A cyber-physical robotic mobile fulfillment system in smart manufacturing: The simulation aspect

K. L. KEUNG [1,2], C.K.M. LEE [1,2,*], Liqiao XIA [1], Chao LIU [3,*], Bufan LIU [4], P. JI [1]

[1] *Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hung Hom, Hong Kong SAR, China*
[2] *The Laboratory for Artificial Intelligence in Design, Hong Kong SAR, China*
[3] *College of Engineering and Physical Sciences, Aston University, Birmingham B4 7ET, UK*
[4] *School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore*

Email Address: dicky-kin-lok.keung@connect.polyu.hk (K. L. KEUNG), ckm.lee@polyu.edu.hk (C.K.M. LEE), liqiao.xia@connect.polyu.hk (Liqiao XIA), c.liu16@aston.ac.uk (Chao LIU), BUFAN001@e.ntu.edu.sg (Bufan LIU), p.ji@polyu.edu.hk (P. JI),

Acknowledgment

This work was supported by *the Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong* (RK2F), *Nanyang Technological University*, Singapore, and *Aston University*, United Kingdom. Our gratitude is also extended to the *Research Committee and the Department of Industrial and Systems Engineering,* The Hong Kong Polytechnic University, Hong Kong and The Innovation and Technology Commission, and The Government of the Hong Kong SAR, Hong Kong, for their support of this project (PRP/002/19FX/K.ZM31), the Laboratory for Artificial Intelligence in Design, Hong Kong SAR, Hong Kong (Project Code: RP2-2). The authors would like to express their appreciation to *the anonymous case company* for their assistance with the data collection.

CRediT authorship contribution statement

K. L. KEUNG: Writing - Original Draft, Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Project administration, Visualization, Writing - Review & Editing. **C.K.M. LEE**: Writing - Review & Editing, Supervision, Funding acquisition, Conceptualization. **Liqiao XIA**: Methodology, Software, Validation, Formal analysis, Writing - Review & Editing, Visualization. **Chao LIU**: Conceptualization, Methodology, Writing - Review & Editing. **Bufan LIU**: Writing - Review & Editing, Formal analysis, Validation, Visualization. **P. JI**: Supervision

Declarations of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

A cyber-physical robotic mobile fulfillment system in smart manufacturing: The simulation aspect

Abstract

Incorporating mobile robots into the production shop-floor helps realize the concept of smart production, and it is considered one of the approaches to enhance manufacturing and operational efficiency and effectiveness by academics and industrial practitioners. This paper develops a cyber-physical robotic mobile fulfillment system (CPRMFS) for tool storage in smart manufacturing. The purpose is to enable Just-in-Time material transfer on the production shop-floor during manufacturing. A decentralized multi-robot path planning adopts graph neural networks (GNN) in the new proposed CPRMFS. We compare multiple classification algorithms for the mobile robots' action prediction, including proposing a spatial-temporal graph convolutional network (ST-GNN) under these circumstances. We also extend the research with the enhanced conflict-based search path planning algorithm. Compared with the existing literature, ST-GNN, under the enhanced conflict-based search, could obtain higher accuracy with an average value of 90% under different scenarios. The practical applicability of the proposed system with the further consideration of ST-GNN is further explained as a reference for manufacturing practitioners who looked out on a confrontation of introducing the mobile robot solutions in their manufacturing site with the goal of enhancing the operation processes.

Keywords: Robotic mobile fulfillment system, cyber-physical production system, smart manufacturing, graph neural networks

1. Introduction

Smart manufacturing is defined as the 'optimal use of labor, material, and energy to produce customized, high-quality products for on-time delivery with technology-drive approach' [1-3]. Generally, a smart manufacturing system can be identified based on several characteristics: context awareness, modularity, heterogeneity, compositionality, and interoperability [4-6]. Furthermore, the system contributes towards resilient and sustainable manufacturing through resource and energy management [7]. In order to attain these characteristics, the system is heavily dependent on existing manufacturing paradigms and emerging IT, which also requires various enabling technologies [8, 9]. With the increasing connectedness brought along by globalization, the field of manufacturing is also emerging to adopt new changes in the industry. The idea of cloud assisting for manufacturing was first proposed in 2010; however, numerous definitions exist for the term 'cloud manufacturing', depending on the author's priorities regarding which aspect those wish to focus on [10, 11]. Fisher, et al. [12] attempted to provide a clear definition through the concepts highlighted by the word cloud, defined as 'the concept of sharing manufacturing capabilities and resources on a cloud platform capable of making intelligent decisions to provide the most sustainable and robust manufacturing route available.' A general concept named cyber-physical production system (CPPS) has been proposed and separated into four layers[11], whereas the manufacturing resource layer is related to both physical resources and capabilities needed during the product's lifecycle.

The virtual service layer is responsible for virtualizing identified resources and repackaging them into cloud services, the global service layer for controlling cloud operational activities, and the application layer acts as the interface between the user and cloud resources [5, 6, 8, 13-20]. The use of digital twins (DT) on shop-floors has also gained significant attention, as it allows for real-time performance monitoring thru captured data and increased situational awareness of the manufacturers [6, 21, 22]. Guo, et al. [22] proposed a shop-floor logistics and manufacturing synchronization model under GiMS. The synchronization model has similarities with rolling horizon flexible production, as both foci are on real-time feedback from field devices. Therefore, the proposed models, assisted with CPPS, allow for fast decision-making regarding logistic and manufacturing problems[23-29].

The concept of smart manufacturing assisted with cloud, DT and Internet-of-Things (IoT) is an emerging trend in the manufacturing industry, and the advantages posed by CPPS, particularly its customer-centric nature accompanied by dynamic, reconfigurable resource provision and production, on top of on-demand customization. Ren, et al. [30] resulted in numerous research and model being proposed to harness the potential of this manufacturing paradigm. Liu, et al. [8] investigated the integration of Industrial Internet-of-Things (IIoT) under the cyber layer and proposed a service-oriented plug-and-play gateway solution. Such a system can facilitate data acquisition, communication, storage, query, and analysis between field-level and cloud platforms. The IIoT gateway collects real-time data from field equipment using an application programming interface and transfers the unified, time-stamped data to the cloud database. The gateway provides users with data privacy protection by selecting specific data to stream to cloud servers, with efficient data management supporting decision-making. A similar system was introduced by Tao, et al. [31] that also combines IoT with cloud computing. The cloud-based production system with an IoT-based service system consists of four layers similar to that proposed by Xu [11]: IoT, service, application, and supporting layer. The team suggested the system facilitates the realization of 4C (Connection, Communication, Computing, Control) operations, plus an intelligent collection of data throughout the manufacturing whole-life cycle. Furthermore, cloud-based production and IoT-based service systems enable machine-to-machine transmission, with service-specific information processing supporting the proactive monitoring and predictive maintenance [6, 32-36].

To further achieve proactive monitoring and intelligent manufacturing, machine learning is a viable method for accurate process recognition training [24, 26]. To reduce the long training time with a large training sample, Liu, et al. [33] proposed using deep transfer learning (DTL) for manufacturing process recognition with IoT devices. The convolutional neural network (CNN) based system uses a pre-trained model to extract low-dimensional features, which will be the base of a fine-tuning adjustment strategy applicable to the entire system. The DTL model achieved higher accuracy than existing models, such as CNN, with similar resource costs. Aside from DTL, there is various method for deep learning, as described by Wang, et al. [37], such as Restricted Boltzmann Machine, a two-layer network with a symmetric connection between units and automatic features extraction. Auto Encoder, an unsupervised learning algorithm that allows for data compression in case of high dimensionality input, and Recurrent Neural Network, features topology connections and is suitable for learning with sequence data [5, 34, 35].

With robotics' rapid development and implementation, academics and industrial practitioners have extensively used robotic-assisted manufacturing systems to reduce human involvement and errors and achieve higher operational efficiency and effectiveness [5, 17, 18, 24, 38]. However, those CPPS with IoT is adopted for the manufacturing process only, without further consideration of the materials and tools storage, not to mention the adoption of mobile robots to reduce overall human involvement and improve the material transfer efficiency. The current literature nonetheless combined or embedded the robotic operation system (ROS) during the manufacturing processes in the cloud-based CPPS. With the adoption of mobile robots assisted in the shop-floor material transfer operation, proactive monitoring of the material and work in process or product movement could be more accurate because of reducing human errors. Given these contemporary industry issues and challenges, the Robotic mobile fulfillment system (RMFS) is a robotic-assisted warehouse operation system for storage purposes. Keung, et al. [39] and Keung, et al. [40] proposed a cyber-physical system (CPS) in an RMFS with a multi-deep layout. The purpose is to utilize the spaces in the warehouse because of the adoption of multiple mobile robots' cooperation with reasonable conflict resolution methods [39-43].

Still, the existing robotic-assisted method is only considered in a traditional warehouse operation. The extension of this storage and picking method could be further extended into the manufacturing system with storing and retrieval processes for reducing overall human involvement and accidents. The manufacturing system operation includes 3D printing tools and parts storage, raw materials storage and usage, finished goods storage, and picking. The robotic-based moving system could enhance overall manufacturing efficiency and effectiveness. The ROS and DT-based nearly real-time simulation system could be further embedded into the CPPS for more precise scheduling and assignment. In contrast, the production orders and schedules could be consolidated from the original CPPS. Therefore, we propose a cyber-physical robotic mobile fulfillment system (CPRMFS) for tools storage in smart manufacturing and improve the graph neural networks, composed of CNN, for decentralized multi-robot path planning from Li, et al. [44] and Li, et al. [45], to achieve a typical layout that authors came up through manufacturing theoretical and practical contemplation. This paper explores the potential behind the RMFS and CPPS in manufacturing tools storage assisted with multi-robots from the perspective of new opportunities for reducing human errors, involvement, and creating value.

The organization of this article has been outlined as follows. First, state-of-the-art research by reviewing the CPPS is presented, and a research gap is also summarized in **Section 2**. Second, a system architecture of CPRMFS considering the 3D printing and mobile robot operation is proposed in **Section 3**. 3D printing is a case example adopted in this manuscript. The purpose of adopting mobile robots' operation in the manufacturing system is to achieve higher mobility, scalability, and the benefits of digitalization and servitization. **Section 3** further introduces the details of the context types of the selected case study. A typical layout is also presented for simulating a manufacturing system assisted with multi-mobile robots. **Section 4** demonstrates the numerical studies of the decentralized multi-robot path planning with different instances under multiple classification algorithms as a comparison. The results show that the further application and development of the existing works provide insight into current and future industrial and practical applications. **Section 5** concludes the paper with managerial implications, practical applicability, and future research works.

2. Literature review

This section summarizes state-of-the-art research on the cyber-physical production system, the cyber-physical system on the shop-floor, and IoT adoption in the warehouse and mobile robots, and concludes the research gaps that motivated this research work.

2.1. A Cyber-physical System

As part of the 4th Industrial Revolution, increasing connectedness between computational entities and the physical world and real-time data processing is highly emphasized as the next step forward. The creation of the CPS was to harness the most recent advancement within the field of computer science and ICT to create a connected environment that incorporates all production levels. Primary emphasis is also placed on integrating human-centred robot collaboration for organic competence with a certain level of autonomy [46]. While CPS architecture can change based on the purpose of the system and implementation method, the system should exhibit several general characteristics, including robustness towards faults, real-time control, and autonomous features such as self-maintenance and organization [47, 48]. The promised benefits and improvements from implementing CPS in real-world applications have led to various models and systems being proposed by academics for use in the manufacturing industry. To fulfill the need for a resilient CPS, Tomiyama and Moyen [47] designed a resilient CPS architecture with fault tolerance, redundancy, self-maintenance, and reconfiguration. The team laid out a technical demonstrator that would satisfy the listed requirements for said CPS, simulating a complete production line with storage, material transport, machining, and processing stations. Each actuator is connected to a sensor to achieve system robustness and automation. The sensor is connected to a dedicated Arduino processor through a mesh topology network. Faults will be analyzed to facilitate reconfiguration so that the root cause for such failures can be avoided. The use of independent subsystems and parallel operations allows for higher resilience where a breakdown will not result in the total failure of the entire production line.

To facilitate the implementation of CPS within industry 4.0, a myriad of systems needs to be integrated, extending the ideas from CPS to CPPS [6, 49]. One such system is fault detection, which is vital for ensuring intelligent and efficient behaviors of CPS through fault isolation and equipment health management [50, 51]. He, et al. [52] presented the Image Processing assisted Computer Vision Technology for Fault Detection System (IM-CVFD). The detecting units depend on real-time computer vision networks, with a priority scheduler for handling latency requirements for separate scenarios. The system within CPS is made compliant with quality of service criteria using group activation mapping (GAM) for internal and external fault detection. Alippi, et al. [53] introduced a model-free fault detection and diagnosis system (FDDS) primarily for use in large-scale CPPS, with the ability to autonomously learn nominal system conditions and possible record faults from data acquired during operation. FDDS complexity is reduced using a Hidden Markov Model (HMM) for inspecting data from sensor clusters for locating and isolating multiple faults. A similar attempt at simplifying fault detection for CPS was made by Chiu, et al. [50], which suggested using integrative machine learning for reduced computational complexity and better applicability. A Random Forest (RF) is first used for a more accurate and stable prediction and to identify critical factors. Then a Time-Series Model is computed using a Long Short-Term Memory Network (LSTM) for data monitoring and prediction. The proposed method could shorten model convergence time with higher predication accuracy. Nevertheless, the application of IIoT can further combine the physical layer of CPS to cyber layer further predictive and preventive maintenance.

Aside from physical fault detection, isolation and detection methods for cyber-security enhancement are also crucial for CPS as they involve a large volume of data transfer using IoT. Palleti, et al. [54] demonstrated using mechanical fault detection and isolation methods such as the Kalman filter and CUSUM test to detect the onset of cyber-attacks. The prior information is generated using the Kalman filter and fed to residual-based attack detection procedures. Combined with the CUSUM test, they form the detection block in FDI. Afterwards, fault identification through sampling and correction can be made at the output of the detection block. The proposed FDI, however, depends on the correct isolation algorithm; otherwise, the process fault might be aggravated. Jiang, et al. [55] demonstrated specifically against fault injection attacks in Confidentiality-critical and Real-time Cyber-Physical Systems (CRCPSs) using cryptographic implementations, which can ensure confidentiality and fault detection, and a heuristic approach for solution approximation. To reduce time complexity and increase solution quality, the team used the Fruit fly Optimization Algorithm with an NSGA-II algorithm-based fast searching mechanism, resulting in 87.93% in solution quality and 19.07% lower execution time. This method showed the advanced concepts for combining CPS into manufacturing compared to the traditional system without implementing the CPS.

In order to realize the potential of CPS, a framework should be developed to provide the necessary flexibility and robustness to the system. Nikolakis, et al. [34] proposed an end-to-end reconfigurable approach using existing container technologies. Interoperability and reusability are increased by utilizing the IEC61499 automation standard with compatible function blocks, which through a varying connection of function blocks (FB), allows for higher flexibility with centralized status monitoring. Meanwhile, the preservation of system efficiency and stability can be completed with containerization. Nikolakis, et al. [34], Monostori [48] suggested using multiple methods to link the planning system with scheduled tasks and to support necessary changes to CPPS deployment. Similarly, the concept of implementing an IEC61499 FB-based CPS was discussed by Yao, et al. [56] for use in a human-robot collaboration system. Combining various FBs can enhance safety with human-side control FB and task-side control FB intervention when risk is detected. Further, combining FB and human input increases flexibility, automating specific steps and resorting to human input when precision assembly is needed.

Facilitating real-time monitoring and manufacturing simulation is crucial to implementing smart manufacturing, emphasizing flexibility and efficiency. Therefore, many academics proposed using DT and CPS, which can contribute to the abovementioned requirements. Ding, et al. [57] suggested a Digital Twin-based CPPS (DT-CPPS) for transparent, data-centric, and model-based autonomous manufacturing. Integrating physical shop-floor (PSF)/ cybershop-floor (CSF) endows DT-CPPS with self-X intelligence and smart interconnection; real-time data can also be transmitted to CSF for better data synchronization and responsiveness production strategies. Likewise, Zhang, et al. [58] also opted to use DT for information exchange and resource sharing within a CPPS. The presented model architecture can be separated into four layers, with the virtual layer being the most important towards DT development, as the virtual environment is built upon a manufacturing cell agent (MCA), relevant model, and knowledge database. The team was able to share the manufacturing resources via DT with the experimental setup. Graessler and Poehler [59] used DT to integrate human workers in a technically autonomous workplace, thus allowing employees to contribute to computational decision-making. The DT is designed to emulate user behavior for the planning system to decide which suitable employee the task can be distributed to it. Further, instantaneous user feedback can also be generated and used for decision-making within the planning system under CPPS [60-62]. Hence, the development mobile robots' operation under DT environment assisted with IIoT could be capable for a simulation-based ROS embedded in CPS.

2.1.1. CPS architecture in shop-floor

Machine tools are the main components in any manufacturing industry. The evolution of the Cyber-Physical Machine Tool (CPMT), which is done through the integration of machine tools, machine process, computation, and networking [63], offers the added advantages of autonomy and flexibility to traditional manufacturing practices [49]. To implement CPMT within the industry 4.0 revolution, different frameworks are proposed to improve system robustness and efficiency. As part of the focus of the fourth industrial revolution, human and robot collaboration models have been developed by different academics. Liu, et al. [64] discussed using augmented reality to integrate humans with CPMT. The AR-assisted Intelligent Window CPMT has main functions: real-time control, AR-enabled process monitoring, AR-enabled machining simulation, and process optimization. The system was designed as an advanced HMI to allow users to interact with the machine aided by real-time data and calculation. The case study concluded that the Intelligent Window framework could supply high-fidelity simulation and a comprehensive perception of the machining environment. Another human-robot interaction system for CPMT was also proposed by Liu, et al. [65] and Liu, et al. [66], which uses MTConnect as a base for a Machine Tool Cyber Twin (MTCT).

The framework is divided into four layers: physical devices, such as cutting tools and sensors; networks, including I2C, Bluetooth, etc.; MTCT, with MTConnect adapter and agent, plus MTCT application; cloud layer, for remote monitoring and data analytics. The team concluded that using MTConnect facilitated unified and efficient data transmission. Further, MTCT allows for real-time status monitoring and data archiving, among other support for better decision-making. A further study of combining AR with MTConnect-based CPMT was also developed by Liu, et al. [65] and Liu, et al. [66], with similar proven results as above. Using DT is also widely proposed by academics. Such a system will give the user a better understanding of the actual physical appearance of the workpiece through visual representation in a digital model. Incorporating AR with DT allows the users to adopt a new way to visualize and interact with the model, along with the ability to manipulate both the data and the machine tool simultaneously [67]. On the other hand, a framework using a cloud-edge system was discussed, with the cloud layer having the ability to conduct advanced data analytics for optimization and quality control [68-70]. The collaborative DT model allows the system to conduct fault recognition with deep learning, together with shorter development time and higher efficiency due to the DT system's enhanced understanding of AM processes [6, 49].

2.1.2. Internet-of-Things with mobile robots

The deployment of IoT allows data communication between various end users and allows them to compute, store, and sense data [22]. As such, it is a crucial element for automation within the manufacturing industry. Various frameworks were designed to enable the use of IoT architecture. Wang, et al. [71] proposed the Advanced Distributed Tensor-Train (ADTT) decomposition methods for better computational efficiency within IoT, allowing other tensor-train to compute in parallel by integrating the reshaped matrices of the sub-tensors with distributed tensor-train decomposition for efficient data processing. An IoT-based health monitoring network was developed by Hossain and Muhammad [72], with seamless data transmission from different sensors to healthcare professionals, data watermarking, and enhancement for identifying theft and clinical error prevention. Due to a large number of connected devices and data exchange, IIoT requires secure communication and data privacy, especially if the system is deployed in strategic areas such as the power grid.

Consequently, models have been proposed to enhance data privacy and security. Chaudhary, et al. [73] described a software-defined network (SDN) that enabled multi-attribute secure communication for IoT. The model combines a cuckoo-filter-based fast-forwarding scheme for communication with attribute-based encryption and third-party peer entity authentication. The fast-warding scheme is designed so the solution can still be implemented even when heavy data flow is presented within the network. Al-Turjman and Alturjman [74] developed a context-sensitive seamless identity provisioning (CSIP) framework with hash and global assertion value for mutual authentication. This proposed framework removes the need for users to provide identity verification for each connection with the system, thus allowing for higher efficiency. A separate security model was proposed by Abuhasel and Khan [75], using a SoftMax-based neural network and improved Rivest-Shamir-Adelman encryption. The model lowered latency and energy consumption with a higher security level than the existing fog-assisted industrial Internet-of-Things model. Another model for secure and efficient IoT data transmission is through blockchain, but there are several limitations to the system's scalability. Liu, et al. [76] suggested an optimization framework using deep learning reinforcement focusing on scalability, decentralization, security, and latency.

As mentioned above, the efficient utilization of robots is a critical factor in CPS, with the high level of automation being a crucial component for dynamic scheduling [2, 5, 77]. However, technologies that enable high intelligence and flexibility within robotic solutions have yet to be perfected; therefore, it is crucial to focus development on such systems [78]. Optimal path planning is necessary for autonomous robot deployment, which has garnered increasing academic attention. Various vision-based guidance systems were proposed, such as one designed by Singh, et al. [79], which uses switching-based SMC with an RGB-D sensor for depth map generation. The angular and linear velocities obtained through onboard sensors are then used for developing a guidance strategy. Similarly, Tai and Liu [80] proposed a vision-based guidance model using a Convolutional Neural Network to support end-to-end learning for feature recognition. Training data is first acquired through remote manual control of the robot, which is then fed back to the CNN. Aside from efficiency, optimal trajectory planning should also consider equipment life. Kruglova, et al. [81] suggested monitoring the degree of wear for each wheel's electric drive, through which the path with the least amount of operations and exert the least amount of wear can be chosen the optimal path assisted with IoT.

Large-scale applications of autonomous robots in the distribution center are expected; hence multi-robot path planning should be considered. Keung, et al. [39] and Keung, et al. [40] proposed a multi-path consideration in a multi-deep RMFS with multiple algorithms for comparison and simulation results under a CPS environment. Keung, et al. [39] and Keung, et al. [40] also mentioned that the mobile robots with different capabilities in the warehouse might consider hardware degradation to ensure all the mobile robots could be communicated through the cloud-based system. For example, different modules might be embedded into the mobile robots for dealing with different tasks in RMFS. Different brands of mobile robots might be adapted to handle different tasks, such as fault detection. For further considering seamless information through the cloud-based CPS system with different parties, the hardware and software degradation might be required to ensure compatible systems.

Different storage patterns are further considered. Still, in RMFS, storage racks and workstations are build-in in a warehouse layout. Optimizing the storage assignment for both the products and the storage units can lead to the higher efficiency of the mobile robots, as it can reduce mobile robots' blockage; and decrease energy consumption, with each mobile robot completing more orders in a single charge. For extending the storage concept into a smart manufacturing unit, Graph Neural Network (GNN) is one of the solutions for solving the multi-path planning with the adoption of mobile robots with a more complex environment. GNN has been the mainstay for decentralized multi-agent path planning, allowing communication-aware trajectory generation and optimization [44, 45, 82, 83]. Li, et al. [44] and Li, et al. [45] developed the Message Aware Graph Attention network (MAGAT) with CNN-based perception and GNN for better inter-robot communication. MAGAT is an extension of the team's previous GNN-based decentralized network [44, 83] and reportedly showed a lower flow time for robots and can achieve high performance in a large-scale and challenging environment. To simplify the learning process for a multi-agent system, Liu, et al. [82] proposed the two-stage attention network (G2ANet) for game abstraction with GNN, which can simplify the problem model found in multi-agent reinforcement learning. Two learning algorithms were created: a policy network (GA-Comm) for communication while making decisions and a critic network for other agents to consider the state and action information.

2.2. Research gap

To the best of the authors' knowledge, the combination of robotic-assisted object movement and storage operations with CPPS has not been discussed and considered in previous literature. The purpose of combining the ROS into the CPPS is to enhance operational efficiency with different modules under the cloud-based production and DT system. Digitalized information and enhanced servitization modes could improve the original manufacturing system. The data could be consolidated and transferred to the cyber layer for further data analysis and prediction. Resources could be synchronized under the proposed CPPS framework. Recent advancements in robotics have shown great potential for enhancing the overall efficiency and effectiveness of the smart manufacturing system [5, 17, 18, 24, 38]. RMFS is a new warehouse system assisted by mobile robots for order pickings and goods retrieval, generally under the cloud-based ROS with a DT-based nearly real-time simulator. In a manufacturing system, materials storage, tools storage, and finished goods storage would affect overall operational efficiency and effectiveness, whereas human errors could affect the overall processing time. With the aid of CPPS, the RMFS in a manufacturing system could be further embedded into CPPS to solve the research gaps. The adoption of robotics started in a different industrial environment to reduce human errors and accidents. The adoption of CPPS in a typical manufacturing system has been shown. In traditional, manual input and human involvement are standard for manufacturing. With the adoption of CPPS, multiple tasks and processes could be simplified, including the robotic process automation (RPA) solution [84]. CPPS is a medium for converting the robotics in the physical layer to a cyber-layer DT-based nearly real-time simulator [85].

3. A cyber-physical robotic mobile fulfillment production system in smart manufacturing

This section introduces the proposed CPRMFS in smart manufacturing. At first, a briefing introduction for 3D printing as a case scenario is explained. Second, the system architecture of a CPPS for tools storage assisted with multi-robots is illustrated. The system architecture is proposed for combining the concept with CPPS and IoT. Third, a schematic diagram of the proposed CPRMFS in smart manufacturing is presented with further clarification.

3.1. The system architecture of the cyber-physical production system for tools storage assisted with multi-robots

Extending those context types assisted mobile robots' operation could reduce human errors and accidents. Those data could be a trigger for those mobile robots' operation. To print an object, selecting a 3D printer is one of the considerations of 3D printing. Vat polymerization is assumed for the case scenario because the adoption could be used for resin and wax. The raw material should be stored in a container and changed for tool storage. Since the raw material is liquid, less structure support is required. The reasons for selecting 3D printing as a case study are the popularity of 3D printing is widely adopted in different industries and could be foreseen that the emerging trends of additive manufacturing are arising by academics and industrial practitioners. Therefore, different parameters should be further considered, and the problems for the tools, goods, and materials storage should be further considered. Also, there are different parameters to control. Apart from the selection of material, setting different parameters is a way to create an object with other properties, i.e., a high-density inner structure of the 3D object increases the strength and toughness. For example, if there is a lack of materials sensed from a particular IoT device embedded in a 3D printer, the ROS could assign a mobile robot to pick up those printing materials in advance instead of idling those 3D printers. The tools storage normally includes the print-removal blades, nozzle cleaning tools, pliers and tweezers, soldering iron, and wipes and towels. The mobile robots could be controlled in a centralized CPPS, including the conflict resolution of the mobile robots. Four context types are typically included in 3D printing manufacturing, including configuration context, expectation-aware context, physical context, and operational context shown in **Fig 1** and **Fig 2**.

- Configuration context: Actual filament diameter, automatic bed leveling on/off, flow rate, and print speed are considered in a 3D printer whose external environment influences its configuration. Those data are transferred to the cloud-based system. For example, the print speed and flow rate could be changed due to different job tasks or the manufacturing schedule.
- Expectation-aware context: The expected error type, expected fan speed, and expected flow rate are the primary awareness of the expectations factors in a 3D printer. With the extension of real-time monitoring and tracking with IoT devices, the temperature on the bed and extruder, the sensing of misalignment, and printing quality is continuously monitored for the 3D printing manufacturing system.
- Physical context: The physical equipment in a 3D printer is one of the concerns during 3D printing-based manufacturing. The sensors measuring the distance between the heat sensor and the hot end, screw-over tightened on the x and y axis, bed cleaning schedule, and leveling issues are the significant factors to monitor during manufacturing and operation. Multiple IoT devices and real-time tracking and monitoring sensors assist the bed's flatness and horizontal balance.
- Operational context: The operational context includes multiple parameters for controlling and monitoring. Errors that appeared in the extruder with temperature and calibration issues should be further considered and aware. The number of errors and the practical serviced life is considered predictive and preventive maintenance. The

operational data could be further analyzed by adopting machine learning to discover the error patterns during manufacturing [23, 24, 26].

To demonstrate how CPRMFS works in smart manufacturing, we assume the application as a 3D printing manufacturing case scenario for simulation. **Fig 1** and **Fig 2** show an example of the smart product service system in a 3D printer product case scenario. Different interfaces could be generated to the control dashboards, including the real-life simulation, DT-based virtual prototype, actual workers' operation and the cooperation between the mobile robot and the workers shown in **Fig 2**. Context-aware modeling is further considered in the CPPS. Multiple contexts are monitored and controlled to ensure the errors can be avoided or conduct predictive maintenance based on data collected through IoT sensors and devices in the 3D printer. A CPPS could be consolidated multiple modules and interfaces under the cloud-based system to achieve a higher user experience as one of the core values and value co-creation. RPA could be embedded for giving suggestions and providing possible solutions to the customer as one of the servitization KPIs during the smart manufacturing product and service system. In a traditional 3D printing-based scenario, multiple data are required to consider to achieve higher operating efficiency and effectiveness. Under standard customization, the manufacturer rearranges the system for product-delayed differentiation with mass customization. Therefore, it can mitigate the trade-off between customization and productivity. The assembly process held by the logistic—worker assembly of the product base on customized orders and delivery to the customer. However, product-delayed differentiation only provides limited differentiation and requires the worker to assemble in the later delivery stage. Therefore, a CPPS assisted with mobile robots' operation may help the manufacturers to provide a higher degree of differentiation and solve the tools storage problem, which facilitates the process of manufacture to lessen the trade-off.

Fig 3 shows the system architecture of a CPPS for tools storage assisted with multi-robots. A 5C CPS architecture concept is considered for classifying the physical and cyber worlds, further considering digitalization and servitization [86-89]. Customer orders assisted with RPA are triggered from the CPPS. Multiple physical devices are connected with IoT to receive raw data, monitor real-time, and conduct commands. In a 3D print, numerous devices should be checked, including the filament, extruder, printing bed, and cooling fan. The purpose is to capture the data for real-time monitoring and predictive maintenance. With the adoption of mobile robots for raw materials and tools storage, mobile robots adopt multiple IoT sensors for collision avoidance and real-time monitoring and tracking for path control and virtualization. In RMFS, the four core elements are a workstation, charging station, mobile rack, and mobile robot. The QR code is clung to the floor for the mobile robot's navigation and collision avoidance purposes. Those devices are transferred the raw data through the IoT edge gateway via an industrial wireless sensor network and 4G/5G mobile network to the cyber layer for data processing. Multiple network nodes are adopted and considered the operation in mobile robots assisted manufacturing systems could be operated fluently. The proposed system is also assumed to include the industry's communication standards and automated analytics.

In the cyber layer, three central components are consolidated in the cloud-based CPPS, including a DT database, digital representation in a cloud-based production system of 3D printing, and RMFS. Based on the data from the 3D printers, the cloud module further transfers that information for digitalization to enhance servitization and resource synchronization during the manufacturing system. In a cloud-based ROS, multiple mobile robots' operations are considered, including 3D printing tools and parts storage, raw materials usage and storage, finished goods storage, and shipments. The ROS triggers the mobile robots' operations in CPPS. Still, different mobile robots might be used for handling different tasks. Therefore, to ensure the CPPS compatible with ROS, the ROS might require degradation to ensure all the mobile robots can seamlessly communicate. Multiple IoT sensors are connected to the 3D printer. The CPPS could consolidate the tools wear to suggest preventive maintenance. Emergency tasks could be fixed in advance; for example, the emergency repair of a 3D printer would be rearranged from the pre-scheduled tasks. Therefore, a real-time virtual prototype considering the space and time dimensions is adopted for collision and deadlock avoidance. The cyber-based CPPS with ROS could be communicated in the context of electronic data interchange, ensuring the operation and manufacturing processes are efficient and effective. The system could trace the component's manufacturing details in real-time, allowing for redesign and avoiding defects. In addition, real-time statistical process control also safeguards against product abnormalities from either human or machining error by calculating the control limits independent of the data sample, featuring low computational time and low memory requirements.

3.2. A schematic diagram of the proposed smart manufacturing and robotic mobile fulfillment system

Fig 4 summarizes a schematic diagram of the proposed system. In the diagram, the yellow dotted line refers to an original task from RMFS, which is moving a rack from a specific area to the workstation. Five areas are considered: the 3D printing raw material area, 3D printing robot-assisted area, disposal area, finished goods area, and maintenance tools, parts, and accessories storage area. The purple dotted line represents the transformation task, changing the original task to a new task in the transformation area. Different top modules are adapted to fulfill the tasks that appeared in the manufacturing and RMFS. For example, modules could be adopted for tools, raw materials, and finished product storage. The mobile robots must change the top module before assigning any new tasks. The ROS is based on CPPS to designate and organize the mobile robots' assignment problem, assuming expectations for monitoring and controlling. The red dotted line refers to the new task of moving the mobile robot with the assigned top module to the 3D printer area or a robot-assisted storage area. The cylinder represents an obstacle to simulating the actual environment in fulfilling the fire safety regulations and building limitations. The proposed assumed only an in/out delivery area and a charging station area. The manufacturing system also requires quality, shop-floor, and maintenance technicians in the operation area. The proposed layer would be an environment for further simulation purposes.

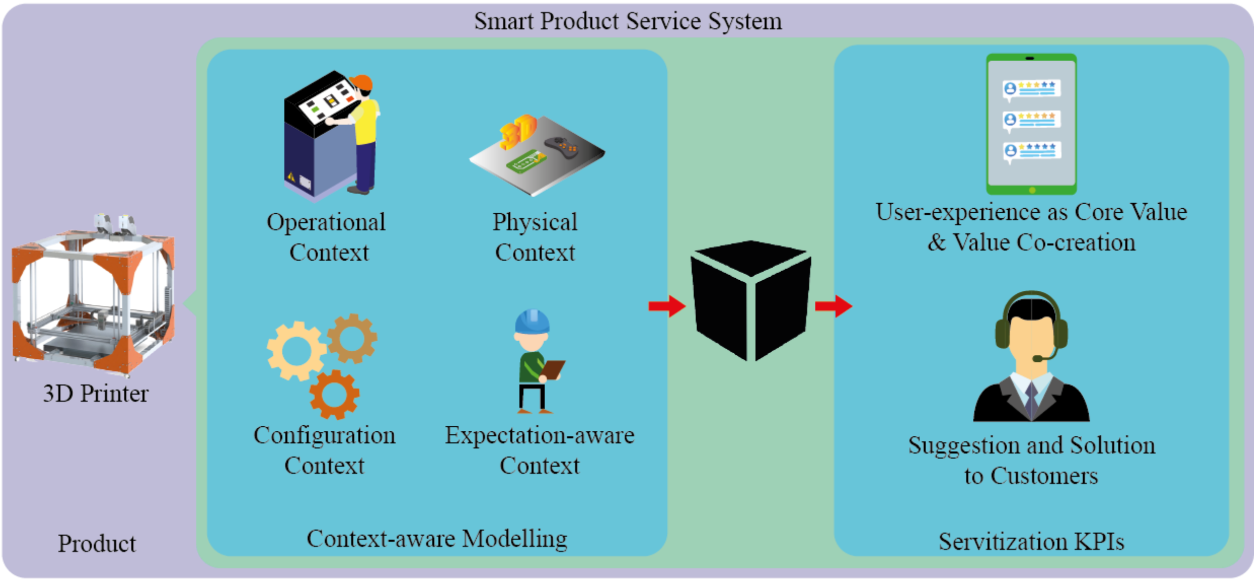

Fig. 1. An example of smart product service system in a 3D printer case scenario

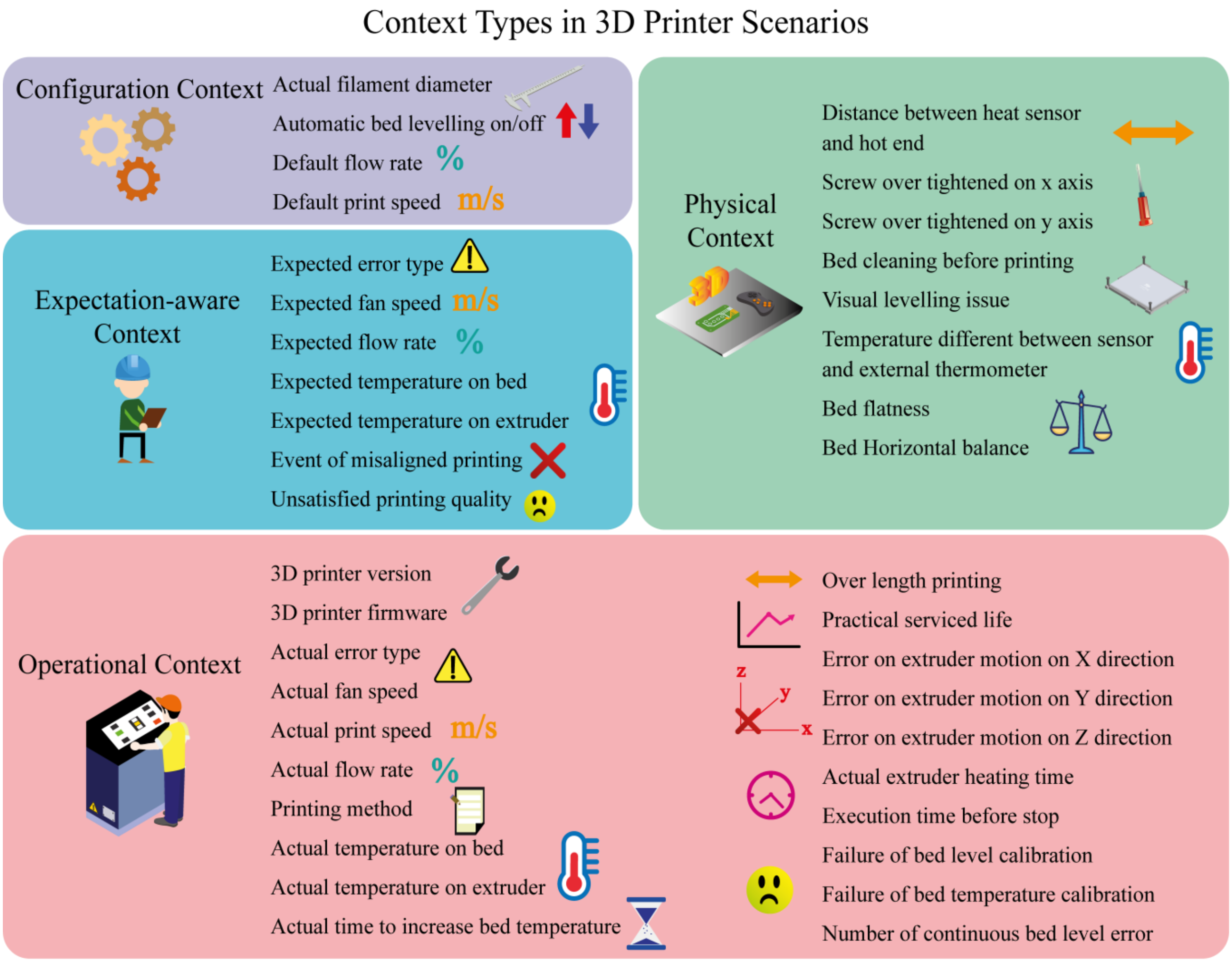

Fig. 2. Context types in 3D printer case scenarios

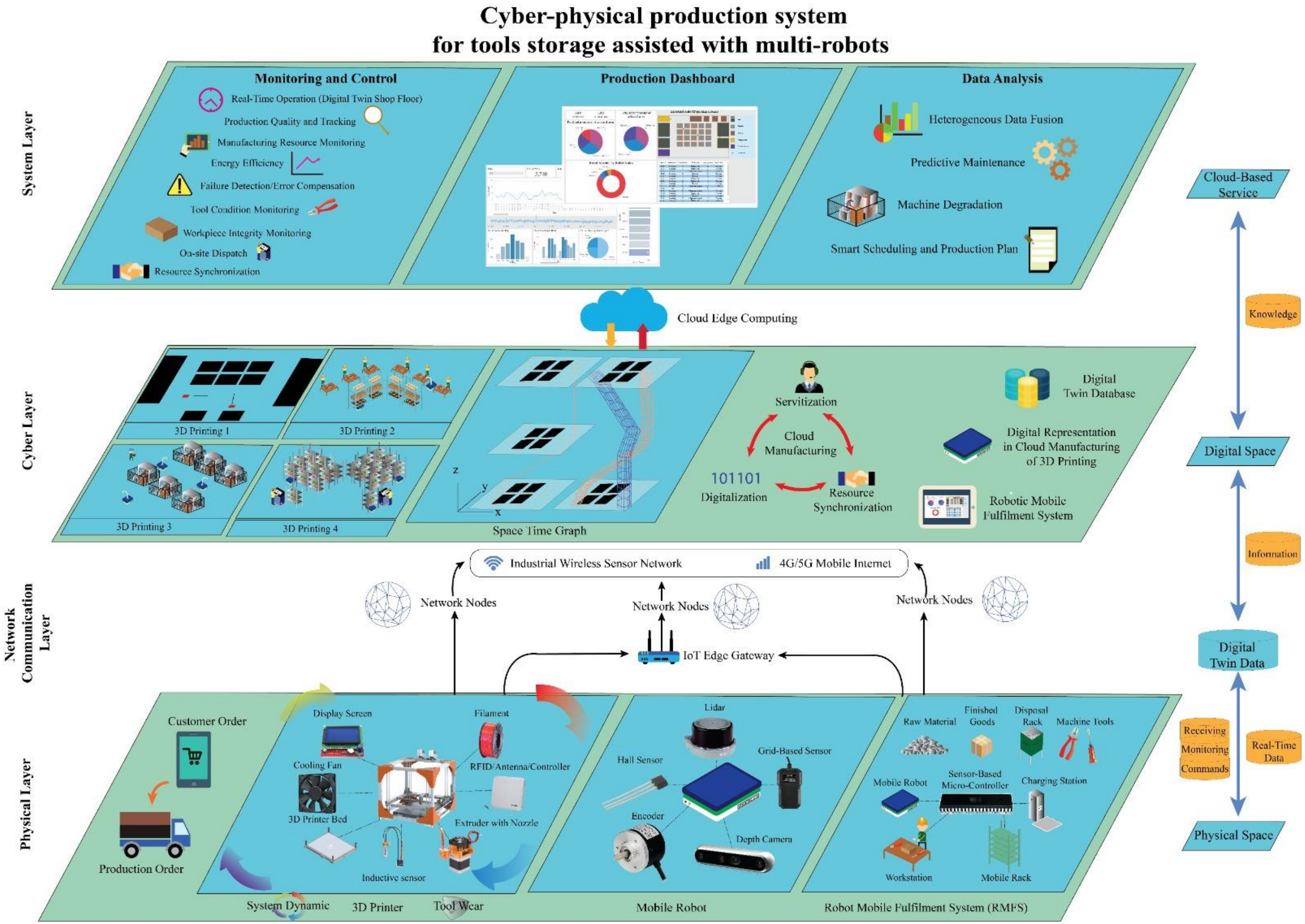

Fig. 3. A system architecture of cyber-physical production system for tools storage assisted with multi-robots

Fig. 4. A schematic diagram of the proposed smart manufacturing and robotic mobile fulfillment system

4. Numerical studies of decentralized multi-robots path planning

4.1. Introduction of the simulation architecture

An IoT-enabled smart manufacturing system is connected based on the CPPS environment. The information achieved from the manufacturing system could be seamlessly stored and transferred to the cloud-based CPPS environment. All the operations' data in the proposed manufacturing system, including the 3D printing modules, mobile robots modules, and the RMFS modules, could be digitalized under the proposed CPPS system architecture. The IoT edge gateway assisted with an industrial wireless sensor network is adopted for data transmission from the physical to the cyber layer. Under the DT database connected with the ROS in the cyber layer, the information is consolidated, and the paths can be calculated and generated based on the proposed action policy network. The classification problem is mainly based on classifying mobile robots' action policies. Customer orders trigger the production orders and storing and retrieving goods and tools in ROS. For example, the 3D printers' operation status will start the tasks of the mobile robot to store or retrieve the tools from the specific area shown in **Fig 4**. The information is transmitted from the physical space to the digital space. The production orders will trigger the movement of the raw materials to the 3D printers, and the customer orders will trigger the movement of the finished goods to the outbound logistics area. The statues of the mobile robots will begin the charging tasks. Moreover, the sensors embedded in the disposal area will trigger the tasks once the setting time is up. Furthermore, the mobile robots could be embedded in different modules under the transformation area. Various tasks would trigger other modules of the mobile robot in the transformation area. Also, the quality technician, shop-floor technician, maintenance technician, and 3D printing operator monitor and check the manufacturing system's status within the digital representation in cloud-based manufacturing.

The proposed simulation architecture is shown in **Fig 5**, based on the environment shown in **Fig 4**. The ROS virtual prototype is embedded in the CPPS. Therefore, all the tasks are triggered by the digitalized information from the CPPS. The input tensor is based on a binary map representation. The significant difference compared to Li, et al. [44] and Li, et al. [45] is that the CPRMFS in smart manufacturing would consider two cases, considering whether the mobile robot does carry or does not carry a rack during the operation. The RMFS operation is based on a goods-to-human conceptualization rather than the traditional AGV human-to-goods warehouse. The mobile robot is adopted under the cloud-based ROS for the path planning and collision avoidance context. This system reduces human operations' overall travelling errors and improves the overall operational effectiveness and efficiency assisted by the robotic solutions under the DT-based virtual prototype. The workers will pick up the goods in the in/out delivery area shown in **Fig 4**. If the mobile robot does not carry a rack, the coordinate position in a rack should not be considered a blocked area because mobile robots can move under the rack. A map is created to calculate the mobile robot's cost without lifting. If the mobile robot is carrying a rack, the coordinate position on the rack should be blocked. The movement of the racks' area should be blocked as an obstacle. Also, obstacles appear on the map because of the construction's fire safety regulations and limits.

There are three channels for the pre-processing stage. The first channel is the partial observation of the manufacturing and RMFS environment. The second channel is the position of the target job tasks or the boundary projection field-of-view, named goal. The third channel is the mobile robots within the field of view. The decentralized framework consists of a CNN based on the raw information from the input tensor and extends with a GNN to exchange information between different mobile robots [44, 45, 82, 83]. The GNN $K = 2$ is assumed for the parameter setting. Multiple algorithms could be adopted for the predictions of the actions. Two undirected graphs $G = (V, E, \xi)$ and $G' = (V', E', \xi')$ with a set of mobile robots V, V' and a set of edges E, E', where $E \in V * V$ and $E' \in V' * V'$ connecting the mobile robots in V. $\xi: E \rightarrow \mathbb{R}$ represents the function that allocates the weight to edges. The network would further consider at time t. For two nodes $\langle v_i, v_j \rangle$ in a graph, the value of adjacent matrix A_{ij} could be denoted as:

$$A_{ij} \begin{cases} 1, v_i \; is \; connected \; to \; v_j \\ \quad otherwise, 0 \end{cases} \tag{1}$$

The higher representation through graph structure could be followed by **Equation (2)**, whereas k is the number of layers, H^k represents in the k layer, $H^{(0)} = x$, $W^k \epsilon F^{k-1} * F^k$, σ denotes the activation function. The adjacency matrix could be further symmetric normalization to concentrate the degree of the adjacent node shown in **Equation (3)**. The aggregation method is shown in **Equation (4)**. **Equation (5)** shows the soft attention with LeakyReLU.

$$H^{(k+1)} = f(H^k, A) = \sigma(AH^kW^k) \tag{2}$$

$$H^{(k+1)} = f(H^k, A) = \sigma(\widetilde{D^{-\frac{1}{2}}}\tilde{A}\widetilde{D^{-\frac{1}{2}}}H^kW^k) \tag{3}$$

$$\sigma(\widetilde{D^{-\frac{1}{2}}}\tilde{A}\widetilde{D^{-\frac{1}{2}}}H^kW^k)_i = \sigma \sum_j \frac{1}{\sqrt{\widetilde{D_{\iota\iota}D_{JJ}}}}\widetilde{A_{\iota J}}H_k \tag{4}$$

$$[H]_{ij} = \frac{exp\left(LeakyReLU(h_{ij})\right)}{\sum_{k \epsilon N_i} \exp\left(LeakyReLU(h_{ik}\right)} \tag{5}$$

The expert algorithm is assumed to be an improved A-star algorithm considering the turning effects shown in **Equation (6)** **[39, 40]**.

$$\begin{aligned} f(c_\beta) = \; & g(c_\beta) + h_1(c_\beta)k_1(|x_r^n - x^0| + |y_r^n - y^0|) \\ & + h_2(c_\beta)k_2\left(\frac{(x_r^{n-1} - x_r^n)(x_r^n - x_r^{n+1}) + (y_r^{n-1} - y_r^n)(y_r^n - y_r^{n+1})}{\sqrt{(x_r^{n-1} - x_r^n)^2 + (y_r^{n-1} - y_r^n)^2} + \sqrt{(x_r^n - x_r^{n+1})^2 + (y_r^n - y_r^{n+1})^2}}\right) \end{aligned} \tag{6}$$

4.2. Results and discussion

Since no public datasets are available for a decentralized multi-robot path planning under a manufacturing-based and multi-deep RMFS environment, we simulate the environment proposed in **Fig. 4** compared with different numbers of mobile robot adoption. The orders are triggered from a real-life company dataset from Keung, et al. [39]. We randomly selected one-day orders and 210 tasks for training and testing purposes. The 210 tasks for different mobile robots are randomly assigned and triggered from the customer orders for manufacturing, including tools storage, raw materials storage, goods storage, disposal storage, and maintenance requirements from the 3D printing. The output from the GNN is 128 features in the five motion primitives. Therefore, the purpose is to classify those five motion action policies. The Adam optimizer with a momentum of 0.9 is selected for the experiment setup. The learning rate was assigned to decay from 10^{-3} to 10^{-6} within 150 epochs by adopting cosine annealing. The batch size is assumed as 64, and the L2 regularization is set to 10^{-5}. The validation is set for every four epochs with 1000 cases that were particular for the training and testing set. Each time step equals each mobile robot to run a forward pass of its local action policy. With cross-validation, the comprehensive performance of the model can be estimated for a real-life situation. The computation was performed with Intel® NUC 10, the configuration of Intel Core i7-10710U @ 1.10 GHz 1.61GHz CPU and 16.0GB RAM under Windows 10 home 64-bit operating system. The configuration of the computation unit uses Python 3.7 version and with the original library from Li, et al. [44] and Li, et al. [45], implemented in PyTorch v1.1.0 [90].

In this session, 10-fold cross-validation was set, and the overall performance is more accurate when improved from enhanced conflict-based search, which is one of the multi-agent pathfinding algorithms [91, 92]. The conflict-based search is based on the constraint tree. Each node consists of constraints, solutions, and total costs. A suboptimality factor should be provided for the search. Enhanced conflict-based search is a two-level search that adopts the focal search for both levels. Enhanced conflict-based search adopts unbounded and bounded suboptimal solutions. $OpenList$ is generated for the information including root under the constraint tree and the root assumed that is carrying an empty set of the constraints. First, the logic is to find individual paths of the mobile robots under the low level. When the $OpenList$ is not empty and no conflict occurred, the program will run until a conflict appeared before finding the best node. If the conflict is appeared, the root would be given to declare as a non-goal task, and two agents are generated to solve the conflict [92]. The enhanced conflict-based search replaced the original expert algorithm from **Fig. 5**.

Multiple algorithms are adopted for training the action policy network, whereas a multi-layer perceptron (MLP) is set as a baseline for comparison. We compare the results with other well-known methods usually adopted in similar RMFS operations, including k-nearest neighbor (KNN), support vector machine (SVM), recurrent neural network (RNN), Gaussian Naive Bayes (GNB), and a spatial-temporal graph neural network (ST-GNN) from Lee, et al. [93] and Yan, et al. [94]. This is the first time adopting an ST-GNN with a k-nearest neighbor for classifying the action policy. The ST-GNN consists of three layers after the input layer, including LSTM, Lambda, and Dense. Classifying those features into three parts of the ST-GNN enhances overall accuracy by adopting different layers. The result is shown in **Table 1**. All the algorithms in the numerical experiments could achieve a relatively higher accuracy result. **Equation (7)** shows that the supervisor learned about the action policy, whereas U_t^* represents an optimal trajectory of actions for all the mobile robots. Z_t^i represents the corresponding maps obtained for the trajectory. A training set $\mathrm{B} = \{(\{Z_t^i\}, \{U_t^*\})\}$. The mapping λ would be further for training propose. The output would be as near as the possible to the corresponding optimal action policy U^* under the cross entropy loss $\mathcal{L}(.,.)$ from Li, et al. [44] and Li, et al. [45]. The proposed method for learning and classifying the action policy has achieved the highest accuracy under the scenario of after improvement from enhanced conflict-based search. $\left\{(Z_t^i, U_t^{*i})_{i=1,\dots,N_{case}, \beta=1,\dots,\mathrm{B}_{max}^i}\right\}$ represent the data collected from the enhanced conflict-based search. Both of the scenarios could achieve more than 90% of accuracy. Therefore, we conclude that the proposed method outperforms KNN, SVM, RNN, GNB, especially under the scenarios with more mobile robots adopted.

$$\hat{\gamma} = \underset{\gamma}{argmin} \sum_{(Z_t^i, U_t^{*i}) \in T} \mathcal{L}\left(U_t^*, \lambda\left(Z_t^i, g_t(Z_t^i)\right)\right) \tag{7}$$

Furthermore, confusion matrices for the trials were generated and were further calculated into matrices of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Accuracy (Acc), Sensitivity (Se), and Specificity (Sp) were calculated based on TP, TN, FP, and FN [95]. Accuracy equals the proportion of true positive and true negative calculated in the selected population. Sensitivity equals the proportion of the true positives, not related to the true negatives.

Specificity equals the proportion of the true negatives not related to the true positives. Precision represents the algorithm's correctness of the TP. F1-score represents the harmonic mean of sensitivity and precision. TP, TN, FP, and FN can also be calculated for generating the Matthews Correlation Coefficient (MCC), Fowlkes-mallows Index (FM), Bookmaker Informedness (BM), and Markedness (MK) [96-98]. MCC majority considers the quality of binary classification. FM represents the similarity between the clusters achieved from the algorithms. BM equals the performance of a dichotomous diagnostic test and measures the probability of a reasoned decision. MK is adopted for how a prediction is enlightened concerning the condition. The statistical inference result is shown in **Table 2**. All in all, compared to different classification algorithms for action policy predictions, ST-GNN with enhanced search algorithms for further learning could obtain a better solution compared to the initial results from Li, et al. [44] and Li, et al. [45] under a new proposed CPRMFS in a smart manufacturing context.

Considering the improved algorithm from enhanced conflict-based search, all the algorithms could be improved compared to the original expert algorithm under different instances settings. Two scenarios are tested under the proposed framework from **Fig. 4**, majorly for adopting the different numbers of mobile robots. Multiple commonly used classification algorithms are adopted for comparison purposes, including the KNN, SVM, RNN and GNB. MLP is set for the baseline provided by the literature. By the ST-GNN further trained from three layers after the input layer, including LSTM, Lambda, and Dense, the results could be enhanced compared to the baseline and others' algorithms. Furthermore, in this paper, an enhanced conflict-based search for the consideration of a two-level search has been further improved compared to the current literature. On behalf of extending the GNN with the consideration of spatio-temporal, the overall results could be obtained with reflectively higher accuracy compared to the common classification algorithm for classifying the action policy. The simulation results could provide insights for future RMFS and shop-floor manufacturing to apply mobile robots for assisting the tools storage and retrieving the materials. The proposed system could be further developed under real-world conditions to enrich overall operational efficiency and effectiveness. The current smart manufacturing system could be embedded in the cloud-based ROS for seamless data transmission and to ensure customer satisfaction in the E-commerce era.

With the help of CPPS, adaptive decision-making and higher cognitive flexibility could be derived from synchronization and a centralized system with learning and predicting from historical data. A CPPS concept combined with ROS in the cloud could benefit servitization, resource synchronization, and digitalization. A cloud-based time-series and knowledge database could store the operational data for further analysis, e.g. storage location assignment, path planning, rack repositioning and collision avoidance. The time-series database in CPRMFS under the manufacturing operation could include multiple cloud systems, cloud-based customer service, and resource synchronization under different parties involved. Adaptive decision-making and cognitive flexibility could be adopted based on the cloud database for further processing the data. Hence, it could enhance overall customer satisfaction and loyalty because of a higher production efficiency based on the CPRMFS in smart manufacturing.

Fig. 6 shows the historical data checking and monitoring interface, and **Fig. 7** shows the real-time data monitoring interface based on a cyber-physical production system under the CPPS. Compared to the traditional manufacturing operation, the existing control dashboard might not be real-time updated. The proposed control dashboards are connected to the cloud-based system for achieving real-time update. Furthermore, the dashboards are also stored the time-series data and the knowledge database data for management decisions. Nevertheless, the interface could also partly show the potential collaboration with different parties for a merge control dashboard. By taking advantage of IoT for digital transformation, a rapid response time and judgment could be done in CPPS, and better knowledge could be developed. The mobile robots assisted in reducing the involvement of human labor in the production site. It improves data visualization of productivity, facilities utilization, and order status. Therefore, higher customer satisfaction can be achieved by reducing human errors. Customers, operation staff, and managers could quickly check and trace the data in a consolidated cloud-based system.

$$\mathrm{ACC} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}} \tag{8}$$

$$\mathrm{Se} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{9}$$

$$\mathrm{Sp} = \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}} \tag{10}$$

$$F_1 = \frac{2\mathrm{TP}}{2\mathrm{TP}+\mathrm{FP}+\mathrm{FN}} \tag{11}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{12}$$

$$\mathrm{MCC} = \frac{(\mathrm{TP}\times\mathrm{TN})-(\mathrm{FP}\times\mathrm{FN})}{\sqrt{(\mathrm{TP}+\mathrm{FP})(\mathrm{TP}+\mathrm{FN})(\mathrm{TN}+\mathrm{FP})(\mathrm{TN}+\mathrm{FN})}} \tag{13}$$

$$\mathrm{FM} = \sqrt{\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}\times\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}} \tag{14}$$

$$\mathrm{BM} = \mathrm{Se}+\mathrm{Sp}-1 \tag{15}$$

$$\mathrm{MK} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}+\frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FN}}-1 \tag{16}$$

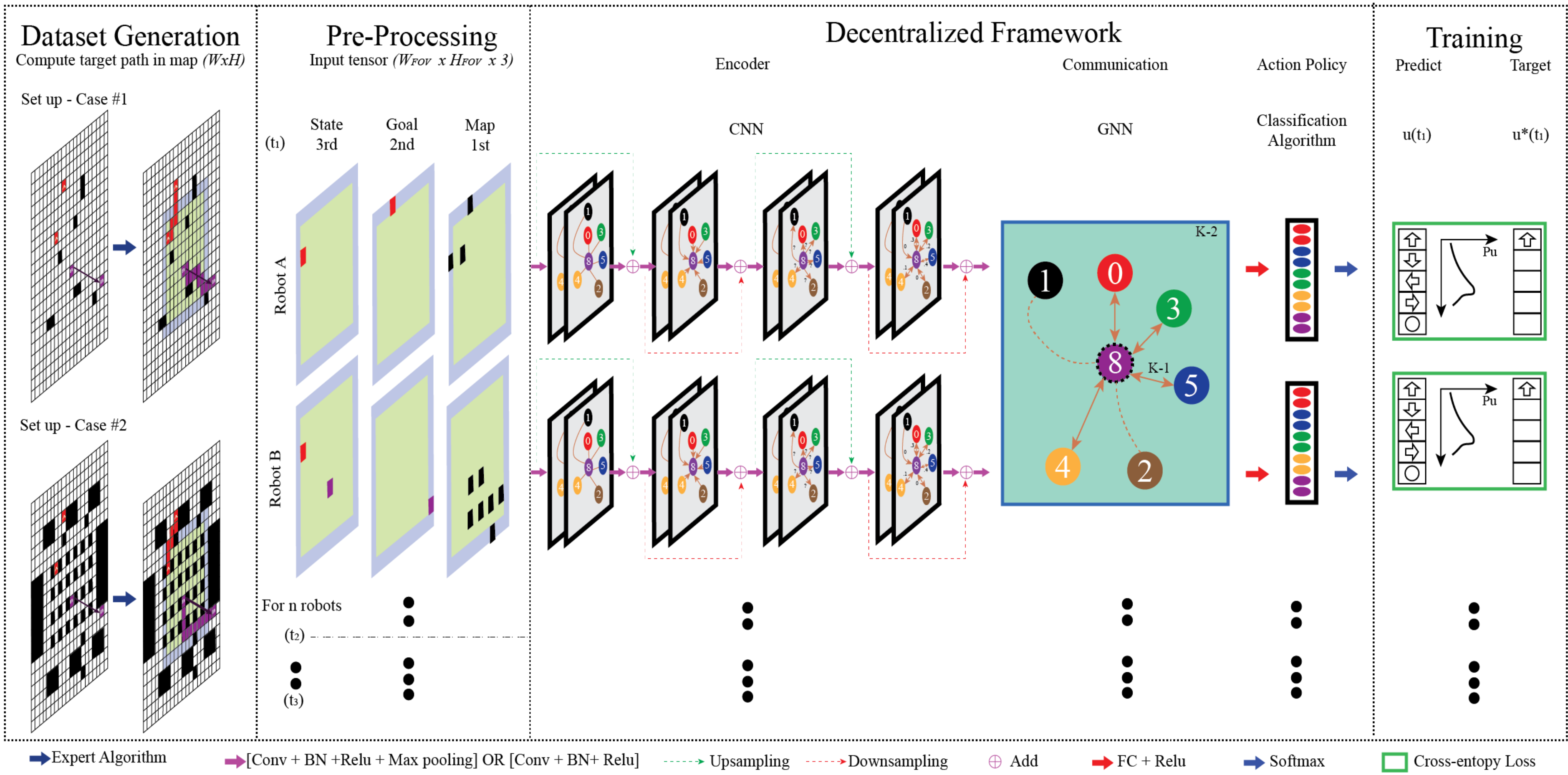

Fig. 5. A proposed decentralized framework for the smart manufacturing and robotic mobile fulfillment system

Table 1

Average accuracy, sensitivity, specificity, F1-score, and Precision for the algorithms

10 mobile robots	Original method from Li, et al. [44] and Li, et al. [45]					**Improved from Enhanced Conflict-Based Search**				
Classification Algorithm	**Acc**	**Se**	**Sp**	**F1-score**	**Precision**	**Acc**	**Se**	**Sp**	**F1-score**	**Precision**
MLP (Baseline)	83.85%	79.41%	98.62%	72.97%	76.06%	91.12%	75.45%	99.10%	79.81%	77.57%
KNN	79.81%	65.93%	99.07%	75.95%	70.59%	87.50%	66.67%	99.15%	76.54%	71.26%
SVM	81.00%	82.02%	98.44%	67.59%	74.11%	90.50%	77.36%	98.83%	75.23%	76.28%
RNN	78.92%	56.67%	98.18%	57.95%	57.30%	90.88%	66.67%	99.18%	76.54%	71.26%
GNB	79.19%	84.27%	97.02%	55.15%	66.67%	92.00%	78.64%	99.06%	78.64%	78.64%
ST-GNN	**87.62%**	**67.02%**	**99.51%**	**85.14%**	**75.00%**	**95.77%**	**77.89%**	**99.10%**	**77.89%**	**77.89%**
20 mobile robots	Original method from Li, et al. [44] and Li, et al. [45]					**Improved from Enhanced Conflict-Based Search**				
Classification Algorithm	**Acc**	**Se**	**Sp**	**F1-score**	**Precision**	**Acc**	**Se**	**Sp**	**F1-score**	**Precision**
MLP (Baseline)	77.42%	76.25%	98.04%	61.00%	67.78%	87.42%	78.26%	98.83%	73.47%	75.79%
KNN	73.96%	56.67%	99.10%	75.00%	64.56%	86.85%	71.43%	99.23%	77.92%	74.53%
SVM	78.00%	72.22%	98.20%	64.36%	68.06%	89.31%	78.35%	99.51%	87.36%	82.61%
RNN	73.21%	72.57%	96.87%	55.78%	63.08%	89.15%	75.95%	99.17%	75.95%	75.95%
GNB	76.54%	80.23%	97.66%	60.00%	68.66%	80.58%	86.67%	99.31%	84.78%	85.71%
ST-GNN	**82.31%**	**62.20%**	**99.06%**	**72.86%**	**67.11%**	**92.50%**	**80.46%**	**99.20%**	**80.46%**	**80.46%**

Table 2

Statistical Significance for the Algorithms

10 mobile robots	Original method from Li, et al. [44]and Li, et al. [45]				**Improved from Enhanced Conflict-Based Search**			
Classification Algorithm	**MCC**	**FM**	**BM**	**MK**	**MCC**	**FM**	**BM**	**MK**
MLP (Baseline)	74.96%	76.12%	78.04%	72.01%	76.58%	77.60%	74.55%	78.65%
KNN	69.56%	70.76%	65.00%	74.43%	70.33%	71.43%	65.82%	75.16%
SVM	73.36%	74.46%	80.47%	66.88%	75.18%	76.29%	76.18%	74.18%
RNN	55.44%	57.31%	54.85%	56.04%	70.38%	71.43%	65.85%	75.21%
GNB	66.53%	68.17%	81.29%	54.45%	77.70%	78.64%	77.70%	77.70%
ST-GNN	**74.65%**	**75.54%**	**66.53%**	**83.75%**	**76.99%**	**77.89%**	**76.99%**	**76.99%**
20 mobile robots	Original method from Li, et al. [44]and Li, et al. [45]				**Improved from Enhanced Conflict-Based Search**			
Classification Algorithm	**MCC**	**FM**	**BM**	**MK**	**MCC**	**FM**	**BM**	**MK**
MLP (Baseline)	66.78%	68.20%	74.29%	60.04%	78.26%	98.83%	74.80%	75.83%
KNN	63.79%	65.19%	55.77%	72.96%	71.43%	99.23%	73.69%	74.60%
SVM	66.66%	68.18%	70.42%	63.10%	78.35%	99.51%	82.03%	82.73%
RNN	61.38%	63.62%	69.44%	54.26%	75.95%	99.17%	75.11%	75.95%
GNB	67.86%	69.38%	77.89%	59.12%	86.67%	99.31%	85.08%	85.72%
ST-GNN	**66.11%**	**67.32%**	**61.26%**	**71.34%**	**80.46%**	**99.20%**	**79.66%**	**80.46%**

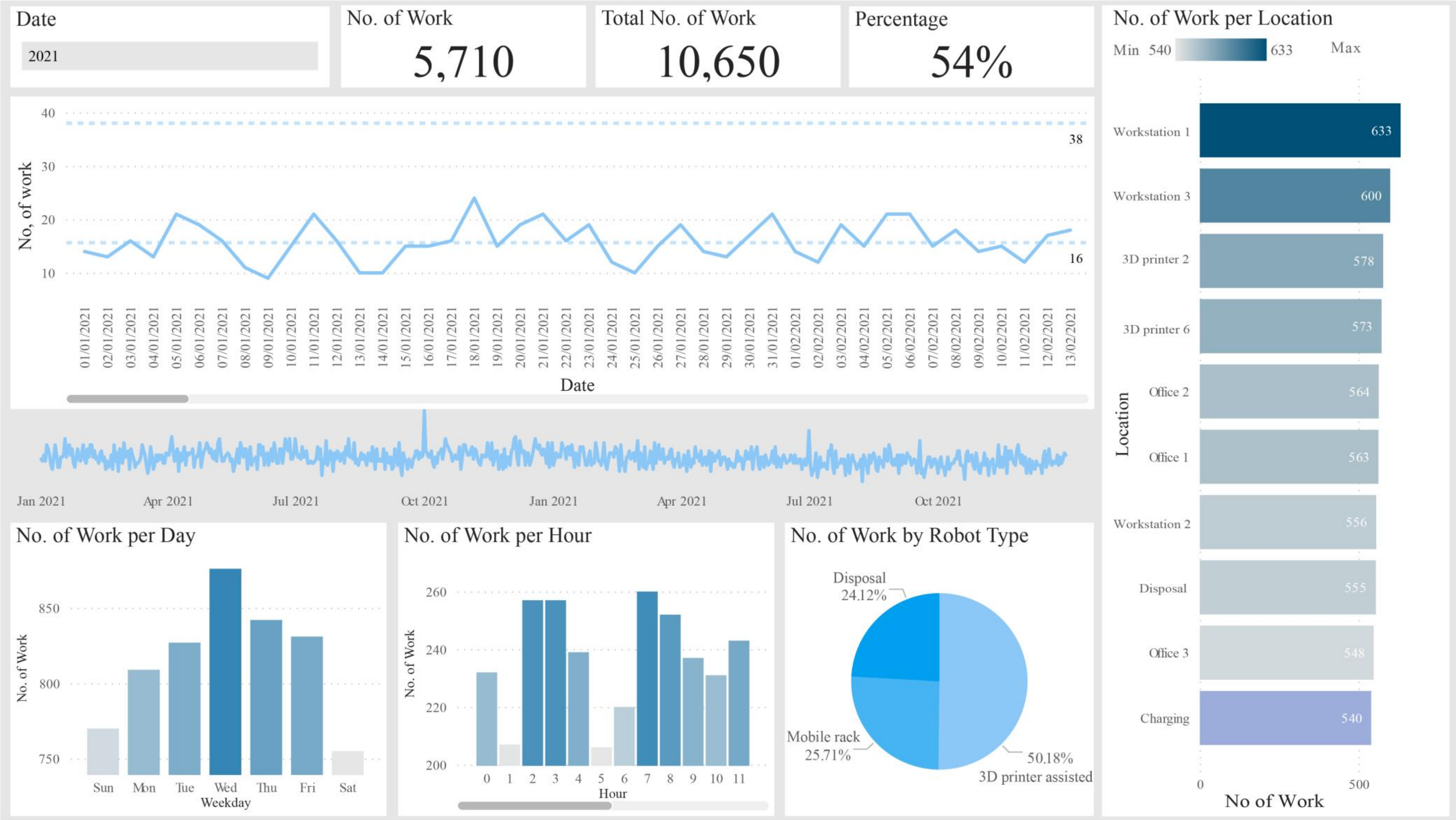

Fig. 6. Historical data checking and monitoring interface

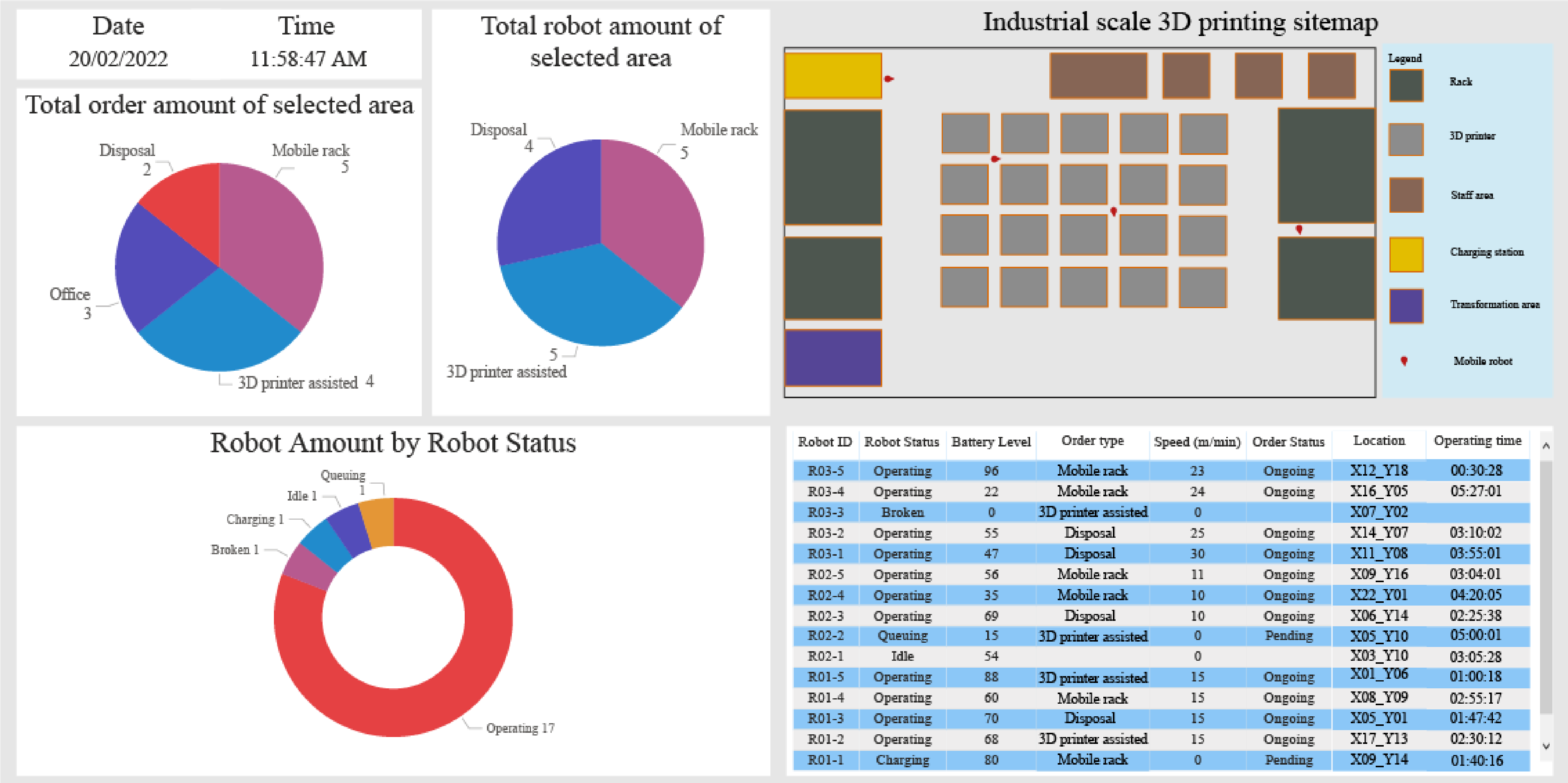

Fig. 7. Real-time data monitoring interface based on cyber-physical production system

5. Conclusion

The study sets out to develop an architecture of a CPPS for tool storage assisted with multi-robots to reduce human labor involvement and errors in the manufacturing site. Graph neural networks are further considered to learn and predict the action policy and avoid conflicts between mobile robots. A schematic diagram of the CPRMFS in smart manufacturing is proposed for the simulation, which could benefit potential participants to adopt RMFS and mobile robots in their manufacturing site.

The significant contributions of this work are summarized as follows:

- The managerial implication of this study is to append the discussion on the role of CPPS assisted with mobile robots for movement and operations in 3D printing manufacturing as a potential for enhancing manufacturing's operational efficiency and effectiveness. This study also explores the possibility of RMFS's adoption in manufacturing to improve storage and retrieval efficiency and effectiveness.
- This paper adopts the ST-GNN to fit the data generated from the original method for the mobile robots' action prediction comparison. Moreover, we also compare the original method with the improved, enhanced conflict-based search. The ST-GNN under enhanced conflict-based search could obtain higher accuracy with similar training time compared to the original method. The testing scenario is based on the actual company customer orders for the simulation. Therefore, the models could also be feasible and have extendibility in different environments or scenarios for practical feasibility.
- The practical applicability of the researched topic is further explained as a reference for manufacturing practitioners who looked out on a confrontation of introducing the mobile robot solutions in their manufacturing site with the goal of either enhancing the operation processes or making use of the data generated from IoT devices for tools storage, raw materials storage, products storage and disposal storage in the smart manufacturing site embedded with RMFS.

The limitation of this study majorly is only to provide a conceptual framework to append the discussion and current literature on RMFS in manufacturing. Therefore, the practical applicability of the proposed framework in this stage might not be testable. Also, the layout of the proposed framework is adopted in a small manufacturing system. The extension of the application should also be tested with the consideration of different facility layout planning. The research could be extended based on the three aspects. First, the experiments with real physical mobile robots and real-life environments, included for the non-grid-based environment, could be adopted for real-time controlling and monitoring. The layout could be further tested with different planning and settings. The path planning algorithm could be further considered for dynamic conflict resolution. The manufacturing site could be further with drones for the tools and materials storage. Second, latency and a context-aware model could be further analyzed during real-life experiments and considered embedded into the current proposed CPPS for a rapid response system. To solve the end-to-end latency of multi-hop micro-services, a micro-service placement for edge-cloud collaborative smart manufacturing could be further considered and extended for the proposed model. Third, the difference between customization and conventional sale is that the co-creation process is added to customization. 3D printing production layout design is still under exploration. 3D printing allows small batch wide varieties production, and mass customization can be achieved by 3D printing technology. Balancing the customization and standardization is important for 3D printing production layout design. Among those 3D printing products, bio-medical device by 3D printing technology requires a high hygiene level of the production site. The mobile robot can reduce manual operation and enable consistency in product quality as just-in-time WIP delivery can be accomplished by CPRMFS. The value-added properties make customization become a trend in consumption patterns. Therefore, the model could be further developed to consider customization in 3D printing in the future.

References

[1] Y. Lu, K. C. Morris, and S. Frechette, "Current standards landscape for smart manufacturing systems," *National Institute of Standards and Technology, NISTIR,* vol. 8107, p. 39, 2016.

[2] C. Yang, Y. Wang, S. Lan, L. Wang, W. Shen, and G. Q. Huang, "Cloud-edge-device collaboration mechanisms of deep learning models for smart robots in mass personalization," *Robotics and Computer-Integrated Manufacturing,* vol. 77, p. 102351, 2022/10/01/ 2022, doi: https://doi.org/10.1016/j.rcim.2022.102351.

[3] R. Y. Zhong, X. Xu, E. Klotz, and S. T. Newman, "Intelligent Manufacturing in the Context of Industry 4.0: A Review," *Engineering,* vol. 3, no. 5, pp. 616-630, 2017/10/01/ 2017, doi: https://doi.org/10.1016/J.ENG.2017.05.015.

[4] S. Mittal, M. A. Khan, D. Romero, and T. Wuest, "Smart manufacturing: Characteristics, technologies and enabling factors," *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture,* vol. 233, no. 5, pp. 1342-1361, 2019/04/01 2017, doi: 10.1177/0954405417736547.

[5] J. Fan, P. Zheng, and S. Li, "Vision-based holistic scene understanding towards proactive human–robot collaboration," *Robotics and Computer-Integrated Manufacturing,* vol. 75, p. 102304, 2022/06/01/ 2022, doi: https://doi.org/10.1016/j.rcim.2021.102304.

[6] Y. Lu, C. Liu, K. I. K. Wang, H. Huang, and X. Xu, "Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues," *Robotics and Computer-Integrated Manufacturing,* vol. 61, p. 101837, 2020/02/01/ 2020, doi: https://doi.org/10.1016/j.rcim.2019.101837.

[7] A. Kusiak, "Fundamentals of smart manufacturing: A multi-thread perspective," *Annual Reviews in Control,* vol. 47, pp. 214-220, 2019/01/01/ 2019, doi: https://doi.org/10.1016/j.arcontrol.2019.02.001.

[8] C. Liu, Z. Su, X. Xu, and Y. Lu, "Service-oriented industrial internet of things gateway for cloud manufacturing," *Robotics and Computer-Integrated Manufacturing,* vol. 73, p. 102217, 2022/02/01/ 2022, doi: https://doi.org/10.1016/j.rcim.2021.102217.

[9] J. Hua, Y. Li, C. Liu, and L. Wang, "A zero-shot prediction method based on causal inference under non-stationary manufacturing environments for complex manufacturing systems," *Robotics and Computer-Integrated Manufacturing,* vol. 77, p. 102356, 2022/10/01/ 2022, doi: https://doi.org/10.1016/j.rcim.2022.102356.

[10] D. Wu, M. J. Greer, D. W. Rosen, and D. Schaefer, "Cloud manufacturing: Strategic vision and state-of-the-art," *Journal of Manufacturing Systems,* vol. 32, no. 4, pp. 564-579, 2013/10/01/ 2013, doi: https://doi.org/10.1016/j.jmsy.2013.04.008.

[11] X. Xu, "From cloud computing to cloud manufacturing," *Robotics and Computer-Integrated Manufacturing,* vol. 28, no. 1, pp. 75-86, 2012/02/01/ 2012, doi: https://doi.org/10.1016/j.rcim.2011.07.002.

[12] O. Fisher, N. Watson, L. Porcu, D. Bacon, M. Rigley, and R. L. Gomes, "Cloud manufacturing as a sustainable process manufacturing route," *Journal of Manufacturing Systems,* vol. 47, pp. 53-68, 2018/04/01/ 2018, doi: https://doi.org/10.1016/j.jmsy.2018.03.005.

[13] X. Zhang, J. Fan, T. Peng, P. Zheng, X. Zhang, and R. Tang, "Multimodal data-based deep learning model for sitting posture recognition toward office workers' health promotion," *Sensors and Actuators A: Physical,* vol. 350, p. 114150, 2023/02/01/ 2023, doi: https://doi.org/10.1016/j.sna.2022.114150.

[14] X. Zhang, J. Fan, T. Peng, P. Zheng, C. K. M. Lee, and R. Tang, "A privacy-preserving and unobtrusive sitting posture recognition system via pressure array sensor and infrared array sensor for office workers," *Advanced Engineering Informatics,* vol. 53, p. 101690, 2022/08/01/ 2022, doi: https://doi.org/10.1016/j.aei.2022.101690.

[15] S. Li, P. Zheng, J. Fan, and L. Wang, "Toward Proactive Human–Robot Collaborative Assembly: A Multimodal Transfer-Learning-Enabled Action Prediction Approach," *IEEE Transactions on Industrial Electronics,* vol. 69, no. 8, pp. 8579-8588, 2022, doi: 10.1109/TIE.2021.3105977.

[16] J. Fan, P. Zheng, S. Li, and L. Wang, "An Integrated Hand-Object Dense Pose Estimation Approach With Explicit Occlusion Awareness for Human-Robot Collaborative Disassembly," *IEEE Transactions on Automation Science and Engineering,* pp. 1-10, 2022, doi: 10.1109/TASE.2022.3215584.

[17] S. Li, P. Zheng, J. Fan, and L. Wang, "Towards Proactive Human Robot Collaborative Assembly: A Multimodal Transfer Learning-Enabled Action Prediction Approach," *IEEE Transactions on Industrial Electronics,* pp. 1-1, 2021, doi: 10.1109/TIE.2021.3105977.

[18] S. Li, J. Fan, P. Zheng, and L. Wang, "Transfer Learning-enabled Action Recognition for Human-robot Collaborative Assembly," *Procedia CIRP,* vol. 104, pp. 1795-1800, 2021/01/01/ 2021, doi: https://doi.org/10.1016/j.procir.2021.11.303.

[19] Q. Li, K. K. H. Ng, Z. Fan, X. Yuan, H. Liu, and L. Bu, "A human-centred approach based on functional near-infrared spectroscopy for adaptive decision-making in the air traffic control environment: A case study," *Advanced Engineering Informatics,* vol. 49, p. 101325, 2021/08/01/ 2021, doi: https://doi.org/10.1016/j.aei.2021.101325.

[20] Q. Li *et al.*, "Effects of the multisensory rehabilitation product for home-based hand training after stroke on cortical activation by using NIRS methods," *Neuroscience Letters,* vol. 717, p. 134682, 2020/01/19/ 2020, doi: https://doi.org/10.1016/j.neulet.2019.134682.

[21] G. Wang, G. Zhang, X. Guo, and Y. Zhang, "Digital twin-driven service model and optimal allocation of manufacturing resources in shared manufacturing," *Journal of Manufacturing Systems,* vol. 59, pp. 165-179,

2021/04/01/ 2021, doi: https://doi.org/10.1016/j.jmsy.2021.02.008.
[22] D. Guo, R. Y. Zhong, Y. Rong, and G. G. Q. Huang, "Synchronization of Shop-Floor Logistics and Manufacturing Under IIoT and Digital Twin-Enabled Graduation Intelligent Manufacturing System," *IEEE Transactions on Cybernetics,* pp. 1-12, 2021, doi: 10.1109/TCYB.2021.3108546.
[23] L. Xia, P. Zheng, X. Huang, and C. Liu, "A novel hypergraph convolution network-based approach for predicting the material removal rate in chemical mechanical planarization," *Journal of Intelligent Manufacturing,* 2021/05/24 2021, doi: 10.1007/s10845-021-01784-1.
[24] P. Zheng, L. Xia, C. Li, X. Li, and B. Liu, "Towards Self-X cognitive manufacturing network: An industrial knowledge graph-based multi-agent reinforcement learning approach," *Journal of Manufacturing Systems,* vol. 61, pp. 16-26, 2021/10/01/ 2021, doi: https://doi.org/10.1016/j.jmsy.2021.08.002.
[25] T. Jing, P. Zheng, L. Xia, and T. Liu, "Transformer-based hierarchical latent space VAE for interpretable remaining useful life prediction," *Advanced Engineering Informatics,* vol. 54, p. 101781, 2022/10/01/ 2022, doi: https://doi.org/10.1016/j.aei.2022.101781.
[26] L. Xia, P. Zheng, X. Li, R. X. Gao, and L. Wang, "Toward cognitive predictive maintenance: A survey of graph-based approaches," *Journal of Manufacturing Systems,* vol. 64, pp. 107-120, 2022/07/01/ 2022, doi: https://doi.org/10.1016/j.jmsy.2022.06.002.
[27] P. Zheng, S. Li, L. Xia, L. Wang, and A. Nassehi, "A visual reasoning-based approach for mutual-cognitive human-robot collaboration," *CIRP Annals,* 2022/04/26/ 2022, doi: https://doi.org/10.1016/j.cirp.2022.04.016.
[28] Y. Liang, P. Zheng, and L. Xia, "A visual reasoning-based approach for driving experience improvement in the AR-assisted head-up displays," *Advanced Engineering Informatics,* vol. 55, p. 101888, 2023/01/01/ 2023, doi: https://doi.org/10.1016/j.aei.2023.101888.
[29] L. Xia, Y. Liang, J. Leng, and P. Zheng, "Maintenance planning recommendation of complex industrial equipment based on knowledge graph and graph neural network," *Reliability Engineering & System Safety,* vol. 232, p. 109068, 2023/04/01/ 2023, doi: https://doi.org/10.1016/j.ress.2022.109068.
[30] L. Ren, L. Zhang, L. Wang, F. Tao, and X. Chai, "Cloud manufacturing: key characteristics and applications," *International Journal of Computer Integrated Manufacturing,* vol. 30, no. 6, pp. 501-515, 2017/06/03 2017, doi: 10.1080/0951192X.2014.902105.
[31] F. Tao, Y. Cheng, L. D. Xu, L. Zhang, and B. H. Li, "CCIoT-CMfg: Cloud Computing and Internet of Things-Based Cloud Manufacturing Service System," *IEEE Transactions on Industrial Informatics,* vol. 10, no. 2, pp. 1435-1442, 2014, doi: 10.1109/TII.2014.2306383.
[32] G. Zhang, G. Wang, C.-H. Chen, X. Cao, Y. Zhang, and P. Zheng, "Augmented Lagrangian coordination for energy-optimal allocation of smart manufacturing services," *Robotics and Computer-Integrated Manufacturing,* vol. 71, p. 102161, 2021/10/01/ 2021, doi: https://doi.org/10.1016/j.rcim.2021.102161.
[33] B. Liu, Y. Zhang, J. Lv, A. Majeed, C.-H. Chen, and D. Zhang, "A cost-effective manufacturing process recognition approach based on deep transfer learning for CPS enabled shop-floor," *Robotics and Computer-Integrated Manufacturing,* vol. 70, p. 102128, 2021/08/01/ 2021, doi: https://doi.org/10.1016/j.rcim.2021.102128.
[34] N. Nikolakis, R. Senington, K. Sipsas, A. Syberfeldt, and S. Makris, "On a containerized approach for the dynamic planning and control of a cyber - physical production system," *Robotics and Computer-Integrated Manufacturing,* vol. 64, p. 101919, 2020/08/01/ 2020, doi: https://doi.org/10.1016/j.rcim.2019.101919.
[35] Y. Gao, L. Gao, X. Li, and X. Yan, "A semi-supervised convolutional neural network-based method for steel surface defect recognition," *Robotics and Computer-Integrated Manufacturing,* vol. 61, p. 101825, 2020/02/01/ 2020, doi: https://doi.org/10.1016/j.rcim.2019.101825.
[36] R. G. Lins, P. R. M. de Araujo, and M. Corazzim, "In-process machine vision monitoring of tool wear for Cyber-Physical Production Systems," *Robotics and Computer-Integrated Manufacturing,* vol. 61, p. 101859, 2020/02/01/ 2020, doi: https://doi.org/10.1016/j.rcim.2019.101859.
[37] J. Wang, Y. Ma, L. Zhang, R. X. Gao, and D. Wu, "Deep learning for smart manufacturing: Methods and applications," *Journal of Manufacturing Systems,* vol. 48, pp. 144-156, 2018/07/01/ 2018, doi: https://doi.org/10.1016/j.jmsy.2018.01.003.
[38] S. Li, R. Wang, P. Zheng, and L. Wang, "Towards proactive human–robot collaboration: A foreseeable cognitive manufacturing paradigm," *Journal of Manufacturing Systems,* vol. 60, pp. 547-552, 2021/07/01/ 2021, doi: https://doi.org/10.1016/j.jmsy.2021.07.017.
[39] K. L. Keung, C. K. M. Lee, and P. Ji, "Data-driven order correlation pattern and storage location assignment in robotic mobile fulfillment and process automation system," *Advanced Engineering Informatics,* vol. 50, p. 101369, 2021/10/01/ 2021, doi: https://doi.org/10.1016/j.aei.2021.101369.
[40] K. L. Keung, C. K. M. Lee, and P. Ji, "Industrial internet of things-driven storage location assignment and order picking in a resource synchronization and sharing-based robotic mobile fulfillment system," *Advanced Engineering Informatics,* vol. 52, p. 101540, 2022/04/01/ 2022, doi: https://doi.org/10.1016/j.aei.2022.101540.
[41] K. L. Keung, L. Xia, C. K. M. Lee, and C. Y. Leung, "A Shortest Path Graph Attention Network and Non-traditional Multi-deep Layouts in Robotic Mobile Fulfillment System," in *2022 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, 7-10 Dec. 2022 2022, pp. 0655-0659, doi:

10.1109/IEEM55944.2022.9989607.

[42] K. L. Keung, C. K. M. Lee, P. Ji, and K. K. H. Ng, "Cloud-based Cyber-Physical Robotic Mobile Fulfillment Systems: A Case Study of Collision Avoidance," *IEEE Access,* pp. 1-1, 2020, doi: 10.1109/ACCESS.2020.2992475.

[43] K. L. Keung, C. K. M. Lee, P. Ji, and J. Huo, "Cloud-based Cyber-Physical Robotic Mobile Fulfillment Systems Considering Order Correlation Pattern," in *2020 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, 14-17 Dec. 2020 2020, pp. 113-117, doi: 10.1109/IEEM45057.2020.9309904.

[44] Q. Li, F. Gama, A. Ribeiro, and A. Prorok, "Graph Neural Networks for Decentralized Multi-Robot Path Planning," in *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 24 Oct.-24 Jan. 2021 2020, pp. 11785-11792, doi: 10.1109/IROS45743.2020.9341668.

[45] Q. Li, W. Lin, Z. Liu, and A. Prorok, "Message-Aware Graph Attention Networks for Large-Scale Multi-Robot Path Planning," *IEEE Robotics and Automation Letters,* vol. 6, no. 3, pp. 5533-5540, 2021, doi: 10.1109/LRA.2021.3077863.

[46] F. Ansari, M. Khobreh, U. Seidenberg, and W. Sihn, "A problem-solving ontology for human-centered cyber physical production systems," *CIRP Journal of Manufacturing Science and Technology,* vol. 22, pp. 91-106, 2018/08/01/ 2018, doi: https://doi.org/10.1016/j.cirpj.2018.06.002.

[47] T. Tomiyama and F. Moyen, "Resilient architecture for cyber-physical production systems," *CIRP Annals,* vol. 67, no. 1, pp. 161-164, 2018/01/01/ 2018, doi: https://doi.org/10.1016/j.cirp.2018.04.021.

[48] L. Monostori, "Cyber-physical Production Systems: Roots, Expectations and R&D Challenges," *Procedia CIRP,* vol. 17, pp. 9-13, 2014/01/01/ 2014, doi: https://doi.org/10.1016/j.procir.2014.03.115.

[49] C. Liu, L. Le Roux, C. Körner, O. Tabaste, F. Lacan, and S. Bigot, "Digital Twin-enabled Collaborative Data Management for Metal Additive Manufacturing Systems," *Journal of Manufacturing Systems,* 2020/05/27/ 2020, doi: https://doi.org/10.1016/j.jmsy.2020.05.010.

[50] M.-C. Chiu, C.-D. Tsai, and T.-L. Li, "An Integrative Machine Learning Method to Improve Fault Detection and Productivity Performance in a Cyber-Physical System," *Journal of Computing and Information Science in Engineering,* vol. 20, no. 2, 2020, doi: 10.1115/1.4045663.

[51] Y. Jiang and S. Yin, "Recursive Total Principle Component Regression Based Fault Detection and Its Application to Vehicular Cyber-Physical Systems," *IEEE Transactions on Industrial Informatics,* vol. 14, no. 4, pp. 1415-1423, 2018, doi: 10.1109/TII.2017.2752709.

[52] Y. He, B. Nie, J. Zhang, P. M. Kumar, and B. Muthu, "Fault Detection and Diagnosis of Cyber-Physical System Using the Computer Vision and Image Processing," *Wireless Personal Communications,* 2021/08/11 2021, doi: 10.1007/s11277-021-08774-9.

[53] C. Alippi, S. Ntalampiras, and M. Roveri, "Model-Free Fault Detection and Isolation in Large-Scale Cyber-Physical Systems," *IEEE Transactions on Emerging Topics in Computational Intelligence,* vol. 1, no. 1, pp. 61-71, 2017, doi: 10.1109/TETCI.2016.2641452.

[54] V. R. Palleti, Y. C. Tan, and L. Samavedham, "A mechanistic fault detection and isolation approach using Kalman filter to improve the security of cyber physical systems," *Journal of Process Control,* vol. 68, pp. 160-170, 2018/08/01/ 2018, doi: https://doi.org/10.1016/j.jprocont.2018.05.005.

[55] W. Jiang, L. Wen, J. Zhan, and K. Jiang, "Design optimization of confidentiality-critical cyber physical systems with fault detection," *Journal of Systems Architecture,* vol. 107, p. 101739, 2020/08/01/ 2020, doi: https://doi.org/10.1016/j.sysarc.2020.101739.

[56] B. Yao, Z. Zhou, L. Wang, W. Xu, J. Yan, and Q. Liu, "A function block based cyber-physical production system for physical human–robot interaction," *Journal of Manufacturing Systems,* vol. 48, pp. 12-23, 2018/07/01/ 2018, doi: https://doi.org/10.1016/j.jmsy.2018.04.010.

[57] K. Ding, F. T. S. Chan, X. Zhang, G. Zhou, and F. Zhang, "Defining a Digital Twin-based Cyber-Physical Production System for autonomous manufacturing in smart shop floors," *International Journal of Production Research,* vol. 57, no. 20, pp. 6315-6334, 2019/10/18 2019, doi: 10.1080/00207543.2019.1566661.

[58] H. Zhang, Q. Yan, and Z. Wen, "Information modeling for cyber-physical production system based on digital twin and AutomationML," *The International Journal of Advanced Manufacturing Technology,* vol. 107, no. 3, pp. 1927-1945, 2020/03/01 2020, doi: 10.1007/s00170-020-05056-9.

[59] I. Graessler and A. Poehler, "Integration of a digital twin as human representation in a scheduling procedure of a cyber-physical production system," in *2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, 10-13 Dec. 2017 2017, pp. 289-293, doi: 10.1109/IEEM.2017.8289898.

[60] F. Tao, Q. Qi, A. Liu, and A. Kusiak, "Data-driven smart manufacturing," *Journal of Manufacturing Systems,* vol. 48, pp. 157-169, 2018/07/01/ 2018, doi: https://doi.org/10.1016/j.jmsy.2018.01.006.

[61] F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "Digital Twin in Industry: State-of-the-Art," *IEEE Transactions on Industrial Informatics,* vol. 15, no. 4, pp. 2405-2415, 2019, doi: 10.1109/TII.2018.2873186.

[62] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, and F. Sui, "Digital twin-driven product design, manufacturing and service with big data," *The International Journal of Advanced Manufacturing Technology,* vol. 94, no. 9, pp. 3563-3576, 2018/02/01 2018, doi: 10.1007/s00170-017-0233-1.

[63] C. Liu and X. Xu, "Cyber-physical Machine Tool – The Era of Machine Tool 4.0," *Procedia CIRP,* vol. 63, pp. 70-75, 2017/01/01/ 2017, doi: https://doi.org/10.1016/j.procir.2017.03.078.

[64] C. Liu, S. Cao, W. Tse, and X. Xu, "Augmented Reality-assisted Intelligent Window for Cyber-Physical Machine Tools," *Journal of Manufacturing Systems,* vol. 44, pp. 280-286, 2017/07/01/ 2017, doi: https://doi.org/10.1016/j.jmsy.2017.04.008.

[65] C. Liu, H. Vengayil, Y. Lu, and X. Xu, "A Cyber-Physical Machine Tools Platform using OPC UA and MTConnect," *Journal of Manufacturing Systems,* vol. 51, pp. 61-74, 2019/04/01/ 2019, doi: https://doi.org/10.1016/j.jmsy.2019.04.006.

[66] C. Liu, X. Xu, Q. Peng, and Z. Zhou, "MTConnect-based Cyber-Physical Machine Tool: a case study," *Procedia CIRP,* vol. 72, pp. 492-497, 2018/01/01/ 2018, doi: https://doi.org/10.1016/j.procir.2018.03.059.

[67] Z. Zhu, C. Liu, and X. Xu, "Visualization of the Digital Twin data in manufacturing by using Augmented Reality," *Procedia CIRP,* vol. 81, pp. 898-903, 2019/01/01/ 2019, doi: https://doi.org/10.1016/j.procir.2019.03.223.

[68] H. Yu, D. Yu, C. Wang, Y. Hu, and Y. Li, "Edge intelligence-driven digital twin of CNC system: Architecture and deployment," *Robotics and Computer-Integrated Manufacturing,* vol. 79, p. 102418, 2023/02/01/ 2023, doi: https://doi.org/10.1016/j.rcim.2022.102418.

[69] W. Li, H. Fu, Z. Han, X. Zhang, and H. Jin, "Intelligent tool wear prediction based on Informer encoder and stacked bidirectional gated recurrent unit," *Robotics and Computer-Integrated Manufacturing,* vol. 77, p. 102368, 2022/10/01/ 2022, doi: https://doi.org/10.1016/j.rcim.2022.102368.

[70] C. Liu *et al.*, "Probing an intelligent predictive maintenance approach with deep learning and augmented reality for machine tools in IoT-enabled manufacturing," *Robotics and Computer-Integrated Manufacturing,* vol. 77, p. 102357, 2022/10/01/ 2022, doi: https://doi.org/10.1016/j.rcim.2022.102357.

[71] X. Wang, L. T. Yang, Y. Wang, L. Ren, and M. J. Deen, "ADTT: A Highly Efficient Distributed Tensor-Train Decomposition Method for IIoT Big Data," *IEEE Transactions on Industrial Informatics,* vol. 17, no. 3, pp. 1573-1582, 2021, doi: 10.1109/TII.2020.2967768.

[72] M. S. Hossain and G. Muhammad, "Cloud-assisted Industrial Internet of Things (IIoT) – Enabled framework for health monitoring," *Computer Networks,* vol. 101, pp. 192-202, 2016/06/04/ 2016, doi: https://doi.org/10.1016/j.comnet.2016.01.009.

[73] R. Chaudhary, G. S. Aujla, S. Garg, N. Kumar, and J. J. P. C. Rodrigues, "SDN-Enabled Multi-Attribute-Based Secure Communication for Smart Grid in IIoT Environment," *IEEE Transactions on Industrial Informatics,* vol. 14, no. 6, pp. 2629-2640, 2018, doi: 10.1109/TII.2018.2789442.

[74] F. Al-Turjman and S. Alturjman, "Context-Sensitive Access in Industrial Internet of Things (IIoT) Healthcare Applications," *IEEE Transactions on Industrial Informatics,* vol. 14, no. 6, pp. 2736-2744, 2018, doi: 10.1109/TII.2018.2808190.

[75] K. A. Abuhasel and M. A. Khan, "A Secure Industrial Internet of Things (IIoT) Framework for Resource Management in Smart Manufacturing," *IEEE Access,* vol. 8, pp. 117354-117364, 2020, doi: 10.1109/ACCESS.2020.3004711.

[76] M. Liu, F. R. Yu, Y. Teng, V. C. M. Leung, and M. Song, "Performance Optimization for Blockchain-Enabled Industrial Internet of Things (IIoT) Systems: A Deep Reinforcement Learning Approach," *IEEE Transactions on Industrial Informatics,* vol. 15, no. 6, pp. 3559-3570, 2019, doi: 10.1109/TII.2019.2897805.

[77] Z. Liu, Q. Liu, W. Xu, L. Wang, and Z. Zhou, "Robot learning towards smart robotic manufacturing: A review," *Robotics and Computer-Integrated Manufacturing,* vol. 77, p. 102360, 2022/10/01/ 2022, doi: https://doi.org/10.1016/j.rcim.2022.102360.

[78] R. E. Andersen *et al.*, "Integration of a Skill-based Collaborative Mobile Robot in a Smart Cyber-physical Environment," *Procedia Manufacturing,* vol. 11, pp. 114-123, 2017/01/01/ 2017, doi: https://doi.org/10.1016/j.promfg.2017.07.209.

[79] P. Singh, P. Agrawal, H. Karki, A. Shukla, N. K. Verma, and L. Behera, "Vision-Based Guidance and Switching-Based Sliding Mode Controller for a Mobile Robot in the Cyber Physical Framework," *IEEE Transactions on Industrial Informatics,* vol. 15, no. 4, pp. 1985-1997, 2019, doi: 10.1109/TII.2018.2869622.

[80] L. Tai and M. Liu, "Mobile robots exploration through cnn-based reinforcement learning," *Robotics and Biomimetics,* vol. 3, no. 1, p. 24, 2016/12/21 2016, doi: 10.1186/s40638-016-0055-x.

[81] T. Kruglova, I. Schmelev, I. Sushkov, and R. Filatov, "Cyber-physical System of the Mobile Robot's Optimal Trajectory Planning with taking into account Electric Motors Deterioration," in *2019 International Multi-Conference on Industrial Engineering and Modern Technologies (FarEastCon)*, 1-4 Oct. 2019 2019, pp. 1-5, doi: 10.1109/FarEastCon.2019.8934193.

[82] Y. Liu, W. Wang, Y. Hu, J. Hao, X. Chen, and Y. Gao, "Multi-Agent Game Abstraction via Graph Attention Neural Network," *Proceedings of the AAAI Conference on Artificial Intelligence,* vol. 34, no. 05, pp. 7211-7218, 04/03 2020, doi: 10.1609/aaai.v34i05.6211.

[83] J. Jiang, C. Dun, T. Huang, and Z. Lu, "Graph convolutional reinforcement learning," *arXiv preprint arXiv:1810.09202,* 2018.

[84] K. K. H. Ng, C.-H. Chen, C. K. M. Lee, J. Jiao, and Z.-X. Yang, "A systematic literature review on intelligent

automation: Aligning concepts from theory, practice, and future perspectives," *Advanced Engineering Informatics,* vol. 47, p. 101246, 2021/01/01/ 2021, doi: https://doi.org/10.1016/j.aei.2021.101246.

[85] J. Wang, Y. Liu, S. Ren, C. Wang, and S. Ma, "Edge computing-based real-time scheduling for digital twin flexible job shop with variable time window," *Robotics and Computer-Integrated Manufacturing,* vol. 79, p. 102435, 2023/02/01/ 2023, doi: https://doi.org/10.1016/j.rcim.2022.102435.

[86] L. Wang, M. Törngren, and M. Onori, "Current status and advancement of cyber-physical systems in manufacturing," *Journal of Manufacturing Systems,* vol. 37, pp. 517-527, 2015/10/01/ 2015, doi: https://doi.org/10.1016/j.jmsy.2015.04.008.

[87] E. A. Lee, "Cyber Physical Systems: Design Challenges," in *2008 11th IEEE International Symposium on Object and Component-Oriented Real-Time Distributed Computing (ISORC)*, 5-7 May 2008 2008, pp. 363-369, doi: 10.1109/ISORC.2008.25.

[88] J. Lee, B. Bagheri, and H.-A. Kao, "A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems," *Manufacturing Letters,* vol. 3, pp. 18-23, 2015/01/01/ 2015, doi: https://doi.org/10.1016/j.mfglet.2014.12.001.

[89] J. Lee, H.-A. Kao, and S. Yang, "Service Innovation and Smart Analytics for Industry 4.0 and Big Data Environment," *Procedia CIRP,* vol. 16, pp. 3-8, 2014/01/01/ 2014, doi: https://doi.org/10.1016/j.procir.2014.02.001.

[90] A. Paszke *et al.*, "Automatic differentiation in pytorch," 2017.

[91] G. Sharon, R. Stern, A. Felner, and N. R. Sturtevant, "Conflict-based search for optimal multi-agent pathfinding," *Artificial Intelligence,* vol. 219, pp. 40-66, 2015/02/01/ 2015, doi: https://doi.org/10.1016/j.artint.2014.11.006.

[92] M. Barer, G. Sharon, R. Stern, and A. Felner, "Suboptimal variants of the conflict-based search algorithm for the multi-agent pathfinding problem," in *Seventh Annual Symposium on Combinatorial Search*, 2014.

[93] C. K. M. Lee, K. K. H. Ng, C.-H. Chen, H. C. W. Lau, S. Y. Chung, and T. Tsoi, "American sign language recognition and training method with recurrent neural network," *Expert Systems with Applications,* vol. 167, p. 114403, 2021/04/01/ 2021, doi: https://doi.org/10.1016/j.eswa.2020.114403.

[94] S. Yan, Y. Xiong, and D. Lin, "Spatial temporal graph convolutional networks for skeleton-based action recognition," in *Thirty-second AAAI conference on artificial intelligence*, 2018.

[95] X. Deng, Q. Liu, Y. Deng, and S. Mahadevan, "An improved method to construct basic probability assignment based on the confusion matrix for classification problem," *Information Sciences,* vol. 340-341, pp. 250-261, 2016/05/01/ 2016, doi: https://doi.org/10.1016/j.ins.2016.01.033.

[96] A. Tharwat, "Classification assessment methods," *Applied Computing and Informatics,* 2020, doi: 10.1016/j.aci.2018.08.003.

[97] D. Powers, "Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation," *ArXiv,* vol. abs/2010.16061, 2020.

[98] T. Fawcett, "An introduction to ROC analysis," *Pattern Recognition Letters,* vol. 27, no. 8, pp. 861-874, 2006/06/01/ 2006, doi: https://doi.org/10.1016/j.patrec.2005.10.010.