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ROBOT COLLABORATION INTELLIGENCE WITH AI

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ABSTRACT

We present a current automation trend, *robot collaboration intelligence*, to control and manage individual industrial robots to collaborate intelligently with advanced AI technologies. To increase the level of flexibility in manufacturing lines and warehouse/distribution centers, flexible agent–type robots such as automated guided vehicles have been adopted in many industries. As information technologies advance, these individual agent robots become smart and the fleet size of agents becomes larger. Robot collaboration intelligence is a newly emerging technology that allows intelligent robots to work in a more effective and efficient way. We introduce this emerging technology with industry cases and provide researchers with new research directions in automation and simulation with AI.

1 INTRODUCTION

Automation has come of age and is playing an increasingly central role in the global economy and in our daily lives. As the former Editor-in-Chief of the IEEE Transactions on Automation Science and Engineering, Dr. Ken Goldberg, mentioned in Goldberg (2016), "One Robot is Robotics, Ten Robots is Automation," the essence of automation comes from the idea of tasks being performed by multiple robots. The *agent mobile robot (AMR)* in this paper refers to an individual robot that can travel and perform a given task independently. The *cooperative AMR system* refers to an automation system in which multiple identical agent robots perform the same type of task in the same environment. Figure 1 shows some typical applications of cooperative AMR systems. The first panel shows an overhead hoist transport (OHT) system in a semiconductor fabrication facility (FABs) in which hundreds of agent robots travel along a track hanging from the roof. The second panel shows automated guided vehicles (AGVs) delivering packages in a warehouse or distribution center. These applications are categorized as automated material handling systems (AMHSs), whose primary function is to deliver a lot of materials. The applications of AMRs are

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not limited to AMHSs. The service robots that provide information and direction guiding in airports or shopping malls are cooperative agent robot systems, as depicted in the third panel in Figure 1.

(a) OHTs in Semiconductor FABs (b) AGVs in Distribution Centers (c) Service Robots in Airports

Figure 1: Applications of multiple agent robots.

The widespread use of cooperative agent robot–based automation systems, or simply *agent robot systems*, originated from market needs and advances in technology. The AMHSs in production lines or warehouse/distribution centers have mostly been of the conveyor type, which can handle the parts or packages at a rapid rate. The initial investment cost of conveyor-based automation is relatively low. As a result, factories with mass production that produce limited types of products are best suited for conveyor type automation. However, the current industry trend is a move toward mass customization and mass individualization (Koren et al. 2015; Gu and Koren 2018), and the use of a conventional conveyor-type automation system in production lines or warehouses/distribution centers may not have enough flexibility to handle the variety of parts or products required. As a result, production lines that produce a large variety of products in a flexible manner have been moving from conventional systems to AMR systems.

Another reason why AMRs have gained popularity is technological advancement. To operate multiple AMRs in an effective way, job assignment and the coordination of resource sharing must be handled effectively. The recent advances in 5G, IoT, and sensor and communication technologies enable AMRs to communicate massive amounts of information in near real-time. Moreover, the innovative computing powers and decision-making algorithms in AI have allowed complicated decision-making on an unprecedented level. For instance, the KAIST and a global material handling system solution company jointly developed an OHT management system and demonstrated the operation of more than 500 OHTs at the same time with AI technology (ILLHOE et al. 2018).

We define *robot collaboration intelligence (RCI)* as technology that enables collaboration between AMRs to effectively and efficiently achieve a goal. As the need for flexible solutions in manufacturing and warehouse/distribution centers continues to increase, the role of RCI becomes increasingly important. With advancements in computing power and AI-based algorithms, RCI can handle a fleet of AMRs in a more intelligent way on a larger scale. In this paper, we present RCI with two industry cases and demonstrate its use of AI technologies. We also present the high-level architecture of the RCI system that we developed. Note that this paper is not intended to present an algorithm nor the method of RCI. Instead, we attempt to summarize for readers and scholars the current industry needs and trends in the new era of automation and guide academia in a new research direction in automation science. This paper serves as a bridge between academia and industry in this emerging area. The next section discusses the characteristics and issues of AMRs and RCI. The third section presents the AI technologies used in RCI and its high-level system architecture. The fourth section concludes and provides possible directions for future research.

2 CHARACTERISTICS OF AMR AND RCI

2.1 Cooperative-AMR system

As defined in the previous section, an AMR is a robot that travels and performs a mission independently. The RCI system defined in this paper is used specifically for cooperative-AMR systems. Therefore, to understand the system's requirements and specifications, it is important to clearly identify the characteristics of the AMR. The characteristics of the cooperative-AMR system are identified as follows:

- High degree of independence
- Mission-specific task
- Mobility
- Fleet operation

The first three characteristics are concerned with the AMRs, whereas the last one is concerned with their cooperative nature. A conveyor belt–based automation system is used as the other extreme example for comparison to the AMR.

First, the AMR is considered an independent automation system in terms of its hardware configuration and software design. For instance, an AGV or OHT is physically a separate material-handling robot. In industry, the manufacturers of AGVs or OHTs sell their products based on units. That is, both hardware and software design can be done independently from the environment in which they are used. AMRs have a greater degree of independence in terms of hardware/software configuration than other automation systems. As an example, with a conveyor belt–based automation system, the hardware configuration cannot be designed independently without knowing the detailed requirements of the environment in which it will be used.

The second characteristic of AMRs is the system's mission-oriented nature. The task or mission of the AMR is clearly defined for most cases in industry. An AMR in an AMHS is used to deliver lots or packages from one place to another. A service AMR is used to provide information and directions. The combined first and second characteristics of AMRs imply that the performance of the individual robot can be measured clearly. Because the mission is articulated and the robots perform the jobs independently, performance measures such as the usage rate and working hours can be monitored intuitively. In contrast, the performance measure of a conveyor system is not as easy as the AMR. Suppose that a conveyor belt is moving a particular part from one machine to another machine in a factory. If the flow of the material is blocked or starved due to an unexpected malfunction of the processing machines upstream or downstream of the machines, the rate of the flow, which is the capacity of the conveyor belt, will be slowed because it relies heavily on the performance of the processing machines. This issue has been discussed in Gershwin and Gershwin (1994).

The third characteristic is mobility and is based on our definition of the AMR. Mobility distinguishes AMRs from processing robots such as 6-axis welding robots. In a car body assembly line, multiple identical welding robots are used to automate the laser welding process. Although they maintain a high degree of independence and perform a mission-specific task, they do not move around. This mobility characteristic is a key concept of RCI.

The last characteristic is fleet operation. Although each AMR can perform a task independently, it usually operates with other robots in industry. As mentioned earlier, the modern memory chip production system uses hundreds of OHTs in a FAB. The picking process in the distribution centers of Amazon.com also operates hundreds of AGVs.

Note that the definition of the cooperative-AMR system is not restricted by the fleet size. As long as more than two AMRs can work together, they can be considered a cooperative-AMR system. The level of intelligence of each AMR is not a part of the characteristics of an AMR. Some AGVs in the market are intelligent enough to navigate the floor autonomously, whereas some AGVs can only travel on a guided rail or a marked pathway. However, both can be categorized as AMRs if they meet the four characteristics above.

2.2 RCI

Again, we define RCI as technology that enables effective and efficient collaboration between AMRs. That is, RCI is the enabler of the cooperative-AMR system. We first discuss the issue of collaboration for the AMRs and present the need for an independent solution for the collaboration management system. The key issue of AMR cooperation is described as follows:

- Systems optimization
- Time and space constraints

As discussed above, the performance of an individual AMR can be easily measured. Note that increasing the productivity of each individual AMR does not necessarily lead to an improvement in the fleet's overall productivity. For instance, in the OHT system of a semiconductor FAB, the overall performance of the fleet of the OHT is the average delivery rate and the delivery time of the lots. However, various studies on autonomous mobile device systems indicate that improving individual performance does not translate directly to overall system performance (Ravankar et al. 2017; Georgé et al. 2010; Pinkam et al. 2016).

The next issue of RCI is time and space constraints. Due to the mobile nature of AMRs, temporal and spatial resource management are directly related to the system's overall performance. For example, AGVs travel on pathways, and an AGV occupies one space at a time; this is interpreted as the AGV's use of a limited resource. Another example is the charge operation of AGVs. Most AGV-based solutions use electric motors with on-board batteries, so they must occasionally charge the batteries. In most practical environments, the number of charging stations is limited, and AGVs must compete for the charging station resource. This means that the RCI system must be smart to enough to coordinate the needs of the AGVs depending on the priority and resource constraints.

Based on these issues, the key functions of RCI can be listed as follows:

- Task management
- Resource control

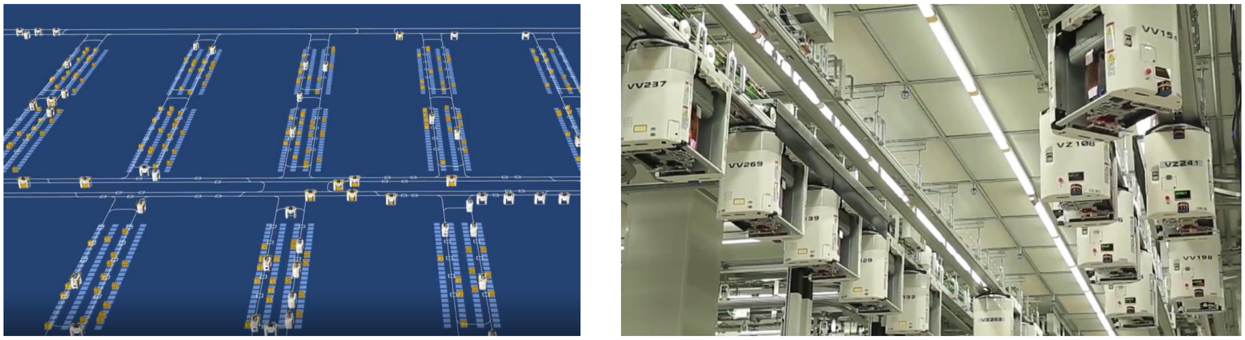
Task management includes the job assigned to each individual AMR. The tasks should be distributed and monitored based upon the system level requirement and the state of each AMR. The resource control is the system-wide management of the resource so that the assigned tasks can be accomplished efficiently. The routing of AMRs and charging control are examples of resource control.

In the past, the management method or algorithms used to deal with these functions addressed each individual solution, such as AGVs or OHTs, or industry sectors, such as semiconductors or flexible job shops, not under the collective context of AMR. AGV fleet management issues and algorithms can be found in Vis (2006). The OHT systems used in semiconductor manufacturing can be found in Kim et al. (2016), Tung et al. (2013), Kong (2007), and Yang et al. (2008), and autonomous robot fleet management is addressed in Alami et al. (1998), Emmi et al. (2014), and Singhal et al. (2017).

As discussed in the first section, due to the new industry needs for flexible robot operations and technological advancements, AMRs have gained popularity in industry.

2.3 Digital Twin

Controlling AMRs to collaborate one another and achieve a system-wide mission is challenging. A intuitive-rule based approach such as a first-come-first-serve (FCFS) or a nearest-assignment, where a job is assigned to a nearest available robot in AGV control is widely used. Mathematical optimization approaches such as mixed integer programming modeling with exact solution approaches or meta-heuristics algorithms have



(a) Simulation-world (b) Real-world

Figure 2: Simulation-world and real-world.

been proposed. However, due to the complex nature of system and scalability issues, these approaches have not been successfully used for industry problems.

The reinforcement learning (RL) based approach has been proposed to deal with the complex control of the fleet of AMRs. RL is an area of machine learning that concerns how a decision maker or software agent must take action in a system or environment to achieve the desired outputs or maximize the notion of cumulative reward (Sutton and Barto 2018). RL is one of three basic machine learning paradigms, alongside supervised learning and unsupervised learning. RL is primarily used to find action rules, called ”policy” for a given environment, described as ”states.” Once the agent has been trained by many experiences, it can select an appropriate action in a short time (Sutton and Barto 2018).

When RL is used for an industry case, a simulation environment is created and agents are trained in the simulation world. Then the trained knowledge is transferred to the actual physical system, making decision based on the insight gained from the simulated environment (Gosavi et al. 2015) (Xia, Sacco, Kirkpatrick, Saidy, Nguyen, Kircaliali, and Harik 2020). This RL-simulation is powerful approach to solve complex models as long as the simulation model is well developed to represent the real world. The agent is trained in the simulation world as if it were in the real world. If the simulation world does not reflect the real world, it could not make a good decision in the real-world.

In order to solve this problem, the idea of using IoT connecting the simulation-world and real-world has been proposed. The initial training of the agent is performed in the simulation-world first. Once the agent is trained enough, the knowledge is transferred to the agent in the real-world. Then the again in the simulation simultaneously runs with the agent in the real-world. If any discrepancy between the decisions in the real-world and simulation-world is identified, the parameters in the simulation is adjusted. Then the agent in the simulation-world is quickly retrained and the updated knowledge is transferred again to update the real-world agent. Since the simulation and real worlds are simultaneously synchronized with IoT, it is also called Digital Twin.

The idea of the Digital Twin based AI approach has been proposed by the authors in the paper and implemented to solve actual industry problems which are discussed in the next section.

3 APPLICATION OF AI IN RCI WITH INDUSTRY CASES

Some of the key enablers of the spread of cooperative AMR systems include innovative computation, sensor, and communication technologies and advances in algorithms. In particular, we show how AI technologies are adapted to RCI to deal with complex cooperative-AMR operations with actual industry cases performed by the authors and industry partners. Two cases are presented – a massive OHT system in a semiconductor FAB, and the stocker systems in a flat-panel display FAB.

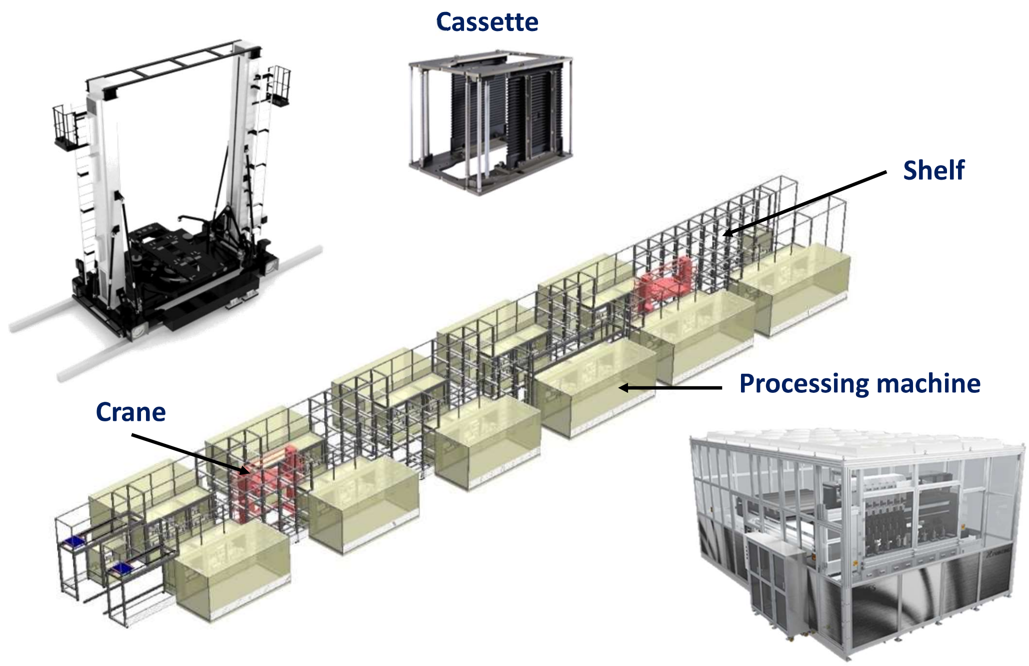


Figure 3: Stocker system.

3.1 OHT systems

The OHT system in a semiconductor FAB consists of OHT vehicles and an OHT track (the "tracks"), as shown in the first panel in Figure 1. The wafer container or lot is carried between processing machines by the OHTs. The market demand has increased rapidly in recent years, so large fleets of OHTs are needed to transport the numerous transportation requests in a FAB. In a modern large-scale wafer processing FAB, more than 1000 OHTs transport around 300,000 lots per day. The number of transportation requests increases with the production volume. One key feature of the OHT system is that operational decisions for vehicles are represented by routing management and OHT-to-lot assignment, which determine the overall performance of large factory systems. Considerable congestion can occur on the track due to the large number of OHTs, and this can adversely affect the FAB's productivity. The challenges of the OHT system are the massive fleet control and the uncertainty of responses. In particular, manufacturing uncertainty can be a more serious problem. For instance, changing material flow patterns or sudden machine failure can cause unpredictable OHT congestion. Typical static routing – such as a short routing based on a travel distance – uses deterministic shortest-path planning with a mathematical optimization approach, but this cannot effectively handle the dynamic nature of the system. To avoid unfavorable congestion in the FAB, dynamic route guidance and vehicle assignment with an awareness of the current traffic situation is essential. Some studies have suggested optimization approaches for the dynamic routing case that collect the information about the traffic state and reroute the vehicle with a mathematical optimization algorithm every time unit. However, this approach was not practically viable due to the computational burden.

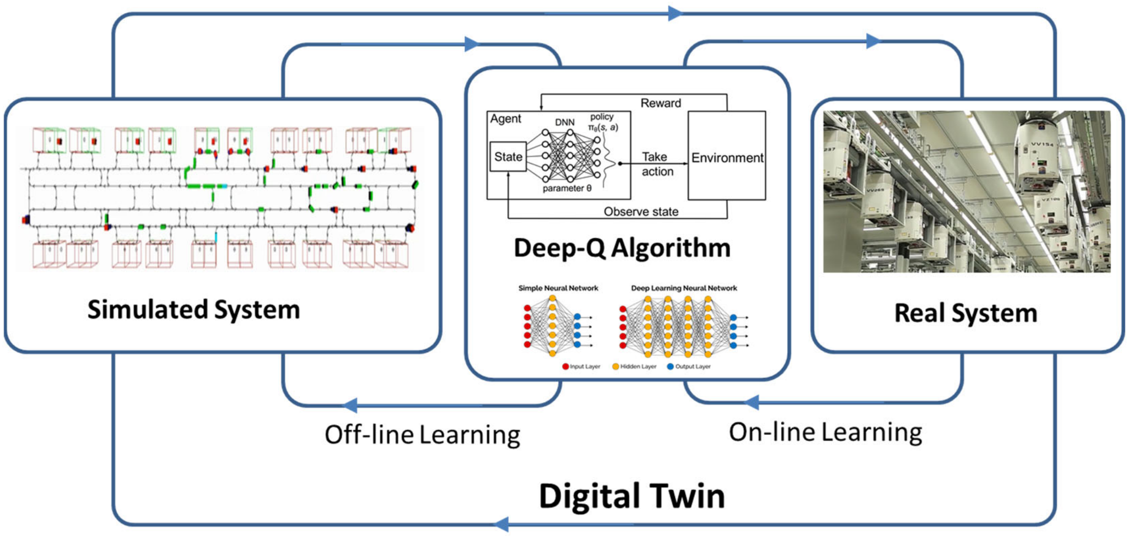


Figure 4: Digital Twin for the stocker system.

The KAIST team, with the industry partner DAIM Research Inc. and Synustech Inc., developed a novel approach based on reinforcement learning. The RL algorithm used in OHT control reflects up-to-date traffic information on the action policy and thus quickly adapts to the ever-changing environment and provides near-optimal actions for routing and AMR assignment. In addition, the computational burden for the updating policy is sufficiently low to enable practical implementation. Thus, it can prevent severe congestion and enhance the overall efficiency of the OHT system in practice. The technical details of the algorithm can be found in Hwang and Jang (2019). Readers are encouraged to watch a video clip of the simulation results posted on the following website: https://www.youtube.com/watch?v=r-WUwqYMD-M.

3.2 Stocker systems in a flat-panel display FAB

The stocker system is the most widely used material handling system for FABs of flat panels, such as liquid crystal display (LCD) and organic light-emitting diode (OLED) display. The stocker system is the main component of the AMHS in LCD and OLED FABs, and it consists of one or two cranes on a single rail and shelves used as buffer spaces. The processing machines are attached to the stocker system as shown in Figure 3. The crane travels along a rail and moves up and down to pick up and set down a cassette. Most flat-panel FABs now use two cranes to increase the throughput of the stocker system, which is referred to as a *dual crane stocker*.

Note that unlike OHT systems in a semiconductor FAB, stocker systems use only two AMRs (i.e., the cranes). It may not seem very complicated to control only two agents, but the two cranes operate in both directions on a single rail and must travel in such a manner to avoid collision; this problem is considered a dynamic traveling salesman problem with uncertain demand, which is one of the most challenging problems in terms of computation and modeling complexities. Most studies in this field focused on the selection of appropriate heuristics (Aydin and Öztemel 2000; Wang and Usher 2005), which is unlike our approach because the dual crane stocker scheduling problem does not have typical scheduling rules.

Recently, the Google Deep Mind team showed that the Deep-Q Network, a combination of RL and a deep neural network (Mnih et al. 2015), could successfully learn policies in Atari games, and it surpassed the performance of all previous algorithms. Inspired by Deep Mind's work, the KAIST team, including the authors of this paper, with the industry partner DAIM Research Inc., developed a scheduling problem based on RL with a deep neural network to approximate the nonlinear relationships among features. In particular, we introduced a novel image-based input shape to accurately represent the state and adopted a convolution layer to account for the interactions between movements. In addition, the team also developed a digital twin-based learning approach that can train the network in a virtual simulation world while the real-time data are fed into the virtual simulator to create possible scenarios and find optimal solutions. We called this double loop digital twin. With the deep-neural network combined with an RL algorithm, we developed an RCI solution for the flat-panel stocker system. The algorithm was used by one of the world's largest manufacturers of LCD and OLED panels to successfully demonstrate that the proposed algorithm significantly improved the performance of the stocker system. The technical details of the algorithm can be found in Hwang et al. (2018). Figure 4 shows the architecture of the digital twin of the stocker system.

3.3 Implication of the cases on RCI

The two cases have the following in common:

- First, they used AI-based algorithms; and
- Second, they were both developed in RCI architecture.

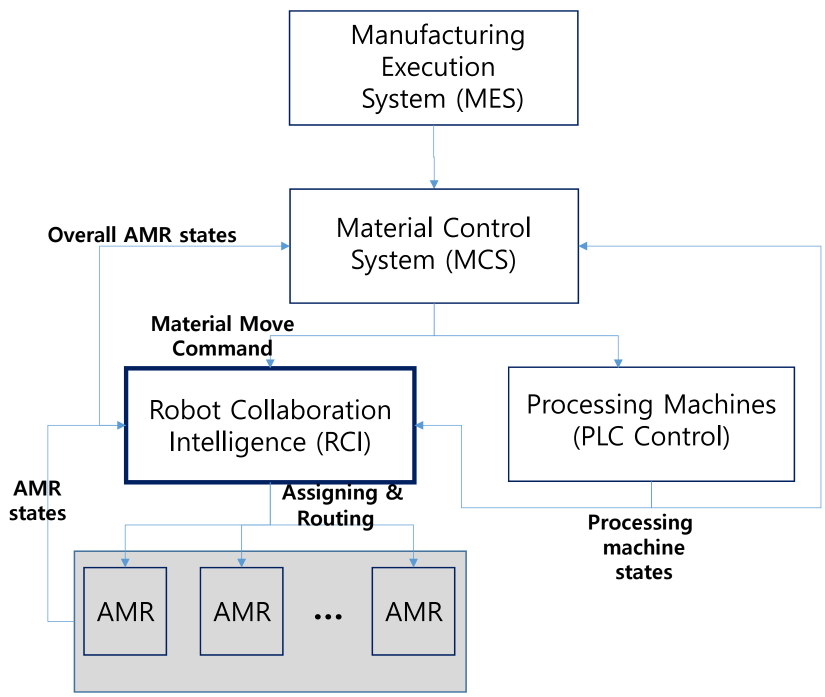


Figure 5: RCI architecture.

Both cases used an RL algorithm to deal with complex assignment and routing issues. We demonstrated that the solutions perform significantly better than the conventional rule-based approaches or mathematical optimization approaches. Also, in both cases, we developed the RCI system to control the AMRs. In the legacy system, the collaborative functions are spread around the factory automation systems. Specifically, robot assignment is done in the robot controllers, and routing is determined for each individual robot. The monitoring function is done at the MES level. This architecture does not provide clear functionality for the collaborative robot operations and can lead to communication delay and data ownership. With the legacy architecture, an AI algorithm that makes heavy use of the data cannot be implemented. In contrast, in the developed architecture depicted in Figure 5, the RCI system is a separate independent subsystem that maintains the data related to the AMR, runs the algorithm, and monitors the AMR. It also communicates directly with the MCS to allow more efficient handling and management.

4 CONCLUSIONS

In this paper, we have defined AMRs and their cooperative nature. Of the many different types of automation, AMR-based automation has distinct characteristics and features. We have defined the issues around the control of multiple AMRs and the need for RCI solutions. We have presented actual cases to show how AI technologies can contribute to RCI and overcome existing technical difficulties. Finally, we have illustrated the high-level architecture of RCI used in the actual development for industries. Although the cases presented in this paper focus on the AMHS in semiconductor and flat-panel display FABs, the concept of RCI also can be applied in the case of service robots. The goal of this paper is to introduce a new category of automation system and to demonstrate the promising opportunities for RCI in academic research. We have shown that an AI-based approach, particularly RL, is effective in RCI and that further research is worthwhile.

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