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Research Article

Research on Nickel-Cobalt-Copper Productive Collaboration and Intelligent Decision-Making Technology in Symbiotic Coupling Enterprises

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This study investigates the research on nickel-cobalt-copper productive collaboration and intelligent decision-making technology for symbiotic coupling enterprises in the Gansu Province of China. The aim is to address the problems of low resource utilization efficiency, weak production collaboration, and an insufficient intelligent decision-making level in the nonferrous metallurgy industry. First, the present situation of nickel-cobalt-copper industry chain-level collaboration in the agglomeration area is analyzed extensively, and the corresponding problems are proposed. Second, the functional framework of productive collaboration and intelligent decision-making is presented from the industrial chain and industrial agent levels. In addition, the design methods of various balance strategies in the production collaboration within the industrial agent are provided. These can realise the daily balance of material, metal, and energy data in an individual industrial agent. Finally, with regard to intelligent decision-making at the industrial chain level, six key measures surrounding different themes are provided to support the implementation of productive collaboration and intelligent decision-making in the nonferrous metallurgy agglomeration area.

1. Introduction

The nonferrous metallurgy industry plays an irreplaceable role in ensuring the construction of key national projects and promoting the steady growth of the national economy [1–3]. Gansu, China, is a famous "hometown of nonferrous metals." There are 38 types of nonferrous metal reserves ranking among the top five in China. These include 10 minerals such as nickel, platinum, palladium, and gallium (which are ranked first in the country). Jinchang (the "capital of nickel"), Baiyin (the "city of copper"), and Jiayuguan (the "city of steel") are three key industrial cities that have formed the agglomeration area of nonferrous metallurgical enterprises [2]. In the agglomeration area, the nonferrous metallurgical industry chain is an upstream and downstream chain between a series of interrelated and interdependent links that are formed around nonferrous metallurgical production and services. These mainly include mineral exploration, ore mining, beneficiation, smelting, metal processing, and other main links. The main upstream businesses are the mining of metal ore and the recycling of metal waste. The main midstream business involves the smelting and processing of nickel, cobalt, and copper. The corresponding products include electrolytic nickel, nickel powder, nickel shot, ferronickel alloy, nickel salt, cobalt metal, cobalt salt, cobalt oxide, copper foil, copper base alloy, copper strip, |and copper bar. The downstream products are sold to the construction, machinery manufacturing, automobile manufacturing, household appliance, power industries, transportation industries, petrochemical industries, and pharmaceutical industries. Among these products, power and construction account for a large proportion of the end consumption of copper [4, 5].

Based on various information flows which are generated by relevant professional information systems within the enterprise, the idea of intelligent decision-making in nonferrous metallurgical enterprises is to support the optimization management and independent decision-making of enterprise business processes at the level of production execution and operation management through the integration of traditional mechanism modeling and data-driven intelligent modeling so as to achieve the optimization operation objectives of improving quality and efficiency, saving energy, reducing consumption, and reducing the environmental pollution. To realise the intelligent decision-making in the symbiotic coupling area of nonferrous metallurgy, the productive collaboration at the industrial chain level is required to support it. For the nickel-cobalt-copper industrial chain, productive collaboration refers to the integration of decentralized production entities with mutual dependence in the agglomeration area through the self-organization and operation mechanism of "competition-cooperation-coordination" to cooperate with each other and work in a coordinated manner to complete the tasks that any single production entity cannot complete or can complete, but the economic benefits are not up to standard. Furthermore, productive collaboration can standardize the business process of symbiosis and interaction between enterprises in the agglomeration area and build a standard production collaboration network to form a production form with overall benefits better than the sum of individual benefits. In recent years, data-driven machine learning methods are more and more widely used in the related research of intelligent decision-making and productive collaboration. The basic idea is to use the above data resources to realise the related functions of prediction, evaluation, scheduling, decision-making, and optimization in the production and manufacturing process. The machine learning method does not need to pay attention to the specific mechanism information of the system [6]. It can effectively mine the correlation between variables based on data [7], mainly including supervised learning (such as linear regression [8], deep learning [9], transfer learning [10]), unsupervised learning (such as clustering [8], principal component analysis [8], and so on), and reinforcement learning (RL) [11, 12].

In the process of nonferrous metallurgical production, the trajectory flow of various materials along the life cycle of processed products is called material flow. Furthermore, the trajectory flow of various energies along the path of conversion, use, and emission is called energy flow [13]. In recent years, some works are focused on decision-making and collaborative relationships among material analysis, energy management, and metal balance based on machine learning techniques. Based on artificial neural network technology, the authors in [14] coordinated the model prediction with an amplification factor with the plant response and studied the prediction of the material and metallurgical balance of the zinc processing plant. Based on the developed neural network model, the authors in [15] studied forecasts of the mass and metallurgical balance at a gold processing plant. The authors in [16] tested random forest, SMO (variation of SVR), linear regression, M5 and M5P (variation of the decision tree), and other machine learning techniques to forecast six geometallurgical variables at the Leveäniemi iron ore mine. Based on linear and quadratic regression, ACE (alternating conditional expectations), ridge regression, random forest, and gradient-boosted models (GBMs), the authors in [17] evaluated the results obtained to forecast the acid consumption, recovery, and impurity in a copper ore processing plant.

Various production departments are involved in the production process of nickel, cobalt, and copper, and the material data are complex [18, 19]. This results in a low overall level of internal and external production coordination and intelligent decision-making of enterprises in the nonferrous metallurgy agglomeration area. The related enterprises in the industrial chain are called industrial agents. The industrial agent has not realized the cross-domain optimization of the process, and the internal production processes and logical production units are relatively independent [18, 20–22]. These cannot realise effective coordination between upstream and downstream processes [23–26] or the flow coordination of materials and energy among agents [27–30]. The aforementioned circumstances generate a scenario wherein the production command and management at the industrial chain level cannot share on-site information in real time or make correct intelligent decisions [31–34]. Consequently, the production scheduling and comprehensive control business would lag behind [35–39].

It is necessary to comprehend the distribution and coordination of the production business relationship network in the agglomeration area [40, 41], the distribution and operation status of each logical production unit, warehouse, instrument [42–44], and the business of resource recycling [45–47]. The key problems include (1) realising an interactive coordination of materials and energy and (2) rationalizing the analysis of interactive information. These two problems must be solved to track the material information and energy information. The balance calculation and analysis [48–53] based on the data obtained from the system can support the technical and economic production indicators of the nickel-cobalt-copper industrial chain. In addition, the balance calculation and analysis determine the weak links of production, tap the production potential, and support intelligent decision-making at the industrial chain level. Finally, we can realise the coordination and decision-making for the material and energy flow between industrial agents and for that between logical production units.

To address the problems encountered in the production process of nonferrous metallurgical enterprises in the agglomeration area, we focus on the production process of the nonferrous metallurgical process. It includes complex physical and chemical transformations. The present situation of the industrial chain and an example of the establishment of a collaborative relationship in the production and processing process of nickel-cobalt-copper are presented considering the production coordination and intelligent decision-making of symbiotic coupling enterprises in the agglomeration area as the core. The main structure of production collaboration and intelligent decision-making is designed, and the key measures to support production collaboration and intelligent decision-making are summarized.

2. Analysis of the Present Situation of the Nickel-Cobalt-Copper Industry Chain-Level Business Collaboration

2.1. Present Situation of the Industrial Chain. The main mineral resource associated with nickel and cobalt in the Gansu Province of China is nickel-bearing sulphide ore. It revolves around the nickel-cobalt-copper smelting in the agglomeration area. The upstream of the nickel industrial chain is mainly aimed at the mining and beneficiation of sulphide and Indonesian laterite nickel ores in the agglomeration area. The midstream completes the smelting and processing of nickel. The main products include electrolytic nickel, nickel powder, nickel pill, and nickel salt. The downstream involves the end-consumer products based on nickel. The upstream, middle, and downstream form a complete industrial chain (see Figure 1).

The upstream of the cobalt industrial chain in the agglomeration area includes cobalt mining, secondary recovery of cobalt-containing waste, and other links. The midstream comprises cobalt products, which have different downstream applications according to classification. Cobalt mainly exists in the form of copper and nickel-associated resources. Nickel cobalt-associated ore, copper cobalt-associated ore, and primary cobalt reserves account for 50%, 44%, and 6%, respectively, of the reserves. The industrial chain is formed based on the mining, smelting, and processing of cobalt ore in the agglomeration area and downstream end consumption (see Figure 2).

Copper smelting in the agglomeration area is completed by two systems: copper synthesis furnace smelting and electric furnace smelting. In the copper smelting system, the copper industry chain is divided into three stages: the upstream is mainly the mining stage and recycling of waste copper, the midstream mainly includes the smelting stage of roughing and refining of copper concentrate or waste miscellaneous copper, and the downstream involves the stage of deep processing of copper. The copper processing products include copper rod, copper tube, copper plate, copper foil, copper wire, and copper-based alloy (see Figure 3).

2.2. Collaborative Relationship between Materials, Metals, and Energy. In the entire production chain of raw material mining, smelting, processing, and end-products of nickel-cobalt-copper, the movement and tracking of materials, energy, and metals have not realized agent-level coordination. Various balance operations have not realized online generation. It is difficult to evaluate and adjust the material, metal, and energy balance. The efficiency of the generation of balance reports of agent-level raw materials, semifinished products, and finished products is low. This cannot satisfy the decision-making requirements of intelligent production scheduling. To improve the economic and management benefits of nickel-cobalt-copper industrial chain, it is necessary to develop toward diversification, refinement, production coordination, and intelligent decision-making for nickel-cobalt-copper series products.

From the control and optimization of the production process to process monitoring and management decision-making, the comprehensive utilization of process data of material flow, metal flow, and energy flow plays a vital role in the safe and efficient production by relevant enterprises in the nonferrous metallurgy agglomeration area. The nickel-cobalt-copper production in the agglomeration area involves a long process and displays a complex material trend. The entire processing process presents a network structure. For example, an industrial agent would produce a variety of finished or semifinished nonferrous metallurgical products, and it generally uses and consumes materials. The production data can be obtained using the instruments at the production site. However, in the actual production process, the unit conversion of the volume and quality of material, metal, and energy data must be addressed, as well as the interference of random and significant errors. This causes the final collected production data to be inaccurate and poses significant difficulties for the monitoring of the production process. This, in turn, results in a decrease in the performance of production optimization and process control, e.g., decision-making based on incorrect process data.

For the nickel-cobalt-copper industrial chain, a collaborative production network is established for the material, metal, and energy flow between different agents and between logical production units in the agglomeration area. The business process of material, metal, and energy flow trends and interactions among symbiotic coupling enterprises are standardized in the agglomeration area. In addition, a standard production collaboration network is constructed. The relevant departments of nickel-cobalt-copper production must arrange the business processes of the material, metal, and energy balance. This can formulate the corresponding management institution. Thereafter, the establishment of full-time material balance posts must be promoted and the organizational structure of the enterprise altered. The standard flow diagram of the material, metal, and energy flow between two industrial agents is shown in Figure 4.

3. Framework of Production Collaboration and Intelligent Decision-Making

3.1. Nickel-Cobalt-Copper Production Coordination and Intelligent Decision-Making in the Industrial Chain. The production process of the nonferrous metallurgical industry is a complex system with significant integration of the physical and information processes. The collaborative production and intelligent decision-making of the entire system involve the information regarding production, quality, sales, and inventory of symbiotic coupling enterprises in the

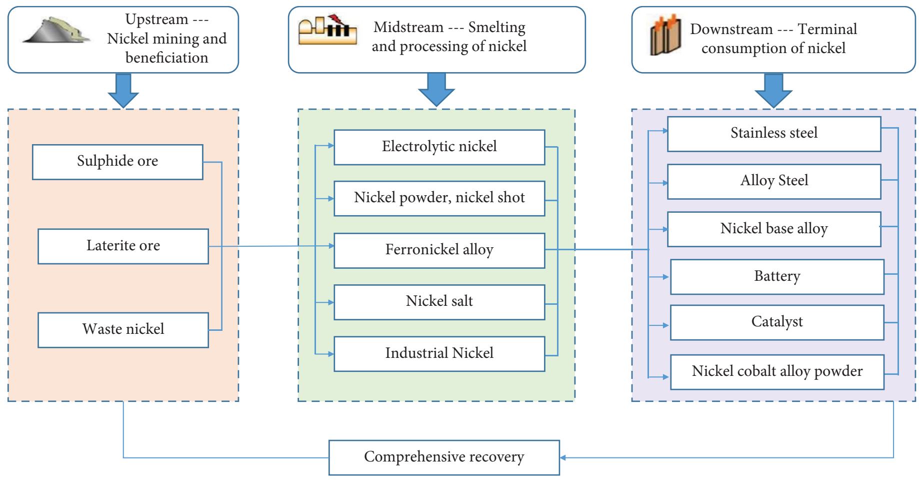

Figure 1: Nickel industry chain.

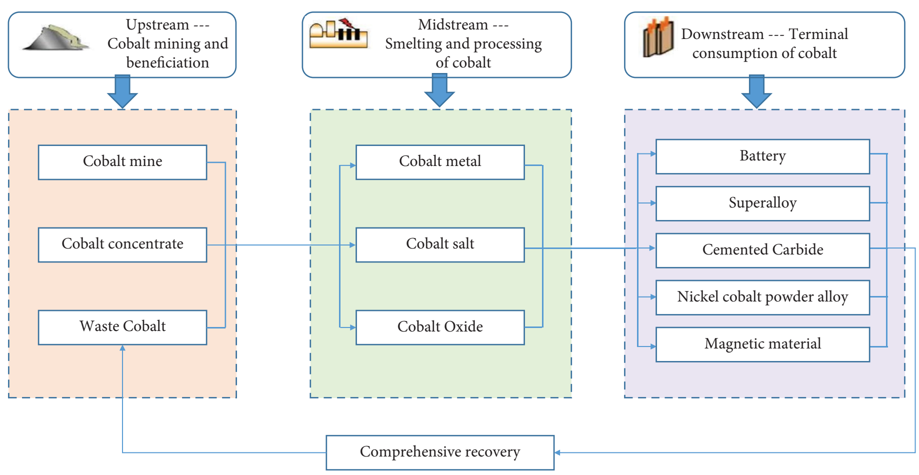

Figure 2: Cobalt industry chain.

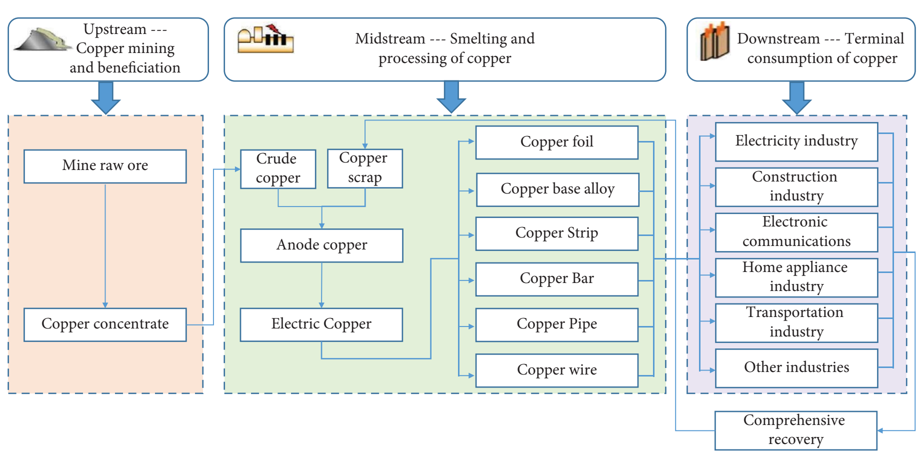

Figure 3: Copper industry chain.

agglomeration area. The collaborative production and intelligent decision-making are controlled by market information, industrial policy, and other external environmental information. The objective of industrial chain-level nickel-cobalt-copper production coordination and intelligent decision-making is to establish IT capability of intelligent optimization decision-making in the process of the non-ferrous metallurgical industry. It can generate the

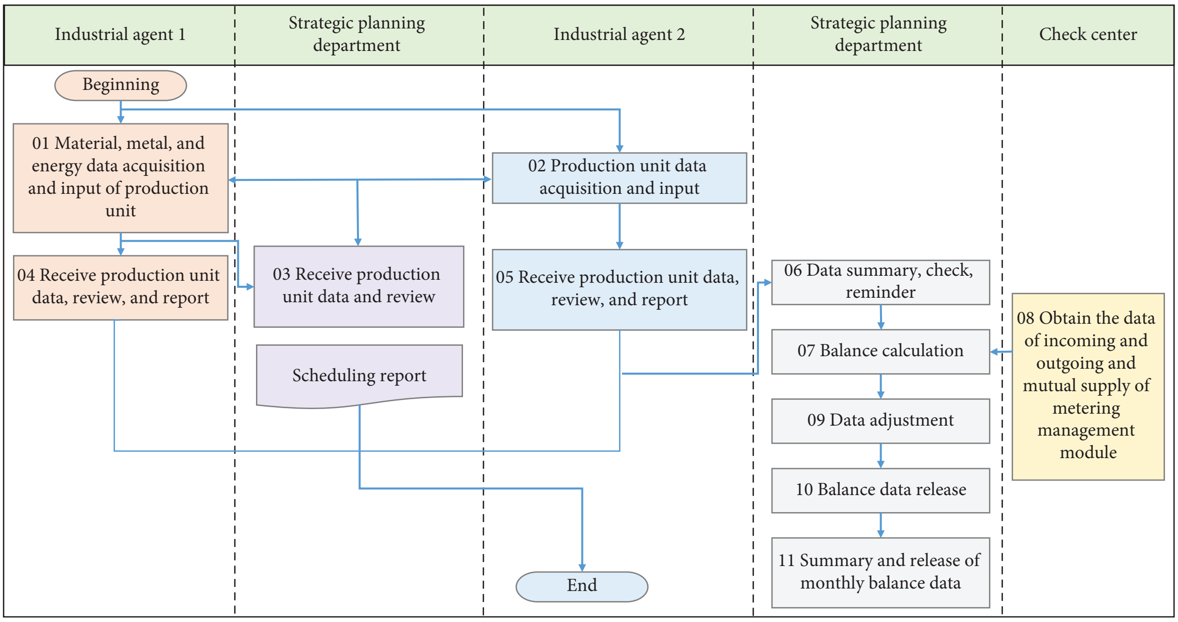

Figure 4: Schematic for coordination of material and metal energy among different industrial agents.

production indicators of coupling enterprises under the conditions of dynamic demand of market information and industrial policy, dynamic adjustment of the production status of symbiotic enterprises, the dynamic constraint of material metal energy consumption, and the dynamic constraint of safety and environmental protection. All of the above aspects can guide production coordination within the industrial agent. Simultaneously, the enterprise in the industrial chain realizes the production collaboration among the logical production units, captures the production data of the entire process in the shortest time, and realizes intelligent decision-making at the industrial chain level. The specific architecture is shown in Figure 5.

The main structure of nickel-cobalt-copper production collaboration and intelligent decision-making at the industrial chain level consists of three layers from the bottom to the top: the production index optimization decision-making layer of the symbiotic coupling enterprise at the industrial chain level, production collaboration and intelligent decision-making layer at the industrial agent-level, and the intelligent optimization control layer at the logical production unit-level.

The production index optimization decision-making layer of the symbiotic coupling enterprise at the industrial chain level can perceive the production data of the entire process. In addition, it can receive market information and policy information in real time. This layer can achieve the production index of "safety, stability, long-term, satisfaction, and excellence" of all enterprises in the agglomeration area to obtain a high-end, intelligent, and green industrial chain. In addition, it can realize integrated production collaboration and intelligent decision-making for planning, production, sales, and service. This layer can enable individuals' wisdom to interact and collaborate with the intelligent decision-making system and can help management decision-makers make accurate decisions in the real-time dynamic internal and external environment.

The industrial agent-level production coordination and the intelligent decision-making layer accept the production indicators of symbiotically coupling enterprises in the agglomeration area from the upper layer. In addition, it must coordinate each logical production unit (intelligent optimization control system) at the lower layer to complete specific production tasks. This layer can support the optimization of production indicators at the nickel-cobalt-copper industrial chain level and can automatically obtain information regarding working condition transitions and resource transformations (materials, metals, and energy) in the production process. This layer can intelligently perceive the variations in material, metal, and energy information, and it can conduct independent learning and independent decision-making. Finally, the layer can achieve an optimal allocation of resources, self-adaptation of working conditions, and an intelligent generation of decision-making. It would assign the optimal production index for the logical production unit of the next layer.

The intelligent optimization control layer of the logical production unit level mainly includes four parts: metallurgical production link, advanced controller, intelligent production optimization, and working condition identification. The intelligent optimal control can extensively integrate the intelligent control system with specific metallurgical production links. The fusion body would have a series of functions such as perception, monitoring, control, optimization, and self-healing. In particular, it has highly advanced capabilities of perception, control, and decision-making in terms of material flow, energy flow, metal flow, and information flow. These include adaptive, self-learning, self-diagnosis, and self-adjustment capabilities, which can address the variations in complex working conditions.

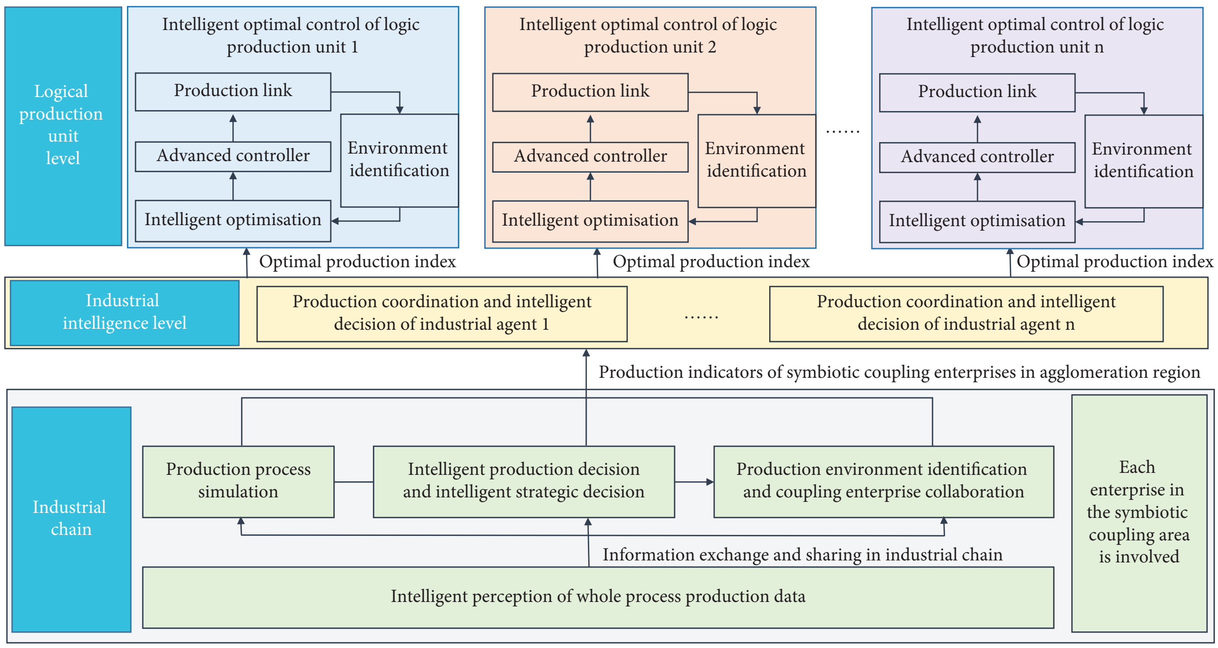

FIGURE 5: Main structure of industrial chain nickel-cobalt-copper production coordination and intelligent decision-making.

3.2. Agent-Level Nickel-Cobalt-Copper Production Coordination and Intelligent Decision-Making. For each industrial agent in the industrial chain, the overall objective of agent-level production coordination and the intelligent decision-making level involves realizing the three types of coordination of materials, metals, and energy within the agent and establishing the IT support capacity of intelligent production planning and intelligent production scheduling at the industrial agent-level. The following are the specific objectives: the industry agent can count the loss of materials, metals, and energy consumption in a timely manner by accurately integrating the measurement data of materials, metals, energy and the revenue expenditure, and inventory of each logical production unit. The above circumstances can ensure that the three types of balance calculation are more accurate and that the calculation cycle is shorter. Moreover, these can further enhance measurement, quality, planning, scheduling, and statistics.

The timely account and actual difference data of materials and metals are provided to the management of the industrial agent, and the causes of the differences are analyzed for the management. Based on the above data, the next rectification plan can be established, and the balance reports of raw materials, semifinished products, and finished products at the industrial chain level can be published regularly. Furthermore, we can ensure the scientific and efficient allocation of materials, metals, and energy and provide a decision-making basis for intelligent production planning and scheduling. This can realize the management of the entire process comprising the issuance and execution of planning and dispatching instructions and feedback. Considering the management of material, energy, and metal flows in the production process as the main line, the framework will integrate production planning and optimization, production scheduling and optimization, material, metal, and energy balances into a whole body. This is to ensure the visualization of information management in the production process, scientizationof intelligent decision-making, optimization of resource utilization, and economization of intermediate materials.

3.2.1. Functional Architecture of the Industrial Agent Level. Based on the design objectives of the above industrial agent-level production collaboration and intelligent decision-making layer, the functional architecture of collaborative production and intelligent decision-making within an individual industrial agent is proposed in this study. It is shown in Figure 6.

As is evident from Figure 6, the architecture is divided into two layers: the collaboration layer and the intelligent decision-making layer in the industrial agent. In the architecture, the functions of intelligent planning and intelligent scheduling are arranged and deployed mainly at the intelligent decision-making level. Planning and scheduling include the main bases of production and operation activities and contribute significantly to the advantages of industrial agents. Production planning is the determination of the production volume in a certain period according to the product market demand, raw material supply, production capacity, device operation, and maintenance plan. In addition, a production plan comprehensively considers the enterprise's management cost and the cost of finished products and semifinished products in the production process. Furthermore, it considers the production, management, and marketing status of the enterprise as the objective to obtain the maximum economic advantages.

Production scheduling and dispatching are the determination of a production and processing solution according to the planning to minimize the total cost, waste, product

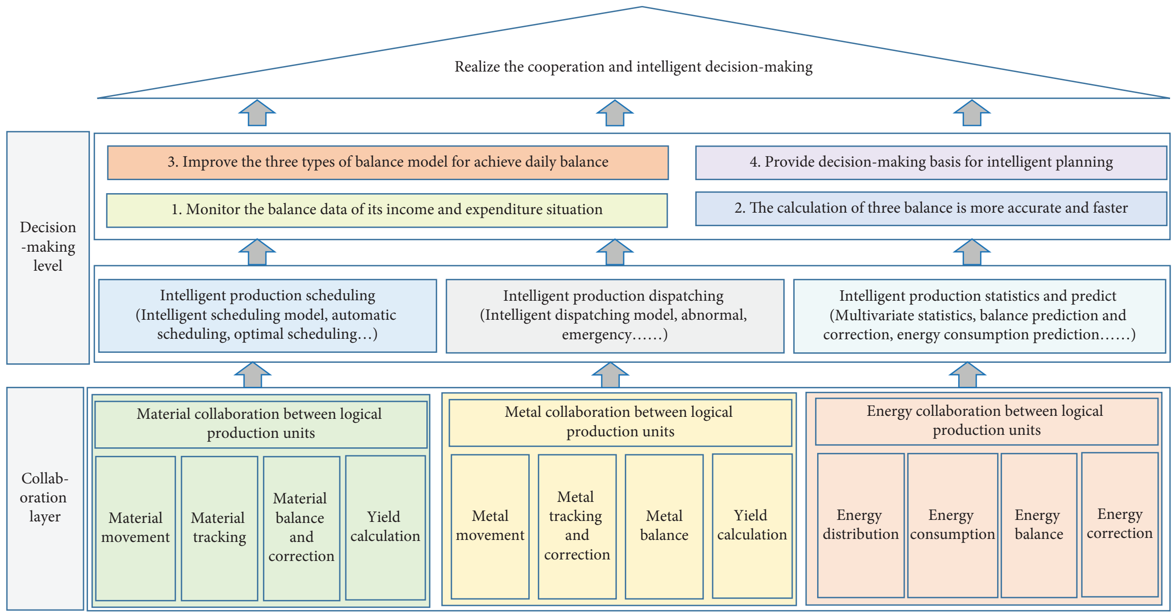

Figure 6: Functional framework of collaborative optimization and intelligent decision-making within industrial agents.

deviation, or time. Intelligent production scheduling mainly includes the generation of an intelligent scheduling model, automatic scheduling, optimal scheduling, and other functions. Intelligent production dispatching mainly includes dispatching model generation, abnormal emergency dispatching, and so on. Intelligent production statistics and prediction mainly include multivariate statistics, balance prediction and correction, energy consumption prediction, and other functions. The material balance strategy of intelligent correction, scheduling balance, and statistical balance is proposed. The shortage of measuring instruments is compensated for by using mobile error detection and alarm technology based on balance out of tolerance. Finally, the problem of excessive measurement data deviation caused by the shortage of measuring instruments is solved completely.

The collaboration layer in the industrial intelligent agent mainly includes the production collaboration among materials, metals, and energy between logical production units. The main functional modules include the following: basic information management, tracking of material, metal, and energy movement, generation of material, metal, and energy balance model, evaluation of this model, adjustment of this model, alarm to indicate abnormal movement of material, metal, and energy, and comprehensive statistics and decision support for the material, metal, and energy.

3.2.2. Design Method of the Balance Strategy in Production Collaboration. It is necessary to design a daily balance strategy through online calculations to realize the daily balance of material, metal, and energy data in an individual industrial agent by improving the three types of balance models in Figure 6 and to realize shift tracking, daily balance, ten-day verification, and monthly settlement. These would, in turn, improve the convenience of use of the three types of balance. The material, metal, and energy data in the logical production unit are summarized in the statistical post of the logical production unit on a daily basis. Thereafter, the relevant data are preliminarily verified and balanced by the statistical post of the logical production unit. The next step involves reporting and summarizing the verified data to the planning department at the agent level. The statistical post of the planning department is responsible for the daily balance within the agent. The balanced convenience of use is improved by designing the self-learning of material and metal routing, automatic data inspection, visual inspection of data, and automatic alarm. The specific design method is shown in Figure 7.

The material, metal, and energy balance model with automatic correction function can support the realization of the statistical objective of "shift tracking and daily balance." The material, metal, and energy balance model are provided mainly to the production statistics department for statistics based on the movement information at the logical production unit level. After the balance results are summarized, these would be used as the data source of statistical balance in the current month. In addition, these can be released to other relevant industrial agents as the data source. The key aspect of the design balance strategy is that the logical production unit manages the data of material, metal, and energy movement and allocation by shift. The statistics post summarizes the data of the three shifts into daily data and reports it to the planning management department. The settlement and mutual material supply data of the production agent are summarized to the agent-level planning department on a daily basis. The agent-level planning department conducts daily balance according to the reported data. At the end of the month, the daily data are summarized to provide an interface for statistical balance. Furthermore, these function as the data source for statistical balance.

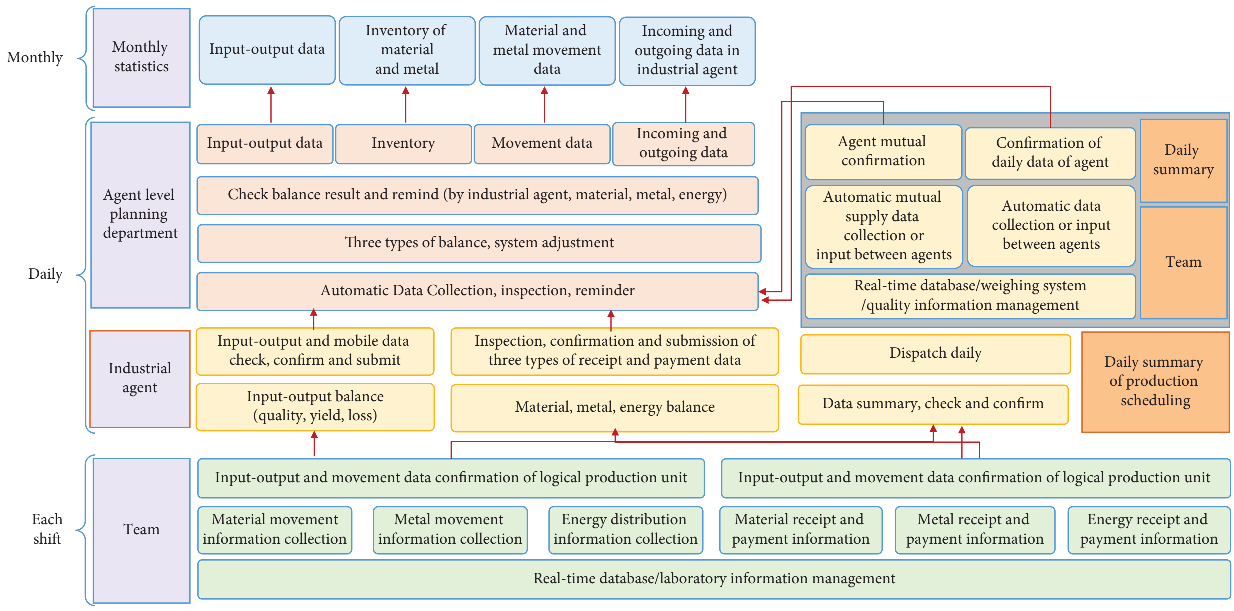

Figure 7: Design method of the balance strategy.

The following are the specific implementation methods:

Step 1. before the end of each shift, the staff shall verify the automatically collected information of material movement, metal movement, and energy allocation on duty in each logical production unit. The staff shall verify the manually entered information regarding material movement, metal movement, and energy allocation on duty in each logical production unit.

Step 2. the approver of the logical production unit reviews the entered data. If the data fail to pass the review, the operator would fill it in again.

Step 3. before the end of each shift, the agent-level measurement department obtains the measurement movement information of the incoming and outgoing units from the movement process of materials and metals and the energy allocation process. For the completed movement, the settlement data would be entered according to the settlement document. For the incomplete movement, the measurement department would issue the movement information within this time.

Step 4. before the end of each shift, the measurement department settles the mutual material supply data between logical production units and enters the settlement data of mutual material supply into the measurement system.

Step 5. after the collection of the three-shift data on each day, the agent-level dispatching post summarizes and reviews the production data and generates a daily dispatching report.

Step 6. the statistician summarizes and reviews the data of the three shifts and reports it to the agent-level planning department for statistics.

Step 7. the measurement department releases the daily settlement data and mutual supply data. These would become one of the data sources of the material balance model, metal balance model, and energy balance model.

Step 8. the statistician of the planning department generates the balance of the current day according to the data of the 24 h statistical cycle and adjusts the daily balance data. The adjustment process can be the balanced setting of the logic production unit or the entire industrial agent. Furthermore, the chain-level adjustment can also be performed through the planning department of the industrial chain level.

Step 9. after the balance adjustment, the planning department can publish the data to other relevant departments. At the end of the month, the data results of the entire month can be summarized and shared with other industrial agents.

4. Key Measures to Support Production Coordination and Intelligent Decision-Making in Nonferrous Metallurgical Industry

Certain corresponding measures need to be proposed around different themes to support the implementation of production coordination and intelligent decision-making at the industrial chain and industrial agent levels. The specific measures include the following:

4.1. Consider Collaborative Office Management as the Core of Intelligent Decision-Making and Highlight the Theme of Office Collaboration.

We establish the IT capability to support the collaborative office management business. The objective of establishing the collaborative office management IT capability is to develop the collaborative work mechanism for administrative and daily affairs at the industrial chain, industrial agent, and logical production unit levels, through the event-driven desktop and mobile office environment. This is conducted to improve the work level and efficiency. The intelligent decision-making related to the IT capability of collaborative office management shall satisfy the following requirements: front-end-oriented presentation, business process-oriented approval, digital document-oriented management, daily affairs-oriented management, and data information-oriented display.

4.2. Consider Enterprise Resource Management as the Core for Intelligent Decision-Making and Highlight the Theme of Resource Collaboration. We establish the IT capability to support the enterprise resource management business. The objective of establishing enterprise resource management IT capability is to develop a unified operation and management platform that integrates production planning, sale management, procurement management, equipment management, project management, financial management, warehouse management, quality management, and other functions. Through effective integration with production execution IT capabilities, the key data and business processes are unified, and the resource allocation efficiency of the enterprise is improved. Intelligent decision support is provided for the management at the industrial chain level with the aid of data analysis capabilities. The intelligent decision-making related to enterprise resource management IT capability shall address the following six core aspects: human resources, finance, materials, assets, equipment, and project.

4.3. Consider Production Execution as the Core for Intelligent Decision-Making and Highlight the Theme of Production Collaboration. We establish the IT capability to support the production execution business. The objective of establishing the production execution IT capability is to develop the information link of material flow, metal flow, and energy flow through all levels of nickel-cobalt-copper production business and form the material, metal, and energy mobile network model that addresses the entire industrial chain. Furthermore, we can effectively integrate and utilize production information based on the production data integration at the industrial chain level. The above aspects can provide an effective means for symbiotic coupling metallurgical enterprises to effectively supervise, guide, and optimize production and operation. The intelligent decision-making related to the IT capability of production execution should focus on the two core lines of planning and production. Furthermore, based on the IT capability, we can realize the closed-loop collaborative management of quality, energy, and other businesses. It specifically involves planning management, production management, quality management, and energy management.

4.4. Consider Health, Safety, and Environmental Protection as the Core for Intelligent Decision-Making and Highlight the Theme of Resource Recycling and Coordination. We establish IT capability to support the health, safety, and environmental (HSE) business. The objective of establishing the HSE-IT capability is to highlight the main line of comprehensive utilization of tailings and waste rock, nickel-cobalt-copper smelting slag, and nickel-cobalt-copper refining solid waste under the constraints of the safety, environmental protection, and health objectives of symbiotic coupling enterprises in the agglomeration area. Thereby, we can realize a close connection of operation management, dispatching operation, and on-site automation. Furthermore, we could respond to risks in advance, eliminate potential hazards, strengthen emergency disposal, and develop an efficient green production environment. In addition to the conventional intelligent decision-making in the production field, intelligent decision-making with health, safety, and environmental protection should also involve the control of managing risks, e.g., health management and environmental protection early warning in the process of operation and management. The above aspects can establish comprehensive risk prevention and control system at the industrial chain level in the nonferrous metallurgy agglomeration area. Intelligent decision-making related to health, safety, and environmental protection should pay attention to two core lines: production management and operation management.

4.5. Consider Production Decision-Making and Decision Feedback as the Core and Highlight the Theme of Closed-Loop Decision-Making. The realization of intelligent production decision-making is to ① adopt advanced and mature information technologies such as real-time database, Internet of things, and virtual reality and ② integrate the basic data of operation management and production operation, which can conduct in-depth data analysis and visual display. In addition, intelligent production decision-making integrates the decision-making feedback mechanisms such as emergency and scheduling. Thereby, it develops the operation decision-making capability with real-time performance and integrated performance in the industrial chain-level of nonferrous metallurgical enterprises in the agglomeration area, which can conduct the real-time command and regulation of production and operation. The production decision-making capability should focus on the following two main lines: the comprehensive display of production decision-making data and the decision feedback linkage related to emergency/scheduling.

4.5.1. Main Line of Comprehensive Display of Production Decision Data. The production decision-making data involves the goal setting of operation and production and the entire process monitoring of a specific production process. The integration based on this main line would provide a platform for the management and production decision-makers at all levels of nonferrous metallurgical enterprises to comprehensively understand the production and operation objectives and the overall state of production in a timely manner. The integration of IT capabilities and functions involved mainly includes the IT capabilities of enterprise resource management. Meanwhile, the integration of IT capabilities focuses mainly on the integration of business information such as that on production planning and scheduling, raw material entry, production and processing, product inventory, and product sales. Thereby, the production situation of the enterprise is displayed comprehensively.

The integration of IT capabilities related to production execution can realize the combination of enterprise production and operation plan with real-time operation processes and dynamic resource tracking. The integration of IT capabilities can realize real-time and visual management of production and operation business (including production planning, production scheduling, metallurgical production, direct supply of raw materials, product sales, device operation, and health, safety, and environmental protection) to improve the level of enterprise production and operation management.

The integration of IT capabilities related to real-time operation monitoring can combine the real-time production data with industrial video and image data of the logical production unit level. Furthermore, it can realize the functions of operation monitoring, inventory monitoring, early warning, and key site video monitoring at the industrial agent-level. Thereby, it can provide support for the production and operation command and management at the industrial chain level. In addition, all types of information can be displayed intuitively with the help of digital plants, Internet of things technology, and various advanced display technologies.

4.5.2. Production Decision Feedback Linkage Main Line Related to Emergency/Scheduling. The integration objective of production decision feedback is to establish linkage feedback and monitoring mechanism for industrial chain-level integration and can thereby improve the capability of professional production management. The linkage feedback mechanism refers to the professional regulation of the daily production and operation process (including the optimization of the production planning and scheduling strategy) as well as the response mechanism for key production events, the variation and adjustment of key production plans, and emergency management of emergencies. The IT capabilities mainly include production scheduling and command IT, emergency management IT, and advanced plan management IT capabilities.

4.6. Consider the Coordination of the Enterprise Strategy and Performance as the Core and Highlight the Theme of Decision-Making Coordination. The establishment of enterprise strategic decision-making is based on technologies and concepts such as data platforms, business intelligence analysis, and big data management. Enterprise strategic decision-making must integrate the data assets at the industrial chain level of nonferrous metallurgical enterprises. The integration can improve the data analysis capability, reflect the value of data assets, and provide timely and effective information support for the production and operation decisions of the management. The strategic decision should focus on the business scenarios addressed by the business decision-making of nonferrous metallurgical enterprises in the agglomeration area. It performs data induction, analysis, and multidimensional display in the form of thematic scenario analysis. In the initial stage, we can focus on factors such as performance and cost. In the subsequent stage, we can establish different element models according to different business focuses to deepen the special topic.

The main line of performance management is under the guidance of the industrial chain development strategy of nonferrous metallurgical enterprises. The objective of performance management is to realize the business indicators of different industrial agents. The performance management can control the overall progress through a comprehensive plan, control the process execution through budget management, and complete the continuous closed-loop control of the process and results through performance evaluation and assessment. The basic data involved may require the support of budget management IT, enterprise resource management IT, human resource management IT, comprehensive statistics management IT, and team performance management IT capabilities.

The main line of cost management is to organize production under the guidance of a symbiotic coupling industrial chain-level comprehensive plan among enterprises in the agglomeration area by considering the production plan as the core. In addition, the main line involves collecting the cost according to the production process to form a closed-loop control with a production plan, process implementation, cost collection, and plan feedback as the elements. The basic data involved may require the following IT capabilities to support and share: enterprise resource management IT, production execution IT, and comprehensive statistical management IT capabilities.

5. Conclusion

The nonferrous metallurgical industry is a typical process industry. It has certain characteristics such as complex process flow, high energy and material consumption, harsh equipment working conditions and environment, large emissions of waste, and severe environmental pollution. The level of production coordination and intelligent decision-making among enterprises with a symbiotic coupling relationship in the agglomeration area is generally low. In most cases, it depends on individuals and knowledge workers. When the market demand, industrial policies, and production factors vary, the industrial chain cannot make timely and accurate assessments, provide corresponding guidance and recommendations for production planning, production operation, and quality control, or realize the optimization of comprehensive production indicators such as product quality, output, energy consumption, material consumption, and various costs at the industrial chain level and industrial agent level.

This study designs the typical collaborative process of materials, metals, and energy among different industrial agents according to the present situation of industrial chain level coordination in the nonferrous metallurgy agglomeration area of the Gansu Province, China. It proposes the framework of nickel-cobalt-copper industrial chain-level production coordination and intelligent decision-making. Thereafter, the framework of agent-level production coordination and intelligent decision-making of nickel-cobalt-copper is presented. In addition, it focuses on the design concepts and methods of various balance strategies in the production coordination of industrial agents. Finally, six key supporting measures surrounding the six themes of office coordination, resource coordination, production coordination, safety coordination, decision-making coordination, and decision coordination are presented to support the implementation of production coordination and intelligent decision-making technology among coupled enterprises in a nonferrous metallurgy agglomeration area.

The framework of production coordination and intelligent decision-making proposed in this paper has been adopted by the research report "Enterprise Production Coordination and Intelligent Decision-making Technology under the Recycling of Resources in Nonferrous Metallurgy Agglomeration Area" of the National Key Research and Development Plan of China. The study results proposed in our paper will be used for the design of collaborative manufacturing in the symbiotic coupling area of nonferrous metallurgy in the following period.

With the application of the industrial chain level and agent level nickel-cobalt-copper productive collaboration and intelligent decision-making framework, a standard production collaborative manufacturing network will be formed in the symbiotic coupling area of nonferrous metallurgy based on the design method of the balance strategy and relying on the key measures supporting production coordination and intelligent decision-making. Through the implementation of the corresponding support system, it can realize the visualization of material information management, conscientization of production intelligent decision-making, optimization of resource utilization, reduction of intermediate materials, improvement of scheduling efficiency, and reduction of material consumption and energy consumption in the production process. At the same time, it can improve production operation efficiency, save labor costs, and reduce operating costs.

In short, with the advancement of production collaborative manufacturing, the production organization coordination problem caused by the complex interaction in the production and manufacturing process of enterprises will be solved. Compared with the traditional production organization mode, it will enhance the competitiveness of enterprises, improve the profitability of enterprises, and more importantly, it will be able to bring together relevant enterprises in the symbiotic coupling area to create more economic and social benefits.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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