IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received August 23, 2018, accepted September 18, 2018, date of publication September 24, 2018, date of current version October 19, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2871724

Artificial Intelligence for Cloud-Assisted Smart Factory

JIAFU WAN[1], JUN YANG[1], ZHONGREN WANG[2], (Member, IEEE), AND QINGSONG HUA[3]

[1]School of Mechanical and Automotive Engineering, South China University of Technology, Guangzhou 510641, China
[2]School of Mechanical and Automotive Engineering, Hubei University of Arts and Science, Xiangyang 441053, China
[3]School of Mechanical and Electrical Engineering, Qingdao University, Qingdao 266071, China

Corresponding author: Zhongren Wang (xfu_wangzhongren@126.com)

This work was supported in part by the National Key Research and Development Program of China under Grant 2017YFE0101000, in part by the Joint Fund of the National Natural Science Foundation of China and Guangdong Province under Grant U180120020, in part by the Science and Technology Program of Guangzhou, China, under Grant 201802030005, in part by the Key Program of Natural Science Foundation of Guangdong Province under Grant 2017B030311008, and in part by the Science and Technology Planning Project of Guangdong Province under Grant 2017B090913002.

ABSTRACT In the context of industry 4.0, the main way to realize the intelligent manufacturing is to build a smart factory integrated with the advanced technologies, such as the Internet of Things (IoT), cloud computing, and artificial intelligence (AI). With the aim to emphasize the role and potential of cloud computing and AI in improving the smart factories' performances, such as system flexibility, efficiency, and intelligence, we comprehensively summarize and explain the AI application in a cloud-assisted smart factory (CaSF). In this paper, a vertically-integrated four-tier CaSF architecture is presented. Also, the key AI technologies involved in the CaSF are classified and described according to the logical relationships in the architecture hierarchy. Finally, the main issues and technical challenges of AI technologies in the CaSF systems are introduced, and some possible solutions are also given. The application of the AI in smart factories has accelerated the implementation of the industry 4.0 to the certain extent.

INDEX TERMS Artificial intelligence, cloud computing, Industry 4.0, smart factory.

I. INTRODUCTION

Due to the rapid development of information technology, computer science, and advanced manufacturing technology, the manufacturing production has been changing from automated production to digitalized and intelligent production [1]. Nowadays, the traditional single and mass production cannot meet market demands for the multiple varieties, small batches, and personalized customization [2]. Therefore, the change from the traditional manufacturing model to the intelligent production model is an urgent issue. In the context of Industry 4.0, the main way to realize the intelligent manufacturing is to establish a smart factory based on the Cyber-Physics Systems (CPS) [3]. The CPS needs the technical support in various aspects, such as IoT, big data, cloud computing, and artificial intelligence (AI) technologies [4], [5].

Smart factories based on the cloud computing have a large number of low-cost resources of storage and computing, which can enable the dynamic reconstruction and optimized distribution, and provide reliable support for the application of industrial big data [6]. Shu *et al.* [7] proposed a cloud-integrated CPS that provides solutions for complex industrial applications from three aspects: virtual resource management, cloud resource scheduling, and lifecycle management. Wang *et al.* [8] demonstrated a cloud-based personalized smart factory application for candy packaging. By using the private cloud and industrial wireless network, the smart production devices can be directly connected to the client terminals to achieve product customization and production. A large number of studies have shown that cloud computing provides an effective solution for resource sharing and information exchange in intelligent manufacturing systems, but only a few studies have specifically integrated the AI technologies into the systems.

Recently, the AI has attracted a lot of attention in various fields including the smart manufacturing. Namely, significant progress has been achieved in many fields, such as image processing, natural language processing and speech recognition [9], [10]. The development of a new generation of AI technologies has also brought new opportunities and challenges to the smart factories. Considering a smart factory as a large information system, it is possible to apply the

AI technologies at different levels of the CaSF. Thus, the AI can be applied to the smart factories to a large extent. Deploying the AI technologies in smart factories has produced many significant changes including the following: 1) smart devices that integrate the AI technologies, such as machine vision, are more accurate and reliable; 2) collaborative mechanisms with autonomous decision-making and reasoning capabilities exhibit more reasonable dynamic behaviors; and 3) data processing methods based on the advanced AI algorithms, such as deep learning, are more accurate and efficient. Therefore, the application of AI technologies has provided a new construction direction of smart factories.

In this work, we improve the traditional manufacturing model by combining the AI with the CaSF. Three main contributions of this work are as follows.

- A four-layer CaSF architecture equipped with the AI technologies is proposed; the proposed architecture consists of four layers, namely the smart device layer, network layer, cloud layer, and application layer. The integration of these four layers constitutes a unified and coordinated smart factory environment.
- The typical AI technologies in the CaSF are classified according to the standard of architecture hierarchy. Namely, the classification is applied to the device's perception and action, optimized network transmission, powerful storage, computing on the cloud, and the data-driven and knowledge-driven system applications.
- The main issues and challenges of the AI technologies in a smart factory are analyzed and discussed.

The rest of the paper is organized as follows. Section II presents a CaSF architecture and briefly points out the integrated AI technologies. Section III classifies and describes the typical AI technologies and their applications in the proposed architecture. Section IV presents the main technical challenges and corresponding solutions of the smart factory. Lastly, Section V gives a brief summary of this work.

II. SMART FACTORY ARCHITECTURE

In the context of the Industry 4.0, the smart factories have been widely researched, and the construction model has also been extensively discussed. Still, there is no a universal implementation standard. Wang *et al.* [11] used the principle of vertical integration in the Industry 4.0 and presented a highly-flexible and reconfigurable manufacturing system. Based on that, Chen *et al.* [12] further integrated the industrial wireless networks and cloud computing to improve the information availability and effectiveness of the multi-agent manufacturing systems. Wan *et al.* [13] proposed the architecture for dynamic resource management in the smart factory, which provides a solution to resource allocation and scheduling in the complex manufacturing environments. In addition, Tang *et al.* [14] presented a cloud-assisted self-organizing intelligent manufacturing system. The listed studies discuss the construction model of a smart factory from different perspectives and provide a reliable reference for related research. However, these system architectures are mainly concerned with the interaction of information and physical systems. There are not many artificial intelligence technologies involved, and the intelligence of the system needs to be improved. Therefore, in our proposed smart factory architecture, more attention is focused on the application of artificial intelligence technologies. In general, a smart factory is built on the basis of digital and automated manufacturing systems by integrating the advanced technologies, such as industrial wireless networks, cloud computing, and AI, to optimize the resources utility and system management to achieve the flexible organization, dynamic reconstruction and optimized production with the aim to meet the changing market demands.

Deploying the AI technologies in smart factories improves the manufacturing system performance in terms of perception, communication, data processing, and analysis [15]. As shown in Fig. 1, the smart factory architecture that we propose consists of four layers, the smart device layer, network layer, cloud layer, and application layer, which correspond to the physical smart manufacturing resources, industrial wireless sensor networks, cloud platforms, and services of system applications. In order to realize the proposed smart factory, we carefully study the integration and application of the related AI technologies.

III. KEY TECHNOLOGIES

The smart factory we propose here represents a flexible, extensible and reliable intelligent manufacturing system, which can autonomously perceive the information of the physical world and understand its meaning, and interact with the environment accordingly. To build such a highly-informative and intelligent system, the application of the AI technologies is indispensable. As shown in Table 1, the related AI technologies are classified from the perspective of different layers in the smart factory.

A. SMART DEVICE LAYER

This layer consists of the smart devices in the product production cycle, such as robotic arms, automated guided vehicles (AGVs), conveyor belts, and smart products, which denote the basis of the smart factory. The multi-variety and individualized production model and a high demand for products quality have set new standards for the perception and action capability of the system devices. Therefore, the AI applications such as machine vision and path planning need to be in focus.

1) MACHINE VISION FOR INTELLISENSE

Recently, machine vision has become more and more used in the intelligent manufacturing field. On the one hand, machine vision has a significant effect on improvement of the accuracy, efficiency, and reliability of the product measurement. Fan and Jing [16] proposed a vision-based shaft parts

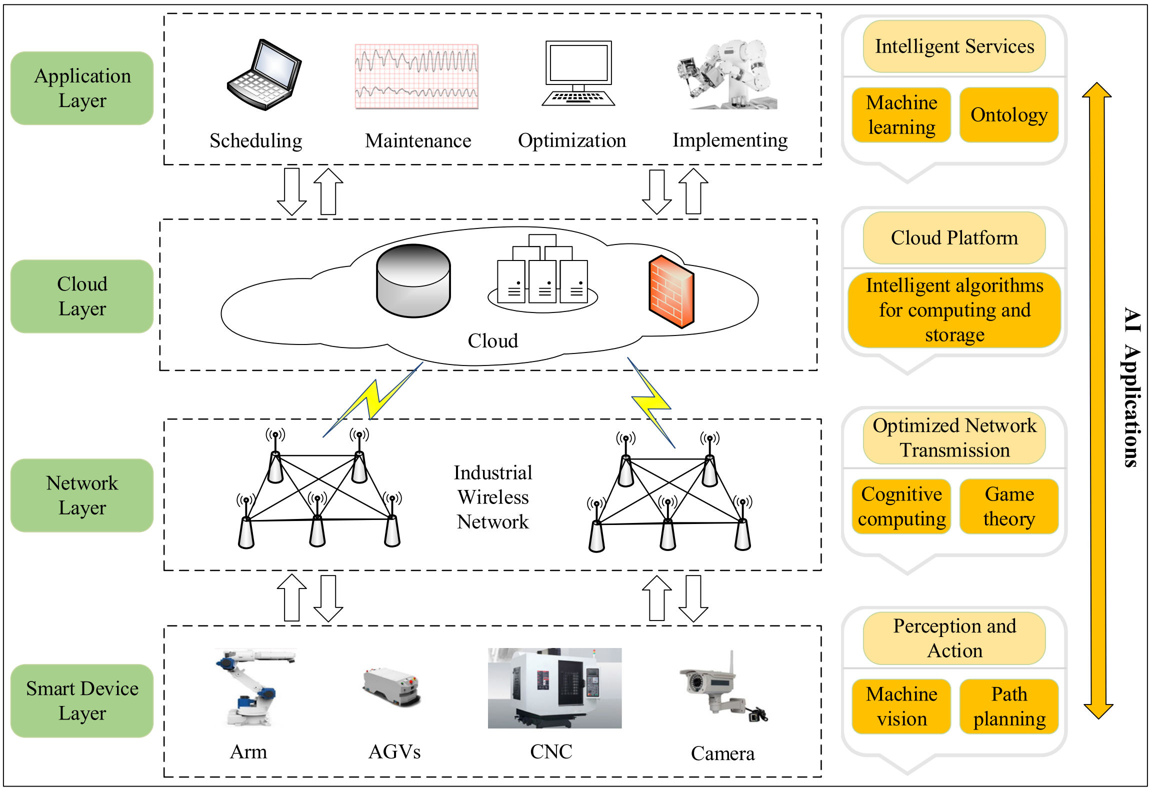

FIGURE 1. The CaSF architecture.

measurement system based on the image processing algorithm which simultaneously ensures the accuracy and robustness of the system. Bao *et al.* [35] proposed a method for dimension measuring based on the machine vision, which ensures a high-reliability, efficient and accurate measurement even when images are disturbed by the external noise. Therefore, the application of machine vision in the image processing algorithms can significantly improve the accuracy of industrial products meeting the market demand for high quality and improving the stability and intelligence of physical devices simultaneously.

On the other hand, quality testing and rapid classification of products are also very important. Kong *et al.* [36] proposed a method for detection of scratches on the product's surface based on machine vision, which achieves quality monitoring under the complex conditions. Xia and Weng [37] presented an industrial sorting robot system based on machine vision that can obtain edge information on the workpiece and identify its shape from the image, and then calculate the coordinates of the central space of the workpiece and complete the workpiece sorting process. The listed studies show that application of machine vision enables the realization of a manufacturing system that can conduct the complex product inspection and classification tasks to achieve a flexible and efficient production model.

2) PATH PLANNING FOR INTELLIGENT MOVEMENT

With the development of industrial robot technology, the number of mobile robots used in the factories has constantly been increasing. In the complex manufacturing environment, the optimization of a mobile robot path not only influences system efficiency but also is closely related to the system energy consumption, time cost, and other related factors. Therefore, the path planning has always been in the focus of smart factories optimization. Zhang and Zhou [18] proposed an improved heuristic search method by comparing the classical path search methods with the traditional path planning strategies, which solves the problem of multi-robot path adaptability and conflict between time and space. Further, Yu et al. [38] proposed a path planning scheme for mobile robots based on a fast-convergent ant colony algorithm, which improves the heuristic factor and helps to avoid the blind pursuit of targets by using the multiple robots to achieve an adaptive adjustment and shorten the searching time. In addition, Li *et al.* [19] proposed a path planning method for mobile robots based on a genetic algorithm and gene rearrangement, which not only shortens the path length but also ensures that robots do not intersect with any obstacle. The listed studies show that by integrating the AI algorithms, such as heuristic search, genetic algorithm, and particle swarm optimization algorithm, into the robot systems, the smart factories with multiple robots can form a stable and orderly

TABLE 1. Applications of AI at various layers of the smart factory.

Layers	Application Objects	Methods	Advantages/Improvements
Smart Device Layer	Shaft parts measurement system	Image processing algorithm [16]	Improved system accuracy and robustness
	Automatic workpiece sorting system	Image judgment and recognition [17]	High-precision classification of workpieces
	Multi-robot system path planning	Improved heuristic search method [18]	Solved the problem of path adaptability and conflicts of time and space
	Mobile robot system path planning	Genetic algorithm and gene rearrangement [19]	Shortened path length and ensured that robots do not intersect with any obstacles
Network Layer	Cognitive industrial wireless network	Generative deep neural network [20]	Implemented different network tasks
	Cognitive wireless sensor network	Bayesian network model [21]	Maximized network awareness and improved network performance
	Wireless sensor network	Variable width channel allocation strategy [22]	Improved resource utilization and transmission efficiency
	Uncertain wireless sensor network	Dynamic Bayesian coalitional game [23]	Improved data transmission performance
Cloud Layer	Distributed industrial system	MapReduce and machine learning [24]	Faster data extraction
	Parallel data processing system	Rough set theory [25]	Handle large-scale incomplete data
	High complexity and dimensional manufacturing data	Clustering and Support Vector Machines [26]	Reduced complexity and dimensionality of manufacturing data
	Cloud resource allocation system	Reinforcement learning [27]	Realization of cloud autonomous decision resource distribution
	Multi-task load balancing method	Active Markov decision [28]	Cloud host load balancing and resource optimization scheduling
Application Layer	Fault diagnosis method	Convolutional neural network [29]	Fault prediction accuracy up to 99.51%
	Equipment status monitoring method	Deep learning [30, 31]	Predicted the remaining life of the equipment
	Resource reconfigurable system	Ontology-based model [32]	Improved resource utilization and promoted knowledge sharing
	Cloud robots system	Intelligent decision [33]	Context awareness and load balancing
	Industrial robots group	Perception and reasoning based on shared knowledge base [34]	Context awareness and group intelligence

intelligent system which makes the production process more flexible and efficient.

Compared with the traditional factories, the multi-robot manufacturing systems are characterized by higher reliability, lower cost, and higher efficiency. Moreover, these systems can solve large-scale, complex problems that require coordination among robots. The methods for path planning optimization include not only the detection and search of path conditions by an individual robot but also the resolution of contradictory conflicts among multiple robots, which imposes higher requirements for resource coordination and scheduling in the system. Although AI algorithms provide many good solutions, they are limited by various factors, so the in-depth research needs to be continued.

Machine vision and path planning are typical applications of artificial intelligence at equipment layer of the smart factory, and the two are closely linked. The former significantly improves the perception of smart devices. At the same time, the improvement of device sensing performance is beneficial to the path planning of mobile robots such as AGVs and robotic arm. In general, machine vision and path planning lay the foundation for the high intelligence of the smart device layer.

B. NETWORK LAYER

The network layer is mainly composed of the industrial wireless sensor networks (IWSNs) and related technologies, and it represents an important part of the smart factory. In the high-information manufacturing environment, the device-to-cloud (D2C) and device-to-device (D2D) communication are becoming more frequent. The increase in the number of smart devices also poses new challenges to the system network, such as network resource distribution and load balancing [39]. Therefore, stable data transmission and real-time information sharing require a flexible and reliable network environment. Due to these new challenges, the traditional industrial networks are no longer convenient, and the application of the AI in the industrial networks brings a new opportunity to the IWSNs.

1) COGNITIVE WIRELESS SENSOR NETWORK

In the smart factory, the increase in data nodes number and data volume raises the requirements for dynamic performance and scalability of the network. As a strong AI technology, the cognitive computing can effectively enhance learning and cognitive ability of the network, significantly improving the quality and efficiency of network transmission in complex manufacturing systems [40]. Due to the excellent performance in network optimization, the cognitive wireless sensor networks are receiving more and more attention.

Network transmission in the manufacturing environment shows comparatively large uncertainty and dynamic, so the learning and reasoning ability represents the major challenge of the existing network environment. The machine learning algorithms, especially neural networks which are specifically popular in the tasks involving classification, learning, and optimization, facilitate the extensive learning and optimization of networks. Ahad *et al.* [41] presented a comprehensive survey of the application of neural networks in wireless networks, highlighting the remarkable versatility of neural networks. Specifically, Zorzi *et al.* [20] proposed a cognitive network model based on a generative deep neural network, which combines the knowledge extracted from the network data with different machine learning algorithms to realize specific network tasks. In addition, Gheisari and Meybodi [21] proposed a learning and reasoning method for cognitive wireless sensor networks based on the Bayesian network to maximize the network awareness and improve the transmission quality. The aforementioned studies show that by integrating the cognitive computing in a multi-node complex industrial environment, the applicability and adaptability of wireless networks can be effectively improved. Although the remarkable results of cognitive wireless networks in the manufacturing environment have not generally been achieved yet, they still provide a reliable research direction for network optimization of smart factories.

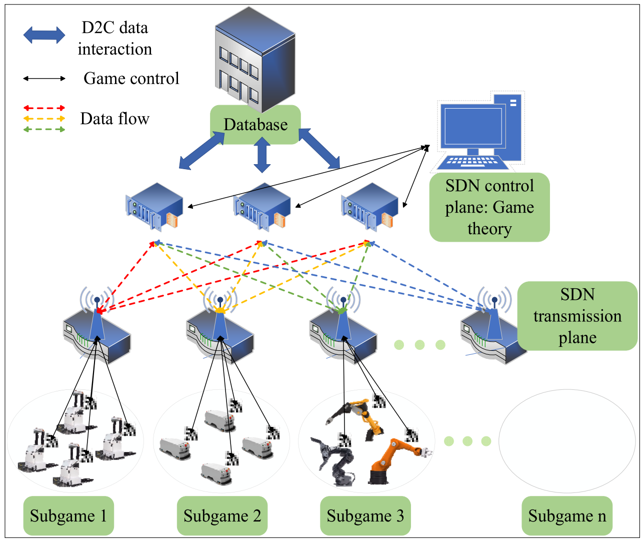

FIGURE 2. The architecture of a software-defined industrial wireless network based on the game theory.

2) GAME THEORY FOR SOFTWARE-DEFINED NETWORK

Due to the increase in the number and types of network services deployed in the manufacturing systems, the automatic optimization and reconfigurability of the network should be considered. As shown in Fig. 2, a software-defined network (SDN) can lower the requirements for hardware using the centralized software control to improve network flexibility and scalability, which facilitates network management and meets the high dynamic network requirements of smart factories. A software-defined IWSNs denotes both industrial applications and extensions to the existing advanced wireless communication technologies, as well as an innovation in the traditional industrial network communications [42], [43].

With the continuous improvement in distributed wireless sensor networks, the role of the game theory model is growing. The game theory itself is a utility-maximizing and multi-agent decision theory that enables agents to interact with each other, which can help to understand and predict the performance of complex sensor network systems needed to optimize the signal transmission and communication [44]. Ma *et al.* [22] combined the non-cooperative game theory and charging mechanism to realize the load balancing and variable-width channel allocation strategy for the wireless sensor networks, which improved the resource utilization and network transmission efficiency. Akkarajitsakul *et al.* [23] put the focus on uncertainty and Bayesian game, and used the Bayesian game model to analyze the uncertainty of nodes' behavior and validated the Nash equilibrium of the dynamic Bayesian game model. Therefore, it was shown that game theory could effectively solve the problems such as network overload and resource utilization imbalance which helps to achieve the reasonable distribution of network resources and dynamic load balancing in the multi-agent industrial wireless network environment [45].

By integrating the game theory and SDN, the software-defined IWSNs can further enhance the network performance and optimize the resource scheduling. As shown in Fig. 2, on the SDN control plane, data transmission of the forwarding plane and reasonable network bandwidth resource allocation are controlled by a game theory model, and the subgames further adjust the different resource requirements between the smart devices in the bottom layer. Thus, network data transmission and resource distribution are optimized, and system flexibility and stability are improved simultaneously.

Cognitive network and game theory are important optimization directions of the smart factory network layer. The two are related and different. In the distributed deployment manufacturing environment, the data transmission density of D2D and D2C is high. The game-based SDN can effectively solve the problem of load balancing between data nodes and rationalization of network resource utilization. Cognitive computing enhances the learning and reasoning ability of the network, and can effectively cope with the high dynamics and uncertainty of the network. Therefore, the organic combination of the two can significantly improve the network transmission performance of smart factories.

C. CLOUD LAYER

In the CaSF system, the integration and analysis of manufacturing data denote the main task. With the powerful, flexible and available storage and computing resources on the cloud platform, the information contained in the big data can be discovered [46], [47]. The distributed and parallel data processing architecture provides an effective solution for large-scale manufacturing data and high-complexity computing tasks, and the virtualization of resources improves the resources intelligent management and distribution on the cloud. Hence, the integration of AI algorithms and cloud computing has effectively improved the data processing efficiency and quality of service (QoS) of the platform.

1) INTELLIGENT ALGORITHMS FOR DISTRIBUTED AND PARALLEL COMPUTING

The continuous growth of manufacturing data brings more valuable production information, which can be used to optimize the production process. However, large-scale, large-volume data also require higher data processing capability. Thus, the traditional data processing methods cannot meet industrial requirements due to the massive manufacturing big data. Therefore, the massive-data processing should be based on the cloud-based distributed and parallel computing [48]. The maturation and development of AI algorithms enable different algorithms to be applied to the parallel architectures to optimize the calculation and storage of big data.

The integration of the AI algorithms and distributed parallel architecture improves system data-processing capability, reduces time delay, and lays a foundation for big data application. Aly *et al.* [24] proposed a new distributed training method that combines a widely-used big data processing framework named the MapReduce and traditional machine learning techniques, making the analysis and information extraction from the industrial big data faster. The parallel computing methods based on the MapReduce framework can process complete data efficiently, but in many cases the data collected by the system are incomplete, and incomplete data bring the obstacles in data processing and analysis. Based on the parallel data processing architecture, Zhang *et al.* [25] used the rough set theory to introduce three different methods based on a parallel matrix to deal with the large-scale incomplete data. A large number of studies show that integration of intelligent algorithms provides the much-needed flexibility, scalability and fault tolerance to the distributed and parallel computing systems.

To fully extract the valuable information from the manufacturing big data, the advanced AI learning algorithms should be used in a distributed and parallel computing architecture because they can significantly increase the speed and efficiency of information extraction. Wuest *et al.* [26] proposed a learning method that combines the cluster analysis and support vector machine (SVM), and effectively overcomes high complexity and dimensionality of the manufacturing data. Li *et al.* [49] proposed a deep convolution calculation model that significantly improves the training efficiency of big data. Therefore, a distributed parallel computing architecture provides the basis for the application of industrial big data, and the introduction of the AI algorithms improves the efficiency and performance of data processing, and their combination promotes the development of industrial big data.

2) RESOURCE VIRTUALIZATION AND INTELLIGENT MANAGEMENT

In order to meet different dynamic demands for resources of multi-tasks, such as those related to the computing and storage in a large-scale distributed smart factory, the virtualization technology virtualizes hardware resources into a resource pool according to the principle ‘‘turn off the redundant, turn on the demanded’’, i.e., forms a cloud infrastructure with high flexibility and reliability [50], [51]. As shown in Fig. 3, the tasks in the manufacturing system send the resource-request signals to the cloud according to the current requirements, and then, the system responds to the commands and allocates resources from the flexible resource pool as needed. Virtualization of resources greatly increases the resources utilization and system flexibility and scalability simultaneously.

In a complex manufacturing environment, the resource distribution mechanism on the cloud affects not only the production efficiency but also the energy consumption. Uncoordinated resource allocation can even cause disruptions in the production process. With the AI development, many intelligent algorithms have been studied and applied to the coordinated distribution and scheduling of cloud resources [52]. Liu *et al.* [27] proposed a resource allocation mechanism based on reinforcement learning. The cloud acquires the

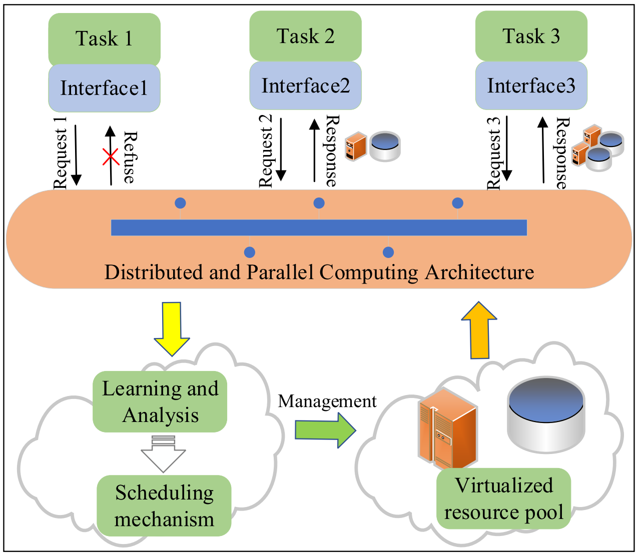

FIGURE 3. On-demand scheduling mechanism of a virtualized resource pool.

autonomous management capability of computing resources through the online learning, and then, decides whether to respond to the actual task request for resources allocation. Therefore, an intelligent cloud with learning and decision-making capability is necessary to manage the elastic resource pool properly and achieve optimal scheduling of system resources. Optimal scheduling of virtualized resources improves the flexibility and reliability of a smart factory, and it is also the basic guarantee for system efficient operation. In addition, the load balancing of cloud physical hosts also affects the task processing and computational efficiency of the data center [28], [40]. Compared with the previous static and temporary load balancing methods, the advanced AI algorithms improve the system dynamic performance and ensure the long-term effectiveness of the load balancing mechanism.

The resource virtualization on the cloud provides the scheduling of resource allocation on demand. The high flexibility of a resource pool simultaneously facilitates system maintenance, reduces system cost, and improves resources utilization. The introduction of AI algorithms makes the cloud more flexible and intelligent, enabling cloud to make the autonomous decisions based on the system's multi-task requests and optimize the resources distribution. The intelligent cloud not only improves system efficiency and resources utilization but also ensures system reliability and stability.

Distributed parallel computing and virtualized storage are two of the main features of the cloud. On the basis of efficient distributed parallel computing, the fusion of intelligent algorithms can effectively extract high-value information from a large amount of manufacturing data, which improves the utilization of data. The virtualization of storage resources greatly improves the storage capacity of the system, and the intelligent management of the resource pool can effectively respond to different needs in the manufacturing system.

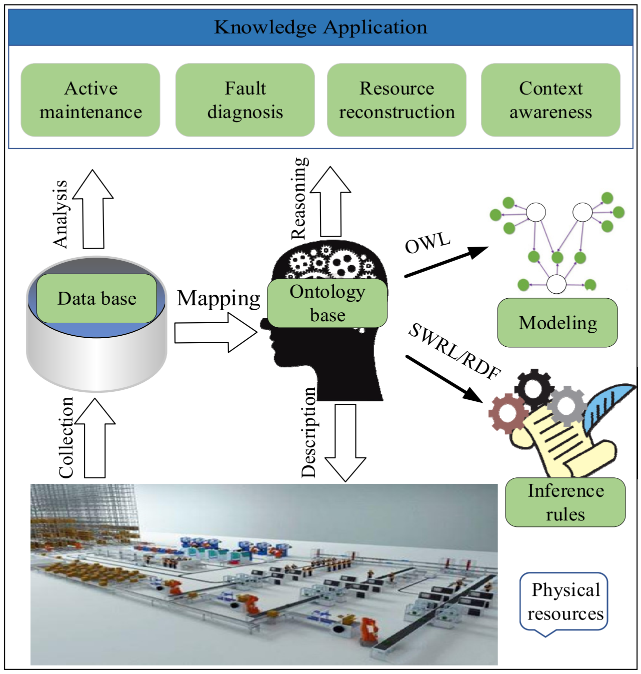

FIGURE 4. The ontology-based knowledge base modeling method.

Therefore, artificial intelligence support for cloud computing is the key to data and knowledge-driven manufacturing model.

D. APPLICATION LAYER

With the continuous update and development of the industrial big data processing methods and tools, together with the cloud platform as reliable support, the big data applications in the smart factory have been developing more and more rapidly. According to the main driving factors, the application of manufacturing big data can be divided into data-driven and knowledge-driven. With the AI expansion, the AI application in active preventive maintenance, resource reconstruction and context awareness service in the smart factories has become research hotspots, Fig. 4.

1) MACHINE LEARNING FOR ACTIVE PREVENTIVE MAINTENANCE

With the development of industrial big data, the application of machine learning in the smart manufacturing field has become increasingly popular, especially in the manufacturing knowledge extraction, assisted decision support, and product and equipment lifecycle management [53], [54]. Moreover, it has become inseparable from the time and resources required for the algorithms and ease setup and maintenance. Currently, the most widely used machine learning methods are the supervised learning, semi-supervised learning, and unsupervised learning methods [55], [56]. The intelligent, active, preventive maintenance mechanism is an effective way to manage manufacturing systems. Susto *et al.* [57] proposed an active preventive maintenance method based on a machine learning algorithm, which comprehensively considers the product performance in different aspects and uses the information on a cost-based maintenance decision system to minimize the expected cost. By using the appropriate machine learning algorithms, the information can be effectively extracted from the manufacturing data, which provides reliable support for the system knowledge utilization. With the high availability of product manufacturing data at each stage, machine learning is becoming a more flexible, more applicable and leaner data analysis tool for cloud-integrated manufacturing systems.

Nevertheless, with the increase in manufacturing data volume, the deep learning methods have been more and more applied to the system's active preventive maintenance, such as intelligent prediction, fault diagnosis, and equipment health-status analysis, because of higher and more accurate data feature recovery capability. Wen *et al.* [29] proposed a new method for intelligent fault diagnosis based on a convolutional neural network, which uses the convolutional layers to train the images transformed from the original signal data; the obtained final prediction accuracy was 99.51%. Xu *et al.* [30] and Yan *et al.* [31] proposed a concept of device electrocardiogram based on deep learning, which monitors device's operational status through the changes in electrocardiograms which are used to predict the remaining useful life of a smart device. Therefore, by applying the deep learning methods to the large-scale, large-volume manufacturing data, the intelligent monitoring and accurate prediction of manufacturing events can be realized, making the production process more reliable and efficient.

2) ONTOLOGY FOR RESOURCE RECONSTRUCTION

Considering the type and quantity of manufacturing resources, the description of resources obtained from different perspectives may differ greatly. Ontology provides a unified conceptual model for domain knowledge description [58]. A set of manufacturing chain values is constructed by establishing the concept of resources and semantic links between them to form a domain knowledge base [59], [60]. Namely, the ontology provides a standardized measure for resource description in a complex manufacturing environment, which greatly facilitates knowledge sharing. Wan *et al.* [32] proposed an ontology-based CPS resource reconstruction method from the perspective of rapid iterative production requirements and reasonable use of resources, which achieved an agile and efficient manufacturing resource allocation. Saeidlou *et al.* [61] used the cloud-based ontology for the semantic description of manufacturing resources in a distributed environment to implement the knowledge storage, reasoning, and retrieval. Zhou *et al.* [62] proposed a model-based knowledge-driven self-reconfigurable machine control system, which uses an ontology representation to describe the knowledge base and rules to complete the machine's automatic reconfiguration process. The ontology-based model has a semantic relationship between resource descriptions, which provides interoperability and flexibility for the system value applications such as manufacturing resource reconstruction.

In the cloud manufacturing, the ontology-based knowledge base can effectively describe the conceptual level and semantic information of manufacturing resources, which provides a new technical reference for the utilization and sharing of manufacturing resources. A brief construction method of an ontology-based knowledge base is presented in Fig. 4. In the framework, the manufacturing resources are expressed in the ontology form, so the real-time status and data of smart devices can be associated with the ontology models. Moreover, the knowledge base realizes the separation of ontology models from related applications. Thus, when the knowledge model is applied to the different scenarios, its integrity will not be destroyed because it has good dynamic performance and separability. Based on the ontology models, the rules between relevant concepts need to be defined to establish a semantic network of manufacturing knowledge, and then, the inference engines (such as the Jena inference tool of java architecture) are used to mine the knowledge value hidden within the data and concept rules [63], [64].

3) CONTEXT AWARENESS SERVICE

With the development of smart devices and AI algorithms, the personalized services based on a context awareness such as intelligent human-machine interaction and intelligent positioning service have become more popular [65]. The real-time personalized services have improved not only system efficiency, but also the QoS. In the CaSF, cognitive computing enables the system to understand the environment and react in real time through the learning of manufacturing data to provide manufacturing context awareness services, which significantly improves the system self-adaptability and intelligence [66].

By using the abundant storage and computing resources on the cloud, Wan *et al.* [33] proposed a context-aware cloud robot architecture for smart factory material handling. This architecture uses the intelligent decision-making mechanisms, cloud-enabled simultaneous positioning, and mapping of AGVs to implement the context awareness and dynamic load balancing, which increases system efficiency and reduces energy consumption. Stipancic *et al.* [34] developed a cognitive robot model to achieve the real-time perception and reasoning, which significantly improves the robot adaptivity, self-recovery, and scalability. Therefore, the context awareness services not only can optimize the production process but also reduce system complexity and improve its intelligence. Specifically, the context-aware systems have the capability of environmental awareness and decision-making in real time, so that they can meet rapidly changing and personalized production needs.

Active preventive maintenance, resource reconfiguration and context awareness service are typical applications of artificial intelligence in smart factories. With the rise of industrial big data, the machine learning methods represented by deep learning provide directions for active preventive maintenance of smart factories. At the same time, through the knowledge extraction of manufacturing data, the ontology-based resource reconstruction method effectively improves the utilization rate of manufacturing resources. In addition, context-aware services based on cognitive computing further enhance the real-time and high efficiency of the system. In general, these intelligent applications effectively improve the intelligence and service quality of smart factories.

IV. ISSUES AND POSSIBLE SOLUTIONS

The integration of AI technologies in smart factories has improved the flexibility, reliability, and efficiency of manufacturing systems. However, there are still some problems and technical challenges worth of discussing.

A. HIGHLY-INTELLIGENT DEVICES

Smart devices denote the basic part of a smart factory, which means that their efficient operation is the precondition and guarantee for the system data acquisition, dynamic reconstruction, and resource scheduling. With the integration of AI technologies in smart factories, the intelligence requirements of the equipment are further enhanced. In a large-scale and heterogeneous smart factory, the manufacturing data are diverse and noisy, but in most cases, only the collection and analysis of one or several parts of valid data are required. On the contrary, we should determine which data to use when storing a large amount of data. Namely, invalid data collection increases network latency and reduces system efficiency [67]. Therefore, in addition to the preliminary classification and processing of the collected raw data, it is also necessary to increase device sensitivity to the required data. Thus, we should clearly grasp the perceptual objects of each device and changes in performance of each operation of a device, and optimize for performance bottlenecks simultaneously. On the other hand, it is also possible to consider the categories of valid data from the aspect of data analysis and optimize the device's ability to perceive signals.

System integrity and coordination are ones of the most important features of a smart factory. Due to the wide range of smart devices in a smart factory, a large number of non-interactive communication protocols are needed which undoubtedly increases system complexity and heterogeneity [68], [69]. To reduce system complexity and optimize cooperation and communication between devices, a unified signal interface should be developed and used between devices, and communication protocols with interoperability should be supported. In this way, the smart devices with cognitive and communication capability could collaborate with each other to complete complex manufacturing tasks.

B. ADAPTIVE NETWORK TRANSMISSION

In a distributed manufacturing environment, the transmission of the node's data and computational tasks are ones of the most important things. However, data transmission and communication in the smart factory require a sufficient network bandwidth. The proposed game theory-based network architecture provides a flexible resources allocation, which eases the competition of multiple nodes. However, due to the large-scale data transmission in D2D and D2C communication, there are inevitably different degrees of network delay [70]. New technologies, such as edge computing, may provide a solution to this problem. The edge computing directly completes the computational tasks of manufacturing nodes via the close-edge nodes with a certain computing ability and storage which effectively reduces the delay of tasks [71], [72].

Regardless of whether the network architecture is based on the game theory or the IWSNs is integrated with the edge computing, there is a priority problem in data transmission between nodes. At the same time, considering too many edge computing nodes will increase system complexity and maintenance cost greatly. Therefore, new algorithms and techniques that solve the task priority problem should be developed. For instance, if a computing task is not suitable for uploading to the cloud, the dynamic protection mechanism should be activated, and the system should transmit that task to the edge node for calculation, thereby improving the system performance.

C. DATA FUSION

The big data allows smart factories to be described and expressed in detail, but most manufacturing data cannot be used directly because of high heterogeneity, dimensionality, and noise [73]. The structure of the output data of different devices or sensors may be different, so the appropriate data processing and fusion must be performed [74]. Although the current cloud platforms contain the interfaces for multiple data types, the data analysis algorithms or tools may require a specific format of input data. Therefore, to improve system robustness and real-time performance, it is necessary to store data in a specific format. Similarly, after the calculation tasks are completed, the data should be output in the same format as it was received, which facilitates data transmission and management.

In addition, the unstructured data, which are present in more than 50% of manufacturing systems, cannot be directly accessed by the data processing tools, which imposes severe restrictions on the results of data-driven production and optimization [75]. However, many researchers believe that this problem can be solved by the AI technologies such as machine learning.

D. CLOUD SECURITY

The security and privacy issues are crucial, especially in a highly-informed smart factory. As already mentioned, cloud computing enhances the scalability and flexibility of intelligent manufacturing systems greatly, but it also brings new security challenges. This is especially important in the case of sensitive, highly-confidential data, which include not only all data generated by the system, but also private data such as user orders and business transactions [76], [77]. Namely, if these data are leaked, both the system and users will suffer from a severe loss of profits and property.

To overcome this problem, the strict access authentication and control management method should be developed and implemented to improve the security level by authorizing and encrypting user access credentials [78]. On the other hand, the automatic detection and classification of a risk represent an efficient solution, which provides a systematic approach to understanding, identifying, and resolving the security risks [79], and where the focus should be on the intrusion detection and prevention services, which indicates that the risk should be discovered in time to avoid greater property damage. Therefore, more efficient algorithms and models related to risks detection and prevention should be developed [80], [81].

V. CONCLUSION

The smart factory is an intelligent manufacturing system based on the CPS, which realizes efficient and reliable production using the advanced technologies such as the AI and cloud computing. This paper proposes a four-layer CaSF architecture developed based on the results of recent researches in the smart manufacturing filed. Namely, the proposed architecture consists of the smart device layer, network layer, cloud layer, and application layer. Also, the AI technologies and algorithms applied in the smart factories are classified from the perspective of different layers. In addition, the main problems and technical challenges of the smart factory are discussed, and possible solutions are provided. The smart factory has introduced the profound changes in the traditional manufacturing industry making it highly-dynamic, extensible and reconfigurable, meeting the flexible and changing market demands. With the aim to further improve the smart factory, in our future work, we will conduct more in-depth researches on the AI and study the cross-disciplinary domain knowledge.

REFERENCES

[1] F. Tao, Y. Cheng, L. Zhang, and A. Y. C. Nee, "Advanced manufacturing systems: Socialization characteristics and trends," *J. Intell. Manuf.*, vol. 28, no. 5, pp. 1079–1094, 2017.

[2] J. Wan, M. Yi, D. Li, C. Zhang, S. Wang, and K. Zhou, "Mobile services for customization manufacturing systems: An example of industry 4.0," *IEEE Access*, vol. 4, pp. 8977–8986, 2016.

[3] J. Wan, D. Zhang, Y. Sun, K. Lin, C. Zou, and H. Cai, "VCMIA: A novel architecture for integrating vehicular cyber-physical systems and mobile cloud computing," *Mobile Netw. Appl.*, no. 19, no. 2, pp. 153–160, 2014.

[4] C. Zhu, Z. Sheng, V. C. M. Leung, L. Shu, and L. T. Yang, "Toward offering more useful data reliably to mobile cloud from wireless sensor network," *IEEE Trans. Emerg. Topics Comput.*, vol. 3, no. 1, pp. 84–94, Mar. 2015.

[5] X. He, K. Wang, H. Huang, and B. Liu, "QoE-driven big data architecture for smart city," *IEEE Commun. Mag.*, vol. 56, no. 2, pp. 88–93, Feb. 2018.

[6] J. Wan *et al.*, "Reconfigurable smart factory for drug packing in healthcare industry 4.0," *IEEE Trans. Ind. Informat.*, to be published, doi: 10.1109/TII.2018.2843811.

[7] Z. Shu, J. Wan, D. Zhang, and D. Li, "Cloud-integrated cyber-physical systems for complex industrial applications," *Mobile Netw. Appl.*, vol. 21, no. 5, pp. 865–878, Oct. 2016.

[8] S. Wang, J. Wan, M. Imran, D. Li, and C. Zhang, "Cloud-based smart manufacturing for personalized candy packing application," *J. Supercomput.*, vol. 74, no. 9, pp. 4339–4357, 2018.

[9] S. S. Rautaray and A. Agrawal, "Vision based hand gesture recognition for human computer interaction: A survey," *Artif. Intell. Rev.*, vol. 43, no. 1, pp. 1–54, Jan. 2012.

[10] E. Cambria and B. White, "Jumping NLP Curves: A review of natural language processing research [review article]," *IEEE Comput. Intell. Mag.*, vol. 9, no. 2, pp. 48–57, May 2014.

[11] S. Wang, J. Wan, D. Li, and C. Zhang, "Implementing smart factory of industrie 4.0: An outlook," *Int. J. Distrib. Sensor Networks*, vol. 12, no. 1, p. 3159805, 2016.

[12] B. Chen, J. Wan, L. Shu, P. Li, M. Mukherjee, and B. Yin, "Smart factory of industry 4.0: Key technologies, application case, and challenges," *IEEE Access*, vol. 6, pp. 6505–6519, 2018.

[13] J. Wan *et al.*, "Toward dynamic resources management for IoT-based manufacturing," *IEEE Commun. Mag.*, vol. 56, no. 2, pp. 52–59, Feb. 2018.

[14] H. Tang, D. Li, S. Wang, and Z. Dong, "CASOA: An architecture for agent-based manufacturing system in the context of Industry 4.0," *IEEE Access*, vol. 6, pp. 12746–12754, 2018.

[15] M. Chen, P. Zhou, and G. Fortino, "Emotion communication system," *IEEE Access*, vol. 5, pp. 326–337, 2016.

[16] J. Fan and F. Jing, "Dimensional inspecting system of shaft parts based on machine vision," in *Proc. Chin. Automat. Congr. (CAC)*, Jinan, China, 2017, pp. 1708–1714.

[17] Z. Liu, B. Zhao, and H. Zhu, "Research of sorting technology based on industrial robot of machine vision," in *Proc. 5th Int. Symp. Comput. Intell. Design*, Hangzhou, China, 2012, pp. 57–61.

[18] Z. Yongxiang and Z. Lei, "Improvement and application of heuristic search in multi-robot path planning," in *Proc. 1st Int. Conf. Electron. Instrum. Inf. Syst. (EIIS)*, Harbin, China, 2017, pp. 1–4.

[19] M. Li, C. Wang, Z. Chen, X. Lu, M. Wu, and P. Hou, "Path planning of mobile robot based on genetic algorithm and gene rearrangement," in *Proc. Chin. Automat. Congr. (CAC)*, Jinan, China, 2017, pp. 6999–7004.

[20] M. Zorzi, A. Zanella, A. Testolin, M. De Filippo De Grazia, and M. Zorzi, "Cognition-based networks: A new perspective on network optimization using learning and distributed intelligence," *IEEE Access*, vol. 3, pp. 1512–1530, 2015.

[21] S. Gheisari and M. R. Meybodi, "A new reasoning and learning model for cognitive wireless sensor networks based on Bayesian networks and learning automata cooperation," *Comput. Netw.*, vol. 124, pp. 11–26, Sep. 2017.

[22] B. Ma, S. He, T. Liang, and C. Lv, "Variable-width channel allocation based on game theory in wireless mesh networks," in *Proc. 8th Int. Congr. Image Signal Process. (CISP)*, Shenyang, China, 2015, pp. 168–172.

[23] E. Akkarajitsakul, E. Hossain, and D. Niyato, "Coalition-based cooperative packet delivery under uncertainty: A dynamic Bayesian coalitional game," *IEEE Trans. Mobile Comput.*, vol. 12, no. 2, pp. 371–385, Feb. 2013.

[24] M. Aly, S. Yacout, and Y. Shaban, "Analysis of massive industrial data using MapReduce framework for parallel processing," in *Proc. Annu. Rel. Maintainability Symp. (RAMS)*, Orlando, FL, USA, 2017, pp. 1–6.

[25] J. Zhang, J.-S. Wong, Y. Pan, and T. Li, "A parallel matrix-based method for computing approximations in incomplete information systems," *IEEE Trans. Knowl. Data Eng.*, vol. 27, no. 2, pp. 326–339, Feb. 2015.

[26] T. Wuest, C. Irgens, and K.-D. Thoben, "An approach to monitoring quality in manufacturing using supervised machine learning on product state data," *J. Intell. Manuf.*, vol. 25, no. 5, pp. 1167–1180, 2014.

[27] H. Liu, S. Liu, and K. Zheng, "A reinforcement learning-based resource allocation scheme for cloud robotics," *IEEE Access*, vol. 6, pp. 17215–17222, 2018.

[28] H. Shen and L. Chen, "Distributed autonomous virtual resource management in datacenters using finite-Markov decision process," *IEEE/ACM Trans. Netw.*, vol. 25, no. 6, pp. 3836–3849, Dec. 2017.

[29] L. Wen, L. Gao, X. Li, M. Xie, and G. Li, "A new data-driven intelligent fault diagnosis by using convolutional neural network," in *Proc. IEEE Int. Conf. Ind. Eng. Eng. Manage. (IEEM)*, Singapore, Dec. 2017, pp. 813–817.

[30] Y. Xu, Y. Sun, J. Wan, X. Liu, and Z. Song, "Industrial big data for fault diagnosis: Taxonomy, review, and applications," *IEEE Access*, vol. 5, pp. 17368–17380, 2017.

[31] H. Yan, J. Wan, C. Zhang, S. Tang, Q. Hua, and Z. Wang, "Industrial big data analytics for prediction of remaining useful life based on deep learning," *IEEE Access*, vol. 6, pp. 17190–17197, 2018.

[32] J. Wan, B. Yin, D. Li, A. Celesti, F. Tao, and Q. Hua, "An ontology-based resource reconfiguration method for manufacturing cyber-physical systems," *IEEE/ASME Trans. Mechatronics*, to be published, doi: 10.1109/TMECH.2018.2814784.

[33] J. Wan, S. Tang, Q. Hua, D. Li, C. Liu, and J. Lloret, "Context-aware cloud robotics for material handling in cognitive industrial Internet of Things," *IEEE Internet Things J.*, vol. 5, no. 4, pp. 2272–2281, Aug. 2018.

[34] T. Stipancic, B. Jerbic, and P. Curkovic, "A context-aware approach in realization of socially intelligent industrial robots," *Robot. Comput.-Integr. Manuf.*, vol. 37, pp. 79–89, Feb. 2016.

[35] N. Bao, Z. Wu, X. Ran, K. Wang, and Y. Xue, "Research on machine vision size measurement method based on particle weight," in *Proc. IEEE 2nd Inf. Technol., Netw., Electron. Automat. Control Conf. (ITNEC)*, Chengdu, China, Dec. 2017, pp. 1498–1503.

[36] L. Kong, Q. Wu, K. Lin, and B. Chen, "Scratch detection of round buttons based on machine vision," in *Proc. 10th Int. Congr. Image Signal Process., Biomed. Eng. Inform. (CISP-BMEI)*, Shanghai, China, 2017, pp. 1–6.

[37] K. Xia and Z. Weng, "Workpieces sorting system based on industrial robot of machine vision," in *Proc. 3rd Int. Conf. Syst. Inform.*, Shanghai, China, 2016, pp. 422–426.

[38] L. Yu, Z. Wei, H. Wang, Y. Ding, and Z. Wang, "Path planning for mobile robot based on fast convergence ant colony algorithm," in *Proc. IEEE Int. Conf. Mechatronics Automat. (ICMA)*, Takamatsu, Japan, Aug. 2017, pp. 1493–1497.

[39] W. Li, C. Zhu, L. T. Yang, L. Shu, E. C.-H. Ngai, and Y. Ma, "Subtask scheduling for distributed robots in cloud manufacturing," *IEEE Syst. J.*, vol. 11, no. 2, pp. 941–950, Jun. 2017.

[40] M. Chen, F. Herrera, and K. Hwang, "Cognitive computing: Architecture, technologies and intelligent applications," *IEEE Access*, vol. 6, pp. 19774–19783, 2018.

[41] N. Ahad, J. Qadir, and N. Ahsan, "Neural networks in wireless networks: Techniques, applications and guidelines," *J. Netw. Comput. Appl.*, vol. 68, pp. 1–27, Jun. 2016.

[42] J. Wan *et al.*, "Software-defined industrial Internet of Things in the context of industry 4.0," *IEEE Sensors J.*, vol. 16, no. 20, pp. 7373–7380, Oct. 2016.

[43] X. Li, D. Li, J. Wan, C. Liu, and M. Imran, "Adaptive transmission optimization in SDN-based industrial Internet of Things with edge computing," *IEEE Internet Things J.*, vol. 5, no. 3, pp. 1351–1360, Jun. 2018.

[44] L. A. Dasilva, H. Bogucka, and A. B. Mackenzie, "Game theory in wireless networks," *IEEE Commun. Mag.*, vol. 49, no. 8, pp. 110–111, Aug. 2011.

[45] C. Ma, J.-P. Sheu, and C.-X. Hsu, "A game theory based congestion control protocol for wireless personal area networks," *J. Sensors*, vol. 2016, p. 13, 2016, Art. no. 6168535.

[46] C. Zhu, H. Wang, X. Liu, L. Shu, L. T. Yang, and V. C. M. Leung, "A novel sensory data processing framework to integrate sensor networks with mobile cloud," *IEEE Syst. J.*, vol. 10, no. 3, pp. 1125–1136, Sep. 2016.

[47] J. Wan *et al.*, "A manufacturing big data solution for active preventive maintenance," *IEEE Trans. Ind. Informat.*, vol. 13, no. 4, pp. 2039–2047, Aug. 2017.

[48] M. H. U. Rehman, E. Ahmed, I. Yaqoob, I. A. T. Hashem, M. Imran, and S. Ahmad, "Big data analytics in industrial IoT using a concentric computing model," *IEEE Commun. Mag.*, vol. 56, no. 2, pp. 37–43, Feb. 2018.

[49] P. Li, Z. Chen, L. T. Yang, Q. Zhang, and M. J. Deen, "Deep convolutional computation model for feature learning on big data in Internet of Things," *IEEE Trans. Ind. Informat.*, vol. 14, no. 2, pp. 790–798, Feb. 2018.

[50] X. Xu, L. Cao, X. Wang, X. Xu, L. Cao, and X. Wang, "Resource pre-allocation algorithms for low-energy task scheduling of cloud computing," *J. Syst. Eng. Electron.*, vol. 27, no. 2, pp. 457–469, 2016.

[51] R. Birke, A. Podzimek, L. Y. Chen, and E. Smirni, "Virtualization in the private cloud: State of the practice," *IEEE Trans. Netw. Service Manag.*, vol. 13, no. 3, pp. 608–621, Sep. 2016.

[52] X. Wang, X. Wang, H. Che, K. Li, M. Huang, and C. Gao, "An intelligent economic approach for dynamic resource allocation in cloud services," *IEEE Trans. Cloud Comput.*, vol. 3, no. 3, pp. 275–289, Apr. 2015.

[53] L. Monostori, "AI and machine learning techniques for managing complexity, changes and uncertainties in manufacturing," *Eng. Appl. Artif. Intell.*, vol. 16, no. 4, pp. 277–291, 2003.

[54] M. Sharp, R. Ak, and T. Hedberg, Jr., "A survey of the advancing use and development of machine learning in smart manufacturing," *J. Manuf. Syst.*, vol. 49, pp. 170–179, Jul. 2018, doi: 10.1016/j.jmsy.2018.02.004.

[55] X. He, K. Wang, T. Miyazaki, H. Huang, Y. Wang, and S. Guo, "Green resource allocation based on deep reinforcement learning in content-centric IoT," *IEEE Trans. Emerg. Topics Comput.*, to be published, doi: 10.1109/TETC.2018.2805718.

[56] Q. Zhang, C. Zhu, L. T. Yang, Z. Chen, L. Zhao, and P. Li, "An incremental CFS algorithm for clustering large data in industrial Internet of Things," *IEEE Trans. Ind. Informat.*, vol. 13, no. 3, pp. 1193–1201, Jun. 2017.

[57] G. A. Susto, A. Schirru, S. Pampuri, S. McLoone, and A. Beghi, "Machine learning for predictive maintenance: A multiple classifier approach," *IEEE Trans. Ind. Informat.*, vol. 11, no. 3, pp. 812–820, Jun. 2015.

[58] T. R. Gruber, "Toward principles for the design of ontologies used for knowledge sharing," *Int. J. Hum.-Comput. Stud.*, vol. 43, nos. 5–6, pp. 907–928, 1995.

[59] X. Chang, R. Rai, and J. Terpenny, "Development and utilization of ontologies in design for manufacturing," *J. Mech. Des.*, vol. 132, no. 2, p. 021009, 2010.

[60] T. Wang, S. Guo, and C.-G. Lee, "Manufacturing task semantic modeling and description in cloud manufacturing system," *Int. J. Adv. Manuf. Technol.*, vol. 71, nos. 9–12, pp. 2017–2031, 2014.

[61] S. Saeidlou, M. Saadat, and G. Jules, "Cloud manufacturing analysis based on ontology mapping and multi agent systems," in *Proc. IEEE Int. Conf. Syst., Man Cybern. (SMC)*, San Diego, CA, USA, Oct. 2014, pp. 2019–2024.

[62] N. Zhou, D. Li, S. Li, S. Wang, and C. Liu, "Model-based development of knowledge-driven self-reconfigurable machine control systems," *IEEE Access*, vol. 5, pp. 19909–19919, 2017.

[63] The Gene Ontology Consortium, "Gene ontology consortium: Going forward," *Nucl. Acids Res.*, vol. 43, no. D1, pp. D1049–D1056, 2015.

[64] L. Lezcano, M.-A. Sicilia, and C. RodríGuez-Solano, "Integrating reasoning and clinical archetypes using OWL ontologies and SWRL rules," *J. Biomed. Inform.*, vol. 44, no. 2, pp. 343–353, 2011.

[65] M. M. Hassan, K. Lin, X. Yue, and J. Wan, "A multimedia healthcare data sharing approach through cloud-based body area network," *Future Gen. Comput. Syst.*, vol. 66, pp. 48–58, Jan. 2016.

[66] O. B. Sezer, E. Dogdu, and A. M. Ozbayoglu, "Context-aware computing, learning, and big data in Internet of Things: A survey," *IEEE Internet Things J.*, vol. 5, no. 1, pp. 1–27, Feb. 2018.

[67] H. Zhang, H. Wang, J. Li, and H. Gao, "A generic data analytics system for manufacturing production," *Big Data Mining Anal.*, vol. 1, no. 2, pp. 160–171, Jun. 2018.

[68] R. Y. Zhong, Q. Y. Dai, T. Qu, G. J. Hu, and G. Q. Huang, "RFID-enabled real-time manufacturing execution system for mass-customization production," *Robot. Comput.-Integr. Manuf.*, vol. 29, no. 2, pp. 283–292, 2013.

[69] A. Girbea, C. Suciu, S. Nechifor, and F. Sisak, "Design and implementation of a service-oriented architecture for the optimization of industrial applications," *IEEE Trans. Ind. Informat.*, vol. 10, no. 1, pp. 185–196, Feb. 2014.

[70] C.-H. Yu, K. Doppler, C. B. Ribeiro, and O. Tirkkonen, "Resource sharing optimization for device-to-device communication underlaying cellular networks," *IEEE Trans. Wireless Commun.*, vol. 10, no. 8, pp. 2752–2763, Aug. 2011.

[71] J. Wan, B. Chen, S. Wang, M. Xia, D. Li, and C. Liu, "Fog computing for energy-aware load balancing and scheduling in smart factory," *IEEE Trans. Ind. Informat.*, to be published, doi: 10.1109/TII.2018.2818932.

[72] J. Liu, J. Wan, B. Zeng, Q. Wang, H. Song, and M. Qiu, "A scalable and quick-response software defined vehicular network assisted by mobile edge computing," *IEEE Commun. Mag.*, vol. 55, no. 7, pp. 94–100, Jul. 2017.

[73] Y. Zhang, S. Ren, Y. Liu, and S. Si, "A big data analytics architecture for cleaner manufacturing and maintenance processes of complex products," *J. Cleaner Prod.*, vol. 142, no. 2, pp. 626–641, 2017.

[74] L. Wang and R. Ranjan, "Processing distributed Internet of Things data in clouds," *IEEE Cloud Comput.*, vol. 2, no. 1, pp. 76–80, Jan./Feb. 2015.

[75] P. Russom, "BI search and text analytics," TDWI Best Pract. Rep., 2007.

[76] C. Esposito, A. Castiglione, B. Martini, and K.-K. R. Choo, "Cloud manufacturing: Security, privacy, and forensic concerns," *IEEE Cloud Comput.*, vol. 3, no. 4, pp. 16–22, Jul./Aug. 2016.

[77] L. J. Wells, J. A. Camelio, C. B. Williams, and J. White, "Cyber-physical security challenges in manufacturing systems," *Manuf. Lett.*, vol. 2, no. 2, pp. 74–77, 2013.

[78] Z. Xia, X. Wang, X. Sun, and Q. Wang, "A secure and dynamic multi-keyword ranked search scheme over encrypted cloud data," *IEEE Trans. Parallel Distrib. Syst.*, vol. 27, no. 2, pp. 340–352, Jan. 2016.

[79] S. Iqbal *et al.*, "On cloud security attacks: A taxonomy and intrusion detection and prevention as a service," *J. Netw. Comput. Appl.*, vol. 74, pp. 98–120, Oct. 2016.

[80] M. Wu, Z. Song, and Y. B. Moon, "Detecting cyber-physical attacks in CyberManufacturing systems with machine learning methods," *J. Intell. Manuf.*, Feb. 2017, doi: 10.1007/s10845-017-1315-5.

[81] S. M. Abdulhamid, M. S. A. Latiff, S. H. H. Madni, and M. Abdullahi, "Fault tolerance aware scheduling technique for cloud computing environment using dynamic clustering algorithm," *Neural Comput. Appl.*, vol. 29, no. 1, pp. 279–293, 2016.

JIAFU WAN was the Director of 18 Research Projects, including the National Key Research and Development Project and the National Natural Science Foundation of China Project. He is currently a Professor with the School of Mechanical and Automotive Engineering, South China University of Technology, China. He has published over 150 scientific papers, including 90+ SCI-indexed papers, 30+ IEEE TRANSACTIONS/Journal papers, 16 ESI highly cited papers, and 4 ESI hot papers. According to Google Scholar, his published work has been cited over 5500 times. His SCI other citations (sum of times cited without self-citations) reached 1500 times according to Web of Science Core Collection. His research interests include industry 4.0, industrial wireless networks, cyber physical systems, Internet of Things, clouding computing, embedded systems, and industrial robotics.

JUN YANG received the B.A. degree in mechanical engineering from the Wuhan University of Technology, China, in 2017. He is currently pursuing the M.S. degree with the School of Mechanical and Automotive Engineering, South China University of Technology, China. His research interests include industrial big data, cloud computing, and machine learning.

ZHONGREN WANG (M'07) was born in 1974. He received the B.E. degree from the Beijing University of Chemical Technology, China, in 1997, and the M.E. degree and Ph.D. degree in mechanical engineering from the South China University of Technology, Guangzhou, in 2003 and 2009, respectively. Since 2003, he has been with the School of Mechanical and Automotive Engineering, Hubei University of Arts and Science. He is currently a Professor and the Leader of the Laboratory of Intelligent Manufacturing and Machine Vision. Over the last 10 years, he has published over 50 journals and conference papers. His current research interests cover smart factory, machine vision, and image processing. He is a Senior Member of the Chinese Mechanical Engineering Society.

QINGSONG HUA received the Ph.D. degree in mechanical engineering from the Clausthal University of Technology, Germany, in 2006. He is currently a Professor with the School of Mechanical and Electrical Engineering, Qingdao University, Qingdao, China. His research interests are renewable energy, including multi-energy systems, and micro grid and distributional SOFC power generation.