Wireless Networked Multi-Robot Systems in Smart Factories

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Abstract—Smart manufacturing based on artificial intelligence and information communication technology will become the main contributor to the digital economy of the upcoming decades. In order to execute flexible production, smart manufacturing must holistically integrate wireless networking, computing, and automatic control technologies. This paper discusses the challenges of this complex system engineering, from a wireless networking perspective. Starting from enabling flexible re-configuration of a smart factory, we discuss existing wireless technology and the trends of wireless networking evolution to facilitate multi-robot smart factories. Furthermore, the special sequential decision-making of a multi-robot manufacturing system is examined. Social learning can be used to extend the resilience of precision operation in a multi-robot system by taking network topology into consideration, which also introduces a new vision for the cybersecurity of smart factories. A summary of highlights of technological opportunities for holistic facilitation of wireless networked multi-robot smart factories rounds off this paper.

Index Terms—Industry 4.0, smart manufacturing, smart factory, wireless networks, multi-agent system, multi-robot systems, cyber-physical system, Internet of Things, wireless communications, AI, machine learning, 5G, uRLLC, 6G, cybersecurity

I. INTRODUCTION

SMART manufacturing technology beyond basic factory automation, also known as Industry 4.0, provides more efficient and flexible production by combining control, robotics, wireless networking, cloud computing, big data analytics, and artificial intelligence (AI) computing, potentially revolutionizing production engineering. Smart factories serve as a critical part of the smart manufacturing process and rely on holistic system integration of computing, control, and networking technologies. A key component in the integration of such diverse technologies, information communication technology (ICT), and more precisely the cutting edge *wireless* networking technology will be integral to connecting the computing and control components in a flexible and reconfigurable way.

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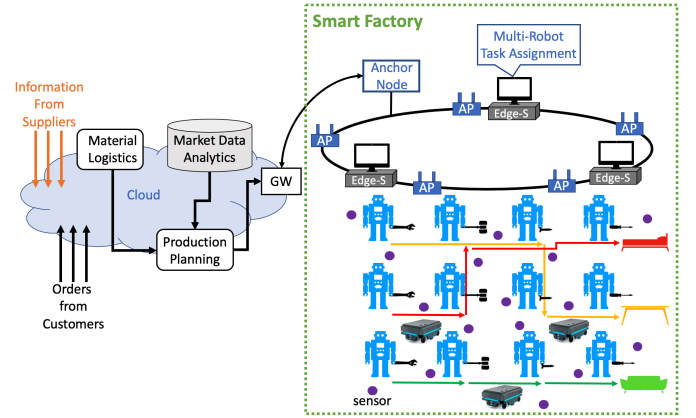G. Fettweis is with the Vodafone Chair, Technical University of Dresden, Germany.

Fig. 1. A Wireless Networked Smart Factory (in the Green Dot Box) Dynamically Adjusted in the Cloud Based Smart Manufacturing

A. Smart Factory: From Industry 3.0 to Industry 4.0

Industry 3.0 takes advantage of computing technology to facilitate factory automation, particularly automated production lines consisting of robot arms with existing wireless or wired networks [1]–[3]. Migrating to Industry 4.0 involves a wider range of technology, namely, AI robotics, industrial Internet of Things (IIoT) and effective connectivity, intelligent sensors, augmented reality, cloud computing, big data analytics, edge computing, digital fabrication such as 3-D printing, cybersecurity and cyber-physical security, etc. [4].

The next step, with the aid of artificial intelligence (AI), is the creation of a *smart factory* also known as *Industry 4.0*. Instead of an automated assembly line factory for the production of a specific product in state-of-the-art manufacturing, smart manufacturing expects to rapidly respond the demand from the market by flexibly arranging production flows for multiple products [5], [6]. Several stages are required to facilitate smart manufacturing:

1) Plan the portfolio of products and corresponding quantities to manufacture, based on the market (online) analysis of supply-demand data that might be from the Internet or an online mechanism. Big data analysis, possibly aided by Machine Learning algorithms, can be gainfully used in this context.

2) Acquire components and materials, and then execute shipping logistics to the smart factory, through the online methodology.

3) Define the production goals and execute flexible and efficient multi-robot operations, given information from

the above two stages. This involves arranging the tasks to robots, determining energy-efficient production flows including moving the unfinished products among robots, and taking appropriate actions for each collaborative robot based on computations by the robots with possible assistance from edge computing or fog computing [7].

Fig. 1 conceptually illustrates the entire process of smart manufacturing. Customers' demands are fed into the cloud and market analytics. Based on the logistics information from the supply chain, the production plan can be developed. For Industry 3.0 of factory automation technology, the production plan is rather fixed, and flexibility is restricted to adjusting the number of (automated) production lines, while each production line is dedicated to one product or production purpose. For smart manufacturing, with the aid of AI data analytics, robotics, sensors, and wireless networking technology [8], [9], ideally, production can be dynamically adjusted to different products at any time. The implementation of advanced ICT is a key to achieve such a goal.

The campus-wide edge network in a smart factory consists of an anchor node (AN) governing a number of access points (APs) to form the extremely high-bandwidth fronthaul networking infrastructure. APs serve wireless communications and networking with sensors and robots in a smart factory. Some edge servers connected by the edge network form edge cloud computing or fog computing resources, which host data analytics and other AI/management functionalities. There are two possible classes of robots, production robots executing manufacturing tasks and autonomous mobile robots enabling production flows. Consequently, a smart factory can be realized with advantageous characteristics: flexibility, rapid decision process assisted by AI and big data analysis, efficiency in the optimization of production flow and energy consumption, reliability, and quality in factory operation. In this paper, we focus on the scope of a smart factory at Stage 3), with a perspective from wireless communications and networking.

B. Re-configurable Multi-Robot Task Assignment in a Smart Factory

A generic technique to translate the goal of production into actions of multiple robots in a smart factory is known as multi-robot task assignment (MRTA). Classic MRTA has been well studied in the literature [10], [11]. Since the production process in a factory typically requires following a certain flow, MRTA in factory automation using fixed production lines is therefore constrained in its optimization. However, wireless networking enables flexible configuration of robots to collaborate in the production process that is adjusted in accordance with time-varying market demand and production plan. Fig. 2 illustrates a flexible configuration of a multi-robot system in a smart factory, where both production robots and transportation robots are required to form the multi-robot system in a smart factory. In Fig. 2, transportation robots are autonomous mobile robots (also known as automated guided vehicles (AGVs) in production research). This introduces another critical concern, energy efficiency for both classes of
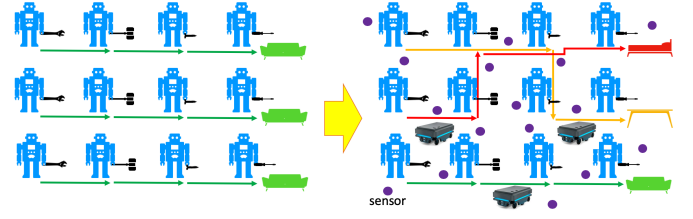

Fig. 2. Fixed configuration of factory automation (left) to flexible configuration of smart factory (right) in accordance with the time-varying production plan.

robots, for smart factories under time-changing configurations of multi-robot systems. It can be seen from the right-hand side of Fig. 2 that flexible and efficient production requires AGVs to move over longer distances. It therefore gives rise to many related new research subjects, such as scheduling, efficient optimization, etc., in energy-efficient transportation in a factory, such as [12]–[14]. Furthermore, this scenario suggests a new multi-objective MRTA problem, namely accommodating both production robots and transportation robots toward computationally effective solutions. In other words, a traditional MRTA considers a relatively static operation for production robots only, with the goal to maximize the throughput of an automated production line or flow. The multi-robot system enabled by wireless networking in a smart factory shall deal with both production robots and transportation robots (i.e. AGVs). Thus an MRTA for production robots must react in a dynamic manner toward time-varying market demands, to optimize the throughput of production, under the constraint of the cost induced by the changes of robots' functions such as the order of operation. Furthermore, the energy consumption in each automated production line of Industry 3.0 is rather fixed. However, the MRTA in a smart factory shall consider the energy to dynamically deploy production robots and the energy for the operation of AGVs. Since this paper focuses on the wireless perspective of multi-robot systems (MRS) in a smart factory, MRTA of a smart factory will be detailed as a research opportunity in Section V-C.

C. Requirements of Wireless Networking for Multi-Robot Smart Manufacturing

Industrial IoT (IIoT) has been brought into the factory automation with various implementations of ICTs. Open platform communication of time-sensitive industrial networking protocol stack has been developed [3], and the Internet Engineering Task Force (IETF) also develops the IPv6 protocol stack and time-hopping in IEEE 802.15.4 to networking industrial sensors [15]. Reliable and fault-tolerant factory automation with video capability has been well developed based on industrial networking, particularly Ethernet [16]. However, from the above illustration of MRTA in a smart factory, production robots and transportation robots may require 100 intelligent control instructions per second, particularly for high-precision production and AGV delivery, implying 1-2 msec latency to transport a wireless communication message/command. Furthermore, wireless networks supporting spatial reconfiguration and ultra-reliability (such as 99.999%

end-to-end reliability) is actually desired, which creates a new dimension of challenge for wireless communication and networking technology.

D. Organization and Contribution of the Paper

This paper provides an overview of smart factories from the perspective of wireless networking by first demonstrating the role of smart factories in the smart manufacturing ecosystem and then facilitating the smart factory as a multi-robot systems. Taking advantage of social learning, the resilient decision process for robots in the production flow can be further uniquely investigated. With thorough overview of wireless networking technology, distributed learning for sensor fusion, and holistic summary of research opportunities, this paper is organized as follows. State-of-the-art wireless networking technologies for factory automation and industrial IoT are summarized in Section II. Some essential wireless networking technologies to facilitate a multi-robot smart factory by properly incorporating computing aspect are expounded in Section III. Due to the special nature of sequential decision processes in multi-robot manufacturing, the resilience of precision operation in a multi-robot system is investigated in Section IV. Finally, the arising technological opportunities are stated in Section V and conclusions are drawn in Section IV. Consequently, wireless networking serves as a pillar technology toward smart factories to enable flexible, resilient and efficient integration of the AI computing and control components and provide a thorough vision of multi-robot smart factories.

II. STATE-OF-THE-ART WIRELESS NETWORKING TECHNOLOGIES FOR INDUSTRIAL AUTOMATION

In this section, we summarize existing wireless networking technologies and evolution under development, which are useful for factory automation and potentially for smart factories.

A. 4G, MTC, 5G and 6G

Migrating from 4G-LTE technology, the fifth generation mobile communications, widely known as 5G, has three pillar technologies: enhanced mobile broadband (eMBB), massive machine-type communication (mMTC), and ultra-reliable and low-latency communication (uRLLC). Traditional human-to-human (H2H) communication requires high-bandwidth multi-media services for speech communication, video streaming, and online social media. The eMBB technology has been enabled by the advances in massive MIMO [17], cloud radio access network (C-RAN) and heterogeneous networks [18], [19], polar codes [20], etc. and is expected to deliver impressive user experience [21].

In addition to H2H communication, one of the purposes for 5G is to network all kinds of "things" such as devices, sensors, actuators, and machines. This is precisely the wireless networking technology to connect the Internet of Things. The first feature of IoT is the number of connected devices, which is far larger than the number of handsets - a fact that has been noted since the late stage of 4G LTE. An innovative technology, machine-type communication (MTC), has been developed in 3GPP [22]. The immediate technical challenge is both to deal with the massive number of MTC devices [23] and the extension of coverage of MTC devices as the sensors and devices may be located in a large geographical range [24]. The physical layer and medium access control technology evolving to mMTC in 5G is reported in [25]. In [26], a simple model to comprehend how MTC can be applied to smart factories is introduced, which indicates a base station can support up to 1,400 MTC devices given access delay less than 70 msec and probability of success in access 0.9 by using RACH channel and $1K$ bits per packet. Although the results appear encouraging for mMTC applications in general, they are insufficient to satisfy requirements for reliable information and privacy in most scenarios of smart factories. Thus, reliable and resilient ways to collect information from operating environments still require further investigations.

IoT involves diverse application scenarios and may consist of several networks that have different design objectives. A new radio access technology, narrowband IoT (NB-IoT), has been developed by reusing the 4G LTE design including numerologies, downlink OFDMA, uplink SC-FDMA, etc. [27]. The spectrum of NB-IoT may be deployed as a standalone carrier or as a part of LTE spectrum, which is particularly compelling for factory wireless networks. Furthermore, the resource mapping of NB-IoT is designed to best co-exist with LTE signals, in any mode of deployment (i.e. in-band, guard-band, standalone). The random access of NB-IoT exploits both time-domain and frequency-domain, with an asynchronous and adaptive hybrid ARQ to support flexible scheduling.

Evolution of the network architecture plays an important role for smart factories. ECHO [28] pursues a reliable distributed cellular core network architecture for hyper-scale public cloud platforms. A significant step beyond the notion of RAN sharing involves sharing of radio resources among tenants (e.g., multiple virtual network operators) via a physical mobile network operator, such as FlexRAN [29]. Orion [30] further enables the dynamic on-the-fly virtualization of base stations and the flexible customization of slices to meet their service needs, which can be used in an end-to-end network slicing setting. Our prior work of SoftAir architecture [31]–[33] enables a holistic software-defined 5G-and-beyond architecture that provides a scalable, flexible and resilient network architecture, along with network management/orchestration tools and traffic engineering solutions. As AI is expected to be an important technological component into 6G [34], [35], AI-integrated campus networks for smart factories and smart communities shall emerge as a critical application scenario described later in Section III of this paper.

B. Device-to-Device Communication and Mobile Edge Computing

Instead of the communication going through the infrastructure network, an alternative way is to allow direct communication between devices, known as device-to-device (D2D) communication [36], [37]. D2D communication shall be managed by the RAN both to limit the interference (either when operated as underlay, or in a separate band), and to provide good energy-efficiency, to result in more reliable and

efficient wireless networking [38], [39]. D2D communication appears to be an attractive solution for many IoT application scenarios [40], while the scalability of large-scale operation may need further investigations. A further important topic that has gathered recent attention is to offload computing tasks to the edge computing or storage, which is known as mobile edge computing (MEC) [41], [42]. Consequently, an integrated system design of wireless communication and MEC including storage can be developed [43] and further applications to the scheduling of smart manufacturing through deep Q-network learning [44].

C. Tactile Internet and Networked Control

Tactile Internet intends to enable real-time communication services for delivering control, touch, sensing and actuation information, such that humans and machines to interact with their environments in real time [45], [46]. Among diverse application scenarios of Tactile Internet, industrial automation and control for high precision and remote operation is one major focus. As indicated in [47], high performance communication such as 5G-NR is required toward the success of Tactile Internet and time-sensitive industrial networks [46], [48]. End-to-end networking latency will play a more important role than other quality-of-service characteristics in traditional 4G cellular communication networks.

Such technologies elevate not only the technological level of production robots but also that of transportation robots. For example, the framework from [49] can be applied to Cooperative Adaptive Cruise Control (CACC)-enabled platooning, which is a common scenario for autonomous mobile robots and AGVs in smart factories. The study does not deal with mobile cellular networks or their shared medium characteristics. Assumptions based on 802.11p systems have been done, with only a round-robin scheme for scheduling, but without concerning packet drop effects.

- Event-triggered computing and self-driven control differs from classical control in that transmission between control components or among agents is not periodic with fixed time-interval duration. A control action may be triggered, and hence transmitted through a network, when the state of a system has a considerable change in magnitude. The authors in [50] have applied this concept to platooning and by following a similar approach as [49], the minimum inter-event time bounds are derived. No specific scheduling or channel access protocol is discussed. The evaluation considers not 5G but 802.11p-based technologies. In [51] a deterministic state-dependent prioritized contention resolution protocol for random channel access for stable network control systems is presented.
- Model-based control was introduced by Montestruque et al [52]. The model is used to generate a control input for the actuator allowing the system to run in open loop for a finite interval of time without the need of feedback. In [53], a framework is proposed for the design of state estimators through observable variables, i.e., observers, taking into account different communication protocols
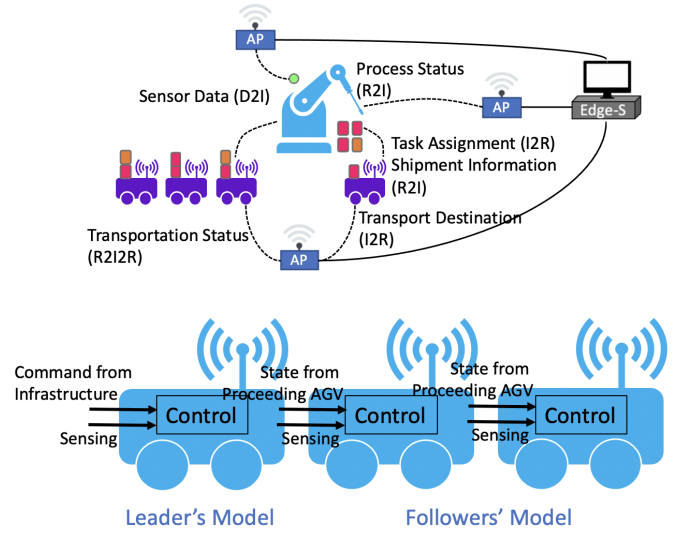

Fig. 3. (Upper) Edge computing as infrastructure instructs production robots and transportation robots through wireless networking. (Lower) A model-aided cooperative adaptive automated network control for a platoon of autonomous transportation robots/AGVs.

and bounds are established for the maximum allowable transmission interval. [54] proposes an algorithm to design an observer in a networked control system. The design of a digital observer for CACC to increase the system robustness to packet loss is presented in [55]. Although there has been substantial advancements in the past years on the different fronts of networked control systems, the recasting application of the generic models to specific collaborative automated vehicular use cases is still in its infancy. Few studies have considered the stochastic effects of wireless communication [56].

Consequently, wireless networked control has recently emerged as an important technology in smart factories. At this early stage, some features of wireless networking have been taken into consideration, such as delay and packet loss in networked control [57], robust control of industrial networked systems over imperfect communication [58], and joint cross-layer optimization in real-time networked control systems [59].

D. SDN/NFV

As MRS consisting of intelligent mobile machines require greater system reliability and safety, uRLLC emerges as a must in wireless networking. To support such a low-latency system demand, software-defined networking (SDN) together with network function virtualization (NFV) in architectural designs, primarily introduced for data center networks and the next-generation Internet, has drawn great attention recently with campus-/enterprise-wide applications [60]. For example, funded by the NSF PAWR program in 2018, COSMOS [61] located in New York City aims at providing a city-scale advanced wireless testbed for real-world experimentation on next-generation wireless technologies. By realizing software-defined mobile networking, the COSMOS platform focuses on enabling ultra-high-bandwidth and low-latency wireless

communications, with tightly coupled edge computing techniques. In [62], mobility management for low-latency layer-2 handover is proposed in SDN-based enterprise networks, without any modification on mobile devices. Targeting at ultra-low latency 5G services, an SDN-based framework is also introduced in [63] for managing reliable live migrations of virtual resources across different IaaS, while ensuring high QoS and a very low downtime without human intervention.

Several studies [64]–[70] have jointly considered low-latency SDN architectures with near-data computing techniques for IoT or WLAN cases. Particularly, while scalable IoT data analytics is given in [64], a fiber-wireless edge computing node is designed and implemented in [65] to enable edge computations for IoT applications. A fog-enabled WLANs is also proposed in [66] for indoor positioning, and a delay-aware task assignment is introduced in [67] for wireless SDN-based edge cloudlets. Moreover, in [68], a literature survey is given on low-latency 5G by considering RAN, core network, and caching solutions. Concerning IEEE 802.11 networks, an SDN-based slice orchestration and MAC management are studied in [71] to ensure end-to-end QoS delivery. In [69], 5G-slicing-enabled SDN is adopted for ultra-low latency autonomous driving service, while the latency is modeled by a GI/M/1 queuing system. Also, a time-efficient access point assignment is presented in [70] for SDN-controlled wireless networks, which takes fast decisions based exclusively on the history of user behavior. However, most of the above designs treat operational and information systems independently and have little concern about the signaling or bulky protocol issues in any of the two systems.

In [72], the SDN architecture is considered for wireless industrial networks, where age-of-information aware channel allocation is designed with regard to the network states and wireless spectrum usage. A secure software-defined access network, namely SESAM [73], is further developed for flexible industry 4.0 manufacturing with robust horizontal handover and low-latency vertical handover. Focusing on an industrial multi-radio access environment, an SDN-based architecture with millimeter-wave links is implemented in [74] to support high-rate stream transmissions with wireless mobility. An SDN framework that integrates mobility management in industrial wireless sensor networks is also analyzed and assessed experimentally in [75]. Nevertheless, a complete software-defined wireless platform in regard to networking latency as the design metric and distributed computation capability in smart manufacturing is still desirable in the literature.

III. WIRELESS NETWORKING FOR A MULTI-ROBOT SMART FACTORY

As indicated in Fig. 1, successful operation of a smart factory involves sophisticated and holistic system design of wireless networking, computing, and control. Applying machine learning and AI to enhance wireless communications and networking is a widely known technological opportunity (see, e.g., [76], [77]). However, for the purpose of achieving multi-robot smart factory, what is the desired wireless networking remains an interesting technological challenge that is detailed in this section.

A. Wireless Robotic Communications and Adaptive Computing

By realizing the control functionality as a kind of computational goal, a new aspect of smart factory technology is integrated with the design of AI computing and wireless networking.

1) Networking for Artificial Intelligence: Although the way for communication to influence multi-robot systems is not well understood yet, some toy examples can be employed to explore how wireless networking impacts the multi-robot systems, and subsequently to understand what is the desired wireless networking for multi-robot systems. In [78], a resource-sharing multi-agent system has been studied by assuming each autonomous agent governed by the finite-horizon reinforcement learns to navigate through Manhattan streets while following the rule of stop sign in the intersections. Wireless networking among these agents (or autonomous mobile robots, autonomous vehicles) is surely expected to improve the average delay of the trips. However, some more interesting observations are found:

- Wireless networking is indeed useful but errors from communication links and multiple access mechanism can significantly degrade the gain from wireless networking.
- The policy and the reward map (rewards mapping onto the street map or a reference coordinate system) of another robot going to interact at the intersection is the desired content of such communication. The age of information is critical as data delayed beyond the horizon are completely useless even when correctly received.
- Consequently, end-to-end networking latency plays the most important role in wireless networking for robots or AI agents, which leads to later discussion in ultra-low latency and ultra-reliability of wireless networking.
- To avoid the potential scalability issue of direct robot-to-robot communication (i.e. ad hoc networking), robot-to-infrastructure-to-robot communication (i.e., two hops of wireless networking) obviously performs better at least in this particular example, while it confines the potential end-to-end networking latency if any ultra-low latency mobile networking exists [79]. This leads to the desirable edge network in a smart factory as in Fig. 1.

A further exploration on collaborative robots was presented in [80], which brought more complicated robot planning into consideration. The above observations remain valid with some extra observations.

- Private reference that each robot generates based on its own exploration of the environment is useful information to exchange with another collaborative robot.
- Real-time ALOHA is proposed as multiple access protocol, which is the modified version of slotted ALOHA by removing re-transmission due to the concern of age of information. The concept of p-persistent multiple access can be incorporated.
- The performance improvement by collaboration through wireless networking can be significant.

More realistic MRS shall be explored to understand wireless robotic communication further.

2) A Generic Model of Multi-robot Interactive Systems: By introducing wireless robotic communication and edge network, edge computing and agent computing can be facilitated in an integral manner. As the smart factory portion in Fig. 1, we consider a set of interacting robots $\mathcal{M} = \{1, 2, \cdots, M\}$, which are possibly connected directly to each other, as well as to a set of J APs in the proximity. These APs are in turn connected to the edge network, which can either be modeled as an edge "cloud", available from all APs, or as a set of N edge servers (ESs). Each robot and each ES have their own computation capability, $D_{\tilde{m}}$ (where $\tilde{m}$ can refer to any type of node, m, j, n. In principle, fusion center (FC) nodes of different sensor networks are also located in the edge network. A robot (or known as an agent in the multi-agent system) computes its actions based on its own on-board observation, and possibly other agents, and such information must propagate through the edge network. For the mth agent (i.e. robot) in $\mathcal{M}$, we define the following variables (all in a particular time t): s_t^m denotes the state of agent m; a_t^m denotes the action by agent m at time t; $b_{t,l}^m$ denotes the agent l's belief of state of agent m at time t; f_{t-1} denotes the sensor fusion/inference based on sensor data $\mathcal{F}_{t-1}$ collected at time $t-1$; $\hat{f}_t$ denotes the prediction of sensor data for time t based on sensor data collected at time $t-1$; o_t^m denotes the on-board sensor information at time t; $U(\cdot)$ represents the utility function based on the application scenarios and related to (i) reward from the environment in ML (ii) risk or loss in operation (iii) energy consumption and other considerations.

The cyber action for a robot is denoted as $a_t^m(\theta_t)$ at time t based on sensor information and other agents' actions, and represented as

$$a_t^m = \arg\max U(s_t^m \mid s_{t-1}^1, \cdots, s_{t-1}^M,$$
$$\text{or } b_{t,l \neq m}^m, f_{t-1} \text{ or } \hat{f}_t, o_t^m) \qquad (1)$$

subject to different constraints, by incorporating a physical operating parameter(s), θ_t, to form the action process in a cyber-physical interactive network [81]. Wireless networking is used to exchange state information and θ_t with previous robots in the same production flow or interacting robots.

3) Adaptive Computing in Multi-Robot Smart Factory: The scenario of multi-robot interactive systems suggests wireless distributed computing [82], [83], emerging a technological frontier of interest in a smart factory. To optimize distributed computations for sensor fusion and control, we may assume a time-slotted and synchronous structure provided that there exists precise network synchronization. On the other hand, the peculiarity of a (smart) factory is that the actions of multiple robots must be in a certain sequential order. Without an universal clock available to all robots and sensors, the entire operation becomes event-triggered or event-driven [84]–[86].

Generalizing the setup of robots and edge-servers in Fig. 1 and (1), we assume each robot generates R computing tasks over time, and each task $r \in \mathcal{R} = \{1, 2, \cdots, R\}$ is indicated by $X_m(r) = [\alpha_m(r), \epsilon_m \alpha_m(r)]$, where $\alpha_m(r)$ denotes the data size of task r and ϵ_m denotes the required computing power. The set $\mathcal{A}_m(r)$ denotes the set of edge servers available for task r, $c_{m,n}(r)$ denotes the channel capacity (assumed to be constant within a duration of execution time) between the robot $m \in \mathcal{M}$ and the ES $n \in \mathcal{N}$ during the processing of task r. Due to the nature of time-changing configuration in a smart factory, this forms a new wireless distributed computing problem. Let $\psi_{m,n}(r)$ represent the computing processing capability allocated by ES n to handle the computing requests for the task r generated on the robot m, where $\psi_{m,n}(r)$ are i.i.d. and adaptive among tasks [87]. Define further the model of event-triggered computing as follows.

- **Semi-Markov states:** $\mathbf{s}_m(r) = [n'_m(r), n_m(r)]$ is the current state including machine association $n'_m(r)$ and previous machine association $n_m(r)$. We assume that the task state transitions follow a continuous-time Markov chain. A new semi-Markovian model and its corresponding state transition probability can be derived.
- **Random events:** $\mathbf{w}_m(r) = [\alpha_m(r), c_{m,n}(r), \psi_{m,n}(r), \forall n \in \mathcal{A}_m(r)]$ is defined as a random event vector, which collects all variables related to task execution. Each of its components is assumed i.i.d. over different tasks with an unknown probability distribution.

The above definitions imply that the event-triggering network association decision depends on the completion time of computation task, i.e., $d_m(r)$ is proportional to task size. We formulate an optimization problem **P** that minimizes average task delay subject to the time average energy consumption constraint by designing association policies $\boldsymbol{a}(r) = \{a_m(r) \in \mathcal{A}_m(r)\}$ as follows:

$$\mathbf{P}: \quad \min_{\{\boldsymbol{a}(r)\}} \sum_{m \in \mathcal{M}} \frac{1}{R} \sum_{0 \leq r \leq R-1} \mathbb{E}\left[d_i(r)\right]. \qquad (2)$$

The above optimization problem **P** is extremely challenging due to the existence of random event $\mathbf{w}_m(r)$ and semi-Markov state $\mathbf{s}_m(r)$, while traditional MDP and model-based reinforcement learning is not applicable due to the unknown state transition probability, the curse of dimensionality, and the coupling introduced by semi-Markov states. Furthermore, from the perspective of event-triggered computing, semi-Markov state $\mathbf{s}_m(r)$ and association decision $a_m(r)$ are operated over the task frame with variable time lengths for different robots, and the association decision time is not synchronized across different robots. To make **P** mathematically tractable, a two-stage online proactive association decision algorithm can be developed [88] as follows.

1) Optimal parameter estimation and optimal association: define $\mathcal{S} = \mathcal{L} \times \mathcal{M}$ as the state space, where $\mathcal{L}$ is the discretized location set, and each state element indicates the admissible server(s) to which the robots can connect. A semi-Markovian process can be developed to describe the behavior of the task r in robot m since the state $\mathbf{s}_m(r)$ satisfies the Markov property and operates in the continuous time $T_m(r)$. By inferring the state transition matrix based on the SNR (or CSI in general) of the wireless connections, and the anticipatory mobility-aware delay function, the proactive network association problem is to minimize the task delay for single robot m.

2) Online Association Decision: To resolve the challenges caused by the semi-Markov states and random events, we first treat the semi-Markov state $\mathbf{s}_m(r)$ as the decision variables and the selection of semi-Markov state is independent of random events $\mathbf{w}_m(r)$. Since the task state should be determined before the observation of random events, the optimization evolves into a constrained Markov decision process or reinforcement learning problem, which can be solved via a stationary randomized policy [89], [90]. Therefore, we can form the second stage of robot's association decision as an online algorithm. After obtaining the parameters for optimization, observing the current semi-Markov state $\mathbf{s}_m(r)$ and random event $\mathbf{w}_m(r)$ at task frame r, the new equivalent optimization is obtained.

A more effective adaptive computing mechanism for event-triggered multi-robot system in a smart factory remains an open problem in wireless distributed computing.

B. Wireless Network Architecture for Edge Computing and Interactive Agents

When each agent in multi-robot systems is running reinforcement learning algorithms, vital information (e.g., policies, values, and references of agents) needs to be exchanged over manufacturing systems. These information exchanges are vulnerable to errors and end-to-end networking latency under the heterogeneous (cloud, edge, and on-board) computing environment. In this section, we aim to develop the wireless network architecture that can satisfy the low-latency need in multi-robot smart manufacturing systems. Particularly, by leveraging edge computing and SDN technologies, we introduce a decentralized software-defined computing architecture to enable ultra-low latency networking. As in Fig. 4, the proposed architecture consists of three types of devices: (i) the AN(s), which hosts and manages virtual clusters, i.e., virtual machines running software-implemented baseband processing functions as the PHY/MAC protocols, (ii) APs equipped with possibly multiple antennas and controlled by virtual clusters to serve agents' transmissions, and (iii) low-latency high-bandwidth optical fibers, which connect the APs to the AN and support accurate, high-resolution synchronization among APs. The architecture refers to IEEE 802.11 wireless local area networks [91] and uRLLC of 5G and beyond [79], [92] in the air interface. Together with the bandwidth reservation and downlink migration from IEEE 802.11ax [93], the proposed architecture extends dedicated short-range radio communication (DSRC) and enables next-generation vehicular services. We detail the data and control planes of the architecture in the following.

1) Wireless Virtualization-Enabled Data Plane: The data plane is an open, programmable, and virtualizable network forwarding infrastructure for endpoint traffic through last-mile open-loop transmissions. It consists of hardware-based APs with limited PHY functionality, i.e., OFDMA, and software-implemented virtual clusters (networks) in ANs, which are connected via fronthaul links using standardized interfaces, such as common public radio interface (CPRI). The ANs
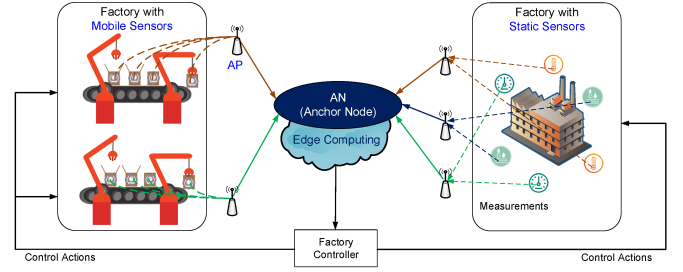

Fig. 4. Decentralized software-defined computing architectures for smart factory with mobile robot platoon.

endowed with edge computing and storage capacity, can serve as a substitute of cloud servers. To achieve ultra-low latency, our previous work [79], [94] suggests to treat an agent as the center (and the only) node of a virtual cluster in which multiple APs serve this agent through cooperative communications [95], to distinguish from traditional concept of cell using one base station to serve multiple mobile nodes. Open-loop wireless communication discarding acknowledgement and re-transmission ensures the minimum possible latency, but requires proactive network association initiated by the virtual cluster (i.e., agent) [96]. The concept of virtual clusters can be straightforwardly realized by radio slicing of virtual networks, where physical radio resources can be mapped into virtual resources and services are delivered by customized virtual slices. Accordingly, a proactive radio resource allocation is

- **Network and Radio Slicing:** If the agent as a mobile node has ultra-low latency traffic, it forms a *virtual cluster* to directly access APs in the communication range of good signal quality, by proactively selecting radio slice(s) communicating with each of the involved APs.
- **Proactive Radio Resource Allocation:** The radio resources are divided into multiple M resource blocks containing N subcarriers and L symbols in each time slot and the serving time is T_1 slots. The virtual cluster selects κ APs of good signal quality and randomly selects a radio slice (portion of radio resource) to communicate with each AP via open-loop communication. Equivalently, the virtual cluster selects an AP in range but κ radio slices.
- **Relay Forwarding Scheme:** Each AP, i.e., network slice, serves like a relay node in cooperative communications to forward the message from AP to AN. We initially adopt amplify-and-forward such that AN combines message signals from κ APs to finally decode the message in the open-loop wireless communication. More complicated modes of decode-and-forward and path-time coded-and-forward remain interesting research subjects.

Although the agent can proactively select whatever to complete open-loop wireless communication inside a virtual cluster without other mobile agents, there might be multiple virtual clusters physically co-locating in the neighborhood, which results in physical multi-access interference. This issue will be resolved by the proposed cluster orchestration in Section III-C.

2) Edge Computing-Enabled Scalable Control Plane: The control plane is handled by ANs and connecting to core network and cloud servers via backhaul. As the ANs govern

the functionalities of APs, the proposed control plane employs this distributed transmit point architecture, which offers excellent cooperative gain and evolvability by aggregating massive technology evolving APs at the ANs. Through the north-bound APIs, both management tools, e.g., as virtual cluster orchestration for traffic monitoring and real-time control/management of vehicular operation, and SDN applications for service providers, like security and privacy solutions, can be developed upon distributed SDN controllers. These components can be designed, deployed and updated to fit the specific and ever-changing needs. Due to the distributed decisions by agents, open-loop proactive access inherits high collision probability and cannot provide useful transmissions without further sophisticated designs. To address this issue via edge computing capability at ANs, we introduce a capacity optimization framework, which employs stochastic geometry [97] to analyze the complex stochastic, time-varying MAI and provides a reference of performance-guaranteed throughput. Based on this optimization, SDN controllers in ANs can develop desirable online control policies, i.e., network association, resource allocation, and communication protocols, to ensure maximum system capacity for multiple access.

We are developing an experimental platform of SDN-based edge network and computing, which contains three data sources with computation workloads, i.e., Odroid-C2, as multi-agents, five commercial wireless routers, i.e., TL-WDR4300, as APs, and high-performance integrated storage devices, i.e., Intel NUC7i5BNK, as intelligent ANs and the cloud server. With 128 MB data chuck and Hadoop application, our preliminary study shows the computing testbed can provide 53% reduction in average read/write time.

C. Ultra-reliable and Ultra-low Latency Wireless Networking

In traditional wireless networks, networking functions between mobile robots and the network infrastructure are centrally controlled by a single base station, while complicated protocol stacks incur considerable networking latency and limit the coordination between base stations. We aim to propose multi-agent cluster optimization (i.e., dynamic AP clustering) upon the multi-robot system using open-loop PHY and edge computing capacity at ANs. The performance of this virtual cluster optimization depends crucially on the choice of AP cooperation cluster for each agent.

Several related works are working on queue-aware resource allocation using Lyapunov optimization with *myopic* queue-length. Some of them [98], [99] focus on average queuing delay and form the optimization problem to ensure that vehicles' data queues are stable. The study in [98] addresses an in-network caching issue by minimizing the time-averaged number of connected base stations while stabilizing the queue-length (and thus latency) of each vehicle. Considering vehicle-to-vehicle networks underlaid vehicle-to-infrastructure networks, the work in [99] maximizes user fairness about vehicles' service rates simultaneously satisfying the constraints of data queue stability, resource re-allocation, and network switching. In [100]–[103], fine-grained performance metrics (e.g., delay distribution and probabilistic bounds) are examined
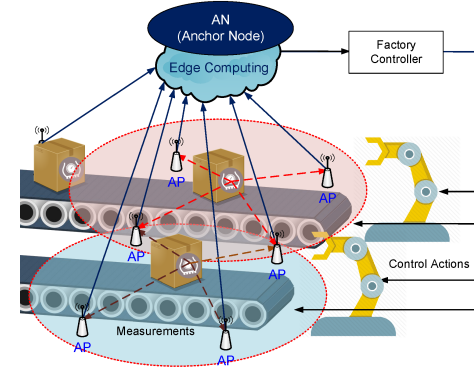

Fig. 5. Virtual cluster formation with agents in the centers of the clusters.

in vehicle-to-anything networks. Accordingly, transmit-power minimization problems are investigated concerning queuing latency and reliability. Concerning dynamic traffic environments, recent studies have incorporated wireless resource management with reinforcement learning [104]–[106], dueling neural networks [107], LSTM-based learning [108], and imitation learning [109], [110]. However, most of these works are lack of full consideration of latency and reliability requirements from industrial applications.

In general, there are two types of clustering: network-centric and agent-centric schemes. In *network-centric clustering* schemes, the entire network infrastructure is divided into non-overlapping clusters, and the APs in each cluster jointly serve all the agents within the coverage area. Although researchers have shown that such disjoint clustering schemes are effective in mitigating the inter-AP interference, agents at the cluster edge still suffer from severe inter-cluster interference. Therefore, an *agent-centric clustering* is designed to achieve optimal "delay-reliability performance" in MRS.

1) Multi-Agent-Centric Clustering: Consider a smart factory with multiple connected agents that follow a sequential operation, for example, a platoon in Fig. 3. Fig. 5 shows a realization of our proposed virtual cluster formation for wireless networking in such a smart factory. Each agent is served by an individually selected subset of neighbouring APs, and different AP clusters for different agents may overlap. Particularly, each agent is treated as the center of a virtual cluster, while multiple APs cooperatively serve this agent using coordinated multi-point (CoMP) transmissions. The agent-centric clustering is limited since these clusters are chosen dynamically and may overlap, but it is preferred when dealing with mobile wireless agents. The design objective with this is to simultaneously minimize the networking latency and maximize end-to-end reliability by jointly optimizing virtual cluster association and radio resource slicing. Precisely, in software-defined edge architectures with wireless network virtualization, AN(s) can collectively slice APs' radio resources (e.g., via OFDMA in downlink or SC-FDMA in uplink in NB-IoT) for each agent's virtual cluster. Accordingly, each AP can simultaneously serve multiple virtual clusters, that is for multi-agent operations in equation (1), with allocated radio slices by leveraging multi-core computing and parallel programming.

The main challenge for such clustering frameworks is the

uncertainty and instability of dynamic IIoT channels due to mobile agents and flexible access of open-loop transmissions for ultra-low latency requirements. To cope, wireless system reliability is often based on the percentage of successfully delivered data within a specific deadline, equivalent to the packet loss rate. For example, the reliability requirement of 5G NR uRLLC use cases [111], [112] is 10^{-5} (or 99.999%) success probability for 32 bytes within 1 ms user plane delay, which indicates the steady-state channel availability. However, this reliability definition cannot fully reflect the time dependence of time-varying channels. Instead, our framework resorts to "real-time reliability" (i.e., the probability that AN successfully receives a message via APs with end-to-end latency less than a required value) and predicted CSI for realistic IIoT channels, based on grant-free PHY and agent mobility. In the following, we detail the proposed methods that deal with such uncertainty and instability while maximizing system reliability and minimizing acceptable latency.

Considering the worst-case scenario of AP deployment and agent dynamics, we assume that these devices are distributed by following two homogeneous Poisson Point Processes (PPPs) in $\mathbb{R}$ with intensities λ_m and λ_j measured in agents and APs per unit length. We denote the agent and AP sets as $\Phi_m = \{m_k, k = 0, 1, 2, ...\}$ and $\Phi_j = \{j_s, s = 0, 1, 2, ...\}$, respectively. We can formulate a delay-reliability-optimal clustering framework as

$$
\begin{aligned}
&\textbf{Find:} \quad l_{mj}(t) \in \{0, 1\}, P_j^m(t) \in [0, P_j^{max}], \\
&\qquad\qquad \forall m \in \mathcal{M} \subseteq \Phi_m, j \in J \subseteq \Phi_j \\
&\textbf{Minimize} \quad \max_{m \in \mathcal{M}} \mathbb{E}\left[D_m(t) | \Phi_j, \Phi_m\right] \\
&\textbf{Maximize} \quad \|\mathcal{M}_A\| + \min_{m \in \mathcal{M}} \zeta_m \\
&\textbf{Subject to} \quad \text{C1: } 1 \le \sum_{j \in J} l_{mh}(t) \le V_{max}, \forall m \in \mathcal{M}; \\
&\qquad \text{C2: } \sum_{m \in \mathcal{M}} P_j^m(t) \le P_j^{max}, \forall j \in J; \\
&\qquad \text{C3: } \sum_{m \in \mathcal{M}} l_{mj}(t) R_m\left(\gamma_m(t)\right) \le C_j, \forall j \in J; \\
&\text{C4: } \gamma_m\left(\left\{\mathbf{P}(t), \hat{\mathbf{H}}(t), \mathbf{1}(t)\right\}\right) \ge \gamma_m^{min}, \forall m \in \mathcal{M}_A \subseteq \mathcal{M}; \\
&\text{C5: } \mathbb{P}\{D_m(t) \ge D_m^{max} | \Phi_j, \Phi_m\} \le 1 - \zeta_m, \forall m \in \mathcal{M}; \\
&\text{C6: } \limsup_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} \sum_{m \in \mathcal{M}} \mathbb{E}\left[Q_m(t) | \Phi_j, \Phi_m\right] \le \infty.
\end{aligned} \tag{3}
$$

Given each realization of agents' and APs' locations, this framework aims to find optimal network association between agents and APs $\{l_{mj}(t)\}$ and APs' power allocations $\{P_j^m(t)\}$ such that the maximum average user plane delay is minimized and, at the same time, the minimum acceptable reliability guarantee is maximized. In particular, $D_m(t)$ and ζ_m are obtained as the end-to-end latency and degree of real-time reliability in C5 for agent m's traffic, respectively, and $\mathcal{M}_A \subseteq \mathcal{M}$ denotes the "available" agent set where the corresponding agents' SINR constraints in C4 can be satisfied via the framework. Constraints C1-C3 presents architectural concerns: C1 ensures agent-AP association, where each agent will be served by at least one AP and the size of virtual

clusters will be limited by the complexity of successive interference cancellation (SIC) decoding (e.g., [113]) for CoMP transmissions; C2 provides APs' transmit power requirements while realizing power resource slicing; C3 ensures total data rates transmitted to APs should be no larger than fronthaul capacities $\{C_j\}$ APs and AN(s) [32], [114]. Given minimum SINR requirements $\{\gamma_m^{min}\}$, constraint C4 indicates that actual SINR values depend on power allocation, SIC technique, network association, and CSI prediction $\hat{\mathbf{H}}(t)$ due to time-varying IIoT channel models. As mentioned, constraint C5 provides the real-time reliability for uRLLC applications, which statistically guarantees the request delay bound $\{D_m^{max}\}$ with $\{\zeta_m\}$ degrees [115], [116]. Constraint C6 provides a *strongly-stable* system [117], [118], which ensures all agents have finite queue-lengths.

The essential advantage of such user-centric clustering schemes is that there exists no explicit cluster edge which used to incur worst performance due to weakest received power and severe interference. It has been validated by our 5G&B SoftAir [114], where 500 Mbps high data-rate can always be supported at each mobile user with millimeter-wave transmissions. Moreover, we extend with eco-vehicular edge networks for connected transportation [119], which use distributed multi-agent reinforcement learning to combat power-hungry edges while assuring system reliability and data rates. The results show that our solution outperforms conventional schemes in energy efficiency and system reliability and coverage with 3GPP cellular-based V2X services [120]. Similar in essence to our work [119], edge Q learners at ANs are expected to solve the cluster optimization in Equation (3) and derive parameters to yield optimal system performance. For example, Lagrange Multipliers analysis can be conducted to convert clustering and scheduling decisions into a Lagrange dual function [121]. Accordingly, a variant of backpressure-based distributed algorithms [122], [123] can be designed, with the aid of Lyapunov stability theory [124]. Time-series deep recurrent learning (e.g., GRU [125]) can be further applied to achieve fast convergence toward optimal solutions while reflecting time-dynamics.

Furthermore, the following techniques can extend diverse and stringent uRLLC services. First, we can extend the clustering framework with our newly defined metric, "mission reliability [126]", to characterize different execution periods in applications. The average time to the first failure upon software-defined edge architectures will be investigated regarding multi-connected paths between agents and ANs and wireless Rayleigh fading. We will examine the tradeoff between mission duration, mission reliability, and the number of available end-to-end paths to further improve the overall reliability for realizing various uRLLC applications. Moreover, we will study error control mechanisms with these networking paths to ensure physical error-rate performance. Inspired by our prior work [127], path-time codes will be developed as the error control coding over open-loop, multi-path transmissions. That is path-time coded-and-forward schemes in multi-agent systems. Forward error-correcting codes (e.g., [128]) can still be applied here; our preliminary study shows that low-density parity-check codes (LDPC) well serve this IIoT purpose with
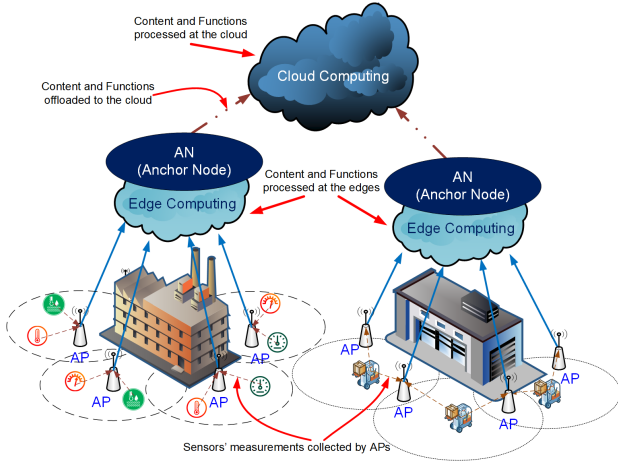
Fig. 6. ANs can cache/offload the data and services between local edge computing and cloud computing.

small-length packets (i.e., 128 or 256 bits packet payload).

2) Data-Driven Edge Computing at Anchor Nodes: Open-loop communication and virtual cells form the core technology of multi-agent smart manufacturing systems to accomplish ultra-low latency with high reliability. Based on these accomplishments, in this section, we introduce novel intelligent edge computing that leverages the synergy of big industrial data and edge computing at the ANs. Big industrial data provides unprecedented opportunities for system architects to understand the requirements and behaviors of mobile sensors and various network elements. This in turn allows for intelligent real-time decision making in a wide range of applications, which greatly improves the network operation efficiency. With its advances, big data-driven optimization allows architects to make optimal decisions with deep insights, such as instantaneous and historic data. Useful information, e.g., the correlation between factory events and data traffic, can be extracted to make decisions based on long-term strategies and to optimize (i) data/resource allocation and caching, (ii) factory event prediction, and (iii) industrial system and data security so that the deployment and operational costs can be significantly reduced.

In the proposed architecture, edge computing at ANs can push the frontier of computing applications, data and services away from centralized cloud computing infrastructures to the logical edge of an industrial network, thereby enabling analytics and knowledge generation to occur closer to the data source. As shown in Fig. 6, the ANs endowed with cloud-like computing and storage capacity, can serve mobile sensors' data as a substitute of the cloud. Extra tasks exceeding the AN's computing capacity are further offloaded to the cloud, resulting in a hierarchical offloading structure among mobile sensors (and APs), ANs, and the cloud. In general, there are two successive phases of edge computing operations with respect to content and services: (i) caching and (ii) offloading. The caching operation refers to caching application services and their related databases/libraries in the edge AN, thus enabling sensor data to be processed locally. Due to limited computing and storage resources of ANs, which services are cached on the AN determines which tasks can be offloaded, thereby

significantly affecting the edge computing performance. On the other hand, the computation offloading operation concerns what/when/how to offload sensors' workload from their local AN to the cloud. The offloading scheme should consider the service availability in edge ANs (i.e., what types of computation tasks/applications) due to the limited resource of ANs. Also, because of wireless mobile sensor networks, the optimization offloading decisions are more complex and coupled both spatially and temporally.

D. Distributed Learning with Sensor Fusion

To facilitate operations in a smart factory with a stringent latency demand, a considerable number of IIoT sensing devices, as illustrated in Figs. 4 and 5, need to be well deployed to collect a massive amount of data for edge computing to help the factory controller make timely decisions to optimize the manufacturing performances of the smart factory [129]. To reduce the latency induced by data communication between the IIoT devices and their ES, distributed learning over a wireless edge network in a smart factory increasingly becomes an important means because it does not require raw data transmission that incurs latency and privacy issues. Recent works in [130]–[133], for example, showed that distributed (deep) learning at the wireless edge can effectively optimize the performances of IIoT systems for various mission-critical applications. Thus, a distributed learning technique can certainly help mobile robots optimize their working trajectories so as to maximize their working accuracy and efficiency by just learning based on their local on-board data and the data of the fusion center in the wireless edge network. Although such a learning technique is similar to the idea of federated learning [134], [135] that aims to preserve the privacy of the data sets across different distributed devices, its main goal is to reduce communication latency in addition to preserving the data privacy [136]–[142]. The previous works on distributed/federated learning across different data sets in wireless networks are still minimal, including federated learning through digital and analog signal combining techniques [143]–[145] and performing computation offloading [146], [147]. How the distributed learning performance is impacted by the imperfect wireless transmissions while adaptive sensing and computing happen between an edge network and mobile robots remains open. More importantly, how event-triggered computing and data processing affect the performance of distributed learning has not been well understood yet.

To clearly and simply address the distributed learning problem over a wireless edge network in a smart factory scenario, consider an AP in a wireless edge network which is connected to an ES associated with M robots in a smart factory. Suppose the M robots have their own on-board sensing data set and no robot is able to access the data set of any other robots because of communication and/or privacy issues. Extending from (1), these M robots aim to achieve a global learning goal by using their own data and sensor fusion data from the wireless edge network when they are triggered by some event. Let $\mathcal{F}^m \triangleq \{F_i^m \in \mathbb{R}^d \times \mathbb{R} : F_i^m = (\mathbf{x}_i^m, y_i^m), \mathbf{x}_i^m \in \mathbb{R}^d, y_i^m \in \mathbb{R}\}$ denote the sensing data set collected and stored at robot m

in which $\mathbf{x}_i^m$ is an input data vector with d feature elements and y_i^m is the labeled (scalar) output of $\mathbf{x}_i^m$. For a data point $F_i^m \in \mathcal{F}^m$, the distributed learning task of interest is to find the global model vector $\vartheta \in \mathbb{R}^d$ that characterizes the output y^m with the loss function $L^m(\vartheta, F_i^m)$ of robot m for all $m \in \mathcal{M}$. Let $\ell^m(\vartheta)$ be the (convex) loss function of robot m given by

$$\ell^m(\vartheta) \triangleq \frac{1}{|\mathcal{F}^m|} \sum_{F_i^m \in \mathcal{F}^m} L^m(\vartheta, F_i^m), \tag{4}$$

where $|\mathcal{F}^m|$ denotes the number of the data points in set $\mathcal{F}^m$. Suppose the AP broadcasts the value ϑ_t of ϑ at time t for the actions of these M robots and the robot m then adopts the following recursive algorithm to update its ϑ^m at time $t + 1$:

$$\vartheta_{t+1}^m = \vartheta_t^m + \rho_t^m \left[\varphi_t^m \nabla_\vartheta \ell^m(\vartheta_t) + (1 - \varphi_t^m) \nabla_\vartheta \ell_m(\hat{\vartheta}_t^m) \right], \tag{5}$$

where $\vartheta_{m,t+1}$ denotes the value of ϑ evaluated by robot m at time $t + 1$, $\rho_t^m \in (0, 1)$ is called the learning rate of robot m at time t, $\varphi_t^m \in \{0, 1\}$ is a Bernoulli random process that is unity if the transmission from the ES to robot m is not in outage at time t and zero otherwise, $\nabla_\vartheta \ell^m(\vartheta_t)$ denotes the gradient of $\ell^m(\vartheta)$ with respect to ϑ evaluated at $\vartheta = \vartheta_t$, and $\hat{\vartheta}_t^m$ denotes the prediction (estimate) of ϑ_t at robot m obtained by (online) deep learning once ϑ_t is not received by robot m due to transmission outage. Note that the transmission outage from the ES to robot m could be delay outage and/or wireless link outage. After the robots update their local model vector at time $t + 1$, they send it back to the ES that calculates ϑ_{t+1} by using the following averaging algorithm:

$$\vartheta_{t+1} = \frac{\left(\vartheta_{t+1}^{ES} + \sum_{m=1}^{M} \left[\phi_{t+1}^m \vartheta_{t+1}^m + (1 - \phi_{t+1}^m) \hat{\vartheta}_{t+1}^m \right] \right)}{M + 1}, \tag{6}$$

where ϑ_{t+1}^{ES} denotes the global model vector ϑ evaluated at the ES by incorporating the fusion sensor data, $\hat{\vartheta}_{t+1}^m$ is the estimate of ϑ_{t+1}^m found by deep learning at the ES once ϑ_{t+1}^m is not received by the AP, $\phi_{t+1}^m \in \{0, 1\}$ denotes a Bernoulli random process that is unity if the transmission from robot m to the ES is not in outage at time $t + 1$ and zero otherwise. Similarly, the transmission outage from robot m to the ES could be delay outage and/or wireless link outage. The whole learning process will terminate whenever $|\vartheta_{t+1} - \vartheta_t|$ is smaller than some predesignated positive small value. Fig. 7 demonstrates the above distributed learning algorithm over a wireless edge network.

There are two main features of the distributed learning algorithm associated with eqs. (4)-(6) that cannot be seen in previous works on distributed learning: One is to model the transmission outage between the ES and its mobile robots by using two Bernoulli random processes ψ_t^m and ϕ_t^m and the other is to compensate the transmission outage between the ES and its robots by using (online) deep learning in order to make the algorithm possess some robustness against the transmission outage. Apparently, the randomness of ψ_t^m and ϕ_t^m and the accuracy of the estimates of ϑ^m in the uplink and downlink significantly impact the convergence performance of the distributed learning algorithm and they are also affected by
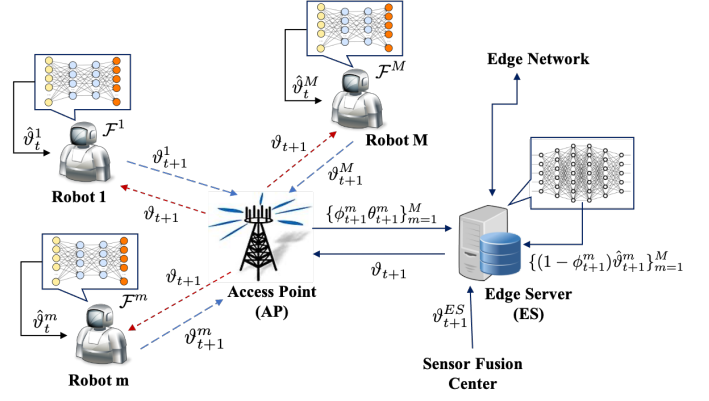

Fig. 7. Distributed learning over a wireless edge network.

wireless channel impairments and co-channel interferences. To clearly demonstrate this point, let us define the total learning error of a distributed learning algorithm over a wireless edge network with M robots as $\sum_{m=1}^{M} |\vartheta_t^m - \vartheta|^2$; its simulation results for the proposed distributed learning in eqs. (4)-(6) and federated learning (without compensating the lost updates of the global and local model vectors) are shown in Fig. 8 when M robots are uniformly distributed in the network and the IIoT channel model given in [148], [149] is adopted to simulate the channel outages between an AP and M robots. As shown in the figure, the proposed distributed learning in eqs. (4)-(6) indeed outperforms federated learning because only its total learning errors reduce to zero for the two values of M within one millisecond. Also, the total learning error of the two distributed learning algorithms increases as M increases. This is because a larger M induces more uplink interference so that the outage probability of the uplink channel from robot m to the AP (i.e., the probability of $\phi_t^m = 0$), which depends on the uplink interference, increases. As such, studying a fundamental interplay between the distribution of ψ_t^m and ϕ_t^m and the convergence performance of the distributed learning algorithm certainly helps us find a connection between the performance of distributed learning and the deployments of APs and SDs in that the fundamental interplay is definitely related to the outage probabilities of the wireless links between the ES and its robots that can be characterized by the stochastic geometry framework in the literature (such as [97], [150]–[155]).

E. Channel Modeling in Smart Factories

The pathloss, shadowing, and fading characteristics of the propagation channel guide the deployment for a given coverage/reliability requirement, or conversely, allow evaluation of coverage for a given deployment. Furthermore, the delay dispersion determines requirements for equalizer or OFDM cyclic prefixes during system design, and angular dispersion relates to the impact that multiple antenna elements have on diversity order and spatial multiplexing. Thus, an understanding of the overall propagation channel is a critical prerequisite in design and analysis of wireless systems for industrial applications [156].

Industrial channels are different from the typical indoor (office) channels in a number of important physical effects.
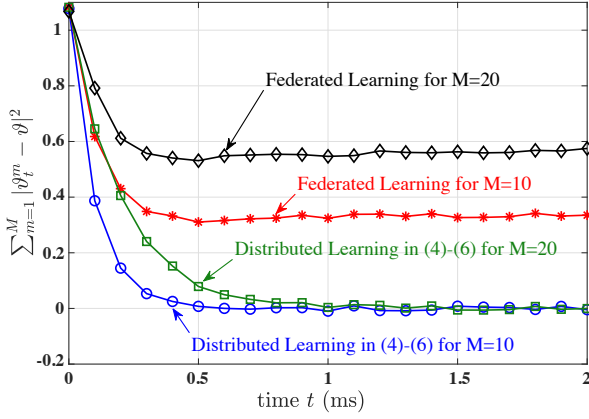
Fig. 8. Simulation results of the total learning errors of the proposed distributed learning and federated learning for different numbers of robots uniformly distributed in a wireless edge network.

Firstly, the dimensions of the halls are much larger than even open-office structures for many people; this allows longer runtimes and reverberations of multipath. The richness of multipath is further enhanced because of the presence of many metallic objects - both machinery, storage tanks, as well as construction elements of the factory environment such as metal grilles, pipes, etc. Finally, the motion of machinery and moving robots enhances time variance. For all these reasons, standard indoor channel models cannot be applied to industrial scenarios.

1) Typical environments and frequency ranges: A large number of measurement campaigns have been performed in a variety of manufacturing locations, which range from relatively small workshops and halls (about 10 m × 10 m) to extremely large production halls that can reach 10,000 m², thus the range between transmitter (TX) and receiver (RX) may be up to 150m, though most measurements only cover up to ≈ 50 m distance. The height of the access point may either be around 2m, or elevated at 5-10 m; the height of the user device is usually restricted to ≈ 1.5m. Many investigations distinguish between the following conditions:

- line-of-sight (LoS): optical line-of-sight, or first Fresnel zone free of obstacles.
- obstructed LoS: some small objects block the LoS.
- non LoS (NLoS): heavy blockage.
- light clutter: often occurs in factory halls with sparsely space machinery, intersected by ailes used for transporting goods.
- heavy clutter: in some factories, heavy metallic machinery is located close together. This gives rise to significant multipath, and strong pathloss if the line-of-sight is blocked.

The main frequency ranges of interest are 0.8, 2.45, and 5.4 GHz, corresponding to the ISM bands, in which Zigbee (IEEE 802.15.4) and WiFi (IEEE 802.11) are located. Some of the work in the 1980/90s dealt with 1.3 GHz, and some recent work discusses 3 GHz since it is of interest for 5G.

2) Pathloss and fading: The local (instantaneous) channel gain can be modeled as the product of three factors: (i) the distance-dependent path gain $G_p(d)$, (ii) a random variable representing shadowing S, and (iii) a random variable representing small-scale fading.

The distance-dependent average path gain is commonly modeled on a dB scale as

$$G_p(d)_{dB} = -10\alpha \log(d/d_0) - \beta \tag{7}$$

where d_0 is some reference distance. The parameters α and β (pathloss coefficient and offset respectively) are extracted from measurements or ray tracing; obviously such a fitting model is only valid for the distance range for which underlying data exist. In a number of papers the above model is specialized to the "fixed intercept" or "close-in" reference model, in which the path gain is fixed to the value of the free-space path gain at a reference distance $d_{ref,CI}$, A few papers also consider a generalization in which the path gain is characterized by a slope n_1 up to a distance d_{break}, and by a slope n_2 at distances beyond that (breakpoint model).

The pathloss coefficient, defined as α in (7) (either for the $\alpha - \beta$ of the fixed intercept model) for LoS, is in the range $1.4 - 1.9$ in a large number of measurements, e.g., [157]–[160], though some coefficients around 2.2 have been measured as well. For LoS, pathloss coefficients are $1.8 - 2.5$ [157], [161], while for NLoS, they can range from 2 to 6, heavily dependent on the environment [159] (in some heavily scattering environments, the $\alpha - \beta$ model provides a strong offset β, but a small α indicating little distance dependence of the attenuation [162]–[164]). Other papers provide an aggregate for a mixture of LoS and NLoS, e.g., [165], [166].

Small-scale fading, i.e., variations around $G_p(d)_{dB}$ are generally described by the amplitude probability function of these variations, which will typically follow a Rayleigh or Rice distribution. The Rice factor is often described as the ratio of the power in the LoS path to the power of all other components; mean Rice factors on the order of $4-8$ dB have been found [160], [166] though extremes up to 20 dB have been identified.

Another impact on the fading arises when the transmitter and receiver are fixed, but scatterers are moving. In a factory environment, such movement can arise not only due to moving people and autonomous vehicles (robots), but also spinning machinery and robot arms making repetitive motions, e.g., to place ICs on a circuit board. The resulting fading is often also Rician in nature, but the Rice factor now becomes the ratio of the power in the time-invariant to those of the time-variant components. This temporal Rice factor (in dB) has been measured to be 12 dB (with 5 dB standard deviation) [161]; to be in the interval $5 - 25$ dB [167], and around 10 dB [168].

3) Delay and angular dispersion: Delay dispersion is traditionally characterized by the power delay profile (PDP), the expectation (over the small-scale fading) of the squared magnitude of the channel impulse response, $\mathbb{E}\{|h(\tau)|^2\}$. From this, further condensed parameters can be derived, in particular the *rms delay spread*, which is the second central moment of the PDP, and the *maximum excess delay*, which is the delay
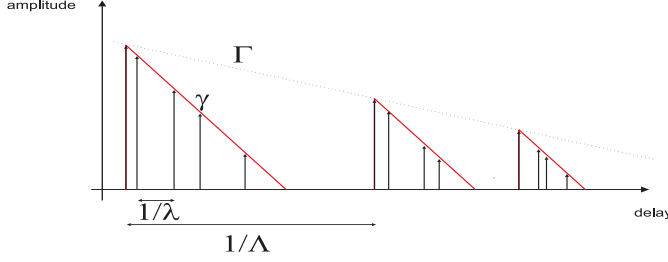
Fig. 9. The Saleh-Valenzuela model.

between the first and the last significant arriving multipath component (MPC), though the latter is very sensitive to the definition of what we mean by "significant".

A wide range of delay spread values has been found in the measurements in the literature. A (typically linear) dependence of delay spread on the distance between TX and RX has been found: e.g., in an NLoS scenario in a manufacturing shop, the delay spread increased from 55 to 80ns as the distance increased from 7 to 33m [159]. Another factor in the delay spread is the size of the factory hall as well as the amount of clutter: for example, the largest delay spreads in the measurement campaign of [165] were found in a large factory hall with light clutter (so that the MPCs could reach reflecting walls). Generally, the delay spreads are in the order of 5-50 (for LoS) and 10-150 (for NLoS), with some outliers, up to about 300-400 ns have been observed [165], [169].

A widely used model for the PDP in the industrial channel is the Saleh-Valenzuela model as Figure 9 [170], which describes the PDP as a sum of clusters, each of which consists of a number of MPCs:

$$\mathbb{E}\{|h(\tau)|^2\} = \sum_{l=0}^{L} \sum_{k=0}^{K} a_{k,l}(\tau)\delta(\tau - T_l - \tau_{k,l}) \qquad (8)$$

where $a_{k,l}$ are the multipath gain coefficients, whose power decreases with delay $\mathbb{E}\{|a_{k,l}|^2\} \propto \exp(-\tau_{k,l}/\gamma)$, where γ is the MPC decay constant, and the power of the clusters decreases exponentially with a different constant Γ. Both the inter-arrival times of rays, and the interarrival times of clusters, are exponentially distributed, with average values $1/\lambda$ and $1/\Lambda$, respectively.

While delay spreads have been measured in several dozen measurement campaigns, angular spreads have been given less attention. Recent work of [160], [171] indicates angular spreads on the order of 50 degree.

4) Frequency dependence and mm-wave systems: Ultrawideband measurements for the 3-10 GHz range were done in [164], [172], [172], [173]. Several interesting phenomena were found: the PDP does not always follow an SV model, but can have a soft onset, so that the PDP rises up to a maximum before decaying; the path gain is proportional to $f^{-2\kappa}$, where $\kappa > 1$, A number of measurements, e.g.,

[161], [174] measure in multiple bands (but a relatively small bandwidth within each band); yet the statistical fluctuations make general statements about frequency dependence difficult beyond a typically increased pathloss when the antenna gains in the different bands are similar.

In mm-wave systems, [175] measured small pathloss coefficients of 1.3 (LoS), 2.2 (OLoS) and 2.7 (NLoS); this paper also investigated delay spread and angular spread, which are consistent with values observed at lower frequencies. [176] performed narrowband measurements in a factory hall and measured pathloss coefficients of 4.1. Overall, the results indicate initial deviations from the better-explored cm-wave band, and more investigations are needed to enable wireless communications in smart factories.

IV. CYBER-PHYSICAL NETWORK ANALYSIS OF MULTI-ROBOT SMART FACTORY

Taking advantage of the state-of-the-art wireless networking that enables massive on-demand link formation, flexible configuration of collaborative missions in multi-robot smart factories can be implemented through multi-level abstraction of cyber-physical networks, as shown in Fig. 10. AI-empowered robots in manufacturing processes are connected as cyber network to collect information and make decisions to attain various production objectives. Unlike a physical network, which is constrained by wireless communications, the cyber network consisting of autonomous decision-making agents is organized in accordance with task allocation which is determined by a corresponding portfolio of products [177]–[181]. Analysis of smart factories from a cyber-physical system perspective poses novel challenges to comprehend the co-evolution of cyber-physical networks [182]. In addition to the transformation of AI computing from rule-based expert systems to data-driven learning systems [7], recent explorations to implement multi-agent learning in a variety of application scenarios demonstrate the importance of communication to facilitate satisfactory collaborative performance [77], [78], [80]. Indicated in Section II-C, though a great body of literature has investigated networked control of linear dynamical systems [183]–[187], there are many active researches as new generation of learning agents are nonlinear and it remains an open problem to understand distributed optimization, communication [188]–[190] and network topologies of multi-agent learning behavior [191]–[196].

One of the special aspects of a smart factory is to take advantage of wireless networking to control the robots of AI computing to flexibly meet the requirement from market needs under the constraint of logistics. To elaborate the integral design of AI computing and wireless networking, in this section, we uniquely look into the role of wireless communication and networking from the view of cyber-physical systems (CPS) by treating robots in a smart factory operating in sequential computing order to illustrate this new concept.

A. Social Learning of Multi-Robot Systems

To manufacture a designated product in the smart factory requires a finite number of agents indexed by $1, 2, 3, ..., M$
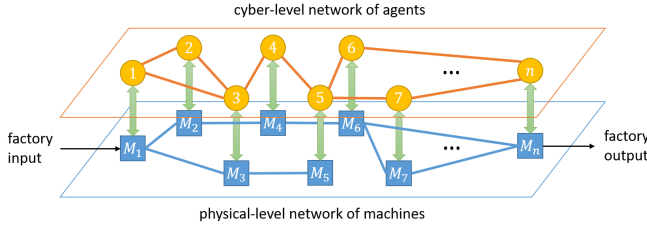
Fig. 10. Smart factory as cyber-physical networks. The physical network is limited by wireless communication, and the cyber network depends on task allocation. Each physical machine has a corresponding intelligent agent handling the cyber decision. Note that the cyber and physical network topologies are not necessarily identical.

corresponding to the indexed robots (or machines) denoted as $R_1, R_2, ..., R_M$. The agent network is characterized by a graph $\mathcal{G}(\mathcal{V}, \mathcal{E})$, where $\mathcal{V} = \{1, 2, 3, ..., M\}$ and $\mathcal{E} = \{(i, j) | i, j \text{ connected}\}$. The neighbor of agent i is denoted as $\mathcal{M}_i = \{j | (i, j) \in \mathcal{E}\}$. The manufacturing steps t proceed sequentially according to agent index $i = 1, 2, 3, ..., M$, which means that the physical network is a single production line processing from R_1 to R_M sequentially. Let $\mathcal{S}$ denote the state space, and a state $s \in \mathcal{S}$ indicates the status of an input object in the manufacturing processes. Let $\mathcal{A}$ denote the action space of agents. For step $t = i$, the agent t takes an action $a_t \in \mathcal{A}$, resulting in a new state $s_{t+1} = h(s_t, a_t)$, where $h : \mathcal{S} \times \mathcal{A} \to \mathcal{S}$ is a function characterizing the physical state dynamics. Given a pair of state and action (s, a), there is a utility function $U_p : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$, which associates the pair with a real number to characterize quality of decision.

When no complete knowledge of h or U_p is available, which is the case described by most data-driven machine learning problems, agent i is trained on a dataset such as

$$\mathcal{D}_i = \{(x_i^{(k)}, a_i^{(k)}, u_i^{(k)})\}_{k=1}^d, \tag{9}$$

where each $(x_i, a_i, u_i) \in \mathcal{S} \times \mathcal{A} \times \mathbb{R}$. Different forms of $\mathcal{D}$ lead to distinct types of learning problems. For instance, if the knowledge of U_p is available, the agent can establish the distribution $\mu(x)$, and optimize its decision by

$$\arg\max_a \mathbb{E}_\mu[U_p(x, a)]. \tag{10}$$

This results in the utility-maximizing decision, and μ is called the belief of the agent. With a new set of information $\mathcal{I}$, the Bayesian learning updates the belief by:

$$\mu(x|\mathcal{I}) = \frac{\mathbb{P}(\mathcal{I}|x)\mu(x)}{\int \mathbb{P}(\mathcal{I}|x)d\mu(x)}. \tag{11}$$

It is important to clarify that the decision is one-shot in a single production line. Although it is possible for an individual agent to formulate reinforcement learning and approximate the system dynamics h in repeated or multiple production line, the agents need to learn from neighbors through the cyber network to approximate h in one round of sequential manufacturing. The process can be written down as the nested functions:

$$s_2 = h(s_1, a_1)$$
$$s_3 = h(s_2, a_2) = h(h(s_1, a_1), a_2)$$
$$s_4 = h(s_3, a_3) = h(h(h(s_1, a_1), a_2), a_3)$$
$$\vdots$$
$$s_n = h(s_{M-1}, a_{M-1}) = h(...h(h(s_1, a_1), a_2), ..., a_{M-1}) \tag{12}$$

We note that (12) addresses the problem of sequential social learning. Namely, agents have to take into account the decisions made by other agents so that they can make better decisions based on more accurate estimation of state dynamics. For each agent $i = 1, 2, 3, ..., M$, the agent updates belief with the decisions collected from cyber network $\mathcal{I} = \{a_j | j \in \mathcal{M}_i\}$. The belief update aggregates neighbor's decisions to facilitate distributed coordination [197]–[201].

The use of social learning in multi-robot smart factories is to deal with the lack of global information about the state dynamics for each agent in the manufacturing processes with flexible production lines. Hence, agents rely on the coordination in the cyber network to infer the state from neighbor's decisions, and the network topology plays a critical role in multi-agent learning behavior [202]–[204].

Now we specify the details of the model of a simple sequential manufacturing process in one production line. The status of the input object is described by a discrete set $\Theta = \{-\frac{M_\theta - 1}{2}, ..., -2, -1, 0, 1, 2, ..., \frac{M_\theta - 1}{2}\}, |\Theta| = M_\theta$, so the state space is set as $\mathcal{S} = \Theta$. The action space is set as $\mathcal{A} = \{-\frac{K_a - 1}{2}, ..., -2, -1, 0, 1, 2, ..., \frac{K_a - 1}{2}\}, |\mathcal{A}| = K_a$. The state evolution is captured by the simple dynamics $h(s, a) = s - a$, and the utility for each agent is the zero-one function $U_p(s, a) = \mathbb{I}(s = a)$. Each agent i holds a flat prior initial belief $\mu_i(\theta) = \frac{1}{M_\theta}$. Each state is associated with a noisy observation which is normally distributed with variance σ^2, that is,

$$X_i | \theta_i \sim \text{Gaussian}(\theta_i, \sigma), \tag{13}$$

where σ is a fixed parameter to represent noise level. Each agent i has the social observation set $\mathcal{Y}_i = \{a_j | j \in \mathcal{M}_i\}$, which contains the previous decisions that can be observed by the agent. Each agent i sequentially makes a decision by optimizing its own posterior expected utility,

$$a_i = \arg\max_a \mathbb{E}_\mu[U_p(\theta_i, a) | x_i, \mathcal{Y}_i] \tag{14}$$

$$= \arg\max_a \sum_{\theta \in \Theta} U_p(\theta, a) \frac{\mathbb{P}(x_i|\theta)\mathbb{P}(\mathcal{Y}_i|\theta)\mu(\theta)}{Z(x_i, \mathcal{Y}_i)}, \tag{15}$$

where $Z(x_i, \mathcal{Y}_i) = \sum_{\theta \in \Theta} \mathbb{P}(x_i|\theta)\mathbb{P}(\mathcal{Y}_i|\theta)\mu(\theta)$ is a normalizing constant.

Upon observing the measurment $X_i = x_i$ and previous decisions made by neighboring agents $\mathcal{Y}_i$, the beliefs are updated to be

$$\forall \theta \in \Theta, \mu_i(\theta) = \mu_i(\theta | x_i, \mathcal{Y}_i). \tag{16}$$

The belief is updated by the Bayes formula

$$\mu_i(\theta | x_i, \mathcal{Y}_i) = \frac{f_{X_i}(x_i|\theta)\mathbb{P}(\mathcal{Y}_i|\theta)\mu_i(\theta)}{\sum_\theta f_{X_i}(x_i|\theta)\mathbb{P}(\mathcal{Y}_i|\theta)\mu_i(\theta)}. \tag{17}$$

With Naive Bayes updating, the observations are treated as coming from the same distribution and conditionally independent in the calculation of the Bayes formula

$$\mathbb{P}(y|\theta_i) = f_{X_i}(y|\theta_i) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y-\theta_i)^2}{2\sigma^2}}, \, y \in \mathcal{Y}_i. \quad (18)$$

Please note that the formulation of the agent's decision making mechanism and the physical manufacturing processes is simplified to illustrate the concept and the potential impact on production performance and system behavior under flexible setting of network topology. In the real-world scenarios, it is necessary to characterize the detailed physical model as dynamical systems which correspond to the machine parameters and production status in the manufacturing processes, and to have further investigations to completely characterize the cyber-physical interactions.

Regardless of the possible variability of complex production flows that can be expected in the operation of a smart factory, the main objective of manufacturing systems is to process chunks of raw material coming from the production flow and turn them into the products demanded, satisfying to a certain degree quality constraints, as efficiently as possible. Therefore, production performance is always the main concern and should be clearly defined in every scenario of smart factory operation.

Although there are many factors that are related to production performance, most of the performance measures put emphasis on different dimensions of efficiency. The three main dimensions of performance measure include throughput, time, and energy efficiency. In analyzing the simple model of a smart factory, we focus on the average yield performance that one production line can generate in terms of products within a specified quality constraint.

With a predetermined target state $\theta = 0$ indicating perfect precision, the overall multi-agent objective is to make the output state $\theta_{out} = s_{m+1}$ satisfying a given constraint Δ, which indicates the maximal tolerance of error executed in the production process and Δ is typically much smaller than the entire possible operating range for the purpose of precise production. The objective is therefore

$$|s_{m+1}| < \Delta. \quad (19)$$

In the numerical experiments, we measure the average yield performance of a single production line under various configuration of parameters such as the size of production line M, the size of state space $|\Theta|$, the size of action space $|\mathcal{A}|$, and the fully connected network and random network with connection probability p_c are used to understand the effect of random links. The average yield performance measure is defined as

$$\text{yield} = \frac{\text{number of } |\theta_{out}| < \Delta}{\text{total number of processes}}. \quad (20)$$

Since Δ is much smaller than the operating range of a robot or a production process. The maximum tolerable deviation (or accumulated error) in a production process might be up to several times of Δ. Consequently, the probability to achieve the yield indicates the reliability of precision production. Above abstract formulation can therefore characterize a sequential
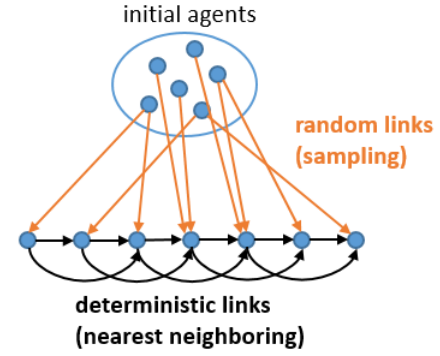

Fig. 11. A heuristic design of network topology.

manufacturing process where the input object suffers from certain random defects and the robots in the production line sequentially reduce the accumulated error as much as possible.

B. Communication Topology of Networked Robots

Communication links are not always perfect, and multi-robot smart factories can leverage the cyber network to enhance decision making under the presence of communication noise. Particularly, teams of wireless robots can improve performance in collaboration to exchange state and action information [80]. It has been shown that different network topologies have their characteristic effect on the production performance due to social learning agents. In sequential manufacturing, a complete network serves as an ideal baseline which describe the situation when agents can synchronize with all other agents, resulting in a stable state dynamics. Furthermore, random networks such as Erdös-Rényi networks, small-world networks, and scale-free networks provide design heuristics in constructing effective network topologies that facilitate good performance of social learning with noisy measurements. Those design heuristics shed light on connectivity and error accumulation, effect of random links and rewiring on stability, bottlenecks caused by high-degree hubs, and the collaboration of local clusters [81].

Agents in the sequential processes are subject to information asymmetry [205]. Later agents always have more information in comparison to preceding agents. For the collaborative multi-agent system, a good strategy is expected to establish information pooling by restricting the network topology of preceding agents. Based on the heuristics, it can be used to construct an effective network topology facilitating social learning:

- **connectedness**: To gain from social learning, the agents have to maintain a large enough set of social observations such that useful information can be aggregated for better decision making.
- **sampling**: Since agents are likely to follow social decisions, the social observations have to include good decisions and drop misleading decisions by means of sampling.

As shown in Fig. 11, referencing the concept of small-world network that is well-known efficient in information flow

[206], given parameters (n, β, p_c, ℓ), the topology of heuristic network is generated by the steps:

- cutoff: Arrange the production line according to the index $1, 2, 3, ..., M$. Decompose the multi-robot system into two sets of agents/robots, initial agents $\{1, 2, 3, ..., \beta\}$ and core agents $\{\beta + 1, ..., M\}$, respectively. This setup is inspired by the social learning and information cascade [202] to maintain robot's operation in the satisfactory range by analog to the formation of desirable information cascade. Please note that fully connected topology might not necessarily deliver desirable collective performance due to potential inconsistent observations [182].
- nearest neighboring: For agent $i \in \{\beta + 1, ..., M\}$, build one link from each agent $j \in \{i - \ell, i - \ell + 1, ..., i - 1\}$ to agent i. Observations from nearest neighboring robots are always critical and useful.
- sampling: For each pair (i, j) where $i \in \{\beta + 1, ..., M\}$ and $j \in \{1, 2, 3, ..., \beta\}$, there is probability p_c to form a link from j to i. Sampling is similar to the random wiring in small-world networks [206].

The simulation shown in Fig. 13 illustrates the yield performance against noise level of the constructed network topology according to the heuristic approach. We generated a network with parameter $(M, \beta, p_c, \ell) = (300, 60, 0.5, 10)$. The size of state space is $|\Theta| = 51$, and the size of action space is $|\mathcal{A}| = 21$. The yield performance is averaged over 1000 iterations of sequential manufacturing processes with the operating accumulated deviation/error $\Delta = 5$. The result demonstrates the idiosyncratic behavior of social learning in the presence of noise. Social learning demonstrates more resilience against noise, but its performance suffers when measurement signals are very accurate since social belief may signify the rare errors. The trade-offs can be used to enhance cyber resilience against adversarial attacks in multi-robot smart factories by implementing switching decision modes [196]. Please note that fully-connected network topology, in addition to consuming more radio resources, results in non-favorable small operating range for the collective performance of sequential decision processes.

C. Impacts of Wireless Links on the Decision Process of a Multi-Robot System

Figure 10 illustrates the operational concept of a smart factory in interacting cyber- and physical-networks. In light of the sequential decision process of multi-robot systems in a smart factory, we demonstrate how the communication network topology influences the sequential decision process and its robustness. It is of further interest to explore how practical wireless networking impacts the sequential decision process in a multi-robot manufacturing system. Under this circumstance, the uncertainty comes only from individual agent's noisy observations about the evolving system state. Information endowed in individual agents' decisions is aggregated through cyber-level networking so that agents can improve decision making by social learning from neighboring agents in case of physical network outages. Practical wireless networking introduces packet/message errors due to channel effects or
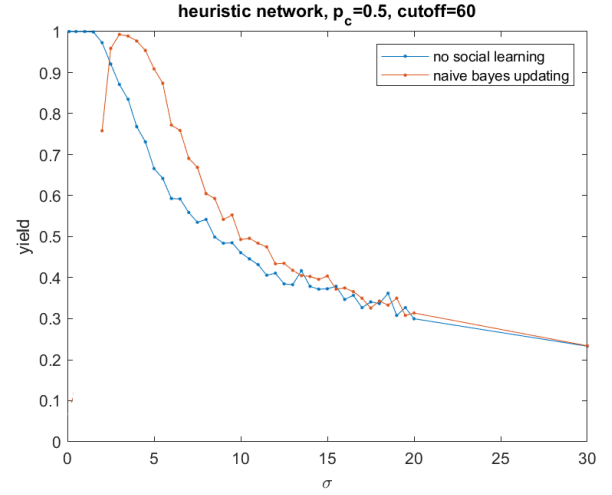

Fig. 12. Social learning better against the noise and extends the operating range of the smart factory given the target average deviation in operation. However, social learning causes further degradation in yield performance when the noise level is very low. Leveraging social learning to innovate adaptive operation strategy in a multi-robot smart factory is desirable.

(multi-user) interference, and the ensuing re-transmissions result in latency of the decision process of a sequential multi-robot system, which involves two fundamental aspects:

- Inconsistency, which can be possibly caused by imperfect wireless communications, between the links that bridge cyber-level and physical network, that is, losing one-to-one correspondence between cyber- and physical-domains: Consequently, wireless networking incurs latency and reliability constraints on the information exchange between cyber- and physical-networks.
- Lack of precise information caused by unreliable data transmission between two cyber-level nodes under short decision cycle in the multi-robot system of a smart factory: For example, due to the evolving state dynamics, the decisions collected from physical network and aggregated in the cyber-level network could be useless in decision making even if the message has been correctly received but beyond the required latency to support two consecutive decisions. More complicated channels (Section III-E) and multi-user communications can further complicate such mechanisms.

In order to reveal the effects of imperfect wireless links in realistic operations, we consider the following aspects:

1) the loss of end-to-end decision information between physical network and cyber network: Imperfect wireless links incur the loss of action a to be performed on the current physical state θ_{now} in the state dynamics $\theta_{next} = \theta_{now} + a$. Therefore, the dynamics with random error becomes

$$\theta_{next} = \theta_{now} + a\xi, \quad (21)$$

where $\xi \sim \text{Bernoulli}(1 - \delta)$ represents that the action has probability of loss δ.

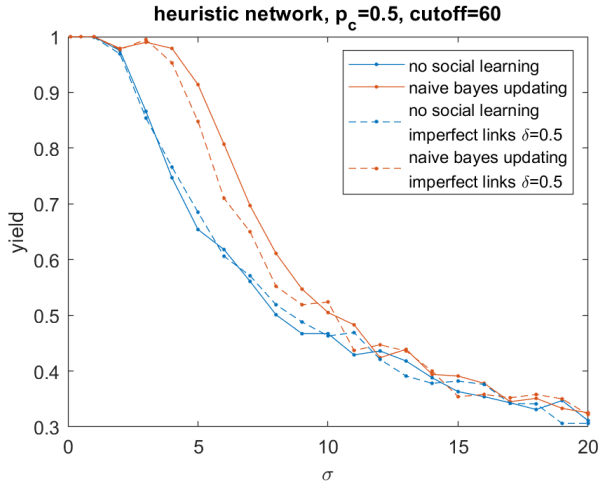2) the loss of end-to-end decisions between agents: Imperfect wireless links cause the loss of information in a

Fig. 13. Social learning improves yield performance against the noise and extends the operating range of the smart factory given the target average deviation in operation. The effect of imperfect wireless links with probability of loss $\delta = 0.5$ is shown in the figure as dotted lines in comparison with the ideal cases which assume no transmission errors.

social observation set $\mathcal{Y}$ with probability δ. Namely, for agent i, each action $y \in \mathcal{Y}_i$ is possible to be lost due to imperfect information transmission. So, it results in the lossy social observation set

$$\mathcal{Y}_i' = \{y_j' = y_j \xi_j | \forall y_j \in \mathcal{Y}_i, \xi_j \sim \text{Bernoulli}(1 - \delta)\} \tag{22}$$

The probability of loss δ in the above formulation serves to include the overall effect of imperfect wireless links such as path loss, packet loss, and errors due to latency, etc.

Due to the idiosyncratic behavior of social learning in the presence of noise, social learning is more resilient against noise, but its performance suffers when measurement signals are very accurate since social belief may signify the rare errors. The trade-offs can be used to enhance cyber resilience against adversarial attacks in multi-robot smart factories by implementing switching decision modes [196]. As the naive social learning is subject to the synchronization problem when the noise level is low, we implement a threshold mechanism such that the agents measure the noise level and decide whether to perform social learning or not. The threshold mechanism can be set as

$$\text{decision mode} = \begin{cases} \text{social learning if } \tilde{\sigma} > \tau \\ \text{individual decision, otherwise} \end{cases}, \tag{23}$$

where $\tilde{\sigma}$ is the agent's measured noise level from the environment, and τ is the threshold value to determine the decision mode.

The simulation shown in Fig. 13 illustrates the yield performance against noise level of the constructed network topology according to the heuristic approach. We generated a network with parameter $(M, \beta, p_c, \ell) = (300, 60, 0.5, 10)$. The size of the state space is $|\Theta| = 51$, and the size of the action space is $|\mathcal{A}| = 21$. The yield performance is averaged over 1000 iterations of sequential manufacturing processes with the operating accumulated deviation/error $\Delta = 5$. In addition,

belief updating by naive Bayesian is deployed with switching decision mode where the threshold mechanism is set to $\tau = 2$. We set the probability of loss $\delta = 0.5$ to characterize the effect of imperfect wireless links on social learning, where the imperfections may be resulting from noise, interference from factory operations, multi-user interference, radio resource utilization, etc.

From Fig. 13, we observe that imperfect wireless links decrease the operation range for the smart factory that adopts social learning. Nevertheless, imperfect wireless links have no significant influence on the performance of individual robot's decision, given high probability of loss. The rationale is straightforward. Since social learning not only relies on the correctness of previous decisions collected in the social observation but also requires at least a number of decisions to trigger effective information pooling for good decisions, the imperfect wireless links cause the loss of decisions and therefore degrade the effect of information aggregation. In the worst scenario, losing track of current state transition does not influence the independent measurement of the next agent, it can be viewed that each robot/agent in the production flow considers itself to be the first (and the only) agent to complete the job at the time instance, which leads to no contribution from other robots.

Please note that the results also signify the resilience of heuristic network design for effective social learning in sequential smart manufacturing. Even though the system operates under a rather high probability of loss, it only shows a mild degradation in operating range of average yield performance, which points out a great potential of network topology design and associated MRTA for multi-robot smart factory. Of course, the optimal and resilient network topology control is subject to further investigations and innovations.

D. Cybersecurity and Resilience of Multi-Robot Smart Factory

The partition of cyber functionality and physical dynamics for cyber-physical networks not only brings the flexibility of system operation but also introduces potential threats of cyber-physical attacks. Beyond conventional cybersecurity issues, attacks on cyber-physical networks exhibit the possibility of cross-domain effects since a compromised agent node in cyber layer can give rise to realistic damage through its capability to operate machine tools that influence physical system dynamics. Moreover, stealthy attacks targeting machine tools or the interlinks between cyber-physical network can also result in misinformation gathering for the agent nodes in cyber layer, leading to unexpected collective behavior such as cascading failures. The interdependency of cyber-physical networks poses new challenges to investigate the cross-layer effect of attacks. A potential cyber-physical attack can possibly cause the misalignment between the agent node and the machine, which may result in unknown random errors or undesirable behavior [207]–[209].

As agent nodes in the cyber layer are connected to Internet-based wired or wireless networks, a cyber attack can compromise a number of agent nodes in the cyber layer. Under

the adversarial command, the malicious nodes can disseminate false or even tiny-tilted information through the cyber network and it is possible to trigger cascading failures due to the accumulation of misleading information. It is worth noting that such insider attacks are usually stealthy and hard to detect as the malicious nodes can operate with benign behavior within the tolerance of the intrusion detection mechanism [210].

Similarly, the machine tools or robots equipped with some sensing capability can be compromised by physical attacks. The attack does not necessarily damage the machine tools directly. Instead, by forging fake tasks in the manufacturing process or manipulating the physical state to be sensed, the attack induces the machine tools or robots to gather misleading information and propagate the misleading information to the cyber layer to cause systematic cascading. Such attacks are hard to identify since the small disturbances added by the attacker can be easily ignored or disguised as measurement noise, and the disturbance may rapidly accumulate through the cyber-physical networks to cause damage or loss of precision in a multi-robot system. Hence, to deal with such novel attacks, it is essential to construct resilience into the cyber-physical networks as a fundamental property through topology control or other means [211]–[217].

In addition to novel social learning to enhance the resilience of MRS in earlier subsections, distributed control has been investigated toward the resilience of cooperative MRS. Resilience of collaborative MRS can be simplified as the synchronization or consensus problem [218], while a simplified but insightful consensus (or synchronization) problem in distributed computing or MRS is the Byzantine Generals Problem (BGP) to allow agents/robots conducting aligned actions. Distributed consensus algorithms have been developed in time-varying connectivity [219]. Practical issues from communication links and sensor data collection have been recently taken into account for the resilience of cyber-physical MAS or against cyber attacks [220]–[222]. In addition to social learning, game theory and/or intelligence through automata provides another approach to deal with the imperfect connectivity [78], [223]. However, to the best of authors' knowledge, consensus and subsequent synchronization algorithms of collaborative cyber-physical MRS remains as an active research area toward practical engineering solutions.

V. TECHNOLOGICAL OPPORTUNITIES

Wireless communications and networking technology, particularly holistic integration with computing and control, has just emerged and required a lot of innovations. We compile some opportunities to develop new systems and solutions in this section.

A. Wireless Networking in Smart Factories

A set of new wireless networking and communication technologies can be identified from Section II and particularly Section III. For example in Section III-B,

- *Timely interference control via control plane design and virtual clustering:* As ultra-low latency traffic typically requires ultra-reliability, a computing-enabled control plane should be employed to provide the optimal multiple access schemes for the uRLLC-based data plane. Moreover, to further ensure the reliability of physical open-loop communications, path-time codes and forward error codes can be applied in the network-level.

- *Edge computing-enhanced downlink access:* When uplink random access is completed, the downlink is expected to follow IEEE 802.11ax [91], [224] using the trigger frame and reservation. However, different from traditional wireless LANs where that downlink happens in the same AP, the edge-computing located with AN shall determine the information from a specific agent to be forwarded to appropriate AP(s) toward other agents that require such information. The forwarding mechanism and networking protocols should be developed to serve the open-loop downlink access, given reliability and end-to-end networking latency [225]. An efficient AP deployment should be considered as well.

- *Accurate information exchanges among agents' reinforcement learning:* As a good number of agents are involved, it is required to have the strategy for each agent's learning in the collaborative MRS, based on appropriate timing to obtain information from other smart/connected agents. Such a strategy for an agent involves (i) on-policy to exploit optimal navigation based on ultra-low latency networking and (ii) off-policy to explore any better alternative, in actor-critic Q-learning. Hence, a Bayesian-adaptive Q-learning [226] can be extended to meet the need. The network protocol will then be fine-tuned to ensure efficient networking for collaborative multi-robot system operation.

From Section III-C, there are still important addenda to facilitate the practical aspects of virtual cluster formation and near-data computations.

- *The cooperation mode of cluster optimization for network massive MIMO:* Based on the proposed dynamic AP clustering, multiuser multiplexing gains of network multiuser-MIMO can be leveraged to further improve global reliability and/or networking latency, by forming virtual directional antennas via the offered very large antenna array. Through the cooperation among APs via the AN, the inter-cluster interference can be eliminated. This means in the asymptotic regime, the interference free systems can be realized from some simple pre-coding schemes as the number of cooperating APs, i.e., the size of antenna array, goes to infinity.

- *Virtual cluster switching/merging:* By considering the agent mobility and/or APs failures, the switching decision and resource reallocation should be performed to always ensure ultra-low latency and high reliability upon open-loop communications. Also, according to the geographical distribution of virtual clusters, the virtual cluster merging can occur for the overlapped APs regarding latency, reliability and interference.

- *Dynamic multi-dimensional resource slicing with adaptiveness:* To achieve truly wireless virtualization, i.e., enable multiple virtual clusters sharing the same phys-

ical network and radio resources, a comprehensive set of multi-dimensional resources, e.g., antenna elements, APs, APs to ANs connections, wireless spectrum, and transmission power, and the slicing mechanism should be investigated with regard to time-varying factors, e.g., agent mobility, channel fading.

- *Content caching and function offloading:* To investigate the extremely compelling edge-computing problems in smart manufacturing, an efficient solution that jointly optimizes service caching and task offloading should be developed with respect to industrial data and applications. In particular, upon open-loop PHY and virtual cells, the objective here is to minimize the computation latency under a long-term energy consumption constraint.

- *Wireless networking for smart machines and MRS:* The communication between robots in any smart environment fundamentally differs from conventional human-to-human (H2H) communication. Many open issues exist, namely, what is the proper information and data to exchange? what are the performance requirements? what is the effective design and spectrum utilization? what is robust and resilient networking and thus networked cyber-physical MRS?

B. Computing and Data Fusion in Smart Factories

Enabled by wireless networking, AI computing and edge computing assisted by the sensor fusion suggest another dimension of technological opportunities.

Regarding privacy-preserving, if not secure, sensor fusion, it is interesting to

- study how to allocate the radio resources to the robots based on the importance of the data sets of the robots if some data sets of the robots may dominate the learning results. For the robots with more important data sets, they should be allocated better and more resources in order to deliver their learning results more reliably.

- analytically comprehend how the sizes of the distributed data sets impact the distributed learning performance. If the sizes of the distributed data sets of the robots are fairly different, the robots with a larger data set will consume more power and suffer from longer computing latency owing to heavier computation load. Accordingly, the convergence performance of the distributed learning algorithm eventually will be dominated by the robot with the largest data set. Hence, how to avoid uneven computing loads among the robots while performing distributed learning would be an important problem that needs to be tackled.

- Effective wireless access to collect sensor data of privacy remains a technology to develop.

In addition, regarding the integral design of wireless networking and distributed computing in multi-robot systems, including security, there are many subjects that require further comprehension toward the efficient and resilient design of a smart factory.

- New channel modeling to accommodate highly time-varying channels with potential impulsive interference

suggests required innovations in communication systems, while ultra-low latency and ultra-reliability arise as the priority concerns. In particular, proactive communication [79], [227], [228] for the purpose of ultra-low latency and learning-based communication and networking [76], [229]–[231], would be promising toward campus-operation 6G technology.

- For industrial informatics, wireless networked multi-robot systems suggest new research topics, namely, throughput-efficient and energy-efficient flexible MRTA, learning-based and predictive scheduling, resilient network topology design/control of precision multi-robot production process, etc. given control or computing commends from wireless networks.

- Adaptive computing between edge computing and agent computing by robots remains in its infancy. Issues such as (i) the strategy for a robot to decide a task to execute by itself or send to the edge; (ii) the method to select appropriate edge servers under dynamic configuration of a smart factory; (iii) how to jointly design the wireless access and adaptive computing; (iv) networked control by AI; remain open.

- Wireless networked multi-robot and human-machine collaboration involves thorough technology development of AI computing, recognition, and wireless communication.

- Smart factory enabled by wireless networking also introduces a new dimension in cybersecurity. The traditional concept of IoT cybersecurity attacks aims to disable certain cyber functions or create physical damages, which suffers from its high potential to be identified at least the sources to launch attacks. Cybersecurity attacks on smart factories can be quite different from this end, aiming at deteriorating the collective performance of multi-robot systems rather than any visible malfunction. Social network analysis of cyber-physical multi-robot systems suggests this new direction of research.

C. Multi-Robot Task Assignment in a Smart Factory

Wireless networking and edge AI enables dynamic MRTA for a smart factory to instantaneously instruct both production robots and mobile transportation robots, which attracts recent attention to investigate such as [232], [233]. As indicated in Section I-B and Fig. 2, the MRTA in a smart factory involves the integral optimization of throughout for production robots and the optimization of energy consumption (or energy efficiency) for transportation robots (i.e. AGVs), which suggests a dual-objective optimization problem [234].

The first technological challenge is to develop a model for time-dynamic work flow for production robots, while considering the energy consumption of AGVs. A reasonable model shall consider both temporal and spatial behavior. Suppose there are M types of production robots for M different jobs and each dedicates to one specific job. There are N_m type-m robots, $m = 1, 2, \cdots, M$, which are denoted as $R_{m,n}, n = 1, 2, \cdots, N_m$. Without loss of generality, they are arranged as shown in Fig. 14. Based on the geometric arrangement, the transportation energy consumption by the AGVs can be
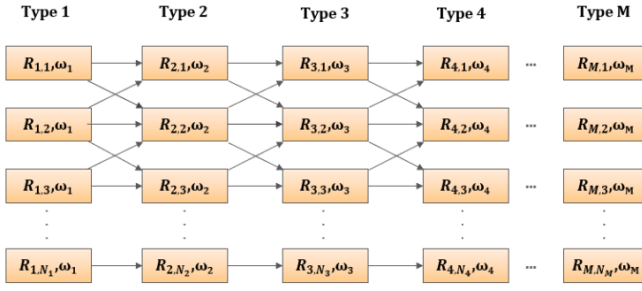
Fig. 14. Temporal-Spatial Model of the MRS in a Smart Factory: Any production is executed from type 1 robot(s) to type M robot(s). The index (m, n) in $R_{m,n}$ corresponds to the spatial index. The directed arrows indicate possible temporal flows in the MRTA. Production schedule in the MRS of a smart factory can be represented as a path in this temporal-spatial model.

determined. w_m denotes the multiplexing capability of a type-m production robot.

Based on this temporal-spatial model, the following technological challenges arise for real-time MRTA in a smart factory:

- How to find the optimal solution of this dual optimization problem and/or computationally efficient algorithms?
- Fig. 14 is based on the fixed locations of production robots and mobile AGVs. Can production robots also change locations?
- What are the impacts of wireless networking to the MRS based on MRTA? How to consequently develop a robust and time-dynamic MRTA algorithm given practical operating environments (e.g. channels and bandwidth)?
- If the MRTA algorithm suggests significant changes in production flow and/or transportation flow from time to time, what is the computationally effective algorithm?

Real-time MRTA enabled by wireless networking is one of the crucial technologies in smart factories, which requires holistic consideration on computing, wireless networking, and control.

VI. Conclusions

Successful realization of a wireless networked multi-robot smart factory involves diverse technologies from AI computing, wireless networking, control and robotic engineering, and the domain knowledge of production and logistics. This paper presents an initiation from wireless networking toward holistic system design to facilitate flexible, productive, energy-efficient, and resilient smart factories, for the benefits of human beings.

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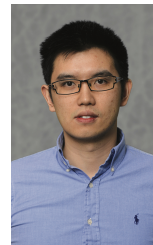
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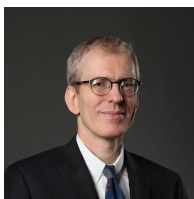
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