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Industrial Big Data Analysis in Smart Factory: Current Status and Research Strategies

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ABSTRACT Under the background of cyber-physical systems and Industry 4.0, intelligent manufacturing has become an orientation and produced a revolutionary change. Compared with the traditional manufacturing environments, the intelligent manufacturing has the characteristics as highly correlated, deep integration, dynamic integration, and huge volume of data. Accordingly, it still faces various challenges. In this paper, we summarize and analyze the current research status in both domestic and aboard, including industrial big data collection, modeling of the intelligent product lines based on ontology, the predictive diagnosis based on industrial big data, group learning of product line equipment and the product line reconfiguration of intelligent manufacturing. Based on the research status and the problems, we propose the research strategies, including acquisition schemes of industrial big data under the environment of intelligent, ontology modeling and deduction method based intelligent product lines, predictive diagnostic methods on production lines based on deep neural network, deep learning among devices based on cloud supplements and 3-D self-organized reconfiguration mechanism based on the supplements of cloud. In our view, this paper will accelerate the implementation of smart factory.

INDEX TERMS Industrial big data, smart factory, data analysis, cyber-physical systems.

I. INTRODUCTION

In recent years, the initiatives such as the ''Industry 4.0'' strategy in Germany, the ''Industrial Internet'' strategy in United States, the ''Manufacturing White Book of Year 2014'' published in Japan, and the ''Made in China 2025'' plan formulated and published in China, have made intelligent manufacturing as an orientation supported by their nations with priority. Under the background of Cyber-Physical Systems (CPS) in ''Made in China 2025'' and ''Industry 4.0,'' it is essential to establish the intelligent factories based on the industrial big data and ''Internet plus.'' Currently, the manufacturing field still faces various global challenges. For example, under the support of emerging information technologies (e.g., industrial wireless networks [1], big data analysis [2], [3], software defined networks [4], [5], CPS [6], [7] and cloud computing [8], [9]), implementation of Ontology modeling towards the intelligent manufacturing product lines, and performing diagnosis, optimization and reconfiguration on intelligent product lines through industrial big data analysis, have important research values and urgent realistic application demands. Investigation and application of the new generation of intelligent manufacturing technologies to improve the flexibility of intelligent manufacturing product lines and the utilization efficiency of the resources have important theoretical significance and engineering application values.

An intelligent factory regards the Cyber-Physical Production System (CPPS) as its kernel and takes deep fusion of information technology and manufacturing technology as its characteristics that will embed the new generation of information technologies such as Internet of things, big data and cloud computing, into different segments of the manufacturing process in order to realize highly efficient production of intelligent products with customization as its characteristics. Since the manufacturing domain has different features from information technology, such as the requirements of real-time, reliability and safety during the product manufacturing process, applying the mature techniques in the information technology will not satisfy the demands of intelligent factory under the new frame of manufacturing. The existing manufacturing equipment is designed to deal with a large volume of same type of products and generally does not have configurability. Moreover, the equipment also does not support the active operation and the maintenance as well as the dynamic reconfiguration during the manufacturing process. Therefore, high-efficient manufacturing of customized products proposed all the new requirements on the configurability of manufacturing equipment and production line such as fault diagnosis of devices and manufacturing systems, optimization and reconfiguration. These require breakthrough core technologies on the foundations of the present information technology to adapt the requirements of intelligent factories.

In contrast to traditional styles of production, the intelligent manufacturing has the following typical characteristics.

- Highly correlated: the intelligent manufacturing systems exist under a networked environment in which manufacturing/detecting /assembling devices, warehouse storage system, transmission system, workpiece, server and surveillance terminals are all interconnected through multiple types of networks such as cabled, wireless and real-time / non-real time, to communicate and exchange data with each other.
- Deep integration: the intelligent physical substance in the bottom layer and the surveillance terminal in the upper layer are interconnected and internetworked with the cloud platform. Different types of information in the system that real-timely uploaded to the cloud platform form the industrial big data and thereby it can simultaneously perform data processing, control and physical operations in a network, break the information barriers of each process, and realize the deep integration of physical environment and information environment, which is the cyber-physical system.
- Dynamic reconfiguration: in order to adapt the efficient production of multi-type and small-batch products, it is necessary to determine the required type of devices and transmission paths according to the health status of the equipment and the type of the workpiece. Since the health status of the equipment and the type of the workpiece are dynamically changing, it is essential to dynamically reconstruct the system source during the operation of systems.
- Huge volume of data: the intelligent manufacturing system must satisfy the small batch of personalization. Each type of intelligent substance needs real-time negotiation on reconstruction to generate large amount of data including the health status of the equipment, the status of the manufacturing process and the product information. The applications of high-speed networks technology, cloud computing technology and big data processing technology enable transmission, storage, processing and analysis of huge volume of data.

High-degree interconnection based on networks and cloud platforms is the foundation of big data processing. The Ontology modeling and the mechanism of dynamic reconfiguration that oriented to intelligent product lines are the key points of flexible and highly efficient manufacturing, while the innovative methods on industrial big data analysis provide conditions for the diagnosis, the optimization and the reconfiguration of intelligent manufacturing product lines. Currently, the intelligent manufacturing and the research on CPS are in the ascendant. However, regarding to the current situations of both domestic and abroad, the realization of intelligent manufacturing is still facing many challenges. Among these challenges, oriented on highly interconnected manufacturing environment and the small batch of personalized need of manufacturing, utilizing the analytical technique on industrial big data to upgrade the performance of the manufacturing system is one of the crucial unsolved scientific problems.

In this paper, our contributions include the following two aspects.

- We summarize and analyze the current research status for industrial big data analysis in smart factory in both domestic and aboard.
- We propose the research strategies for industrial big data analysis, including acquisition schemes, Ontology modeling, predictive diagnostic methods based on deep neural network, and three-dimensional self-organized reconfiguration mechanism.

The rest of this paper is organized as follows. Section II gives the current research status in both domestic and aboard. Section III analyzes the research strategies for industrial big data analysis. Finally, Section IV concludes the paper.

II. CURRENT RESEARCH STATUS IN BOTH DOMESTICS AND ABROAD

The research status associated with this study project both at home and abroad, comprises of five aspects: industrial big data collection, modeling of the intelligent product lines based on Ontology, the predictive diagnosis based on industrial big data, group learning of product line equipment and the product line reconfiguration of intelligent manufacturing.

A. INDUSTRIAL BIG DATA COLLECTION

The rapid development of micro-electronic technology, embedded technology, measurement and control technology and communication technology, has achieved significant improvements in data collection methods and data processing techniques both at home and abroad [10]. In the application background of wireless sensor network (WSN) and the Internet of Things (IoT), large scale sensing data acquisition and transmission has been a hot topic of investigations in recent years and data fusing is a commonly used technique for the acquisition of data processing [11]. Wang [12] proposed the self-adaptive unscented Kalman algorithm and applied this algorithm into industrial IoT to perform data fusion processing. Huang *et al.* [13] proposed the compressive sensing algorithm based on data fusion tree in WSN. Aiming at the problem of wireless location under harsh environment, Prieto *et al.* [14] proposed the self-adaptive data fusion algorithm to enhance the positioning accuracy. Under the environment of intelligent manufacturing, the industrial big data associated with manufacturing product lines includes the data of equipment conditions, products and the manufacturing process, where these data have periodical signals, real-time alarm, and equipment logs, etc. Since the big data associated with product lines are distributed in different locations of manufacturing environment and there are different types of data, the traditional data fusion schemes aiming at the same signal of multiple data sources, cannot provide good solutions to the problem of efficient acquisition of big data from the manufacturing product lines. In recent years, the software defined industrial IoT [15] and the concept of OPC UA [16] have provided new ways for the big data acquisition and information interaction of product lines under the manufacturing environment. The software defined data acquisition nodes are capable of adapting all sorts of data inputs by means of dynamic configuration of software that has strong flexibility.

B. ONTOLOGY MODELING ORIENTED TO THE MANUFACTURING ENVIRONMENT

Ontology is originated from Philosophy. Since the Ontology provides modeling method and deduction mechanism towards the concepts and the mutual relations of a specific domain, it is widely applied in the domains of information science such as artificial intelligence, semantic network and software engineering [17], [18]. The Ontology modeling of a specific application scene in the manufacturing domain provides brand new visual angles to the realization of detection and alarm, resource allocation of product lines and performance optimization. Zhang *et al.* [19] oriented to the astronautical domain, proposed the cooperative modeling method between astronautical products and performance prototype based on Ontology, and provided theoretical foundations towards the establishment of cooperative model on multi-subject products. Fang *et al.* [20] established the knowledge Ontology of product design as the bottom layer of framework in order to address the problems such as multi-subject cross and tremendous amount of knowledge resources in the domain of complicated product design. They introduced the multiple influence factor synthetic weighting and the semantic increment achieving precise retrieval results. Kolchin *et al.* [21] aimed at the most widely applicable Ontology in the domain of IoT and performed analysis by dividing the Ontology into five major categories. Kotis and Katasonov [22] described the knowledge information of things through the establishment of Ontology model oriented to IoT on the basis of multi-type Ontology such as sensors. In the domain of home automation, Wang and Turner [23] described the electric machine that is the sub-concept of controllable electrical system through the establishment of DogOnt Ontology. Wang *et al.* [24] proposed the comprehensive Ontology oriented to knowledge representation that described the concepts such as Ontology service, observation and measurements. Kotis and Katasonov [25] proposed an Ontology model that describes the multiple automated deployments in the heterogeneous IoT. Venkatesh *et al.* [26] applied statistical learning and the method of Ontology to design a new middleware architecture of IoT providing relatively better solutions to the problem of IoT expansion due to heterogeneous data. The above-mentioned schemes achieved the modelling establishment and initial reasoning, but are still unable to provide efficient solution plans to the key problems such as resource allocation and performance optimization under the environment of manufacturing. Nevertheless, these schemes provided brand new styles of thinking on the diagnosis and reconfiguration of product lines under the environment of intelligent manufacturing.

C. PREDICTIVE DIAGNOSIS BASED ON BIG DATA

The complexity and the scale of modern industrial systems are constantly growing and the corresponding increased faults are influencing the reliability and the effectiveness of the system, which makes the fault diagnosis unprecedented important [27]. Li *et al.* [28] proposed the methods of fault detection and diagnosis on all the sensors for the screw chiller system based on the support vector data description algorithm. Hui *et al.* [29] proposed the support vector machine (SVM)–Dempster-Shafer evidence theory in order to solve the outcome contradiction and classification accuracy problems of SVM. With the rapid development of network, data storage and data acquisition capacities, the traditional schemes on fault prediction and diagnosis in the aspects of feature extraction or model training, are unable to adopt to the present huge volumes, diversity and high-rate of data [30], [31]. In recent years, domestic and foreign scholars have discovered that deep learning has distinctive effects in big data processing of numerous fields. Krizhevsky *et al.* [32] upgraded the accuracy rate of recognition of ImageNet images from the 74.2% of traditional intelligent methods to 83.6% by establishing the deep learning model. Baldi *et al.* [33] utilized the deep learning scheme to search exotic particles in high energy physics and demonstrated that the deep learning scheme could enhance the searching capabilities of colliders. Hence, some scholars applied the deep learning scheme into the predictive diagnosis of faults in order to satisfy the requirement of predictive diagnosis in even larger extent under the background of big data. Tamilselvan and Wang [34] innovatively proposed the multi-sensor health diagnostic scheme based on deep learning and used case analysis to demonstrate that the deep belief network categorization model in the health diagnose of complex systems displays even better diagnostic performance in contrast to other categorization schemes. Tran *et al.* [35] proposed the faults diagnostic method on the reciprocating compressor air valve based on Teager-Kaiser energy operators and deep belief networks. The analysis the failure classification performance proved that the proposed scheme is highly reliable and adaptable to industrial reciprocating machinery compared to the correlation vector machine and the BP neural network. Jia *et al.* [36] proposed the intelligent fault diagnostic method for rotational electric machine based on deep neural networks and the diagnostic results indicated that this method had realized the self-adaptive extraction on the fault characteristics of measurement signals and accurate recognition of health status. Aiming at the current status that the fault diagnosis of current sensing electric motors mostly adopts supervising learning to extract the features of faults, Sun *et al.* [37] proposed a deep neural network that melted the noise-removal coding into sparse automatic coder realizing the feature extraction of unsupervised learning and applied that to the fault diagnosis of sensing electric motors. The above-mentioned predictive diagnostic schemes based on deep learning mostly assume that the training data is tagged data and apparently are unable to satisfy the necessity of manufacturing big data in product lines. Thus, establishing a predictive diagnostic scheme that can directly perform training on the original signals in time domain will have significant importance.

D. GROUP LEARNING OF THE EQUIPMENT ON PRODUCT LINES

In the environment of intelligent manufacturing, the authors introduced the previous configuration experience of similar working procedures, achieved the group learning of similar working procedures that will significantly optimize the working efficiency of the equipment on the product lines and reduced the intensity of maintenance. In recent years, scholars from both domestic and abroad conducted several investigations towards the self-adaptive learning, group learning theory and methods regarding to the devices such as industrial robotic arms, mobile robots and have gained some achievements.

Wu *et al.* [38] utilized the radial basis function (RBF) neural network as a mechanical arm with completely unknown parameters and designed a new self-adaptive neural control algorithm in the joint space; RoboEarth [39]. They integrated typical applications of multi-class robot tasks and stored the codes of running task that oriented to multi-class robots, which attracted considerable attentions from academic and industrial fields. Seo *et al.* [40] proposed to exploit Q-learning and cascaded SVM to enable the robots to have the capability of learning. Iwanaga *et al.* [41] proposed the approach of manually evolution, while haven't totally demonstrated its effectiveness. Arumugam *et al.* [42] proposed the cloud computation platform DAvinCi based on Hadoop and ROS, in which the data-sharable model was integrated. Riazuelo *et al.* [43] proposed semantic mapping based on RoboEarth and attempted to construct a universal interface that interacts cloud and the bottom layer. In addition, aiming to grab mechanical hands, multiple research institutes make their own databases public, such as Columbia Grasp dataset [44] and the KIT object dataset in Massachusetts Institute of Technology [45]. Most of the above-described studies, by the association with big data and cloud computation, attempted to realize the technical sharing towards the Robots in the bottom layer in the cloud terminal and thereby achieved group learning. However, under the environment of manufacturing, there are also a large amount of product line devices that do not integrate hardware such as the embedded equipment does not have the learning capabilities of ‘‘code-level’’ prior technical skills. What they did more is that they referenced the configuration parameters similar as the product line equipment as well as their running effects exhibiting relatively better configuration parameters of similar equipment through the ‘‘learning’’ task and optimized the performance of operations on the equipment. Lee *et al.* [46] proposed to use similar equipment to establish a practical example of cloning at its cloud terminal, compared and evaluated the behavior of similar products through the ‘‘snapshotting’’ technology and optimized the configuration of bottom layer equipment in order to improve the flexibility and self-adaptability of the equipment. Based on clustering and curve fitting, Wang *et al.* [47] proposed the prediction mechanism of remaining effective life span based on the similarity of prior samples. Currently, the main objectives of multiple scientific research teams both domestic and abroad, are still to make the group learning on all sorts of Robot equipment as the major tasks and to establish the learning mechanism on all types of product line equipment under the manufacturing environment that will have significant importance in achieving intelligence and flexible manufacturing and maintenance.

E. RECONFIGURATION OF INTELLIGENT MANUFACTURING PRODUCT LINE

The dynamic reconfiguration of manufacturing systems is usually viewed as an important attribution on the system for dealing with inner/outer uncertain factors and strengthening the elasticity of itself. In recent years, the dynamic reconfiguration of manufacturing system has attracted considerable attention from the academics both at home and abroad. Wang *et al.* [48] pointed out that highly flexible intelligent factories are the keys to deal with the necessity of multi-specification, small batches and personalization, and proposed a type of dynamic reconfiguration mechanism that was focused on the alternatively manufacturing of multi-type complete intelligent workpieces. Wang *et al.* [49] established a reconfiguration time-point decision method for reconfigurable manufacturing systems that simultaneously considered the processing functions and processing capabilities. Azaiez *et al.* [50] constructed the self-organized global framework of manufacturing unit by comprehensively utilizing the techniques such as SDN, OPC uniform structuring and Robot modeling languages. This framework achieved the reconfiguration of manufacturing units through the functions of adding or deleting. Xu *et al.* [51] considered the problem of process reconfiguration for the reconfigurable manufacturing system on the expansion capabilities of production, and designed an original and effective method on process reconfiguration. Lope *et al.* [52] proposed a robust, efficient self-organizational technique based on learning automatic machine theory, ant-colony algorithm and response threshold model to deal with task allocations in the multi-Robot system. Haddou-Benderbal *et al.* [53] believed that the unavailability of equipment will severely influence the performance of reconfigurable manufacturing systems and designed a hybrid inspirational algorithm that quickly searches the available equipment to substitute the unavailable equipment. Renna and Ambrico [54] determined the required amount, layout and workload of equipment when the external demand changes by establishing multiple mathematical models in order to promote smooth reconfiguration process of unit manufacturing system. Sakhaii *et al.* [55] constructed the integrated hybrid combinative planning model to promote the equipment layout, process improvement and labor arrangements inside the dynamic manufacturing unit when equipment is not reliable. Delgoshaei and Gomes [56] established a multi-stage scheduling model and supplemented it with several universal inspirational deduction schemes to solve the scheduling problem of unit manufacturing systems in the scene of unreliable equipment and uncertain prime cost. Wu *et al.* [57] proposed a robust deadlock control strategy based on Petri network aiming at the automatic manufacturing system with unreliable resources. The above-described research studies have some sort of reference values towards the study of this research project. However, they are still not fully compatible to the manufacturing domain when the health status of intelligent equipment dynamically changes. The unsolved difficult problems still exist on the reconfiguration mechanism of intelligent production line under the expected or unexpected failures on equipment.

III. RESEARCH STRATEGIES

Different from the traditional manufacturing environments, intelligent manufacturing has its own features and also brings some problems. The research strategies could be divided into five aspects: acquisition schemes of industrial big data under the environment of intelligent manufacturing, Ontology modeling and deduction method based intelligent product lines, predictive diagnostic methods on production lines based on deep neural network, deep learning among devices based on cloud supplements and three-dimensional self-organized reconfiguration mechanism based on the supplements of cloud. Fig. 1 shows the key technologies for big data analysis in smart factory.

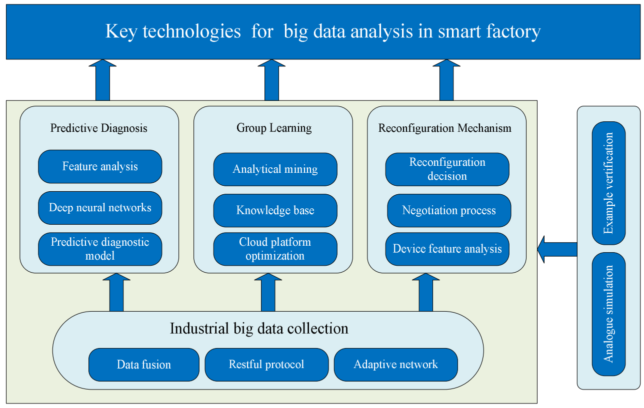

FIGURE 1. Key technologies for big data analysis in smart factory.

A. ACQUISITION SCHEMES OF INDUSTRIAL BIG DATA UNDER THE ENVIRONMENT OF INTELLIGENT MANUFACTURING

In the environment of intelligent manufacturing, the traditional sensing data fusion schemes are not capable of achieving efficient acquisition of big data in the manufacturing production lines. The proposed concepts of software-defined sensing networks and software defined industrial IoT in recent years, have provided new directions of thinking in big data acquisition on the production lines in the manufacturing environment. They adopt the software-defined data acquisition nodes by means of dynamic configuration from the software that is able to adapt data inputs of different characteristics and different types, and displays strong flexibility. The authors plan to perform their study towards the problems as follows: industrial big data fusion schemes under the environment of intelligent manufacturing; data acquisition nodes supporting the Restful webpage service protocol; software-defined data acquisition method; self-adaptive network bandwidth allocation algorithm based on software definition; and information interaction among the equipment based on OPC UA.

B. ONTOLOGY MODELING AND DEDUCTION METHOD BASED INTELLIGENT MANUFACTURING PRODUCT LINES

Compared with traditional manufacturing environments, the intelligent manufacturing emphasis the high flexibility of manufacturing process, the intelligent scheduling of product line resources and the optimization of manufacturing performance. The traditional mathematical models are unable to handle intelligent manufacturing systems due to the complicated categories of equipment in the product lines and the continuous expansions of equipment. In order to realize the flexible resource allocation, detection alarm and performance optimization of intelligent manufacturing product line, the authors plan to perform research on the following problems: Ontology modeling and restriction supplements of manufacturing product lines; association of knowledge base and database, endow data with semantics; inference mechanism based on Ontology and restrictions; realization principles of warning detection, resource allocation and performance optimization based on Ontology and inference.

C. PREDICTIVE DIAGNOSTIC METHODS ON PRODUCTION LINES BASED ON DEEP NEURAL NETWORKS

The modern devices have complicated structures and there are mutually coupled highly nonlinear dynamic characteristics among multiple devices. Moreover, the fault problems are different under different scenes and the characteristics of signals to be processed are also different. In order to ensure high efficiency and accuracy of predictive diagnostic schemes

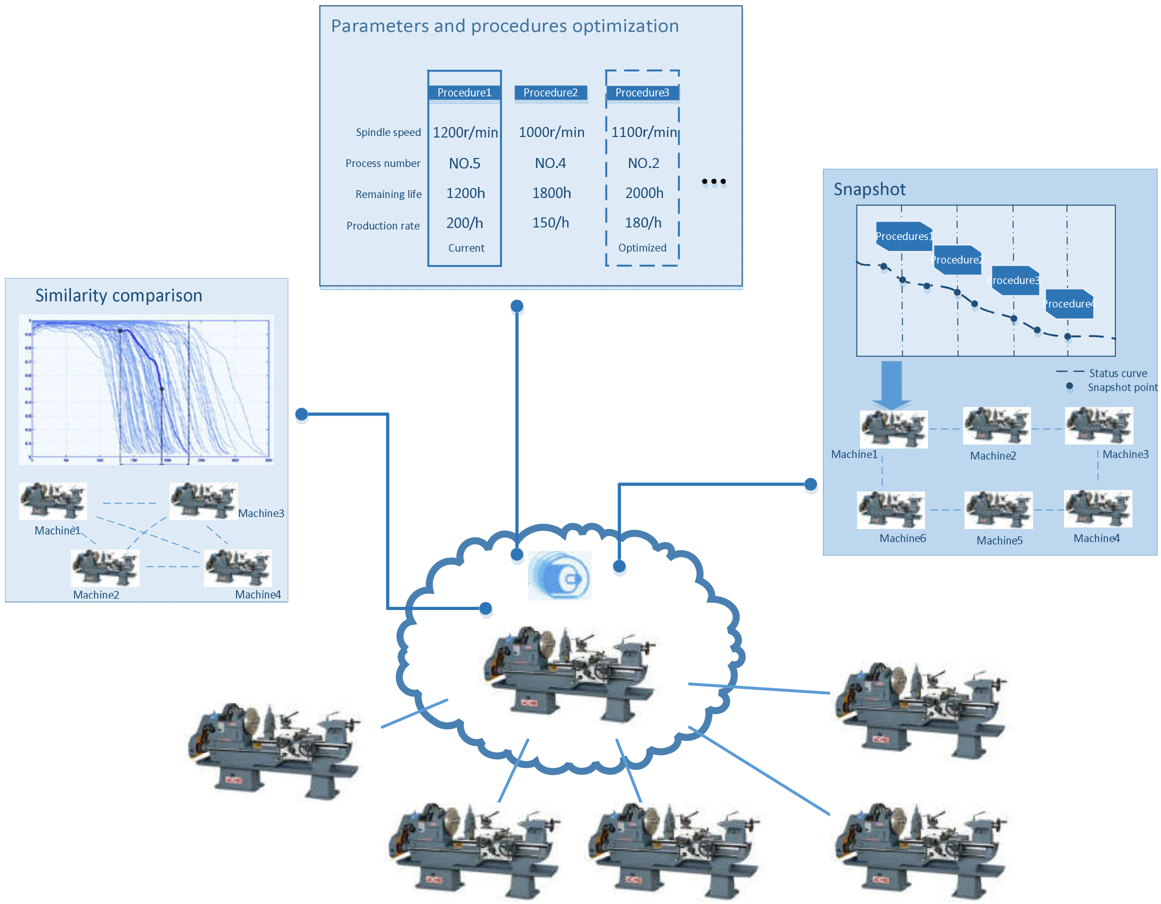

FIGURE 2. **Group learning among devices based on cloud supplements.**

on product lines under the background of industrial big data, a predictive diagnostic method that is universally adaptable to multiple data types is proposed. The authors plan to conduct research on the following aspects: feature analysis on the data of manufacturing product lines; feasibility analysis of deep learning schemes applicable to the predictive diagnosis of product lines; the predictive diagnostic models of product lines based on deep neural networks; analyzing the effective and universal compatibilities of the predictive diagnostic methods.

D. GROUP LEARNING AMONG DEVICES BASED ON CLOUD SUPPLEMENTS

Fig. 2 shows the group learning among devices based on cloud supplements. The oriented complexity of tasks is different due to the varied degrees of hardware integration on the product-line leveled devices. Regarding to the devices with high degrees of hardware integration (such as all types of Robots), the efficiency on task execution of devices can be significantly upgraded by learning the executing experience of similar tasks. While regarding to the devices with low degrees of hardware integration, the parameter configuration and the subsequent work procedures of devices can be optimized by learning the historical status information of similar devices. The authors plan to conduct comprehensive study on the following problems: optimization of private cloud platforms based on the environment of intelligent manufacturing; establishing the dynamic knowledge base oriented to specific tasks at the cloud terminal for devices facing high degree of hardware integration. The knowledge base information will be updated after learning and executing the "coding-level" knowledge by the device; establishing the logs of status information on the devices oriented to lower degree of hardware integration at the cloud terminal. The parameter configurations and the subsequent work procedures of the devices will be optimized by means of dynamically analyzing and digging the logs of status information of similar devices.

E. THREE-DIMENSIONAL SELF-ORGANIZED RECONFIGURATION MECHANISM BASED ON THE SUPPLEMENTS OF CLOUD

Fig. 3 show the three-dimensional self-organized reconfiguration mechanism based on the supplements of cloud. Under the environment of intelligent manufacturing, the expected and unexpected faults of intelligent devices will trigger the

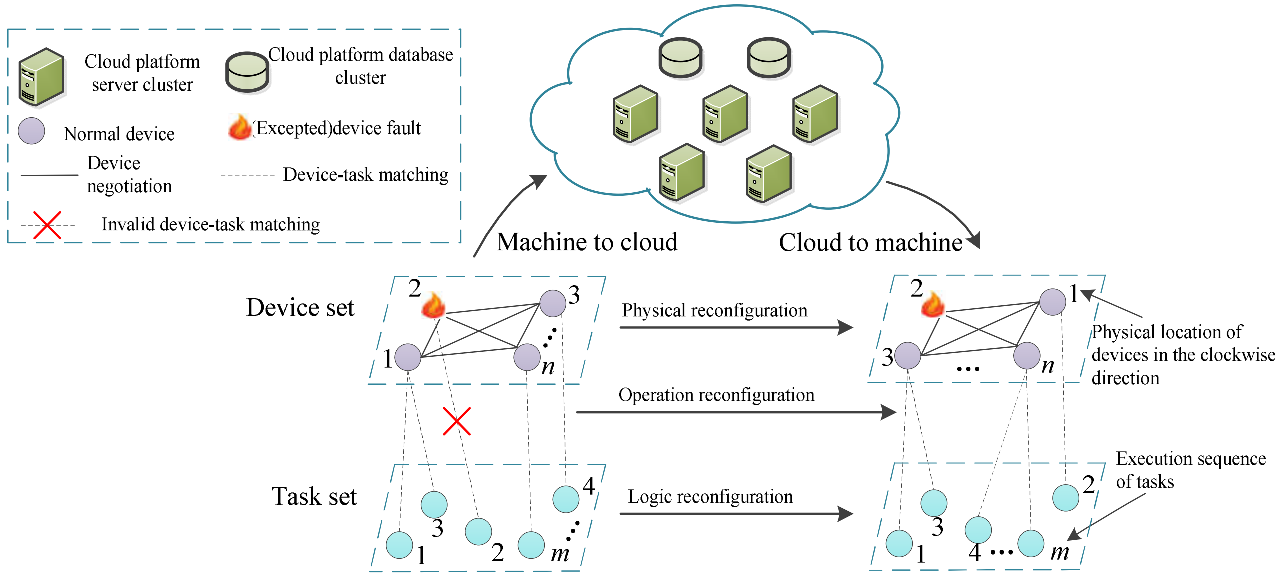

FIGURE 3. Three-dimensional self-organized reconfiguration mechanism based on the supplements of cloud.

events of product line reconfiguration. While performing reconfiguration, adopting the reconfiguration strategy based on self-organization and cloud supplements of intelligent devices will ensure the achievement of predicted effects on the performance of product lines. The authors plan to conduct detailed research on the following subjects: task-specific feature analysis on intelligent devices; the coordinating process of device-oriented behaviors, the logic sequences of tasks and reconfiguration on the physical locations of devices; the decision method of intelligent devices; the communication architecture on the interaction of intelligent devices and cloud levels; and the inactivation control models of product lines.

IV. CONCLUSIONS

In this paper, we first comprehensively review and study the current status at home and abroad from the aspects of industrial big data collection, modeling of the intelligent product lines based on Ontology, the predictive diagnosis based on industrial big data, group learning of product line equipment and the product line reconfiguration of intelligent manufacturing. By this way, we reveal the challenges and problems the smart factory faces. Further, we point out the inadequacy of data analysis under the traditional manufacturing environments, and propose our research strategies and detailed research on the following aspects: acquisition schemes of industrial big data under the environment of intelligent manufacturing, Ontology modeling and deduction method based intelligent product lines, predictive diagnostic methods on production lines based on deep neural network, deep learning among devices based on cloud supplements and three-dimensional self-organized reconfiguration mechanism based on the supplements of cloud. This provides thoughts for future studies.

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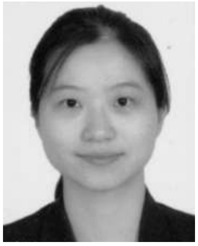

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