Sintered CO Emission Prediction Based on CSSM-GBRT

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Abstract: As the core process for CO emissions in the steel industry, accurately predicting the CO generation trend during the sintering process is the key prerequisite for understanding its formation mechanism and grasping emission patterns. It is also an essential foundation for optimizing sintering process parameters and promoting related technological innovations and upgrades. To address the challenge of precise prediction caused by the nonlinearity, lag, and volatility of CO emissions in steel sintering, a CSSM-GBRT hybrid model is proposed. This model uses LSTM to deeply extract long-term dependent features from multidimensional sequences such as wind box temperature, oxygen content, and quicklime flow, then applies GBRT for secondary correction of the LSTM residuals, realizing a dual mechanism- and data-driven approach. Experimental results demonstrate that CSSM-GBRT achieves a coefficient of determination R^2 of 0.9514, reduces RMSE to 98.52 ppm, and reaches a MAPE of only 0.84%. SHAP analysis indicates that cumulative compressed air volume, O_2 concentration in the main flue, and the temperature on the northern side of the wind box are the key factors influencing CO emissions. By integrating key sintering process parameters with emission data, this model can deeply elucidate the intrinsic relationships between solid fuel combustion efficiency, high-temperature reduction reaction intensity, and CO generation, enabling precise prediction of emission trends at different stages, such as low-temperature, low-oxygen high-CO and high-temperature, high-oxygen low-CO conditions, thereby providing technical support for source control and efficient management of CO emissions in the steel industry.

Keywords: Steel Sintering; CO Emission Prediction; Temporal Dynamic Changes; Nonlinear Correlation; Process Parameter Optimization

1. Introduction

As a foundational industry of the national economy, the iron and steel industry ensures sustainable socio-economic development while simultaneously facing severe environmental governance challenges [1]. China's steel industry accounts for over 50% of global steel carbon emissions; in 2022, domestic emissions exceeded 1.8 billion tons, representing more than 15% of the national total [2]. As a critical link in the steel production process, the sintering process accounts for 40%–50% of the industry's total CO emissions. the CO mass concentration in the flue gas from the sinter machine head is typically as high as 8, 000–10, 000 mg/m³, with a flue gas generation intensity of 4, 000–6, 000 m³/t per ton of sinter, making it a primary target for pollutant control in the steel industry [3].

CO emissions pose significant dual hazards to both the environment and human health: not only do they disrupt the chain reaction balance of atmospheric photochemistry and synergistically generate photochemical smog with nitrogen oxides, but they also cause systemic hypoxic damage by binding efficiently with hemoglobin. Research indicates that every 1 mg/m³ increase in the daily average atmospheric CO concentration can lead to a 1.12% rise in cardiovascular mortality. To implement "Dual Carbon" goals, the Ultra-Low Emission Treatment Plan for the Iron and Steel Industry explicitly requires that enterprises in key regions complete retrofitting by 2025, with over 80% of national capacity meeting ultra-low emission standards. This imposes higher requirements for the precise prediction and proactive regulation of CO in sintering flue gas

[4-5].

The generation and emission of CO during the sintering process are influenced by multiple factors, including temperature, oxygen concentration, fuel properties, and process parameters. the generation mechanism is complex, involving a series of physical and chemical processes such as gradient combustion of solid fuels, high-temperature reduction of iron ore, and water-gas shift reactions, with emissions exhibiting distinct staged characteristics [6-7]. Accurately grasping the generation laws and emission dynamics of CO is key to achieving proactive process optimization. Current process optimization and technology R&D rely on the precise prediction of CO generation trends and variation characteristics, leading to the development of various specialized predictive models within the industry. Among these, exhaust gas curve time-series prediction models focus directly on dynamic CO concentration forecasting. A representative example is the Attention-Based Convolutional Aggregation (ABCA) model, which integrates deep learning technologies—including aggregation structures, causal dilated convolutions, attention mechanisms, and residual connections—to achieve high-precision predictions of CO and CO_2 curves for the next 32 seconds, with coefficients of determination (R^2) reaching 0.9386 and 0.8566, respectively [7]. Additionally, process variable prediction models target parameters that are difficult to measure directly, such as alloy yield, utilizing K-medoids clustering combined with Time-aware Long Short-Term Memory (T-LSTM) networks to enhance prediction accuracy by distinguishing between different operating conditions and addressing the impact of data time intervals [9-12].

However, existing predictive models are mostly developed for smelting stages such as converters and suffer from insufficient adaptability to the specific conditions of the sintering process, characterized by violent gas-solid reactions, complex bed structures, and significant fluctuations in flue gas composition. Some models exhibit issues such as delayed real-time response and limited prediction accuracy under multi-parameter coupling, failing to meet the actual needs for precise control of the sintering process. Consequently, based on the correlation between key sintering process parameters (temperature, oxygen concentration, fuel characteristics, bed structure, etc.) and CO emissions, this paper constructs a predictive system integrating the CSSM-GBRT (Carbon Sintering Sequencer-Gradient Boosting Regression Tree) model with a clustering-based data augmentation framework. Furthermore, based on the correlation characteristics of CO emissions under different sintering conditions, a data augmentation method utilizing cluster analysis is proposed. By introducing homologous sintering data from cross-production lines with similar operating conditions, this method expands the training sample space, enhancing the model's generalization capability while maintaining data relevance and scenario consistency. Through algorithmic collaborative optimization and data space expansion, this integrated framework achieves a dual improvement in the accuracy and robustness of CO emission predictions in iron and steel sintering.

2. Mechanism of CO Generation and Emission Patterns in Iron and Steel Production

2.1 Mechanism of CO Generation

In the sintering stage of iron and steel production, the generation of carbon monoxide (CO) is a typical process accompanied by complex physical and chemical transformations, and its emission has become a core issue in pollution control and carbon reduction within the steel industry [13]. From the perspective of generation mechanisms, CO primarily originates from the incomplete combustion of solid fuels and the reduction reactions of iron oxides under high-temperature conditions [14-15]. During the sintering process, solid fuel does not burn uniformly but exhibits a typical gradient combustion mechanism. This stems mainly from the thermodynamic stratification of the sintering bed in the vertical direction, forming—from top to bottom—the sinter zone, combustion zone, preheating zone, drying zone, and over-wet zone. the essence of this layered structure is the dynamic equilibrium of heat and mass transfer between the gas and solid phases, and its morphology is profoundly influenced by fuel characteristics, airflow permeation rates, and moisture migration patterns. In the combustion zone, the oxidation reaction of carbon exhibits staged characteristics as the temperature rises [16]. When the temperature is below 800°C, the reaction between carbon and oxygen is dominated by incomplete combustion, generating a large amount of CO. As the temperature rises to the 800–1000°C range, high-valence iron oxides (such as $Fe_2O_3$and Fe_3O_4) in the combustion zone and adjacent areas begin to be reduced by solid carbon, first forming low-valence oxides such as FeO, and subsequently being partially reduced to metallic iron; this series of reduction reactions continuously releases gaseous CO [17]. Simultaneously, coke particles at high temperatures act as catalysts in the water-gas reaction($C+H_2O \rightarrow CO+H_2$), serving as another source of CO [18]. Furthermore, carbonate minerals in the mixture decompose at high temperatures to release CO_2, which can then undergo a gasification reaction ($CO_2+C \rightarrow 2CO$)with carbon in a high-temperature reducing atmosphere, further converting into CO. Consequently, the generation of CO is the result of multiple interwoven reaction paths, and its yield is comprehensively regulated by temperature distribution, local oxygen concentration, fuel reactivity, and the presence of catalysts [19-20].

2.2 CO Emission Patterns

CO emission is not a uniform or continuous process; rather, it is a staged phenomenon closely related to the sintering process, characterized by distinct spatial and temporal distribution features. the entire process can be clearly divided into three stages, each exhibiting significant differences in flue gas temperature, oxygen concentration, and CO content [21].

The first stage is the initial ignition period, corresponding to the head area of the sintering machine. At this time, the surface fuel is ignited by the ignition gas. Due to the intact bed structure and low permeability, oxygen consumption occurs rapidly while the proportion of solid fuel involvement remains low. Consequently, the flue gas is characterized by "low temperature, low oxygen, and low CO, " and CO generation has not yet reached its peak [22].

The second stage is the combustion diffusion and core reaction period, located in the middle section of the sintering machine. As the combustion layer gradually moves downward, the combustion intensity of the solid fuel increases significantly, leading to a sharp rise in oxygen consumption and the formation of a distinct localized hypoxic environment in the middle of the material bed. Meanwhile, the heat storage effect of the bed causes the temperature in this zone to rise rapidly; however, as the flue gas passes through the already formed upper sinter layer, it is cooled, resulting in no significant rise in the temperature of the discharged flue gas. Due to limited oxygen diffusion and uneven airflow distribution, a strong reducing atmosphere forms in local areas [23]. Under these conditions, the fixed carbon in coke breeze or anthracite is difficult to oxidize completely into CO_2, primarily generating a large amount of CO through incomplete combustion:

$$2C(s)+O2(g) \rightarrow 2CO(g) \Delta H=-221 kJ/mol \quad (1)$$

It is this unique "low-temperature, low-oxygen" atmosphere that makes the incomplete combustion of carbon and the reduction of iron oxides particularly intense. CO is generated and accumulated in large quantities; thus, the flue gas in this stage exhibits "low temperature, low oxygen, and high CO, " with the emission concentration reaching the highest point of the entire process.

The third stage is the sintering completion period, located at the tail end of the sintering machine. By this time, the sinter layer has basically formed and extended to the bottom of the bed, significantly improving bed permeability and reducing airflow resistance. Fuel consumption is nearing its end, oxygen consumption decreases, and the oxygen content in the air passing through the bed is relatively abundant, prompting more complete combustion of the remaining fuel. Simultaneously, the high-temperature sinter layer heats the airflow, causing the temperature of the discharged flue gas to rise. During this stage, \$CO_2\$ generated earlier can undergo an endothermic gasification reaction (i. e., the solution loss reaction) with the red-hot coke, further increasing the CO concentration in the waste gas:

$$\mathrm{C(s)} + \mathrm{CO_2(g)} \longrightarrow 2\mathrm{CO(g)} \quad \Delta H = +172\ \mathrm{kJ/mol} \quad (2)$$

Additionally, carbonates in the mixture decompose at high temperatures to release \$CO_2\$, which can also be further converted into CO through similar gasification reactions in the high-temperature reducing atmosphere [24]. Ultimately, the CO concentration discharged from the main flue is not a simple reflection of the combustion state at a single moment, but a comprehensive superposition of waste gases from different sintering stages (drying, preheating, combustion, and cooling) along the length of the pallet.

Therefore, accurately analyzing the spatial-temporal correlation between process parameters and CO emissions is an important prerequisite for constructing high-precision predictive models. In terms of emission contributions, incomplete fuel combustion is the primary source of CO, accounting for approximately 60% of total emissions; carbonate decomposition and its subsequent conversion contribute about 30%; and CO generated during the ignition stage accounts for approximately 10%. This staged emission pattern provides a clear spatial-temporal basis and theoretical guidance for implementing targeted process regulation and source emission reduction [25].

2.3 Challenges in the Precise Prediction of Sintering CO Emissions

Sintering is a core process in the iron and steel smelting flow, characterized by a high coupling of material and energy flows; its operational state directly determines the quality and cost of blast furnace burden. As a typical gas-solid multiphase reaction process, the sintering system exhibits significant large-lag, strong non-linear, and non-stationary characteristics, which pose massive challenges to the precise prediction of CO emissions [26].

First, the sintering machine involves complex interactions across multiple physical fields, including combustion, heat transfer, and stratified permeability. Fluctuations in a single variable (such as windbox temperature) are often amplified through non-linear mapping networks, causing CO emissions to exhibit violent dynamic changes that traditional linear models struggle to capture. Second, the sintering process spans a significant spatial and temporal scale. From material charging and ignition at the machine head to exhaust gas discharge at the tail, there is a physical transport lag of up to several dozen minutes. Furthermore, this lag time drifts dynamically with fluctuations in operating parameters such as pallet speed and bed thickness, leading to severe causal misalignment between input and output signals on the timeline [27]. Additionally, the harsh electromagnetic environment of industrial sites causes collected data to be mixed with substantial non-Gaussian noise and outliers, further increasing the difficulty of high-precision modeling.

In response to these issues, existing research primarily focuses on two directions: mechanistic modeling and data-driven modeling, yet limitations remain. Although mechanistic models based on reaction kinetics have clear physical significance, they rely on key parameters that are difficult to identify online—such as "effective diffusion coefficients" and "reaction rate constants"—causing prediction accuracy to drop significantly during operational drift.

With the development of artificial intelligence, machine learning algorithms such as Support Vector Regression (SVR) and Random Forest (RF) have been widely applied. However, these shallow models typically ignore the long-term dependencies of time series, making it difficult to analyze the historical inertia of the sintering process [28-29]. Although Recurrent Neural Networks (RNN) and their variants (LSTM) effectively solve the problem of temporal memory, a single network often struggles to simultaneously balance smooth global trend prediction with the precise capture of local mutation details when processing high-dimensional industrial data, making it prone to falling into local optima [30-32].

In view of this, the present study proposes a Gradient Boosting Regression Tree (GBRT) model that utilizes the unique gating mechanism of Long Short-Term Memory (LSTM) networks to capture the long-term evolution trends of sintering parameters. the model leverages the powerful residual approximation capability of GBRT to perform a secondary correction on the LSTM prediction deviations. This strategy aims to resolve the difficulties of large-lag temporal modeling and strong non-linear residual fitting simultaneously through the complementary advantages of these algorithms.

3. Construction of a CO Emission Prediction Model Based on CSSM-GBRT

3.1 Feature Construction for Sintering CO Emissions

This study is based on high-frequency operational data from a sintering production line of a steel enterprise. It conducts an in-depth analysis of the key process mechanisms influencing carbon monoxide emissions and, on this basis, proposes a systematic framework for model feature engineering. the dataset fully reflects the entire production status, ranging from raw material mixing, ignition, and sintering to circular cooling treatment and flue gas purification.

The core rationale for feature construction lies in systematically transforming the physical and chemical mechanisms that influence CO generation and conversion during the sintering process into modelable variable expressions. Its fundamental significance is to provide model inputs with clear process orientation, thereby supporting the establishment of emission prediction models that possess both high precision and strong interpretability.

First, based on the fundamental mechanisms of combustion and mass transfer, state features reflecting process equilibrium and stability are constructed. For instance, indicators related to the "air-fuel ratio" are directly linked to combustion efficiency, while synergistic indicators of the "pressure-flow" system characterize the operational stability of the flue gas system. These features translate process knowledge into quantifiable stability metrics, establishing a physical foundation for the model to identify operational states.

Second, addressing the spatial-temporal characteristics of the dynamic sintering progression, temporal and dynamic features are introduced to capture process evolution. By using sliding windows to extract statistical measures and variation trends of key parameters (such as windbox temperature), the transient and cumulative effects of the sintering process can be characterized. Specifically, by identifying peaks or inflection points in the windbox temperature sequence, soft-sensing features for the "Sintering Burn-Through Point" can be constructed. This explicitly introduces this critical process state into the model, enhancing its ability to judge process phases.

To cope with the time-varying nature of operating conditions in actual production, different production intensity conditions are partitioned based on operational parameters such as pallet speed and fan frequency, and statistical distribution features are constructed under each condition. This approach embodies the "state-dependent" modeling philosophy, enabling the model to distinguish process behavior under different production rhythms. Meanwhile, interaction terms between key variables (such as the coupling of oxygen content and bed thickness) are constructed to reveal complex interactive influences beyond the linear effects of single variables, thereby more comprehensively reflecting the inherent coupling mechanisms of the process.

Finally, a multi-time-scale feature representation is formed by integrating instantaneous values, short-term statistics, and medium-to-long-term trends. This fusion aims to simultaneously reflect the immediate state, recent evolution, and sustained trends of the process, equipping the model with response capabilities across time scales to better align with the continuous dynamic characteristics of actual production.

By combining this mechanism-based feature construction method with the physical laws revealed by correlation analysis, not only is the systematic understanding of CO generation and emission reduction mechanisms enhanced, but a solid foundation is also laid for establishing high-precision, highly interpretable emission prediction and process optimization models. This method ensures that model features possess clear process significance, allowing the model output to directly support process control decisions—such as optimizing air volume distribution and adjusting the matching relationship between pallet speed and temperature curves.

3.2 Carbon Emission Model Based on CSSM-GBRT

The CSSM-GBRT prediction model constructed in this study deeply integrates the advantages of Long Short-Term Memory (LSTM) networks and Gradient Boosting Regression Trees (GBRT), falling within the categories of deep neural networks and ensemble learning methods in the field of machine learning. This model is specifically designed for time-series prediction tasks in complex industrial processes such as sintering. Its core architecture and workflow are illustrated in Figure 1.

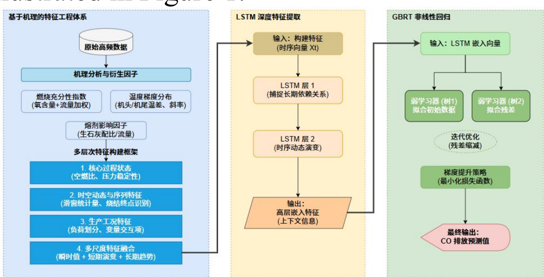

Figure 1. Core Architecture Diagram of the Model

The model first performs deep feature extraction on the input multidimensional time-series data through the LSTM (Long Short-Term Memory) module. This module effectively captures the long-term dependencies and dynamic evolution patterns embedded within production parameters; it is particularly suitable for processing process variables with strong temporal correlations, such as the combustion environment sequences, temperature gradient evolution, and raw material ratio fluctuations discussed in the previous analysis. Through the high-level abstraction of the LSTM multi-layer network, the raw data is transformed into a set of embedded feature vectors rich in temporal contextual information.

Subsequently, these embedded features are fed into the GBRT (Gradient Boosting Regression Tree) prediction module. Building upon the features extracted by the LSTM in the previous stage, the GBRT employs an iterative optimization strategy: by continuously constructing new regression trees based on the prediction residuals of preceding trees, it systematically reduces model error, thereby precisely fitting the complex non-linear mapping relationship between CO emissions and various process features. This design equips the model with both the powerful representation capabilities of LSTM for temporal patterns and the outstanding fitting and generalization performance of GBRT for complex non-linear relationships.

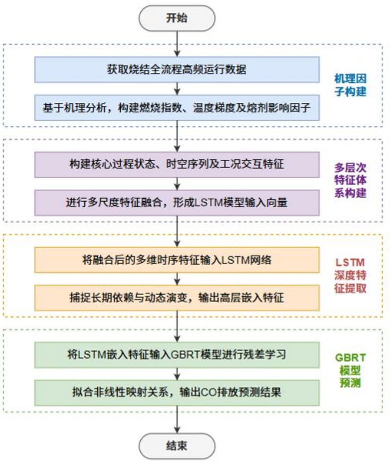

Figure 2. Flowchart of Carbon Emission Prediction

The complete prediction flow of the model is illustrated in Figure 2. Its essence lies in taking the multi-level feature system constructed earlier based on mechanistic analysis—including core process state features, spatial-temporal dynamic sequence features, and operational interaction features—and achieving intelligent fusion and deepened representation through the LSTM, followed by high-precision prediction via the GBRT. Consequently, the CSSM-GBRT model is not only an advanced predictive tool but also serves as a critical bridge connecting process mechanistic knowledge (such as the correlation laws between oxygen content, temperature fields, raw material ratios, and emissions) with final emission prediction results. It provides a reliable data-driven solution for the real-time optimization and precise control of the sintering process.

4. Experimental Results and Analysis

4.1 Dataset Description and Feature Correlation Analysis

This experiment is based on time-series data collected from the actual production process of a sintering plant. Following data cleaning, denoising, and sliding window construction, the total sample size incorporated into the modeling was over 4, 000 entries. To eliminate the influence of dimensional differences on model training, standardized processing was performed on all continuous variables.

To deeply analyze the complex mechanism of CO generation, the correlation between various process parameters and CO emissions was first analyzed using a Pearson correlation coefficient matrix. the results, as shown in Figure 3, indicate that combustion environment parameters (such as main flue oxygen concentration and exhaust gas flow rate) are significantly negatively correlated with CO emissions, with correlation coefficients of -0.48 and -0.45, respectively. Based on this, a combustion adequacy index feature can be constructed to systematically characterize combustion conditions through the weighted combination or dynamic proportional relationship between oxygen content and gas flow.

Meanwhile, the spatial distribution of the temperature field exhibits clear heterogeneity: the windbox temperature at the machine tail is negatively correlated with CO emissions, while the windbox temperature at the machine head shows a positive correlation. Accordingly, sintering process temperature gradient features were constructed by calculating the slope of windbox temperature changes along the pallet direction, the temperature differences between different windbox groups, and their moving standard deviations, thereby quantifying the uniformity and dynamic evolution of the sintering zone. Additionally, the quicklime flow rate in the raw material system shows a strong positive correlation with CO emissions. Consequently, a flux impact factor can be designed, constructed by integrating the blending ratios of quicklime with iron ore fines and return fines, alongside their flow rate time-series fluctuation characteristics.

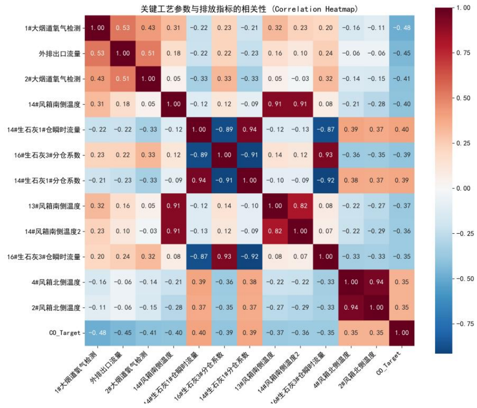

Figure 3. The Correlation Between Key Process Parameters and Emission Indicators

4.2 Performance Evaluation of Predictive Models

To construct a high-precision soft-sensing model for CO emissions, this study systematically compared five regression algorithms: Support Vector Regression (SVR), Random Forest (RF), Gradient Boosting Regression Tree (GBRT), XGBoost, and LightGBM. Building upon these, a CSSM-GBRT prediction model was further proposed, designed to effectively integrate the predictive strengths of various base learners. Model performance was comprehensively evaluated using the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). the performance comparison results for each model on an independent test set (representing 20% of the total samples) are summarized in Table 1. Experimental results indicate that among the individual models, GBRT and XGBoost performed most prominently, with both achieving an R^2 exceeding 0.80. However, the proposed CSSM-GBRT prediction model achieved the optimal predictive performance: its R^2 increased to 0.9514, while the RMSE significantly decreased to 98.52 ppm. All indicators were markedly superior to the best-performing individual models and the baseline SVR model. the scatter plot of predicted versus actual values shown in Figure 4 further visually confirms the superiority of the CSSM-GBRT model: the prediction points are tightly clustered around the y=x diagonal, demonstrating the model's ability to track the dynamic changes of CO emissions during the sintering production process with high precision, as well as its excellent fitting capability and robustness.

Table 1. Comparison of Performance of Different Prediction Models on the Test Set

Model	R^2	RMSE (ppm)	MAE (ppm)	MAPE (%)
SVR (Baseline)	0.7515	207.60	91.73	3.31
RandomForest	0.7706	199.45	92.90	3.34
LightGBM	0.7910	190.38	90.62	3.27
XGBoost	0.8046	184.07	89.63	3.22
GBRT (Sklearn)	0.8166	178.34	85.27	3.07
CSSM-GBRT	**0.9514**	**98.52**	**45.10**	**0.84**

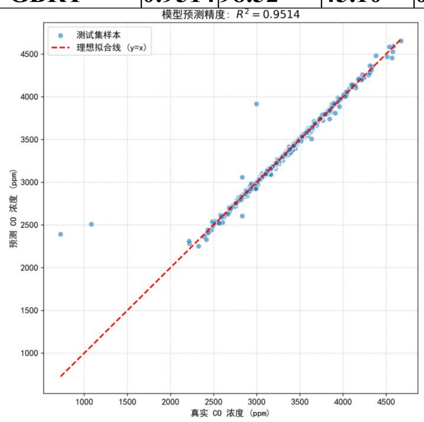

Figure 4. Scatter Plot of Predicted Values Versus Actual Values

4.3 Interpretability Analysis of Model Mechanisms Based on SHAP

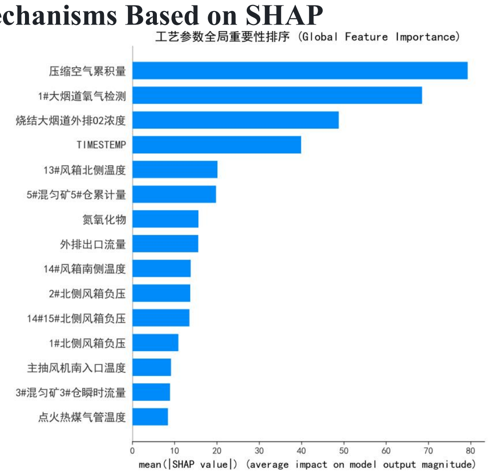

Figure 5. Global Importance Feature Ranking Chart of Process Parameters

To break the "black box" nature of the ensemble model, this study introduces the SHAP (SHapley Additive exPlanations) method to quantify the marginal contribution of process parameters to CO emissions from both global and local dimensions.

The feature importance ranking in Figure 5 shows that the top three features with the greatest impact on the model output are, in order: cumulative compressed air volume, main flue oxygen detection, and O_2 concentration in the sintering main flue exhaust.

Cumulative compressed air volume, as the primary influencing factor, is typically used for combustion-supporting atomization in igniters or the back-blowing system of dust collectors. the SHAP bee-swarm plot in Figure 6 shows that high values of this feature (red dots) correspond to higher CO emissions (SHAP value > 0). This may be because excessively high compressed air consumption implies increased ignition energy consumption or increased dust collection resistance, reflecting instability in the system's operating conditions.

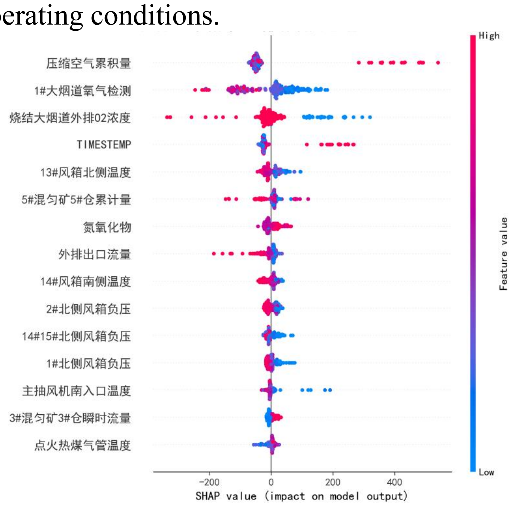

Figure 6. Mechanism Diagram of the Influence of Key Process Parameters on CO Emissions

Regarding the inhibitory effect of oxygen concentration, Figure 6 clearly demonstrates a negative correlation between main flue oxygen detection and CO emissions. Red data points (high oxygen content) are primarily distributed in the negative SHAP value region, further confirming the combustion mechanism where an oxygen-rich environment helps suppress CO generation. Temperature indicators, such as the temperature on the north side of the windboxes, also exhibit high importance, indicating that the temperature distribution along the length of the sintering machine (i. e., burn-through point control) is a critical factor affecting emissions.

5. Conclusion

Constructing a CO prediction system based on iron and steel sintering process data is a key technical path supporting the implementation of the "Dual Carbon" strategy in the steel industry. Through Pearson correlation analysis, this paper found a strong non-linear correlation between sintering process parameters (such as temperature, oxygen concentration, and fuel characteristics) and CO emissions.

A CSSM-GBRT sintering CO prediction model was proposed, which utilizes deep neural networks to mine the relationships between sintering process parameters, flue gas monitoring data, and CO emissions. the model exhibits good universality and can effectively reflect CO emission trends under different sintering conditions. Using data from the sintering process of a specific steel enterprise as the test subject, the results demonstrate that the model's MAPE, MAE, and RMSE are all superior to those of models such as XGBoost and LightGBM. This provides a data reference for steel enterprises to optimize sintering processes and formulate precise emission reduction strategies.

In the future, in-depth analyses of the correlation between process parameters and CO emissions, as well as CO prediction research, will continue to be carried out for the sintering process. the focus will be on optimizing the model's input parameter system by integrating the multi-condition coupling characteristics of the sintering process, incorporating key variables such as bed structure and flue gas circulation parameters to refine the model, and expanding adaptability studies across sintering machines of different scales.

Acknowledgments

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