

Optimization of “Deoxidation Alloying” Batching Scheme

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Abstract

In this paper, a mathematical model was established to predict the deoxidation alloying and to optimize the type and quantity of input alloys. Firstly, the GCA method was used to obtain the main factors affecting the alloy yield of carbon and manganese based on the historical data. Secondly, the alloy yield was predicted by the stepwise MRA, the BP neural network and the regression SVM models, respectively. The conclusion is that the regression SVM model has the highest prediction accuracy and the maximum deviation between the test set prediction result and the real value was only 0.0682 and 0.0554. Thirdly, in order to reduce the manufacturer's production cost, the genetic algorithm was used to calculate the production cost mathematical programming model. Finally, sensitivity analysis was performed on the prediction model and the cost optimization model. The unit price of 20% of the alloy raw materials was increased by 20%, and the total cost change rate was 0.7155%, the lowest was -0.4297%, which proved that the mathematical model established presented strong robustness and could be certain reference value for the current production of iron and steel enterprises.

Keywords: alloy yield, gray correlation analysis method, back propagation neural network model, regression support vector machine model, genetic algorithm

1. Introduction

Deoxidation alloying is an important process in steel smelting. At the end of smelting, different steel types need to add different amounts and different kinds of alloys to make their alloying elements reach the standard and finally make the finished steel meet the specific requirements in some physical properties. With the increasing production of high value-added steel in the steel industry, how to establish a mathematical model for deoxidation alloying based on historical data, to predict and to optimize the type and quantity of alloy inputs, which is an important problem to solve for the major iron and steel enterprises.

The traditional alloying material addition method has the experience calculation method, the simple theory calculation method, the iteration search method and so on (Li *et al.*, 1995; Liu *et al.*, 2004). If according to the fixed yield rate or empirical value of different elements to calculate the addition of various alloys instead of forming an automatic batching model based on the prediction of recovery rate and cost optimization algorithm, it will be difficult to realize the automatic optimization and cost control of the current secondary alloy batching. At present, there are some optimization models about the alloy batching. For example, the linear programming model considering the effect of added alloy material weight on raw steel weight and alloy yield (Huang and Du, 2003). The yield estimation model based on gray model and the linear programming model constitute the alloy composition control model (Yuan *et al.*, 2006). The principal component analysis model of the main factors affecting the historical revenue rate was obtained and the multi-objective optimization model with the highest historical revenue rate of each element was adopted (Zheng, 2019). However, the above model still has some shortcomings. For example, the linear programming model is not applicable to the case where the content of elements in molten steel is not specific. Again, it takes a lot of data to get through the historical rate.

A research based on the smelting data and commonly used alloy composition data provided by the 9th MathorCup university mathematical modeling challenge in 2019 was conducted. Modern steelmaking technology is mainly converter steelmaking. According to the requirements of steel type, after adding materials to the converter, insert the

oxygen gun into the furnace from the top and the oxygen flow with purity greater than 99% is blown into the high pressure. In this way, the high-temperature steel directly with oxygen flow oxidation reaction removes impurities. When the chemical composition of the molten steel and the ambient temperature meet the process requirements, the steel can be prepared. The process is shown in Figure 1.

At this time, there must be a certain amount of dissolved oxygen remaining in the metal, which will bring many defects: (1) the pouring process cannot be carried out smoothly; (2) it destroys the rational structure of ingot; (3) oxygen ages solid steel and increases its hardness, magnetism and resistivity.

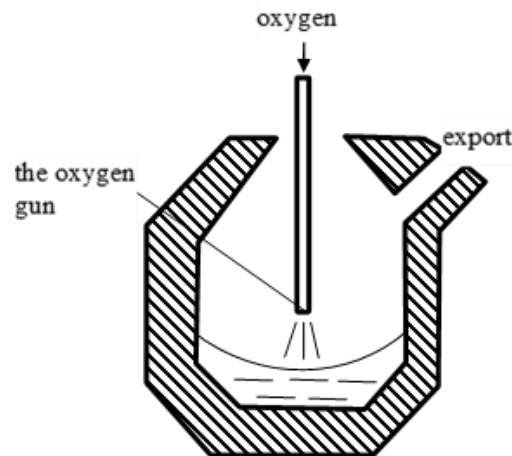


Figure 1. Schematic diagram of modern steelmaking technology

Therefore, the remaining oxygen in the metal must be removed before the steel is produced or poured. the amount of oxygen in a metal can be reduced to the limit by adding one or more elements that are more oxidizing than iron, that is, deoxidation.

2. Method

2.1 Obtaining the Main Factors Affecting the Alloy Yield of Carbon and Manganese

2.1.1 Data Preprocessing

It is assumed that the data are reliable and the experimental data are imported into the preprocessing, normalization and operation process of the model. The success rate of the model for predicting the yield of C and Mn depends on the content of C and Mn in molten steel. Due to the influence of instrument precision, reliability, field measurement environment, furnace temperature and other factors, it is inevitable that there were anomalies in the process of data collection. If these data are used for prediction, the success rate and accuracy of prediction will decrease. In this step, not only the meaningless and missing given data should be eliminated, but also the given data should be ensured to a certain degree of stability, that is, the large data should be eliminated. Generally speaking, the commonly used criteria for judging gross data are: PauTa Criterion, Chauvenet Criterion, Romanovs Criterion, Grubbs Criterion, Dixon Criterion (Chen *et al.*, 2007). In addition, considering the dimensional difference between different quantities, it is necessary to normalize the data before applying various solving methods.

Romanovs Criterion for elimination of data: the principle of the Romanovs Criterion is that firstly to delete a suspect measured value and then by the *t*-distribution test whether the measurement value of the elimination contains gross error, so this method is also called *t*-test.

Specific contents:

Select significance degree α and data processing length n to find the corresponding coefficient K in the *t*-distribution table;

Calculate the mean value of the processed data;

Calculate the criteria for processing data;

If $|\text{detection value} - \text{mean}| > (K * \text{standard deviation})$, then the detection value is gross data and needs to be removed.

2.1.2 Determine the Influencing Factors of Alloy Yield

In the actual production, the alloy yield is directly related to the terminal content of the converter of each element, the content of the positive sample of continuous casting, the amount of alloy material input and the content of its chemical composition. We can determine the historical data of the alloy yield from these data. There is also an indirect relationship

between the alloy yield and the furnace environment and the molten steel weight. Therefore, the converter terminal temperature, the molten steel net weight, the converter terminal point and the alloy material input quantity should all be considered as factors affecting the alloy yield. The formula for calculating the yield of element i alloy is as follows:

$$i \text{ elemental alloy yield} = \frac{\text{Element } i \text{ absorbed by molten steel}}{\text{total weight of element } i \text{ added}} \quad (1)$$

First, the furnace number with missing data was removed and a valid value for the yield between [0,100%] was got. Then, the Romanovs Criterion was used to delete the gross data to obtain 184 sets of data of C alloy yield and 189 sets of data of Mn alloy yield.

2.1.3 Correlation Analysis

We need to quantify the correlation between the possible influencing factors and the ally yield of C and Mn. The commonly used correlation analysis includes chart correlation analysis, covariance and covariance matrix, correlation coefficient, unitary regression and multiple regression, information entropy and mutual information selection. Starting from correlation coefficient, the gray correlation analysis method was chosen (the GCA method). Since the oxygen content in molten steel is not given, the effect of oxygen content should not be considered on the absorption of alloy chemical elements by molten steel in the establishment of correlation model and subsequent prediction model.

Correlation analysis is a grey process based on grey system, by comparing the time series among factors to determine which are the dominant ones. In other words, the degree of correlation of the sequence is determined by the degree of similarity of the trend of the curve. The factors affecting the ally yield of C and Mn were studied and analyzed, so two "many-to-one" grey correlation analyses were conducted.

(1) Data normalization

Min-max Normalization, also known as deviation Normalization, is a linear transformation of the original data that maps the resulting values between [0 to 1]. The conversion function is as follows:

$$x_i^* = \frac{x_i - \min\{X\}}{\max\{X\} - \min\{X\}} \quad (2)$$

Where:

$\max\{X\}$ = the maximum value of sample data.

$\min\{X\}$ = the minimum value of sample data.

(2) Gray correlation coefficient calculation

The sequence of influencing factors, that is, the comparison number:

$$X_i = (x_i(1), x_i(2), \dots, x_i(k), \dots, x_i(n)), i = 1, 2, 3, \dots, 24 \quad (3)$$

Reference number:

$$Y_j = (y_j(1), y_j(2), \dots, x_i(k), \dots, y_j(n)), j = 1, 2 \quad (4)$$

The formula for calculating the correlation coefficient is as follows:

$$\xi_{ji}(k) = \frac{\min \min |x_j(k) - x_i(k)| + \rho \max \max |x_j(k) - x_i(k)|}{|x_j(k) - x_i(k)| + \rho \max \max |x_j(k) - x_i(k)|} \quad (5)$$

Where, $\xi_{ji}(k)$ is the i -th comparison sequence and the j -th reference sequence. $\min \min |x_j(k) - x_i(k)|$ 、 $\max \max |x_j(k) - x_i(k)|$ are the minimum and maximum values after the difference between the reference sequence matrix and the comparison sequence matrix. The reciprocal of $|x_j(k) - x_i(k)|$ is the antiderivative distance and its magnitude determine the degree of correlation. ρ is the resolution, which is usually between [0,1].0.5 was valued.

Because of the factor $\xi_{ji}(k)$ can only reflect the correlation between point and point, the correlation information is scattered, so it is not convenient to describe the correlation between sequences. $\xi_{ji}(k)$ was deduced together and the calculation formula of correlation degree is defined as follows:

$$r_{ji} = \frac{\sum_{k=1}^n \xi_{ji}(k)}{n} \quad (6)$$

Where, r_{ji} represents the degree of correlation, the positive effect is the positive correlation, conversely the negative correlation, $|r_{ji}|$ greater than 0.7 is a strong correlation, less than 0.3 is a weak correlation. The coefficients of each influencing factor are obtained as shown in Figure 2.

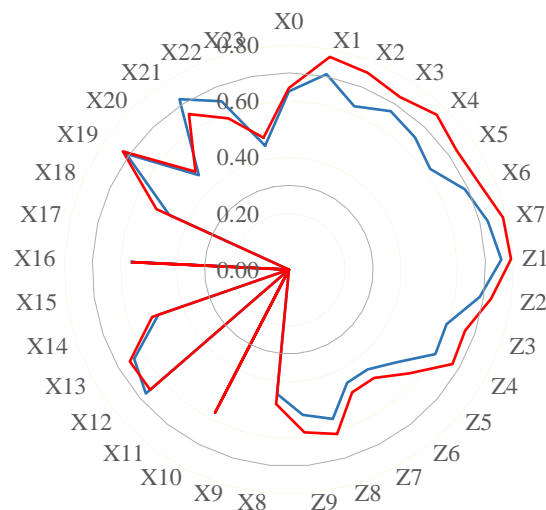


Figure 2. C and Mn yield correlation

The description of the used notation in Figure 2 is as follows:

X0: the converter number;

X1: the terminal temperature of converter;

X2, X3, ... X6: terminal C, terminal Mn, terminal S, terminal P, terminal Si;

X7: the net weight of molten steel;

X8~X23: some kinds of alloys;

Z1~Z9: Ceq_val, Cr, Ni_val, Cu_val, V_val, Al_val, Als_val, Mo_val, Ti_val;

Y1: the yield of C;

Y2: the yield of Mn.

In summary, the main factors affecting the yield of C are the terminal temperature of converter, the net weight of molten steel, the positive sample Ceq_val, the petroleum coking agent, and the manganese silicon alloy FeMn68Si18 (qualified block). The main factors affecting the yield of Mn are the terminal temperature of converter, terminal C, terminal Mn, terminal S, terminal P, terminal Si, the net weight of molten steel, Ceq_val, Cr and the petroleum coking agent.

2.2 Predicting the Alloy Yield by Different Kinds of Model Respectively

In order to ensure the reliability of the model and the accuracy of the prediction, several prediction models should be introduced to verify each other, so as to establish a comprehensive prediction model. Considering the complexity of the operational model, neural network and support vector machine were taken into consideration. In the process of specific model operation, 184 groups of effective C alloy data were divided into 160 training sets and 24 testing sets and 189 groups of effective Mn alloy data were parted into 160 training sets and 29 test sets. The training set is the training data used to build the model and the testing set is used to test the prediction accuracy of the model. In addition, the stepwise multiple regression analysis model, the BP neural network model and the regression support vector machine model for training and predicting were used and the prediction model with high prediction accuracy through the comparison and analysis of various prediction methods was obtained.

2.2.1 The Stepwise Multiple Regression Analysis Model

The essence of the stepwise multiple regression method is to introduce variables into the model one by one, to conduct F test after each introduction of explanatory variables and to execute *t* test for variables that have been introduced one by one. When previously introduced explanatory variables become less significant due to subsequent introduction of explanatory variables, they are eliminated to ensure that only significant explanatory variables are included in the regression equation before each introduction of a new variable. This is an iterative process until no significant explanatory variables are selected into the regression equation to ensure that the final set of explanatory variables is optimal (Zhou, 1990).

Stepwise regression algorithm steps:

Step1: A unary regression model of p regression independent variables is established as follows:

$$Y = \beta_0 + \beta_i X_i + \varepsilon, i = 1, \dots, p \quad (7)$$

The value of the F test statistic of the corresponding regression coefficient of the variable X_i is calculated, denoted as $F_1^{(1)}, \dots, F_p^{(1)}$, the maximum value $F_{i_1}^{(1)}$ is taken and the calculation formula is as follows:

$$F_{i_1}^{(1)} = \max\{F_1^{(1)}, \dots, F_p^{(1)}\} \quad (8)$$

For the given significance level α , make the corresponding critical value $F^{(1)}$, when $F_{i_1}^{(1)} \geq F^{(1)}$, then X_{i_1} is introduced into the regression model and I_1 is remembered as the selected variable index set.

Step2: A binary regression model of dependent variable Y and independent variable subset is established, with a total of $p-1$:

$$\{x_{i_1}, x_1\}, \dots, \{x_{i_1}, x_{i_1-1}\}, \{x_{i_1}, x_{i_1+1}\}, \dots, \{x_{i_1}, x_p\}$$

The value of the F test statistic of the corresponding regression coefficient of the variable is calculated, denoted as $F_k^{(1)} (k \notin I_1)$, the maximum value $F_{i_2}^{(1)}$ is taken and the calculation formula is as follows:

$$F_{i_2}^{(1)} = \max\{F_1^{(1)}, \dots, F_p^{(1)}\} \quad (9)$$

For the given significance level α , make the corresponding critical value $F^{(2)}$, when $F_{i_2}^{(1)} \geq F^{(2)}$, then X_{i_2} is introduced into the regression model and I_2 is remembered as the selected variable index set. Otherwise, the operation that introduce the variables ends.

Step3: The dependent variable and the variable subset $\{x_{i_1}, x_{i_2}, \dots, x_k\}$ are considered if no variable is introduced after the F test, it ends; otherwise, Step2 is repeated.

2.2.2 The BP Neural Network Model

Artificial neural Network (Zhuo, 2011) is a complex Network system that is connected by a large number of simple basic elements - neurons. It can process information in parallel and non-linear by simulating the way of processing information in human brain. BP neural network, through the training of sample data, constantly modify the network weight and threshold value, was used, so that the error adjustment direction is always along the direction, where the error drops the fastest, so as to approximate the expected output.

The establishment of neural network cannot be separated from activation function. In the neuron, the inputs are weighted and add up to a function called the activation function. If the activation function is not used, each layer of output is a linear function of the input at the top and no matter how many layers there are in the neural network, the output is a linear combination of the inputs. If used, the activation function introduces a nonlinear factor to the neuron, so that the neural network can arbitrarily approximate any nonlinear function, so that the neural network can be applied to many nonlinear models. Generally speaking, there are two activation functions: Sigmoid function and Tanh function.

2.2.2.1 Create the BP Neural Network Model

The BP neural network with three layers of multiple input and single output to build the prediction model was used, in which the number of hidden layer neurons is 10. Taking the yield of alloy C as an example, the topology diagram of network structure is shown in Figure 3.

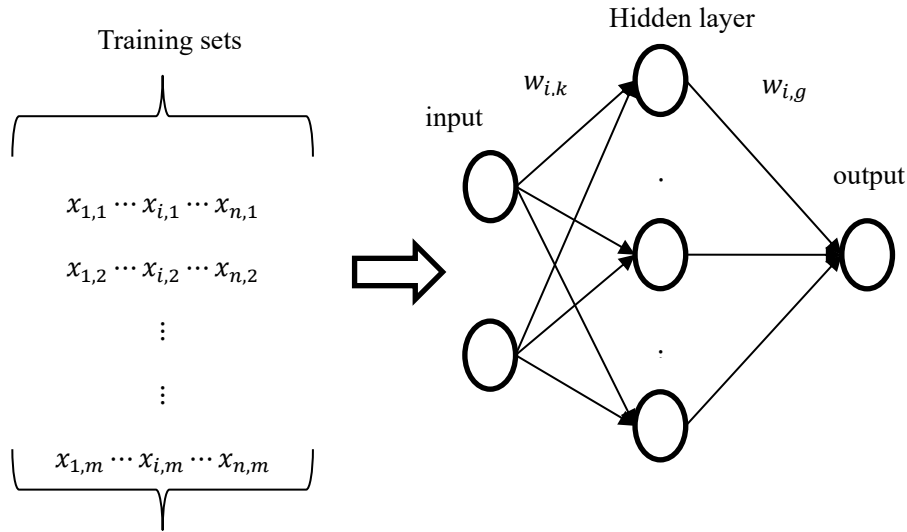


Figure 3. BP neural network structure topology

Sigmoid differentiable function and linear function as activation function of the network were used. Tansig function as the activation function of hidden layer neurons and Logsig function as the activation function of the neuron in the output layer were, respectively, chosen.

2.2.3 The Regression SVM Model

Traditional Support Vector Machine (SVM) is a generalized linear classifier that classifies input data according to supervised learning. The decision boundary of this classifier is the maximum-margin hyperplane for solving the learning samples, that is, the interval of the two classes is the maximum (Zhou, 2016). In order to extend SVM from solving classification problems to solving regression problems, that is to solve regression fitting problems, Smola and Schölkopf (2004) introduced ϵ -insensitive loss function on the basis of SVM, as follows:

$$L(z) = \max(0, |z| - \epsilon) \tag{10}$$

Thus, Support Vector Machine for Regression is obtained. At this time, the standard SVM algorithm is also known as Support Vector Classification (SVC) and its hyperplane decision boundary is the regression model of SVR, as the following formula:

$$f(x) = w^T x + b \tag{11}$$

The basic idea of SVR is no longer to find the maximum margin hyperplane to separate the two types of samples, but to find the maximum margin hyperplane to minimize the error of all training samples from the classification plane, as shown in Figure :

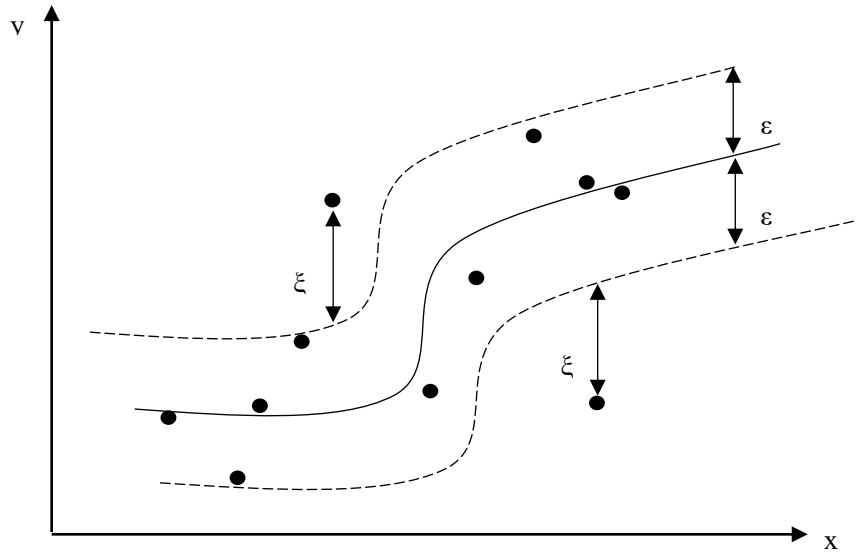


Figure 4. Schematic diagram of regression support vector machines

The SVR is optimized in the following quadratic convex form:

$$\max \frac{1}{2} \|w\|^2 \tag{12}$$

$$s. t. |y_i - f(x)| \leq \varepsilon$$

Using the relaxation variables ξ, ξ^* to represent the piecewise value of the ε -insensitive loss function can be obtained:

$$\begin{aligned} \max \frac{1}{2} \|w\|^2 + C \sum_{i=1}^N (\xi_i + \xi_i^*) \\ s. t. \begin{cases} |y_i - f(x)| \leq \varepsilon + \xi_i \\ \xi \geq 0 \\ \xi^* \geq 0 \end{cases} \end{aligned} \tag{13}$$

Similar to the soft margin SVM, Lagrange functions and dual problems can be obtained by Lagrange multipliers $(\alpha, \alpha^*, \mu, \mu^*)$:

$$\begin{aligned} \mathcal{L}(w, b, \xi, \xi^*, \alpha, \alpha^*, \mu, \mu^*) \\ = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^N (\xi_i + \xi_i^*) - \sum_{i=1}^N \mu_i \xi_i - \sum_{i=1}^N \mu_i^* \xi_i^* \\ + \sum_{i=1}^N \alpha_i [f(X_i) - y_i - \varepsilon - \xi_i] + \sum_{i=1}^N \alpha_i^* [f(X_i) - y_i - \varepsilon - \xi_i^*] \\ \max \sum_{i=1}^N [y_i(\alpha_i^* - \alpha_i) - \varepsilon(\alpha_i^* + \alpha_i)] - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N [(\alpha_i^* - \alpha_i)(X_i)^T (X_j)(\alpha_j^* - \alpha_j)] \end{aligned} \tag{14}$$

$$s. t. \begin{cases} \sum_{i=1}^N (\alpha_i^* - \alpha_i) = 0 \\ 0 \leq \alpha_i \leq C \\ 0 \leq \alpha_i^* \leq C \end{cases} \tag{15}$$

The dual problem has the following KKT conditions:

$$\begin{cases} \alpha_i \alpha_i^* = 0, \xi_i \xi_i^* = 0 \\ (C - \alpha_i) \xi_i = 0, (C - \alpha_i^*) \xi_i^* = 0 \\ \alpha_i [f(X) - y_i - \varepsilon - \xi_i] = 0 \\ \alpha_i^* [y_i - f(X) - \varepsilon - \xi_i^*] = 0 \end{cases} \quad (16)$$

The form of SVR that can be obtained by solving is as follows, that is, SVR can be solved by kernel method to obtain nonlinear regression results (Han,2010).

$$f(X) = \sum_{i=1}^m (\alpha_i^* - \alpha_i) X_i^T X + b \quad (17)$$

2.3 Calculating the Production Cost Mathematical Programming Model

The optimization model of molten steel deoxidation alloying operation cost is established according to the method of linear programming, which is composed of objective function, decision variables and restrictions. The objective function is to meet the minimum cost of the alloy and the decision variable is the input amount of the alloy material. Restrictions include the constraints on the composition of the steel species, the constraints on the amount of alloy and the smelting technical specifications.

After the mathematical planning model is established, the optimization model should be solved. Simplex genetic and simulated annealing algorithms are often used to solve the optimization models. The ordinary simplex method can solve linear programming problems, where all the vectors are non-negative and the constraints are " \leq ", the two-stage simplex algorithm can solve "=", " \leq ", " \geq " and mixed constraint linear programming models. It is worth noting that although the simplex method is faster and simpler in operation, the accuracy is lower. Therefore, at the level of theoretical derivation, we prefer to use genetic algorithms to solve the model.

2.3.1 Linear Programming Model

(1) Decision variable

When adjusting the molten steel composition of a specified steel type, it is usually necessary to add multiple alloy materials. A total of r kinds of alloy materials is set to adjust the m element composition index of the molten steel. The amount of each alloy x_1, x_2, \dots, x_r is the decision variable (Yang,2014).

(2) Objective function

The objective function is to minimize the total cost of alloy use, as the following formula:

$$\min F(X) = P_1 M_1 + P_2 M_2 + \dots + P_r M_r = \sum_{i=1}^r P_i M_i \quad (18)$$

Where $F(X)$ is the total cost of the alloy, the unit is dollar; p_i is the unit price of the i -th alloy material, the unit is dollar $\cdot \text{kg}^{-1}$; M_i is the amount of i -th alloy material, the unit is kg.

(3) Restrictions

The alloy element content constraint should meet national standards. Each alloy material contains multiple elemental components. After all alloy materials are added to the molten steel, the chemical composition of the molten steel must meet the national standards for the elemental composition of steel types required. In actual production, it is usually specified that the composition of the specified element in the molten steel is controlled within a certain upper and lower limit range, as shown in Formula 19:

$$E_{jmin} \leq \frac{\sum_{i=1}^r C_{iA_j} x_i Y_{A_j} + M_{st} C'_{stA_j}}{\sum_{i=1}^r x_i Y_{A_j} + M_{st}} \leq E_{jmax} (j = 1, 2, \dots, m) \quad (19)$$

Where:

r = the number of available alloy materials;

m = the number of elements controlled in molten steel;

E_{jmin} = the control target lower limit of the j -th controlled element in the molten steel and the unit is %;

E_{jmax} = the control target upper limit of the j -th controlled element in the molten steel and the unit is %;

Y_{A_j} = the yield of A_j of the alloying element in the specified steel type in the cost optimization model and the unit is %.

In summary, the cost optimization model for molten steel deoxidation and alloying operations has been constructed, as

follows:

$$\begin{aligned} \min F(X) &= P_1M_1 + P_2M_2 + \dots + P_rM_r = \sum_{i=1}^r P_iM_i \\ \text{s. t. } \left\{ \begin{aligned} E_{jmin} &\leq \frac{\sum_{i=1}^r C_{iA_j}x_iY_{A_j} + M_{st}C'_{stA_j}}{\sum_{i=1}^r x_iY_{A_j} + M_{st}} \leq E_{jmax} (j = 1, 2, \dots, m) \\ M_1, \dots, M_r &> 0 \end{aligned} \right. \end{aligned} \tag{20}$$

2.3.2 Solving Process of Genetic Algorithm

For the above multivariate linear programming model, the genetic algorithm which is easy to obtain the global optimal solution was used. (Tao and Guo, 2003).

(1) Coding

A binary code for chromosomes were used. The string length of an individual refers to the number of types r of alloy. The term in the string is denoted by a , recorded as $a_i^{k_m}$, that is the i -th alloy material in the m -th chromosome k_m string, then the chromosome can be expressed as follows:

$$a_1^{k_m}, a_2^{k_m}, \dots, a_r^{k_m} = (A_1^{k_m}, A_2^{k_m}, \dots, A_n^{k_m}) \tag{21}$$

Where, $A_i^{k_m} = a_i^{k_m} (i = 1, 2, \dots, r)$.

(2) Initial population

The individuals of the initial group are randomly generated. Different from the traditional optimization methods, the starting point of genetic algorithm iteration is not one, but a group. The initial population is a randomly generated binary code string whose length corresponds to the length L of the chromosome.

(3) Fitness

The purpose of optimizing the target allocation is to minimize the total cost of the whole deoxidizing alloying operation process of steel, so the objective function $F(x)$ is taken as the individual fitness.

(4) Duplication

Copy the existing good ones, add them to the new group and remove the bad ones. Generally, the roulette method is used to select excellent individuals. The roulette method means that the probability of individuals being selected depends on the relative fitness of individuals, as follows:

$$p_i = \frac{F_i}{\sum_{i=1}^r F_i} \tag{22}$$

Where, p_i represents the probability that individual i is selected; F_i represents the fitness of the individual; $\sum_{i=1}^r F_i$ said the sum total of population fitness.

(5) Mating

Mating individuals randomly select new self-replicating groups, using roulette, which means trying to select the best and eliminate the worst.

About the rules of mating, a common method was adopted, namely, randomly select a mating site, the genes before the mating site of the two offspring inherit the genes before the mating site of the parents and the genes after the mating site are selected by the heterologous gene order. The parameters that control the number of individual exchanges are determined as follows:

$$M_c = p_c \times M \tag{23}$$

Where p_c is the exchange probability and M is the number of individuals in the group.

(6) Variation

Randomly changing a gene in any individual and then adding the individual to a new population. The probability of mutation can be derived as follows:

$$p_m = \frac{B}{ML} \tag{24}$$

Where B represents the number of mutated genes in each generation; M represents the number of individuals in the

population; L is the number of genes in an individual. According to practical experience, p_m is usually 0.005~0.1, and the mutated gene is generated randomly.

(7) Termination

The maximum genetic algebra MAX is 100. Once the number of iterations of the genetic algorithm reaches MAX, the operation is stopped and the result is output. At the same time, if the fitness difference of the optimal individuals in the adjacent two generations is less than an arbitrarily small integer, the algorithm also terminates.

3. Results

3.1 Stepwise Multiple Regression Results

Through the stepwise regression algorithm, the prediction alloy yield of C and Mn and the real values were calculated, as shown in Figure 5 and Figure 6, respectively:

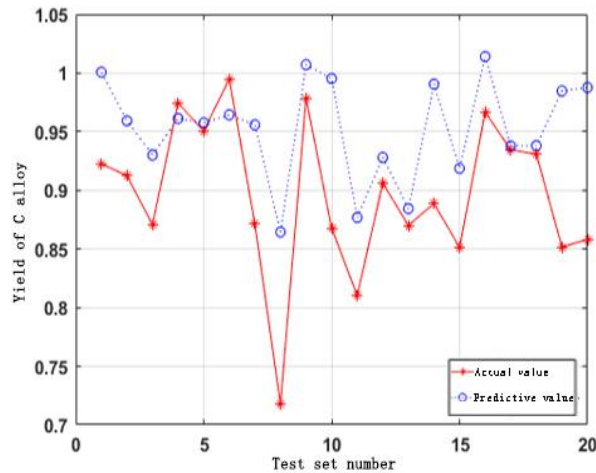


Figure 6. Comparison of predictive values of C alloy yield with the real values

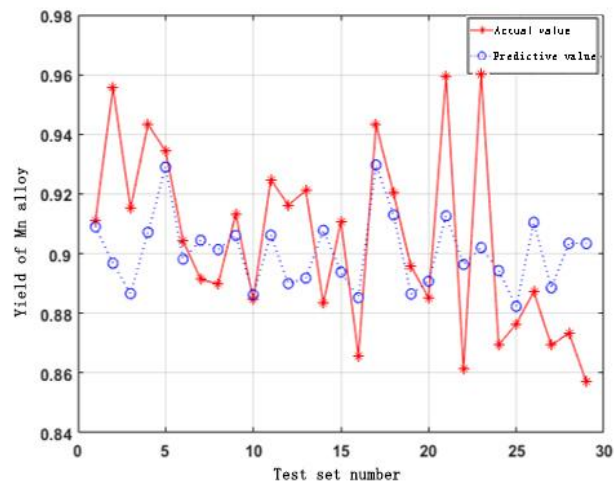


Figure 6. Comparison of predictive values of Mn alloy yield with the real values

Where, the maximum deviation between the prediction results and the real values of the alloy yield of C and Mn is 0.1470 and 0.0588, respectively. Therefore, the stepwise multiple regression analysis model can predict the yield of alloy accurately.

3.2 BP Neural Network Prediction Results

By establishing a three-layer multi-input single-output BP neural network, the prediction ally yield of C is shown in Figure 7 and the prediction ally yield of Mn is shown in Figure 8.

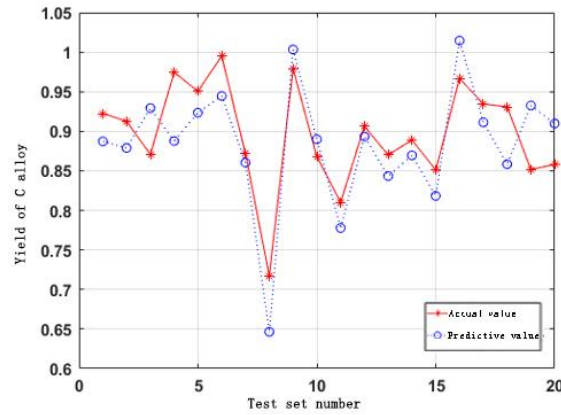


Figure 7. Comparison of predictive values of C alloy yield with the real values

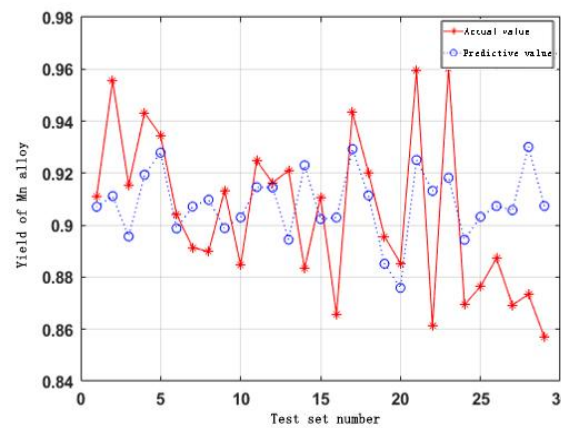


Figure 8. Comparison of predictive values of Mn alloy yield with the real values

In the comparison between the prediction results and the real values of the alloy yield of C and Mn, the mean square error (MSE) of C alloy is 0.1093 and the maximum deviation is 0.0868. The mean square error (MSE) of Mn alloy is 0.1368 and the maximum deviation is 0.0567. It can be seen that the minimum deviation of the BP neural network prediction model is small and it has a relatively accurate prediction effect on alloy yield.

3.3 The Regression SVM Results

From the prediction model of the regression SVM, the alloy yield of C and Mn were predicted. The training results of the training set and the test results of the test set are shown in Figures 9 to 12.

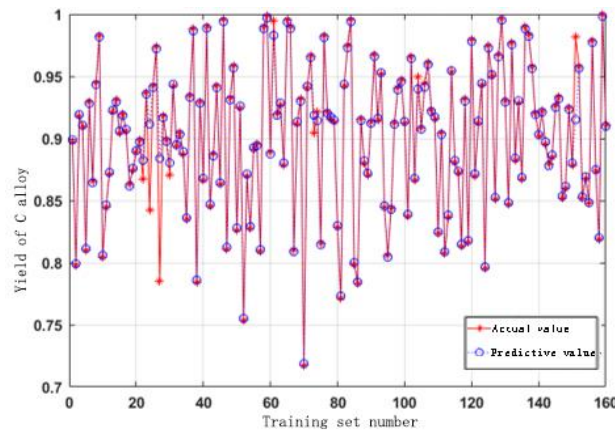


Figure 9. Comparison of predictive values of C alloy yield training set with the real values

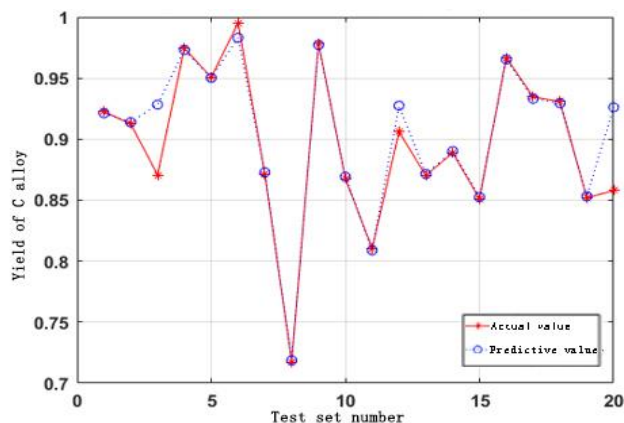


Figure 10. Comparison of predictive values of C alloy yield test set with the real values

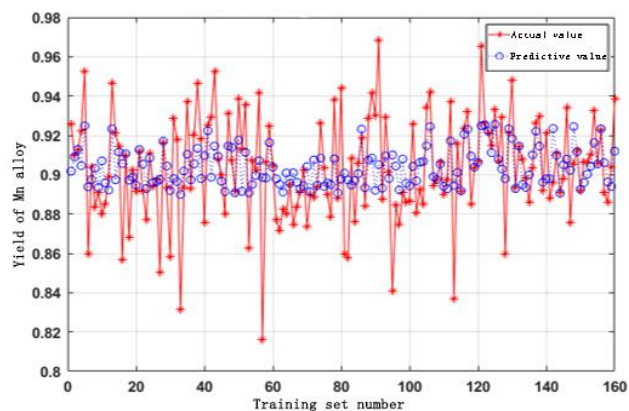


Figure 11. Comparison of predictive values of Mn alloy yield training set with the real values

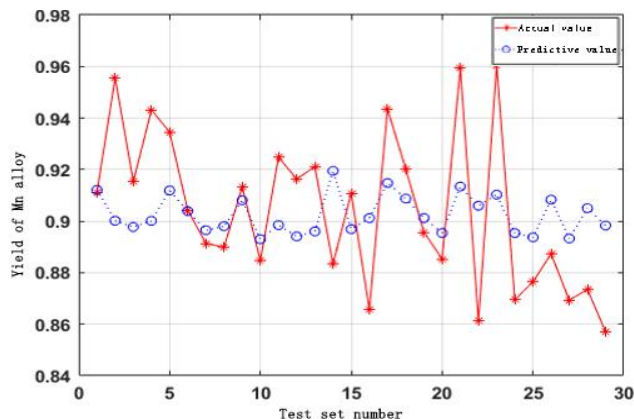


Figure 12. Comparison of predictive values of Mn alloy yield test set with the real values

As can be seen from the above figure, the mean square errors between the prediction results of the C and Mn alloy yield test sets and the real values are 0.0216 and 0.1363, respectively; The maximum deviations of the C and Mn are 0.0682 and 0.0554, respectively. It can be seen that the regression SVM model has a better prediction effect on the alloy yield, and it is better than the previous two models.

3.4 Comparative Analysis of the Three Models

The maximum deviation values of the three models are shown in Table 1.

Table 1. Comparison of the maximum deviation values of the three prediction models

Maximum deviation	C alloy	Mn alloy
Stepwise MRA model	0.1470	0.0588
BP neural network model	0.0868	0.0567
Regression SVM model	0.0682	0.0554

From the table above, the three models have the effect of gradual optimization on the prediction of alloy yield. Among them, the regression SVM model is the optimal prediction one and the maximum deviation values of C and Mn alloys are 0.0682 and 0.0554, respectively, which has a good estimative effect.

The prediction results of the error C alloy yield of the three models are shown in Figure 13.

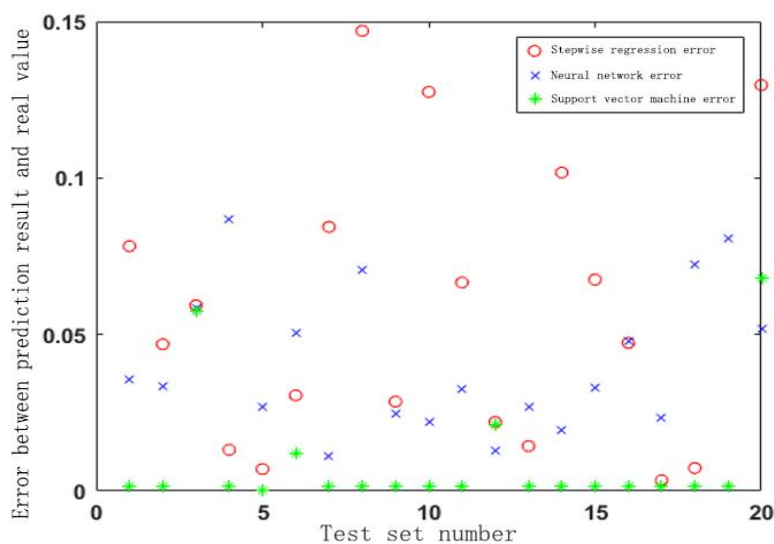


Figure 13. Comparison of prediction results of C alloy yield of three models

As shown, the error value of the regression SVM is significantly smaller than the stepwise MRA error and neural network error.

3.5 Genetic Algorithm Cost Calculation Results

In order to prevent the computation time from taking too long, set the population size as 50 and the maximum genetic algebra as 100 and run the genetic algorithm by means of relay evolution. Through the genetic algorithm, the schemes of alloy batching that can be solved are shown in Table 2.

Table 2. Cost solution results of genetic algorithm

Furnace number	7A06820	7A06851	7A06876	706811.000	7A6787.000
FeVN FeV55N11-A	0.000	0.000	0.000	0.000	0.000
Low alumino-silicon	0.000	0.000	0.000	0.000	0.000
Vanadium nitrogen alloy(imported)	0.000	0.000	0.000	0.000	0.000
Ferrovandium (FeV50-A)	0.000	0.000	0.000	0.000	0.000
Ferrovandium (FeV50-B)	0.000	0.000	0.000	0.000	0.000
Silicon aluminum calcium	0.000	0.003	0.000	0.000	0.000
Silicon aluminum alloy FeAl30Si25	0.000	0.001	0.061	0.064	0.000
Silicon aluminum manganese alloy ball	0.000	0.004	19.403	0.000	13.368
Silicon-manganese surface (Silicon manganese slag)	0.008	0.003	46.576	195.496	215.490
Ferrosilicon (Qualified block)	0.000	0.000	0.000	0.000	0.000
Ferrosilicon FeSi75-B	1.330	7.825	0.000	0.000	0.000
Petroleum coke recarburizer	30.447	14.146	81.442	84.440	51.272
Manganese-silicon alloy FeMn64Si27	0.000	0.000	31.483	0.002	28.833
Manganese-silicon alloy FeMn68Si18	1453.380	1290.456	1470.847	1338.594	1273.184
Silicon carbide (55%)	114.175	8.664	118.716	1.698	102.807
Silicon calcium carbon deoxidizer	0.000	0.138	0.020	0.199	0.000
Original cost(dollar)	3269.11	3250.94	3369.24	3465.80	3185.29
Cost after optimization (dollar)	1812.80	1526.10	1980.26	1827.85	1889.39
Optimization ratio	44.55%	53.06%	41.07%	47.26%	40.68%

Unit: kilogram

According to the above table, the original costs of the five furnace Numbers in the randomly selected forecast are 3269.11, 3250.94, 3369.24, 3465.80 and 3185.29 dollars, respectively. The cost after optimized configuration is 1812.80, 1526.10, 1980.26, 1827.85 and 1889.39 dollars, respectively. The optimization ratio reached 44.55%, 53.06% and 41.07%, 47.26% and 40.68%, respectively. Therefore, this model has a good cost optimization effect.

4. Discussion

To explore the robustness of the model, the unit price of 16 alloys were increased by 20% respectively, and randomly selected furnace number 7A06820 for cost analysis. The results are shown in Table 3.

Table 3. Sensitivity analysis of alloy prices

	Initial cost	Total cost after 20% change in alloy price	Variation	Rate of change
FeVN FeV55N11-A	1812.80	1819.58	6.78	0.3740%
Low alumino-silicon	1812.80	1813.16	0.36	0.0200%
Vanadium nitrogen alloy (imported)	1812.80	1822.98	10.18	0.5616%
Ferrovandium (FeV50-A)	1812.80	1813.75	0.95	0.0524%
Ferrovandium (FeV50-B)	1812.80	1824.27	11.47	0.6327%
Silicon aluminum calcium	1812.80	1810.86	-1.94	-0.1070%
Silicon aluminum alloy FeAl30Si25	1812.80	1810.95	-1.85	-0.1021%
Silicon aluminum manganese alloy ball	1812.80	1823.64	10.84	0.5980%
Silicon-manganese surface (Silicon manganese slag)	1812.80	1823.05	10.25	0.5654%
Ferrosilicon (Qualified block)	1812.80	1810.44	-2.36	-0.1302%
Ferrosilicon FeSi75-B	1812.80	1821.44	8.64	0.4766%
Petroleum coke recarburizer	1812.80	1805.01	-7.79	-0.4297%
Manganese-silicon alloy FeMn64Si27	1812.80	1812.78	-0.02	-0.0011%
Manganese-silicon alloy FeMn68Si18	1812.80	1822.34	9.54	0.5263%
Silicon carbide (55%)	1812.80	1819.66	6.86	0.3784%
Silicon calcium carbon deoxidizer	1812.80	1825.77	12.97	0.7155%

Unit: dollar

According to the above table, when the unit price of each alloy changes by 20%, the maximum total steelmaking cost is 1825.77 dollars, which is 12.97 dollars more than the initial cost and the rate of change is 0.7155%. The minimum cost is 1805.01 dollars, which is 7.79 dollars less than the initial cost and the rate of change is -0.4297%. Among the 16 kinds of alloy raw materials added, the maximum cost change rate is less than 1%. Therefore, the mathematical model established in this paper has strong robustness and is applicable to the decision analysis of steel mills.

5. Conclusion

Due to the problems that steel companies must face when improving their competitiveness by ensuring the quality of molten steel while minimizing the production cost of alloy steel, a mathematical model of deoxidation alloying was established through historical data to predict the alloy yield and to optimize the type and quantity of input alloys. Firstly, the GCA method was used to quantify the influencing factors of alloy yield, which has a more accurate prediction effect. Secondly, the stepwise MRA, the BP neural network and the regression SVM models were used to predict the yield of C and Mn alloys. After comparing the prediction results, we conclude that the regression SVM model is more appropriate. Thirdly, in order to reduce the manufacturer's production cost, the cost optimization model uses the idea of mathematical programming, with the minimum cost of alloys as the objective function, the input amount of alloy materials as the decision variable, and the steel grade composition limits determined by national standards as restrictions. Then, the genetic algorithm was used to calculate the production cost. Finally, to explore the robustness of the model, the unit prices of 16 alloys were increased by 20%, and the largest change rate was 0.7155%, the lowest was -0.4297%, which proved that the mathematical model can be a certain reference value for the current production of iron and steel enterprises. However, the model still has shortcomings. When establishing the cost optimization model, the upper limit of the amount

of alloy material input was not used as a constraint. In production practice, there is usually a maximum amount of alloy material restrictions $M_i \leq G_i$, where G_i is the maximum allowable amount of the i -th alloy material. Therefore, the limitation of the maximum amount of material input will have a certain impact on the cost, but it has not taken into account.

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