Sintering is an important production process in iron and steel metallurgy. Carbon fuel consumption accounts for about 80% of the total energy consumption in the sintering process. To enhance the efficiency of carbon fuel consumption, we need to determine the factors affecting carbon efficiency and build a model of it. In this paper, the CO/CO₂ is taken to be a measure of carbon efficiency, and a cascade predictive model is built to predict it. This model has two parts: the key state parameter submodel and the CO/CO₂ submodel. The submodels are built using particle swarm optimization-based back propagation neural networks (PSO-BPNNs). Based on the mechanism analysis, spearman’s rank correlation coefficient (SRCC) and stepwise regression analysis (SRA) are used to determine the relationship between the process parameters, in order to determine the inputs of each submodel. Finally, the results of a simulation show the feasibility of the cascade model, which will serve as the basic model for the optimization and control of the carbon efficiency of the sintering process.

Keywords: sintering process, CO/CO₂, spearman’s rank correlation coefficient (SRCC), stepwise regression analysis (SRA), back-propagation neural network (BPNN)

1. Introduction

The sintering process is the second most energy-consuming process in steelmaking. The main source of the energy consumed in the sintering process is the combustion of carbon, which accounts for 8% to 10% of the energy consumed in the steel production process [1]. To find ways to reduce energy consumption, it is necessary to find a way to describe how the process parameters affect the carbon efficiency to make it possible to predict the carbon efficiency. The CO/CO₂ can reflect the combustion efficiency of solid carbon in the sintering process, so it is used in this study as the metric for measuring carbon efficiency.

The combustion mechanism of carbon in the sintering process is very complex. In order to establish a predictive model of carbon efficiency, the combustion mechanism of the coke and carbon flow in the sintering process should be analyzed. The thermodynamic and kinetic characteristics of the combustion of solid fuel in the sintering bed were analyzed, and the combustion of carbon at different temperatures was elucidated in [2, 3]. In addition, some experts have analyzed the energy flow and material flow in iron and steel metallurgy to determine the factors that affect CO₂ emissions [4–6]. Above all, there have been numerous studies on the combustion mechanism of coke and carbon flow, but there has been no analysis of the correlation between carbon gas emissions and the process parameters in the sintering process.

There are two main ways of modeling industrial processes: mathematical modeling and data-driven modeling. Mechanism models of carbon combustion [7, 8] in the sintering process are based on a deep analysis of the conservation energy and mass. The large difference between the experimental environment and the actual environment makes it difficult for the mechanism model to be used widely in the field. Data-driven modeling provides an effective way to build an industrial process model based on actual process data, such as artificial neural network (ANN) [9, 10], support vector machine (SVM) [11], Gaussian process regression (GPR) [12], or other data-driven methods. SVM parameters were optimized via the PSO algorithm to develop a model that predicts the sintering conditions [13]. A two-layer BPNN model for silica and sulfur, one based on an analysis of the historical data of a blast furnace was presented in [9]. A three-layer BPNN was established to predict the content of FeO and the drum strength of sinter [14]. There have been some studies done on the carbon efficiency of the sintering process. For example, the comprehensive carbon ratio (CCR) is used as a metric for the carbon efficiency [15–17]. The sintering parameters were analyzed using the principal component analysis (PCA) method, and then the back propagation neural network (BPNN) was used to predict the CCR [16]. A discrete wavelet transfer based on BPNN was built to predict the CCR [17]. As the sintering process of iron ore is very complex, the single data driven model is not sufficient to describe the entire process. In addition, since the single model does not take the influence between the parameters into account, its generalizability can hardly satisfy the actual needs. It is therefore necessary to develop a model based on the parameters that
This paper describes a cascade predictive model for CO\textsubscript{2}, one which solves the problem of how to improve the carbon efficiency of iron ore sintering. The remainder of the paper is organized as follows. Section 2 introduces the sintering process and its characteristics, explaining the modeling scheme of the CO\textsubscript{2}. Section 3 discusses the mechanism analysis and the correlation analysis of process data, determining the framework of the cascade predictive model. Section 4 describes the use of a PSO-BPNN to build each submodel and how the sample data are processed. Section 5 presents the verification results based on actual process data, demonstrating the effectiveness of the modeling method. Finally, Section 6 contains some concluding remarks.

2. Description of Sintering Process and Modeling Scheme

This section first describes the sintering process and its characteristics. It then explains the modeling scheme of the CO\textsubscript{2}.

2.1. Sintering Process and its Characteristics

The sintering process is an important production process in iron and steel metallurgy. Its product is sinter, the main raw material that goes into a blast furnace. A typical sintering process includes proportioning, mixing, igniting, sintering, breaking, cooling, and segregating.

The carbon in the sintering process mainly comes from proportioning. The utilization rate of carbon energy is affected by many production processes after proportioning. The sinter material is tiled onto a moving trolley to form a sinter bed. The surface of the sinter bed is ignited by the igniter, which initiates the sintering process. With the bellows, the sinter material is burned from top to bottom. As the combustion temperature increases, the sintering material forms a wet layer, a preheating and drying layer, a combustion layer, and other areas. Most of the physical and chemical reactions in the sintering process are completed in the combustion layer, such as coke combustion, liquid phase formation, carbonate decomposition, and sulfide decomposition. All combustion process material changes are shown in Fig. 1.

The sintering process has three important characteristics that must be considered in building a model.

1) Mechanism complexity: The sintering process is an industrial process that involves a variety of physical and chemical reactions, such as heat exchange, water evaporation, solid-phase reaction, and redox reaction. Some of the process parameters are difficult to detect accurately. In addition, as the data detection on process itself tends to interfere greatly, error is significant, and some important state parameters cannot be detected online. The entire sintering process is extremely complex.

2) Various types of process parameters: There are four types of parameters involved in sintering.

- Raw material parameters: the SiO\textsubscript{2} content (C\textsubscript{SiO\textsubscript{2}}), the CaO content (C\textsubscript{CaO}), the MgO content (C\textsubscript{MgO}), the proportion of coke (P\textsubscript{C}), and the proportion of carbon dioxide (P\textsubscript{CO\textsubscript{2}}) which is the sum of the proportion of dolomite and limestone, etc.
- Operating parameters: the speed of the moving grate (V\textsubscript{r}), the speed of the round roller (V\textsubscript{R}), the height of the sintering bed (H), the speed of water added (P\textsubscript{W}), etc.
- State parameters: the bellows negative pressure (P), the burn-through point (BTP), the temperature of the exhaust gas at the BTP (T\textsubscript{BTP}), etc.
- Non-measurable parameters: the temperature of the combustion layer, the permeability of the sintering bed, etc.

3) Nonlinearity: There are approximately 14 chemical and physical reactions involved in sintering. They are interrelated and some of them strongly depend on the environment inside the sinter bed. There are many factors that influence the stability of the sintering process, and their relationships are strongly nonlinear.

2.2. Modeling Scheme

In this study, a modeling procedure for predicting the CO\textsubscript{2} is devised, as shown in Fig. 2.

Building an accurate predictive model is a prerequisite for the evaluation of carbon efficiency, and the key steps to building a predictive model are to select an effective modeling method and to select the appropriate inputs, based on the characteristics of the sintering process.

In this study, the potential inputs of the model are selected by analyzing the mechanism of the sintering process. The complexity and strong nonlinearities of the sintering process make it difficult to accurately determine the inputs by the mechanism analysis, and a large number of inputs may be obtained. Therefore, this paper uses both mechanism analysis and data analysis to find the appropriate inputs. This method not only improves the accuracy of the model but also reduces the computational cost.

The characteristics of the sintering process determine the different effects that the raw material parameters, operating parameters, and state parameters have on the CO\textsubscript{2}. If one selects the inputs without considering the relationships among them, it will be difficult for the accuracy of the model to satisfy the actual needs. It will also be difficult to show the effects of various parameters.
3. Mechanism Analysis and Correlation Analysis of Process Data

In this section, the main factors affecting CO/CO₂ are determined through the mechanism analysis and correlation analysis of process data. Then, the effect of each parameter on CO/CO₂ is analyzed and the key factors affecting CO/CO₂ are determined. Finally, the framework for the cascade predictive model for the CO/CO₂ is devised.

3.1. Mechanism Analysis

The combustion of coke is the main source of energy in the sintering process, and the proportion of coke can affect the sintering temperature and environment. Different degrees of combustion will produce different products: CO and CO₂. An adequate supply of oxygen is required for the combustion of the coke to be sufficient. The combustion rate of coke is directly proportional to the ambient temperature of the reaction, and the sintering temperature is indirectly reflected in $T_{BTP}$. The carbon gas emission rate also has an important impact on the combustion rate of coke.

The proportion of carbonate solvent also has a direct effect on the amount of carbon gas in the sintering process. Limestone is an important component of the carbonates among the sintering ingredients, and its main component is CaCO₃. The decomposition of limestone is a complex chemical reaction which not only involves the decomposition of the limestone itself but also the diffusion of CO₂ in the CaO product layer and the boundary layer. The decomposition rate of limestone has a positive correlation with the ambient temperature and the discharge rate of CO₂. The discharge rate of CO₂ depends on the particle size of the limestone and the permeability of the sintering bed. The decomposition of limestone is an endothermic reaction. Heat is released by the coke combustion in the sintering process, and 10–20% of this heat is used for the decomposition of limestone.

Since the burning time of the sinter material on the sintering machine is limited, the sinter material must be completely combusted before reaching the BTP. Therefore, the speed of the moving grate and the height of the sintering bed have important effects on the combustion efficiency of the coke in the sintering process. Sufficient permeability of the sintered bed can guarantee the complete combustion of coke. The permeability is proportional to the proportion of returned sinter in the raw mix and inversely proportional to the height of the sintering bed. The proportion of water added and the speed of the rollers also have an important impact on the permeability of the sintering bed.

During the sintering process, a large amount of binding-phase liquid is formed, and its composition and amount also have an important effect on the temperature in the sintering bed. Depending on the chemical composition, the liquid phase can be divided into two types: silicates and ferrates. In the highly basic sintering process, the content of calcium ferrite liquid (CaO·Fe₂O₃) is the main factor affecting the quality of the sinter. The temperature range for the formation of calcium ferrite liquid is 500–600°C. Liquid phase has better heat transfer performance at high temperature, so the formation of a sufficient amount of calcium ferrite can be beneficial to the full combustion of the coke. Dolomite (CaCO₃·MgCO₃) is added to the sinter material to increase the sinter yield.

The above discussion shows that the permeability and temperature of the sintering bed are the key factors determining the CO/CO₂. Because temperature and permeability are difficult to detect in an actual process, it is necessary to find a method that can reflect these two states in the actual process. The coke combustion and carbonate decomposition occur in the combustion layer. The temperature of the combustion layer is the highest at the BTP, which is the place where the combustion layer reaches the grate. Therefore, the temperature at the BTP can be used to reflect the temperature of the combustion layer. In practice, the frequency of the bellows is generally fixed, so the permeability of the sintering bed can be indirectly reflected by the negative pressure of the bellows. Therefore,
in this study, $T_{BTP}$ and $P$ are used to reflect the temperature and permeability of the sintering bed. The mechanism analysis shows that the key inputs for the prediction of the CO/CO$_2$ are $V_T$, $V_R$, $P_W$, $H$, $T_{BTP}$, $P$, $P_{RS}$, $P_C$, $P_{CS}$, $C_{CaO}$, $C_{SiO_2}$, and $C_{MgO}$.

### 3.2. Correlation Analysis of Process Data

The mechanism analysis that is used to determine the main factors affecting CO/CO$_2$ is simple and instructive. However, the relationship between the determined factors and CO/CO$_2$ is qualitative, and the result of the mechanism analysis is just an ideal result. Therefore, this section quantitatively analyzes the relationship between each parameter and CO/CO$_2$ as well as the relationship between the determined factors and influencing factors. Then, SRA analysis is used to filter the influencing factors. The factors that have little influence on the state parameters can be removed, and the coupling between parameters themselves from the data.

The correlation analysis of the data can be divided into two parts. (1) SRCC analysis is first used to analyze the relationship between the key state parameters and the influencing factors. Then, SRA analysis is used to filter the influencing factors. The factors that have little influence on the state parameters can be removed, and the coupling of the parameters can be reduced. (2) SRCC analysis is used to analyze the relationship between the influencing factors and the CO/CO$_2$. The above analysis not only reduces the number of inputs for each submodel but also reduces the coupling between the parameters, both of which greatly improve the accuracy of the predictive model.

There are a variety of correlation analysis methods, such as regression analysis, typical correlation analysis, and Pearson analysis, which require that the data have a large sample size and a Gaussian distribution. However, the sample data in the sintering process often cannot meet the above requirements. Therefore, this study employed SRCC analysis because it has no specific requirements for the distribution of the sample data.

Spearman’s rank correlation coefficient (SRCC) is used to study the correlation between two variables based on ranked data [18]. If it is supposed that the original data $X_i$ and $Y_i$ have been arranged in ascending order, the SRCC of $X_i$ and $Y_i$ is the following:

$$
\rho = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n} (X_i - \bar{X})^2 (Y_i - \bar{Y})^2}}
$$

where $\bar{X}$ and $\bar{Y}$ are the averages of $X_i$ and $Y_i$, respectively. $\rho$ is in the range $[-1, 1]$.

Stepwise regression analysis (SRA) can filter and remove the variables that cause multiple colinearity. The basic idea of SRA is to introduce variables into the model one by one and do an F test and T test on the introduced variables and selected variables, respectively. If the original variable is no longer significant after the new variable is introduced, it is deleted. In this way, the last retained variables are both important and have no serious multiple colinearity [19].

#### 3.2.1. Correlation Analysis for Inputs of Key State Parameter Submodel

The analysis in subsection 3.1 reveals that the material parameters that may affect the key state parameters are $P_{RS}$, $P_C$, $C_{MgO}$, $C_{CaO}$, $C_{SiO_2}$, and $P_{CS}$, and the operating parameters that may affect the key state parameters are $V_R$, $V_T$, $H$, and $P_W$. SRCC analysis is used to analyze the relationship between the key state parameters and these parameters. When the confidence level is 0.05, the correlation is significant. The results are shown in Table 1. Because of the strong coupling between the parameters in the sintering process, SRA is used to select the variables that influence the state parameters determined and presented in Table 1. When the confidence level is 0.05, the correlation is significant. The greater the standard coefficient $b$ is, the greater the impact on the state parameters will be. The analysis results are shown in Tables 2 and 3.

### Table 1. SRCCs for raw-material and operating parameters as well as state parameters.

<table>
<thead>
<tr>
<th></th>
<th>$V_T$</th>
<th>$H$</th>
<th>$P_W$</th>
<th>$V_R$</th>
<th>$C_{SiO_2}$</th>
<th>$C_{MgO}$</th>
<th>$C_{CaO}$</th>
<th>$P_{RS}$</th>
<th>$P_{CS}$</th>
<th>$P_C$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P$</td>
<td>0.274</td>
<td>-0.565</td>
<td>0.364</td>
<td>-0.414</td>
<td>-0.022</td>
<td>0.062</td>
<td>-0.488</td>
<td>-0.427</td>
<td>-0.166</td>
<td>0.038</td>
</tr>
<tr>
<td>Sig.</td>
<td>0.012</td>
<td>0.000</td>
<td>0.003</td>
<td>0.000</td>
<td>0.141</td>
<td>0.184</td>
<td>0.000</td>
<td>0.000</td>
<td>0.011</td>
<td>0.442</td>
</tr>
<tr>
<td>$T_{BTP}$</td>
<td>-0.471</td>
<td>0.447</td>
<td>-0.050</td>
<td>0.247</td>
<td>-0.357</td>
<td>0.344</td>
<td>0.034</td>
<td>0.025</td>
<td>0.052</td>
<td>0.609</td>
</tr>
<tr>
<td>Sig.</td>
<td>0.000</td>
<td>0.000</td>
<td>0.595</td>
<td>0.030</td>
<td>0.001</td>
<td>0.001</td>
<td>0.442</td>
<td>0.323</td>
<td>0.525</td>
<td>0.000</td>
</tr>
</tbody>
</table>

### Table 2. SRAs for $P$ and influencing factors.

<table>
<thead>
<tr>
<th></th>
<th>$V_T$</th>
<th>$H$</th>
<th>$P_W$</th>
<th>$V_R$</th>
<th>$C_{SiO_2}$</th>
<th>$C_{MgO}$</th>
<th>$C_{CaO}$</th>
<th>$P_{RS}$</th>
<th>$P_{CS}$</th>
<th>$P_C$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P$</td>
<td>0.041</td>
<td>-0.467</td>
<td>0.288</td>
<td>-0.362</td>
<td>-0.018</td>
<td>0.015</td>
<td>-0.541</td>
<td>-0.384</td>
<td>0.008</td>
<td>0.064</td>
</tr>
<tr>
<td>Sig.</td>
<td>0.455</td>
<td>0.000</td>
<td>0.000</td>
<td>0.003</td>
<td>0.365</td>
<td>0.631</td>
<td>0.000</td>
<td>0.010</td>
<td>0.515</td>
<td>0.434</td>
</tr>
</tbody>
</table>

### Table 3. SRAs for $T_{BTP}$ and influencing factors.

<table>
<thead>
<tr>
<th></th>
<th>$V_T$</th>
<th>$H$</th>
<th>$P_W$</th>
<th>$V_R$</th>
<th>$C_{SiO_2}$</th>
<th>$C_{MgO}$</th>
<th>$C_{CaO}$</th>
<th>$P_{RS}$</th>
<th>$P_{CS}$</th>
<th>$P_C$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{BTP}$</td>
<td>-0.345</td>
<td>0.477</td>
<td>0.011</td>
<td>0.082</td>
<td>0.432</td>
<td>-0.363</td>
<td>0.049</td>
<td>0.065</td>
<td>0.024</td>
<td>0.628</td>
</tr>
<tr>
<td>Sig.</td>
<td>0.000</td>
<td>0.000</td>
<td>0.222</td>
<td>0.118</td>
<td>0.003</td>
<td>0.000</td>
<td>0.158</td>
<td>0.210</td>
<td>0.101</td>
<td>0.000</td>
</tr>
</tbody>
</table>
Table 4. SRCCs for CO/CO₂ and influencing factors.

<table>
<thead>
<tr>
<th></th>
<th>P</th>
<th>TBT P</th>
<th>SiO₂</th>
<th>CMgO</th>
<th>C₇₆O</th>
<th>PKS</th>
<th>PKS</th>
<th>Pₐ</th>
</tr>
</thead>
<tbody>
<tr>
<td>CO/CO₂</td>
<td>-0.553</td>
<td>0.665</td>
<td>0.055</td>
<td>0.046</td>
<td>0.086</td>
<td>-0.036</td>
<td>-0.449</td>
<td>0.624</td>
</tr>
<tr>
<td>Sig.</td>
<td>0.000</td>
<td>0.000</td>
<td>0.647</td>
<td>0.118</td>
<td>0.525</td>
<td>0.240</td>
<td>0.002</td>
<td>0.000</td>
</tr>
</tbody>
</table>

4.1. Sample Data Processing

For the key state parameter submodels, the state parameters cannot be measured directly, so P and TBT P are obtained through soft sensing. For the CO/CO₂ submodel, the values of CO and CO₂ are measured at the plant using an instrument. The material and operating parameters are obtained from the proportioning and operating specifications, respectively.

In this paper, the processing of sample data consists of three steps: First, because the historical data collected in the sintering process contains noise, the zero phase filter is used to filter the data. Then, the entire sintering process takes about two hours. The acquisition of the parameters involves a certain period of time, so time series registration is used to deal with this problem, ensuring the consistency of the parameters in the timing. Finally, the sampling period is determined by the change in CO/CO₂, and the process data are sampled during this sampling period.

In addition, to understand the distribution of parameters in order to select the appropriate correlation analysis method, statistical analysis is used to analyze the sample data in subsection 3.2 and to find whether all the parameters are consistent with the Gaussian distribution.

Since the process parameters are of different magnitudes, it is necessary to normalize the data. All variables x are normalized by the following equation:

\[ X'_i = \frac{X_i - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (2) \]

where \( X_i \) is the original sample data, \( X_{\text{max}} \) is the maximum value of \( X_i \), and \( X_{\text{min}} \) is the minimum value of \( X_i \).

4.2. Prediction of the Key State Parameters and CO/CO₂

Considering the sintering characteristics described in Section 2, the general modeling method is unlikely to predict CO/CO₂ accurately. One way to cope with the characteristics of the sintering process is to employ a neural network (NN) which has the ability to fit nonlinear data. A neural network, which is based on the black box modeling theory, can learn from the sample data to achieve an accurate prediction. This is very consistent with the characteristics of industrial process modeling.

A BP neural network is a multilayer, feedforward neural network used to optimize the weight of a multilayer feedforward neural network, and it is very suitable for industrial process modeling. The learning process of the BP algorithm includes signal forward propagation and error back propagation. The neuron output of each layer is calculated by setting the network structure as well as the weight and threshold of the previous iteration. If the ac-
tual output is not in conformity with the expected output, the BPNN enters the back propagation phase of error. The output error is returned along the original connection path, and it is distributed to all neurons in each layer to calculate the influence of weights and thresholds on the total error. By constantly adjusting the weights of each layer, the error is reduced to an acceptable degree or reduced to reach a preset number of learnings [20].

In the BPNN using a gradient descent algorithm to train the objective function to find the minimum value, the definition of the objective function is the following:

\[ E = \frac{1}{2}(o_o - o)^2 \]  \hspace{1cm} (3)

where \( o_o \) is the predicted value of BPNN and \( o \) is the actual value.

Suppose that the input of BPNN is \( u_i \) \((i = 1, 2, 3, ..., n)\) and the number of neurons in the hidden layer is \( m \). Then, the output of BPNN is the following:

\[ y_o = \sum_{j=1}^{m} w_{ij} \tanh\left( \sum_{i=1}^{n} w_{ij} u_i + b_j \right) + b_o \]  \hspace{1cm} (4)

where \( w_{ij} \) is the weight between the \( i \)-th input neuron and the \( j \)-th hidden layer neuron, \( w_{ij} \) is the weight between the \( j \)-th hidden layer neuron and the output neuron, and \( b_j \) is the threshold for the hidden layer, and \( b_o \) is the threshold for the output layer.

Since the BP algorithm uses a gradient descent-based local search algorithm to optimize the parameters of the model, it is easy to fall into the local optimum and affect the global optimization. This can be avoided by choosing appropriate initial weights and thresholds. Particle swarm optimization (PSO) can be used to find reasonable initial weights and thresholds for the BPNN. The particle swarm optimization (PSO) has many merits, such as few parameters, easy implementation, high precision, and fast searching speed. It has a good global search capability for nonlinear problems and has been widely used in many fields. In engineering practice, the combination of PSO and BPNN is generally more efficient than one or the other individually. Therefore, PSO-BPNN models are used to predict \( P, T_{BTP} \) and \( CO/CO_2 \).

Real number coding is used in this study. A particle has \( n \) dimensions: \( n = I \cdot J + J \cdot J + J \cdot I + 1 = (I + 2) \cdot J + 1 \), where \( I \) and \( J \) are the numbers of the inputs and hidden layers, respectively. The velocity vector of a particle is \( V = (v_1, v_2, ..., v_n) \), \( v_o \in [-0.5, 0.5] \). This determines the displacement of the particle at each iteration. The position vector of a particle is \( Z = (z_1, z_2, ..., z_n) \), \( z_o \in [-1, 1] \).

Suppose that \( pbest^k \) and \( gbest^k \) are the local optimum position and the global optimum position for the \( k \)-th iteration, respectively. When these two optimal values are found, the velocity and position of the particle are updated according to the following equations:

\[ v_{d}^{k+1} = v_{d}^{k} + c_1 r_1 (pbest^k - z_d^k) + c_2 r_2 (gbest^k - z_d^k) \]  \hspace{1cm} (5)

\[ z_d^{k+1} = z_d^k + v_d^{k+1} \]  \hspace{1cm} (6)

where \( c_1 \) and \( c_2 \) are learning factors, \( c_1 = c_2 = 2 \), \( r_1 \) and \( r_2 \) are random numbers in the range \([-1, 1]\). \( w(k) \) is the inertia weight coefficient for the \( k \)-th iteration, which is updated by the following:

\[ w(k) = w_{\text{max}} - \left( w_{\text{max}} - w_{\text{min}} \right) \frac{k}{\text{maxgen}} \]  \hspace{1cm} (7)

where \( w_{\text{max}} \) and \( w_{\text{min}} \) are the maximum and minimum values of \( w(k) \), respectively. \( w_{\text{max}} = 0.9, w_{\text{min}} = 0.4, k \) is the number of the current iteration, and \( \text{maxgen} \) is the maximum number of iterations.

The algorithm for predicting the key state parameters and \( CO/CO_2 \) is described as follows.

Step 1 : Initialize the BP network structure and the particle swarm.

- number of neurons in the input layer, hidden layer, and output layer: \( x, y, \) and \( z \)
- learning rate: \( \eta \)
- number of training samples: \( N \)
- index of current iteration: \( k = 0 \)
- local optimum position and global optimum position: \( pbest^k \) and \( gbest^k \)
- maximum number of iterations: \( \text{maxgen} \)
- position (weights and thresholds) and velocity of each particle: \([-1, 1]\)
- size of population (number of particles): \( D \)
- error index of iteration: \( \varepsilon \)

Step 2 : Use (3) to calculate the fitness of each particle and find \( pbest^k \) and \( gbest^k \) by comparing the fitness values of all the particles.

Step 3 : Update the positions and velocities of the particles using (5) and (6).

Step 4 : If the accuracy requirement is met or the maximum number of iterations is reached, then stop the search. Otherwise, go to Step 2.

Step 5 : Output the optimal weights and thresholds for the BPNN model.

Step 6 : Use the BP algorithm to train the neural network with the optimal weights and thresholds until the algorithm stops.

Step 7 : Output the predicted key state parameters and \( CO/CO_2 \).

Step 8 : Stop.

The cascade predictive model of \( CO/CO_2 \) based on PSO-BPNN can be divided into two parts: (1) PSO-BPNNs are built to predict the key state parameters \( P \) and \( T_{BTP} \), and the inputs for each submodel are shown in Fig. 2. (2) A PSO-BPNN submodel is built to predict the \( CO/CO_2 \), the output of the state parameters submodels, and the raw material parameters \( P_C \) and \( P_{CS} \) as inputs.
5. Verification and Discussion

This section discusses, based on actual process data, the validity of the modeling method. Historical data collected from a sintering workshop are used to verify the predictive models for $P$, $T_{BTP}$, and $CO/CO_2$. Filtering, sequential registration, and sampling for historical data are used to obtain 450 samples, and all the data are normalized to the range $[-1, 1]$.

5.1. Verification of Predictive Models for $P$ and $T_{BTP}$

The predictive models for $P$ and $T_{BTP}$ are built in subsection 4.2, and the inputs of the models are determined in subsection 3.2.1. The parameters for the PSO-BPNN models are determined by trial and error. Training for the predictive models stops when $MSE \leq 0.001$ or the maximum number of iterations is reached. The PSO-BPNN models parameters are set as follows: the maximum number of iterations for the predictive models is 400, and the size of the population is 60; the number of training times is 600; the learning rate is 0.1; and the number of hidden neurons for the $P$ and $T_{BTP}$ predictive models are 20 and 18, respectively. The other parameters use the defaults. Among the 450 samples, 400 samples are used for training; the remaining 50 are used for testing.

Figures 4–7 show the simulation results for $T_{BTP}$ and $P$. A statistical analysis of the $T_{BTP}$ prediction results shows that the prediction errors for 43 samples (86% of the total) are in the range $[-1\%, 1\%]$, and the errors for 50 samples (100% of the total) are in the range $[-2\%, 2\%]$.

The maximum relative prediction error is 1.9%. The analyses for $P$ show that the prediction errors for 41 samples (82% of the total) are in the range $[-1\%, 1\%]$, and the errors for 50 samples (100% of the total) are in the range $[-2\%, 2\%]$. The maximum relative prediction error is 2%. These verification results show that the prediction precision for the key state parameters is very high.

5.2. Verification of Predictive Model for $CO/CO_2$

The predictive model for $CO/CO_2$ is built in subsection 4.2, and the inputs of the model are $T_{BTP}$, $P$, $PC$, and $PCS$. The parameters of the model are determined by trial and error. The PSO-BPNN model parameters are set as follows: the maximum number of iterations is 500, the size of the population is 50, the number of hidden neurons is 17, and the other parameters are the same as in subsection 5.1. Among the 450 samples, 400 samples are used for training, and the rest are used for testing.

In order to demonstrate the superiority of this model, the prediction accuracy of the model is compared with the single-BPNN model and the single-PSO-BPNN model. The single-BPNN model and the single-PSO-BPNN model use the raw material parameters, operating parameters, and state parameters as inputs, but they do not take the relationship between the parameters into account. Three models are simulated using the same sample data. The following three criteria are used to evaluate and compare the models:
PSO-BPNN model than for the single-BPNN model means that the combination of PSO and BPNN in our model is more precise and yields less variation.

However, the table shows that \( \bar{e} \), \( e_{\text{max}} \), and \( \sigma \) of our model are the smallest among the three models, which verifies the effectiveness of the model in this paper. In this model, the relationship between the parameters is taken into account, solving the problem of nonlinear and strong coupling in the sintering process. The prediction accuracy can meet the requirements of sintering production, which is important to the reduction of energy consumption in the sintering process.

6. Conclusion

The sintering process plays an important part in iron and steel production. The sintering process has many complex properties, such as mechanism complexity, multiple types of parameters, strong coupling and nonlinearity, etc. It is difficult to build a predictive model for the carbon efficiency of the sintering process. In this paper, the model takes the sintering characteristics and the relationship between the parameters into account. The model not only solves the problem of nonlinear and strong coupling but also explains to the relationships between parameters well. The simulation results show that our model is more accurate than the single-BPNN model and the single-PSO-BPNN model, and it can meet precision requirements in the actual production environments. Our model can therefore lay the foundation for carbon efficiency optimization in the sintering process.

Table 5. Absolute relative error for three modeling methods.

<table>
<thead>
<tr>
<th>Model</th>
<th>( (0,2%) )</th>
<th>( (2%,4%) )</th>
<th>( (4%,+\infty) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single-BPNN</td>
<td>25</td>
<td>14</td>
<td>11</td>
</tr>
<tr>
<td>Single-PSO-BPNN</td>
<td>38</td>
<td>9</td>
<td>3</td>
</tr>
<tr>
<td>Our model</td>
<td>46</td>
<td>4</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 6. Evaluation results for three modeling methods.

<table>
<thead>
<tr>
<th>Model</th>
<th>( \bar{e} )</th>
<th>( \sigma )</th>
<th>( e_{\text{max}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single-BPNN</td>
<td>3.643</td>
<td>2.553</td>
<td>7.532</td>
</tr>
<tr>
<td>Single-PSO-BPNN</td>
<td>2.441</td>
<td>1.335</td>
<td>5.151</td>
</tr>
<tr>
<td>Our model</td>
<td>1.122</td>
<td>0.564</td>
<td>2.425</td>
</tr>
</tbody>
</table>

In the above evaluation criteria, \( N \) is the number of samples, and \( o_{a}(i) \) and \( o(i) \) are the \( i \)-th actual value and predicted value, respectively. The smaller \( \bar{e} \) and \( e_{\text{max}} \) are, the more precise the model is. The smaller \( \sigma \) is, the smaller the variation in the results is.

Figures 8 and 9 show the prediction results for the three models. Of all the models, our model comes closest to the target.

Table 6 shows a statistical analysis of the absolute relative error. About 46 samples (92\% of the total) are in the range \([0\%,2\%]\) for our model. For the single-BPNN model and the single-PSO-BPNN model, there are 25 samples (50\% of the total) and 38 samples (76\% of the total) in the range \([0\%,2\%]\), respectively. The results show that our model has the least variation.

Table 7 shows the evaluation results of the three models. The fact that the criteria are smaller for the single-

References:

A Cascade Prediction Model of CO/CO₂ in the Sintering Process

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