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Review Article

Developments and Challenges in High-Performance Operation Control of Large-Scale Blast Furnace

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Abstract: The large-scale blast furnace ironmaking system, characterized by extremely complicated mechanism, multiphase/field coupling, dynamical working circumstances and unbalanced data set, is facing several problems in information detecting, object modelling, safety manufacturing and operation controlling. How to keep blast furnace in a secure and steady status, i.e., ensuring high efficiency and safety of ironmaking process under various conditions has become a major issue in operational control of industrial system. Many scholars have tried to improve the operation control level of large-scale blast furnace. However, the existing research mainly focuses on individual processes of the blast furnace, lacking studies on intelligent coordinated optimization of the entire ironmaking process, including raw material yard, sintering, and blast furnace operations. In order to help researchers to have a better understanding of the ironmaking process, we have made a comprehensive review of the current developments and future trends in the research of large-scale blast furnace. In this paper, we first introduce the backgrounds and characteristics of ironmaking process, as well as analyze the challenges in different research fields. Then, key technologies and current progress of information perception, feature modelling, fault diagnosis and optimal control in large-scale blast furnace are summarized. Furthermore, the future developments and potential applications of blast furnace ironmaking process are outlined in the end.

Keywords: Blast Furnace, Information Perception, Process Modelling, Fault Diagnosis, Optimal Control

1. Introduction

In the steel manufacturing process, the large-scale ironmaking system centered around the large blast furnace shown in Figure 1 is a critical step for the conversion of iron-bearing materials [1]. It is also the most energy-intensive, highest-emission, and costliest stage, accounting for 75% of the comprehensive energy consumption of steel production, 80% of the total atmospheric pollutant emissions from steelmaking, and 60%-70% of the total manufacturing costs in the steel industry [2]. Furthermore, as a key front-end process in the steelmaking workflow, the quality and efficiency of the blast furnace ironmaking process determine the steel quality and production efficiency of the entire steel manufacturing process. Hence, large blast furnace ironmaking is at the forefront of energy-saving, emission reduction, and efficiency improvement in the steel industry.

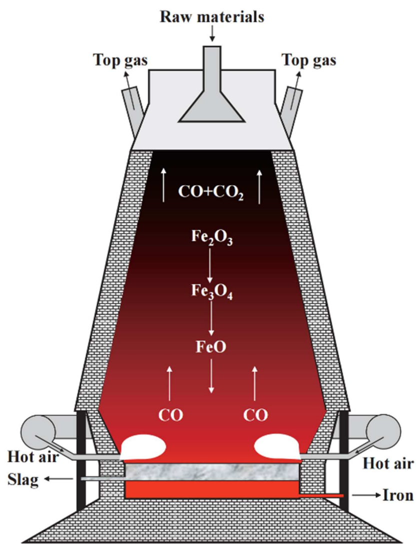

Figure 1. Blast furnace ironmaking process.

In recent years, to promote the sustainable development of the steel industry, various steel-producing nations around the world have formulated corresponding development plans and action strategies. In 2013, the European Commission proposed the "Steel Action Plan" to prevent the decline of the steel industry and established specific measures to promote its development, including legal revisions, industry restructuring, and energy policies [3]. Around the same time, the European Steel Association released the "Low-Carbon Steel Technology Roadmap 2050" plan [4], which focused on research related to the simulation model of carbon dioxide emissions in the steel industry and formulated emission reduction strategies. In 2016, the "Fossil-Free Steel Industry" initiative was launched by Swedish steel company SSAB, mining company LKAB, and energy company Vattenfall. The initiative aimed to research and develop production processes that replace coke and coal used in blast furnaces with hydrogen, achieving carbon dioxide emissions-free steel production [5]. In 2017, South Korean steelmaker POSCO developed a plan to promote the construction of smart factories and launched a research program with the core technologies of the Internet of Things, big data, and artificial intelligence, aiming to enhance steel production efficiency [6]. In 2011, the China Iron and Steel Industry Association and the China Nonferrous Metals Society jointly compiled the "2011-2020 China Iron and Steel Industry Science and Technology Development Guidelines", which set forth the development goals and planning guidelines for the Chinese steel industry from 2011 to 2020.

Currently, the green, efficient, and intelligent development of large-scale ironmaking systems in China faces common challenges such as heavy environmental burdens, low resource utilization efficiency, low overall energy efficiency, and low production efficiency [7]. Therefore, driven by the urgent need to enhance the scientific and technological innovation capabilities and overall competitiveness of the bulk basic materials industry under the major strategic plan "Made in China 2025" and in line with the "Iron and Steel Industry Adjustment and Upgrading Plan (2016-2020)" in China, it is essential to promote the overall and multi-level coordination and optimization of the ironmaking system, and advance the intelligent manufacturing of large blast furnaces. This can be achieved through comprehensive upgrades based on "detection-modeling-diagnosis-control-optimization", ultimately realizing green and efficient production in large blast furnaces [8-12].

2. Research Challenges

The steel production process mainly consists of the ironmaking system and the steelmaking system, with the ironmaking system being the most complex and crucial part. In the ironmaking system, iron ore undergoes processes such as blending, sintering/pelletizing, and blast furnace smelting, ultimately transforming into molten iron, which is then sent to the converter for steelmaking (as shown in Figure 2) [13-15]. The large blast furnace, as a key process in the ironmaking system, is the core link for the conversion of iron-bearing materials and carbon energy flow. Its internal complex and harsh reaction environment, involving the coupling of gas-liquid-solid phases and high-temperature, high-pressure, and strong corrosive conditions, make it difficult to control.

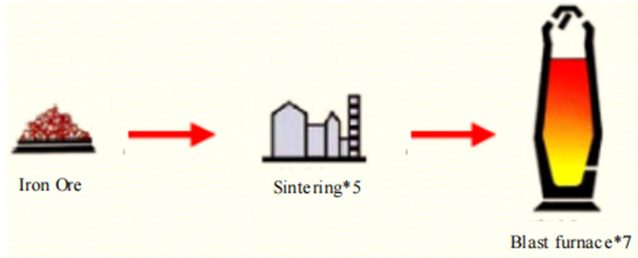

Figure 2. *Flow chart of ironmaking process.*

Traditional blast furnace operation principles, based on ironmaking mechanisms and expert experience, require adjusting the production conditions of the blast furnace using a combination of "bottom regulation as the foundation and top-bottom regulation combined" [16]. Under the condition of timely and accurate grasp of the changes and trends in the blast furnace operation, stable and smooth ironmaking in the blast furnace is achieved by adjusting burden distribution, air supply system, heat system, and slag-making system [17]. However, within the current research and engineering context, to achieve high-performance operation control of large blast furnaces, numerous challenges need to be addressed in the aspects of detection, modeling, diagnosis, control, and optimization.

2.1. Challenges in Perceiving Operational Information

The operation of large blast furnaces must be based on real-time signals of energy and quality flow, multiphase and multi-field coupling operations, physical and chemical reactions, and other process information. However, due to limitations in existing detection technology and the harsh working conditions within the blast furnace, it is difficult to obtain or retain operational information and process parameters, such as the distribution of gas flow, burden distribution, molten iron temperature, and pulverized coal injection rate, leading to incomplete process information and even failure of the detection mechanism, resulting in a lack of crucial information during the ironmaking process in the blast furnace [18]. For instance, blast furnace ironmaking is a distributed system of thermal flow field and an infinite-dimensional system. The accurate measurement of its temperature and other operational parameters lies in the sensor configuration. The distribution of the thermal flow field within the furnace is estimated by equipping a large number of temperature sensors in the furnace lining and cooling system [19]. However, in the current blast furnace design and construction process, the approach is limited to installing as many sensors as possible to maximize the acquisition of temperature information. This engineering solution lacks theoretical basis, and inappropriate sensor configuration can lead to inconsistent, uncertain, and incomplete information detection, making the detection system difficult to maintain. Due to the lack of key information detection mechanisms and inaccuracies in measuring critical variables, material tracking cannot be achieved at the blast furnace production site. Consequently, real-time responses to changes in on-site conditions become challenging, and operational control remains at a relatively crude level, making it difficult to ensure optimal ironmaking conditions in large blast furnaces [20, 21].

2.2. Challenges in Behavior Characterization

The optimization control, online safety analysis, and abnormal condition diagnosis of large blast furnaces all require accurate models of the ironmaking process. However, the frequent variations in the properties of raw materials for the blast furnace often lead to significant changes in production conditions. Due to the complexity of the relationships between input conditions, state variables, and production objectives, existing models cannot fully describe these relationships, resulting in a certain level of blindness in process control [22].

Inside large blast furnaces, not only temperature fields, gas flow fields, and burden flow fields are involved, but also the complex coupling of mass transfer, heat transfer, and heterogeneous reactions among gas, liquid, and solid phases. These complexities make the multiphase and multi-field coupling extremely challenging. Large blast furnaces not only exhibit multiple spatial and temporal scales but also possess characteristics such as non-uniformity, non-steadiness, non-equilibrium, and non-linearity. These features render existing mathematical descriptions and numerical simulation methods inadequate to address the model representation of the multiphase and multi-field coupling in large blast furnaces. As a result, they cannot fundamentally support online optimization and control of large blast furnaces [23, 24].

Although a large amount of operational data and experiential knowledge has been accumulated in the production process of large blast furnaces, the blast furnace data-driven models or expert systems established currently almost neglect the microscopic mechanisms of blast furnace operation. They merely rely on macroscopic reaction mechanisms and subjective experiential judgments to make rough qualitative correlations, lacking the effective integration of mechanistic analysis, operational data, and production knowledge. As a consequence, they fail to meet the requirements of fine-tuned control aimed at energy conservation, consumption reduction, and emissions reduction in large blast furnaces [25].

2.3. Challenges in Safe Operation Diagnosis

The ironmaking process in large blast furnaces is a complex physical and chemical process, with numerous variables affecting the production state and significant coupling between these variables. Large blast furnaces lack complete and accurate mathematical models, direct measurements of key internal states, and sufficient historical data on abnormal furnace conditions [26]. These characteristics make it challenging to detect and diagnose abnormal furnace conditions at an early stage. By the time these conditions exceed the alarm threshold and operational parameters are adjusted, it is often difficult to avoid consequences such as decreased ironmaking quality and output, increased energy consumption and emissions, prolonged downtime, and even equipment damage, reduced service life, or major safety accidents [27]. Additionally, the aforementioned features of blast furnaces also prevent the use of existing theories for real-time reliability assessment, operational safety evaluation, and furnace life prediction, which are crucial for ensuring the safety and service life of blast furnace equipment. The ironmaking process in large blast furnaces constitutes an extremely complex nonlinear dynamic system, lacking complete observability and direct means of adjustment, rendering existing fault-tolerant control theories unsuitable for the self-repair of abnormal operating conditions in blast furnaces [28].

2.4. Challenges in Process Control

The ironmaking process in large blast furnaces is a complex industrial process characterized by multivariable, strong coupling, nonlinearity, significant time delays, inadequate regulation means, and a combination of batch and continuous operations. It faces challenges in achieving and maintaining steady-state optimality concerning both heat balance and reaction equilibrium. This includes addressing adjustments and recovery under disturbance conditions [29]. Essentially, the process control problem involves controlling and maintaining the balance of multiple physical field distributions in large blast furnaces, which is crucial for energy conservation, emission reduction, and consumption reduction. Disruption of the balance point can lead directly to high energy consumption and low performance indicators. Severe disturbances to steady operation may even cause shutdowns and accidents, resulting in significant energy and resource wastage [30].

The physical fields within the blast furnace include the distribution of gas flow fields, burden surface shapes, softening and melting zones, and thermal conditions. The interactions among these multiple fields make dynamic corrections difficult. The stable control of these critical process parameters still relies on manual operation based on experience. Currently, the production process of large blast furnaces does not adequately consider the segregation in physical field distributions caused by the coupling of multiple physical fields or the parameter field distribution patterns formed by interactions at multiple phase interfaces. As a result, it is challenging to implement real-time control to eliminate the effects of abnormal furnace conditions such as hanging burden, hanging scaffolds, clogging, and difficult flow on the ironmaking process. This leads to furnace damage, increased energy consumption, reduced output, and even hindered production [31]. Existing industrial control technologies cannot achieve comprehensive optimization control of process indicators such as production yield, quality, and energy consumption during the production process. They fail to ensure the operational optimization of large blast furnace production, making it difficult to truly achieve the goal of energy conservation, emission reduction, and consumption reduction.

2.5. Challenges in Process Optimization

The ironmaking process in large blast furnaces exhibits characteristics such as nonlinearity and multiple constraints. To optimize the process indicators in blast furnace operation, research on optimizing operational parameters is mainly focused on four major control systems: burden distribution, air supply system, heat system, and slag-making system. By combining top-level and bottom-level adjustments, optimizations are made to the raw materials charged into the furnace, burden surface shape, gas flow distribution, and furnace hearth heat, among others [32]. However, as a high-temperature, high-pressure, and large-scale closed reactor, the blast furnace has a complex internal structure and operating mechanisms. It involves numerous parameters with spatial and temporal coupling distributions, multiple coexisting laws, and mutual interferences. Optimize for a single objective may lead to deterioration in other indicators, necessitating multi-objective optimization [33-35].

For example, optimizing the burden distribution in the blast furnace requires considering the chemical composition, metallurgical properties, and usage ratios of sinter, pellets, and lump ores. Additionally, it needs to meet the requirements of the ironmaking process, including coke properties, slag-making system, blast air supply system, alkali metal content, as well as the cost of the produced molten iron and overall energy consumption. Moreover, large blast furnaces have multiple spatial and temporal scales, and the significant time delays associated with these scales may lead to an insignificant control effect and a lack of timely and clear feedback results [36]. Therefore, the operation optimization of the ironmaking process in large blast furnaces faces challenges in establishing the objective function, dealing with overly complex constraints, and handling the coupling of control variables.

3. Academic Developments

The iron and steel industry is a fundamental raw materials industry for a country, and its development is an important indicator of a country's economic strength. In 2018, China, as the world's largest steel producer, accounted for 51.31% of global crude steel production for the first time, surpassing half of the total output. According to the "China Iron and Steel Industry Development Report (2016 edition)" released by the China Iron and Steel Industry Association, with China's economy transitioning from high-speed growth to a new normal and undergoing supply-side structural reforms, the Chinese iron and steel industry will further enhance the decisive role of the market in resource allocation, promote continuous reform, innovation, transformation, and green development.

However, large blast furnace production environments are harsh, and safety requirements are extremely high, making it difficult for conventional technological innovations to be tested and applied on blast furnaces. Therefore, the research team led by Sun Youxian from Zhejiang University has constructed, for the first time, a large blast furnace quasi-physical parallel experimental verification cloud platform (as shown in Figure 3). The parallel experimental verification platform consists of a laboratory platform (including a remote data center, remote monitoring center, remote operation and control center, remote diagnosis center, and remote optimization center) and an industrial field platform (including detection, modeling, control, diagnosis, and optimization subsystems). This platform provides a testing environment for various algorithms aimed at high-performance operation control of large blast furnaces.

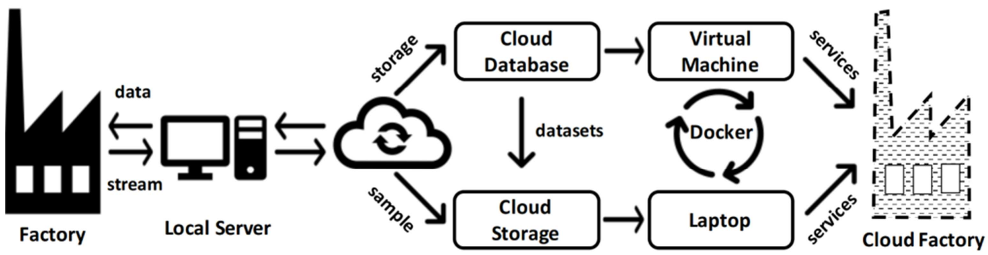

Figure 3. *Cloud platform for process industry.*

3.1. Ironmaking Process Information Detection

Currently, the information detection in the ironmaking process of large blast furnaces mainly focuses on the distribution of top gas flow, burden surface shape, softening and melting zone position, and furnace hearth erosion. Scholars and companies have conducted extensive academic research and engineering practices regarding these research hotspots. The distribution of top gas flow directly affects the temperature distribution inside the furnace, the position of the softening and melting zone, the thermal load on the furnace wall, and the thermal balance inside the furnace. The cross-shaped thermocouple gun at the furnace top is an essential device for detecting furnace top temperature and gas flow distribution in the ironmaking process of the blast furnace. In [37], they studied the principle of rapid replacement of the cross-shaped thermocouple gun and reduced its impact on the blast furnace downtime. In [38], they used the least squares support vector machine algorithm to construct a temperature prediction model for the cross-shaped thermocouple gun in the blast furnace and optimized the LS-SVM model parameters through particle swarm optimization algorithm. In [39], they processed infrared images using fuzzy C-means clustering and statistical methods to obtain the distribution of the gas flow center and gas utilization in the furnace.

In terms of visualizing the burden surface in the blast furnace, technologies such as CCD cameras, infrared thermal imagers, radar detectors, and laser detectors have been developed [40]. [41] introduced a color-controllable infrared camera monitoring and recording system and its practical application in monitoring the burden surface of the 1080m^3 blast furnace at Hengyang Valin Steel Tube Co., Ltd. In [42], researchers used a reasonable selection of radar numbers and detection points, combined with least squares and NURBS surface global interpolation methods, to fit the surface and generate the burden surface of the blast furnace. In [43], they showed that Xingcheng Special Steel's new No. 1 blast furnace first used 3D laser scanning technology to measure the burden surface, obtaining rich three-dimensional burden surface information along the circumference of the blast furnace. This allowed real-time acquisition of distance and angle information in various directions, enabling analysis of the burden load and surface shape.

The internal physical and chemical changes in the softening and melting zone are a crucial control aspect for ensuring the smooth operation of the blast furnace, and they deeply influence the smelting intensity and smoothness of the blast furnace operation. In [44-46], the scholars used X-ray, time-domain reflectometry, and radioactive isotope determination methods to detect and locate the softening and melting zone, allowing analysis of the corresponding physical and chemical reactions in the area. In [47], they investigated the distribution of unburned coal particles inside the inverted V-type, V-type, and W-type softening and melting zones, and used the Euler method to numerically simulate the accumulation distribution of unburned coal particles inside the blast furnace. In [48], they reconstructed the gas, liquid, and solid three-phase flow, counterflow, and cross-flow conditions by detecting parameters such as gas concentration, gas temperature, direct/indirect reduction degree, batch weight, and theoretical combustion temperature. This allowed obtaining the shape and position of the softening and melting zone.

Regarding the study of furnace hearth erosion, [49] established a three-dimensional steady-state heat conduction model by measuring the temperature using thermocouples embedded in the furnace hearth. They detected the distribution of erosion positions at the bottom of the furnace hearth with the 1150°C erosion line as the control line. In [50], they used temperature data feedback from temperature sensors embedded in the furnace hearth to solve the numerical heat transfer equation using the gradient descent algorithm to find the optimal boundary moving step factor. They established a monitoring model for furnace hearth erosion conditions and calculated the erosion morphology and remaining thickness of the furnace hearth lining.

3.2. Ironmaking Process Model Construction

Ironmaking process modeling for large-scale blast furnaces has been the subject of research both domestically and internationally. In [51], the immune system cloning selection mechanism and vaccination strategy were introduced into the particle swarm optimization (PSO) algorithm. They improved the PSO algorithm to optimize the weights and thresholds of the backpropagation (BP) neural network to predict the coke ratio and achieve energy-saving and emission reduction. In order to reduce carbon dioxide (CO_2) emissions, [52] conducted an in-depth study on the operation mode of steel enterprises based on resource allocation characteristics. They established a mathematical model to analyze the impact of CO_2 emission factors and reveal how resource allocation in the steel manufacturing system affects resource consumption and the ecological environment. To analyze the complex multiphase and multi-stream flow inside the blast furnace, [53] used the finite element method to calculate the external solid flow model. Additionally, in [54], the finite volume method was used to solve the equations for mass, heat, momentum conservation, and chemical substances, demonstrating that the combination of coal injection and oxygen enrichment can effectively reduce the coke ratio, increase production yield, and enhance combustion efficiency.

The blast furnace thermal regime can be represented by physical heat or chemical heat. Physical heat refers to the iron temperature, while chemical heat represents the silicon content in the iron. Predicting the silicon content in the iron in advance can assist the furnace operator in understanding the thermal conditions inside the blast furnace and judging the working status of the hearth. A low silicon content in the iron indicates cooling of the furnace, leading to abnormal blast furnace operation, requiring actions such as increasing the blast temperature, injecting more pulverized coal, or reducing the feeding rate. On the other hand, a high silicon content indicates intense reactions inside the furnace, causing unnecessary fuel waste, thus requiring stable temperature control to maintain steady and efficient operation. Previous studies [55-58] have achieved good predictive results for the silicon content in the iron using models such as generalized autoregressive conditional heteroskedasticity, sliding-window Takagi-Sugeno fuzzy neural network, particle swarm optimization of support vector machines, principal component analysis, and partial least squares regression. Based on these predictions, further researchers [59-61] used fuzzy classifiers, support vector machines, and Bayesian networks to forecast trends in silicon content changes, aiding operators in anticipating changes in blast furnace operation in advance.

The distribution of burden materials in the throat region significantly impacts the stable and efficient operation of the blast furnace. In modeling the burden distribution, some studies [62] employed kernel extreme learning machine to construct a predictive model for process parameters, and then treated the burden distribution as a multi-objective optimization problem solved through an improved two-stage intelligent optimization strategy. Others [63] first calculated the coordinates of the radar at the furnace top and then used multiple radar data to solve cubic equations for calculating the burden distribution before the multi-layer zone. Additionally, studies [64] investigated the burden distribution considering non-uniform descent rates and compared geometric profile models with stream function models, with the latter proving to be more effective in describing the burden distribution in irregularly shaped furnace walls. Discrete element methods were also applied in research [65] to study burden distribution and discussed the influence of key parameters such as chute angle and friction coefficient. The burden distribution also affects the shape and position of the cohesive zone, thus influencing the operational conditions of the blast furnace. Regarding the cohesive zone, research [66] elucidated the mechanisms of iron ore softening and melting and their potential effects on the blast furnace cohesive zone. The study [67] discussed the gas and powder flow patterns under different cohesive zone shapes, while another study [68] presented a method to simulate gas flow distribution in the cohesive zone. Additionally, CFD simulations were utilized to study the multiphase flow and reaction processes in the cohesive zone [69].

3.3. Ironmaking Process Fault Diagnosis

The faults in the blast furnace ironmaking process specifically refer to abnormal furnace conditions, and fault diagnosis in the ironmaking process is crucial for the safe and stable operation of large blast furnaces. Existing methods for diagnosing abnormal furnace conditions in large blast furnaces can be broadly categorized into two main types: expert system-based methods and data-driven methods, with data-driven models further divided into machine learning and multivariate statistical analysis.

Expert system-based methods for diagnosing abnormal furnace conditions in large blast furnaces rely on establishing a rule base based on ironmaking knowledge and manual experience. They then design a set of reasoning and decision-making methods to diagnose abnormal furnace conditions. In literature [70], a method for extracting characteristic parameters to determine abnormal furnace conditions in blast furnaces is proposed based on statistics and fuzzy mathematics. An abnormal furnace condition determination method is also provided based on fuzzy inference. Literature [71] analyzes the characterization parameters of abnormal furnace conditions in blast furnaces from various aspects, considering ironmaking theory and actual production conditions. They extract feature values through statistical analysis and establish a comprehensive expert system for abnormal furnace condition warning in blast furnaces, combining fuzzy inference with production rules. Literature [72] uses fuzzy mathematics theory to handle uncertain knowledge and organizes it using If-Then rules for blast furnace abnormal condition diagnosis. Literature [73] employs artificial intelligence and fuzzy mathematics concepts, using a combination of forward and backward reasoning strategies to diagnose ten types of abnormal furnace conditions. For four specific abnormal furnace conditions, namely hanging burden, pipeline issues, hearth accumulation, and collapse, literature [74] constructs reasoning graphs and employs rule-based methods for diagnosis. Literature [75] uses forward reasoning, driven by input data, to match rules during the reasoning process and provides the credibility of various furnace conditions.

Methods for diagnosing abnormal furnace conditions in large blast furnaces based on machine learning primarily use monitoring data from normal and abnormal furnace conditions for model training. In literature [76], a Bagging-based support vector machine ensemble architecture is constructed, and a novel abnormal furnace condition diagnosis model is proposed within this framework. To speed up the fault diagnosis process, literature [77] introduces a cost-sensitive least squares support vector machine. Considering the imbalance in blast furnace data samples, literature [78] provides a fault binary classification method based on self-organizing maps and fuzzy inference systems. Literature [79] proposes a blast furnace operating condition monitoring method based on fuzzy logic and neural networks, used to detect abnormal furnace conditions and predict furnace cooling. Bayesian networks are applied to model and diagnose abnormal furnace conditions in literature [80]. Based on an improved autoregressive model, literature [81] extracts variable autocorrelation and cross-correlation information to achieve complex dynamic industrial process monitoring. After in-depth analysis of blast furnace smelting characteristics, literature [82] identifies generalization and adaptability as two important features for blast furnace condition judgment.

Methods for diagnosing abnormal furnace conditions in large blast furnaces based on multivariate statistics utilize changes in the relationships between monitoring variables during the ironmaking process for fault diagnosis research. In literature [83], a sliding window hidden Markov model is proposed for online multimodal monitoring, and at the same time, literature [84] also applies this method to detect unknown faults in blast furnaces. Literature [85] introduces a change point detection method based on graph theory, enabling the monitoring of abnormal furnace conditions in the ironmaking process. Minor faults in the ironmaking process may be overlooked by operators as disturbances, which can pose significant safety risks to blast furnace production. Therefore, literature [86] achieves the diagnosis of minor faults in the blast furnace using robust principal component tracking. For the multivariate detection problem in blast furnaces, literature [87] uses projection methods to reduce the dimensionality of multivariate monitoring information and implements principal component model design, testing, and online algorithms for process detection. The blast air blowing process in the blast furnace can also affect the furnace condition. In literature [88], a recursive variable statistical analysis method is proposed, and an index switching strategy is employed to eliminate the impact of hot blast stove switching.

3.4. Ironmaking Process Operation Control

Researchers both domestically and internationally have established process control models based on mechanistic models, data-driven approaches, intelligent models, and expert systems, aiming to achieve semi-automatic or fully automatic closed-loop operation for ironmaking in blast furnaces. Zhejiang University, Tsinghua University, Shanghai Jiao Tong University, Northeastern University, and Central South University have collaboratively developed a hybrid operation control system of large-scale blast furnace (as shown in Figure 4). This system includes two small closed-loop control circuits and one large closed-loop control circuit, which are respectively responsible for controlling the burden distribution at the furnace top, controlling the hot metal quality at the furnace bottom, and optimizing the overall operation of the blast furnace. This control system was validated in the No. 2 blast furnace of Liuzhou Iron & Steel Group, achieving significant results in the field with a 9.9% increase in the furnace utilization coefficient, an 8.3 kg/t reduction in fuel ratio, a 9.4% improvement in hot metal quality rate, and a 40% decrease in idle-blowing rate over one year of actual operation.

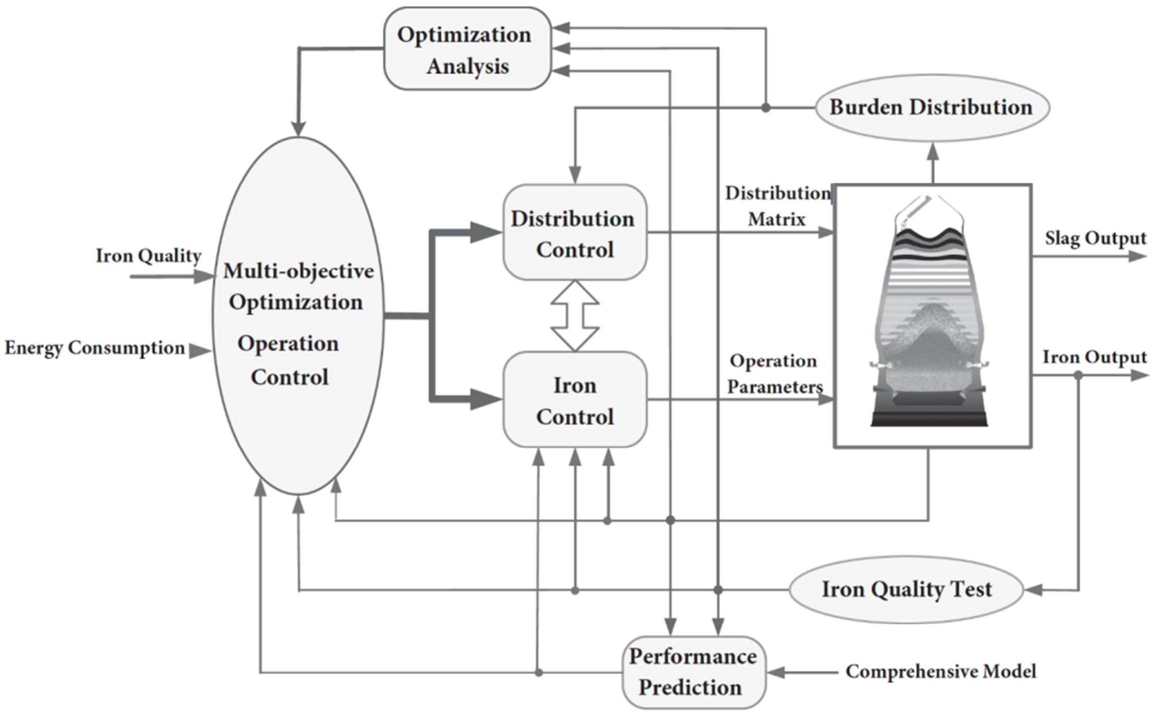

Figure 4. *Hybrid operation control system of large-scale blast furnace.*

Regarding the control of burden distribution at the furnace top, literature [89] establishes a mathematical model based on the analysis of blast furnace structure, ore size, and material flow trajectory to control the burden distribution in bell-less top furnaces. By using gas utilization rate as an energy consumption index and employing support vector machines to predict state parameters, literature [90] controls the burden distribution through changes in the burden matrix based on the trend of energy consumption index. Literature [91] first establishes a clustering method based on dynamic time warping and adaptive resonance theory, and then optimizes process indicators using reinforcement learning to achieve control over the burden distribution. Based on the data of burden distribution obtained from radar probe measurements, literature [92] controls the burden matrix for the closed-loop control of burden distribution in the blast furnace, using the difference between the ideal burden surface and the actual burden surface determined by fuzzy support vector machines. With the increase in blast furnace gas utilization and permeability, reducing the coke ratio in the ironmaking process is imperative. Literature [93] achieves a reduction in coke consumption during the burdening process by controlling the optimal position and amount of the charging materials in the furnace top hopper.

In terms of hot metal quality control, considering the crucial importance of silicon, sulfur, and phosphorus content in pig iron for the economic operation of blast furnaces, literature [94] applies state-space method for predicting and controlling the hot metal quality indicators. Literature [95] proposes a method for controlling the silicon and sulfur content in hot metal based on neural networks and expert systems. Literature [96] uses sliding-window linear Volterra filter for predicting and controlling the silicon content in hot metal. In contrast, literature [97] utilizes a dynamic linear adaptive control method to control the hot metal quality indicators. Besides chemical composition, hot metal quality indicators also include the physical temperature of hot metal. Literature [98] achieves the control of hot metal temperature using the Hammerstein-Wiener model. Literature [99] builds a model tree to relate operational parameters with hot metal temperature, enabling the control of the internal thermal state in the blast furnace through predicting the hot metal temperature.

In other aspects of blast furnace control, literature [100] proposes a temperature control method for the thermal insulation zone to improve the reaction efficiency inside the furnace. For the control of top pressure in the blast furnace, literature [101] models the top gas pressure based on subspace identification to maintain stability in top pressure after the operation of blast furnace gas pressure recovery turbine. Similarly, to maintain stable top pressure, literature [102] uses fuzzy decoupling control to limit the fluctuation range of top gas pressure within ±2kPa. For the control of slag-making process, literature [103] employs extreme learning machine to control the slag-making system in blast furnace production with different operating conditions. By combining fuzzy rules and neural networks, literature [104] presents a domain knowledge-based optimization control method for blast furnace gas flow distribution. To control the nitrogen oxides content in the exhaust gas emission from the blast furnace, literature [105] simulates chemical reactions in the fluid using computational fluid dynamics to assist operators in controlling the blast furnace hot blast temperature and composition. For controlling the liquid level in the hearth, literature [106] calculates the slag-iron generation rate to provide engineering personnel with recommendations on opening and closing the tapping hole.

3.5. Ironmaking Process Operation Optimization

In order to improve the performance indicators of large blast furnaces and ensure their overall operation is in the optimal state, it is necessary to accurately characterize the dynamic coupling relationship between process indicators such as hot metal quality, production, and energy consumption, and the quality of raw fuels, operational parameters, and state parameters. Additionally, real-time monitoring of performance indicators and their trend changes in large blast furnaces, along with deep optimization of raw fuel quality and key process parameters, is required. Furthermore, coordinated optimization decisions must be made for multiple operating parameters to regulate the performance indicators of large blast furnaces.

Regarding the single-objective optimization problem in blast furnace ironmaking, when the steel market environment is favorable for maximizing hot metal production, literature [107] optimizes the hot metal yield by constructing theoretical models and analyzes the effects of oxygen enrichment rate, wind rate, blast humidity, sinter ratio, and pulverized coal injection. To achieve a higher pulverized coal utilization rate, literature [108] optimizes operational parameters such as oxygen enrichment rate, wind velocity, and coal powder particle size based on computational fluid dynamics and grey relational analysis. Literature [109] introduces a wavelet neural network based on probability density function and its application in optimizing the blast furnace top temperature. For minimizing CO_2 emissions, literature [110] establishes multiple mass and energy conservation equations and solves the objective function using quadratic programming. Literature [111] utilizes particle swarm optimization to obtain the optimal solution for the difference between the actual and ideal burden surfaces, which is then applied to optimize the blast furnace burden distribution. Literature [112] employs machine learning algorithms to identify and optimize operating parameters that affect the economic and technical indicators of the blast furnace. Literature [113] uses ANSYS to simulate the temperature and flow fields inside the blast furnace and optimizes the ironmaking process indicators by adjusting operating parameters such as cold air flow rate and pulverized coal injection.

Regarding the multi-objective optimization problem in blast furnace ironmaking, literature [114] solves the Pareto boundary values of throat cooling loss, gas flow rate, throat velocity, utilization coefficient, and coke ratio using multi-objective genetic planning and evolutionary neural network algorithm. To achieve the goal of "energy saving, reduction of consumption, emission reduction, and production increase", literature [115] optimizes process parameters based on modern thermodynamic theory. Similarly, for energy saving and emission reduction, literature [116] establishes material and energy conservation equations as constraints and takes cost, CO_2 emissions, and carbon loss as optimization objectives, optimizing control variables such as coke ratio, coal ratio, wind temperature, and metalization rate of furnace burden. Literature [117] first establishes the mapping relationship between operational parameters and process indicators based on BP neural network and then solves the multi-objective problem using genetic algorithm to find the operating conditions that simultaneously achieve the lowest cost and coke ratio while maximizing hot metal quality. Building upon this, literature [118] investigates the multi-objective optimization problem in large blast furnaces based on LSTM neural network and NSGA-II genetic algorithm, and the research results are verified in industrial sites, showing significant optimization effects on various process indicators.

4. Conclusion and Outlook

After years of rapid development, China's iron and steel industry has transformed from backwardness to standing side by side with the iron and steel powerhouses in Europe and America. Especially in the field of large blast furnace ironmaking, it has achieved numerous remarkable achievements that have drawn worldwide attention. However, the existing research mainly focuses on individual processes of the blast furnace, lacking studies on intelligent coordinated optimization of the entire ironmaking process, including raw material yard, sintering, and blast furnace operations [119-122]. This has resulted in issues such as high energy consumption, low efficiency, poor coordination, and unstable product quality in ironmaking production, severely hindering the green, efficient, and intelligent development of the steelmaking process. Currently, research conducted within the "detection-modeling-diagnosis-control-optimization" framework still has the following deficiencies:

Lack of fine material blending and dynamic tracking;

Difficulty in precise regulation and strong subjectivity in operations;

Delayed detection and low credibility in abnormal condition monitoring;

Insufficient intelligent optimization decision-making methods.

4.1. Key Information Perception and Tracking

In the raw material blending yard, to address issues such as frequent fluctuations in material information and the inability to determine performance indicators in real-time, research focuses on intelligent tagging techniques based on material information detection, intelligent supplementation techniques based on spatiotemporal scale matching, and intelligent verification techniques based on reading labels. These methods achieve full-process tracking of material information. During the sintering process, for the difficulty in accurately measuring the content of ferrous oxide online, research explores intelligent perception methods that integrate multiple heterogeneous features and multiphase thermodynamic models.

To overcome the low signal-to-noise ratio and high noise in detecting the sinter layer thickness and red layer morphology in the sintering machine, the study investigates the fusion of infrared thermal imaging and stereoscopic vision imaging for detecting the sinter layer thickness and red layer morphology. In the blast furnace ironmaking process, due to the harsh environment at the top of the furnace, making it challenging to detect furnace burden information, the research focuses on multi-spectral, multi-lens, and multi-dimensional holographic imaging methods and techniques for furnace burden imaging. Additionally, to address difficulties in accurately detecting key parameters of molten iron, such as temperature, flow rate, and dust content, due to the high temperature, fast flow, and high dust in the taphole, research explores online perception methods and techniques using non-cooled infrared imagers and high-speed industrial cameras. To tackle the global challenge of real-time online detection of molten iron composition, the study investigates intelligent perception methods that combine laser-induced breakdown spectroscopy and hyperspectral techniques.

Furthermore, to deal with the slow erosion process of the blast furnace lining, complex furnace wall structure, and difficulty in obtaining the furnace thickness, research focuses on online detection methods and techniques for furnace thickness based on shock wave reflection theory. Finally, the study analyzes the correlation between individual processes such as raw material blending, sintering, and blast furnace operations in terms of time, space, and functionality. It explores deep fusion and collaborative methods for multi-source, multi-dimensional, and multi-scale key information, aiming to lay a scientific data foundation for intelligent coordinated optimization in large-scale ironmaking systems.

4.2. Intelligent Raw Material Blending Methods and Implementation

For uniform raw material blending in the blending yard, research focuses on optimal blending theories and methods under multiple constraints such as the blending ore grade and alumina content. The sintering process is a complex coupled chemical reaction process, making it difficult to characterize its internal mechanisms, and the empirical knowledge gained from on-site experience may have a limited shelf life. However, process data contains rich internal patterns of the sintering process. Therefore, research is conducted on intelligent raw material blending methods for the sintering process that integrate sintering mechanisms, operational data, and expert experience while satisfying conditions related to sintering ore chemical composition, quality, and strength.

For large-scale blast furnace charging research, it is essential to meet requirements related to molten iron quality, slagging regime, harmful element load, smooth operation, etc. The focus should not be limited to the details of multivariate coupling within the blast furnace smelting process. Instead, it should explore blast furnace intelligent raw material blending theories and methods from the perspectives of energy flow, material flow, and information flow.

The interactions and constraints between uniform raw material blending, sintering ore blending, and large-scale blast furnace charging are complex and involve intricate coupling factor transmissions among the three. To achieve optimal raw material blending for the entire ironmaking system, it is necessary to consider coordinated optimization among the three blending systems. Hence, the study integrates process mechanisms, material information, and experiential knowledge to investigate multi-level intelligent and coordinated raw material blending methods and their implementation in large-scale ironmaking systems.

4.3. Intelligent Optimization of Operational Parameters

Based on the real-time detection technology of the internal endoscopic three-dimensional material surface in the charging process, research is conducted to achieve intelligent operation control of the three-dimensional shape optimization of the blast furnace charging process. By considering the desired ideal material surface shape under different burden and furnace conditions, the actual material surface distribution is adjusted optimally, including adjustments to the chute angle, the number of charging circles at each angle, and the circular angle of the chute, to make it close to the ideal material surface shape. This approach enables stable and low-consumption operation of the blast furnace.

A multi-objective operation control system is established, relating to the iron quality indicators (molten iron temperature, Si content) and energy consumption indicators (fuel ratio) to key control inputs such as hot air and coal injection. Research is conducted to implement a multi-objective operation optimization control method for ironmaking processes in the blast furnace with a focus on optimizing both iron quality and fuel ratio. To obtain iron ore raw materials with stable composition and uniform particle size for the blast furnace ironmaking process and to reduce uncertainties and fluctuations in blast furnace production and operation control, research is conducted to comprehensively consider the sintering end point and sinter quality in an intelligent control method for the sintering process. Additionally, an intelligent optimization control method for the sintering raw material blending process is studied, with the aim of achieving high-quality sinter with low costs.

4.4. Intelligent Monitoring and Diagnosis of Operational Conditions

Research is conducted on the intelligent dynamic monitoring of leakage conditions in the sintering machine, which integrates data and knowledge. Based on multiple sensor data sources, such as sintering fan current, voltage, waste gas temperature, bed thickness, oxygen content, etc., the leakage rate in the sintering machine is dynamically monitored in real-time. The relationship between the leakage rate and sintering production indicators (yield, quality, power consumption, etc.) is also studied.

Methods for early detection of abnormal conditions in large blast furnaces based on artificial intelligence are investigated, including unsupervised learning-based multi-mode adaptive identification methods and deep learning-based early detection methods for time-varying mode conditions. Artificial intelligence-based diagnostic methods for abnormal conditions in large blast furnaces are studied. This includes unsupervised data clustering methods considering multivariate correlations and abnormal condition diagnostic methods based on transfer learning under imbalanced sample conditions.

Methods for the collaborative integrated monitoring and diagnosis of multi-process-coupled ironmaking systems are explored. The coupling relationship between sintering and subsequent ironmaking processes is analyzed to understand the impact of sintering on the subsequent ironmaking process. The combination of blast furnace variables, such as charging matrix, material distribution, material surface curve, with sintering process variables is investigated. Process operation knowledge is also integrated with operational data to achieve collaborative integrated monitoring across multiple processes.

4.5. Intelligent Collaborative Optimization and Scheduling

To address the challenges of decentralized production processes and diverse equipment networks with inconsistent production objectives in sintering and blast furnace operations, an integrated modeling approach based on deep learning, dynamic programming, and distributed networks is proposed. This approach achieves integrated optimization and scheduling modeling for sintering and blast furnace operations, considering multiple constraints such as production objectives and equipment networks. For the variability in ore grade and coke quality, equipment status switches, and diverse production indicators, a route optimization method based on graph theory, EM algorithm, and genetic algorithm is proposed. This method optimizes the process paths by coupling the quality of raw materials, equipment status, and production indicators.

Considering the dynamic changes and mutual influences of process parameters, operating parameters, and process parameters in multiple processes, a multi-objective optimization control method based on neural networks, random forests, and NSGA-II algorithm is proposed. This method achieves dynamic optimization of process parameters across multiple processes, focusing on energy saving, cost reduction, and achieving optimal process matching. An indicator system and evaluation method are proposed for intelligent collaborative optimization in large-scale ironmaking systems. This allows information fusion and mechanism coupling in large-scale ironmaking systems, constructing a verification platform for intelligent collaborative optimization and scheduling in large-scale ironmaking systems.

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