition, Krahe, et al. [21] aim to automate product design by implementing Deep Learning algorithms to identify design patterns to a product family out of their underlying latent representation. This study used classes of tables, chairs and sofas, and extracted knowledge to automatically generate new latent object representations fulfilling different product feature specifications. Obviously, this study provides the trend to become an automated design to support smart manufacturing; the product family can be created according to given product specifications. However, it still needs to improve in terms of dimensional errors.

<table>
<thead>
<tr>
<th>TABLE I. APPLICATION OF AI TECHNIQUES IN PRODUCT DESIGN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Applications</td>
</tr>
<tr>
<td>Customer needs analysis</td>
</tr>
<tr>
<td>Cost estimation for design guidance</td>
</tr>
<tr>
<td>Material selection</td>
</tr>
<tr>
<td>Prediction of structure and properties</td>
</tr>
<tr>
<td>Predictive 3D model</td>
</tr>
</tbody>
</table>

It can be observed that existing data (e.g., CAD library, existing pattern of product family, previous data design) is attractive to many researchers in order to facilitate designers to reduce time-consuming tasks and design mistakes during the product design stage. As mentioned above, Bermejillo Barrera, et al. [20] and Krahe, et al. [21] aim to use historic data to transfer conventional designs into automated designs using AI. On the other hand, Vasantha, et al. [39] use the previous data design, such as features and configurations, to propose a predictive CAD system that suggests design engineers new valve designs. Moreover,
this study also mentions that the productive system should be a user interaction rather than fully automated because the designer interaction can be used to improve the accuracy of this system. While this study has completed to facilitate the design a valve, there are also opportunities to improve the functionality of the system, such as expanding the scope to multitype features.

V. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

According to the overall review on AI application for product design for smart manufacturing, the challenges and the future research directions can be summarised as follows:

- Analysing the customer needs faces the challenge of dealing with natural languages. Natural language often does not use technical terms which makes direct translation into a technical design language difficult. Moreover, understanding and analysing the whole product ecosystem is complex and can be time-consuming. Zhou, et al. [22] pointed out that mapping customer needs to product attributes still needs more research.

- Material selection still poses research challenges. Dealing with material selection in a balanced manner between technical design and industrial design is difficult due to the fact that industrial design considers subjective aspects such as e.g. emotion, aesthetic, perception, which can be difficult to map to technical specifications. In addition, the lack of datasets and structured methods for industrial design can lead to unpredictable outcomes [40]. Ferreira, et al. [34] highlighted that 96% of designers require smart material selection tools which are not available yet.

- Product designers, especially during product development, often use previous knowledge and know-how. Design procedures based on designer’s experience becomes very individual. This makes knowledge transfer between designers challenging. Know-how and designer experience is valuable. Efficient knowledge capture and use through AI is still an open challenge.

VI. CONCLUSIONS

As the fourth industrial revolution plays a significant role globally, various industries pay more attention to transforming traditional systems into smart systems. AI is one crucial tool that is used for transferring a conventional system into an intelligent system. This paper has presented an overview of smart manufacturing and AI application. It shows how AI can and has enhanced the product design stages. Three substages, i.e. conceptual design, embodiment design, and detail design have been considered in terms of using AI. Examples of using AI for converting the customer needs to design requirements in the conceptual design stage, and implementing AI for decision making in materials selection correctly in the embodiment design stage is discussed. The paper also highlights that some activities in product design still require further research. This includes analysis of customer needs to find hidden requirements, and managing of product design historical data to improve designs from reconstruction of historical data, and developing tools for materials selection.

REFERENCES


Digital Circuit Simulator Development with CNN Integration

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Abstract—This paper investigates a machine learning integrated circuits simulator design and development. It aims to provide a prototyping framework that may assist digital integrated circuit engineers in designing digital circuits utilising machine learning support. Currently, there is no existing solution on the applications that integrated digital simulator with machine learning. Many digital simulators cannot be extended due to lack of API, and they would struggle to generate datasets in real-time for the simulation models. The developed platform focuses on designing the overall application and the implementation aspects of the machine learning integration. In particular, a sophisticated gate-level simulator was developed using C++ and LUA programming languages; the gate-level simulator contains various features to be effortlessly integrated with most python machine learning libraries via a communication channel. Also, convolutional neural network model is adopted, which directly communicate with the simulator by retrieving live datasets and controlling the simulator by prediction scores. An example has been given as a case study for demonstrating the developed prototype.

Index Terms—Digital integrated circuit simulator, Machine learning, Convolutional neural network, Software engineering, Computer-aided design

I. INTRODUCTION

The Microprocessors currently power our modern technologies such as phones, home computers or even gigantic data centres. A microprocessor is an electronic component that is implemented on a single integrated circuit (IC). ICs allow us to fabricate extremely small chips; we can fit millions or even billions of tiny electrical components that can form complex digital circuits. IC’s do not always have to be microprocessors, they can contain any circuits inside them; circuits can be classified into two categories: 1) combinational circuit is a memoryless circuit, and it is a pure function where output is only dependent on the input; 2) sequential circuits can have a memory, normally works with a clock signal.

Modern processors and logic chips can contain thousands of logic gates that make up digital circuits, while the digital circuits help us to create and design complex structures such as memory, adders [4]. In neuroscience, the equivalent-circuit models [5]–[8] are widely used where the modelling validation can be produced via the IC simulation. Digital circuits can be classified into two categories: 1) combinational circuit is a memoryless circuit, and it is a pure function where output is only dependent on the input; 2) sequential circuits can have a memory, normally works with a clock signal.

Nowadays, machine learning (ML) can solve various decision-making problems where the standard coding instruction approach is not viable. Deep neural networks can learn how to solve complex problems by learning something from experience rather than by instructions. The main goal of machine learning algorithms is to build models that can learn from large datasets and optimise accuracy over time without being programmed [9]. Motivated by ML, we investigate if it is helpful to complete the digital circuit simulator automatically.

It has been shown that the IC design is challenge in practice while the complexity would be reduced if a simulator can be designed and developed to achieve the basic functions mentioned above. Some existing results have been demonstrated in [10]. However, the latest ML technique has not been included into the existing designs. Thus, this paper aims to research and develop a sufficient real-time gate-level simulation platform. Different from existing applications, the presented platform is given with machine learning supports. In particular, the convolutional neural network [11] has been introduced into the platform. In summary, the contributions of the paper are given as follows: 1) designing and developing a performant gate-level simulator and 2) researching, implementing and testing two deep neural network models and integrating those models with the simulator environment, for example, placing logic gates in a specified area or connecting logic gates.
II. REQUIREMENT ANALYSIS

The objective of this application is to design and implement a digital circuit simulator software that can be effortlessly integrated with python machine learning libraries; ease of integration will allow developers to test out various machine learning models. Based on the analysis, implement those models using python and perform multiple tests. The favourable outcome of this platform is to have a performant digital circuit simulator with an interactive graphical interface; users should be able to create complex or simple circuits using various logic gates. Also, usage of deep machine learning to assist or generate circuits automatically by training.

Thus, the software requirement can be divided into three parts: Part A will be the largest chunk of the project as a custom digital circuit simulator is developed. Part B will develop the ML extension for the simulator with Python communication. Then, this part is to establish a connection between part A and B; allowing the machine learning integration with the main application. Finally, Part C, this stage will test the prototype with a functional demo, the ML interacts with the simulator and learns.

The functional requirements will outline the main features that the final product is required to implement. The Functional requirement, shown in the list below, defines the most significant functions which must be implemented and designed. Part A: Circuit Simulator.

1) Initialise an application Window and add various input listeners such as resizing/dragging and closing. The Window class should also include a while() loop; while() will contain application update cycles. The window name, dimension, frame limit should be defined before execution.

2) Dynamic Graphical interface implementation: an implementation should allow the dynamic attachment of various components to the window; these components include icons, inputs, charts, text, lists, buttons, toolbars, anchors. The UI components should be dynamically added (Random ID) and handled.

3) The application should be able to change the cursor to different bitmap images, the custom cursor will provide interaction feedback; for example, when a user enters a node-connection mode, the cursor will have a wire symbol. Implementation should support multiple cursors.

4) The application architecture should support “modules”, modules can be added, removed, and disabled while the application is running.

5) The application should include standard modules/widgets: Env Service, Saved circuits, Console, Tools, Machine Learning, Waveform viewer, Stats, Simulation, left toolbar, right toolbar.

6) The Modules/Widgets should be able to extend the graphic class; this class will create a consistent widget UI inside the window; the widget can be dragged, closed, and resized. Each module can specify widgets content, such as buttons, inputs, text.

7) The widgets – “Env Service, saved circuits, Console, Tools, Machine Learning, Waveform viewer, Stats, Simulation, left toolbar, right toolbar” should all be functional and have a purpose. Also, each widget should be added to the left toolbar for quick access.

8) LUA scripting language should be integrated with C++; LUA integration will be used for loading logic gates and chips from files.

9) 13 default logic nodes must be created using .lua files. The implementation should scan the directory and load all .lua files. Loaded nodes should be automatically added to the right quick-access toolbar. The default nodes include: “AND, NAND, NOR, NOT, OR, POW, XNOR, XOR, BUTTON, CLK, BULB, REL, CTR 4” logic nodes.

10) The graphical canvas should be implemented; it should render logic nodes, wires, states, various visual helpers. The canvas should also allow the user to visually manipulate logic nodes by dragging, removing, connecting.

11) All connected logic nodes inside the canvas must be simulated, simulation should accept a vector stack of logic nodes and simulate them one by one. The logic node simulation instruction is defined in the .lua file.

12) Experiment with different optimisation methods for the logic nodes simulator; (eg levelisation, GPU offloading). The canvas/simulator should be offloaded to a separate thread – detached from the main renderer window.

13) The circuits chunks can be saved and loaded back using the “saved circuits” widget. Circuit connections and relationships should be maintained. The JSON file format will be used to save circuit chunks.

Part B: Machine Learning.

1) Python and C++ must communicate using shared memory. Both applications should send or request data from each other. (eg Python may request canvas pixel data for training AI and the simulator may request some instructions).

2) Python Machine learning implementation should save trained models for future use.

3) Convolutional neural network implementation. The dataset should be provided by simulator using the map communicator.

4) Once Training is finished, the application should output various evaluation metrics such as accuracy, F-score.

Part C: Software Testing via a demo.

1) AI should learn where to place the components on the canvas, the user can manually highlight preferred location and components to be placed, also AI should place them without any collisions.

2) AI should be able to accurately connect logical components.

III. ARCHITECTURE DESIGN

Good architecture design is a foundation for a stable and scalable application. As previously discussed in the require-
ments and analysis chapter, the simulator architecture implementation will follow a modular approach. This section will discuss implemented architecture for the circuit simulator, describe different system components, folder structure and overall design.

A. Design layers

The application architecture was designed and implemented in a modular manner. Modularity allows the application to be scalable and modifiable; adding new features or various neural network models must be a simple process. To accomplish system modularity, different parts of the system architecture were divided into multiple layers; layers start from core systems and ending with modifiable/dynamic components such as widgets and logic nodes. Hierarchical architecture allowed the author to separate different system functionalities into separate layers, every higher layer (higher position/rank) can communicate with the layer below but not vice versa. This approach makes sure that the foundational functionalities are not dependent on the non-essential features such as the implementation of a waveform viewer. The limitations of this approach are that the foundational system must be designed correctly, or the entire system will be buggy and hard to maintain. Figure 1 demonstrates final architecture implementation in a simplified hierarchical layout style; the start or parent layer of the architecture starts from "OS". The modular architecture will require more user memory as the modules must be loaded and unloaded dynamically; the module reloading must be accomplished in a memory-safe way and avoiding any crashes.

B. Application initialisation

Application initialisation is inside the main class called neuralgate.cpp, this class is responsible for setting everything up and initialising different components in a specific order. The activity figure (Fig. 2) clearly shows the stages of application initialisation and the main thread loop.

C. Folder structure

After every major update or multiple bug fixes, the source code is compiled into binaries (executable or .exe files), it is necessary to pack compiled binaries into a specific folder structure. The purpose of folder structure is to separate various resources by format type, this makes navigating the final product much easier and folders content is self-documenting by using the appropriate folder names. The compiled binaries will also require libraries in a dynamic-link library format or .dll for short, these libraries are being loaded at runtime; libraries such as sfml.dll, lua.dll, opengl.dll, if these libraries are missing the application will fail to start. The application will only fail to start if essential .dll libraries are missing, the “content” folders do not have to include anything; the application will handle file-missing exceptions.

IV. IMPLEMENTATION

This section will overview and discuss the implementations of different parts of the system and implementation of machine learning models, because of the application scale, not all features or functions will be included here; only major functionalities such as user interface, modules, simulation, convolutional neural network have been given in the paper.

A. Graphical user interface

The graphical user interface implementation was decided to be developed from scratch, a custom-built interface provides lots of control over performance and functionality. Originally,
the GUI was implemented statically, adding new features, or changing existing code was problematic and time-consuming; in the final product, GUI implementation was redesigned to allow modular architecture. New GUI architecture provides lots of flexibility and ease of adding different UI elements such as buttons, inputs, charts to the main window. Currently, GUI has the implementation of text, icons, input, chart, widget, list, button, toolbar, and anchor elements. In the original GUI implementation, elements rendering was done pixel by pixel, to increase rendering performance most of the elements were offloaded to OpenGL, offloading graphical elements to the OpenGL increased performance by a lot. To further improve GUI performance, GUI is only being updated when the user is performing actions such as clicking on a button or dragging a window. Lots of polish was done to make GUI smooth and interactive, user can resize, close move windows around. Fig. 3 demonstrates the final user interface for the simulator application. The final product looks like the functional requirements prototype.

B. Developed modules

The application has a modular architecture. Each module can be added or removed without affecting the core functionalities. The modules do not depend on each other and can work independently. Each module can bind to many parts of the application, for example, Module A can bind its functions to the main application loop, circuit simulation thread or even rendering stages; this allows modules to have different execution points and work with data structures at different levels. Every module can also extend a graphical user interface, this allows modules to be visual, but it is not always required; some modules can run as a background process. The implementation of modules is dynamic, meaning modules can be loaded or unloaded while the simulator is running. Tools, Waveform Viewer, Status Bar, etc. have been developed.

C. Simulation

Logic gate simulation is the major feature of my application, every single logical node in the circuit must be simulated correctly for every single simulation tick, simulation tick speed can be defined by the user. To begin simulating a circuit, the circuit class must be passed to the simulator thread, circuit class is like a container that holds various logic gates in a vector array. The simulator class simply simulates every node in the circuit vector, also in some cases simulator will traverse linked connections; the simulator will check if the previous node was simulated, this will continue until the simulator reach a parent node or simulated node. This implementation is basic and may not be efficient as in the worst-case scenario all nodes will be traversed. The Circuit class contains few optimisations utilities such as levelisation or grouping which reduce the need for node traversal. Every simulated logic node contains an abstract function called run(). The run() function requires few arguments (input nodes and current signal state), the input nodes will be used to decide the logical node signal level (HIGH or low).

The simulation implementation is a runnable component, meaning the simulation class is offloaded into a different thread, this will separate window renderer and simulator; this approach will prevent the main window and system from freezing when simulating large circuits. The limitation and problem with this approach are that both threads (simulator and core system) need to be synchronised to avoid any deadlocks or exceptions from accessing the same resources (this will crash the application). The simple solution is to make the simulator thread wait when logical nodes or circuits are being accessed by the main system.

D. Canvas

Canvas is a class that handles circuit rendering; the purpose of the canvas class is to visually represent circuits. Every placed node on the canvas is colour-coded based on its output signal, if the output signal is 1; node colouring will be light (HIGH), else node colouring will be dark (LOW). When logical nodes are connected, the wires between connected nodes will be rendered with representing power colour. Activity Diagram in Fig. 5 demonstrates the overview of canvas rendering stages, each stage can be turned off using a console command.

E. Python NMAP & Machine Learning

Establishing communication between python and the simulator is an important task, various investigations were done to find a reliable and fast approach to establish communication between two languages. The simple method will be by sharing
a local file and taking turns in reading or writing; this method will significantly slow down the performance. The second method is using the python C++ library and integrating the python code directly into the source, this method will reduce the flexibility and restrict us from experimenting with different neural network models. The decided method is to use a hMapFile object which is included in windows.h library, the hMapFile can be used both by python and C++, disadvantage of this approach is that the application will only function on windows machines. This method allows both applications to communicate fast, this is done by accessing memory directly.

The class in my simulator implementation is named Nmap, this class can dynamically put multiple buffers on the memory or receive data. Python implementation is like the simulator, it can receive or put things on the buffer. This method can be dangerous as if both applications will try to write, the buffer will be corrupted. To prevent simultaneous write operations, both applications take turns, initially the simulator will put various things such as app_id, pixel_array_data and some other arguments to the buffer and start listening to any changes. If python implementation successfully reads the buffer; it will save the buffer copy to a local variable and respond with a message, instruction, or data, if the simulator notices the changes in the data buffer, it will start rewriting. Fig. 6 demonstrates how both python and the simulator communicate; both the simulator and neural network can exchange data using the communication channel.

F. CNN module

The convolutional neural network is the primary model that will be utilised for analysing and finding patterns in the circuit simulator. The hyper-parameters and number of layers may vary from problem to problem and can be modified by the user.

For the convolutional model demonstration, the circuit simulator generates lots of datasets with various node placement accuracy; the generated dataset will be used to train a convolutional neural network. The goal of the model is to place nodes in the correct position without any guidance. Nodes must be placed in the greenish area. This method is planned to be integrated with the reinforcement learning model. The convolutional model is used to place the node in the specified area (Fig. 7), but the model can be adapted for many potential scenarios or problems.

V. Demonstration

This section will discuss various methods used to improve simulator performance and stability, also present software testing for code quality and functionalities.

A. Levelisation

Levelisation is an algorithm used to optimise large or small circuits. Levelisation is an optimisation process that sorts logic gates by order, normally when a new logic gate is appended to the vector stack, the logic gates in the stack will not contain any specific order, this means simulation will go over the entire vector stack and simulate each node; this process requires multiple passes to simulate all logic gates. The levelisation technique solves this problem by ordering all logic gates in the circuit. The levelisation algorithm starts from the main inputs in the circuit and traverses to the output gates; the algorithm will assign an order number or level to the logic gate node class; the level will be used to sort logic gates in ascending order. After the levelisation method is applied, the simulation must simulate logic gates once, starting from the lowest order gate.

Fig. 8 shows the levelisation algorithm in practice, our circuit is divided into groups, this change will greatly affect how our simulation is being simulated; simulation will start by executing the first nodes called “input” nodes, then middle nodes, and finally our output nodes. The disadvantage of this approach is that some circuits such as a flip-flop or any asynchronous circuits (circuit with loopback) are unlevelisable. The problem can be solved by splitting the looped wire into a virtual connection.

B. CNN metrics

Evaluation of the neural network model is essential for determining how accurate and consistent the final trained
model is. The final product will include convolution NN model performance metrics. To evaluate convolution neural network, K-fold cross-validation is being used, this method segments the dataset into multiple folds; multiple-segmented datasets will be used to train multiple models. This method helps in detecting overfitting or failing to generalise a pattern.

C. Unit testing

The unit testing covers most critical functionalities that may break the simulator application if they fail, unit testing ensures the critical functionalities still operate after code changes. Coupled with unit testing, some critical operations also have exception checking and managing inside the function body to avoid any wrong inputs. Fig. 9 is an example of unit testing implemented on major functionalities and passing.

VI. Conclusions

The main objective of this paper is to present a CNN-integrated digital circuit design and development. The specification requirements have been analysed which leads to a solid foundation for implementation. The biggest challenge is to develop AI that can connect components and generalise the designs. In the current prototype, the CNN model has been achieved to position and levelisate the nodes. As a case study, the presented work linked many different paths, as the authors gained deeper insights into hardware technologies and machine learning. The developed software has a start point and gives many different opportunities for future work. A variety of machine learning models [12] can be applied to the current system to develop and advance machine learning integration with integrated circuits. The vision for this platform is to assist integrated circuit makers at the design stage, produce various AI models that do different things such as, optimisation wire length, placement, generating optimised solutions based on the specification. In particular, the Reinforcement Learning module will be developed for node connection correction as next target with software extension mechanism [13].

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References

Deep Learning on FPGAs with Multiple Service Levels for Edge Computing

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Abstract—In the Internet of Things (IoT) era, deep learning is emerging as a promising approach for extracting information from IoT devices. Deep learning is also employed in the edge computing environment based on the demand for faster processing. In the edge server, various hardware accelerators have been proposed in recent studies to speed up the execution of such DNNs. One such accelerator is Xilinx’s Deep Learning Processor Unit (DPU), designed for FPGA-based systems. However, the limited resource capacity of FPGAs in these edge servers imposes an enormous challenge for such implementation. Recent research has shown a clear trade-off between the "resources consumed" vs. the "performance achieved". Taking a cue from these findings, we address the problem of efficient implementation of deep learning into the edge computing environment in this paper. The edge server employs FPGAs for executing the deep learning model. Each deep learning network is equipped with multiple distinct implementations represented by different service levels based on resource usage (where a higher service level implies higher performance with high resource consumption). To this end, we propose an Integer Linear Programming based optimal solution strategy for selecting a service level to maximize the overall performance subject to a given resource bound. Proof-of-concept case study with a deep learning network of multiple service levels is carried out with a deep learning network of multiple service levels of DPs on a physical FPGA has also been provided.

I. INTRODUCTION

Deep learning has recently emerged as a canonical methodology in a variety of domains, including computer vision, bioinformatics, natural language processing, and robotics, to mention a few [1]. The reason behind its success can be attributed to its ability to learn from huge volume of data. Another field which is known for generating huge amount of data is Internet of Things (IoT). Recently, Tiny machine learning (TinyML) is also emerging as a new Internet of Things (IoT) prospect that calls for putting the ML algorithm within the IoT device, thanks to rapid advancements in the shrinking of low-power embedded devices and improvements in the optimization of machine learning (ML) algorithms [2].

Many recent research works have considered using deep learning networks to process the IoT data [3]. As a promising result, deep learning has successfully predicted home electricity consumption based on the data from smart meters [4]. Deep learning has also been used to provide location aware services in indoor environments and marketing in retailers [5].

Modern IoT systems demand fast processing, where data needs to be processed in smaller scale platforms rather than execution of complex process of data transfer to a cloud server for analysis. Hence, it will be worth mentioning that the use of centralized cloud for computation of deep neural network will generate bottleneck due to transfer of large set of data with limited network performance [6]. In such scenario, edge computing [7]–[9], a prolific technology for IoT services, emerges as a promising solution. Edge computation offloads the computing tasks from centralized cloud to the edge server located near the IoT devices. Moreover, edge computing is well suited for the applications like deep learning as its intermediate data size is smaller than the input data size. Self driving car is another emerging example of employing deep learning on edge environment [10].

Hardware makers are exploiting existing hardware, such as CPUs and GPUs, as well as developing bespoke application-specific integrated circuits (ASICs) for deep learning, such as Google’s tensor processing unit (TPU) to speed up deep learning inference [11]. Deep Neural Network accelerators based on field-programmable gate arrays (FPGA) are another promising method, as FPGA can enable fast computing while keeping reconfigurability [11]. The deep learning processing unit (DPU) is developed as a general accelerator on an FPGA to handle multiple CNN layers, such as convolution, pooling, and activation, and to meet various CNN architectures [12].

Recent research works [13], [14] have assumed that the edge server has sufficient hardware resources (FPGAs or cpus) in terms of computation capacity (memory size) to successfully extract intermediary features using deep learning layers. However, this assumptions will not be true in many cases. In case of resource constrained edge computing environment [15], it has also been observed that there exists scenarios where completion of tasks is more critical than achieving the higher performance [3], [15]. Hence, in order to carry out successful execution of deep learning in a resource constrained FPGA-based edge computing framework, we consider each deep learning network, to be equipped with multiple distinct implementations represented by "service levels". Each implementation of the learning network produces the same result of prediction or classification, but with different levels of performance (in terms of GOPs). Higher service level will return higher performance however, it can typically be achieved at the expense of more resource (i.e. DPU size...
The idea of of having different service levels for deep learning network is supported by the research findings reported in [16]. In this research, the authors have found out that out of all, the memory requirement weight parameters contribute most to the memory footprint. The research further proves that a reduced precision in representing 20% weight parameters results in 1% performance loss. Taking cue from these findings, we propose a strategy for deploying deep learning for IoT into the edge computing environment. Depending upon availability of resource budget each deep learning network on an edge server is executed at a particular service level.

In this paper, we develop the algorithmic support for efficient implementation of deep learning into the FPGA-based edge computing environment, where multiple versions of DPUs are used for executing the neural networks. Specifically, we answer the following question: Given a upper-bound on available resources in an edge computing environment (maximum area/resource capacity of the FPGA), how do we ensure that the DPUs will efficiently execute deep learning network in a specific service level, while maximizing the overall performance (GOPs) of the process.

The contributions of this work are summarized as follows:

- Introduction of framework for deploying deep learning in FPGA-based edge computing framework of IoT systems with multiple service levels.
- Development of Integer Linear Programming (ILP) based technique to obtain optimal selection of service level for deep learning network.
- Evaluation of the proposed ILP based strategy with simulation experiments.
- Exhibition of the proof-of-concept by a case study which implements image classification applications on DPUs with multiple service levels with various area requirements.

II. SYSTEM MODEL AND PROBLEM DESCRIPTION

In the proposed system model, Deep Learning Processor Unit (DPU) from AMD-XILINX FPGA have been employed to speed up the execution of Convolutional Neural Networks (CNNs). In [17], [18], the authors have showed that although each CNN can only consume one DPU, many DPUs can be constructed together on an FPGA to enable concurrent CNN operation. Each DPU has its own requirements of computing resources and BRAMs.

Without loss of generality, we assumed an FPGA-based edge computing environment where the edge server is equipped with FPGAs, where each FPGA may contain multiple DPUs. In the given edge computing environment, let us assume that \( D \) denotes the set of \( N \) DPUs available in an FPGA: \( D = \{D_1, D_2, ..., D_N\} \).

It has been assumed that based on the degree of FPGA resources allocated, each DPU will be equipped to execute the deep learning network for testing in different service levels based on the available resources. An DPU, at any instant, will execute the deep learning model in any one service level among the possible \( q \) service levels i.e., \( l_i = \{l_{i1}, l_{i2}, ..., l_{iq}\} \). Hence, \( j^{th} \) service level of \( D_i \) can be denoted as \( l_{ij} \). The service of a level is proportional to its level-ID. Thus, 1 is the lowest and \( q \) denotes the highest execution level.

It can be concluded that higher be the service levels, higher will be its resource consumption. This resource consumption could be in terms of energy consumption, memory consumption of the FPGA. On the other hand, execution of the network in high service level will result in more enhancement of the performance level of the testing process. Service levels with varying degrees of performance Vs. resource trade-offs can be obtained by controlling the degree of resources incorporated in the DPU [18]. This concept has also been validated in Section V. This work assumes that, higher be the service level of \( D_i^{l_j} \), higher is its resource consumption \( Res_{ij} \) (\( l_{ij} > l_{ij}^{l_j} \Rightarrow Res_{ij} > Res_{ij}^{l_j} \)). \( Res_{ij} \) denotes the resource consumed by \( D_i \) while it executes the deep learning network in \( j^{th} \) service level. Similarly, we have also assumed that performance \( per_{ij}^{l_j} \) will be assigned to \( D_i^{l_j} \) if the \( i^{th} \) edge-server (\( E_i \)) successfully executes the deep learning network in \( j^{th} \) service level by fulfilling the resource demand.

We have assumed an resource constrained edge computing environment as stated in [15]. Thus, we are imposing the following constraints i.e. i. The overall resource budget \( R_{total} \) is fixed for the FPGA. The detailed calculation of is provided in Section V. ii. Having the given \( R_{total} \), each DPU has to finish the execution of deep learning network by selecting a service level.

Problem Description: Given \( N \) DPUs equipped to execute deep learning network in \( q \) service levels, determine a service level for each DPU such that the overall testing performance is maximised, while satisfying the given constraints. The pictorial description of the problem is given in Figure 1.

III. ILP BASED LEVEL SELECTION STRATEGY

In this section, we present an Integer Linear Programming (ILP) solution to our proposed problem. For this purpose, we define a binary decision variables: i. \( Z = \{Z_{ij}^{l_j} : i = 1, 2, ..., N; j = 1, 2, ..., q\} \). Here, indices \( i \) and \( j \) respectively denote DPU ID and corresponding selected service level ID. \( Z_{ij}^{l_j} = 1 \), if DPU \( D_i \) executes in \( j^{th} \) service level and obtains \( Per_{ij}^{l_j} \) performance value. \( Z_{ij}^{l_j} = 0 \), otherwise.

We now present the required constraints on the decision variable to model this problem before presenting its overall objective function.
TABLE I
RESOURCE AND PERFORMANCE VALUES FOR EACH DPU

<table>
<thead>
<tr>
<th></th>
<th>$D_1$</th>
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<th>$D_2$</th>
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</tr>
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</table>

TABLE II
OUTCOME: ILP

<table>
<thead>
<tr>
<th>DPU</th>
<th>Selected level</th>
<th>Obtained performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D_1$</td>
<td>3</td>
<td>16</td>
</tr>
<tr>
<td>$D_2$</td>
<td>2</td>
<td>6</td>
</tr>
<tr>
<td>Total obtained performance</td>
<td></td>
<td>38</td>
</tr>
</tbody>
</table>

1) **Resource Constraint:** The deep learning network has to be executed on FPGA within the total available resources in FPGAs, $\bar{R}_{total}$. This essentially means that the summation of consumed resource by each DPU should not exceed the given budget for the entire FPGA. This constraint is imposed through the following equation.

$$\sum_{i=1}^{N} \sum_{j=1}^{q} Res_i^j \times Z_i^j \leq \bar{R}_{total} \quad (1)$$

2) **Service level Uniqueness Constraint:** Each DPU will only be allowed to execute the deep learning network in at most one service level. That is,

$$\sum_{j=1}^{q} Z_i^j \leq 1, \forall i \in [1, N], Z_i^j \in \{0, 1\} \quad (2)$$

3) **Objective:** The objective of the formulation is to choose that feasible solution which maximizes the overall performance of the prediction / testing process through appropriate choice of service levels. Hence, the objective can be written as follows:

$$\text{Maximize } \sum_{i=1}^{N} \sum_{j=1}^{q} Per_i^j \times Z_i^j \quad (3)$$

A. **Example: Proposed strategies at work**

In this section, we have illustrated the working mechanism of the proposed strategy through an example for ease of understanding. Let us assume, there exists three DPUs, i.e., $D_1$, $D_2$ and $D_3$ in an FPGA, resource demand ($Res_i^j$) and corresponding performance $Per_i^j$ value for each service level is provided in Table I. We have also assumed that the available overall resource budget ($RES_{BGT}$) is 35. The total obtained result is shown in Table II. We have solved the ILP based technique for the same input values, provided in Table I through CPLEX solver [19] and the obtained outcome is presented in Table II.

IV. **Simulation & Results**

The performance of the proposed strategy has been evaluated using simulation based experiments. In this current experimental scenario, We have considered that the FPGA is capable of executing deep learning network in 3 distinct service levels and FPGA consists of 3 DPUs, as shown in [17]. The area consumption and corresponding performance values have been taken from [20].

A. **Results**

Experiments have been conducted to evaluate the performance of the proposed strategy i.e., ILP based technique. The performance metrics which have been considered for the evaluation are:

1) Average service level allocated to each DPU
2) Normalized Obtained Throughput (NOT), NOT is defined as the ratio between the ultimately achieved performance value for the DPU and the maximum possible achievable throughput by executing the network at their highest service level. Mathematically, NOT can be formulated as:

$$NOT = \frac{\sum_{i=1}^{N} \left( \frac{Per_i^j}{Per_{max}} \right)}{N} \times 100\% \quad (4)$$

![Fig. 2. Average allocated level Vs RES_BGT](image-url)
**RES_BGT.** This is because the NOT value obtained by the strategy is proportional to the allocated levels to the DPU and therefore, average levels allocated to all edge servers increase with available resource budget (as shown in Figure 2).

V. EXPERIMENT FOR PROOF OF CONCEPT

In this section, we provided a proof-of-concept that each DPU in the FPGA can be configured with different service levels by varying the resource utilization. To this end, we implement a deep learning-based image classification application on an AMD-Xilinx ZCU102 development platform (e.g. Zynq UltraScale+ XCZU9EG-2FFVB1156 MPSoC). This platform has been configured with a Petalinux-based operating system on an MPSoC, and it is configured with 3 separated DPs within the programmable logic fabric. The Xilinx DPU is a configurable computation engine dedicated to convolutional neural networks. The degree of parallelism utilized in the engine is a design parameter and application. It includes highly optimized instructions and supports most convolutional neural networks, such as VGG, ResNet, GoogleNet, YOLO, SSD, MobileNet, FPN, and others. Each DPU is configured into different architectures with different hardware resource-allocation strategies so that the different architectures represent different “service levels,” as stated in Section II.

To set up the onboard system, we have built the image file using an AMD-Xilinx Vitis 2022.1. Since AMD-Xilinx has already provided some standard developed packages, we re-designed the image file by exporting the packages and running the TCL scripts in Vitis. Two packages are used in the image file production, a MPSOC standard image system, and a ZCU102 base platform. The MPSOC standard image system package contains a prebuilt Linux kernel and root file system that can be used with any Zynq, ZynqMP, or Versal board for embedded Vitis platform developers.

In our experiments, a series of DPUs with different configurations are used as different service levels, listed in Table IV. The name of the architecture represents the peak performance of the DPU. For instance, B512 means the DPU can conduct up to 512 operations in one clock. To implement those service levels, we experimented with various parallelism techniques inside a DPU.

There are three dimensions of parallelism in the DPU convolution architecture - pixel parallelism (PP), input channel parallelism (ICP), and output channel parallelism (OCP). Figure 4 explains the meaning of each three dimensions, and pixel parallelism is 2, input channel parallelism and output channel parallelism both equal to 3 respectively in this figure. The input channel parallelism is always equal to the output channel parallelism. The different architectures require different programmable logic resources. The larger architectures can achieve higher performance with more resources. The parallelism for the different architectures is listed in Table III.

The experiment flow is described in Figure 5. An image classification application is running on the board, and the application is executed, split into several separated tasks through the OS on Cortex A53, and sent to different configured DPUs.

We use a Resnet-50 network to classify the image stream file with multi-thread (8). With the API interference provided by AMD-Xilinx, we deployed the neural networks in the application.

The proposed framework can also be extended to other classification neural networks, and different model parameters would lead to a different strategy for resource allocation. Usually models with more parameters will have better accuracy (like Resnet50/Resnet25).

The program also measured the power consumption, the accuracy of the classification tasks, and the total execution time.

Three types of resources are required i.e., LUTs, BRAMs, and DSPs on the different architectures of DPUs, and the resource consumption has been described in Table IV.

There are 8 different architectures (levels) deployed on the DPUs on board, and each setting means a single DPU structure, which has different sizes of LUTs, BRAMs, and DSPs. We use these three parameters to describe the resource required with a 3-dimension vector (LUT, BRAM, DSP). Each element in the vector means the usage of the LUT or BRAM, or DSP on the DPU.

### Table III

<table>
<thead>
<tr>
<th>DPU Architecture</th>
<th>PP</th>
<th>ICP</th>
<th>OCP</th>
<th>Peak operations</th>
</tr>
</thead>
<tbody>
<tr>
<td>B512</td>
<td>4</td>
<td>8</td>
<td>8</td>
<td>512</td>
</tr>
<tr>
<td>B800</td>
<td>4</td>
<td>10</td>
<td>10</td>
<td>800</td>
</tr>
<tr>
<td>B1024</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>1024</td>
</tr>
<tr>
<td>B1152</td>
<td>8</td>
<td>10</td>
<td>10</td>
<td>1152</td>
</tr>
<tr>
<td>B1600</td>
<td>8</td>
<td>10</td>
<td>10</td>
<td>1600</td>
</tr>
<tr>
<td>B2304</td>
<td>8</td>
<td>14</td>
<td>14</td>
<td>2304</td>
</tr>
<tr>
<td>B3136</td>
<td>8</td>
<td>14</td>
<td>14</td>
<td>3136</td>
</tr>
<tr>
<td>B4096</td>
<td>8</td>
<td>16</td>
<td>16</td>
<td>4096</td>
</tr>
</tbody>
</table>

### Table IV

<table>
<thead>
<tr>
<th>DPU Architecture</th>
<th>LUT</th>
<th>BRAM</th>
<th>DSP</th>
</tr>
</thead>
<tbody>
<tr>
<td>B512</td>
<td>27993</td>
<td>73.5</td>
<td>78</td>
</tr>
<tr>
<td>B800</td>
<td>30468</td>
<td>91.5</td>
<td>143</td>
</tr>
<tr>
<td>B1024</td>
<td>34471</td>
<td>105.5</td>
<td>154</td>
</tr>
<tr>
<td>B1152</td>
<td>33258</td>
<td>133</td>
<td>164</td>
</tr>
<tr>
<td>B1600</td>
<td>38716</td>
<td>127.5</td>
<td>232</td>
</tr>
<tr>
<td>B2304</td>
<td>42842</td>
<td>167</td>
<td>326</td>
</tr>
<tr>
<td>B3136</td>
<td>47667</td>
<td>210</td>
<td>436</td>
</tr>
<tr>
<td>B4096</td>
<td>53540</td>
<td>257</td>
<td>562</td>
</tr>
</tbody>
</table>

However, LUTs, BRAM and DSPs are using different units. To bring the notion of “RES”(resource) as stated in earlier
The resource consumption for different DPU architectures is shown in Table V. These results align with our idea proposed in Section 2 and depict that the expense of higher resource consumption can achieve higher service levels. Now, we will look at how these different service levels represent the notion of performance variations.

### Table V

<table>
<thead>
<tr>
<th>DPU Architecture</th>
<th>$R_l$</th>
<th>$R_r$</th>
<th>$R_d$</th>
<th>$Res$</th>
</tr>
</thead>
<tbody>
<tr>
<td>B512</td>
<td>10.18</td>
<td>8.06</td>
<td>3.10</td>
<td>13.35</td>
</tr>
<tr>
<td>B600</td>
<td>11.12</td>
<td>10.03</td>
<td>4.64</td>
<td>15.68</td>
</tr>
<tr>
<td>B1024</td>
<td>12.13</td>
<td>13.49</td>
<td>6.51</td>
<td>19.27</td>
</tr>
<tr>
<td>B1600</td>
<td>14.13</td>
<td>13.98</td>
<td>9.21</td>
<td>21.91</td>
</tr>
<tr>
<td>B2304</td>
<td>15.64</td>
<td>18.31</td>
<td>12.94</td>
<td>27.34</td>
</tr>
<tr>
<td>B3136</td>
<td>17.39</td>
<td>23.03</td>
<td>17.30</td>
<td>33.65</td>
</tr>
<tr>
<td>B4096</td>
<td>19.53</td>
<td>28.18</td>
<td>22.30</td>
<td>40.90</td>
</tr>
</tbody>
</table>

For the performance evaluation, we evaluated it with estimated performance and onboard performance. The estimated performance is defined by the peak operations of different DPU architectures, and a higher peak operation refers that the higher data throughput will be handled per clock cycle. We use the average processing time $t$ in a single task for the onboard performance to evaluate the efficiency of the DPUs. We choose $1/t$ to describe the onboard performance. The higher the value is, the better the performance is. The on-board and estimated performance are shown in Fig. 6.

Table V and Fig 6, validate the proposed concept in Section 2 via a real-life case study in physical FPGA. By using different settings of the DPUs, we can obtain a combination of different configurations for hardware resource allocations and the corresponding performance parameters. We can conclude that choosing the DPU at a high service level will enhance...
the performance level. Hence, the Service levels with varying degrees of performance Vs. Resource trade-offs are obtained by controlling the degree of resources incorporated in a DPU.

VI. CONCLUSION

In this work, a new concept of efficient implementation of deep learning with multiple service levels for IoT into the FPGA-based edge computing environment has been introduced. The problem has been formulated as an optimization problem where each DPU can execute the network with different service levels by exhibiting performance Vs. Resource trade-offs. An ILP-based strategy to maximize overall performance without violating the resource constraint has been proposed. Experimental analysis reveals the practical efficacy of our scheme. The proposed scheme can achieve 80% of throughput. Finally, a case study that implements deep learning network with multiple service levels on DPUs (on an FPGA) has been presented. The higher the resource consumption of a DPU architecture, the higher the performance will be. Thus, the obtained trend from these experiments proves that the proposed concept is valid in a real scenario on physical FPGA.

When deploying models in practical situation, resource limitation may be dominated the application requirements. Therefore, this strategy can be used as a bridge to minimise the variance by using different sizes of models, and to achieve the best performance in terms of accuracy, speed and power consumption for the application needs at run-time.

In the future, we will propose a heuristic-based strategy, and an end-to-end hardware (FPGA) validation of the software outcomes will be presented.

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A simulated annealing hyper-heuristic algorithm for process planning and scheduling in remanufacturing

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Abstract—Remanufacturing is considered as one of the major technologies for extending the life cycle and improving the remaining value of end-of-life (EoL) products. Different from the traditional common manufacturing process, the remanufacturing process has more influential factors due to the uncertain condition and complex physical structure of the EoL products. These factors will affect the planning process of feasible process routes and the scheduling process of machines allocation. Moreover, the process planning and scheduling are related and interact with each other. Therefore, it is well worth researching the integrated process planning and scheduling problem in remanufacturing (IPPSR). This paper proposes the simulated annealing-based hyper-heuristic algorithm for solving the IPPSR under stochastic process time. Firstly, the mathematical model for IPPSR is proposed with the basic assumptions and notations. Then, taking GA, NSGA2 and SPEA2 as low-level heuristic algorithms to determine the optimal process routes under the task precedence constraints. Simultaneously, construct the simulated annealing as the high-level heuristic algorithm for achieving the minimum makespan of the scheduling process. Next, the performance of the proposed algorithm is validated through the comparison with the open-source dataset and algorithms. Our proposed algorithm can achieve the lowest makespan with lower iterations. Finally, the future research directions and challenges are discussed.

Index Terms—Hyper-heuristic algorithm, integrated process planning and scheduling, remanufacturing, simulated annealing algorithm

I. INTRODUCTION

With the numerous increasing number and variety of end-of-life (EoL) products, remanufacturing has been commonly adopted for increasing the remaining value and extending the life-cycle of EoL products [1]. The process of remanufacturing can be regarded as the combination of a series of industrial processes, mainly including retrieve, disassembly, cleaning, inspection, reprocessing, reassembly, and testing [2]. Through the remanufacturing process, the condition of remanufactured EoL products should be the same as newly manufactured products. The materials and costs can be saved by replacing those broken spare parts and repairing the rest spare parts in good condition [3]. Therefore, remanufacturing is regarded as one of the most environment friendly and resource conservation methods [4].

In order to manage and improve the operational capacity and efficiency of remanufacturing process, the process planning and scheduling problems should be addressed. Traditionally, process planning and scheduling in manufacturing are treated as two separate research problems, which are two consecutive process activities and always influence and interact with each other [5]. However, different from the typical sequential manufacturing process, the remanufacturing process is variable and affected by the alternative disassembly process sequence routes and the uncertainty of processing time because of the condition and variety of the EoL products [6]. Moreover, the separate process planning and scheduling problems are two optimization problems, which may have conflicts between different optimization goals and lead to restraints on resource utilization and production efficiency [7]. Therefore, the research on integrated process planning and scheduling for remanufacturing (IPPSR) has become more meaningful. Through the review on IPPSR, there are only few papers focusing on this topic. Zhang et al. first proposed the two-layer simulation-based genetic algorithm for optimizing the processing capacities and total performance of IPPSR [8]. Wen et al. developed the IPPSR model with bio-random variable restraints and propose the hybrid intelligent algorithm for achieving better optimization outcomes from the IPPSR model [9]. Gong et al. established the hybrid multi-objective evolutionary algorithm (HMEA) for improving the speed of the optimization process of IPPSR and validating the performance of the proposed algorithm through the comparison to other existing algorithms [10]. Though the current research on IPPSR still has limitations, the integrated process planning and scheduling (IPPS) has been widely applied in other research topics, such as manufacturing [11], job-shop problem (JSP) [12], and supply chain [13], etc.

In this paper, the hyper-heuristic algorithm (HH) is proposed for dealing with the optimization process in IPPSR. The stochastic parameter is also introduced for representing the uncertain process time of the EoL products. The rest of this paper is arranged as follows. Based on the proposed assumptions and notations, the mathematical model with stochastic parameter is established in section II for representing the IPPSR. The background, encoding strategy, research framework and flowchart of the proposed HH are introduced in section III. The computational experiment based on the benchmark data is carried out and the outcomes are analysed and discussed in section IV. The conclusion and future research direction are presented in section V.
II. PROBLEM DEFINITION

The basic descriptions, assumptions and mathematical model of the IPPSR are proposed in this section.

A. Descriptions and assumptions of the problem

According to the physical structure and operational characteristics of the EoL products, each sub-part of EoL products can be classified into different job groups. Each job group contains one or more optional process tasks and the optional process can be processed by multiple machines under different process time. To make it clearer, Table I is the demonstrate example data format intercept from Appendix VI. The remanufacturing process of EoL products can be classified into three examples of data format interception from Appendix VI. The remanufacturing process time. To make it clearer, Table I is the demonstrate example data format interception from Appendix VI. The remanufacturing process of EoL products can be classified into three examples of data format interception from Appendix VI. The remanufacturing process.

It is easy and feasible to determine the optimal process sequence routes of the simple physical structure and single species of EoL products. However, the difficulties of determining the optimal process sequence routes are geometrically increased because of the non-deterministic polynomial (NP) characteristic of this optimization problem [14]. According to [8], after determining the optimal process sequence routes, the scheduling process in IPPSR is equivalent to the job shop scheduling problem (JSSP). There are some basic assumptions and notations for constructing the mathematical models of IPPSR in this paper:

- All machines are available and capable to process the given task. The transport and adjust the time of machines are not considered.
- A machine can only process one given task in each job at a time, and there is no disturbance and failure account.
- The EoL products have no hazardous jobs and tasks, which means no prior tasks or jobs. The tasks and jobs are subjected to the process precedence sequence.
- The materials and instruments for remanufacturing process are sufficient and infinite.

Based on the above assumptions, the related notations applied in the mathematical model are defined and described in Table III.

B. The mathematical model of IPPSR

Based on the proposed assumptions and notations, the mathematical model of IPPSR is constructed as follows:

The minimum makespan is the optimization goal as shown in Equation (1). The inequality (2) represents the makespan is no lower than the completion time of task in job in process route . Inequality (3) restricts the constraints of tasks among each job. The tasks should be assigned into one optional job group at a time and processed by one optional machine through the optional process sequence, the principles are regulated by Equations (4), (5) and (6) respectively. Equation (7) indicates the processing time is stochastic and obeys the normal distribution.

\[
\min f_1 = MS 
\]  
(1)
MS ≥ C_{njr}, \forall (n, j, r) = (1, 1, 1), \ldots, (N, J, R) \tag{2} \]
\[ C_{njr} - C_{n(j-1)r} ≥ x_{njmr}\tilde{t}_{njmr}, \quad \forall (n, j, r) = (1, 1, 1), \ldots, (N, J, R) \tag{3} \]
\[ \sum_{j=1}^{J} x_{njmr} = 1, \forall (n, r, m) = (1, 1, 1), \ldots, (N, R, M) \tag{4} \]
\[ \sum_{r=1}^{R} x_{njmr} = 1, \forall (n, j, m) = (1, 1, 1), \ldots, (N, J, M) \tag{5} \]
\[ \sum_{n=1}^{N} x_{njmr} = 1, \forall (n, j, r) = (1, 1, 1), \ldots, (N, J, R) \tag{6} \]
\[ \tilde{t}_{njmr} = t_{njmr} + N \left[ \mu_{njmr} \cdot (\sigma_{njmr})^2 \right] \tag{7} \]

III. The proposed hyper-heuristic algorithm

In this paper, we implement the hyper-heuristic (HH) algorithm for optimizing the IPPSR. The review of HH is processed and the details of the proposed framework and flowchart of HH are introduced in the following sub-sections.

A. Review of the hyper-heuristic algorithm

The HH algorithm is a novel approach for solving complex optimization problems, which constructs the high-level heuristic (HLH) algorithm for manipulating a series of low-level heuristic (LLH) algorithms to gain the optimal solution [15]. Different from the traditional combination or layer optimization algorithms, the hyper-heuristic algorithms are advanced strategies, which operate on the search space of LLHs and automate generating new heuristic algorithms for solving optimization problems [16].

The common conceptual model of the HH algorithm is shown in Fig. 1. The unique characteristic of this model is the domain barrier, which divides the LLHs and HLH into two different domains. The LLH domain and HLH domain are regarded as the problem domain and strategy domain, respectively [17]. After determining the related pre-setting input parameters, the LLHs are adopted to generate the optimal solution sets which formulate the optimal solution space. Initially, the HLH starts to evaluate the outcomes of the whole optimal solution space rather than evaluate the single optimal solution, this process can also be regarded as the evaluation of a single heuristic algorithm in LLH. Following, the HLH can automatically generate the non-dominated optimal vector through the combination with the optimal solution space from the selected LLH. The generated non-dominated optimal vector will be the initial optimal solution which is the input parameter of the next iteration. The optimal solution sets will output when meeting the maximum iteration times or without an update of the optimal solution sets, which is considered as the optimal solution for the specific problem.

There are some advantages of the HH algorithm. The LLHs are constituted by a batch of heuristic algorithms, which can protrude and apply the advantages of different heuristic algorithms. The extensibility of the HH is also great because of the combination of LLHs. In addition, the HH algorithm can automatically generate the optimal solutions with iterations.

Theoretically, the space of LLH is unlimited which can combine a large number of heuristic algorithms. However, the whole efficiency and performance of the HH algorithm will be reduced by those redundant useless heuristic algorithms. It is well worth researching and identifying the suitable numbers and combinations of LLHs as well as the chosen of the HLH.

B. Encoding strategy

The optional process routes of EoL products must satisfy the precedence sequence constraints. The input format in this paper is the proposed sequence dependency matrix containing the setup times of job(j)-task(t). The rows of the matrix represent the current j-t in the form j+t where j and t are the index of job and task, respectively. The columns represent the previous j-t. A matrix value at index (j+t, x-y) represents the setup time to schedule j+t j_t after j+t x-y on a machine. Matrix values with the value -1 represent cases where the current j-t (row) cannot be scheduled after the previous j-t (column). The partial format of the sequence dependency matrix is shown in Table III.

C. Low-level heuristics

The LLHs are the underlying component in the hyper-heuristic algorithm, which is operated and selected by the HLH algorithm. The higher complexity of chosen LLH algorithms will affect the overall performance of the hyper-heuristic algorithm. However, the simple LLHs may not achieve the optimal solution to the research problem. Therefore, this paper adopts GA, NSGA2, and SPEA2 as LLHs. The GA is one...
of the most typical evolutionary algorithms, which has a strong search ability and is easy to process. However, the parameters of GA have to be manually settled and the search speed is relatively slow [18]. The NSGA2 and SPEA2 are two multi-objective evolutionary algorithms [19]. The NAGA2 introduces an elite strategy and non-dominated sorting for improving the precision and speed of the optimization process. The SPEA2 applies nearest neighbor density estimation for achieving a better precise searching strategy. The above three LLHs have their advantages and disadvantages, and the computing complexity of these LLHs are relatively simple. In this paper, the LLH algorithms are called and applied from the JMetalPy, which is an open-source package for multi-objective optimization with heuristics [19]. To the best knowledge of the author, it is the first attempt to combine the above three classic algorithms as LLHs in the HH algorithm.

D. Simulated annealing high-level heuristics

The HLH algorithm is the key component for determining the performance of the hyper-heuristic algorithm. Traditionally, hyper-heuristic algorithms are divided into four main categories based on the mechanism of HLH, mainly including random selection, greedy strategy, meta-heuristic algorithm, and learning method [17]. This paper chose the simulated annealing (SA) algorithm as the HLH algorithm for operating and generating the LLHs. The compute complexity is relatively simple and suitable for solving parallel complex multi-objective optimization problems. However, the convergence rate is slow and the performance is sensitive to the initial parameters and values. Therefore, applying the SA algorithm as HLH can avoid setting initial parameters and achieve better global optimal solutions through the automatic selection of the LLHs. The framework of the process of the hyper-heuristic algorithm is shown in Fig. 2.

IV. COMPUTATIONAL EXPERIMENTS AND RESULTS

This proposed hyper-heuristic algorithm is implemented in Python and runs on an Intel Core i7-9700K CPU 3.6 GHz computer with 32GB RAM. All the experiments were repeated 10 times under certain given the stochastic process time of the proposed algorithms in comparison.

A. Benchmark data

According to the [10], there has no standard benchmark data for IPPSR under stochastic process time. Therefore, this paper adopts the online open-source data which contains 50 jobs, 222 tasks and 8 machines for the job-shop scheduling problem with the precedence constraints and optional machines. The benchmark data is tested and processed by Tabu search and GA (The dataset and related algorithms can be assessed through the link in the Appendix VI).

In this research, based on the online dataset, we add the stochastic parameter to the run speed of the machine, which equates to represent the uncertain process time for determining the optimal process sequence and achieving the minimum makespan. Then, compare the performance of the proposed hyper-heuristic algorithm to the Tabu search, GA as well as two other low-level heuristic algorithms (NSGA2 and SPEA2).

B. Parameter settings

According to the Tabu search and GA, the parameters are set as shown in Table IV. In order to eliminate the interference from extraneous variables, the initial parameters are set the same as the Tabu search and GA.

C. Experiment outcomes and analysis

Because of the introduced stochastic parameter, the computational experiments are carried out 10 times for each compared algorithm and take the average number as the outcomes. The average and best makespan with the iterations are represented in Fig. 3 and Fig. 4, respectively. In this, we can identify the proposed HH algorithm and Tabu search have significant greater performance than the other three low-level heuristic algorithms. The HH algorithm has the same downward trend as the Tabu search and achieves slight improvement compared to the Tabu search.

In which, we can identify the proposed HH algorithm can achieve the minimum makespan and best performance.

![Fig. 2. Framework of simulated annealing based hyper-heuristic algorithm](image-url)
compared to other algorithms. In both figures, the proposed HH algorithm and Tabu search can obtain greater performance than the other three algorithms. In Fig. 3, all of the algorithms have a sharp decrease trend within the first 50 iteration times, which indicates the slack spaces of the calculate ability are sufficient. After around 50 iteration times, the outcomes of the three LLHs tend to be stabilized with a slight decrease and the final optimal makespans are allocated in the 5000-5500 interval. Whereas the proposed HH and Tabu search have the continued steady decline trend and realize to obtain the minimum makespan around 4000.

Though the HH algorithm has the same downward trend as the Tabu search, the proposed HH can achieve improvement and better performance compared to the Tabu search, which can get a lower makespan when through the same iteration times and get the minimum makespan with lower iteration times.

The related index parameters and research outcomes are recorded in Table V. At the initial stage of the makespan, the hyper-heuristic algorithm and Tabu search both achieve the optimal minimum makespan without standard deviation and variance. As for the final stage, only the proposed HH algorithm can achieve the minimum makespan without standard deviation and variance as well. Moreover, the iterate running speed of the proposed HH algorithm is greater than other compared algorithms. The standard deviation and variance in this research can reflect the stability and robustness of the optimization algorithms, the lower value means greater performance. Therefore, the performance of the proposed HH algorithm is superior to other compared algorithms with greater stability and robustness.
V. CONCLUSION AND FUTURE WORK

In this paper, the simulated annealing based hyper-heuristic algorithm is proposed for dealing with the integrated process planning and scheduling in remanufacturing (IPPSR). In order to reflect the uncertain characteristic of EoL products, the stochastic process time is implemented. According to the operation principle of the hyper-heuristic algorithm, we adopt GA, NSGA2 and SPEA2 as low-level heuristic algorithms and apply simulated annealing algorithm as high-level heuristic for optimizing the process planning and scheduling in remanufacturing simultaneously. The better performance of the proposed hyper-heuristic algorithm can be validated through the computational experiment via the benchmark data and the comparison to other optimization algorithms.

However, this research is an attempt to amplify the research on IPPSR, which have some limitations. The benchmark datasets and cite papers on IPPSR are still limited. Therefore, there are some recommendations from different aspects for indicating future work on IPPSR:

- As for the IPPSR, the current mathematical model is relatively simple, only considering the uncertainty of EoL products. However, the IPPSR should have introduced more influential factors to construct more realistic scenarios. (Such as the breakdown of machines, EoL products containing hazardous parts, etc.).
- As for the HH algorithms for IPPSR. The combination of LLHs can be substituted or combined by other heuristic algorithms because of the good expansibility of the HH algorithm. And the HLH can also be replaced by other advanced optimization algorithms or methods (For example, the reinforcement learning method is becoming more and more popular [20] which is suitable for applying as HLH) for further improving the performance of the IPPSR.
- As for the optimization goals in IPPSR, there are only two optimization goals including the optimal sequence routes and the minimum makespan. However, there are a great number of indicators that could be the optimization goals (such as cost, revenue, smoothness, etc.). Some of the optimization goals may have a greater and clearer conflict with each other, which have greater challenging in integration considering the multi-objective goals.
- As for the evaluation indicators of the performance of optimization algorithms in IPPSR. Apart from the validation from the computational experiments and comparison to other optimization algorithms through benchmark data. It is also feasible to validate the performance of optimization algorithms through the related evaluation indicators (such as the number of non-dominated optimal solutions, hypervolume, and epsilon etc.).

VI. APPENDIX

Link to open-source and experiment benchmark data: https://github.com/mcFadd/Job_Shop_Schedule_Problem
https://github.com/jMetal/jMetalPy

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Energy Conversion Model and Extrusion 3D Printing of Piezoelectric Composite Energy Harvesters

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Abstract—Piezoelectric energy harvesters can realize conversion from mechanical energy to electric energy and power the electronic devices. In this work, based on the electro-elastic model of piezoelectric composites, considering the influence of external load on the piezoelectric coupling, a mathematical model for calculating the energy output of the piezoelectric energy harvesters is established through the coupled equations of elastic and electric fields, Kirchhoff’s Circuit Law and the law of charge conservation. Barium Titanate/polydimethylsiloxane (BTO/PDMS) composites were fabricated by extrusion 3D printing. In addition to the conventional extrusion in air, a new water bath extrusion approach was also used to prove its feasibility in preparing piezoelectric composites. The results show that water bath extrusion has advantages in maintaining the shape of the structure. Moreover, the piezoelectric properties were evaluated by falling ball impact tests. The peak-to-peak value of the pulse produced by the energy harvester extruded in air and water bath were 1.74 V and 3.31V, respectively. The energy harvesters extruded in water bath achieved 1.9 times of output voltage of that extruded in air.

Keywords- piezoelectric composite energy harvester; mathematical model; extrusion 3D printing; water bath

I. INTRODUCTION

The application of wearable flexible electronic devices requires a large number of portable or wearable power supply. As a promising technology, flexible energy harvesters have received extensive attention due to their ability to harvest and utilize energy from the environment to power electronic devices [1], [2]. Due to the special crystal structure of piezoelectric materials, charges will be generated on the surface when external stress was applied. The energy conversion can be realized by energy harvesters through piezoelectric behavior [3]. Among piezoelectric materials, although lead-containing ceramics have better energy conversion performance, lead is biologically toxic and not suitable for wearable devices. Lead-free Barium Titanate (BTO) has become one of the research hotspots. BTO ceramic has good energy conversion effect with piezoelectric coefficient $d_{33}$ 190 pC/N [4]. Piezoelectric ceramics are brittle and not applicable to wearable devices directly. Therefore, scholars disperse ceramic ceramics in a polymer matrix and package it to improve the ductility and enable materials to work at a large strain [5]. Polydimethylsiloxane (PDMS) is chemically stable and easy to form, so it is one of the most popular matrix materials [6].

The properties of piezoelectric materials will affect the energy conversion performance of harvesters, and composite properties have been extensively studied. Krishnaswamy et al. [7] calculated the effective piezoelectric coefficients by the electro-elastic model to evaluate the performance of piezoelectric composites with different structures and matrix materials, which can be used for composite design. Nafaria and Sodano [8] also studied the properties of composite materials with different structures. Mori-Tanaka model and finite element method (FEM) were used to calculate the piezoelectric coefficients and the results were verified by experiments. Although above models can accurately evaluate the performance of piezoelectric composites, the influence of external load on electric potential is not considered. It is well known that the properties of piezoelectric materials are not equivalent to those of energy harvesters. When the energy harvester is connected to a circuit, electric charges are generated on the surface of the piezoelectric material under the applied pressure, and a current is formed, which in turn generates an electromotive force through the load. Since the load and the piezoelectric material are in the same circuit, the electromotive force of the load will also affect the potential on the surface of the piezoelectric material, thereby affecting the electric field distribution inside the material.

There are many fabrication methods for piezoelectric composite energy harvesters. Yang et al. [9] prepared Barium Titanate/polyvinylidene fluoride (BTO/PVDF) composites by casting, and the output voltage was 9.3 V under the 12 N force compression. Gao et al. [10] prepared BTO micro-platelets/PDMS composites by spin coating. The maximum output voltage and current of energy harvesters are 6.5 V and 140 nA by motor bending. Materials extrusion 3D printing technologies can also be

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used to fabricate piezoelectric composites by depositing the material through a nozzle to make the desired structure. The extrusion materials called ink should have shear thinning behavior, which is conducive to material extrusion and shape retention after extrusion [11]. Piezoelectric composites fabricated by extrusion 3D printing are formed layer-by-layer, which reduces the material agglomeration during curing compared to the casting method. Material distribution can also be controlled by this method. Kim et al. [12] compared the BTO/PDMS film prepared by fused deposition modeling extrusion 3D printing and solvent casting. It was found that higher degree of agglomeration, porosities, and cracks would appear on the bottom surface of cast films. However, due to the fluidity of printing materials, extrusion 3D printing has the disadvantage of low printing resolution. The low viscosity of BTO/PDMS materials results in significant material flow during printing and curing, resulting in poor fabrication quality [13]. In order to improve the printing resolution, scholars have proposed a method by immersing the printing substrate and the nozzle in distilled water, which can utilize the pressure of the water to restrict the flow and deformation of the material. This method is helpful to improve the printing quality, but it has not been applied to the preparation of piezoelectric composites for flexible energy harvesters.

In this work, on the basis of electro-elastic model, the influence of external load on the piezoelectric coupling and the electric field distribution of piezoelectric materials is considered, and combining Kirchhoff's Circuit Law and the law of charge conservation, a mathematical model is established to calculate the energy output of piezoelectric energy harvesters. The energy harvesters are fabricated by above-mentioned extrusion 3D printing technologies. The feasibility of the water bath extrusion is verified, and the piezoelectric properties of energy harvesters prepared by conventional extrusion and water bath extrusion are compared and analyzed.

II. ENERGY CONVERSION MODEL OF ENERGY HARVESTERS

Piezoelectric energy harvesters can convert the mechanical energy into electrical energy for power supply of electronic devices. This process is shown in Fig. 1. When the piezoelectric material is connected to the circuit, under the action of alternating pressure, the alternating charges formed on the surfaces of the piezoelectric material will generate a current through the outer loop, thereby powering to load.

Figure 1 The schematic diagram on how energy harvester to power devices

The amount of piezoelectric charges generated is affected by the stress field, the electric field and the coupling of the two, and the physical law of them can be expressed by (1)-(6). The mechanical behavior of composite materials satisfies Newton's Second Law, and the electrical behavior satisfies Gauss's theorem, which can be described using (1)-(2), as follows [7], [14]:

\[ T_{ij} + f_j = \rho_i u_j \]  
\[ D_{ij} = \rho_i t \]

where, \( T_{ij} \), \( f_j \), \( \rho \) and \( u_j \) are the stress tensor, body force, material density and displacement. And \( D_{ij} \) and \( \rho_i \) refer to electric displacement vector and body charge density.

The relationship between strain and displacement, and that between the electric field and electric potential are described as follows:

\[ S_{ij} = \frac{1}{2} \left( u_{ij} + u_{ji} \right) \]

\[ E_i = -V_j \]

where, \( S_{ij} \) is strain tensor, and \( E_i \) and \( V \) respect electric field and electric potential.

The coupling relationship between strain and the electric field of piezoelectric material are [15]:

\[ T_{ij} = C_{ijkl} S_{kl} - e_{ij} E_k \]

\[ D_{ij} = e_{ijkl} S_{kl} + e_{ik} E_k \]

where, \( C_{ijkl} \), \( e_{ijkl} \) and \( e_{ik} \) are elastic, piezoelectric and dielectric constant tensors, respectively.

As shown in Fig. 1(b), the load and the piezoelectric material are in the same loop. When the charges pass through the load, an electromotive force will be formed, which will inevitably affect the potential on the surface of the piezoelectric material and even the electric field distribution inside the material. Thus, additional governing equations need to be added to consider the influence of load’s electromotive force.

When the resistance value of the external load is \( R \), the connection point between the electrode and the conductor is taken as the node to establish Kirchhoff's First Law, and the Kirchhoff's Second Law is established for the whole circuit. Combining the law of charge conservation, the following equations can be obtained:

\[ I(t) = \iint_{A} J(t) \, dA \]

\[ I(t)R = V \]
\[ \nabla \cdot J(t) + \frac{\partial \rho_c(t)}{\partial t} = 0 \tag{9} \]

where, \( I \) is the current in circuit and \( J \) refers to the current density on the electrode surface.

Overall, equations (1)-(9) show the complete physical process of the energy harvesters powering the load by physics laws. For piezoelectric composite materials, the piezoelectric constant \( e_{ijk} \) of matrix is 0 because there is no piezoelectric effect on matrix material. If the body force is not considered, \( f_j \) in equation (1) is 0.

When the external load is not pure resistance, the formula (8) can be modified according to Kirchhoff's Second Law. Mechanical boundary conditions and zero-potential points can be set according to the specific application. The electrical energy utilized by load can be obtained by integrating the product of the voltage and current of the load.

### III. FABRICATION AND PERFORMANCE TEST OF ENERGY HARVESTERS

#### A. Materials

The piezoelectric material used in the experiment is BTO (99.9%, metals basis, \( d<100\text{nm} \), purchased from Aladdin, Shanghai. Dow Sylgard PDMS 184 is used as matrix. Copper sheets with a thickness of 0.1 mm are used as the electrode. The energy harvesters are packaged by PDMS and PI films.

#### B. Fabrication process of BTO/PDMS films

The schematic of energy harvester structure is shown in Fig. 2. The energy conversion is realized by the piezoelectric composite material in the middle, and copper sheets are used as electrodes and they are connected to the load through conducting wire which allows for charges generated by the piezoelectric material moving. The PDMS and Polyimide (PI) film is used to package and protect the composite material.

The piezoelectric composite film of energy harvesters can be formed by printing raster pattern with appropriate line separation. The schematic diagram of the printing path is shown in Fig. 4. Under the above-determined printing conditions, the line separation \( d \) of the raster pattern is selected according to the line width of extrusion, and the printing process path can be determined.

#### C. Fabrication of energy harvesters and piezoelectric voltage measurement

Based on the printing parameters and printing path determined above, the energy harvesters could be fabricated. A piezoelectric composite film was prepared by extrusion on a copper sheet, and 3 layers were printed to ensure that the composite material has sufficient thickness. After printing, the composite material was placed in an oven, and after being treated at \( 80 \, ^\circ \text{C} \) for 1 hour, another copper sheet was placed on the top surface of the composite material as the top electrode, and then heated for 1 more hour until the material was completely cured. PDMS was set on both sides of the obtained moving platform, and the material can be distributed on demand through the movement of three axes. The schematic of traditional extrusion in air and water bath extrusion is shown in Fig. 3. We used the nozzle with an inner diameter of 22 G (410 \( \mu \text{m} \)) for extrusion, and the extrusion pressure and printing speed were determined by experiment. For the printing pressure, different pressures from small to large were applied to extrude ink until the material can flow out of the nozzle continuously and stably, and the corresponding pressure can be determined as a reasonable extrusion pressure. The printing speed is determined by single line extrusion. Different speeds were chosen to print the line structure on copper. The structures were measured after printing. We chose 20 sections of printed lines for each speed and calculated the average size. The extrusion speed can be chosen according to the measurement results.

![Figure 2 Schematic of energy harvester structure](image_url)

![Figure 3 Schematic of traditional extrusion in air and water bath extrusion](image_url)

![Figure 4 Schematic of raster pattern printing path](image_url)
"electrode-composite-electrode" sandwich structure and wrapped with PI film.

In order to evaluate the output of energy harvesters, falling ball impact tests were adopted. A steel ball with a mass of 32.85 g was dropped freely from a height of 300 mm and hit the energy harvester. The output voltage was measured by the oscilloscope to evaluate the energy conversion performance.

IV. RESULTS AND DISCUSSION

A. Fabrication parameters analysis

In the material extrusion 3D printing process, the inner diameter of the nozzle, extrusion pressure and printing speed directly affect the printing quality. The smaller the inner diameter of the nozzle, the higher the printing resolution. However, the nozzle with small diameter is easy to block. The 22 G nozzle is, therefore, selected in this work, which can ensure the smooth extrusion progress. In extrusion process, the extrusion pressure should be greater than the internal friction between the flow layers of ink. However, it should be noted that if the pressure is too high, more materials will be easily extruded, which is not conducive to fabrication. The choice of printing speed is also critical. If the speed is too slow, materials are easily accumulated. In return, if the speed is too fast, the material will be pulled or even broken.

For conventional extrusion process, namely extrusion pressure in air, when the pressure is less than 60 kPa, only droplets can be printed, and the extrusion process of material is discontinuous. When the pressure is less than 100 kPa, although materials can be continuously extruded, it is not uniform. When the pressure reaches 100 kPa, the extruded material is stable, so 100 kPa is selected as the extrusion pressure for conventional extrusion process. The extrusion pressure is also determined by the same method for water bath printing. Since the pressure of water is higher than that of air, the extrusion pressure used in the water bath extrusion needs to be higher than the pressure in the air. When the extrusion pressure reaches 130 kPa, the material can be extruded more stably. Therefore, 130 kPa is used in water bath extrusion.

Fig. 5 shows the line structures obtained at different speeds in extrusion process in air and water bath. The selected processing speed is in the range of 10 mm/s - 40 mm/s. Table 1 shows the average cross-sectional width of the printing structure at four extrusion speeds. It can be found that with the increase in printing speed, the resolution of lines printed in air gradually improves. For water bath extrusion, a better resolution can be obtained at a low or medium speed (10-30 mm/s). After flowable materials curing to form the solid, the difference of printed lines width through different extrusion methods will be more obvious.

Although the difference in the width of lines printed in different methods measured immediately after printing is not that great, as the curing time increases, the advantages of the water bath to restrict the material flow will be more obvious, and the difference in resolution between two methods will be larger after curing. It is because the water bath can effectively restrict the material flow during curing. However, when the speed is high (40 mm/s), the printing performance will be worsened. This is due to the high-speed moving of the extrusion nozzle agitates water, which can cause the instability of the system and further affect the fabrication quality of the extrusion 3D printing. In addition, during the heating and curing process, the air dissolved in the water will gather at the interface of the two materials, affecting the structure quality or even causing the failure of printing.

![Figure 5 Line structure extrusion in air or water bath extrusion](image)

<table>
<thead>
<tr>
<th>Printing speed (mm/s)</th>
<th>Line width printed in air (mm)</th>
<th>Line width printed in water (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>3.313</td>
<td>2.444</td>
</tr>
<tr>
<td>20</td>
<td>2.476</td>
<td>2.399</td>
</tr>
<tr>
<td>30</td>
<td>2.401</td>
<td>2.323</td>
</tr>
<tr>
<td>40</td>
<td>2.210</td>
<td>2.408</td>
</tr>
</tbody>
</table>

Overall, a pressure of 100 kPa is used in extrusion in air and 130 kPa is used for water bath extrusion. The same speed 30 mm/s is chosen. The experiment results show that the line widths, which can also be regarded as the printing resolution, are 2.401 mm and 2.323 mm, for two extrusion methods. Therefore, when the printed line separation is 2 mm, there is no spacing between the two lines, and the film can be obtained. The overlap rate of the line extruded in the air is 20.05%, and the overlap rate of the water bath printing line is 16.15%.
B. Preparation and evaluation of energy harvesters

Using above-mentioned fabrication parameters, energy harvesters have been processed. The number of piezoelectric layers is 3, and the energy harvesters are prepared after package, as shown in Fig. 6(a). The size of the harvesters is 30 mm×20 mm. The copper electrodes were connected to the oscilloscope through wires for measuring the output voltage. Falling ball impact tests were used to evaluate the performance of energy harvesters obtained by two extrusion methods, and the generated waveform is shown in Fig. 6(b) and (c). After the ball hits the harvester, it will bounce back and hit multiple times. The figure shows the waveforms of the first 4 impacts. The voltage generated at the first impact is the largest. The maximum positive and negative pulses generated by the harvesters extruded in the air are 0.93 V and -0.81 V, respectively, and the peak-to-peak value is 1.74 V. The maximum positive and negative pulses generated by the harvester extruded in the water bath are 1.45 V and -1.86 V, respectively, and the peak-to-peak value was 3.31 V, which was 1.9 times of the harvesters extruded in air. It indicates that water bath extrusion can be used to prepare piezoelectric composite energy harvesters, and energy harvesters fabricated by water bath printing have better energy conversion performance. The possible reason for the high output voltage of the water bath extruded harvesters is good shape retention during printing and curing in bath. On the one hand, the collapse of the structure is reduced and the thickness of the harvesters is large, which is beneficial to the high output voltage. and on the other hand, the flow of the material is reduced, so that the material and the structure are more uniform.

![Figure 6. The energy harvester and output voltage waveform: (a) energy harvester; (b) output voltage waveform generated by harvester extrusion in air; (c) output voltage waveform generated by harvester extrusion in water bath.](image-url)

V. CONCLUSION

In this work, considering the influence of external load on the piezoelectric coupling, a mathematical model for calculating the energy output of the piezoelectric energy harvesters is established based on the electro-elastic model of piezoelectric composites. The BTO/PDMS flexible energy harvesters are prepared by extrusion 3D printing technology, and their energy conversion performance of harvesters is tested and compared. The influence of water bath environment on the energy conversion performance of the energy harvesters is also analyzed. The main conclusions are as follows:

(1) For mathematical model, the influence of external load on piezoelectric coupling is analyzed. Considering the stress and electric field distribution of materials, piezoelectric coupling law, Kirchhoff’s Circuit Law and the law of charge conservation, the mathematical model of energy output calculation of piezoelectric collector is established;

(2) The processing parameters are determined through extrusion experiments. The extrusion pressure used in extrusion in air is 100 kPa and the printing speed is 30 mm/s. Under this condition, the resolution of line structures printed is 2.401 mm. The extrusion pressure used in water bath extrusion is 130 kPa and the printing speed is 30 mm/s. Under this condition, the resolution of line structures printed is 2.323 mm. The structures printed in water bath environment has a higher resolution than those in air;

(3) Experiment results show that water bath extrusion can be used to prepare piezoelectric composite energy harvesters, and energy harvesters fabricated by water bath printing have a better energy conversion performance. Falling ball impact tests were adopted to evaluate the piezoelectric performance of energy harvesters. The peak-to-peak value of the pulse produced by the energy harvester extruded in air and water bath are 1.74 V and 3.31V, respectively. The energy harvesters extruded in water bath achieved 1.9 times of output voltage of that extruded in air.

Energy harvesters prepared by these two methods can be used to modify the model. In future research, we hope to solve the mathematical model we established and verify and modify the model by testing the output power of energy harvesters connected to the circuit, as well as evaluate the performance of piezoelectric composite energy harvesters with different processes and materials.

DATA STATEMENT

Data associated with this publication are openly available at University of Strathclyde knowledge database.

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Abstract— In a high-mix, low-volume (HMLV) manufacturing environment, operators had long relied on paper instructions to identify product variations, which have cognitive disadvantages that digital assembly guidance and assistance systems addressed. Together with AR technology, the digitalised systems are used in guiding, training, designing and planning manual assembly. However, their implementation faces challenges arising from the high variation of products and the authors’ expertise required. As easy tasks have negligible benefit under AR guidance, it is proposed that a multi-mode adaptive guidance system use AR guidance only at necessary assembly steps. This paper proposes an Adaptive Digital Guidance System for HMLV manufacturing, which includes a multi-mode assembly assist system for varying tasks complexity. The assembly information is shown adaptively based on the type of assembly process, user experience level, and task complexity. The assembly information manager application is proposed to track product variation and complexity in order to recommend appropriate instructional visual assets. The operator’s experience profile will group similar product variations while tracking the user’s improvement in task performance for each variant. Finally, all of these systems will be integrated into a proposed framework to create an adaptive digital guidance system.

Keywords— Extended Reality, digital assembly assistant, dynamic digital instruction, operator 4.0, mass customisation

I. INTRODUCTION

High-Mix Low-Volume (HMLV) industry arises from current customers’ demand in mass production for customizability and personalisation of products, where customizability is perceived as a form of quality. While having the same expectations on speed, quality and price that they are normally accustomed to with the high-volume products [1]. This swift the manufacturing today from high-volume, low-mix production to high-mix, low-volume production.

Manufacturers leverage this trend to set themselves apart from their competitors. Unlike high-volume, low-mix environment, HMLV industry is volatile, with high product variation and fluctuating demand. Manual assembly line remains an economical and reliable manufacturing system for responding to the HMLV market trend. Although automated production has been used in electronic manufacturing, the costs of assembly and inspection are prohibitively expensive for SMEs. Large manufacturers continue to rely on manual assembly in their production area as setup and maintenance costs for automated systems are ineffective. Human operators have the advantage in terms of flexibility, adaptability, and cost [2].

With high variation in assembly, the effectiveness of the instruction manual becomes the key determinant of the operator’s performance. When the cognitive ergonomics of the instruction manual were evaluated, it was discovered that they fail to address the cognitive issue of the operators [3]; contributing up to 50% of the workload of the total task [4]; and prolonged exposure to complex assembly drawing leads to mental tiredness, particularly in inexperienced operators [5]. Therefore, assembly guidance systems are being developed to help operators cope with the increasing mental load. Utilising AR technologies, they provide visual assistance in the form of digital instructions to the operators. The information is accurate and timely in order to minimise the cognitive workload required to understand the instructions.

Prior research, however, indicates that simple tasks do not benefit from AR guidance. An adaptive assembly guidance system can use AR visualisation selectively, based on task complexity and user experience, to minimise the user’s mental workload and authoring time. This study proposes a framework for an adaptive digital assembly guidance system that tracks product variations and users’ experience with them; providing guidance that suits their progressing competency in specific assembly tasks.

II. LITERATURE REVIEW

Research work on the selection of different types of AR virtualisation methods shows partial benefits of using AR for work instructions; with low complexity tasks gained minimal benefits. [6-8]. This inconsistency in their advantages let some to conclude that the quality of instructions is more important than the method of viewing them [6, 9]. The quality can be improved in terms of cognitive ergonomics of instructional
content, where adaptive instructional content could cater for different user profiles. Such as providing the user with feedback according to their responses, to display the content dynamically according to the user’s response time. [10, 11]. The adaptive content could be used to check their work progress with the presence of key markers and provide corrective information [12].

AR graphical interface can influence the user’s comprehension of the instruction. With that, choosing which visual cues to provide (arrows, circles, boxes, 3D animation) is a key authoring aspect. Yin, Gu, Qiu and Fan [13] proposed a virtual hand gesture indicator to guide users during the assembly. While Radkowski, Herrema and Oliver [14] suggest that the AR graphics interface should be designed according to the assembly task’s complexity.

Program authoring is one of the main challenges in implementing an assembly guidance system. The processes are time-consuming and require expertise [15-17]. Coupled with the lack of economies of scale in HMLV, it makes the adoption of AR instructions less beneficial than high volume production counterparts. Recent research aims to improve authoring for AR assistance through automatic generation of assembly instruction [18] or simplifying the authoring process for end-user AR content creation with an authoring template in Unity3D [19].

As the benefits of the AR digital guidance system, in terms of work completion time and error rate, are a factor of scale in its application, the question of diminishing return remains. Should manufacturers create elaborate AR assembly instructions for every assembly; or digitalising the assembly instruction from paper is sufficient to bring substantial improvement in worker’s productivity. The balance between potential benefits and ergonomics challenges of AR technology for assembly guidance is debatable. Research often points out that the weight of a head-mounted display (HMD) and its limited field of view, are two of the main ergonomics issues. [10, 20-22]

Apart from HMD devices, the ergonomics also concerns the user interface. Industrial testing has shown that prolong usage of AR could cause visual fatigue, particularly when HMD is being used, and reduces concentration performance levels [23]. Although AR shows a reduction in head and neck movement, the information displayed on the device can be distracting or disorientating [24].

Therefore, the aim of this conceptual framework is to provide an adaptive digital guidance system which harnesses the advantage of AR for complex work processes, while adapting to the user experience level in handling the work tasks for greater cognitive ergonomics.

III. FACTORS OF CONSIDERATION IN HIGH-MIXED ENVIRONMENT

On top of the challenges of AR application in manufacturing, the high mixed manufacturing environment made the implementation of AR technology for digital guidance challenging. Several factors are considered when designing the conceptual framework.

A. Selective Usage of AR

One study explained that in easier tasks, there is no significant improvement in time of perception and response selection. Not many mental resources were required to match the visual angle, and therefore user was also less likely to make errors [25].

Other effects could be due to unfamiliarity [26], non-adaptive instruction or poor user acceptance [27]. Although some factors have been found to determine the substantial benefit of AR, there is yet to have a comprehensive classification of task complexity in relation to the benefit of AR assembly assistant systems. This is important in HMLV, as the variation of task complexity increases with production variation. Clear frameworks and methodology are necessary to determine which assembly tasks should be assisted by AR to harness the full benefit of AR guidance.

The application of AR for digital assembly assistance and guidance is not absolute. Many adaptive AR assembly guidance systems featured an information level scale suited to the user’s experience level [10, 11, 28, 29]. They range from simple text instructions for the experienced user, to accurate 3D rendering of the workpiece for novice users. Therefore, the assembly guidance system should utilise these two factors in designing the digital instructions for assembly guidance. Matching task complexity with the level of information provided can reduce the user’s mental workload in understanding the instructions, while minimising the authoring effort of the instruction.

Using AR selectively on required complex tasks could also minimise the ergonomic downside of AR, especially with HMD. It minimises the use of AR on simple tasks which provided negligible benefits. Reducing the user’s exposure time with AR, to reduce the effect of cyber-sickness.

B. Workers’ Learning Curve in High Mix Production

The learning curve describes the performance improvements of workers gained from repetition and experiences. This information would then be useful for making managerial decisions [30]. For example, each worker’s exposure to an individual product model is modelled to help production managers to define the optimal assignment scheme for models and workers. It reduces the production and quality setback of workers during the initial learning period on new models.

The huge product variation in HMLV poses challenges in mapping the worker’s learning curve. As some of the mass customisations were done by product modularisation, products can be clustered into similar model families based on their similarity [31]. This can reduce the data collection to generate the learning curves profile of the workers. Product variations can be analysed and classified according to variables. The variables can be quantitative or qualitative, to describe the product in terms of assembly complexity. From there, models are grouped into homogenous families through cluster analysis of the variables.

However, if the product variation can be automatically assessed, it would enable greater flexibility and speed in production management and control. In the context of an assembly guidance system, it would lower the authoring time and effort, while enabling adaptive assembly information to be presented as the worker progresses on the learning curve.

C. Measuring Worker’s Experience

From the literature review, the knowledge to correlate instructional information and the operator’s experience is well established. Notice operator is provided with more information as compared to an experienced operator. This is
in line with findings from the investigation on the effect of AR guidance on assembly workers.

However, for the purpose of categorising workers’ level of competency, tracking workers’ experiences is another challenge in HMLV. The result of the operator’s performance is rarely being tracked and monitored for continuous improvement of the AR instruction guide. Most of the systems do not monitor the operator’s performance as they advance through the learning curve. As such, the operator’s experience level would have to be manually updated by the supervisor. Geng, Song, Pan, Tang, Liu, Zhao and Ma [29] system proposed that the operator’s task performance is recorded and compared against standard operation time to adjust the level of information provided to the user in the subsequent attempt on the same task.

However, in a high-mix environment, without a fixed product line, it is hard to monitor their experience in handling new variations. Therefore, it is suggested that an automatic task performance monitor can be used to track their performance in handling individual variation.

D. Type of AR Graphical Interfaces on the Effectiveness of AR Assembly Assist

Apart from authoring AR easily, providing suitable visual assets for assembly guidance can minimise the user’s mental workload and instruction authoring time. Most common type of AR visual assets used for typical assembly operations follows a general convention.

Gattullo, Evangelista, Uva, Fiorentino and Gabbard [32] systematically reviewed the visual interface of AR systems in the industry. The comprehensive study reveals that the visual assets used between 1997 to 2019 can be categorised into 8 classes: text, photograph, video, sign, auxiliary model, drawings, technical drawing, and product model.

They noted that CAD models of the actual product and auxiliary ones, are mostly world-fixed (dynamically attached to the real object) and often animated. Visual assets that are rectangular (drawing and photograph) tend to be screen fixed and static. Texts were both screen- and world-fixed equally, and never animated. The colour coding method was not often used in all of the surveyed AR systems.

The types of visual assets being used are often tied to their purpose. Although there is a clear tendency for the AR assist systems to use a certain type of asset, the authors note that they are not necessarily the optimal choice for the AR assist interface design. The definition of optimal AR interface has many factors to be considered such as cognitive effort, behaviour and situation awareness, authoring, occlusion, style etc.

Comparison of the usage of concrete AR (CAR) and abstract AR (AAR) often led to inconclusive results, with no statistical significance in task completion time [9, 33, 34]. One of the authors suggests that a floor effect had been reached in the difficulty of the assembly when using AR. However, concrete AR shows advantages in error reduction and lower NASA TLX score. Therefore, they suggested that CAR is more suitable for complex tasks where the error rate is more crucial than completion time.

As noted by Jasche et al. [33], the authoring time of CAR is significantly longer than the AAR. Additional work required with higher expertise is prohibitive for the participation of non-AR developers on the shop floor. The justification of selecting CAR over AAR to outweigh error rates over task completion time in complex tasks has yet to have a clear guideline. Therefore a clear classification of task complexity could guide AR authors to match the task complexity with a suitable visual interface.

Evaluations to benchmark one AR graphical interface against the other often shows inconclusive statistical significance in terms of task completion time. Such investigation would involve a huge sample size, taking into account gender, age group, experiences etc. Therefore, some of the guidelines for designing AR would suggest based on the common types of visual assets used by the industry [32,35]. Although they may not be the most optimum choice, these examples would provide a common starting point for AR instructions’ authors.

In addition, this paper proposes that the consideration in deciding the type of visual assets and interface presented to users should be based on the task complexity and the user’s level of experience in that task.

IV. A CONCEPTUAL FRAMEWORK OF ADAPTIVE DIGITAL GUIDANCE SYSTEM

Fig. 1 shows the proposed framework of adaptive digital assembly assist which has four parts: (i) Assembly Sequence Planner, (ii) Digital Assembly Guidance System, (iii) Assembly Guidance Information Manager, and (iv) User Task Experience Profile.

A. The Process Flow of the System

The first part is the assembly planning software where the CAD model of the assembled parts is imported. The assembly sequence is then planned on CAD software such as SolidWorks by the engineers.

From there, the assembly sequence file will be imported into Assembly Guidance Information System. Instructions for each assembly step will be written. Based on each part’s geometry and type, text instructions and assembly task complexity, suitable default visual assets will be suggested for first-time users. Instruction authors can choose to use the suggested visual assets or make changes to them as they wish. Once the visual assets of each assembly step are confirmed, the instruction can be tested in an author’s version of the digital guidance system. If the result is satisfactory, the information will be stored as the Task Experience Profile.

The user will begin by logging into the system and selecting a task based on the production schedule. The system will check the experience of the user in handling each individual assembly step and its parts. If any steps and parts are new to the user, the guidance system would load the default assembly guidance information. Conversely, a lower level of information will be given to steps where the user has previous engagement according to their experience profile.

From there the assembly instructions and visual assets will be loaded from the database according to the user’s experience profile.

Assembly instructions for each step will be presented to the user one at a time. These will be shown on the monitor as a digital instruction manual for simple tasks, and AR instructions for complex tasks. If the user encounters complex assembly tasks which require 3D spatial recognition, the
Digital Assembly Guidance system will advise the user to put on the HMD for a first-person AR view.

By limiting the use of AR for only complex tasks, the system reduces ergonomic issues of prolonged AR exposure, minimising the wearing time of HMD while performing their tasks. AR on the monitor will also be used selectively to reduce the loading and tracking time required during the initialisation of assembly instructions. This approach of targeted AR guidance maximises the advantage of both traditional digital instructions and AR, by assigning the most suitable instructional mode for individual assembly steps.

Fig. 1. The Digital Adaptive Assembly Guidance System.

On the screen, the user can choose to increase the level of information presented by clicking “Show More”. The action will be recorded on the profile, which is to be shown the next time. There is also a button to flag issues with digital instructions, assembly parts and sequence to the supervisor.

After the user performed each of the steps, their completion time will be recorded. If the step completion time is faster than the previous attempt, the assembly assist system will update them in the user’s profile, such that less amount of information will be presented the next time. If the user performs worse than the previous attempt, the system will decrease the user’s competency level in that step, thus displaying more information the next time.

This will repeat for each of the assembly steps until the whole assembly task is completed. After that, the system will send feedback to the production schedule, and a new task will be assigned to the user to start the assembly process again.

B. The Functionality of Each Part

The following subsections describe the functionality of each part in detail.

1) Assembly Sequence Planner

The work process sequence is planned manually according to the task based on the technical drawings, CAD diagrams and existing instructions. These task sequences will be used to analyse the task complexity for each step.

2) Digital Assembly Guidance System

It is connected to the production schedule for assembly task selection. The system loads files for assembly into the template, containing information such as assembly model, sequence, instructional text, and visual assets. It then presents the assembly steps one at a time. The time spent on each step would be recorded as step completion time. It also allows users to flag issues with instructions, assembly parts and sequence to the supervisor.

3) Assembly Guidance Information Manager

This module analyses assembly steps from the type of parts, parts geometry, and assembly instructions’ text to arrive at suitable visual assets/interfaces suggestions for the author. Authors can choose to accept all suggestions or refine them to their preference. These accepted visual assets will be the default visual guidance interface for first-timer. Subsequent visual assets for a higher and lower level of information can be configured in this module to suit users with different learning curves.

4) User Task Experience Profile

This module is a database that would save the number of times the user encountered individual steps, the parts involved and their completion time. Similar parts and processes are analysed, and examined by the supervisor, to be grouped together. The error made by the user during the task will be recorded. The experience level of each step is updated when there are changes in task completion time on the subsequent attempt.

V. CONCLUSION AND FUTURE WORK

In this paper, the framework for an adaptive digital guidance system based on AR technology is proposed for a high-mix manufacturing system with manual assembly. With the technical limitations in the industrial application of AR, this paper proposed a system which only selectively uses the AR for assembly guidance and instructions for high complexity tasks. This would utilise the advantage of AR, while minimising authoring efforts and ergonomic issues associated with prolonged AR usage. The proposed system is adaptive towards different users with varying levels of experience with the specific products, as well as the task complexity. By providing the optimal level of information at the right time, users’ mental workload in comprehending work instructions reduced.

The proposed framework emphasised identifying and outlining the features and key functionality of each of the 4 parts in order to deliver an adaptive system for the HMLV environment. The underlying methodologies and mechanisms for achieving such goals are under investigation. Future work would focus on developing methods of identifying task
complexity, which would then aid in the selection of appropriate visual assets for easier AR authoring.

ACKNOWLEDGMENT

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From human-human collaboration to human-robot collaboration: automated generation of assembly task knowledge model

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Abstract—Task knowledge is essential for robots to proactively perform collaborative assembly tasks with a human partner. Representation of task knowledge, such as task graphs, robot skill libraries, are usually manually defined by human experts. In this paper, different from learning from demonstrations of a single agent, we propose a system that automatically constructs task knowledge models from dual-human demonstrations in the real environment. Firstly, we track and segment video demonstrations into sequences of action primitives. Secondly, a graph-based algorithm is proposed to extract structure information of a task from action sequences, with task graphs as output. Finally, action primitives, along with interactive information between agents, temporal constraints, are modelled into a structured semantic model. The proposed system is validated in an IKEA table assembly task experiment.

Keywords—human robot collaboration; learning from demonstration; assembly; human centric manufacturing

I. INTRODUCTION

With the increasing demand for human-robot collaboration (HRC) in manufacturing scenarios, task-level planning systems were proposed to generate collaborative robot motions at different levels of abstraction [1] [2]. However, these systems typically require some form of prior knowledge about the task as prerequisites, such as task graphs models and grounding. In most existing works, such task knowledge is usually pre-programmed by domain experts [3]. Manually specifying the task graphs and action primitives by domain experts is time-consuming and not user friendly. Thus, it is highly desirable to enable robots to perform them automatically. This paper proposes a system that segments and interprets primitive actions of an assembly task from video demonstrations, constructs the task graph, builds semantic model of action primitive as robot skill library and transfers them to enable human-robot collaboration, based only on demonstrations of human-human collaboration.

Robot learning from demonstrations (LfD) has seen a fast development in recent years [4], especially in manipulation tasks. The methods and learning outcomes vary according to the content of the demonstration. The assembly demonstration is a structured activity that normally contains several subtasks and many action primitives. An efficient two-step solution has been proposed to extract task knowledge from such multi-step demonstrations [5], [6]. It first segments the demonstration into primitive action sequences, and then represents the demonstrated behaviours using structured graph models. In this work, we adapt this method, using a vision-based parser to track the motions of the demonstrators and objects, defining a set of heuristic rules to segment the demonstration into primitive action sequences, and extracting task knowledge models from these segments.

A task graph provides the task structure information required by the robot to plan for the task with uncertainties. One kind of task graph is the and/or graph [7], which is a widely used hierarchical model. An algorithm was proposed recently to generate and/or graphs automatically by recognizing the sequential and independent relationships of primitive actions [8]. However, this method assumes that “the sequential actions are not interrupted by parallel actions during the demonstration”. This assumption is not always true. The reason is that the execution of parallel actions is independent. Thus, the sequential actions may be interrupted by parallel actions. To address situations when this assumption does not apply, we propose an algorithm that models the task structure into a directed graph by identifying action-action relationships. The generated directed graph is easily transformed into an and/or graph.

Different from LfD from a single agent, learning from dual agents is complex as agents may perform interactive actions in the demonstration, such as handover. Thus, action pair is present to describe interactive actions. In addition, the temporal constraints of an action pair are analyzed. The action primitives as well as their interdependencies are stored in a semantic model, which provides query and reasoning interfaces that are easy to use by the robot.

With the aim of transferring task knowledge from human-human collaborations to human-robot
collaborations, this work studies the automated generation of assembly task knowledge models. The key contributions of this work are summarized below:

- We propose a vision-based parser that is capable of real-time segment human-human demonstrations into sequences of action primitives without prior training.
- We provide an algorithm to automatically extract task structure knowledge and generate task graphs from action sequences.
- We construct a semantic model as a library of the learned skills, with interfaces for task planning in HRC.
- We design an experiment to validate the proposed methods. In the experiment, an IKEA iiwa LBR robot could learn to collaborate with a human in the task.

In the rest of the article, section II gives a brief overview of LfD and task knowledge modelling. Section III, components of the proposed system are provided in terms of a vision-based parser, task graph modelling and semantic models. Then, an assembly experiment is designed to test the proposed methods. Finally, our paper concludes in section V.

II. RELATED WORK

In the HRC content, knowledge engineering normally contains the experience acquisition, knowledge interpretation, constraints analysis, and modelling of task knowledge, with the task model being the output. There are various task model acquisition methods, including manual specification [8], [9], interactive learning, and learning from demonstrations. Anahita, etc. [10] proposed an interactive learning method where a human can teach a robot to construct hierarchical task models through demonstrations based on the structure information of objects and data flow between tasks. However, generating task knowledge models from demonstrations in HRC, which is the core of our method, has been paid limited attention until now.

Knowledge interpretation is one of the most important procedures of knowledge acquisition from a real-world demonstration. Despite the advancement in computer vision techniques, automatic acquisition of symbolic task representation of LfD-acquired skills remains difficult [2]. An effective solution of symbolic abstraction is to interpret the demonstration and segment actions by applying intuitive physical knowledge. In the literature [11], an ontology-based parsing method was used to reason daily activities in virtual reality (VR) environment, recognising basic actions such as take, reach, etc. The parser is based on a VR engine, which provides state information about agents and objects. In this work, a vision-based phaser is proposed to interpret the demonstration in the real world.

The generation of a hierarchical task model essentially is a process of interpreting the relationship of action primitives. In terms of the learning methods, Hayes et al [2] provided a transformation algorithm from task graph to hierarchical task model. Cheng et al [8] proposed a sequential/parallel task model and a corresponding algorithm that can identify the relationship of primitives. However, these works did not integrate with LfD based knowledge interpretation methods. We propose a novel task graph generation algorithm that integrates with the LfD based parser module.

When learning from complex activities, an effective way is that a structured model can be constructed to store the interpreting knowledge of the demonstration. In [12], the obtained semantic information transformed into an ontology-based model, know-rob [13], and it provides interfaces for querying and reasoning for action planning.

III. SYSTEM

All components of the proposed system are shown in Figure 1, which consists of five steps. In step 1, two demonstrators conduct an assembly task collaboratively. Then, a vision-based parser is used with a set of rules to interpret the demonstration into sequences of action primitives. In step 3, through analysing action relationships, task structure information is extracted and then a task graph is constructed. Step 4 identifies the semantic information of the grounding skills and store this knowledge into a semantic model. The task graph and semantic model are used for symbolic-level planning in an HRC assembly task.

Demonstrations are performed in a real lab environment, and two demonstrators conduct assembly tasks in a master-slave way. One of the partners is the principal operator, and the other one performs as an assistant. The ultimate goal of the robot is learning to act as an assistant to humans in assembly activities.

A. Vision-based parser

The scheme of the parser is shown in Figure 2. In general, firstly the skeleton model of demonstrators and the simplified model of objects are modelled based on the visual and depth information, and the 3D position info is obtained. Then, the kinematic information of both human and objects are calculated. The human poses are recognized based on the obtained status of humans and objects in real-time.

![Figure 2](image-url)
TABLE I. THE STATE VARIABLES (SV) OF HANDS OF DEMONSTRATORS AND OBJECTS

<table>
<thead>
<tr>
<th>SV</th>
<th>Types</th>
<th>Examples</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>handmoving ((h))</td>
<td>boolean</td>
<td>handmoving ((hl_{lefthand}) = \text{true})</td>
<td>The velocity of moving hand is above 0.15m/s</td>
</tr>
<tr>
<td>inhand((h))</td>
<td>objects</td>
<td>inhand ((hl_{lefthand}) = \text{leg1})</td>
<td>The finger of the hand is attached around an object and finger-hand distance (&lt; 5\text{cm})</td>
</tr>
<tr>
<td>hand2hand ((h_1,h_2))</td>
<td>boolean</td>
<td>hand2hand ((h_1, \text{lefthand}, h_2, \text{righthand}) = \text{true})</td>
<td>The distance between hand1 to hand2 (&lt; 15\text{cm}), and at least one of hands has an object inhand,</td>
</tr>
<tr>
<td>intouch ((o_1,o_2))</td>
<td>boolean</td>
<td>intouch ((\text{leg1}, \text{table}) = \text{true})</td>
<td>The minimum distance between object1 and object 2 is less than 3cm.</td>
</tr>
</tbody>
</table>

Note: \(h\) denotes the hands of humans; \(o\) denotes the object \(s\)

<table>
<thead>
<tr>
<th>Action</th>
<th>idle</th>
<th>grasp</th>
<th>move</th>
<th>handover</th>
<th>screw</th>
<th>hold</th>
</tr>
</thead>
<tbody>
<tr>
<td>handmoving ((h))</td>
<td>F</td>
<td>F</td>
<td>T</td>
<td>-</td>
<td>-</td>
<td>F</td>
</tr>
<tr>
<td>inhand((h))</td>
<td>(\emptyset)</td>
<td>(\emptyset)</td>
<td>(\emptyset)</td>
<td>(\emptyset)</td>
<td>(\emptyset)</td>
<td>(b)</td>
</tr>
<tr>
<td>hand2hand ((h_1, h_2))</td>
<td>F</td>
<td>F</td>
<td>F</td>
<td>T</td>
<td>F</td>
<td>F</td>
</tr>
<tr>
<td>intouch ((l,f))</td>
<td>-</td>
<td>T</td>
<td>F</td>
<td>-</td>
<td>-</td>
<td>F</td>
</tr>
<tr>
<td>intouch ((l,h))</td>
<td>-</td>
<td>-</td>
<td>F</td>
<td>-</td>
<td>T</td>
<td>-</td>
</tr>
</tbody>
</table>

Note: \(f\) to be assembled objects in the experiment, \(l\): experimental platform, \(b\): to be assembled objects in the experiment, \(t\): true; \(F\): false; \(-\): Variables that do not affect classification results.

cartesian coordinates of key points of humans. Objects are marked by Apriltage [15] to get the key point coordinates of objects in cartesian space, which can be easily transformed to the pose and position information.

Due assembly tasks are mainly finished by the hands of workers, the velocity detection of hands is necessary. Given the skeleton model of demonstrators, the speed \(v_t\) of the hand at time \(t\) is derived from the position of the hand at different points in time. The velocity of speed can be approximated by wrist joint speed. Thus, \(v_t\) is formulated as follows:

\[
v_t \approx \text{dis}(w_t, w_t) \cdot \text{fps}/(t_t - t_f)
\]

\(v_t\) represents the speed of the hand; \(w_t\) is the cartesian coordinates of the wrist at time \(t\); \(\text{fps}\) denotes frame rate per second; \(\text{dis}(\cdot)\) denotes a function that returns the distance between two points.

Object detection or tracking is required to obtain the poses of objects in each task and can be simplified using methods such as colour-based detection [16]. In this work, the spatial position of objects in each frame is abstracted into basic geometrical elements, such as line segments, flat surfaces. For example, a table leg, which is a cuboid, is simplified as a line segment \(l_{P_1P_2}\), and \(P_1P_2\) are endpoints of the line segment (refer to Figure 2. ). The distance from the hand to the table leg is represented by the minimum distance between key points of the hand to the line segment.

\[
d_t = \text{min(\text{dis}(l_{P_1P_2}, h_t))}
\]

\(h_t\) denotes the key points of hand at time \(t\); \(\text{min}(\cdot)\) is a function that returns the minimum value in the matrix.

Due to the complexity of the assembly process, it is difficult to recognize action segment activities directly from the demonstration. Thus, a state-of-the-art method [6] is adapted and extended in this work. This is a knowledge-based method, which applies intuitive physical knowledge to interpret the demonstration. The segmentation process consists of two steps: (1) defining state variables; and (2) classifying actions based on rules. The defined state variables are listed in TABLE I. In terms of types, examples, and description, the state variables consist of two types, hand state variables, and environment state variables. handmoving\((h)\), in-hand\((h)\) and hand2hand\((h_1, h_2)\) belongs to previous category. Note hand2hand\((h_1, h_2)\) is extended that is set to monitor the interaction between different agents. In addition, intouch\((o_1, o_2)\) is set to monitor the interaction of objects.

The physical knowledge of action is designed as rules to classify the action, and it is listed in 0Handover is a critical action between different agents, where one agent passes objects to another one. This action starts when the hands of the two agents are approaching each other and one of the hands is grasping an object. The finish point is that the object pass to the other agent and hands are gradually far away from each other. The segmentation points are set when the action status changes, and action segmentation is realized. The segmentation information is used to automatically generate task graphs and semantic models.

**B. Automated task graph construction**

By applying the action segmentation, the approach in Section 3.A. the action sequences \(\Xi = [\xi_1, \xi_2, ... \xi_n]\) of demonstrators is extracted from the performed demonstration, where \(n\) is the total number of demonstrations of assembly activity. \(\xi_i = [a_{1}{^i}, a_{2}{^i}, ... a_{m}{^i}]\) means sequences of action primitives with \(m\) action units \(a_{m}{^i} = \text{[motion, objects]}\) that normally contains a motion and a relevant object, for example, \(a_{1}{^i} = \text{[move, table leg]}\). In an assembly task, the actions in different demonstrations are usually the same, but the sequence of primitives vary. Besides, the action sequences may contain actions unrelated to the task, such as idle states. These actions should be removed from action sequences.

The proposed method aims to construct a task graph from action sequences \(\Xi\), which is easy to transform into a hierarchical task model. The key of constructing task graph \(g = [n, e]\) is to identify the relationship of all action primitives, with node \(n\) representing the action primitives and edge \(e\) denoting the transition between actions. Based on the identified relationships, it is easy to connect the primitives to form a task graph. We define a series of relationships of action primitives and the corresponding identification methods. Then, an algorithm is proposed that forms a task model. The identification method of nodes and edges in the task graph is introduced based on the relationship of primitives.
### Algorithm 1: Task graph generation

<table>
<thead>
<tr>
<th>Line</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Input $\Xi$</td>
</tr>
<tr>
<td>2</td>
<td>Output graph</td>
</tr>
<tr>
<td>3</td>
<td>1: init graph, $A$, headnodeSet, endnodeSet</td>
</tr>
<tr>
<td>4</td>
<td>2: $A = \text{generationPRM}(\Xi)$</td>
</tr>
<tr>
<td>5</td>
<td>3: initAction $= \text{findInitAction}(A)$</td>
</tr>
<tr>
<td>6</td>
<td>4: headnodeSet $= \text{initAction}$</td>
</tr>
<tr>
<td>7</td>
<td>5: while then do</td>
</tr>
<tr>
<td>8</td>
<td>6: for each action $a_1$ in headnodeSet do</td>
</tr>
<tr>
<td>9</td>
<td>7: actions$= \text{findFollowupAction}(a_1)$</td>
</tr>
<tr>
<td>10</td>
<td>8: endnodeSet append (action)</td>
</tr>
<tr>
<td>11</td>
<td>9: for each action $a_2$ in action do</td>
</tr>
<tr>
<td>12</td>
<td>10: graph.addEdge ($a_1,a_2$)</td>
</tr>
<tr>
<td>13</td>
<td>11: end for</td>
</tr>
<tr>
<td>14</td>
<td>12: end for</td>
</tr>
<tr>
<td>15</td>
<td>13: if endnodeSet is empty then</td>
</tr>
<tr>
<td>16</td>
<td>14: Break</td>
</tr>
<tr>
<td>17</td>
<td>15: Else then</td>
</tr>
<tr>
<td>18</td>
<td>16: headnodeSet $= \text{endnodeSet}$</td>
</tr>
<tr>
<td>19</td>
<td>17: endnodeSet.clear</td>
</tr>
<tr>
<td>20</td>
<td>18: End if</td>
</tr>
<tr>
<td>21</td>
<td>19: End while</td>
</tr>
</tbody>
</table>

In the industry assembly process, actions may have a dependent relationship with each other due to the physical features of products. Specifically, we define five relationships of action primitives, including pre-order action, post-order action, independent relationship, immediate predecessor action (IPA), immediate successor action (ISA). First of all, we define the primitive relationship matrix (PRM), denoted by $A$ in the equation below, for a task, which represents the specific relationship of different primitive. It is defined as:

$$A = \begin{bmatrix}
\alpha_{a_1a_1} & \cdots & \alpha_{a_1a_n} \\
\vdots & \ddots & \vdots \\
\alpha_{a_na_1} & \cdots & \alpha_{a_na_n}
\end{bmatrix}$$

When $\alpha_{a_ia_1}=1$, action $a_i$ is the **preorder action** of $a_1$. The $a_i$ should be finished before $a_1$ starts. The pre-order action produced consequence is required by the execution of action $a_1$. The preorder action set of $a_i$ is represented as $\Phi_i$. To identify that $a_i$ is the pre-order action of $a_1$, all action sequences $\Xi$ are going through to check the occurrence of $a_i,a_j$. If $a_j$ occurs before the occurrence of $a_i$ in all sequences, $a_j$ is the pre-order action of $a_i$; otherwise, not.

When $\alpha_{a_ia_1}=-1$, action $a_i$ is the **post order action** $a_j$. Action $a_i$ should be finished before $a_j$ starts. The relationship of post order is the inverse of preorder. The identification process is similar to it.

When $\alpha_{a_ia_j}=0$, action $a_i$, $a_j$ are **independent**. The action $a_i$, $a_j$ can occur in any order. If the relationship of $a_i$, $a_j$ is not post order or pre order, $a_i$, $a_j$ are independent.

If $a_i$ is ISA of $a_j$, the occurrence of $a_i$ is directly after action $a_j$. The mathematic formulation of ISA is:

$$\exists i \in (1,n), \Phi_i = \Phi_j + a_j$$

If $a_i$ is the IPA of $a_j$, the occurrence of $a_j$ is directly before action $a_i$. ISA is the inverse of IPA. If $a_i$ is the IPA of $a_j$, $a_j$ is the ISA of $a_i$.

The proposed algorithm is shown in Algorithm 1. The input of the algorithm is $\Xi$, the sequence of action primitives extracted from the demonstration. The output Graph is a task graph, which shows the structure information of an assembly task. HeadnodeSet is used to store a series of action primitives, which is regarded as the head node of an edge in the graph. EndnodeSet is a list that contains the corresponding endnode of headnodeSet. Line 1 initializes the variables Graph, $A$, headnodeSet, endnodeSet to be empty. Line 2 generates a PRM matrix with $\Xi$ as input by using the identification method in Section 3.B. Line 2 find the initial nodes of the Graph, by using the following formulation.

$$\exists i \in (1,n), \Phi_i = \phi$$

When the preorder action set of an action primitive is empty, the action is regarded as the first node of Graph. In line 4, the headnodeSet is assigned with the values of InitialAction. Line 5-19 find the endnode of headnodes and then construct edges in graph till to end iteratively. Line 6-8 find the endnodeSet of each action in headnodeSet. The searching rules of endnodeSet is based on the ISA identification rule. Line 9-11 add edges in Graph by connecting headnotes and endnodes. Line 13-15 define the break rule: the graph is not updated in this loop. When endnodeSet is empty, the graph does not add a new edge in this loop, then break the loop. Otherwise, endnodeSet is used as a new headnodeSet, in the meantime, the old headnodeSet is cleared.

### Structured, semantic model

As the vision-based parser discover sequences of the action of two demonstrators, segmented grounding skills are modelled into a semantic model in this section. During the task execution, workers conduct some collaborative actions. While modelling their collaborative behaviours, temporal constraints analysis of actions is necessary.

The information stored by the semantic model is summarized as follow: (1) properties of the action primitives; (2) the manipulated objects information; (3) the action constraints of the interaction between demonstrators.

![Figure 3. The semantic model of action primitives](image)

#### 1) Constraint analysis

The learned action primitives can be categorised into the main action $a_m$ and assistive actions $a_n$, performed by the principal operator and the assistant respectively. In an
assembly task, the cooperative behaviours of the operators generally consist of active and assistive actions. Thus, we construct cooperative action pair \( p = [a_m, a_a] \). The identified rule of \( p \) is that: if \( a_m \) and \( a_a \) work on an object physically interactively, the \([a_m, a_a]\) is action pair. Especially, actions in \( p \) is not necessarily a single action unit, but sometimes a sequence of actions.

The temporal constraints exist between actions in \( p \). The execution time of action in the demonstration is an interval \([t^l_{aa}, t^r_{aa}]\), and \( t^l_{aa} \) is the beginning time and \( t^r_{aa} \) is the end time. We define two types of temporal constraints, (1) prior. The assistive action should be done before the main action. The constraint is formulated as follows:

\[
T^l_{aa} < T^r_{aa} \leq T^r_{am},
\]

(2) meantime. The assistive action should be done during the execution of the main action. The constraint is formulated as follows:

\[
t^l_{aa} \leq T^r_{am} < T^r_{am} \leq t^r_{aa}.
\]

2) Semantic model
The constructed semantic model is visualized in Figure 3. The properties of actions have motion, objects and trajectories. The motion is classified into mainAction and assistiveAction. The semantic model contains action pairs that contain the joint action of human and robot. During the HRC execution, we utilize the semantic model to control the robot, the robots can do joint action with humans based on the observation. The model can record action primitives and constraints. The model provides interfaces for querying and reasoning, and it can be used as a robot skill library.

IV. EXPERIMENT

In order to evaluate the proposed methods, a real assembly task is set by using an IKEA table (LACK) that has a tabletop and four table legs. We simplify the assembly process, with only two legs to be screwed into the tabletop, as assembling the other two legs is repetitive work. The objects to be assembled are placed on a platform. Two participants stand on the opposite sides of the platform. The main operator stands near the tabletop and far away from the table legs. Thus, the assistant is asked to handover the legs to the main operator. Besides, the assistant is asked to hold the tabletop to keep it stable, while the main operator is screwing the legs. All participants have read the assemble instructions of the table. 4 individuals participated in performing the assembly task. In total, the system records and interprets the assembly process 18 times. The demonstrations are recorded by an Intel RealSense D435 camera.

A. The performance of action segmentation
Figure 4. displays examples of the action segmentation of the human-robot collaboration demonstration in the assembly task, including the duration of action primitives and the transition between different actions. The action primitives performed by different demonstrators were mostly the same, with some differences in duration and order.

In order to evaluate the accuracy of the action recognition of the proposed methods, we obtained the ground truth by playing back the recorded videos and manually labelling the actions of every video frame. If the value is different from the result identified by the algorithm, the recognition result is incorrect. Accordingly, the recognition accuracy of all 18 demonstrations was 91%. The main reason for the failures is the misestimation of visual tracking. For example, hands may be blocked by objects (e.g., legs), which leads to the inaccurate position estimation of the captured key points of hands.

B. Task graph generation

The input of the task generation algorithm in this task only needs the action sequences of two demonstrations (Figure 4.) First of all, all ‘idle’ actions that are unrelated to the task are eliminated. Then, the segmentation data is fed into algorithm 1 to generate the task graph, shown in Figure 5. By using the algorithm in [2], a hierarchical task model is obtained by transforming the task graph (Fig. 5b).

The number of required demonstrations to completely generate a task graph using the proposed algorithm depends on the structure of the task. Suppose a task has \( q \) levels in hierarchical model and \( p \in \{1, 2, ..., q\} \) level has \( i_p \) independent nodes, which has \( c_{i_p} \) children. max \( (c_{i_p}) \)
means the number of the children of the node with the maximum children in level \( p \). The number of required demonstrations to construct a complete task graph is 
\[
\prod_{p} \max \left( e_{ip} \right)
\]
by using the proposed algorithm. The time complexity of our algorithm is \( O(m \cdot n^3) \), where \( m \) is the number of demonstrations and \( n \) is the number of action primitives.

C. Semantic model

In symbolic-level HRC task execution, the semantic model can be used to search for action primitives as well as the assistive action based on the main operator’s action. In this section, we present two examples of how these can be done. Besides, the invoking mode and functions of this model during HRC execution are illustrated.

The first function of the model is to search for an action primitive. The search requires a motion name and an object name to be given. An example of the search result is shown as follows.

```plaintext
action: (name: 'hold_table_top', type: 'assitive action'
motion: (name: 'hold'),
object: (name: 'table_top'),
trajectory: (list)
```

Another function is to search for a corresponding assistant action. The search requires the main operator’s action name and is based on the rules of assistive action. The example shown below queries the assistive action of action 'screw_table_leg1'.

```plaintext
action: (name: 'screw_table_leg1', type: 'main action'
motion: (name: 'screw'),
object: (name: 'table_leg1'),
trajectory: (list),
assistiveType: (type: 'meantime'),
assistiveAction: (action: 'hold_table_top'))
```

D. Assembly task execution

We test our constructed models in an assembly experiment using a Kuka iiwa LBR robot. A task graph-based action planner is used [3]. We modify the planner by replacing the Bayesian model with our proposed semantic model for querying the assistive action. Figure 6 shows that a robot is assisting a person in an assembly task, where the person is assembling an IKEA table. The action of the robot is planned by the planner. An experimental video is attached to this paper.

Figure 6. A robot collaborates with a person in an assembly task.

V. DISCUSSION AND CONCLUSION

Preparing knowledge models for symbolic planners in HRC is a time-consuming, user-unfriendly task. In this letter, we presented a system for automated knowledge model generation through visual demonstration interpretation, task graph modelling and semantic model generation. Despite the complexity of the assembly task, the parser achieved an accuracy of 91%. The task graph model was generated using only two demonstrations with an acceptable time complexity \( O(m \cdot n^3) \). The semantic model was tested in a real-world assembly experiment using an IKEA table.

ACKNOWLEDGMENT

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REFERENCES

Abstract—Increasing attention has been paid to remanufacturing which plays an important role in environmental protection and circular economy. Disassembly is a key operation in remanufacturing, repair, and recycling. Several robotic disassembly developments have shown that the use of robots in disassembly is feasible; however, the programming of robots is usually complex, schedule-based, and time-consuming. Recent research about self-learning robotics and human-robot collaboration have created an opportunity for schedule-free robotics, in which various machine learning and deep learning techniques have been developed. This paper attempts to review the development of self-learning robots with applications in robotic disassembly and remanufacturing. Key algorithms, designs, control methods, and future research directions have been highlighted and analysed. This review paper serves as a useful resource for researchers in the areas of robotics, smart remanufacturing, and disassembly automation.

Keywords—Self-Learning, Disassembly, Robotics, Learning Methods, Reinforcement Learning (RL)

I. INTRODUCTION

Discarded end-of-life (EOL) products is a global challenge and can have significant environmental and economical impacts. EOL treatment, i.e. recycling, reuse and remanufacturing, exploits the remaining value of materials and components in EOL products. Product disassembly is one of the key steps in EOL treatments. Disassembly aims to retrieve parts from the returned products. Due to the dimensional uncertainties and geometrical variations in the returned EOL products, disassembly is usually carried out manually. These uncertainties and variations result in complexities at both the operational and planning levels, which make the disassembly processes difficult and time-consuming [1].

As the remanufacturing process grow in scale, there is a need to increase the efficiency of disassembly [1, 2]. Robotic disassembly is a new approach proposed to reduce labour costs and improve productivity. However, industrial robots tend to be used in structured and repetitive tasks, and cannot effectively cope with uncertainties and complexities of disassembly [3].

Developments in the areas of industrial automation and robotics can help improve productivity, and contribute to creating industrial machines with capabilities beyond simple reasoning [4]. A few optimisation algorithms have been developed to support automatic disassembly planning, including locating detachable components, finding feasible assembly sequences, and optimising robotic motions [5-8].

A cognitive robotic system was built using visual detection and intelligent reasoning [9].

Disassembly robots are generally implemented using schedule-based automation, in which robotic operations are pre-defined. The implementation of schedule-based automation requires product specifications, such as product structure, geometry, and component quantities. Due to the large number of unknown variations of returned items, using schedule-based automation in disassembly is difficult.

To tackle these challenges, a variety of techniques have been developed, including creative disassembly tools for breaking specific connections [10, 11] and destructive/semi-destructive procedures [12]. The cognitive robotic disassembly system becomes more resilient to these uncertainties thanks to the trial-and-error technique outlined in Ref [13].

Another new approach, namely schedule-free automation, has been proposed for disassembly robotics. Schedule-free automation’s aim is to use less structured motion plans in industrial automations. This approach is usually implemented via the use of smart sensors, e.g., a vision system, as well as powerful control strategies with adaption or learning capabilities.

Schedule-free automation is still at a very early development stage and many key techniques are missing. For example, some characteristics data of disassembly is not accessible e.g., quasi-static parameters of disassembly operations and invisible internal conditions.

Machine learning (ML) has been proposed to improve the performance and efficiency of disassembly. This paper focuses on the self-learning robotic system that can be used to develop schedule-free disassembly robotics, which is the key difference between this paper and other review papers in the area of robotic disassembly [2, 14].

The aim of this paper is to provide a comprehensive review of the state-of-the-art in self-learning robots with a particular focus on their applications in disassembly and remanufacturing. The next sections of the paper are organised as follows: Section II presents the schedule-based automation for disassembly. Section III outlines the implementation of schedule-free automation in disassembly. Bibliographical analysis of existing works on self-learning robotics based on disassembly is discussed in Section IV. Section V provides a conclusion and discussion of open research areas in self-learning and robotic disassembly.
II. SCHEDULE-BASED AUTOMATION FOR DISASSEMBLY

A. Remanufacturing & Disassembly

Disassembly of returned product is a key step in remanufacturing [15-17] and one of the primary steps of EOL processes. Disassembly involves extracting and separating the desired components, parts, and materials from products [18, 19]. Disassembly is also a key step of repair and maintenance [20]. However, disassembly is not merely the reverse of assembly due to uncertain conditions of the returned products, which makes it more challenging to automate than assembly [21-23]. It has usually been performed manually and is labour-intensive [1]. In the remanufacturing process, one of the biggest challenges is the uncertainty in the condition of the returned EoL products [2]. The profitability of companies may improve when uncertainty is reduced, and disassembly is one of the processes affected by high-level uncertainties [24]. Reduced uncertainty in disassembly has several benefits for production planning and control, including improved component matching, shorter lead times for new parts purchases, and lower inventory costs [22].

Robotic technologies have developed over the last few decades, hence enabling disassembly to be achieved with minimal human intervention or in a collaborative manner between machines and human operators. The human-robot collaboration overcomes the problems associated with partial-automation by integrating robotics into human activities, which may be an effective method for enhancing productivity [25].

B. Robotic Disassembly

Disassembly automation has been a focus of research over the past two decades [26]. The uncertainty of product structure, models, and conditions, as mentioned in the introduction, is the main challenge in robotic disassembly. There are four levels of disassembly research, namely, the reverse logistics level, the task planning level, the sequence level, and the operation level. Disassembly planning and scheduling are the two major areas of these four levels [27]. A number of studies have been done on the uncertainties that exist at the planning level; for example, Genetic Algorithm (GA) has been utilised to generate a disassembly sequence based on information about components and bill-of-material [28]. Alshibli et al. [29] have studied task allocation and robotic disassembly of end-of-life (EOL) products. Torres et al. have presented a task planner for two cooperative multi-sensory robots [3]. In the work by Duffoua et al. [30], automated tools and fixturing systems were developed for achieving high-level flexibility and robustness. In the work by Knoth et al. [31], an intelligent robotic disassembly process was developed using a vision system to identify components for extracting components. For the disassembly of LCD screens and TVs, Vongbunyong et al. proposed the concept of "cognitive robotic system," which again makes use of a vision system [32]. To recover valuable material from EOL iPhones, a Daisy robot was used to disassemble old iPhones and reuse cobalt from recycled batteries in new batteries [33].

C. Human-robot collaboration

The intension of using human-Robot collaborative disassembly is to achieve high-level flexibility in the disassembly system to effectively handle uncertainties [34, 35]. Human–robot collaboration combines robot efficiency and human adaptation in complex tasks [36]. The use of compliance through active compliance control and passive accommodation helps improve adaptability and mitigate uncertainty. In the area of cellular manufacturing, human–robot collaboration systems have proven to be effective [37].

Due to high-level uncertainty and unpredicted operations in disassembly, a human-robot disassembly system can be a more effective solution than manual systems [38, 39]. This approach allows robots and human operators to work together in a disassembly task [40]. The work by Parsa and Saadat [41] presented a human-robot collaborative system for the disassembly process and a systematic framework. The work by Huang et al. [42], demonstrated two collaborative robots and a human operator carrying out disassembly tasks by controlling the robots’ active compliance joints based on force and torque sensing and position control. Over the past few years, a group at the University of Birmingham has been working on robot-facilitated disassembly. The research involves utilising collaborative robots (e.g. KUKA LBR) [43], performing tasks like unfastening screws [44], removing pegs from holes [45], and disassembling press-fits [18]. As part of a human-robot collaboration (HRC), Mukherjee et al. have explored the levels of human-robot interaction, including human motion intention prediction, various aspects of safety, learning by demonstration, and manipulation using machine learning (ML) (Section III) [46]. However, due to limitations related to accuracy and speed, or computational resources, coordinating and scheduling HRC tasks effectively in disassembly have not been widely validated [47, 48].

III. PERSPECTING OF USING SCHEDULE-FREE AUTOMATION IN DISASSEMBLY

Machine learning (ML) can help improve the performance of manufacturing processes by reducing uncertainties. In the work by Vongbunyong et al. [9], the learning and revision strategy for disassembly systems using cognitive robots is proposed. The revision concentrated on process improvement and optimization at the operational level, where vision system and disassembly operation unit uncertainties are directly implicated. After a given number of revisions, the system is capable of handling multiple product models and automatically creates the disassembly sequence plan (DSP) and disassembly process plan (DPP).

Unsupervised learning (UL), supervised learning (SL), and reinforcement learning (RL) are the three types of learning algorithms. In SL, learning data is labelled, and the model is known before learning. SL is typical in solving regression and classification problems. RL can be used to learn without labels and to evaluate data features [49]. RL is a method based on rewarding desired behaviors and/or

1 In the revision, the existing knowledge base is changed so that more data of known models have been frequently disassembled to improve performance.
punishing undesired ones. In general, a RL agent is able to perceive and interpret its environment, take actions and learn through trial and error.

RL has different classifications, which are shown in Fig. 1. But each of these learning methods has strengths and weaknesses, which are detailed in Table I. A variety of RL algorithms from a theoretical perspective are presented in [49].

Other disassembly sequence planning approaches include fuzzy-rough set (FRS) [50], Tabu search (TS) [51], greed randomised adaptive search procedure (GRASP), and Dijkstra's algorithm (DA) [37].

A robot with self-learning capability can use ML, DL and RL to learn from interactions with its surroundings [4, 52]. Self-learning robotics has been adopted in industrial applications.

In the work by Gibbons et al. [53], an automated visual inspection system for remanufacturing was developed by using image data for modelling remanufacturing inspection. The use of the Gaussian mixture model for training an inspection model based on machine learning was proposed. For classifying samples of components recorded by the camera, Chigozie et al. [54] used deep learning. Deep learning is a subtype of machine learning in artificial intelligence that can learn autonomously from unlabelled or unorganised data. Recent developments in image processing and voice recognition have adopted deep learning techniques [55, 56].

RL is also one of the most prominent disciplines in machine learning. RL can be used to efficiently solve a variety of challenges in the area of artificial intelligence [57], and its research value has been widely acknowledged in a number of fields, including manufacturing, robot control [58], and autonomous driving [59]. A number of well-known academic institutes and businesses (such as DeepMind [60], University of California Berkeley [61], OpenAI [62], and Google Brain [56]) have made considerable progress in this area but still face significant obstacles [63], including sample inefficiency, higher training costs, uncertain models, and dimensional disaster. Furthermore, the majority of robot RL research is still in the simulation stage, which is far from implementations in physical environments [49].

In human-robot interactions (HRI), key research and developments have been about prediction, control, and decision-making. A robot can be programmed using reinforcement learning in combination with demonstrations. For example, manually guiding the robotic arm can teach a collaborative robot how to grip an object [4, 46, 57]. RL can also be applied to robotic agents to learn high-precision assembly/disassembly skills instead of just transferring human skills to robots [64]. When executing high-precision processes, RL provides a flexible approach that minimise working time, intricacy in the development lifecycle, and human error [65]. Recent research has demonstrated the importance of RL in robotic manipulation tasks [56, 66-68].

Deep learning (DL) is a type of machine learning that employs multilayer nonlinear operating units. The deep abstract feature representation is automatically acquired from a large quantity of training data using the output of the bottom layer as input. DL has been an effective tool in image processing, audio recognition, natural language processing, robot control, and many other disciplines. DL is more conducive to reducing gradient dispersion and local optimum than classic multilayer NN algorithms, as well as avoiding the curse of dimensionality produced by high-dimension data. Deep belief network, stacked autoencoder, recurrent neural network, and convolutional neural network (CNN) are examples of representative structures for DL. Through interactions with the environment in different domains, RL allows agents or robots to learn decision making. Various Deep Reinforcement Learning (DRL) techniques that combine the perceptive abilities of DL and the judgmental abilities of RL have been proposed to achieve end-to-end learning with direct control of the output [56, 69, 70]. Table II shows an overview of published articles on learning-based robot disassembly.

![Fig. 1. Classification of RL algorithms](image_url)

<table>
<thead>
<tr>
<th>Category</th>
<th>Strengths</th>
<th>Weaknesses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value-based RL</td>
<td>A flexible and easy-to-implement solution</td>
<td>The reward function design is difficult, and it consumes significant memory if the state is large and discontinuous [71].</td>
</tr>
<tr>
<td>Policy-based RL</td>
<td>A simpler and easier approach than convergence value-based RL, it directly optimises the objective function and finds the best strategy.</td>
<td>Local optimum is easy to converge, and high variance is encountered [72].</td>
</tr>
<tr>
<td>Model-based RL</td>
<td>Easy to converge and faster training</td>
<td>Model and design reward functions are difficult to obtain [73, 74].</td>
</tr>
<tr>
<td>DRL</td>
<td>Decision making, perception, convergence more rapidly, and less data association</td>
<td>There are inefficiencies in the data, high sample complexity, instability, local optimum, and difficulty designing reward functions [75].</td>
</tr>
<tr>
<td>IRL</td>
<td>Easy to quantify reward function and obtain reward function</td>
<td>By varying the reward function, it is easy to reach the same expert policy [76, 77].</td>
</tr>
<tr>
<td>Meta-RL</td>
<td>Faster learning with a flexible, small-scale sample</td>
<td>Space of large-scale parameters and quadratic gradients [75].</td>
</tr>
</tbody>
</table>

![Table II. A summary of articles in the field of robot learning and disassembly](table_url)
<table>
<thead>
<tr>
<th>Publications</th>
<th>Techniques/Methodologies</th>
<th>Details</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>[78]</td>
<td>Neural network (DCNN)</td>
<td>Accurate prediction of human motion in human-robot collaboration during the disassembly of the desktop computer product.</td>
<td>2019</td>
</tr>
<tr>
<td>[9]</td>
<td>Machine Learning</td>
<td>Presenting the advanced behavior control (i.e., knowledge, learning, and revision) for cognitive robotic disassembly automation</td>
<td>2015</td>
</tr>
<tr>
<td>[20]</td>
<td>Reinforcement Learning (Model base)</td>
<td>Presenting the state of the art of contact-rich disassembly operations.</td>
<td>2021</td>
</tr>
<tr>
<td>[79]</td>
<td>Reinforcement Learning (Value-based Q-learning algorithm)</td>
<td>Unscreeing</td>
<td>2019</td>
</tr>
<tr>
<td>[80]</td>
<td>Deep Learning (YOLO)</td>
<td>Fastener detection for unscrewing</td>
<td>2021</td>
</tr>
<tr>
<td>[81]</td>
<td>Deep Learning (ResNet)</td>
<td>Screw detection for unscrewing</td>
<td>2021</td>
</tr>
<tr>
<td>[84]</td>
<td>Reinforcement learning (Monte Carlo)</td>
<td>Solving large scale disassembly line balancing problem (DLBP)</td>
<td>2014</td>
</tr>
<tr>
<td>[85]</td>
<td>Reinforcement Learning (Q-Learning)</td>
<td>Determining Selective Disassembly Sequence Planning for the End-of-Life Products with Structure Uncertainty</td>
<td>2021</td>
</tr>
<tr>
<td>[86]</td>
<td>Reinforcement Learning (DQN)</td>
<td>The modelling and control of flexible and hybrid disassembly systems with both manual and autonomous workstations</td>
<td>2022</td>
</tr>
<tr>
<td>[87]</td>
<td>Deep Learning (YOLO)</td>
<td>Locating and classifying six different types of screw heads with different sizes for screwing</td>
<td>2022</td>
</tr>
<tr>
<td>[88]</td>
<td>Reinforcement Learning (SARSA)</td>
<td>Separating the bulb from the casing</td>
<td>2019</td>
</tr>
</tbody>
</table>

IV. BIBLIOMETRIC ANALYSIS

A. Publication Collection

The bibliographic dataset which is used for this research has been collected from the Web of Science (WOS) repository in March 2022 using the keywords “Learning” and “disassembly”. This research limits the search duration between the years 2010 to 2022. In this work, the search string was used to download a text file containing publication information such as title, abstract, keywords, source of journals, etc. suitable for viewing with VOSviewer software.

A total of 187 papers on learning-based disassembly were retrieved by using this method, 26 of which were about disassembly robots. Fig.2 shows a summary of the number of publications based on self-learning robotics over the period. The articles were then examined in terms of keywords and citations.

B. Publication Analysis

This research used keyword analysis to provide a major result on the progress and future trend of robotics assembly research using the Learning approaches.

The total number of keywords detected in the dataset was 120. Finally, this project opted to filter the keywords with a minimum co-occurrence of 1 and came up with a total of sixteen keywords. Fig.3 gives the co-occurrence map of the selected terms from abstracts and titles of publications. The word "disassembly" is the one with the most frequency in frequency terminology (27). Other high-usage keywords include "reinforcement learning" (23), "tasks" (23), and "robots" (18). The co-occurrence frequency is shown by the distance between the terms in this graph. The co-occurrence number is high if the distance between the terms is short, and it is low if the distance is long.

Another well-known approach for analysing prominent publications is citation analysis. The most impactful works in the specified field in the last ten years were found using the WOS findings. Fig.4 shows a summary of the articles with the most citations. It can be seen that adopting machine learning techniques in robotic disassembly is a growing and emerging research direction.

V. CONCLUSION

The paper describes techniques for robotic disassembly, then reviews the existing literature on using machine learning in robotic disassembly.
Moreover, to determine the research trend in this area, a bibliographic review of the previous decade's literature has conducted. Furthermore, the study identifies potential future research avenues by identifying prominent research phrases in this domain.

VI. REFERENCES


Abstract—Handling mass customized products is one of the key challenges in manufacturing and logistic industries. Flexible solutions which can cater to novel objects are desirable in these industries which are continually producing unique catalogues of products. However, most of the robotic grasping solutions on the market are not suitable for novel objects in high mix and low volume scenarios. Currently, the gaps in the areas of grasping accuracy and speed are impeding the widespread adoption of robotic grasping in these industries. This research aims to improve the grasping capability for novel objects and demonstrate robotic grasping using soft grippers based on data driven learning to accommodate novel objects with varying shapes and textures.

We compare data driven approach with deep reinforcement learning (DRL) approach and found that the limitations of DRL such as being data-intensive, complex, and collision-prone reduce its industry readiness level. Therefore, we opt for PointNetGPD which is a data driven approach in this research. We have also performed a comprehensive market survey on tactile sensors and soft grippers with consideration of factors such as price, sensitivity, simplicity and modularity. Based on our evaluation, we choose Rochu two-fingered soft gripper with our customized Force Sensing Resistors (FSR) force sensors mounted on the fingertips because of Rochu’s modularity and compatibility with these tactile sensors.

Finally, we conduct data training using soft gripper configuration and test various fast-moving consumer goods (FMCG) products inclusive of fruits and vegetables which are unknown to the database. The grasping accuracy is improved from 75% based on Push and Grasp to 81% based on PointNetGPD. Our versatile grasping platform is independent of gripper configurations and robot models.

Keywords—Versatile Grasping, Deep Reinforcement Learning, High Mix and Low Volume, Tactile Sensor,

I. INTRODUCTION

Robotic grasping is an area of development requiring intricate collaboration between both software and hardware grasping elements as seen in Figure 1. This need for collaboration opens up various possibilities for improving the current state of this ever-evolving technology [1]. This research tackles challenges faced by pre-programmed robots in the manufacturing and logistics industries. These robots are suitable for limited applications and require reprogramming whenever new applications arise [2]. This limitation restricts them from deployment for fast-changing processes in the manufacturing and logistic industries. Moreover, these robots are unable to grasp or pick novel and unknown objects in high mix low volume production scenarios. These highly mixed objects, otherwise known as stock keeping units (SKUs), possess various types of physical characteristics which can be challenging for a robotic system: heavy, light, flat, soft, rigid, small, large, deformable, fragile, translucent, etc.

To tackle these challenges, we propose a versatile soft gripping method with tactile sensor feedbacks, which is a further improvement from PointNetGPD baseline[3]. A robotic grasping system has been developed and demonstrated previously based on Push and Grasp [4] with limited grasping accuracy and success rates of 75% for novel non-textured and textured objects. This research will advance the development of PointNetGPD in two ways; by focusing on improving grasping capability for novel objects and demonstrating robotic grasping using soft grippers based on deep learning to accommodate novel objects with varying shapes and textures. Our research includes the development of a flexible grasping technique using deep learning for soft grippers, usage of sensor information as a feedback loop to work together with the vision data for robotic grasping stability validation, and improvement of the accuracy and success rate of the grasping model to 81%. Our existing work excludes designing and developing new robotic grasping tools such as a finger gripper or soft gripper.

II. LITERATURE REVIEW

A. Soft Gripping Technology

Soft gripping technology can be mainly classified into three categories: actuation-based gripper, controlled stiffness, and
controlled adhesion. By reducing control complexity based on material softness and mechanical compliance, soft grippers are an example of morphological computation. Researchers have been focusing on advanced materials and soft components such as silicone elastomers and shape memory materials in recent years. Besides, gels and active polymers draw a lot of attention for lighter and universal grippers due to its inherent material properties [5]. In addition, stretchable distributed sensors embedded in or on soft grippers greatly enhance their interaction with objects. However, research on soft grippers still face challenges including but not limited to sensor fusion, miniaturization, payload, reliability, speed, and control. In summary, soft gripping technology advances with material science, processing power and sensing technology.

**B. Tactile Sensor**

Our selection of force sensor is based on sensitivity, flexibility, simplicity, and cost. With these considerations in mind, resistive force sensors are the most ideal for robotic grasping as their properties are well-balanced among the above-mentioned considerations. Although these normal pressure sensors generally offer a single contact point and possess relative low energy efficiency, they are adequately sensitive, simply, flexible, and yet inexpensive. This is as opposed to capacitive force sensors which boast excellent sensitivity, spatial resolution and large dynamic range but suffer from hysteresis and a high level of complexity. The most recommended resistive force sensors to purchase are FSR’s FA201, FA400, and FA402 Force Sensing Resistors (see Figure 4) as well as those from the Arduino Kit. The sensor dimension is around 15.7 mm which fits comfortably on our Rochu soft fingertip which is 24 mm approximately.

**C. Data Driven Approach**

In general, grasping can be done on three types of objects: unknown, familiar, and known [7, 8]. Unknown objects are those whose models are inaccessible to the robot which, hence, prioritizes the identification of the objects’ structures or features from sensory data. This system generates and ranks the objects instead of working with a lack of grasp experience [9, 10]. At the other end of the spectrum, known objects are objects which have been encountered by the robot. Hence, grasps have already been generated by the system previously. Bridging unknown and known objects are familiar objects, which possess similarities to known objects despite never having been encountered previously. Grasping of familiar objects requires the robot to find an object representation and a similarity metric to transfer comparable grasp experiences from known objects to the familiar objects. Because of the complexity, current research mainly focuses on developing deep learning models for grasping unknown objects, with some prominent ones utilizing DCNNs [11], RGBD images, and depth images of a scene [8]. These methods are generally successful in determining the optimal grasp of various objects, but they are often restricted by practical issues such as limited data and difficulty in testing.
We have narrowed down two prevailing and advanced data driven approaches: PointNetGPD and GraspNet [12, 13] as shown in Figure 5. GraspNet is an open project for general object grasping that is continuously enriched. It contains 190 cluttered and complex scenes captured by two popular RGBD cameras (Kinect A4Z and Realsense D435), bringing 97,280 images in total. Each image is annotated with accurate 6D pose and the dense grasp poses for each object.

In total, the GraspNet dataset [12] contains over 1.1 billion grasp poses. However, PointNetGPD performs better when the raw point cloud is sparse and noisy[3]. As a result, we proceed with PointNetGPD.

D. Deep Reinforcement Learning Approach

Policy gradient methods, model-based methods and value-based methods are three of the most popular deep reinforcement learning methods [14, 15]. They enable development of smarter and more adaptable robotic grasping algorithms. These algorithms can be further divided into two categories: off-policy learning and tactile feedback as demonstrated in Figure 7.

Tactile feedback is an alternative algorithm class to off-policy learning. An algorithm utilizing this policy can realize grasps provided by a coarse initial positioning of the robotic hand above an object. In this DRL policy, exploitation and exploration are balanced through the use of a clipped surrogate objective within a maximum entropy reinforcement learning framework. Tactile and force sensing can provide a proprioceptive knowledge about grasping stability and success, thus regrasping or rearrangement can be activated to improve grasping versatility [16]. However, deep reinforcement learning-based approaches are data-intensive, complex, collision-prone, and might not be suitable for robotic manipulations (especially efficient light-weight manipulation) [16, 17]. As a result, DRL is not industry ready yet as of now when compared to Data Driven Approach.

III. METHODOLOGIES

In this paper, we demonstrate the development of PointNetGPD for versatile grasping in details including each of the approach, the results from each of the algorithms, the advantage, and disadvantages, respectively. The contents that we have developed are as follows:

1. Sensor feedbacks on grasping success and stability
2. Grasp pose detection based on point cloud and PointNetGPD

A. Sensor feedbacks on grasping success and stability

The current gripper used in the setup is a 2-finger soft gripper configuration from ROCHU soft robotic gripper group. The gripper is selected due to its grasping ability to suit a more diverse set of grasp object: the contact surface of the gripper has elasticity to slightly wrap around the targeted grasp object, this creates higher traction while grasping onto objects compared to normal rigid 2-finger grippers.

These are the main conditions considered when we mount the force sensors on the pneumatic gripper:

- Sensor calibration
- Actual use condition, grip stability and slippage
- Sensor placement for accurate position of gripping contact

The force sensors are calibrated by measuring its raw voltage output against a calibrated load cell at multiple samples.
of force values; two examples of the calculated curve fitting of the sensor readings of varying characteristics are conducted. The calculated results show varying exponential curve trend among the set of sensors used, so we chose a pair that have similar force to voltage curve outputs for reading and visual interpretation consistency. The force sensors were initially mounted on the pneumatic gripper with the force sensor contact area exposed for direct contact to the grasping objects to ensure that the measured force is true to the calibrated curve readings.

However, the contact plates have very low grip traction due to its flatness and rigidity of the contact surface, objects that are grasped slip off the gripper and force sensor easily while lifting off the table surface. To increase the gripping traction, we wrapped silicone rubber (or grip) tape around the force sensor contact surface as shown on the right of Figure 8. The silicone rubber tape dampens part of the measured contact force during the object grasping action; this affected the force value output from the grasping actions and the readings from here onwards were taken without reference to the force curve reading from the initial calibration. Grasping trials on all viable objects for picking, as shown in Figure 9, were conducted in a simple sequence of gripping of object (step 1), followed by raising the object off the table (step 2), the object is then either released to be dropped (step 3a) or placed back on the table if the object is fragile (step 3b).

The general output readings from force sensor are shown in Figure 6, results shown on the left are from objects which follow step 1, 2 and 3a (dropped) and on the right from objects which follow step 1, 2 and 3b (placed back on table).

The voltage drop is measured from the force sensors as contact with the grasp objects occur. Seldom occurrence of slippage and misalignment of the force sensor contact point with the grasp objects is still present. Tabulating the results across the trials, the current grasp detection is determined to be positive as long as there is a voltage drop of 20% present in either of the mounted tactile sensor.

B. Robotic Grasping Based on PointNetGPD

To improve the grasping performance, we use a grasping algorithm with evaluation network and tactile sensor feedbacks to produce best grasping pose directly from raw point cloud input. The advantage of this evaluation network is the capability able to analyze complex geometry even through the point cloud is sparse. RGB-D camera such as RealSense camera is utilized to capture raw 3d point cloud.

Usually in grasp detection, we have to find out the object grasping position and orientation. Given a specified grasping object, \( g=(p, r) \in \mathbb{R}^6 \) stands for grasping 3D space configuration where \( r=(r_x, r_y, r_z) \) and \( p=(x, y, z) \) represents the orientation and position of the end of arm tool (EOAT) respectively. There are several grasping candidates are generated from deep learning network, in this case, we need to evaluate to check which candidate is with higher quality. PointNetGPD provides a network architecture and grasp representation. In this network, PointNet uses point cloud represented by gripper configuration to fit the grasping object. Potential local grasping pose candidates will be generated with the best scores. This approach is mainly to eliminate the ambiguity caused the different experiment (especially camera) settings. Specifically, for the gripper approaching, parallel and orthogonal directions of the gripper as the XYZ axes respectively, while the origin is located at the bottom center of the gripper. After getting the smaller and segmented point cloud, N points is the quality estimator which will go through the networks. Overall, PointNetGPD is lightweight with only 1.6 million parameters when compared to other traditional grasping quality evaluation methods [3].

The PointNetGPD network is trained using YCB dataset, which covers many objects that we usually see in our daily life. These objects are also the ones that we used in our demonstration. In the algorithm evaluation phase, we use Intel Real-sense D435 camera and UR 10 robot with soft gripper. We have tested the grasping algorithm performance using cluster scene. Figure 10 shows the result sample of the grasping pose generation from PointNetGPD, it generates several grasping candidates by showing the green gripper poses. Lastly in Figure 11, the red grasping pose is the selected grasping pose which is with the highest grasping quality among all the grasping candidates.
IV. RESULT ANALYSIS

Figure 12(a) show our system setups. Intel RealSense D435i camera that is mounted on a camera fixture was used to obtain the point cloud of the scene. UR10e robot and Rochu two-finger soft gripper are used to execute the robotic grasping. A Linux workstation was used to communicate with UR10e robot by Ethernet and ROS middleware, Realsense Camera via USB port and control the I/O of the soft gripper via RTDE socket. A noise and table point cloud removal filter was also created to reduce the computation load based on Aruco Marker as can be seen in Figure 12(a) as well. All the grasping poses were simulated and validated in ROS MoveIt before sending to the real robot for execution as can be seen in Figure 12(b). In addition, the Linux computer is also to retrain algorithm using the soft gripper configuration. The UR robot would pick the objects from the table and place them into the blue bin.

Figure 12(c) demonstrate the grasping pose generation and decision-making process based the metrics we pre-defined in the core algorithm. To be more specific, based on the filtered object point cloud, PointNetGPD would randomly sampling grasping poses for different objects and then through combination of grasping quality metrics including force closure and Grasping Wrench Space (GWS), the algorithm would decide the best suitable and quality grasping pose in current setting.

For our current research, we only adopt single agent for the computing. It takes 10-15 seconds to find the most suitable pose and another 5 seconds for the robot execution. In future works, we would explore options of parallel computing with multi agent CPUs or GPUs to accelerate the grasping pose detection process. Figure 12(f) demonstrate some grasping in action.

Soft gripper is capable of handling fragile and deformable products such as fruit and vegetables. Rigid gripper like Robotiq might face issues when handling fragile products, e.g., damage on the surface, deformation etc. Besides, fruits and vegetables are relatively larger in size and irregular in shape as well which causes problems for rigid gripper, as it might be limited by the finger distance.

Figure 12(d) and (e) shows the two demonstration scenarios we created by randomly place the non-textured and textured objects on the surface, then the robotic system performs the grasping action based on the checkpoint that we obtained from the training. We conducted around 100 grasping in total using selected FMCG products inclusive of fruits and vegetables. It can reach around 80 percent grasping successful rate using the Rochu soft gripper including novel or unknown objects. But due to the limitation of the soft
gripper, which is payload, it affects the grasping successful rate as well. The Deep Learning based grasping pose detection, however, is rather stable and accurate. The grasping pose detection rate can reach above 90% for PointNetGPD. All of these are significantly improved from the previous DRL methods, where 75% grasping successful rate is met.

V. CONCLUSION

In this study, we first conduct literature survey and market sensing for soft gripper, tactile sensing technology, data driven and Deep Learning base grasping pose detection methods. Based on the comparison results, we proceed with data driven approach with Rochu soft gripper and resistor-based force sensors mounted on the fingertips. PointNet GPD algorithm is chosen as the core algorithm due to its advantages in raw point cloud processing and large numbers of grasping data base. Moreover, we retrain the PointNetGPD with our own gripper configuration. The results show that the PointNetGPD perform quite well in terms of grasping pose generation for known and even unknown objects. In terms of grasping rate, we achieve around 81% for chosen FMCG products, fruits and vegetables with the payload limitation of soft grippers. Future works will be focusing on software packaging and easy deployment on the cloud. Despite that, further improvement in terms of grasping speed and accuracy will be addressed as well.

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Robotic disassembly of electric vehicle batteries:
an overview

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Abstract—Electric vehicle (EV) batteries reach the end of their service lives in 5-8 years. The repair, remanufacturing and recycling of EV batteries can have significant economic and environmental impacts. Disassembly, a key process in repair, remanufacturing recycling, is usually a manual task. Due to the growing number of end-of-life EV batteries, robots have been proposed to be used in EV battery disassembly. Nevertheless, the high-level complexity and uncertainty in disassembly actions make it difficult to automate EV battery disassembly. This paper gives an overview of the current approaches adopted in EV battery disassembly, and robotic techniques that have the potential to be employed in battery disassembly. We propose a classification of EV battery disassembly actions and identify key future research and innovation directions.

Keywords—EV battery; robotic disassembly; disassembly sequence plan; human-robot collaboration; deep reinforcement learning

I. INTRODUCTION

The electric vehicle (EV) battery market has been rapidly growing for years. In 2020, more than 10 million electric vehicles were on the road worldwide [1]. Most EV batteries are guaranteed for 5-8 years or 100,000 miles [2], and end-of-life EV batteries are recycled by the manufacturer. The recycling of EV batteries has become increasingly important [3]. Given that the existing recycling methods are unsafe and less efficient [4], automated equipment needs to be involved in the remanufacturing of EV batteries.

A robotic disassembly system can provide a safe environment for workers and reduce disassembly costs, but the adoption of robotic disassembly in EV battery disassembly has been limited due to the complex structure of EV batteries [5]. Due to having no unified standard, the structures of batteries from different manufacturers are also different [4]. This makes the use of robotic disassembly difficult.

This paper provides a brief review of research on the robotic disassembly of electric vehicle batteries. In the second section, this paper presents current challenges in the EV battery disassembly. The third section discusses the key robotic technologies that can be adopted in the EV battery disassembly. In the fourth part, this paper elaborates environmental and economic impacts of the EV battery disassembly. Finally, the paper summarises previous works and illustrates opportunities in the future research of the EV battery disassembly.

II. CHALLENGES IN EV BATTERIES DISASSEMBLY

At the end of the service life of an EV battery pack, some of its modules can be direct re-used, and others may be recycled. Due to the different battery designs adopted by different manufacturers, the structure and layout of battery packs and modules can be different [3].

Figure 1 shows three types of EV battery packs and their internal structures. In general, an EV battery has a three-level structure: battery pack, battery module, and cell.

The main method of the EV battery disassembly is still manual. Due to the high-level dexterity in manipulation and the potential safety risks due to electrical shocks, manual operators are usually required to obtain certain qualifications for carrying out this work [6]. A survey by the Automotive Industry Institute found that there are 170,000 motor technicians in the UK, this is less than 2% of the workforce [6]. Therefore, the disassembly of EV batteries is usually associated with high labour costs.

Typical components of EV batteries include electronic components, wiring, looms, busbars, modules, etc. In addition, there are auxiliary components such as cooling and connection ports [7]. A variety of tools are required in the disassembly of EV batteries for removing fasteners and screws of different components as well as, many auxiliary operations such as cleaning. Usually, these operations need to be carried out in narrow spaces with poor accessibility [8].
The EV battery disassembly process has two major steps. The first step is the disassembly of the battery pack into battery modules, which may involve test (e.g., voltage test), charging, and discharging of the packs and the modules. The second step is to disassemble battery modules into battery cells. Challenges in the two steps can be very different.

There are two major barriers in the adoption of robots in the disassembly of EV batteries: high-level variations in parts (due to different designs) and in end-of-life conditions [4]. Figure 2 details some of the challenges in the two-step process. Some batteries reach the end of their service lives due to damaged cells, and others are due to other types of damages (e.g., wiring, circuits, and deformations). End-of-life (EoL) batteries are difficult to disassemble [9]. The high-level variations include many aspects. The first is the design diversity of EV batteries. As shown in Figure 1, these are three common EV battery designs. The lack of a standardized design is a huge challenge for disassembly. Also, standardized EV battery designs will not be easy to achieve for some time to come. This means that the architectures, configurations, shapes of EoL EV batteries - some important parameters for robotic disassembly - are quite different. The second is the diversity of disassembly tasks. The design of EV batteries is complex, which leads to a wide variety of disassembly tasks. Since there are mechanical, electronic, and chemical modules inside EV, they are connected in many ways. For example, the disassembly of sticky joints or welded joints in battery modules is very difficult for robots. Finally, there is the diversity of disassembly targets. There are many disassembly purposes for EV batteries, such as recycling of available materials, battery module testing, charging, and discharging, etc. Due to the different purposes of disassembly, a unified robotic disassembly system cannot be used, which is also one of the challenges.

Another challenge is uncertainty of conditions. As with many EoL devices, there can be significant uncertainty about the performance and condition of EV batteries [4]. The mechanical structure of some EoL batteries is not obviously damaged, and this disassembly state is relatively simple for robots. However, there are many EoL batteries with incomplete mechanical structures. For example, rust, looseness, damage of components. In addition, due to the different functional systems inside the battery, such as the battery management system (BMS), if this system is scrapped, the robot will disassemble the electronic module, which is different from the mechanical module. In addition, due to the safety problem of EV batteries, robotic disassembly requires more non-destructive disassembly, which is also a challenge due to the uncertainty of EV battery conditions [9].

Current robots and automation technologies applied to manufacturing processes are usually in highly structured environments in which robot motions are repetitive. The application of robots to the EV battery disassembly is still difficult, considering the complexity and uncertainty in the EV battery disassembly process. Here, we listed four major types of techniques that can be adopted in the EV battery disassembly.

A. Schedule-based robotic disassembly of EV batteries
A key challenge in the robotic disassembly of the EV batteries is the scheduling of disassembly sequences. This is a complex problem as different disassembly sequences will cause disassembly efficiency and resource consumption to be different. The scheduling of disassembly sequences has become an established research area, which looks at developing planning algorithms [10]. This problem is known as disassembly sequence planning (DSP) [11].

There are three main steps in DSP [11]. The first is to determine the disassembly method of an end-of-life product. Next, describing the priority relationship among the parts of the product could be used for this disassembly method. Finally, planning methods should be used to select the best solution. This topic can improve the production efficiency of enterprises [12], and thus there are many active research projects in the area of DSP.

There are several objectives in DSP, including but not limited to disassembly cost and disassembly time (which may involve basic disassembly time, tool changing time, travelling time, and other aspects that may affect disassembly). There is also research looking at reducing the number of disassembly operations, parts, and tools. In addition, researchers have also modelled the environmental and economic impacts. Some researchers also investigate the difference between destructive and non-destructive disassembly, and that between partial disassembly to complete disassembly.

Based on the schedule-based disassembly research, there are many DSP studies in the area of EV batteries [13]. Figure 3 shows the disassembly sequence of an Audi Q5 hybrid battery pack [7]. The main operations in the disassembly of EV batteries are removal, cutting, and unscrewing. These operations cover a majority of the operations in the disassembly of an EV battery. As it can
be seen from Figure 3, some repetitive tasks that can be carried out by robots, though some may be difficult to automate.

Figure 3. The disassembly sequence for EV battery pack [7]

Using robots in the EV battery disassembly can be achieved by automating the simple and repetitive manual operations, and the whole disassembly process will be carried out jointly by human operators and robot machines. Therefore, the efficiency of human-machine collaboration and human-robot coexistence [14] has become a key. Another key research direction is to enhance the dexterity of robotic manipulation to allow more disassembly operations to be automated.

B. Improvement of automation in robotic disassembly

As for robot-assisted disassembly systems, using robots in more processes will greatly improve the automation and efficiency of disassembly. The basis of robot disassembly is robot programming.

Offline programming is one of the basic programming approaches. The operator programs the robot using a compiler which includes functions such as robot basic motions and sensor feedback. There are two kinds of programming methods: text-based programming and graphics-based programming [15].

The offline programming tool is limited by the robot manufacturer/designer, and the requirements for the operator to do text-based programming are relatively high. Lead through programming is also a basic programming approach. It requires the robot to be led to all the positions in the tasks and record the movements in the controller. The users are able to move the robot to a target position through the teach pendant. In addition to the teach pendant, many robots have walk-through programming capabilities. The walk-through programming means that the operator manually guides the robot to complete the movement. Moreover, the demonstration programming can program a robot by demonstrating the task to transfer directly, let the robot record behaviours [16].

There are already certain cases where full automation has been built for disassembly. For example, Apple designed a disassembly line for the iPhone [17] where a mobile phone can be disassembled into 8 parts. This approach, under certain conditions (e.g. high volume and high remaining value in the end-of-life products), has the potential to be widely promoted.

C. Improvement of human-robot collaboration in robotic disassembly

As shown in Figure 4, simple human-robot coexistence cannot improve the intelligence of disassembly, therefore, it is necessary to improve the efficiency of interaction between humans and robots to realise human-robot collaboration [18].

Figure 4. The left side of the figure shows that there is no interaction between the human and the robot. From the left side to the right side, more and more interactions, and finally achieve human-robot collaboration [19].

Human-robot collaboration is a new approach of using robots in which humans and robots share a workspace and cooperate in tasks [19]. Figure 5 shows a workstation for human-robot collaboration - humans and robots can work together or individually. This method can improve the flexibility of the robot during the processing, but the interference between the human and the robot may affect the processing strategy. A new type of industrial robot - collaborative robots (cobots) - has created new opportunities in remanufacturing and disassembly processes. When robots and humans collaborate, their interactions can disrupt the system, making processing uncertain and complex. Therefore, solving the problems that occurred in the human-robot interaction is the key to the successful implementation of human-robot collaboration.

Figure 5. Human-robot collaboration disassembly workstation [23]

Collision is one of the most common problems in human-robot interaction. Motion planners use various sensors (e.g. cameras, lasers) to capture the position and pose of the human operator and develop strategies for collision avoidance. Researchers can improve the performance of collision avoidance by improving the sensor capture efficiency and implementing reactive collision avoidance [20]. The above research belongs to the pre-collision strategy, which is used to prevent harmful contact between humans and robots [19]. Since the relative motion between humans and robots is difficult to predict, the pre-collision strategy is also proposed. This strategy can limit the contact force in an appropriate range.
Direct force control is a method of controlling the robot using the measured contact force [21]. Furthermore, a hybrid control method is proposed. Hybrid position/force control methods can combine vision and force, and control robots to navigate in unknown environments. In addition to force, admittance or impedance control is also a contact control strategy. This control strategy has good robustness to disturbances and uncertainties [22]. Impedance strategy controls the external force based on the measured position, while admittance strategy controls the position based on the measured external force. Ott et al. propose a hybrid control strategy that combines the compliance of impedance control and the unknown locations adaptation in admittance control [23]. It improves the stability and performance characteristics in the interaction between humans and robots.

While implementing a control strategy, it is common to limit the workspace of a robot (e.g. position, velocity, and acceleration) [24].

To improve the efficiency of human-robot interaction, another key topic is the communication between humans and robots. Voice control has been proved a feasible approach. Besides voice control, gesture recognition, eye registration detection, and haptic control are also good interaction approaches [25].

There are many applications of human-robot collaboration in the field of disassembly. For example, Huang et al. studied the disassembly of a car water pump - a robot assists the human in the process of extracting components from the pump [26]. In many industrial scenarios, the removal of screws is an important task in the human-robot collaborative workstation. Collaborative robots can search, locate, and remove screws [27]. In addition to specific disassembly actions, robotic systems can generate disassembly sequences through the product information provided by intelligent agents and can be able to autonomously execute disassembly tasks [28].

D. Schedule-free robotic disassembly

There is an emerging research area where researchers are developing self-modelling and self-programming capabilities with a research vision to achieve schedule-free robotic disassembly [29].

Robot disassembly involves many complex contact problems. Traditional robotic manipulation usually adopts an open-loop approach. This approach is highly stable but relies heavily on a structured environment. There are also robot systems that can perform closed-loop manipulation due to having high-precision sensors. This closed-loop control method relies heavily on high-precision sensors [30]. The robotic disassembly system for EV batteries needs to be able to complete movements, grasping, cutting, and unscrewing in complex environments. The complexity and uncertainty in objects’ geometry, mass, and the operating environment are significant challenges in the automation of the EV battery disassembly using traditional industrial robots.

Some technologies such as artificial intelligence (AI) can help many key problems in the robotic disassembly of EV batteries. AI techniques can help continuously update the disassembly control strategy and achieve self-learning. This control approach, which focuses on software and algorithms, reduces the need for high-precision sensors and can deliver good manipulation performance. Deep reinforcement learning (DRL) is considered a reliable algorithm for robot control. As shown in Figure 6, DRL enables agents to make decisions using high-dimensional and unstructured input data. DRL has been used in solving many robot manipulation problems [31]. Figure 7 shows an architecture of using DRL in robot manipulation control. The inputs are the current joint angles, end-effector positions, velocities, accelerations, etc. The robot also gets the input through the sensors. The resulting control command changes the torque or speed of the robot. When a task is completed, a reward is generated, and the control strategies improve in interactions.

Figure 6. Deep reinforcement learning

Figure 7. A schematic diagram of robotic manipulation control using DRL.

There are two major factors in using DRL in robot manipulation: sample efficiency, and generalisation ability. For robotic manipulation, sample efficiency refers to how much data is required to get a good control strategy [31]. Imitation learning is a feasible approach, which improves sample efficiency by obtaining data from expert demonstrations rather than rewards [31]. Some model-based algorithms are also very effective for improving sample efficiency. This method uses artificial data created by a model to train a policy instead of the actual data.

The generalisation problem is the key to transferring the learned policy into new tasks. To understand generalisation problems, many researchers have worked on meta-learning. The purpose of meta-learning is to solve new learning tasks using only a small number of training samples. Furthermore, meta-learning combined with other algorithms can perform tasks quickly and efficiently in complex unstructured environments.
IV. ECONOMIC AND ENVIRONMENTAL IMPACT OF ROBOTIC EV BATTERIES DISASSEMBLY

Undoubtedly, the robotic disassembly of EV batteries is a good guarantee for the safety and health of workers. However, robots, especially robots with higher intelligence, will bring different risks. The intelligence of robots relies on AI methods, in other words, on data training. In real world practice, the generation, recording and access of large amounts of data are all challenges. Data collection in ML methods requires tedious experiments. However, even with the successful collection of large amounts of data, its usability is an issue. From the application of AI in engineering practice, the key to robotic learning is to train generative models with good training data. Therefore, practitioners need databases to store industrial big data.

The reliability of AI in engineering practice has always been an issue. The reliability of dataset training is highly case-dependent. The recognition accuracy of the same trained model for different products varies greatly. Therefore, during the disassembly practical process, checking the reliability and repeatability of the AI model becomes the key. Especially for dangerous operations, its probability of success needs to be rigorously evaluated. Due to the importance of data and the large amount of data, the security issues brought by data storage also need to be taken seriously. Power systems, natural disasters, and human error all have the potential to compromise data security. At the same time, the attacks of competitors also need to be guarded by enterprises.

Robotic disassembly of EV batteries should consider overall sustainability. We often overemphasize the benefits of automation when discussing the economic and environmental benefits of EV batteries, however, there are some contradictions in actual implementation.

First, economic costs are critical for companies. The direct costs of general robotics and automation equipment are low and pay for themselves quickly. However, for AI approach, its custom design comes at a high cost. Also, it can be expensive to train, deploy, and maintain.

Second, disassembly and recycling revenue also depends on a variety of factors. The chemical composition of EV batteries is the key value for recycling, but the supporting logistics system and market maturity are also important. This will not only affect the economic benefits, but also the investment in intelligent systems.

Third, the potential pollution and carbon footprint of the disassembly process and system are key to the environmental benefits. Robotic system-led automation systems have been widely implemented, and consideration of environmental factors has become the norm. But the potential contamination of AI systems requires research. A recent survey shows that even complex AI model training can lead to high carbon emissions. Therefore, a robotic disassembly system should monitor and report carbon emissions during operation to optimize its energy performance to meet environmental sustainability goals.

V. SUMMARY AND OPPORTUNITIES

This paper provides an overview and forward-looking perspective on robotic disassembly of EV batteries.

Robotic disassembly has important value in the circular economy processes of EV batteries (e.g. remanufacturing and recycling). Robots can greatly reduce labor costs and have great potential to improve safety and efficiency.

The challenges in the robotic disassembly of EV batteries are discussed and research progress on robotic disassembly of EV batteries is reviewed. This review shows that the previous robotic disassembly of EV batteries tends to focus on schedule-based disassembly. And great progress has been made in robot disassembly automation and intelligence.

This paper also provides a forward-looking perspective on robotic disassembly of EV batteries. We believe schedule-free disassembly should be promoted and can be established by means of AI. Robots for schedule-free disassembly will offer a new approach that offers economic and environmental benefits, but this development will be accompanied with new risks, e.g. data-related.

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Utilizing Lexicon-enhanced Approach to Sensitive Information Identification

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Abstract—Large-scale sensitive information leakage incidents have occurred frequently, causing huge impacts and losses to individuals, enterprises, and society. Most sensitive information exists in unstructured data, making it challenging for people to identify when it is leaked, an important cause of information leakage. Therefore, sensitive information identification from unstructured data has received extensive attention. In addition, the smallest unit of Chinese is a character, so its lexical boundary is flexible, which makes it very difficult to identify sensitive information in Chinese. It is worth mentioning that there are no publicly available datasets in this field of sensitive information identification due to the sensitivity. To address the above challenges, we first create the SPIDC (Sensitive Personal Information Dataset in Chinese) and release it as a public resource for related research. Second, we apply the existing sensitive information identification methods on the English datasets to the Chinese datasets. In addition, to solve the problem of uncertainty and ambiguity of Chinese vocabulary boundary, we apply three lexicon-enhanced technologies from NER (Named Entity Recognition) to the Chinese sensitive information identification for the first time. Experimental results on the SPIDC show that the lexicon-enhanced approach has better performance than other methods.

Index Terms—Sensitive information identification, unstructured data, lightweight model, sensitive personal information, lexicon-enhanced approach

I. INTRODUCTION

The rapid development of big data, the Internet, and 5G has provided humanity with endless development prospects, but it has also resulted in numerous sensitive information leakage events. According to Risk Based Security [1], data breaches worldwide reached 36 billion in 2020, a record high. Moreover, remote work and digital transformation due to the COVID-19 pandemic also increase the risk of data breaches. According to IBM’s 2021 Cost of a Data Breach Report [2], the average cost of a data breach in 2021 is $4.24 million, a 10% increase from 2020, the most significant single-year cost increase in the last seven years. Therefore, effectively avoiding sensitive information leakage is an urgent problem to be solved. The Data Security Law of the People’s Republic of China, officially promulgated on June 10, 2021, is the first fundamental law in data security in China. This law states that data security requires taking the necessary measures to ensure that data is inadequately protected and lawfully used. The protection of sensitive information in Chinese has received increasing attention. Guo et al. [9], Pogiatz et al. [22], and Ding et al. [6] pointed out that sensitive information often resides in unstructured data, making it difficult for people to detect data leakage. Therefore, identifying sensitive information from unstructured data is beneficial to avoiding data leakage and protecting sensitive information.

Presently, sensitive information identification in Chinese is mainly focused on document-level sensitivity identification [4] [5], which turns the sensitive information identification problem into a binary classification problem, detecting whether or not the document contains sensitive information. However, this kind of coarse-grained sensitive information detection has not met many real requirements. People may not only need to know whether the document is sensitive but also need to redact or sanitize sensitive information from the document for privacy reasons [8]. As a result, token-level methods for sensitive information identification are required. Token-level sensitive information identification in Chinese mainly uses the heavyweight model BERT (Bidirectional Encoder Representation from Transformers) [6] [7]. However, the BERT model has several network layers and a considerable parameter magnitude, making it bulky and costly to pre-train. Therefore, lightweight and token-level methods for sensitive information identification from unstructured data in Chinese must be investigated.

Lightweight and token-level methods for sensitive information identification have received numerous studies in English datasets. Ong et al. [8] proposed the BiLSTM (Bidirectional Long Short-Term Memory) to determine a specific token from a sentence is sensitive or nonsensitive. Guo et al. [9] proposed a BiLSTM+Attention model to identify sensitive information...
from unstructured data in English. However, these models do not perform well when placed directly in Chinese datasets because Chinese is not naturally segmented and thus requires models to determine the boundaries of sensitive information, which increases the difficulty of the model prediction. Therefore, unique lightweight and token-level models are needed for sensitive information identification in Chinese according to the characteristics of Chinese datasets.

In addition, one of the challenges in sensitive information identification is the lack of public datasets [10]. This is because many policies and laws do not allow the disclosure of sensitive information to protect privacy or maintain commercial confidentiality, making it difficult to find any data that contains large amounts of sensitive data.

Therefore, we first constructed SPIDC \(^1\) (Sensitive Personal Information Dataset in Chinese). The dataset contains much sensitive information and is tagged with token-level sensitive information. To legitimize its disclosure, we have added some fictitious sensitive information or restructured the original sensitive information. Furthermore, we apply existing models on English datasets to Chinese datasets to achieve lightweight, sensitive information identification. The essence of such methods is character-based sensitive information identification. However, the Chinese suffer from blurred word boundaries and ambiguity, limiting such methods’ performance. Consequently, we apply three lexicon-enhanced technologies from NER (Named Entity Recognition) to Chinese sensitive information identification for the first time. In general, the main contributions of our research are as follows:

- We construct a Chinese corpus with a large amount of sensitive information. Furthermore, manually label each element of the corpus to form SPIDC. We release the SPIDC as a public resource for related research.
- This paper applies several lightweight, sensitive information identification models designed for English datasets to Chinese datasets. The performance of each model is verified in the SPIDC and used as the baseline in this paper.
- This paper applies three lexicon-enhanced technologies from NER to Chinese sensitive information identification for the first time to improve the accuracy of sensitive information identification. The lexicon-enhanced approach enables the model to fully use lexical information to eliminate ambiguity caused by unclear Chinese word boundaries. Experimental results show that the lexicon-enhanced methods outperform other baselines, and the best F1 score can reach 99.32%.

II. RELATED WORK

A. Dataset in sensitive information identification

Studies on sensitive information rarely publish their datasets. Publicly annotated datasets for token sensitivity labeling are less common. The data used in the research [6] [8] [9] [22] was not publicly available because of sensitive information issues. The number of entities with sensitive information in the dataset in [6] and [8] did not exceed five thousand. The small number of total sensitive information samples tends to cause the low generalization ability of the model. Although the number of sensitive information entities in [9] was upwards of 70,000, the number of non-sensitive information was almost equal to the number of sensitive information, which indicate that the content of the text is relatively simple. This is because, in reality, more data is a much more significant proportion of non-sensitive information and only a tiny proportion of sensitive information. Although Paccosi et al. [11] made the dataset publicly available, only part of the dataset was disclosed, and the number of sensitive information entities disclosed was only 1439.

B. Document-level sensitive information identification


C. Token-level sensitive information identification

Many works of literature resort to sequence labeling models to achieve token-level sensitive information identification. In contrast to document-level classification, the sequence labeling models can label each element in the sequence, enabling sensitive information identification at the token level. Gomez-Hid et al. [14] applied NER to identify sensitive tokens in a corpus. Guo et al. [9] proposed ExSense, a method for sensitive information identification from unstructured data that employed a content-based and context-based extract mechanism. Ong et al. [8] constructed a context-aware DLP system that detects sensitive information at the document, sentence, and token levels.

D. Lexicon-enhanced approach

NER aims to tag entities in a given input sequence, such as names, locations, and organizations. Our work can also be seen as a special case of NER, identifying sensitive information entities in unstructured data. There are two basic Chinese NER models: word-based and character-based models. The word-based model first uses the existing CWS (Chinese Word Segmentation) system for word segmentation and then applies the word-level NER model to label the entities [15] [16]. Nevertheless, the CWS system will invariably segment sentences wrongly. This will cause NER to make errors in predicting entity categories. As a result, character-based approaches have been shown to be effective empirically [17] [18].

Word information is not fully utilized in character-based NER methods, which limits the performance of this model. Studies in recent years have examined adding word lexicons into character-based models. Zhang et al. [19] proposed a

\(^1\)https://github.com/Yan-cc-l/Sensitive-Personal-Information-Dataset-in-Chinese
LSTM variant named Lattice-LSTM (lattice-structured LSTM) to incorporate lexical information. Gui et al. [17] proposed a lexicon-based graph neural network, which can capture global contextual information and local composition information and solve the problem of blurred word boundaries in Chinese through an iterative aggregation mechanism. Ma et al. [18] proposed the SoftLexicon method to integrate the word lexicon into the character representations.

III. THE CONSTRUCTION OF SPIDC

In this section, we describe in detail how the SPIDC is established. Since corpora containing sensitive information are rarely made public, we need to build a new corpus containing sensitive information. In addition, to legalize the public data set, we also need to reorganize the sensitive information and even add some fictitious sensitive information. In order to achieve token-level sensitive information recognition, we also need to label this corpus with token-level sensitivity.

<table>
<thead>
<tr>
<th>Type</th>
<th>Specific categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Personally identifiable information</td>
<td>ID card; Passport; Driver’s license; Social security card; Residence permit; etc.</td>
</tr>
<tr>
<td>Network identification information</td>
<td>QQ; WeChat; Weibo; E-mail address; etc.</td>
</tr>
<tr>
<td>Other personal information</td>
<td>Personal phone numbers; Sexual orientation; Marriage history; Religious beliefs; Undisclosed criminal records; Precise positioning information; etc.</td>
</tr>
</tbody>
</table>

A. Definition of sensitive personal information

The premise of sensitive information identification is to define what sensitive information is to be identified. In this work, we focus on the identification of sensitive personal information. The Chinese National Standard defines “sensitive personal information as personal information that, if leaked, illegally provided or misused, may endanger the safety of persons and property, and is highly likely to damage a person’s reputation, physical or mental health, or discriminatory treatment, etc.”. This paper follows this definition and categorizes sensitive information into personal identification information, network identification information, and other personal information. Sensitive personal information examples of each type are as Table I.

B. Construction of corpora containing sensitive information

The texts of the SPIDC are obtained from the China Judges Online and Sina Weibo. The China Judgment Online uniformly publishes the effective judgment documents of the People’s Courts at all levels in China. The personal information of the parties was masked before the judgments were published. However, we artificially add some fictitious and sensitive information such as ID numbers, passports, phone numbers, and marital histories. This is done to ensure that the SPIDC is made public compliance with privacy protection laws. Sina Weibo is a Chinese social networking platform where many users exchange short, real-time updates, but it also contains much sensitive information. Weibo’s text contains numerous Internet buzzwords that are tough for machines to comprehend. Therefore, data drawn from Weibo enriches the SPIDC and ensures that the SPIDC is challenging for modern models. In order to disclose Weibo data legally, some important sensitive information was deleted, and the remaining sensitive information is reorganized. For example, we put all email addresses that appear in the texts into a resource pool and then randomly put the email addresses in the pool back into the texts. Even if the sensitive information is real, it cannot be used directly or correlated with other information.

C. Annotation of SPIDC

We use the sequence labeling model in unstructured data to identify sensitive information at the token level. The sequence labeling strategy chosen in this paper is "BMES". In detail, ‘B’ represents the beginning of a sensitive information, ‘M’ represents the middle of a sensitive information, ‘E’ represents the ending of a sensitive information, ‘S’ represents a separated sensitive word, and ‘O’ represents non-sensitive words. According to the types of sensitive information, there are 13 types of tags for sequence elements, as shown in Table II. The total number of entities with sensitive information in the SPIDC reaches 14,459, and the number of entities in each sensitive information category is counted in Table III. Examples of the SPIDC are shown in Fig1.

### TABLE II

<table>
<thead>
<tr>
<th>Type</th>
<th>Tag</th>
</tr>
</thead>
<tbody>
<tr>
<td>Personal identification information</td>
<td>B-L, M-L, E-L, and S-L</td>
</tr>
<tr>
<td>Network identification information</td>
<td>B-N, M-N, E-N, and S-N</td>
</tr>
<tr>
<td>Other personal information</td>
<td>B-T, M-T, E-T, and S-T</td>
</tr>
<tr>
<td>Non-sensitive information</td>
<td>O</td>
</tr>
</tbody>
</table>

### TABLE III

<table>
<thead>
<tr>
<th>Type</th>
<th>Amount</th>
</tr>
</thead>
<tbody>
<tr>
<td>Personal identification information</td>
<td>3085</td>
</tr>
<tr>
<td>Network identification information</td>
<td>3612</td>
</tr>
<tr>
<td>Other personal information</td>
<td>7762</td>
</tr>
</tbody>
</table>

IV. LEXICON-ENHANCE APPROACH

To improve the accuracy of sensitive information identification in Chinese, we apply three lexicon-enhanced technologies from NER to Chinese sensitive information identification for the first time. This part details the three technologies Lattice-LSTM [19], LGN (Lexicon-based Graph Network) [21], and SoftLexicon [18] on how to introduce lexicon information. Formally, let $s = c_1, c_2, \ldots, c_n$ denote a sentence, where $c_i$ denotes the $i$-th character.
A. Lattice-LSTM

Lattice-LSTM mainly integrates lexical information into character information through the following steps. Firstly, the input sentences are matched to a predefined lexicon. Then a edge is directly generated from $c_i$ to $c_j$ if the sentence’s subsequence $w_{i,j}$ matches a term in the lexicon. By allowing a character to be connected to numerous other characters, all lexicon matching results relating to that character are retained. Lattice-LSTM has carefully modified the standard LSTM to perform the above modeling.

In a standard LSTM, the hidden state $h_i$ and memory cell $c_i$ of each time step is updated as follows:

$$ h_i, c_i = f(h_{i-1}, c_{i-1}, x^i_j) $$  \hspace{1cm} (1)

However, in Lattice-LSTM, the hidden state $h_k$ and memory cell $c_k$ of $c_i$ are now revisited by:

$$ h_k, c_k = f(h_{k-1}, c_{k-1}, x^i_j, h_{s<k>, k}, c_{s<k>}) $$  \hspace{1cm} (2)

where $s_{s<k>}$ denotes the list of subsequences of sentence $s$ that match the lexicon and end with $c_{k}$, $h_{s<k>}$ denotes the corresponding hidden state list $\{h_i, \forall s_{s<k>} \in s_{s<k>}\}$, $c_{s<k>}$ denotes the corresponding memory cell list $\{c_i, \forall s_{s<k>} \in s_{s<k>}\}$, and $f$ is a activation function.

B. Lexicon-Based Graph Neural Network

LGN uses lexical information to build a graph neural network. The graph neural network improves the interaction between characters, words, and sentences through continuous aggregation and updating.

Graph Construction A directed graph $g = (v, \delta)$ was used to model input, where graph nodes denote each input character $c_i \in v$, and $\delta$ is the collection of edges. If there is a potential word $w_{i,k}$, then constructs one edge $e_{b,c}$, in $\delta$, from the beginning character $c_b$ to the ending character $c_c$. In addition, transpose the above graph $g$ to obtain a reversed graph $g^T$ with all edges reversed. And concatenate the reversed graph $g^T$ with the original graph $g$ as the final outputs.

Aggregation

a) Node Aggregation: For the node $c_i$ and incoming edge $E^i_{c_i} = \{y_i, c_{i,k}\}$. LGN uses multi-head attention to aggregate $c_{k,i}$ and corresponding predecessor nodes $c_k$ for each node $c_i$, as follows:

$$ e\rightarrow c : l^i_c = \text{MultiAtt}(l^i_c, \{y_k, c_{i,k} : c_{i,k}\}) $$  \hspace{1cm} (3)

where $t$ denotes the aggregation at the $t$-th step and $[x : x]$ denotes concatenation operation.

b) Edge Aggregation: The entire subsequence of matched characters $C_{b,c} = c_b, \ldots, c_c$ is used for edge aggregation, as follows:

$$ e\rightarrow c : e^i_{b,c} = \text{MultiAtt}(e^i_{b,c}, C_{b,c}) $$  \hspace{1cm} (4)

c) Global Aggregation: The global relay node aggregates each character node and edge to capture long-term dependencies and advanced features, as shown below:

$$ g^c_i = \text{MultiAtt}(g^c_i, C_{b,c}) $$  \hspace{1cm} (5)

Recurrent-based Update Module Node update, edge update, and global relay node update all use the recurrent-based update module. Therefore, here we only introduce node updates, as follows:

$$ \xi_i^t = [c^i_{t-1}]; \chi_i^t = [\hat{c}^i_{t-1}; g^i_{t-1}] $$

$$ \hat{a}_i^t = \sigma(W^a \xi_i^t + V^a \chi_i^t + b^a_i), a = \{i, f, l\} $$

$$ \hat{u}_i^t = \tanh(W_{ca} \xi_i^t + V_{cv} \chi_i^t + b_{ca}) $$

$$ \hat{i}_i^t, \hat{f}_i^t, \hat{l}_i^t = \text{softmax}(\hat{i}_i^t, \hat{f}_i^t, \hat{l}_i^t) $$

$$ i^t_i = \hat{i}_i^t \cdot c_{i-1}^t + \hat{f}_i^t \cdot \hat{c}^t_i + \hat{l}_i^t \cdot u^t_i $$

where $W, V, b$ are trainable parameters. $\xi_i^t$ is the concatenation of adjacent vectors of a context window,$\chi_i^t$ is the concatenation of the global information vector $g^t_i$ and the $e\rightarrow c$ aggregation result $c^t_i$. The gates $\hat{i}_i^t$, $\hat{f}_i^t$, and $\hat{l}_i^t$ control information flow from global features to $c^t_i$.

C. SoftLexicon

In the SoftLexicon method, lexicon information is incorporated into the input encoding layer in three steps.

Categorizing the matched words First, all matching words for each character $c_i$ are grouped into four word sets "BMES" to preserve segmentation information. For each character $c_i$, the four set is constructed by:

$$ B(c_i) = \{w_{i,k}, \forall w_{i,k} \in L, i < k <= n\}, $$

$$ M(c_i) = \{w_{j,k}, \forall w_{j,k} \in L, 1 <= j > i < k <= n\}, $$

$$ E(c_i) = \{w_{j,i}, \forall w_{j,i} \in L, 1 <= j < i\}, $$

$$ S(C_i) = \{c_i, \exists c_i \in L\}. $$

Fig. 1. Two examples from the SPIDC dataset. We can find from example 1 that the ID is fictitious because the birthday of Li Xuejuan is different from the birthday in the ID number. Therefore, disclosing SPIDC will not violate personal privacy. B-X represents the beginning of sensitive information of category X, M-X represents the middle part of sensitive information of category X, and E-X represents the end of sensitive information of category X.
where L denotes the lexicon.

**Condensing the word sets** After obtaining the "BMES" word set of each character, each word set is compressed and converted into a fixed dimensional vector. Use a weighting algorithm to exploit the word information further. Let \( r(w) \) denote the frequency that a matched word \( w \) occurs in the train data, the weighted representation of the word set \( S \) is obtained as follows:

\[
v^s(S) = \frac{2}{R} \sum_{w \in S} r(w) q^w(w)
\]

where

\[
R = \sum_{w \in B,M,E,S \cup \emptyset} r(w)
\]

**Combining with character representation** The last stage is to incorporate the representations of four word sets into a single fixed-dimensional embedding, which is then added to each character’s representation. To keep as much information as possible, concatenate the representations of the four phrases. The final representation of each character is as followed:

\[
e_{\mathbf{B},\mathbf{M},\mathbf{E},\mathbf{S}}(B, M, E, S) = [v^s(B); v^s(M); v^s(E); v^s(S)],
\]

\[
x^c < -[x^c; e_{\mathbf{B},\mathbf{M},\mathbf{E},\mathbf{S}}(B, M, E, S)].
\]

where, \( v^s \) represents the weighting function above.

V. EXPERIMENTS

Few lightweight models implement Chinese token-level sensitive information identification. Therefore, we apply the existing models on English datasets to Chinese datasets and use them as the baselines of this experiment. Not only that, we introduce a lexicon-enhanced approach to Chinese sensitive information identification; this approach can make it possible to achieve excellent results without using heavyweight models. Standard precision (P), recall (R), and F1-score (F1) are used as evaluation metrics.

**A. Baselines**

Part of the baselines of this experiment is set with reference to the paper [9].

**BiGRU** (Bidirectional Gated Recurrent Unit) [20] The BiGRU modeled the context of the input sequences to learn a probability distribution over sequences. The logistic sigmoid function was then used as the output unit.

**BiGRU+CRF** (Conditional Random Field) [21] The character embeddings were concatenated to form the global token representation. Then, BiGRU generated an emission probability score by processing the forward and backward token representation sequences. Finally, the CRF decoded the sequence of labels by associating the emission probability score with a transition probability score.

**BiLSTM** [8] A bidirectional LSTM Network was introduced to determine a specific token from a sentence as sensitive or non-sensitive [8]. Each token in the document was represented by word embedding. The BiLSTM layer processed the word embedding feature vector, and its output was passed to the sigmoid function, which determined the sensitivity of the token.

**BiLSTM+CRF** [22] The BiLSTM-CRF model was used to identify sensitive information in conversational data [22]. Following an input sequence embedding layer, bidirectional LSTM layers were utilized to obtain a contextual representation of the input sequences, followed by a CRF layer to learn various limitations and rules within entity categories.

**BiLSTM+Attention** [9] BiLSTM+Attention model was used to pinpoint sensitive information in unstructured data in English [9]. Each token in the input sequence was represented by an embedding vector. The BiLSTM layer received the embedding vectors. The attention layer came next. The last layer was a fully linked layer that used the softmax activation function to classify each element in the sequence.

**B. Results and Analysis**

<table>
<thead>
<tr>
<th>Methods</th>
<th>Type</th>
<th>F1</th>
<th>P</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>BiGRU</td>
<td>88.23</td>
<td>88.71</td>
<td>87.75</td>
<td></td>
</tr>
<tr>
<td>BiGRU+CRF</td>
<td>92.96</td>
<td>94.85</td>
<td>91.13</td>
<td></td>
</tr>
<tr>
<td>BiLSTM</td>
<td>89.55</td>
<td>94.31</td>
<td>85.25</td>
<td></td>
</tr>
<tr>
<td>BiLSTM+CRF</td>
<td>94.51</td>
<td>94.57</td>
<td>94.45</td>
<td></td>
</tr>
<tr>
<td>BiLSTM+Attention</td>
<td>95.05</td>
<td>95.87</td>
<td>94.24</td>
<td></td>
</tr>
<tr>
<td>Lattice-LSTM</td>
<td>99.08</td>
<td>99.32</td>
<td>98.64</td>
<td></td>
</tr>
<tr>
<td>LGN</td>
<td>98.81</td>
<td>98.98</td>
<td>98.65</td>
<td></td>
</tr>
<tr>
<td>SoftLexicon</td>
<td>99.32</td>
<td>99.45</td>
<td>99.18</td>
<td></td>
</tr>
</tbody>
</table>

Table IV presents comparisons among various methods on the SPIDC. Among all baselines, BiLSTM+Attention achieves the best results in F1 and P, 95.05 and 95.87, respectively. This is because Attention can make the model give more weight to locally important information, which is very important for sensitive information identification. In addition, comparing the results of BiGRU and BiLSTM with BiGRU+CRF and BiLSTM+CRF, it can be found that CRF can significantly advance the model’s performance. Because CRF incorporates transfer features, it considers the output labels’ sequential nature and learns some constraint rules to ensure that the predicted labels are correct.

Table IV also shows that all lexicon-enhanced technologies achieve better results than the baselines in all three metrics. The best result in the lexicon-enhanced method is 4.5% higher than the best in the baselines, showing that the lexicon-enhanced approach is more suitable for sensitive information identification in Chinese. While baselines are character-based models, they cannot deal with ambiguity effectively, so they are prone to errors in the boundary prediction of sensitive information. The Lexicon-enhanced technologies achieve better results because they integrate a large amount of rich lexical information and increase the model’s ability to perceive the boundary of sensitive information. Among the lexicon-enhanced technologies, SoftLexicon achieves the best results in F1 and R with 99.32 and 99.18, respectively. Although it
is slightly inferior to Lattice-LSTM in the P, it still maintains a comparative advantage.

Figure 2 shows the F1 score of baselines and lattice-enhanced technologies against the number of training iterations. The lexicon-enhanced technologies outperform the baselines in terms of accuracy and convergence speed, as seen in the graph. This is because the lexicon-enhanced approach is wholly independent of word segmentation and yet more effective in using word information. Thanks to the freedom of choosing lexicon words in context disambiguation.

VI. CONCLUSION AND FUTURE WORK

In this work, we focus on sensitive information identification in Chinese. Since there is no publicly available Chinese dataset with sensitive information, we created a dataset named SPIDC. Not only that, we make the SPIDC public available for related research. There are few lightweight models for sensitive information identification in Chinese. Therefore, we first apply several lightweight and sensitive information identification models designed for English to Chinese datasets and use them as the baseline. Uncertain Chinese lexical boundaries and ambiguity limit the performance of these models. Consequently, for the first time, we deploy three NER lexicon-enhanced technologies to Chinese sensitive information identification. To validate the lexicon-enhanced approach, we compare the experimental results with all baselines, and the results show that lexicon-enhanced technologies can perform better sensitive information identification. Finally, we analyze the three lexicon-enhanced technologies introduced, and the results show that SoftLexicon achieves the best outstanding performance.

One limitation of this study is that it requires many labeled data sets. However, there are few labeled data sets in reality, and manual labeling requires enormous costs. Considering this weakness, we explore using a semi-supervised learning algorithm to identify sensitive information without a labeled data set.

REFERENCES

BERT-based Sentiment Analysis of Chinese Online Social Movements

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Ministry of Emergency Management, Shenzhen, China;
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Abstract—Online social movements are a group of netizens with the same or similar purpose, spontaneously discussing and disseminating certain information, trying to attract more people to participate, and creating a public opinion on the Internet or even a social atmosphere of anxiety. Online social movements analysis can reveal the evolution of sentiment during the movements and therefore prevent the relevant social disasters from happening. The literature shows the lack of public sentiment analysis text datasets and effective analysis methods for Chinese online social movements. In this paper, we classify sentiment into four categories: positive, anger, anxiety, and weak negative. We believe anger and anxiety are the two most important sentiments in forming an online social movement. Afterwards, we first time create a public sentiment analysis dataset about Chinese online social movements, and then propose a bidirectional encoder representation from transformers (BERT)-based model to classify the sentiment. Moreover, we use the focal loss in the BERT model rather than cross entropy loss to address the imbalance issue in the dataset. The proposed BERT-based model is compared with six baseline methods. The results show that our method outperforms those baseline models by achieving higher macro-F1 scores.

Index Terms—Chinese online social movements, sentiment analysis, BERT, focal loss

I. INTRODUCTION

With the further development and popularization of the Internet in China, online social media has become an essential channel for people to obtain information, and more and more people participate in it. While people enjoy the joy brought by the Internet, online social movements are also happening all the time. To respond to the netizens having some shortcomings:

- Manual work is costly and time-consuming, which is not suitable for the growth of the internet scale.
- Monitoring and sentiment analysis system is too simple to deal with the complex situation, especially in handling the feature of online social movements since it only focuses
on the negative and positive sentiment and ignores the differentiated sentiment. To overcome these shortcomings, we would like to use Chinese microblog data which contains rich sentiment information and take good advantage of the feature of the online social movement data in which the sentiment is not just positive and negative but fine-grained, then use sentiment analysis technology in natural language processing (NLP) to distinguish emotions in microblog data.

Sina Weibo is the most popular social media in China. Meanwhile, it is the platform that many online social movements were born and spread. As mentioned above, the sentiments between an online social movement and a normal event are distinguishable since the emotion of anger and anxiety is crucial in an online social movement but uncommon to see in a normal event. We propose a novel approach to analyze the online social movement based on the netizens’ sentiment on Sina Weibo. An immediate difficulty is there are no sentiment datasets about online social movements available as far as we know. In this paper, we collect the reviews about online social movements and encode these reviews manually and propose a BERT-based model which gains the best performance of macro-F1 compared with other sentiment analysis methods. The main contributions of this paper are as follows:

- We propose a novel approach to help people to distinguish online social movements by using sentiment analysis about anger and anxiety not only about positive and negative emotions.
- We create an open sentiment dataset\(^1\) about online social movement in Chinese for filling the gap of this part of the work and hope to help future research work.
- We propose a BERT-based model which alleviates the problem of class imbalance in this dataset and gains the best performance of macro-F1 compared with other sentiment analysis methods.

II. RELATED WORK

A. Online Social Movements Analysis

Online social movements are common worldwide and researchers mainly use case analysis methods, text analysis methods, and some NLP technology such as sentiment analysis. Reference [6] used case analysis methods about two online social movements in China which verified the role of emotions such as anger and anxiety and suggested that the government and the media should respond promptly before the situation get out of control, but did not give specific countermeasures. In [5], researchers analyzed the sentiment in Tweeting India’s Nirbhaya protest based on LIWC which is an academic software based on a lexicon that can calculate the presence of emotional categories as a ratio. The results show that anger and anxiety account for a certain proportion of all negative emotions in the early and middle stages of the event which is different from ordinary events. However, the sentiment predictions may not be accurate since the lexicon is made by expert experience. As we know, both offline and online social movements have emerged around the world in the wake of the COVID-19 outbreak, clouding our moods and fueling mistrust in public organizations such as governments. Study [8] analyzed the sentiment and topic in the wake of the COVID-19 outbreak, which used long short-term memory (LSTM) recurrent neural networks for sentiment classification and showed that people are more negative than before. However, the classification is about positive and negative emotions, and positive and negative are common to see in a normal event, so it is not suitable for detecting online social movements. Therefore we would like to use the two distinguishing emotions of anger and anxiety in addition to the positive and negative to capture the feature of sentiment in online social movements using sentiment analysis technology.

B. Sentiment Analysis

Sentiment analysis is a branch of NLP that has received much attention in recent years. It is also known as opinion mining and tendency analysis. Sentiment analysis has been widely used in movie reviews, stock markets, traffic conditions, and many other related work to help people and organizations make better decisions. Broadly, there are two main types of methods including lexicon-based approaches and machine learning approaches.

The lexicon-based method is to create a dictionary manually, and each word in the lexicon has a corresponding sentiment polarity. The sentiment of an entire sentence is determined only by the sentiment words in the sentence. It is worth noting that the construction of sentiment lexicons is closely related to expert experience, which means that the effectiveness of the lexicon depends on whether the lexicon is well thought out. In [9], a lexicon is built in which corpus is the comments in MySpace to classify the sentiment strength of a sentence and use a support vector machine as a classifier. This method also shows better performance in other social media such as Twitter and Facebook [10]. This lexicon-based method can maximize the preservation of features in sentiment analysis problems when word embedding methods have not progressed. However, when the scale of the network continues to expand, the expressions of emotions of different groups are more abundant and complex, which cannot be dealt with by lexicon alone, i.e. this method is not applicable. Now, this kind of lexicon is used more as an auxiliary tool.

In recent years, machine learning such as deep learning and transfer learning has attracted increasing research interest. Convolutional neural networks (CNN) have been used to perform a sentiment classification task. In [11], a 7-layers architecture model is applied using word2vec and CNN to analyze sentences’ sentiment. CNN can capture key features and further deepen the network layer with the pooling operation. This seems to be exactly what sentiment analysis needs since the sentiment of an entire sentence is often defined by keywords. However, when encountering long-distance dependent aspect-level sentiment analysis problems, CNN can not handle this issue well. In [12], the bidirectional long short

\(^1\)https://github.com/hyqaq/osmdataset2022
term memory (BiLSTM) was used to capture the context information effectively, which means that the representation of the word embedding is more complete. Moreover, the attention mechanism is another way to get contextual information, and study [13] shows the effectiveness of the attention mechanism when combined with the deep neural network. It is worth noting that transfer learning has recently achieved good results in 11 NLP tasks including sentiment analysis tasks [14]. By fine-tuning the pre-trained model named BERT, study [15] achieves state-of-the-art results on multiple public datasets for sentiment classification. In [16] and [17], a pre-trained model BERT has also been used in Chinese microblogs and e-commerce reviews, showing effectiveness on Chinese corpus.

Considering that the pre-trained model can represent the whole sentence more generally and the attention mechanism can obtain the context information very well, we use BERT to obtain the word embedding of the complete sentence in this paper.

III. DATA INTERPRETATION AND ANALYSIS

A. Data Interpretation

Sina Weibo was chosen as a source of the dataset for this study because of its strong presence in social media and because many online social movements were born and spread on it. In this paper, we choose 6 events that took place within the past five years consisting of 4 online social movements and 2 normal events. In total, we crawled nearly 15 thousand raw comments by their topic. We eliminated duplicate comments containing images. Nickname formats like 用户123456789(user123456789) were rejected because these users may violate the community convention or be withdrawn from the account. Then we finally get 13,807 comments. Sentiment analysis has been extended to identify psychological states of people’s hidden internal states, such as political irony. For our Sina Weibo data, the purpose is not to identify opinions or the hidden mental states of people but to determine the role of directly expressed emotions in communication. Therefore the focus of the data is to identify people’s emotional expression rather than the hidden internal state or the reader’s hidden internal state. As mentioned in Section 1, anger and anxiety are the most distinguished emotions in an online social movement. In this data, the comments are classified into 4 categories: positive emotions, anger, anxiety, and weak negative emotions. The positive category includes positive and neutral comments. The negative emotions that do not belong to anger or anxiety are classified as weak negative emotions. Consecutive use of exclamation and question marks is seen as a reinforcement of sentiment which may cause weak negative sentiment to be classified as anger or anxiety.

Table II gives examples of emotion in our Sina Weibo data. The encoder knows which event he is encoding in order to understand the context. Meanwhile, three encoders are used in this annotation work for a more accurate result. Then we use the voting strategy for the final result and the comment will be re-mixed into the original data if the opinions of the three are different from each other. If there is disagreement on a comment again, the comment is decided by the chief encoder.

B. Data Analysis

On Sina Weibo, users can not send comments longer than 140 characters normally which is a common feature of online social media. The length distribution of the comments is shown in Fig. 1. Most of the comments in this dataset are shorter than 100 characters. This dataset contains 5152 positive comments, 949 angry comments, 682 anxious comments and 7024 weak negative comments. The proportion of each sentiment is 37.3%, 6.87%, 4.94%, 50.9%. Furthermore, the overall summary of the contents of this dataset is listed in Table I. Class imbalance is the obvious feature of this dataset. The imbalance ratio is the most commonly used measure to describe the imbalance extent of a dataset, which is defined as the maximum sample size of the majority class divided by the minimum sample size of the minority class. The ratio of class imbalance in this dataset is 10.3 which means that the minority classes might be difficult to classify.

<table>
<thead>
<tr>
<th>Sentiment</th>
<th>Count</th>
<th>Proportion (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>positive</td>
<td>5152</td>
<td>37.3</td>
</tr>
<tr>
<td>anger</td>
<td>949</td>
<td>6.87</td>
</tr>
<tr>
<td>anxiety</td>
<td>682</td>
<td>4.94</td>
</tr>
<tr>
<td>weak negative</td>
<td>7024</td>
<td>50.9</td>
</tr>
</tbody>
</table>

IV. BERT-BASED SENTIMENT ANALYSIS

In order to address the class imbalance issue and improve the performance in distinguishing the sentiment, we propose a BERT-based model combined with a loss function proposed by [18]. We feed the last hidden state of the BERT model to a fully connected layer to predict the sentiment. The proposed model is shown in Fig. 2.

We use the sum of token embeddings and position embeddings as the input representation. As shown in Figure. 2, we denote input embedding as $E$. Token embeddings contain
TABLE II

EXAMPLES OF COMMENTS IN THE DATASET

<table>
<thead>
<tr>
<th>Comment</th>
<th>Sentiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>发生这种事情，但凡有点良知的老师校长都会悲伤。但是校方的公告和回应都是冷冰冰，这种没人性的教育工作者该受到我们的国家教育之耻！！ (When such a thing happens, all teachers and principals will be a little conscience will be sad, but the school’s announcements and responses are cold. It is a shame for our country to educate such inhuman educators! :) )</td>
<td>anger</td>
</tr>
<tr>
<td>很离谱，谁都有子女亲戚小孩上学，将心比心，如果这种事情发生在自己身上，叫天天不应，又该怎么办？现</td>
<td>anxiety</td>
</tr>
<tr>
<td>这次热搜没有消失，希望公共媒体能在相对弱势受害者一方，给家属一个交待……(This time, the hot news has not disappeared. I hope the public media can stand on the side of relatively vulnerable victims and give an explanation to their families...)</td>
<td>weak negative</td>
</tr>
<tr>
<td>希望学校还原事情真相让事件不要复杂化引起社会舆论压力。（It is hoped that the school will restore the truth of the matter so that the incident will not be complicated and cause public opinion pressure.)</td>
<td>positive</td>
</tr>
</tbody>
</table>

the information of sentiment. Position embeddings contain the position information of each word and the relative position information which means contextual information. The symbols [CLS] and [SEP] mean the start and the end of a sentence which can be removed in this sentiment analysis task but we keep this for unification with the original BERT model embeddings.

When we have the input embeddings, then we fine-tune the original BERT model and extract the feature information. The BERT model uses bidirectional transformers which can get rich information from the whole sentence and realistic representation. The attention mechanism can capture the contextual information and extract the important tokens which are crucial in sentiment analysis. Moreover, this multi-headed self-attention mechanism can increase the amount of information saved without increasing the time complexity. Then we feed the last hidden state of the BERT model as the input of the fully connected layer.

However, the class imbalance issue is not considered in the original BERT model. So in our model shown in Fig. 2, we adopt a novel loss function named focal loss which was proposed by [18] while keeping the model structure mentioned above unchanged. Also this is a difference between our model and the original BERT model. The original focal loss was proposed to address the class imbalance regarding computer vision for binary classification. The focal loss function for multi-class is shown in (1).

\[
L_{fl} = -\sum_{i=1}^{n}(1 - \hat{y}_i)^\gamma y_i \log(\hat{y}_i) \tag{1}
\]

where \( n \) denotes the class number, \( y_i \) denotes the ground truth, \( \hat{y}_i \) denotes the probability distribution of the prediction, and \( \gamma \) denotes a weight parameter. Moreover, the original loss function is cross entropy(CE) loss which is shown in (2).

\[
L_{ce} = -\sum_{i=1}^{n} y_i \log(\hat{y}_i) \tag{2}
\]

We can see that when a difficult sample is misclassified with low confidence, i.e. \( \hat{y}_i \) is small, the weighting factor becomes close to 1 retaining contributions to the total loss. On the contrary, when an easy sample is correctly classified with high confidence then that sample’s contribution becomes small. Therefore, our model can pay more attention to the minority classes which are difficult to classify compared with the original model using CE loss.

V. EXPERIMENTAL STUDIES

A. Experimental Environment

In this paper, the hardware environment used in experiments is Intel Xeon E5(8 cores), 16G memory and GTX 1080 Ti. The software platform is Ubuntu 20.04 and the development environment is Python3.8. Our model and comparative experiments are implemented in PyTorch.

B. Data Set

The corpus in this experiment is crawled from Sina Weibo as mentioned in Section III. In total, 11,045 comments are in the training set and 2762 comments are in the test set. The number of comments in each category is shown in Table III. Examples of the comments in the dataset are shown in Table II.
C. Evaluation Indicators

The dataset in this paper is a particular unbalanced one. In order to more comprehensively measure the performance of the model on the imbalance dataset, we use macro-F1 rather than micro-F1 because the value of macro-F1 is susceptible to the minority classes since it treats each category equally and micro-F1 is more vulnerable to major classes. Furthermore, the F1 scores of anger and anxiety are also used to measure the performance of the model in the minority categories.

Let Precision<sub>i</sub>, Recall<sub>i</sub> and F1<sub>i</sub> denote precision, recall and F1 score with respect to Class <i>i</i> among <i>n</i> classes. The formula for calculating the macro-F1 score is as follows:

\[
F1 = 2 \times \frac{\text{Recall}_i \times \text{Precision}_i}{\text{Recall}_i + \text{Precision}_i}
\]

(3)

\[
\text{Macro - F1} = \frac{\sum_{i=1}^{n} F1_i}{n}
\]

(4)

D. Baselines

To show the effectiveness of the model we proposed, we compare it with six baseline methods, as listed below:

- **TextCNN**: In [11], this method was used to handle sentiment analysis tasks which has 3 pairs of convolutional layers and pooling layers in the architecture and used the word2vec to compute vector representations of words.

- **TextRNN**: This method is based on RNN and is used in [12] which both use bidirectional networks to get context information.

- **TextRNN+Att**: The attention mechanism is combined with BiLSTM in [19] to capture the significant information.

- **TextRCNN**: In this approach, the sentences are represented by BiLSTM then a CNN architecture is used to capture the important feature and classify [20].

- **DPCNN**: In [21], the architecture of the whole model is like a pyramid which is realized by pooling and equal length convolution.

- **BERT**: This approach takes advantage of transfer learning and is trained on a large corpus using attention mechanism and transformer structure to obtain important information [14]. This approach is different from the methods above and this is a pre-trained method which means when facing different tasks, it only needs to fine tune the model for the task and does not need to retrain the whole model parameters.

E. Hyperparameters Setting

The hyperparameters related to the experiment include epochs, learning rate, batch size, γ value, and so on. In all experiments, the learning rate is $10^{-5}$, the batch size offered to the model once is 16. We use the early stopping method to train the models in both our and baseline models. We train comparative models for a maximum of 200 epochs using Adam and early stop training if the validation loss does not decrease for 1000 consecutive steps. In baseline models, the embedding of words is 300-dimensional vectors trained by word2vec. As for other parameters in baseline models, we use the same parameters as the original paper.

As we mentioned in Section IV, the focal loss is important in handling class imbalance issues which can control the error of back propagation according to the difficulty of distinguishing the categories. There is a parameter γ in the focal loss. The value of γ has an important impact on the weight. When the γ value is too small, the loss function will degenerate into the cross entropy loss. When the γ value is too large, the gradient direction is unstable and the training of models is difficult. According to the original paper [18], the γ value is set from 2 to 5. Table IV shows the macro-F1 with different γ values. Moreover, the macro-F1 score reaches a maximum value of 72.66% when the γ value is 3.

<table>
<thead>
<tr>
<th>Macro-F1</th>
<th>γ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.56</td>
<td>2</td>
</tr>
<tr>
<td>0.56</td>
<td>3</td>
</tr>
<tr>
<td>0.56</td>
<td>4</td>
</tr>
<tr>
<td>0.56</td>
<td>5</td>
</tr>
</tbody>
</table>

F. Comparison and Results

Experimental results are given in Table V. We compare CNNs and RNNs and their family models with our model. The results show that the CNNs are more effective than RNNs in our comparative model. The difference between CNNs and RNNs is the structure for capturing the information. CNNs focus on the most important information using pooling layers and RNNs try to capture the long-distance information using recurrent structure. And the CNNs structure is more suitable because the sentiment polarity of a sentence depends on a few important words in most cases. Moreover, it can be seen that the attention mechanism is effective when combined with RNNs because the attention mechanism can focus on the information that is more critical to the current task in the massive input information. However, the pyramid structure combined with CNNs does not work well. The reason may be that the model weakens some key information in the long and deep network structure, and adulterates unimportant information at the same time. These methods mentioned above are traditional deep learning methods.

When we compare the pre-trained method BERT to widely used traditional deep learning methods, the experimental results show that the pre-trained method outperforms the
deep learning method. The macro-F1 score of the pre-trained method is generally 5% to 10% higher than that of traditional methods. It proves that the pre-trained method can better represent the meaning of texts and can capture the feature compared with traditional methods because the pre-trained model has a huge number of model parameters and the attention mechanism can better capture the real meaning of a word in this task. Another reason may be the extra knowledge help the model to understand the sentence more precisely.

When comparing the BERT model with our model, we can see that our method achieves better results and the macro-F1 is nearly 1% higher than the BERT model. Moreover, the F1 score for anger is 61.20% and the F1 score for anxiety is 68.57% in our model. It shows that our model is more effective in handling class imbalance issues. This illustrates that the loss function in our model can pay more attention to the minority class since the minority class is easily neglected by the model.

VI. CONCLUSION

Online social movements contain rich sentiment information in which anger and anxiety are the most prominent. In this paper, we create a dataset about online social movements in China which has the feature of class imbalance. Also, we propose a novel BERT-based model combined with the focal loss to address the class imbalance issue. The results show that our model can capture more emotional information and outperform numerous baseline methods including the original BERT model. However, there are rich approaches to handle class imbalance issues so as to identify sentiment more accurately. In subsequent research, we would like to make further improvements to the BERT model and try more methods such as data augmentation.

REFERENCES

Abstract—A dynamic recurrent neural network is seen to be the most efficient nonlinear approach to time series prediction, especially if its architecture is grown to construct the prediction model. To further advance its performance, this paper develops a hybrid evolutionary algorithm to grow and train the network and its dynamic architecture holistically. The training approach is based on the genetic algorithm (GA) and the fastest quasi-Newton algorithm Broyden–Fletcher–Goldfarb–Shanno (BFGS). The proposed GA-BFGS method is suitable for training both discrete structural parameters and continuous weighting parameters of the network and is applicable to parallel computation. This approach eliminates the need for setting any hyperparameters of the neural network for the highest possible optimality and accuracy to emerge. The method is tested on the Mackey-Glass time series and its forecasting performance is compared with currently widely adopted deep learning methods such as the long short-term memory (LSTM) and echo state networks (ESN) models. Results show that the proposed method incurs lower losses, requires a smaller network size, and performs faster.

Keywords—dynamic recurrent neural network; hybrid evolutionary algorithm; parallel computation; time series prediction

I. INTRODUCTION

Time series forecasting refers to modelling from historical data and forecasting trend in a certain period of time ahead. Many kinds of time series such as finance [1], epidemiology (e.g., COVID-19) [2] and traffic volumes [3] are often of interest and of challenge to forecast. Conventional methods such as ARIMA [4] and Bayesian [5] methods appear to be difficult automatically to reveal the state of a dynamical, and especially non-stationary, system and to discover the relationship among its variables.

Recurrent neural networks (RNNs), such as long short-term memory (LSTM) [2] and echo state networks (ESN) [6, 7], are increasingly popular in time series forecasting because they utilise memory for characterising chronological moments. However, there exist difficulties of training and instabilities in the network due to the complexity of their multi-layer architecture [8]. Since mathematical theory shows that, similar to power series approximation, multiple neurons in a single layer can also deliver function approximation, a Lateral-Delay Neural Network (LDNN) with a single layer was proposed [9]. It only needs relatively short-term memory and proves offering high optimality and high convergence through growing the network. On time series forecasting, however, it does not consider adaptivity or robustness for problem variations. For example, a network’s parameters like the time delay and the type of activation functions can change and need to adapt to the characteristics of the time series problem.

On network training, gradient-based algorithms like adaptive moment estimation (Adam) [10] and the fastest quasi-Newton algorithm Broyden-Feltcher-Goldfarb-Shanno (BFGS) [11] are widely used. However, they suffer from gradient vanishing [12] and exploding problems [13]. They are also easy to fall into the trap of local optimum when the search space is multimodal. Conversely, derivative-free optimizers like the genetic algorithm (GA), particle swarm optimization (PSO), and simulated annealing (SA) can compensate for the disadvantages of it. For example, Li et al [14] have shown that the GA and Powell’s Conjugate (PC) work best on multimodal and unimodal discrete problems, respectively. However, the GA still faces problems like consuming excessive computational resources and being relatively sub-optimal. If the search space is continuous, gradient-based techniques like BFGS may be faster and more reliable. Hence, the best approach would be a combination of both.

Therefore, this paper introduces adaptive parameters into the non-stationary neural network for better forecast and generalization abilities. Due to the network’s embedded discrete parameters, a GA-BFGS hybrid algorithm is proposed to train the network. To speed up and to investigate the training parallelism, parallel computation is used to train both discrete structural parameters and continuous weighting parameters of the network.

II. ADAPTIVE NETWORK ARCHITECTURE

Similar to the power of power series approximation, the Phase-space Reconstruction and Takens theorem claim that an m-dimensional embedded phase space can be reconstructed for infinitely long, noise-free time series with d-dimensional chaotic attractors if m \geq 2d + 1. Therefore, for a time series generated by a non-linear dynamic system

\[ x = \{x_1, x_2, x_3, \ldots, x_N\} \]  

(1)

the phase space can be reconstructed by suitable delay time τ and embedding dimension m:

\[ X(t) = \{x(t), x(t-\tau), x(t-2\tau), \ldots, x(t-(m-1)\tau)\} \]  

(2)

Cao and C-C [3,15] are widely used to obtain τ and m.

However, these methods tend to need complex computation and sometimes cannot compute accurate results. Nonetheless, these ideas have inspired the idea of efficiently constructing a neural network, such as growing the network to reduce forecasting error [9]. Thus, a proposed network starts from the smallest network with one hidden neuron. Then dynamic time delay units and hidden neurons are added to grow the network.
Following that, discrete structural parameters and continuous weighting parameters of the network are trained by optimization algorithm to access the minimum error. The session is repeated until the loss satisfies the target or converges. Fig. 1 shows this process.

The choice of activation function and delay time often varies with the problems being addressed thus demands the specific expertise and always cost a large amount of time for researchers to trail. An alternative is to encode these parameters into feasible solution space, being searched by effective optimization algorithm automatically. Table 1 presents commonly used activation function and delay time is encoded as integer.

Fig. 1. Growing a dynamic recurrent network.

<table>
<thead>
<tr>
<th>ACTIVATION FUNCTIONS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Activation Function</td>
</tr>
<tr>
<td>Sigmoid</td>
</tr>
<tr>
<td>Tanh</td>
</tr>
<tr>
<td>Relu</td>
</tr>
<tr>
<td>Sine</td>
</tr>
<tr>
<td>Linear</td>
</tr>
</tbody>
</table>

### III. TRAINING METHODOLOGY

#### A. Prediction Model of Each Growing Stage

Define input series $X$:

$$X = [x_1, x_2, ..., x_N]^T \in \mathbb{R}^N$$

for the output after neural network $Y(X)$:

$$Y(X) = [x_{1+T}, x_{2+T}, ..., x_{N+T}]^T$$

where $T$ is future $T$-step value of $x$.

Assume $\hat{a}_{j,k}$ is the delayed input of a hidden neuron and $h_k(\hat{a}_{j,k}, x_j)$ represents the activation function of a neuron, where each hidden neuron is $k=1, ..., N$. The delay time between two hidden neurons is $d_{k-1}$. The maximum delay time is set to maxDelay.

$$\hat{a}_{j,k} = \begin{cases} 0, & 1 \leq j \leq \text{maxDelay}, k = 1 \\ h_{k-1}(\hat{a}_{j-d_{k-1}-1-k-1}, x_j-d_{k-1}) & \text{otherwise} \end{cases}$$

Define $H_k(X)$ as the output of the $k$th hidden neuron:

$$H_k(X) = [\hat{a}_{2,k+1}, ..., \hat{a}_{j=N,k+1}, h_k(\hat{a}_{N,k}, x_N)]^T \in \mathbb{R}^N$$

The state matrix $A(X)$ can be defined as:

$$A(X) = [H_1(X), H_2(X), ..., H_N(X)] \in \mathbb{R}^{N \times N}$$

Define a weight matrix $W_n$ which has all the weights between each hidden neuron and output neurons:

$$W = [w_1, w_2, ..., w_n]^T \in \mathbb{R}^n$$

The prediction $F(X)$ of the network for the time series $X$ is:

$$F(X) = \text{linear}(A(X)W) \in \mathbb{R}^n$$

The mean square error can be defined as and it needs to be minimized by training algorithm proposed.

$$MSE = \frac{1}{N} \| Y(X) - F(X) \|^2$$

#### B. Parallel Hybrid Training Algorithm

Since the dynamic recurrent neural network proposed has both discrete structural and continuous weight parameters. A hybrid algorithm needs to be designed to optimize them. Li et al have proven that the GA performs best [14] in multimodal problems compared with other derivative-free algorithms like PSO, SA and pattern search (PS). However, it may cost much time and is relative sub-optimal due to the posterior characteristics and guideless. On the other hands, gradient based optimizer is good at finding local optimum but suffers poor global search ability. Therefore, by combining local and global optimization algorithms, the advantages of the two are well utilized (fast and local accuracy of the local optimizer, global accuracy of the global optimizer).

PC is recommended combined with GA in [14], but it may cost much time and for the continuous search space gradient-based optimizer which determines the direction of descent by pre-processing the gradient using curvature information is fast and has high accuracy as well [11]. Adam has seen to be the most popular to train neural networks for the rapid convergence but its generalization ability is poor which may fail to converge in some extreme condition [16]. Therefore, a faster alternative BFGS may be more efficient and.

Before crossover and mutation operators in each generation, local optimization is implemented and only network parameters are optimized at this stage. Moreover, due to the independence of each individual. Parallel computation can be applied to reduce the computing time. After it, each individual finds its nearest local optimum and share information through crossover and mutation operators. Details are illustrated in Algorithm 1.
Algorithm 1: Parallel GA-BFGS

Input: Population size, crossover rate, mutation rate, maximum generation
Output: Solution with highest fitness
1: Randomly initialize a population
2: while i < maximum generation number and not converged do
3:     offspring ← roulette wheel selection with cross rate
4:     fit ← evaluate each individual's fitness
5:     parfor \( j \) = 1,...,population size do
6:         x\(_j\) ← BFGS (x\(_j\))
7:     end
8:     do crossover in offspring
9:     do mutation in offspring
10:    fit ← evaluate each individual’s fitness
11: replace the worst-fit individuals with elite individuals
12: end

IV. EXPERIMENT AND RESULT ANALYSIS
A. Comparison of Optimization Algorithms
To test the properties of algorithm, three benchmarks introduced by [10] are used and they are:

\[
\text{Optimality} = 1 - \frac{\bar{f}_0 - \tilde{f}_0}{\bar{f} - \tilde{f}} \in [0,1] \quad (11)
\]
where \( \bar{f} \) and \( \tilde{f} \) are the upper and lower bounds of \( f \).

\[
\text{Accuracy} = 1 - \frac{\|x_0 - \tilde{x}_0\|}{\|\bar{x} - \tilde{x}\|} \in [0,1] \quad (12)
\]
where \([\tilde{x}, \bar{x}]\) represents the search range.

Convergence (Con) = \( \min\{C^b, \text{MaxFEs}\} \quad (13) \)
where \( b \in [0,1] \) and \( C^b \) means test is stopped when Optimality exceeds \( C^b \). MaxFEs is the maximum function evaluations of test.

All the benchmark tests are conducted on two unimodal CEC benchmarking problems [17, 18] which are shown in Table II. Three derivative-free method PS, NM, PC and one gradient decent method BFGS are used to search for the minimum.

<table>
<thead>
<tr>
<th>Name</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quartic</td>
<td>( f_1(x) = \sum_{i=1}^{D} x_i^4 )</td>
</tr>
<tr>
<td>Rosenbrock</td>
<td>( f_2(x) = \sum_{i=1}^{D-1} 100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2 )</td>
</tr>
</tbody>
</table>

The dimension \( D \) is set to 10. For quartic function, search range is set as \( x_i \in [-1.28,1.28]^D \) and \( f_1(x) \in [0, 147.64] \). For Rosenbrock function \( x_2 \in [-5,5]^D \) and \( f_2(x) \in [0, 810324] \).

In order to compare these optimizers fairly, the starting point is random selected and fixed to make sure for every optimizer, they begin from the same start point. MaxFEs is set to 4e4 and all the parameters of optimizers are default in MATLAB (2022a). The FEs are performed on PC of and Intel Core Xeon Gold 5220R 2.20 GHz CPU. Table III presents the comparison of these optimizer on 3 benchmarks and Fig. 2 shows the optimization process.
B. Mackey-Glass Series Prediction

Mackey-Glass equation is a model for the variation in the quantity of blood cells in human body and always as the benchmark to test the predicting performance of nonlinear models. The system is defined by the first-order delay-differential equation:

\[
\frac{dx(t)}{dt} = \frac{ax(t-\tau)}{1+x(t-\tau)^2} - bx(t)
\]  

(14)

where \(a=0.2\), \(b=0.1\), \(c=10\). When \(\tau > 16.8\), the sequence exhibits chaotic properties with no periodicity. To solve the Mackey-Glass time-lag differential equation, the fourth order Runge-Kutta is applied with step interval 0.01, sampling interval is 1 and the time delay \(\tau=17\). Totally 1200 points are generated and in order to eliminate the influence of the initial state as noise, the first 118 data points are discard. Training set contains the first 400 point, 100 points are validation set and the rest is test set.

**Experiment 1**: Comparison of Hybrid and Pure Algorithm.

To evaluate the merit-seeking capability of pure GA, pure BFGS and hybrid GA-BFGS and avoid the influence of the structure of network. The number of hidden neurons is set to 10, each delay time unit is set to 1 and all the hidden neurons are tanh. Then three optimizers aim to decrease error and search for the best solution for parameters of neural network. To ensure the reliability of training algorithm. MSE on validation set is logged and Fig. 3 shows the MSE of each iteration.

Initial population is random set and fixed so that all optimizers start from the same condition. BFGS converges faster than GA and gains smaller error. After combining them together, the advantages of two optimization algorithm are fully exploited which leads faster convergence and smaller error.

**Experiment 2**: One-Step Ahead Prediction.

To comprehensively evaluate the performance of proposed model forecasting ability. Several indicators are given to measure the accuracy of prediction: RMSE, NRMSE, MAE, MAPE, SMAPE, \(R^2\).

In prediction of Mackey-Glass series, many authors set fixed delay time in advance [6, 19, 20]. The best delay time for the sequence can be determined by C-C method, which is 4. In this experiment, delay time is contained in the search space where maxDelay is set to 10 and it is dynamic chosen in time delay units with the growth of neural architecture.

Using the growing method and hybrid optimizer to train the networks for one-step ahead prediction. RMSE is logged as the network growing in Fig. 4. Both the training RMSE and validation RMSE are decreasing with the growing of neural network. When it grows to ten hidden neurons and stops since it reaches maximum number of hidden neurons set in advance.

Fig. 5 shows that the proposed method achieves a good prediction on future moment with RMSE is 2.29e-04 and error does not exceed 6e-04. Compared with the result in Fig. 3 where the time delay and type of activation function is fixed, neural network generated dynamically reached lower loss which proves the effectiveness of dynamically architecture.

The performance of one-step ahead prediction is compared with other widely used models in time series prediction and published articles. For LSTM and CNN-LSTM, time delay and window size are set as 10, filter size and number of filters are 6 and 64, respectively, learning rate is 0.005 and other hyperparameters are default. The network size of different prediction models is presented in Table V where the proposed method grows dynamic architecture and other models are fixed.

![Fig. 4. RMSE curve with network growing](image)

![Fig. 5. True and predicted values and error plot](image)
### TABLE V. SIZE OF EACH PREDICTIVE MODEL

<table>
<thead>
<tr>
<th>Neural Networks</th>
<th>Size</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Our Method</strong></td>
<td>1-10-1</td>
</tr>
<tr>
<td>LSTM</td>
<td>10-20-20-1</td>
</tr>
<tr>
<td>CNN-LSTM</td>
<td>10-20-20-1</td>
</tr>
<tr>
<td>ELM</td>
<td>10-20-20-1</td>
</tr>
<tr>
<td>CCNN (2022) [21]</td>
<td>4-12-1</td>
</tr>
<tr>
<td>ForGAN-GA (2019) [22]</td>
<td>36-64-1/32-256-1</td>
</tr>
</tbody>
</table>

Results in Fig. 6 show that proposed method performs much better than other deep learning models in terms of accuracy. Moreover, it also proves the validity of the network that single layer with only 10 hidden neurons is enough to achieve high precision forecasting, which save great time and computing resources.

#### Experiment 3: Multi-Step Ahead Prediction

Multi-part prediction determines the robustness of a time-series model, and two methods are concerned. The first one is to train the model to predict the multi-step value in the future directly, and the second one is to recursive use of one-step ahead model to implement prediction. The latter is chosen because the data is closer the relevance is higher, directly performing multiple steps forecasting may cause failure predictions because unrelated historical information.

Applying the trained network for iterated one-step ahead prediction to forecast future values. Due to the error accumulating in iterated prediction, prediction becomes worse and worse. However, through Fig. 7 even at a large prediction horizon, proposed method is still able to match the real value for a long time.

#### C. Comparison of Serial and Parallel Computation

Parallel computing with multiple processors can increase the speed of computing. To quantify it. Time spent on optimisation from only 1 to 24 processors is recorded and inverted as speed. Network architecture is the same as experiment 1 and initial population size is set to 10, 20, 40 respectively.
Fig. 8 shows the results that at beginning running speed increases as more cores added but converges due to bottlenecks in network transmission and size of data. Moreover, if higher the computational volume, the greater the parallel computing boost with almost 7 times improvement for 10 population size, nearly 13 times improvement for 20 population size and about 20 times improvement for 40 population size. Therefore, in growing network, the scale of parameters may become large so that parallel computation is necessary to be applied to decrease the computing time.

V. CONCLUSION AND FUTURE WORK

This paper develops a hybrid evolutionary algorithm based on the GA and the fastest quasi-Newton algorithm BFGS to grow and train a dynamic recurrent neural network. It is seen to be the most efficient nonlinear approach to time series prediction with growing method. The proposed GA-BFGS method is suitable for training both discrete structural parameters and continuous weighting parameters of the network. Thus, the network trained can adapt to characteristics of different time series. Moreover, parallel computation can be applied, with CPU speedup efficiency up to the number of neurons. This approach eliminates the need for setting any hyperparameters of the neural network for the highest possible optimality and accuracy to emerge. The method is evaluated on the Mackey-Glass time series and its forecasting performance is compared with currently widely adopted deep learning methods such as the long short-term memory (LSTM) and echo state networks (ESN) models. Results show that the proposed method performs faster with lower losses (RMSE: 2.29e-04) which achieves 89.6% reduction compared to the most popular deep learning model LSTM and a smaller network size (10 hidden neurons).

In future studies, various evaluation indicators will be considered for adapting to different problems. The growing method is to be applied to deep learning models where necessary for more complex tasks.

ACKNOWLEDGMENT

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REFERENCES

An Explainable Regression Framework for Predicting Remaining Useful Life of Machines

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Abstract—Prediction of a machine’s Remaining Useful Life (RUL) is one of the key tasks in predictive maintenance. The task is treated as a regression problem where Machine Learning (ML) algorithms are used to predict the RUL of machine components. These ML algorithms are generally used as a black box with a total focus on the performance without identifying the potential causes behind the algorithms’ decisions and their working mechanism. We believe, the performance (in terms of Mean Squared Error (MSE), etc.) alone is not enough to build the stakeholders’ trust in ML prediction rather more insights on the causes behind the predictions are needed. To this aim, in this paper, we explore the potential of Explainable AI (XAI) techniques by proposing an explainable regression framework for the prediction of machines’ RUL. We also evaluate several ML algorithms including classical and Neural Networks (NNs) based solutions for the task. For the explanations, we rely on two model agnostic XAI methods namely Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP). We believe, this work will provide a baseline for future research in the domain.

Index Terms—Explainability, Interpretability, Predictive Maintenance, Regression, Remaining Useful Life, LIME, SHAP.

I. INTRODUCTION

In the modern world, the scope of industries has expanded a lot. These days industries are generally equipped with a large number of modern machines resulting in a significant increase in production. However, the performance of these machines may degrade over time if proper care is not taken, thus, they need a continuous monitoring and maintenance process. Maintenance of machines in industries is a tedious and time-consuming process and generally needs to take different factors into account. However, thanks to the recent advancement in technology, industry 4.0 have opened new opportunities for predictive maintenance [1].

Predictive maintenance is one of the key aspects of modern industries especially after the fourth revolution of industry. It allows for monitoring, analyzing, and determining the condition of machine components for early detection of potential faults. The process generally involves data acquisition, data processing, and making intelligent decisions on the basis of the collected data to improve and optimize maintenance processes. Predictive maintenance generally involves different tasks. One of these tasks is the prediction of remaining useful life (RUL) of machines installed in a factory.

Thanks to the recent advancement in Machine Learning (ML) and sensor technology, it is possible to automate the prediction of RUL of machines by training ML algorithms on the data collected through a diversified set of sensors installed in the machines. The literature already reports the effectiveness of a wide range of ML algorithms in predictive maintenance in general and in predicting the RUL of machines in particular. However, these ML algorithms are used as a black box with total focus on their performance (i.e., accuracy and Mean Squared Error, etc.) without providing any insights on the working mechanism and cause behind the decisions of these algorithms. In such a critical application, accuracy/MSE alone is not enough to build the stakeholders’ trust in ML prediction rather more insights on the causes behind the predictions are needed [2].

In this paper, we propose an explainable ML framework incorporating a couple of model agnostic explainable AI techniques for the prediction of the RUL of machines. The proposed framework provides insights into the ML model’s predictions allowing the stakeholders to analyze the main causes of machine degradation. These insights not only build stockholders’ trust in the framework but also allow them to tune the model for better predictive performance.

The key contributions of the work can be summarized as follows:

- We propose an explainable framework incorporating multiple regression and explainability methods for predicting the RUL of machines.
- We also evaluate several regression methods including multiple classical and Neural Networks (NNs) based techniques. Moreover, we analyze the results of two model agnostic methods for the explanation of our regression algorithms.
- In extensive experimental setup, we evaluate the potential and applicability of explainable AI methods in predictive maintenance.

The rest of the paper is organized as follows. Section II provides an overview of the related work. Section III describes
the methodology of the proposed framework. Section IV provides a detailed description of the dataset, experiments, and experimental results. Finally, Section V concludes the work.

II. RELATED WORK

In this section, we provide an overview of the existing literature on both predictive maintenance and explainable AI. In the first part, we focus on the literature on predictive maintenance by highlighting some recent works in the domain. In the second part, we provide an overview of explainable AI techniques and key applications where AI could be beneficial.

A. Predictive Maintenance

The literature reports several interesting works on predictive maintenance, where different aspects of predictive maintenance are explored [1], [3]. Predictive maintenance generally involves three activities namely (i) data acquisition, (ii) data processing, and (iii) maintenance decision making, and the research in the domain mainly focuses on these areas [4]. For data acquisition, the predictive maintenance techniques heavily depend on sensor technologies, which provide relevant and useful information on the machine conditions. Based on the nature of sensors, predictive maintenance techniques can be roughly divided into three categories including (i) existing sensor-based maintenance, (ii) test-sensor-based maintenance, and (iii) test signal-based maintenance techniques [5].

The literature also reports several interesting frameworks of intelligent data processing and handling for predictive maintenance. For instance, Shcherbakov et al. [6] provides an overview of several data processing techniques and pipelines for data handling and processing for cyber-physical systems maintenance. Similarly, Yan et al. [7] provide a detailed overview of the challenges associated with heterogeneous industrial data handling and processing for predictive maintenance.

Predictive decision-making is one of the most explored topics in predictive maintenance. To this aim, several interesting solutions have been proposed over the years. The majority of the initial efforts in this direction rely on conventional/statistical ML algorithms, such as Random Forest (RF), Support Vector Machines (SVMs), and decision trees [3]. For instance, Kusiak et al. [8] relied on two classical ML algorithms namely decision trees and SVMs, which were trained on feature vectors composed of 60 sensor readings, for the predictive maintenance of wind turbines. Other classical ML algorithms that are widely used for predictive maintenance include RF and Naïve Bayes. These algorithms are normally trained raw sensor data or handcrafted features depending on the nature of the data [3]. A vast majority of the literature also relies on fuzzy logic and Hidden Markov Models (HMMs) for predictive maintenance. For instance, Zaki et al. [9] and Omorogbe et al. [10] employed Fuzzy logic and HMMs for predictive maintenance of renewable energy systems, respectively. However, recently the trend shifted towards the use NNs, and the majority of the recently proposed solutions rely on different types of NNs, such as MLP, Convolutional Neural Networks (CNNs), and Long short-term memory (LSTM) [3]. The choice of these algorithms mainly depends on the nature of the data. For example, CNNs are mostly used for predictive maintenance using visual content [11], [12]. LSTM-based solutions, on the other hand, are more effective for the analysis of sequential/time series data [13], [14].

B. Explainable AI

Over the last few years, explainable/interpretable AI got the attention of the research community. The literature reports several studies where it is demonstrated that in critical applications, such as healthcare, education, defense, and transportation, predictive capabilities of ML algorithms alone are not enough rather the algorithms should be interpretable [2], [15]. Explainability/interpretability, which aims at highlighting the causes behind the AI models’ predictions, could be obtained either by developing explainable AI algorithms or providing an explanation of the so-called black-box AI algorithms [16]. However, there is a trade-off between accuracy/performance of AI algorithms and interpretation [17]. Therefore, a majority of the explainable AI frameworks rely on model agnostics methods for the interpretation of AI models [2], [18]. To this aim, several interesting techniques are proposed. Some most commonly used techniques include LIME [19], SHAP [20], Grad-CAM [21], and DiCE [22].

Some key applications in which explainable AI has been widely explored include healthcare [23], education [24], security [25], and other smart cities applications [2]. The applications of explainable AI have been recently also introduced in industry [26]. However, most of the literature aims to analyze its applicability, challenges, and advantages in different industrial applications [26]. For instance, Shukla et al. [27] analyzed the opportunities of explainable AI in aerospace predictive maintenance. The authors also provide a detailed overview of the challenges associated with predictive maintenance in the domain. In contrast to most of the works reported in the literature, in this work, we propose an explainable regression framework for one of the most crucial applications of predictive maintenance namely the prediction of the remaining useful life of a machine.

III. METHODOLOGY

Figure 1 provides the block diagram of the proposed explainable predictive maintenance framework. The framework is mainly composed of two components namely (i) features selection and ML-based prediction, and (ii) explanation of the predictions. In the first part, we rely on several ML algorithms for the prediction of the remaining useful life of the machine components. In the second part, two different algorithms are used for the explanation of the model’s predictions. We note that the main contribution of the work lies in the explanation part. In the next subsections, we provide a detailed description of each of the phases.

A. ML-based Prediction

For the prediction of the useful remaining life of the machine components, we rely on several algorithms including (i)
Random Forest (RF), (ii) ElasticNet with Generalized Linear Models (GLMs), (iii) Gradient Boosting, (iv) Support Vector Machines (SVMs), and a (v) Neural Network (NNs) model. A description of each of the methods is provided below.

- **RF-based Prediction:** RF is one of the most widely used methods. In this work, we use it as one of our baseline methods. In this approach, as a first step, a shallow RF model is used to identify more important/influential features by plotting a chart of feature ranking. After the plotting feature ranking, the less important features (i.e., sensors values) are dropped. An RF model is then trained on the selected features. Table I provides the values of hyperparameters of the model used in the experiments.

- **SVM-based Prediction:** Our second baseline method is based on SVMs. SVMs are one of the most widely used algorithms for classification problems. However, it is rarely used for regression. It follows the same rules and criteria for regression tasks where the aim is to identify a function approximating the mapping from the input to real numbers based on training samples. One of the key processes in SVM-based prediction is the selection of hyperparameters values. To this aim, we rely on a grid-search algorithm to find the best combination of SVM hyperparameters. Grid search is an exhaustive search method that tries all the possible combinations and picks the one with the best possible results. However, the complexity of the method increases with an increase in the number of hyper-parameters. It is more suitable for methods with fewer hyper-parameters.

- **Gradient Boosting-based Prediction:** Our third method is based on Gradient Boosting [28], which is also one of the most widely used algorithms for classification and regression tasks. It is an ensemble method where multiple learning algorithms, which are also called weak learners, are combined to obtain better predictive performance. In our case, the weak learners are based on decision trees. Similar to the other models, we rely on the grid-search approach for the selection of hyperparameters of the model.

- **ElasticNetGLM-based Prediction:** Elastic net regularization pairing with GLMs is one of the widely used regularization methods. It allows to filter out unimportant and highly correlated features and helps to improve the performance of the model. In this work, we use an ML library namely Scikit-learn for the implementation of the ElasticNetGLM model. For tuning the hyperparameters of the model, we rely on the grid-search algorithm that allows us to find the best combination of the hyperparameters. Table II provides the summary of the parameters used in the model.

- **NNs-based Prediction:** Based on the proven performances in other applications, we also propose an NNs-based solution for the prediction of the useful remaining life of the machine components. To this aim, we propose an MLP regressor model. Our MLP regressor is composed of a total of 50 hidden layers, which are trained using backpropagation without an activation function in the output layer. Moreover, we used the square error as the loss function resulting in continuous values as an output.

<table>
<thead>
<tr>
<th>Attribute</th>
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<tbody>
<tr>
<td>max-depth</td>
<td>9</td>
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<tr>
<td>max-features</td>
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<tr>
<td>min-samples-leaf</td>
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</tr>
<tr>
<td>min-samples-split</td>
<td>2</td>
</tr>
<tr>
<td>n-estimators</td>
<td>10</td>
</tr>
</tbody>
</table>

Table I: Parameters setting of the FR model.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Value</th>
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<tbody>
<tr>
<td>Alpha</td>
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<tr>
<td>l1-ratio</td>
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</tr>
<tr>
<td>copy-X</td>
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</tr>
<tr>
<td>fit-intercept</td>
<td>True</td>
</tr>
<tr>
<td>selection</td>
<td>Cyclic</td>
</tr>
<tr>
<td>tol</td>
<td>True 0.0001</td>
</tr>
</tbody>
</table>

Table II: Parameters setting of the ElasticNetGLM model.

<table>
<thead>
<tr>
<th>Attribute</th>
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</thead>
<tbody>
<tr>
<td>Model</td>
<td>MLP Regressor</td>
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<td>Hidden Layers</td>
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</tr>
<tr>
<td>Max Iteration</td>
<td>1000</td>
</tr>
<tr>
<td>Learning Rate</td>
<td>Adaptive</td>
</tr>
</tbody>
</table>

Table III: Parameters setting of the MLP model.
B. Model’s Explanation

For the models’ explanation, we mainly rely on two methods namely (i) LIME, and (ii) SHAP. In the next subsections, we provide a detailed description of each of the methods.

1) LIME-Local Interpretable Model-Agnostic Explanations: LIME [19] is one of the most commonly used methods for the interpretation of ML models’ predictions. One of the key advantages of LIME is that it is a model agnostic method and could be used for the explanation/interpretation of any model. For the explanation of an ML model, LIME perturbs the input samples and analyzes the changes in the prediction of the model. This simple working mechanism makes it a preferable choice for model interpretation compared to model-specific methods, which require a deeper understanding of the underlying models.

LIME provides local interpretation, which means the model’s behavior is described by analyzing the response of a model to changes in a single data sample. Here the intuition is to analyze causing behind a particular prediction by answering questions like “why was this prediction made?” or “which features caused the prediction?”. It produces results in the form of a list of explanations highlighting the contribution of the individual feature as detailed in Section IV. We note that the idea and working mechanism of LIME is different from a related concept of “feature importance”, which is generally conducted over the entire datasets.

LIME could be used for the explanations of models deployed in different application domains including textual, tabular (i.e., sensor data), and visual content. The literature already reports the effectiveness of the method in several interesting human-centric applications, such as healthcare and other smart cities applications [2].

2) SHAPE-Shapley Additive Explanations: Our second explanation approach is based on another state-of-the-art technique namely SHAPE. The method was introduced by Lundberg et al. [20] to cope with the limitations of the existing methods. Similar to LIME, SHAPE provides explanations of individual predictions and could be used for the explanation of any model. However, in contrast to LIME, SHAPE provides both local and global explanations. The main difference between global and local explanations lies in the level/scope of explanation. The global interpretations/explanations include complete insights into the general/orrall behavior of the model. The local explanations/interpretations describe the causes behind a decision on an individual data sample.

Similar to LIME, SHAPE could be used for the explanation of ML models trained on different types of data including textual, visual, and tabular data. The literature reports the effectiveness of the method in several application domains, such as healthcare, defense, agriculture, etc [2], [29], [30].

IV. EXPERIMENTS AND RESULTS

A. Dataset

For the evaluation of proposed solutions, we used a dataset composed of the engine degradation simulation (C-MAPSS) data, which is collected in a simulated engine degradation environment under different combinations of operational conditions and modes [31]. The dataset is provided by the Prognostics Center of Excellence (PCoE) where the data is based on time series ranging from the working state to the failure state of the components. The dataset provides a 24 features vector containing 21 sensor readings and 3 operational settings. The sensor readings are mostly related to temperature, pressure, the fan speed of an engine, fuel, etc. The description of all of these sensor readings is provided in Table IV.

The dataset is widely used for fault detection and prognostics (i.e., predicting the time at which the machine components will no longer work). In this paper, we are interested in predicting the Remaining Useful Life (RUL) of machine components, which is a continuous target/value. We treat the problem as a regression task. The dataset is composed of more than 20,000 data samples, which are divided into training and test sets. The training set is composed of 16504 samples while the test set contains 4127 samples.

Table IV: Description of the sensor readings provided in the dataset.

<table>
<thead>
<tr>
<th>Sensor No</th>
<th>Readings</th>
<th>Sensor No</th>
<th>Readings</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Total temperature at intake</td>
<td>4</td>
<td>Total temperature at LPC outlet</td>
</tr>
<tr>
<td>2</td>
<td>Pressure at fan inlet</td>
<td>5</td>
<td>Total pressure at LPC outlet</td>
</tr>
<tr>
<td>7</td>
<td>Total pressure at LPC outlet</td>
<td>8</td>
<td>Physical fan speed</td>
</tr>
<tr>
<td>9</td>
<td>Physical core speed</td>
<td>10</td>
<td>Engine pressure ratio</td>
</tr>
<tr>
<td>11</td>
<td>Engine pressure ratio</td>
<td>12</td>
<td>Ratio of fuel flow to VO2</td>
</tr>
<tr>
<td>13</td>
<td>Corrected fan speed</td>
<td>14</td>
<td>Corrected core speed</td>
</tr>
<tr>
<td>15</td>
<td>Burner enthalpy</td>
<td>16</td>
<td>Burner exit temperature</td>
</tr>
<tr>
<td>17</td>
<td>Burned fuel</td>
<td>18</td>
<td>Demanded corrected fan speed</td>
</tr>
<tr>
<td>20</td>
<td>LPT coolant burned</td>
<td>21</td>
<td>HPC constant burned</td>
</tr>
</tbody>
</table>

B. Experimental Results

In this section, we provide the experimental results of the proposed work. Firstly, we report the results of all the algorithms employed in this work followed by some samples of the explanations produced by LIME and SHAP.

1) Prediction Results: Table V provides the experimental results of all the algorithms employed in this work including the classical and NNs-based solutions in terms of Mean Squared Error (MSE) and Mean Absolute Error (MAE) on a test set containing a total of 4127 samples. We note that there is a trade-off between performance and explainability. The classical ML algorithms are more explainable compared to NNs, however, their performance is generally on the lower side. Similar trends have been also observed in this work. As can be seen, the MSE and MAE values for the NNs-based solution are significantly lower compared to the classical algorithms, such as RF and SVMs.

As far as the explanations of the NNs-based solutions is concerned, this could be overcome with the use of model agnostic methods of explainability. Next, we analyze the explanations provided by two model agnostic explainable AI methods.

2) Model Explanations via LIME and SHAP: Figure 2 and Figure 3 provides explanations generated by LIME and SHAP method, respectively. In this sample, the actual value of RUL...
Table V: Experimental results in terms of Mean Squared Error (MSE) and Mean Absolute Error (MAE) on a test set containing 4127 samples.

<table>
<thead>
<tr>
<th>Method</th>
<th>MSE</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>RF</td>
<td>1767.06</td>
<td>29.84</td>
</tr>
<tr>
<td>ElasticNetGLM</td>
<td>2043.03</td>
<td>34.60</td>
</tr>
<tr>
<td>Gradient Boosting</td>
<td>1768.45</td>
<td>29.92</td>
</tr>
<tr>
<td>SVMs</td>
<td>2043.03</td>
<td>34.60</td>
</tr>
<tr>
<td>MLP</td>
<td>1742.08</td>
<td>25.46</td>
</tr>
</tbody>
</table>

of the machine component is 151 cycles while the predicted value is 148.35 cycles.

In Figure 2, the features (i.e., sensor values) on the right side in red color are the ones that contribute to increasing the prediction values while the ones in blue color are the features that have a negative effect or decrease the predicted value. For example, the values of the sensors 11, 7, 2, etc. on the right side indicate that the machine component is in a good condition and its RUL is supposed to be high. The sensor value on the left side in blue color, for example, sensor -1 = < 518.67 indicates that the conditions of the component are not good and it tries to reduce the predicted RUL value.

Figure 3 provides the explanation of the same sample. Similar to LIME, SHAP explanations are also composed of several values including:

- The predicted value (i.e., 148.35)
- The base value, which is the average of the model output over the training dataset.
- The feature values that contributed to the prediction. The red values are the feature values that increased the predicted value while the values in blue color (i.e., sensor - 14 = 8.151) contributed to the reduction of the predicted RUL value. In other words, the sensor values in red color mean the condition of the component is good while the blue ones indicate something is wrong with the component.
- The size/length of the arrow shows the impact of the feature on the prediction. For example, in the given sample, sensor-11, sensor-12, and sensor-14 have a higher impact on the prediction.

V. CONCLUSIONS AND FUTURE WORK

In this work, we proposed an explainable regression framework for the prediction of the RUL of machine components. We evaluated several ML techniques including classical ML and NNs approaches for the prediction. For the explanation of the models, we employed two different models agnostic explainable AI methods. The explanation provided by these methods is very insightful that could help the stakeholders in making correct decisions in such critical applications. The explanation of the models could also help the developers to rectify the limitations of their proposed solutions. In the future, we aim to further extend the scope of the work by tackling more relevant tasks of predictive maintenance.

REFERENCES

Figure 2: Sample explanations provided by LIME. Here the actual value of RUL of the component is 151 while the predicted value is 148.3.

Figure 3: Sample explanations provided by SHAP. Here the actual value of RUL of the component is 151 while the predicted value is 148.3.


An Investigation of GCN-based Human Action Recognition Using Skeletal Features

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Abstract— Human action recognition is one of the most challenging and attractive areas in the field of computer vision. Conventional research on human action recognition has mainly focused on data modality of video or optical flow. However, the human skeletal feature has much stronger expressive power of motion dynamics, which is not sensitive to illumination and scene variation. Owing to the advantages of deep learning approaches on skeleton data in recent years, many pilot approaches have been proposed, which are merited by their significant performance enhancements on both baseline and large-scale datasets. This research investigates these models and their breakthroughs, especially focusing on the graph convolution network (GCN) and skeleton-based data techniques. The report work mainly covers the following aspects: comparing RNN, CNN and GCN-based approaches from the perspective of their operational logics; a detailed review of the best referred models in recent years; a development framework of skeletal feature-based human action recognition framework is proposed with preliminary assessments using benchmarking datasets; and finally, the envisaged future directions for skeletal feature-based human action recognition study are discussed.

Keywords: Human Action Recognition; Skeleton Data; GCN

I. INTRODUCTION

Human action recognition refers to the process of identifying and understanding human actions and is critical for series of real-world applications, for example, it can be used in autonomous navigation system [1] to ensure the safety of road traffic, and for video surveillance [2], where dangerous human behaviors can be detected. Other applications have also included human-computer interaction [3], entertainment [4], and video retrieval [5].

In general, raw input data for human action recognition includes several modalities and can be divided into visual modalities and non-visual modalities [6]. This study focuses on skeleton-based data, which falls into the category of visual modalities. Skeleton data is encoded from the trajectories of human body joints for both intra-frame and inter-frame joints. Other objects and background information in frames are ignored. Therefore, such data can effectively represent the characteristics and various changing trends of human behaviors. Skeleton data can be mainly acquired by applying video-based pose estimation algorithms [7] or depth sensors [8].

Skeleton data is becoming more important than other data modalities because of the following aspects: 1) For spatial information, the position relationship of intra-frame joints plays an important role in modeling the intrinsic relation of structural information [9][10]. 2) For temporal information, different positions of the same joint show strong temporal relationship with an inter-frame manner [9][10]. 3) For the co-occurrence relationship, once spatial and temporal information is applied for learning and modeling simultaneously, the co-occurrence relationship is reflected [9]. 4) Compared to the most used RGB and optical flow, skeleton data has a small total amount of data, so the computational burden is correspondingly small [11]. 5) Skeleton data is not sensitive to background noise and illumination changes [11].

The main contributions of this study can be summarized as follows: 1) From the point of skeleton-based human action recognition, this study compares RNN, CNN and GCN approaches from the perspective of development logic of deep learning principle. 2) The focus of this paper is to give a detailed review of the 11 papers with the highest citation rate in recent years, since a lot of relevant literatures have been reviewed in previous surveys [6][9][10][11][12][13] in recent years. 3) This study, for the first time, presents a development framework of skeleton-based human action recognition approaches, and analyzes the evolution and development logic among each method.

II. BACKGROUND OF GCN

A. Deep Learning-based Action Recognition with Skeleton Data

In RNN-based methods [14][15][16], skeleton sequence was usually constructed as a sequence of coordinate vectors due to the inherent suitability of RNN for handling time series data. However, although the impressive results have been achieved, the biggest drawback is that it ignores the spatial information which always carry strong dependencies in skeleton-based data [11]. Meanwhile, RNN and long-short term memory (LSTM) can usually model the long-term context...
information in temporal dimension, but it is difficult to complete the modeling of high-level features [17]. Therefore, there are certain limitations in using RNN to deal with skeleton-based data for human action recognition.

To solve the shortcomings of RNN in identifying skeleton-based data, many studies then investigated the possibility of using CNN-based methods [3][18]. The idea of using CNN is based largely on its success in image processing. Firstly, skeleton-based coordinate data is transformed into 2D pseudo images, and then human action recognition is completed by using CNN to identify and predict images. Based on remarkable achievements of CNN to images, the results in skeleton-based data were also sound. However, CNN brings new problems. For example, to obtain 2D pseudo images and encode temporal information, the corresponding computational complexity is significantly increased. In addition, the learning and modeling of long-range relationship is still a problem [10].

Neither RNN nor CNN can completely model the complicated spatial temporal human body skeleton. Since skeleton can be naturally represented as a graph, the joints of human body are represented as vertices, and the bones connecting the joints are illustrated as edges. It's naturally much more expressive than sequence vectors or 2D pseudo images. Therefore, the GCN-based methods have natural advantages in graph structure utilization. It can not only generate skeleton structure of arbitrary form, but also distinguish various information in spatial and temporal domain to the maximum extent. Many studies have consistently proved that GCN is a more suitable method for extracting human body skeleton data than sequence vectors or 2D pseudo images [19][33][34].

B. Spatial and Spectral Domain GCN

The principle of building GCN on graph generally follows two flows, spatial-based and spectral-based approaches.

The research of spatial-based approaches started much earlier than spectral-based approaches. It inherits ideas from building RNN on graph to define graph convolutions by information propagation. Spatial-based approaches define convolutions directly on the graph-based topology. Operations such as message-passing and representation methods are used to aggregate information between vertices and make a prediction. The major challenge of spatial-based approaches is defining the convolution operation with differently sized neighborhoods.

Spectral-based approaches have a solid mathematical foundation in graph signal processing. Spectral-based approaches define graph convolutions by introducing filters from the perspective of graph signal processing, where the graph convolutional operation is interpreted as removing noises from graph signals. Operations such as the graph Fourier transform, or its extensions are used to aggregate vertex information and make a prediction. The drawback is that it is computationally expensive since the kernel is defined in Fourier space and the graph Fourier transform is expensive to compute.

III. SKELETON-BASED HUMAN ACTION RECOGNITION WITH GCN

A. Naive Spatial Temporal GCN

Wang et al. [20] proposed the idea of representing skeleton data as graphs, which laid a foundation for the subsequent works. Then Yan et al. [19] proposed spatial temporal graph convolution networks (ST-GCN) based on deep learning principle. Before ST-GCN [19] was proposed, the conventional ways for handling skeleton-based data are hand-crafted parts and the mechanism of traversal. The main pain points of those methods are the limitation of expression potency, difficulty in generalization, and low algorithm efficiency. To solve the above problems, ST-GCN [19] first proposes to use spatial temporal method to address human action recognition problems with GCN.

As shown in Fig. 1, each blue vertex represents a joint of human body, and edges are divided into spatial edges and temporal edges. The spatial edges refer to the edges connecting intra-frame vertices, while the temporal edges refer to the connections of the same vertex between consecutive frames. Firstly, the set of $V$ and $E$ are defined, where $V$ is constructed in a single frame, while $E$ is constructed in a single frame and consecutive frames, respectively. Secondly, the network structure and corresponding sampling function and weight function are defined on this basis. In addition, several feasible partitioning strategies are analyzed. Adopting deformable convolutional networks [21] to skeleton data is one of the highlights worth mentioning in this structure, the authors set offset to learn the three types of vertices in partitioning. Finally, the spatial temporal model is proposed.

At the implementation level, the network sets 9 spatial temporal graph convolution layers. To avoid overfitting, data augmentation is applied, which has been verified in related research [22]. In addition, TCN [23] is used as the baseline in this paper, and this method has been applied in a series of subsequent studies [24][25][26][27] as well. The experimental results show that ST-GCN [19] has better performance in both unconstrained and constraint datasets. The two major datasets, Kinetics-Skeleton [28][7] and NTU RGB+D [29], are also utilized as baseline in subsequent studies.

ST-GCN [19] has several outstanding advantages, which play a leading role in subsequent research work.

- It introduces the idea of applying spatial temporal method in GCN to approach the skeleton-based human action recognition.
- This network architecture supports datasets containing different numbers of joint or joint connectivity.
- It is a generic design with automatic learning of spatial and temporal patterns from input data.
- This kind of spatial temporal GCN has excellent expressive power and generalization capability.
- Input data is compatible with 2D datasets, such as skeleton data converted by OpenPose [7], and 3D datasets, such as NTU RGB+D [29].

- This spatial temporal GCN can be used as an effective supplementary way to learn human action by RGB or optical flow.

However, as more research being carried out, some drawbacks of ST-GCN [19] have been revealed, namely:

- **Drawback 1:** It is designed as a fixed graph structure based on the natural physical structure of human skeleton. Therefore, the semantic connections between each joint in each frame are ignored [30][12].

- **Drawback 2:** The skeleton graph is heuristically predefined, and it represents only the physical structure of the human body. Therefore, it is possibly suboptimal for human action recognition tasks [24][25].

- **Drawback 3:** The structure of GCN is hierarchical, with its different layers containing multiple levels of semantic information. However, because the topology of the graph is fixed at all layers, which lacks the capability and flexibility to model the multiple layers of semantic information contained in all layers [24][30][31].

- **Drawback 4:** Using a fixed graph structure may not be the best solution for all samples used to distinguish between different action classes [24].

- **Drawback 5:** The feature vectors attached to each vertex contain only the 2D or 3D coordinates of the joint that can be considered as first-order information (spatial coordinates of joints and bones) of skeleton data. However, second-order information (bones lengths or directions), representing bone features between a pair of joints, is not explored [24][9].

- **Drawback 6:** The joint connections in different positions are unbalanced. When torso joints are overly smooth, limb joints may remain in a less smooth state, which is leading to difficulties in sharing features between two limb joints [25].

- **Drawback 7:** Its convolution kernel can only collect local features, and the skeleton graph of physical connection lacks flexibility, which is not conducive to the distinction between actions [12][27][32][26][33][34].

- **Drawback 8:** Its design is exceedingly sophisticated, and over parametric, which leads to inefficient model training and inference [12][27].

- **Drawback 9:** It defines the receptive fields of spatial graph and temporal graph based on intuition. However, the expressive power of this definition is limited [27][35][33][34].

To address the above-mentioned shortcomings, there are 10 key papers reported major improvements on the ST-GCN [19] from different angles, which can be divided into the following categories: devised spatial temporal GCN, two-stream GCN, attention GCN, encoder-decoder GCN, and other Misc. (see Table I).

### B. Devised Spatial Temporal GCN

1) **NAS-GCN**

The core purpose of this model [30] is to automatically design neural network structure for skeleton based GCN. Its main innovation is to combine the skeleton-based GCN problem with neural architecture search (NAS) [36] and adapt it to the skeleton-based problem by adjusting and enhancing the NAS [36] method.

Different from the conventional spatial-based or spectral-based GCN approaches, this work builds a dynamic graph based on various semantic information through the interaction between joints, while other methods compute the importance weight of different representations or frames.

The method proposed in this paper [30] mainly includes the following two points that deserve our attention:

a) **For the search space**

It utilizes gaussian function used in 2s-AGCN [24] to compute the connection strength between two vertices. In the search space, Chebyshev polynomial functions of different orders are built on various layers, and the network determines the order and polynomial composition of each layer.

Previous NAS [36] reduces computational effort by searching a single block. However, the authors argue that different feature layers contain different levels of semantic content and therefore prefer to use layer-specific mechanisms to build graphs. So, the search is conducted across the entire GCN network instead of each individual block.

b) **For the search algorithm**

A devised way of combining cross-entropy evolution strategy [37] and importance-mixing (CEIM) is proposed. It applies gaussian distribution to model the architecture and updates the search process according to the feedback information. Meanwhile, the algorithm improves the sampling efficiency by mixing the samples of the current epoch with the samples of the previous epoch. Also, it
captures implicit associations, especially higher-level features, and thus improves the robustness of action recognition [12].

2) **MS-G3D**

Liu et al. proposed a disentangled multi-scale aggregation scheme and a unified spatial temporal graph convolution (G3D) operator [33].

a) **Disentangled multi-scale aggregation scheme**

By defining the k-adjacency matrix, a multi-scale aggregation scheme is used to remove redundant dependencies between features of different neighborhood vertices. It addresses the problem of biased weights by eliminating the redundant dependence of closer neighborhood weighting with distant neighborhood weighting. Moreover, k-adjacency matrices are relatively sparse, which can represent the graph structure efficiently.

b) **Unified spatial-temporal graph convolution (G3D) operator**

A typical scenario is listed in this paper. If features are captured through independent spatial only and temporal only modules and then integrated, certain complex situations will be difficult to deal with. For example, after the propagation and aggregation of a pair of strongly correlated joints through several convolutional layers, the degree of correlation between them are reduced and the redundant information is increased. To solve this problem, a convolution operator, named G3D, is designed. It utilizes an extended sliding window to skip the smooth stream of information across space-time connections. The design of G3D refers to the definition of receptive fields in 3D convolutional network [38]. Best performance is achieved when G3D is applied to long-range and factorized modules.

Finally, feature extractor (MS-G3D) is built by fusing the above two solutions. Unlike most other approaches, this paper presents a disentanglement approach that has achieved outstanding performance. Another point is that dilated convolutions [39] are applied to multi-scale aggregation, which effectively controls the complexity of the network architecture.

Same as 2s-AGCN [24], the authors improved the efficiency of recognition by fusing joint information and bone information. The difference is that MS-G3D [33] achieves higher recognition efficiency while the total number of parameters is reduced.

3) **MST-GCN**

The authors proposed that based on the consideration of short-range joint dependencies and short-term trajectory, existing research do not deal with modeling the distant joints relations and long-range temporal information satisfactorily. The problems mainly include two aspects. First, they introduce additional modules or adaptively learn the relationship between vertices. Second, the higher-order polynomial of adjacency matrix is adopted. A few previous methods [32][24][40][33] only partially solve these problems.

The purpose of this model [34] is to solve the two problems mentioned above. To be specific, a multi-scale spatial graph convolution (MS-GC) module and a multi-scale temporal graph convolution (MT-GC) module are defined. Then, a multi-scale spatial temporal graph convolution network (MST-GCN) is proposed by stacking the block combined with MS-GC and MT-GC.

a) **MS-GC module**

The key inspiration is from Res2Net [41], which is a successful practice in CNN. In contrast to Res2Net [41], the MS-GC module also exploits smaller groups of filters to split a feature into fragments in a channel dimension. Meanwhile, spatial graph convolution is used to replace 3×3 convolution in CNN design, thus forming hierarchical residual-like architecture. Without adding more parameters, this design can capture larger receptive fields and obtain both short-range and long-range joints. Finally, all fragments will be concatenated to help model convergence.

b) **MT-GC module**

MT-GC module is an extension of MS-GC module in temporal. It utilizes a set of sub-temporal graph convolutions to form hierarchical residual-like structures.

c) **MST-GCN**

MST-GCN is a network structure formed by stacking modules composed of MS-GC and MT-GC. It is worth mentioning that another method is to capture long range features using multi-scale is MS-G3D [33]. Both of them significantly increase temporal receptive fields, but they adopt different ways. MS-G3D [33] utilizes paralleled 3×1 kernel sizes combined with dilated window, while MST-GCN [34] uses single block of a hierarchical architecture.

Additional, as an extended application of Res2Net [41] on GCN, the following two points are worth further discussion: 1) Res2Net [41] can be used as an independent block to plug into other mainstream CNN backbone such as ResNet [42] or ResNeXt [43] to expand receptive fields. 2) Res2Net [41] discusses the integration with cardinality dimension [43] and squeeze and congestion [45] blocks. However, no relevant experiments about how to adopt above two points in GCN are conducted in this paper.

C. Two-Stream GCN

1) **2s-AGCN**

The authors of this paper [24] firstly put forward two deficiencies of ST-GCN [19]. First, the topology of graph is the same at each layer, which therefore lacks the flexibility. Second, compared with the data-driven graph structure, it is difficult for the fixed graph structure to get the optimal value for all the samples in various categories.

Then, several improvement strategies are creatively proposed. It is worth learning from the following two points: 1) Although ST-GCN [19] can process 2D and 3D skeleton datasets, only first-order information is considered. Apart from first-order information, in this paper, bone information including length and direction information is further explored. Therefore, an adaptive two-stream network is constructed together with joint information. 2) In view of the low flexibility of ST-GCN [19], the adjacency matrix is divided into three parts in this paper. Part 1, same as the definition of ST-GCN [19],
represents the original structure of human body. Part 2, the network training completely relies on the data-driven method, which has no restrictions on capturing features of objects. Part 3, gaussian function is utilized to compute the strength of connection between two joints. The method of data dependence is adopted, and a unique graph can be learned for each data sample.

Additionally, this output is another key research achievement after ST-GCN [19], many subsequent studies [26][30][27][33][35] are based on this paper.

2) **DGNN**

In this paper [35], the directed acyclic graph (DAG) is explored to represent the relationship between joints and bones. Meanwhile, directed graph neural network (DGN) is designed to analyze and predict joints and bones and their relationship. Finally, spatial and temporal information is sent to a two-stream network for action recognition task.

The major contribution is that the skeleton-based data is defined as DAG instead of undirected graphs defined by other GCN-based methods. It takes the root vertex as the center of gravity in the human body skeleton and defines the direction of each bone accordingly. It also includes how to update the acquired features by two functions, namely updating function and aggregation function.

Based on the consideration of directed graph, incidence matrix is innovatively adopted while implementing the directed graph network (DGN) block. Furthermore, the drawback of adjacency matrix used by the conventional methods [19][24] are analyzed in detail. It provides an important reference for skeleton-based human action recognition using directed graph.

It should be mentioned that its computational complexity is extremely high, with exceeding 100 giga floating-number operations (GFLOPs) [27], due to the application of directed graph and the fusion strategy of multi-streams.

3) **SDGCN**

In this model [26], the ideas of two well-known networks, ResNet [42] and DenseNet [46], are adopted to enhance the capability of GCN in skeleton data.

Specifically, a cross domain spatial residual layer is designed to build residual blocks. However, how to apply the key function as avoiding problems of vanishing/exploding gradients in GCN is not mentioned here. The paper does not even specify the number of layers of its network. Therefore, there may be room for further research on GCN by using residual networks.

In combination with DenseNet [46], feature-map of each layer accumulating data of all previous layers is applied to capture global information, which is undoubtedly very effective. Intuitively, this design can handle learning problems such as the relationship between distant bones and joints. However, the authors do not conduct experiments on this angle.

In addition, for the common feature of the two previous works [42][46] i.e., reducing the possibility of vanishing-gradient problem, this paper has not given a discussion.

To sum up, residual networks and dense networks are introduced into GCN and well combined in this paper. Meanwhile, there are still some open problems worthy of further discussion.

D. **Attention GCN**

1) **STGR**

Li et al. introduce a Spatio-temporal graph routing (STGR) [25], which adaptively learns the internal higher-order connections of physically separated joints.

It also aims at the problem that the fixed skeleton structure of ST-GCN [19] is not conducive to feature learning. The STGR [25] can acquire both spatial and temporal dependencies between each pair of joints by adopting two sub-networks respectively, i.e., the spatial graph router (SGR) and temporal graph router (TGR). Then, by acquiring the dynamic graph topology, its model will be composed of STGR [25] and ST-GCN [19].

In addition, this paper presents several unique observations. For example, the joint connections in different positions are unbalanced. When torso joints are overly smooth, limb joints may remain in a less smooth state, which is leading to difficulties in sharing features between the two limb joints. Then, while constructing of SGR, the idea of sub-group is proposed. The skeleton joints are divided into torso joints and non-torso joints, and the results of different partitioning strategies are compared and analyzed. The empirical data for capturing the optimal solution are obtained. Another point of view is that highly correlated joints tend to mean that they are also more closely related in feature learning. These fresh viewpoints are worthy of reference and discussion in future research.

However, since the human body is a whole, so some intrinsic semantic information may be lost when the human skeleton is divided into several parts.

2) **STF**

The authors of this paper [31] mainly point out the following two drawbacks in other methods: 1) Most existing methods do not explicitly embed higher-order spatial temporal importance into the spatial connection of vertices. 2) The advantage of using the attention mechanism in identifying action sequences is not fully utilized.

Then, improvement strategies for the above two aspects are proposed: 1) A To-a-T Spatio-temporal Focus (STF) module is proposed with a re-defined adjacency matrix which can model the higher-order spatial temporal dynamics. It also shows the importance of the input skeleton sequence. 2) STF exploration loss, STF divergence loss and STF coherence loss on the gradient based spatial temporal focus are defined. These loss terms can ensure that the prediction of classifier can be based on all the key vertices and predict various classes according to different human body parts. At the same time, among the stacked STF modules, using the focus of the high-level GCN module to help the learning of the low-level GCN module.
It is worth noting that part of this work is built on MS-G3D [33]. It points that the k-adjacency matrix defined by MS-G3D [33] cannot model the high-order relationship in the spatial temporal domain. While this model defines a dynamic adjacency matrix based on the k-adjacency matrix to solve this problem.

**E. Encoder-Decoder GCN**

1) **AS-GCN**

In AS-GCN [32], the meaning of joint information is identical to other conventional methods. However, bone information is expressed as actional links (A-links) and structural links (S-links) respectively. Where A-links are used to capture latent dependencies between any joints, and S-links are used to represent higher-order relationships of actions.

Then an actional-structural graph convolution (ASGC) is proposed. Meanwhile, temporal convolution network (TCN) [23] is used to capture spatial and temporal features respectively.

The main feature of this paper is that the encoder decoder framework of neural relational inference (NRI) model [47] is combined with the design of generation of A-links. And gated recurrent unit (GRU) [48] is utilized in the design of decoder modeule.

In addition, this work adds a head for prediction purpose. That is, while completing the recognition task, precise prediction can be made to the future pose.

F. Misc.

1) **Shift-GCN**

Cheng et al. [27] come up with two common problems in conventional GCN architectures. First, the computing complexity is generally heavy. Second, the receptive fields of spatial and temporal graph are predefined heuristically, in other words, they lack flexibility and can be optimized.

The solution to above problems is to refer to the idea of shift convolution [49] applied in CNN and adapt this practice in GCN. It is another successful example of migrating a CNN innovation to GCN domain. At the same time, lightweight point-wise convolutions are used to solve the problem of low flexibility of receptive fields.

In this paper, two solutions for building of spatial skeleton graph and temporal skeleton graph are presented respectively. The conventional scheme and the proposed method are compared and analyzed in detail, which is very helpful to understand the idea of this work.

IV. DEVELOPMENT FRAMEWORK

Based on the critical analyses carried out in this research, a skeleton and GCN-based human action recognition framework is proposed. Its operational process can be divided into four stages as shown in Fig. 2. The representative networks at each stage are ST-GCN [19], 2s-AGCN [24], MS-G3D [33] and MST-GCN [34] respectively.

A summary of each development process as following:

**A. Path 1, from ST-GCN to AS-GCN**

AS-GCN [32] designs actional-links and structural-links to address incapacity of ST-GCN [19] to capture relationships between distant joints (7th drawback), obtaining action-specific latent dependencies and representing higher order relationships respectively.

**B. Path 2, from ST-GCN to 2s-AGCN**

2s-AGCN [24] points out four directions (2nd to 5th drawback) in which ST-GCN [19] can be improved and proposes two major improvement schemes. First, a data-driven approach is used to parameterize both the global graph and individual graph to extend the flexibility of the model. The second is to make use of the second-order information of the skeleton data and construct an adaptive graph convolutional network for prediction.

**C. Path 3, from ST-GCN to STGR**

STGR [25] puts forward the idea of sub-group in view of the two shortcomings (2nd and 6th drawback) of ST-GCN [19] and divided human body joints into torso joints and non-torso joints. Then, the results of different partitioning strategies are compared and analyzed, and the empirical data that can get the optimal are obtained.

**D. Path 4, AS-GCN to MS-G3D**

The adjacency matrix defined in AS-GCN [32] has bias in local region and vertices with high degree, it is not conducive to capture the dependencies of long-range vertices. MS-G3D [33] defines a k-adjacency matrix to address this problem, which is also more efficient.

**E. Path 5, from 2s-AGCN to MS-G3D**

Combining the ideas of 2s-AGCN [24] and DGNN [35], MS-G3D [33] adds a learnable graph residual mask to dynamically handle edges under the premise of the defined k-adjacency matrix. It optimizes the prediction for all possible actions and inhibits the biased weighting problem to certain extent.

**F. Path 6, from 2s-AGCN to NAS-GCN**

NAS-GCN [30] refers to the idea of 2s-AGCN [24], that is using both first order and second order information simultaneously and fusing the results of them to do prediction. At the same time, the improvement for two disadvantages (1st and 3rd drawback) of ST-GCN [19] is proposed.
G. Path 7, from 2s-AGCN to DGNN

DGNN [35] borrows the idea from two-stream network architecture [1][24] and makes predictions through two streams. The difference is that the method of fusing spatial stream and motion stream is used here to improve performance. In addition, a solution to the infllexibility of receptive fields in conventional GCN (9th drawback) is also provided.

H. Path 8, from 2s-AGCN to SDGCN

SDGCN [26] introduces a scheme by combining the advantages of ResNet [42] and DenseNet [46]. Taking ST-GCN [19] and 2s-AGCN [24] as baseline, the effectiveness of the method is verified by the experimental results discussion.

I. Path 9, from 2s-AGCN to Shift-GCN

Aiming at several drawbacks (7th to 9th drawback) of conventional GCN, Shift-GCN [27] is proposed to apply shift convolution [49] to GCN. In particular, the proposed non-local shift graph convolution can significantly reduce the burden of computation. It is one of the few improvement schemes for the 8th drawback. At the same time, more flexibility has been achieved in defining the receptive fields.

J. Path 10, from MS-G3D to STF

The work of STF [31] is partially built on MS-G3D [33]. The k-adjacency matrix defined in MS-G3D [33] cannot model the high-order relationship in the spatial temporal domain, then a dynamic adjacency matrix based on the k-adjacency matrix is defined to solve this problem.

K. Path 11, from MS-G3D to MST-GCN

To obtain multi-scale spatial information, earlier methods [32][24][40][33] utilize methods such as applying higher-order polynomials to the skeleton data adjacency matrix, which achieve good performance, but also greatly increase the computational complexity. As the transition of Res2Net [41] in GCN, MST-GCN [34] utilizes subnet and hierarchical residual architecture to well control the overall computation burden.

Meanwhile, in terms of multi-scale temporal modeling, MST-GCN [34] adopts a single block, which is different from the previous method [33], by using 3×1 kernel size. And the accumulation of short- and long-range information is carried out through hierarchical architecture.

L. Path 12, from NAS-GCN to MST-GCN

While certain skeleton data-based methods [30][33] generate multi-scale structural features through higher-order polynomials, MST-GCN [34] transfers the idea of Res2Net [41] from CNN to GCN. It uses residual connections to stack several sub-graph convolutions to capture short range vertices dependencies and distant vertices relations simultaneously.

In addition, in the process of temporal modeling, compared with the earlier methods [19][32][24][30], which used fixed kernel size, MST-GCN [34] applies subtemporal graph convolutions. This approach can increase the temporal receptive fields, and finally assign the model with multi-scale representation capability of temporal information.

V. PERFORMANCE COMPARISON

A. Datasets

The most used datasets for human action recognition with skeleton-based data are Kinetics-Skeleton [28], NTU RGB+D [29], and NTU RGB+D 120 [50].

1) Kinetics-Skeleton

Kinetics 400 human action dataset [28] contains around 30000 video clips in 400 classes, which can be retrieved from YouTube. There are 240436 and 19794 samples for training and testing respectively. The skeleton version is converted by publicly available OpenPose [7] toolbox. Top-1 and Top-5 accuracies are reported following the conventional protocols [28][19].

2) NTU RGB+D

NTU RGB+D [29] contains 56880 action clips in 60 classes. The clips are all captured from 40 subjects with 3 camera views recorded simultaneously. The recommendation for reporting the accuracy by two ways: Cross-Subject (X-Sub) and Cross-View (X-View). For the former setting, half of the subjects are split for training and others for testing respectively; for the latter, samples captured by camera 2 and camera 3 are for training and others for testing accordingly.

3) NTU RGB+D 120

NTU RGB+D 120 [50] is an expansion of NTU RGB+D [29] in the number of subjects and action classes. It contains 114480 action clips in 120 classes, which are captured from 106 subjects with three camera views. Similarly, Cross-Subject (X-Sub) and Cross-Setup (X-Setup) are recommended as the evaluation protocol. The split principle is same with NTU RGB+D [29] for the former setting; for the latter, half out of the 32 setups are split for training and others for testing respectively.

The reason for choosing above three datasets is because the scenarios they covered are complementary. The Kinetics-Skeleton [28][7] obtained through the public available toolbox is 2D skeleton data, compared to the 3D data of NTU series since it is obtained through depth sensors. However, since the NTU series is captured in a lab environment, it has constraint data only. As per Kinetics-Skeleton, which is probably a mix of constraint and unconstraint data, as it is all from the Internet. Additionally, the Kinetics-Skeleton [28][7] contains 18 joints per human body, while 25 joints in the NTU series.

B. The Comparative Analyses

Most of subsequent studies of ST-GCN [ST-GCN] follow its experimental settings. The performance comparison of several state-of-the-art methods is shown in Table II, Table III and Table IV.

Methods typically achieve higher performance on Kinetics-Skeleton [28][7] also produce consistent results on NTU RGB+D [29]. The exception is the rankings of DGNN [35], NAS-GCN [30] and SDGCN [26].

Only a few methods with outstanding performance [27][33][34][31] on NTU RGB+D [29] gave results on
TABLE I. IMPROVEMENT SCHEMES FOR ST-GCN

<table>
<thead>
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<th>Spatial Temporal GCN</th>
<th>Two-Stream GCN</th>
<th>Attention GCN</th>
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<td>1</td>
<td>[30]</td>
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<td>[24]</td>
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<td>[24]</td>
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<td>[33], [34]</td>
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<td>[32]</td>
<td>[27]</td>
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<td>8</td>
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<td></td>
<td></td>
<td>[27]</td>
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<tr>
<td>9</td>
<td>[33], [34]</td>
<td>[35]</td>
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<td>[27]</td>
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</table>

The first column indicates the drawback ID in Section III.

TABLE II. COMPARISONS OF THE TOP-1 AND TOP-5 ACCURACY ON THE KINETICS-SKELETON DATASET

<table>
<thead>
<tr>
<th>Methods</th>
<th>Top-1 (%)</th>
<th>Top-5 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ST-GCN [19]</td>
<td>30.7</td>
<td>52.8</td>
</tr>
<tr>
<td>STGR [25]</td>
<td>33.6</td>
<td>56.1</td>
</tr>
<tr>
<td>AS-GCN [32]</td>
<td>34.8</td>
<td>56.6</td>
</tr>
<tr>
<td>2s-AGCN [24]</td>
<td>36.1</td>
<td>58.7</td>
</tr>
<tr>
<td>DGNM [35]</td>
<td>36.9</td>
<td>59.6</td>
</tr>
<tr>
<td>NAS-GCN [30]</td>
<td>37.1</td>
<td>60.1</td>
</tr>
<tr>
<td>SDGCN [26]</td>
<td>37.4</td>
<td>60.3</td>
</tr>
<tr>
<td>MS-AAGCN [51]</td>
<td>37.8</td>
<td>61.0</td>
</tr>
<tr>
<td>MS-G3D [33]</td>
<td>38.0</td>
<td>60.9</td>
</tr>
<tr>
<td>MST-GCN [34]</td>
<td>38.1</td>
<td>60.8</td>
</tr>
<tr>
<td>STF [31]</td>
<td>39.9</td>
<td>/</td>
</tr>
</tbody>
</table>

TABLE III. COMPARISONS OF THE TOP-1 ACCURACY ON THE NTU RGB+D DATASET

<table>
<thead>
<tr>
<th>Methods</th>
<th>X-View (%)</th>
<th>X-Sub (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ST-GCN [19]</td>
<td>88.3</td>
<td>81.5</td>
</tr>
<tr>
<td>STGR [25]</td>
<td>92.3</td>
<td>86.9</td>
</tr>
<tr>
<td>AS-GCN [32]</td>
<td>94.2</td>
<td>86.8</td>
</tr>
<tr>
<td>AGC-LSTM [44]</td>
<td>95.0</td>
<td>89.2</td>
</tr>
<tr>
<td>2s-AGCN [24]</td>
<td>95.1</td>
<td>88.5</td>
</tr>
<tr>
<td>SDGCN [26]</td>
<td>95.7</td>
<td>89.6</td>
</tr>
<tr>
<td>NAS-GCN [30]</td>
<td>95.7</td>
<td>89.4</td>
</tr>
<tr>
<td>DGNM [35]</td>
<td>96.1</td>
<td>89.9</td>
</tr>
<tr>
<td>MS-AAGCN [51]</td>
<td>96.2</td>
<td>90.0</td>
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<td>MS-G3D [33]</td>
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<td>91.5</td>
</tr>
<tr>
<td>Shift-GCN [27]</td>
<td>96.5</td>
<td>90.7</td>
</tr>
<tr>
<td>MST-GCN [34]</td>
<td>96.6</td>
<td>91.5</td>
</tr>
<tr>
<td>STF [31]</td>
<td>96.9</td>
<td>92.5</td>
</tr>
</tbody>
</table>

TABLE IV. COMPARISONS OF THE TOP-1 ACCURACY ON THE NTU RGB+D 120 DATASET

<table>
<thead>
<tr>
<th>Methods</th>
<th>X-Setup (%)</th>
<th>X-Sub (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shift-GCN [27]</td>
<td>87.6</td>
<td>85.9</td>
</tr>
<tr>
<td>MS-G3D [33]</td>
<td>88.4</td>
<td>86.9</td>
</tr>
<tr>
<td>MST-GCN [34]</td>
<td>88.8</td>
<td>87.5</td>
</tr>
<tr>
<td>STF [31]</td>
<td>89.9</td>
<td>88.9</td>
</tr>
</tbody>
</table>

Different from the high performance on NTU series, the efficiencies on Kinetics-Skeleton [28][7] are generally under-expected, even Top-5 achieved only around 60%. How to improve the efficiency on video-based datasets may have greater significance for end-to-end applications in the real world.

VI. CONCLUSIONS AND FUTURE WORK

This research investigated recent advancements in GCN-based human action recognition using skeletal features. It is observed that the adjacency matrix is best suited for expressing the structure of undirected graphs. One exception is DGNN [35], where the structure of a graph is represented by incidence matrix as a directed acyclic graph.

MST-GCN [34] exposes the weakness with higher-order polynomials of the skeleton adjacency matrix that generates huge number of parameters. A MS-GC module for splitting subsets is a viable way forward. The STF module [31] implements a dynamic adjacency matrix scheme, which is based on a thorough analysis of all previous adjacency matrix designs. It achieved the best performance identified in this study.

For the future direction of human action recognition research, the existing studies have laid a solid foundation. In addition, it is envisaged a rewarding arena in combining skeleton data with other data modalities.

REFERENCES


Zhang, Xikun, Chang Xu, and Dacheng Tao. "Context aware graph convolution for skeleton-based action recognition." In Proceedings of the IEEE/CVF conference...
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Attribute Guided Graph Convolutional Network with Stronger Generalization for Person Re-identification

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Abstract—Person re-identification (ReID) aims to match and track people in a surveillance system with non-overlapping camera views. It is a key challenge for person ReID to learn robust and discriminative person representations. However, in the real world, similar person appearance, different image angles and changing person attributes make the task very difficult. To tackle this problem, we propose the attribute guided graph convolutional networks (AG-GCN) to design a model with stronger generalization. Specifically, an attribute transfer module is introduced into the framework to revise person attributes to obtain diverse person feature expression. In addition, we apply graph convolutional networks to combine attributes with body parts as a more fine-grained representation of the person. The experiment results conducted on Market 1501 and DukeMTMC-ReID datasets show that our method outperforms state-of-the-art attribute-based methods on a single dataset and generalizes better on other datasets.

Index Terms—Person ReID, Graph convolutional network, Semantic segmentation

I. INTRODUCTION

Person ReID task intends to retrieve images of people with the same identity as the query from large datasets. It is very important for finding/tracking missing people or criminals in the video surveillance system. However, in video surveillance scenarios, it is difficult to match the same person across different cameras caused by variables such as low resolution and shooting angles. Researchers have applied some methods previously used for object detection to person ReID, and gradually formed their own research paradigm. Nowadays, the main research directions can be divided into metric learning [1–3] and representation learning [4–6].

In recent studies, researchers have gradually focused on attribute-based person ReID methods. Adding attribute information to do the person ReID task is a way to utilize local features. Similar to how our human eye works, it is able to further focus on local features of people and use them as an important basis for matching when we cannot reason about classification from global features. The input to our task is the image, and the most shallow/easily accessible feature in the image is the color. For example, the person in Fig. 2 can be described as “a young woman with long hair wearing a white top, a yellow skirt, and a backpack on her upper arm”. Since the attributes of age, gender, and clothing color are relatively intuitive descriptions of people, adding these attributes can generate accurate person profiles, so the model is highly interpretable. Combined with the global features, the final inference of the model could be “She is Helan”.

In this work, we classify the attributes of the person into intrinsic and extrinsic attributes. Intrinsic attributes include "age"
and "gender", while extrinsic attributes include "handbag", "upper white", "lower yellow", etc. People are then sorted according to intrinsic attributes. We introduce an attribute transfer module that exchanges extrinsic attributes between two images with the same intrinsic attributes, which can enrich different attribute styles of the same person. In addition, we also tested the effect of attribute transfer between people with different intrinsic attributes. The results indicate that the transfer effect is indeed poor, suggesting that only transferring attributes between people with the same intrinsic attributes can produce high-quality results, as illustrated in Fig. 1. Intrinsic attributes are internal characteristics of people with long change cycles. Therefore, intrinsic attributes can be used as the global description of the person. Extrinsic attributes are external characteristics of the person, with short change cycles and variable change styles. The overall pipeline is divided into two parts. In the first half, we extract the visual features of the image after attribute revising by CNN. In the second half, we use the attribute guided graph convolution networks to extract the local features, and guide the parameter update through multiple loss functions. To obtain more fine-grained local features, a pre-trained semantic segmentation model is used to obtain masks for all body parts of the person, as illustrated in Fig. 2. We utilize graph convolutional networks to build fine-grained attribute features of people. In the graph, the weights of the connecting edges indicate the relevance of the nodes, as illustrated in Fig. 3. Graph convolutional networks are used to obtain attribute-attribute correlation, attribute-part correlation, and part-part correlation simultaneously.

Fig. 2. Segmentation performance on the Market-1501 dataset on a pre-trained model for semantic segmentation. Note that with the pre-trained model, the person in the original input picture is segmented into 7 parts, including 6 body parts and global. The six segmented body parts are represented by different colors and the global is represented as the background.

II. RELATED WORK

A. Attribute-based methods.

Adding attribute features helps the person ReID model to learn more discriminative feature representations, allowing the network to learn fine-grained person features. However, data annotation is time-consuming and laborious, so in [8], the authors proposed a semi-supervised learning framework based on human attribute modeling. In [6], the authors manually annotated the people attribute data, and proposed Attribute Person Recognition (APR) network. APR network uses the manually labeled person attributes data to greatly improve the speed of person ReID. In [5], the authors proposed an Attribute Attention Network (AANet) including three main tasks. AANet unifies identity categories, body local information, and person attributes into a single framework to jointly learn a feature with high discriminative. In [4], the authors proposed a transferable joint attribute and identity deep network (TJ-AIDL), and applied the semantic attribute to the video dataset. TJ-AIDL outperforms many previous methods by transferring the attribute feature space and identity feature space in an untrained dataset.

B. Graph Neural Network

Graph neural network is more and more used in computer vision. [9] proposed CNN-like neural architecture on graphs because of the effectiveness of CNN in feature extraction. In [10], the authors proposed a graph semi-supervised learning algorithm, which can deal with non-European space problems that CNN cannot solve. In [11], the authors introduced the attention mechanism into the graph convolution neural network. By constructing masked self-attention, each node in the graph can assign different weights according to the characteristics of adjacent nodes. In [12], the authors proposed Spatial Temporal Graph Convolutional Networks (ST-GCN) for skeleton-based action recognition. [13] introduced the second-order momentum information and adaptive update topology connection module. After adding multi-stream data input [14], it has exceeded the pure CNN algorithm and is the state of the art in the field of human pose estimation.

III. METHODOLOGY

The overall framework is illustrated in Fig. 4. In the first half, we utilize the attribute transfer module to revise the attributes of the input image, and then use the CNN to extract the visual features. In the second half, we use the pre-trained semantic segmentation model to extract the person body parts mask and obtain the specific location information of each part. Furthermore, the person attributes are composed by word embedding in a lookup table, which is heuristic corresponding to person body parts. The second half utilizes graph convolutional networks for inference to solve the task of attribute identification and identity identification.

A. Attribute transfer module

An attribute transfer module is introduced to transfer attributes from one person to another, with people from the Market 1501 and DukeMTMC-ReID datasets. The attribute transfer module is trained in advance and the parameters are not updated during the training process. The module consists of a structure encoder $E_s$, an attribute encoder $E_a$, and a decoder $D$. Specifically, when training on the Market 1501 dataset, the input of the structure encoder is the image $x_i$ from the Market1501 dataset, the output is $E_s$. The input of the attribute encoder is the image $x_j$ with the same intrinsic attribute in the two datasets, the output is $E_a$. Finally, the decoder gets the attribute transformed image $y$. $E_s$ mainly extracts the spatial information of $x_i$ and $E_a$ mainly extracts the spatial information of $x_j$. The decoder combines the spatial and attribute information to get the transformed image $y$.
the attribute information of \( x_j \). Therefore, the requirement for attribute information of \( x_i \) is not high. In order to better extract spatial features, \( x_i \) is transformed into a gray image \( x_{gi} \) before input to the structure encoder.

The original images in the dataset that do not transfer other image attributes are called "daily wear" and indicate the daily attribute style of the person. For the sake of training convergence and testing accuracy, the "daily wear" should be the main part, while the transformed images are used as a complement to the attribute diversity. By controlling \( E_a \), we can choose which attributes to transfer and change \( f_{attributes} \) after the transfer. For example, if we want to transfer "upwhite" from \( x_i \) to \( x_{gi} \), then the corresponding "Torso" of \( x_i \) should be changed to "upwhite".

\[ G_{i,j} = \begin{cases} 1 & \text{if } A_i \text{ corresponds to } P_j \\ 0 & \text{otherwise} \end{cases} \]

The fourth part represents the correlation between human body parts. Although most people's bodies are physically intact, considering the occlusion problem, the human body may not all appear under the camera. Therefore, based on the previous fine-grained semantic segmentation model, we can get the human body parts mask. Assuming that there is no part \( p \) in the query, the elements corresponding to the part \( p \) row and column are all equal to 0, and the values of other elements are:

\[ \{G_{i,j}\}_{i,j\neq p} = \frac{N_{(p-p)}}{N_p}. \]

Therefore, in the case of camera occlusion, although we cannot use the information of some parts of the human body for comprehensive analysis, we can focus on the information of parts that are not obscured.

\[ \hat{z} \in \mathbb{R}^{NA} \] as the prediction score like [6]. By judging whether the person in the query has this attribute, which are all nodes of the graph. Through word embeddings, person attributes are associated with body parts. For example, the relationship between short-hair and head is closer, and the relationship between Jeans and upper leg is closer.

**B. Graph-based reasoning**

We follow the graph learning formulation proposed in [10], which called graph convolution network. Graph convolution network updates the node representation by transmitting information between nodes, and applies the traditional feature extraction idea of CNN to the graph structure. Our proposed attribute-guided model is denoted by \( G = (V, E) \in \mathbb{R}^{NG \times NE} \), while \( V = \{A_1, A_2, ..., P_1, P_2, ..., P_7\} \). \( A_i \) represents the attribute feature node of the person and \( P_j \) represents the body part. The number of attribute nodes is \( N_a \) and the number of part nodes is \( N_p \). The whole matrix is divided into four parts. The first part represents the correlation between attributes, the second and third parts represent the correlation between attributes and parts, and the fourth part represents the correlation between parts.

Specifically, the first part represents the correlation between attributes. The higher the probability that two attributes appear in the same graph, the stronger the correlation between them. For example, women have a higher correlation with long hair. In the second and third parts, we make heuristic correspondence between person extrinsic attributes and body parts, and intrinsic attributes such as age and gender are taken as global features. For example, 'wearing hat' corresponds to 'Head', 'upwhite' corresponds to 'Torso', and 'carrying bag' corresponds to 'Lower Arm'.

\[ \{G_{i,j}\}_{i,j\neq p} = \frac{N_{(p-p)}}{N_p}. \]

Therefore, in the case of camera occlusion, although we cannot use the information of some parts of the human body for comprehensive analysis, we can focus on the information of parts that are not obscured.

\[ \hat{z} \in \mathbb{R}^{NA} \]

**C. Multi-task loss**

In the network training process, visual features are first extracted through the backbone network, and then global features \( f_{global} \) are obtained through global average pooling(GAP). After this, a BNNNeck structural layer proposed by [15] was introduced. Since ID loss and Triplet loss apply to cosine distance and Euclidean distance respectively in the ReID task, the convergence of ID loss can be effectively facilitated by adding an additional BN layer before the FC layer. Then, the output \( f_{bnn} \) is concated with the graph convolution output feature map \( f_{gcn} \) of the second half as the overall feature of the network model, and passes through a FC layer to re-identify and classify person and calculate the person-id loss function. In addition, the first half calculates the hard triplet loss and center loss, and the second half calculates attribute loss.

**Attribute loss.** We define \( \xi \in \mathbb{R}^{NA} \) as the prediction score like [6]. By judging whether the person in the query has this attribute.
attribute, we can add an attribute label to the person. The ground-truth \( z_k \in \{0, 1\} \) indicates whether the person has k attribute. The total attribute loss can be obtained by calculating the sum of the loss functions, which computed as

\[
L_a = -\frac{1}{N \cdot N_A} \sum_{i=1}^{N} \sum_{k=1}^{N_A} z_k^i \log (\sigma(\hat{z}_k^i)) + (1 - z_k^i) \log (1 - \sigma(\hat{z}_k^i))
\]

(3)

**Person-id loss.** The purpose of designing person-id loss is to reduce the intra-class feature gap in the process of network training. By using person-id loss, the network can converge better. Given a query I, after the first half of network processing, the visual feature \( f_{bnn} \) is obtained, which represents the global feature, and the attribute feature \( f_{gcn} \) is obtained after the second half of the network processing, which represents the local information. The identity prediction scores are computed as follow

\[
s = \text{softmax} \left( FC \left( f_{bnn} \odot f_{gcn} \right) \right)
\]

(4)

where \( \odot \) denotes the concatenate operation. The score vector \( s \) classified to each identity is obtained through FC layer and softmax layer. \( s_i \) is the probability that the person will be classified in category \( i \), and \( t_i \) is the true identity of query \( i \). The id loss is computed as

\[
L_{id} = -\frac{1}{N} \sum_{i=1}^{N} t_i \log s_i.
\]

(5)

**Total loss.** As an end-to-end learning model, the loss function calculated for each task branch needs to be added together as the final loss function. The calculation is as follows:

\[
\mathcal{L} = \alpha_1 \mathcal{L}_{id} + \alpha_2 \mathcal{L}_{hard \ triplet} + \alpha_3 \mathcal{L}_{center} + \alpha_4 \mathcal{L}_a.
\]

(6)

Where \( \alpha_{1-4} \) represent the weight parameters. Hard triplet loss[16] is an improvement of triplet loss. Considering that the image features of the person will be different after the attribute transfer, it is difficult to achieve convergence in network training. We use the hard triple loss instead of the traditional triple loss to mine the difficult cases and improve the training effect of the network. Center loss[17] utilizes the ideas of central clustering and softmax inter-class loss, and applies intra-class constraints to central clustering and inter-class constraints to softmax. Softmax loss can separate different categories of features, and center loss can make similar features cluster together. Around the centroid, more discriminative depth features are learned. Therefore, hard triplet loss and center loss can help the network converge to higher accuracy and improve the matching accuracy of the query.

**IV. Experiments**

**A. Dataset**

To evaluate our model AG-GCN, comparative experiments are conducted on two commonly used person ReID datasets Market-1501[7], DukeMTMC[18]. Both datasets have been
labeled with person attributes. We first tested the effect of training test on the same dataset, and then did a comparative experiment of transfer learning.

An overview of the datasets is shown in Table 1.

**TABLE I**

<table>
<thead>
<tr>
<th>Datasets</th>
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<th>Train ID</th>
<th>Test ID</th>
<th>Attributes</th>
<th>Images</th>
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<tr>
<td>Market-1501</td>
<td>6</td>
<td>751</td>
<td>750</td>
<td>27</td>
<td>32668</td>
</tr>
<tr>
<td>DukeMTMC</td>
<td>8</td>
<td>702</td>
<td>702</td>
<td>22</td>
<td>36411</td>
</tr>
</tbody>
</table>

**B. Implement details**

In this paper, we choose ResNet50[19] as the backbone network and modify it in some places. Specifically, we connect the feature maps of different stages of the backbone network to achieve multi-stage feature fusion. In addition, we changed the final $7 \times 7$ pooling operation to global average pooling (GAP) to reduce the interference of background information and noise to make the spatial location information of the features more robust. Adam is chosen as the optimizer with parameters $\beta_1=0.9$, $\beta_2=0.99$. We set the initial learning rate of the backbone network to 0.001, which was reduced to 1/2 of the original after every 20 epochs, while we also set the learning rate of the GCN to 0.01. The part labels are separated into 7 classes as shown in Fig. 2, while the attribute labels were transformed into word embeddings of $N_A \times 300$. Note that $N_A$ corresponds to the number of attributes in the dataset, which is 30 on the Market1501 dataset[7] and 23 on the DukeMTMC-ReID dataset[18]. The model is trained for 80 epochs with a batch size of 32. All experiments were performed on an NVIDIA Tesla P100 GPU.

**C. Evaluation**

We compare our method with state-of-the-art attribute-based methods and their transfer learning results, using mAP, Rank-1, Rank-5 and Rank-10 as evaluation metrics.

**TABLE II**

<table>
<thead>
<tr>
<th>Datasets</th>
<th>Methods</th>
<th>mAP</th>
<th>R-1</th>
<th>R-5</th>
<th>R-10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market 1501</td>
<td>AANet[5]</td>
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<td>93.9</td>
<td>—</td>
<td>98.6</td>
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<td></td>
<td>APR[6]</td>
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<td>87</td>
<td>95.1</td>
<td>96.4</td>
</tr>
<tr>
<td></td>
<td>APDR[20]</td>
<td>80.1</td>
<td>93.1</td>
<td>97.2</td>
<td>—</td>
</tr>
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<td></td>
<td>AFFNet[21]</td>
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<td>93.7</td>
<td>—</td>
<td>—</td>
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<tr>
<td></td>
<td>BoT[15]</td>
<td>85.9</td>
<td>94.5</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>DG-Net[22]</td>
<td>86.0</td>
<td>94.8</td>
<td>—</td>
<td>—</td>
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<tr>
<td></td>
<td>AG-GCN(ours)</td>
<td>86.7</td>
<td>94.8</td>
<td>97.2</td>
<td>98.8</td>
</tr>
<tr>
<td>DukeMTMC-ReID</td>
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<td>86.4</td>
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<td>—</td>
</tr>
<tr>
<td></td>
<td>APR</td>
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<td>73.9</td>
<td>—</td>
<td>—</td>
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<tr>
<td></td>
<td>APDR</td>
<td>69.7</td>
<td>84.3</td>
<td>92.4</td>
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</tr>
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<td></td>
<td>AFFNet</td>
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<td>84.6</td>
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<td>BoT</td>
<td>76.4</td>
<td>86.4</td>
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<td>—</td>
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<tr>
<td></td>
<td>DG-Net</td>
<td>74.8</td>
<td>86.6</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td></td>
<td>AG-GCN(ours)</td>
<td>78.1</td>
<td>88.4</td>
<td>95.6</td>
<td>96.8</td>
</tr>
</tbody>
</table>

It can be observed from the Table 2 that our method outperforms state-of-the-art attributed-based methods. Specifically, we outperforms APR by 19.8% and 7.8% at mAP and R-1 in the dataset Market 1501, respectively. In the dataset DukeMTMC, we outperforms APDR by 8.4% and 4.1% at mAP and R-1 respectively. Our AG-GCN model combines visual features with human attribute features, rather than simply using only visual features. Therefore, our AG-GCN model is more efficient. Some retrieval results are illustrated in Fig. 5. The result of our proposed model can exceed most mainstream attribute-based methods, demonstrating the effectiveness of exploiting attribute information in graph structures for person ReID task.
TABLE III

<table>
<thead>
<tr>
<th>Methods</th>
<th>Market 1501 → Duke</th>
<th>Duke → Market 1501</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mAP</td>
<td>R-1</td>
</tr>
<tr>
<td>LVPR</td>
<td>29.0</td>
<td>54.0</td>
</tr>
<tr>
<td>TJ-AIDL</td>
<td>23.0</td>
<td>44.3</td>
</tr>
<tr>
<td>CSGLP</td>
<td>27.1</td>
<td>47.8</td>
</tr>
<tr>
<td>DG-Net</td>
<td>36.3</td>
<td>53.2</td>
</tr>
<tr>
<td>AG-GCN</td>
<td>38.8</td>
<td>56.6</td>
</tr>
</tbody>
</table>

To prove that our method is more generalized, we conducted transfer experiments on Market 1501 and DukeMTMC-ReID. We have separately selected LVPR[23], TJ-AIDL[4], CSGLP[24] and DG-Net[22] to compare the cross-domain approach, and the results are shown in Table 3. Specifically, when testing on DukeMTMC ReID with Market 1501 as the source dataset, our AG-GCN outperforms DG-Net by 6.8% in mAP and 3.4% in R-1. And when testing on Market 1501 with DukeMTMC ReID as the source dataset, our AG-GCN outperforms LVPR by 2.1% in mAP and 0.3% in R-1. The transfer results show that our AG-GCN model is much better than other attribute-based methods in generalization.

V. CONCLUSION AND OUTLOOKS

In this paper, we focus on discovering a generalized way to utilize person attributes to model the task of person ReID. We propose an attribute transfer module to simulate real-world changes in people’s dress by modifying person attributes. However, our model also has limitations on some scenarios. As shown in Fig. 5, the error in the retrieval results for the third person may be due to the overlapping of attributes. The difference in the pattern of their tops cannot be distinguished by "upwhite" alone. And the occlusion problem also has an impact on recognition results. In future work, a background transfer module can be introduced to change the background of each input image. This ultimately allows the model to focus more on the person itself.

ACKNOWLEDGMENT

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Distracted Driver Behavior Detection Based-on An Improved YOLOX Framework

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\textit{Abstract}—With the surge of the number of cars, road traffic accidents occur frequently because of drivers’ distracted attention and abnormal behaviors, which causes huge losses to people's lives and property. To alleviate this issue, an improved deep learning model based on YOLOX framework was proposed in this research to detect driving behavior changes in real-time. An attention mechanism – Convolutional Block Attention Module (CBAM) - was introduced in multiple scales of feature layers to form the backbone of YOLOX network. A widely used data science competition platform was adopted for distracted behavior model training. The State Farm Distracted Driver Detection Dataset was used for model validation and performance benchmarking. Experimental results have indicated promising performance gain using the revised model over the original YOLOX framework in terms of mAP and inference time.

\textbf{Keywords}-YOLO; CBAM module; Distracted driving behavior; mAP

\section{I. INTRODUCTION}

With the emergence of automobile, the ways people travel has dramatically changed and the distances no longer become a barrier for people to communicate with each other. Human beings began to step into the industrial age, which also means the traditional handicraft industry was gradually replaced by the machine industry and marks an important turning point in the history of human development.

Since the 21st century, with the rapid growth of economy and people's living standards improvement, cars have become an indispensable means of transportation in every family's daily life. However, with the surge of the number of cars, road traffic accidents occur frequently, causing huge losses to people's lives and property.

According to the NHTSA's (U.S. National Highway Traffic Administration) latest investigation report, driver fatigue and distracted driving behaviors claimed 795 and 3,166 lives in 2017 \cite{1}. In France, the accident report issued by the French National Police Agency shows that distracted driving causes 14.9\% of the injury accidents and 20.6\% of the death accidents \cite{2}. In the Australian state of Victoria, unsafe driving behaviors are responsible for between 9\% and 20\% of road accidents.

Research on traffic accidents in various countries and relevant literature shows that usually about 20\% to 30\% of fatal traffic accidents are caused by drivers' mental distraction like temporary attention loss. This data is still considered a conservative estimate, and driver’s distracted behaviors in actual road traffic accidents may be much higher \cite{3}. Therefore, it is particularly important to detect driver’s distracted state quickly and accurately, which can not only remind and supervise drivers safe driving timely, but also enable the development of automated safety technology to benefit the mass.

According to current studies, the number of collision accidents can be reduced by 10\% to 20\% if driving state monitoring system is used \cite{4}. Therefore, a set of accurate and reliable, non-invasive, high-precision but sensitive driving behavior monitors can undoubtedly improve the safety of drivers and develop traffic safety order to a new height.

Based on this background, an improved deep learning algorithm based on YOLOX \cite{5} framework was proposed in this research to recognize the drivers’ distracted behavior on the road. Ten categories of distracted driving behaviors are extracted from 79,726 images as the experiment dataset which is from Kaggle Challenge, a widely used data science competition platform. The dataset was normalized in this research for generating the ground truth label information that are essential to any YOLO-based network models. Section II reviewed the related work about drivers’ distracted behaviors detection; Section III introduced the driving behaviors detection framework of this improved YOLOX algorithms; Section IV demonstrated; and, Section V concluded the experiment results about the improved YOLOX framework, including parameters, floating-point operations per second (FLOPS), mean average precision (mAP) and average inference time, all of which are satisfied.

\section{II. RELATED WORK}

Driver’s distracted behaviors, such as holding a mobile phone, drinking and talking to passengers, may directly lead to attention distraction and improper maneuvering operation. Fig. 1 illustrates the process of distracted driving behavior recognition. With the improvement of social safety awareness, how to accurately identify drivers’ behavior and timely issuing a warning has become a research hotspot in recent years.

Nobuyuki Kuge et al. \cite{6} proposed a driving intention prediction system based on hidden Markov model in the early 20\textsuperscript{th} century, which could better recognize the driver's intention when they wanted changing the lanes on the road, but the range of applications is relatively narrow.
Zhao et al. [7] proposed a fast drivers’ illegal behaviors recognition algorithm by using neural network based on multi-layer perceptron in 2012, but the facial and hand skin color areas are easily connected, and the recognition rate is relatively low.

TM Pham et al. [8] used Adaboost to detect the target area of the drivers’ face and used Clifford to reduce the false detection results as much as possible in 2019.

Dwivedi K et al. [9] used softmax layer to identify drivers’ distracted state in 2014. Gong et al. [10] proposed a facial behavior prediction technology for fatigue recognition in 2015, by using the projection of drivers’ face feature structure. The improved method reduces the error detection rate compared with the traditional method but has little effect in the light changing conditions.

Fang et al. [11] proposed an improved fusion SSD model in 2019, an end-to-end training method is adopted to simplify the related tasks process, which has good robustness and practicability in distraction recognition.

III. FRAMEWORK AND MODULES

With the development of object detection and recognition, YOLO series [5] always pursue the optimal speed and accuracy trade-off for real-time applications.

YOLOX was proposed by Megvii Technology in 2021. This framework utilized modified CSPNet as the backbone, adopted anchor free mode and integrates other advanced detection technologies, such as decoupled head, strong data augmentation, label assignment, etc. Thus, YOLOX has dramatically raised in detection performance and maintained high speed for real-time reasoning.

Figure 1. The process of distracted driving behavior recognition.

Figure 2. The structure of an improved YOLOX framework

Figure 3. The structure of CBAM module [15]
A. Framework

An improved YOLOX framework was proposed for on-road driver distracted behavior recognition in this research. The principle of the algorithm is described as follows and Fig. 2 illustrates the improved YOLOX framework.

- Data sources: A state farm distracted driver detection dataset was used to simulate the image acquisition process of distracted driving behaviors. Some work has done for the dataset to be normalized to adapt to the YOLOX network structure.
- Attention Module: An attention module named CBAM was added in the original YOLOX network to adjust the influence of different pixels on the detection results, so as to separate out more significant features.
- Outputs: Through the YOLOX head network, the category, position, and confidence value of each prediction box can be obtained by NMS (non-maximum suppression) operation. Finally, each distracted drive behavior can be recognized by the improved network. Confidence and IoU function [12] are defined as follows:

\[ \text{Confidence} = \Pr(\text{behavior}) \cdot \text{IoU}_{\text{proof}} \]  
\[ \text{IoU}_{\text{proof}} = \frac{\text{Detection} \cap \text{GroundTruth}}{\text{Detection} \cup \text{GroundTruth}} \]

\( \Pr(\text{behavior}) \) indicates whether the main driving behavior feature falls in a grid, the value equals to 1 if a grid has the main feature or it equals to 0 if a grid does not. IoU represents the coincidence degree of prediction box and ground truth. Detection is the prediction driving behavior box and Ground Truth is the original labeled information in the dataset.

B. Loss Function

For obtaining the more accurately results, loss function is used to reduce the gap between the predicted results and the ground truth. It is the aim of the loss function to progressively bring the model to convergence during training.

The loss function of YOLO series includes four parts [5,13], The final Loss result is the sum of formula (3) to (6):

- The loss of predicted central coordinates.
  \[ \lambda_{\text{coord}} \sum_{i=0}^{B} \sum_{j=0}^{B} \ell_{xy} = \lambda_{\text{coord}} \sum_{i=0}^{B} \sum_{j=0}^{B} \left[ \left( x_i - \hat{x}_i \right)^2 + \left( y_i - \hat{y}_i \right)^2 \right] \]

- The loss of width and height in predicted bounding box.
  \[ \lambda_{\text{coord}} \sum_{i=0}^{B} \sum_{j=0}^{B} \ell_{wh} = \lambda_{\text{coord}} \sum_{i=0}^{B} \sum_{j=0}^{B} \left[ \left( \sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left( \sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right] \]

- The loss of category.
  \[ \sum_{i=0}^{B} \sum_{j=0}^{B} \ell_{\text{obj}} \sum_{c} \left[ \ell_{\text{cls}} (p_i (c) - \hat{p}_i (c))^2 \right] \]

- The loss of confidence in the predicted bounding box.

\[ \sum_{i=0}^{B} \sum_{j=0}^{B} \ell_{\text{obj}} \sum_{c} \left[ \ell_{\text{cls}} (p_i (c) - \hat{p}_i (c))^2 \right] \]

Thus, the whole loss function is combined with (3), (4), (5), (6) functions.

While focal loss function was used in YOLOX network for eliminating unsatisfied predicted results caused by the unbalanced category of training samples and the samples that is difficult to classify.

\[ FL(p_t) = - \alpha_t (1 - p_t)^\gamma \log(p_t) \]

\( p_t \) represents the probability of a certain category. \( \log(p_t) \) represents the cross entropy of that category. \( \alpha_t \) is a modulating factor.

When \( pt \rightarrow 0 \), the loss value of FL(pt) is higher, otherwise FL(pt) is lower. Therefore, the weights of positive and negative samples, the weights of category that is easy or difficult to classify can be controlled by the focal loss function.

C. Attention Module

In the driving behavior scenes, the pixels in different positions and channels on a detected image may have different effect on feature extraction, an attention mechanism was introduced in this paper, that is, it can be used to adjust the influence of different pixels on the detection results to obtain more significant features. This attention mechanism is added into the backbone of the YOLOX network. It can further integrate three scale extracted feature maps and obtain more prominent driving behavior features.

The principle of an attention mechanism is as follows: the importance weights should be learned from different positions or channels in the feature map, and the learned importance weights are multiplied by the original feature value to output new feature map.

The most widely used attention mechanisms include SENET (squeeze-and-congestion Net) [14] and CBAM (Convolutional Block Attention Module) [15]. SENET is the channel attention mechanism module, and CBAM is the attention mechanism module combining channel and space information.

Considering the complex conditions of distracted driving behavior recognition. CBAM module is introduced in this research. It can obtain more significant features and improve the accuracy of driving behavior recognition. Channel attention module in CBAM keeps the channel dimension unchanged and only compresses the spatial dimension, so the module is sensitive to driving behavior category information. Spatial attention module in CBAM keeps the spatial dimension unchanged and the channel dimension is compressed, so the module is sensitive to driving behavior position information. Fig. 3 shows the structure of CBAM module.

In this improved YOLOX framework, CABM is introduced in three different scales of feature layers of the backbone of the network. Features can be accurate extracted and fused from the above layers through up- sampling and down-sampling. Fig. illustrates the structure of CBAM. Compared with the structure of YOLOX network, the process of feature extraction is as follows:
• Adding cbam1 module before the feature map of 20×20×1024 passing through the 2D convolution process for fusing with larger feature map.
• Adding cbam2 module before the feature map of 40×40×512 up-sampling and fusing with 20×20×1024 feature map.
• Adding cbam3 module before the feature map of 80×80×256 up-sampling and fusing with 40×40×512 feature map.

These feature layers are then sent into the YOLO head network to obtain the final confidence of each prediction box. The NMS algorithm is used to remove the prediction box with large IOU and low confidence, and output the image with prediction box and confidence.

IV. EXPERIMENT

To accurately analyze the accuracy, computational speed, and processing conditions of driver distracted behavior recognition framework without human intervention, the network parameters, Giga Floating-point Operations Per Second (GFLOPS) and recognition accuracy of the improved recognition module were tested and recorded using standard driver distracted detection datasets and common classical PACAL VOC [16] datasets.

A. Data

State Farm Distracted Driver Detection Dataset [17], a dataset of 2D dashboard camera images initially released in Kaggle Challenge, a widely used data science competition platform in 2016.

Kaggle claims approximately 332,000 data scientists on its job boards. It has partnered with organizations such as NASA, Wikipedia, Deloitte and Allstate for its competitions. Kaggle Challenge prepares the data and a description of some issues. Kaggle offers a consulting service which can help the host do this, as well as frame the competition, anonymize the data, and integrate the winning model into their operations.

The above-mentioned dataset was trained for distracted behavior recognition and had 79,726 images, and contained ten driving behavior types ranging from c0 to c9. Fig.4 illustrates different 10 driver behaviors.

However, the dataset only provided raw 2D images and no annotation information. Thus, some work focused on dataset standardization prior to training neural network, i.e., taking 3 types distracted behaviors as an example, that is c0: normal driving, c2: talking on the phone - right, c3: texting - left, and a total of 6877 annotation files containing ground truth information was added in the dataset, all of which were suitable for the YOLOX framework, dividing this dataset into train set, trainval set, and validation set, with an 8:1:1 percentage among subsets.

B. Implementation

The improved driver distracted behavior recognition algorithm is designed using the Pytorch framework. The server operating systems used for method deployment are Ubuntu Linux release (20.04) and Windows 10. A PC with a 3.7-GHZ CPU and an RTX3080 GPU card with 32 GB of video memory was used for the experiments.

C. Model training

The original and improved YOLOX framework were all used for driver distracted behavior recognition in this paper. It consists of 3 types of YOLOX different frameworks and a total of 6 deep learning models. TABLE 1 describes parameters size and GFLOPS, and the mean average precision in different YOLO frameworks. TABLE 2 shows the mAP results of 3 types of behavior in State Farm Distracted Driver Detection Dataset in the improved YOLOX framework, when the training epoch is 100 rounds and using tiny YOLOX models, such as YOLOX_s, YOLOX_nano and YOLOX_tiny.
TABLE I. WEIGHT COEFFICIENT AND MAP COMPARED WITH ORIGINAL YOLO NETWORK

<table>
<thead>
<tr>
<th>Method</th>
<th>Model</th>
<th>Model Params (M)</th>
<th>FLOPS (G)</th>
<th>mAP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original YOLOX</td>
<td>s</td>
<td>8.95</td>
<td>26.68</td>
<td>81.70</td>
</tr>
<tr>
<td></td>
<td>Nano</td>
<td>0.91</td>
<td>1.08</td>
<td>80.08</td>
</tr>
<tr>
<td></td>
<td>Tiny</td>
<td>5.04</td>
<td>6.45</td>
<td>80.98</td>
</tr>
<tr>
<td>Improved YOLOX</td>
<td>s</td>
<td>9.09</td>
<td>26.81</td>
<td>83.60</td>
</tr>
<tr>
<td></td>
<td>Nano</td>
<td>2.25</td>
<td>6.89</td>
<td>81.21</td>
</tr>
<tr>
<td></td>
<td>Tiny</td>
<td>5.06</td>
<td>15.17</td>
<td>83.47</td>
</tr>
</tbody>
</table>

TABLE II. THE AP OF 3 DRIVING BEHAVIORS IN DIFFERENT MODELS OF THE IMPROVED FRAMEWORK

<table>
<thead>
<tr>
<th>Class index</th>
<th>behavior type</th>
<th>AP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>s</td>
</tr>
<tr>
<td>1</td>
<td>normal driving</td>
<td>0.9824</td>
</tr>
<tr>
<td>2</td>
<td>talking on the phone - right</td>
<td>0.9901</td>
</tr>
<tr>
<td>3</td>
<td>texting - left</td>
<td>0.9568</td>
</tr>
</tbody>
</table>

D. Results

1) Time consumption

Inference time consumption relates to the time required for a queued image to be processed by the improved YOLOX network framework to detect distracted driving behavior. It can indicate the computer performance of a network. TABLE 3 shows the average inference time of 3 types distracted behavior detection using different models in the improved YOLOX framework.

TABLE III. AVERAGE INFRINGEMENT TIME BETWEEN DIFFERENT BEHAVIORS AND YOLOX MODELS

<table>
<thead>
<tr>
<th>Class index</th>
<th>behavior type</th>
<th>Average inference time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>s</td>
</tr>
<tr>
<td>1</td>
<td>normal driving</td>
<td>0.2005</td>
</tr>
<tr>
<td>2</td>
<td>talking on the phone - right</td>
<td>0.2124</td>
</tr>
<tr>
<td>3</td>
<td>texting - left</td>
<td>0.2104</td>
</tr>
</tbody>
</table>

2) Visualization

In this section will give a visual expression of the improved YOLOX network. In Fig.5, visualization results have been presented on State Farm Distracted Driver Detection dataset. It is found that each drive behavior can be accurate labeled. It is helpful for driver to regulate their driving behavior and protect them from security threats. Fig.6 illustrates PASCAL VOC visualization results compared with original YOLOX model. Fig. 6(a) was the original detection results and Fig. 6(b) was the improved detection results. It was revealed that there were misjudgments and unrecognized object categories using original YOLOX framework while the improved YOLOX framework had a satisfied detection results.

Figure 5. Driver distracted behavior recognition visualization

V. CONCLUSIONS

In this research, an improved YOLOX framework is devised to handle the issue of drivers’ distracted behavior recognition. The CBAM module is developed into different scales of feature map layers before operational fusion. The design has ensured more significant features to be abstracted for significantly improved accuracy in recognition process. The datasets used for model validation and testing are COCO, PASCAL VOC, and State Farm Distracted Driver Detection Dataset to ensure objective benchmarking.

In the experiments, compared with original YOLOX framework in parameters, namely, the GFLOP and mAP aspects, improved YOLOX has consistent better performance in Tiny model. In addition, compared with the average inference time by using different lightweight module in improved framework to recognize three distracted behaviors, Nano model also recorded faster speed on detection performance.

Future work will focus on the improved YOLO architecture with more controllable, as well as self-adaptive, CBAM mechanism for better handling the model generalization issues.

ACKNOWLEDGMENT

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Particleboard Surface Defect Inspection Based on Data Augmentation and Attention Mechanisms

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Abstract—Inspection accuracy of surface defect is very important for particleboard production. However, the insufficient defect samples seriously restrict the quality of vision and deep learning-based inspection result. The small-scale defects on particleboard surface are also a major challenge to the input of network models. This paper proposes a method based on data augmentation and attention mechanisms to solve these problems. A hardware platform was designed to take surface defect images. The methods of traditional data augmentation and GAN have been applied to increase the amount of defect samples. The Poisson Fusion technique was adopted to generate defect images albeit varied backgrounds to for network training. The SSD network was deployed as the optimization model. The devised optimization schemes replaced the feature extraction network (VGG) with ResNET18 and ResNET50 respectively before fusing with the DCGAN module. During the training stage, a transfer learning-based method was developed to pre-train the optimized network through COCO2017 dataset to improve the training speed and accuracy. The experimental results showed that the scheme of "ResNET50 + Attention" outperformed benchmarked solutions with a peak performance on particleboard surface defect inspection reaching 96.79%.

Keywords—Surface defect; SSD; Data Augmentation; Attention Mechanism

I. BACKGROUND

With the improvement of people's living standard, people's demand for wood products is increasing, which makes its demand exceed the supply of wood. As a result, trees are being cut down and cannot be replaced in time all over the world, which has a great impact on the environment and even leads to global warming[1]. Particleboard is a very common substitute for wood, which can use residues and non-wood plant fibers as production materials, so it becomes more and more important, and the application and the need of it are also increasing[2]. However, there will inevitably be some surface defects in the process of particleboard production, which will affect the application of it and even affect the quality of its products. Therefore, it is very useful to inspect the surface defects of the particleboard quickly and accurately.

II. LITERATURE REVIEW

The traditional inspection method for particleboard surface defects is manual inspection, but due to the low efficiency and accuracy of this method, it can no longer meet the requirements of the industrial production. The continuous increase in labor costs is another important reason why manual inspection is not suitable for industrial production. With the improvement of computer technology and computation power, computer vision-based (visual) inspection technology has developed rapidly.

In the early stage of defect inspection by visual technology, the features of different defects needed to be extracted at first, and then different defects could be identified according to these features. Guo Hui et al. used the gray level co-occurrence matrix and hierarchical clustering method to identify the surface defects of particleboard, which realized the inspection under the conditions of high precision and high resolution accurately[3]. Liu et al. used the random forest algorithm to inspect the surface defects of particleboard, which improved the inspection speed[4]. However, these methods all require people to set key parameters of defect features. As a result, the inspection is greatly affected by human subjective judgement, and the generalization ability of the method is reduced, which make its inspection result less effective in industrial field.

With the development of deep learning technology, it has achieved excellent performance in complex applications, and its use in industrial field has become more and more extensive. Compared with the traditional feature extraction method, deep learning technology does not need to manually set feature parameters, and can use the network model to automatically learn the features of different defects to achieve accurate inspection of defects. The AlexNet[5] network model proposed by Hinton and Alex in 2012 has brought deep learning algorithms into the practical stage in the field of image detection, which effectively solves the problem of network gradient diffusion and overfitting. In 2014, Ross B. Girshick et al. proposed the R-CNN[6], which successfully applied CNN to the detection of object for the first time. In 2015, K. He et al. proposed the SPP-Net[7] network model by improving the R-CNN, which allowed the initial input image size to be unlimited and greatly improved the computing speed. Since the appearance of R-CNN, many of its applications have been reported, albeit the increased complexity of these algorithms. According to the detection process of the network model, it can generally be divided into a two-stage model and a one-stage model.
The more successful two-stage models mainly include: Fast R-CNN[8], Faster R-CNN[9] and Mask R-CNN[10]. Although the detection accuracies of these network models are high, their detection speed are often not satisfactory. Hence, they are difficult to be directly applied to industrial inspection. On contrast, the one-stage detection model, namely a few, YOLO1-6, SSD and RetinaNet had intrinsic advantage on the speed aspect. Wei Liu et al. proposed the SSD algorithm[11], which is a multi-object detection algorithm that can directly predict object categories and bounding boxes, and is very suitable for the application in the field of defect inspection. Joseph Redmon et al proposed the YOLO network model[12], which treats the detection process as a regression task, and further improves the detection speed. Researchers have made several improvements and optimizations to SSD and YOLO to suit different detection accuracies and efficiencies[13-15].

There is still a big challenge in the application of deep learning technology if it is applied in the industrial field, that is, deep learning requires a large number of sample data to train the network model to achieve the ideal result. But in the production process, it is difficult to collect enough defect samples for training. Data augmentation technique can be used to expand the amount of defect samples. The traditional data augmentation method is to increase the amount of sample images by translation, rotation and scaling[16] With the development of neural networks, researchers began to use networks to generate synthetic images to increase the amount of samples. The popular and successful method is the generative adversarial network (GAN)[17]. Guo et al. used GAN to synthesize more than 8 times of training samples and improved the classification accuracy by about 3%[18]. In order to overcome the insufficient data problem, the method of transfer learning is proposed in this research. It uses a large number of datasets to pre-train the network so that the network can learn enough patterns, and then uses a small amount of target sample data to adjust the network to meet the needs of the inspection task. For example, Liu et al. used transfer learning techniques to improve inspection accuracy to 99% with only 30-50 defect samples[19].

III. METHODOLOGY

Through statistical analysis, the common surface defects which can affect the quality of the particleboard mainly include dirty, pit and shave. In order to realize high precision inspection of defects on the surface of particle board, the deep learning method is used. Firstly, the particleboard defect samples need to be taken. Since the frequency of the emergence of surface defects is very low, the amount of samples that can be taken is limited. Hence, the second step is to expand the amount of collected sample images. The data augmentation strategies are traditional data augmentation methods and generative adversarial network(GAN). The traditional method mainly includes cropping, rotating, scaling, and increasing the noise. The defect images generated by the GAN also need to be fused with the images of non-defective surface by the Poisson fusion method to generate the synthetic defect images, which size is suitable for training the network model. The next step is to choose a suitable network model for training. The SSD network model was selected as the basic network model and optimized by updating its feature extraction network and integrating the attention mechanism. To further improve the precision of the network model, the transfer learning method is used to pre-train the network model and adjust it to the target task through the insufficient real sample data. The research methodology is shown in Figure 1.

A. Image Acquisition

Defect image acquisition is the basis work of the particleboard surface defect inspection. By setting the type, position and angle of the light source, the particle board defect characteristics can be displayed more obviously on the image, which can make the defect image clearer. The defect samples are manually labeled according to defect types, and divided into training set and test set, which are respectively used for training and testing of the network model.

B. Data Augmentation

1) Traditional Data Augmentation

The traditional data augmentation method mainly improves the diversity of the sample by cropping, rotating, scaling, and adding the noise. These simple methods can effectively increase the amount of samples, avoid model over-fitting, and improve the performance of the algorithm.

2) Generative Adversarial Network

Generative adversarial network (GAN) is a deep learning model based on a generator network and a discriminator network. GAN establishes an adversarial

![Image Acquisition Diagram]

- **Image Acquisition**
  - Light Source
    - Type
    - Position
    - Angle
  - Camera

- **Data Augmentation**
  - Traditional Method
  - GAN
  - Poisson Fusion
  - Crop
  - Rotate
  - Scale
  - Noise

- **Network Optimization**
  - SSD
  - VGG
  - ResNET
  - Attention Mechanism

- **Network Training**
  - Transfer Learning

Figure 1. Devised hybrid model and operational pipeline
strategic process. The generator generates simulated data based on the original data. In contrast, the discriminator distinguishes real and fake data as correctly as possible [20]. In the process of training, the generator is constantly optimized to make the generated data more realistic, and the discriminator is constantly optimized to make its own

Generative adversarial network (GAN) is a deep learning model based on a generator network and a discriminator network. GAN establishes an adversarial strategic process. The generator generates simulated data based on the original data. In contrast, the discriminator distinguishes real and fake data as correctly as possible [20]. In the process of training, the generator is constantly optimized to make the generated data more realistic, and the discriminator is constantly optimized to make its own judgment more accurate. Finally, the realistic synthetic data can be generated according to the characteristics of the original data[21].

DCGAN model is a successful GAN improvement model in recent years[22]. Therefore, it is chosen to generate the synthesized defect image of particleboard to solve the problem of insufficient samples. The structure of DCGAN model is shown in Figure. 2.

The input of the generator is a 100-dimensional Gaussian noise, and it is transformed into an image which size is $4 \times 4 \times 1024$ through a fully connected layer. Next, the size of the image is increased to $64 \times 64 \times 3$ through 4 convolutional layers, which is considered to be the generated sample. The input of the discriminator are generated sample and real sample, and the output is a probability of determining whether the generated sample is fake or real. Based on the probability, the network of the generator and discriminator will be fine-turned.

3) Poisson Fusions

Since the synthetic image generated by the generative adversarial network is only a single target image, it can be used as an effective training sample only after it is fused with the background image. To make the fused image conform to the characteristics of the real sample, the boundary of the fusion between the target and the background should be smooth. Poisson's fusion method not only makes the fusion boundary smoother, but also optimizes the target image to conform to the global style of the background image[23]. The effect of traditional fusion method and Poisson fusion method is shown in Figure. 3.

The boundary between the target and the background generated by the traditional fusion method is not smooth, but the target in the image generated by Poisson Fusion method can adapt to the background image well.

Figure 3. The effect of traditional fusion method and Poisson Fusion; (a) defect image generated by GAN; (b) background image; (c) fused defect image by traditional method; (d) fused defect image by Poisson Fusion.
Therefore, surface defect images generated by Poisson fusion method can be used as sample data for model training.

C. Optimize SSD Network

1) Improve Feature Extraction Network

The features extracted by VGG which is the feature extraction network lack semantic information with strong anti-interference ability and detail information. The size of particleboard surface defects is always very small. Therefore, the effect of feature extraction using VGG is not ideal. To improve the ability of SSD to inspect small-scale defects on particleboard surface, VGG is replaced with Resnet18 and ResNet50 in this research with deeper network layers and rich semantic information.

Because there will be overfitting phenomenon at the deeper network layers in ResNet50, the dropout layer is added to the network which can deactivate part of the neural network to obtain better fitting and generalization ability. Behind the SSD feature extraction layer, five other feature extraction layers of different sizes are added, which can inspect targets of different sizes respectively, and it is conducive to the inspection of different sizes defects of the particleboard.

2) Fuse Attention Mechanism

The attentional mechanism has been proved to significantly improve the performance of deep convolutional neural networks. In the proposed network, the convolutional neural network has deep layers. In order to improve the performance of the model without increasing its complexity, ECA-NET module is added before the five feature extraction layers behind the backbone, which only adds a few parameters but achieves excellent results. The structure of the proposed network is shown in Figure. 4.

D. Transfer Learning

To further overcome the problem of insufficient samples and improve the accuracy and training speed of the model, transfer learning method is used. The proposed network model is pre-trained on COCO2017 which is a big and public data set, so that the model can learn enough knowledge. And then the particleboard defect data set is used to train the model and optimize the parameters to achieve the defect inspection task.

IV. EXPERIMENT AND ANALYSIS OF RESULTS

A. Experiment Platform

In order to effectively achieve the inspection of the particleboard surface defect, a hardware platform for the experiment was made up. The model of the camera is MER-1520-13U3C which resolution is 4608 × 3288 pixels. The model of the lens is H0514-MP2 which focal length is 5mm. The camera was fixed above the particleboard vertically. Two LED light sources was fixed at an angle about 20°-35°. Through this platform, surface defect image of particleboard can be taken, such as dirty, pit and shave. The hardware platform and defect images are shown in Figure. 5. The computing workstation was configured with 1 GPU (NVIDIA GeForce RTX 3060), 1 CPU (AMD Ryzen 7 5800H), and 16G RAM.

B. Dataset Preparation

The amount of defect images taken through the hardware platform was 915. Since the amount was limited, the traditional data augmentation method and DCGAN were used to expend that. Through the traditional method, the amount of sample was expanded to 2096, which method mainly included cropping, rotation, scaling and adding some noises. Through the method of DAGAN, the amount of defect image is expanded to 3406.

The parameters of DCGAN are shown in table I. In order to comprehensively display the effect of defect images generated in different epochs, 9 images were randomly selected each time for display when the epochs were 0, 100, 500 and 1000 respectively. The Figure. 6 shows the process of generating dirty images. It can be seen that as the epoch increases, the synthetic image of the defect becomes more and more realistic. Finally, the synthetic defect image and background image need to be...
fused by Poisson Fusion method, and the fused image was used to train the network model. The Figure 7 shows the fused defect image.

### TABLE I. THE PARAMETERS OF DCGAN

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Meaning</th>
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<td>0.0002</td>
<td>Learning rate</td>
</tr>
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<td>Bs</td>
<td>128</td>
<td>Training batch</td>
</tr>
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<td>nz</td>
<td>100</td>
<td>The dimension of the input noise</td>
</tr>
<tr>
<td>ngf</td>
<td>64</td>
<td>The size of the generator feature map</td>
</tr>
<tr>
<td>ndf</td>
<td>64</td>
<td>The size of the discriminator feature map</td>
</tr>
</tbody>
</table>

![Figure 6](image)  
**Figure 6.** The process of generating dirty images by DCGAN.

![Figure 7](image)  
**Figure 7.** The fused defect image.

Table II shows the amount of defect images after data augmentation. The image dataset was divided into two folders which were named train, and test with a ratio of 9:1 respectively.

### TABLE II. THE RESULT OF DATA AUGMENTATION

<table>
<thead>
<tr>
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<th>Dirty</th>
<th>Pit</th>
<th>Shave</th>
<th>Total</th>
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<tbody>
<tr>
<td>Original amount of defect samples</td>
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<td>315</td>
<td>299</td>
<td>915</td>
</tr>
<tr>
<td>Amount of defect samples after traditional method</td>
<td>690</td>
<td>711</td>
<td>695</td>
<td>2096</td>
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<tr>
<td>Amount of defect samples after DCGAN</td>
<td>1050</td>
<td>1151</td>
<td>1205</td>
<td>3406</td>
</tr>
</tbody>
</table>

### C. Network Training

In order to find the best network model, according to the optimization method proposed in this paper, four schemes were selected for training respectively which were “ResNET18”, “ResNET18+Attention”, “ResNET50”, “ResNET50+Attention”.

The models selected were pre-trained on COCO2017 dataset and then trained on particleboard surface defects dataset. In the learning process, the batch size was 2, the initial learning rate was 0.0001, and its decay was 0.0001. The Adam optimization algorithm was adopted. It can be found that the networks were all convergent after 30 epochs. The results of loss function curves were exhibited in Figure 8.

D. Evaluation Indicators

The Average Recall rate (AR) and mean Average Precision (mAP) are two common evaluation indicators to check the performance of the network models, which can objectively reflect the inspection accuracy of the model.

E. Analysis of Results

Different network optimization schemes will produce different inspection results. According to different feature extraction networks and whether the attention mechanism is integrated, four optimization schemes were selected and those network models were trained respectively. The results are shown in the table III and Figure 9. It can be seen that the scheme of “ResNET18” has the lowest inspection result which mAP is only 81.63%. But after fusing the attention mechanism, its accuracy increased to 86.45%. The scheme of “ResNET50” has a good inspection result. However, after fusing the attention mechanism, its mAP reaches 96.79%, which is the best inspection result. Figure 10 showed the particleboard inspection results in industrial sites.

![Figure 8](image)  
**Figure 8.** The results of loss function curves of the proposed schemes.

![Figure 9](image)  
**Figure 9.** The results of mAP curves of the proposed schemes.
V. CONCLUSION

To achieve the high accuracy inspection of surface defects on particleboard, this paper carried out a series of investigation on data augmentation and attention mechanisms for improving the network optimization effects. Firstly, the hardware platform of defect acquisition was set up. Secondly, traditional data augmentation methods and DCGAN were integrated and then optimized to increase the amount of particleboard defect samples for more robust training results. Thirdly, a chosen SSD network model was adapted to optimize the entire pipeline through replacing the feature extraction network and fusing innovative attention mechanisms. Through evaluation of the state-of-the-art feature extraction networks, ResNET50 had been identified and implemented in the hybrid model developed in this research. The ECA-NET module, which is one of the assessed attention mechanisms, was also integrated in the operational pipeline of the devised model that significantly improves the accuracy of the inspection outcome. Finally, the transfer learning method was introduced to ensure efficient train process of the proposed model. In the designed experiments, the accuracy of particleboard surface defect inspection reaches 96.79% which is superior than other solutions. Future work will see more tests and evaluation of the devised hybrid model on wider industrial inspection domains, such as PCB board and free-form surfaces, for improving its applicability and robustness.

VI. FUNDING

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REFERENCES


Sensorformer: A Memory-efficient Transformer for Industrial Sensor Fusion

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Abstract—The deep learning model, Transformer, and its variants have achieved state-of-the-art performance in many domains, such as natural language processing, vision recognition, protein structure prediction, as well as industrial multi-sensor data processing tasks. However, the high memory usage and \(O(N^2)\) computational complexity of Transformer can result in the high cost and low efficiency in industrial scenarios, especially in the case of edge computing. To mitigate this problem, we propose a novel auto-decorrelation block based on the Fast Fourier Transform and the self-attention mechanism of Transformer to reduce memory occupation and computational complexity. Instead of removing the related data, this model merges the correlated channels progressively throughout the whole inference process. The proposed method was tested on a public dataset based on condition monitoring of a hydraulic system. Results demonstrated that our proposed method reduced memory usage to around one-fifth of its original size while maintaining similar inference accuracy. The inference time can also be 2 times faster. This allows the transformer to be used for industrial multi-sensor data processing tasks in a more resource-efficient and faster manner.

Index Terms—Deep Learning, Transformer, Fast Fourier Transform, Smart Manufacturing, Sensor Fusion, Process Monitoring

I. INTRODUCTION

Nowadays, smart manufacturing empowered by big data, artificial intelligence, deep learning, and other advanced data-driven technologies has attracted a high level of attention. The main reason behind this is the availability of sensor data and infrastructure for communication and computing, such as industrial internet of things (IIoT), cloud/edge computing, and high-performance graphic/tensor processing unit (GPU/TPU). Therefore, there is a growing interest in mining the information contained in multiple sensor data to aid in the diagnosis [28], process monitoring [1], and remaining useful life [2], which are expected to improve the automation, robustness, and intelligence of the current industrial systems [4].

Deep learning as one of the emerging data-driven technologies is being widely used in industrial sensor data analysis since it has a strong feature extraction ability and a deep understanding of the detailed physical mechanisms is not necessary. These features are very preferable when dealing with complex manufacturing processes where a large amount of data is available. For example, Wilhelm et al. used a convolutional neural network (CNN) with a short connection to estimate the temperature inside a motor in [5] to avoid mathematical modelling. Wang et al. proposed a Long Short Term Memory (LSTM) based method to detect anomalies in industrial big data [6]. In addition to conventional deep learning algorithms, such as CNN, LSTM, Recurrent neural network (RNN), and their variants, Transformer, a self-attention-based architecture, has been in focus recently, as it has shown the state-of-the-art performance in many domains, such as natural language processing [7], vision [9], and protein structure prediction [8]. The Transformer method offers the following advantages over similar techniques:

- Compared with the local pattern-matching process (fixed kernels) of CNN, the self-attention mechanism can adap-
tively discover the large-range dependencies by its attention mechanism, hence, it has stronger modelling capabilities and it may be a more efficient way to extract high-level information [10] [11].

- Transformer has remarkable extensibility, which means significant performance improvements can be observed as the model gets larger, such as Turing Natural Language Generation (Turning-NLG) [12] and Generative Pre-trained Transformer (GPT) [13].
- Some studies have shown that it has the ability to combine different modalities, which is beneficial for making more comprehensive inference [14].

In the field of industrial sensor data processing, researchers have applied many Transformer-based methods for fault diagnosis [15], condition monitoring [16], and sensor fusion tasks [17], where they have achieved remarkable performance improvement. However, since the computational complexity of the transformer is $O(N^2)$, and the memory usage is also the square of the sequence length, computing time and required resources increase with the number of sensors (length of sequence) [18], especially for processing the high sampling rate sensor data. This can result in a significant occupation of resources in industrial applications, which means less efficiency and more cost, especially in the case of edge computing. The commonly used Principal Components Analysis (PCA) and the removal of highly related sensor data can effectively reduce the sequence length of the input, however, they may not be the best choice for a multi-sensor system. In terms of PCA, the principal components could be less representative than the original data, as the components with small variances may represent influential information. As for removing the highly related sensor, for example, in [19], it may contradict the original purpose of designing a multi-sensing system. The purpose of introducing redundant sensors is to increase the robustness of the monitoring system or to detect the same physical quantity at different locations. These data can be highly related to each other. If these sensor data are removed in the pre-processing stage to reduce the length of the input sequence, then this can result in the loss of many advantages of a multi-sensor system.

In this paper, we proposed Sensorformer to mitigate the problems mentioned above. We integrated an auto-decorrelation block based on the Fast Fourier Transform (FFT) with the self-attention block to reduce memory occupation and increase computing speed. Instead of removing the related data, this model automatically merges the related data during the processing of the data. In addition, due to the inherent $O(N \log N)$ computational complexity of FFT, the self-attention-based auto-decorrelation block can also reduce the computational complexity from $O(N^2)$ to $O(N \log N)$, hence the memory occupation and computing time can be reduced significantly.

The remaining of this paper is organised as follows: Section II describes the architecture of the proposed Sensorformer. Section III explains the experiment setup and model configuration, and section IV shows the experiment results. Finally, conclusions are drawn in Section V.

II. SENSORFORMER

A. Overall architecture

Sensorformer is composed of two different blocks, the self-attention block and decorrelation block as shown in Fig.1 where N and M represent the number of blocks, Q, K, and V are Query, Key, and Value respectively similar to Transformer in [7]. The former block is the original transformer self-attention block which is used to establish the unified feature representation of multi-sensor data [7], and the latter block is used to reduce the sequence length before sending the data to the transformer block by merging the correlated channels automatically. Our Sensorformer harnesses the removal of correlated channels as an inner block of the deep learning model, which can progressively merge the correlated channels throughout the whole inference process. Note that the number of merged channels will increase with the number of decorrelation blocks. The feed-forward layer of the decorrelation block is used for non-linear projection and its weights can be updated automatically during the backpropagation process, hence the calculation of the correlation coefficient will not be restricted to linear calculation.

The classifier used in our model is a simple one-layer neural network, and the feed-forward layer is a three-layer neural network with a ReLU activation function.
B. Model input

The input of this model can be described by $X \in \mathbb{R}^{d \times L}$, where $L$ is the time window size of one sample, and $d$ is the sequence length that is affected by the sampling rates of multiple sensors. For example, if we have a 1-second time window sample consisting of 2 sensors with the sampling rates of 10(Hz) and 50(Hz) respectively, $L$ will be 10 and $d$ will be $\frac{10(\text{Hz})}{10} + \frac{50(\text{Hz})}{10} = 6$. $X_i \in \mathbb{R}^{1 \times L}$ denotes the $i$-th element of the input sequence.

C. Decorrelation layer

The decorrelation layer shown in Fig.1 can be illustrated by Fig.2. We propose this mechanism with channel-wise data mergence to improve the efficiency of information utilisation and reduce computation load. The mechanism of this layer will be explained in the following subsections.

1) Pearson correlation coefficient calculation: In this research, Pearson’s correlation coefficient is used to measure the correlation, which can be described by the following equation:

$$\rho_{X,Y} = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y}$$  (1)

To simplify the calculation, based on stochastic process theory, the following equation is used in practice to estimate Pearson’s correlation coefficient [20]:

$$R_{X,Y, \hat{t}} = \lim_{L \to \infty} \frac{1}{L} \sum_{i=1}^{L} X_i Y_{i, \hat{t}}$$  (2)

where

$$X_i = \left( \frac{X_i - \bar{X}}{\sigma_X} \right), Y_i = \sum_{i=1}^{L} X_i - X_i$$  (3)

$\sigma_X$ and $\hat{X}$ are standard deviation and mean value of $X_i$. Note that $Y_i$ is the reference variable which means the correlation between $X_i$ and the sum of the rest of the channels is evaluated here by $R_{X,Y, \hat{t}}$. This operation is to avoid calculating $C_L^2$ times the correlation coefficient to identify the related channels. In this case, only an $L$-times calculation is needed. The following equation is used to describe the correlation between $X_i$ and $Y_i$ at the time delay $\tau$:

$$R_{X,Y, \hat{t}}(\hat{t}) = \lim_{L \to \infty} \frac{1}{L} \sum_{i=1}^{L} X_i Y_i(\hat{t})$$  (4)

Based on Wiener-Khinchin theorem, for computational efficiency, $R_{X,Y, \hat{t}}(\hat{t})$ can be derived by FFT [21]:

$$S_{XY}(f) = F(X_i) F^*(Y_i) = \int_{-\infty}^{\infty} X_i e^{-i2\pi ft} dt \int_{-\infty}^{\infty} Y_i e^{-i2\pi ft} dt$$  (5)

$$R_{XY}(\tau) = F^{-1}(S_{XY}(f)) = \int_{-\infty}^{\infty} S_{XY}(f) e^{i2\pi f \tau} df$$  (6)

where $\tau \in \{1, \cdots, L\}$, $F$ and $F^{-1}$ represent the FFT and its inverse, $F^*$ means $F$’s conjugate matrix. As $R_{XY}(\tau)$ for $\tau \in \{1, \cdots, L\}$ can be obtained at the same time by FFT, the computational complexity is $O(L \log L)$. The entire process mentioned above can be described by the dashed box in Fig.2.

2) Channel mergence with time delay calibration: As shown in Fig.3, this layer is used to align the correlated channels at their maximum similarity based on the correlation coefficient matrix obtained in the last section. Then the correlated channels will be fused into a single channel, hence the sequence length can be reduced in a reasonable manner.
Firstly, the signal is rolled \( \tau_i \) steps to make sure the channels can be fused at their maximum similarity. This is because the time delay between sensor data may vary due to factors such as the location of the sensors or the characteristics of the industrial process. Fusing the sensor data at their maximum similarity can mitigate the impact of this time delay effect on the fused data. \( \tau_i \) is calculated by the following equation:

\[
\tau_i = \arg \max_{i \in \{1, \cdots, d\}} \left( R_{X_i,y_i}(\tau) \right)
\]

Then, the \( k \) most relevant channels are fused into one channel based on the SoftMax scores of their correlation coefficients. The channel mergence layer can be described by the following equations:

\[
\{\tau'_1, \cdots, \tau'_k\} = Topk\{\tau_1, \cdots, \tau_i\}
\]

\[
\hat{R}_{Q,K}(\tau'_1), \cdots, \hat{R}_{Q,K}(\tau'_k) = \text{SoftMax} (1 - R_{Q,K}(\tau'_1), \cdots, 1 - R_{Q,K}(\tau'_k))
\]

\[
\text{ChannelMergence} (Q_k, K_k, V_k) = \sum_{i=1}^{k} \text{Roll}(V_k, \tau'_i) \hat{R}_{Q,K}(\tau'_i)
\]

where \( Topk(*) \) is the operation that takes the largest \( k \) values, and \( \text{Roll}(*) \) is the rolling operation mentioned above. Note that the SoftMax is calculated based on \( (1 - R_{Q,K}(\tau'_k)) \). This is because the channels that are highly correlated with other channels are expected to have smaller weights, thus making channels that are less correlated have large weights. \( R_{Q,K} \) is the correlation coefficient between \( Q \) and \( K \). Note that \( k \) is a hyper-parameter that controls how many channels will be merged at each of the decorrelation blocks. The output of ChannelMergence is a single channel, and this merged channel will be concatenated with the rest of channels. Therefore, the channel number of the decorrelation layer output will be \( d - k + 1 \).

The multi-head operation used in Sensorformer can be described in the following equations:

\[
\text{MultiHead}(Q, K, V) = \text{Concat} (\text{head}_1, \cdots, \text{head}_h)
\]

where \( h \) is the number of heads. Each \( \text{head}_h \) is the operation of the whole decorrelation layer, and the input of each head can be described by \( X_{\text{head}_h} \in \mathbb{R}^{d \times \frac{\text{norm}}{max} \times \text{min}} \).

### D. Decorrelation block

Similar to the self-attention block of Transformer, as shown in Fig.1, the decorrelation layer is connected to a feed-forward layer via a shortcut connection [28] and layer normalisation [29]. The feed-forward layer also has its shortcut connection and layer normalisation.

### III. Experiment Setup and Model Parameters

This experiment compared the inference speed, memory usage, and prediction accuracy of the original Transformer and our proposed Sensorformer on the same dataset (details below). The size of the Transformer and Sensorformer were kept the same to make them comparable. The details of this experiment are explained in this section.

#### A. Experiment dataset

The proposed method was tested on a public industrial multi-sensor dataset: Condition Monitoring of a Hydraulic System, and it was created by Helwig et al. in the experiment described in [22]. This experiment used 17 sensors with different sampling rates to measure different physical quantities at different locations of a hydraulic system as shown in Table I. Based on these sensor data, the system conditions as shown in Table II were expected to be identified. The total number of attributes for one data snapshot was \( \frac{8(sensors) \times 60(s) \times 1(Hz) + 2(sensors) \times 60(s) \times 10(Hz) + 7(sensors) \times 60(s) \times 100(Hz)) = 43680, \) and the time window size was 60 seconds, hence, as described in previous section, the input space can be described by:

\[
\mathcal{X} \in \mathbb{R}^{728 \times 60}
\]

The data were normalised to \( 0 \) to \( 1 \) based on the following equation:

\[
X_{\text{norm}} = \frac{x_i - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}
\]

### B. Experiment environment and Sensorformer parameters

This experiment was conducted on Google Colab environment with NVIDIA Tesla P100 PCIe 16 GB, and Pytorch was used as the deep learning framework. The hyper-parameters of Sensorformer and Transformer are shown in Table III.
<table>
<thead>
<tr>
<th>Hyper-parameters</th>
<th>Sensorformer</th>
<th>Transformer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Batch size</td>
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</tr>
<tr>
<td>Learning rate</td>
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<tr>
<td>Initialisation</td>
<td>Orthogonal</td>
<td>Orthogonal</td>
</tr>
</tbody>
</table>

IV. EXPERIMENT RESULTS AND DISCUSSION

In this experiment, we tested the performance of the Transformer and Sensorformer with 100% GPU occupancy to compare the memory efficiencies. As shown in Table III, both models used the same parameters and they were both set to the same size (12 blocks). For the Transformer, the depth was 12 self-attention blocks. As for the Sensorformer, it was composed of 4 decorrelation blocks and 8 self-attention blocks. The results are shown in Fig. 4, the inference time and memory usage represent the average inference time and average memory usage of a single sample with the 100% GPU memory usage. Based on the results, it can be found that with maximum GPU occupation, our proposed method takes only 50% of the inference time of the Transformer. In terms of memory usage, Transformer uses 4.6 times more GPU memory than Sensorformer. When deploying deep learning models for industrial multi-sensor data processing, lower memory usage and less inference time mean more data can be processed with the same computational resources. Our proposed method is therefore more efficient and less costly.

As described in [7], in the self-attention mechanism, the similarity calculation is based on the multiplication of two matrices of $K(n,d)$ and $Q(d,n)$, where $n$ is the length of the input sequence and $d$ is the embedding dimension. This results in its computational complexity being $O(n^2d)$. In comparison, the similarity calculation of our proposed decorrelation layer is based on the Pearson correlation coefficient which can be converted to FFT-based calculation, hence the $O(n\log n)$ computational complexity is achieved. In addition, our proposed decorrelation block also reduces the input sequence length progressively. Therefore, compared to Transformer, our proposed model has more advantages in terms of resource occupancy.

The result of the accuracy of our proposed method can be found in Table IV. The accuracy was evaluated by the following equation:

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

(14)

Based on the results, Sensorformer achieved the top four accuracies. Compared with the 12-block Transformer, the accuracy of Sensorformer only dropped by 0.3%, but the memory efficiency and inference speed improved significantly.

V. CONCLUSION

The deep learning model, Transformer, has achieved state-of-the-art performance in many domains, including the industrial sensor data processing domain. However, due to the high memory usage and $O(N^2)$ computational complexity, it can be resource-consuming, especially for processing industrial multi-sensor data with high sampling rates. In this paper, we proposed Sensorformer with a novel decorrelation block based on Fast Fourier Transform and the self-attention architecture to reduce memory usage and inference time. This method does not require the removal of highly relevant sensors during the data pre-processing phase, hence the robustness and comprehensiveness introduced by redundant sensors can be kept. The experiment results show that compared with the original Transformer architecture, Sensorformer takes only half of the inference time, and uses one-fifth of the GPU memory of the Transformer with remarkable accuracy.

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REFERENCES


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<td>Berghout et al. [23] (2021)</td>
<td>Auto-NAH</td>
<td>100%</td>
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<td>100%</td>
<td>96.4%</td>
<td>99.1%</td>
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<td>Wu et al. [24] (2020)</td>
<td>EGMSVMs</td>
<td>100%</td>
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<td>100%</td>
<td>76.5%</td>
<td>94.1%</td>
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<tr>
<td>Gupta et al. [25] (2021)</td>
<td>SECM</td>
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<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>92.3%</td>
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<td>Lei et al. [26] (2019)</td>
<td>PCA+XGBoost</td>
<td>N/A</td>
<td>96.58%</td>
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<td>N/A</td>
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<tr>
<td>Huang et al. [19] (2021)</td>
<td>Deep CNN</td>
<td>100%</td>
<td>100%</td>
<td>99.0%</td>
<td>99.4%</td>
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<tr>
<td>Prakash et al. [27] (2020)</td>
<td>ANN+XGBoost</td>
<td>99.54%</td>
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</tbody>
</table>

Our results
- Sensorformer: 99.57% 100% 95.52% 98.57% 98.2%
- Transformer: 99.57% 99.79% 97.76% 96.78% 98.5%

Data-driven Process Parameter Optimisation for Laser Wire Metal Additive Manufacturing

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Abstract – Laser Wire Additive manufacturing (LWAM) requires a clear understanding of process parameters and their effects on the geometry and wider material properties of the parts produced to support the production of consistent, repeatable quality parts. Furthermore, its ability to capitalise on using novel alloys depends on efficient characterisation of optimum process parameters. In this work, a method for identifying the range of usable parameters is presented, which produces sufficient data to train Cascade Forward Neural Networks, which are capable of predicting process windows and basic LWAM track geometries for 316L stainless steel. The performance of these networks provides the foundation for further work to identify optimum process parameters and, through transfer learning, may reduce the experimental requirements for the process development of other alloys.

Keywords—Additive manufacturing; Laser Wire Metal Additive Manufacturing; Directed energy deposition; Machine Learning

I. BACKGROUND

Laser Wire Metal Additive Manufacturing (LWAM or LWMAM) is a subset of the group of metal additive manufacturing technologies known as Direct Energy Deposition (DED) [1]. All of which use an energy source to create a melt pool, delivering metal powder or wire feedstock into it to create a metal bead. These beads or ‘tracks’ are built up in layers to create cladding on existing metal parts or to form new, fully dense parts which are net shape or near net shape. Fig. 1 shows a simple schematic of the LWAM process where wire of diameter, \( d \) is fed at speed \( u \), into a laser beam of diameter \( D \) and power, \( P \), moving at speed, \( v \) to create a track of height, \( h \), and width, \( w \).

LWAM is a growing technology area, particularly given the scale and complexity of the parts that are possible, whilst being cleaner and safer than powder-based equivalents. LWAM is also more energy efficient than other wire based DED processes which use other energy sources (for example wire arc or plasma). LWAM can also manufacture parts out of alloys that are not usable in conventional manufacturing processes due to the higher temperatures achieved in the melt pool. However, significant challenges remain for the technology, particularly that of consistency of the quality of repeat parts and between machines, and the reliance on trial and error to refine the process window for each individual part [2-4]. These challenges are broadly a result of the LWAM process being sensitive to variables such as laser configuration, shield gas type and flow, material type, geometry of the part and the thermal field established during the manufacturing process.

Key to addressing these challenges is developing robust methods for structured parameter optimisation, planning and control to ensure the repeatable fabrication of defect-free parts with desirable microstructures and mechanical behaviour. The methods must be themselves repeatable and transferable between alloys and processes, capitalising on the data gathered to reduce the time needed to deliver this and to support qualification of the part and process.

AM Process optimisation is a systematic, numerical characterisation of the process and the subsequent identification of the optimum machine configuration and process parameters to achieve particular targets. Optimal process parameters throughout the printing process are fundamental to a high-quality part and the effects of varying these parameters can be most easily seen in the deposition of simple tracks. Multiple parameters and the resulting geometric and physical properties must be considered to fully optimise a process. To address the complex interactions between parameters and properties Machine Learning (ML) tools are increasingly being used in metal AM research[3].

ML is valuable in AM because of its ability to process non-linear problems, it can cope well with outlying data, it is computationally fast, once trained, and has the ability to understand complex problems without the need for accurate calibration of input parameters[3, 5, 6]. Shallow Artificial Neural Networks (ANNs), such as Cascade Forward Neural Networks, are particularly suited to the
non-linear relationships between process parameters and resulting properties. A multi-layer network can learn any finite input-output relationship arbitrarily well, given enough hidden neurons [7].

A significant limitation of ML within the AM field is the relatively small datasets available to train ML models. There are a number of mitigations to this, such as combining experimental data with data from numerical modelling tools [6], using models to generate training data, transfer learning [8] and data augmentation [9]. Despite this, relatively simple shallow ANNs have shown reliable predictions for the distortion of simple parts [5], material properties [10] and thermal modelling [6].

This paper intends to build upon the current understanding and use ML techniques to develop a framework for optimising process parameters for creating single track geometries using LWAM technology. The approach focusses on specific outcome targets for the track geometry so as to build a foundation for improving process optimisation and control in more complex multi-layer builds.

II. EXPERIMENTAL METHODS

The experiments were conducted using a Meltio M450 laser metal wire printer, which uses six laser diodes with a wavelength of 976nm, fed via fibre optics to collimators mounted coaxially around the deposition head. The desired laser power is spread equally between the lasers, giving the system a maximum power of 1200W, Fig. 2 shows the side profile of the print head configuration.

The deposition head remains fixed and the print bed, with substrate attached, moves in the x, y and z plane below. Argon shielding gas is fed locally to the melt pool from the deposition head at a rate of 5.5 litres per minute. The system was configured to use 1 mm diameter 316L stainless steel wire, building onto 15 mm thick 316L stainless steel substrates mounted to the print bed, which is cooled to 13°C. 50mm long tracks were printed 5mm apart, deposited in a random order across the plate, with a three-minute pause between depositions to minimise the effects of substrate heating on the resulting track geometries. This ensured substrate temperature was below 40°C, thereby enabling a fair comparison throughout the trial.

Optimisation studies involved analysing the effect of changes in the laser power $P$, the laser head speed, $v$, and the wire extrusion rate, $u$, on the resultant track geometry of single-track builds. The investigation comprised two steps, the first a broad assessment of the ability to produce tracks of an acceptable geometry (as determined by visual inspection – acceptable being defined as a track that could be selected for using in a part build with a consistent visually smooth top and profile and clean, straight edges securely bonded to the substrate), the second a more refined appraisal of the influence of process parameters on the track geometry for “Good” tracks.

For the broad assessment, the power was varied from 550 to 950W in increments of 100W, the laser speed from 5 mm/s to 35 mm/s and the wire extrusion rates from 5 mm/s to 55 mm/s. In order to avoid an excessive number of failed prints, on the basis of recommendation of [11], the Wire Speed Factor (WSF - the ratio of the wire to laser speed) was limited to values greater than two. In total, 246 tracks were printed in this first section of the investigation, with approximately 5% of the tracks repeated five times.

From the first set of experiments, the upper and lower bounds for head and extrusion speed were determined for each power level. From this, a Multi-Level Factorial Design of Experiment (DOE) method was used to design the second set of experiments using Minitab statistical software. General full factorial designs were created for the same powers as the previous experiment and within the limits of speeds identified, the design used two factors, laser and extrusion speed for each power, with three or four levels depending on the range of parameters evaluated, 151 tracks were produced. Of these tracks, 37 were deemed good and were reprinted on 3mm thick 316L plates overlaying the 15mm substrate. This was performed not just to ensure repeatability, but in order to permit the tracks to be placed on the bed of an Olympus LEXT OLS5100 Laser Microscope so that the geometry of the tracks could be measured.

Measurements with the laser microscope were taken at five places across the length of each track, 10mm at each end of each track was omitted to avoid skewing the measurements by the effects of the ‘laser switch on’ and ‘laser switch off’ process of the machine. Track height and width was measured and the standard deviation of these calculated to indicate consistency. Fig. 3 shows the typical track height and width geometry measured by the microscope. Measurements were filtered using a traveling average filter to remove noise from the measurement process.

Measurement data for the geometry of the track were used, along with input process data, to train ANN models. MATLAB r2020a was used to create the models in the

![Figure 2 - Schematic of the Meltio print configuration](image1)

![Figure 3 - Typical geometries for the tracks as measured by the laser microscope](image2)
study and Cascade Forward Neural Networks were selected after a comparison of the performance of a number of different neural network architectures. The networks were repeatedly trained in loops of 200 cycles with different configurations of layers and node numbers to find the highest R ratio and the lowest Mean Square Error (MSE). It was found that two hidden layers were most effective, with 20 nodes in the first and 14 in the second. Fig. 4 shows the configuration of the network. The default transfer functions for the hidden layers were used, Hyperbolic Tangent Sigmoid for the first and Linear for the second. The training function used was Levenberg–Marquardt and the performance function was MSE. 70% of the data were randomly selected to train the networks, 15% were used for verification, and 15% for testing.

Two sets of Cascade Forward Neural Networks were trained, the first to predict whether the track would be successful, based on the track quality assessment, the second to predict track geometry. Both networks used the input parameters of power, head speed, extrusion rate and WSF. The first network had the track quality as the response, which was represented as a value between 0 and 1, which was interpreted as a confidence level, where values above 0.8 were considered ‘Good’. The second used the measured track geometry information, which included track width, height standard deviation of width and height along its length (to indicate consistency and ‘waviness’ of the track) and the height to width ratio.

### III. RESULTS AND ANALYSIS

An image of a plate with deposited tracks is shown in Fig. 5. Across all of the experiments, a small proportion of the tracks (4%) were classified differently on their repeat going from ‘Good’ to fail or vice versa, resulting in some parameter combinations appearing ambiguous as to whether they could produce successful tracks. There were however clear windows where combinations of parameters were identified that produced consistently good quality tracks. These process windows are plotted in Fig. 6, for powers of 550W, 750W and 950W.

Measurement data for the 37 “good” tracks, used in the second ANN, are shown in Table 1. Broad trends in these data can be observed. At a given power and extrusion rate, as the laser head speed increases, the width and height of the track both tend to decrease. Similarly, for a fixed laser head speed, as the extrusion rate increases, so do both the track height and width. These relationships are expected from the conservation of material deposited. When the head speed and extrusion rate are fixed and the power increased, the track height decreases and the width tends to increase. For all these cases the effect on the track height is much clearer than on the width. All these trends agree with observations in the literature [12, 13].

Image a. in Fig. 7 shows a successful track within the process window, for a laser power of 950W. Outside of the process window, different types of defective tracks can be identified. As the head speed increases, for the same extrusion rate, (image b) the track cross sectional area must decrease, and reduced substrate melting prevents

### TABLE I. PROCESS AND GEOMETRY DATA FOR “GOOD” TRACKS

<table>
<thead>
<tr>
<th>Power (W)</th>
<th>Laser Head Speed (mm/s)</th>
<th>Extrusion Rate (mm/s)</th>
<th>WSF</th>
<th>Width (mm)</th>
<th>SD of Width (mm)</th>
<th>Height (mm)</th>
<th>SD of Height (mm)</th>
<th>H-W Ratio</th>
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<tbody>
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<td>850</td>
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</table>

Figure 4 - Schematic of the configuration of the ANN

Figure 5 - Examples of deposited tracks

![Figure 4 - Schematic of the configuration of the ANN](image_url)

![Figure 5 - Examples of deposited tracks](image_url)
good bonding. Conversely as the head speed slows, (image c) the track cross section increases and unstable wavy tracks are formed from the excessive material in the melt pool. At a given laser head speed, when the extrusion rate is too slow, (image d) the energy input per unit volume of material is too high and the wire melts before it reaches the substrate, creating intermittent balls of melted material. When the extrusion rate is too high (image e) there is insufficient energy to melt the high throughput of material.

Predictions for geometry and track success were made using the test data and the two Cascade Forward Neural Networks designed for geometry and quality. To address the relatively small number of training data, particularly for track geometry, data augmentation was used to improve the network training, whereby the data was used twice by appending it in reverse order to the training data set. This resulted in 74 response variables for track geometry training, validation and testing. All tracks printed throughout the experimental process were evaluated as ‘Good’ or ‘Failed’, resulting in 511 responses, with augmentation this provided 1022 response variables for track quality.

Track quality predictions resulted in track success being accurately predicted in 98% of cases. Albeit random, most of the test data was likely within the known region of working parameters, given the initial stage of characterisation. It can be seen from Fig. 8 that the ML predicted process window is wider than identified using the experimental data. This is to be expected given the wider inferences that the ML model will make using the whole training dataset. For clarity, in this figure, known failed tracks are also marked, to show that the predictions do not extend to spaces where build failures are known.

All of the ML predicted windows encompass some tracks which were measured experimentally as failed, in all cases these points had tracks which were repeated and categorised as ‘Good’. These regions were drawn outside of the boundary for good parameters in the above analysis. It demonstrates the network’s ability to accommodate outlying data points and the challenge of producing repeatable results in LWAM at the boundaries of the process window. Further experimental work is required to confirm this wider window. The size and accuracy of the windows is sufficiently close to support the successful predictive capability of this approach.

Fig. 9 show the measured height, width and their standard deviations for the test dataset and their correlation with the ANN’s predicted values. Fig. 9 shows the points are scattered closely to the target line which represents a perfect correlation, the fit line and the R2 value for this reflects the closeness of the correlation, one indicating a perfect correlation. The results show that the models have a high accuracy for prediction of height and
the standard deviation of height owing to stronger experimentally observed effects on track height. The width measurements have lower accuracy, which supports the observation from the track geometry analysis, that there was not a strong link between track width and the process parameters. The strength of the models for prediction is sufficient to support parameter planning and further refinement of process parameter for single track printing, and particularly to support identifying optimum aspect ratios for defect free track overlap [12].

IV. CONCLUSION AND RECOMMENDATIONS

A method that can identify the usable range of process parameters in the form of a process window has been developed. This process produces sufficient data to train ML models in the form of two shallow Cascade Forward Neural Networks, which can effectively identify process windows and to predict basic track geometries, which have sufficient accuracy to support a subsequent parameter optimisation process.

This work has also demonstrated that track geometries produced using LWAM conform with other DED research in terms of the basic relationships between track height and width and the laser head speed and extrusion rate.

This study will be further extended to investigate whether the models and data produced can be used to support the prediction of process windows for other alloys and as a result reduce the volume and cost of experimental work required to create a similar process window.

REFERENCES

INAS: Incremental Neural Architecture Search

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Abstract—Sharing the weights of Super-Net is a common method to improve the efficiency of model performance evaluation in Neural architecture search (NAS). Existing weight-sharing NAS typically uses a fixed Super-Net to be search space, but the Super-Net design relies on the valuable experience of experts for different tasks. When the training dataset or metric is changed, the expert has to design again to obtain optimized architecture. Therefore, we argue that dynamic Super-Net is beneficial to discover promising architecture with less manual intervention during the search stage. Furthermore, we observed that most evolved NAS algorithms ignore the potential connection between the input node and neural operator. This paper describes an incremental neural architecture search (INAS) method that searches for an outstanding neural network architecture by dynamically increasing Super-Net size. And we proposed an improved Heredity Algorithm (HA) as a search strategy, in which overwriting operator is used to process input node and neural operator coding. The overwriting operator can further preserve the outstanding individual genes to offspring and accelerate search convergence. Finally, we performed the experiment on CIFAR10. The search model from our INAS method achieves the highest accuracy 97.97%, beyond the state-of-the-art methods. At the same time, we retrained the same architecture on CIFAR100 and obtained 86.17% accuracy on the test set, which proves that the architecture obtained by the algorithm has good generalization ability.

Keywords—Neural architecture search, Heredity algorithm, Neural network

I. INTRODUCTION

The success of deep learning (DL) owes much to the discovery of a novel architecture [1, 2] amongst other factors. DL architectures are now becoming more and more complex, and the increasing capacity of a DL network are resulting in an exponential growth of candidate architectures to search for, which are difficult for human experts to handle [2]. To address this challenge, a method of automatically designing neural architectures called neural architectures search (NAS) has been proposed. NAS has helped image classification [3-6], object detection [7, 8] semantic segmentation [9], and data segmentation [10].

As shown in Figure 1, when design an NAS algorithm, one needs to address three issues: search space, search strategy, and performance evaluation. The search strategy samples a candidate architecture from the search space first. Then, performance evaluation is undertaken to estimate candidate architecture’s performance on unseen data and guide the search a posteriori. The search space defines what candidate architectures are represented and, if encoding is used, whether the space is purely numerical or mixed numerical-logical. The search strategy dictates the efficiency of optimization and is hence the most important step.

Figure 1. A typical a-posteriori NAS process.

Seminal work on NAS started by restricting the search space to a parental network and then pruning it to an efficient offspring network using an evolutionary search strategy[11].Its NAS coding represented the entire network in one long string and trained candidate network architectures from random initialized weights to improve the architecture performance. Zoph and Le removed the limitation of parent network and searched a whole architecture with reinforcement learning(RL) [12]. Search takes a lot of computing resources due to assessing the candidates’ performance [13]. In order to make a effective use of the weights of trained architecture within
a parental network, ENAS [14] was recently proposed for a large Super-Net, where all candidate architectures are encoded in a directed acyclic subgraph of the Super-Net. This allows newly sampled architectures to be evaluated on a validation set by sharing the weights of the Super-Net without the need for additional training, thereby speeding up the performance evaluation in NAS. Still, this approach requires the design of a fixed Super-Net architecture as a search space for the specific task. Once the structure of the parental Super-Net is determined, the depth of candidate networks is also determined. The search changes the layer operations for a candidate network and the connection between the layers. Hence, the fixed Super-Net must be carefully designed to keep the balance between high accuracy and efficiency. Unfortunately, when the training dataset or metric of NAS is changed, the NAS needs to be redesigned by experts, as there is no perfect guideline for the search space.

Since a subsequent neural architecture is often related to a previously trained architecture, a similar candidate module could thus be obtained more efficiently by growing the network. Forming such a search space was researched into, with a successful application to time series prediction [13]. This paper therefore attempts to combine the advantages of the space growth and the ENAS to develop an Incremental Neural Architecture Search (INAS) method. The INAS is hence expected dynamically to change the size of the Super-Net and break through the performance limits of fixed Super-Net structures to achieve excellent performance. The proposed method aims to dynamically increase the search space and to reduce the influence of the initial Super-Net on the optimal model, thereby reducing the cost of an expert’s design. As a neural operator type is closely related to its input, we bind the input coding and operator coding as a gene group to maintain their potential connection. Further, we propose an improved Heredity Algorithm (HA) [15] for the search strategy, as an HA uses an overwriting operator instead of an evolutionary crossover operator to preserve the genes better for architectural design.

The rest of this paper is organized as follows. Section 2 reviews NAS-related work. Section 3 presents the proposed INAS framework and algorithm. Section 4 conducts experiments and analysis test results. Conclusions are drawn with discussions in Section 5.

II. RELATED WORK

NAS has become an emerging research field since Zoph and Le demonstrated that reinforcement learning (RL) can discover good architectures in CIFAR-10 and Penn Treebank benchmark tests [12]. Baker et al. regarded a neural layer selection process as a Markov decision process and trained an agent through combining Q-learning and c-greedy strategy in RL to obtain an optimal neural architecture and its hyper-parameters [3]. These methods, however, require sampling the structure of a complete neural network (NN) and then spending a lot of time training and evaluating it. When a deep neural network is involved, the search space consists of complex connections with layers. The resultant operations will become high dimensional and hard to optimize with limited resources.

To reduce the overhead and complexity of NAS, the pruning [11] and growing [13] search spaces can be combined. For example, a cell-based search space was considered [14, 16-19], which only needs to search a small cell structure and stack repeatedly to form a new network architecture rather than explore the whole architecture. These cells are easier to reproduce and optimize. For example, a typical cell-based search space called a NASNet [16] is proposed to accelerate the search process. In the NASNet, a neural architecture consists of two repeated motifs termed a Normal Cell and a Reduction Cell. A Normal Cell mainly comprises a units operator used to extract advanced features and return a feature map of unchanged dimension. A Reduction Cell mainly produces a feature map whose height and width are reduced by a factor of two. In general, a Normal Cell is formed with convolution or pooling with a stride of 1, and the size of the output feature map remains unchanged. The stride of Reduction Cell usually is 2, which means that the size of the output feature map will be halved. A typical example based on two-type cells in NASNet is shown in Figure 2, where a Reduction Cell is inserted after stacking N Normal Cells. To make full use of trained candidate architecture weights, a weight-sharing strategy from ENAS [14] is applied to the evaluation process. It regards the search space as a directed acyclic graph, and a candidate architecture is a subgraph of a well-designed complex Super-Net. Candidate architecture can inherit neural weights from Super-Net and evaluate performance without any training resources. With a weight-sharing strategy, ENAS can evaluate a large number of candidate architectures by training a Super-Net only, breaking the limitation that traditional NAS needs to train each sampled architecture to gain evaluation scores continuously.

The effect of the search space and the search strategy is crucial for the final performance of NAS [20]. In addition to using RL as a search strategy [14, 15, 21, 22], another common approach is using an evolutionary algorithm (EA) such as the Genetic Algorithm (GA) [11, 13, 23]. In forming an image classifier, for example, Real et al. used a single-layer model as the starting point with a GA generating a limited set of basic operations [4]. Similarly, a genetic convolution NN (CNN) was represented as a string with fixed-length binary codes for a GA to reproduce, mutate and select the best candidate [5]. Search for CNN architecture with variable-length particle swarm optimization (PSO) was also proposed, using a chain structure [24]. This was extended to a MOPSO/D-Net using multi-objective PSO to balance the performance and complexity of the selected architecture [2].

Like most weight-sharing NAS methods (i.e., [7, 14, 25, 26]), we use an ENAS search space as a base search space. Figure 3 shows a sampled architecture with three
intermediate nodes, where \( C_k \) represents the output of \( k \)-th cells. Specially, when \( k < 0 \), \( C_k \) is the input \( X \). \( N_i \) is index of intermediate node. The edge represents the flow of data and candidate operator, and all candidate operators are shown in TABLE I.

![Diagram](image)

Figure 3. A sampled architecture and vector coding.

We use a decimal string whose length is \( 4N \) (each intermediate node has two input ID and corresponding neural network operator) to encode candidate architecture. \( N \) is the total number of intermediate nodes, and only \( C_{k-2}, C_{k-1}, N_i (i < k) \) are inputs of \( N_k \).

<table>
<thead>
<tr>
<th>ID</th>
<th>Type of network layer</th>
</tr>
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<td>0</td>
<td>3 \times 5 max pooling</td>
</tr>
<tr>
<td>1</td>
<td>3 \times 3 avg. pool</td>
</tr>
<tr>
<td>2</td>
<td>skip_connect</td>
</tr>
<tr>
<td>3</td>
<td>3 \times 3 convolution</td>
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<tr>
<td>4</td>
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<tr>
<td>5</td>
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<td>6</td>
<td>5 \times 5 dilated convolution</td>
</tr>
<tr>
<td>7</td>
<td>zeros</td>
</tr>
</tbody>
</table>

III. PROPOSED METHOD

A. Incremental Search Space Strategy

In the initial phase, we search for locally optimal architectures within a limited area. When the searched round reaches the preset value, utilize the current optimal architectures as basics to extend vector coding, so that we can explore more complex and excellent neural network architecture. Expanding the existing architectures can give the search strategy a better starting point. At the same time, it can fully use the model features obtained from a small search space and improve search efficiency and accuracy.

In this paper, all candidate models are substructures of the Super-Net. Candidate architecture can quickly obtain the evaluation performance through the weight sharing strategy[56]. As the search space incrementally expands, the same expansion occurs in the corresponding Super-Net. In the extended Super-Net, the wights of the original node have been fully trained, but the expended node weight is random initialization. Therefore, the search space expansion strategy needs complete coding expansion and Super-Net training to ensure that the candidate model can quickly evaluate performance.

This paper expands the search space by adding new nodes to the cell structure. Firstly, randomly select two nodes as input of new node from the existing node sets. Then random sample two network operations from the candidate operating space and act on the data tensors of the input nodes respectively. Finally, connect the new node data to the final output node. Corresponding vector coding must add the new node’s connection information (input node ID and sampled operation type ID).

Figure 4 shows the cell structure and vector coding changes when the number of intermediate nodes in the cell expands from 3 to 4. The new node information generated after the expansion is marked in red. As seen from the figure, every new node increases the vector coding length of the cell by 4 bits. In Figure 4, \( N_1 \) and \( N_2 \) are selected from the existing nodes as the input nodes of \( N_3 \) by uniform random. Then select the network operator for each input separately, and use \( 3 \times 3 \) dilated convolution (corresponding type id is 5) for the data tensor from \( N_2 \). A \( 5 \times 5 \) Depthwise separable convolution (corresponding id is 4) operation is performed on the data tensor from \( N_3 \). After expansion, the number of intermediate nodes changed from 3 to 4, and the vector coding length varied from 12 to 16.

![Diagram](image)

Figure 4. Expanded cell structure and vector coding.

When the search space expands, in addition to the increased vector coding, a more important issue is that how the expanded Super-Net inherits the weight parameters of the trained model in order to evaluate the new model’s performance rapidly. The Super-Net before expansion is used as a pre-training model to initialize the expanded Super-Net and fine-tuned it through a small amount of training. Specifically, when the search space finishes expansion, a new Super-Net is first constructed according to the expanded search space and randomly initializes all weight. Then, use the original weight to cover the random initial weight if same structural part exists in the expanded Super-Net. At this point, the expanded Super-Net will contain the previously trained weight and random initialization parts. We employ the backpropagation algorithm to train the extended candidate architectures and synchronize the weight to Super-Net, so as to train the initialized weight part in the Super-Net.

B. Improved Heredity Algorithm for INAS

In order to obtain better model search efficiency and accuracy, this paper first applied Heredity Algorithm (HA) [15] to NAS and proposed an improved HA for INAS. The improved HA uses gene blocks as the smallest unit for gene exchange and performs independent mutation method for position and operation coding.

Generally, the choice of network operation type will be affected by the data tensor on which it acts. In this paper, the input node ID and the corresponding network operation type ID are bound as gene blocks to maintain
the potential relationship between input data and operation. The gene block is the smallest unit for gene transfer in the overwriting operator. To fine-tune node ID and network operation types, the mutation operator still mutates in units of individual gene codes to generate new gene values.

Different from the crossover operator of genetic algorithm that generates new individuals by exchanging two parent's genes. The overwriting operator only allows the individual with higher fitness values to transmit genes to the lower individual and generates new individuals by covering part of genes of a lower individual. Suppose individuals $A$ and $B$ are selected as parents to produce new individuals, and the fitness value of individual $A$ is greater than $B$. The overwriting operator will randomly select a certain proportion of gene blocks from individual $A$ to cover the corresponding gene of $B$. The proportion of gene transmission is called Lamarckian genetic probability $p_t$. The number of gene blocks transmitted is $n_t$, $p_t$ and $n_t$ are calculated as shown in equation (1), where $f(*)$ is the fitness calculation function. $N$ is the total number of gene blocks, and $[*]$ indicates that the calculation results are rounded down. The gene overwriting process is shown in Figure 5(a). Overwriting operator processing will generate two new individuals. The new individual $A'$ completely comes from the original individual, and the new individual $B'$ introduces some genes from individual $A$ while retaining part of the original individual’s genes.

\[
\begin{align*}
P_t &= \frac{f(A)}{f(A) + f(B)}, \quad f(A) > f(B) \\
N_t &= \lfloor p_t \times N \rfloor
\end{align*}
\]

This paper uses a single point mutation operator like most genetic algorithms to mutate the gene code. According to the different mutation locations selected, the mutation can be divided into two types: connection mutation and operation mutation. The mutation process is shown in Figure 5(b). The odd mutation position means connection mutation will perform, and the input node ID will be modified. A new node ID is randomly sampled from the preceding sequence as the mutation position gene. When the mutation position is even, the network operation will perform, and the network operation type will change. An operation type ID is randomly selected from the candidate neural network operation table to cover the mutation position.

### C. Algorithm Overview

Algorithm 1 details shows the search process of the incremental neural network architecture search (NAS). Among them, $\phi(*)$ is the model performance estimator, which is used to return the candidate architecture’s evaluation performance evaluation. The estimator $\phi(*)$ is implemented in the following way. When a new network architecture needs to be evaluated, it directly uses the weight parameters from the same structure in the SuperNet and forward-propagates to get the validation set on the accuracy. This paper uses the accuracy of the candidate architecture on the validation set as the evaluation metrics to obtain a neural network architecture with higher accuracy.

**Algorithm 1: The NAS Algorithm**

**INPUT:** Maximum number of intermediate nodes $N_{max}$; model performance estimator $\phi(*)$; max iterations $I_{max}$; population size $P$; the probability of overwriting $p_o$ and mutation $p_m$.

**OUTPUT:** optimal neural network architecture $\Lambda^*$

1. Best accuracy $f^* \leftarrow 0$
2. While $N < N_{max}$ do
3. Built Super-Net with $N$ intermediate nodes
4. if $N > 1$ then train expanded Super-Net
5. Initialize a population $pop$
6. While iter $< I_{max}$ do
7. Create a new population $New_{pop}$ $\leftarrow \emptyset$
8. While $i < N_p$ do
9. Select architecture $\Lambda^i$ from $pop$
10. $f^i \leftarrow \phi(\Lambda^i)$ evaluate $\Lambda^i$ performance by $\phi(*)$
11. if $f^i < f^*$ then
12. $f^* \leftarrow f^i$
13. $\Lambda^* \leftarrow \Lambda^i$
14. End While
15. $pop \leftarrow$ new population from roulette selection
16. Select an architecture $\Lambda$ to train one epoch, the selected probability is $p(A^i) \leftarrow \frac{I}{I_{max}}$
17. According to $p_o$, two individuals $(\Lambda^i$ and $\Lambda^j)$ are randomly selected as parents to perform overwriting operator, and append new individuals to $New_{pop}$
18. Randomly mutate individuals based on $p_m$
19. End While
20. End While
21. Return $\Lambda^*$

### IV. EXPERIMENTAL TESTS

To evaluate the performance of the proposed NAS algorithm, our experiments are conducted using the CIFAR-10 (C10) and CIFAR-100 (C100) [27] benchmark data sets for image classification. The CIFAR-10 is a ten-category dataset, with 60K images, of which 50K images are split to be a training set and 10K to be a test set. Each object is an RGB image of a size of $32 \times 32$. The CIFAR-100 are similar to CIFAR-10, but each set belongs to 100 categories of nature objectives, making more challenging for recognition and generalization. During the search phase, we split 10K images from the training set as the validation set and use all the training data to train searched neural architecture in augmenting stage. All the experiments are run in NVIDIA Tesla V100 GPUs, and all code implements are based on PyTorch.

In our experiment, the parameters of $HA$ are set as follow. The maximum number of intermediate nodes is $N_{max} = 10$, the maximum number of iterations is $I_{max} =$
150, the population size is $N_p = 100$, and the probabilities of overwriting $p_o$ and mutation $p_m$ are set as 0.8 and 0.2, respectively. For the remainder of the hyperparameters, we use the values from the ENAS [13] experiment for comparison, and the augment hyperparameters are set based on DARTS [17], because of the official hyperparameters no provided. The detailed settings are summarized in Table II. The normal and reduction cells for an optimal model are shown in Figure 6.

<table>
<thead>
<tr>
<th>Hyperparameters</th>
<th>Search phase</th>
<th>Augment phase</th>
</tr>
</thead>
<tbody>
<tr>
<td>batch size</td>
<td>64</td>
<td>96</td>
</tr>
<tr>
<td>init channels</td>
<td>16</td>
<td>36</td>
</tr>
<tr>
<td>epochs</td>
<td>150</td>
<td>600</td>
</tr>
<tr>
<td>optimizer</td>
<td>SGD</td>
<td>SGD</td>
</tr>
<tr>
<td>learning rates</td>
<td>0.025/10</td>
<td>0.025/10</td>
</tr>
<tr>
<td>weight decay</td>
<td>3e-4</td>
<td>3e-4</td>
</tr>
<tr>
<td>momentum</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>nb cells</td>
<td>6</td>
<td>20</td>
</tr>
</tbody>
</table>

Refer to the suggestion from [28], multiple data augment method is used to assess the performance of optimal network architecture. In the INAS, we applied enhancements such as standard deviation correction, random crop and random horizontal flip. Other techniques used in recent work have also been used, such as the cutout of size 16 (C), path dropout of probability 0.2 (D), an auxiliary tower with a weight of 0.4 (A), AutoAugment (AA) [29], and increasing the initial number of channels from 36 to 50 (50C).

We compare the HA-based INAS method with the state-of-the-art methods and some well-known manually designed architectures. The results are shown in Table III. Where some methods do not provide test result of C100, “-” is utilized to represent unknown performance. In C10 test, the INAS architecture achieved the state-of-the-art accuracy of 97.97%. When we apply the same optimal architecture to C100 validation, it reaches 86.17% accuracy. It is worth mentioning that all values of hyperparameters are not fine-tuning for better comparison. All results prove the fact that the optimal architecture from INAS can achieve excellent performance and robustness within a relatively short period of time. An outstanding performance can be toilless reached by searching an appropriate architecture in smaller dataset. Then the searched architecture is utilized to train and validation in the large datasets of same type.

![Normal Cell](image1.png)

![Reduction Cell](image2.png)

**Figure 6.** Normal and Reduction cell structures of an optimal model

<table>
<thead>
<tr>
<th>Method</th>
<th>Search (GPU days)</th>
<th>Cost</th>
<th>Search Strategy</th>
<th>C10-Test Accuracy (%)</th>
<th>C100-Test Accuracy (%)</th>
<th># Params. (M)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResNet (depth=110) [29]</td>
<td>-</td>
<td>-</td>
<td>manually</td>
<td>93.57</td>
<td>74.84</td>
<td>1.7</td>
</tr>
<tr>
<td>DenseNet-BC (k=40) [30]</td>
<td>-</td>
<td>-</td>
<td>manually</td>
<td>96.54</td>
<td>82.82</td>
<td>25.6</td>
</tr>
<tr>
<td>VGGNet[31]</td>
<td>-</td>
<td>-</td>
<td>manually</td>
<td>93.34</td>
<td>71.95</td>
<td>20.04</td>
</tr>
<tr>
<td>NASNet-A/CutOut [16]</td>
<td>1800</td>
<td>RL</td>
<td>97.35</td>
<td>-</td>
<td>2.3</td>
<td></td>
</tr>
<tr>
<td>NASNet-B [16]</td>
<td>1800</td>
<td>RL</td>
<td>96.27</td>
<td>-</td>
<td>2.6</td>
<td></td>
</tr>
<tr>
<td>Block-ONN-S [32]</td>
<td>90</td>
<td>RL</td>
<td>95.62</td>
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<td>6.1</td>
<td></td>
</tr>
<tr>
<td>AmoebaNet-A[33]</td>
<td>3150</td>
<td>evolution</td>
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<td>-</td>
<td>3.2</td>
<td></td>
</tr>
<tr>
<td>Hierarchical evolution[34]</td>
<td>300</td>
<td>evolution</td>
<td>96.25±0.12</td>
<td>-</td>
<td>15.7</td>
<td></td>
</tr>
<tr>
<td>ENAS+CutOut [13]</td>
<td>0.45</td>
<td>RL</td>
<td>97.11</td>
<td>-</td>
<td>4.6</td>
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<tr>
<td>DARTS+CutOut [17]</td>
<td>4</td>
<td>gradient-based</td>
<td>97.24±0.09</td>
<td>-</td>
<td>3.3</td>
<td></td>
</tr>
<tr>
<td>PC-DARTS+CutOut [18]</td>
<td>0.1</td>
<td>gradient-based</td>
<td>97.43±0.04</td>
<td>-</td>
<td>3.6</td>
<td></td>
</tr>
<tr>
<td>SNAS+CutOut [35]</td>
<td>1.5</td>
<td>gradient-based</td>
<td>97.15±0.02</td>
<td>-</td>
<td>2.8</td>
<td></td>
</tr>
<tr>
<td>Large-scale Evolution [4]</td>
<td>2750</td>
<td>evolution</td>
<td>94.6</td>
<td>-</td>
<td>5.4</td>
<td></td>
</tr>
<tr>
<td>Large-scale Evolution [4]</td>
<td>2750</td>
<td>evolution</td>
<td>-</td>
<td>77.0</td>
<td>40.4</td>
<td></td>
</tr>
<tr>
<td>EcoNAS [6]</td>
<td>8</td>
<td>evolution</td>
<td>97.38±0.02</td>
<td>-</td>
<td>2.9</td>
<td></td>
</tr>
<tr>
<td>INAS + CDA</td>
<td>2.84</td>
<td>evolution</td>
<td>97.47±0.02</td>
<td>82.96</td>
<td>5.73</td>
<td></td>
</tr>
<tr>
<td>INAS + CDAAA</td>
<td>2.84</td>
<td>evolution</td>
<td>97.88±0.02</td>
<td>85.35</td>
<td>5.73</td>
<td></td>
</tr>
<tr>
<td>INAS + CDAAA +50C</td>
<td>2.84</td>
<td>evolution</td>
<td>97.97±0.06</td>
<td>86.17</td>
<td>10.38</td>
<td></td>
</tr>
</tbody>
</table>

**Table III.** Comparisons between the proposed algorithm (INAS) and the state-of-the-art competitions.
V. CONCLUSION AND FUTURE WORK

Combining the advantages of pruning and growing a neural network, we have developed an incremental neural architecture search approach. This approach can dynamically increase the size of the Super-Net for optimal performance. In order to preserve excellent individual genes in the offspring and to maintain the potential connection between the input nodes and corresponding neural operators, we use a novel heredity algorithm as the search strategy. Experimental results on the CIFAR-10 and CIFAR-100 benchmark data sets show that our proposed method is able to find promising architectures with higher accuracy than existing methods in a short period of time.

We notice that in our current method, every time an intermediate node is increased, the Super-Net has to start training again. Therefore, our future work includes the design of a more efficient search space that can reuse the trained weights and reduce Super-Net training as much as possible, even if the intermediate nodes change. Further, we shall investigate the use of a model performance predictor to replace real network training and evaluation for accelerated learning.

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Advanced Machine Learning Approach of Power Flow Optimization in Community Microgrid

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Abstract— With the increasing penetration of distributed renewable energy (DERs), the electrical grid is experiencing, on a daily basis, rapid and massive fluctuations in power and voltage profiles. Fast and precise control strategies in real-time have played an important role to ensure that the power system operates at an optimal status. Solving real-time optimal power flow (OPF) problems while satisfying the operational constraints of the community microgrid (CMG) is considered a promising technique to control the fluctuations of renewable sources and loads. This paper adopts a new deep reinforcement learning algorithm (DRL), called Twin-Delayed Deep Deterministic Policy Gradient (TD3), to solve the real-time OPF with consideration of DERs and distributed energy storages (DESS) in the CMG. Training and testing of the algorithm are conducted on an IEEE 14-bus test system. Comparative results show the effectiveness of the proposed algorithm.

Keywords: Reinforcement Learning (RL), Deep Reinforcement Learning (DRL), Optimal Power Flow (OPF), Twin-Delayed Deep Deterministic Policy Gradient (TD3), Community Microgrid (CMG).

I. INTRODUCTION

Community microgrids (CMGs) have emerged as an effective method to accommodate new energy sources like solar photovoltaics (PVs) and wind turbines (WTs) in the power system. The high penetration of these sources into the power system has become clearly observed due to climate change, and environmental protection. Distributed energy resources (DERs), like PVs and WTs, are distinguished by their uncontrollability and intermittency, thus making the grid operator not be able to control and predict their generation. The penetration of DERs has formed huge challenges to the grid operators to ensure that the modern power systems operate at high efficiency and reliability. Dealing with these challenges requires a faster solution to the high-dimension non-convex real-time OPF problems.

In recent years, a number of promising methods have been proposed to solve the OPF problem. Reference [1] uses the swarm intelligent method to solve the OPF problem. However, the nonlinear characteristic of the loads, generators, and other devices that connect to the system makes this optimization method inefficient to find the optimum solution for the OPF problem [2]. On the other hand, evolutionary optimization algorithms have emerged as techniques to transact with the nonlinear characteristics of the OPF problem. However, these techniques require plenty of time or a relatively small space of policies to reach the optimal solution [3].

Reference [4] proposes a stochastic optimization (SO) method to solve the OPF problem. This method depends on finding the distribution of uncertain variables like loads and PVs in the OPF problem. However, the SO requires a large amount of time to calculate a number of scenarios that are used to form the uncertainty distribution [5]. In contrast to the SO, model predictive control (MPC) algorithm is proposed in [6] to solve the multi-phase OPF problem. The MPC algorithm is a very efficient method to reach an optimum solution; however, the performance of the algorithm relies mainly on the prediction precision of the load and renewable energy generation in the power grids, which is difficult to achieve in reality [7].

On the other side, machine learning (ML) has gained wide popularity in recent years, due to its superior ability to take fast decision making even with existing high uncertain variables in the power systems. ML is able to extract useful information from historical data and uses this information to solve an OPF problem. Among the ML approaches, reinforcement learning (RL) is considered an efficient approach to tackle the real-time OPF problem due to its capability to learn the best strategies to reach optimum solutions by searching historical data [8].

Reference [9] proposes Double Deep Q Learning (DDQN), which is a deep RL (DRL) algorithm to solve the stochastic OPF by considering the uncertainty of the load demand and wind turbines. The deep neural network (DNN) that is used in this reference works as an action-value function approximator. However, the DDQN works by discretizing the action space. Since the OPF is a continuous optimization problem, the discretization of the action space leads to loss of some information; thus, DDQN may converge to suboptimal solutions [10].

A number of RL algorithms have been used to deal with continuous environments. In [11], Deep Deterministic Policy Gradient (DDPG) is used to solve real-time OPF by adjusting the active and reactive power of the generators. The proposed approach is tested on the IEEE 118-bus system and the simulation results show that the DDPG reached the optimum solution much faster than the interior-point method. Reference [12] uses a state-of-art ML method which is based on Deep Policy Gradient (DPG), called Proximal Policy Optimization (PPO), to solve real-time OPF. The PPO is highly effective to work with high-dimensional and continuous action space like OPF. Moreover, PPO is able to take multiple actions at the same time, which gives this method superiority over the traditional ML methods. The proposed approach is tested on the IEEE 33-bus system, and the simulation results...
demonstrate that PPO can provide a more resilient control strategy than the stochastic programming method.

Inspired by the recent researches, this paper presents a new ML algorithm with continuous action search to solve real-time alternating current (AC) OPF (ACOPF) in the CMG that is equipped with DERs and distributed energy storages (DESs). The real-time ACOPF problem is formulated as Markov decision process (MDP), and then the twin-Delayed Deep Deterministic Policy Gradient (TD3) is used to solve the MDP. This paper takes into consideration the uncertainty of the WTs, PVs, and load demand, and the objective is to minimize the total power loss by controlling the active and reactive power of the DERs and DESs. The RL agent has been developed to ensure the CMG is operating under safe and reliable conditions, meaning that the agent actions must satisfy all operational constraints.

II. PROBLEM FORMULATION

A CMG can be represented as a set of buses \( \mathcal{N} \) that are connected with each other by transmission lines (TLs), where \( \mathcal{N} \) is a set of positive integers. The TLs can be represented as a matrix \( \mathcal{E} = \mathcal{N} \times \mathcal{N} \) that demonstrates the relation between buses within a CMG. All CMG devices \( \mathcal{D} \) are connected to single or several buses, which might withdraw power from the grid, e.g., loads, or inject power into the grid, e.g., DERs. Each bus \( i \in \mathcal{N} \) in the CMG can be represented by several variables that determine its status, including a current \( I_i \), voltage level \( V_i \), active power \( P_i^{(\text{bus})} \) and reactive power \( Q_i^{(\text{bus})} \). The active or reactive power injection into or withdrawal from the bus can be obtained by calculating the active and reactive power of the device \( d \in \mathcal{D} \) that connects with it. The devices in the CMG are divided into three subsets \( \mathcal{D}_{\text{DER}}, \mathcal{D}_{\text{L}}, \text{and } \mathcal{D}_{\text{DES}} \). \( \mathcal{D}_{\text{DER}} \) represent the DER that can only inject power into the CMG, while \( \mathcal{D}_{\text{L}} \) is passive loads that can only withdraw power from the CMG. On the other hand, \( \mathcal{D}_{\text{DES}} \) is a storage unit that can inject and consume power into/from the grid. The proposed CMG works in connection with the main grid, which is used to provide a voltage reference and also to balance the power level in the CMG.

The objective function of the OPF problem, as shown in (1), is to minimize the power loss while the security constraints are satisfied. The optimization horizon is one day, and the time interval (timestep) is a 15-minutes, and thus 96 time steps a day.

\[
\min_{t=0}^{96} P_{D_{\text{loss}}} + P_{D_{\text{DES loss}}} + P_{D_{\text{DER loss}}} \tag{1}
\]

where \( P_{D_{\text{loss}}} \) is the total transmission energy loss that occurs as a result of leakage in TLs. \( P_{D_{\text{DES loss}}} \) is the total energy loss that happens due to leakage in storage units. This loss occurs because DESs have charging and discharging efficiency factors \( \eta \). \( P_{D_{\text{DER loss}}} \) is the total energy loss that happens when the generation of DER is curtailled. This curtailment is necessary when the generation power of the DER is higher than the required power capacity of TLs, \( P_{D_{\text{loss}}} \), \( P_{D_{\text{DES loss}}} \), and \( P_{D_{\text{DER loss}}} \) can be calculated by using (2), (3), and (4), respectively.

\[
P_{D_{\text{loss}}} = \sum_{d \in \mathcal{D}} P_{d,t+1} \tag{2}
\]
\[
P_{D_{\text{DES loss}}} = \sum_{d \in \mathcal{D}_{\text{DES}}} P_{d,t+1}(1 - \eta) \tag{3}
\]
\[
P_{D_{\text{DER loss}}} = \sum_{g \in \mathcal{D}_{\text{DER}}} P_{g}^{(\text{max})} - P_{g,t+1} \tag{4}
\]

where \( P_{g}^{(\text{max})} \) is the maximum generation power of the DER, and \( P_{g,t+1} \) is the renewable energy production after curtailment. \( P_{d,t+1} \) in (2) is transmission energy loss that occurs in TLs as a result of passing power to the loads, while \( P_{d,t+1}(1 - \eta) \) in (3) is a power loss of the batteries.

The solution of the OPF problem must be considered the DERs, DESs, and network constraints. Equations (5), and (6) represent the physical limitation of DERs and DESs, while (7) and (8) are used to add an additional constraint on the reactive power injection when the active power of the DERs or DESs is close to the maximum value. Equations (9) and (10) represent additional constraints on the active power injection/withdrawal of storage units. The DESs cannot withdraw (charge) an active power when the current state of charge \( SoC_d \) indicates that the storage unit is full \( SoC_d \). On the other hand, DESs would not be able to inject (discharge) an active power when the \( SoC_{\text{hi}} \) is empty \( SoC_d \).

\[
P_{g} \leq P_{\text{g}} \leq P_{\text{g}} \tag{5}
\]
\[
Q_{g} \leq Q_{g} \leq Q_{g} \tag{6}
\]
\[
Q_{g} \leq Q_{g} + Q_{g} \tag{7}
\]
\[
Q_{g} \geq Q_{g} + Q_{g} \tag{8}
\]
\[
P_{g} \geq \frac{1}{\Delta t} (SoC_{g,t-1} - SoC_{g}) \tag{9}
\]
\[
P_{g} \leq \frac{1}{\Delta t} (SoC_{g,t-1} - SoC_{g}) \tag{10}
\]

where \( Q_{g,1} \), \( Q_{g,2} \), \( Q_{g,3} \), and \( Q_{g,4} \) are constant values and \( \Delta t \) is the time difference during \((t, t + 1)\). Two types of network constraints are considered in this paper, which must be satisfied all the time. The first constraint is the voltage magnitude of the buses which must be within acceptable limits, as is given in (11). The second constraint, as is shown in (12), represents the maximum value of the apparent power that can flow from bus \( i \) to bus \( j \).

\[
V_{i} \leq V_{i,t} \leq \bar{V}_{i} \tag{11}
\]
\[
\bar{S}_{ij,t} \leq \bar{S}_{ij,t} \tag{12}
\]

III. MARKOV DECISION PROCESS OVERVIEW

The MDP is used to model the CMG framework, which can be divided into four parts: \( (\mathcal{X}, \mathcal{A}, \mathcal{R}, \mathcal{P}) \), representing state space, action space, reward function and transition function, respectively. The goal of the RL agent is to learn an optimal policy \( \pi^* \) by continuously interacting
with the CMG environment to maximize a cumulative reward as depicted in Fig. 1. As the optimization of the real-time OPF is a sequential decision-making problem, the RL agent receives a vector of state \( s_t \in \xi \) and reward \( r_{t-1} \in \mathbb{R} \) at timestep \( t \). Based on this information, the agent provides actions \( a_t \in \mathcal{A} \) to the CMG environment.

![Fig. 1 The environment framework](image)

The environment adds a next load demand \( P_{DL,t+1} \), and maximum generation of PVs \( P_{max}^{PV,t+1} \) and WTs \( P_{max}^{WT,t+1} \) before curtailment to the agent actions. Then, the next state function receives \( a_t, P_{DL,t+1} \), \( P_{max}^{PV,t+1} \) and \( P_{max}^{WT,t+1} \) and uses the Newton-Raphson method to determine all bus voltages of the CMG and the active and reactive power of the main grid.

The next state function updates the values of all the currents, voltages, active and reactive powers of the CMG, resulting in a new state \( s_{t+1} \in \xi \) which are sent to the RL agent to process again. Furthermore, it uses (13) to calculate the reward \( r_t \):

\[
r_t = \max \left( \pm r_{clip}, - \left( \Delta E_{loss,t+1} + \lambda \phi(s_{t+1}) \right) \right)
\]

(13)

where \( \Delta E_{loss,t+1} \) is the total power loss, and \( \phi(s_{t+1}) \) is a penalty term associated with excess limitation of the operating constraints, \( \lambda \) is a weighing hyperparameter. \( r_{clip} \) is used to make the reward function within a finite range \( \pm r_{clip} \). The agent uses (13) to learn optimal policy \( \pi^* \) that minimizes the power loss while the operational constraints are satisfied.

A. State space \( \xi \)

The state space \( \xi \) is used to describe the CMG environment and also used as the input of RL algorithm. \( s_t \in \xi \) includes the active and reactive powers \( P_{device}^{active}, Q_{device}^{reactive} \) of all devices in the environment \( d \in \mathcal{D} \), charge level of the storage unit \( (S_oC_d) \), \( d \in \mathcal{D}_{DES} \), the maximum power generated from DERs \( P_{g}^{max} \) at time \( t \). The environment reaches a terminal state \( \xi_{term} \) when \( t = 96 \) timesteps or Newton-Raphson method could not find a solution to (14) as a result of the actions that are taken by the RL agent.

\[
P_{t}^{bus} + i q_{t}^{bus} = V_{t}I_{t}^* \quad \forall i \in \mathcal{N}
\]

(14)

where \( I_{t}^* \) is the complex conjugate of the current \( I_t \).

B. Action space \( \mathcal{A} \)

Given the state \( s_t \in \xi \) of the CMG at a specific timestep \( t \), actions \( a_t \in \mathcal{A} \) are taken by the RL agent to determine the curtailment value of active power or reactive power of the DERs, and to set the active power or reactive power injection into or withdraw from DESs. These actions must satisfy the constraints of DERs, DESs, and network stability all the time.

C. Transition function \( P \)

Since the WTs and PVs power generation and load demand for next timestep are stochastic, the state transitions of \( \{P_{g,t+1}\} \in \mathcal{D}_{DER} \) and \( \{P_{d,t+1}\} \in \mathcal{D}_{DL} \) are dependent on the CMG randomness. State transition in the CMG occurs in three steps as is shown in Fig.1. Once the agent selects actions \( a_t \), the environment combines the next step power generation and the load with selected actions and passes them to the next state function which maps the next state \( s_{t+1} \in \xi \) with current (state \( s_t \), action \( a_t \)) pair and determines the reward.

D. Reward function \( \mathbb{R} \)

\( \mathbb{R} \) represents the reward signal after action \( a_t \) is taken in \( s_t \) and it is defined as:

\[
r_t = \begin{cases} 
\max \left( \pm r_{clip}, - \left( \Delta E_{loss,t+1} + \lambda \phi(s_{t+1}) \right) \right) & \text{if } s_{t+1} \notin \xi_{term} \\
\frac{-r_{clip}}{1-\gamma} & \text{if } s_{t+1} \in \xi_{term}
\end{cases}
\]

(15)

where \( \gamma \) is a constant value. Using a clipping parameter \( r_{clip} \) in reward function is to ensure that any transition from a non-terminal to a terminal state produces a very high negative reward. The objective of the clipping function is to encourage the RL agent to lean a policy \( \pi^* \) that avoids all the scenarios that might make the CMG collapse.

The total power loss \( \Delta E_{loss,t+1} \) consists of three parts as defined in (2)-(4). Equation (16) is used to represent all the power loss in the CMG.

\[
\Delta E_{loss,t+1} = \sum_{d \in \mathcal{D}_{L}} P_{d,t+1} + \sum_{d \in \mathcal{D}_{DES}} P_{d,t+1}(1-\eta) + \sum_{d \in \mathcal{D}_{DER}} (P_{g,t+1}^{max} - P_{g,t+1})
\]

(16)

The penalty term \( \phi(s_{t+1}) \) adds a high negative reward when the agent violates the operating constraints. The penalty term can be obtained as:

\[
\phi(s_{t+1}) = \left( \max_{i \in \mathcal{N}} \left( 0, |V_{i,t+1}| - \bar{V}_{i} \right) \right)
\]

\[
+ \max_{i \in \mathcal{N}} \left( 0, |V_{i,t+1}| - \bar{V}_{i,t+1} \right)
\]

\[
+ \sum_{eij \in \xi} \max_{\xi_{i,j,t+1}} \left( 0, |S_{i,j,t+1}| - \bar{S}_{ij} \right) - \bar{S}_{ij}
\]

(17)

where \( |S_{i,j,t+1}| \neq |S_{i,j,t+1}| \) due to TL loss. The first part of (17) represents the limits of the allowed voltage at each bus, which is necessary to maintain the stability of the CMG. The second part is referred to the maximum rating of the power that can flow in the TLs. This constraint is
essential to prevent TLs from overheating. This reward $\Phi(s_{t+1})$ is defined to have a higher negative value than energy loss $\Delta E_{\text{Loss, t+1}}$, because unsatisfying the network constraints can lead to damaging the CMG infrastructure.

IV. OPTIMIZATION METHODS

A. MPC

An MPC algorithm is used to solve the multi-stage OPF problem to evaluate the RL agent's performance in a specific environment. An MPC algorithm can efficiently solve the OPF problem, especially if the prediction of load demand and DERs generation is highly accurate over the optimization horizon.

B. TD3 algorithm

The goal of the TD3 agent is to minimize the total power loss without violating the network constraints or shedding the load. The agent controls the power outputs of DERs and DESs under different load conditions. The RL agent trains through historical data which is called offline training and then applies this model in real-time application.

TD3 is a DRL approach that combines DQN with DDPG. The TD3 is an actor-critic approach that contains both the actor-network and the critic network. The critic network is a Q-value network that takes states and actions as inputs and the output of this network is the estimated Q-value function. The actor-network performs policy improvement to update the policy according to the Q-value function that generates the critic-network. In other words, the actor-network produces an action for the following state. The critic network is in charge to evaluate the policy (policy evaluation) by generating Q-value estimated and computing the difference (temporal difference) between this value and the value generated by the actor-network. Instead of maximizing the Q-value function, the critic network evaluates the gradient of the Q-value to find the orientation of the change action for getting a higher Q-value estimated. Consequently, the actor-network updates its weights in the direction of the gradient of the loss function. TD3 is called "twin" because it uses two critic-networks, two actor networks, and two Bellman equations. Also, it is called "delayed", because the policy is updated less than the Q-value function. This delayed update makes the value estimation have a lower variance. Therefore, lower variance means better policy. TD3 uses action smoothing and utilizes this technique to trade-off between exploitation and exploration. TD3 adds noise to the target action, to make it harder for the policy to exploit Q-function errors by smoothing out Q along with changes in action.

TD3 uses the backpropagation method on the critic loss to determine the parameters of the networks. It updates the parameters of the actor-network every two iterations by implementing the gradient ascent on the output of the first critic network. As is shown in Fig.2, the TD3 agent takes the states of the CMG as inputs and according to optimal policy, the agent provides actions to the environment.

V. CASE STUDY

A. Network architecture

The proposed approach (TD3) is tested on an open-source OPF environment called Gym-ANM [13], which provides the researchers the ability on designing its own microgrid topology, OPF equations, and modifying the characteristics of loads, DERs, and DESs, and testing RL algorithms. The proposed topology of the CMG used in this paper is shown in Fig.2. The CMG is connected with the main grid, and consists of fourteen buses, where solar PVs and WTs work as DERs in buses 2, 3, 7, and 10, respectively, while, the DESs (ES in Fig. 2) are located in buses 8 and 12. The rated power of the WTs and solar PVs are 50 KW and 35 KW, respectively. The capacity of the installed DESs are 200 KWh. The charging and discharging efficiency $\eta$ are both set as 90%. The characteristics of all CMG devices is summarized in Table 1.

B. Experimental details

In this section, the performance of TD3 and other DRL algorithms are compared against the MPC algorithm with a perfect forecast of the CMG data. These algorithms are tested on a modified IEEE 14-bus system. Training set is created by generating random data for each load and DER for seven days (672-time steps) as shown in Fig. 3. The RL agents will be trained for 200 episodes with these data. The performance of the RL agents are tested in five random days, which represent the testing set. To make the CMG...
model close to reality, the weather is supposed to be cloudy on Day 1, which means the generation of solar PV is zero as is shown in Fig. 4. Moreover, the weather on Day 2 is assumed to be windy which means the wind turbine generate power at the maximum limits as shown in Fig 5. The weather in the rest of the testing set is presumed to be normal as shown in Fig 6. It is worthy to mention that the MPC algorithm is fed by perfect forecast data which means the forecasted data error is 0%. In reality, it is impossible to predict the future load demand and DERs generation with a 0% error rate.

### TABLE 1. Descriptions of each device (loads, DERs, DESs)

<table>
<thead>
<tr>
<th>Number of devices</th>
<th>Type of device</th>
<th>( P_d ) (KW)</th>
<th>( P_d ) (KW)</th>
<th>( Q_d ) (KVAR)</th>
<th>( Q_d ) (KVAR)</th>
<th>( \eta )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Load</td>
<td>-20</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>PV</td>
<td>35</td>
<td>0</td>
<td>35</td>
<td>-35</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Load</td>
<td>0</td>
<td>-20</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>WT</td>
<td>50</td>
<td>-50</td>
<td>50</td>
<td>-50</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Load</td>
<td>0</td>
<td>-15</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>PV</td>
<td>35</td>
<td>0</td>
<td>35</td>
<td>-35</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Load</td>
<td>0</td>
<td>-20</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>DES</td>
<td>50</td>
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<td>50</td>
<td>-50</td>
<td>0.9</td>
</tr>
<tr>
<td>9</td>
<td>Load</td>
<td>0</td>
<td>-20</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Load</td>
<td>0</td>
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<td>-</td>
<td>-</td>
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<tr>
<td>11</td>
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<td>0</td>
<td>-20</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>WT</td>
<td>50</td>
<td>-50</td>
<td>50</td>
<td>-50</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>DES</td>
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<td>50</td>
<td>-50</td>
<td>0.9</td>
</tr>
<tr>
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<td>Load</td>
<td>0</td>
<td>-20</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>Load</td>
<td>0</td>
<td>-20</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>Load</td>
<td>0</td>
<td>-20</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

C. Performance evaluation

Equation (15) is used to evaluate the performance of the proposed algorithms, and we make a comparison with the simulation results between TD3 algorithm and other DRL algorithms, e.g., PPO, soft actor-critic (SAC), DDPG, and Advantage Actor-Critic (A2C). Moreover, we
compare the results of all DRL algorithms against the MPC approach.

D. Comparison results

As shown in Fig 7, among all the DRL algorithms, the proposed approach (TD3) has the minimum power loss, except on the day 3. This indicates that the performance of the TD3 algorithm outperforms A2C, SAC, PPO and DDPG in terms of power loss minimization. MPC results are also given in Fig 7 (black dashed curve), which is plotted as the benchmark to demonstrate the optimal results obtained by the traditional optimization method. Although the performance of the MPC method is better than the TD3 algorithm on all testing days, it is not suitable to solve real-time OPF since it takes much longer time to find an optimal solution. The results show that TD3 is 3.8 times faster than MPC. As highlighted before, MPC cannot work efficiently without having perfect forecasted data.

VI. CONCLUSION

The increasing penetration of solar PVs, WTs, and energy storages present major challenges for the operation of the CMG. In this paper, DRL based approach is proposed for management of the CMG under uncertainties. The real-time OPF problem is formulated as an MDP, then the TD3 is used to extract optimal operation of the CMG by using DRL from the historical data. The proposed algorithms are tested on IEEE 14-bus system and the simulation results show that the TD3 algorithm outperforms the state-of-art DRL algorithms like PPO and A2C.

Future work includes exploring improvements in the performance of the proposed method in terms of how to enhance the optimality while preserving the feasibility at the same time. We will also use long-time data to train the models and real data for validation of the models. We intend to include hyperparameters optimization and use practical data to test the algorithm in our future work. Furthermore, more realistic system operation conditions should be applied to validate the robustness of the proposed method.

REFERENCES

Development of a Robotic Arm Control Platform for Ultrasonic Testing Inspection in Remanufacturing

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Abstract—Remanufacturing improves sustainability in manufacturing industry by reducing the use of new components. As a key process of remanufacturing, inspection is responsible for evaluating the state of key components for future remanufacturing plans. For inspecting the non-working equipment waiting for further operations, non-destructive testing (NDT), such as ultrasonic testing (UT), is the optimal method to use. Currently, most UT is implemented manually, which is not stable on accuracy due to environmental and human factors. To tackle this issue, an automatic NDT inspection implemented with a robotic arm control platform was proposed. It is still challenging how to implement robotic inspection more effectively and efficiently. To ensure the implementation of the manipulation, simulation should be executed firstly, the implementation in the real world is made subsequently. A control platform based on robot operating system (ROS) was developed for simulation and experiment of robotic inspection. A monocular camera was used to reconstruct the object to plan paths for the robotic arm. Contact force control was used to improve the accuracy of autonomous scanning. The platform was tested in simulation environment and implemented in the real world.

Keywords—robotic arm; NDT; ROS; simulation; remanufacturing;

I. INTRODUCTION

Manufacturing industry uses natural resources and generates wastes, which are harmful to the environment. For components used in manufacturing machinery, the waste problem is also serious, e.g., a component will be disposed if it fails while some of its parts are still functional. Circular economy is an alternative to the ‘take-make-waste’ style traditional linear economy [1]. Remanufacturing is an important value recovery option for material circular economy [2]. It takes the used or refurbished parts to rebuild an as-good-as-new conditioned product to extend the lifetime of the original component. Remanufacturing saves up to 80% cost [3] and 85% energy [4] than using all new components. The processes of remanufacturing include disassembly, cleaning, inspection, repairing and replacing parts, reassembly, and testing. The annual number of research publications has been over 20 times larger in recent 3 years than that of 2 decades ago [5].

Inspection is a key process of remanufacturing which can make remanufacturing more time-effective and cost-effective [6]. It can be carried out during normal maintenance to assess the remanufacturability of the key components, which evaluates whether the component is worthwhile to be remanufactured. Besides, it can be used to estimate the remaining useful life (RUL) of the object. The more accurate the RUL is estimated, the more time-effective the remanufacturing can be [7]. Inspection can also help to assess the detailed features of the defects in components, make the plan of the remanufacturing method and the schedule of maintenance and remanufacturing. Achieving thorough information about the object makes remanufacturing more cost-effective. In these inspection stages, the machine has been shut down and its components were in static states, therefore the typical measurement methods, such as vibration monitoring, are not suitable for this situation. Among inspection methods, non-destructive testing (NDT) methods are evaluable methods which can assess the overall state without destructing the object when the object is not in operation [8].

Ultrasonic testing (UT) is one of the most important NDT methods. It has many advantages, e.g., all kinds of materials can be inspected, which is better than some methods, such as eddy current can only be applied to conductive materials. UT is an NDT method suitable for many types of internal defects, such as cracks and microcracks in the subsurface of the components. Internal crack is a key early stage defect type of rolling contact fatigue, which is normally for bearings [9]. Internal voids and excessive working load are the possible reason for the internal cracks. Manufacturing tools, such as die and mould, which are suffering from high thermal fatigue, often undertake internal and surface cracks [10]. Therefore, key components, e.g., bearings and mould need accurate UT for future remanufacturing. Accurate UT can provide a reliable assessment of the component, e.g., the shape, location and property of internal cracks. However, since the probe should be attached and normal to the surface and a contact force should be applied to guarantee good inspection quality. The couplant used in UT also increases the difficulty of implementation. Since the high sensitivity of UT, a small movement of the probe will make a significant change in the result. The missing out of signal
at critical positions makes UT time-consuming. Currently, most UT in industry are carried out manually, the results vary due to the level of technique of the operators. Scanning a large surface with a small transducer is also time-consuming and labour-intensive. Moreover, the results of inspection should be assessed by expertise, which costs more time and is not reliable. A more efficient and effective inspection method can save time and cost of remanufacturing [6]. Robotic arm, as an important tool in the era of Industry 4.0, can implement inspection in an autonomous, accurate and stable way.

Collaborative robotic (cobot) arm, as an alternative to the industrial robotic arm, is used in industry due to its convenience and simplicity of use. Cobot can supply better safety to human operators and more potential usages since it has more safety setup and more possibilities to learn from skilled human operators [11]. There are challenges in robotic UT, for example, the probe should be perpendicular to the surface, the probe should contact the surface, and the manipulation of the probe should be accurate despite the loss of surface friction due to fluid couplant. There have been application cases of robotic UT, however, the current application of robotic UT is normally for large components with regular shapes, and the accuracy can be improved when applied to irregular shapes. The equipment currently used in UT is complex, for example, industrial robot, depth camera or stereo vision system. The proposed control platform of an improved robotic UT method with simplified equipment, i.e., robotic arm and a monocular camera, is studied to realise the automatic inspection in this study. The platform can implement the control both in the simulation and experiment real-world. Before experiment in the real world, simulation is necessary to improve efficiency, eliminate errors and verify the methods. It helps to save cost and time to implement new methods on actual equipment. The control platform is established based on robot operating system (ROS). The advantage of ROS is that it has the potential to extend the study from simulation to the real world.

The rest of the article is organised as follows: the state-of-the-art is reviewed in the next section. The overall architecture of the control platform is introduced in section 3. The simulation and experiment are carried out in section 4. The conclusion and future works are drawn in section 5.

II. RELATED WORKS

Inspection has been one of the most important applications of robotic arm. The suitable applications for robotic UT inspection are implementing tasks in hazardous places or difficult tasks for human operators [12]. The research of robotic UT has been applied to inspections of the reactor of a nuclear power plant, the component in the aerospace industry [13]. A 3-axis robotic arm was used to inspect a plate part processed with hybrid manufacturing using an industrial robotic arm in aerospace industry [14]. However, the shape of the object was limited to a plate due to the robotic arm. Robotic arm was integrated with aerial vehicles to inspect the pipelines and tanks in plants [15]. Another solution was to move the specimen with the robotic arm [16]. This application was used in immersion UT in which the specimen was immersed in the water. In the study from the University of Strathclyde, a roller phased array probe and depth camera were used to check pipe and staircase shaped components [17]. A KUKA industrial robotic arm was used to drive the probe. Software based on Matlab was used to program the path. Multi-robot application has been used to inspect large components [18]. Force and torque control were used for accurate control of the probe.

To implement robotic UT, the object should be perceived to plan for paths. Robotic arm can scan the known object by using the pre-defined path with the help of a spline interpolation algorithm and computer-aided design (CAD) digital model [19]. However, it cannot be used for an unknown object. Contact force was measured to estimate the surface of the object by combining the position information with coordinate measuring machine (CMM) [20]. The disadvantage is that the process is slow. Researchers also plan scanning paths based on non-contact reconstruction methods. The methods were to use laser sensor [21], projector [22], or computer vision (CV) system [23] since the equipment became more accurate and more affordable. Only CV method is considered in this study. Stereo vision and RGB-D cameras have been used in prior research, the disadvantage of these kinds of cameras are the price of equipment and the accuracy of estimation of the disparity map. Moreover, if stereo vision or RGB-D camera is used, an extra stand should be designed for the cobot to hold the camera, since its view is limited, the extended-sized end effector of the robotic arm requires a big moving space. Moreover, they need more computational capacity to work. Therefore, the regular monocular camera Robotiq WristCamera is used to reconstruct the surface of the object. This camera is an accessory installed on the end effector of the cobot, it does not increase the size of end effector and moves with the cobot. No extra accessory is needed for this solution.

According to the position of the camera, the monocular method can be catalogued as single-view, multi-view and hybrid methods. For single-view method, only one image from one position is used to reconstruct the object. A massive dataset is needed to train the learning model which is not suitable for unknown objects. Hybrid method uses multi-view images to train the single-view reconstruction model. In this study, the camera is installed at the end effector of the cobot, the acquisition of multi-view images is feasible. For components to be remanufactured, each part has a different size and shape, so training method is not suitable. Therefore, the traditional multi-view method is used. For monocular CV, the challenge is to establish a 3D model with the estimate of depth information. Algorithms have been studied to solve the depth problem [24]. Structure from motion (SfM) and synchronised localization and mapping (SLAM) can be used to reconstruct the environment. For offline and small object application in this study, SfM is suitable. In SfM, common feature points in image pairs are matched to structure the relative positions of the camera. Scale-invariant feature transform (SIFT) is the most used and robust descriptor to find features. Then features are matched by a matcher between image pairs. With the positions of matched feature points, the relative
There have been robotic platforms and software used in academic research to implement the control of robotic arm. Matlab is the most used platform, it has an extension toolbox application of robotic control. It is easy to implement control, however, for some types of robots, it is difficult to communicate with the real-world robot. ROS has to be used combining with Matlab. ROS is used by many researchers since it is open-source and feasible for most types of robots. It has a better overall performance and supported by most software. Gazebo is a simulation software based on ROS. Morse is similar to Gazebo, but the support and compatibility for robots are worse. CoppeliaSim (formerly V-REP) is a commercial software mainly for industrial robots. It is difficult to modify the world setup of the simulation scene. Blender is a general animation platform; it performs well in robot simulation with a good real-time performance. RoboDK is a simulation tool that draws attention gradually. It has an easy-to-use user interface; it is easy to establish simulation environment. However, it also uses OPC UA protocol, which is difficult to implement communication with a real robot. Furthermore, since the software is not open-source, the support of robots is not enough [28]. Payment is needed when achieving full functions. The number of publications on these platforms and software since 2012, using the keywords “robotic arm”, “simulation” and the name of robot simulation platform and software is listed in Fig. 1.

In most prior research, industrial robot was used to implement the inspection of regular objects. Cobot is used in this project to simplify robotic UT. To extend the advantages of cobot, a control platform with computer vision is established for the future implementation in the real-world and potential future extension to more functions [29].

III. ARCHITECTURE

In this study, a control platform for robotic arm is established. A simulation platform is established based on robot operating system (ROS) [30] at first. Subsequently, the manipulation of the simulated robotic arm is synchronised with the real-world robot. A single camera is used to reconstruct the surface of the object. The camera is installed at the end effector of the robotic arm and moves with the robot. The robot plans its path according to the CV information. 3D surface modelling and force control are combined to control the cobot (see Fig. 2).

Compared to other platforms, ROS has a better adaptability and generalization, which can almost be implemented on all types of robots, in both simulation environment and real-world. ROS is used based on Linux operating system. Different version ROS is suitable for different version of Linux system. Ubuntu 18.05 is used as the operating system in the virtual machine VMWare on a Windows computer, ROS Melodic is used accordingly.

In Linux system, the documents are separated in different folders for ROS. The configuration of ROS environment should be coded in a bash document, which sets up environment and sets working directory to the ROS folder every time when starting ROS. The folders are named as packages in ROS. In different packages, the documents communicate with each other in a distributed communication framework. Nodes, topics, services and messages are the basic structure of ROS. ROS master acts as the core function of ROS. It provides naming and registration services for all the ROS node, making sure the nodes can communicate with each other. All the ROS functions are broken up into sections, each section is named a node in ROS. The nodes can publish messages to topics, which can be shown and logged in simulation. For example, the force measurement at the end effector, the images from the camera are all topics. To subscribe to a topic means receiving messages from the topic. Reply and request can be realised by services [31].

For the robot simulation structure, unified robot description format (urdf) is the document type to define the robot or object in the simulation environment. The documents are structured as XML links. It is used to describe all the physical features of the virtual robot. The CAD model of the robot can be imported by the Solidworks stl document or Collada dae format. Joints are defined as the real robotic arm, in UR5e case, they are shoulder, shoulder lift, elbow, wrist 1 and wrist 2. The main parts between every two joints are named links. When defining each joint, a parent link and a child link should be assigned. All the joints and links can be customised, for example, there are ‘fixed’ (fixed joint cannot move) and ‘revolute’ types of joint (revolute joint connects two links that can rotate around the link), box and cylinder types of link. The transformation information from parent to child links should be listed in the definition of joints. These parameters are all set using XML code.

MoveIt is a robot manipulation framework which controls the motion planning of the robot and
communicates with interactive simulation tools. It can calculate the physical relationship between each link and joint. It estimates the collision possibility between each link, calculates the reverse kinematics and sets default positions and parameters of controllers for the robot and gripper. After configuring the MoveIt setup assistant, the MoveIt configuration package can be generated for future use.

Launch file is the executable file in ROS, which combines all the nodes that users need. It contains all the setup parameters including the urdf needed, the position of the object, MoveIt configuration, start up the simulation software, simulation configuration, etc. The launch file can be launched in the terminal window in Linux. When starting roslaunch, it automatically starts roscore, which contains ROS master, ROS parameter server, and a ROSOut logging node.

ROS has the application programming interface (API) to C++ and Python. The main API of the robot controllers is C++. Python can be used to program other functions, such as the trajectory planning of the robot. The computer vision algorithm can be also coded via API. OpenCV library is used to fulfill the computer vision functions. All the codes can be executed by using “rosrun” command. To the real robot, communication via Ethernet is possible. The Ethernet cable connects the host computer and the control box of UR5e. The control code in C++ or Python is also available for real robots.

Gazebo is a simulation software based on ROS. The virtual robot and environment can be built and visualised in Gazebo software; however, the robot is not interactive in this software, it can be controlled via codes. World file is used in Gazebo as the simulation environment. The object and other obstacles can be defined in the world description file. ROS visualizer (RViz) is a visualised control tool based on MoveIt, it can be used to control the simulation model with an interactive way and synchronise it in Gazebo and the real-world robot. In RViz, it is possible to test various planners and visualise the output. However, there is limitations in RViz, for example, only one target can be planned in each step. Besides RViz, C++ and Python code can be used to control the robot via ROS. The overall architecture of ROS is shown in Fig. 3.

IV. EXPERIMENT

The simulation model of the robotic arm UR5e is established in ROS. Urdf is used to build the physical shape of the robot [32]. After setting up the main body of the cobot, the camera is added on the final joint of the cobot in simulation. The simulation link has the same size of the real camera in the lab. Finally, the 2-finger 85 mm gripper is attached to the final joint of the cobot [33]. The 2-finger gripper is installed based on the camera joint. This complete cobot is used for future simulation application.

For the simulation environment, it is established to imitate the surroundings in the lab. The table with the height of 0.75m and the cobot frame with the height of 0.675m are established as sdf (simulation description format) document and attached in the world setup document. The objects are placed on the table. All the elements including the cobot and the surrounding objects are rendered in the simulation software Gazebo (see Fig. 4).

To make the computer vision system work in simulation environment, a computer vision plug-in function is used and inserted into the link of the customised camera. The size of acquired image is 800*800 (pixels), the direction is vertical to the direction of the gripper (see Fig. 4). The camera is manipulated by robotic arm to different positions. The images of the object from different perspective are taken to reconstruct the 3D model. SfM method is used in this study. RoboDK was also tested, it is difficult to insert a similar camera link in the robot simulation model.

For path planning, a controller is designed to fulfil the function. An ‘effort controller’, ‘joint_position_controller’ is used to control the position and the force during operation. The positions of the joints of robotic arm are inputs, the forces and torques at joints are outputs. PID control is currently used to control the accuracy of manipulation. The effort controller can help eliminate the position error of the robotic arm.

The hardware of the real robot, UR5e, is connected to the platform via Ethernet. By setting the UR5e package for synchronisation and the IP address configured on the teach pendant of UR robot, the scripts can be sent and received via two ports under the IP. The joints and kinematic model in simulation are linked to the real ones of the robot. The original controllers are position controllers with tuned PID parameters. Other types of controllers can be also selected in future tests. For the hardware of robot, ‘remote control’ mode is selected to
To realise the synchronisation of the real physical robotic arm and the simulation arm, the launch files should be ran by the platform. They will establish the communication with the real robot, then the setup of the controller and kinematic model will be established via Moveit configuration. The robotic arm is controlled to scan the surface of the object cube (see Fig. 5). The real robotic arm has the same poses as the simulation arm. The poses of the robotic arm are set in the simulation environment by coding in Python.

Multi-view pictures are taken by a monocular camera. Using SIFT and ORB feature descriptors, the features are detected and matched. Subsequently, sparse point cloud and dense point cloud are generated using patch-based reconstruction method via Colmap. The computer vision algorithm is realised via python coding. Based on the point cloud, path can be planned. Each point in the point cloud can be set as target point, and using principal component analysis (PCA) method, normal vector of each point can be calculated. The shortest path can be planned using nearest neighbour algorithm.

V. CONCLUSIONS AND FUTURE WORK

As a conclusion, the related works of robotic inspection, computer vision and robotic arm control platforms were reviewed. A control platform for UR5e robotic UT scanning was established in this study. The simulation model has been built and tested. The method of establishing a simulation platform and the structure of ROS were introduced in this article. The communication between the virtual model and real-world robot has been tested. The position and movement of the virtual and real robot can be synchronised. Many types of research work, e.g., computer vision and path planning algorithms can be
tested on this platform. It proves that the control platform based on ROS is implementable for future study.

The current virtual model only includes the robot and gripper. The ultrasonic probe should be included in the simulation in the future study. The computer vision system in simulation is different from real-world, which has blurry and with noises. The algorithm in simulation should be improved when applied in real-world. The generalisation and adaptability of monocular computer vision algorithm should be improved. For current path planning, raster style scanning is used, however, it is not suitable for all applications. Therefore, in future applications, other types of path planning are needed for particular objects and situations, such as spiral. Object-based path planning method is needed for future robotic UT inspection. The comparison of commanded path points and actual positions of the end effector of the robotic arm will be implemented in future research.

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Flexible personnel scheduling in large multi-product unpaced asynchronous assembly lines

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Abstract—Employees are one of the effective factors in increasing productivity. The efficiency and effectiveness of employees increase with increased job satisfaction. Considering the priorities of employees in work environments is one of the factors of job satisfaction. This research presents a new multi-objective nonlinear mixed-integer scheduling model for staff scheduling in large unpaced asynchronous assembly lines. In this model, production planning is independent of the impact of human resource management. This model considers the competencies and priorities of each employee and the competency requirements required to assign each employee to the assembly activities. Each employee has four options: the duration of the shift, assembly activities, the number of transitions between assembly activities at different stations, and the start time of each break. This model aims to allocate employees to assembly activities while minimizing operating costs and employee dissatisfaction. For validating the model, a small problem with theoretical data solves by CPLEX. Due to personnel scheduling problems are NP-Hard. Solution times of exact approaches are high, which is not acceptable even for small problems. By considering large assembly lines with many personnel and requiring solutions in short and fast times and indicating that this proposed model is applicable, this model should be solved by Meta-heuristic methods so that the results show the efficiency of this model.

Keywords—Flexibility; Nonlinear mixed-integer programming; Personnel scheduling; Un-paced asynchronous assembly lines.

I. INTRODUCTION

This research has been done on personnel scheduling in a large, un-paced asynchronous multi-product assembly center. Different assembly activities are performed in different stations, the number of assemblers required in each station varies depending on the type of assembly activity assigned to that station and the type of product to be assembled. Due to product changes in the production line and individual qualifications required for each product and each assembly activity at each station, there are often large waves of staff movement between stations, which stops the assembly operation and reduces the productivity of the production line. It also causes employee dissatisfaction [1]. This research presents new mathematical modeling of employee scheduling in a large un-paced asynchronous assembly center. In this model, production planning is considered fixed, and there are selective priorities for employees in four cases, including the length of daily working hours, preferred activities, the number of preferred transfers between different stations, and the start time of breaks. In this model, personnel are assigned to assembly activities on different products at different stations to minimize operating costs and employee dissatisfaction while maintaining the production schedule. Operating costs include the cost of the duration of staff presence in regular and overtime hours, the cost of increasing or decreasing staff from the center, the cost of allocating staff to assembly activities, revenue from allocating staff to a second (non-productive) activity useful to the organization, idle costs, staff transfers and staff dissatisfaction including penalties for deviations (positive or negative) from the number of preferred staff transfers, penalties for deviations (positive or negative) from preferred employee hours, penalties for allocating staff to assembly activities that they are not interested in it and the penalty resulting from the deviation (positive or negative) from the starting time of the breaks is preferred. The problem is modeled in a nonlinear mixed-integer programming model.

Many papers are considering the priorities for personnel in different areas. In recent years there have been many articles on staff scheduling with priorities. These priorities include weekends off, working night shifts, isolated days on and isolated days off [2], weekdays off and overtime [3], days off or holidays, equality of shifts and compatible assignments among workmates [4], minimum and maximum working hours per week [5], type of work shifts [6], the number of consecutive night duties and work shifts [7], work in certain geographical areas, worker-customer pairing and customer’s preferred skills [8], shift-type [9], a certain type work [10], day-shift [11], and work shifts [12]. Most articles in this area are related to physician scheduling, nurse scheduling, home care scheduling, and workforce scheduling and routing. According to the review article of [13] and the searches made, there are very few articles on workforce scheduling considering the priorities in production.

Sabar et al. [1] considered a paced multi-product assembly center. They presented a mathematical model in which workers can be cross-trained and allowed to move between workstations to perform assembly tasks. The assignment of workers has to be made according to criteria.
such as required and available competencies and preferences. Sabar et al. [1] on multi-skilled worker assignment ignore the heterogeneity inherent in multi-skilled workers that it is proficiency level. Three types of worker preferences are taken: the work shift duration, the assignable activities, and the number of transfers between activities.

Ruiz-Torres et al. [14] presented a scheduling model that this model maximizes two objectives simultaneously, one related to customer service satisfaction (number of jobs completed on time) and the other related to worker satisfaction. In another article, Ruiz-Torres et al. [15] describe a general scheduling assignment problem with multiple criteria related to worker satisfaction and overall shop efficiency. This problem considers the assignment of various jobs to multiple workers.

Complied with a classification fulfilled by Boysen et al. [16], assembly lines based on line control are classified into paced, un-paced synchronous, and un-paced asynchronous. In a paced assembly line, constant cycle time is considered for all stations. The slowest station determines the cycle time in the un-paced synchronous assembly line. The un-paced asynchronous assembly line transfers workpieces to the next station whenever the required operations are completed. To continuously operate, the buffers are installed in-between stations.

The present paper is an extension of the work of [1] for un-paced asynchronous assembly lines. The present paper attempts to present a comprehensive model covering many aspects of production environments. In the model of [1], the time to complete each job is the same regardless of what worker performs the job, as well as the length of time for the various assembly activities, set up time, idle time, the duration of the secondary activity and the duration for transfer between stations, are considered a constant period. Also, in this model, production planning is independent of the effect of human resources management.

According to a review paper by [13] and the literature presented in the present paper and the search, the following points can be cited as the contributions of this research. (1) Modeling is performed for un-paced asynchronous assembly lines. Along these lines, the time of performing different assembly activities on different products is not the same. (2) The competency of multi-skilled workers differs in skill set and proficiency level. Differences in proficiency level further affect the processing time of the various assembly activities and the duration of set up of multiple products (3) Staff selectable priorities have been increased, and four types of individual priorities are considered. These individual preferences are shift duration, assignable activities, the number of transfers between stations, and break start times. Considering these contributions, the model is closer to the reality of production environments.

Since most of the production lines are similar to the un-paced asynchronous assembly lines, this model is applicable in many manufacturing environments.

II. Model Description

In this section, the indicators, sets, parameters, and variables of the model are introduced, and then the objective function and constraints are expressed.

A. Model indices

i: Activity, e: Worker, p: Stage, t: Shift start period, k: Station, n: Number of daily breaks, g: Number of products.

B. Model sets

E: Workers, N: Number of breaks, T: Shift start times, K: Workstations, I: Activities, I_A: Assembly activities, I_{sk}: Assembly activities on station k, I_{pk}: Assembly activities on product g at station k, I_{setk}: Line startup activities, when producing product g at station k, I_s: Non-productive activities, I_{bn}: Breaks available, I_m: Transfers available, I_{id}: Available idle, P: Steps assigned to each worker, F: Shifts of each worker, I_{aie}: Undesirable activities for each employee, I_{aie}: Activities that each employee is indifferent to assigning.

C. Model parameters

bs_e: income for unit time of assigning worker e to staff activity. I_{tr}: The competence vector of worker e, which is equal to one if worker e has the necessary qualifications to perform activity i, otherwise it is equal to zero, c_{r e}^t: The cost per unit is the time allotted to worker e for assembly activities, c_{r e}^t: The cost per unit is the time worker e is present at the assembly center during overtime, c_{r e}^t: The cost per unit is the time worker e's presence at the assembly center during regular working hours, c_{r e}^t: Calculates the cost per unit of time allotted to worker e in transfers, c_{r e}^t: The cost of adding a worker to the center in period t, c_{r e}^t: The cost of reducing a worker from the center in period t, d_{min e}: The minimum time required for the presence of each worker if he has started his shift, dt_e: The duration of activity i, d_{max e}: The maximum allowable duration of idle of each worker in each shift, h_{r e}: The preferred working time of worker e, t_{re}: is the desired number of worker transfers e, s_{iken}: The preferred starting time for the nth worker's break, s_{k}: The utility vector of worker e is assigned to the assembly activities that the worker is authorized to perform, a_{max e}: The maximum regular working time allowed for worker e, a_{max e}: The maximum duration of overtime allowed for worker e, p_{e tr}^+: The penalty for each unit is a positive deviation from the number of preferred worker transfers e, p_{e tr}^-: The penalty for each unit is a negative deviation from the number of preferred worker transfers e, p_{e bn}^+: The penalty for each unit is a positive deviation from the number of working units preferred by worker e, p_{e bn}^-: The penalty for each unit is a negative deviation from the starting point of the nth worker's break period, p_{e bn}^-: The penalty for each unit is a positive deviation from the starting time of the nth working preference of worker e, pe_{e}^a: Penalty for worker's dissatisfaction with his allocation to assembly activities. (If dissatisfied pe_{e}^a \geq 0 and pe_{e}^a = 0 if indifferent and pe_{e}^a \leq 0 if satisfied), n_i: The maximum duration of a worker's attendance in each period in the periods in which the shift begins, n_i: The maximum duration of a worker's presence in any presence period other
than the period in which the shift begins, \( y_t \): is the start time of each shift.

**D. Model variables**

- \( a_{ip} \): A binary variable (zero or one) that indicates whether worker \( e \) is assigned to activity \( i \) in period \( p \) or not.
- \( b_{en} \): A binary variable (zero or one) that indicates whether worker \( e \) should be assigned to the \( n \)th time break. If it has to be assigned, it's the number one, otherwise it takes zero.
- \( t_{en} \): A binary variable (zero or one) that indicates whether worker \( e \) is present in the period \( p \) in the center. If it is present in phase \( p \) in the center, this variable takes the number one, and if it is not present in the center in period \( p \), it takes the number zero.
- \( s_{en} \): The non-negative integer variable indicates when worker \( e \) starts the \( n \)th break, \( n m_{e} \): The non-negative integer variable expresses the number of worker transfers \( e \), \( t_{ae} \): The non-negative integer variable expresses the duration of the time units assigned to worker \( e \) by assembly activities, \( t_{ie} \): The non-negative integer variable expresses the duration of the worker's idle time units, \( t_{me} \): The non-negative integer variable expresses the duration of the time units of assigning worker \( e \) to non-productive activities, \( t_{ne} \): The non-negative integer variable expresses the number of workers who start their shift at turn \( t \), \( n_{ne} \): non-negative integer variable expressing the number of workers who finish their shift in turn \( t \) and are not present in turn \( t + 1 \), \( x_{et} \): The binary variable (zero or one) indicates whether worker \( e \) starts his shift in period \( t \) or not. If it is the start of work in this period, it is number one, otherwise it is zero.
- \( e_{df} \): The variable zero or one indicates whether the worker \( e \), who started his shift in period \( t \), is also present in period \( t + 1 \). If it is present, the number will be one and otherwise it will be zero.
- \( a_{ep} \): A non-negative integer variable that represents the duration of activity \( i \) at stage \( p \) by worker \( e \), \( v_{ae} \): The non-negative integer variable expresses the maximum allowable duration of worker’s presence in the center, \( W_{e} \): The non-negative integer variable calculates the working time units of worker \( e \) in regular working time, \( o_{ae} \): The non-negative integer variable calculates the working time units of worker \( e \) in overtime, \( h_{pe} \): The non-negative variable calculates the positive deviation of the preferred working time units of worker \( e \), \( h_{ne} \): The non-negative variable calculates the negative deviation of the total working time units preferred by worker \( e \), \( tr_{pe} \): The non-negative variable calculates the positive deviation from the number of preferred worker transfers \( e \), \( tr_{ne} \): The non-negative variable calculates the positive deviation from the number of preferred worker transfers \( e \), \( s_{pe} \): The non-negative variable calculates the negative deviation from the starting start of the \( n \)th turn of the worker's turn, \( p_{e} \): The integer variable calculates the number of assembly activities assigned to the worker \( e \), depending on whether the worker is interested in that activity or not. In this case, for desirable activities, a negative coefficient of one and for undesirable activities of each worker, a positive coefficient of one is considered and then their sum is calculated according to these coefficients.

**E. The objective function**

The objective function consists of a total of ten functions. The tenth function consists of a sum of several functions, the number of functions of which depends on the number of breaks considered in the working day. The \( F_{1} \) function is considered negative because it is of revenue type. The rest of the functions are of cost type.

Minimize \( F_{1} + F_{2} + F_{3} - F_{4} + F_{5} + F_{6} + F_{7} + F_{8} + F_{9} + F_{10} \) (1)

Which are:

1. The cost of the duration of the presence of each worker in regular and overtime.
   \( F_{1} = \sum_{e \in E} (c_{e}^{w} w_{e} + c_{e}^{o} o_{e}) \) (2)
2. The cost is to increase or decrease the staff.
   \( F_{2} = \sum_{e \in E} (c_{e}^{n} n_{p} + c_{e}^{n} n_{e}) \) (3)
3. The cost of allocating to the assembly activity.
   \( F_{3} = \sum_{e \in E} (c_{e}^{a} t_{ae}) \) (4)
4. The income of allocating to non-productive activities.
   \( F_{4} = \sum_{e \in E} (b_{e}^{s} t_{se}) \) (5)
5. The cost of idle of employees.
   \( F_{5} = \sum_{e \in E} (c_{e}^{i} t_{ie}) \) (6)
6. It is the cost of moving employees.
   \( F_{6} = \sum_{e \in E} (c_{e}^{m} t_{me}) \) (7)
7. Penalty resulting from deviation (positive or negative) from the number of preferred transfers of employees.
   \( F_{7} = \sum_{e \in E} (p_{e}^{tr} + p_{e}^{tr} - tr_{pe}) \) (8)
8. Penalty resulting from deviation (positive or negative) from the preferred working time units of employees.
   \( F_{8} = \sum_{e \in E} (p_{e}^{ht} + h_{pe} + p_{e}^{ht} - h_{ne}) \) (9)
9. The penalty of the allocating to assembly activities.
   \( F_{9} = \sum_{e \in E} (p_{e}^{a} p_{e}) \) (10)
10. The penalty resulting from the deviation (positive or negative) from the start of the rest period of each worker.
    \( F_{10} = \sum_{e \in E} \sum_{n \in N} (p_{e}^{bn} + sb_{en} + p_{e}^{bn} - sb_{en}) \) (11)

**F. Model Constraints**

The number of workers who start their shift at each turn.
\( \sum_{e \in E} x_{et} = n_{p} \quad \forall t \in T \) (12)

The number of workers who start their shift in turn \( t \) and end their shift in period \( t + 1 \),
\( n_{m+1} = \sum_{e \in E} (x_{et} - ed_{ef}) \quad \forall t \in T, f \in F, f = t + 1 \) (13)

Each worker can start their shift once during the planning horizon, which is a working day.
\( x_{et} - ed_{ef} \geq 0, \quad \forall e \in E, f \in F, t \in T \) (14)
The maximum length of time allowed for each activity is
\[ \nu_e - \sum_{t \in E} \nu_t x_{et} - \nu_e d_{ef} = 0, \forall e \in E, f \in F \] (15)
The duration of each worker in the center should not exceed the maximum time allowed.
\[ \sum_{p \in P} d_{ep} - \nu_e \leq 0 \quad \forall e \in E \] (16)
The duration of each stage is the allocation of activities.
\[ -\sum_{t \in E} d_{ep} \sum_{t \in E} d_{at} a_{i\text{ep}} = 0 \quad \forall e \in E \quad \forall p \in P \] (17)
Scheduled assembly activities on the production line must be performed.
\[ \sum_{e \in E} \sum_{p \in P} a_{i\text{ep}} = 1 \quad \forall i \in I \] (18)
The starting time is the first stage of work of each worker.
\[ y_{i1} - \sum_{t \in E} y_t x_{et} = 0 \quad \forall e \in E \] (19)
The start time of each step for each worker, except for the first step.
\[ -y_{i\text{ep}+1} + \sum_{t \in E} s_{i\text{t}} a_{i\text{ep}} = 0 \quad \forall e \in E, \forall p \in P \] (20)
The starting time of each work phase for each worker if it is assigned to one of the activities, which is equal to the sum of the start time of the previous stage and the duration of the previous stage, otherwise it is equal to zero.
\[ y_{i\text{ep}}(t_{i\text{ep}}) - d_{i\text{ep}-1}(t_{i\text{ep}}) - y_{i\text{ep}-1}(t_{i\text{ep}}) = 0 \quad \forall e \in E, \forall p \in P \] (21)
Each worker in a step can be assigned to one of the activities if in the previous step it is assigned to one of the activities in each step, each worker must be assigned to one of the five defined modes, if a worker is not assigned to any of the five modes in one step, it means that the worker has left the center in that step, so in the next step in the center, that worker cannot be assigned to any activity.
\[ t_{i\text{ep}} - t_{i\text{ep}-1} \leq 0 \quad \forall e \in E, \forall p \in P \] (22)
Each stage of presence, each worker can be assigned to only one activity.
\[ -t_{i\text{ep}} + \sum_{i \in I} a_{i\text{ep}} = 0, \forall e \in E, \forall p \in P \] (23)
Determining which breaks will be assigned to each worker depending on the start period of the shift and the duration of the shift. If a worker has started his/her work in the first shift, he/she will be given a break in the first half of the day.
\[ b_{en} - x_{et} = 0, \forall e \in E, \quad t = 1, \quad n = 1 \] (24)
If a worker is present at the center for two shifts, a lunch break is given to that worker.
\[ b_{en} - e_{ef} = 0, \forall e \in E, \forall f \in F, \quad n = 2 \] (25)
If a worker has started his/her work in the first shift and is present in the center in the second shift or starts his/her work in the second shift, the worker will be given an afternoon rest.
\[ b_{en} - x_{et} - e_{ef} = 0, \forall e \in E, f \in F, \quad t = 2, \quad n = 3 \] (26)
During each shift, each worker can be assigned to the scheduled breaks only once.
\[ -b_{en} + \sum_{i \in I} \sum_{p \in P} d_{i\text{ep}} a_{i\text{ep}} = 0, \forall e \in E, \forall n \in N \] (27)
It is the start time of each break for each worker.
\[ -s_{b\text{en}} + \sum_{i \in I} \sum_{p \in P} s_{i\text{t}} a_{i\text{ep}} = 0, \forall e \in E, \forall n \in N \] (28)
If a worker is idle in the p + 2 stage, he/she can be assigned to one of the activities in the p + 2 stage only if he/she is in a displacement state in the p + 1 stage.
\[ -\sum_{i \in I} a_{i\text{ep}+1} + \sum_{i \in I} a_{i\text{ep}} + \sum_{i \in I} a_{i\text{ep}+2} \leq 1, \forall e \in E, \forall p \in P \] (29)
If a worker is assigned to an assembly activity in one station in step p, he/she can be assigned to one of the assembly activities in another station in step p + 2 only if he/she is in the displacement mode in step p + 1.
\[ -\sum_{i \in I} a_{i\text{ep}+1} + \sum_{i \in I} a_{i\text{ep}} + \sum_{i \in I} a_{i\text{ep}+2} \leq 1, \forall e \in E, p, \forall p \in P \] (30)
If a worker is on the move in stage p-1, he/she must be assigned to assembly activities in stage p.
\[ \sum_{i \in I} a_{i\text{ep}+1} + \sum_{i \in I} a_{i\text{ep}} = 2, \forall e \in E, p \in P \] (31)
If a worker is on the move in stage p, he/she must be either assigned to assembly activities or idle in stage p-1.
\[ -\sum_{i \in I} a_{i\text{ep}+1} + \sum_{i \in I} a_{i\text{ep}-1} + \sum_{i \in I} a_{i\text{ep}-1} \leq 1, \forall e \in E, \forall p \in P \] (32)
The total duration of the allocation of each worker to the assembly activities.
\[ -t_{ae} + \sum_{i \in I} \sum_{p \in P} d_{i\text{t}} a_{i\text{ep}} = 0, \forall e \in E \] (33)
The total duration of the allocation of each worker to non-productive activities.
\[ -t_{ae} + \sum_{i \in I} \sum_{p \in P} d_{i\text{t}} a_{i\text{ep}} = 0, \forall e \in E \] (34)
The total duration of the allocation to the movement.
\[ -t_{ae} + \sum_{i \in I} \sum_{p \in P} d_{i\text{t}} a_{i\text{ep}} = 0, \forall e \in E \] (35)
The total duration of idle of each worker.
\[ -t_{ae} + \sum_{i \in I} \sum_{p \in P} d_{i\text{t}} a_{i\text{ep}} = 0, \forall e \in E \] (36)
The total duration of each worker's stay at the center.
\[ -t_{ae} + \sum_{i \in I} \sum_{p \in P} d_{i\text{t}} a_{i\text{ep}} = 0, \forall e \in E \] (37)
The number of transfers assigned to each worker.
\[ n_{ae} + \sum_{i \in I} \sum_{p \in P} a_{i\text{ep}} = 0, \forall e \in E \] (38)
Calculating the positive or negative deviation of the working time units is the preferred priority of each worker.
\[ t_{ae} + h t_{ae} - h t_{ae} = h t_{ae}, \forall e \in E \] (39)
The positive or negative deviation from the number of preferred transfers of each worker (if he has started his shift on this working day).
\[ n_{ae} + t_{ae} - t_{ae} - t_{ae} \times (\sum_{t \in E} x_{et}) = 0, \forall e \in E \] (40)
The positive or negative deviation from the preferred start time of each break for each worker.
\[ s_{b\text{en}} + s_{b\text{en}} - s_{b\text{en}} - s_{b\text{en}} = 0, \forall e \in E, n \in N \] (41)
The sum of desirable or undesirable activities assigned to each worker.
\[ -p_{ae} + \sum_{i \in I} \sum_{p \in P} a_{i\text{ep}} - \sum_{i \in I} a_{i\text{ep}+1} \leq 0, \forall e \in E \] (42)
To determine the duration of regular and overtime, the if-then constraint is used as follows:

\[ \text{if } t_{we} \leq r_{max,e} \text{ then } \alpha_e = 0, \quad \forall e \in E \]  

\[ \text{if } t_{we} \leq r_{max,e} \text{ then } w_e = t_{we}, \quad \forall e \in E \]  

\[ \text{if } t_{we} \geq r_{max,e} \text{ then } \alpha_e = t_{we} - r_{max,e}, \quad \forall e \in E \]  

\[ \text{if } t_{we} \geq r_{max,e} \text{ then } w_e = r_{max,e}, \quad \forall e \in E \]  

\[ 0 \leq w_e \leq r_{max,e}, \quad \forall e \in E \]  

\[ 0 \leq \alpha_e \leq r_{max,e}, \quad \forall e \in E \]  

The minimum duration of each worker's stay at the center.

\[ \text{if } \sum_{t_e \in T} x_{et} = 1 \text{ then } t_{we} \geq d_{min,e}, \quad \forall e \in E \]  

\[ \text{if } \sum_{t_e \in T} x_{et} = 0 \text{ then } t_{we} = 0, \quad \forall e \in E \]  

The minimum duration of idle allowed by each worker.

\[ t_i \leq d_{max,e}, \quad \forall e \in E \]  

III. EVALUATE THE PROPOSED MODE

In this section, a numerical example is introduced to evaluate the proposed model and its efficiency. Two workstations have been considered for this assembly center. In this center, three product models are assembled. The time of assembly activities on each of the products is different in both stations. Assembly work is performed on all three products in both stations. When changing the product in each station, a start-up time is considered. This schedule is for one day. The duration of regular working time allowed for each employee is 9 hours, of which 15 minutes of rest time in the first half of the day, 30 minutes of rest time in the middle of the day for lunch, and 15 minutes of rest in the second half of the working day.

A worker is required to perform each assembly activity. The minimum time for each worker to be at the center is 120 minutes if they begin their shift. The number of workers available in this center is seven workers. The production planning is in Fig. 1.

Workers can start work in two shifts, one in the morning and the other in the afternoon. If a worker is at one station at stage \( t_1 \), he/she can only be assigned to the assembly at stage \( t_3 \) if he/she is on the move at stage \( t_2 \). Also, if a worker is idle at stage \( t_1 \), he/she can only be assigned to assembly activity at stage \( t_3 \), if it is moving at stage \( t_2 \). In other modes of change, movement is not permitted.

Table I shows the skill of each worker in performing assembly activities. In this table, one is entered if the worker has the authority to perform the assembly activity, and zero otherwise. Also, this table shows the penalties for workers to be allocated to assembly activities, the number +10 for activities that the worker likes, -10 for activities that the worker does not like, and zero for activities that the worker is indifferent to being assigned. Table II shows the selected priorities of the workers. Tables III, IV, and V show the costs, penalties, and parameters used in the numerical example.

The presented model is written in the form of a text file that can be read by CPLEX software. This problem has 8772 variables (8478 binary variables and 294 integer variables) for two stations, three products, and seven workers, 806 linear constraints, and 77 nonlinear constraints. CPLEX software version 12.1 and an Intel (R) Core (TM) i7cpu processor computer with 8 GB of memory have been used to run this program. The number of iterations and the duration of solving this numerical example are 2,147,483,648 and 769453.34 seconds, respectively. The optimal objective function is equal to 8362, and the results obtained are in Table VI.

As shown in Table VI, workers number 1, 2, 4, and 6 start their morning shifts, and workers 5 and 7 start their shifts in the afternoon. Workers 1, 4, 5, and 7 have one shift, workers 2 and 6 have two shifts in the center, and worker 3 is not present on this working day. Workers number 1 and 4, four steps; workers 5 and 7, seven steps; workers 2 and 6, twelve steps are present in the center. The start time of the first half of the day for workers 1 and 6 is at 10:30, worker number 2 at 10:15, and worker number 4 at 10:45. For workers number 5 and 7, morning rest are not considered because they are not present in the first work shift. Lunch break is intended for workers who work two shifts. Workers number 2 and 6 start their lunch break at 2 o'clock. The start of rest of the third half of the day is planned for workers 2 and 6 at 14:30 and workers number 5 and 7 at 16 and 15:51, respectively. The shift duration of workers 1, 2, 4, 5, 6, and 7 is 165, 405, 180, 255, 495, and 246 minutes, respectively. The duration of idle, second activity, and movement of each employee are also shown in this table.

![Figure 1. Production planning](#)

**TABLE I. SKILLS AND PENALTIES**

| Workers | a001 | a002 | a003 | a004 | a006 | a007 | a008 | a009 | a010 | a011 | a012 | a013 | a014 | a015 | a016 | a017 | a018 | a019 | a020 | a021 | a022 |
|---------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
|         | 1    | 0    | 0    | 0    | 1    | 0    | 1    | 0    | 0    | 0    | 0    | 0    | 0    | 1    | 0    | 1    | 0    | 0    | 0    | 0    | 0    |
|         | 2    | 1    | 0    | 1    | 0    | 1    | 0    | 0    | 1    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    |
|         | 4    | 0    | 1    | 0    | 0    | 0    | 1    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    |
|         | 5    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    |
|         | 6    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    |
|         | 7    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    | 0    |

**TABLE II. WORKERS' PREFERENCES**

<table>
<thead>
<tr>
<th>Workers</th>
<th>h_{we}</th>
<th>t_{we}</th>
<th>\text{spb}_{i,j}</th>
<th>\text{spb}_{i,k}</th>
<th>\text{sp}_{i,j}</th>
<th>\text{sp}_{i,k}</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 240</td>
<td>2 100</td>
<td>200</td>
<td>420</td>
<td>234</td>
<td>435</td>
</tr>
<tr>
<td></td>
<td>2 300</td>
<td>3 60</td>
<td>435</td>
<td>435</td>
<td>330</td>
<td>170</td>
</tr>
<tr>
<td></td>
<td>3 495</td>
<td>1 165</td>
<td>280</td>
<td>390</td>
<td>390</td>
<td>390</td>
</tr>
<tr>
<td></td>
<td>4 240</td>
<td>0 180</td>
<td>240</td>
<td>429</td>
<td>330</td>
<td>429</td>
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<td></td>
<td>5 400</td>
<td>1 234</td>
<td>345</td>
<td>435</td>
<td>345</td>
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<td></td>
<td>6 240</td>
<td>0 110</td>
<td>280</td>
<td>390</td>
<td>390</td>
<td>390</td>
</tr>
<tr>
<td></td>
<td>7 495</td>
<td>3 120</td>
<td>335</td>
<td>435</td>
<td>345</td>
<td>435</td>
</tr>
</tbody>
</table>
Since the optimal solution time of this problem by using CPLEX solver for this small problem is high and since there are a large number of workers in large assembly centers that must be scheduled in a short and fast time. Therefore, it is recommended that this model be solved with other solution methods, including metaheuristics.

IV. CONCLUSION AND FUTURE RESEARCH

In this research, a new mathematical model for personnel planning in a large un-paced asynchronous multi-product center is presented, taking into account the individual competencies and skills of the workers and six priority items for them, and two levels of flexibility. Flexibility includes the start time of shifts and the start time of daily rest. The priorities include the duration of work, the number of transitions between activities in different stations, the type of activity determined, and the start time of morning break, lunch break, and afternoon break. This paper considers a non-linear mixed integer programming model for the problem. A small numerical example is solved using the CPLEX solver to evaluate the model. Since personnel scheduling problems are NP-hard problems, the computational time required to solve these problems with exact methods is not acceptable, even for small problems. Therefore, considering large assembly environments with many employees and the need to provide a solution in a short and fast time, and to show the applicability of this model, it is necessary to solve this model using other solution methods, including metaheuristics.

According to the results and findings of this study, the most important suggestions for future research are: The duration of the assembly activities be considered as a random variable, the competence of individuals to perform various assembly activities can be defined as fuzzy, the time of different activities by different workers can be considered according to their skill level, and a mutual relationship between production planning and human resource planning be considered for future research.

REFERENCES


Counting assistant through multi-sensor fusion for inventory monitoring

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Abstract—A large number of parts are used in the production activities of the assembly plant. The quantity and quality of these parts in the process of transportation, distribution, use, and recycling in the factory have an impact on production. With large amount of parts and tools, how to provide the right types and quantity of parts at the time and right location becomes the key to business success. The traditional method uses manpower which is costly and time-delayed. Previous single sensor monitoring has its own limitations. For example, weight recognition is hard to determine when multiple type items are mixed. Visual identification is susceptible to problems such as occlusion and difficulty in identifying dense areas and every item needs to be tagged by using RFID.

Therefore, this paper introduces the multi-sensor method, which uses a mathematical approach to fuse weight and visual data to predict different types and quantities of parts in small containers.

This study also provides a case study, simulated classification and counting of Aircraft General Standard(AGS) parts, which are mainly fasteners. They are small in size, expensive, and difficult to identify by a single sensor. Fusion results show up to 80\% in average accuracy which is an improvement over single vision(73\%) and weight detection up to 50\%.

Index Terms—Item identification, Inventory monitoring, Sensor fusion, Aircraft General Spares , Vision, Weight, Industry 4.0

I. INTRODUCTION

In a typical the factory floor, large number of parts are consuming in manufacturing assembling process, to achieve successful internal logistics result, while parts are show at the right place right amount and a right time. To understanding the logistics and performance, monitoring those activities are necessary. Counting and classification are two main way to do this. In a factory where parts are sent to the workbench by a “shop”, to avoid running out of stock on the assembly line, operators tend to take more parts than are required, which results in waste. We have therefore designed a counting system to help the “shop” to give the right number of parts and types when they are sent out, thus improving material utilization.

Traditional method manpower is required to repeat inventory checks at certain intervals, or to count each dispatch at once, which is time-consuming and costly.

Although there are some cases where a single sensor can be used for specific tasks, generally come with limitations such as weight only single type of object can be detected or classify. On the other hand, RFID needs to be marked on every object inspected, and marking a large number of unrecyclable parts is also labour-intensive and may cause changes to the external shape of the part. To overcome these challenges, detection based on multi-sensor fusion will introduce in this paper. This combines the advantages of two or more sensors to improve predictive performance. There have been similar studies on unmanned supermarkets, such as ‘Just Walk-Out Technology’ grab and go in unmanned supermarket implement by Amazon [1] and AIM3S cashier-less convenience stores [2]. These unmanned supermarkets solve the pain point of queuing for checkout in supermarkets and provide more accurate real-time inventory to reduce out-of-stock scenarios. The advantages of automated inventory monitoring applications in supermarkets could also applied in manufacturing scenarios, precise inventory control gives less out-of stock event and reduce waste hence less assembly line downtime and higher profit. Unlike retail most products are display on the shelf, parts in assembling line are stored in some kind of storage device, such as Euro container, they will stacked or place racks compartment in order to save space and ergonomics purpose. Manufacturing assembling parts often come with similar shapes, similar sizes(e.g. nuts with different diameter) and more dense detection area (e.g. large number of parts in a box). Hence, location-based information like unmanned supermarket products are fixed in a shelf location may not be efficient for this study.

II. BACKGROUND AND RELATED WORK

Inventory management involving forecasting, determining requirement, abstracting data and decision making. To reduce execution errors such as over-picking and out-of-stocks, inaccurate inventory counting and deliver parts to incorrect location, hence bring down logistics performance lost sales on retail or interrupt production in manufacturing [3]. Thus, companies have to conduct manual stock inspection regularly. Most common stock counting methods are base on peri-
odicit accouting such as cycle counting and residual balance counting [4]. This can abstract the type and quantity of the items, or even time, position and quantity of the items. These information would not only help inventory control and production planning but also helps predicting inventory for further decision making. In most of cases, labour base inspection is not the cost-effective and time-efficient method, resulting in delays in decision-making. Thus, to solve the shortcomings of manpower, sensor-based detection is proposed.

A. Sensor based item identification

A single type of sensor can detect, classification and localisation with some limitations and they are already widely used in factory automation.

1) Weight: As one of the physical contact detection, Weight-base identification is low cost, mature and robust technology has been widely used in inventory monitoring. Due to its physical characteristics, it is not easily interfered with by external factors such as light and interference in a dense space. The weight different of the event is the a key information, which can be used for estimated availability of the container, a common load cell application is implemented on a shelf or on a table [5], [6], but it cannot be distinguished when the weight of a particular object is a multiple of other object.

There is also the use of piezoresistive textile sensors in smart retail to detect the objects, quantity, placement, and displacement time on the shelf with loads range between 0.5 to 1.5 kg [7]. Since the piezoresistive sensor is placed under detected object, the approximate position of the object can be obtained, imply that the type of the object can be estimated (pre-input information is required and only the same type of detected object can appear in a position).

Additionally, capacitive sensing mat based technology can be placing the object vertically on the pressure sensor, inferring the shape of the orientation of the object to judge the type or quantity of the object [8], [9]. The Four legs method can detect tabletop activity to determine the location of the product [5]. In addition, it can compare the pre-input product location information to infer the type and number of objects [2]. But nor textile or capacitive sensing can effectively solve the case where the measurement has a container i.e. items are place in a box. Therefore, the assistance of another type of sensor will become necessary.

2) Vision: In recent years, with the development of machine learning, computer vision has become an increasingly popular detection method. Common ones are autonomous vehicles [10], product quality inspection [11], face recognition [12], shelf inspection, and more.

Although vision identification has made significant progress in recent years, due to limitations such as neural networks and light propagation, it still has the following disadvantages:

- Vision technology is affected by light and installs angle, it is also easier to occlusion;
- Blind zone in the box due to camera installed angle;
- Image occlusion due to a large number of boxes place on the rack;
- Over-training the neural network or not having enough training set.

3) Radio frequency identification (RFID): According to the German patent [13], RFID technology already used for inventory monitoring. Most cases can be effectively detected in boxes level instead of items level [13], [14]. Additionally, the position of the detection object can be estimate by the signal strength or the angle of different receivers [14], [15]. RFID also has its limitations. For example, interference is likely to occur in dense or metal area detection, labels have to be tagged to every detected object and a large number of receivers are expensive. To reduce interference issue in rack, Yuan [16] has propose a phase difference measurement based tag positioning method. In summary, RFID can be effectively detect larger objects such as pallet or boxes, but it is not suitable for item-level detection in large scale.

4) Binary output sensor: Other alternative technologies such as infrared or physical contact switch, they are easy to implementation, low-cost, low power consumption [16]. However, it gives binary output, means that they have limited classification ability.

5) Ultrasonic beacon: Ultrasonic beacons may also be applied for indoor tracking. With the addition of unique receivers for each object, the positioning and tracking of objects can be obtained such as humans or machines, but this has a large uncertainty for smaller objects such as fastener tools [17].

6) Application: There are companies that provide multi-sensor inventory and check out, such as Amazon [7], it based on a large number of cameras, weight sensors, and RFID. A small scale supermarket cases call ’JUST WALK OUT’ technology in supermarket making the customers grab and go shopping experience [1]. When the customer picks up the goods, the system integrating computer vision, sensor fusion and deep learning algorithms will work together, thereby improving the reliability and accuracy of the results. RFID was used in early versions [19]. But more is that it uses a large number of cameras to scan the code as soon as the customer enters the store to confirm the identity. Tracking with a large number of cameras installed on the ceiling [20]. These cameras detect not only the products and their location, but also they track shoppers [31]. It automatically recognizes the products that customers take from shelf and then does not need to line up to check out. The back-end database that is constantly updated through the information collected by the sensor,thus reducing the out of stock event. However, JWOT is very expensive and it is not real-time, customer need to wait 10 minutes to few hours according to customer report in order to receive a receipt, this waiting time is unacceptable in the assembling line. In addition, the system can only accommodate up to 20 people in store at the time [20].

B. AGS parts

Aircraft General Spares or Aircraft general standard(AGS) parts are mainly for fasteners, they are small items such as bolts, nuts, rivets etc. Which is common parts for modern aircraft. They come in different sizes and are generally stamped
with part numbers. In aircraft assembly line, the operator takes the AGS from "shop" and then continuously consumes these parts during the production activity. In order to avoid AGS out of stock in production, operators are likely to pick more parts than needed. Due to safety and contamination issue, most of oversupplied parts cannot be recycled and hence causing valuable AGS parts are wasted.

III. SYSTEM FRAMEWORK

While each type of sensor has its advantages and disadvantages and a single sensor can only collect limited information. This article uses the combination of vision and weight sensors to compensate for the occlusion of vision due to light, dense stacking of parts, the error caused by the inconsistent test environment; as the weight sensor is difficult to effectively identify different types of products at one time, but its hardly effect by the disadvantage factor of vision. This research will explore the fusion of these two types of sensors, by using mathematical fusion methods to archive better inventory monitoring results. This automatic method is used to detect what is in the box placed on the table, so as monitoring picking activities and hence inventory level.

(a) Round washers
(b) Flat square washers
(c) External coach screw
(d) Studding connectors

Fig. 1. Different AGS parts were used for the experiment

A. Boundary and constrain

An automated detection system that can deal with extreme cases of various situations is very challenging. Since this research still in early stage, some boundary and constrain are set in this stage to avoid over complicating the system, and all operations should make like normal human behavior i.e. not to fool the system, moving the parts or box at high speed, maintain a stable external environment, focus on the monitoring parts type and quantity. To explain the scope of this paper, we make the following assumptions:

1) Upper and lower weight boundary

Due to the maximum weight limit of the weight sensor, the total weight of each test case must be less than or equal to the maximum weight limit, e.g. 5 kg. quantity for each type of parts o will be limited. Moreover, the total weight would include the detected object’s weight plus box’s weight while the minimum total weight is equal to zero i.e. empty shelf, no box.

2) According to reality, no more than 10 types of objects appear in each identification.

3) The maximum quantity of a single type item is limited by the box’s volumes. The volume of each object is different, only a limited number of objects can be placed in each box, limiting the maximum number of objects based on prior knowledge. Currently, maximum of 20 parts are allowed in one box.

4) Total weight during the detection is a constant. The signal received by the weight sensor is constantly changing, we will take the average value as a reference during a unit time.

Through the collection of sensors and the properties of the detection target input in advance, the system will determine the objects within the detection range based on the following previous information.

- Total weight(W): Measured by weight sensor including weight of all boxes and the objects;
- Number of types of item in the data set (up to 10);
- Item’s properties, including weight, volume as well as vision properties(pre-trained model);
- RGB picture images from the camera.

B. Algorithms

This study adopts Decision In-Decision Out(DEI-DEO) when using the fusion method of mathematics. The output would show the type and number of objects. In the case of receiving multiple sensor output at the same time, there will be three situations in Figure 2.

Were W represents the output signal of the weight sensor, V represents the model of the visual output, which can be seen from the Figure 2.

If the weight and vision outputs are identically defined as intersection, implying that both types of sensors confirmed the same result, the result will be output directly. Disjoint is the opposite, the two types of sensors will not have any identical results, this situation will not be discussed in this paper due to conflicting messages from the two sensors. The overlapping is the most common case, some of the output from vision and weight are identical, and the final output will be determined by the noisy channel model. See Figure 3 for the algorithms corresponding to different situations.
The pseudocode for list of combinations can be shown in Algorithm 1 below.

### Algorithm 1 An algorithm for list of combinations

**Require:** $W_n, h, x \geq 0$

**Ensure:** $h_1x_1 + h_2x_2 + \ldots + h_nx_n = W_n$

1. $W_n \leftarrow$ Total weight
2. $x \leftarrow$ Individual weights of each type of object
3. $M_n \leftarrow W_n/x$ \(\triangleright\) Maximum quantity
4. $h_n \leftarrow 0$

   while $W_n \neq 0$, $h_n \leq M_n$ do

   if $h_1x_1 + h_2x_2 + \ldots + h_nx_n = W_n$ then return $h_1$, $h_2$, ..., $h_n$

   else

   $h_1 \leftarrow h_1 + 1$
   $h_2 \leftarrow h_2 + 1$
   $\ldots$
   $h_n \leftarrow h_n + 1$ \(\triangleright\) Iterate separately for each $h$

   end if

end while

- Object 3 are external coach screw with weight 14g;
- Object 4 are studding connectors with weight 41g.

#### A. Weight only

As the measure object properties are prior knowledge, it can be transfer to an integer programming problem.

Mathematically, let the total weight measured by the weight sensor is $W$. Where the weight of each object $h_n$ are known. Due to natural of fact, all numbers will be are positive integer or zero. Therefore, Equation (1) become:

$$h_1x_1 + h_2x_2 + \ldots + h_nx_n = W_n$$

The main object of this paper is item-identification, for which correctness is defined as each combination coinciding identical with the actual type and quantity.

Using integer programming for object quantity $h_n$ in the equation(1) and computer assistance, all the combinations can be calculated. In general, the number of attempts will increase exponentially while number of type object increase. Since assumption (1) (2) (3) the quantity for each item $x_n$ are limited, with ten or less, the number of attempts will significantly reduced. This would gives the number of each object(quantify) $x_1, x_2, \ldots, x_n$.

Consider the error from the load cell sensor, according to experience for load cells with a carrying capacity of 2-5kg the error is within $\pm 5g$, the tolerance was set to be 5g. Thus, obtaining the closest set or sets of results. Similarly, this significantly reduces the number of combinations.

The accuracy, $W_{\text{accuracy}}$, can be expressed as:

$$W_{\text{accuracy}} = \frac{1}{\text{Number of combinations}} \times 100\%$$

In the case of weight identification it can be seen from Table I that the accuracy decreases rapidly with the increase of type and quantity.

In the designed this is the first output step and it will the activation of the camera to trigger the image recognition.
### Table I
Confident Level for Weight Identification

<table>
<thead>
<tr>
<th>Number of types</th>
<th>Accuracy 1</th>
<th>Accuracy 2</th>
<th>Accuracy 3</th>
<th>Accuracy 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>50%</td>
<td>25%</td>
<td>16%</td>
<td>6.6%</td>
</tr>
<tr>
<td>2</td>
<td>25%</td>
<td>14%</td>
<td>9%</td>
<td>1.1%</td>
</tr>
<tr>
<td>3</td>
<td>25%</td>
<td>11%</td>
<td>6.7%</td>
<td>0.86%</td>
</tr>
<tr>
<td>4</td>
<td>5.6%</td>
<td>1.6%</td>
<td>0.82%</td>
<td>0.61%</td>
</tr>
</tbody>
</table>

Fig. 4. Weight only identification accuracy for different types of quantity

### B. Vision only

When designing visual identification, camera angles and camera types may impact the result, as neural networks are improving in recent years, the resolution of the camera may not have to be high-end. From previous experience for small objects 500-720 pixels is more common for training and computation. As for the frame rate, since the object is placed on the static weighing sensor and not taken down until the end of the detection, 10 fps or more is sufficient to obtain a clear view. In addition sufficient light was maintained in the study, the type and placement of the cameras was constant in the experiment and it is beyond the scope of this article to optimise these factors.

### Table II
Confident Level for Vision Identification

<table>
<thead>
<tr>
<th>Number of types</th>
<th>Accuracy 1</th>
<th>Accuracy 2</th>
<th>Accuracy 3</th>
<th>Accuracy 4</th>
</tr>
</thead>
<tbody>
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<td>1</td>
<td>100%</td>
<td>100%</td>
<td>83%</td>
<td>87%</td>
</tr>
<tr>
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<td>100%</td>
<td>87%</td>
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<td>56%</td>
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<td>3</td>
<td>83%</td>
<td>66%</td>
<td>56%</td>
<td>58%</td>
</tr>
<tr>
<td>4</td>
<td>75%</td>
<td>56%</td>
<td>54%</td>
<td>49%</td>
</tr>
</tbody>
</table>

We define the accuracy of the vision identification as follows:

\[
V_{\text{accuracy}} = \frac{\text{Correct identification per type}}{\text{True quantity}} \times 100\%.
\]

Fig. 5. Vision only identification accuracy for different types of quantity

### C. Combination of weight and vision

The results of a single weight and visual identification were described previously, in this section it is described how a prior knowledge and these two sensor modalities can be combined to estimate a final prediction. We use the noisy channel model for prediction, which is based on matching the predictive input from weight sensing with visual information.

In the previous noisy channel model study, the main purpose was spelling correction by generating candidates choice maximum probabilities from corpus [18]. In this study the expected combination is found from the camera giving the decision, and from the weight sensing of the combinations it obtains.

The following factors were used to obtain the closest results when applying the model:

- Higher probabilities is given to the combination with the largest quantity of type in visual detection;
- Distance between the guess and the correct answer
- If the distances are too large, compare with the original group by increasing the number of guessed parts to see if more results are obtained;
- The closer the measured weight is to the calculated combination, the more probabilities is given;
- Selecting from weight calculation combinations where the quantity is equal to larger than vision identify;
- An equal number of parts of two or more types allows for greater possibilities.

Similarly, define the fusion accuracy as the fusion result being intersection with the actual situation, the item’s quantity and types match the correct combination. The results are shown in Figure 6, with the fused data showing an improvement over the single type sensor (Figure 4 and 5).

### V. Conclusion

In this paper, a system is proposed for the automatic detection of the type and quantity of parts in a dense area. A mathematical noisy channel model is used to fuse the
list of combinations from weight difference and the camera identification. This results in an accuracy of up to 80%, higher than single vision or weight identification. Future work will expand the system to allow more types and quantity parts to be detected, as well as optimising the image recognition model. Furthermore, experiment with machine learning methods to compare fusion performance.

REFERENCES


Abstract—Cyber-Physical Production Systems (CPPS) play a vital role in realizing the vision of Industry 4.0. In the last decade, various machine learning methods have been implemented in manufacturing systems to improve their intelligence. However, few review papers on machine learning applications in CPPS have been published. In this context, this paper presents a survey of machine learning applications in Cyber-Physical Production Systems. Both bibliometric analysis and qualitative analysis have been conducted based on the related literatures published in the last decade. We identified the major research issues with respect to machine learning applications in CPPS, i.e. anomaly detection, predictive maintenance, fault management, efficiency, quality assurance, and scheduling. The review results show that although machine learning has been extensively applied in manufacturing, its applications in CPPS have not been widely studied. Based on the detailed discussions of the research issues and challenges, this paper indicates the current limitations of CPPS and demonstrates the great advantages and potential for applying machine learning in CPPS in future research.

Keywords—Cyber-Physical Production System; machine learning; review; anomaly detection; predictive maintenance; scheduling

I. INTRODUCTION

In smart manufacturing, Cyber-Physical Production Systems [1] rely on the developments of computer science, information and communication technologies, manufacturing science and technology. They consist of autonomous and cooperative elements and sub-systems from processes through machine up to production and logistics networks. The roots of CPPS include intelligent manufacturing systems, biological manufacturing systems, reconfigurable manufacturing systems and so on. CPPS can be regarded as a vital step in the development of manufacturing systems [2]. CPPS have some characteristics, one of them is that the data can be accessed and analyzed with the help of machine learning technologies, therefore the systems became more and more intelligent.

Machine Learning (ML) [3] is widely used in many fields for handling large amounts of historical data in order to make predictions or decisions. ML methods can be classified into traditional ML and deep learning (DL). The traditional ML methods mainly focus on study mechanism by imitating the way of human solving problems. The representative approaches include Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Artificial Neural Network (ANN), and so on. Deep learning is a class of ML methods, which employ multi-layers neural network to progressively extract features from massive data. There are many categories about ML methods. The common classification is by learning styles, namely, unsupervised learning, semi-supervised learning, supervised learning, reinforcement learning (RL).

In CPPS, ML methods are also used to analyze the collected data. From January 2012 to April 2022, there are 1005 publications related to CPPS. After Selection, there are 31 papers retained to review literatures of ML technologies applied to CPPS. However, there are few review papers about ML methods applying to CPPS in the era of Industry 4.0 [4]. Consequently, we propose the following three Research Questions with respect to the development of ML approaches applied to CPPS:

RQ1: What are the trends and focuses of CPPS research in the last decade?

RQ2: What is the current status of ML technologies in CPPS?

RQ3: What are the major research issues and challenges of ML technologies in CPPS?

This paper attempts to answer the above three questions by reviewing the publications about ML technologies used in CPPS. Section 2 summarizes the related literatures and analyzes the publications in the last decade in the aspect of annual publication volume, country and institution, and keywords. Section 3 introduces ML technologies researched in CPPS. Research issues and challenges are highlighted in section 4. Finally, the conclusions are summarized.

II. BIBLIOMETRIC ANALYSIS OF RESEARCH RELATED TO CPPS IN THE LAST DECADE

Over the past decade, research on CPPS related on ML covers a wide range of topics, and there are many publications. In order to make an investigation on research trend and focus on CPPS, this section provides a bibliometric analysis by utilizing the data gathered from Scopus database.
A. Annual Publication Volume

Fig.1 shows the annual publication volume of research on CPPS and ML approaches applied to CPPS from January 2012 to April 2022. The blue bars in Fig.1 show that the annual publication number is increasing year by year before 2019. From 2012 to 2013, there are few publications related to CPPS. In 2014, Monostori [5] enumerated the root, expectation, and main challenges, therefore, many researchers turn their eyes on the CPPS. From 2015 to 2019, the amount of publication has increased sharply. From 2019 to 2021, the volume of papers has small fluctuations. The orange bars represent the publications related to ML technologies applied to CPPS. From 2018, there are some papers about ML technologies published, and the publication quantity is increasing year by year. From the overall point of view, the papers employing ML algorithms are relatively few, therefore, there is a great space of introducing ML technologies to CPPS in order to improve the manufacturing productivity.

Figure 1. Annual publication volume about CPPS and ML technologies applied to CPPS. The orange bars denote publication volume of ML technologies applied to CPPS.

B. Country and Institution

The papers searched from Scopus database are contributed by the world researchers. These publications come from 11 countries sorted by the publication quantity in Fig.2. Germany has dominated the research on ML technologies applied to CPPS in the last decade with the highest publication volume (53%). China ranked at the second place with 11%. The other leading countries include Portugal (6%), Korea (6%), Austria (6%), respectively.

In the last decade, there are 36 institutions which contribute publications in the field of CPPS with ML technologies. OWL university of Applied Science ranked the first place, they published four papers. Some leading institutions, including Branch University of Trier, Darmstadt University of Applied Sciences, Donghua University, Fraunhofer Application Center Industrial Automation IOSB-INA, Fraunhofer IOSB-INA, University of Trier, all ranked the second place, they all published three papers.

C. Keywords Analysis

To figure out the trends of research on CPPS using ML technologies in the last decade, author keywords are used to analyze research trend. There are 99 keywords which are searched from Scopus database that authors provide. From the result, the keywords of top three include CPPS, Machine Learning, Industry 4.0. Deep Learning, Reinforcement Learning, and Anomaly Detection all ranked the fourth place. The following keywords include Predictive Maintenance, Cyber Physical System, Smart Factory, and Timed Automation. Table 1 shows the keywords and count.

<table>
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<td>Deep Learning</td>
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III. ML TECHNOLOGIES APPLIED IN CPPS

ML is an intelligent method which can learn new knowledge from the history data. Using ML technologies, equipment in CPPS is more intelligent than before. This part reviews the ML methods in CPPS from three aspects, a) traditional ML methods, b) DL, c) RL.

A. Traditional ML Methods Applied in CPPS

After investigated the publications, we find that in traditional ML methods, classification and dimensionality reduction are often used. Classification is a supervised method, namely, dataset should be labelled. The training data are used to get a model, and this model can predict the label of new data. There are many classification methods used in CPPS, such as, Logistic Regression (LR), Naïve Bayes (NB), Gradient Descent (GD), K Nearest Neighbors (KNN), DT, RF, SVM, and so on. In CPPS, there are some dimensionality reduction algorithms. When the features extracted are high-dimensional, they will cause various problems, such as sparse sample data, difficulty in distance computing. Principal Component Analysis (PCA), Dynamic PCA (DPCA), and Kernel PCA (KPCA) are introduced to solve the above problem.

B. DL Applied in CPPS

DL methods, part of a broader family of ML, are widely used in many fields, including Computer Vision, CPPS, and so on. Compared with the traditional ML
technologies, the results of DL are better due to the large amount of training data and computing power currently available. DL modern model is constituted of multiple layers, and different layer extracts higher-level features progressively. The methods applied in CPPS include Neural Network (NN), Autoencoders, Deep Belief Nets (DBN), Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), Restricted Boltzmann Machines (RBM), Siamese Neural Networks (SNN), Deep Neural Network (DNN). Part of these approaches are used for predicting maintenance and detecting fault and anomaly.

C. RL Applied in CPPS

RL is a branch of ML, which let the agents to take actions in an environment for obtaining the cumulative reward in order to replace the dispatching rule in a work center. RL usually has four fundamental factors, namely, Policy, Reward Function, Value Function, and Environment. There are many different classifications of RL methods. According to the strategy of agent action selection, RL methods can be classified into three types, such as methods based on value-based, policy-based, and actor-critic. The value-based method chooses the relevant action of max-value function, which can obtain global optimal value. The policy-based method mainly maximizes the cumulative returns to update the policy, and its policy function is easily calculated. The actor-critic method updates the strategy according to the value-functions, and it has fast training speed.

IV. RESEARCH ISSUES AND CHALLENGES

Based on a comprehensive review, we identify the following issues to be discussed. The issues include anomaly detection, predictive maintenance, fault management, efficiency, quality assurance, and scheduling.

A. Anomaly Detection

Anomaly usually means the pattern in data that is not in accord with expected behavior, such as abnormal timings, abnormal signal sequences, and abnormal signal values. Anomaly detection means that anomaly would be detected by ML methods.

In hybrid systems, the signals have two states, namely discrete and continuous, how to deal with the continuous signal is a challenging problem. Deep Network Timed Automaton was employed to discretize the continuous signal [6]. If there is a verification procedure, the results of this system will be better. Hranisavljevic et al. [7] made use of DBLs to transform continuous signals to discrete signals. The original discrete signals and discretized patterns were combined to analyze the behavior of system. If the behavior was inconsistent with the normal states, there was an anomaly to exist. The experimental data of high rack storage system and ATM card reader are used to evaluate the presented algorithm, and the results are promising. In production system, there are many behaviors related to timing information, however, the existing methods do not consider this vital information. Maier et al. [8] categorized the model formalisms, and evaluated them by specific features in order to judge that whether the model recognized and detected the abnormal events automatically. This method is effectively proved, which is faster than the existing approaches of timed automation learning. In the smart manufacturing system, there are abundant sensors data, analysis of these data can bring diverse benefits. But abundant data will create some problems, such as curse of dimensionality. Eiteneuer et al. [9] presented a two-phases algorithm by using autoencoder to reduce data dimension in order to detect anomaly. Three real-world datasets are employed to verify that the algorithm outperforms other methods.

In the traditional solutions, there are two methods to represent data in the one-class classification methods. The first one is to model the underlying data, and the second one is to identify an explicit boundary around the data. Li et al. [10] [11] proposed a new approach based on non-convex hulls to represent decision boundaries of one-class classification. The approach based on one-class SVM is used to detect the abnormal points out of the n-dimensional oriented non-convex hull. The artificial data and data sets collected from real CPPS are employed to verify the NoCH algorithm. The drawback of this algorithm is that it may encounter a high over-fitting risk due to the oriented non-convex hulls as the decision boundary. As the products become more and more complex, it leads that CPPS must deal with massive data. Intelligent assistance system is good at to solve these problems. Niggemann and Frey [12] introduced an analytical method based on data driven by three examples. The first example is about hybrid production system which is very common in real life. CPPS learn the regular pattern of hybrid timed automata to detect the anomaly behavior. The second example is about continuous production process. Self-organizing feature maps (SOM), as an unsupervised ML method, can handle the data without no prior knowledge to detect the abnormal events. The third example is about energy analysis. The proper solution is to analyze the real time data with ML methods, then compare the above results with history energy case of these equipment.

To handle anomalies in CPPS, the discrete and continuous data should be considered together, and a proper method can solve this problem very well.

B. Predictive Maintenance

In plant, equipment maintenance can reduce shutdown times and improve efficiency of production line. The publications of predictive maintenance are discussed from the aspects of classical ML methods and DL.

Smart textile industry as a high complex integrated factory has numerous kernel components which connect with thousands of spindles. Basit et al. [13] developed an intelligent diagnosis system by using Genetic Algorithm to support the decision system. This intelligent system can predict the abnormal cases and faults by using the states of each component, which can also locate position of the abnormal spindle. This approach is very effective in the real system. Schenkelberg et al. [14] researched the relationships between machines and faults data, maintenance, and profit. They proposed a method based on dynamic Bayesian network in order to predict the economic effect of maintenance on profitability and plan the maintenance activities. The object-oriented Bayesian
network can be used as the first step in the above approach to reduce system complexity.

In CPPS, data is usually high dimensional, while the frequency of faults and failure examples is not high. Existing methods do not consider that similar units will generate similar behavior including same data stream or same faults. Klein et al. [15] [16] used Siamese neural network (SNN) to handle the expert knowledge and proposed an attribute-wise encoding of time series based on two dimensional convolutions. The experimental results show that this approach is very effective. Bampoula et al. [17] presented a method based on LSTM-Autoencoders to estimate the remaining useful life and evaluate the condition of hot rolling milling machine. The experimental results show that this approach can reduce the redundant and prevent stoppage in the production line. This method can be further improved in the aspect of optimization of network hyperparameters. In the smart workshop, there are many intelligent equipment to create numerous data which can be used to evaluate reliability and predict maintenance of equipment. But there are some challenges to handle these data with new theories and optimization algorithms. Chen et al. [18] presented a DNN method to analyze the reliability of equipment with time series data. The experimental results show that the proposed method has high predictive accuracy when evaluating the reliability of a cylinder in the small trolley. This method can be generalized to deal with time serial data of other industrial fields.

Predictive maintenance is considered as a crucial factor of corporate performance. ML methods, especially DL, need massive data to train the model, but it is difficult to obtain sufficient data, and it is more difficult to label these data.

C. Fault Management

The competitive indicator of modern industrial economy is to improve production efficiency and reduce production loss. ML technologies can be employed to manage faults in order to quickly restore production line. The publications are investigated from prediction stage and detection stage.

In prediction stage, Zhang et al. [19] developed a predictive tool for fault by combining PCA and gradient boosting DT to predict faults before production stop. The experimental results are effective, and the accuracy is as high as 73%. The predictive tool can be further upgraded to diagnose the reason of faults. In condition monitoring system, DNN is employed to detect the faults in CPPS. But the adversarial examples can affect the performance of DNN. Specht et al. [20] introduced a method named CyberProtect to prevent misclassification against attacking by adversarial examples. The results show that the misclassification rate decreases significantly from 80% to 28%. The machine states should be analyzed to quickly detect faults in CPPS. This work is completed by hand, but the worker who has different experiences will create different effects. Engelmann et al. [21] proposed a new concept based on ML technology to identify the machine set-up actions. In the future work, the proposed method can be improved if the type of changeover can be further classified.

In detection stage, Webert et al. [22] reviewed the existing publications about the methods of managing procedure, and discussed the method for faults detection. In the future work, the automated methods of fault prioritization can be given more attention. In this complex system, worker cannot quickly find the errors by hand in most circumstance. Balzereit et al. [23] presented a data-driven method to recognize the causal dependencies in CPPS. This approach is constituted of two layers. The first layer handles the machine data with clustering analysis or PCA. The second layer deals with the result of first layer by the method based on rules, such as DT. This presented method is very smart, which can quickly find the faults.

From the above analysis, we can know that locating the position of fault is a challenging problem. Fault prioritization should be given more attention in the future.

D. Efficiency

Efficiency is an important key for a workshop. The publications are investigated from improving work efficiency and reducing costing.

About improving work efficiency, Shin et al. [24] presented a holonic-based mechanism for a self-learning factory by learning the past experiences to automatically predict the performance results in order to reduce the energy consumption in the production process of machine tools. In that mechanism, the prediction ability is supported by the ML and transfer learning methods. In a company, the changeover is a vital factor, which can affect the overall equipment effectiveness. In existing system, this work is completed by hand, but the worker who has different experiences will create different effects. Engelmann et al. [25] proposed a new concept based on ML technology to identify the machine set-up actions. In the future work, the proposed method can be improved if the type of changeover can be further classified.

About reducing cost, Bakaken et al. [26] proposed a multi-agent RL learning approach which can consider the policy of other participants and at the same time can make many participants work together. RL is very suitable for solving this kind of problem. The heuristic and simulation-based method is employed to find the optimal control tactics for distributed generation, but it is very expensive to obtain the exact model. The promising results are verified. The method can be extended to the highly complicated and dynamic environments. Machine vision is a high efficiency method, which has the advantage of judging and measuring by replacing the work needing human eyes. Kumar et al. [27] developed a cost-effective machine vision system to obtain the real-time data in order to improve efficiency. The proposed system can be used to detect geometric irregularities and workpiece surface, which greatly reduce the costing. Micro smart factory (MSF) is a modular manufacturing system which is a useful solution to reduce production cost by fast reconfiguration to adapt new production. But MSF has difficulties in optimizing the method of production. Park et al. [28] presented a production controlling method based digital twin and RL. This approach substituted the existing scheduling rules in the instance stage of MSF, which can be extended as a resilient solution to most industrial fields.
Some of these methods can improve efficiencies in single production line, but the feasibility of these methods in complex production line is not verified.

E. Quality Assurance

Quality assurance is a complex challenge in the data processing method; therefore, the approach must employ ML to analyze data in plants and processes.

Artificial intelligence is a very important method for quality assurance in production and automation technology. Wiemer et al. [29] presented a holistic method based on the V-model which could promote data quality on transaction data. In this method, most of relevant approaches in the participating disciplines were combined to create a new holistic process model. The presented approach greatly enhanced the security of operation in CPPS. The video-based method is very common in many industries, which can make the system including CPPS more intelligent and further improve production quality. Malburg et al. [30] developed an object detection system of video-based monitoring to detect workpiece and recognize failure circumstances. The detection accuracy was as high as 90%. In the future, the object detection module can be integrated into other systems to track the workpieces.

In the machine shop, part of equipment cannot be updated in time. This will bring a mounting loss. The network segregation technologies seem to be a proper solution to solve this problem. By incorporating ML technologies to automate network segregation, Saghezchi et al. [31] grouped network end-devices according to the traffic pattern. The experimental results show that the accuracy of the presented method is 99.4%. PCA can be integrated into the method, and the number of features can be reduced from 22 to 6 with no declining in accuracy. In CPPS, the man, production, and machine are connected to work together, therefore network security in this system is very important. If key nodes of the network are attacked, the production line, commercial service, and human life will have a devastating impact. Saghezchi et al. [32] employed ML technologies to detect network anomaly and construct different data driven model to detect the Denial-of-Service attacks of CPPS in Industry 4.0. The features of 45 bidirectional network flow are extracted, which can be used to create many labeled datasets to train and test the ML model. 11 ML methods, including supervised, semi-supervised, and unsupervised methods, are employed to evaluate performances of the proposed method. The results show that supervised methods have better performances than other methods.

In CPPS, there are some challenges in quality assurance. Some of the reasons are that data from difference sources with different data types and numerous parameters. When new devices are integrated into the conventional network, they will bring a series of critical research problems.

F. Scheduling

Scheduling aims to short time and improve productivity; therefore, the results of scheduling have a direct economic effect on the benefits of plant.

Job shop scheduling is one of the important issues in the manufacturing, especially for the system needing high flexibility. Kardos et al. [33] introduced a RL method to reduce average sale time of production order in the production system. The experimental results show that in dynamic environment application of RL can shorten the average lead time, further, the promoting effect will be more obvious if the environment is more sophisticated. In textile spinning, multi-automated guided vehicles play a vital role, which can save much time if the path planning technology is very effective. Farooq et al. [34] introduced an improved genetic solution to optimize multi-automated guided vehicles path. The advantage of this method is that fitness function is decided by the machine selection strategy and other factors. According to the simulation results, the total path distance is shortened. In smart manufacturing system, there are numerous kinds and quantities of productions. The production engineer has difficulty in effectively optimizing the production process by history records. Kuhnle et al. [35] implemented an order automatic dispatching system based on RL. In the real environment, the experimental results show that the approach is superior to the heuristic methods, and, it is very suitable to popularize in the semiconductor industry.

From the above results, we can know that scheduling processes is one of the main challenges in CPPS. To solve this problem, we can manage the real-time information of different devices and decentralize the decision-making of autonomous architectures and smart agents.

V. CONCLUSION

ML technologies have already been progressively applied to CPPS. CPPS and ML technologies joint together can improve the efficiency of the entire manufacturing process. This paper mainly reviews the publications from January 2012 to April 2022 with respect to ML technologies applied to CPPS. Based on the analysis of publications, the most prominent research issues are identified and discussed, including anomaly detection, predictive maintenance, fault management, efficiency, quality assurance, and scheduling. Our review shows that although ML has been extensively applied in manufacturing, its applications in CPPS have not been widely studied. Based on the detailed discussions of the research issues and challenges, the current limitations of CPPS have been identified and the great advantages and potential for applying ML in CPPS are demonstrated. The authors believe that ML is a key technology to address the research challenges in CPPS and it will greatly improve the production flexibility and efficiency of CPPS in the era of Industry 4.0.

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REFERENCES

Abstract—Robots are constantly becoming more integral in the day-to-day lives of humanity. To do this, they have to accomplish tasks autonomously in dynamically changing environments. Dynamic objects often need to be handled differently than static objects because they cause changes in the environment. To solve the problem, we propose a 3D-Multi-Layer-Multi-Representation map. The overall map consists of multiple layers with custom semantics and custom representation types. A static layer models the static environment using an octomap. A second layer models generic dynamic objects as bounding boxes. Semantic segmentation is used to decide which measurement belongs to a dynamic object. These are all objects of beforehand defined classes. This allows customized update strategies for both types of objects. The experiments show that this increases the accuracy and efficiency of the overall map, as well as the individual layers. A third layer, the human layer that stores the poses of all persons, is added to the map. This allows to precisely see what a human is doing in the exact moment. Using different representation types, the overall map does not only have a higher accuracy and efficiency, but also provides more in-depth knowledge of the scene.

Index Terms—Robotics, Mapping, Multi-Layer-Map

I. INTRODUCTION

In the modern world, robots are continuing to integrate more and more into our everyday lives. A variety of different robot types are introduced in different fields to enhance the quality of life of humanity. Cleaning robots help with arduous and time-consuming work, such as vacuuming or mopping [1]. There are also solutions for robots that can assist humans in accomplishing tasks, for example to fulfill manufacturing tasks [2]. Robots can also assist elderly or disabled people to guarantee them a higher degree of independence [3]. What those robots have in common is that they need to act and move autonomously in a dynamic environment. Maps are an integral part of achieving such an autonomous behavior. A map provides a comprehensive overview of the environment with the information required for different tasks, such as the areas the robot can navigate on.

There are several challenges when creating and maintaining/updating such maps. How a new measurement changes the map, depending on the measurement itself, the other measurements and the current state of the map, is determined by the update strategy. One major challenge is noise from the sensors that are used to construct the map. The sensor results fluctuate around the real position of a point. So, one task of a map is to fuse multiple noisy measurement to get the real position. However, the noise can vary for different objects. For example, visual-based sensors often struggle with windows or glass doors. It is still important to model their position accurately to avoid collisions, which might require another update strategy for those objects. There are other problems in the environment of a robot, such as dynamic objects. A typical example for a dynamic object that can be found around a robot is the human. But also simpler objects, such as doors and chairs, can regularly change their position. Motion results in measurements that are contrary to the current map; the old position is free and a new one is occupied. The same happens in case of noise, but while noise should not affect the map, motion should do just that. So, different update strategies are necessary for each case.

How the map deals with those problems also depends on the type of the map. Maps are an abstraction of the environment, reduced to the required information. The optimal representation depends entirely on the required information. Single points can mark positions. Bounding boxes or more complex polygons can mark areas. Meshes can give a detailed look on surfaces, and skeletons with multiple connected key points can show the posture and motion of non-rigid bodies.
Each representation type has its individual pros and cons and needs specific data/strategies to be constructed and updated.

We address these problems by introducing a 3D-Multi-Layer-Multi-Representation (MLMR) map, as shown in Fig. 1. This novel map representation type models the environment using several layers with different semantic meanings. This allows the application of a customized update strategy for critical objects, such as windows or dynamic objects, to increase the accuracy of the map. The layers can have different representation types, such as meshes or skeletons, to support the specific requirements of a particular layer and the tasks of a robot. Different tasks can also use only a subset of layers when necessary to filter out interfering information. For example, a localization can ignore the positions of dynamic objects to avoid a drift towards the new position of those objects.

The remainder of this work is structured as follows: First, Sect. II will give an overview of related work on maps, and how they try to tackle the above named problem. Then, Sect. III will describe how the MLMR map is constructed and how different layer can be designed. In Sect. IV several tests are run to evaluate the solution. Finally, Sect V gives a brief summary of this work and takes a look at future work.

II. RELATED WORK

Different kinds of maps are used for mapping and navigational purposes, each with its individual advantages and disadvantages. One rather straightforward type is the point cloud type. A point cloud consists of points belonging to the surface of any object in the environment. Those points are taken by a sensor that measures the distance from an object to itself. The local position is transferred to the global space and stored along with other measured points. Point clouds are easy to create but seeing as the number of points can become very high, operations on it can become time-consuming. One often used solution to reduce the search space for these tasks are grid-based maps. The key idea of grid maps is to discretize the space by placing a grid on it. All measurements within one grid cell are fused. The reduction of search space compared to point cloud depends on the chosen size of the cells.

Occupancy grid maps (OGM) were first introduced by Moravec and Elfes [4]. Each cell stores whether it is occupied or free. Probabilities are used to model the free and occupied state. Each cell that contains a measured point is updated as occupied, and the cells in between this measurement and the the sensor are updated as free. The update strategy and number of affected cells can vary for different sensors [5]. The probabilistic design allows filtering noise from unreliable sensors over multiple measurements. A few erroneous measurements do not directly result in a change of the map. Modelling the free space explicitly allows the reaction to changes in the environment. When an object moves away, the cell switch to free when it receives multiple free measurements.

OGM can be used as costmaps for path planning. Occupied cells and cells close to them have a higher cost than free cells. By minimizing the cost of a path, the shortest path on free area is taken. Lu et al. [6] propose to use multiple layer costmaps. Each layer has its own semantic meaning, and they are used to construct the overall master map. The influence of a particular costmap on the master map depends on its semantic meaning. Each map is updated independently of the other costmaps. For example, Lu et al. introduce a static map, that shows the static structure of the room. Additionally, an obstacle avoidance layer holds the short-term sensor data to quickly react on e.g. dynamic objects that are not in the static map. The individual update strategy also allows maps that do not depend on range sensors of the robot. For example, there could be a map with regions that a robot should not enter independent of the actual state of this area, so-called virtual borders proposed by Sprute et al. [7]. Those regions should not change because of incoming sensor data.

OGMs for the three-dimensional case [8] have the major problem that the memory usage grows rapidly for larger areas. Reducing the resolution saves memory, but a lot of information that might be necessary for navigation is lost. Hornung et al. [9] propose to structure the cell in an octotree structure. This increases the access time of the cell, but if the depth of the tree is constant, the access time is also constant. More importantly, the octotree structure allow the fusion of cells that have the same state. The cells of one parent cell can be fused to one big cell if they all have the same state. The parent gets the state as its child nodes, and its child nodes are truncated. The hierarchical tree structure also allows working on the map at different resolutions. This can speed up operations that do not need detailed information. Those operations can ignore the higher resolution cells. Global search problems can also take advantage of the tree structure. A first search can be performed on the lower resolution map, and the result can be refined on higher resolutions.

Our work proposes a solution that aims to combine the best from previous works to build a map for path planning and navigation in 3D space. We join the multi semantic layer design of the costmap approach with the octomap approach as the basic layer to model the static environment with as little noise as possible. The multi layer design is extended to support multiple representations, to optimally model the different semantics. This increases the efficiency of the map and allow it to store richer information. The different layer can share information to mutually increase the quality. The focus of this work is on the map representation itself and not the construction process, for example simultaneous localization and mapping. However, this process can also benefit from the additional data, such as semantic information [10].

III. MULTI LAYER MULTI REPRESENTATION MAPS

A. The Pipeline

The MLMR map is constructed following the pipeline shown in Fig. 2. The pipeline takes data measured by multiple sensors as input I. One of the inputs must be a distance sensor of some kind to measure the shape of the environment. In our case, a Lidar camera generates depth imaged \( I_D \) of the environment. To convert this image to a point cloud, the intrinsic parameters \( I_F \) of the camera are given. Another
important piece of information for mapping is the ego motion of the measuring device $I_T$ to insert the measured data in the map at the right place. An additional input is the RGB image $I_{RGB}$ congruent to the depth image.

At the end of the pipeline is the MLMR map $M$ that models the whole environment. The MLMR map consists of several layers. As a basic layer, an octomap $M_O$ is applied to model the static structure of the environment. This layer is the minimum requirement to allow navigation. Additional layers focus on challenging parts of the environment and represent them in the most efficient way for a given use case. The additional layers improve the overall map as well as the individual layers, increasing the accuracy and providing richer information. The measurements are processed separately for each layer. So, the performed steps depend entirely on the particular layer. However, information can be shared between the processing of the layers. For example, the generic dynamic object layer shares the information about its used classes with the basic map layer. The basic map can use this information to ignore those classes, since they are already stored in another layer. Before, generating the layers, one step is performed to support every layer, the semantic segmentation step. This step generates a semantic map based on $I_{RGB}$, that gives information about the class of the underlying pixel in $I_{RGB}$ and $I_R$. Furthermore, the semantic map is used to improve the quality of every layer.

**B. Static Layer**

The static layer, the octomap layer acts as is the basic layer for navigation. The construction of this layer uses $I_D$, $I_T$, and $I_{T_R}$. The first step is the filtering step. When no additional layers are used in the MLMR map, this step filters points in $I_D$ that are at maximum distance because they indicate erroneous measurements. When other layer are used, such as the generic dynamic object layer, more measurements may be filtered because their position is stored in another layer as well. Ignoring those measurements can increase the efficiency of an update and also increase the accuracy of the static map. The remaining points are used to construct the octomap. The points are transferred in global 3D space using $I_T$ and $I_{T_R}$. The occupied probability of voxels that contain a point are increased, and the probabilities of those in between the various points and the device are reduced.

The semantic information of the measurements generated previously is stored in the voxels of the octomap to provide richer information. Each voxel holds an array of class probabilities. Those probabilities are the average probabilities of all incoming measurements. The class of the voxel is determined by the class with the highest probability. This allows the distinction of different objects in the octomap layer, which is otherwise not possible without the additional time-extensive analyzing steps. The objects in an octomap consist of an unknown subset of all voxels that only show the shape of objects. There is no line between close objects in the map. The semantic information introduces this line between different objects in the octomap.

**C. Generic Dynamic Object Layer**

The generic dynamic object layer is added to the MLMR map to handle all dynamic objects that should not be stored in the static layer. A dynamic object is every object of a previously defined class, for example chairs, robots, cats, or humans. The individual objects are stored as bounding boxes. This representation is chosen because it models the at least occupied space of the underlying object using only eight points. The least occupied space is important for navigation purposes to avoid collision. The reduced number of points allows a fast construction of this layer and supports otherwise time-consuming operations, such as transformations, or tests whether a point is inside or outside an object. This layer stores the latest position of every currently seen dynamic object in a list and when an object disappears, the bounding box is removed from the list.

The first step of constructing the layer, shown in Fig. 2, is to extract the objects belonging to the defined classes. The semantic segmentation map is used to find these. This
map defines the classes of each measurement in \( I_D \). Using this classes, all measurements belonging to one object are extracted. This is done by applying the flood fill algorithm on \( I_D \) together with the classes from the semantic segmentation. Therefore, every neighboring measurement with the same class and a depth difference in \( I_D \) smaller than a threshold \( t_D \) are considered to be belonging to the same object. The points belonging to the same object are then inserted in the layer by calculating the minimum enclosing rectangle and adding it to the list of bounding boxes.

The object classes stored in this layer are given to the static layer. The static layer uses the semantic information to filter out measurements of those classes. Since their occupied area is stored in the bounding box layer, it is not required to store them in the static layer. The class information of the other classes is still stored in the voxels. Due to the slow changes of the probabilistic update, the position of dynamic objects are delayed anyway, and it is more accurate to use the bounding box position for navigation. This also increases the quality of the static layer itself because dynamic objects often cause additional noise. Every voxel that was at some point seen as occupied by a dynamic object must be explicitly removed by seeing it as free area again. Those who are not seen again will stay erroneously occupied.

### D. Human Layer

Another layer is added to the MLMR map to show its ability to provide a robot richer information by using different representation types. For this purpose, a human layer is added to the other two layers. Humans are often of special interest because the robot has to interact with them frequently. This layer is specifically designed to model them as poses. A pose consists of important key points of the human body, such as legs, arms, hips, shoulders, and a head. Analyzing those key points can provide information on what the person is doing, for example sitting, walking, or waving. With this information, the robot can react to specific gestures. Similar to the bounding box layer, the pose layer stores the current position of every currently seen human in a list of postures.

The first step to create the pose map detects humans and their poses by applying a pose estimator on the \( I_{RGB} \). The estimator generates the key points for every person in image coordinates. Those 2D points are converted to 3D points by taking an average depth value of the surrounding pixels in \( I_D \). When all points are converted, the 3D pose is added to the pose list. The semantic segmentation is used as additional input to filter false positive key points. When the class at the position of a key point in the semantic map is not human, it is probably a false positive key point and should not be included in the pose.

### IV. Evaluation

To test the MLMR map, three experiments are run. The first one focuses on the reduction of the noise in the octomap by filtering dynamic objects. The second experiment evaluates how the bounding box layer can increase the efficiency of the overall map. Finally, the last experiment tests how the person map can provide additional information.

The sequence for the test is recorded specifically for this approach to include many typically scenarios and challenges for autonomous robots. It shows a smart home scenario with multiple rooms, a variety of furniture, carpets on the ground and pictures on the wall. Multiple people are walking and sitting in the environment. Over the sequence, the number of people seen varies depending on the sequence. Additionally, the sensor that records the input data moves too. The sequence consists of 437 frames, each consisting of a color image, a depth image, a manually labeled segmentation image, the camera position and the intrinsic parameters. An example of the first three image types is given in Fig. 3. Some images contain strong backlight and motion blur, which reduce the quality of the segmentation and the depth measurements. The segmentation is labeled manually; there are 30 classes in total. The most important classes for the experiments are the human, couch, ground, wall, carpet, and door classes.

#### A. Experiment I

The effect of filtering dynamic objects in the static is evaluated by constructing a map from all frames with and without the of filtering dynamic objects. The final map should maximally store the final position of the dynamic objects. Removing those without a filtering step would require seeing the room without any dynamic object in the end. However, every other voxel that is occupied because of a previous

<table>
<thead>
<tr>
<th>Octomap processing steps</th>
<th>Noise voxels from dynamic objects</th>
</tr>
</thead>
<tbody>
<tr>
<td>without filtering and free space</td>
<td>10,840</td>
</tr>
<tr>
<td>without filtering</td>
<td>1,166</td>
</tr>
<tr>
<td>with filtering and free space</td>
<td>87</td>
</tr>
</tbody>
</table>

**TABLE I:** The numbers of erroneously occupied voxels caused by dynamic objects for different processing steps.

---

Fig. 3: The corresponding RGB image, depth map, and segmentation map from the used sequence.
position of a dynamic object is considered as a noise voxel. The first time, the map is constructed without filtering dynamic objects and without modelling the free space. Thus, every voxel that changed to occupied, for example because of a dynamic object, cannot switch back. This experiment acts as baseline, to show the number of voxels affected by dynamic objects, as shown in Tab. 1. These voxels can also be seen in the visualization of the map in the left image in Fig. 4.

The second run is performed without filtering dynamic object, but with modelling the free space. Occupied voxels caused by dynamic object should be removed by seeing the same area as free again. In the final map, this run has 1,166 erroneously occupied voxel caused by dynamic objects. The map is also shown in the middle image in Fig. 4. The results show that modelling free space reduces the noise drastically but still frequently fails to remove the voxels caused by dynamic objects. Whenever a region is not seen again, those voxels cannot be removed. In the sequence, there are three reasons why an area is not seen again. The first cause of the false occupied voxels on the ground, is that the camera simply does not see them again. The second reason that causes a part of the human voxel flowing in the air, is that the object moves towards the camera. The camera cannot see the free space behind the object, and therefore it cannot remove these voxels. The last reason for the falsely occupied voxels is caused by an open door behind them. The area behind the door is too far away to have reliable results. Without these measurements, the free space between them and the camera is not inserted, and the voxel cannot be removed. More extensive motion is required to remove those voxels, which is a general downside of removing dynamic object by only modelling free space.

The last run is performed with filtering dynamic objects and modelling free space. There are only 87 erroneously occupied voxel in the map, which can also be seen in the right image of Fig. 4. Since all measurements with the person class are filtered out, they do not cause any noise in the map. The 87 voxels are caused by measurements where the semantic segmentation results in the wrong class. Those voxels are still inserted in the map with their wrong class, which is why they cannot be seen as person voxels in Fig. 4. There they can only be seen as a hole or elevations on the ground along the path of the human. The only chance to recover those voxels is by modelling the free space, which fails in the 87 cases.

The octomaps in Fig. 4 also show the capabilities of storing the semantic segmentation in the voxels. This allows distinguishing objects from each other. There is a clear line between floor and couch and floor and wall. Also, very flat object such as carpets or pictures, that usually are on the same plane in the map as the floor or wall, can be seen now. The orange marked voxels of the carpet can be clearly distinguished from the green ground, even though no difference can be seen in the structure of the voxels.

B. Experiment II

The second experiment evaluates the ability of the generic dynamic layer to increase the efficiency of the mapping, while reliably modelling the occupied space of dynamic objects. The layer during runtime is shown in Fig. 5. Concerning the efficiency, the saved time and number of map updates in the octomap are observed. Modelling the objects as bounding boxes decreases the runtime from 433 seconds to 418 seconds. There are 672,859 less occupied update operations in the map, with a total of 15,887,070 operations. Still, the generic dynamic object layer indicates the position of every seen dynamic object without exceptions. In some cases, two objects close to each other are fused. However, the bounding box always models the at least occupied space of the underlying object because it contains ever measured point of that object.
Fig. 6: The pose layer allows distinguishing a walking person (left) from a sitting person (right).

So, by applying the second layer, the efficiency increases, while modelling all necessary information.

C. Experiment III

The last experiment evaluates the capability of an additional layer to provide richer information. The human layer is a prime example of such a layer. The goal of this layer is to provide the position and occupied area of humans. Additionally, it should give more in-depth information about what the human does. To test the ability to show the position of humans, the false positive and false negative poses in the map are counted. The poses are generated by the pose estimator from Fang et al. [11]. Filtering the generated key with the semantic segmentation results in an overall number of seven false positives and zero false negatives. Whenever a person is seen, there is a pose for it. So, the layer can show the position of human without an error. That the pose provides more in-depth information is shown in Fig. 6. The image shows that a sitting person can be clearly differentiated from a walking person.

Additionally, tracking based on the tracking-by-detection paradigm is applied. The position of humans at the current time step are associated to the positions of humans at the previous time step based on the average distance of their key points. When there is such an association, the ID of the previously seen human is passed to the new one. By doing so, it was possible to construct a path from the first seen position to the last seen position, without any interruption or identity switch of two persons. This information could be used to predict the future path of a human and avoid those regions for navigation.

V. CONCLUSION AND FUTURE WORK

In this work, we have proposed a new 3D-Multi-Layer-Multi-Representation map for mapping and navigation. The overall map consists of several layers, each with a custom semantic meaning. Depending on the data a layer stores, the representation type of the different layers can vary. This allows the best modulation for a given use case. We constructed a map, consisting of a static layer with an octomap representation and a generic dynamics object layer built by a set of bounding boxes. As shown in the experiments, the differentiated modelling of dynamic and static objects in two layers with a customized update strategy increases the accuracy and efficiency of the overall map as well as of the individual layers.

We applied a third representation specifically for humans that uses poses to store the current state of each person. This layer shows how additional layers can provide more in-depth information of the current scene. The pose indicates what the person is doing at any given moment. Simple tracking can also be applied to allow following the person through a scene.

In future work, the tracking can be extended to predict the path of humans. This information can be used by the navigation to avoid those regions. An additional layer can store a probability map with regions that may be occupied by moving objects. The information of the static environment can improve the prediction further, by excluding impossible paths, for example paths through a wall. Another possible step in future work can focus on exploiting the semantic information in the octomap. Robots could be instructed to avoid certain undergrounds, such as carpets. Furthermore, positions of certain objects, for example pictures on the wall, can be given as navigation goals to the robot. The layered design of the map allows endless extensions to the MLMR map that can store rich information for nearly any robotic task.

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An Overview of Human-Robot Collaboration in Smart Manufacturing

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Abstract — Industry 4.0, characterized as smart manufacturing, has revolutionized the industrial world with cutting-edge technologies such as collaborative robots and artificial intelligence etc. Productivity and efficiency are two key factors that determine the success level of manufacturing. Many manufacturers are eager to adopt adaptive, intuitive, collaborative and smart techniques to improve the production lines, including key manufacturing machines and other equipment. In this scenario, robotic systems are playing an increasingly vital role to decrease the need for human labour and increase automation level. Material waste is also decreasing as employing robots could provide both stability and accuracy during work. Currently, great research efforts are growing to respond to market size changes and customization processes. Researchers are focusing on enhancing the interactions between humans and robots in the work environment to exploit the benefits of human experience and the capabilities of robotic systems at the same time. This paper presents an overview of Human-Robot Collaboration (HRC) systems that are being employed in smart manufacturing to address the need for collaboration interactions between humans and robot. The research gaps, challenges and future work directions on HRC are highlighted and analysed towards smart manufacturing.

Keywords: Literature review; Human-Robot collaboration; Smart manufacturing; Cobot; Industry 4.0

I. INTRODUCTION

Human-Robot Collaboration (HRC) systems are increasingly used in the manufacturing sector such as the automotive and food industries. The trend of utilizing robots in manufacturing is changing. For now, researchers are making distinct efforts to exploit human experience, decision-making, and critical thinking abilities, with the robot’s strength, repeatability, and accuracy to perform complex tasks [1]. In the long run, human execution of repetitive, low paid and risky tasks will be limited within smart factories as the human operators will shift into the work area where different and advanced role responsibilities may be required [2]. Manufacturers are transforming their working environments to be smarter and more reliable in response to changing market requirements and custom-made products. As a result, flexible solutions are becoming increasingly important to address these challenges [3]. By employing HRC systems in smart manufacturing areas, the chance of enhancing productivity and efficiency is becoming feasible.

Human-Robot Interaction (HRI) in smart manufacturing areas is classified and highlighted in this overview study. Human-robot collaboration is the primary interest of this research since collaborative robots are being used in HRC systems to facilitate this interaction. Examples of industrial sectors are presented to show the advantage of implementing collaborative robots with intelligent sensing and vision systems in production lines. Future work and estimated research directions are presented lastly in this paper.

II. HUMAN-ROBOT INTERACTION CLASSIFICATION

Industrial robots are playing a crucial role in the competition among companies to augment production. In 2019, the International Federation of Robotics stated that the robot production industry was likely to grow by 13% worldwide[4]. Additionally, many companies are focusing on special features to be offered in the robotic system they are interested in, such as requiring more human-friendly, adaptable, and safer robots [5]. With the emergence of collaborative robots (“cobots”), companies of all sizes will be able to employ robots and enhance the productivity and flexibility of production processes. As a result, industrial enhancement can be influenced by integrating human-robot interaction phases. The robot needs to be working with or collaborating with a human operator[6]. Human-robot interaction is primarily determined by the task to be performed, shared workspace, direct contact, and simultaneous and sequential processes. So, the interactions between humans and robots can be classified into four main types [7, 8]:

• Coexistence interaction: human operator and robot are working without intersecting each other workspace. They can work on the same task but at different times and places. Their connection is limited only by existing in the same facility [9].
• Synchronization interaction: The same workspace might be shared by a human and a robot. Agents perform tasks by providing instructions to each other. In this scenario, the human operator and robot are looking at the same target in sequential order.
• Cooperation interaction: operators and robots can access the same technological resources to obtain information about the work task. But both are intending to perform their work interest.
Overlapping workspace can occur but there is no direct connection between them.

- Collaboration interaction: human operators and robots work together to accomplish the same task, which may be challenging. Direct contact between the system agents is possible and under their control.

Table 1 summarizes human-robot interaction features considering the shared contents of work tasks, direct contact, and simultaneous and sequential processes [10].

<table>
<thead>
<tr>
<th>Shared Content</th>
<th>Interaction</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Coexistence</td>
</tr>
<tr>
<td>Work Task</td>
<td>×</td>
</tr>
<tr>
<td>Direct Contact</td>
<td>×</td>
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<tr>
<td>Simultaneous process</td>
<td>×</td>
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<tr>
<td>Workspace</td>
<td>×</td>
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<tr>
<td>Sequential process</td>
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III. DEFINITION AND CLASSIFICATION for HUMAN-ROBOT COLLABORATION

In the HRC systems, the primary focus is to combine both human operator experience and robot abilities, while they should be physically separated during work [11]. However, collaboration interaction allows both operator and robot to always be in a direct connection and target the same task. The investment in developing collaborative working areas is increasing with specific interest given the ability of human operators to share and exchange information with robots to improve productivity and work efficiency [12]. This indicates the flexibility of creating a direct connection between the human operator and the robot [13]. HRC systems are designed to work intelligently as the production objectives are being delivered feasibly. Technological enhancements proposed in smart manufacturing areas allow the human operator to be working efficiently [14]. As a result, human operators will be able to influence the whole production process, especially in critical decision-making stages. On the other hand, collaborative robots can communicate with the human operator as they are built with intuitive interfaces and sensory systems. As such, they can support the operator in repetitive tasks, working in risky areas and other tasks requiring high effort and stability [15]. Additionally, ordinary programming approaches are enhanced through the fourth industrial revolution. Therefore, non-expert operators can work and communicate with the robot simply. Gestures, speaking and eye blinking etc can be used instead of traditional tools to interact with the robot during work. Therefore, the work is developed to be proactive instead of reactive [3].

Human-robot collaboration is determined by the agent’s effort dynamics, the nature of work concerns, human operator satisfaction, and the ease of critical information transferring between operators and cobots [16]. Accordingly, the HRC system can be classified into four main aspects that are outlined in Fig. 1.
A. Collaboration levels

The HRC system is organized depending on the operator and robot collaboration. Thus, researchers have made considerable efforts to standardize the collaborations between humans and robots in the shared environment. In [16, 17], the latest levels of collaborations in the HRC system are classified as follows:

- Independent: both humans and robots are focusing on different tasks separately.
- Sequential: both human operators and robots execute sequential operations at different times focusing on the same work task.
- Simultaneous: both working type and time will be the same, but different processes.
- Supportive: same workpiece and process will be carried out by both operator and robot in a synchronization manner.

B. Work roles

Depending on the type of task performed, human operators and robots have different roles in the industry [18]. In terms of [16], the HRC system can be examined by three different types of roles assigned to human operators or robots.

- Supervision: the relationship between human operator and robot is defined as master-slave. The human is the master.
- Peer: the human operator and the robot determine or maintain the work rate.
- Subordinate: the robot would be the master in this relationship type.

C. Safety control modes

For system safety, the protection of human operators is of paramount importance. In [19, 20], researchers identified the human operator faults, environmental conditions and engineering errors as the main reasons why failure is likely to occur in the human-robot working area. The International Organization for Standardization (ISO) has therefore developed safety standards to ensure the safety of both system agents during the work process. For instance, ISO 10218-1 and ISO 10218-2 were established for parts installation and operations safety [21]. ISO 15066 was released in 2016 with special safety control modes to enhance the integration area especially when operation parameters are derived, such as force and speed [22]. So, mandatory safety modes for a safe working area are strongly recommended for the HRC system installation. The safety tools classification is summarized as follows:

- Safety monitored stop: once the human operator enters a specified safety area, the robot will hold its position.
- Hand guiding: the human operator will be able to move the robot manually without the need for an external force source.
- Speed and separation monitoring: the robot’s force and speed are limited to the safety zones regarding the human operator’s location.
- Power and force limiting: the robot will be able to work within a certain range of force and torque. So, it will not be exceeding them to cause injuries.

D. Communication interfaces

In the HRC system, the communication and programming approaches are built more intuitively. The traditional programming and interfaces applied to control and drive robots are based on conventional coding [23]. Thus, the current HRC efficiency and flexibility require enhanced communication levels to adapt all the human movements and possible connection aspects with the robot during the work. Latest communication approaches are emphasized in [16, 24] to be developed and adopted. For instance: body gestures, facial/eye tracking, voice commands and haptic interfaces, etc.

IV. SMART MANUFACTURING

As part of Industry 3.0, automation solutions were focused on automating the production process and controlling components with sensors and actuators, allowing the human operator to observe production and make slight adjustments to the working environment [25]. The digitalization of the industrial world, however, has changed and affected manufacturing processes significantly [26]. Therefore, operating systems are highly recommended to be more intelligent to work in collaboration and adapt to the work conditions that are determined by market change [27]. The fourth industrial revolution is characterized by “smart manufacturing” as production has become more sustainable and digitally integrated [28]. Industry 4.0 enhancements have provided interesting terminologies outlined in Fig.2. Currently, manufacturers are focusing on enhancing the production levels by employing these features. So, the company’s strength will be increased against its competitors. Data exchange, value-added services, digitization and customized products and the green industry are the future of the industrial world [29]. These landscapes are enabled in smart manufacturing through four main approaches: big data, Internet of Things (IoT), cloud computing, and analytics [30]. As a result, Industry 4.0 adoption can...
integrate the whole manufacturing system resulting in smart products and services, smart manufacturing and working areas [31]. In addition, these approaches are reducing the cost and energy waste of manufacturing processes.

a) Smart manufacturing technologies

In smart manufacturing systems, there are more than ten intuitive technologies that are aiming to improve the work environment and the processes. Four technologies are highlighted to support the implementation of the HRC system in smart manufacturing. Through them, the system’s efficiency and productivity are enhanced significantly.

- Artificial intelligence (AI): As a result of the vast data generated from connected machines in the factory, the two subsets of AI are playing a significant role in analyzing and evaluating generated data to produce valuable information. Machine learning (ML) and deep learning (DL) are the main techniques representing the AI technology adopted in smart manufacturing [32].
- Augmented reality (AR): The remote assistant can be enabled to support the operator in improving the workplace as the production data are visualized [27, 33].
- Collaborative robots (Cobots): A new face of industrial robots can be working in complex working situations with a human operator in the workspace safely.
- Digital twin (DT): The manufacturing system and its components can be designed in a digital environment. So, engineers can exploit the gathered data to support human operators to conduct production without causing a gap in the production line as the digital twin is a virtual method that is used for validation while designing and implementing the HRC system [34].

b) HRC in smart manufacturing – Industrial cases

HRC system is implemented in many industrial sectors such as the food processing sector and automotive industry [35].

- Food industry

The food industry plays a key role in the European economy as some shops produce up to 10,000 meals daily [36]. The manufacturing cycle consists of three major stages: farming, production and finally, ready meals to be sent to the market. Food sector leaders are focusing on transforming the business strategy to be based on demand. This was especially important in the early stages of the COVID-19 pandemic, which negatively impacted supply chain resilience [37]. Therefore, the emergence of digitalization and industry 4.0 technological contributions are highly required to lead the transformation of food production to enhance the sustainability of this sector [38].

Robotics in agriculture is enhancing the collection of information about plants, soil and crop growth. In [38], it is stated that incorporating sensing approaches will increase the sustainability and flexibility of the robotic system, reflecting ultimately the entire production process. The implementation of sensors is increasing the system’s reliability through intelligent packaging, as sensors are built to provide real-time data about the expiry date of the products [39]. Fruit harvesting is utilized by employing a robot attached to a gripper camera to perform both picking and inspection processes[40]. By integrating an image processing system with the camera, quality control assurance can be enhanced. In addition, installing a vision system with the cobot will enhance the consumer confidence that this food is safe and clean as the camera will be able to detect foreign bodies like glasses or plastic. According to [36], in catering facilities, there are several processes (e.g., cooking, baking), and the production challenge lies at the end of the line. Food is processed in this area through manual steps, which are light and can be performed by humans, but they require a high level of repetitive ability, which the human worker lacks at this point.

The food industrial sector requires continuous advancements and developments. Challenges may arise while implementing Industry 4.0 technologies and trusting industrial robots to be collaborating with a human operator to perform tasks. However, a delay in implementing these systems will delay the opportunity to benefit from these technological advances, and therefore no tangible change will occur in the industrial sector. The HRC system adoption will gradually assure production processes are working ideally considering that some tasks can't be automated and require human expertise such as feeding machines with components to keep the work continuous.

- Automotive industry

Automotive is the largest industrial sector in the world. Considering the UK only, 3.7 million employees are working in the automotive sector and the economical contribution of the UK economy is about $26 billion [37]. In the automotive industry, assembly cells are playing an important role where 83% of production units involve assembly tasks [16]. However, some manual operations are still needing more flexibility and robustness to be performed efficiently; thus, relying on the industrial robot to perform these tasks alone may not be a practical solution as human abilities can’t be fully replaced [41]. Therefore, the focus is to combine both abilities of humans and robots to work in collaboration while safety is assured to prevent any accident during the work [22].

From [8], in the assembly stage, the collaborative robot is responsible for the screwing task through the sensing integration with a human operator who will be able to share the work area and task. Also, installing the vision system is allowing the collaborative robot to collect information about the working environment and the human intentions that will be used for further
improvements such as path planning and human movement predictions. As a result, the implementation of the HRC system is showing the needed capacity to perform complex tasks.

V. KEY FINDINGS AND FUTURE RESEARCH DIRECTIONS

In the age of industry 4.0, many opportunities are arising to get the benefits of emerging technologies [42]. AI, AR, DT and HRC approaches are employed in smart manufacturing to transform data processing into digital processing and controlling. Therefore, designing smart systems will lead to high-quality real-time data exchange, zero wasted efforts and better data management [43]. Focusing on HRC applications, HRC is the future alternative to conventional robotic and automation systems. As conventional systems require significant installation efforts and experts to program and control. In addition, old machines need to be upgraded so they can collaborate with HRC units in the production line [44]. HRC systems enable humans to work more efficiently and effectively with robots through intuitive interfaces [16].

The main target of employing HRC systems in the industry is to reduce the interaction complexity between humans and robots during work. Whereas, the implementation of collaborative robots in smart manufacturing systems is currently limited to simple and short-age production processes. In [36], the aim of employing a collaborative robot was only to increase efficiency through automating the catering process. However, collaborative robot technology requires intuitive approaches to design and program. Therefore, the system complexity is limiting the opportunity of expanding the use of collaboration robots in industry. So, the human operator’s confidence to be working with the new tools and technologies will be affected, especially when a work occasion occurs and requires the operator to share experience and take a critical decision. HRC system should be perfectly designed and built and human-robot roles need to be carefully designed and purely perceived [45]. In addition, existing HRC applications are designed mainly to increase productivity and efficiency levels with low safety insurance in the working areas [42]. Therefore, implementing collaborative robots in various industrial sectors is limited too. Consequently, the implementation of HRC in smart manufacturing requires a comprehensive design phase to enhance operational features. Future work should be focused on how to maintain safety and accessibility to reach the level of a flexible human–robot collaboration system in smart manufacturing. Additional effort relating to this research will be investigating to employ of novel concepts and algorithms for the better implementation of HRC systems in real-world industrial applications.

VI. CONCLUSION

The presented overview has firstly covered the Human-Robot Interaction (HRI). The collaborative relationship between humans and robots was then discussed by defining, classifying and characterizing the Human-Robot Collaboration (HRC) as a complete working system. The structural components of the HRC system were presented to emphasize the importance of the HRC system design. The overview has also highlighted smart manufacturing with a focus on four major technologies that emerged in the age of Industry 4.0. The food and automotive industries were discussed in this paper as two examples of industrial sectors. Collaborative robots are implemented in these sectors with the use of intelligent techniques such as sensing and vision systems. The efficiency of employing HRC systems in these industries was able to showcase the significance of HRC in current industries. The collaborative robots’ approach is a promising technology that can leverage manufacturing efficiency. By exploiting the human operator’s knowledge and the collaborative robot abilities, the production lines will take a new direction for further technical improvements. At the same time, it is very important to consider that the industrial world will require stable and intuitive solutions that can be adapted in many industrial areas. Therefore, the current challenges of HRC like complexity, rigidity, safety and interfacing need to be widely and deeply researched [46]. Adapting HRC in manufacturing with an assurance of the safety levels will be critical. The future HRC system must be carefully designed and developed to identify the roles of the human and collaborative robot to maintain constant levels of production if a technical issue occurs suddenly during work or working environments has to change abruptly.

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A Novel Control Architecture for Mobile Robots in Safety-Critical Applications

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Abstract—Mobile robots have become more and more common in public space. This increases the importance of meeting safety requirements of autonomous robots. Simple mechanisms, such as emergency breaking, alone do not suffice in these highly dynamic situations. A more sophisticated situational assessment and planning is needed as part of the high-level process control. This paper presents the concept of a safety-critical Robot Control Architecture for mobile robots based on a Hierarchical Finite State Machine. It expands already existing architectures by putting the focus on concurrency, interruptibility and code reusability to allow for straightforward implementation of safety mechanisms such as internal diagnostics systems. In doing so, this concept presents the template of a new type of state machine implementation. It is demonstrated with the application of a delivery robot in the scope of a German research project.

Index Terms—mobile robots, state machine, safety, software architecture

I. MOTIVATION

The operation of mobile robots in public spaces has become more common in recent years. An instance is the utilisation of mobile robots for the automated last-mile delivery of goods. Prominent examples are the delivery robots from Starship Robotics\(^1\) or Yandex\(^2\). When operating robots in public space, the aspect of safety is particularly important [1]. Here, robots are being confronted with more unforeseeable situations, dynamically changing environments and people inexperienced in the interaction with such machines [2]. To navigate these situations without posing a risk to itself or its surroundings, the robot has to meet strict safety requirements. This is especially relevant when official permit is required for the operation. These requirements can originate from local traffic rules, regulations, norms and cyber security guidelines [3]. They demand special considerations in the design and development of robotic hardware and software.

The overall level of safety of a robot can be derived from its functional safety and its safety of the intended functionality [3]. Functional safety refers to the systems promeness to internal errors as well as its capabilities to react and resolve these. Functional safety can be addressed by increasing the systems stability by thoroughly testing and reusing its code base as well as internal monitoring systems during runtime.

Safety of the intended functionality on the other hand refers to the system’s ability to safely react to unforeseen situations. The most fundamental requirement for this is to allow the robot to interrupt its current behaviour at any point in time. This demands a certain degree of concurrency to run safety checks while progressing the main task. Furthermore, simple mechanisms such as instantly stopping the robot do not suffice. The robot needs to be able to assess the situation, select a series of next steps and act accordingly. It follows that the robot’s behaviour in such situations must be part of the high-level process control, or Robot Control Architecture (RCA).

An RCA orchestrates a robot’s set of base functionality such as autonomous ride or obstacle detection such that the robot executes a predefined high-level task and provides a software architecture pattern to be used in the development process. To our knowledge, current RCA approaches do not sufficiently consider aspects such as concurrency, interruptibility and code reusability to support the implementation of safety mechanisms. We arrive at this conclusion in Section II after presenting and discussing the most popular RCA implementations. To address the shortcomings of these implementations, a new concept of control for mobile robots is introduced, which allows for a straightforward integration of safety features. The objective of this paper is to present the concept and its main mechanisms and discuss its benefits and drawbacks (Section III). The concept has been implemented in an exemplary application in a public space delivery robot within the scope of a German research project. The project and its main findings is presented in Section IV. Finally, Section V concludes this paper and presents the potential for further developments.

II. CURRENT RCA IMPLEMENTATIONS

A popular framework for developing robotic software applications is the Robot Operating System (ROS)\(^3\). Here, the robot’s functionality is implemented in so-called ROS nodes that can communicate in a bus-like infrastructure using either a publish/subscribe or a request/response communication pattern. Several RCA libraries for ROS including SMACC

\(^1\)https://www.starship.xyz

\(^2\)https://sdg.yandex.com/

\(^3\)https://www.ros.org/
[4], SMACH [5] and FlexBE [6] exist that allow for an orchestration of these nodes to fulfill a high-level task. This section will discuss to what extent safety features, such as interruptibility, are supported in these architectures. To do so, we will give a short introduction to Hierarchical Finite State Machines (HFSM), followed by the introduction of the single-method approach, the currently predominant way to implement HFSM based RCAs. Finally, we will discuss the advantages and disadvantages of the single-method approach with specific consideration of applications with strict safety requirements.

### A. Hierarchical Finite State Machines

Hierarchical Finite State Machines are a widely used concept in robot control architectures. Examples include [4]–[7] and [8]. Behaviour Trees (BT) can be considered the most prominent alternative to HFSMs. However, they still seem to be in the maturing process [9] and an overwhelming majority of robotic projects presented in the literature such as [10]–[13] and [14] use a HFSM based implementation as RCA. For that reason BT based RCAs are not considered here.

Software architectures based on HFSMs divide the system’s overall task into smaller subtasks, or states, that are sequentially connected by transitions. A state may have any number of outgoing transitions depending on the possible outcomes of its functionality. A transition from one state to another is triggered by an event. This can either be initiated internally, for example by the completion of a state’s functionality, or externally, for example through user input.

In contrast to FSMs, HFSMs allow for nested states, in which case an initial child state is defined that the system assumes when transitioning to its parent. Hierarchical states have been introduced to address the common critique that FSMs are prone to high complexity with a growing number of states and transitions [15].

### B. The Single-Method Approach

To the best of our knowledge, all current HFSM based RCAs use, in essence, an object-oriented approach with one class per state containing a dedicated method in which the functionality of this state is implemented. Based on the return value of this method, the state machine determines which transition to execute next. Current implementations that follow this approach include [4]–[6] and [16]. In the following, we will consolidate such implementations under the name single-method approach.

The single-method approach is well suited for implementing robotics tasks that can be separated into a set of subtasks that are executed strictly sequential. However, it shows drawbacks with regards to the system’s and its codebase’s concurrency, testability and reusability. The following will discuss these in further detail.

A system’s level of concurrency refers to its ability to do multiple computations in parallel or, on a broader scale, to execute multiple pieces of functionality at the same time. In real-live robotics applications with strict safety requirements, it is often not feasible to separate the robot’s task into strictly sequential subtasks. Especially when considering safety features such as internal diagnostics or teleoperated intervention, the system is required to execute a certain amount of background functionality in order to ensure the safety of the robot as well as its surroundings without blocking the overall task’s progression. It follows that RCAs need to support concurrency to a certain degree to allow for the implementation of safety features. By forcing developers to implement the whole functionality of one state in a single method, single-method approach RCAs do not provide a convenient way to execute certain parts of a state’s functionality concurrently. Although there have been efforts to introduce concurrency into HFSMs by either using orthogonals [4] or by introducing synchronization states [17], these approaches seem overly cumbersome when concurrency is required at the majority of the process’ states.

Another aspect of a robots safety is the stability of the software it’s running. The more stable the system is, the less likely it is that a malfunction causes the system to fail and possibly cause hazardous behaviour. A very common approach to ensure a system’s correctness and stability as well as to cope with its susceptibility to human error during the implementation process is to cover the codebase with unit tests [18]. In addition, unit test protocols can be used in technical assessments as part of the system’s proof of reliability. Implementing proper unit tests requires the system’s components to be loosely coupled and highly cohesive. A system is considered loosely coupled if its individual components have few references to one another. A highly cohesive system is one in which each component has a well defined and narrow range of functions.

The single-method approach encourages developers to join all components required in one state into a single method and thus promotes a tighter coupled and less cohesive codebase. This increases the implementation effort required to cover the codebase with unit tests as well as the error proneness of the system and the tests themselves.

One way to increase a systems testability is to ensure code reusability or to allow developers to reuse parts of their implemented functionality. Reusing thoroughly tested code wherever possible can drastically reduce the overall implementation effort and thus the system’s susceptibility to human error in the implementation process. In robotics applications it is common to see a system executing certain pieces of functionality, such as manoeuvring, object detection or interacting with it’s environment multiple times along the overall process. Additionally, other functions such as internal diagnostics are required to run continuously, across the whole span of the process. RCAs adopting the single-method approach offer a convenient way to reuse functionality on state level, in that single states can easily be duplicated and inserted at a different part of the process. On a broader scale, they also allow for the reuse of behaviour on a subsystem level, meaning the reuse of a set of connected states, even though this arguably requires some refactoring effort depending on the state machine’s interconnectedness [9].
However, they do not provide a convenient way to divide states into more atomic functions that run concurrently and to reuse this sub-state-level functionality. In conclusion, one can see that concurrency as well as a high degree of testability and code reusability of a robot’s software system directly contribute to a robots safety and thus are vital for its operation in applications with strict safety requirements. Current RCA approaches do not properly meet these demands. In particular, applications that require a technical assessment and an operation permit need a new RCA approach that provides better ways to develop a safe and stable system.

III. The New Architecture

This section will introduce a new HFSM-based approach to RCAs, which addresses safety requirements by allowing a higher degree of concurrency, code reusability and testability. In this approach, instead of having a single method for each state, the functionality of one state is defined as a set smaller functions or features. Each feature is implemented by a dedicated software component or feature node and executed concurrently. Feature nodes are activated and deactivated by a separate node called Mission Control which is responsible for the execution of the state machine functionality itself. Nodes can communicate with one another using a one-to-many publisher/subscriber communication pattern. To do so, messages are being posted on dedicated topics and nodes can subscribe to a topic to receive the respective messages. To carry out the defined process, Mission Control uses one topic to broadcast state transitions, another one to receive events that trigger these transitions.

In addition, this approach further decouples the state machine’s functionality and its State Machine Definition (SMD). Here, SMD refers the set of states and transitions that make up the representation of one specific process. It is written and stored in a dedicated file. The state machine’s functionality, implemented by Mission Control, includes loading the SMD file and based on its contents storing the system’s current state and executing transitions according to incoming events. Figure 1 shows a UML class diagram of a small system with Mission Control and one feature node. There are no dependencies of Mission Control node and feature nodes.

Fig. 1: A reduced UML class diagram of a system with Mission Control and one feature node. There are no dependencies of Mission Control node and feature nodes.

A transition is defined by its source and its target state as well as the event by which it is initiated. An optional data field allows developers to add static data to the transition that will be passed to the target state.

III-E will discuss the benefits and limitations of this approach. Mission Control and feature nodes. One can see that there are no dependencies of Mission Control and the feature node. The following sections will use the SMD file to discuss states and transitions (Section III-A) and error handling (Section III-B) in further detail. Mission Control and feature nodes will be introduced in sections III-C and III-D. Finally, Section III-E will discuss the benefits and limitations of this approach.

A. States and Transitions

The implementation of a state consists of two parts: the list of features required in this state and the actual implementation of these features. This section will focus on the first aspect, the latter one will be discussed in Section III-D.

The list of required or active features is part of the state definition in the SMD file. Listing 1 shows an exemplary definition of the state drive_to_coordinates. A state definition contains the active_features array (lines 6 to 11) in which each feature is referenced by its unique identifier. In this example, these are autonomous_ride, horn, localization and teleoperation. Note that no actual implementation is done at this point.

As this approach is based on a HFSM, it allows states to be made up of one or more child states. These can be added to the states array (line 4). If this is the case, one child state needs to be identified as initial_state (line 3) to be assumed on first entry. The transitions array (line 5) contains all transitions that originate from one of the children. Child states inherit the active_features from their parent state, which allows for a structured and concise definition of each state.

Listing 1: The state definition is made up of the list of active features and optional hierarchy definitions

```json
1 { 2   "drive_to_coordinates": { 3     "initial_state": "",
4     "states": [],
5     "transitions": [],
6     "active_features": [
7       "autonomous_ride",
8       "horn",
9       "localization",
10      "teleoperation"
11     ]
12   }
13 }
```

A transition is defined by its source and its target state as well as the event by which it is initiated. An optional data field allows developers to add static data to the transition that will be passed to the target state.
**B. Error Scenarios**

To allow the robot to react instantly and reliably in critical situations, this architecture introduces a global error state and error scenarios. One can think of an error scenario as an event that requires the robot to react immediately in a certain way, regardless of its current state. Listing 2 shows a definition of an error state with one error scenario in the SMD file.

Listing 2: The definition of the global error state consists of a list of active features as well as the list of error scenarios

```json

1 {  
2   "active_features": [  
3     "horn",
4     "localization",
5     "teleoperation"
6   ],
7   "scenarios": [{  
8     "name":  
9       "controller_connection_lost",
10      "trigger":  
11        "controller_disconnected",
12      "resolve_trigger":  
13        "controller_connected",
14      "inactive_features": [  
15        "teleoperation"
16      ]
17   }]
18 }
```

An error scenario is comparable to a transition in that it is initiated through the same event and trigger mechanism as transitions (lines 10 and 11) and it will force the system to assume a new state, namely the error state. It differs from standard transitions in that its definition does not require a source state. Instead, implicit transitions are created going from each non-error state into the error state, using the error scenario’s trigger. This leads to a reduced amount of implementation effort and a more readable SMD file. It further differs from standard transition in that it requires a resolve_trigger (lines 12 and 13). An event containing the resolve trigger of an error scenario indicates that said error scenario is resolved and that the robot can resume its previous state.

The global error state is the state the system assumes as soon as one of the defined error scenarios occurred. After assuming this state the system will collect additional error scenarios that occur and will only leave the error state once all error scenarios have been resolved. This allows the robot to automatically run the appropriate error recovery procedures. Much like other states, the definition of the error state contains a list of required features (lines 2 to 6). In the definition of error scenarios, developers can then state features to be removed from that list in case said scenario occurs (lines 15 to 16). This allows the system to deactivate certain functionality once an error in the respective feature node (see Section III-D) has been detected.

**C. Mission Control**

The Mission Control (MC) node is the central unit of the state machine. It is responsible for loading the SMD file and checking its content for syntactic correctness and semantic integrity. After that, the purpose of MC is to keep track of the system’s current state, execute transitions based on incoming events and communicate state changes to the feature nodes. Figure 2 shows how this interaction of MC and feature nodes is realized through the following two topics:

The topic mission_control/state_event allows feature nodes (see Section III-D) to post event messages that are used to initiate state transitions. Examples of such events are the arrival at a certain destination, a detected internal malfunction or user input. These messages contain a trigger that is matched with the transition triggers mentioned in Section III-A to determine the transition to be executed. These messages may also contain optional data in a key-value structure that allows feature nodes to pass on computational results to upcoming states.

The mission_control/state_change topic is used to broadcast state change messages of the system. These contain identifiers of the new and previous states as well as the list of features required in the new state and data that has been attached through previous state events.

Fig. 2: The Mission Control node and feature nodes communicate through state event and state change messages.

**D. Feature Nodes**

A feature node is a node that is responsible for executing the functionality of one or more features. Feature nodes subscribe to the mission_control/state_change topic and use these messages to determine whether or not their functionality is required. They use the mission_control/state_event topic to publish events that represent the results of their computation and internal sanity checks. Additional data that is required to execute a node’s functionality will be
passed in the respective message received through the mission_control/state_change topic.

The functionality of a feature node is typically either a one-time computation, such as a network request, or a continuous process based on one or more data streams such as object detection. Nodes of the former nature use the received state change messages to trigger their functionality once and finish their computation by informing Mission Control about their success or failure using a state event. Nodes of the latter kind simply store the information passed in state change messages and use it with each incoming data message to check whether their feature is currently required or not or unsubscribe and resubscribe the respective topic altogether. These nodes may publish multiple state events, one for each time their computations yielded a desired result. These processes are depicted in Figure 3.

E. Benefits and Limitations

The division of state behaviour into features that can be activated and deactivated on demand introduces a new way to reuse functionality not only on state level but also on sub-state level. In current, single-method approach based implementations this is not supported since the functionality of one state is bundled into a single function. Features can easily be shared across multiple states without requiring any extra implementation effort. The concept of features also leads to a more cohesive, loosely coupled and thus easier to test code base compared to existing single-method approaches. Since each feature is implemented in a dedicated node and executed in a separate process, this approach introduces concurrency at the core of its architecture. The extent to which this high degree of concurrency introduces additional computational load is still subject of ongoing research. Decoupling Mission Control and feature nodes allows for state transitions to be initiated at any point in time and by any part of the system meaning the process can be interrupted any time. This property introduces new ways to implement safety features and complex recovery routines into the high-level process. In other RCA implementations, developers are forced to add safety checks into the state implementation, which drastically increases its complexity. Since Mission Control and feature nodes are executed in separate processes, the overall system’s stability is increased. However, like other RCA implementations, this approach uses a central control unit that can act as a single point of failure. Finally, the separation of SMD and its implementation drastically reduces the effort to exchange SMDs and thus to switch from one use case to another. It also allows for a straightforward SMD syntax and semantics validation. However, the text-base definition can lead to long and complex files. Different approaches such as graphical interfaces or automatic generation should be investigated.

IV. REAL-LIVE APPLICATION

The RCA concept introduced in this paper has been successfully implemented in the TaBuLa-LOG research project. This section gives an overview of the project and outlines how the RCA was used to meet its safety requirements.

In the scope of the TaBuLa-LOG project, an autonomous delivery robot is developed and operated on public roads and sidewalks in the district Duchy of Lauenburg, Germany. The robot delivers internal mail between different branches of the local administration. To cover farther distances, it makes use of an autonomous passenger shuttle that has been implemented in the public transport in a previous project [19].

The robot was controlled by the presented RCA together with 18 feature nodes providing the functionality of 22 features. The code base was covered by a total of 345 unit tests. The final State Machine Definition is made up of 13 states, 21 transitions and 2 error scenarios. In the defined process, 10 features are reused at least once, 4 safety-related features were used in the majority of the process. A teleoperated intervention feature for example is used in 12 states and another, internal diagnostics system in all 13 states.

For the robot to be allowed to operate in public space in Germany it must comply with the respective laws and regulations and be granted permission by the local authorities. Naturally, safety considerations play the main role in the assessment process. During the life span of the TaBuLa-LOG project, German traffic law did not provide a legal framework for fully autonomous driving. Instead, it required an operator to monitor the robot and to be able to take control of it or stop it altogether at any point in time. In addition, a comprehensive safety concept that covers functional safety [20], safety of the intended functionality [21] and cybersecurity [22] is mandatory. A key component of the robot’s safety concept
is the internal diagnostics system that continuously supervises each of the robot’s subsystems. It monitors all components required to carry out the current step of the process and triggers error scenarios and thus safety or recovery protocols in case of failures or malfunctions. The highly concurrent and event-based nature of the proposed RCA allows the system to be interruptible at any step of the process not only by the operator but also by the internal diagnostics system and other safety features.

The final mandatory assessment of the robot and its safety concept was conducted by the German technical inspection agency TÜV Nord. The assessment was carried out in two steps. The first step focused on the robot’s hardware design with its range of functions being reduced to teleoperation and internal diagnostics such as monitoring of the connection to the controller. The second step of the assessment covered the automated ride itself and other safety-critical functionality such as object avoidance or right-hand driving. The developed robot passed both steps of the assessment.

V. CONCLUSION

In this paper, a new approach to Hierarchical Finite State Machine (HFSM) based robot control architectures (RCA) is presented for addressing safety concerns when operating in public space. These includes interruptibility, concurrency as well as code reusability and testability of the code base. It is shown that the single-method-approach adopted by current RCA implementations is not suited to meet these requirements. Consequently, a new approach is introduced. In this approach, the functionality of states is defined as a set of atomic functions that are implemented in separate, concurrent software nodes. The orchestration of these nodes into states is done in a separate State Machine Definition file which is parsed and executed in a dedicated node. This allows for straight forward ways to reuse functionality on a sub-state level and to implement safety features and complex recovery routines. With this approach, this paper presents a template for other robot developers, who are confronted with designing a control architecture for robots in safety-critical environments.

The proposed architecture was implemented, evaluated and demonstrated on a mobile robot in a real-live application in the scope of a German research project. The developed robot successfully underwent the technical assessments required to be granted a permit for operation in public space.

Future work will include a more comprehensive comparison with current RCA implementations to better quantify the benefits of this approach and an intuitive tool to design State Machine Definitions, as the current textual approach can lead to large and hard to comprehend files. In addition, much like other RCA implementations, this approach uses a central unit responsible for the execution of the State Machine which can act as a single point of failure and thus poses a threat to the overall system’s stability. This should be the subject of further research.

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Novel Software Architecture for an Autonomous Agricultural Robotic Fruit Harvesting System

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Abstract—This paper introduces a novel system architecture developed for a custom built, agricultural, autonomous fruit harvesting robot and presents proof of concept results for the system using the GMapping[1] SLAM algorithm. The robot has been developed for use in a state-of-the-art indoor vertical fruit growing environment. The system architecture and robot transformation coordinate frames are described before initial proof of concept navigational experiments are conducted and results presented. A global SLAM and local path planning novel navigational system is also proposed as part of future development of the system.

Index Terms—Navigation, Software Architecture, SLAM, Robotics.

I. INTRODUCTION
With advancements in the capabilities and reduced cost of unmanned ground vehicles and their peripherals, such as LiDAR and stereo camera sensors, robotic manipulator arms and drones, many new applications are becoming increasingly commercially viable.

One such application is the automated harvesting of fruit farms. This industry may benefit dramatically from the use of such technology, reducing both waste and increasing crop yield having a system capable of functioning 24 hours a day, providing constant harvesting when it is required.

This paper introduces a novel system architecture developed for a custom built agricultural autonomous fruit harvesting robot and presents proof of concept results for the system using the GMapping [1] SLAM algorithm. The mobile base is a Clearpath Husky A200 with two UR3 Robotic manipulator arms, a Velodyne VLP-16 3D laser scanner and UM7 Intertial Measurement Unit (IMU) (Fig.1). It is designed to operate autonomously in a large, unstructured, dynamic environment for autonomous fruit harvesting in a state-of-the-art vertical growing facility.

There are a number of challenges presented in this type of environment. The growing baskets are suspended from the ceiling and raised and lowered as required, as such the robot local operating environment frequently changes, ensuring no consistent structure for navigation. This required a software architecture to be developed with adaptability in mind, to facilitate the use of two manipulator arms in parallel with the mobile base, but to also enable rapid customisation for additional capabilities to be implemented as the system development progresses.

With these requirements, the most appropriate choice of software to develop the system would be Robot Operating System (ROS). This provides the necessary flexibility to integrate multiple components and keeps with the "Plug and Play" approach. This allowed for an adaptable base architecture to be developed, to enable navigation and the robotic arm functionality in parallel, whilst ensuring rapid customisation and integration is possible as additional aspects of the system are developed and completed and sensors/peripherals are added.

Through using ROS’s coordinate frame system, sensors and peripherals can also be rapidly connected and linked to the robot description of itself, its transformation tree, as and when required for each aspect of the system.

The following details the overall software architecture and components therein, the custom transformation tree linking each component and initial experimental results of the system, before discussing the next part of this work.

II. BACKGROUND AND RELATED WORK
The use of robotics in industrial and commercial environments has seen significant advancement in recent years, with improving capability developments and a reduction in cost in unmanned air vehicles (UAV) and unmanned ground vehicles (UGV) facilitating their applicability in a wide variety of settings. Many labour intensive, repetitive and often dangerous tasks can now be carried out by autonomous robotics, improving both efficiency, productivity and safety in these areas.
Autonomous robots have been employed for some time in hazardous tasks such as search and rescue, explosive ordinance disposal and geographic mapping in inaccessible or inhospitable environments, but are also increasingly finding use in more industrial and commercial settings such as automated delivery, warehouse management, manufacturing and for the purpose of this system in agricultural settings.

Agri-Robotics has been an active research field for a number of decades, as far back as the early 1900's, a frequent contribution being automated driving system utilizing GPS [2][3][4][5]. These systems often requiring human supervision if not direct involvement. But with improving autonomous unmanned robotics technology, many new applications are now becoming feasible and actively seeing development.

The application of autonomous robots in agriculture has many benefits, through increased productivity with continuous, efficient harvesting and reduced waste with pest detection and removal to name a few. These systems also have the potential to operate in synchronization, using multiple robots to further improve their capabilities and applications.

Navigation in an agricultural type of environment has many challenges. The environment itself being large, open and often with uneven terrain can lead to rapidly accumulating error in position. This drift if unaccounted for can quickly and dramatically reduce the system localisation accuracy. GPS has long been a solution for the automated traversing of farm environments [2], but with GPS often relying on the area being outdoor it may not always have the accuracy required in all settings and is not a reliable option for this system. This solution would not be suitable for this project as the facility is predominantly in an indoor, closed environment, and requires centimetre precision when traversing throughout each row of vertical hanging baskets in order for the arms to operate as intended and without damaging the fruit or vertical growing system.

There have also been efforts for GPS assisted, remote controlled agricultural robots as seen in [3]. This system is used for ploughing, seeding and leveling. The Thorvald II [6] system is an example of a mechanically modular agricultural robot, designed to be re-configurable for many different environments. This system again often rely on GPS which can not be guaranteed in the environment, or human input for control. RASberry [4], a system based upon Thorvald also using GPS as well as LiDAR for navigation, operates in ground based poly-tunnels, with its localisation based upon a combination of GPS and LiDAR data for movement.

The system proposed is designed to operate in an indoor vertical growing facility, with no rigid ground based structure nor guarantee of GPS being available. The accuracy of GPS if available would also be insufficient for the system to move between each narrow row as it finishes harvesting in each of them. It will also be required to operate entirely autonomously without outside assistance from a human.

A potential solution considered for these requirements was through natural or artificial beacons[9][10]. This type of navigation uses artificial or natural way points such as landmarks, coloured markers or WiFi to determine and update a systems location. This type of way point system may not require prior knowledge of the environment, but may need constant maintenance in a dynamic agricultural setting. This would not be suitable as the interior environment itself is dynamic and frequently changing in regard to the position of the vertical growing baskets. This may render natural or artificial landmarks or coloured markers unreliable as there visibility would not be guaranteed with the frequently changing position of the vertical hanging baskets, with WiFi also being unreliable if not unavailable in this environment. The terrain being soil, dust and plants would also effect the visibility of ground based beacons, reducing their reliability, requiring both time and labour to maintain.

The most appropriate solution for this system is that of a combination of global simultaneous localisation and mapping (SLAM) for larger, less absolute accuracy dependent areas, and a precise local path planning controller for navigation between rows and to keep the robotic arms in operational range.

SLAM has been an active research area for many years with a wide variety of differing methods developed using multiple combinations of sensors[1][7][12][13][14], including LiDAR with efforts such as GMapping[1] and Google Cartographer[7] and RGB-D camera based systems such as ORB-SLAM[11] and RTABMap[8]. These systems use sensory information to determine a robot’s pose whilst keeping track of its position as it moves through an environment, simultaneously localising and updating the map as it moves throughout an area.

With this move-update method, the frequently changing environment can be mapped and localised to in real time. A LiDAR based SLAM system for global navigation combined with an RGB-D camera based local path planning method would provide an ideal solution for this type of dynamic environment. This paper presents a novel software architecture design and implementation for the facilitation of two robotic manipulators working in parallel with a robotic base for strawberry harvesting in a state-of-the-art vertical growing facility. It demonstrates the system functioning through experimentation and provides a platform for the implementation of a novel perception system, and the continued development of a novel autonomous navigation system, as part of a larger project. The whole robot system is shown in Fig.2. The vertical farm shown in Fig.3.

III. SYSTEM OVERVIEW, SOFTWARE ARCHITECTURE AND COORDINATE FRAMES

The software architecture presented was designed for a custom built UGV base, the requirements being the parallel operation of two robotic arms and the base and flexibility for additional components to be implemented as the project progresses. The base is a mobile platform (Husky A200 Robot) providing the mobility for robotic arms, and the two arms are 6 DOF manipulators (UR3), each of which has a custom built gripper for strawberry picking (see Fig.2).

The architecture has been developed primarily with modularity
in mind, to enable each component to be integrated into the system as development is completed, whilst also enabling future developments and improvements to be connected to the system. The modules of the system can function independently or combined to form the larger system, whilst maintaining a constant functional prototype. An overview of the system architecture is shown in Fig.4.

A. Architectural Components

The system is separated into multiple independent components as follows:

- Perception System
- User Interface
- Navigation and Robotic Arm Control
- UR3 Arm Control
- Navigation Control

The UGV’s components are interlinked with the perception system providing coordinates for both fruit harvesting and the navigational controller to ensure the arms will be in the correct operational location relative to the vertical baskets in each row. The system can be thought of in layers. The first is the perception system required for accurate positional control. The second is the local positional control to keep the mobile base in the correct position in each row for the perception system to operate. And the third is the global positional control to ensure the robot can move in and to the correct area in the global environment. The system is controlled through a user interface, enabling a user to access both independent module functionality, such as navigation or each arm, as well to begin and exit autonomous operation.

B. Perception System

The perception system is the basis of this project. It is an existing system developed for this custom robot as part of this project, with the systems architecture and navigation control being developed to facilitate its functionality. The robot is required to operate in a large, open environment when moving to each row and to operate in a precise localised environment when moving through each row to ensure the fruit is not damaged and the arms are in the correct location to harvest the fruit. The perception system utilises a deep neural network for each arm to detect and calculate the joint angles to harvest the fruit using a custom built gripper.

C. Navigation, Robotic Arm Control and Multiprocessing

The navigation and UR3 arm control class combines the separate modules of the system and passes these as functions to the user interface. The process threads from each module are called in this class in their respective functions. This enables the base, one or both arms to function independently or in parallel dependent on the robots operational requirements. With each robotic manipulator being controlled by a separate deep neural network, the arms are separated into left and right arm classes with their respective functions and can be operated both in parallel and independently, as with the mobile base.
D. Navigational Control

The navigational control is designed to keep the robotic arms in position relative to the vertical hanging baskets. This requires both local and global positional control as the robot moves throughout the farming facility and through each row. This has been separated into three classes, a base navigational controller for basic operation, a local positional control class, and global simultaneous localisation and mapping (SLAM) control class. The global SLAM software uses the laser scanner to generate a 2D topological map of the global environment as a proof of concept for the navigation system overall, to determine its capability in at first a laboratory setting before an agricultural environment.

E. Robot Description and Coordinate Frames

The navigation system is built using the ROS software libraries. The robot being entirely custom built meant a new description of itself was introduced to know where each component and sensor is in relation to the rest of the robot. The description ensures that each component transformation is following the same coordinate system as the robot moves. This can be done through a ROS’s coordinate frames system. A visual representation of the robot and its transformation tree is shown in Fig. 5.

F. Transformation Tree

A transformation tree represents a coordinate system for all components in a robot. When the robot moves, all of the robots components are then transformed around a single point of reference, removing the need to keep track of each component. This system also enables rapid customisation for additional sensors and peripherals such as adding additional sensors, and enables multiple robots to operate in the same world environment using multiple maps. The transformation tree representing the components of this robot is shown in Fig. 6. The coordinate system follows the ROS convention of:

- **Earth Link**: A global link that can enable multiple robots to operate using multiple maps.
- **Map Link**: A global frame of reference generated by the robot’s laser scanner.
- **Odom Link**: A local frame of reference obtained through the robot’s IMU.
- **Base Link**: A frame of reference related directly to the robot, a point on the robot to which all other components are linked.

The relevant links in the transformation tree for this robot can be see in detail in Fig. 6. The base link is the center of the top plate of the mobile base, to this the front and rear bulkheads are linked. The velodyne mount is then linked to the center of the front bulkhead, with the Velodyne sensor and IMU linked to the velodyne mount. The robot and its sensors are initiated by a launch file when the robot is started. The custom description is passed to the control launch file to initialize the connected sensors and the base launch file to initialize the required ROS nodes when the robot is started, giving it an accurate representation of itself.

![Fig. 5. Visual Representation of the Robot with Transformation Links](image)

![Fig. 6. Transformation Tree](image)

IV. NAVIGATION IN AN AGRICULTURAL ENVIRONMENT

The robot is required to move throughout the farm environment and identify specific rows to traverse between whilst maintaining a constant distance between the robotic arms and the fruit plants, this whilst ensuring it does not damage the fruit or lose its position to ensure the perception system can operate.

This requires a novel navigation system to be developed based on both global and local path planning requirements. A global requirement is to ensure the robot travels to the correct row, This may be periodically, one after another or decided ahead of time by a drone or other robotic system at
Another location in the global environment. In order to navigate to the required location, the system must constantly update its perception of the area as the vertical hanging baskets frequently move position whilst it is operating and the density of plants in the baskets also frequently changes, this meaning a pre-existing map may not accurately reflect the current environment. When the vertical baskets move, areas below them previously occupied are no longer.

The second requirement of the navigation system is to ensure the robot keeps within a set distance of the plants in order for the perception system to operate. If the robot moves too far from the fruit or too close, it may lose its view and be unable to function, or damage the fruit or growing system itself. To ensure the robot stays within these parameters, a novel solution for local path planning and following is also a requirement. With the fruit plants in the environment between each row varying in density, as such the laser sensor was tested in between a row to determine if it was capable of detecting the plants whilst travelling through the row. The final requirement of the navigation system is to be dynamic and adaptable to obstacles in the environment. The farming facility has many employees, potentially other robotic systems and the vertical hanging baskets changing position, This requires the robot to be able to detect and avoid these obstacles as they move.

**B. Global SLAM result in Laboratory Environment**

The initial laboratory testing of the system was to determine whether the system architecture and transformation tree as a whole was correctly implemented. To complete this, the GMapping SLAM algorithm was integrated into the software and was able to generate an accurate 2D topological map of the laboratory environment as shown in Fig. 8.

![Fig. 8. Laboratory SLAM 2D Map](image)

**C. Global SLAM and Local Path Following in a Farm Environment**

The robot initial performance in the farm environment also proved to be successful. The purpose of this experiment was to determine if the laser scanner is capable of detecting the vertical hanging baskets either side of each row as their vertical position frequently changes.

The system was able to determine these with reasonable accuracy as seen in Fig. 8. But this would not be precise enough to ensure the robotic arms are able to operate. The local path planning will be implemented using a novel RGB-D camera system, being developed as part of this project and the navigation system in our next step work.

![Fig. 9. Vertical Farm Row](image)

**A. Navigational Experiments**

With the system architecture and robot description complete, the system was then tested in both a laboratory and agricultural environment, using the GMapping SLAM algorithm. This initial testing was to ensure the system functioned correctly with each component of the software tested independently and in parallel. The robot navigational capabilities were also tested using the GMapping SLAM algorithm. The laser scanner (Velodyne) is used to scan a 2D map. A scan is shown in Fig. 7. The 3D scan and SLAM are under development.

![Fig. 7. Velodyne Lab Outline](image)
environment also has translucent areas at its boundaries which may have impacted the laser sensor’s ability to detect a solid boundary.

![Fig. 10. Global SLAM in Farm Environment](image_url)

Though the initial testing of the system in a laboratory environment and a smaller local environment such as a row in the farm were reasonably successful, the system was incapable of mapping the larger global farm environment as shown in Fig. 10. The drift rapidly became an issue in the larger environment with the GMapping[1] algorithm unable to compensate for the lack of boundaries in close proximity. Nevertheless, the purpose of this experimentation was to determine the basic navigational capabilities of the robot and its ability for each component to function in parallel. To that end the proof of concept was successful, whilst also determining the limits of the system.

V. CONCLUSION

This paper details a novel software architecture for a custom built unmanned ground vehicle. The system was tested in both a laboratory and farm environment, with the experimental results showing the system to operate as expected. The experiments were conducted as a proof of concept for continued development of the system.

With the initial system built and tested, the next components to be developed are an improved 3D global SLAM capability using a LiDAR sensor, and an additional RGB-D camera to be connected to the Velodyne mount. A novel local path planning system will also be developed for accurate navigation in between rows.
Pattern Analysis of COVID-19 Based On Geotagged Social Media Data with Sociodemographic Factors

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Abstract—The world has faced a catastrophic global crisis of COVID-19 caused by coronavirus and called for analyzing the affected areas in any country. The study helps to understand how the second wave affected different states in India concerning sociodemographic factors, such as population density, economy, and unemployment rate. During the lockdown, the sudden impact of staying at home has led to increased social media usage, where people expressed their opinions on multiple topics. Twitter provides timestamp and sometimes spatial information of the tweets generated. Using the geotagged Twitter dataset, a study in India is performed in this work considering the second wave of COVID-19, which occurred approximately from April to June 2021. It analyses the temporal and spatial patterns of the geotagged tweets generated from all the states during the period mentioned above. Also, topic modeling and sentiment analysis are performed to understand the concerns discussed by the people. We use different states’ sociodemographic factors and machine learning algorithms to divide the population into high and low categories to understand the topic prevalence in different socioeconomic groups. This study reveals that the low socioeconomic groups have shared more concerns, urging the government to help fight the COVID-19 pandemic.

Index Terms—COVID-19, Geotagged tweets, Sociodemographic factors, Spatio-Temporal patterns, Topic modeling.

I. INTRODUCTION

COVID-19 is an acute respiratory disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). India has taken strict measures during three consecutive waves to stop the transmission of the virus by implementing a lockdown all over the country and making strict quarantine rules for the affected and the susceptibles. However, the second wave of COVID-19 occurred in March-June, 2021, rising with several new variants of COVID-19, such as the delta variant and possible side effects of the treatment like black fungus. Social media is a critical medium for health-related queries for public health emergencies, including the massive COVID-19 pandemic. Especially Twitter has the edge over other social media platforms, which provides quick real-time content and access to networks of related conversations via hashtags. Moreover, Twitter can be used to determine trends in local public responses to a health crisis when socioeconomic status is considered. Sociodemographics of a population are different features such as age, economy, education, and gender, which will help differentiate the group of people. Understanding the public responses and reactions during the pandemic across India with socioeconomic disparities helps in future policy making.

The study focuses on learning Twitter users’ opinions and concerns during the second wave in different socioeconomic groups. The geotagged Twitter dataset is considered for the study; the tweets from April to June 2021 originating from India are only considered. Spatial and temporal patterns of the tweets are studied to understand where the tweets are generated from over different periods. Topic modeling is analyzed to discover the themes communicated by users. Sentiment analysis helps observe the percentage of tweets favoring COVID-19, against it and neutral. A supervised classification approach is used to classify the socioeconomic groups concerning factors such as population density, economy, and unemployment rate. Different machine learning algorithms are used in the study, such as Support Vector Machine (SVM), Random Forest, Gradient Boost (XGB), Multi-layer Perceptron (MLP), Artificial Neural Network (ANN), and Hybrid Random Forest with Linear Model (HRFLM). Classifying the population into high and low categories based on socioeconomic status will give a deeper analysis of the topic prevalence in different states. Therefore the main objectives of the study are:

- Analysing spatial and temporal patterns to understand when and at what period the most number of tweets are generated during the COVID-19 second wave.
- Sentiment analysis to find out the users’ emotions during the pandemic.
- Topic modeling to understand the concerns discussed by users and topic prevalence of different socioeconomic groups concerning COVID-19.

This manuscript is organized as follows: Section II addresses the background of the work, Section III highlights the dataset and methodologies, and Section IV details the experimental analysis and results. The conclusions are highlighted in Section V.

II. LITERATURE SURVEY

An ample amount of work in the fields is directly related to social media data analysis for different applications. Baucum et al. [1] have looked at how panic and distress language changed over time with the proximity of the Orlando shooting

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incident in 2016. Hence, panic words declined significantly over the period. The pattern was highest near the attack, whereas distress words declined slightly over time and higher distance from Orlando. Jiang et al. [2] have aggregated tweets to the county level relying on the location data from each tweet by analyzing how often each user in each area has sent tweets. Wang et al. [3] have investigated the educational dataset from Twitter. They have looked at individual data, aggregated it as a function of time or location, and used spatio-temporal patterns, sentiment, and content analysis on a large geotagged Twitter dataset to illustrate the impact of COVID-19 on the education system. They have also captured the most critical matters, such as funding and tuition, were the concerns of students. Roy et al. [4] have discussed that there is a connection between people’s migration patterns and sociodemographic factors in the context of a pandemic. Social distance appears to be a useful approach for reducing COVID-19 transmission. They focused on sociodemographic indicators, including the economy and race of the population in the USA. Bijo et al. [5] have developed COVID-19α which is an interactive tool that allows epidemiologists and policymakers to easily undertake interesting comparative research by visualizing symptom-related tweets in a Spatio-temporal manner. Gao et al. [6] have integrated large-scale mobility data to create a human mobility tracking web page to show how mobility has changed across the country as a result of statewide stay-at-home orders. Flanagan et al. [7] have analyzed vulnerability as a social condition or a measure of demographic groups’ resilience in the face of tragedy. The vulnerabilities were divided into four main themes: socioeconomic status, household composition, disability, minority status and language, housing and transportation. Mueller et al. [8] have explored NeuralGenderDemographer. This convolutional neural network model labels the user’s binary gender and uses Latent Dirichlet Allocation to analyze the gender of the users who actively tweeted during the MeToo movement. Mandel et al. [9] have deduced location and gender from the retrieved tweets and used the classifier to evaluate the socioeconomic factors of the messages in the discussion. By classifying all the remaining messages, they analyzed sentiment trends over time by gender and region. Su et al. [10] have demonstrated that Twitter may be used to discover individual-level reactions to infectious disease outbreaks while considering the effects of socioeconomic resources and disease prevalence at the local level.

The related work primarily deals with Twitter data analysis or the sociodemographic factors; a very limited number of work have been done relating the Twitter data analysis with sociodemographic factors on a local scale.

III. DATASET AND METHODOLOGY

This section briefly discusses about the dataset and methodologies for this study related to the Twitter data analysis.

A. Dataset

The dataset of geotagged tweets is collected from IEEEDataport [11]. We have used the TWARC API to hydrate tweets, i.e., obtaining the complete details of tweets, such as date and time, tweet id, full text (tweet), user name, coordinates, name of the place, and the country where it originated. The tweets are filtered for India from April to June 2021, during the second wave of COVID-19. All these tweets are geotagged, i.e., containing the latitude and longitude of the user posting the tweet. The number of tweets in April, May, and June are 2208, 2584, and 1392 respectively, hence 6184 tweets in total.

<table>
<thead>
<tr>
<th>Month</th>
<th>Number of Tweets</th>
</tr>
</thead>
<tbody>
<tr>
<td>April</td>
<td>2208</td>
</tr>
<tr>
<td>May</td>
<td>2584</td>
</tr>
<tr>
<td>June</td>
<td>1392</td>
</tr>
</tbody>
</table>

The dataset for the sociodemographic factors are collected from official government websites of India, such as CoWIN [12] for the confirmed number of cases, IndiaCensus [13] for population, PLFS [14] for economy and unemployment rate. The factors considered for the supervised classification are population density, unemployment rate, Economic status (GDP), and confirmed number of COVID-19 cases.

B. Methodology

The methodology of the study in Fig. 1 is divided into four phases, as follows: data collection and pre-processing, text processing, supervised classification of sociodemographic factors, and topic prevalence of socioeconomic groups.

![Figure 1. Sequence of workflow for twitter data analysis](image-url)
1) Collection and Pre-processing of Tweets: The initial process consists of extracting the geotagged tweets database from the dehydrated Twitter data [11]. The dehydrated Twitter data contains the unique tweet id of COVID-19 tweets. This dehydrated data is passed as input to a dehydrator application (TWARC) to extract the original tweet and the metadata, such as user name, country, state, and geolocation of the device. The steps followed in pre-processing are:

- Remove all the url punctuations, such as https, ://, and www, present in the tweets
- Remove contractions from the data, which is the shortened form of a word
- Remove punctuations, such as comma, colon, semi-colon, period, hyphen, and many more commonly used punctuation marks
- Perform lemmatization to reduce inflectional forms
- Restrict the language of tweets to English
- Remove stop words such as a, an, the, which are used for making a sentence clear for humans to understand, but they do not have any value in terms of the context

In this work, pre-processing plays a crucial role as the extracted data may contain many unwanted components with missing values and special characters in the middle of a tweet. It is essential to handle such data and convert it into a structured format for meaningful analysis.

2) Spatio-temporal Pattern Analysis of Tweets: The Spatio-temporal pattern analysis of the tweets includes the following components:

- Daily tweet distributions for the temporal analysis
- For each tweet, interpret the UTC zone to the local time zone based on the spatial information provided by the tweet
- Display the volume of tweets according to the location information for the spatial pattern of the tweets

3) Sentiment Analysis: Tweets are a significant source of sentiment data. This is useful in assessing public sentiment for a wide range of issues. For understanding the emotion of tweets, the TextBlob library [15] is utilized, which takes a different approach to sentiment analysis; it is rule-based and involves a pre-defined list of classified terms. Furthermore, emotions are determined using semantic relationships and the occurrence of every term in a sentence, resulting in a more accurate output.

4) Topic Modeling: Topics are commonly occurring terms in a cluster of documents or corpus. The topic model is helpful for information retrieval from the vast corpus and unstructured data. Topic modeling is a statistical technique for finding the topics in large documents with the help of regular expressions and dictionary-based keyword searching techniques. For example, for the topic search of “social media”, the topic model should result in examples like Twitter, Instagram, Facebook, and LinkedIn. We have used the technique namely Latent Dirichlet Allocation (LDA) [16] for topic modeling.

The LDA algorithm assumes the corpus has numerous themes, each generating words based on a probability distribution. LDA analyzes which topics or themes would construct a meaningful document. Mallet variation of LDA [16] is implemented because LDA uses a variational Bayes sampling algorithm that is faster but gives a less accurate score when compared to mallet LDA, which uses a Gibbs sampling algorithm [17].

Once the stop-words are removed from the corpus, data is lemmatized. Using lemmatized words, a dictionary is formed. This dictionary will give us a list of unique words in the corpus. Once the dictionary is ready, the document term matrix is created. Every row in the document term matrix represents a document, and each column represents a word. This document term matrix is the input to the LDA model.

5) Supervised Learning with Sociodemographic Factors: The sociodemographic factors such as the Population density, Unemployment rate, Number of confirmed COVID-19 cases, and Economic status of the state, considering the GDP of Indian states, are fit to different supervised classification models (MLP classifier, Support Vector Machine, Gradient Boosting, HRFLM, Neural Network, and Random Forest) to predict high, low categories of economic groups. Previous research has revealed that the tree-based classification models, such as Random Forest (RF), Gradient Boosting, and Support Vector Machine (SVM), perform better in infectious disease transmission modeling. As a result, these models are employed to classify socioeconomic groups concerning the sociodemographic factors considered. A MLP classifier, an Artificial Neural Network with one hidden layer, and a Hybrid Random Forest with the linear model are also implemented to compare the accuracy of the tree-based classifiers.

Gradient Boosting (XGB) is a decision tree that builds trees one by one, with each new tree assisting in correcting errors caused by the prior tree. However, it tends to overfit when the model complexity increases. Random Forest uses random data sampling to train each tree independently. Unlike other classification algorithms, such as SVM or Naive Bayes Classifier, the Multilayer Perceptron Classifier and Artificial Neural Network relies on an underlying neural network and finds the relationship between linear and non-linear data to perform the task of classification.

The HRFLM (Hybrid Random Forest with Linear Model) [18] method is implemented to improve accuracy. Previous studies that have been conducted for models, such as SVM, RF, ANN, and MLP, have resulted in limitations in feature selection. In contrast, the HRFLM approach uses all attributes without regard for feature selection. After pre-processing, the top three Machine Learning algorithms suitable for the data are selected for further analysis.

IV. RESULTS & ANALYSIS

A. Spatio-Temporal Patterns

The temporal patterns of the tweets observed in Fig. 2 are visualized daily and how the tweets originated from India during three different months is also shown. We observe that the tweets peaked during May 2021, when the second wave was on the rise, and declined towards the end of June 2021, when the second wave ended.
The spatial patterns of the tweets are visualized in Fig. 3 on the Indian Map, which enabled us to observe the pattern of tweets spread across India. We have assumed that more tweets originating from a state indicate that it is highly affected because all the collected tweets are related to the topic COVID-19. Most tweets originating during the second wave are from highly affected states, such as Karnataka, Maharashtra, and Delhi. Significantly fewer tweets are observed in Northeastern states.

B. Sentiment Analysis

For a sentiment task, TextBlob [15] (refer to section II) returns a float in the range [-1.0, 1.0], where -1.0 indicates negative polarity and 1.0 indicates positive polarity. This score can potentially be zero, which denotes a statement’s unbiased evaluation because it does not contain any terms from the training set.

The number of tweets concerning each sentiment category is plotted and visualized in Fig. 4. The Neutral tweets counts are 1094, 1223, 633, Positive tweets counts are 80, 1041, 607, and the Negative tweets counts are 313, 350, 152 for the months of April, May and June, respectively. The sentiment analysis of all three months shows an increase in percentage of positive tweets every month. However, the percentage of negative tweets decreased from April-May to June gradually during the end of the second wave. It decreased gradually when the number of cases declined in June 2021.

C. Topic Modeling (LDA)

Topic coherence measures a how easily interpretable a single subject matter is to the humans. These measurements distinguish between subjects that might be semantically interpretable subjects and subjects that might be artifacts of statistical inference. Initially, we give the number of topics to the model as 20. Then we adjust the number of topics and check the corresponding high coherence score to select the optimal number of topics. The LDA model, which gives the best coherence score, is considered for further processing of visualizing the topics.

The coherence scores for April, May, and June are calculated for the initial twenty topics as 0.4413, 0.4230, and 0.5386, respectively. However, the model is trained to find out the best coherence score by varying the number of topics. The best coherence score is found for an optimal number of topics 282 are 0.7228, 0.6746, and 0.7498 for the respective months.
Table II
TOPICS IN INCREASING ORDER OF IMPORTANCE DISCUSSED IN APRIL TO JUNE, 2021

<table>
<thead>
<tr>
<th>Month</th>
<th>Topics</th>
</tr>
</thead>
<tbody>
<tr>
<td>April</td>
<td>vaccine, dose, state, pfizer, cdc, stay-home, covishield, 1st, astrazeneca, surge</td>
</tr>
<tr>
<td>May</td>
<td>case, rise, spike, stock, sensex, daily, issue, blood, clot, concern</td>
</tr>
<tr>
<td>June</td>
<td>delta, variant, death, black, fungus, chennai, demand, fight, hit, lakh</td>
</tr>
</tbody>
</table>

The different topics represented in Table II for each month suggest the themes spoken in that particular month by the Twitter users. For example, in April 2021, there was a discussion about different types of vaccines being rolled out in the world, such as astrazeneca and in May 2021, there was a discussion about the stock market, sensex, and the month of June 2021, there was discussion about black fungus and delta variant of SARS-CoV2. Therefore, different themes were observed during different periods.

D. Supervised Classification

Including sociodemographic factors (Population density, Unemployment rate, Economic status of the state considered by GDP) and the number of COVID-19 cases in the socioeconomic group is classified using a supervised classification approach involving six separate algorithms. The number of COVID-19 cases is used as the response variable whose variation is dependent on the rest of the other variables. For supervised classification, we have used two types of labels, high and low socioeconomic states. The state is considered to have high socioeconomic status if the GDP (usually ranging from 0-20.92%) is above 10.39%, and the Unemployment rate (usually ranging from 0-29.6%) is lower than 7.6% and others as low socioeconomic states. The data was split into train and test sets for the model implementation, with 70% of the data being used for training and the rest for testing each model.

Table III
ACCURACY SCORES OF THE MODELS

<table>
<thead>
<tr>
<th>Model</th>
<th>Accuracy Score (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>80.183</td>
</tr>
<tr>
<td>RF</td>
<td>90.461</td>
</tr>
<tr>
<td>XGB</td>
<td>91.679</td>
</tr>
<tr>
<td>MLP</td>
<td>84.485</td>
</tr>
<tr>
<td>ANN</td>
<td>95.452</td>
</tr>
<tr>
<td>HRFLM</td>
<td>96.888</td>
</tr>
</tbody>
</table>

Table III shows that the HRFLM technique has the highest accuracy compared to the other classification models.

Table IV
ACCURACY ANALYSIS OF THE CLASSIFICATION MODELS

<table>
<thead>
<tr>
<th>Metrics</th>
<th>SVM</th>
<th>RF</th>
<th>XGB</th>
<th>MLP</th>
<th>ANN</th>
<th>HRFLM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precision</td>
<td>0.868</td>
<td>0.921</td>
<td>0.924</td>
<td>0.881</td>
<td>0.935</td>
<td>0.948</td>
</tr>
<tr>
<td>Recall</td>
<td>0.742</td>
<td>0.875</td>
<td>0.906</td>
<td>0.817</td>
<td>0.943</td>
<td>0.954</td>
</tr>
<tr>
<td>F1 Score</td>
<td>0.800</td>
<td>0.897</td>
<td>0.914</td>
<td>0.847</td>
<td>0.938</td>
<td>0.950</td>
</tr>
</tbody>
</table>

The misclassification rates reported by the models are specified in Table IV. F1-score, Precision, and Recall metrics are included as part of the analysis. The precision of machine learning models is defined by the correctly classified positive samples, i.e., true positives (TP) divided by the total number of true positives (TP) and false positives (FP). In Table IV, precision is shown, and the highest precision is 0.948, reported by the HRFLM.

\[
\text{Precision} = \frac{TP}{TP + FP}
\]

The percentage of true positives found out of all the optimistic predictions is called recall. In Table IV, recall values are shown, and the highest recall is 0.954, reported by HRFLM.

\[
\text{Recall} = \frac{TP}{TP + FN}
\]

F1-score considers both recall and precision. It is defined as the harmonic mean of precision and recall. Table IV shows the highest F1 score of 0.950 for the HRFLM.

\[
\text{F1-Score} = \frac{(\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}} \times 2
\]

E. Topic Prevalence of Socioeconomic Groups

After classifying socioeconomic groups using supervised techniques, it is observed that the states with a large number of vulnerable people, a high unemployment rate, and a low GDP are considered as the low socioeconomic groups. In contrast, the states with fewer unemployment rates and high GDP are considered high socioeconomic groups.