Advanced Engineering Informatics 52 (2022) 101530

Contents lists available at ScienceDirect

Advanced Engineering Informatics

journal homepage: www.elsevier.com/locate/aei

Edge intelligence and agnostic robotic paradigm in resource synchronisation and sharing in flexible robotic and facility control system

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ARTICLE INFO

Keywords:
Agnostic robotic paradigm
Cloud-edge computing
Flexible robotic and facility control system
Unmanned ground vehicles
Robotic mobile fulfilment system

ABSTRACT

The agnostic robotic paradigm (ARP) represents a recent development as the use of robots becomes more common, and there is a need for agnostic robots to cope with rich artificial objects environments. All parties and stakeholders need to seize the imminent opportunity and act on ushering in the revolutionary changes of contemporary robotic and facility control solutions. The scalability and effectiveness of robotic enterprise solutions depend primarily on the availability of operational information, robotic solutions, and their information infrastructure. However, different functions and software of robotics and facilities are being launched in the market. Therefore, this paper investigates the implementation of the emerging ARP for the Industrial Internet of Things (IIoT) and resource synchronisation flexible robotic and facility control system to address this challenge. We propose an Artificial Intelligence (AI) edge intelligence and IIoT-based agnostic robotic architecture for resource synchronisation and sharing in manufacturing and robotic mobile fulfillment systems (RMFS). We adopted simultaneous localisation and mapping (SLAM) as one of the edge intelligence, provided the simulation results, and tested with multiple parameters under different conflicts. Our research suggests that purposely developing an ARP for flexible robotic and facility control system via IIoT assisted with AI-edge intelligence are a good solution for both operational and management level under a cloud platform.

1. Introduction

1.1. Problem description

Under the COVID-19 pandemic, the increasing consumer demand for online shopping burdens manufacturer and warehouse storage operations due to the enormous variety of products. As a result, all the stakeholders within the supply chain are concerned about enhancing the overall operation efficiency under the limited human resources situation to fulfil customer satisfaction and expectation [1,2]. To enhance the overall efficiency, Industrial Internet-of-Things (IIoT)-based manufacturing and warehouse models, aided by emerging technologies such as autonomous robots and related computing facilities, are widely adopted, through which enterprises can fully automate certain business and industrial activities [3–6]. Nevertheless, resource synchronisation between different robotic software is essential in enhancing the overall operational efficiency as it would allow robots to multi-task instead of being constrained. This move can be beneficial to improve the service quality, ensure compliance with rules and regulations, reduce human errors, standardise the workflow procedure, and visualise the robotic and facility activities in an intelligent factory setting. However, every year, we can see different functions of robots and facilities being launched in the market [7,8]. All robotic and facility control systems are brand-made products and have different in-house solutions, which becomes a significant barrier for efficient control of all the entities in a unified system [9,10]. The communication between multiple smart units may not necessarily improve the process efficiency as per users' expectations, as the digitalisation of smart units and integrated approach between the centralised control system and smart units requires seamless integration [11–13]. However, no appropriate solution has been

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https://doi.org/10.1016/j.aei.2022.101530
Received 28 September 2021; Received in revised form 5 January 2022; Accepted 7 January 2022
Available online 13 February 2022
1474-0346/

launched in the market. Although there are standard technologies in use between different brands of robots, such as Simultaneous Localisation and Mapping (SLAM) for scanning surrounding and map validation, Wifi for the control connection, each of the robots has a unique control program and language. It will be difficult for a production line that comprises robots with different software and facilities for the user to control such a wide array of systems to complete the specified tasks. Consequently, this will drop flexibility and efficiency within the production line [14–16].

The concept of Industry 4.0 (I4.0) has been promoted in different countries [17]. Advanced human–machine interaction is one of the crucial features that a smart factory requires. Some manufacturing factories have started to adopt collaborative robots to work with human labors so that human workers' ergonomic and physical demands can be reduced while the productivity and quality of the products can be increased. It is vital to understand what factors may affect the interaction among operators and robots. Trust has been proven to be a crucial factor determining how well the operators can interact with the robots. Only with a reasonable trust level can the robots' capabilities be fully utilised, and the performance of the robots can be maximised and the investment. Moreover, the deployment of multiple sets of robotic and facility control systems becomes a challenge to most industries due to the non-unified system of each robot. Using a smart manufacturing plant as an example, the sensing technology on the smart unit can enable it to observe possible obstacles and human surroundings, ensuring safety and conflict-free path planning, it may need to communicate with the automatic turnstile and elevator to grant them access right to different floors and office areas in the building [1,11–13]. The example mentioned above indicated that artificial intelligence (AI) edge intelligence at the local level and cloud-edge computing at the global level could provide a certain level of intelligence, flexibility, superior perception, integrability, mobility, and adaptability in the smart factory.

Despite that, the challenge of implementing a comprehensive design for flexible manufacturing utilising a robotic mobile fulfilment system (RMFS) still needs to be considered [18–21]. Flexible manufacturing can be defined as minimising the workstation configuration according to a different product or assembled parts demand to maximise the workstation utilisation [22,23]. However, as the size of the smart robot is fixed to fit its controllable workstation, reduced compatibility between different robots will isolate the automation solution. Under these circumstances, it requires users to design a specification and request the third party to customise the robot that fits their application scenario, which induces high cost for the robot and lack flexibility [24–30]. If the application scenario is changed, the users need to re-design the decision and system logic of the robot. The service and maintenance costs will be high, and the adoption of this robot will not be cost-effective. In addition, a deployment period is required when implementing a new solution to change the overall design, which affects the original order schedule. Hence, users may not have the incentive to utilise application-oriented smart factory solutions [7–10].

Consequently, the lack of user-defined functions in the smart units may induce unfavorable results and affect operational decisions. Not every robot and facility control unit can be produced in-house, as the research and development of the smart units may involve different domains of knowledge and take time. From the third parties' perspective, they would instead provide robotic and facility units with the most common function to achieve a higher level of generalisation and commercialisation than provide highly customised solutions to gain a larger market share. One way to solve this problem is to enable the communication between the cloud (centered decision) and the smart units [31], but the timespan of the two-way communication may not satisfy the requirements for real-time decision, and sometimes it is not necessary to have a centralised decision requirement.

Given these contemporary industry issues and challenges, the paper aims to develop AI edge intelligence and cloud-edge computing for flexible robotic and facility control systems. AI edge intelligence in this paper means the function of the robot itself, like obstacle avoidance, while the cloud-edge computing in this paper refers to the system for robot job assignments. The paper considers the emerging technology of AI edge intelligence, cloud-edge computing, wireless sensing technology, data analytics, adaptive decision-making, swarm robotics, facility control design, and modularised control systems. Each smart unit edge device and its intelligence can be viewed as the components or modules of the system. When new smart units are introduced in the smart factory, the edge device can be customised on the smart unit and create a new module in the robotic and facility control system. Users can rely on a unified control system to monitor, control and command the smart units and review their current job status. The system serves as a solution bundle as a robust, IT-driven, modularised control system for future robotic and facility control systems. Upon completing this paper, AI edge intelligence and cloud-edge computing for flexible robotic and facility control systems will be designed and developed to achieve better solution robustness, real-time context awareness, and situation awareness of smart units through digitalisation and servitisation. The robots in the system can then be assigned to various tasks in accordance with company needs, instead of being limited to specific functions based on its unique language, in addition to better intercommunication and collaboration between units [32–35].

The contributions of this article are outlined below. First, a comprehensive literature review considering the agnostic robotic paradigm (ARP), the cloud-edge computing and edge intelligence, robotic and resource synchronisation and sharing in a smart manufacturing context, and the research gap is presented in Section 2. The connection between the Cyber-Physical System (CPS), cloud computing, and edge intelligence has been exhaustively covered to support the ARP is summarised in the Section 2. The nearly-real time data from the physical layer assisted with edge intelligence are converted and transmitted to the control layer and stored in the cloud-based database applied in multiple scenarios considered in multiple of researches. SLAM technique is further studied and explored for the ARP-based architecture and the CPS cyber layer. The challenges, needs, and proposed solutions regarding the robotic and facility control system have also summarised in Section 2. Section 3 illustrates the edge intelligence and ARP in resource synchronisation for the flexible robotic and facility control system. The proposed system can make remarkable changes to the design of future AI-edge intelligence and cloud-edge computing for flexible robotic and facility control systems. The traditional robotic and facility control approach can automatically perform a single task and perform with only a single brand of robots and machines. The robotic and facility control with different brands is separately for operation without cooperation assisted with ARP and agnostic AI. Our proposed system significantly improve the robotic and facility control via agnostic AI for a smart unit. The practical implication of ARP and agnostic AI is to enhance the overall operating and manufacturing efficiency and effectiveness. Multiple brands of robotics and machines can cooperate, operate, and communicate with each other. Edge intelligence and agnostic AI with the SLAM technique enhance the overall control processes in robotic and facility systems under the cloud-based system architecture. A holistic view of the proposed system and its benefits have been thoroughly discussed in guidance, searching, driving and motor control, digitalisation and servitisation, user-centric intelligent module, and adaptive decision-making. The proposed ARP architecture solve the multiple robots cooperation with different brands under the flexible robotic and facility control system. Therefore, conflict resolution with the aid of edge intelligence and agnostic AI could be considered to reduce the accidences that appear in the system. Afterward, the numerical studies with mapping, localisation, and shortest path planning with collision avoidance are presented in Section 4. Under different speed limit zone settings, the parameters should be changed to deal with different conflicts to enhance overall operational efficiency and ensure the collision between mobile robots and humans will not appear in the cloud-based system with an assist with the edge intelligence and agnostic AI. The summary of the research and the concluding remarks with managerial insights and practical implications are raised in Section 5.

2. Literature review

2.1. An overview of the agnostic robotic paradigm

In the field of robotics and AI, one of the recent development focuses is the ARP. As robots become more common adoption than before, there is a need for agnostic robots to cope with environments with rich artificial objects [36–39]. The reason for proposing the ARP is to convert and combine different robotics to obtain resource synchronisation in the robotic and facility control system. While there exist various types of sensors, it is infeasible for a platform to use every type of detector for object tracking; on the other hand, implementing an agnostic paradigm can introduce a robust and generic approach to the problem of object tracking in a target-rich environment. Ošep, et al. [40] proposed the Class-Agnostic Multi-Object Tracker (CAMOT), a vision and segmentation mask-based region tracker that allows for pixel-precise data association with coarse geometric scene understanding future frames predictions and object classification. The use of a region classifier gives CAMOT the ability to track arbitrary objects even if no semantic information is available. The team showed that the system could perform better than the standard detection-based tracking system and track both known and unknown objects with high precision at distances up to 15 m. Chiatti, et al. [41] developed a similar system for task-agnostic object recognition based on few-shot image matching and other publicly available data. Using a pre-trained Convolutional Neural Network can help improve the system's starting performance, and the accuracy for object matching can be further increased by introducing a general L2 normalisation before comparing image embeddings. Aside from object tracking, the agnostic paradigm can assist in swarm robotics systems. Unlike typical designs where the swarm is directed to complete a specific task or behaviour, controllers can mix and match to complete various complex tasks by generating a set of general and straightforward swarm behaviours. Gomes and Christensen [42] introduced a quality diversity evolutionary algorithm for general swarm behaviours, which can assist the swarm controller in discovering various high-quality solutions to non-trivial tasks. Compared to task-specific evolution, the proposed system matched the solution quality even if the evolution process was conducted without referencing the case study tasks. It was also found that there were enough controllers present in each behavior space that were useful to solving the specified tasks and that the behaviour space is moderately continuous. Hence, under the ARP, the cloud-based system can be consolidated for different robotics in the facility to enhance the overall operation effectiveness and efficiency [43–49].

2.2. Cloud-edge computing and edge intelligence

2.2.1. Cyber-Physical system

The CPS is a type of intelligent computing system for use mainly in the manufacturing industry. Integrating physical systems with computational programs allows for real-time data processing and accessing [50–54]. CPS is also considered an essential element towards I4.0, as the system is responsible for the increasing interconnectivity of machines using sensors and local networks, leading to an efficient, intelligent, and self-adaptable manufacturing model [29,53–59]. To effectively implement CPS within the industry, it is necessary to develop a transparent model as guidelines [60–62]. Lee, et al. [63] introduced a 5-level CPS structure, named the 5C architecture, to serve as a step-by-step guide for implementing CPS in manufacturing applications. The architecture is separated into five levels; smart connection involves the accurate information collection through sensor network or commercially available controller system, along with tether-free data transferring to a central server; data-to-information conversion focuses on extracting information from collected data, which can then be used by various management models such as prognostics and health management; cyber level is the central information hub where the information gathered will be analysed and used for performance comparison between machines; cognition level is used for relaying the comparative information within the system to the users, which is used to optimise manufacturing; the last layer is the configuration layer, acting as the resilience control system to make connected machines self-configure and conducted the adaptive decision making [29,55–59].

Further improvement on CPS was proposed by various academics that aims to improve control strategy and deployment of the system within the I4.0 context. Abidi, et al. [64] used a fuzzy harmonic search algorithm (FHS) to optimise the control parameters for calculating the optimal solution, in addition to cyber and physical parameter estimation using maximum allowable delay bound (MADB). The team compared the results with other standard algorithms such as heuristic search (HSA), Grey Wolf optimisation, etc. They reported that FHS could outperform HSA, with a lower sampling period and network utilisation rate, and have the lowest cost function with fewer iterations numbers. Overall, the system was able to provide improved control performance and communication reliability. Lian, et al. [65] integrated the industrial CPS with warehouse mobile robots, with a hierarchical scheduling architecture between the control and physical layer, allowing for improved path planning through topological map modelling and collision avoidance between robots in real-time. Compared with other planning algorithms, the model proposed by Lian was able to obtain a higher task efficiency while keeping system congestion and planning time low. While I4.0 is being realised in large scale manufacturing, other small and medium scale production have to adopt to the changing market in order to maintain competitiveness [66–70]. With the changing trend in the consumer market, focusing on small batches and customer-oriented production, a system will have to be adopted that allows for flexible manufacturing to support one-of-a-kind production (OKP). Using CSP in this sense allows for high customisation, system changeability, and production efficiency. Huang, et al. [71] proposed using CFS for OKP, with a pull control strategy for guiding the system's deployment. Instead of a complete deployment of CFS, which will be costly for small and medium businesses, the team proposed a non-full deployment with Capacity-slack Constant Work-in-progress (CSC) model. As CPS emphasises on data collection and analysis for system monitoring, it is possible to incorporate the system with fog-edge-cloud computing, facilitating automatic algorithms application and data processing. Local intelligence and cloud-based computing can be classified as the physical and cyber layers, respectively [46,51–55,72–74].

2.2.2. Cloud-based computing

Cloud-based computing, which can be found in the cyber layer of CPS, is a model that relies on a central data server for all processing and analysing tasks, providing all connected users with integrated resources and communication [75–77]. Cloud computing provides services with high reliability, dynamic scalability, and availability over the Internet. With the increasing use of the IoT system in daily life, a new type of cloud-based network called Mobile Cloud Computing has been introduced in recent years, allowing the user access to server resources without needing hardware equipment [78–80]. However, this system is not without drawbacks, as the IoT network places a high priority on data sharing, making security of both data transmission and storage vital [81–83]. Wazid, et al. [84] proposed the lightweight and secure authentication system for cloud-based IoT network LAM-CIoT, using the ROR model and AVISPA tool, which allow the proposed scheme to prevent standard cyber-attack methods. In addition, the system is also capable of providing intractability and anonymity to users.

Another point to consider when implementing the cloud-network to IoT model is IoT devices' energy usage and data transmission. Proper management of power usage within the IoT devices can increase the entire system's efficiency and reliability through uninterrupted information gathered by sensors. Al-Kadhim and Al-Raweshidy [85] proposed 4 MILP-based optimisation programs for cloud-based IoT, namely Standby Routes Selection Scheme (SBRS) for node reliability, Desired Reliability Level Scheme (DRLS) for network traffic power consumption, Reliability-based Sub-channel Scheme (RBS) for mitigating interference, and Reliability-based Data Compression Scheme (RBDS) for links' capacity limit. The proposed model was able to reduce the average power consumption of IoT devices by up to 60 %. Using existing hardware infrastructure can act as access points for relaying information between connected mobile devices, such as robots, and the cloud servers, allowing for a larger scale of operation and better situation awareness of the devices. Varma, et al. [86] developed a Dynamic Path Selection methodology for Cloud-based Multi-hop Multi-robot (DPS-CMM) model for indoor warehouse networks. The original infrastructure will access connected robots and store local network maps and task information with data from connected devices. The cloud network can then combine the information gathered from various access points within the area and form a complete topology map. The extension of cloud computing can be extended to cloud manufacturing and offers adaptive, secure and on-demand manufacturing services over the IoT. The system can then utilise this information to provide the optimal path to the robots, plus extending the service timespan of the robotic network under the manufacturing system.

2.2.3. Edge intelligence

The concept of edge intelligence and edge computing is relatively new and is used within the physical layer of CPS. Instead of just utilising cloud servers for data analysis and processing, edge servers will be added close to the user's end and near edge IoT [87–89]. This will allow for implementing a cooperation framework, with the edge servers focusing on near-time/real-time data analysis and pre-processing data collected from edge IoT networks. In contrast, the cloud servers can conduct data mining and big data analysis with the information from the edge servers, which can be used to assist deep learning and other data cognitive abilities [29,47,56–59]. Furthermore, as the edge platform is closer to the edge IoT, the amount of data transfer and bandwidth will be lowered, along with lower latency in data transmission, further facilitating a lower operational cost and faster response time [90–92]. Ding, et al. [93] suggested a cloud-edge framework for cognitive science, which involves a shallow model at edge server and a deep model on a cloud server. The data collected by the edge network will be pre-processed through EdgeCNN and fed back to the cloud network, where using CloudCNN can assist the shallow model in deep learning and increase accuracy. A similar deep learning model using a cloud-edge network was proposed by Cui, et al. [94] for use in indoor mobile robots. The robot will use a vision system to obtain the image of the surrounding environment, which is then sent to edge servers for real-time analysis. Long-term data matching will be done using deep learning with data analysed in the cloud server, allowing for target detection and classification.

Edge computing and cloud-edge cooperation model can also be used in Industry IoT-based manufacturing [95,96]. The separation of cloud and edge layers in the production line allows for higher efficiency and production rate. This is partly due to the system's ability to continuously improve the edge layer through in-depth big data mining and analysis, which can then be fed back to the edge server for higher precision calculations in the market forecast and production schedule. The cloud-edge network can also be used on unmanned aerial vehicles (UAV) and unmanned ground vehicles (UGV) working in groups [97]. The Advanced Search and Find System (ASAFS) allows for multiple drones to cooperate through fast information sharing ability offered by edge computing, to locate a specific item within a predefined area; while the UAV-Edge-Cloud system with emphasis on quality of service proposed by Chen, et al. [98] used the edge-cloud network to support a fast model matching computation and to provide a platform for UAV swarm cooperation in terms of efficient knowledge sharing plus collaboration.

While the combination of edge intelligence and IoT promises higher connectivity and efficiency, the system heavily relies on internet connectivity between devices and within the cloud-edge network [10,14–16,36–38,50–52]. The connection of IoT through open-sourced networks such as Wi-Fi and 4/5G networks will increase the network's vulnerability towards cyberattacks and data theft [99]. The extension of the edge intelligence assisted with multiple methods, including SLAM, should be widely considered in manufacturing and warehousing to reduce the accidents and errors that appear. By incorporating the system with blockchain technology, we can further increase the security of the edge computing system. Kang, et al. [100] introduced a consortium blockchain model for a vehicular edge network, with the security of the data-sharing system guaranteed by two smart contracts. Each local data aggregator will broadcast their collected metadata to other local data aggregators for verification, ensuring the data is in line with the system pre-set through comparison with a hash value of shared data block. Similarly, a smart edge resources scheduling scheme using consortium blockchain was proposed by Zhang, et al. [101], with a credit-differentiated data approval system. The use of credit coins for reaching consensus instead of the number of edge nodes allows for better efficiency, and blockchain technology ensures the resource transection is tamper-resistant through decentralised storage. Moreover, as edge intelligence system often involves machine and deep learning through data analysis, data security and privacy is crucial to ensure no processed data is leaked outside of the system. Therefore, multiple methods can be found out the edge resources, and SLAM technology is one of the methods without widely adopted in the warehousing and manufacturing system to avoid the conflict that appeared under multiple robots cooperation.

2.2.3.1. Simultaneous localisation and mapping. SLAM is crucial to the development of UAV and UGV. It allows the vehicle to update its knowledge of the surrounding environment layout and understand its position in an unknown environment using edge intelligence, rather than transferring the data to the cloud for further processing. It is possible to integrate the system with a cloud-based network to support large-scale IoT applications, especially since SLAM requires high computing power. Relocating this task to a separate cloud platform allows for lowered cost and higher operating efficiency of the robot, as the onboard computer can be used for other tasks. Kamburugamuve, et al. [102] suggested using a Rao-Blackwellized Particle Filtering (RBPF) model integrated with SLAM. The system utilises parallel implementations of algorithms, allowing for faster computation time and lowering cost as the computation can be split between several processors within the cloud network instead of being handled by a single machine. Parallel processing between split servers allows for greater accuracy as the model can handle a more significant number of particles. Besides cloud-network integration, the SLAM system can also be used with edge or fog computing for higher operating efficiency and lower power consumption of connected devices. Sarker, et al. [103] proposed a hybrid Fog-Edge-Cloud structure for indoor mobile robots, using the concept of IoT and offloading heavy computational tasks to edge or cloud networks. This system combines the advantage of edge network being closer to end devices, which will reduce network latency and bandwidth usage and improve system reliability by preventing single point failure events common in centralised computing models, such as the robot-to-cloud model. As the SLAM system relies on the information feedback from various sensors, it will need to extract any meaningful features from the captured data in order to form a map of the surrounding environment. This process is the most resource-intensive, straining the battery and computational performance of the robot. A more effective model is needed to strike a balance between energy consumption and efficiency. Fang, et al. [104] introduced an FPGA-based ORB feature extractor SLAM. The FAST-based feature detection computation locates and calculates feature points, while the steered BRIEF algorithm will then compute the feature points' descriptors. The team reported that using ORB feature extractor running at 203 MHz, they were able to minimise computation latency by up to 51% along with a higher throughput rate; while lowering energy consumption

2.3. Robotic and resource synchronisation and sharing in the smart manufacturing context

In the I4.0 setting, resources synchronisation is crucial for handling fluctuating production orders and resource uncertainties. A dynamically adjustable resource and decision-making system allow the business to readjust its operating strategies based on the current market and customer demand. To introduce flexibility within a large-scale production system, a cloud-based smart-resources hierarchy was proposed by Zhang, et al. [105]. Production service system enabled by cloud-based smart resource hierarchy (PnSS-CSRH) uses open resources management and the AUTOM framework, allowing for a highly dynamic IoT-enabled synchronised production system. The hierarchy can match the suitable software to specific equipment, increasing overall efficiency and advanced resource management and production decision-making, facilitating synchronised planning and IoT-based production. Using smart gateways and plug-and-play devices gives users the ability to receive comprehensive real-time updates from connected devices, contributing to the synchronisation effort. The team reported that using PnSS-CSRH can increase efficiency by up to 28.7% and lower storage occupancy time to 45 hrs. Another factor that a company needs to consider is its survivability in a market crash event. Using the current global COVID pandemic as an example, in order to continue operation, management needs to be resilient in the face of uncertainty. Through resources and configuration synchronisation, a company can maintain or even grow its market. The introduction of Industrial IoT, cloud computing, and artificial intelligence allow for such a dynamic and resilient real-time manufacturing system to be possible. Guo, et al. [106] introduced the Graduation Intelligent Manufacturing System (GiMS) for a synchronisation-oriented reconfiguration of fixed-position assembly islands (FPAI). GiMS features real-time operational visibility and cloud servers acting as operation managers and operators in charge of implementing the configuration changes. The team reported that specific items can be grouped to assembly islands that are also handling similar products from the same family in the proposed system, significantly reducing setup and waiting time to 89 units, compared to more common manufacturing methods such as first-come-first-serve and earliest due date. The number of tardy jobs and configured setup is also drastically lower.

2.3.1. Robotic mobile fulfilment system

With the introduction of e-commerce, warehouse activities have increased drastically. To cope with the rising demand, a new type of automated warehouse system called RMFS is introduced. The system relies on a small robot fleet to handle retrieval-and-storage tasks between the picking and storage areas, where storage units containing the necessary products are delivered to the picking area for manual packing. Being a relatively new system, numerous optimisation models are being proposed to further increase the system's efficiency. Gharehgozli and Zaerpour [107] proposed an adaptive large neighbourhood search algorithm to minimise the travel time of the robot for pod retrieval. The team also studied the problem of pod return location selection by modelling it as a generalised asymmetric travelling salesman problem. The case study showed that the proposed model has a 27% higher efficiency than a truncated CPLEX model and outperforms other common heuristics by up to 24%. Jiang, et al. [108] suggested a novel picking-replenishment synchronisation mechanism (PRSM) that considers both replenishment efforts and picking efficiency within the robotic forward area, using a variable neighbourhood search procedure integrated with a divide-and-conquer paradigm. The team reported a 40–60% shelf visit reduction depending on parameter settings and handled a more extensive scale problem set.

2.4. Research gap

The above literature review shows that previous research mainly investigates scenarios involving one single robot, showing that a robot can complete and unlearn tasks without any sensory-motor experience but with content-agnostic information processing [109]. However, there is a lack of studies investigating the coordination between robot of different brands and their respective supporting infrastructures. In general, a separate system will be adopted in the manufacturing or warehouse context for the operation of the mobile robot. The current works of literature considered adopting edge intelligence to conduct the conflict resolution or cloud-based centralised system for controlling the entire operation. The problems of current edge intelligence may not be suitable for different brands' mobile robots' cooperation because of its diversity system. Such coordination effort may involve extensive overhead and challenges in a real-life setting. Therefore, an edge intelligence and agnostic robotic paradigm in resource synchronisation under the manufacturing or warehouse context should be considered to enhance operational efficiency and effectiveness. The centralized cloud-based robotic control system appears the latency issues for transferring the information from the cyber layer back to the physical layer. Considering the virtual prototype for considering the SLAM to solve the multiple conflicts that appeared in different brands should be adopted under the edge intelligence and ARP in resource synchronisation and sharing in flexible robotic and facility control systems. To the best of the authors' knowledge, no scholars are combining the concepts for AI, ARP, and edge intelligence for resource synchronisation under the cloud-based centralised system. The purpose is to convene and enhance the overall efficiency of the manufacturing and warehousing system. In addition, the development and deployment time for the smart units and the related facilities, plus the resulting system downtime, is crucial statistics for a company to consider when evaluating if it is worthy of adopting. However, current literature neglected to show the details of such deployment timespans, such as those in Table 1. In addition, previous research has investigated the possibility and efficiency of the industrial robot under the flexible manufacturing concept. In contrast, the possibility and efficiency of implementing the in the smart unit and smart manufacturing have rarely to be considered due to the challenge, in reality, for example, the replacement duration of the smart unit and facility during the maintenance period, the compatibility to the current robot when the production line is requested to change to fulfill the product requirement. To address this research gap, we proposed a framework for developing AI edge intelligence and cloud-edge computing for flexible robotic and facility control systems as follows.

3. Edge intelligence and agnostic robotic paradigm in resource synchronisation

This section introduces the proposed IIoT-based ARP under edge intelligence in resource synchronisation and sharing for flexible robotic and facility control systems. First, the system architecture for the IIoT-based ARP for flexible robotic and facility control systems is proposed. Second, the mechanism of edge intelligence for flexible robotic and facility control system is developed. Third, the cloud computing and agnostic AI for flexible robotic and facility control system at the operational level are explained. Fourth, the extension for the big data analytics and AI-based knowledge elicitation for flexible robotic and facility control system at the management level is elaborated. Fifth, the holistic view of the proposed system and its benefits are concluded.

3.1. The system architecture of IIoT-based agnostic robotic paradigm for flexible robotic and facility control system

To demonstrate how cloud computing and edge intelligence can be

Table 1
The Challenges, needs, and proposed solutions regarding the robotic and facility control system.

Scope	Industrial needs	Challenges	Proposed solutions
Agnostic Robot	Innovative robotic and facility units	Introducing new robotic and facility units to the company and integrating the units in the current system may involve extensive overheads	The system with content-agnostic information processing, the robot can be easy to adapt regardless of the brand as, without any sensory-motor experience, the robot can achieve the goal for unlearned sort [109]. The system integrates new robots faster and easier and allows existing workers to manage a diverse fleet of robots.
	Fast deployment time for new automation technology	Implementation of new automation deployment is time-consuming	We expected that the deployment of new intelligent units could be in the time span of hours or days instead of measuring by weeks or months. The proposed system is a “turnkey” automation solutions and robot programming tool.
	New technology with minimum effect on current reliability and availability of the system operations	robotic and facility control system downtime	The proposed system treats every edge-device control unit as a module. By integrating the new module to the current robotic and facility control system, we expected that the system downtime and upgrade could be minimised or have no effect on daily operations.
Fast-fashion robotics-as-a-service	Replacing the operations by automation technology, robotics, and smart facility units from time to time	Novel robotic solutions launched every year and frequently change-over robotic solutions create massive pressure on IT development	The proposed system can leverage the deployment time and the timespan for integrating new robotic and facility control units to the current system and accommodating frequent change-over, new tasks, and rapidly responding to requirement changes.
	Compatibility to current robotic and facility control units	Various robotic and facility control units’ brands are different, and they have their own APIs or control methods, which make every automation solution isolated.	The proposed system is compatible with the advanced robotic and facility control units using edge device control.
	Training time and cost	Newly deployed smart robotic and facility control systems may increase the training time and cost for the current staff.	The proposed system provides a standard robotic and facility control method using the edge devices, and employees can quickly adapt to the new system.
Automatic robotic and facility control solution	Labour shortage	Companies face labour shortage issues and need time to hire, train and retain the labour.	Robotic and facility control units can replace human workers for routine job tasks. The proposed system can empower companies to solve hiring challenges by augmenting the workforce with automation. This boosts output and frees up existing employees for high-value tasks.
	Efficiency control of the robotic workforce	Management of different types of robotic and facility control system	The proposed system can control various robotic and facility control in a unified system. The users can control several smart units to complete a task collaboratively via cloud-edge computing.
	Context and situational awareness	Different robotics and facility control units may not share the same level of context and situational awareness, e.g., restricted area, potential obstacles, blockage area due to stochastic events in smart cities	The proposed system will continuously perceive the operational errors, status, and information from the AI-edge intelligence and communicate to the cloud platform. With this real-time information, the cloud system can overview the shared situational awareness in the smart city [110]. Other smart units can also perceive the same context and situational awareness and react accordingly.

adapted to connect the relationship between the operational and management level in the context of flexible robotic and facility control system, we propose an IIoT-based ARP under edge intelligence, and CPS in resource synchronisation system assisted for manufacturing and warehouse storage as shown in Fig. 1 and Fig. 2. Fig. 1 shows the operation and management level of the proposed ARP in robotic and facility control system for the resource synchronisation. For the operational level, the autonomous mobile robot communicate with the third parties mobile robot through the proposed ARP architecture. With an aid with the edge device and intelligence, the raw data transferred to cyber layer as the management level to conduct the data-driven analytics and agnostic AI analytics. Fig. 2 is further elaborated the situation based on

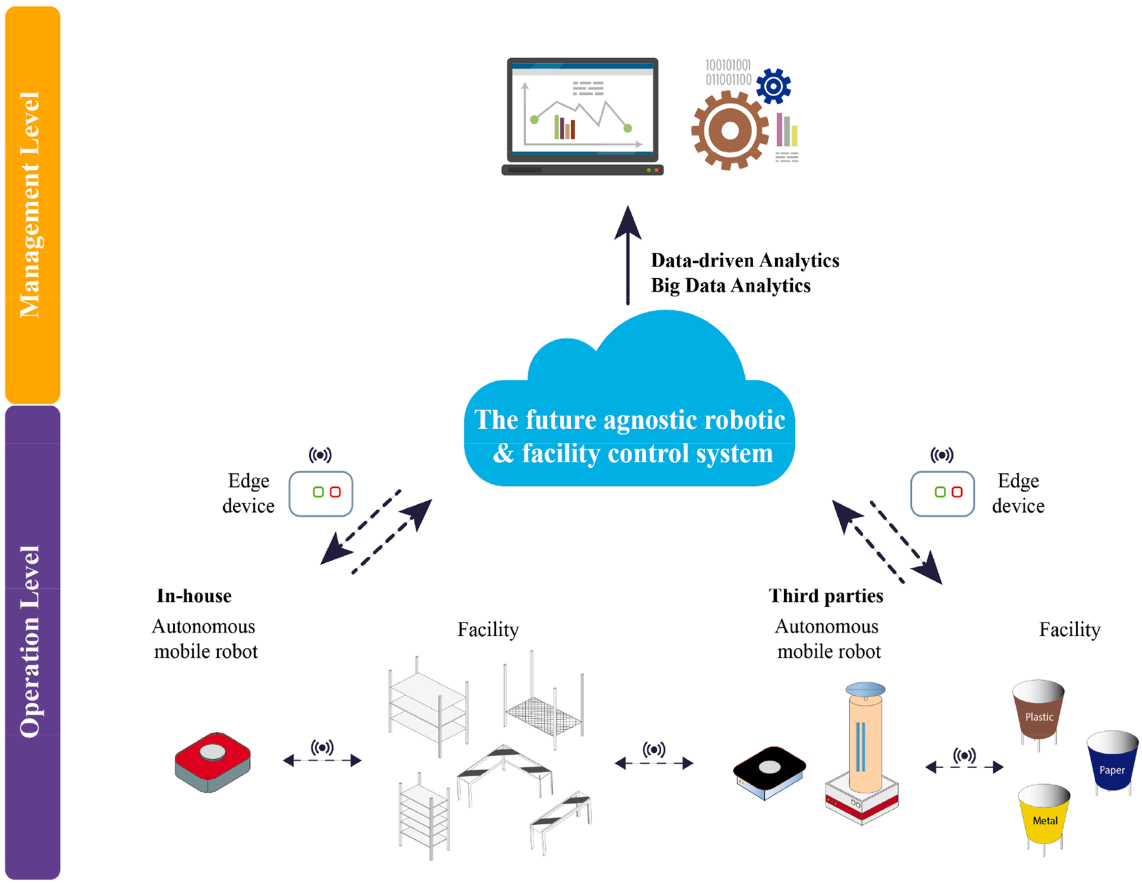

Fig. 1. Operation and management level of the proposed agnostic robot and facility control system.

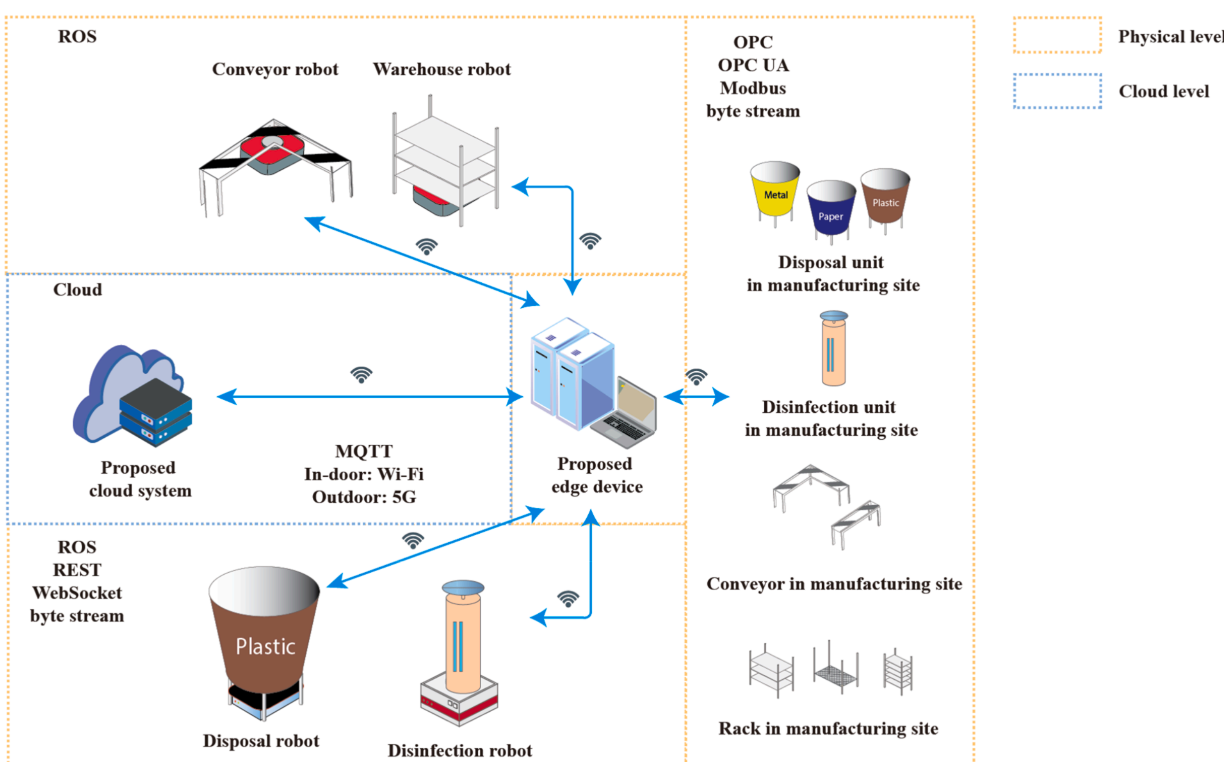

Fig. 2. Cyber-physical system of the proposed agnostic robot and facility control system.

the physical level and the cyber level under the CPS architecture.

The proposed system consists of four major components, including edge device for robotic and facility units, cloud-edge computing and agnostic AI for flexible robotic and facility control system at the operational level, big data analytics, and AI-based knowledge elicitation for flexible robotic and facility control system at management level, and the modularised and resizable system considering the in-house and third-party robotic and facility units. The four main components will be illustrated in detail in the following section. The synergistic effect of AI and edge computing can streamline the robotic and facilitate collaboration and cooperation smoothly. The edge device can directly control the smart unit to respond to real-time decisions, such as collision avoidance with different types of robots and mobile robot speed adjustment, and perceive or convey the context and situational awareness as environmental information to the cloud platform. The cloud knowledge database further analyses the safety zone settings and the collision avoidance methods under each scenario.

Different functions of robotics are used under the proposed architecture. All robotic and facility control systems are brand-made products and have their in-house solutions, which becomes a significant barrier to the control of all the entities efficiently in a unified system. The communication between multiple smart units may not necessarily improve the process efficiency per users' expectations, as the digitalisation of smart units and integrated approach between the centralised control system and smart units requires seamless integration. However, no appropriate solution has been launched in the market, and no similar literature exists. The architecture has introduced the ARP for integration to adopt different robots in the system. The major disadvantage of adopting this approach is to downgrade the version to ensure the system's capability. If the robot or robotic technologies open their communication protocol via ROS, REST, WebSocket, or byte stream, only minor systems or software degrade on the edge device and cloud service. Moreover, if the facility units open their communication protocol via OPC, OPC UA, Modbus, or byte stream, the only minor system or software degrade on the edge device and cloud service to fulfil different systems' capability.

The proposed architecture is to design a cloud system to accommodate the control system of the above protocol. The concept of flexible manufacturing is adopted to enhance the flexibility of the manufacturing system and includes the RMFS for storing raw materials, disposal items, and finished goods. Mobile robots can move conveyors, and the conveyors are assumed to be moved and changed the location. The E-commerce based customers' demands drive the production orders. Tailor-made products or a wide variety of products will be considered in the manufacturing process. Therefore, combining different brands' mobile robots allows the system to communicate through edge intelligence, including the conveyor robots and the workstations. Nevertheless, cloud-edge computing can process the data captured by the edge device on each smart unit, consolidate the status of all robotic and facility units, and provide control for task completion by one or several smart units. A transformation area is applied as the system is shown in Fig. 3. Different robots can be transformed to handle different tasks assigned through the cloud system under the CPS. It also leads to conflict resolution for multiple robots operation in a flexible robotic and facility control system. With these data-driven approaches, cloud manufacturing can better control various types of robotic and facility control units and deliver a high level of automatic decision control method with existing collaborative robotics information, with nearly real-time data signal from each intelligent unit.

The advanced robotic and facility control improves the process and overall efficiency. It is common knowledge that corporate robotic and facility control systems are usually connected via WSN or Wi-Fi to integrate with the users' current system. This integration is an excellent method to incorporate a new robotic and facility control technology with the existing system and enable the enterprise to coordinate the edge-based robotic and facility control application. However, the deployment of multiple sets of robotic and facility controls becomes a challenge to most industries. The communication between the centralised system and the smart robotic and facility control can be set up via edge devices and edge computing, and a company can adopt a robotic

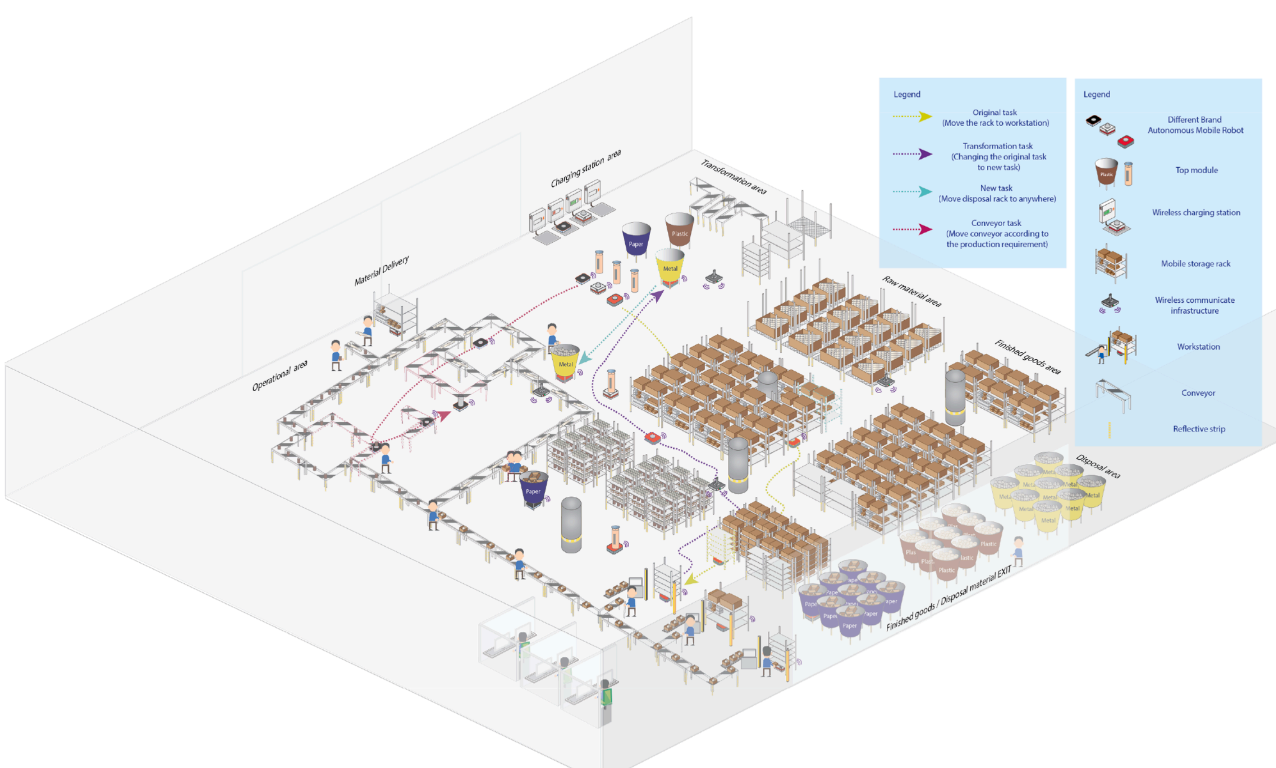

Fig. 3. Schematic diagram of the proposed agnostic robot and facility control system.

and facility control management system to control multiple smart units. The operation process may require two robots to collaborate. A second robot needs to ensure the absence of human subjects in a particular area before the disinfection robot can start the disinfection process. In this regard, there is a need to have a centralised system to control the multiple smart units for collaboration and cooperation, and each smart unit to have a certain level of intelligence in responding to real-time decision-making.

3.2. Edge intelligence for robotic and facility units

The edge device for robotic and facility units is essential for the development of the smart factory. Combining the development of IIoT, AI, wireless sensing technology, autonomous mobile robots, the smart facility can perform tedious daily operations efficiently and effectively without human intervention. The smart units are now equipped with more emerging sensing technologies, which enable enhanced context and situational awareness. The communication protocol may involve a significant computational time and process by considering the direct communication between the cloud and the robotic and facility units. Several functions can be pre-programmed based on the application scenarios and stored in the edge devices, as shown in Fig. 4. The mapping, localisation sensors, and SLAM technique could be aided the smart units in adjusting motion and speed. This application can also implement an emergency protocol to stop or avoid an obstacle or passers-by in the smart factory. Furthermore, the edge device can accumulate and store the sensing data without frequent communication with the cloud. The stored data can be zipped as a package and submitted to the cloud server when necessary. One of the advantages of applying edge intelligence is compatible with multiple brands' robotic adoption in the robotic and facility system. A series of information would be transferred to the cloud system, including the battery level, localisation information, mobile robots' coordination and the availability of the robots, task sequencing, and assignments schedule as a nearly-real time transfer. Some of the data are required for nearly-real time transfer, but some of the information can store and zipped as a package to the cloud server while the robotic and manufacturing system is not operated. Moreover, data security and privacy are crucial to ensure no processed data is leaked outside of the system. The industrial public cloud and private would be adopted for storing different data and information to ensure the overall data security problem. For instance, a disinfection robot can also be equipped with different sensors for air quality detection. The time-series data such as air contaminants can be collected and measured by different add-on sensors on the disinfection robot, and the time-series records stored on the edge device for a certain period; while the actual log data and package can be uploaded to the private industrial cloud in twice-daily, daily or weekly intervals before the task completion or when necessary as shown in Fig. 5.

One primary function in the edge device is to purchase localisation and navigation of the mobile robot. Collaborative situational awareness and context-aware computing with multiple sensing technologies, including LIDAR, In-door positioning via Wi-Fi, and out-door positioning via 4G/5G is an example of the implementation. In collaborative situational awareness and context-aware computing via fuzzy control and soft computing techniques, hybridisation of these localisation and navigation data from multiple sources can be done by swarm intelligence, e.g., particle swarm intelligence, genetic algorithm, artificial bee colony algorithm, and artificial intelligence, e.g., neural network, recurrent neural network, neural-fuzzy inference system, to support autonomous navigation in a dynamic environment. Different algorithms can be adopted from time to time to achieve better localisation and navigation performance. The model training will be done in an experimental environment at the site. Calibration will be done during actual operations and updated in a pilot test. The problem will be more complex and involve communication latency if the smart manufacturing system uses various robotic and facility units of third parties.

The edge device can relieve the communication latency through tasks pre-programming and user-defined functions, plus enforcing a standard communication protocol between the cloud and the edge. The decision logic and task complexity of the disinfection robot can be

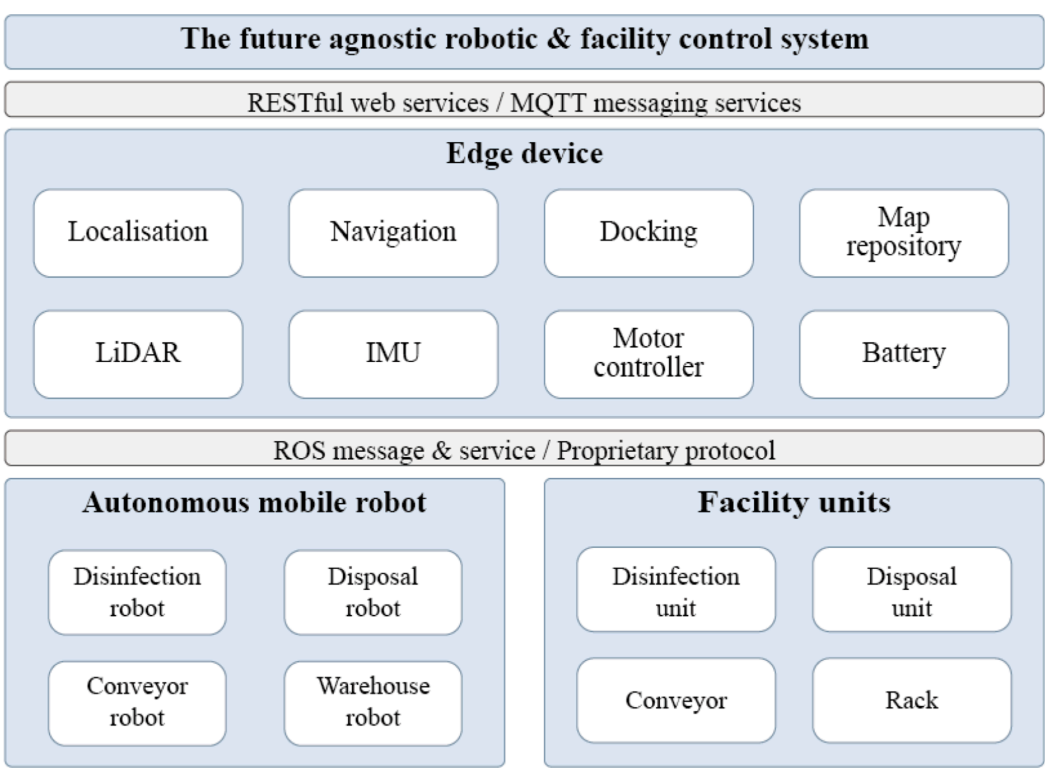

Fig. 4. The architecture and function of the edge devices and the corresponding applications in mobile robot and facility.

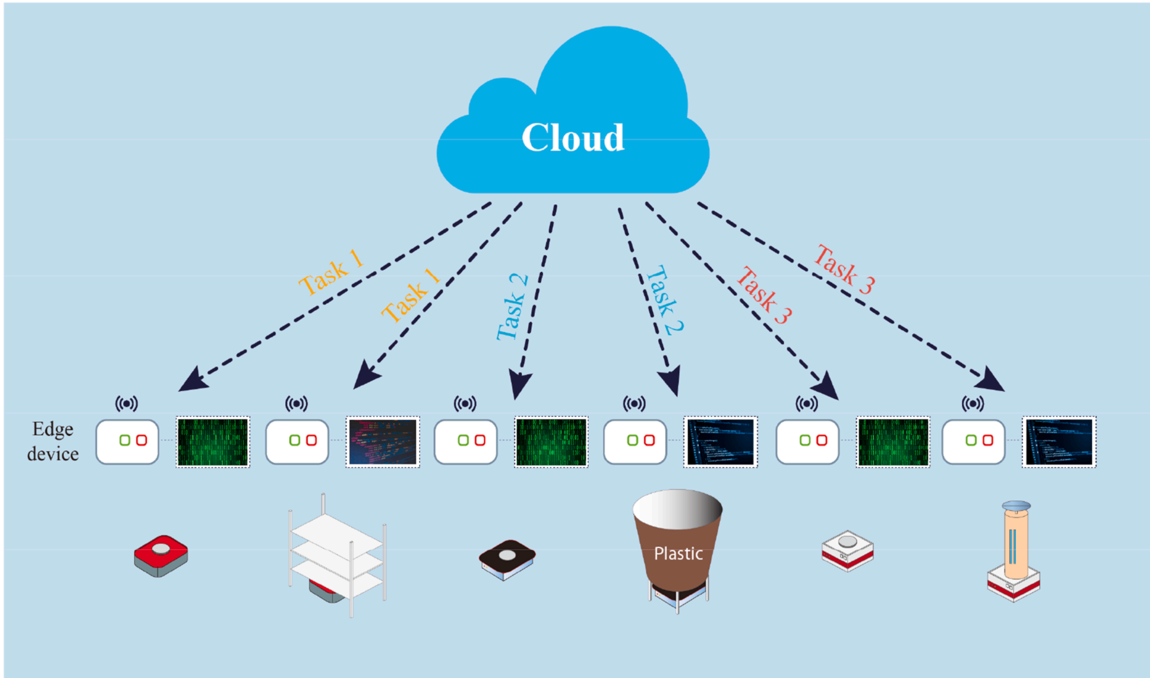

Fig. 5. Relief of computational loading with the various robot and facility units via edge devices.

further enhanced. The edge device connects the new units and the system. The communications between the system and the edge device will follow our unified program coding, as shown in Fig. 6, while the communications between the edge device and the new smart units will follow the protocol of the units designed by the third parties. With this approach, the set-up of the new units can be done without any intervention or main system revamp. Once the edge device is appropriately developed, the installation of new units would be quick, as the communication protocol between the edge device and the system is standardised. For example, without any local intelligence, the

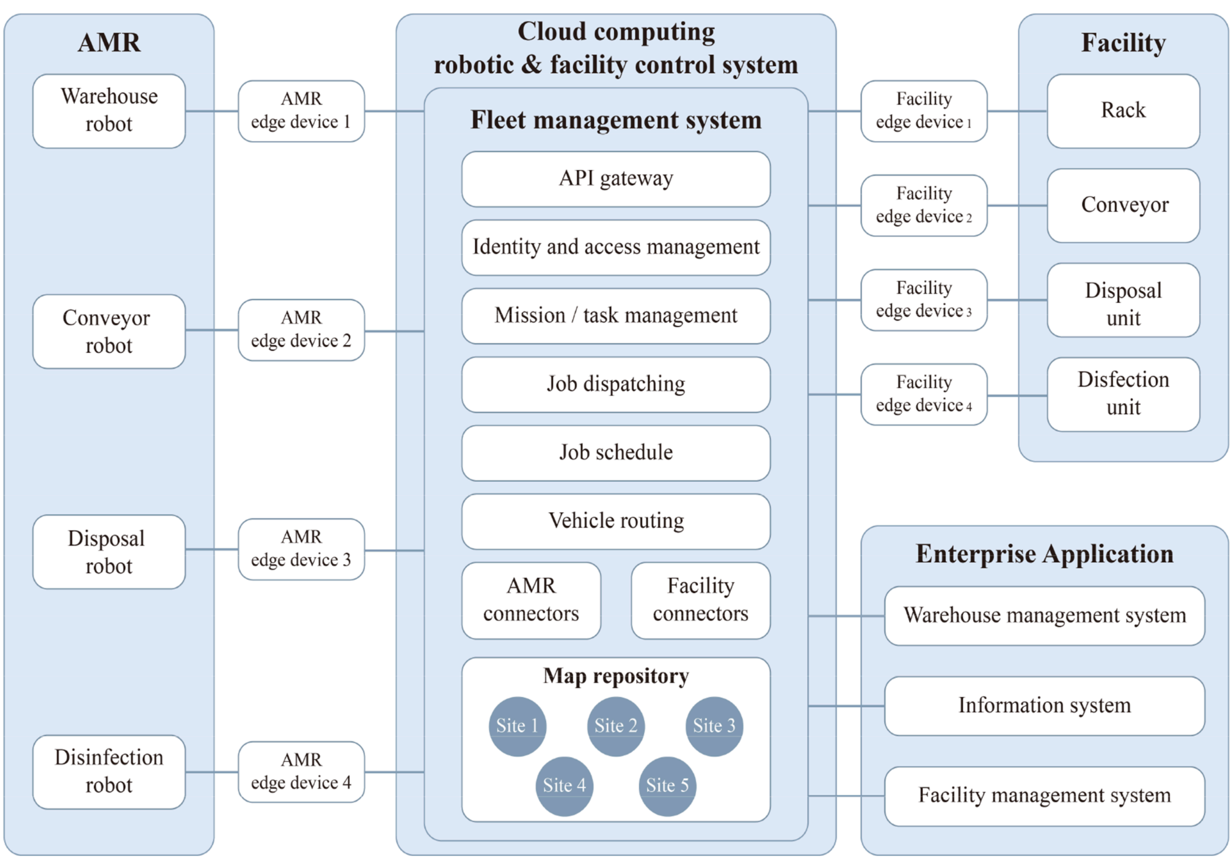

Fig. 6. The proposed architecture of agnostic robotic and facility control system.

disinfection robot will just follow the map stored locally and perform the disinfection tasks as a low-level decision and task. The edge device can command this robot to conduct a collision-avoidance routine in the vicinity to ensure the absence of obstacles in the site through map scanning before commencing operations as a high-level decision and task. This function may also allow the disinfection operations to be performed automatically in different areas compatible with different robots. These functions can be done locally without extensive communication between the cloud server and the smart units, plus offering a real-time, customised, flexible, and programmable local AI decision for complex tasks using the cache-assisted awareness information.

3.3. Cloud computing and agnostic AI for flexible robotic and facility control systems at the operational level

The context and situational awareness can be enhanced with different types of sensing technology on the robot. Local intelligence and cache-assisted perception at the edge level are critical functions in the proposed system. However, not all tasks can be completed individually and require cooperative and collaborative decision logic and AI of different smart units. Therefore, a cloud-edge decision is more desirable in this application scenario. Human intelligence can surpass a robot in completing a complex task with unstructured and structured data, as human beings have a higher level of cognitive capabilities, conceptual thinking, user-centric intelligence, and knowledge augmentation. Cognitive technology and robot design with human-like capabilities are often dreamed of but are yet to be achieved. Alternatively, the proposed architecture can utilised the benefits of collaborative decision logic and AI from different smart units to mimic human-like behaviours and automate a process. The cloud-edge decision and adaptation strategy via swarm robot and facility control can be envisaged for the decision that cannot be made locally.

Robotic and facilitating collaboration and cooperation will be the key strategy in future smart factories. With the support of the highly digitalised robotic and facility control system, the proposed architecture can enhance business flow or operations. For example, the major challenge in the last-mile logistics for courier delivery is that the courier may not complete the delivery due to a failed delivery attempt, perhaps due to the receiver not being available. One key technology to revamp this problem is using RMFS. The receivers can pick up their parcels whenever they are free. This method can successfully reduce the number of failed delivery attempts. From the receivers' perspective, they may wish to get their parcels at their preferred time at the final destination. By integrating all the relevant robotic and facility control logic, the last-mile logistics of the courier delivery can also be done by robots, which have been launched in the market. The robotic and facility control system can command the delivery robot to complete the delivery in the smart manufacturing system. To reach the final destination, the delivery robot may need to be granted access to different buildings and control the elevator. With this approach, we could further enhance customer satisfaction. However, the industry lacks such systems that can command and control various types of robots and facilities with different third-party robots and smart facilities. The last-mile delivery needs a single robot or facility to complete the tasks and collaborate with different smart units.

In the scenarios of robotic and facility control at cloud, multiple robots will perform several tasks as mentioned in Fig. 7 and Fig. 8. To achieve a high level of applicability of the system, the cloud system, including the industrial public and private cloud, in a nearly-real time control needs to check the availability of robots, ensure sufficient battery level at run time, and operational sensing data. This information can provide a large amount of sensing and operational data for further big data analytics, including massively parallel computing, regression modelling, regression trees classification, clustering techniques. The information related to customers' personal information of supply chain's stakeholder information would be stored in a private cloud or even adopting the blockchain for transaction purposes. Digitalised information flow processes benefit from streamlined, speedy, and optimised workflows and processes to replace routine manual tasks. The digitalisation of material flow in workflows or processes requires identification and tracking technologies. These technologies are the significant enablers of digitalisation and servitisation in smart factories. Therefore, the proposed architecture can generate the corresponding requirement and number of robots in fulfilling a specific task via

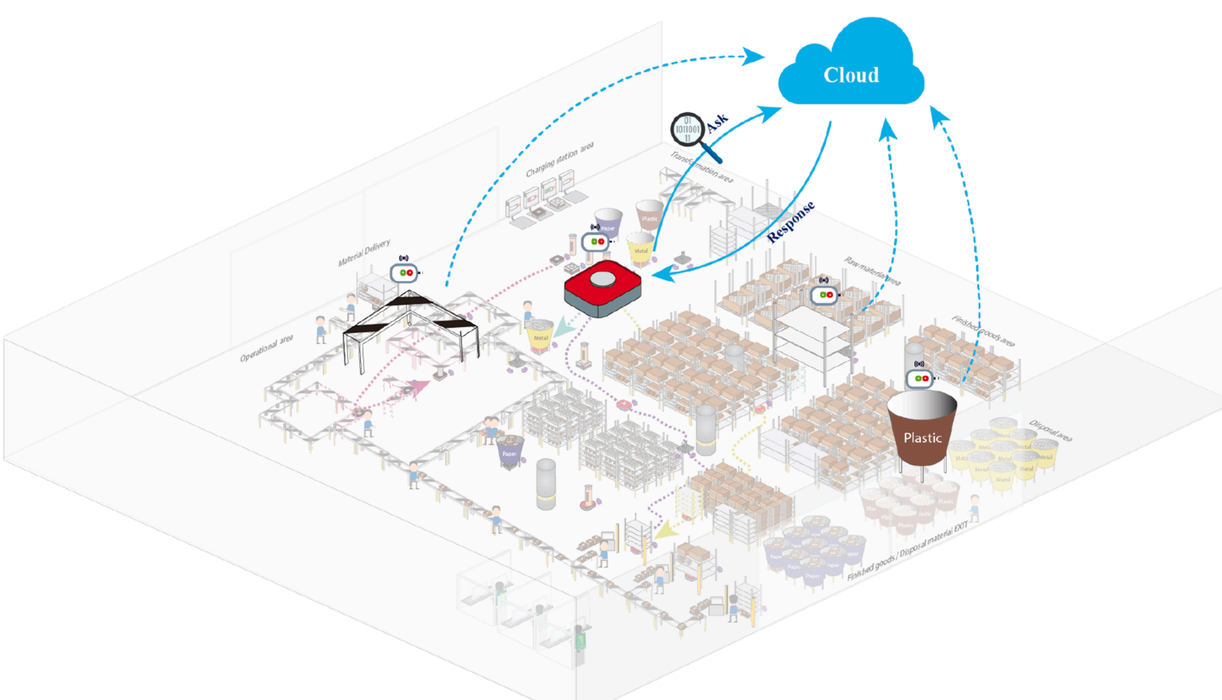

Fig. 7. The schematic diagram of cloud-edge computing robotic and facilitate collaboration and cooperation.

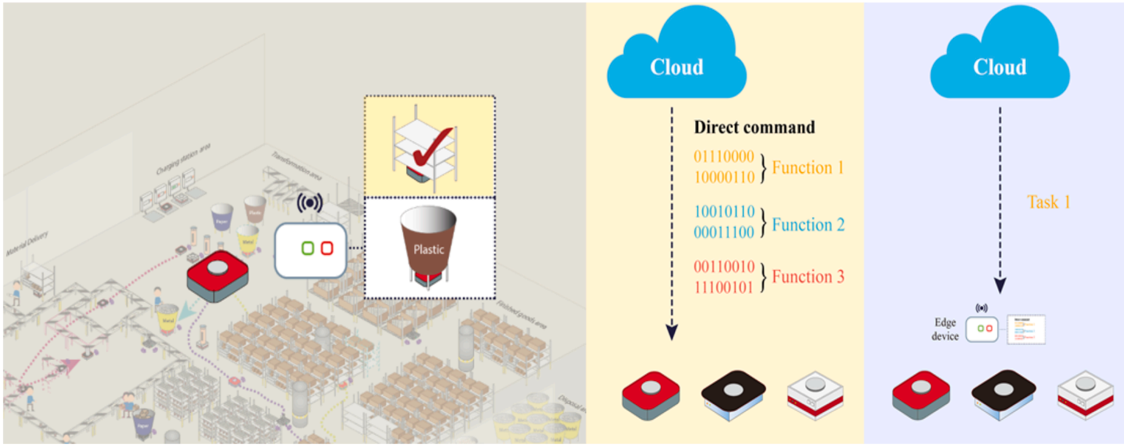

Fig. 8. Computational loading with and without the edge devices.

knowledge elicitation. We expected that a knowledge graph is one way to perform the AI-based knowledge elicitation and big data analytics in the cloud. With the proposed system, we can take the philosophy of swarm robot design to a higher cognitive level.

Taking the example of the delivery robot, the design and functionality of its application may be limited by the management capability. We can observe that most enterprises cannot fully utilise their robotic and facility assets since they lack a "central decision-maker" in the robotic and facility control system. For the commercial robotic product, ROS is the commonly known control system. Robotic companies may open direct communication with ROS. However, the company may use WebSocket for data exchange, and the user cannot directly access ROS with the robots under different brands may serve only one or two functions, as integrating and coordinating the work tasks with different robots and facilities complex. The robots mainly serve the function of material transfer, and different functions may need different sets of business processes and fleet (robotic and facility unit) to be completed. A set of delivery robots can serve different business functions in the smart factory, and we would need a cloud-based "central decision-maker" to coordinate all these events through the cloud, as shown in Fig. 7. The proposed architecture can be unlocked the potential of effective management of smart units, which requires a decision logic at the cloud-edge level, as shown in Fig. 8. Considering the direct communication between the cloud and the robotic and facility units, the communication protocol may involve a significant computational time and process. Several functions can be pre-programmed based on the application scenarios and stored in the edge devices. The existing MQTT protocol is the communication protocol between the proposed cloud system and the edge device. The MQTT control platform only focuses on the communication protocol. However, our proposed cloud system will also perform high-level decision-making, including robot/facility access control, path planning, and order. Fig. 9 shows the operation logic of mobile robots from Swagger.

3.4. *Big data analytics and AI-based knowledge elicitation for flexible robotic and facility control systems at the management level*

The proposed system offers an optimised organisational process experience and provides visibility enhancement of the process performance. With enterprise-wide implementation, the top management can increase the performance of a business process, as the automated business process and workflow are digitalised. Automating workflow and processes significantly improves the corporate visibility of the decision process with the support of emerging real-time monitoring technologies, including CPS, IoT, and sensing technology. Enhancing visibility continually improves tactical, strategic, and adaptive decision-making, providing an overview of the digitalised business workflow and process. Operational visibility enhancement is another distinctive

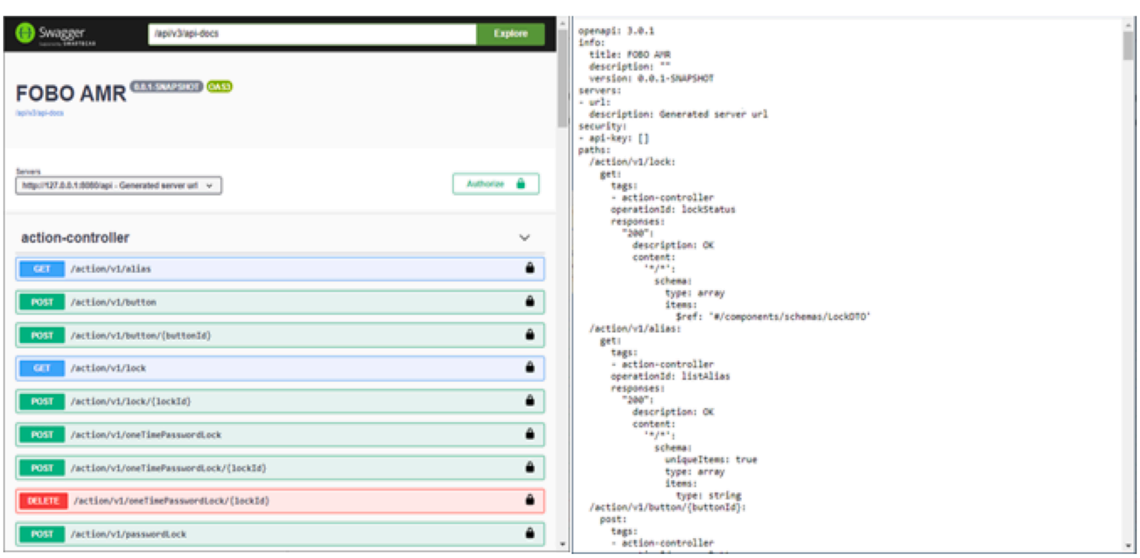

Fig. 9. An example for Swagger operation for mobile robot.

advantage of the proposed system. All decision processes are digitalised, and the system can ensure the processes are compliant with the rules and regulations. The activities of remote-control processes and automatic agents by vision control can be closely monitored in a human-robot collaboration workplace. AI-based knowledge elicitation is also an essential function in the system to help the top management identify any needs for changing fleet combination or fleet size adjustment. The agnostic AI enables value co-creation between robot and facility fleet and system configuration design by utilising the data of user behaviours and requirements for smart connected robots and facilities via big data analytics. The value co-creation process is driven by the embedded sensors, IoT and CPS. The knowledge elicitation process can also be integrated with smart units and automatically retrieve user behaviours and demands for future review. This customer-oriented business intelligence approach offers data-driven analytics, customer relationship management, and value co-creation for developing new customised solutions and delivers to top management a more sophisticated overview of user comments and requirements in system lifecycle management.

It is vital to have a hybrid, modularised, and resizable system design concept of flexible robotic and facility control to stimulate application-oriented design solutions. The system is an application-driven technology consisting of an automated mobile robot and smart facility units. A holistic automation strategy automatically extracting event logs in real-time and periodically updating the AI engine via pruning, regularisation, and retraining using real-world cases is necessary to improve the robustness of a solution. The designs must be adaptable to environmental changes, context-aware data, and customised service in business workflows and processes. Sensing technology and context-aware computing support AI to achieve self-adaptation to the environment with limited human intervention. Based on the needs of the automated mobile robot and facility units, the system can increase the fleet size of the smart units and accommodate the new robots or new facility units provided by the third party. Each new robot or facility unit will be regarded as a “module” in the system. Therefore, the system upgrade or modification would not affect the original system performance with minimal system downtime and would be able to perform routine operations smoothly.

3.5. The holistic view of the proposed system and its benefits

To sum up, with the proposed system, the following smart units can enjoy enhanced and augmented functions.

- Guidance: The edge device can compute and estimate the speed and rotation angle along the prepared path. Further, when the automated mobile robot perceives obstacles along the pre-determined path, the device can calculate the possible re-rerouting solutions and return the automated mobile robot to the original path.
- Searching: The path decision is perceived from the decision at the cloud-edge level. The path planning will be divided into different segments with start–end nodes. The edge device will calculate a set of start–end nodes in different path segments and execute the automated mobile robot motion decision. At the same time, the edge device will keep monitoring any signals or operational failures during the automated mobile robot operations. This approach could minimise the possibility of computation overload at the cloud level and permit a certain level of local AI on smart edge units.
- Driving and motor control: The edge device will leverage the path computation of the automated mobile robot and execute its path planning. The edge device mainly controls the motion speed, acceleration, and deceleration in real-time, and the computed solutions will also transfer to the cloud for further validation. The motor control and driving decision will become more effective, with less intervention by the cloud system and time latency between the cloud-edge communications.
- Digitalisation and servitisation: With the support of the edge device, specific AI algorithms can be executed in nearly real-time for specific information flow and value-added services performed for the smart facility units. The information related to nearly real-time operation would transfer to the cloud system immediately for the system’s operation. The cognitive level of the facility units can be further enhanced. Cognitive decisions can be achieved by processing structured and unstructured data in business management through natural language processing, image and video processing, and big data analytics.
- User-centric intelligent module: Understanding users’ needs and wants is vital to value co-creation and the user experience in automated business process management in a smart factory. The performance of the AI engine and software agents in edge devices and the cloud-edge decision is the key to success. A more powerful AI engine to handle user-centric, cognitive-based, and data-driven user requirements in smart facility units can become a reality soon. Under different speed limit zone settings, the parameters should be changed to deal with different conflicts to enhance overall operational efficiency and ensure the collision between mobile robots and humans will not appear in the cloud-based system with an assist with the edge intelligence and agnostic AI.
- 24/7 non-stop operations: Automated processes with a specific cognitive level can work without human intervention.

4. Numerical studies

To simulate the idea of the robot and facility collaboration, we used cloud-based ROS on the cloud platform alongside with gazebo simulator to model and test different aspects of the whole collaboration and cooperation process. ROS is an open-source framework for interconnecting different robot software in a system as a resource synchronisation under the cloud-based consolidation system. Its modular design enables users to divide the task of creating complex robot behaviour into different subsystems. The gazebo is an open-source simulator developed to effectively and realistically simulate the environment faced by robots in operation. The computation was performed with the configuration of Intel Core I7 3.60 GHz CPU and 16 GB RAM under the Ubuntu 18 operating environment. The proposed numerical studies were coded using the C++ language. It is highly integrated with ROS and provides the essential physics engine and plugins to simulate a digital twin (DT) environment. There are three types of robots representing robots of different models. Three different top modules, including two types of conveyor belts and one lifting module shown in Fig. 10 and Fig. 11. Top modules are interchangeable with the robots. The simulator adopts standard models provided by the gazebo and AWS Robomaker Small House World developed by Amazon Robotics. Both are open-source packages. The size is 70 m $\times$ 20 m, and the general layout is shown in Fig. 10. The simulation is based on different collisions that appeared in the system, where human-robot collaboration is considered.

4.1. Mapping and localisation

All the robots should be localised in the environment. Localisation means the robot can perceive the environment using its sensor information and utilising the data to infer the robot’s location concerning its environment. The ROS navigation stack provides various packages for the realisation of SLAM. At the first stage, we used gmapping package which uses robot odometry data and LIDAR scan data to build an occupancy grid map describing the environment as shown in Fig. 12. Since the environment changes consistently, moving objects have to be cleared out in the original map for better localisation. At the second stage, the Adaptive Monto Carlo Localisation (AMCL) package in the navigation stack is used to localise the robot in the map, as shown in Fig. 13. It is a particle filter-based localisation to track the position and orientation of the robot in the map generated before. In the real world,

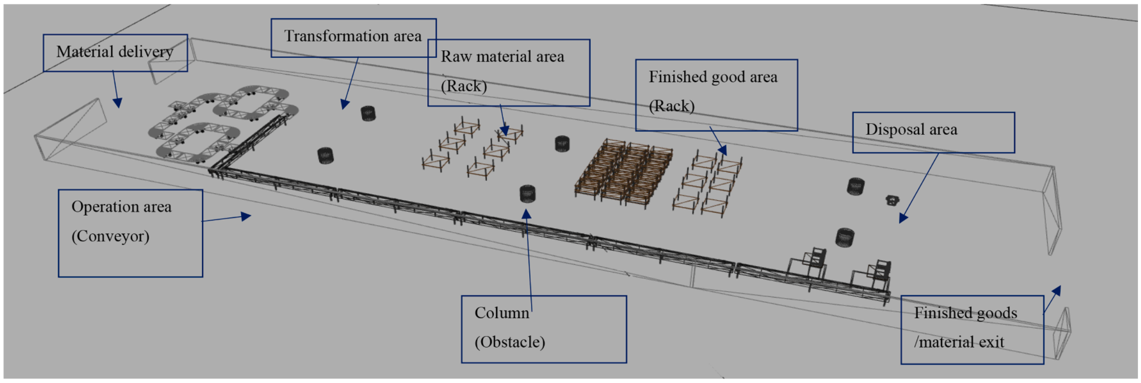

Fig. 10. Simulator in gazebo virtual environment.

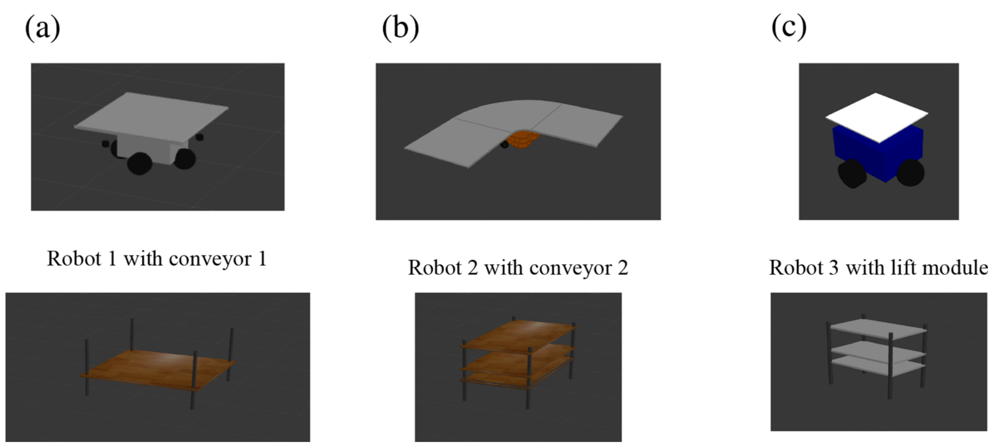

Fig. 11. Three types of mobile storage racks in the simulation.

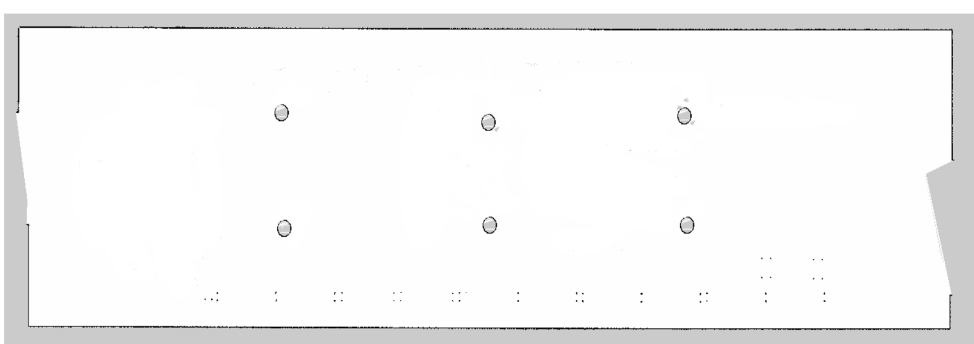

Fig. 12. Map generated with moving obstacles cleared.

additional features have to be installed for better localisation quality, but for simulation purposes, any potential localisation problem will not be addressed for now.

4.2. Path planning collision avoidance methodology

The global path planning is solved by the standard pathfinding algorithms such as Dijkstra and A-star search algorithm. For the obstacle avoidance part, a dynamic window approach is used. DWA is an obstacle avoidance algorithm which is first proposed by Fox, et al. [111]. The basic idea of the algorithm is to choose the optimal velocity using the cost function at every control interval. It is divided into two parts. The first part is to limit the search space of possible velocities, which can be divided into three spaces. The first space defines velocity candidate as a tuple (v, ω) where v is the translational velocity and ω is the rotational velocity. The second space ensures that the robot can stop before colliding with any obstacles if the velocity is chosen. The third space restricts the velocity that can be reached by the robot, given its acceleration and deceleration limits. It is also called the dynamic window. $Heading(v, \omega)$ is the target reward for the robot heading to the target. $Dist(v, \omega)$ is the distance reward that measures the distance between the robot and the nearest obstacle. $Vel(v, \omega)$ is the forward reward for the robot with fast movements. The resultant search space is given by:

$$V_r = V_s \cap V_a \cap V_d \quad (1)$$

The second part is to choose the optimal velocity. The optimal velocity must maximise the cost function:

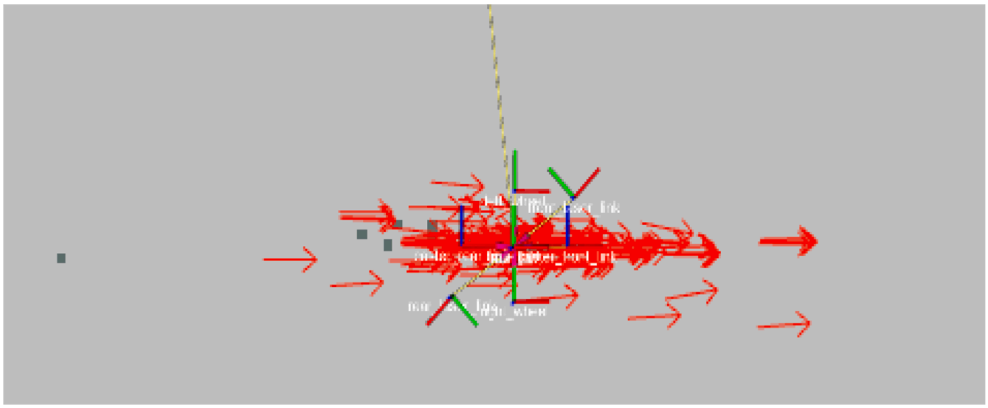

Fig. 13. Process of AMCL localisation.

$$G(u,r) = \alpha \cdot heading(u,r) + \beta \cdot dist(u,r) + \gamma \cdot vel(u,r) \tag{2}$$

4.3. Speed limit zone

There will be two types of speed limit zone, static limit zone and robot limit zone. The static speed limit zone is defined by a convex polygon with all edge coordinates given, as shown in Fig. 14. If the robot location is inside the speed limit zone, its maximum velocity is limited to its safety velocity. In our simulation, the restricted velocity is 0.3 m/s. To determine whether the robot is inside the polygon, we consider each edge of the polygon. Consider two points (x_i, y_i) and (x_{i+1}, y_{i+1}), the equation of the line is $y - y_i = \frac{y_{i+1} - y_i}{x_{i+1} - x_i}(x - x_i)$, $where (y - y_i)(x_{i+1} - x_i) - (x - x_i)(y_{i+1} - y_i) = 0$. To determine the side of the point (x_p, y_p) lies, it is required to substitute the point to the equation, $A = (y_p - y_i)(x_{i+1} - x_i) - (x_p - x_i)(y_{i+1} - y_i)$. If $A > 0$, (x_p, y_p) is on the left of the line; If $A < 0$, (x_p, y_p) is on the right of the line and if $A = 0$, (x_p, y_p) is on the point line on the interior of a convex polygon speed limit zone. The pseudo-code is shown in Table 2. Assuming each edge is oriented in the counter-clockwise direction, if the point lies on the left of every edge, the point is inside the polygon. The robot limit zone is defined by a center rectangle with adjustable length and width, as shown in Fig. 15. Any object detected inside by the LIDAR inside the zone will cause the robot to lower the maximum speed to 0.3 m/s.

Table 2
The pseudo-code of the speed limit zone.

Input	A list of vertexes (x_i, y_i) of the limit speed zone, lase vertex is the same as the first index
Output	True or false whether the robot is in the limit speed zone
	is_inside = true
	For each vertex v_i (x_i, y_i) in vertexes:
	If vertex is last:
	Break
	$A = (y_p - y_i)(x_{i+1} - x_i) - (x_p - x_i)(y_{i+1} - y_i)$ //substitute point to edge (v_i, v_{i+1})
	If $A < 0$: // lie on the right of the line is inside = false
	Return is_inside

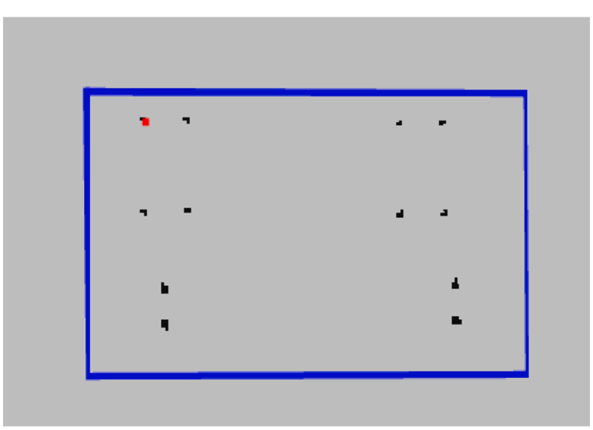

Fig. 14. Static speed limit zone, indicated by the area enclosed by the blue rectangle.

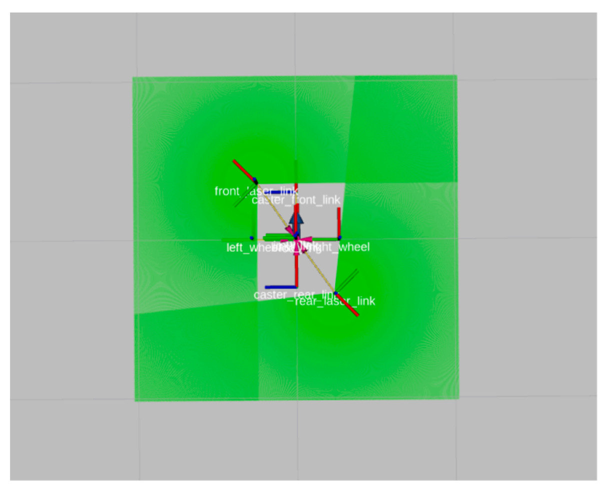

Fig. 15. Robot speed limit zone, indicated by the highlighted green rectangle.

4.4. Simulation results

To resolve the problem of human-robot conflict using DWA, the human-robot interaction is divided into five generic scenarios during the operation, which would be happened. The simulation is to resolve the current problems to reduce accidents that appear in real-life situations.

1. Robot path is obstacle-free, acting as the control case (Fig. 16)

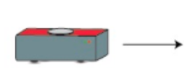

Fig. 16. Robot path is obstacle-free, acting as the control case.

2. Static obstacles: the robot encounters a static obstacle along the path (Fig. 17)
3. Head-on conflict: the robot encounters a human incoming in the driving direction (Fig. 18)
4. Cross-on conflict: the robot encounters a human incoming in the lateral direction (Fig. 19)
5. Diagonal conflict: the robot encounters a human incoming in the diagonal direction (Fig. 20)

To replicate the scenarios in our simulation, we spawn a walking person along with the robot in the gazebo simulator. Both the person walking maximum speed and the robot's maximum speed are set to 1 m/s. Fig. 21 shows an example of the environment setup for head-on conflict.

We use one type of robot with a different speed limit zone for the test, one with 1 m × 1 m and the other with 2 m × 2 m. In the dynamic windows approach, the heading term α rewards high speed and affects mission time the most. For the DWA tested instance, the normal practice is testing the parameter as $(0.8, 0.1, 0.1)$. The normal practice parameter is set based on the current works of literature' assumption. In general, $(0.8, 0.1, 0.1)$ would be set as a default setting and a baseline for multiple scenarios comparison. By extending this assumption, we extend the parameters for our scenarios to test which would be better for different conflicts resolution. The results are stored in the industrial knowledge database and for other AI-edge training purposes. Under different conflicts, the edge intelligent will assign the different parameters setting to solve the conflict. In our simulation test, four sets of parameters (α, β, γ) are tested for each scenario:$(0.8, 0.1, 0.1)$, $(0.6, 0.2, 0.2)$, $(0.4, 0.3, 0.3)$ and $(0.2, 0.4, 0.4)$. α is set to 0.8, 0.6, 0.4 and 0.2. β and γ are set to be equal. Three parameters are assumed to normalise to 1. The last approach is the stop and goes approach; the robot follows the global plan and stops when obstacles are in front of the robot. It serves as a control group compared to DWA. Each approach in the scenario is repeated 30 times in the simulation, and the average time of the missions is recorded. Fig. 22 shows a simulator demonstration, where the blue line is the robot trajectory under the head-on conflict during one of the testings.

Subtracted by the time given by the obstacle-free path as the control case, Table 3 and Table 4 shows the average time of missions for different scenarios and approaches. Under different speed limit zone settings, the parameters should be changed to deal with different conflicts to enhance overall operational efficiency and ensure the collision between mobile robots and humans will not appear in the system. In the case scenario, all the information and data items through the cloud-based system are queried in a real-time database, and the query results are imported to the PowerBI dashboard for the data visualisation shown in Fig. 23. The relatively static data will be displayed as texts, while some of the changing availability data will be displayed as different types of real-time streaming and changing graphs dynamically. Typically, for the common practice, the data updating rate is around 15 s for each update, but the ratio can be changed and customised through the PowerBI dashboard interface.

To conclude, mobile robots can move around and are not restricted to one geographical location the capability to move around in the flexible and intelligent manufacturing and warehousing system. The E-commerce based customers' demands drive the production orders, which leads to the desire for tailor-made products or a wide variety of products that will be considered in the manufacturing process. Mobile robots require to adopt intelligent and flexible manufacturing and warehousing to enhance operational efficiency and effectiveness. The proposed system can assist with the AI-edge intelligence, and cloud-edge computing for flexible robotic and facility control systems can conduct nearly real-time monitoring and controlling for the robots' conflict resolution and store the data under the knowledge cloud for further data analysis. The speed limit zone adoption assisted with edge devices for the conflict avoidances in the flexible manufacturing and warehousing system could enhance the overall driving and searching control. The traditional robotic and facility control approach can automatically perform a single task, but the robotic and facility control with different brands is separately for operation without cooperation. Our proposed system significantly improves robotic and facility control via agnostic AI for smart and flexible manufacturing and warehousing systems and user-centric, cognitive-based, and data-driven user requirements in smart facility units.

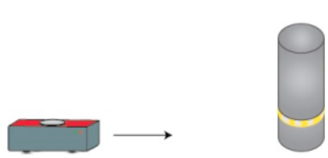

Fig. 17. Static obstacles: the robot encounters a static obstacle along the path.

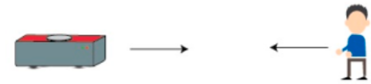

Fig. 18. Head-on conflict: the robot encounters a human incoming in the driving direction.

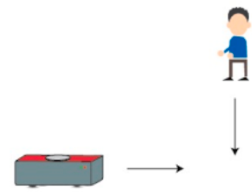

Fig. 19. The robot encounters a human incoming in the lateral direction.

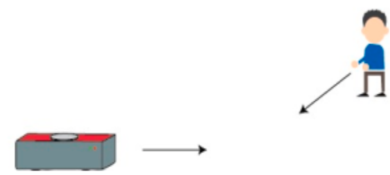

Fig. 20. Diagonal conflict: the robot encounters a human incoming in the diagonal direction.

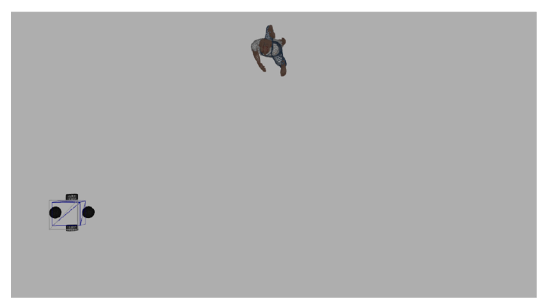

Fig. 21. Gazebo environment for cross-on conflict.

5. Concluding remarks

In the near future, smart applications will appear everywhere, including the workplace, commercial activities, and our domestic lives. All parties and stakeholders need to seize the imminent opportunity and ushering in the revolutionary changes of contemporary robotic and facility control solutions. The scalability and effectiveness of robotic

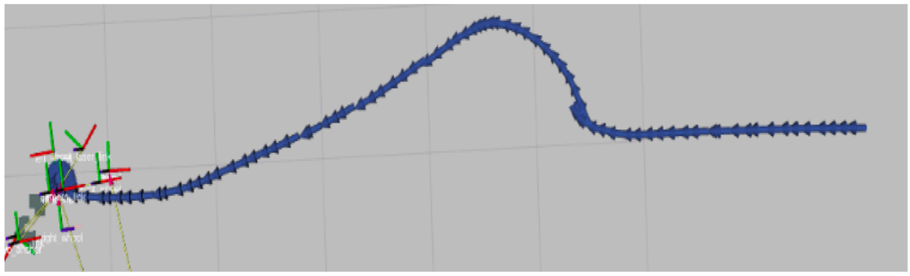

Fig. 22. Simulator demonstration (the blue line represents the robot trajectory under the head-on conflict).

Table 3
The average time of missions under $1m*1m$ speed limit zone.

	DWA (0.8, 0.1, 0.1)	DWA (0.6, 0.2, 0.2),	DWA (0.4, 0.3, 0.3)	DWA (0.2, 0.4, 0.4)	Stop only
Obstacle free	0 s	0 s	0 s	0 s	0 s
Static obstacle	**+0.46 s**	+0.53 s	+0.66 s	+0.60 s	(*inf*)
Head-on	+5.93 s	**+5.57 s**	+6.11 s	+5.99 s	(*inf*)
Cross-on	**+3.73 s**	+3.83 s	+4.40 s	+4.01 s	(*inf*)
Diagonal	**+1.52 s**	+1.59 s	+2.41 s	+2.55 s	(*inf*)

Table 4
The average time of missions under $2m*2m$ speed limit zone.

	DWA (0.8, 0.1, 0.1)	DWA (0.6, 0.2, 0.2),	DWA (0.4, 0.3, 0.3)	DWA (0.2, 0.4, 0.4)	Stop only
Obstacle free	0 s	0 s	0 s	0 s	0 s
Static obstacle	+1.23 s	**+1.09** s	+4.25 s	+4.79 s	(*inf*)
Head-on	+6.36 s	+6.87 s	**+5.82 s**	+6.31 s	(*inf*)
Cross-on	**+4.54 s**	+4.91 s	+5.55 s	+6.02 s	(*inf*)
Diagonal	**+2.22 s**	+2.55 s	+3.92 s	+4.43 s	(*inf*)

enterprise solutions depend mainly on operational information, robotic solutions, and their information infrastructure. Engineering informatics become a driving factor for future smart factories and provide actionable insights on data analytics and artificial intelligence by operations monitoring, security, effective control, and adaptive decision making.

The managerial implications are to propose a system that can make remarkable changes to the design of future AI-edge intelligence and cloud-edge computing for flexible robotic and facility control systems. The traditional robotic and facility control approach can perform only a fixed location manufacturing system without mobile robots. Our proposed system significantly improves the robotic and facility control via agnostic AI for a smart unit. A holistic view of the proposed system and its benefits have been thoroughly discussed in guidance, searching, driving and motor control, digitalisation and servitisation, user-centric intelligent module, and adaptive decision-making. The proposed architecture requires agnostic robots with different brands' to cooperate under the flexible robotic and facility control system. The edge intelligence under the proposed framework assisted by the algorithms we proposed can reduce the number of conflicts in the system. The cloud-based system can assist with nearly real-time monitoring and further data storage and analysis through the private industrial cloud. The agnostic AI will provide a unifying code between the cloud-and-edge communication, which can (1) control in-house smart units, (2) generalise the control logic, interact with different types of smart units and perceive the environments, and (3) access smart big data analytics via the cloud service. We proposed an edge device for smart units and aimed to provide the local intelligence at the edge level for practical implication. Users or top management can configure the programming logic on the edge device. The users can tailor their desired functions and operational scenarios in the edge device for a real-time decision. An edge device attached to the robot has stored a manufacturing system map in the local database and user-defined programming logic. The temporal locality-aware, spatial locality-aware, and mobility-aware caching can enable self-context and situational awareness operations at different floor levels of a building in the robotic and manufacturing system. The cache-assisted perception and localisation help the smart unit to perform self-aware operations. In this regard, the proposed approach is viable for further development and less investment cost in future upgrades.

This paper aims to investigate and design a modularised robotic and facility control system and its AI edge intelligence and cloud-edge computing. The system is expected to provide a seamless system integration approach with overarching functionality, capable of connecting with different types of smart robotic and facility units by using smart-edge devices. With this proposed approach, enterprise management can easily integrate new robotic and facility control units with a low level of system downtime, achieve better real-time context and situation awareness of smart units and enhance the overall efficiency of robotic and facility control. Motivated by the challenges mentioned above and futuristic opportunities, this paper also aims to develop an integrated cloud-edge computing and flexible robotic and facility control system and enable the AI-edge intelligence on each smart unit via edge device. We believe that the proposed system can relieve the control of different brands of robot/facility units with the proposed edge devices and ensure a high level of applicability. Nevertheless, the new edge devices are still functional and have a less marginal investment on further edge device design. Meanwhile, we foresee that the newly launched mobile robot will follow these standard protocols for robot and facility design, as the agnostic robotic paradigm help reduce their barriers to entering the market. With the use of the proposed system, users can enjoy controlling multiple robots and facility units using the public cloud system.

The research could be extended in the future based on the fifth aspect. A key aspect is a system downgrading for integrating different

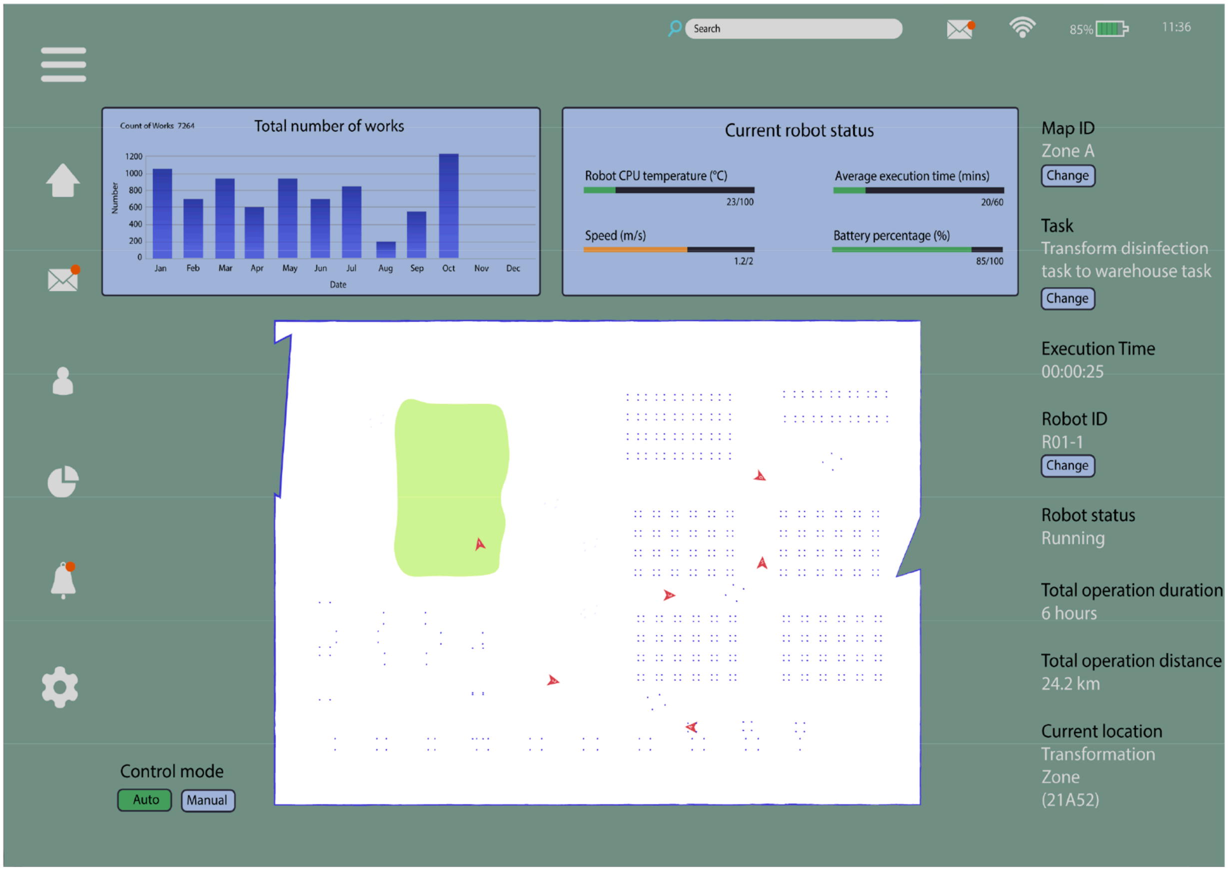

Fig. 23. Data visualisation of real-time streaming results of smart robot in a unified platform using Power BI Dashboard.

brandings of robot software as a centralised system for the ARP. A compatible system should be developed and automatically embedded for different robots adopted in different systems. AI-based robotic process automation should be proposed for future solutions to enhance overall operational efficiency and effectiveness. Cloud manufacturing is one of the research areas through the ARP. With the aid of ARP, visualisation on DT-based cloud manufacturing and on-site dispatching can be further extended and organised. Second, multiple algorithms for path planning and collision avoidance should be considered, especially for handling multiple robots operated simultaneously. The problem of deadlock for multiple robots should also be considered. Third, the layout can be changed based on different parameters or designed as a dynamic layout. This paper considers a single layout in the real-life case scenario. The layout can be extended as multiple layers of manufacturing plants or two separate manufacturing and storing locations. Fourth, multiple devices can be considered and combined in the edge intelligence. The image-based fault detection and diagnosis on the manufacturing lines can be installed and used in the current architecture to reduce human errors and emission rates [112–117].

Declaration of Competing 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.

Acknowledgment

The research is supported by the *Department of Aeronautical and Aviation Engineering, The Hong Kong Polytechnic University, Hong Kong SAR*. Our gratitude is also extended to the Research Committee of the Department of Aeronautical and Aviation Engineering, The Hong Kong Polytechnic University and the Innovation and Technology Fund – Partnership Research Programme (ITF-PRP), Innovation and Technology Commission, HK Government, HKSAR for support of the project (PRP/102/20FX); the Natural Science Foundation of China (72101144) and Shanghai Pujiang Program (21PJC067). The research is partially supported by student project codes (RJ1D). The authors would like to express their appreciation to the anonymous case company for their assistance with the data collection.

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