Main Components and Neuroanalysis of Automatic Steel Water Deoxygenation Alloy Ingredients

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Abstract: At present, how to establish a mathematical model of deoxygenation alloying link through historical data, predict and optimize the type and quantity of alloy input online, and minimize the production cost of alloy steel while ensuring the quality of steel and water. It is an important issue for major steel companies to improve their competitiveness. Based on the main component and neural network and multivariate nonlinear regression theory, based on the existing alloy historical data, this paper optimizes the ingredients scheme of "deoxygenation and alloying" of steel and water, establishes the mathematical model, calculates the historical harvest rate of the main elements, and predicts the historical harvest rate of the main elements. Combined with the price of the alloy, the automatic ingredient scheme of the steel water deoxygenated alloy is given, and the cost of the steel water deoxygenated alloy is optimized.

1. Major issues of research
Calculate the historical rate of elemental yield of C and Mn: For the first problem, to calculate the historical yield of C and Mn, it is necessary to screen the reduced data and establish the elemental historical yield model to solve. When looking for indicators that affect the historical yield of elements, Principal Component Analysis is used to calculate the contribution rate of C and Mn indicators respectively, and the main factors affecting the yield are selected.

Predicting the final yield of carbon and manganese elements: For the second problem, the final yield of carbon and manganese is predicted by various objective conditions and the amount of raw materials. The relationship between several indicators and the final yield is obviously non-linear. There is also a reversible reaction in the chemical reaction, and the amount of the substance affects the output of the final material. Considering the complex and vague relationship, the neural network is initially used to learn and train a large amount of raw data, and the actual yield of carbon and manganese is predicted.

The carbon and nitrogen element yield and alloy cost are optimized as two goals: for problem three, not only the final output but also the actual economic factors. Borrowing the idea of multi-objective optimization, the carbon and nitrogen element yield and alloy cost were optimized as two goals. And to establish multivariate nonlinear regression equations to solve this model, in order to convert to a single variable optimization problem, we set $D_M$ to find the maximum value of this function variable, use Matlab's powerful computing power, borrow the second question model to traverse the result, and get the optimal solution: for carbon element: when molten steel temperature, converter end temperature, molten steel net weight, vanadium The weight of iron (FeV50-A) added, the weight added for ferrovanadium (FeV50-B), and the weight added by the silicon-aluminum alloy FeAl30Si25 are: 1700,
2. question retelling

2.1. Introduction
Deoxidation alloying in steelmaking is an important process in iron and steel smelting. For different steel grades, at the end of the smelting, different amounts and different kinds of alloys need to be added to meet the standard of the alloying elements, which ultimately makes the finished steel meet certain requirements in certain physical properties.

2.2. Question raised
Problem 1: The deoxidation alloying of molten steel mainly focuses on the content of five elements of C, Mn, S, P and Si. Please calculate the historical yield of C and Mn according to Annex [1], and analyze the main factors affecting the yield.

Question 2: Based on Question 1, build a mathematical model to predict the yield of C and Mn elements, and further improve the model and algorithm to maximize the prediction accuracy of the yield of these two elements.

Question 3: The price of different alloy materials is different, and the choice directly affects the cost of deoxidation alloying of molten steel. According to the prediction result of the alloy yield in question 2 and the reference [2], the mathematical model is established to realize the optimization calculation of the deoxidation alloying cost of molten steel, and the alloying scheme is given.

3. problem analysis

3.1. Analysis of Question 1
For question 1, since the data obtained needs to be screened and identified, according to the literature and problem requirements, the index of other elements and the temperature at the end of the converter are 0. Then, based on the reduced data, the historical yields of the two elements C and Mn are established to determine the historical yield of any batch of C and Mn. According to the data of the indicators to be analyzed, the principal component analysis method is used to determine the contribution of each index to the historical yield of C and Mn, so as to find out the main indicators. In order to further determine the relationship between each index and the historical yield of C and Mn, the linear regression equation was obtained by least squares method and principal component estimation.

3.2. Analysis of Question 2
For question 2, we need to predict the final yield of carbon and manganese by various objective conditions and the amount of raw materials. Considering the complex and fuzzy relationship, we initially use neural network to learn and train a large amount of raw data to predict. The actual yield of carbon and manganese elements.

3.3. Analysis of Question 3
For question 3, we must not only consider the level of final output, but also the actual economic factors. Obviously, this is a multi-objective optimization problem, which is optimized by taking carbon and nitrogen element yield and alloy cost as two goals. A multivariate nonlinear regression equation is established to solve this model and an optimal solution is given.
4. model hypothesis

4.1. Assume that the measured data is true and accurate;

4.2. Assume that the missing data are random deletions;

4.3. Assuming that the upper limit of the number of neural network iterations is sufficient, the objective function can be converged;

4.4. Assume that the individual influence components are linearly independent;

5. symbol description

Symbol description is shown in Table 1.

| Serial number | symbol   | Significance                                      |
|--------------|----------|--------------------------------------------------|
| 1            | $S_c$    | Alloy final $c$ element yield                    |
| 2            | $T_c$    | Total carbon mass contained in the input alloy   |
| 3            | $S$      | The coefficient of total influence factor affecting the historical yield of $C$ and $Mn$ |
| 4            | $S_{Mn}$ | The final amount of $Mn$ element in the alloy    |
| 5            | $T_{Mn}$ | The mass of total manganese contained in the input alloy |
| 6            | $J$      | Neural network secondary performance index coefficient |
| 7            | $\delta$ | Metal yield                                     |
| 8            | $M$      | Total content cost                              |
| 9            | net      | Neural network prediction model                  |
| 10           | $C$      | Regression coefficient of coefficient of influence factor |

6. model establishment and solution

6.1. Problem 1 Model Establishment and Solution

6.1.1. Problem 1 Model Establishment

This problem requires the calculation of the historical yield of $C$ and $Mn$ elements based on the historical statistics of the annexes and the analysis of the main factors affecting their historical yield. The alloy yield refers to the ratio of the final amount of alloy obtained per unit time to the initial input. The data were filtered by reference [1], and the abnormal data was removed to obtain the calculated raw data for the two elements of $C$ and $Mn$. For the $C$ and $Mn$ elements, the historical yields were calculated separately, and the main factors affecting their historical yields were analyzed.

6.1.2. Establishment of the historical income rate model of $c$ elements

Let the final $C$ element of the alloy in any batch of the batch be obtained as $sc$, and the end $C$ content of the alloy converter is $He$. The continuous casting $C$ content is $Lc$, and the net weight of molten steel is $M$ kg, which has the following relationship:

$$S_c - M * (L_c - H_c)$$

After screening, the types of alloy materials are ferro-vanadium (FeV50-A), ferrovanadium (FeV50-B), silicon-aluminum alloy FeAl30Si25, silico-manganese surface (silicon-manganese slag), ferrosilicon (qualified block), ferrosilicon FeSi75-B, petroleum coke recarburizer, manganese silicon alloy FeMn64Si27 (qualified block), manganese silicon alloy FeMn68Si18 (qualified block), silicon carbide (55%), silicon calcium carbon deoxidizer 11 kinds of alloy materials containing $C$ element,
respectively Let the weight of the corresponding input alloy material be a1, a2,...,a11, and the percentage of C-containing elements corresponding to the 11 kinds of alloy materials is b1, b2...b11, then
\[ T_c = \sum_{i=1}^{11} a_i b_i \]
among them The total carbon content contained in the alloy material.

From this, the historical yield of the batch c element of each calf can be obtained.
\[ \eta_c = \frac{S_c}{T_c} \]

So far, the historical income model of the c element has been established.

6.1.3. Establishment of historical yield model of Mn element
Let the final Mn element yield of the alloy in any batch of the furnace be, the alloy converter end point Mn content is, the continuous casting Mn content is. The net weight of molten steel is M kg, which has the following relationship:
\[ S_{Mn} = M \times (L_{Mn} - H_{Mn}) \]

After screening, the types of alloy materials are silicon-aluminum-manganese alloy balls, silicon-manganese surface (silicon-manganese slag), manganese-silicon alloy FeMn64Si27 (qualified block), manganese-silicon alloy FeMn68Si18 (qualified block) with Mn element, respectively. The weight of the input alloy material is c1, c2, c3, and c4 kinds of alloy materials corresponding to the percentage of MN-containing elements d1, d2, d3, d4, then:
\[ T_{Mn} = \sum_{i=1}^{4} c_i d_i \]
among themThe total carbon content contained in the alloy material.

From this, the historical yield of Mn elements in each batch can be obtained.

6.1.4. C, Mn historical yield model Alloy C absorption and feed
The above algorithm is introduced by using EXCEL’s own formula, and the final C element obtained by each batch of the batch is obtained as Sc, the total carbon element mass Tc of the input alloy material, and the historical yield of C element \( \eta_c \). The curve of the absorption of C element and the amount of feed is shown in Figure 1.

The curve of the absorption of Mn element and the amount of feed is shown in Figure 2; the comparison of the historical yield of C and Mn is shown in Figure 3.
It can be seen from the above that the absorption amount of the alloy of C and Mn is approximately the same as the change trend of the feed amount.

6.1.5. Influence on the historical yield model of C and Mn elements
Because there are many factors affecting the historical yield of elements, and the factors affecting the historical yield of C and Mn are different, it can be seen that the influencing factors of the historical yield of each element have certain correlation. The factors affecting the historical yield of C elements are shown in Table 2; the factors affecting the historical yield of Mn elements are shown in Table 3.

### Table 2: Factors Influencing the Historical Yield of Element C

| Influencing factor                                      | Continuous casting                                      |
|--------------------------------------------------------|--------------------------------------------------------|
| Converter end temperature                              | Continuous casting                                      |
| Molten steel net weight                                | Ferrovanadium (FeV50-A)                                 |
| Ferrovanadium (FeV50-B)                                | Silicon aluminum alloy FeAl30Si25                        |
| Silicon manganese surface (silicon manganese slag)     | Ferrosilicon (qualified block)                          |
| Ferrosilicon FeSi75-B                                  | Petroleum coke recarburizer                             |
| Manganese silicon alloy FeMn64Si27 (qualified block)   | Manganese silicon alloy FeMn68Si18 (qualified block)    |
| Silicon carbide (55%)                                  | Silicon calcium carbon deoxidizer                        |
Table 3: Factors affecting the historical yield of Mn

| Influencing factor                                           |
|-------------------------------------------------------------|
| Converter end temperature                                   |
| Continuous casting Mn                                        |
| Molten steel net weight                                     |
| Silicon manganese surface (silicon manganese slag)           |
| Manganese silicon alloy FeMn64Si27 (qualified block)         |
| Manganese silicon alloy FeMn68Si18 (qualified block)         |

Based on the above analysis, this paper uses the idea of dimensionality reduction, using principal component analysis (PCA), combined with SPSS factor analysis to separate the two elements separately, finds the influence indicators that mainly affect the two elements of C and Mn, and carries out the significance test. The principal component analysis method steps are as follows: The schematic diagram of the principal component analysis method is shown in Figure 4.

After the principal component analysis method finds the principal component, and linearly regresses the factors affecting the historical yield rate, the principal component estimation method is used to overcome the least squares (ls) estimation when the design matrix is ill (ie, there is multicollinearity). Instability, get a more accurate regression equation.

6.1.5.1. Principal Component Analysis Model Establishment

Principal component analysis (Principal Component Analysis) was introduced in 1901 by Pearson for non-random variables. In 1933, Hotelling extended this method to random vectors, based on strict mathematical theory. Use represents p influencing factors, To indicate the weight of each influencing factor, the total influencing factors are:

$$S = \sum_{i=1}^{p} x_i t_i$$

The influencing factors of each study correspond to a total impact value, recorded as.

Assume, As The sample observation is the base variable, if it can be found. Make. The largest value indicates that the p variables have reached the maximum variation. Usually prescribed. Under this constraint, the optimal solution of the above formula is the principal component direction.

Assume. Represents the ith principal component, Can be set

$$Z_1 = t_{11}A_1 + t_{12}A_2 + \cdots + t_{1p}A_p$$
$$Z_2 = t_{21}A_1 + t_{22}A_2 + \cdots + t_{2p}A_p$$
$$\cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots$$
$$Z_p = t_{p1}A_1 + t_{p2}A_2 + \cdots + t_{pp}A_p$$

For each i, there is a rule of the above formula. And weight Make to reach maximum, Vertically And make to reach maximum. By analogy, the number of p principal components can be determined at this point, and the contribution rate of the principal components is compared by weight, and the principal component analysis method based on the maximum variance theory is obtained.

6.1.5.2. Establishment of principal component estimation model

Consider a linear regression model
among them: For the observation vector $Y$, for regression parameters $\beta$, is a random error vector $\varepsilon$, for the design matrix $X$, for the least squares estimation, if principal component estimation is used, the instability exhibited by the least squares (LS) estimation in the design of the ill-conditioned state (i.e., the existence of multicollinearity) can be overcome.

If the column vector is set, then the standard orthogonalization of the significant vector, then the least squares method can be changed to

$$Y_n = Z_n a_n + \varepsilon_n$$

According to the proof and reversal of Yang Hu et al., it can be concluded that the one-parameter principal component estimation expression [3] is:

Consider linear combinations and take special

$$w_i = \begin{cases} \frac{1 - \theta}{\lambda_i^{(n)}}, & i = 0 \\ (1 - \theta)(\frac{1}{\lambda_i^{(n)} - \frac{1}{\lambda_i^{(n)}}}), & 1 \leq i \leq r_n \\ 1 - \frac{1}{\lambda_i^{(n)}}, & i = r_n \\ \theta(\lambda_i^{(n)} - z_i^{(n)}), & r_n < i < p \\ \theta\lambda_p^{(n)}, & i = p \end{cases}$$

For smooth parameters, and

$$A_n = \text{diag}(\frac{\theta - 1 + \theta}{\lambda_1^{(n)}}, \ldots, \frac{\theta - 1 + \theta}{\lambda_p^{(n)}}, \theta\lambda_1^{(n)}, \ldots, \theta\lambda_p^{(n)})$$

The regression parameters corresponding to the principal component analysis method can be obtained.

6.1.6. Solving the influencing factor model of Mn element historical yield

Step 1 results in a correlation coefficient matrix $R$

$$R = \begin{bmatrix} r_{11} & z_{12} & \cdots & z_{1p} \\ r_{21} & z_{22} & \cdots & z_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ r_{p1} & z_{p2} & \cdots & z_{pp} \end{bmatrix}$$

among them

$$r_{ij} = \frac{\sum_{i=1}^{p}(x_{ij} - \bar{x}_i)(x_{ij} - \bar{x}_j)}{\sqrt{\sum_{i=1}^{p}(x_{ij} - \bar{x}_i)^2} \sqrt{\sum_{j=1}^{p}(x_{ij} - \bar{x}_j)^2}}$$

Its meaning is between the original variables Correlation coefficient between.

Step 2 calculates the contribution rate of each principal component.

The eigenvalues and eigenvectors of the correlation coefficient matrix $r$ are calculated by using SPSS, and then the contribution rate of each principal component and the cumulative contribution rate are further obtained. The contribution rate of each principal component and the cumulative contribution rate are shown in Table 4.
Table 4: Contribution rates of principal components and cumulative contribution rates

| Eigenvalues | Percentage of variance | Contribution rate (%) | Cumulative contribution rate (%) |
|-------------|------------------------|-----------------------|----------------------------------|
| 2.008       | 33.466                 | 33.466                | 33.466                           |
| 1.169       | 19.490                 | 19.491                | 52.957                           |
| 1.030       | 17.172                 | 17.171                | 70.128                           |
| 0.909       | 15.157                 | 15.157                | 85.285                           |
| 0.845       | 14.085                 | 14.086                | 99.371                           |
| 0.038       | 0.629                  | 0.629                 | 100.000                          |

It can be seen that among the six indicators, the cumulative contribution rate of the sixth index is extremely small, and the first five indicators have a contribution rate of 99.371%, so the first five indicators are selected as the main components. That is, the last manganese silicon alloy (Mn68) is discarded.

**Step 3 principal component estimation regression:**

The linear regression equations of least square method and principal component estimation are obtained by Matlab programming.

\[ n = c + k_1x_1 + k_2x_2 + k_3x_3 + k_4x_4 + k_5x_5 + k_6x_6 \]

The least squares linear regression coefficient is \( c = 0.533 \). The factors affecting the least squares method are shown in Table 5.

Table 5: Influencing factors of least squares method

| Influence factor coefficient | Numerical value          |
|-----------------------------|--------------------------|
| Converter end temperature k1| -0.359e-04               |
| Continuous casting Mnk2     | -66.79                   |
| Molten steel net weight k3  | 0.13e-04                 |
| Silicon manganese surface (silicon manganese slag) k4 | -0.37e-03 |
| Manganese silicon alloy FeMn64Si27 (qualified block) k5 | -0.327e-03 |
| Manganese silicon alloy FeMn68Si18 (qualified block) k6 | -0.31e-03 |

Among them, the principal component is estimated to be linear regression \( c = -1.129 \). The factors affecting the principal component analysis are shown in Table 6.

Table 6: Coefficients of Principal Component Analysis

| Influence factor coefficient | Numerical value |
|------------------------------|-----------------|
| Converter end temperature k1 | 0.0011          |
| Continuous casting Mnk2     | -31.41          |
| Molten steel net weight k3  | 4.51e-06        |
| Silicon manganese surface (silicon manganese slag) k4 | -0.618e-03 |
| Manganese silicon alloy FeMn64Si27 (qualified block) k5 | 4.00e-05 |
| Manganese silicon alloy FeMn68Si18 (qualified block) k6 | 2.561e-06 |

**Step 4 fit degree comparison:**

Estimation of linear regression check \( 2 = 0.1301 \), linear regression of least squares method tech1 = 0.0298, Obviously the principal component estimates more accurately.
6.1.7. C element historical yield rate influencing factor model

**Step1 results in a correlation coefficient matrix**

The calculation method is the same as that of Mn, and will not be described here.

**Step2 calculates the contribution rate of each principal component**

The eigenvalues and eigenvectors of the correlation coefficient matrix \( r \) are calculated by using SPSS, and then the contribution rate of each principal component and the cumulative contribution rate are further obtained. The contribution rate and cumulative contribution rate of each principal component are shown in Table 7.

| Eigenvalues | Percentage of variance | Contribution rate (%) | Cumulative contribution rate (%) |
|-------------|------------------------|-----------------------|----------------------------------|
| 3.244       | 23.170                 | 23.170                | 23.170                           |
| 2.064       | 14.743                 | 14.743                | 37.913                           |
| 1.698       | 12.129                 | 12.129                | 50.042                           |
| 1.270       | 9.072                  | 9.072                 | 59.114                           |
| 1.079       | 7.704                  | 7.703                 | 66.817                           |
| 0.960       | 6.861                  | 6.861                 | 73.678                           |
| 0.888       | 6.341                  | 6.341                 | 80.019                           |
| 0.842       | 6.014                  | 6.014                 | 86.033                           |
| 0.735       | 5.248                  | 5.248                 | 91.281                           |
| 0.446       | 3.187                  | 3.187                 | 94.468                           |
| 0.289       | 2.063                  | 2.063                 | 96.531                           |
| 0.238       | 1.698                  | 1.698                 | 98.229                           |
| 0.152       | 1.088                  | 1.088                 | 99.317                           |
| 0.096       | 0.683                  | 0.683                 | 100.00                           |

The principal component analysis of C and Mn elements is shown in Figure 5 (a). The next two figures show the principal component analysis of carbon and manganese.

**Fig. 5 (a)** C. Principal Component Analysis of C Elements; **Fig. 5 (b)** Mn. Principal Component Analysis of Mn Elements

The above figure reflects the variation of the characteristic values of 14 influencing factors. It can be seen from the chart that only the first six indicators can be accumulated to accumulate a cumulative contribution rate of 73.678%. Therefore, the first six indicators can be taken as the main component.
Step 3 Principal Component Estimation Regression: The least squares method and principal component estimation linear regression equation are obtained by Matlab programming.

\[ \eta_c = c + k_1x_1 + k_2x_2 + \ldots + k_{12}x_{12} \]

The least squares linear regression coefficient is \( c = 0.8776 \). The least squares influence coefficient is shown in Table 8.

| Influence factor coefficient | Numerical value | Influence factor coefficient | Numerical value |
|------------------------------|----------------|------------------------------|-----------------|
| Converter end temperature    | 0.0001         | Continuous casting, positive| -402.7387       |
| coefficient k1               |                | c coefficient, k2           |                 |
| Molten steel net weight      | 0.0000         | Ferrosilicon FeV50-A        | -0.0018         |
| coefficient k3               |                | coefficient K4              |                 |
| Ferrovanadium (FeV50-B)      | 0.0002         | FeAl30Si25 coefficient      | -0.0008         |
| coefficient K5               |                | K6                           |                 |
| Silicon manganese surface    | -0.0001        | Ferrosilicon (qualified     | 0.0006          |
| (silicon manganese slag)     |                | block) coefficient          |                 |
| coefficient                  |                |                              |                 |
| Ferrosilicon FeSi75-B        | 0.0004         | Petroleum coke recarburizer | -0.0042         |
| coefficient                  |                |                              |                 |
| FeMn64Si27 coefficient       | -0.0001        | FeMn68Si18 coefficient      | -0.0001         |
| Silicon carbide (55%)        | -0.0008        | Silicon calcium carbon      | -0.0004         |
| coefficient                  |                | deoxidizer coefficient      |                 |

The coefficient calculated by the least squares method can approximate the relationship between the influencing factors of each batch of batches and the historical yield of final output. Among them, the principal component estimated linear regression \( c = 0.9338 \). Principal component analysis influence coefficient is shown in Table 9.

| Influence factor coefficient | Numerical value | Influence factor coefficient | Numerical value |
|------------------------------|----------------|------------------------------|-----------------|
| Converter end temperature    | -0.0001        | Continuous casting          | -34.0360        |
| coefficient k1               |                |                              |                 |
| Molten steel net weight      | 0.0000         | Ferrovanadium (FeV50-A)     | 0.0000          |
| coefficient k3               |                |                              |                 |
| Ferrovanadium FeV50-B        | 0.0001         | FeAl30Si25 coefficient      | -0.0001         |
| coefficient                 |                |                              |                 |
| Silicon manganese surface    | 0.0000         | Ferrosilicon (qualified     | 0.0000          |
| (silicon manganese slag)     |                | block) coefficient          |                 |
| coefficient                  |                |                              |                 |
| Ferrosilicon FeSi75-B        | -0.0001        | Petroleum coke recarburizer | 0.0003          |
| coefficient                  |                |                              |                 |
| FeMn64Si27 coefficient       | 0.0000         | FeMn68Si18 coefficient      | -0.0001         |
| Silicon carbide (55%)        | 0.0001         | Silicon calcium carbon      | -0.0007         |
| coefficient                  |                | deoxidizer coefficient      |                 |

Step 4 significant comparison:
Notable degree principal component estimation linear regression check \( 2 = 0.0652 \), least squares linear regression check \( c = 0.0428 \), Obviously the principal component estimates more accurately.
6.1.8. Model sensitivity analysis

In addition to verifying the rationality of the system, it is necessary to introduce more reasonable parameters to evaluate the system. Here we use the cloud model[3] to perform sensitivity analysis on the model we built. The cloud model represents the characteristics of the data by three quantities of expectation, entropy, and super-entropy. The degree of certainty of the data is determined by calculating the digital features of the cloud droplets by generating sufficient cloud droplets for the known data to verify the level of the data. Here, we respectively substitute the same values of the evaluation scores obtained by principal component analysis of C and Mn into the cloud model, and perform sensitivity analysis to obtain the reduction maps of the two scoring models shown in the following figure.

The picture on the left is the reduction map of carbon, and the picture on the right is the reduction map of manganese. C, Mn element sensitivity analysis chart is shown in Figure 6 (a), Figure 6 (b).

By reducing the graphs of the C and Mn evaluation models, we can find that the vast majority of the scores are more than 0.6, which is consistent with the distribution of reasonable data. Among the data with a certain degree of C and Mn of 0.8 to 1, it occupies the vast majority of the entire judgment. At the same time, the model is also highly discrete. Therefore, the sensitivity of the model is relatively good, and the historical harvest rate of both can be accurately and objectively reflected.

6.2. Problem 2 Model Establishment and Solution

6.2.1. Establishment of prediction model for carbon and manganese elements

According to the results of the first principal component analysis, our second question only considers the important indicators selected by the first question. For the carbon element, we consider the converter end temperature, the converter end point C, the net weight of molten steel, and the ferrovanadium (FeV50-A), vanadium iron (FeV50-B), silicon aluminum alloy FeAl30Si25, for the manganese element we consider the endpoint temperature, converter end Mn, molten steel net weight, silicon manganese surface (silicon manganese slag), manganese silicon alloy FeMn64Si27 (qualified block). According to the actual input of these indicators, the yield of carbon and manganese is predicted. The neural network can fully approximate the complex nonlinear mapping and establish a neural network identification model as the prediction model. The combination of neural networks and model predictive control provides a powerful tool for solving the control of complex industrial processes. On this basis, the control law is obtained.[2] BP neural network prediction model flow chart is shown in Figure 7.
Figure 7. Flow chart of BP neural network prediction model

Where s is a given value. Take the secondary performance indicator function:

$$J = \min \left\{ \sum_{j=1}^{n} e^2 (k + j) + \sum_{j=1}^{n} r_j u^2 (k + j - 1) \right\}$$

among them, Control function

$$\Delta u(k + j - 1) = u(k + j - 1) - u(k + j - 2)$$

by Find

Algorithm steps:
Step1 calculates the desired input reference trajectory
Step2 is predicted by the neural network, generating a predictive output from the filter
Step3 prediction error calculation:
Step4 ask for the quadratic performance function, obtain the optimal control law, use As the first control signal, as the input of the control object, then go to the second step.

Therefore, to ensure the accuracy of the prediction results of this algorithm, there are the following methods of self-identification.

$$\hat{y}^{(i)} = \sigma \left( \psi x^{(i)} + b \right)$$

$$L\left( \hat{y}^{(i)}, y^{(i)} \right) = \frac{1}{2} \left( \hat{y}^{(i)} - y^{(i)} \right)^2$$

among them $\hat{y}^{(i)}$ is training sample. The corner mark on the right represents a training sample and $x^{(i)}$ is a prediction of the training sample. the greater the deviation between the prediction and the actual result, that is, the lower the prediction accuracy, usually we calculate the stored function as the following formula.

We have defined the loss function for a single training sample. The following formula is used to measure the prediction accuracy of the prediction algorithm for the entire training set. In fact, it is to accumulate the "loss" of each sample and then average it. This loss function for the entire training set is called the cost function. The larger the calculation result, the greater the cost, that is, the less accurate the prediction.

$$J(x, b) = \frac{1}{n} \sum_{i=1}^{n} L\left( \hat{y}^{(i)}, y^{(i)} \right) = \frac{1}{2} \sum_{i=1}^{n} \left[ \left( \hat{y}^{(i)} \log \left( \hat{y}^{(i)} \right) + \left( 1 - \hat{y}^{(i)} \right) \log \left( 1 - \hat{y}^{(i)} \right) \right) \right]$$
In general, the neural network uses a loss function to find the error between the predicted result and the true value to determine whether the predicted result is correct. The greater the error, the less accurate the prediction.

6.2.2. Carbon and manganese element prediction model
Substituting past historical data into the neural network prediction model yields the following results:

For the prediction of carbon yield:
When the molten steel temperature, the converter end temperature, the net weight of molten steel, the weight added by ferrovanadium (FeV50-A), the weight added for ferrovanadium (FeV50-B), and the weight added by the silicon-aluminum alloy FeAl30Si25 are: 1645, 0.0008, respectively. At 72950, 0, 0, and 1560, the predicted carbon content yield was 0.912. The error map and training curve and the automatic correction sampling map are shown in Figures 8 and Figures 9 and Figures 10 and Figures 11:

![Figure 8 Training and Automatic Correction Sampling Diagram](image)
![Figure 9 Training Diagram](image)
![Figure 10 Error Diagram](image)
![Fig. 11 Training and Auto-Correction Sampling Diagram](image)

As can be seen from the figure, the algorithm has a fast convergence speed and a small error, and has a large prediction accuracy.

For the prediction of manganese yield:
When the molten steel temperature, the converter end temperature, the net weight of molten steel, the weight added by the silicon manganese surface (silicon manganese slag), and the weight added by the manganese silicon alloy FeMn64Si27 (qualified block) are 1705, 0.0012, 74550, 0, 50, respectively, the predicted yield of manganese is 0.924. The error map and training curve and the automatic correction sampling map are shown in Figures 12, and Figures 13 and Figures 14 and Figures 15 below:

![Figure 12 error error diagram](image)
![Figure 13 training and automatic correction sampling diagram](image)
6.2.3. Algorithm Improvement
The above bp algorithm uses the most conventional conjugate gradient method. Below we improve the modified algorithm:

(1) Additional momentum term
This is an optimization method[4] that is widely used to accelerate the convergence of the gradient descent method. The core idea is that, in the gradient descent search, if the current gradient falls in the same direction as the previous gradient, the search is accelerated, and vice versa.

The parameter update items of the standard bp algorithm are:

\[ \Delta \omega (t) = \eta g(t) \]

In the formula, the gradient calculated for the t-th iteration, For the parameter adjustment of the t-th iteration, \( \eta \) is the learning efficiency. After adding the momentum term, the parameter based on the gradient descent is updated as:

\[ \Delta \omega (t) = \eta \left[ (1 - \mu) g(t) + \mu g(t-1) \right] \]

among them, For the momentum factor, the above equation is equivalent to:

\[ \Delta \omega (t) = \alpha \Delta \omega (t-1) + \eta g(t) \]

among them, For the forgetting factor, indicates the adjustment effect of the direction and size information of the last gradient drop on the current gradient drop.

(2) Adaptive learning rate
The additional momentum method faces the difficulty of selecting the selection rate, which leads to the contradiction between convergence speed and convergence[2]. Then consider the introduction of learning rate adaptive design, here is an adaptive design:

\[ \eta (t) = \sigma(t) \eta (t-1) \]

Is the adaptive learning rate factor for the tth iteration.

After correcting the algorithm code, the following comparison chart is obtained as shown in Figure 16:
Figure 16 Comparison of the correction algorithm before and after

It can be seen from the figure that the improvement is closer to the actual value than before the improvement, and the improved algorithm converges faster and more stably during the running of the code.

6.3. Problem 3 Model Establishment and Solution

6.3.1. Establishment of the problem 3 model

In the second question, we have already obtained the prediction relationship between the various ingredients and environmental conditions on the final output of carbon and manganese. In the third question, we must not only consider the final output, but also consider actual economic factors. Obviously, this is a multi-objective optimization problem, which is optimized by taking carbon and nitrogen element yield and alloy cost as two goals.

The specific ideas are as follows:

When the converter blowing process reaches the end point, a certain amount of oxygen remains in the molten steel. For the next smooth casting or refining, a certain amount of deoxidizing alloying agent should be added according to the requirements of the steel type to make the molten steel reach the specified degree of deoxidation and make the molten steel The content of elements such as silicon and manganese meets the requirements of the regulations. The theoretical calculation formula for the amount of alloy added is:

\[
\text{Medium Specifications} = \frac{\omega [M]_{\text{Mn,Min}} - \omega [M]_{\text{Mn,Max}}}{\omega [M]_{\text{Mn,Min}} - \omega [M]_{\text{Mn,Max}}} \times \text{Steel output (t)}
\]

among them: Specify the M element content for the steel grade; The remaining M element in the molten steel at the end point; The amount of M element contained in the alloy added to adjust the M content; the amount of tapping is the mass of molten steel poured into the ladle; The yield of alloying elements is the percentage of the mass of alloying elements entering the molten steel to the total amount of alloying elements added.

In order to turn multi-objective planning into a single-objective plan, we set \(D = \frac{\delta}{M}\), among them \(\delta\) For the yield, \(M\) For the total alloy cost. So we set up the following objective function: For carbon, we have:

\[
\max D = \frac{\delta}{M}
\]
For manganese, we have

\[
\delta = \text{net}(T, n, m, m_{\text{FeV50-A}}, m_{\text{FeV50-B}}, m_{\text{FeAl30Si25}}, m_{\text{FeMn64Si27}})
\]

\[
M = P_{\text{FeV50-A}} m_{\text{FeV50-A}} + P_{\text{FeV50-B}} m_{\text{FeV50-B}} + P_{\text{FeAl30Si25}} m_{\text{FeAl30Si25}} + P_{\text{FeMn64Si27}} m_{\text{FeMn64Si27}}
\]

among them: \(\text{net}\) the function that was developed for the neural network prediction model established in question two, \(n\) for the converter end temperature, \(m\) for the end of the converter, \(m_{\text{FeV50-A}}\) the weight added for ferrovanadium (FeV50-A), \(m_{\text{FeV50-B}}\) the weight added for ferrovanadium (FeV50-B), \(m_{\text{FeAl30Si25}}\) the weight added for the silicon aluminum alloy FeAl30Si25, \(m_{\text{FeMn64Si27}}\) the weight added for the silicon manganese surface (silicon manganese slag), \(P_{\text{FeMn64Si27}}\) the weight added for the manganese silicon alloy FeMn64Si27 (qualified block), and \(P\) it corresponds to the price per ton of the corresponding substance.

6.3.2. Problem 3 Model Solving

We will extract 100 samples from the algorithm to compare the cost before and after optimization. The yield, D comparison: before and after the optimization cost comparison chart is shown in Figure 17; optimization C, Mn element historical yield comparison chart shown in Figure 18; optimization parameter D before and after comparison chart shown in Figure 19.
It can be seen from the figure that the cost is significantly reduced after optimization, but there is not much difference in the yield. However, the parameter d we set is obviously increased, indicating that our basic algorithm is correct. The reason why the result is not quite satisfactory is that the function setting of parameter d is still not considered. Under this algorithm, we get the optimal material allocation scheme as:

For carbon elements: when the molten steel temperature, the converter end temperature, the net weight of molten steel, the weight added by ferrovanadium (FeV50-A), the weight added for ferrovanadium (FeV50-B), and the weight added by the silicon-aluminum alloy FeAl30Si25 are respectively When 1700, 0.0018, 72950, 10, 0.5, and 1560, the maximum D is 0.051. At this time, the carbon element yield is large, and the cost is low.

For the manganese element: molten steel temperature, converter end temperature, molten steel net weight, silicon manganese surface (silicon manganese slag) added weight, manganese silicon alloy FeMn64Si27 (qualified block) added weights of 1755, 0.0012, 73050, 0, 30 At the time, the maximum D is 0.059. At this time, the manganese element has a large yield, and the cost is low, which meets the requirements of the subject, and achieves the goal of cost reduction.

7. model evaluation and promotion

7.1. Evaluation of the model

7.1.1. Advantages of the model
In solving the first question, we use the principal component analysis method to establish a historical yield model that affects C and Mn, and compare them according to the corresponding data. In order to make the results more reasonable and tend to normalize, in essence, we need to introduce The principal component estimation model is verified and the principal component estimation is found to be more accurate. At the same time, we use the cloud model to test the C and Mn's judgment results and establish the correctness of the functional relationship.

In solving the second question, we use the neural network prediction model, which has a wide range of applications and can be used to predict the data over the years. At the same time, it contains the loss function for error analysis and better establish C, Mn. Forecast data. At the same time, we introduce additional momentum terms, adaptive learning rate to improve BP neural network prediction, and make the results more accurate.

In solving the third question, we define the ratio between the yield and the alloy cost, and transform the multi-objective optimization problem into a single-objective optimization problem, which makes the solution process more clear.

7.1.2. Disadvantages of the model
In solving the problem one, the factor explanation of the principal component analysis method does not have a complete theory, and it is impossible to say what the main factors of the specific extraction are. The interpretation of the historical yield of C and Mn is not so strong. In the second problem, BP neural network learning speed is slow, network training failure is more likely, and there is a certain error.

7.2. Promotion of the model
In this paper, we study the optimization problem of molten steel batching scheme based on machine learning. We give the expression of target optimization, and use this model to increase the constraint conditions to facilitate better promotion and utilization. In data prediction, a time series based prediction model can be used, and if it is combined with a neural network, good results can be obtained. Genetic algorithm, immune algorithm and other intelligent algorithms can be used to optimize the batching scheme to make the model more accurate and reasonable.
8. Conclusion
Since the 1990s, computer automatic ingredients have been studied in foreign countries. So far, an automatic ingredient model has been formed with alloy yield prediction and cost optimization algorithm as the main body. This model can realize the function of automatic deoxygenation alloying. In addition to the deoxygenation and alloying model introduced in some workshops of domestic steel companies, other steelmaking workshops have not yet adopted this technology. Instead, the addition of various alloys is calculated according to the fixed acquisition rate or experience value of different elements. It is difficult to realize the automatic optimization and cost control of the current furnace alloy ingredients. The yield of the alloy refers to the ratio of the weight of the alloy element absorbed by the steel water during deoxygenation and the total weight added to the element. In the process of steel water deoxygenation alloying, the yield of the alloy is affected by many factors, and it is difficult to use the explicit expression to determine. Through the study of the above problems, the important link in steel smelting and the situation of the ingredient plan of "deoxygenation and alloying" of steel water are simulated. This research has very important significance and reference value for domestic and foreign counterparts.

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References
[1] Chen Jianting. Multivariate time series prediction method based on improved bp neural network [j]. Electronic Technology and Software Engineering, 2019(05): 163-165.
[2] Zou Lin, Cai Xin, Hao Jinrong. Optimal allocation of water resources based on dual-objective immune particle swarm optimization algorithm [j]. Computer Simulation, 2018, 35(12): 296-301.
[3] Yang Hu. Large sample properties of principal component estimation [j]. Journal of Chongqing Jiaotong University, 1995 (01): 1-7.
[4] Chang Qiang, Zhao Wei, Zhao Yangjie. Data classification prediction and implementation based on neural network [j]. Software, 2018, 39(12): 207-209.
[5] Han Min, Xu Qiao, Zhao Yao, Yang Xilin, Lin Dong. Multi-objective optimization model for converter alloy addition based on particle swarm optimization algorithm [j]. Control and Decision, 2010, 25(12): 1901-1904.