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Transforming and Upgrading the Nonferrous Metal Industry with Artificial Intelligence

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Abstract: Nonferrous metals are important, fundamental, and strategic materials for the national economy and national defense industry. In recent years, the nonferrous metal industry has made great progress in China. However, it is still facing the challenges of green, efficient, and intelligent development. In the nonferrous metal industry, the production conditions are complicated; the raw materials are changeable; and requirements for resources, energy, and environmental protection have become increasingly strict. Therefore, novel techniques are needed to cope with these complex changes and strict requirements for sensitive perception, precise operation, intelligent analysis, and quick decision-making. The rapid development of artificial intelligence provides the core techniques for the transformation and upgrading of nonferrous metal production processes. This paper discusses three main aspects: development and bottlenecks of the nonferrous metal industry, two cases of transforming and upgrading the nonferrous metal industry with artificial intelligence, and the challenges faced by artificial intelligence in the transformation and upgrading of nonferrous metal production.
Keywords: nonferrous metal industry; artificial intelligence; intelligent manufacturing; transformation and upgrading.

1 Present situation and challenges faced by the nonferrous metal industry

In the report of the 19th National Congress of the Communist Party of China, General Secretary Xi Jinping called for accelerating the construction of manufacturing power and the development of advanced manufacturing industries, with particular emphasis on accelerating the development of the substantial economy and building a solid foundation for a modernized economy. The substantial economy is the foundation of a country's economy, the fundamental source of wealth creation and an important pillar of the country's prosperity. In a 2018 government work report, Prime Minister Li Keqiang clarified that the implementation of *China Manufacturing 2025* is important to promote a strong industrial base, intelligent manufacturing, green manufacturing, and other major projects. *China Manufacturing 2025* has determined the overall strategy of building and manufacturing a strong country in China from the national level, and promoting intelligent manufacturing is the main direction [1]. The nonferrous metal industry is the cornerstone of China's substantial economy, an important support for the realization of a strong manufacturing country, and one of the main battlefields for China's structural reform and green development. The development of intelligent manufacturing is particularly important.

Since the reform and opening up, through the introduction, digestion and absorption of technology, and independent innovation, China's nonferrous metal industry has achieved remarkable results in terms of equipment upgrading, process technology improvement, capacity structure adjustment, and overseas resource development and utilization. At present, China has become the world's most complete and largest nonferrous metal manufacturing and consumer country, forming a relatively complete modern nonferrous metal industry system. However, China is still not a strong manufacturing country in the nonferrous metal industry. It still faces the challenges and problems of green and high-efficiency development. The main factors are as follows:

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① High-quality resources are exhausted, the proportion of difficult resources is large, and production equipment and technological levels need to be further improved. ② Waste water, waste gas, and waste solid emissions are large, energy consumption is large, and energy efficiency and environmental protections need to be further improved. ③ The degree of automation of the production process is not high, the dependence on operators is large, and the optimization of production control needs further intelligent automation. ④ Enterprise production, operation, and management lack an agile decision-making mechanism that responds quickly and actively to market changes, and the level of intelligent decision-making needs to be further improved. Resources, energy, efficiency, and the environment are the main bottlenecks restricting the development of China's nonferrous metal industry. The greening, efficient transformation, and upgrading of China's nonferrous metal industry is urgently required. To this end, intelligent manufacturing is the only way for the nonferrous metal industry to become green and efficient. The green selection and smelting technology for efficient and comprehensive utilization of complex mineral resources, the intelligent and independent control of the production process, and the intelligent level of enterprise decision-making are the key issues for the efficient and green transformation and upgrading of China's nonferrous metal industry.

The new round of scientific and technological revolution and industrial transformation has formed a historic intersection with China's accelerated transformation of economic development mode, providing a major opportunity for the nonferrous metal industry to implement an innovation-driven development strategy. The close integration of modern information technology (such as the new generation of artificial intelligence and big data) with the nonferrous metal industry provides an important technical guarantee for the transformation and upgrading of China's nonferrous metal industry. It is of great significance to the intelligent manufacturing of China's nonferrous metal industry to drive the green and efficient transformation with artificial intelligence.

2 Case study of transforming and upgrading nonferrous metal industry with artificial intelligence

Intelligent manufacturing is a human-machine integrated intelligent system composed of intelligent machines and human experts. It carries out intelligent activities such as analysis, reasoning, judgment, conception, and decision-making in the manufacturing process, as well as expanding, extending, and partially replacing human experts in the manufacturing process. The mental work in China has become a recognized high technology that enhances the overall competitiveness of manufacturing. In the nonferrous metallurgical production process, the production of raw materials is varied, the working conditions are complex, and the production process is both complex and long. From the requirements of transformation and upgrading to green, efficient, and intelligent production, it is necessary to respond through sensitive knowledge, fine operation, intelligent analysis, and agile decision-making, while handling these complex changes and stringent requirements. Therefore, artificial intelligence technology plays an important role in the process of greening and increasing the efficiency and intelligence of the nonferrous metal industry; it has several practical applications and economic effects. In this section, the important role and significance of artificial intelligence technology (in assisting the optimization and upgrading of the nonferrous metal industry) are explained from both the control and the decision-making levels. This is discussed using the example of intelligence-raising of the flotation process, based on distributed machine vision and purchasing knowledge automation of raw materials in smelting enterprises.

2.1 Intelligent upgrade of the froth flotation process based on distributed machine vision

Mineral processing is an important part of the processing of mineral resources. The level of ore dressing directly affects the recovery rate of mineral resources and environmental benefits. Froth flotation is a major mineral processing method widely used in industrial sectors such as steel, nonferrous metals, and coal. Froth flotation is a process route in which a flotation agent is added to the slurry to produce a stable bubble carrying the ore particles; it also involves the collection of ore-containing material by collecting the froth containing the mineral point. Because of the long process flow of froth flotation, frequent fluctuations of mineral source components, variable working conditions, and the inability to detect on-line quality indicators, the production process relies mainly on the visual characteristics (such as distribution, color, and virtual reality) of the multi-stage multi-slot froth according to the experience of the operators. Comprehensive correlation analysis and judgment of flotation and working conditions completes the coordinated operation of multi-tank addition, position, flow, blast volume, and other factors, as shown in Fig. 1. However, because of human subjectivity, large analytical error, and low work efficiency, it is difficult to cope with changes in raw materials in a timely manner. This results in unstable working conditions, frequent fluctuations in production indicators, and unstable quality of concentrate products. This in turn causes excess consumption of chemicals, low resource recovery rate, and serious environmental pollution.

As an important branch of artificial intelligence, machine vision has been widely used in various industries of the national economy. An industrial machine vision system converts the target into an image video signal through an image video capture device, extracts the features of the target through the image video processing system, and guides and controls the production process through feature recognition. Therefore, machine vision has the potential to enable the use of machines to replace human perception and cognition. It has the characteristics of fast processing speed and high precision, which can greatly improve the flexibility and automation of production. Moreover, in high-risk and high-volume repetitive production processes, machine vision has more perceptual power and more accurate recognition capabilities than human vision. In order to solve the defects of manual operation in the flotation process (by introducing machine vision technology), using distributed machine vision to extract froth image sensitive features enables real-time prediction of the metal grade in the production process, flotation condition identification, and coordinated, optimized control of the flotation process. Therefore, it can effectively cope with frequent changes in mineral source conditions, improve the resource recovery rate, reduce chemical consumption and pollutant emissions, and provide one of the key technologies for incorporating intelligence in the flotation process [2]. Fig. 2 shows the flow chart of intelligent identification and coordinated optimization control of the froth flotation production process on the basis of distributed machine vision.

2.1.1 Flotation froth image sensitive feature extraction and key indicator prediction

From a sensitivity analysis of the froth on the change of the agent, sensitive features such as froth size, texture, flow velocity, color, stability, and bearing capacity during the flotation process can be determined. Through certain feature description methods, the characteristics and mechanism of the froth image are combined. Model and operational data to achieve metal grade prediction (Fig. 3) can provide a basis for the identification, analysis, and coordinated control of the flotation process [3–5].

2.1.2 Identification of working conditions in the flotation process based on froth image features

The flotation process conditions and the froth image have a strong correlation; different working conditions produce different froth image features, and different froth images can reflect different production conditions. Aiming at the relationship between machine vision features and working conditions, a multi-

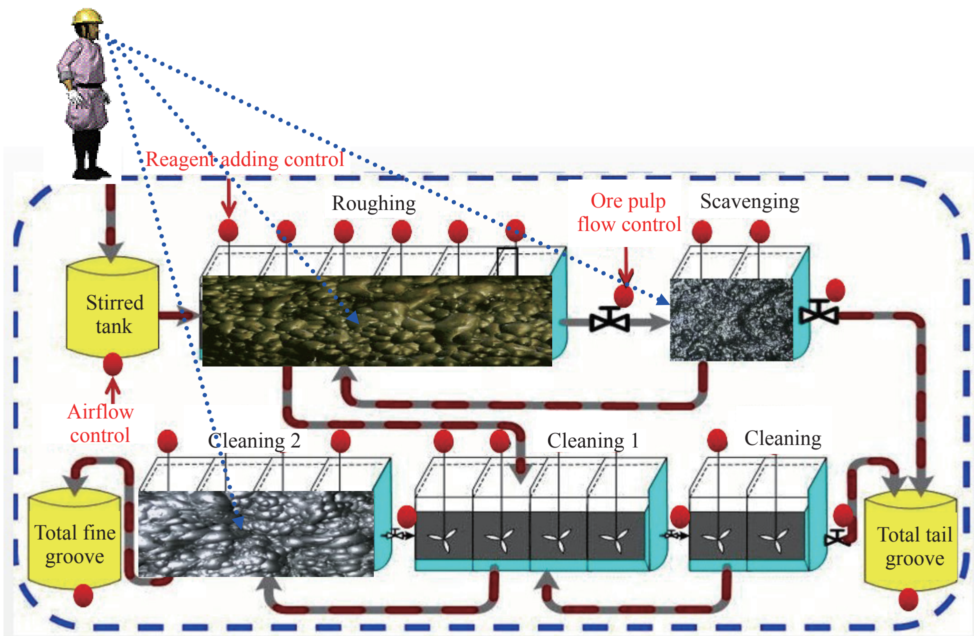

Fig. 1. Artificial-based froth feature analysis and operation.

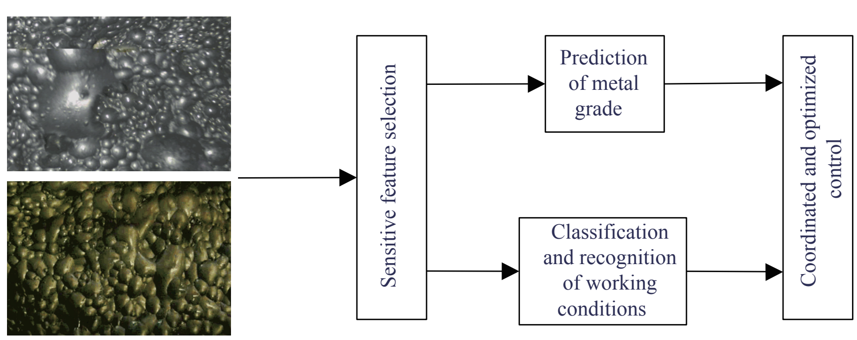

Fig. 2. Intelligent recognition and coordinated optimization control of the flotation process based on machine vision.

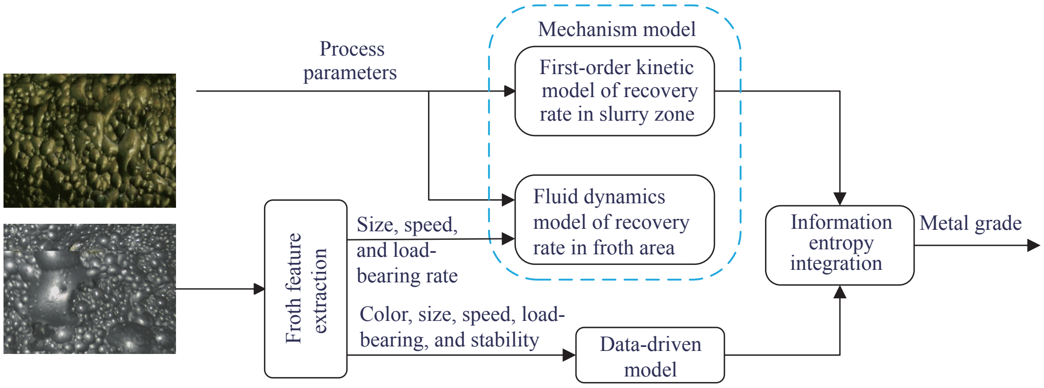

Fig. 3. Intelligent prediction modeling of metal grade in the flotation process.

case intelligent identification method based on machine vision features can be established, such as flotation intrusion type recognition based on fusion of froth image features and process parameters, self-learning recognition of dosing health status based on dynamic distribution features of froth size, recognition of ill-conditioned conditions based on multi-scale froth features, and embedded prior knowledge clustering [6–8].

2.1.3 Full-flow intelligent coordination optimization control of flotation based on froth image sensitive features

Intelligent coordination optimization is based on the analysis of froth image features from different processes and intelligent identification of working conditions. Thus, the best froth image characteristics of each process can be determined, and through the automatic control of the amount of operation (such as dosing volume and air volume), it can be ensured that the working conditions are running at an optimal state, thus changing the method of manual observation of froth and manual adjustment [9−11]. Fig. 4 shows the intelligent coordinated optimization control scheme for flotation based on froth image sensitivity.

This research has been applied to a number of mineral flotation enterprises, achieving intelligent operation based on automatic identification, analysis, and control of froth images, stabilizing the concentrate grade, effectively improving the recovery rate of valuable metals in the beneficiation process, and achieving positive social and economic benefits.

2.2 Automating procurement knowledge of raw materials in smelting enterprises

In modern nonferrous metal industry enterprises, most manual labor has gradually been replaced by machines. The management and control of enterprises mainly relies on knowledge workers, and the core is knowledge-based work. With the expansion of enterprise scale and the extensive application of information technology, knowledge workers are unable to do the work given the new information environment and massive amounts of data. Manual operation and decision-making are subjective and inconsistent, and the overall optimization of the entire process of industrial production cannot be realized. The promotion, accumulation, and transfer of knowledge is difficult. Knowledge-based work is the use and creation of knowledge. Its core requirements are the tasks of complex analysis, accurate judgment, and innovative decision-making [12]. Knowledge automation mainly refers to the automation of knowledge-based work [13]. The prestigious McKinsey Global Institute has identified knowledge-based work automation as the second most disruptive technology in its report entitled *Disruptive technologies: Advances that will transform life, business, and the global economy* [14]. Therefore, knowledge automation has great potential and broad prospects in the nonferrous metal industry.

This paper takes the lead procurement decision of a lead-zinc smelting enterprise as an example to illustrate the significance of knowledge automation. China's nonferrous metal smelting enterprises often face the following problems in the procurement of raw materials: raw materials sources are wide (often more than 100 suppliers), the composition is complex and varied, the grades and prices are different, the production scale of enterprises is large, and the demand for raw materials is large. Further, raw material procurement occupies a large amount of capital. Production has strict quality requirements for raw materials, such as metal grade and impurity content. For continuity of production, enterprises must have reasonable inventory to address various uncertain factors. There is a disconnect between the product and raw material markets.

In past production management, raw material procurement of the enterprise was mainly based on the decisions of experienced procurement personnel, which is typical knowledge-based work. When making manual decisions, we must consider the procurement objectives, external conditions, supply status, business conditions, and complex issues such as capital, inventory, and supplier relationships; these often cause losses to the company because of incomplete decision-making. To this end, the lead-zinc smelting enterprise has built an automated system for raw material procurement decision-making knowledge, as shown in Fig. 5.

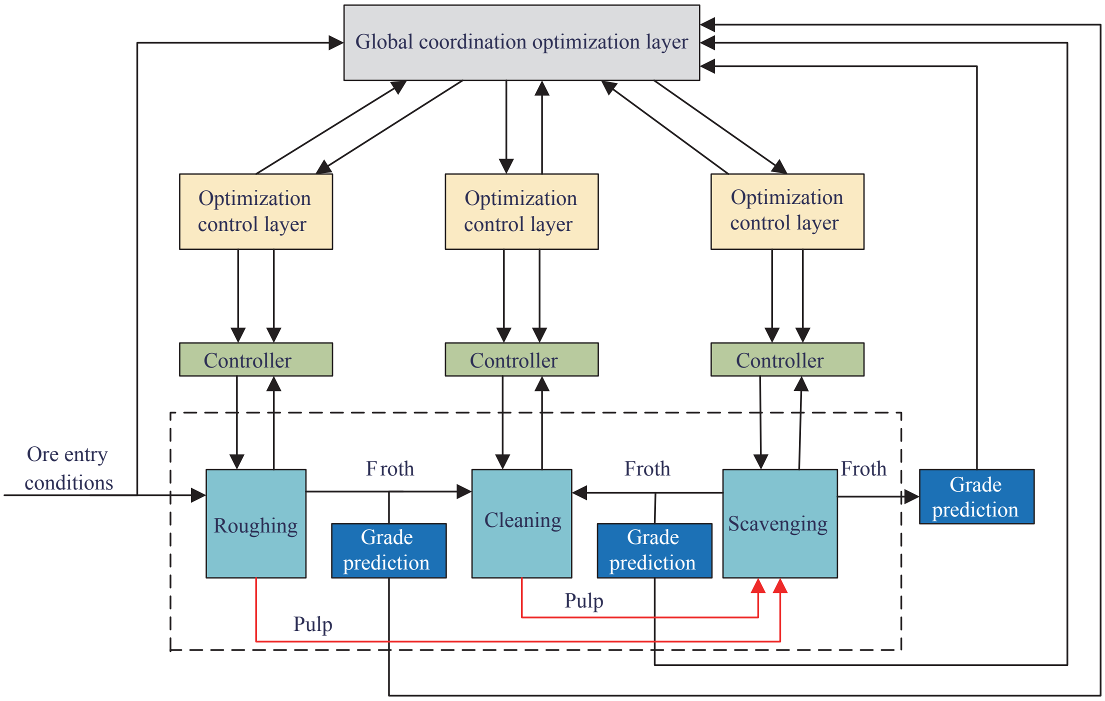

Fig. 4. Coordinated optimization control framework for the flotation process.

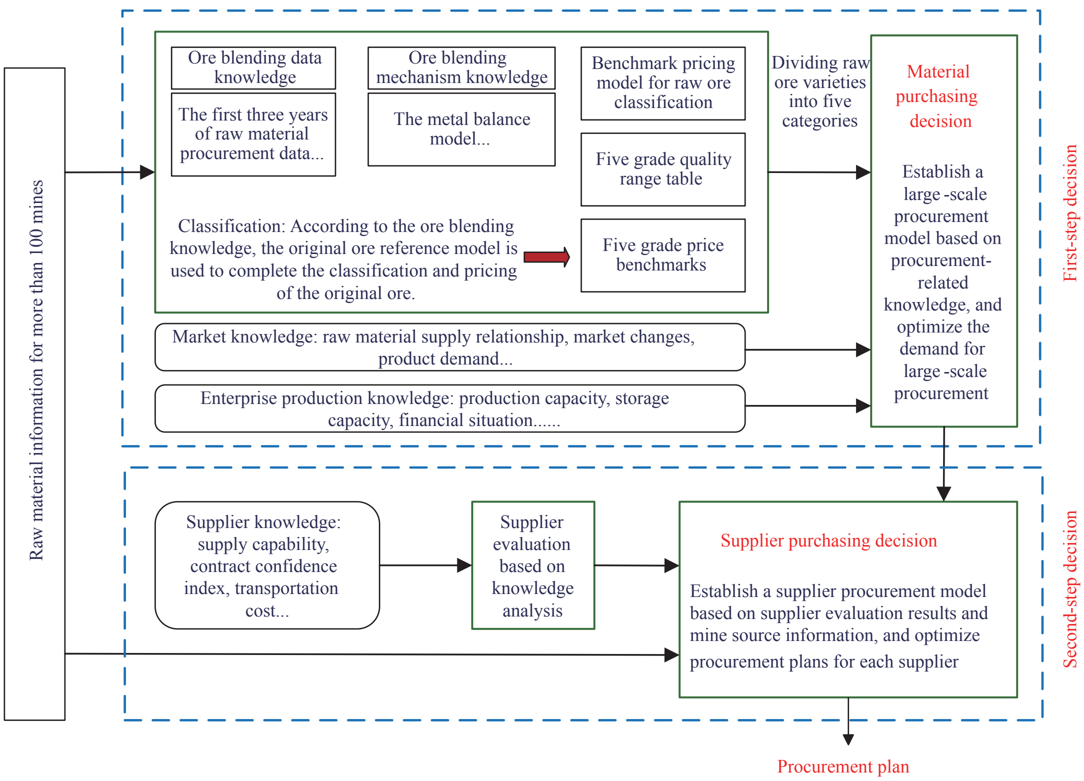

Fig. 5. Knowledge automation system for enterprise raw material purchase decisions.

In the decision-making process, the decision-making of raw materials procurement from more than 100 mines is divided into a two-step decision: First, according to the knowledge of ore-matching data, knowledge of the mineralization mechanism, and the classification model of raw ore, more than 100 kinds of mineral resources are divided into several categories according to their quality. Each type of procurement funding is the minimum target to meet the production requirements, establish a raw material classification procurement model, and determine the purchase amount of each type of raw material according to the classification procurement-decision model, market knowledge, and enterprise production knowledge. In the actual procurement process, the procurement decision makers also need to consider the same type of concentrate, which may vary in price depending on the region and subcontractor; each subcontractor may execute different contracts. The quantity of the goods can exceed the contract quantity, and some suppliers cannot fulfill the contract quantity; some sub-contractors belong to the operating company, and the grades of concentrates provided each year may be different. To this end, the second step is to further optimize each type of procurement, that is, optimize the suppliers' procurement plan on the basis of the results of the classification decision and according to a supply procurement model established based on the supplier evaluation results and mineral source information. The two-step decision-making and knowledge automation system procurement plan draws on the idea of artificially making purchasing decisions based on knowledge, which not only simplifies the calculation of optimization decisions, but also can easily be used for the same class of mineral resources when the supply from a certain source is insufficient for supplier reasons. Finding alternative suppliers can avoid the drawbacks of manual decision-making, saving companies millions to tens of millions of dollars in raw material procurement each year [15,16].

These two cases illustrate the possibilities from the control level and the decision-making level. Artificial intelligence technology can help the intelligent manufacturing of nonferrous metals to realize the transformation from traditional production methods to green, efficient, and intelligent production methods. With the help of artificial intelligence technology, the establishment of intelligent autonomous systems with intelligent perception, cognition, control, and decision-making and coordination is the only way to achieve green and efficient production of nonferrous metals.

3 Transforming and upgrading the nonferrous metal industry: Challenges to artificial intelligence

The main path to efficiency, green transformation, and upgrading of the nonferrous metal industry is increasing production process intelligence. The key is to realize the intelligent perception, cognition, and decision-making of the production process through artificial intelligence technology.

The development history of artificial intelligence technology can be divided into two major genres. One is a rule-based method represented by framework knowledge and semantic networks. It imitates the method humans use to understand and process objects and builds a rule system to solve intelligent problems from top to bottom. The second is based on data statistics, represented by machine learning and neural networks. It relies on large-scale data sets and powerful computing resources and obtains the computing model from bottom to top through training to achieve the purpose of intelligent computing. The success of systems from IBM's Deep Blue to AlphaGo demonstrates that data-oriented artificial intelligence has strong vitality. Its decision-making aims to find the best solution by evaluating and learning from precise information according to the rules of winning or losing. Its applicable objects are still the problem of closed sets, complete rules, and limited constraints, and have already achieved important applications in the fields of Internet, security, and finance. Because of the complexity and large-scale nature of the nonferrous metal industry, its intelligent transformation and upgrading poses a higher challenge to artificial intelligence technology.

The problems faced by increasing the intelligence of the nonferrous metal production process mainly include: ① There is a need to face interference, uncertain dynamic production environments, multi-temporal scales, and incomplete data sets for global situational awareness and cognition. ② The production situation is difficult to represent, and the complex information corresponding to production control and decision-making is difficult to calculate. It is necessary to learn to address fragmented tacit knowledge contained in small sample data with incomplete conflicts. ③ The process mechanism is complex and cannot be accurately modeled. It is difficult to optimize cooperative operation with multiple process coupling. ④ The factors that affect decision-making are unclear in definition, inconsistent in scale, and feature multi-objective conflict. It is difficult to make stratified and cross-domain agile decision-making. It is clear that nonferrous metal industry production does not meet the existing premise of closed sets, complete rules, and limited constraints and increasing its intelligence is a challenge for artificial intelligence. To increase the intelligence of the nonferrous metal production process, the top-down rules and the bottom-up data should be effectively combined in the physical space of man–machine information in nonferrous metal industrial production processes. The intelligent nonferrous metal industry is realized from the aspects of intelligent sensing of the nonferrous metal manufacturing environment, intelligent autonomous control of human-machine system coordination, and dynamic intelligent optimization decision-making. The main scientific issues include:

(1) Complex process dynamic modeling and dynamic sensing of working conditions: ① Dynamic modeling, virtual simulation, and visualization of production processes with complex mechanisms. ② Rapid detection technology of material composition and special production parameters in complex environments. ③ Multi-source, heterogeneous, and multi-modal dynamic data feature representation and extraction. ④ Dynamic data perception of operational conditions combined with big data and mechanism knowledge.

(2) Dynamic cognition and knowledge discovery: ① Deep

learning modeling of time series and causal relation for multiple spatiotemporal data. ② Deep learning of temporal spatial causality associated with multiple spatio-temporal dynamic data. ③ Knowledge association modeling and self-learning methods. ④ Multi-source knowledge integration and transfer learning in the production process.

(3) Knowledge-driven multi-objective dynamic decision making in a big data environment: ① Big data and knowledge-driven, multi-scale, multi-conflict target and dynamic collaborative decision-making theory. ② Intelligent autonomous control methods with high dynamic performance. ③ Dynamic performance evaluation and intelligent adjustment methods for the production process.

(4) Information physics system integration and collaboration: ① Autonomous coordination control and intelligent optimization of man-machine systems. ② Defense and security of information physics systems. ③ Man-machine cooperation decision-making and mutual learning in an uncertain and open environment.

4 Conclusions

At present, China's nonferrous metal industry is in a critical period, transitioning from quantity to quality in terms of production equipment and process technologies, and it is urgent to realize green and efficient production through intelligent production processes. The deep integration of artificial intelligence technology and the nonferrous metal industry can provide strong support for the transformation and upgrading of the nonferrous metal industry and build China's nonferrous metal industry with technological leadership. Meanwhile, it can also promote the further development of artificial intelligence technology and realize the coordinated development of industrial and ecological civilization.

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