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Human–Cyber–Physical Systems (HCPSs) in the Context of New-Generation Intelligent Manufacturing

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A B S T R A C T

An intelligent manufacturing system is a composite intelligent system comprising humans, cyber systems, and physical systems with the aim of achieving specific manufacturing goals at an optimized level. This kind of intelligent system is called a human–cyber–physical system (HCPS). In terms of technology, HCPSs can both reveal technological principles and form the technological architecture for intelligent manufacturing. It can be concluded that the essence of intelligent manufacturing is to design, construct, and apply HCPSs in various cases and at different levels. With advances in information technology, intelligent manufacturing has passed through the stages of digital manufacturing and digital-networked manufacturing, and is evolving toward new-generation intelligent manufacturing (NGIM). NGIM is characterized by the in-depth integration of new-generation artificial intelligence (AI) technology (i.e., enabling technology) with advanced manufacturing technology (i.e., root technology); it is the core driving force of the new industrial revolution. In this study, the evolutionary footprint of intelligent manufacturing is reviewed from the perspective of HCPSs, and the implications, characteristics, technical frame, and key technologies of HCPSs for NGIM are then discussed in depth. Finally, an outlook of the major challenges of HCPSs for NGIM is proposed.

1. Introduction

Intelligent manufacturing is a general concept that has been continuously evolving with the development and integration of information technology and manufacturing technology. In general, intelligent manufacturing has passed through the stages of digital manufacturing and digital-networked manufacturing, and is evolving toward new-generation intelligent manufacturing (NGIM), due to the recent fast-paced development and influential breakthroughs that have been occurring in the internet, big data, and artificial intelligence (AI) [1–14]. Although the intelligent manufacturing is constantly evolving [15–24], its fundamental goals remain the same: namely, to improve quality, increase efficiency, reduce costs, and enhance competitiveness through unrelenting efforts toward optimization. From the perspective of system constitution, an intelligent manufacturing system is always a human–cyber–physical system (HCPS)—that is, a kind of composite intelligent system comprising humans, cyber systems, and physical systems with the aim of achieving specific goals at an optimized level [25–28]. In other words, the essence of intelligent manufacturing is to design, construct, and apply HCPSs in various cases at different levels.

NGIM is characterized by the in-depth integration of new-generation AI technology with advanced manufacturing technology, and is the core driving force of the new industrial revolution. In order to promote the development of NGIM, this work presents an examination of the implications, characteristics, technical frame, and key technologies of HCPSs for NGIM, along with an outlook of the major challenges of HCPSs for NGIM.

The rest of this paper is organized as follows: Section 2 reviews the evolution and development of manufacturing systems, and Section 3 analyzes the implications of HCPSs for NGIM from system and technology perspectives. A technical framework and key technologies of HCPSs for NGIM are presented in Section 4. Finally, major challenges are outlined in Section 5.

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2. Evolution of HCPSs for intelligent manufacturing

2.1. Phase I: Human–physical systems for traditional manufacturing

Humans first learned to make and use tools more than two million years ago [29]. Progressing from the Stone Age through the Bronze Age to the Iron Age, these early simple production systems lasted for over a million years, powered by human and animal labor. With the development of the First Industrial Revolution, which was marked by the invention of the steam machine, and the Second Industrial Revolution, which was marked by the invention of the electric motor, humans have continually invented, created, and improved various machines and applied them to manufacture all kinds of goods [13]. These traditional manufacturing systems, which were comprised of humans and physical machines, replaced a significant amount of manual labor and substantially increased manufacturing quality, efficiency, and societal productivity.

A traditional manufacturing system consists of two major components—namely, humans and physical systems such as machines—and is therefore a human–physical system (HPS), as shown in Fig. 1. In an HPS, physical systems, through which working tasks are completed, act as the "executing body," while humans are the "master." Humans are both the creators of physical systems and the managers and users of physical systems. In an HPS, many of the activities required to complete the working tasks—such as perception, cognition, learning, analysis, decision-making, control, and operation—must be supplied by humans. For example, in machining with traditional machine tools, operators must carefully observe, analyze, manipulate, and control the machining process. A general schematic of an HPS is shown in Fig. 2.

2.2. Phase II: HCPS1.0 for digital manufacturing

The manufacturing sector entered the era of digital manufacturing in the middle of the 20th century, driven by the development and wide application of information technologies including computers, communication, and numerical control [30–33]. The information revolution, which was marked by digitalization, led and promoted the Third Industrial Revolution [34–36].

Compared with traditional manufacturing systems, digital manufacturing systems are characterized by the emergence of a cyber system between the human and physical system, transforming the previous binary HPS into the ternary HCPS, as shown in Fig. 3. A cyber system consists of software and hardware; its main function is to complete various tasks that were previously performed by human operators, including sensing, analysis, decision-making, and control. For example, in machining with a computer numerical control (CNC) machine tool, which is equipped with a cyber system called the CNC system, the CNC system can automatically direct the machine tool to complete the machining processes according to digital machining programs provided by the operators [37].

Digital manufacturing can be defined as first-generation intelligent manufacturing, and the HCPS for digital manufacturing will be referred to herein as HCPS1.0. Compared with the HPS, HCPS1.0 has substantially enhanced capabilities—especially in computation,

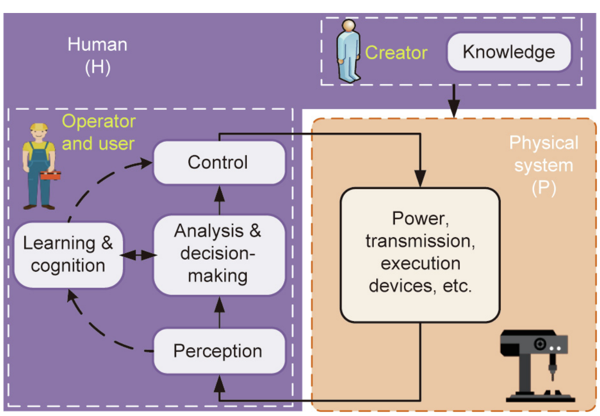

Fig. 1. An HPS for traditional manufacturing.

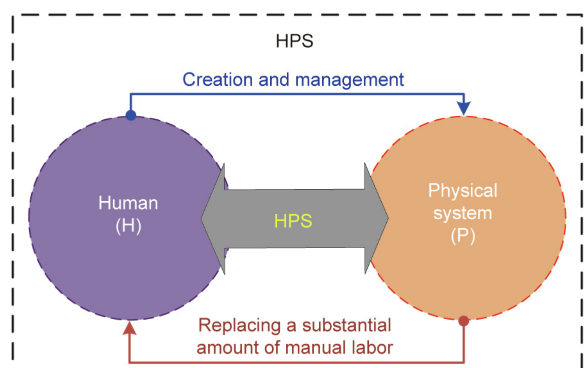

Fig. 2. Schematic of an HPS.

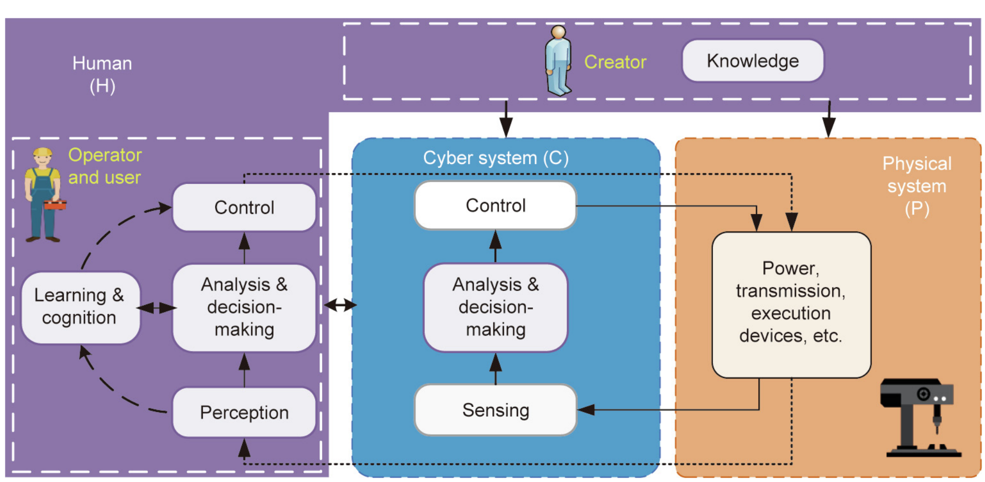

Fig. 3. HCPS1.0 for digital manufacturing.

analysis, precision control, and perception—due to its integration of the strengths of humans, cyber systems, and physical systems. The result is remarkable: Manufacturing systems based on HCPS1.0 have significant improvements in aspects such as automation, efficiency, quality, stability, and the ability to solve complicated issues. In addition, not only can the manual labor of operators be further reduced, but also some of the mental work can be performed by cyber systems, thus effectively increasing the efficiency of knowledge dissemination and utilization. A schematic for HCPS1.0 is shown in Fig. 4.

As shown in Fig. 4, the upgrade from binary HPS to ternary HCPS generated two new binary subsystems: the human–cyber system (HCS) and the cyber–physical system (CPS) [26,38,39]. The CPS theory was first proposed by American scholars at the beginning of the 21st century [40,41] and has been employed as a core technology of Industry 4.0 in Germany [42,43].

In addition, the introduction of cyber systems has fundamentally transformed the feature of machines by transforming them from unary physical systems to binary CPSs (i.e., intelligent machines). In this sense, the Third Industrial Revolution can be regarded as the beginning of the Second Machine Age [13].

In the context of HCPS1.0, while physical systems continue to act as the "executing body," cyber systems perform a significant amount of analysis, computation, and control work previously performed by humans. Humans are still the "master." First, both physical systems and cyber systems are designed and created by humans. The underlying analysis, computation and control models, methods, and rules are all developed by humans by drawing upon theoretical knowledge, experience, and experimental data and programming these into the cyber systems. In addition, the operation of HCPS1.0 relies on the knowledge and experience of the operator to a significant extent [44]. For example, when machining with CNC machine tools, as mentioned above, operators must program the machining process appropriately according to their knowledge and experience, monitor the process, and make adjustments where necessary.

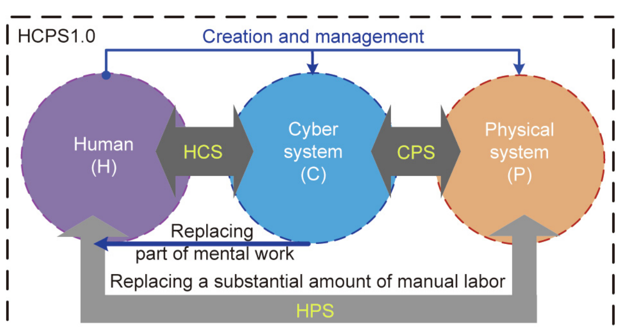

Fig. 4. Schematic of HCPS1.0. HCS: human–cyber system; CPS: cyber–physical system.

2.3. Phase III: HCPS1.5 for digital-networked manufacturing

By the end of the 20th century, the rapidly developing internet technology had been widely applied to the manufacturing industry, driving a transformation from digital manufacturing to digital-networked manufacturing [17,45–47]. Digital-networked manufacturing is, in essence, "internet + digital manufacturing" and can be defined as second-generation intelligent manufacturing. The digital-networked manufacturing system remains an HCPS; however, it is referred to herein as HCPS1.5, since it has fundamental differences compared with HCPS1.0 for digital manufacturing, as shown in Fig. 5. The most significant difference lies in the cyber system. In the cyber system of HCPS1.5, the Industrial Internet and the cloud platform are critical components that can connect relevant cyber systems, physical systems, and humans, thus serving as a tool for system integration. Information exchange and coordinated and integrated optimization have become important parts of the cyber system. Meanwhile, the humans in HCPS1.5 have become a network-connected community with common value-creation goals, and include the people from the enterprise hosting the system along with its suppliers, sales agents, customers, and so on. These changes transform the manufacturing industry, both from a product-centric model to a customer-centric model and from a production manufacturing pattern to a production–service manufacturing pattern.

The essence of digital-networked manufacturing is the realization of extensive connections of humans, processes, data, and things through networks, and the reshaping of the manufacturing value chain through in-enterprise and inter-enterprise integration, cooperation, sharing, and optimization of various resources. For example, CNC machine tool manufacturers and their suppliers can engage in remote-operation maintenance of their own products

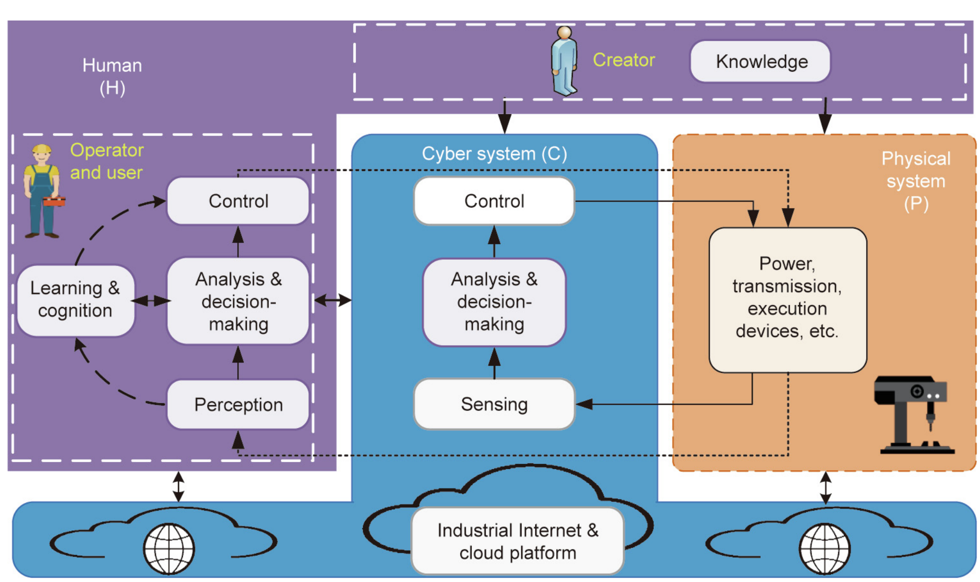

Fig. 5. HCPS1.5 for digital-networked manufacturing.

through networks, in order to jointly create values with the enterprises using their products. Enterprises using CNC machine tools can also create added value through the integration and optimization of in-enterprise sources regarding design, production, service, and management [37,48,49].

2.4. Phase IV: HCPS2.0 for NGIM

Modern manufacturing enterprises generally face strong demands for improvement in quality, efficiency, and quick market response. These demands have raised an urgent need for a revolutionary industrial upgrade for the manufacturing industry. On a technical level, it is still difficult for digital-networked manufacturing to overcome the huge difficulties faced by the manufacturing industry; thus, further manufacturing technology innovation and upgrades are greatly desired.

Since the beginning of the 21st century, huge progress has been made in information technologies such as the internet, cloud computing, and big data [12,50–52]. The integration of these technological advances is leading to the strategic breakthrough of new-generation AI, which has become the core technology of a new round of scientific and technological revolution [2,5,53–55].

The in-depth integration of new-generation AI technology with advanced manufacturing technology is leading to NGIM [1]. Breakthroughs and broad applications of NGIM will reshape the technological architecture, production mode, and industrial pattern of the manufacturing industry. The information revolution, which is marked by AI, is leading and promoting the Fourth Industrial Revolution.

The NGIM system remains an HCPS; however, it is referred to herein as HCPS2.0, since it has essential differences in comparison with HCPS1.5 for digital-networked manufacturing, as shown in Fig. 6. As in the shift from HCPS1.0 to HCPS1.5, the most distinct changes occur in the cyber system. A new component is introduced to the cyber system of HCPS2.0, enabling it to perform self-learning and cognition by using new-generation AI technology; this leads to greater power in aspects such as perception, decision-making, control, and—most importantly—the capability to learn and generate knowledge. The knowledge base in the HCPS2.0 cyber system is jointly built by humans and by the self-learning and cognition module of the cyber system; thus, it contains not only the knowledge provided by humans but—more importantly—the knowledge learned by the cyber system itself, and particularly the knowledge that is difficult for humans to describe and process. Moreover, the knowledge base is able to constantly upgrade, improve, and optimize itself through self-learning and cognition during the application process. To use a metaphor, the relationship between humans and cyber systems has fundamentally changed from one of "giving fish" to one of "teaching how to fish" [1,2,6]. A schematic of HCPS2.0 is shown in Fig. 7.

HCPS2.0 for NGIM can not only bring about revolutionary changes in the means and efficiency of creating, accumulating, utilizing, imparting, and inheriting manufacturing knowledge, but also significantly increase the ability of manufacturing systems to handle uncertain and complicated problems, thereby leading to vast improvements in manufacturing system modeling and decision-making. For example, in machining with intelligent machine tools, a digital model of the entire machining system can be built through sensing, learning, and cognition, and can then be used to optimize and control the machining process in order to obtain high machining quality and efficiency as well as low energy consumption [48,49,56].

The role of humans as "master" is even more prominent in HCPS2.0 for NGIM [28,57–61]. As the creators, managers, and operators of intelligent machines, humans' abilities and skills will be greatly improved and their intellectual potential will be fully unleashed for further emancipation of the productive forces. Knowledge engineering will free humans from a significant amount of intellectual and manual labor and allow them to engage in more valuable creative work.

In summary, intelligent manufacturing will better serve humans. Having evolved from HPS to HCPS1.0 and then from HCPS1.0 to HCPS1.5, intelligent manufacturing is evolving from HCPS1.5 to HCPS2.0, and will advance stage by stage, spiraling up and expanding in an infinite process, as shown in Fig. 8.

3. Implications of HCPS2.0 for NGIM

HCPS2.0 is a system architecture and technical framework for NGIM, which can offer a guide to effectively solve various problems in the upgrading of manufacturing industry. The implications of

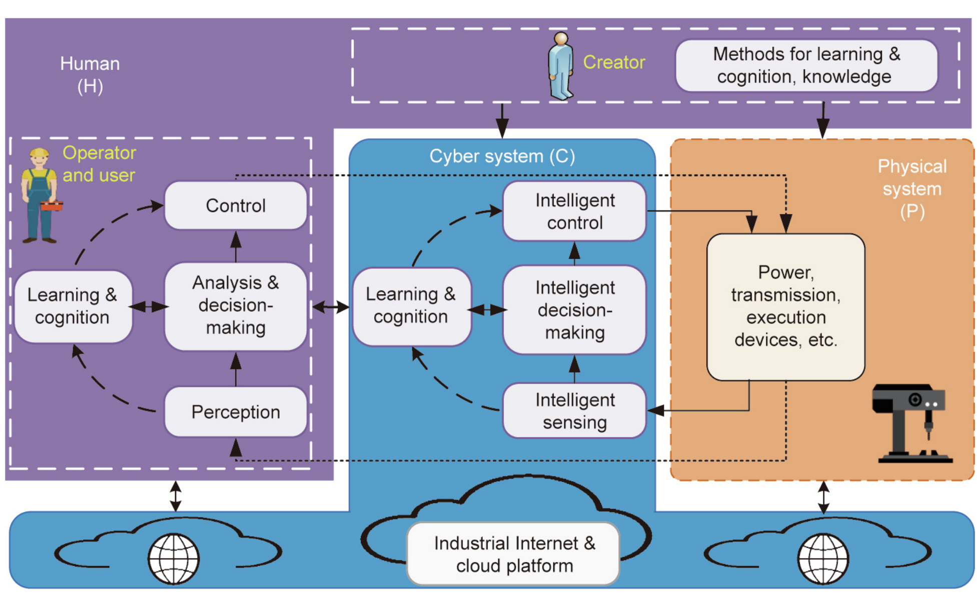

Fig. 6. HCPS2.0 for NGIM.

HCPS2.0 for NGIM may be described from both system and technology perspectives.

3.1. The system perspective

HCPS2.0 for NGIM is a composite intelligent system that comprises relevant humans, AI-capable cyber systems, and physical systems, with the aim of achieving specific manufacturing goals at an optimal level. In this paradigm, physical systems, which execute the energy and material flows of manufacturing activities and complete the manufacturing tasks, act as the "executing body." AI-capable cyber systems act as the core of the information flows of the manufacturing activities, and help humans to complete the necessary perception, cognition, analysis, decision-making, and control of the physical systems for their optimized operation. Humans play the role of the "master"; they are the creators of physical systems and cyber systems, so the intelligence of cyber systems—no matter how powerful—comes from humans. In addition, humans are the operators and users of physical systems and cyber systems, so humans remain in the central position and possess the highest right to make decisions and enact control.

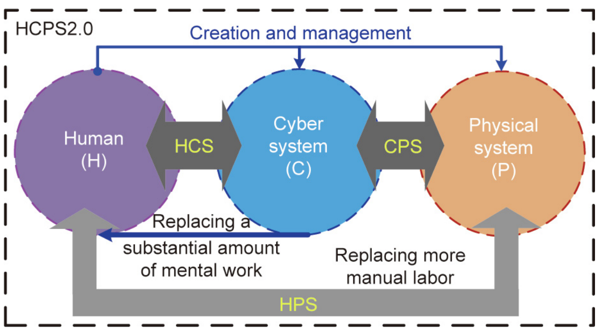

Fig. 7. Schematic of HCPS2.0.

HCPS2.0 for NGIM should be geared to comprehensively upgrade all manufacturing activities, including research and development (R&D), production, sales, service, management, and system integration, in order to substantially increase quality, efficiency, and competitiveness. In other words, the essence of NGIM is to construct and apply different HCPS2.0 systems serving different purposes and integrate them as a network of HCPS2.0 systems in order to deliver a revolutionary improvement of societal productivity. In general, HCPS2.0 for NGIM possesses three main characteristics: intelligence, grand systems, and ubiquitous integration.

First, intelligence is the primary characteristic of HCPS2.0 for NGIM, as HCPS2.0 systems can always keep their status and behavior optimal through autonomous learning and adjustment.

Second, HCPS2.0 for NGIM can establish grand systems through system integration. In general, HCPS2.0 for a manufacturing enterprise includes three functional systems—intelligent products, intelligent production, and intelligent services—and two supporting systems—the intelligent manufacturing cloud and the Industrial Internet [52,62,63].

Third, HCPS2.0 for NGIM presents the unprecedented feature of ubiquitous integration [4,64–66]. From one perspective, internally dynamic integration in an enterprise is pursued for intelligent

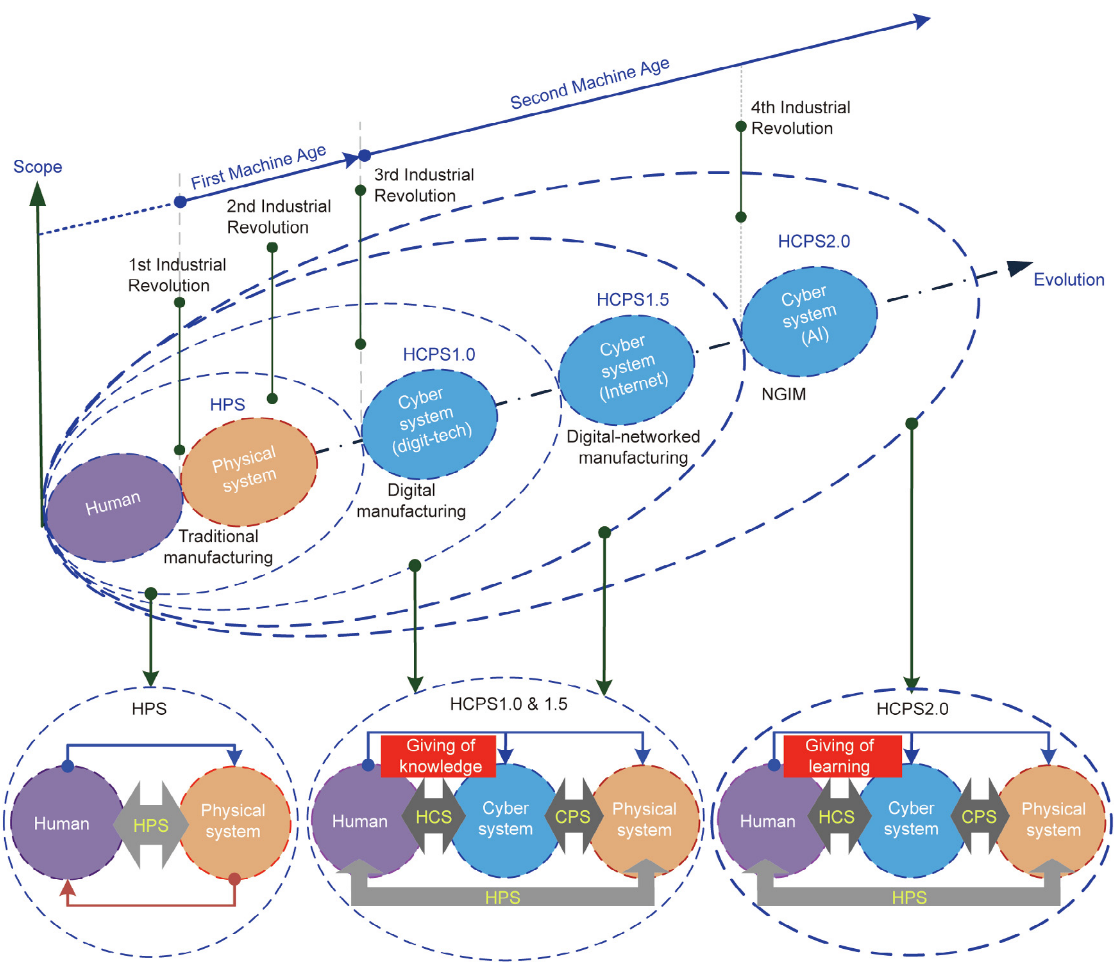

Fig. 8. Evolution of HCPS-based intelligent manufacturing.

design, production, sales, services, and management processes, resulting in vertical integration. The Industrial Internet and the intelligent manufacturing cloud enable integration, sharing, collaboration, and optimization among enterprises, resulting in horizontal integration. From another perspective, externally deep integration should be promoted between manufacturing, financial, and upstream and downstream industries. This integration will result in the new commercial co-development of service-oriented manufacturing and production-based services. In addition, NGIM has the potential to integrate with intelligent cities, intelligent transportation, intelligent healthcare, and intelligent agriculture to form a giant system of intelligent ecosystems—an "intelligent society."

3.2. The technology perspective

In HCPS2.0, the cyber systems are equipped with powerful intelligence by leveraging new-generation AI, thereby enabling three major technological characteristics [6,67].

The first, most critical, characteristic is that the cyber systems have the ability to solve uncertain and complex problems; furthermore, problem-solving methods shift from the traditional model of emphasizing causality to an innovative model of emphasizing correlation, and further toward an advanced model of deeply integrating correlation with causality. This shift will lead to fundamental improvements in the modeling and optimization of manufacturing systems [5–7,13].

The second most important characteristic is that the cyber systems have capacities such as learning, cognitive skills, and the generation and better utilization of knowledge [2,53–55,68–70]; these will lead to revolutionary changes in the efficiency of knowledge generation, utilization, importation, and accumulation, and to the significant promotion of the marginal productivity of knowledge as a core productive element [2,53–55,68–70].

The third characteristic is the formation of human–machine hybrid-augmented intelligence, which gives full scope to and synergistically integrates the advantages of human intelligence and machine intelligence. This will result in the innovation potential of humans being fully unleashed and the innovation capacities of the manufacturing industry increasing tremendously [2,5,8].

Overall, HCPS2.0 is currently in the stage of weak AI or narrow AI (ability to accomplish a narrow set of goals, e.g., play chess or drive a car) and will gain rapid development as AI advances from narrow AI to strong AI or general AI (ability to accomplish virtually any goal, including learning) [2,5,71].

HCPS2.0 can be regarded as a universal solution that will effectively solve the challenges occurring in the transformation and upgrading of the manufacturing industry, and that can be widely applied for product innovation, production innovation, and service innovation in discrete manufacturing and process-oriented manufacturing. HCPS2.0 is expected to progress as follows:

HCPS2.0 will enable manufacturing systems with new-generation AI technology. While there are many approaches to the innovation-driven development of manufacturing engineering, two are particularly important. The first of these approaches is original innovation in manufacturing technology, which is fundamental and of the utmost importance. The second approach is the application of common enabling technologies to promote manufacturing technology, which can result in the development of innovative manufacturing technology through the integration of the two technologies, and which can be used to upgrade various manufacturing systems. This kind of innovation is revolutionary, integrative, and universal. The common enabling technologies of the last three industrial revolutions were the steam engine, electric motor technology, and digital technology, respectively; in the Fourth Industrial Revolution, the common enabling technology is AI technology [1]. The in-depth integration of these generic enabling technologies with manufacturing technologies drives revolutionary transformation and upgrading of the manufacturing sector. Therefore, NGIM based on HCPS2.0 will be the main driver of the innovation-driven development of the manufacturing sector and the main roadmap of its transformation and upgrading.

However, new-generation AI technology must be thoroughly integrated with technologies in the manufacturing domain to create NGIM technologies. Because manufacturing is the foundation and enabling technologies are used to upgrade manufacturing, enabling technologies can give full scope only through in-depth integration with manufacturing technologies. To sum up, manufacturing technologies are the fundamental technology, while intelligent technologies are the enabling technology; thus, there should be dialectical unity and integrative development between these technologies. From a perspective that focuses on intelligent technology, NGIM can be seen as the endeavor to promote and apply advanced information technologies. From a perspective that focuses on manufacturing technology, however, NGIM can also be seen as the endeavor to employ generic enabling technologies to promote innovation in and the upgrading of manufacturing systems in different industries.

4. Technical framework of HCPS2.0 for NGIM

4.1. Overall architecture of HCPS2.0

The overall architecture of HCPS for intelligent manufacturing can be described from the three dimensions of intelligent manufacturing: the value dimension, the technical dimension, and the organizational dimension [72,73], as shown in Fig. 9.

4.1.1. The value dimension of intelligent manufacturing and the functional properties of the HCPS

The fundamental goal of intelligent manufacturing is to achieve value creation and value optimization by the construction and application of HCPSs. The value of intelligent manufacturing is mainly reflected in product innovation, intelligent production, intelligent services, and system integration [74,75], which correspond to product (R&D) HCPS, production HCPS, service HCPS, and integrated HCPS, respectively.

When products are made to be digital, networked, and intelligent through innovation, their product functions and performance

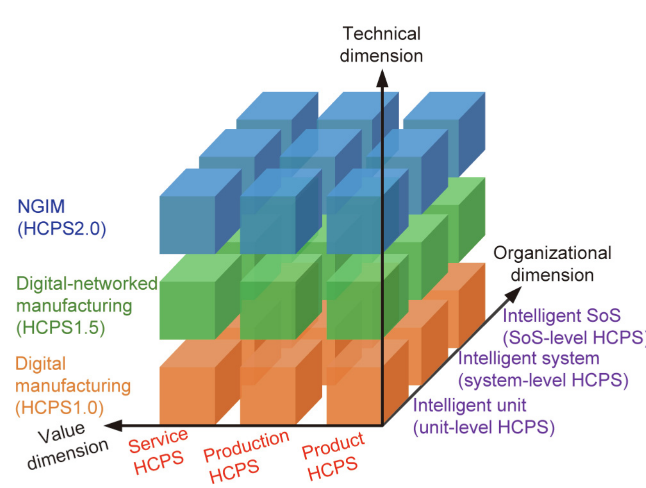

Fig. 9. Overall architecture of intelligent manufacturing based on HCPS. SoS: system of systems.

are enhanced, which increases their added value and market competitiveness. Meanwhile, it is important to increase product quality and efficiency in product design by applying innovative processes via digital, networked, and intelligent technologies [76]. Product innovations can be further divided into categories such as product design innovation, evaluation and validation innovation, and their integration. Product (R&D) HCPSs can likewise be further divided.

Intelligent production will realize high-quality, flexible, efficient, and sustainable product manufacturing by comprehensively enhancing production and management innovation via digital, networked, and intelligent methods [75,77]. In general, production activity can be divided into process design, process engineering, quality assurance, production management, and their integration. Some of these links can be further divided. For example, process engineering can be divided into multiple production lines and their integration, and a production line can be further divided into equipment and their integration. Likewise, production HCPSs can be further broken down into sub-layers.

Intelligent services include user-centric services that are provided throughout the life-cycle of products via digital, networked, and intelligent technologies [63,74,78,79]; such services include customization and remote operation and maintenance, which extend to service-oriented manufacturing and production-based services. In this way, intelligent service HCPSs can be divided into customization service HCPSs and remote operation and maintenance HCPSs, among others.

As a key characteristic of NGIM, deep integration is an important aspect of the way in which NGIM delivers its value [4]. Given the functional properties of HCPSs, their deep integration will lead to multifunctional, integrated, and complex HCPSs.

4.1.2. The technical dimension of intelligent manufacturing and the technical properties of HCPS

The technology of intelligent manufacturing has evolved from digital manufacturing (HCPS1.0) to digital-networked manufacturing (HCPS1.5), and then to NGIM (HCPS2.0), as shown in Fig. 10 [1]. Digital manufacturing is the foundation of intelligent manufacturing, and has evolved through three basic paradigms. Digital-networked manufacturing provides the necessary network infrastructure for intelligent manufacturing while integrating the business value chain. On the basis of previous two paradigms, NGIM makes manufacturing capable of true AI by integrating advanced manufacturing technology with new-generation AI technology and is a core technology of a new round of industrial revolution.

The three basic paradigms of HCPS-based intelligent manufacturing reflect the intrinsic patterns of the development of intelligent manufacturing. These three paradigms have unfolded progressively—each with its own characteristics and each solving problems in its respective stage—thus reflecting the progression of the integrated development of advanced information technology and manufacturing technology. However, the three basic paradigms are not entirely independent; rather, they are iterative and correlated with each other, thereby reflecting a fusion in the characteristics of intelligent manufacturing development [35].

4.1.3. The organizational dimension of intelligent manufacturing and the systematic properties of HCPS

The organization of intelligent manufacturing consists of three levels—intelligent unit, intelligent system, and intelligent system of systems (SoS)—which correspond to unit-level HCPS, system-level HCPS, and SoS-level HCPS, respectively [39,80,81].

An *intelligent unit* is the smallest functional unit of intelligent manufacturing. It is comprised of humans, cyber systems, and physical systems. An *intelligent system* integrates multiple intelligent units through the industrial network to achieve automated data flow in a larger scope and across broader areas. It helps to improve the breadth, accuracy, and depth of manufacturing resource allocation across production lines, workshops, and businesses to form a system-level HCPS. An *intelligent SoS* is a system that integrates multiple intelligent systems through Industrial-Internet-based integration across systems and platforms. It creates an open, coordinated, and shared industrial ecosystem, thus forming an SoS-level HCPS. The three-level architecture model of HCPS for intelligent manufacturing is shown in Fig. 11.

In summary, the overall architecture of HCPS2.0 for NGIM can be described using the multi-level hierarchical structure shown in Fig. 12.

4.2. Key technologies of unit-level HCPS2.0

For a unit-level HCPS2.0, regardless of its purpose (whether a design system, production equipment, etc.), the critical technologies can be divided into the three categories of manufacturing domain technologies, machine intelligence technologies, and human–machine collaboration technologies, as shown in Fig. 13.

4.2.1. Manufacturing domain technologies

Manufacturing domain technologies are the technologies involved in the physical systems of an HCPS; they include generic manufacturing technologies and specialized domain technologies [9]. Intelligent manufacturing has its roots in manufacturing. Therefore, manufacturing technologies are a basic technology of HCPS for intelligent manufacturing. Meanwhile, intelligent manufacturing not only involves discrete manufacturing and

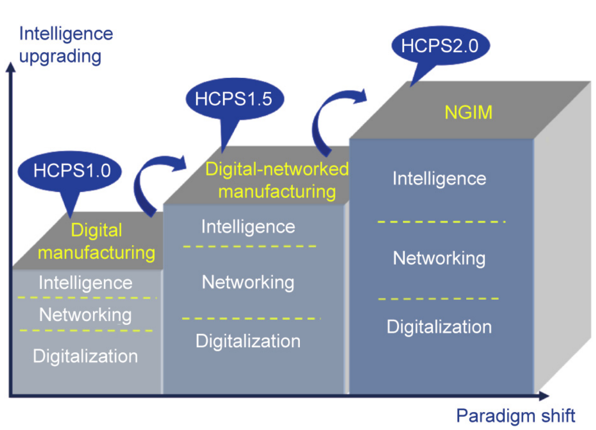

Fig. 10. Three basic paradigms of intelligent manufacturing [1].

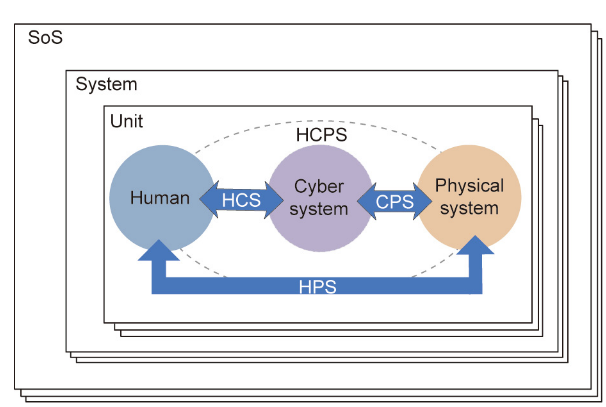

Fig. 11. Three-level architecture model of HCPS for intelligent manufacturing.

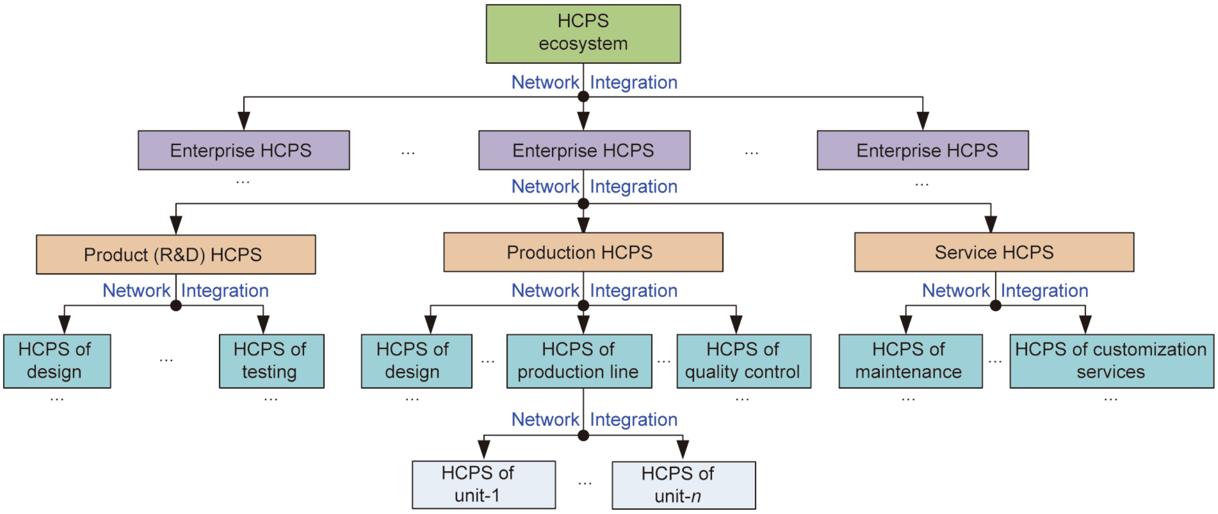

Fig. 12. Hierarchical levels of HCPS2.0 for NGIM.

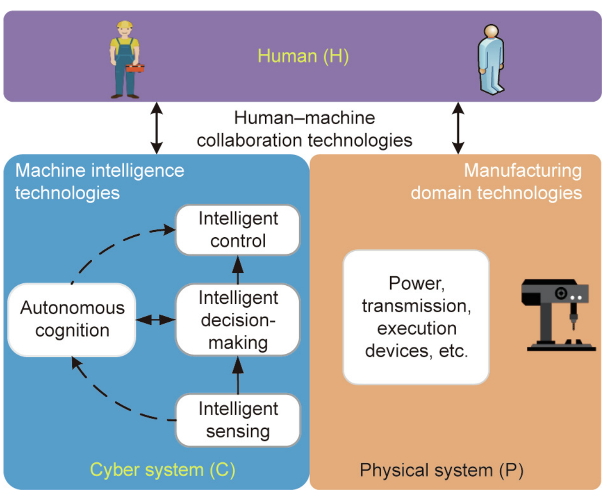

Fig. 13. Technology diagram of unit-level HCPS2.0.

process-oriented manufacturing, but also covers all of the product life-cycle. Therefore, it encompasses a broad range of manufacturing domain technologies [9], which can be grouped according to different perspectives. From the perspective of production processes, for example, these technologies can be divided into cutting technology, casting technology, welding technology, plastic-forming technology, heat treatment technology, and additive manufacturing technology, among others [82–86].

4.2.2. Machine intelligence technologies

Machine intelligence technologies are the technologies involved in the cyber systems of an HCPS2.0. These technologies are based on the in-depth integration of AI technology with manufacturing domain knowledge, and are capable of achieving specific HCPS goals. Cyber systems direct HCPSs by helping humans with the necessary perception, cognition, analysis, decision-making, and control of HCPSs so that their physical systems can run optimally. Machine intelligence technologies are mainly divided into the following four groups: intelligent sensing, autonomous cognition, intelligent decision-making, and intelligent control.

(1) **Intelligent sensing.** Sensing is the foundation and precondition of cognitive learning, decision, and control. Here, the task is to effectively acquire all kinds of internal and external information, including the acquisition, transmission, and processing of information. Critical technologies include sensing plan design, high-performance sensors, and real-time and intelligent data collection [87,88].

(2) **Autonomous cognition.** The task of cognition is to effectively acquire the knowledge that is required for the system to achieve its goals; this task is key to effective decision-making and control. The cognitive tasks of HCPS2.0 are generally completed based on collaboration between cyber systems and humans. Therefore, it is necessary to solve problems related to the autonomous cognition of intelligent machines and human–machine collaboration. The core task of the autonomous cognition of intelligent machines is system modeling (including parameter identification); key technologies involve the self-learning of model structure, self-learning of model parameters, and model evaluation and self-learning optimization [85].

(3) **Intelligent decision-making.** The task of intelligent decision-making is to assess the system status and determine the optimized action. The decision-making tasks of HCPS2.0 are generally completed based on collaboration between cyber systems and humans. Therefore, it is necessary to solve problems related to the intelligent decision-making of machines and human–machine collaborations. Key intelligent decision-making technologies involve the accurate assessment of system status, optimization of the decision-making model, and the predictive analysis of decision risk [73].

(4) **Intelligent control.** The task of control is to adjust the system based on decisions in order to achieve the system's goals. This task is necessary in order to solve the problems of division of labor and coordination of human–machine collaboration and the autonomous control of machines. The core issue of intelligent control is to deal with the uncertainty of the system itself and the environment, and to develop intelligent control technology such as adaptive control [85,89].

4.2.3. Human–machine collaboration technologies

Intelligent manufacturing presents many uncertain and complex problems that cannot be solved by human intelligence or by machine intelligence alone. Human–machine hybrid-augmented intelligence is a typical characteristic of new-generation AI [70]. It is a core critical technology of HCPS2.0 for NGIM that involves human–machine collaboration at the cognition, decision, and control levels, as well as human–computer interaction technology [60,61].

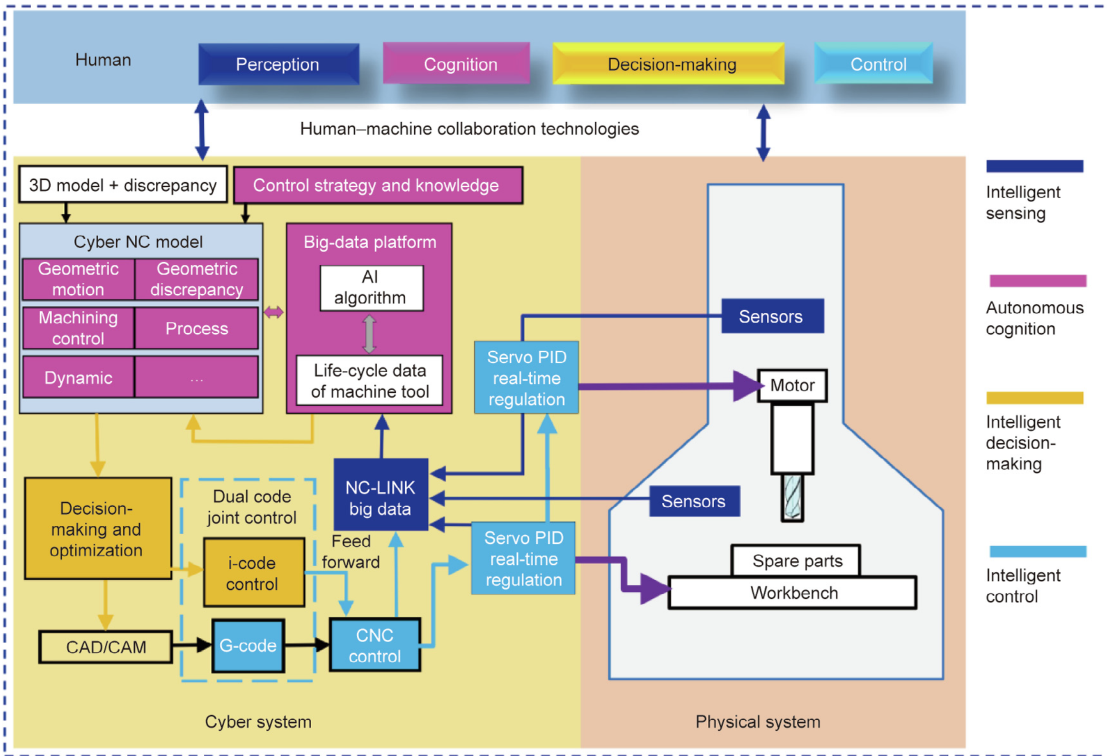

Fig. 14. Unit-level HCPS2.0 and intelligent machine tools. CAD: computer-aided design; CAM: computer-aided manufacturing; NC: numerical control; PID: proportional–integral–derivative. i-code stands for intelligent code, which is a new adaptive intelligent controlling code.

Unit-level HCPS2.0 is the foundation of NGIM. Fig. 14 shows the schematic of an intelligent machine tool as a unit-level HCPS2.0: an advanced cyber system capable of intelligent sensing, autonomous cognition and intelligent decision-making, and intelligent control implementation of the machine tool (i.e., physical system) [56].

4.3. Key technologies of system-level HCPS2.0 and SoS-level HCPS2.0

Integration is the essential characteristic of system-level and SoS-level HCPSs, which are geared to integrate information and achieve optimal resource allocation with a larger scope [4]. Integration can take place at different levels of breadth and depth, and thus deliver an open, coordinated, and shared ecosystem at the level of a production line, shop floor, enterprise, or industry. While HCPSs at different levels vary in terms of the content integrated and functions delivered, they have basically the same structure and implementation architecture. Fig. 15 presents the system structure and implementation architecture of an enterprise-level HCPS2.0. This is a system of HCPSs that includes an intelligent

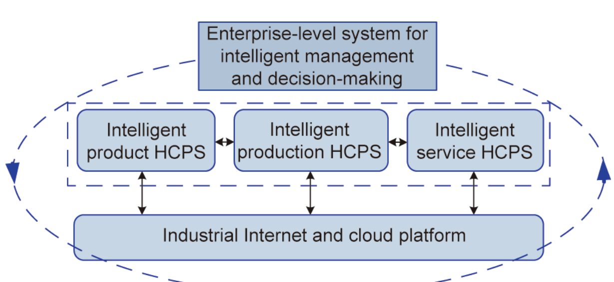

Fig. 15. Enterprise-level HCPS2.0.

product HCPS, intelligent production HCPS, and intelligent service HCPS, which are integrated through the Industrial Internet and cloud platform and controlled by an enterprise-level intelligent management and decision-making system.

In addition to the enabling technologies of the abovementioned unit-level HCPS2.0, system-level HCPS2.0 and SoS-level HCPS2.0 have their own critical technologies, which are mainly system integration technologies. These include generic technologies such as the Industrial Internet, cloud platforms, and industrial big data [12,51,52,71,79,90], as well as technologies that are required to achieve system integration, management, and decision-making, such as enterprise-level intelligent decision-making technologies and systems, intelligent production scheduling technologies and systems, intelligent security management technologies and systems, and so forth.

Fig. 16 illustrates the schematic of the commercial COSMOPlat platform as a system-level HCPS [91]. This HCPS platform allows users to be involved in the entire process from idea to design to order to ownership. Its quintessence is "user-centricity," and its core is "user connections": connection between user and all elements, connection between user and machine, and connection between user and the entire process, thus, ultimately, achieving mass customization for better business benefits and customer service level.

5. Major challenges in HCPS2.0 for NGIM

As a core technology of the Fourth Industrial Revolution, NGIM is unprecedented in terms of the sectors involved, issues to be studied, and challenges to be overcome [20,40,73,92–99]. Corresponding to the three major technological advancements discussed in Section 3.2, NGIM faces three major challenges: system modeling, knowledge engineering, and human–machine symbiosis.

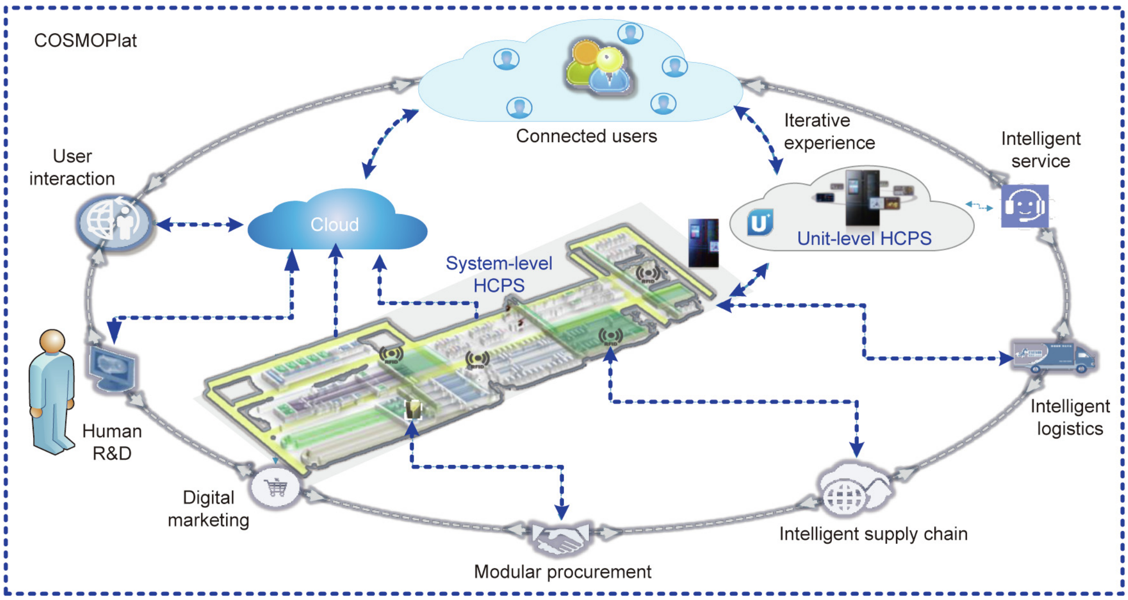

Fig. 16. System-level HCPS in the COSMOPlat.

5.1. System modeling: In-depth integration of mathematical modeling and big-data-driven intelligent modeling

System modeling is key to CPSs and to digital twin technology [22,42,49,74,77,100–102]. The effective establishment of models of manufacturing systems at different levels is the foundation of optimal decision-making and the intelligent control of manufacturing systems. Although mathematical modeling can ably reveal the objective laws of the physical world [103], it is inadequate to handle the highly uncertain and complex issues in intelligent manufacturing systems [49,75,104]. Big-data-driven intelligent modeling could solve these issues [5,53]. In theory, a hybrid modeling method based on the in-depth integration of mathematical modeling and big-data-driven intelligent modeling could fundamentally improve the modeling of NGIM systems based on HCPS2.0; however, such a method presents the following major challenges:

(1) In big data intelligent modeling, how can industrial big data be acquired and managed with greater efficiency? How can the effective learning of knowledge in big data be enabled? How can the ability to solve uncertain and complex problems be further improved [50,93,97,105–107]?

(2) In hybrid modeling, how can full scope be given to the strengths of each of the two modeling methods, and how can they be integrated synergistically into hybrid modeling? For example, how can manufacturing system dynamic models be effectively established [11,67,75,103,108]?

5.2. Knowledge engineering: In-depth integration of manufacturing technology (root technology) and intelligent technology (enabling technology)

In essence, NGIM is an advanced manufacturing knowledge engineering activity, in which manufacturing systems in different industries are enabled by digital-networked intelligent technologies to bring about revolutionary changes in how manufacturing domain knowledge is generated, utilized, and shared. These changes will lead to even more advanced forms of intelligent manufacturing [21,109] that will drive a new round of industrial revolution. Advanced manufacturing knowledge engineering involves the integration of manufacturing technology (root technologies) and intelligent technology (enabling technologies). It presents the following three major groups of challenges:

(1) A challenge in manufacturing domain technology (root technology) development is the question of how to continue to achieve innovation in the diverse aspects of this technology, such as design, process, materials, and industrial form [86,110,111].

(2) Challenges in intelligent technology (enabling technology) development include how to achieve steady improvements in universality, stability, and security, and how to advance from weak AI to strong AI [2,53,54,70].

(3) Even more significant challenges are presented by the crossover from the in-depth integration of manufacturing technology and intelligent technology [112–114]. These include: How can manufacturing technology be effectively enabled with intelligent technology? How can intelligent technology be utilized in the manufacturing sector to develop and advance manufacturing domain knowledge? How can dynamic digital twin models be established and optimized to enhance different manufacturing systems? How can the enormous gaps be bridged between manufacturing technology and digital technology, between different academic disciplines, between enterprises, and between experts? How can entrepreneurs, technologists, and skilled workers grow into champions for NGIM in the manufacturing sector?

5.3. Human–machine symbiosis: In-depth integration of humans and CPSs (intelligent machines)

Intelligent manufacturing based on HCPS calls for humans to take on a greater role in order to form a human–machine symbiosis [2,8,28,38,57–60,70,73,115,116] that will bring diverse challenges, including the following:

(1) How can the effective division of work and cooperation between humans and intelligent machines be better achieved? How can the individual advantages of human intelligence and machine intelligence be fully utilized and inspired by each other in order to simultaneously grow [53,70]?

(2) How can human–machine hybrid-augmented intelligence be achieved [70]?

(3) How can safety, privacy, ethical, and other issues that may be introduced by AI and intelligent manufacturing be addressed [2,99]?

In line with the ancient Chinese concept of harmony between humans and nature, there should be close cooperation and in-depth integration between humans and CPSs (i.e., intelligent machines) in order to realize NGIM systems as a harmonious state of human–machine symbiosis, and in order to move these technologies forward for the benefit of humankind.

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Compliance with ethics guidelines

Zhou Ji, Zhou Yanhong, Wang Baicun, and Zang Jiyuan declare that they have no conflict of interest or financial conflicts to disclose.

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