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Research
AI Energizes Process Manufacturing—Perspective

Intelligent Manufacturing for the Process Industry Driven by Industrial Artificial Intelligence

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ABSTRACT

Based on the analysis of the characteristics and operation status of the process industry, as well as the development of the global intelligent manufacturing industry, a new mode of intelligent manufacturing for the process industry, namely, deep integration of industrial artificial intelligence and the Industrial Internet with the process industry, is proposed. This paper analyzes the development status of the existing three-tier structure of the process industry, which consists of the enterprise resource planning, the manufacturing execution system, and the process control system, and examines the decision-making, control, and operation management adopted by process enterprises. Based on this analysis, it then describes the meaning of an intelligent manufacturing framework and presents a vision of an intelligent optimal decision-making system based on human–machine cooperation and an intelligent autonomous control system. Finally, this paper analyzes the scientific challenges and key technologies that are crucial for the successful deployment of intelligent manufacturing in the process industry.

1. Introduction

There are two main types of manufacturing industry: discrete industries, which include machinery and equipment manufacturing; and process industries, which are represented by important raw material industries, such as the petrochemical, metallurgy, building material, and energy industries. Manufacturing is an essential basic industry of the national economy, and is an important force supporting sustained economic growth and the global economy. Discrete manufacturing is a physical process, and its products can be counted individually. Therefore, it is easy to digitalize the manufacturing process, to emphasize personalized needs and flexible manufacturing. However, the production and operation mode in the process industry have prominent characteristics that are not easily digitalized. For example, raw materials change frequently, production processes involve physical and chemical reactions, and the mechanisms involved are complex. A production process is continuous and cannot be stopped, and problems in any part of the process will inevitably affect the whole production line and the quality of the final products. The raw material composition, equipment status, process parameters, and product quality of some industries cannot be measured in real time or be comprehensively measured. The abovementioned characteristics of the process industry are manifested in difficulties in measurement, modeling, control and optimization, and decision-making.

After decades of development, China's manufacturing industry continues to develop rapidly, with a substantial increase in its overall scale and continuous enhancement of its comprehensive strength. At present, China is the world's largest manufacturing country, with the most comprehensive categories and the largest scale; it is also the only country in the world with industries in all the industrial categories listed under the United Nations Industrial Classification [1,2]. The main problems experienced in China's manufacturing industry are high energy consumption, high resource consumption, lower value-added products, and high environmental pollution. Therefore, high efficiency must be achieved while "greening" manufacturing processes. High efficiency is necessary in order to realize the optimal control of comprehensive production indices, such as product quality, output, cost, and consumption. It is also needed in order to realize safe and reliable operation of the whole production process under situations in which the market and/or raw materials may change. Thus, high efficiency will lead to high performance and high added-value products, while maximizing the profits of enterprises. "Greening"

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is the efficient use of energy and resources, such that the consumption of energy and resources is as low as possible, leading to zero emission of pollutants and environmental conservation [3–7].

Intelligent manufacturing has become the core high technology for enhancing the overall competitiveness of the manufacturing industry. Artificial intelligence (AI) technology has become an important trend in industrial manufacturing. For example, general AI technology was first proven to be suitable for diagnosis and prediction problems in complex industrial scenarios [8,9]. AI technology accelerates the development of intelligent manufacturing [10–13]. The development trend of intelligent manufacturing is shown in Fig. 1 [14].

The emergence of the steam engine and the feedback governor based on mechanical technology triggered the First Industrial Revolution; the emergence of electrical power and the control system based on electrical technology led to the Second Industrial Revolution; and the emergence of the program logic controller (PLC) and the distributed control system (DCS) triggered the Third Industrial Revolution. From these three industrial revolutions, it can be seen that the development of efficient new energy and information technologies is the key to changing the industrial production mode and enhancing its competitiveness. Steam engines and power generation equipment made it necessary to use control systems when steam and electricity became energy sources. Feedback control technology enabled the mechanical governor to control the speed of steam-powered mechanical sewing machines, while feedback control technology and logical sequence control technology enabled the electrical control system to control the stable operation of the conveyer belt in electric-powered slaughterhouses. The PLC and DCS, which were invented through the close integration of computer technology and control technology, greatly improved the automation of large-scale production lines.

At present, with the rapid development of AI, the mobile internet, cloud computing, the Industrial Internet, and other technologies, we are currently within the Fourth Industrial Revolution. Developed countries have implemented re-industrialization strategies to strengthen their manufacturing innovation and reshape new competitive advantages in the manufacturing industry. Some developing countries are also accelerating their plannings and strategies actively participating in the global industrial redivision of the workforce, and seeking a favorable position in the new round of industry competition [7,15]. Within the general trend of the global industrial development, developed countries are using their leading edge in the field of information technology to accelerate the establishment of intelligent manufacturing industry. For example, in October 2016, the National Artificial Intelligence Research and Development Strategic Plan set out by the US National Science and Technology Council stated that AI can be used to improve the operation of manufacturing processes, enhance the flexibility of manufacturing processes, improve product quality, and reduce cost [16]. In May 2018, the US White House hosted the Summit on Artificial Intelligence for American Industry, at which the attendees were organized into industry-specific sessions to share novel ways in which industry leaders were using AI technologies to empower the American workforce, grow their businesses, and better serve Their customers [17]. The US National Science Foundation (NSF) also stated that AI has the potential to transform all aspects of American industry and create new hope for advanced manufacturing [18]. In August 2020, the National AI Research Institutes of the US NSF issued a new funding opportunity focusing on eight themes, of which the AI Institute in Dynamic Systems is one. The AI Institute in Dynamic Systems supports fundamental AI, machine learning theory, algorithms, and related engineering and scientific research and education for real-time sensing, learning, decision-making, and prediction in order to lead the development of safe, reliable, and efficient AI [19]. The research and development budget priorities of the United States in both the fiscal years 2020 and 2021 revealed that, in order to ensure that the United States remains at the global forefront of science and technology discovery and innovation, priority should be given to smart and digital manufacturing—especially systems enabled by the Industrial Internet of Things, machine learning, and AI [20,21]. After its Industry 4.0 initiative, Germany launched the development and application of "learning systems" in September 2017 to make future work and production more flexible and resource efficient [22]. In November 2018, the German Federal Government announced its AI strategy, which emphasized that AI is a key component and essential driver promoting the smart monitoring, management, and control of industrial processes, in order to render them more flexible and thus promote Industry 4.0 to the next level [23]. In addition, the United Kingdom announced the UK Industry 2050 Strategy, Japan proposed the i-Japan Strategy, and Republic of Korea launched the Manufacturing Innovation 3.0 Strategy. Facing the new adjustment in the global industrial competition brought by the Fourth

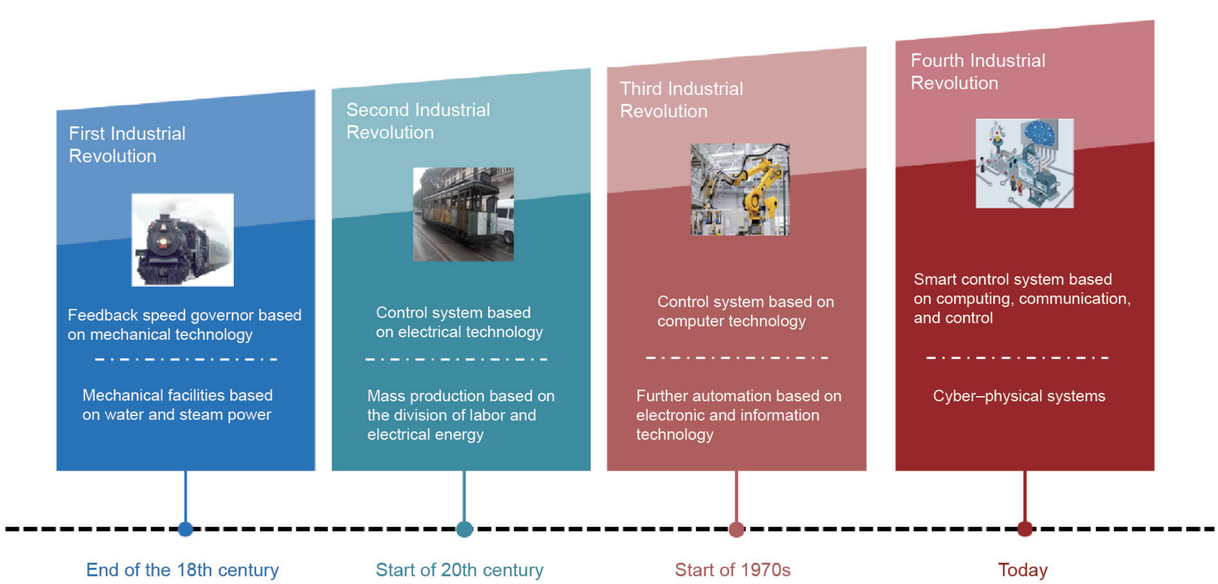

Fig. 1. Roadmap of the First, Second, Third, and Fourth Industrial Revolutions. Reproduced from Ref. [14] with permission of Science China Press, © 2016.

Industrial Revolution, the Chinese Academy of Engineering led a research report entitled "New-Generation Artificial Intelligence-Driven Intelligent Manufacturing." The report proposed that the goal of the new generation of intelligent manufacturing, which marks the second stage of China's intelligent manufacturing (2025–2035), should be to make China's intelligent manufacturing technology and application level at the forefront of the world [24,25].

Intelligent manufacturing has become the core high technology for enhancing the overall competitiveness of the manufacturing industry. Intelligent manufacturing is the main direction for China to achieve manufacturing power [7,26]. To achieve the leapfrog development of the process industry (i.e., jumping from a lower technological level to a much higher one while skipping intermediate levels), it is necessary to integrate intelligent manufacturing with the characteristics and goals of the process industry; to make full use of big data; to deeply integrate information technologies, such as AI, the mobile Internet, cloud computing, modeling, control, and optimization, with the physical resources of the process industry; and to develop various new functions to achieve the goals of intelligent manufacturing [13,27–30]. In order to enable industrial AI and the Industrial Internet to play an irreplaceable role in intelligent manufacturing in the process industry and to accelerate the development process of China's manufacturing industry toward digitalization, networking, and intelligence, this paper takes the intelligentization of the entire process of the manufacturing and production of the process industry as the application scenario and describes the meaning of intelligent manufacturing for the process industry, proposes research directions, and suggests research methods.

2. Analysis of the current status of decision-making, control, and operation management in the whole production process of the process industry

The current status of decision-making, control, and operation management in the whole production process of the process industry is shown in Fig. 2 [13]. A process enterprise comprises a three-tier structure consisting of the enterprise resource planning (ERP), the manufacturing execution system (MES), and the process control system (PCS). The enterprise manager obtains the enterprise resource information through the ERP system and makes decisions regarding the target ranges of the comprehensive production indices, including product quality, output, energy consumption, material consumption, and cost, based on his or her experience and knowledge. The production manager obtains production information through the MES and uses her or his experience and knowledge to decide the target value ranges of production indices for the whole process of manufacturing and production. The operation management and process engineer obtains the operating conditions through the PCS, obtains production information through his or her senses (i.e., sight, hearing, and touch), and then makes decisions based on his or her experience and knowledge in order to reflect the target value ranges of the operational indices of the quality, efficiency, and consumption of the product processing of the industrial process. According to the target value ranges of the operational indices and the actual production situation, the operator decides the control command for the PCS based on her or his experience and knowledge. The PCS causes the output of the controlled process to follow the control command by controlling the whole manufacturing and production process, thereby controlling the quality, efficiency, and consumption operational indices of the processed product, as well as the production indices of the whole manufacturing and production process within the target value ranges [31,32].

Although most enterprises have deployed the three-tier structure system or the two-tier structure system of MES and PCS, these systems mainly realize information integration and management functions [32]. Decisions on enterprise objectives (i.e., profit, environmental protection, etc.), resource planning and scheduling, operational indices, production instructions, and control commands are still made by knowledge workers based on their knowledge and experience. However, knowledge workers cannot realize integrated optimal decisions on enterprise objectives, production

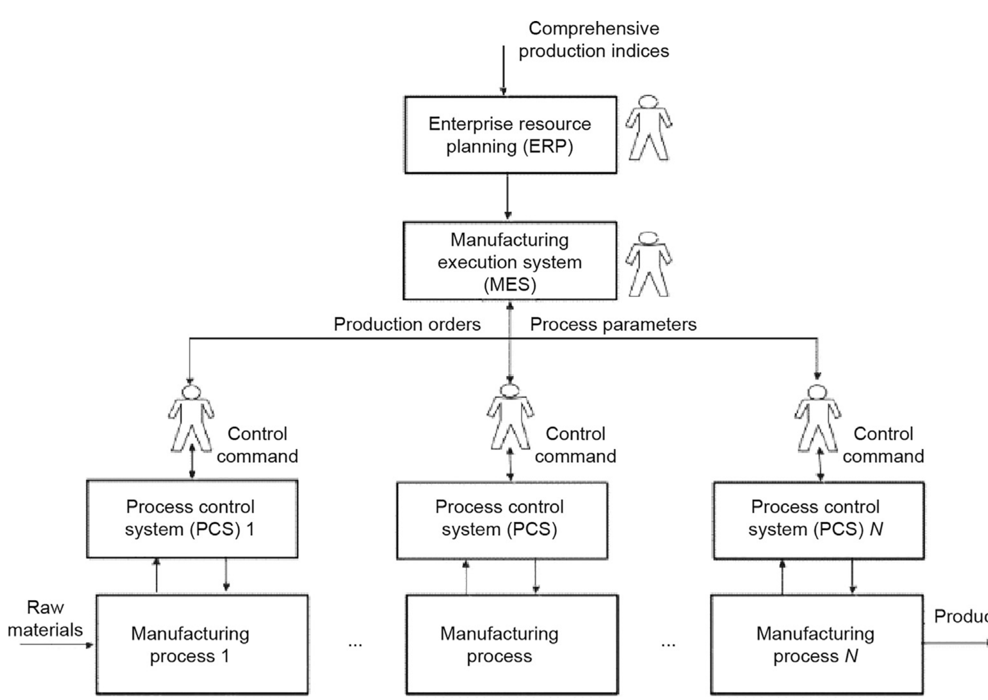

Fig. 2. The current status of decision-making, control, and operation management in the whole production process of the process industry. Reproduced from Ref. [13] with permission of Acta Automatica Sinica, © 2020.

planning and scheduling, or seamless integration and optimization of ERP and MES. Fig. 3 [13] depicts the decision-making, control, and operation management of the whole production process of the process industry, which can be viewed as a cyber–physical system (CPS) with humans [33]. Operators and knowledge workers obtain production information from the information system, and obtain multi-source heterogeneous production information through their human senses of sight, hearing, and touch. They then use their brains' capability for learning, cognition, analysis, and decision-making, together with their own experience and knowledge, to make decisions regarding comprehensive production indices, production indices for the whole manufacturing and production process, operational indices, and control system commands.

It is difficult to achieve global optimization of the whole manufacturing and production process, since humans cannot perceive dynamically changing operation conditions in a timely and accurate manner [34]. Moreover, human decision-making behaviors constrain the development of the process [35]. In general, the current focus of China's process industry is on the automation of the material transformation process of industrial equipment and the informatization of the production process, operation management, and enterprise management. There is a lack of research on the automation and intelligence of knowledge work in process design, resource planning, and production process operation management.

The development of the mobile internet, edge computing, cloud computing, and the fifth-generation mobile communication technology (5G) has led to the birth of industrial AI and the Industrial Internet. The essence of industrial AI is to combine general AI technology with specific industrial scenarios in order to achieve innovative applications, such as design model innovation, intelligent production decision-making, and optimal resource allocation. Industrial AI grants an industrial system the capabilities of self-perception, self-learning, self-execution, self-decision-making, and self-adaptation, allowing it to adapt to a complex and changeable industrial environment and complete diversified industrial tasks; this ultimately improves production efficiency, product quality, and equipment performance [36]. The Industrial Internet provides enterprises with the opportunity to obtain industrial big data, which drives the development of industrial AI technologies as well as changes in scientific research models and methods [37]. Examples include the emergence of CPS and convergence research [38], which have promoted the digitalization, networking, and intelligence of industrial process manufacturing. The Fourth Industrial Revolution will realize the automation and intelligence of manufacturing knowledge work [4,13,19,33].

3. The meaning and vision of intelligent manufacturing for the process industry

Intelligent manufacturing for the process industry is a manufacturing model characterized by the realization of management and decision-making for the whole manufacturing and production process, along with intelligent optimization and intelligent autonomous control. The goal of intelligent manufacturing is to "green" enterprises and increase their efficiency to a high level. As shown in Fig. 4 [13], the operator's knowledge work becomes automated, and the control system and manufacturing process are transformed into an intelligent autonomous control system. The knowledge work of enterprise managers and production managers is made more intelligent. ERP and MES are changed into an intelligent management and decision-making system based on human–machine cooperation. The original three-tier structure of the enterprise, consisting of ERP, MES, and PCS, is transformed into a two-tier structure, consisting of an intelligent management and decision-making system of human–machine cooperation and an intelligent autonomous control system, as shown in Fig. 5 [13]. The decision-making, control, and operation management of the whole manufacturing and production process are transformed into a CPS. As shown in Fig. 6 [13], the intelligentization of the whole manufacturing and production process will automate and intelligentize the knowledge work of operators and knowledge workers. The knowledge workers in the CPS are planners, managers, and decision-makers [34].

The intelligent management and decision-making system based on human–machine cooperation is mainly composed of three subsystems: intelligent optimal decision-making, a virtual manufacturing process, and operating condition recognition and self-optimization control [14,34]. The desired functions of this intelligent management and decision-making system are as follows:

(1) Perceiving market information, production conditions, and operating conditions of the manufacturing process in real time;

(2) With the goal of high efficiency and enterprise "greening", realizing integrated optimal decision-making of the enterprise's comprehensive production indices, planning and scheduling indices, whole-process production indices of manufacturing and production, operational indices, production indices, and control commands;

(3) Achieving remote and mobile visual monitoring of the dynamic performance of the decision-making process;

(4) Through self-learning and self-optimization decision-making, realizing collaboration between humans and the intelligent optimal decision-making system, so that decision-makers

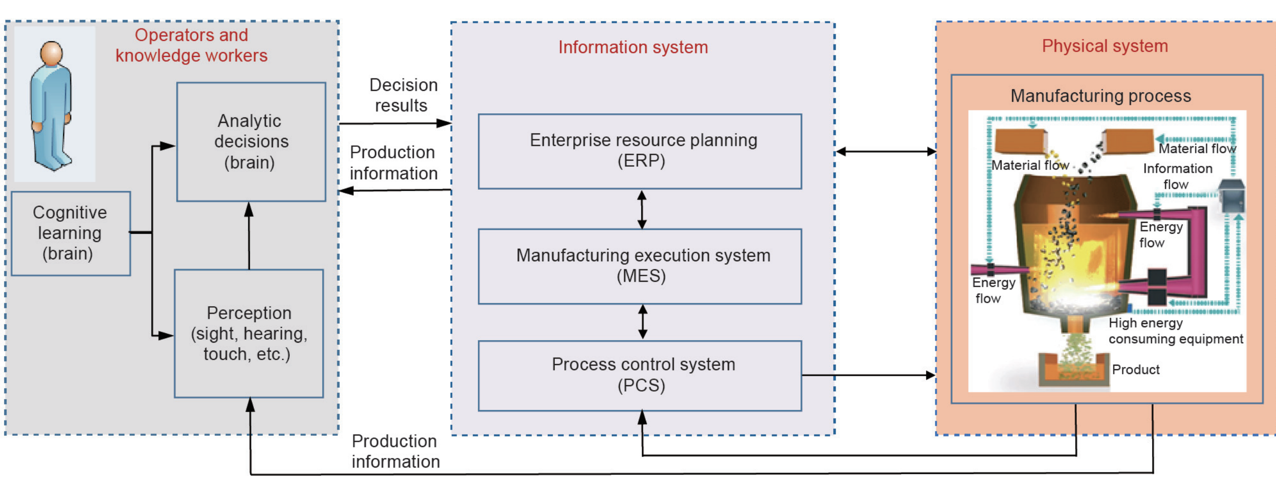

Fig. 3. A cyber–physical system with humans. Reproduced from Ref. [13] with permission of Acta Automatica Sinica, © 2020.

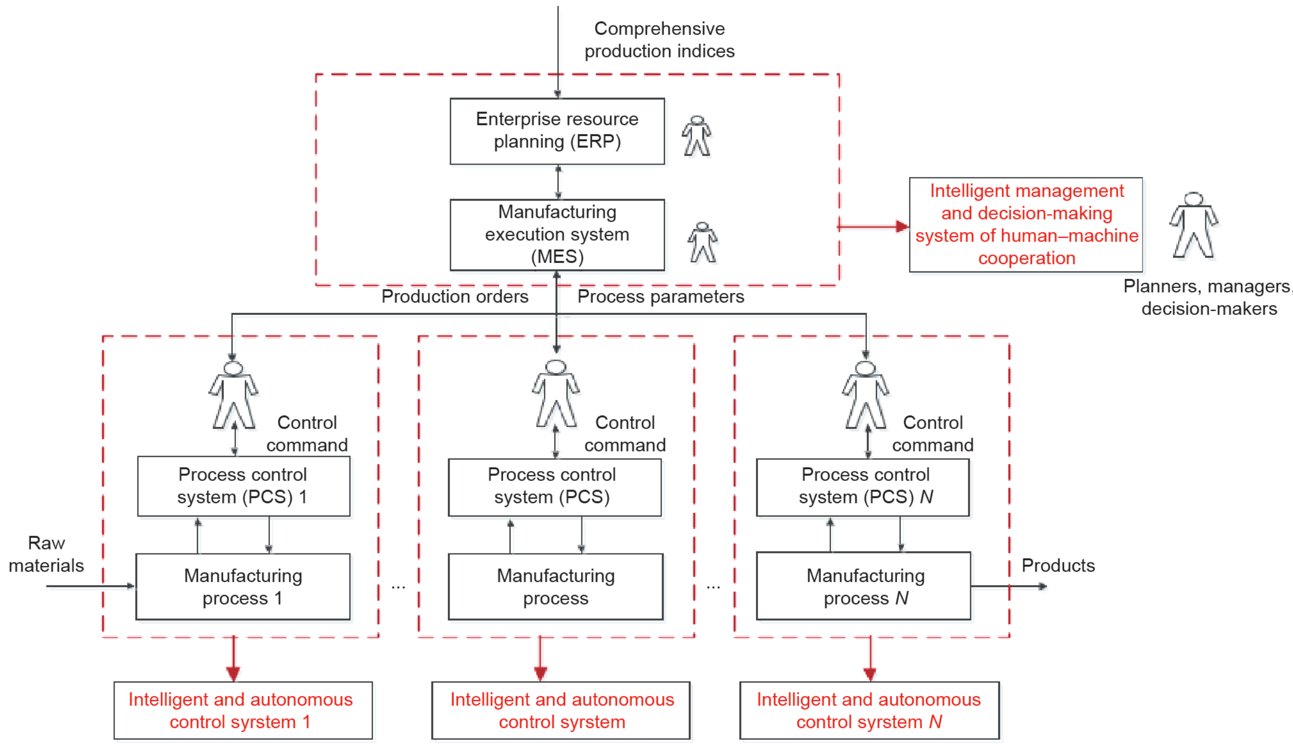

Fig. 4. The intelligent manufacturing and production process. Reproduced from Ref. [13] with permission of Acta Automatica Sinica, © 2020.

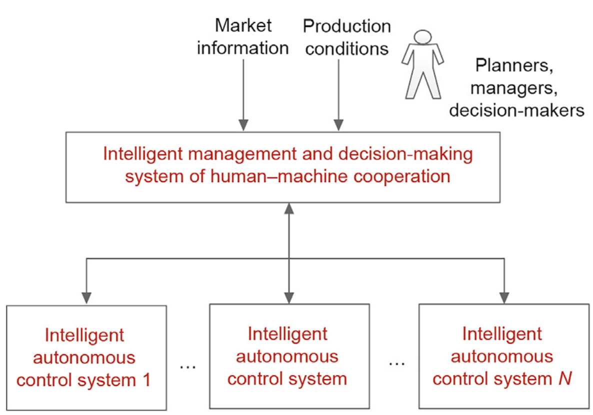

Fig. 5. The manufacturing process changed from a three-tier structure to an intelligent two-tier structure. Reproduced from Ref. [13] with permission of Acta Automatica Sinica, © 2020.

can accurately optimize decision-making in a dynamically changing environment.

The intelligent autonomous control system is mainly composed of three subsystems: intelligent operation optimization, high-performance intelligent control, and operating condition recognition and self-optimization control. The desired functions of this intelligent autonomous control system are as follows:

(1) Intelligently perceiving changes in production conditions;

(2) With the goal of optimizing the operational indices, adaptively making decisions for the set value of the control system;

(3) Intelligently tracking changes in the set value of the control system with a highly dynamic performance, and controlling the actual operational indices within the target value ranges;

(4) Achieving real-time remote monitoring and mobile monitoring, and predicting and eliminating abnormal operating conditions, so that the system is operated in a safe and optimal manner;

(5) Cooperating with the intelligent autonomous control systems of the other industrial processes that make up the whole production process in order to achieve global optimization of the whole production process.

4. Scientific challenges and key technologies

The intelligentization of the whole production process in the process industry poses challenges to modeling, control, and optimization based on mathematical models or causal data in automation science and technology. Industrial AI and the Industrial Internet provide new methods and technologies to achieve the intelligentization of the whole production process for the process industry.

Although the definition of industrial AI is unclear and changes over time, the core goal of industrial AI research and its application is to achieve the automation and intelligence of knowledge work in current industrial production activities, with the aim of significantly improving their economic and social benefits. Such activities include production and process design, operation management and decision-making processes, and manufacturing processes and the control of operation and management—activities that currently rely on human perception, cognition, analytical decision-making capability, experience, and knowledge.

The research goals of industrial AI are to realize the automation and intelligence of knowledge work; to develop AI algorithms and AI systems for the recognition, prediction, and decision-making of operating conditions by using industrial big data; and to design software for human–machine cooperation management, intelligent decision-making, and AI systems that supplement and enhance the capabilities of knowledge workers in production and design processes. Moreover, AI algorithms, arithmetic power, and human–computer interaction are issues that cannot be ignored [39].

The emergence and development of the Industrial Internet have been accompanied by the development of big data, CPS, the Internet, and other information technologies, as well as a major

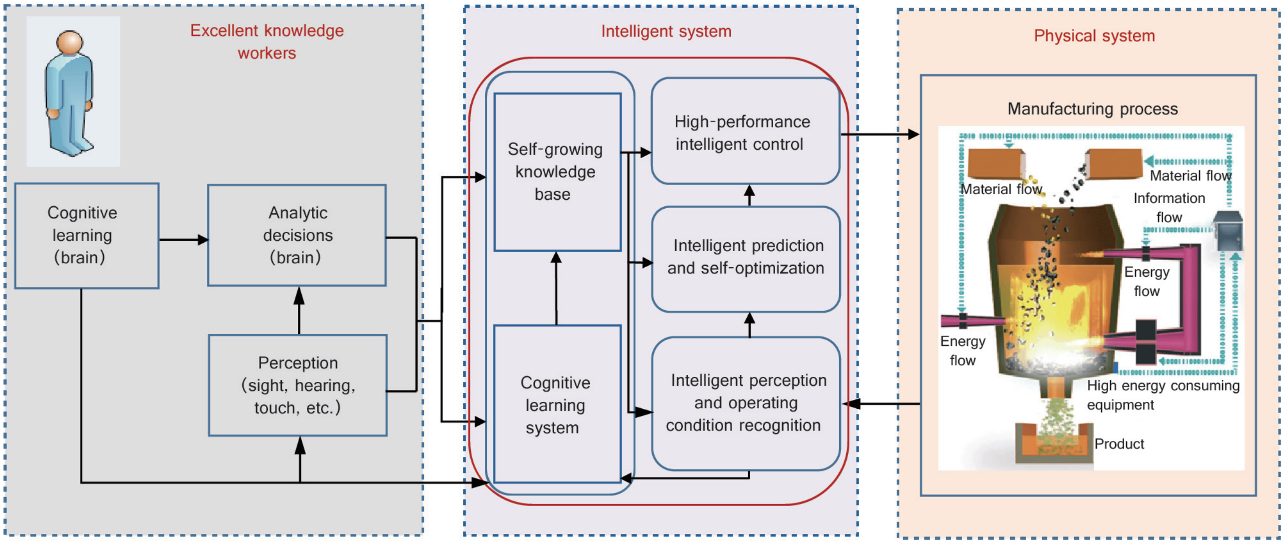

Fig. 6. The manufacturing and production process cyber–physical system. Reproduced from Ref. [13] with permission of Acta Automatica Sinica, © 2020.

demand for advanced manufacturing and intelligent manufacturing. In October 2012, General Electric in the United States proposed the concept of the Industrial Internet in a white paper entitled "Industrial Internet: Pushing the Boundaries of Minds and Machines." In January 2011, the German Industrial Science Research Alliance proposed the Industry 4.0 strategy. In November 2011, the Industry 4.0 strategy was included in the High-Tech Strategy 2020. Recently, both the United States and Germany have developed strategies for the development of the Industrial Internet in combination with AI technology. On 18 October 2019, Chinese President Xi Jinping sent a congratulatory letter to the opening ceremony of the Industrial Internet Global Summit, which was held in Shenyang, the capital of Northeast China's Liaoning Province. In this letter, Xi stated that breakthroughs are being made in Industrial Internet technologies with the accelerating new round of science and technology revolution and industrial transformation, and that these breakthroughs are injecting new impetus into the economic innovation of all countries, while providing new opportunities for the integrated development of global industries. China attaches great importance to the innovative development of the Industrial Internet, Xi said, adding that China is willing to work with the international community to enhance the innovation capability of the Industrial Internet, so as to realize the integrated development of industrialization and informatization on a broader, deeper, and higher level [40]. This statement indicated the direction for the high-quality development of China's Industrial Internet. In order to make the Industrial Internet into a powerful driving force for the high-quality development of China's manufacturing industry, it is essential to carry out research on the mode and path of the high-quality development of the Industrial Internet.

Given the development status of China's process industry, the need to achieve digitalization, networking, and intelligence, and the development goals of industrial AI and the Industrial Internet, we propose that the following scientific issues need to be resolved:

(1) Recognition and feedback control of complex operating conditions based on a combination of dynamic system modeling and deep learning;

(2) Knowledge mining of dynamic characteristics, operation, and decision-making based on a combination of mechanism analysis and industrial big data analysis;

(3) Human–machine cooperative optimal decision-making based on a combination of prediction, feedback, and reinforcement learning;

(4) Integration of intelligent optimal decision-making and control with multi-conflict targets and multi-conflict constraints, on multiple time scales.

In order to tackle these scientific problems, it is necessary to adopt the concepts of the CPS and convergence research [37]. Convergence research is a new research paradigm and mindset that is characterized by being problem driven. The problems addressed by convergence research are challenging scientific research problems or major challenges involving social needs, which require interdisciplinary collaborative research. In order to solve such complex problems, it is necessary to integrate knowledge, methods, and expertise from different disciplines in order to form a new framework to promote scientific discovery and innovation. Combining disciplinary methods and technologies is the best—or even the only—strategy to solve such complex problems. Team science is becoming a more typical research mode [41,42]. To this end, we propose that the following key technologies urgently need to be resolved:

(1) Intelligent perception and recognition of multi-scale and multi-source information on operating conditions in complex industrial environments;

(2) Fast and reliable transmission technology for 5G-based multi-source information in complex industrial environments;

(3) Intelligent modeling, digital twin technology, and visualization technology of complex industrial systems based on a combination of system identification and deep learning;

(4) Prediction and traceability of key process parameters and production indices;

(5) Intelligent autonomous control technology for complex industrial systems;

(6) Intelligent optimal decision-making for human–machine cooperation;

(7) Intelligent optimal decision-making and control integration technology;

(8) "End-edge-cloud" collaborative realization technology for industrial AI algorithms.

5. Conclusion

In order to realize industrial intelligence in the process industry, it is necessary to deeply integrate industrial AI and the Industrial Internet with the domain knowledge work of the process industry, and to develop AI algorithms and AI systems that supplement and enhance the capabilities of knowledge workers. This article reviewed the shortcomings of the existing decision-making, control, and operation management of the entire production process in the process industry, and described the meaning of and presented a vision of intelligent manufacturing in the process industry. Given the development status of China's process industry and the need for digitalization, networking, and intelligence, challenging scientific issues and key technologies toward intelligent manufacturing for the process industry were proposed.

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Compliance with ethics guidelines

Tao Yang, Xinlei Yi, Shaowen Lu, Karl H. Johansson, and Tianyou Chai declare that they have no conflict of interest or financial conflicts to disclose.

References

[1] Liu K. [70 years of self-dependence, hard struggle: China has become the largest manufacturing country with all industrial categories]. Guangming Daily. 2019 Sep 21. Sect. 10:(col. 1). Chinese.
[2] Qian F, Zhong W, Du W. Fundamental theories and key technologies for smart and optimal manufacturing in the process industry. Engineering 2017;3(2):154–60.
[3] Ge W, Guo Li, Li J. Toward greener and smarter process industries. Engineering 2017;3(2):152–3.
[4] Gui W, Chen X, Sun Y, Xie Y, Zeng Z. Knowledge-driven process industry smart manufacturing. Sci Sin Inf 2020;50(9):1345–60.
[5] Mao S, Wang B, Tang Y, Qian F. Opportunities and challenges of artificial intelligence for green manufacturing in the process industry. Engineering 2019;5(6):995–1002.
[6] Chinese Academy of Engineering, National Natural Science Foundation of China. [Research on development strategy of big data and knowledge automation for manufacturing process]. Report. Beijing: Chinese Academy of Engineering, National Natural Science Foundation of China; 2016. Chinese.
[7] Chai TY, Ding JL. Smart and optimal manufacturing for process industry. Strateg Stud Chin Acad Eng 2018;20(4):51–8.
[8] Eager J, Whittle M, Smit J, Cacciaguerra G, Lale E. Opportunities of artificial intelligence [Internet]. Luxembourg: European Parliament; 2020 Jun [cited 2021 Jan 11]. Available from: https://www.sipotra.it/wp-content/uploads/2020/07/Opportunities-of-Artificial-Intelligence.pdf.
[9] Yuan Y, Ma G, Cheng C, Zhou B, Zhao H, Zhang HT, et al. A general end-to-end diagnosis framework for manufacturing systems. Natl Sci Rev 2020;7(2):418–29.
[10] Ding H, Gao RX, Isaksson AJ, Landers RG, Parisini T, Yuan Y. State of AI-based monitoring in smart manufacturing and introduction to focused section. IEEE ASME Trans Mechatron 2020;25(5):2143–54.
[11] Panetto H, Weichhart G, Pinto R. Special section on Industry 4.0: challenges for the future in manufacturing. Annu Rev Contr 2019;47:198–9.
[12] Yang T. Guest editorial of the special session on industrial artificial intelligence. Acta Automatica Sin 2020;46(10):2003–4.
[13] Chai TY. Development direction of industrial artificial intelligence. Acta Automatica Sin 2020;46(10):2005–12. Chinese.
[14] Chai TY. Industrial process control systems: research status and development direction. Sci Sin Inf 2016;46(8):1003–15. Chinese.
[15] Lee J, Li X, Xu Y, Yang S, Sun KY. Recent advances and prospects in industrial AI and applications. Acta Automatica Sin 2020;46(10):2031–44.
[16] Baru C, Daimler E, Ferguson R, Forbe N, Harder E, Ferguson R, et al. The national artificial intelligence research and development strategic plan [Internet]. Washington, DC: National Science and Technology Council, Networking and Information Technology Research and Development Subcommittee; 2016 Oct [cited 2021 Jan 11]. Available from: https://www.nitrd.gov/pubs/national_ai_rd_strategic_plan.pdf.
[17] Summary of the White House summit on artificial intelligence for American industry [Internet]. Washington, DC: the White House Office of Science and Technology Policy; 2018 May 10 [cited 2021 Jan 11]. Available from: https://trumpwhitehouse.archives.gov/wp-content/uploads/2018/05/Summary-Report-of-White-House-AI-Summit.pdf?latest.
[18] Statement on artificial intelligence for American industry [Internet]. Washington, DC: National Science Foundation; 2018 May 10 [cited 2021 Jan 11]. Available from: https://www.nsf.gov/news/news_summ.jsp?cntn_id=245418.
[19] Important notice—change in individual eligibility restrictions [Internet]. Washington, DC: National Artificial Intelligence (AI) Research Institutes; 2020 Sep 21; [cited 2021 Jan 11]. Available from: https://www.nsf.gov/news/news_summ.jsp?cntn_id=301176&org=NSF.
[20] Fiscal year 2020 administration research and development budget priorities: memorandum for the heads of executive departments and agencies [Internet]. Washington, DC: Executive Office of the President; 2018 Jul 31; [cited 2021 Jan 11]. Available from: https://www.whitehouse.gov/wp-content/uploads/2018/07/M-18-22.pdf.
[21] Fiscal year 2021 administration research and development budget priorities: memorandum for the heads of executive departments and agencies [Internet]. Washington, DC: Executive Office of the President; 2019 Aug 31; [cited 2021 Jan 11]. Available from: https://www.whitehouse.gov/wp-content/uploads/2019/08/FY-21-RD-Budget-Priorities.pdf.
[22] Gu G. [Germany: artificial intelligence keeps the pace with Industrial 4.0]. Science and Technology Daily. 2018 Apr 10; Sect. 2. Chinese.
[23] The Federal Government's artificial intelligence strategy [Internet]. Berlin: Federal Ministry for Economic Affairs and Energy; [cited 2021 Jan 11]. Available from: https://www.de.digital/DIGITAL/Redaktion/EN/Standardartikel/artificial-intelligence-strategy.html.
[24] The Research Group for Research on Intelligent Manufacturing Development Strategy. Research on intelligent manufacturing development strategy in China. Strateg Stud Chin Acad Eng 2018;20(4):1–8.
[25] Zhou Ji, Li P, Zhou Y, Wang B, Zang J, Meng L. Toward new-generation intelligent manufacturing. Engineering 2018;4(1):11–20.
[26] Chai TY, Ding JL, Gui WH, Qian F. Research on the development strategy of big data and manufacturing process knowledge automation. Beijing: Science Press; 2019. Chinese.
[27] Ding JL, Yang CE, Chen YD, Chai TY. Current status and prospects of intelligent optimization decision-making systems for complex industrial processes. Acta Automatica Sin 2018;44(11):1931–43. Chinese.
[28] Kusiak A. Smart manufacturing must embrace big data. Nature 2017;544(7648):23–5.
[29] Cyber–physical systems, program announcements and information [Internet]. Washington, DC: National Science Foundation; 2009 Feb 27 [cited 2021 Jan 11]. Available from: https://www.nsf.gov/pubs/2008/nsf08611/nsf08611.pdf.
[30] Chinese Association of Automation. [Automation discipline development roadmap]. Beijing: China Science and Technology Press; 2020. Chinese.
[31] Chai TY. Challenges of optimal control for plant-wide production processes in terms of control and optimization theories. Acta Automatica Sin 2009;35(6):641–9.
[32] Chai TY, Jin YH, Ren DX, Shao HH, Qian JX, Li P, et al. Contemporary integrated manufacturing system based on three-layer structure in process industry. Control Eng China 2002;9(3):1–6. Chinese.
[33] Zhou Ji, Zhou Y, Wang B, Zang J. Human–cyber–physical systems (HCPSs) in the context of new-generation intelligent manufacturing. Engineering 2019;5(4):624–36.
[34] Chai TY. Artificial intelligence research challenges in intelligent manufacturing processes. Bull Natl Nat Sci Found China 2018;32(3):251–6.
[35] Gil Y, Greaves M, Hendler J, Hirsh H. Amplify scientific discovery with artificial intelligence. Science 2014;346(6206):171–2.
[36] [Industrial intelligence white paper] [Internet]. Beijing: Industrial Internet Industry Alliance; 2020 Apr 26 [cited 2021 Jan 11]. Available from: https://www.miit.gov.cn/ztzl/rdzt/gyhlw/cgzs/art/2020/art_e1842c433fce43e39a45ce96be50213a.html. Chinese.
[37] Yuan Ye, Tang X, Zhou W, Pan W, Li X, Zhang HT, et al. Data driven discovery of cyber physical systems. Nat Commun 2019;10(1):4894.
[38] Convergence research at NSF [Internet]. Washington, DC: National Science Foundation; 2020 [cited 2021 Jan 11]. Available from: https://www.nsf.gov/od/oia/convergence/index.jsp.
[39] Dai Q. [Some thoughts on artificial intelligence computing capabilities, algorithms, and testing]. Chin Assoc Artif Intell Newsl 2020;10(11):1–4.
[40] Xi sends congratulatory letter to Industrial Internet Global Summit [Internet]. Beijing: Xin Hua Net; 2019 Oct 18 [cited 2021 Jan 11]. Available from: http://en.people.cn/n3/2019/1018/c90000-9624243.html.
[41] National Academies of Sciences, Engineering, and Medicine. Graduate STEM education for the 2lst century. Washington, DC: The National Academies Press; 2018.
[42] National Academies of Sciences, Engineering, and Medicine. The endless frontier: the next 75 years in science. Washington, DC: The National Academies Press; 2020.