Research Status and Application Analysis of Intelligent Prediction for Key Blast Furnace Parameters

Yifan Huang[1], Jiazhe Ji[2], Shengle Li[1], Yeqing Zhu[3], Jing Dong[3*]
[1]*College of Metallurgy and Energy, North China University of Science and Technology, Tangshan, Hebei, China*
[2]*College of Artificial Intelligence, North China University of Science and Technology, Tangshan, Hebei, China*
[3]*College of Science, North China University of Science and Technology, Tangshan, Hebei, China*
**Corresponding Author*

Abstract: Blast furnace ironmaking is a central process in the steel industry, where key operational parameters critically influence efficiency and product quality. Traditional empirical methods often fail to address the complexity and variability of smelting, underscoring the need for intelligent prediction to improve operational stability. This study reviews current research and industrial applications of intelligent prediction for major blast furnace parameters, analysing control mechanisms and quantitative characterisation methods for blast volume, blast temperature, oxygen enrichment, pulverised coal injection, and blast kinetic energy. It further examines the functional roles and mechanistic relationships of process state variables, such as pressure differential, permeability, and gas utilisation, and quality indicators including molten iron silicon content and temperature. Finally, based on typical applications involving multi-source data fusion, deep learning, and ensemble modelling, the study outlines advanced frameworks such as multi-objective optimisation and digital twins, offering practical strategies for cost reduction, efficiency improvement, and sustainable development in the steel industry.

Keywords: Blast Furnace Process; Metallurgical Mechanisms; Data-Driven; Intelligent Prediction; Model Integration

1. Introduction

Blast furnace ironmaking is the core step in steel production and a major contributor to industrial energy use, strongly influencing both product quality and energy efficiency. the International Energy Agency reports that the steel sector is currently the world's second-largest source of carbon emissions, after the energy sector [1]. Therefore, improving energy efficiency, reducing emissions, and increasing productivity while keeping furnace operation stable and hot metal quality consistent has become a key technical challenge for the global steel industry [2].

Blast furnace operation is governed by many parameters, covering raw materials, control settings, process states, and hot metal quality. Control variables such as blast volume and temperature directly affect heat transfer, gas flow, and smelting intensity. State indicators like pressure differential and gas utilisation describe internal gas flow, burden reactions, and thermal conditions [3]. Quality metrics, including hot metal silicon content and temperature, respond quickly to furnace changes and thus need real-time monitoring and reliable prediction [4].

Traditional blast furnace optimisation mainly depends on mechanistic models of heat and mass transfer and in-furnace reactions. Yet high data noise and strong nonlinearity mean these models often cannot capture real production complexity [5]. With the growth of industrial big data and intelligent algorithms, data-driven methods have become an effective alternative. Machine learning and deep learning can mine nonlinear patterns from process data, improving prediction and control of key furnace parameters [6].

Motivated by these demands, this paper combines data-driven modelling with mechanistic analysis to review parameter sensing, computational inference, and intelligent prediction for blast furnace operation. It discusses the limits of traditional mechanistic models and detection methods, and shows why data-driven approaches are needed to forecast parameter changes. the paper also compares major algorithms in multi-source data fusion and prediction, outlining their advantages and drawbacks. Based on practical blast furnace workflows, this study aims to support intelligent optimisation in steelmaking and advance efficient, low-carbon ironmaking.

2. Operational Control Parameters of Blast Furnace Processes

Operational parameters regulate the in-furnace heat supply and reaction intensity by adjusting conditions such as blast volume, oxygen enrichment, and kinetic energy.

1) Blast Volume: Appropriate blast volume enhances the contact efficiency between gas and burden, thereby improving the reduction reactions. Although electromagnetic flowmeters are commonly used for monitoring, measurement errors often necessitate indirect estimation based on top-gas composition. the calculation is as follows:

$$V_{\text{wind}} = \frac{[\varphi(N_2)V_{\text{gas}} - 0.8(w(N)_{\text{material}} + w(N)_{\text{CIR}}) - V_{N_2\text{-Add}}]}{(1-\varphi)(1-\omega)} \tag{1}$$

where V_{wind} and V_{gas} represent the required blast volume and the generated dry gas volume per tonne of hot metal, respectively, $m^3 \cdot t^{-1}$; $\varphi(N_2)$ is the volume fraction of component *D* in the top gas,%.

2) Blast Temperature: High blast temperature improves gas fluidity, promotes reduction reactions, maintains the thermal balance of the hearth, and reduces the risk of solidification. Modern blast furnaces typically utilise radiation pyrometers to ensure accurate temperature measurement.

3) Oxygen Enrichment:Increasing oxygen enrichment enhances the reduction efficiency of the burden, reduces gas consumption, and elevates furnace temperature and smelting intensity. the oxygen enrichment is calculated as:

$$\text{Oer}(\%) = \frac{(0.21 \times V_{\text{wind}}) + (Q_{\text{oxy}} \times b)}{V_{\text{wind}} + Q_{\text{oxy}}} \times 100\% \tag{2}$$

where Q_{oxy} denotes the industrial oxygen flow rate, $m^3 \cdot h^{-1}$; *B* is the oxygen purity,%.

4) Pulverised Coal Injection Rate:Insufficient coal injection leads to incomplete combustion and a decrease in hearth temperature. Current monitoring methods commonly combine electronic weighing systems with ultrasonic Doppler and capacitive noise techniques to measure coal powder flow.

5) Blast Kinetic Energy:High blast kinetic energy improves gas distribution and promotes reduction reactions, while low kinetic energy may cause burden hanging or clustering. the calculation is expressed as:

$$E = \frac{1}{2}mv^2 = \frac{1}{2} \times \left(\frac{\rho_0 V_{\text{wind}}}{60gn}\right)\left(\frac{V_{\text{wind}}}{60nf} \cdot \frac{273+t}{273} \cdot \frac{1}{p_1}\right)^2 \tag{3}$$

where ρ_0 is the air density under standard conditions, $kg \cdot m^{-3}$; f is the cross-sectional area of a single tuyere, m^2; and p_1 is the hot-blast pressure, kPa.

3. Process State Parameters of Blast Furnace Operation

3.1 Furnace Pressure Differential

The pressure differential reflects the stability of gas flow and heat distribution inside the blast furnace. A low differential indicates gas channeling and insufficient gas utilisation, whereas an excessively high differential may imply increased energy consumption and temperature fluctuations. Differential pressure transmitters are commonly used to measure the pressure at the furnace top and the hot-blast main, with the calculation expressed as:

$$\Delta P = P_1 - P_2 \tag{4}$$

where P_1 is the hot-blast pressure, kPa; and *B* is the furnace-top pressure, kPa.

However, due to limitations in sensor placement and fluctuations in furnace conditions, the measured differential cannot fully capture the real-time operational state. Therefore, data-driven approaches are required for advanced prediction, as illustrated in **Fig. 1**.

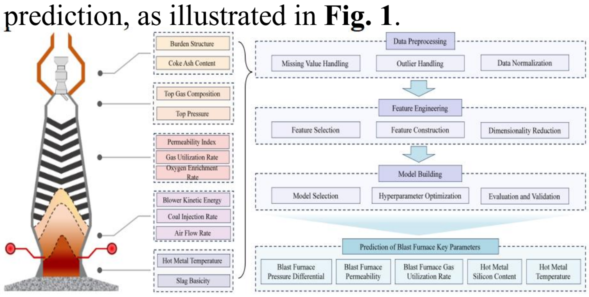

Figure 1. Data-Driven Modelling Steps

Liu *et al.* [7] applied the Extra Trees algorithm with hyperparameters tuned via grid search and cross-validation. Jiang *et al.* [8] assessed feature contributions to pressure differential using partial dependence plots and SHAP, and introduced SVR to reduce overfitting, achieving 94.45% accuracy. Qin *et al.* [9] used volatility-based variable selection and an LSTM model, improving hit rate by 0.89% over a decision tree. Shi et al. [10] combined XGBoost with a BP neural network and merged outputs by reciprocal-error weighting; sparrow search optimisation of hyperparameters increased R^2 by 19.5%.

3.2 Blast Furnace Permeability Index

The permeability index characterises counter-current flow between the burden and furnace gas. A low value implies weak local reduction and heat exchange, while an overly high value may indicate burden loosening, gas channeling, and poorer gas utilisation. Conventional monitoring systems (e. g., ATmega16L-based setups [11]) are typically slow, less accurate, and costly to maintain, which limits real-time online tracking. As a result, recent work has shifted toward data-driven automatic prediction. the index is calculated as follows [13]:

$$T_z = \frac{Q}{P_1 - P_2} = \frac{Q}{\Delta P} \tag{5}$$

where Q is the cold-blast flow rate, $m^3 \cdot s^{-1}$; and ΔP is the total pressure differential, kPa.

ELM builds predictive models by minimising training error and weight norms. Improved versions, such as PLS-ELM [12] and KELM [13], better handle nonlinearity and collinearity. Feature selection methods (e. g., maximum information criterion [14], random forest [15], and correlation analysis) are commonly used to refine inputs. Jiang *et al.* [16] used SHAP to show that coal injection rate, pressure differential, and blast velocity have the strongest influence.

To capture multi-scale patterns in furnace data, time–frequency decomposition is often used. Liang *et al.* [17] decomposed signals with wavelets into seven bands and built SVM sub-models, obtaining a 0.024 prediction error. Liu *et al.* [18] applied VMD and modelled each band with PSO-BP, raising accuracy by 3%. Zheng *et al.* [19] combined frequency-domain analysis with SVM and recursive correction, achieving R^2=0.967.

Deep learning and hybrid approaches further improve prediction. CNNs extract multi-scale features, and have been coupled with sequence models: Liu *et al.* [20] used KPCA–CNN features followed by LSTM prediction, while Chu et al. [21] fed CNN outputs into a GRU to mitigate gradient vanishing. Yu *et al.* [22] proposed an LSSVM–ANN hybrid with mean-shift clustering to distinguish operating conditions and support adaptive optimisation.

3.3 Blast Furnace Gas Utilisation Rate

The gas utilisation rate indicates how efficiently energy is converted in a blast furnace. A low value implies incomplete reactions, higher energy use, and greater cost, whereas a high value corresponds to a lower coke rate and better efficiency. Although gas composition can be monitored with infrared and thermal-conductivity analysers, the harsh furnace environment (high temperature and pressure with heavy dust) often requires offline sampling, limiting real-time monitoring. Data stability is further reduced by sensor faults, noise, and operating fluctuations, which hinders online optimisation. the utilisation rate is calculated as:

$$\eta_{CO} = \frac{\varphi(CO_2)_{\%}}{\varphi(CO)_{\%} + \varphi(CO_2)_{\%}} \times 100\% \tag{6}$$

where $\varphi(i)_{\%}$ represents the volume fractions of different gas components,%.

To overcome the limits of direct measurement, data-driven models have been used for online estimation and short-term prediction. Early methods such as RF [23] and ELM [24] captured nonlinearities but were sensitive to parameters and less stable. Later work introduced EEMD and noise-assisted variants [25] to alleviate mode mixing. Building on this, Shi *et al.* [26] coupled CEEMDAN with an SVM–LSTM hybrid, improving decomposition quality and the stability of intrinsic mode functions.

To improve robustness, researchers have also used autoencoder-based methods and joint time–frequency analysis. Huang *et al.* [27] employed a convolutional autoencoder for denoising and dimensionality reduction, then predicted with k-nearest neighbours through sample matching in the latent space. Liu *et al.* [28] combined regularised self-representation with a multi-scale spectrogram wavelet neural network to suppress non-stationary noise and capture time–frequency features, increasing the hit rate by 2.14%.

Fluctuations in smelting intensity (SI) strongly affect the link between gas utilisation and gas flow distribution. To handle differing mechanisms across SI levels, Guo *et al.* [29] classified SI with weighted kernel FCM and then applied supervised PCA and SVR for segmented prediction, improving model adaptability and stability. Fan *et al.* [30] developed a composite Bayesian network using sliding-window event extraction to build state and lag networks, and a temporal decoupling strategy to suppress equipment interference, leading to better prediction and scheduling under gas disturbances.

4. Product Quality Evaluation Indicators

4.1 Silicon Content in Molten Iron

The silicon content of molten iron reflects the thermodynamic state and reduction reactions within the blast furnace. A low silicon level indicates insufficient hearth heat, which may lead to chilling, whereas an excessively high level suggests uneven thermal distribution and may trigger abnormal conditions such as hanging or slipping burden. Measurement techniques include X-ray fluorescence and compound-generation methods [31], which offer high accuracy but require complex procedures. Laser-induced breakdown spectroscopy (LIBS)[32] enables rapid response and is suitable for online detection. Although silicon content can also be estimated indirectly using thermodynamic formulas, such methods neglect process fluctuations and fail to capture the dynamic behaviour of the furnace in real time:

$$\lg[Si]+0.0552[Si]=\left(-\frac{26038}{T}\right)-2\lg(0.97P_1+1)-0.032A-B-16.085 \tag{7}$$

where T is the furnace temperature, K; $[i]$ is the mass percentage of element *i* in molten iron,%; *C* is the slag basicity, (%CaO)/(%Al_2O_3).

Mechanism-based models are grounded in heat balance and reaction theory and thus work best under steady furnace conditions, while data-driven models are more adaptable to changing states. For example, Li *et al.* [33] applied an LSTM-RNN to learn temporal dependencies in silicon fluctuations. A hybrid FCM–NARX model [34] combines operating-state clustering with nonlinear dynamic prediction, improving robustness under unstable conditions. Trend-classification methods [35] further help identify complex operating patterns.

Model performance is often improved through hyperparameter tuning. Optuna [36] and particle swarm optimisation (PSO)[37] have been used to optimise gradient boosting decision trees and temporal convolutional networks, yielding clear gains in R^2; the results are summarised in **Fig. 2**. Recent work has also moved toward more practical pipelines. Raza *et al.* [38] developed a framework that integrates data cleaning, collinearity treatment, and model training to support efficient deployment. Zhang *et al.* [39] coupled TimeXer with random forest and added trend-consistency checks and expert-knowledge fusion to build a self-learning rule base for operational decision support.

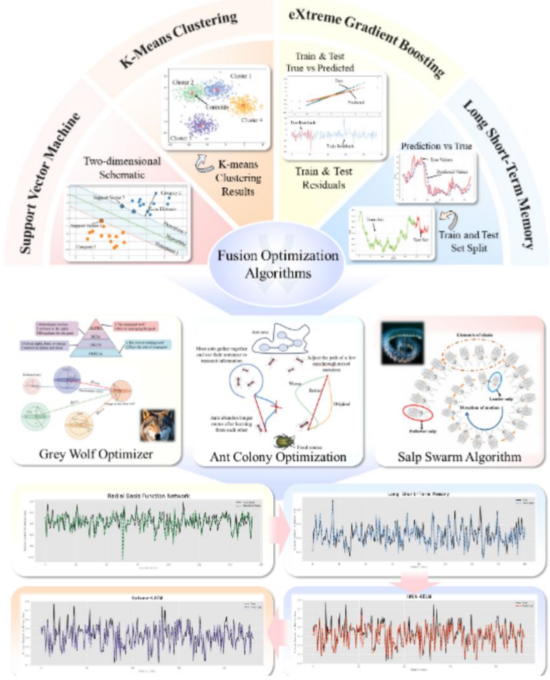

Figure 2. Model Building and Optimisation Effect

Time delays caused by chemical reactions and heat transfer pose a major challenge to prediction accuracy. To address fixed lags, methods such as weighted moving averages [40] and correlation analysis are used to align inputs and outputs in time. Multi-scale tools like wavelet decomposition [41] then help extract lag-related features at different scales. Deep learning models, especially RNN-based approaches, are now widely used because they can learn temporal dependencies and dynamic delays automatically [42]. With forgetting mechanisms and transfer learning, they better capture nonlinear, time-varying lag effects. Recent studies further embed time-delay estimation into soft-sensor models; for instance, Jiang *et al.* [43] treated delays as tunable model parameters constrained by expert knowledge, enabling temporal reconstruction and improving causal fidelity.

4.2 Hot Metal Temperature

The hot metal temperature reflects the thermal balance within the furnace. Common temperature-measurement approaches fall into two categories: contact methods (e. g., optical fiber and blackbody cavity techniques [44]) and non-contact methods (e. g., infrared thermometry [45]). the former features fast response and low cost but suffers from poor durability, whereas the latter provides real-time, high-resolution measurements suitable for full-field monitoring; however, it is susceptible to dust and fume interference and thus requires calibration and correction. the corresponding temperature expression can be obtained by rearranging Eq. (7).

Hot metal temperature is determined by burden composition, oxygen supply, and heat transfer. Since conventional measurements cannot capture fast fluctuations or anticipate upcoming changes, predictive models are critical for online monitoring and control. Data-driven methods such as SVR [46] and ELM are widely used. Combining ICEEMDAN with RVM improves noise resistance and accuracy [47], while fuzzy-rule approaches provide interpretable trend prediction [48]. Meta-heuristic optimisers, including improved Harris hawks optimisation and PSO, further enhance performance by tuning wavelet neural networks and ELM, respectively [49].

To address the dual challenges of inaccurate temperature measurements and the limitations of single-model approaches, recent studies have explored combined measurement–modeling frameworks. Zhou *et al*. [50] proposed a stacked ensemble model that fuses thermocouple data with temperature images. By incorporating CAE-based feature extraction and ensemble learning, the method enables high-accuracy real-time prediction (R^2=0.95), demonstrating the effectiveness of synergistic optimization between measurement and modeling.

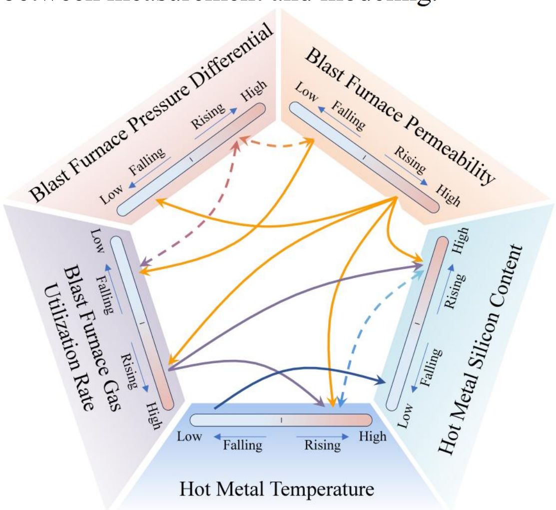

Figure 3. Mechanisms for Inter-Parameter Relationships (The start and end arrows indicate the impact of changes in the former on the latter; the bidirectional dashed arrows represent interactions.)

Good permeability lowers pressure drop, improves gas utilization, and stabilizes gas flow and heat transfer, which raises hot metal temperature and silicon reduction. Higher gas utilization further strengthens furnace heat intensity, while a suitable pressure drop helps maintain smooth flow and thermal balance. the interactions among the five parameters are shown in **Fig. 3**.

5. Conclusions and Future Work

This study develops intelligent prediction models for blast furnace states and hot metal quality using multi-source industrial data. By integrating machine learning, deep learning, and statistical methods, it enhances short- and long-term forecasting to support energy efficiency, stable operation, and quality control.

Despite strong performance in nonlinear, high-dimensional time-series prediction, current data-driven methods still suffer from poor robustness to abrupt changes, difficult multi-source data fusion, limited interpretability, and high computational and data-quality demands, which constrain industrial use. Future work will mainly address:

1) Multi-objective coupled prediction: joint models capturing inter-parameter dependencies for better furnace-state prediction.

2) Mechanism–data hybrid modeling: incorporating metallurgical principles to improve interpretability and robustness.

3) Multi-source fusion and closed-loop control: combining measurements and physics/model outputs with IoT/edge computing for real-time prediction and control.

4) Digital twins and simulation: developing blast furnace digital twins for simulation, online optimization, and early fault warning.

More accurate prediction and early warning can cut energy and material waste, stabilize hot metal quality, and support automation and process optimization.

References

[1] ZHANG J, SHEN H, CHEN Y, et al. Iron and Steel Industry Emissions: A Global Analysis of Trends and Drivers [J]. Environmental Science & Technology, 2023, 57(43):16477.

[2] GUO Z Y, ZHANG J L, JIAO K X, et al. Research on low-carbon smelting technology of blast furnace – optimized design of blast furnace [J]. Ironmaking & Steelmaking, 2021, 48(6):685.

[3] ZHANG J L, DUAN S J, YUAN W N, et al. Numerical simulation of gas flow distribution in the shaft of oxygen blast furnace [J]. Iron and Steel, 1-15[2025-03-25].
[4] HAN Z Z. Research on metallurgical technology of blast furnace ironmaking based on artificial intelligence [J]. Metallurgical and materials, 2024, 44(11):62.
[5] SHI Q, TANG J, CHU M. Key issues and progress of industrial big data-based intelligent blast furnace ironmaking technology [J]. International Journal of Minerals, Metallurgy and Materials, 2023, 30(9):1651.
[6] LIU S, FENG W, ZHAO J, et al. Collaborative Optimization Model of Blast Furnace Raw Materials and Operating Parameters Based on Intelligent Calculation [J]. ISIJ International, 2024, 64(8):1229.
[7] LIU S, ZHAO Y D, ZHANG Z, et al. Research on blast furnace pressure difference prediction model with integrated learning [J]. Electronic Measurement Technology, 2022, 45(2):31.
[8] JIANG D, WANG Z, LI K, et al. Machine Learning Models for Predicting and Controlling the Pressure Difference of Blast Furnace [J]. JOM, 2023, 75(11):4550.
[9] QIN Z J, HE D F, FENG K, et al. LSTM-based modelling method for predicting pressure difference in blast furnace under oxygen-enriched blast conditions [J]. Metallurgical Industry Automation, 2024, 48(2):84.
[10] SHI Y H, ZHANG S H, LIU X J, et al. Prediction of blast furnace pressure difference based on a combined model of XGBoost and BP optimized by SSA [J]. Journal of Iron and Steel Research, 2024, 36(8), 1019.
[11] LI H, ZHOU H L. Design of Monitoring Instrument with Good Air Permeability of ATmega16L-based Single-chip [J]. Taiyuan Science and Technology, 2009(7):94.
[12] SU X, ZHANG S, YIN Y, et al. Prediction model of permeability index for blast furnace based on the improved multi-layer extreme learning machine and wavelet transform [J]. Journal of the Franklin Institute, 2018, 355(4):1663.
[13] LIU S X, YIN Y X, ZHANG S. Prediction model of kernel extreme learning machine for permeability index of blast furnace [J]. Control Theory & Applications, 2023, 40(1):65.
[14] TAN K, LI Z, HAN Y, et al. Research and Application of Coupled Mechanism and Data-Driven Prediction of Blast Furnace Permeability Index [J]. Applied Sciences, 2023, 13(17):9556.
[15] ZHAO J, LI H W, LIU X J, et al. Prediction model of permeability index based on Xgboost [J]. China Metallurgy, 2021, 31(3):22.
[16] JIANG D, WANG Z, LI K, et al. Analysis of Blast Furnace Permeability Regulation Strategy Based on Machine Learning [J]. steel research international, 2024, 95(3):2300590.
[17] LIANG D, BAI C G, WEN L Y, et al. Intellectual prediction of a permeability index for blast furnaces [J]. Journal of Chongqing University, 2009, 32(4), 376.
[18] LIU X, ZHANG Y, LI X, et al. Prediction for permeability index of blast furnace based on VMD–PSO–BP model [J]. Journal of Iron and Steel Research International, 2024, 31(3):573.
[19] ZHENG J, LI W J, AN J Q. Multi-step prediction model of blast furnace permeability index based on multi-time scale [J]. Metallurgical Industry Automation, 2024, 48(2):114.
[20] LIU X J, LI T S, LI X, et al. Prediction of blast furnace permeability index based on KPCA-CNN-LSTM model [J]. Metallurgical Industry Automation, 2024, 48(2):103.
[21] CHU L M, CUI G M. Predicting blast furnace permeability index: a deep learning approach with limited time-series data [J]. Metallurgical Research & Technology, 2024, 121(2):215.
[22] YU Z, LI X, WANG B, et al. A hybrid prediction model of blast furnace permeability index combining least square support vector machine and artificial neural network [J]. Ironmaking & Steelmaking, 2024:03019233241288764.
[23] ZHAO J, LI H Y, LI X, et al. Gas utilization ratio prediction of blast furnace based on intelligent model [J]. China Metallurgy, 2021, 31(3):93.
[24] LI Y, ZHANG S, YIN Y, et al. A Soft Sensing Scheme of Gas Utilization Ratio Prediction for Blast Furnace Via Improved Extreme Learning Machine [J]. Neural

Processing Letters, 2019, 50(2):1191.
[25] JIN Y T, ZHANG Y J, LIU X J, et al. Prediction for utilization rate of blast furnace gas based on EEMD-BAS-RBF [J]. Journal of Iron and Steel Research, 2023, 35(11):1330.
[26] SHI L, LIU W H, CAO F J, et al. Combined forecast of blast furnace gas utilization rate based on CEEMDAN-SVM-LSTM [J]. China Measurement & Test, 2023, 49(1):86.
[27] HUANG Q, LIU Z, LUO M, et al. Forecasting of blast furnace gas utilisation rate via convolutional autoencoders and K-nearest neighbour methods [J]. Ironmaking & Steelmaking, 2024, 51(10):1075.
[28] LIU C, LI J, LI Y, et al. Denoising Multiscale Spectral Graph Wavelet Neural Networks for Gas Utilization Ratio Prediction in Blast Furnace [J]. IEEE Transactions on Neural Networks and Learning Systems, 2024, 1.
[29] GUO Y P, AN J Q, ZHAO G Y. Time-series prediction model of gas utilization rate in a blast furnace considering smelting intensity classification [J]. Metallurgical Industry Automation, 2024, 48(2):60.
[30] FAN J, WU D, LU S. A Compound Bayesian Networks Gas Prediction and Scheduling Method for Blast Furnace Systems Under Various Scenarios [EB/OL]. Rochester, NY:Social Science Research Network, 2025[2025-03-02].
[31] ZHANG L, MA Z W. Progress and development of on-line continuous analysis technology of compo nents in iron and steel smelting [J]. Industrial Me trology, 2012, 22(1):54.
[32] HAHN D W, OMENETTO N. Laser-Induced Breakdown Spectroscopy (LIBS), Part II:Review of Instrumental and Methodological Approaches to Material Analysis and Applications to Different Fields [J]. Applied Spectroscopy, 2012, 66(4):347.
[33] LI Z L, YANG C J, LIU W H, et al. Research on hot metal Si-content prediction based on LSTM-RNN [J]. CIESC Journal, 2018, 69(3):992.
[34] FONTES D O L, VASCONCELOS L G S, BRITO R P. Blast furnace hot metal temperature and silicon content prediction using soft sensor based on fuzzy C-means and exogenous nonlinear autoregressive models [J]. Computers & Chemical Engineering, 2020, 141:107028.
[35] LI J, HUA C, YANG Y, et al. Fuzzy Classifier Design for Development Tendency of Hot Metal Silicon Content in Blast Furnace [J]. IEEE Transactions on Industrial Informatics, 2018, 14(3):1115.
[36] MENG L, LIU J, LIU R, et al. Prediction of Silicon Content of Hot Metal in Blast Furnace Based on Optuna-GBDT [J]. ISIJ International, 2024, 64(8):1240.
[37] REN Y, XING X, WANG B, et al. Prediction Model for Silicon Content of Hot Metal Based on PSO-TCN [J]. Metallurgical and Materials Transactions B, 2024, 55(4):2837.
[38] RAZA O, WALLA N, OKOSUN T, et al. Prediction of Silicon Content in a Blast Furnace via Machine Learning:A Comprehensive Processing and Modeling Pipeline [J]. Materials, 2025, 18(3):632.
[39] ZHANG Y, LIU X, LIU R, et al. A New Method for Prediction and Decision-Making of Silicon Content in Hot Metal: A Hybrid Approach Based on Machine Learning and Process Optimization [OL]. Rochester, NY:Social Science Research Network, 2025[2025-02-28].
[40] CUI Z Q, HAN Y, YANG A M, et al. Intelligent prediction of silicon content in hot metal of blast furnace based on neural network time series model [J]. Metallurgical Industry Automation, 2021, 45(03):51.
[41] DINIZ A P M, CÔCO K F, GOMES F S V, et al. Forecasting model of silicon content in molten iron using wavelet decomposition and artificial neural networks [J]. Metals, 2021, 11(7):1001.
[42] JIANG K, JIANG Z, XIE Y, et al. A Trend Prediction Method Based on Fusion Model and its Application [C]//2018 13th World Congress on Intelligent Control and Automation(WCICA). 2018:322.
[43] JIANG Z, JIANG K, XIE Y, et al. A Cooperative Silicon Content Dynamic Prediction Method With Variable Time Delay Estimation in the Blast Furnace Ironmaking Process [J]. IEEE Transactions on Industrial Informatics, 2024, 20(1):626.
[44] HU J W, XUE X Q, WANG W R. Research on Continuous Temperature Measurement Technology for Blast Furnace Molten Iron [J]. Chinese Journal of Scientific Instrument, 1987(4):433.
[45] PLANINSIC G. Infrared Thermal

Imaging:Fundamentals, Research and Applications [J]. European Journal of Physics, 2011, 32(5):1431.

[46] WANG Z Y, JIANG D W, WANG X D, et al. Prediction of blast furnace hot metal temperature based on support vector regression and extreme learning machine [J]. Chinese Journal of Engineering, 2021, 43(4):569.

[47] XU W, HE Z H, YANG K, et al. Prediction of molten iron temperature based on ICEEMDAN-KPCA-RVM [J]. Metallurgical Industry Automation, 2024, 48(1):18.

[48] LUGHOFER E, POLLAK R, FEILMAYR C, et al. Prediction and Explanation Models for Hot Metal Temperature, Silicon Concentration, and Cooling Capacity in Ironmaking Blast Furnaces [J]. steel research international, 2021, 92(9):2100078.

[49] LIU Z, FANG Y, LIU L, et al. An improved Harris hawks optimizer with enhanced logarithmic spiral and dynamic factor and its application for predicting molten iron temperature in the blast furnace [J]. Engineering Reports, 2024, 6(12):e12974.

[50] ZHOU G, LIU W, YU Y, et al. Advancing Blast Furnace Thermal State Prediction:A Data-Driven Approach Using Thermocouple Integration and Multimodal Modeling [J]. steel research international, n/a(n/a):2400896.

