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Invited Review

Key issues and progress of industrial big data-based intelligent blast furnace ironmaking technology

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Abstract: Blast furnace (BF) ironmaking is the most typical "black box" process, and its complexity and uncertainty bring forth great challenges for furnace condition judgment and BF operation. Rich data resources for BF ironmaking are available, and the rapid development of data science and intelligent technology will provide an effective means to solve the uncertainty problem in the BF ironmaking process. This work focused on the application of artificial intelligence technology in BF ironmaking. The current intelligent BF ironmaking technology was summarized and analyzed from five aspects. These aspects include BF data management, the analyses of time delay and correlation, the prediction of BF key variables, the evaluation of BF status, and the multi-objective intelligent optimization of BF operations. Solutions and suggestions were offered for the problems in the current progress, and some outlooks for future prospects and technological breakthroughs were added. To effectively improve the BF data quality, we comprehensively considered the data problems and the characteristics of algorithms and selected the data processing method scientifically. For analyzing important BF characteristics, the effect of the delay was eliminated to ensure an accurate logical relationship between the BF parameters and economic indicators. As for BF parameter prediction and BF status evaluation, a BF intelligence model that integrates data information and process mechanism was built to effectively achieve the accurate prediction of BF key indexes and the scientific evaluation of BF status. During the optimization of BF parameters, low risk, low cost, and high return were used as the optimization criteria, and while pursuing the optimization effect, the feasibility and site operation cost were considered comprehensively. This work will help increase the process operator's overall awareness and understanding of intelligent BF technology. Additionally, combining big data technology with the process will improve the practicality of data models in actual production and promote the application of intelligent technology in BF ironmaking.

Keywords: BF ironmaking; intelligent BF; industrial big data; machine learning; integrated mechanism and data

1. Introduction

Blast furnace (BF) ironmaking accounts for more than 70% of the cost and energy consumption of the whole steel process [1]. Complex physical and chemical phenomena occur simultaneously in the BF ironmaking system. Gases, liquids, and solids exhibit multi-phase and multi-substance coexistence. Meanwhile, as all the phases change continuously, a number of random external interference factors come into play. The variables involved in the BF process, such as raw fuel, operation, furnace status, and product, are of mixed type, have high dimensions, and are large-scale. BF variables are characterized by strong coupling, nonlinear and large hysteresis. Therefore, BF is considered one of the most complex metallurgical reactors. The BF is a typical "black box" that cannot be observed directly. Internal parameters cannot be measured in real time; hence, real-time and accurate information is relatively lacking. Most of the current mathematical models of BF ironmaking are mechanism based. Given the fluctuation in environment, operation, and BF status, the mechanism model shows poor applicability to this complex dynamic process. The prediction accuracy of these models is low, and accurate acquisition of the complex relationship between key parameters, such as operation parameters, furnace status, and quality of hot metal, is difficult. Meanwhile, the traditional expert system mostly relies on experience and knowledge. Due to the great difference in the level of BF operators, the manual judgment is unstable, and determining the BF status accurately and dynamically presents difficulty.

Big data technology has been successfully applied in many areas of the steel industry [2–8]. BF ironmaking is the core process of iron and steel production. The potential for energy saving and emission reduction by relying on traditional and conventional technologies is close to the physical limit. Only by obtaining innovative technological breakthroughs can the low carbonization of BF ironmaking be further realized. BF is a huge treasure house that collects the history, experience, and rules of the ironmaking system, but

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considerable production data and experience knowledge have not been fully explored and scientifically expressed. With the vigorous development of data science and information technology, intelligent technologies, such as machine learning and deep learning, have been adopted to integrate data with mechanics. The "fidelity" relationship among raw fuel, process operation, BF running state, and quality of molten iron was explored quickly, and an advanced model of BF ironmaking with high efficiency, low cost, and high fidelity was established. A good interaction among the intelligent evaluation, prediction of furnace status, and the independent optimization decision of operation was achieved. This good interaction is expected to solve the traditional difficulties of characterization of BF data, description of BF status, and control of BF operation.

Thus, aiming to apply big data technology in BF ironmaking, the digital and intelligent transformation of steel production, the progress of intelligent BF technology, and research on intelligent BF technology at Northeastern University (NEU) were investigated and discussed in this work (Fig. 1).

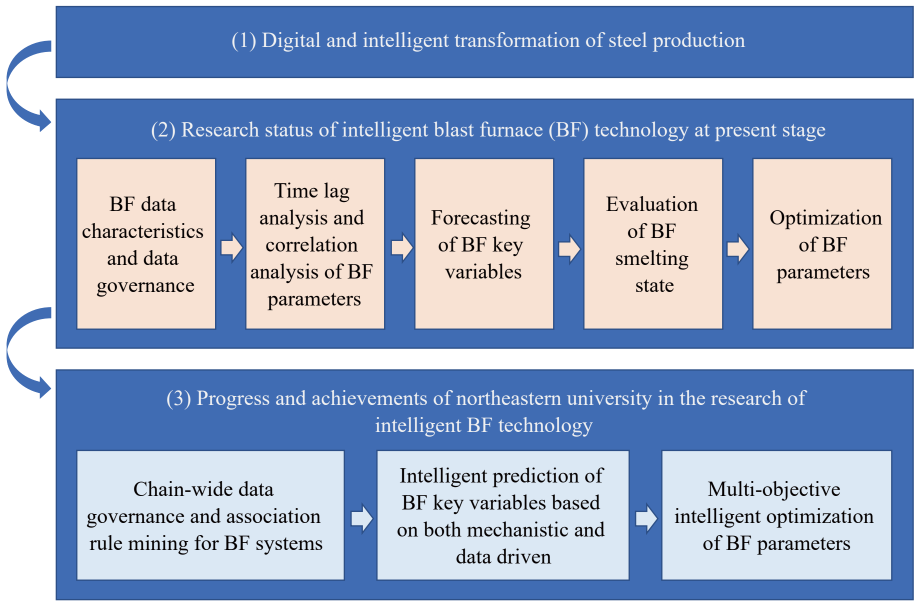

Fig. 1. General flow of articles.

2. Digital and intelligent transformation of steel production

With the rapid development of next-generation artificial intelligence (AI), big data, and cloud computing technologies, intelligent manufacturing has become the commanding height of strategic competition among major countries [9]. Given the high technical complexity and good information foundation, the digital and intelligent transformation of steel production has attracted considerable attention, whether it was the internal demand of the field or external guidance of the policy.

The steel industry has an urgent need for digital technology. The iron and steel industry is a large and complex process industry, with black boxes within each process. The extremely complex steel production process is characterized by multiple variables, strong coupling, non-linearity, and large lags. Additionally, the steel production units are controlled in silos, and the interface between the units is not seamless. These serious uncertainties are major challenges for the steel production process. Despite the "black box" and other uncertainty issues, the digital and intelligent transformation of the steel industry is imperative.

Digital and intelligent technologies have great potential in the steel industry. The steel industry is a digital technology application scenario with rich resources. The processes of BF smelting, converter smelting, electric furnace smelting, continuous casting, and rolling are all "black box" processes, which are the best scenarios for the application of digital and intelligent technologies. With the help of big data technology, the "black box" problem prevailing in the process industry can be quickly solved, and the effect of amplification, multiplication, and superposition can be achieved. The steel industry also has a wealth of data resources. The steel industry's data-aware and automated control systems have resulted in the accumulation of a wealth of data. This vast amount of data contains important rules for the production process and is the most valuable resource. Additionally, the steel industry has the advantage of direct feedback to empower materials. If laws within the iron, steel, billet, and rolled parts are explained clearly through real-time big data analysis, and if feedback control is carried out to form a closed-loop feedback empowerment system, the problems caused by various disturbances can be rectified in a timely manner.

The European Union released a steel technology platform plan called European Steel Technology Platform, which gave priority to the development of big data, intelligent modeling, multi-process integration, self-organizing production, and other technical fields; it takes each process as information physical system to further improve the steel production indexes [10]. Pohang Iron and Steel Company (POSCO) [11–13] developed the "POSFrame" intelligent factory platform, effectively connecting the accumulated steel manufacturing technologies with big data and AI, and developed an intelligent steel system. Since 2017, AI technology has been used to predict the furnace status from five variables, namely, permeability, attachments on the furnace wall, combustion of pulverized coal, temperature of hot metal, and output, and gradually realized the intelligence of BF. JFE Steel Corporation (JFE) [14] established the data science project department in 2017 and the information physics system research and development department in 2019. By March 2020, JFE had completed the intelligent transformation of eight BFs.

Based on the current situation of the Chinese steel industry, compared with developed countries, a huge gap exists in the application of AI in the industrial field. Particularly, the basic automation of the ironmaking process is weak, data collection and management are difficult, and the smelting process is a typical black box problem. A large space is available for improving the deep application of digital twinning and information physical systems of ironmaking systems. Intelligence is an important strategic direction for developing the steel industry in China. The state has issued a number of decisions and deployments to guide the acceleration of the development and technology research of intelligent manufacturing industries related to the whole steel process to promote the high quality intelligent transformation and upgrading of the steel industry in the new era and enable green manufacturing. By combining the process knowledge, mechanism model, and AI, companies have made breakthroughs in key technologies, such as big data platform construction, intelligent equipment diagnosis, automatic quality analysis, and advanced production line scheduling in some processes. Steel enterprises, such as Baosteel and Shougang, have developed intelligent manufacturing plans and built industrial data centers and intelligent technology research and development platforms [15]. The realization of digitalization through big data intelligence is an important guarantee for the steel industry to improve energy efficiency and reduce carbon emissions. The development of a digital economy is a major demand for the realization of the dual carbon goal of ironmaking. It is expected to reduce CO_2 emission by 6%–10%.

3. Key issues of intelligent BF technology

3.1. Management of BF data

3.1.1. Characteristics of the BF data

BF data mainly include "BF body data" and "BF auxiliary system data." BF body data refers to the operational data, such as the top temperature, static pressure and, permeability collected by various sensors. Auxiliary data mainly refer to the data of raw fuel, coal injection, etc. Nearly 2000 parameters need to be considered by BF operators in daily operation. In the BF database, approximately 18 million hourly frequency and daily frequency data are generated each year [16]. The sequenced data collected by sensors comprise the characteristics of some equipment, such as the numerous measuring points, high frequency, and high throughput. Given that the ironmaking process is composed of different systems, the data sources are spread, and the data acquisition frequencies of different systems differ [17]. For a wide range of resources and different data sources, BF data are usually independent of each other, and "data islands" are formed to isolate data. Meanwhile, the BF has a complex data structure. Besides the sequenced data, such as temperature, pressure, and flow rate collected during production, it provides infrared thermal imaging video data, such as flame temperature; thus, the data are also multi-mode [18]. Given the complex gas, solid, and liquid reactions in BF, changes in one parameter will lead to the linkage change in one or more parameters, and the information contained among parameters will overlap. Thus, information redundancy exists among the BF parameters. The interior of the BF is a high-temperature and high-pressure environment and here, the working environment of the electronic sensor is poor, and frequent damage will lead to noise, abnormal, and missing data [19–20]. Additionally, as the full automation of BF data is not yet realized, some data still need to be manually filled in and uploaded to the database. Therefore, the data are non-standard and incorrect.

3.1.2. Governance of the BF data

The completion of complex data cleaning and integration of BF and improvement in the quality of BF data are the basis for realizing intelligent BF ironmaking. Missing data, abnormal data, and inconsistent data frequency are the most common and important problems in BF data (Table 1).

(1) The data loss of BF is mainly caused by sensor failure, operator error, and database storage failure. Two methods are used to deal with missing data: direct deletion of missing data and filling in missing data. When a small or a large amount of BF data are missing, deletion is a direct and efficient processing method. For example, when the missing percentage of BF data is less than 5%, deleting the missing data will not affect the validity [19]. When the missing data rate exceeds 60%, the research value of the data is lost. When BF data are intermittently missing for a short time, interpolation can be used to supplement the missing data [21]. This can be done for data that are stable, regular, and predictable and show no abnormal fluctuations under normal furnace conditions, like pressure, temperature and other high frequency data, and furnace status in a short time. However, when BF data are missing for a long period, the occurrence of abnormal fluctuation cannot be estimated due to the long period of data missing. At this point, the correlation between the missing data variables and other complete variables can be analyzed (for example, a significant correlation exists between permeability and total pressure difference), and the relationship between

Table 1. Data pre-processing of BF

Type	Class	Method	Description
Missing data processing	Small amount of missing data（<5%）or significant amount of missing data (>60%)	Delete	Efficient and effective
	Intermittently short-term loss of data	Interpolation	High-frequency and predictable
	Continuously long-term loss of data	Machine learning	Correlations between other variables
Outlier data processing	Manual input error or sensing device failure	Statistical methods such as box plot and three-sigma; Machine learning methods such as clustering and isolated forests; Process methods such as operating guidelines of BF	Delete or correct or as missing value
	Abnormal furnace state		Save and analyze separately
Mixed-frequency data processing	High-frequency data are converted to low-frequency ones	Average or sum or latest value	Information waste
	Low-frequency data are converted to high-frequency ones	Copy	Information inflation
	Mixed-frequency data model	Mixed data sampling and mixed frequency vector autoregression	Lossless

them can be established by machine learning to fill in the missing data.

(2) Abnormal BF data are mainly divided into data anomalies caused by manual input errors, sensor equipment damage, and some indicators exceeding the upper and lower limits. The identification methods of abnormal BF data can be divided into statistical [22–23] (such as three-sigma method and box diagram method) and machine learning methods [24–25] (such as clustering method and isolated forest method). The three-sigma and box diagram show high efficiency in eliminating outliers, but the three-sigma criterion requires the approximate distribution of data, and the coefficient of the difference between the upper and lower quartiles of the box diagram needs to be artificially set. Using the machine learning to recognize outliers has a high recognition rate but consumes more time. However, the effective combination with the BF production process is ignored by most researchers. For instance, the reasonable range of parameters in the BF operating policy is based on the specific summary and calculation. BF operating policies not only quickly screen the original data but also verify abnormal data identification results. In addition, after identifying the outliers it is necessary to observe whether the data of other parameters at the same moment are also abnormal, in order to determine whether the cause of the abnormal data is the abnormal furnace condition or other reasons. Strictly speaking, the outlier data caused by abnormal BF status do not really have an abnormal value. Thus, abnormal data detection should be differentiated based on whether the furnace status is abnormal or not.

(3) The frequency of BF data is inconsistent and mainly restricted by data acquisition cost. The inspection frequency of raw fuel, slag, and iron is generally at the hour or day level, and the collection frequency of monitoring data, such as temperature, pressure, and flow rate, is at the minute or second level. Different data thicknesses are not conducive to the establishment of correlation analysis and prediction model. Usually, frequencies are made constant before analysis and modeling are carried out. High frequency data are averaged or summed, and the latest value of high frequency data is selected, which causes the loss of BF information and cannot truly and completely reflect the change in BF status. To maximize the information in different frequency data, researchers put forward the mixed-frequency data model [26–27]. The model is useful in avoiding data information increase and loss during artificial data processing and improving the accuracy of correlation analysis and prediction model.

3.2. Time-delay analysis and correlation analysis of the BF data

3.2.1. Time-delay analysis of the BF data

During the process of BF ironmaking, when a certain control measure is obtained by the operator, a certain period is needed for the decision variables to play a controlling role, a phenomenon called lag. Most existing methods are based on the correlation coefficient or manual experience method to obtain the maximum correlation of a certain lag time. Gao [28] calculated the lag time between the blast volume, oxygen content, permeability, and coal injection based on the autocorrelation coefficient method. An *et al.* [29] showed that the gray relative correlation analysis method was used to analyze the time lag between BF operation, gas usage rate, [Si], and BF status. Li *et al.* [22] assigned weights to the control parameters on the same day, day 1 later, and day 2 later through manual experience and carried out aging processing. However, in the actual production process, the lag time of parameters is uncertain and changes within a certain range in different stages or under various working conditions, and the parameters fluctuate to different degrees within this range. Therefore, this kind of method may cause inaccurate lag time and the lack of fluctuation information, resulting in the inconsistency with the actual furnace status. Wang *et al.* [30] proposed a time lag analysis method for BF parameters with uncertain time delay information. By calculating the time lag at different stages, the lag time range of parameters was obtained. Then, the mean value and variance of the process parameters corresponding to the lag range were used as the model input, effectively improving the accuracy of model prediction.

3.2.2. Correlation analysis of the BF data

Association analysis, also known as association rule mining, can discover the relationship between items in the data set and determine the association pattern between item sets, such as the Apriori and the frequent pattern-growth (FP-growth) algorithm. The number and quality of rules based on the preset minimum support degree and minimum confidence degree can be controlled by the FP-growth algorithm, especially for the high quality rules. The BF data are noisy and easily jittered, and the FP-growth algorithm with low data requirements is suitable for their processing. Li [16] adopted FP-growth algorithm to determine the association rules between the quality of sinter and coke ratio, permeability index, and heat load, and the reasonable control range of sinter quality parameters were quantified and obtained. However, the data applied in the Apriori and FP-growth and their mining results must be discrete. Although most of the BF data are sequenced, the results of data mining should be accurate values or ranges. Ming [31] put forward the concept of temporal association rules to solve the problem of furnace status prediction. Based on this, a weighted temporal association rule was constructed to reflect the time value of data, and its effectiveness was proven by simulation experiments.

3.3. Prediction of the key variables for BF

3.3.1. Important feature screening of BF

The BF ironmaking process is complex, and the data of the BF system originate from many sources and have a wide range. However, among these many parameters, the covariates that have an evident relationship with a specific key index of BF are limited. In contrast, if irrelevant factors or weakly correlated factors are selected, not only the prediction accuracy of the model will decrease, but the training speed of the learner will also increase. Therefore, the accurate dimensionality reduction of BF data is needed. The methods commonly used in processing BF data include feature extraction and selection.

(1) Feature extraction is an essential process in machine learning in terms of dimensionality reduction and removal of irrelevant and redundant data, and it can increase the efficiency and effectiveness of machine learning. Feature extraction is very different from feature selection, though both are means of data dimensionality reduction. The former includes the conversion of arbitrary data into numerical features that can be used for machine learning while the latter is the application of these features to machine learning. Feature extraction is generally applied for processing data from high-dimensional to low-dimensional feature space through mathematical methods. The original feature space is changed if different attributes are combined to obtain a new one. For example [32–34], principal component analysis, kernel principal component analysis, and independent principal component analysis have been adopted to achieve the dimensional-reduction treatment of BF parameters. Feature extraction, while enabling dimensionality reduction, can also construct more meaningful underlying variables to help generate deeper insights into data. However, the physical meaning of the new features constructed by feature extraction is far from that of the original features, and the extracted features show weak interpretation [35], which is very unfavorable for guiding the operation of the BF and analyzing the causes of abnormal furnace status.

(2) The feature selection of BF includes feature sequencing and combination (Fig. 2(a) and (b)). Feature ranking method is used to score each feature by the specific evaluation criteria, and the features are sorted in descending order based on the score and the first *k* features as input features of the prediction model are selected. For example [36–37], the features showing a strong correlation with key indicators of BF are screened out using Pearson correlation coefficients, Spearman correlation coefficients, and maximal information coefficient (MIC). Although the characteristic selection method has a high efficiency, the coupling relationship between BF parameters is ignored. Feature combination can be divided into global, sequence, and random searches. Although the optimal feature combination has been found by global search, the calculation cost is extremely high. For 100-dimensional BF parameters, there are 2^{100} characteristic combinations. Sequential searches can be divided into forward, backward, and bidirectional searches. The time complexity of the sequence search is low, but the feature subset is locally optimal [35,38]. Random search is better than sequence search, exceeding the locally optimal solution has a certain probability, and the approximate optimal solution can be found. Common random search methods include particle swarm optimization and genetic algorithms [39–41]. The model prediction accuracy or error is a metric used to measure the overall performance of feature combination, and it is better than feature ranking, which is used to estimate the score of a single feature. Practically, multiple feature selection methods can be combined to improve the efficiency and performance of the model (Fig. 2(c)). For example, the feature sorting method is used to remove irrelevant features, and the optimal feature subset is selected by the feature combination method.

In the process of characteristic selection of BF, the distinction between ex ante and ex post variables should be given considerable attention. If the ex post variables exist in the feature set, the model will lose its meaning. Additionally, characteristic selection of BF should be combined with the metallurgical process. Over-reliance on algorithms will occasionally lead to the elimination of important features. For example [23,42], BF characteristics were first screened from the BF smelting mechanism, and the remaining characteristics were screened by feature selection technology.

3.3.2. Forecasting of BF key variables

With the continuous development of big data technology, many machine learning algorithms have achieved good results in the application of prediction of BF key variables; such machine learning algorithms include those of support vector machine (SVM) [35,43–44], gradient lift [45–48], neural net-

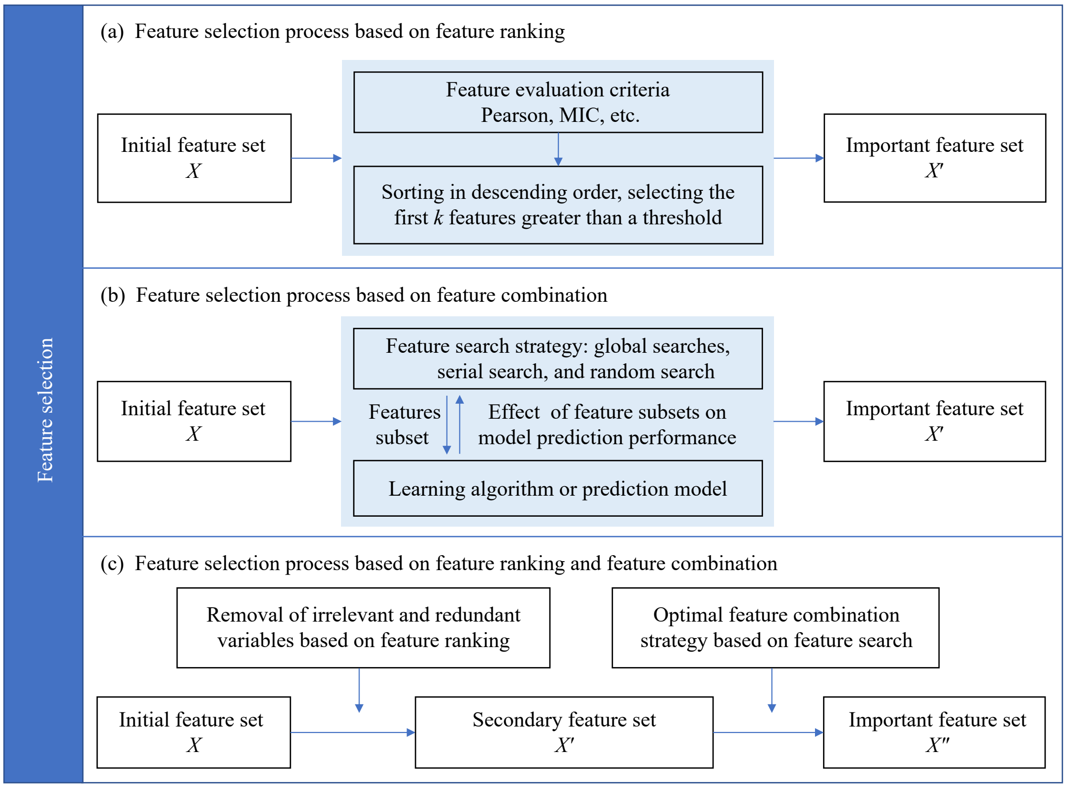

Fig. 2. Feature selection methods for BF.

work [36,49–50], and ensemble learning [22,51–52].

The SVM is a machine learning algorithm based on statistical theory. It has many unique advantages in solving small-sample, nonlinear, and high-dimensional pattern recognition problems. Wang *et al.* [36] built a prediction model for temperature of hot metal by support vector regression and extreme learning machine. The prediction model based on the support vector regression algorithm was superior, with 5.5% higher prediction than that of the extreme learning machine. The gradient lift is an ensemble learning algorithm and machine learning technique commonly used in regression and classification. It generates a prediction model in the form of a set of weak prediction models. Zhao *et al.* [45] used XGBoost to build a prediction model of BF permeability. XGBoost showed great advantages compared with the random forest and linear regression models, and the accuracy of the model was 94.27% within the error range of ±1.5%; it can accurately predict the permeability index of the next hour. BF ironmaking is a dynamic time series. The reaction process of BF is gradual, and the current furnace status is correlated with historical furnace condition and requires a neural network to dynamically remember and keep the persistence of historical information while learning the new information. The long- and short-term memory neural network (LSTM) has achieved remarkable results in the BF parameter prediction. Cui *et al.* [49] introduced neural network time series model to realize the intelligent prediction of silicon content in hot metal, and the absolute error of prediction was less than 0.2% under the condition that the confidence interval of prediction results was more than 95%.

By constructing and combining multiple learners to complete learning tasks, more significant generalization performance was obtained, and the stability of the learning system was also enhanced by ensemble learning [51]. A combined model based on complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) and SVM and LSTM was proposed to improve the prediction accuracy of the gas utilization rate [52]. LSTM and SVM were used to predict the decomposed high- and low-frequency modes, respectively. Finally, a combined prediction model of the gas usage rate was established, and it was more accurate than the single SVM model and LSTM model.

The prediction models of BF key variables can be roughly divided into two categories: regression analysis and time series prediction models. For BF operators, determining the changing trend of the furnace status at the next moment in advance and guiding the BF production were more valuable. The time series prediction cannot be randomly divided into the training and test sets, such as in the regression analysis prediction, but should be divided based on the time sequence of data. Given the approximate data distribution of the randomly divided training and test sets, the accuracy of the prediction model will be inflated, which is one of the most common problems in the current research. Additionally, the predictive models in some studies achieved high accuracy rates, but the ex-post variables were used as input variables to the model, which is a fatal problem. Therefore, the BF smelting process in the modeling process must be understood to avoid such problems.

3.4. Evaluation of BF status

In traditional BF operation, the furnace status is judged by the experience of operators. The advantage of expert experience is the very high degree of integration with metallurgical theory and actual furnace conditions. However, due to the limited energy of operators, they can only deduce and make decisions about furnace conditions by focusing on changes in a small number of key indicators. A comprehensive analysis was conducted on raw fuel conditions, operating system, and furnace status. Therefore, a long recovery cycle of furnace status was required through expert experience. With the development of AI technology, the stability of the BF status was evaluated using big data and machine learning methods, and some achievements have been obtained. At present, the evaluation methods of BF status based on big data technology are mainly divided into three categories (Fig. 3).

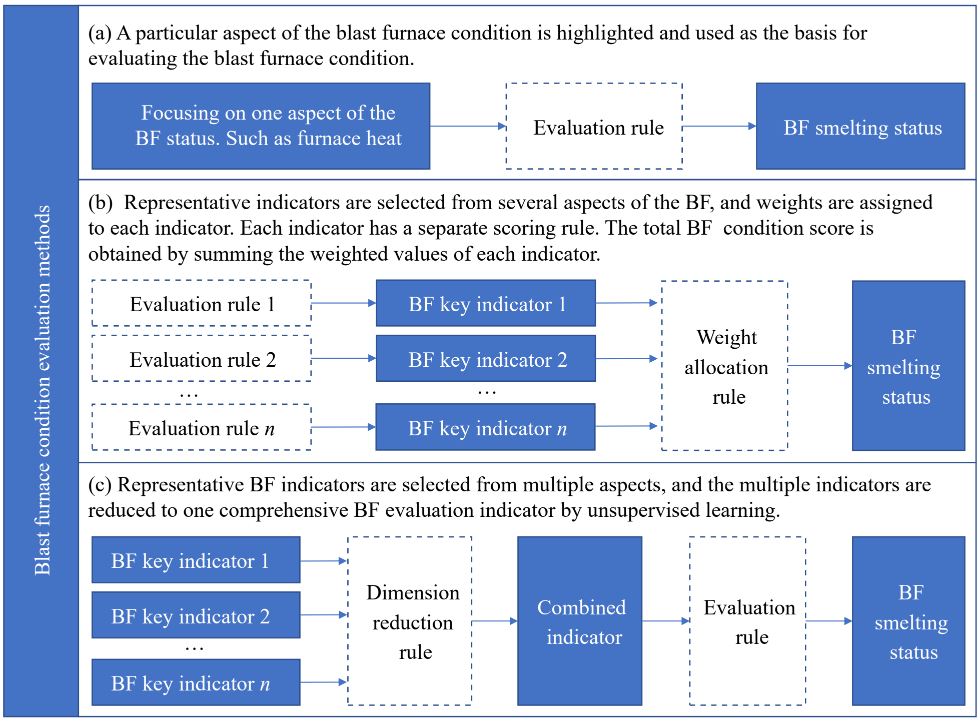

Fig. 3. Evaluation methods of BF status.

(1) One aspect affecting the BF status is considered and used as the basis for evaluation. Such as furnace heat or coke ratio. Although this kind of method greatly reduces the difficulty of characterizing the BF status, it is a one-sided comprehensive evaluation. Particularly, when the selected index is in a reasonable range, the actual performance of the BF may be poor due to the influence of other factors. Zhao [53] analyzed the BF status from the perspective of BF temperature, and various machine learning algorithms were used to evaluate the BF status by assessing whether the BF was cooling or heating. The furnace temperature level is only one of the important indexes, and the status cannot be reflected completely.

(2) Some representative indexes are selected from many aspects of BF. Each index is assigned a weight, and an independent scoring rule is established for each index. Finally, the score for each index is weighted and summed to obtain a total score to evaluate the BF status. By classifying the various parameters, setting weights, and limiting the range of the upper and lower limits and interval scores for each index, the comprehensive BF evaluation and analysis model of the smooth smelting index has been established by Maanshan Iron and Steel Co., Ltd, China, and the quantitative scoring method was adopted to evaluate real-time parameters [54]. As a result, the BF status was reflected more comprehensively by the selected wide range of BF parameters. The disadvantage was that the expert experience was applied to judge the scoring rules of parameters, and valuable information in the BF data was not fully used. Therefore, the evaluation system is more difficult to update due to the lack of intelligent algorithm support.

(3) Representative indexes are selected from various aspects of BF, and the dimensions of the selected indexes are reduced to a comprehensive index or category label instead of the whole original index set to evaluate the BF status through unsupervised learning. For example [55–56], multiple indexes of BF are selected as basic parameters, and the comprehensive indexes of BF status are calculated through factor analysis or principal component analysis. The advantage is that multiple indexes of BF are concentrated into one comprehensive index, and judging the furnace status by observing the comprehensive index becomes more convenient and efficient. However, the disadvantage is that the common factor interpretation after concentration by factor analysis or principal component analysis cannot be completely determined. Additionally, the traceability of the comprehensive index worsens after the 2D reduction processes, which indicates that the initial factors causing the BF status disorder cannot be accurately located when the status index deteriorates. Jiang [57] and Ren [58] used K-means clustering algorithm

to convert multiple BF parameters into a category or grade label by which the BF status was classified and evaluated directly; however, this special label required an accurate definition. Additionally, with the increase in the number of parameters involved in clustering, the clustering space became more complex, and the overlap of the clustering boundary became more evident.

Given the complex characterization of BF status, many researchers have used the quality and production of hot metal and fuel consumption indicators to represent the smooth operation of a BF. The output and energy consumption of BF are the final indicators, and the quality of the process is reflected by the quality of the results. A smoothly functioning BF is represented by high output and low energy consumption, and the opposite condition is a sign of poor BF conditions. Through the weighing and evaluation of hot metal production, [Si], and fuel ratio, Deng *et al.* [42] evaluated the comprehensive BF status. This description was not accurate enough, and the logic of cause and result was reversed. Meanwhile, a stable furnace status is the basis of high yield and low consumption; it is the reason but not the result. If the furnace status is ignored in the pursuit of output and energy consumption, the benefit is short-lived. Once the furnace status becomes abnormal, the loss becomes greater, and the life of the BF is affected. Therefore, when evaluating the BF status, not only the quality of output and energy consumption but also the quality of indicators reflecting the BF status, such as permeability index, heat load, furnace temperature, and gas usage rate, should be considered.

Additionally, a large number of BF operation data contain the deep characteristics of the BF smelting process; however, the BF mechanism is not fully analyzed and used, and only the conventional data-driven modeling algorithm is used to build the BF model, which is bound to present difficulty in achieving the ideal effect [59]. Additionally, most proposed methods for BF fault diagnosis only diagnose BF states using short-term scale data. However, the probability of faults is also related to the long-term scale running state of the BF. An *et al.* [60] presented a two-layer fault diagnosis method for BFs on multiple time scales. The deterioration trend of the BF was analyzed on a long-term scale, and an improved Dempster–Shafer evidence method was designed to diagnose the faults of the BF on a short-term scale. Compared with the traditional method, this novel method improves the accuracy of furnace condition diagnosis. To date, specific abnormal furnace status has been diagnosed and analyzed by most researchers, and no complete evaluation system of the BF status has been observed. The excellent BF status evaluation model not only makes a comprehensive and scientific evaluation of the BF status but also traces and analyzes the cause accurately when the status fluctuates or is abnormal. Therefore, we should establish a complete furnace condition evaluation system from four aspects, such as BF-operating state label, state score, condition prediction, and BF operating condition root cause analysis.

3.5. Optimization of BF parameters

Improvement in the economic benefit, reduction of the smelting cost, and realization of the low carbonization production should all be based on the stable operation of BF. When the furnace status fluctuates or is about to fluctuate, providing timely optimization suggestions for the operator to prevent the occurrence of abnormal furnace status or to restore the furnace status in time with minimum cost is the key to ensure the stable operation of the BF. Given the complexity of the BF smelting process and the limitation of the automation level, the stable production of BF at this stage mainly depends on the operation of technical personnel, and true closed-loop control cannot be realized. A more effective way is recommending optimization suggestions to the operator through the BF optimization model and assisting the operator in guiding stable production.

In the actual production, the optimization of BF is mainly based on metallurgical theory or expert experience [61–63]. Although it is highly explanatory and low risk, the efficiency is low. With an increasing number of researchers engaged in this research, big data technology achieved preliminary results in dealing with parameter optimization of the BF. This parameter optimization is mainly divided into single-and multi-objective optimizations (Table 2).

The single-objective optimization of BF is usually based on the local aspect. Although the solved optimization strategy can exert a good optimization effect on the target index, it will also cause an uncertain influence on other indicators of BF, which cannot meet the comprehensive requirements of high quality, low consumption, high yield, and smooth running of BF; therefore, achieving the expected effect on practical applications is difficult. Tian *et al.* [64] established the optimized model of the BF fuel ratio. And although the optimization effect of the fuel ratio was predicted, the influence on furnace status during the implementation of the adjustment scheme was ignored. If the furnace status is not smooth,

Table 2. Optimization of the BF parameters

Type	Advantages	Disadvantages
Single-objective optimization	The solution is easier, and the optimization effect is better.	The combined requirements of high quality, low consumption, high production, and stability of the blast furnace could not meet.
Multi-objective optimization	Multiple objectives are coordinated so that each objective is as optimal as possible.	The optimization model is complex and difficult to solve. The Pareto optimal solution is applied directly, and the final solution selection is difficult.
Multi-objective converted to single-objective	The difficulty of optimization is greatly reduced.	The allocation of weights is subjective to a certain extent.The objective function is complex when the objectives are constrained to each other.

the final optimization effect will be greatly reduced. In the multi-objective optimization problem of BF, a strong coupling is observed between indexes, and the performance improvement of one index may cause the performance reduction of another or more indexes. Attaining all the indexes of BF to reach the optimal value is difficult. The best method is to compromise and coordinate the treatment among indexes.

Common multi-objective optimization methods include linear programming, genetic algorithms, and particle swarm optimization. For example [65], the linear programming method was adopted to establish a mathematical model for BF ironmaking optimization with energy consumption and cost as objective functions. The optimization variables and constraints were determined based on the objective functions and BF process characteristics. Then, the multi-objective optimization results were obtained through a single-objective optimization. Li *et al.* [22] applied the genetic algorithm to optimize the two objectives of coke ratio and permeability, which can be controlled in a rational range by Pareto optimal solutions. Dong [66] established a multi-objective optimization model for coke ratio and output of hot metal of BF using particle swarm optimization algorithm. However, with the increase in the number of optimization objectives, the complexity of the optimization model increased, which was disadvantageous for obtaining the solutions.

Therefore, the multi-index optimization problem of BF is usually converted into a single-index problem by the weight method. For example [67], the weighted method was applied to convert the cost, energy consumption, and carbon dioxide emission of BF ironmaking into a comprehensive index to solve the multi-objective optimization problem. However, the distribution of the weighted value of each index of BF is subjective. When the objectives are restricted to each other, the objective function will become very complicated.

In the study of BF parameter optimization, especially the multi-index optimization problem, the Pareto optimal solutions are not unique. From the results, an approximate optimization effect was achieved. However, given the complexity of the BF ironmaking process, practical application results will vary greatly. A selection mechanism for an optimal strategy suitable for the current furnace status from many Pareto optimal solutions is a powerful standard to measure the applicability of the optimization model. If attention is only paid to the optimization effect, and the constraints of BF production conditions are ignored, the application of the optimization strategy will be poor. The stable and smooth operation of BF practical production must be ensured. The operator expects to stabilize the furnace status by controlling the operation with the most convenience, lowest risk, and lowest cost. Therefore, in the feedback optimization strategy, we should not only pay attention to the optimization effect but also comprehensively consider the feasibility and cost of operations. Only with low risk, low cost, and high return as the optimization criteria can big data technology be promoted to achieve better results in the application of BF optimization control.

4. Research of intelligent BF technology at NEU

Some preliminary works on the development and application of intelligent BF ironmaking technology have been carried out by Professor Chu's team from NEU. Both the theoretical foundation and practical experience were accumulated, and some results revealed good industrial applications. According to the process and data characteristics of BF ironmaking, the historical and real-time data of the whole process were integrated. On the basis of data preprocessing, an intelligent BF model was developed by integrating process mechanisms, data analysis, and expert experience and using the time series correlation analysis method and big data AI technologies, such as deep learning and integrated learning. This new technology is described in Fig. 4. Based on the whole BF ironmaking process on an industrial big data platform, ironmaking data were managed in a standardized way, and data quality was improved. A digital twin-model learning system for BF was proposed based on the fusion of process mechanisms, data algorithms, and expert experience, where the state of the BF smelting process was scientifically analyzed based on online multi-objective optimization and dynamic control systems to guide the safe, stable, low carbon, and efficient production of BF. The ultimate goal was to improve the low-carbon and intelligent level of the BF ironmaking process.

4.1. Data management and association rule mining for the whole BF system

In accordance with the BF ironmaking process, the production historical and real-time data, including the raw materials and fuel data, operation data, smelting status data, and slag and iron data, were collected, and the detailed classification is presented in Fig. 5. Based on data preprocessing technology and expert experience, data conversion, missing value and outlier identification, scientific processing, and data standardization were carried out. Through mixed-frequency data processing, the problem of data sample imbalance caused by different data acquisition cycles of various processes was solved, and evident improvement was observed among data that could not be directly matched and invoked between different processes. Finally, standard and high-quality data for correlation analysis and intelligent prediction were provided by scientific data management to ensure the accuracy of the intelligent model.

For the aspect of delay and correlation analysis, based on MIC analysis, the influences of BF raw materials and fuel and operating parameters on the time lag of BF key indicators were analyzed. The sliding time window was adopted to solve the lag results within 0–6 h (within the smelting cycle of small BFs), and the corresponding time lag with the maximum correlation was extracted. With permeability index as an example, a part of the results is shown in Fig. 6. The lag time for permeability index due to blast pressure was 14 min, and the lag time of coal injection on permeability index was

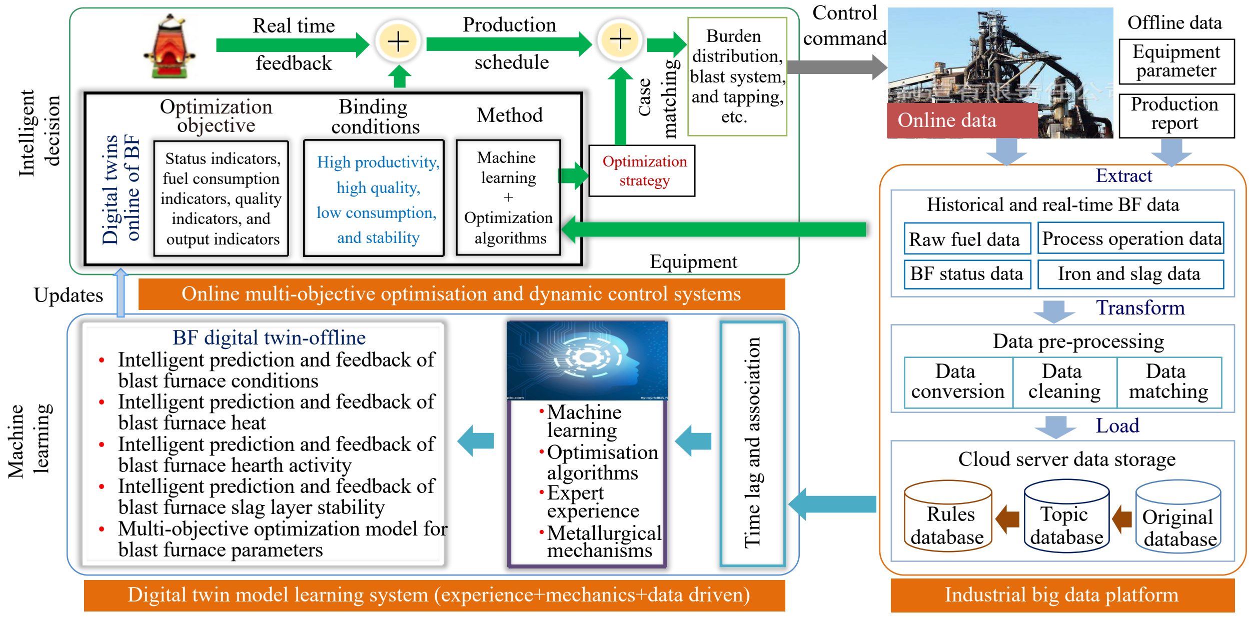

Fig. 4. Intelligent BF technology integrating industrial data, metallurgical mechanism, and expert experience proposed by NEU.

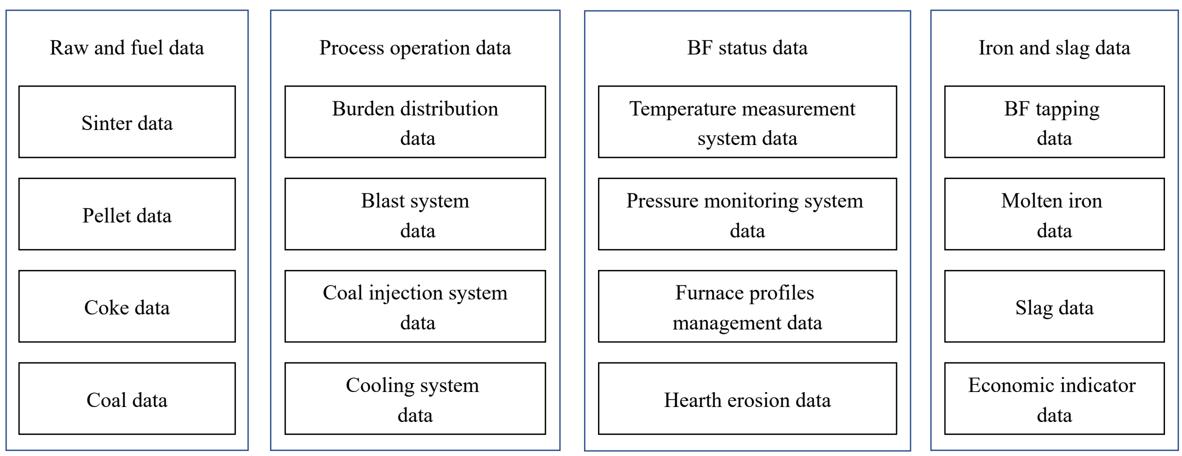

Fig. 5. Collection and classification of BF data.

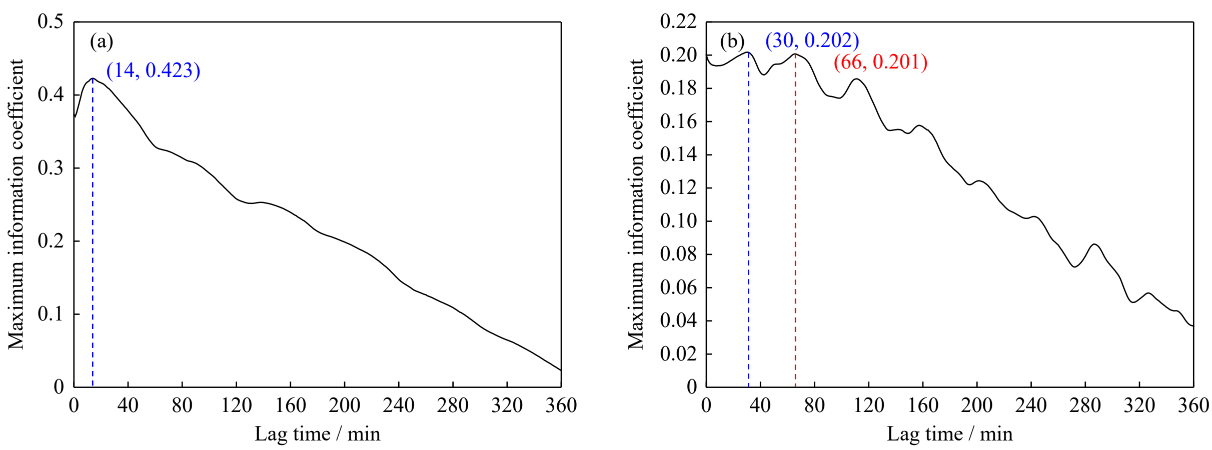

Fig. 6. Lag time of blast pressure (a) and coal injection (b) on permeability index.

30 min. Additionally, the FP-growth algorithm was used to mine the association rules for the key parameters of BF status from raw materials and fuel and operating parameters, important factors associated with the key parameters were extracted, and the reasonable range of BF operation was quantified. Some results are listed in Table 3. For example, when the blast volume was in the range of 2058.4 to 2157.0 m^3/min, the hot air temperature ranged from 1183.4 to 1229.0°C, oxygen enrichment was in the range of 6653.34 to 7299.0 m^3/min, coal injection was in the range of 15981.32 to

Table 3. Rules for correlating blast furnace operating parameters with permeability index

No.	Affiliation rules	Result	Confidence / %
1	Blast temperature ∈ (1094.0, 1153.43], blast volume ∈ (1943.0, 2016.56], and oxygen enrichment ∈ (4201.0, 6037.21]	Permeability index ∈ (71.0, 82.48]	94.9
2	Blast volume ∈ (1943.0, 2016.56] and blast temperature ∈ (1094.0, 1153.43]	Permeability index ∈ (71.0, 82.48]	92.7
3	Coal injection ∈ (15981.32, 17875.56], blast volume ∈ (1943.0, 2016.56], and blast temperature ∈ (1094.0, 1153.43]	Permeability index ∈ (71.0, 82.48]	91.5
4	Blast volume ∈ (2058.4, 2157.0], blast temperature ∈ (1183.4, 1129.0], oxygen enrichment ∈ (6653.34, 7299.0], and coal injection ∈ (15981.32, 17875.56]	Permeability index ∈ (82.48, 88.73]	95.4
5	Coal injection ∈ (15981.32, 17875.56], blast volume ∈ (2058.4, 2157.0], and oxygen enrichment ∈ (6653.34, 7299.0]	Permeability index ∈ (82.48, 88.73]	93.6
6	Coal injection ∈ (15981.32, 17875.56], blast temperature ∈ (1183.4, 1129.0], and oxygen enrichment ∈ (6653.34, 7299.0]	Permeability index ∈ (82.48, 88.73]	90.2

17875.56 kg/h, and the permeability index was within 82.48 to 88.73.

4.2. Intelligent prediction of key variables of BF driven by mechanism and data

In terms of the prediction of the direct key variables of BF, the radial coke load and drop point of the burden calculated by the BF burden distribution simulation model as derivative features, six machine learning methods, including SVM, random forest, gradient-boosted regression trees, XGBoost, light gradient-boosting machine, and artificial neural network, were applied to predict the coking ratio, permeability index, heat load, and production hot metal. To avoid the adaptability difference of a single machine learning method to different data characteristics and variable parameters, we used the hyperparameter tuning technology and ensemble learning to optimize the above intelligent model to further improve the accuracy, stability, and generalization of the prediction model. After optimization, the deviation between the predicted and actual values of each parameter was significantly reduced, and the coefficient of determination (R^2) was more than 0.9. This indicates that the prediction effect was good, and the model had an excellent robustness performance, realizing the accurate prediction of the key parameters of the BF operating status (Fig. 7). The BF key parameter prediction model was predicted 1 h in advance with an R^2 of 0.9186 for the coke ratio prediction model, 0.9314 for the permeability index prediction model, 0.9026 for the heat load prediction model, and 0.9228 for the iron production prediction model.

In terms of predicting the indirect key variables of BF, the physical and chemical heats of hot metal were used to characterize furnace heat. A slag–iron heat index model based on the BF process principle was established using the heat and carbon–oxygen balances in the high-temperature zone of the BF. An intelligent prediction model of BF heat with high frequency and accuracy was constructed by integrating industrial big data, smelting mechanism, and expert experience (Fig. 8). The accuracy of the temperature of hot metal prediction model was 92.16%, with an error range of ±10°C, and that of [Si] in prediction model was 90.34%, with an error range of ±0.1%. The furnace temperature prediction results were predicted 1 h in advance. An intelligent prediction model of BF heat has been applied online in steel enterprises. During the application period, the prediction accuracy was more than 90%. Additionally, the stability rate of the BF temperature increased by 30%. Moreover, the mechanism and data dual-driven modeling method was used to realize the intelligent evaluation and prediction of the activity of the BF cylinder and the thickness and stability of the slag crust. The related research results have been applied in the industry.

4.3. Multi-objective intelligent optimization of BF ironmaking parameters

With the coke ratio, permeability index, and thermal load of BF as the core optimization objectives and constraining the criteria of high yield, low consumption, high quality, and smooth behavior, genetic algorithms and machine learning were adopted to conduct multi-objective optimization of the nonlinear system of BF ironmaking. Then, the comprehensive optimal interval of the key variables of BF was obtained. A part of the results are shown in Fig. 9 and Table 4. The red points are the Pareto fronts, and the blue points denote the non-Pareto solutions resulting from the optimization algorithm process. The ranges of Pareto optimal solutions for the coke ratio and permeability index obtained by the improved optimization algorithm were reduced to [340.1, 349.2] and [2.53, 2.57], respectively. Based on multi-objective optimization results, the BF operator can select the corresponding control parameters from them, considering the BF production requirements and its smelting conditions, to achieve optimal control of the BF. During the application of the technology in a steel plant, the qualified rate of hot metal increased from 74.5% to 86.8%, the stability of the coke ratio and permeability index significantly improved, and the fuel cost was reduced by 2.5 yuan per ton of hot metal.

5. Conclusions and prospect

(1) The implementation of intelligent technology has been actively promoted by domestic and foreign steel enterprises. Basic data platforms and intelligent system architecture were built, and the application of big data and information physics systems in the steel field was explored. Intelligence is an im-

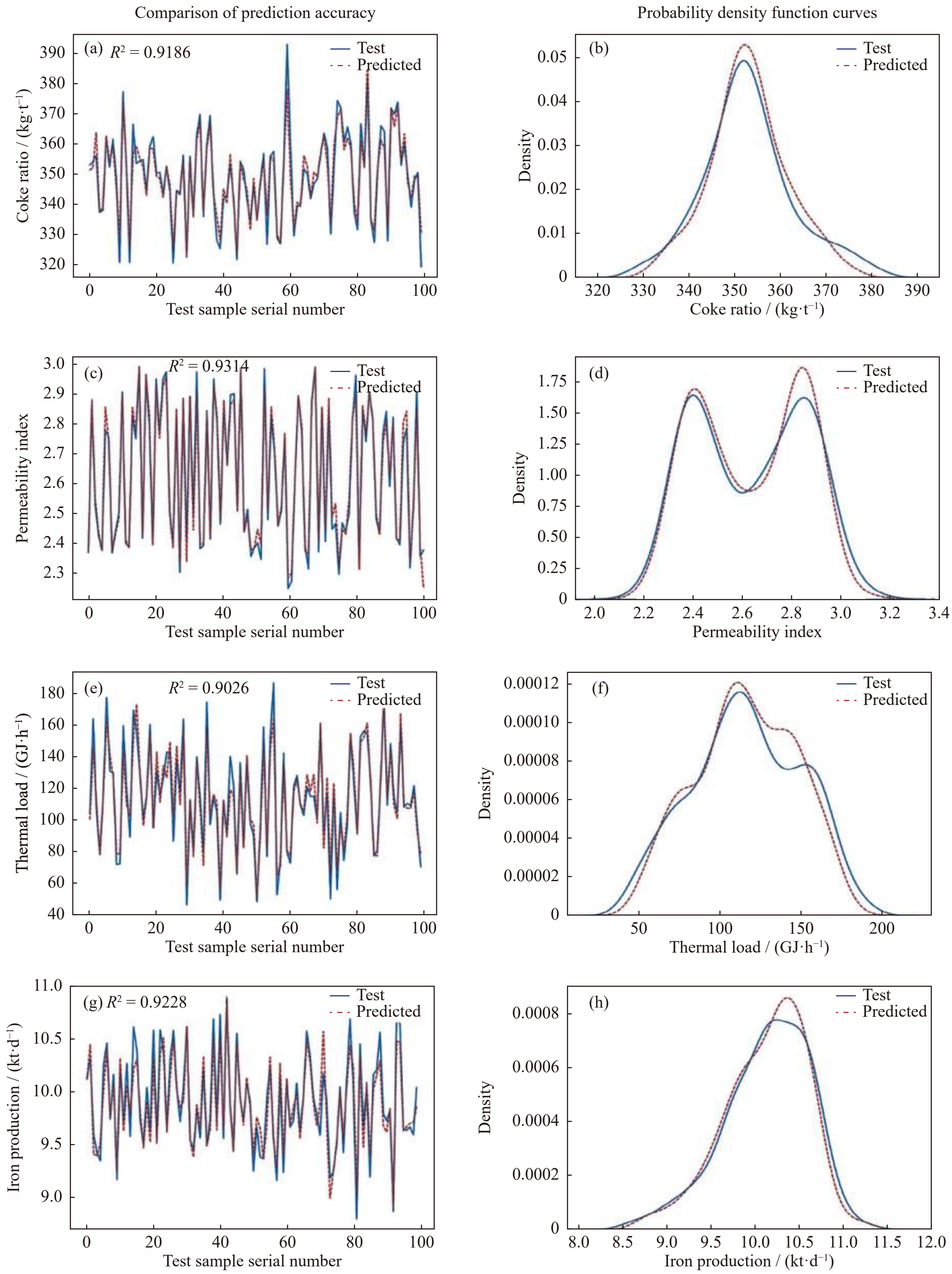

Fig. 7. Accurate prediction of the BF coke ratio (a, b), permeability index (c, d), thermal load (e, f), and iron production (g, h) based on machine learning.

portant strategic direction for developing the steel industry. A number of policy decisions have been made in our country to promote intelligent transformation and upgrading of the steel industry.

(2) For the aspect of BF data preprocessing, regarding problems, such as missing data, abnormal data, and difficulty in matching data, the data problems and characteristics of the algorithm itself must be comprehensively considered. Here, data processing methods were scientifically selected, and cleaning and integration of complex data of BF were completed, which was conducive to improving the authenticity, accuracy, and integrity of data in multiple dimensions and

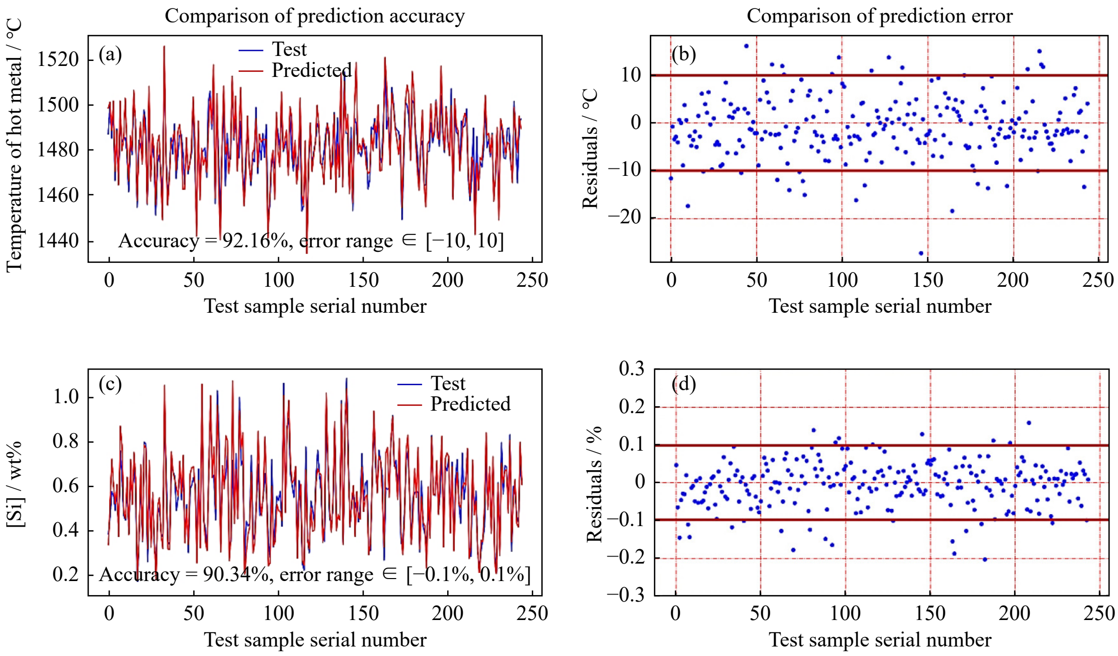

Fig. 8. Prediction results of (a, b)temperature of hot metal and (c, d) Si content in hot metal ([Si]).

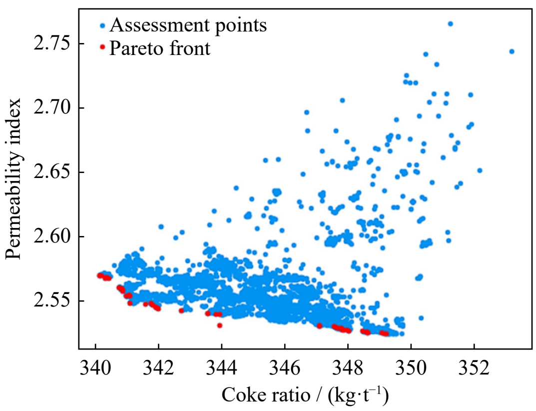

Fig. 9. Results of multi-objective optimization of BF parameters.

enhancing data quality effectively.

(3) For the analysis of important BF characteristics, elimination or weakening of the influence of BF raw materials and fuel conditions and operation on the time lag of economic indicators through time lag analysis was beneficial and improved the accuracy of data. Based on this, through the BF process mechanism combined with feature selection and extraction technology, the selection of important BF features was effectively completed to ensure the accuracy of the logical relationship between the operating parameters and economic indicators. Additionally, for the complex BF smelting process, the data model not only obtained a high accuracy but also assisted the BF operator in guiding the production. Thus, a mechanism that will enable the model and its features to attain good interpretability is an important research direction in the future.

(4) For the BF parameter prediction and furnace status evaluation, their changing trends must be mastered in advance to assess and stabilize the running status. However, relying on experience to judge the trend of furnace conditions and determine the status accurately and dynamically was difficult. Also, the results of the data-driven BF status evaluation method showed poor interpretation, and tracing the cause of furnace status disturbance was difficult. Therefore, an intelligent BF model integrating data information and process mechanism was built to achieve the accurate prediction of key indicators and scientific evaluation of BF status. Future research is needed to identify abnormal furnace conditions, especially the use of AI techniques to predict abnormal furnace conditions. Additionally, BF parameter prediction and furnace status evaluation model should be combined

Table 4. Pareto solution set (partial results)

No.	Sinter basicity	Sinter strength / %	Coke breaking strength, M_{40} / %	Coke abrasion strength, M_{10} / %	…	Slag basicity	Pellet ratio / %	Coke ratio / (kg·t^{-1})	Permeability index	Thermal load / (GJ·h^{-1})
1	2.05	81.3	90.7	5.20	…	1.24	25.7	340.1	2.57	130.78
2	2.05	81.3	90.7	5.20	…	1.24	25.7	340.1	2.57	130.99
3	2.05	81.3	90.7	5.20	…	1.24	25.9	340.2	2.57	135.25
…	…	…	…	…	…	…	…	…	…	…
48	2.17	84.0	91.2	5.12	…	1.25	34.3	349.1	2.53	126.09
49	2.17	84.1	91.2	5.11	…	1.25	34.3	349.2	2.53	126.57
50	2.18	84.0	91.2	5.12	…	1.25	34.2	349.2	2.53	126.43

with expert systems to maximize the use of AI technology to improve BF production efficiency.

(5) For the multi-objective optimization of BF parameters, the low risk, low cost, and high return should be considered as optimization criteria, and the risk degree, operation cost, and optimization effect of the optimization strategy should be comprehensively evaluated. The operation with the lowest risk, and the lowest cost was finally applied to improve smooth smelting. The ultimate goal of BF parameter optimization is to achieve closed-loop automatic control of the BF, which is still difficult to achieve under current production conditions and operating technology, especially when furnace conditions fluctuate drastically. Therefore, further research on the optimization and control of BF conditions is still needed, especially with regard to feedback under abnormal furnace conditions.

(6) AI technology has a huge potential to be used in solving "black box" problems and optimizing the BF ironmaking process. With the effective integration of process mechanics and AI technologies, the future of the BF ironmaking process will be highly automated, digital, and intelligent and no longer rely on the experience and feelings of operators. The current research will increase operator's awareness of intelligent BF technology. Meanwhile, the gradual application of big data technology in BF has a positive effect on improving the BF status. However, the current level of application of AI technology in ironmaking is at a technical inflection point from "impractical" to "practical," and a number of bottlenecks must be solved before it can be deemed "very useful." To achieve an intelligent BF, considerable work should be explored and improved continuously.

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Conflict of Interest

Mansheng Chu is an editorial board member and Jue Tang is a youth editorial board member for this journal and were not involved in the editorial review or the decision to publish this article. All authors declare that there are no competing interests.

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