Smart Factory Production and Operation Management Methods based on HCPS

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***Abstract*—The human–cyber–physical system (HCPS) is a composite intelligent system comprising humans, cyber systems, and physical systems with the aim of achieving specific manufacturing goals at an optimized level. Smart factory is an important carrier of a new-generation intelligent manufacturing. In order to achieve the comprehensive collaboration of human-machine-thing and other elements in the smart factory, the HCPS is introduced to the smart factory in this paper. Firstly, a smart factory model is constructed based on human-cyber-physical (HCPS). Then, according to the characteristics of big data, Internet-of-Things(IoT) and artificial intelligence(AI), the management methods of smart factory is proposed, including production design, resource intelligent management and knowledge discovery. Finally, a guiding technology architecture of human-centered smart factory production and operation management is given. The smart factory based on HCPS is of great significance to realize the full use of various resources, and agile management.**

***Index Terms*—Human-cyber-physical system, Smart Factory, Production and Operation, Management Methods**

I. Introduction

In recent years, with the rapid development of new technologies such as big data, cloud computing, and AI, intelligent manufacturing is evolving toward a new-generation intelligent manufacturing. As an important carrier of the new-generation intelligent manufacturing, the smart factory is the main focus for China to promote the national strategy of "Made in China 2025" [1], [2].

Compared with traditional factories, the smart factory is a real-time production network that realizes human-machine-thing interconnection through high-speed industrial Internet. It has complex features of dynamic, flexible and agile. Meanwhile, its goal is to continuously improve product quality, performance and service levels, and reduce resource consumption. In this case, the smart factory needs the matching operation management methods and technologies that integrate product design, production, and service.

Along with the industrial revolution, the management theories and methods of production and operation have also emerged, such as Scientific Management represented by Taylor, Maslow Incentive Theory, Simon's Decision and Management Science, Immediate Production, Lean Production, Total Quality Management, Supply Chain Management, etc [3], [4]. These laid the theoretical foundation for the study of smart factory operation and management methods. However, new requirements have been put forward for the innovation of management methods in the context of human-centered, collaborative, green and intelligent manufacturing [5]–[7].

The human-cyber-physical system (HCPS) is a new-generation intelligent manufacturing system,which comprises humans, cyber systems, and physical systems with the aim of achieving specific manufacturing goals at an optimized level. Compared to traditional cyber–physical system (CPS), the central role of human is emphasized. The efficiency of human knowledge management and application is effectively improved by transferring human's manufacturing experience and knowledge to cyber system and physical system [2], [8]–[10]. In order to achieve the comprehensive collaboration of human-machine-thing and other elements in the smart factory, this work introduces HCPS to the smart factory, and proposed operation and management methods of smart factory according to the characteristics of big data, Internet-of-Things(IoT) and AI.

The rest of this paper is organized as follows: a smart factory model is constructed based on human-cyber-physical (HCPS) in Section II. Then, Section III, IV, V propose the management methods of smart factory in production design, resource intelligent management and knowledge discovery respectively. Finally, a guiding technology architecture of human-centered smart factory production and operation management is given in Section VI.

II. Smart Factory Model Based On HCPS

New technologies such as IoT and big data have changed the boundaries of traditional factories. Smart factory production operations and management should be deeply integrated with data and information resources, and achieve multi-agent collaboration and full use of resources. Therefore, the smart factory system model is constructed as shown in Fig 1. It is mainly consists of three layers: Execution Layer, Production and Operations Layer, Technology and Method layer. Its

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bottom layer is supported by a HCPS with comprehensive sensing (observable), well regulated and controlled (controllable), and multi-agent collaboration. Furthermore, it has the ability of learning and cognition, and can cope with the problems of complex and uncertainty [11], [12]. The upper layer is Technology and Method layer consisting of two major supporting systems: Industrial Internet and cloud computing. On one hand, real-time data from the Industrial Internet can be cleaned, analyzed, mined and stored through cloud computing. On the other hand, the intelligent security system of Industrial Internet can provide reliable guarantee for the production and operation.

The core part is the production and operation layer consisting of three functional systems: intelligent products designing, intelligent production, and intelligent services. To meet the demands of users, it can provide lean product design, production and services throughout the entire life cycle. Meanwhile, it takes advantage of the technical advantages of big data, cloud computing and industrial internet.

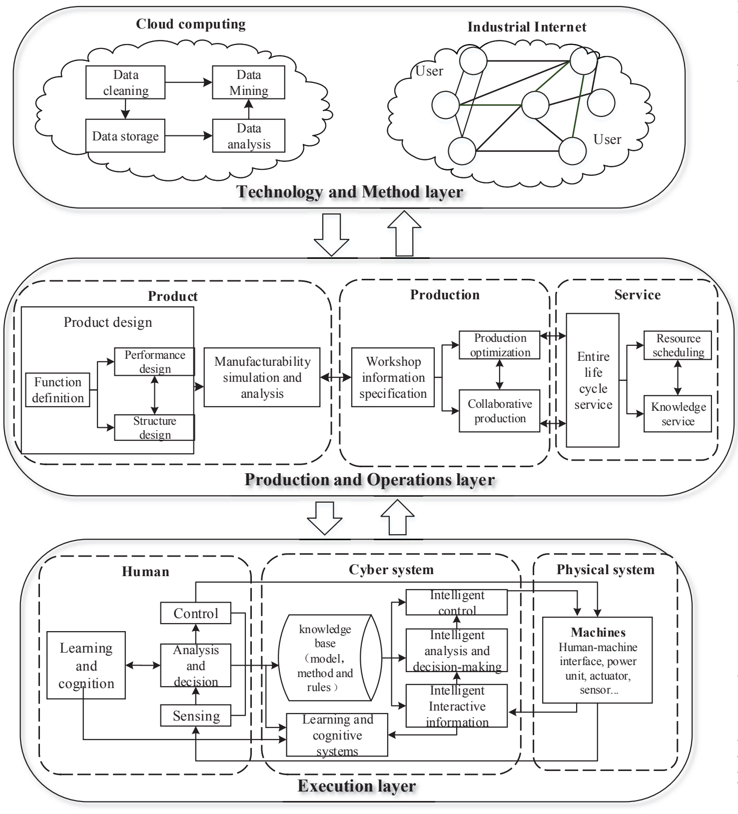

Fig. 1. The model of smart factory based on HCPS

III. Methods On Product Design and Production Integration Management

In the context of the new-generation intelligent manufacturing, logistics, information flow and capital flow are interconnected, the smart supply chain has brought fundamental changes to the design and production management model. In particular, the integrated design and production model have brought disruptive changes and challenges to the design and production of smart factory [13]. Therefore, in order to achieve the integrated design and production model, this paper proposes two management methods for product design and production in smart factory: designing adaptive online design and production network collaboration mechanism, constructing intelligent scheduling and dynamic optimization model, which are of great significance for shortening product lifecycle, improving product quality and reducing costs.

A. *Design and production integration model*

The collaboration of data and information is the basis for design and production integration model. Therefore, we propose a method of integrating the Product Lifecycle Management (PLM) system and the Enterprise Resource Planning (ERP) system. PLM system and ERP system are actually application systems for different goals. The PLM system is to capture, control, modify, and use data from product life cycle, such as product design and configuration, process planning [14]. The main goal of the ERP system is to control the production planning process, procurement and inventory management, and service, thereby balancing the relationship between expected product sales and required resources [15].

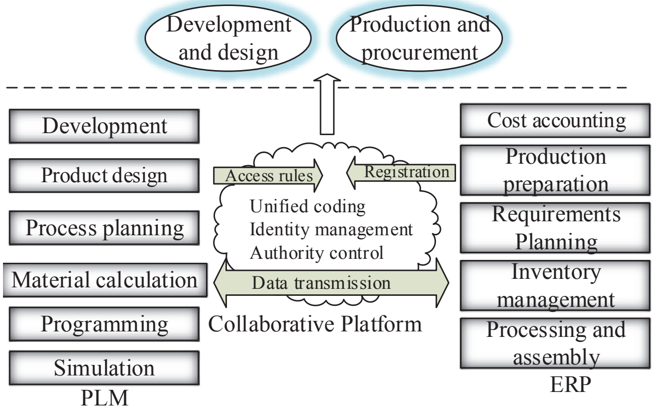

Fig. 2. Design and production data collaboration system

Combing the product structure data provided by the PLM system with the configuration management data of ERP system, a data collaboration platform can be established, as shown in Fig 2. On one hand, the basic data required for production such as material definition, BOM, and process route are transferred from the PLM system to the ERP system. On the other hand, the PLM system queries information from the ERP system, such as raw material prices, inventory, and manufacturing costs of semi-finished products. And then it designs costing or quotation, or eliminates inventory backlog.

Furthermore, the platform should have the following functions:

- Registered users of the ERP system can call the PLM function, and can use general browsing applications to find and read product data.
- The access rules of PLM must ensure the completeness of the product definition data. And the product definition

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data must be controlled by the PLM system throughout the entire life cycle of the product.

B. Intelligent Scheduling and Dynamic Optimization Model

Intelligent scheduling is also known as sorting or resource allocation optimization [16], [17]. The traditional fixed production line will gradually fail to meet the user's customized demands, and the modular production scheduling method that can be dynamically combined will become the main development direction. However, the uncertainties are the main limiting factors to achieve intelligent scheduling.

Considering the uncertain factors, we propose to establish a multi-stage and multi-dimensional Robust optimization model for production scheduling problems in smart factories. After the model is solved, the resource scheduling scheme with the least loss in the worst case is obtained. The machine learning method can be applied to analyze the data generated in the smart factory, and the specific distribution information of the uncertainty factors (such as the task duration) is obtained. Then, a data-driven distributed robust optimization model is constructed. Finally, the convex optimization method can be applied to solve the model, and a robust resource allocation scheme can be obtained.

For example, assume that $t_{i,j}$ is the time required for task i to be produced on device j, and its distribution belongs to an uncertain solution $p^t_{i,j}$ (such as the mean variance uncertain set $\{f : E[D^t_i] = \mu^t_i, Var[D^t_i] = \sigma^t_i\}$, where E is the expected function, Var is the variance.). Assume that $x^t_{i,j}$ is the state of task i on device j at time t (=1, for production; =0 for no production), the function h is the cost function of task consumption on the device. Then resource scheduling model based on distributed robust optimization $min\{\sum_{i,j,t} E_{p^t_{i,j}}[h(x^t_{i,j} \bullet p^t_{i,j})]\}$ can be constructed. Finally, according to the dual theory, the problem can be transformed into mixed linear integer programming, semi-definite program, conic program and so on.

IV. Methods on Resource Intelligent Management

In the context of big data and AI, there are many types of resources in smart factory, including human, hardware equipment, software, financial resources, materials, time, space, standards, patents, and so on. Moreover, resources have many unique characteristics, such as service distribution, network connectivity, state transparency, structural diversity, and behavioral dynamics. If these resources are effectively integrated to achieve resources intelligent management, it can helpful for mining and improving the intelligent characteristics of resources and realizing the value-added of resources. Therefore, this paper intends to implements intelligent management of resources from two methods: resource classification management and resource collaborative sharing mechanism.

A. Resource Classification Intelligent Management

Through the classification management of resources, adaptive management and control, it is helpful to explore and enhance the intelligent characteristics of resources and realize the value added of resources.

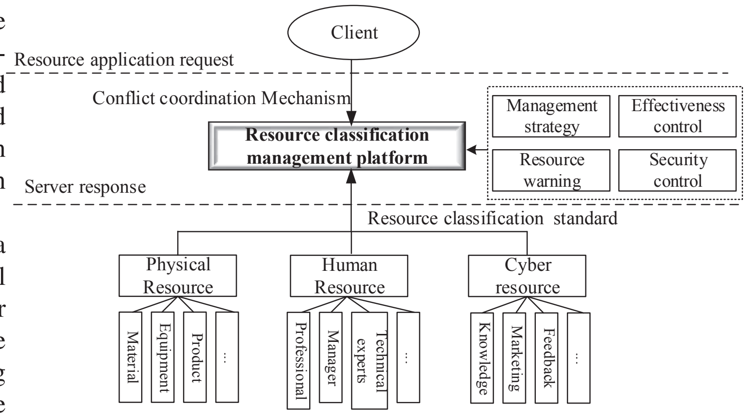

Fig. 3. Platform of Resource Classification Intelligent Management

As shown in Fig 3, it is an intelligent classification management system for smart factory resources. Firstly, according to the smart factory model and combining the characteristics of different resources, a classification standard for smart factory resources is proposed. The resources in the smart factory are divided into three categories: human resources, physical resources and cyber resources. Human resources are important resources in smart factories. With the rapid development of AI technology, although intelligent manufacturing systems can already run autonomously, machine failures may also put the system into a deadlock. Therefore, intelligent manufacturing systems need to integrate human knowledge and experience. And people should be kept in the process control loop and participate in the decision-making of the system. Physical resources refer to physical resources that exist in the physical world, and mainly include Equipment, Material, and product. Cyber resources not only include information from the product lifecycle (such as design scheme, distribution processing, packaging, loading, marketing and sales, service management). It also includes feedback from users, such as user comments, preferences, and behaviors.

Then, the resources are uploaded to the resource classification management platform according to the classification standard. The platform is aimed at improving the efficiency of resource distribution in smart factory. At the same time, rules and operating mechanisms are used to collect, express and integrate resources effectively, so as to provide service carriers to meet user demands.

On one hand, the operation of the platform can be controlled for effectiveness and security through management strategies such as pricing, contracts. And the shortage of resources can be warned in advance. On the other hand, in order to meet the resource application request from the client in time, a multi-agent and conflict coordination mechanism can be established to coordinate resource occupation and other issues.

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B. Collaborative and Sharing Mechanism of distributed resources

The resources smart factories are distributed, heterogeneous, and dynamic in smart factory. They need to be shared and coordinated with each other in order to serve production and customers, and achieve value creation finally. From a system perspective, adding the resource values is a strategic way to create value for smart factory. Therefore, in order to realize the collaborative and sharing of resources in smart factory, we need to focus on the following aspects.

- Research on information security and management mechanism during resource coordination and sharing: The blockchain is a "distributed ledger". Each node can display the general ledger, maintain the general ledger, and cannot tamper with the ledger [18], [19].The technical characteristics reflected by the blockchain can just meet the information security problem of distributed resource sharing in smart factory.
- The Incentive mechanism for resource sharing:Meeting demand and creating value is the purpose of resource collaboration and sharing in smart factory. But for stakeholders, improving service levels or reducing costs may lead to asymmetry in benefits and payments, thereby reducing the initiative for resource sharing. Therefore, the evolutionary game methods can be used, such as pricing design, contract design or smart contracts. Then, we can construct the model and study the optimal collaboration and sharing strategies to motivate stakeholders to share resources.

V. Methods On Knowledge Discovery and Management

Knowledge is an important resource for smart factory to gain competitive advantage. Under the background of big data and industrial Internet, we can realize intelligent knowledge services for different roles through knowledge discovery and effective management in production and operation practices, so as to better transform data and knowledge into benefits and values.

A. Construct a Smart Factory Knowledge System

The smart factory operation system is an open, shared, multi-agent, multi-level network structure. The accumulation of all kinds of knowledge brings great challenges to the smart factory production and operation. Therefore, the construction of knowledge system to meet the needs of different users is a problem that must be solved for the production and operation knowledge discovery and management of intelligent factory. Therefore, constructing a smart factory knowledge system that meets the demands of different users is a problem that must be solved.

In the process of production and operation, different roles have different concerns, and their requirements and knowledge are also different. Therefore, the key to knowledge service is to provide personalized knowledge to meet the personalized demands of different users. From the multi-level perspective, a smart factory knowledge system is constructed based on different granularity knowledge in this paper, as shown in Fig 4. According to the source of knowledge, the knowledge in the smart factory can be divided into external knowledge and internal knowledge. External knowledge is mainly summarized and classified from government, society, market and other aspects. Internal knowledge is further classified based on different role requirements, mainly including management level knowledge, design level knowledge, production level knowledge, operation level knowledge and service level knowledge.

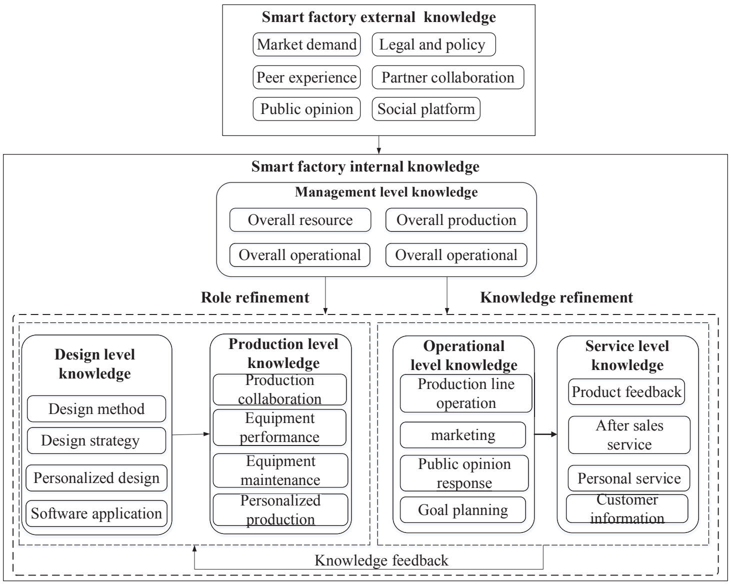

Fig. 4. Smart Factory Knowledge System Framework

B. Knowledge Discovery Method for Big Data of Smart Factory

In the context of Industry 4.0, big data has become a strategic resource for smart factory, which also is an important reference for production and operation management [20].Mining more information and knowledge from massive data helps to better realize intelligent knowledge services and applications. Currently, data mining technologies used commonly include machine learning algorithms (such as association analysis, cluster analysis, sequential pattern analysis, and predictive analysis, etc.), deep learning algorithms, big data analysis based on computational intelligence (such as swarm intelligence, evolutionary computing, etc.) [21], [22].

However, data incompleteness is a common problem in industrial big data. We can use data analysis models and methods of Rough Set Theory to obtain the knowledge that meets the demands of users with minimum cost. For example, Three-way Decision approach [23] can be introduced to the smart factory market evaluation. By analyzing the risks of the three-way (including positive domain, negative domain, and boundary domain) brought by the market evaluation scheme, the optimal decision is selected so that the market evaluation has the minimum decision risk.

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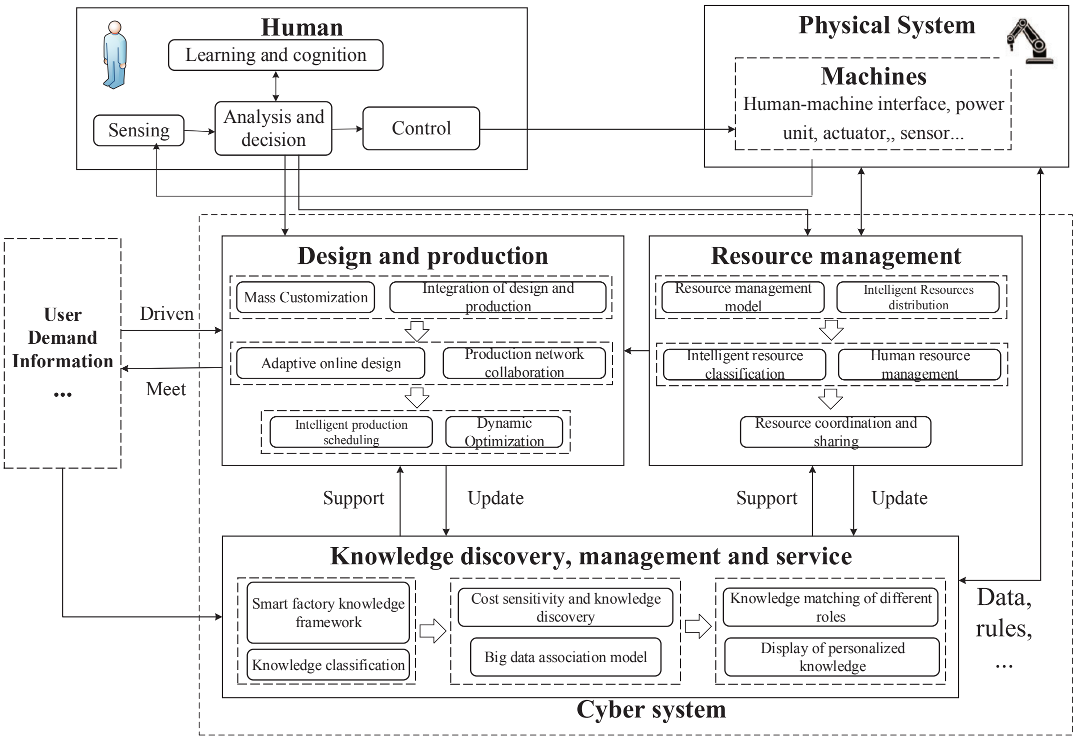

Fig. 5. Human-centered smart factory production and operation management technology architecture

Assume that X_R and X_B are the set of schemes that meet and do not meet user demand C; a_P, a_B, and a_N represent the three actions of receiving a scheme, delaying a decision, and rejecting a scheme respectively. Because different actions will result in different losses, then, λ_{PP}, λ_{NP}, and λ_{BP} respectively represent the loss of actions a_P, a_B, and a_N when the user's demand C is meet. Similarly, λ_{PN}, λ_{NN}, and λ_{BN}, respectively represent the loss of actions a_P, a_B, and a_N when the user's demand C is not meet. Using three-way decision expectation risk calculation methods, the decision risks of the rough set including positive domain, negative domain, and boundary domain are obtained as follows:

$$R(a_P \mid \Theta) = \lambda_{PP} Pr(X_R \mid \Theta) + \lambda_{PN} Pr(X_B \mid \Theta),$$

$$R(a_N \mid \Theta) = \lambda_{NP} Pr(X_R \mid \Theta) + \lambda_{NN} Pr(X_B \mid \Theta),$$

$$R(a_B \mid \Theta) = \lambda_{BP} Pr(X_R \mid \Theta) + \lambda_{BN} Pr(X_B \mid \Theta).$$

Where, $R(a_i \mid \Theta)$ is the decision risk of market evaluation scheme, $Pr(X_R \mid \Theta)$ is the prior probability of market evaluation as scheme X_R, and $Pr(X_B \mid \Theta)$ is the prior probability of market evaluation as scheme X_B.

According to the minimum risk principle of three-way decision rough sets, the optimal market evaluation decision rules of smart factory can be obtained as follows:

If $R(a_P \mid \Theta) < R(a_N \mid \Theta)$ and $R(a_P \mid \Theta) < R(a_B \mid \Theta)$, then decide $POS(\Theta)$;

If $R(a_N \mid \Theta) < R(a_P \mid \Theta)$ and $R(a_N \mid \Theta) < R(a_B \mid \Theta)$, then decide $NEG(\Theta)$;

If $R(a_B \mid \Theta) < R(a_P \mid \Theta)$ and $R(a_B \mid \Theta) < R(a_N \mid \Theta)$, then decide $BND(\Theta)$.

VI. Technology Architecture of Smart Factory Production and Operation Management

Smart factory is a large system based on HCPS. In addition, human-centered should be the key to the production and operation for two main reasons. On one hand, the realization of intelligent, flexible production and operation is inseparable from human management. Because managers use most of the funds, facilities, equipment, etc. to organize production and operation. On the other hand, the production and operation in smart factory is driven by the user's demand information. As shown in Fig 5, the technology architecture of the "human-centered" smart factory production and operation management methods is given. Firstly, the relationship between human and cyber systems has changed qualitatively. Human can participate in controlling the operation of cyber systems because of analysis and decision-making capabilities. Moreover, human can transfer part of the cognitive and learning brainwork to the cyber system, enabling the cyber system to cognize and learn. Then, the main role of machines in the physical system is to schedule the specific resources of human and cyber system. Next, from the three aspects of product design and production management, resource management, and knowledge discovery and management, guiding technical methods are proposed, and it is expected to realize the collaboration and optimization of the entire life cycle. Specific methods such as optimizing design and production by implementing adaptive online design

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and production network collaboration. We can also research from the aspects of intelligent resources classification, constructing smart factory knowledge systems, and matching of different role knowledge.

On the whole, the smart factory is a closed-loop feedback system. The market demand information drives the operation and maintenance of the Human-Cyber-Physical system, and then the human, cyber and physical three systems are related to each other, and they are continuously collaborative and optimized to meet the user's demand with high efficiency and high quality.

VII. Conclusion

In the context of the new-generation of intelligent manufacturing, smart factories need matching product-production-service integrated control and optimization management theories, methods, and technologies. For this purpose, a smart factory model based on HCPS is constructed. We have repositioned the role of human in factory management, and propose management methods in product design and production, resource management, and knowledge discovery of smart factory. Through the integration and application of data and knowledge in each stage, a feedback mechanism can be formed. Finally, a "human-centered" production and management technology architecture is proposed, which can guide the coordination and optimization of the entire life cycle including design, production, operation and maintenance. This work can provide guiding management methods for achieving efficient collaboration and value sharing, resource scheduling optimization and knowledge services, and adapting to dynamic market needs.

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