Quality Control Model of Ore Processing Based on Elman Neural Network

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Abstract. In this paper, by establishing Elman neural network and decision tree model, the quality control of ore processing is studied and reasonably predicted.Predict the product quality and the temperature corresponding to the target quality. Elman neural network model is established, training set and output set are input for training, and test set is input into neural network to obtain the relative error of real value and training value; After verification, the relative error between our real value and training value is within 100% ± 5%, and the model is accurate; Finally, the input value is substituted to obtain the forecast data.Establish the mathematical model of product qualification rate. The decision tree model is established by using SPSS, and the decision tree system is constructed by using the four factors of system setting temperature, raw ore parameters, process data and final ore quality. Through inspection, our R 2 is 0.999991, close to 1, and the model fitting is good. Compared with other parameters, it can be found that the model has good sensitivity and high accuracy. Finally, the input data is sent into the model to get the final prediction results.

Keywords: ELMAN neural network; Decision tree; Product quality; Temperature corresponding to the target mass; Pass rate.

1. Introduction

In the huge system of industrial production, iron ore is the basic raw material of iron and steel industry, which is widely used in all sectors of the national economy and all aspects of daily life. In recent years, not only has China's steel production increased rapidly, Brazil and India also have many steel production plans, and the steel industry of the former Soviet Union is also recovering. The international competition in ore export and ore source transaction is increasing. In the current economic flood of global integration, if you want to occupy a high place and improve your competitiveness, the only way is to optimize technology and improve professionalism, so as to obtain better ore processing quality [1].

Ore processing is a complex process. In the process of processing, voltage, water pressure and temperature, as important factors affecting ore processing, directly affect the quality of ore products. Processing and determination is a relatively complex work, and the analysis results are affected by factors such as the homogeneity of sample processing, the rationality of purity, the correct selection of analysis methods, and the standardization of analysis operations. In the process of ore collection, processing and testing, sample processing and testing are the key stages to determine the final phase of the ore, and the sample processing method and process flow determine the direction of ore processing. Only after a series of high-quality processing can we have good test results.

Improving the quality of ore processing can directly or indirectly save non renewable mineral resources and energy required for processing, thus promoting energy conservation and emission reduction, and helping to achieve the "double carbon" goal. As a large industrial production country, China's optimization of processing quality is also a strong boost to China's economic and technological development. The research on the quality control of ore processing and reasonable prediction is of great practical value for the collection, processing, analysis and testing of ore samples, and has far-reaching practical significance for social and industrial development.

For raw ores of different types and parameters, this paper analyzes the impact on the four quality indexes A, B, C and D by changing the temperature parameter in the processing method for a period

of time, obtains the corresponding processing and production rules, and reasonably predicts the quality index of ores according to the given temperature parameter.
See Table 1 for the meaning of symbols in this paper

Table 1 Symbol Description

Symbol	Illustration	Company
T_1	System I temperature	℃
T_2	System II temperature	℃
Mse	Mean square error	/
M_i	Raw ore parameter i	/
$Index(A,B,C,D)$	Ore quality(index A，B，C，D)	/

2. Product quality prediction

Using the production and processing data [1], the model is established based on three factors: temperature, ore parameters and ore quality. Based on this, we use Elman neural network algorithm to analyze this problem [2-6] (Figure 1).

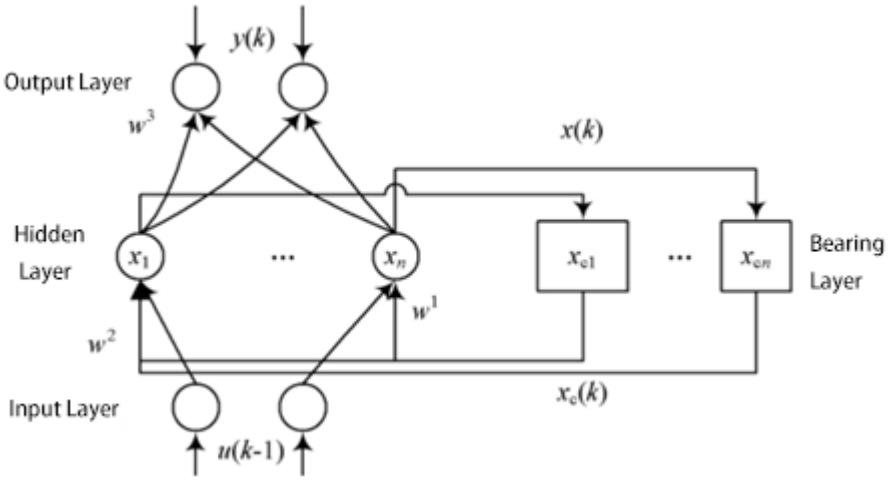


Figure 1 Elman neural network architecture

First, the temperature value and product quality value after data processing are used as the training set. The number of neurons in the input layer is equal to the dimension of the input data feature, and the number of neuron nodes in the output layer is also equal to the dimension of the output data label. Therefore, the temperature T_1, T_2 of System 1 and System 2 , and ore parameter M_1, M_2, M_3, M_4. The neural network is trained by taking 6 factors as input layer indexes and 4 factors of ore quality indexes *IndexA*, *IndexB*, *IndexC* and *IndexD* as output layer indexes.

Set the number of training layers and training times. The number of neurons in the hidden layer is not fixed. If fewer hidden layer neurons are selected, the learning degree of the network will be reduced or even unable to learn; When the number of nodes is large, the network training process will slow down, and it is difficult to predict the situation. Only when the number of hidden layer neurons is controlled within a reasonable range, can the network model learn well. Therefore, in order to reduce the error and obtain a more accurate model, we deduce the range of hidden layer nodes according to the following formula, determine the optimal number of hidden layer nodes, and train the input layer and output layer within the range to obtain the minimum error rate and prediction model:

$$h = \sqrt{m+n} + a \quad (1)$$

Where, h is the number of hidden layer nodes, m is the number of input layer nodes, n is the number of output layer nodes, and a is generally taken as a constant between 1-10. In this question, m=6, n=4, and the value range of h is 4-13.

The receiver layer is used to remember the output value at a time point on the hidden layer, so the number of neurons in the receiver layer is the same as that in the hidden layer, which is 4-13.

After training with training set and output set, the input index of training set is used as the input of test set (Figure 2):

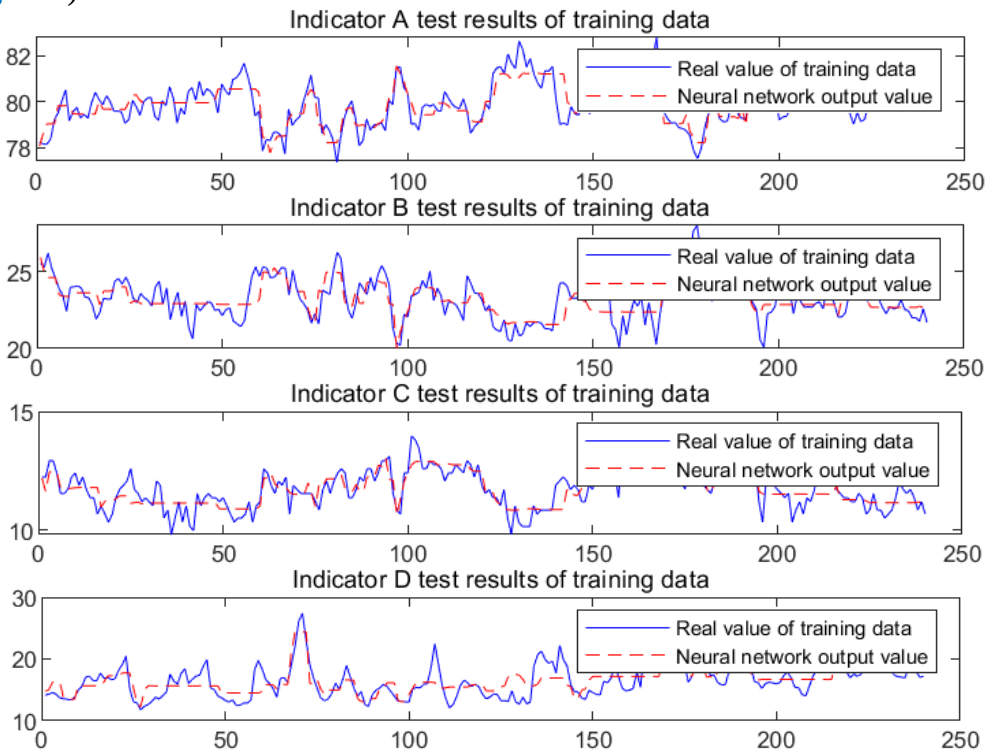


Figure 2 Elman Neural Network Training Data Test Results

Calculate the relative error between the test result of training data and the true value (Figure 3):

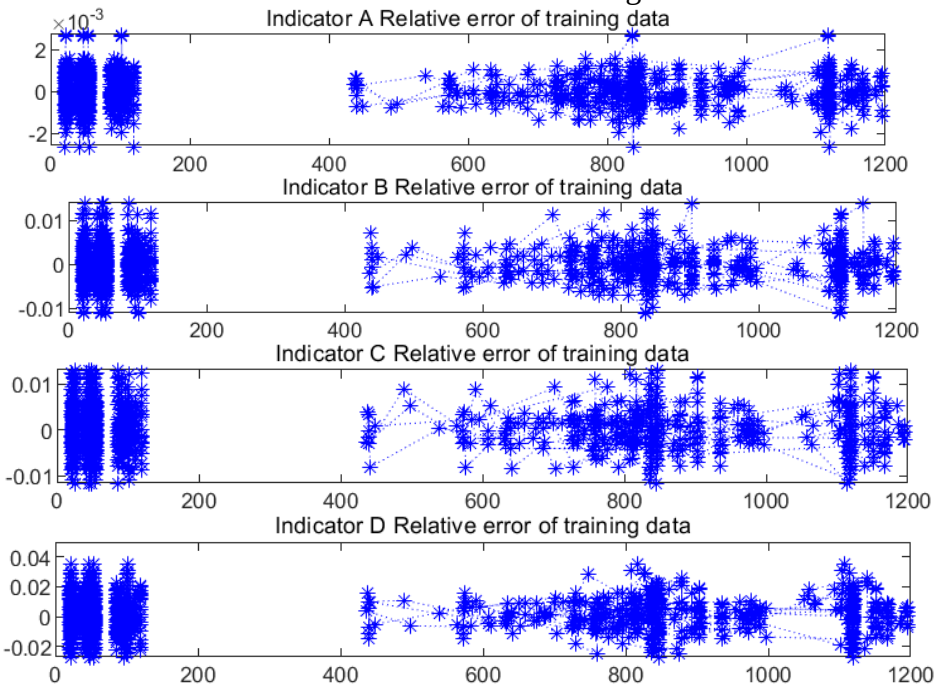


Figure 3 Relative Error of Elman Neural Network Training Data

According to the relative error image of the training data test result obtained by Elman neural network, it can be seen that the relative error between the prediction result and the expected value is 100% ± 10%. According to the test, the Elman neural network model is established.
Substitute the input variables of the predicted values into the neural network to obtain the results (Table 2):

Table 2 Product Quality Calculation Results

Time	System I temperature	System II temperature	Indicator A	Indicator B	Indicator C	Indicator D
01-23	1404.89	859.77	80.051511	23.245402	10.759963	17.055273
01-23	1151.75	859.77	79.950002	23.251097	11.989014	15.784485

3. Determination of temperature corresponding to target mass

In this section, Elman neural network algorithm is used to analyze the problem according to the raw ore parameters and the set temperature of the product target quality backstepping system provided in the previous chapter [2].

First, the raw ore parameters and product quality values after data processing are used as training sets. The number of neurons in the input layer is equal to the dimension of the input data feature, and the number of neuron nodes in the output layer is also equal to the dimension of the output data label. Therefore, we take the ore parametersM_1, M_2, M_3, M_4 and the ore quality *IndexA*, *IndexB*, *IndexC*, *IndexD* as the input layer indicators, and the temperature T_1, T_2 of System1 and System2 systems as the output layer indicators to train the neural network.

After training with training set and output set, the input index of training set is used as the input of test set (Figure 4):



Figure 4 Elman Neural Network Training Data Test Results

Calculate the relative error between the test result of training data and the real value (Figure 5):

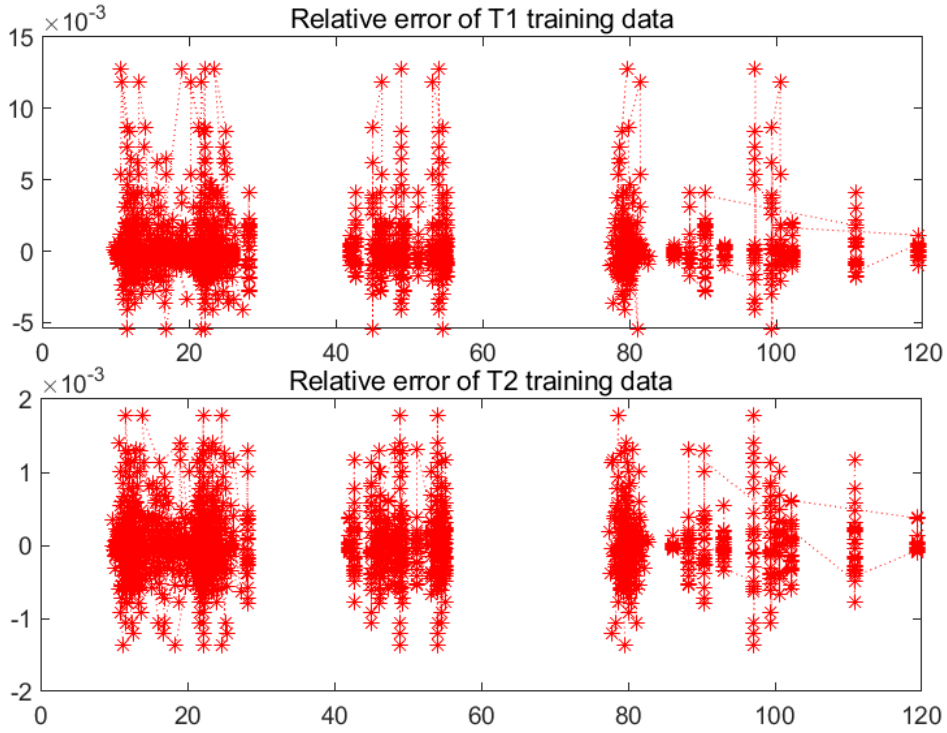


Figure 5 Relative Error of Elman Neural Network Training Data

According to the relative error image of the training data test result obtained by Elman neural network, it can be seen that the relative error between the prediction result and the expected value is 100% ± 5%. According to the test, the Elman neural network model is established.

Substitute the input variables of the predicted values into the neural network to obtain the results (Table 3):

Table 3 Temperature Corresponding to Target Mass

Time	Indicator A	Indicator B	Indicator C	Indicator D	System I temperature	System II temperature
2022-01-24	79.17	22.72	10.51	17.05	1242.6099	781.8625
2022-01-24	80.10	23.34	11.03	13.29	1188.1701	753.2421

4. Mathematical model of product qualification rate

Using the production and processing data from 2022-01-25 to 2022-04-07, namely temperature, process data, ore parameters and ore quality, the model is established [1] The model predicts the ore quality by specifying the system setting temperature, process data and ore parameters, so as to obtain the ore product qualification rate [7-10].

Due to the large number of data features in building the neural network, the number of iterations increases exponentially, and the training time is prolonged, we adopt a more three-dimensional decision tree model for dynamic fitting and prediction.

Let X be a discrete random variable with finite value, and its probability distribution is:

$$P(X = x_i) = p_i\ , i = 1,2, \dots , \mathrm{n} \tag{2}$$

Then the entropy of random variable X is defined as:

$$H(X) = -\sum_{i=1}^{n} p_i log p_i \tag{3}$$

Set random variables (X, Y). The conditional entropy $H(Y|X)$ represents the uncertainty of the random variable Y under the condition that the random variable X is known.

$$H(Y|X) = \sum_{i=1}^{n} p_i H(Y|X = x_i) \tag{4}$$

$$p_i = P(X = x_i), i = 1,2, \dots, \mathrm{n} \tag{5}$$

$$g(D, A) = H(D) - H(D|A) \tag{6}$$

Given the definition, the information gain $g(D, A)$ of feature A to training data set D is the difference between the entropy $H(D)$ of set D and the conditional entropy $H(D|A)$ of D under given conditions of feature A:

$$g(D, A) = H(D) - H(D|A) \tag{6}$$

The information gain $gR(D, A)$ of feature A to training dataset D is defined as the ratio of its information gain $g(D, A)$ to the entropy $HA(D)$ of training dataset D about the value of feature A:

$$gR(D, A) = \frac{g(D,A)}{HA(D)} \tag{7}$$

$$H_A(D) = -\sum_{i=1}^{n} \frac{|D_i|}{|D|} log_2 \frac{|D_i|}{|D|} \tag{8}$$

n is the number of characteristic A values.

Gini index $Gini(D)$ represents the uncertainty of set D, and Gini index $Gini(D, A = a)$ represents the uncertainty of set D after $A = a$ segmentation (similar to entropy). The smaller the Gini index, the smaller the uncertainty of the sample.

In the classification problem, suppose there are K classes, and the probability that the sample points belong to class k is pk, then the Gini index of the probability distribution is defined as:

$$Gini(p) = \sum_{k=1}^{K} p_k(1 - p_k) = 1 - \sum_{k=1}^{K} {p_k}^2 \tag{9}$$

For this problem, the decision tree model is established through SPSS, and the parameters are as follows (Table 4, Figure 6):

Table 4 Relevant Parameters of Decision Tree

	MSE	RMSE	MAE	MAPE	R^2
Training Set	0.001	0.035	0.014	0.018	0.997
Test Set	1.05	1.025	0.856	1.082	-1.075

*Blue represents real value, green represents predicted value

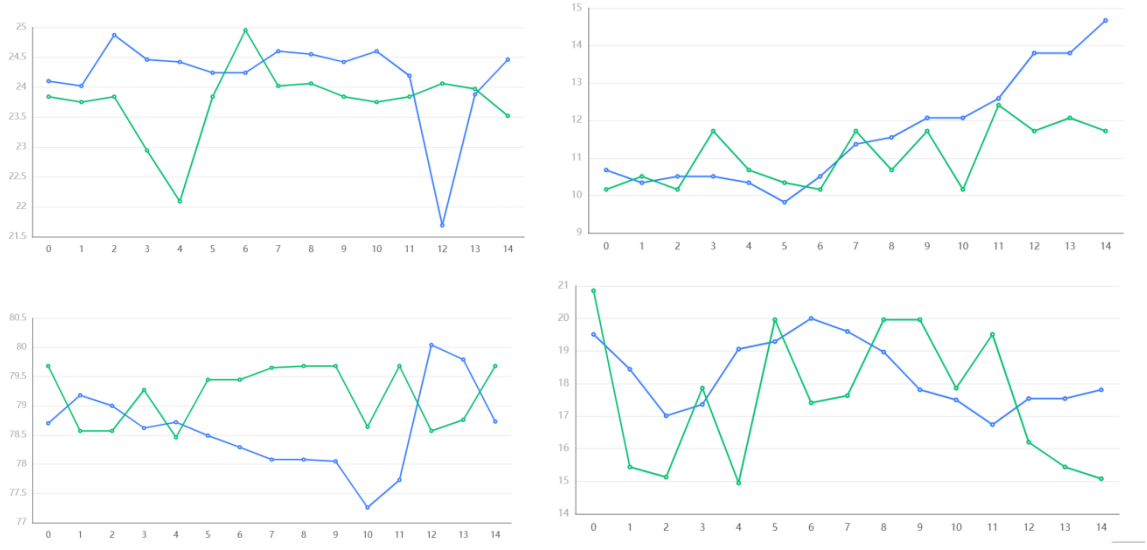


Figure 6 Decision tree fitting data

Substitute the input variable of the predicted value into the solution to get the result (Table 5):

Table 5 Prediction Results

Time	System I set temperature	System II set temperature	Pass rate
2022-04-08	341.40	665.04	0.50624413
2022-04-09	1010.32	874.47	0.30996352

5. Model evaluation and promotion

The Elman neural network model presented in this paper can not only well express the relationship between mineral processing quality and system temperature, raw stone parameters, but also has the following advantages:

(1) The model has high accuracy, and also ensures the preciseness of the structure.

(2) Matlab and SPSS software are used for data processing of this model, which requires high accuracy.

(3) This model uses big data for analysis to get results, which is also applied to other problems

(4) In addition, this model is also applied to the identification of benign and malignant medical tumors, intelligent driving and other related fields, with profound realism and huge application prospects.

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