Research on Intelligent Decision Making Technology for Coal Sorting System

Lingyue Li[1,*], Pengfei Yun[2], Fengliang Guo[2], Xianpeng Wang[1], Jie Li[1], Ziyao Wang[1], Xiaoping Tang[1], Xiaoping Ding[1]

[1]Huadian Electric Power Research Institute Co., Ltd., Beijing, 100031, China
[2]Shaanxi Huadian Yuheng Coal and Electricity Co., Ltd., Yulin, Shaanxi, 719000, China

*Corresponding author: 1263653199@qq.com

Abstract. This paper introduces the research on intelligent decision-making technology for coal sorting system. In order to solve the problems of high dependence on manual experience, insufficient automation level, and lack of unified data management platform in the production process of Xiaojihan Coal Mine Coal Preparation Plant, an intelligent model of the process system was constructed through experimental and theoretical innovation research. The industry challenges of applying intelligent coal preparation technology were overcome, and a coal sorting intelligent decision-making system with independent intellectual property rights was developed. Industrial experiments were conducted to achieve flexible production of the coal preparation plant.

Keywords: intelligent decision; coal; sorting.

1 Introduction

The main coal preparation equipment in China's coal preparation plants is heavy medium coal preparation equipment [1-3]. Most of the heavy medium coal preparation equipment in coal preparation plants is still manually operated, which has poor manual operation effect and high labor intensity, bringing very unfavorable factors to the production of coal preparation plants[4]. In order to enable Xiaojihan Coal Preparation Plant to have the ability to make quick and scientific decisions during production, respond quickly to fluctuations in the coal market, automatically adjust key production parameters, and achieve flexible production, a smart brain decision-making system for coal preparation plants has been developed [5-6].

2 Prediction of the Sorting Effect of Heavy Medium Shallow Groove

To predict and optimize the effect of heavy medium sorting, when the sorting density changes, density prediction is achieved by shifting the distribution curves of different

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sorting densities. Currently, there are two commonly used methods for shifting the distribution curves, Ep value unchanged and I value unchanged.

According to the variation pattern of model parameters, it is possible to predict the distribution curve and sorting process indicators under different sorting densities. It is known that the sorting density of the heavy medium shallow groove sorter is δ p=1.557g/cm^3, and the Ep value is 0.04. By translating the distribution curve based on the principle of constant Ep value, the distribution rates of clean coal and gangue can be obtained, enabling the prediction of clean coal yield and ash content at different sorting densities.

By establishing a reselection process database and a production evaluation model library, analyzing the properties of raw coal, calculating theoretical indicators such as selectivity and quantity quality efficiency, and analyzing historical data of coal quality; Based on the characteristics of raw coal, considering constraints such as product quality and yield, and following the principles of maximizing clean coal yield and economic benefits, search for the corresponding ash content of clean coal that maximizes economic benefits; On this basis, using historical data such as raw coal ash content, clean coal ash content, non-magnetic content, and sorting density, as well as big data technology, the sorting density under known clean coal ash content and sorting conditions is predicted to obtain the sorting density that maximizes economic benefits; By fully integrating models such as intelligent medium addition, intelligent heavy medium control, and intelligent pressure filtration, a smart brain decision-making model for coal preparation plants is constructed to achieve flexible production.

In response to the complex situation of multiple coal types being selected, multiple products, multiple indicators, and varying product inventory levels, linear programming, intelligent optimization algorithms, and other technologies are used to optimize the product structure of the coal preparation plant. The refined coal yield, calorific value, ash content, sulfur content, moisture content, sales volume, and other limiting indicators are used to comprehensively consider user requirements as well as the prices and costs of different quality products, thereby maximizing the economic benefits of the coal preparation plant.

Examine the product price measurement method of Xiaojihan Coal Preparation Plant, establish a prediction model for clean coal quality indicators, conduct correlation tests on calorific value, total sulfur, clean coal ash content, volatile matter, and total water, determine input parameters based on the strength of the correlation between parameters and calorific value, and determine the optimal input parameters based on the accuracy after training. It can be analyzed that the main factors highly correlated with calorific value are ash content and volatile matter, and ash content is basically linearly correlated with calorific value.

3 Sorting Density Prediction based on Big Data

Collect data on ash content of clean coal, ash content of selected raw coal, magnetic content, and sorting density from the coal preparation plant. Use BP neural network to establish a relationship model between raw coal ash content, clean coal ash content, magnetic content, and sorting density. Based on the maximum economic benefit of clean coal ash obtained under certain raw coal ash conditions, call the model to predict the sorting density required for producing the clean coal ash content.

Perform data cleaning and use the standard deviation method to remove outliers in ash content data. The comparison before and after is shown in Figure 1.

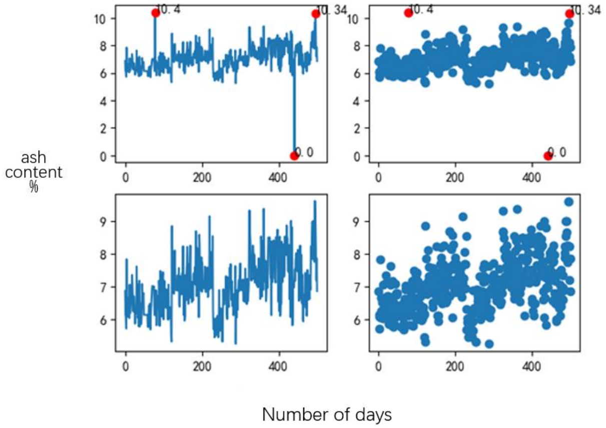

Fig. 1. Comparison before and after removing outliers in ash content data using standard deviation method

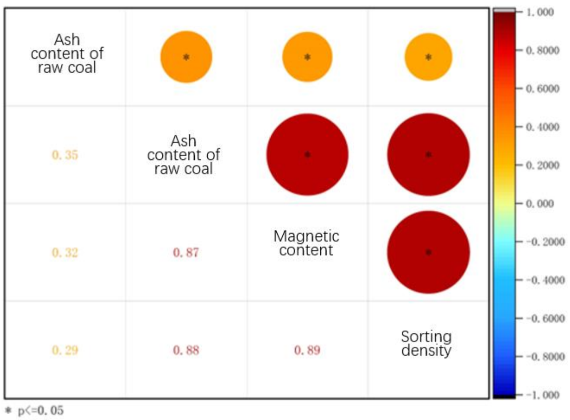

Fig. 2. Heat map of correlation coefficient matrix

From the correlation coefficient chart, it can be seen that the correlation coefficients between sorting density and ash content and magnetic content of clean coal are 0.88 and 0.89, respectively, indicating a high degree of correlation. The correlation coefficient between sorting density and selected raw coal ash content is only 0.29, but from a significance perspective, three parameters including clean coal ash content, magnetic content, and selected raw coal ash content are significantly correlated with sorting density. From Figure 2-3, it can also be seen that the sorting density has a significant linear relationship with the ash content and magnetic content of clean coal.

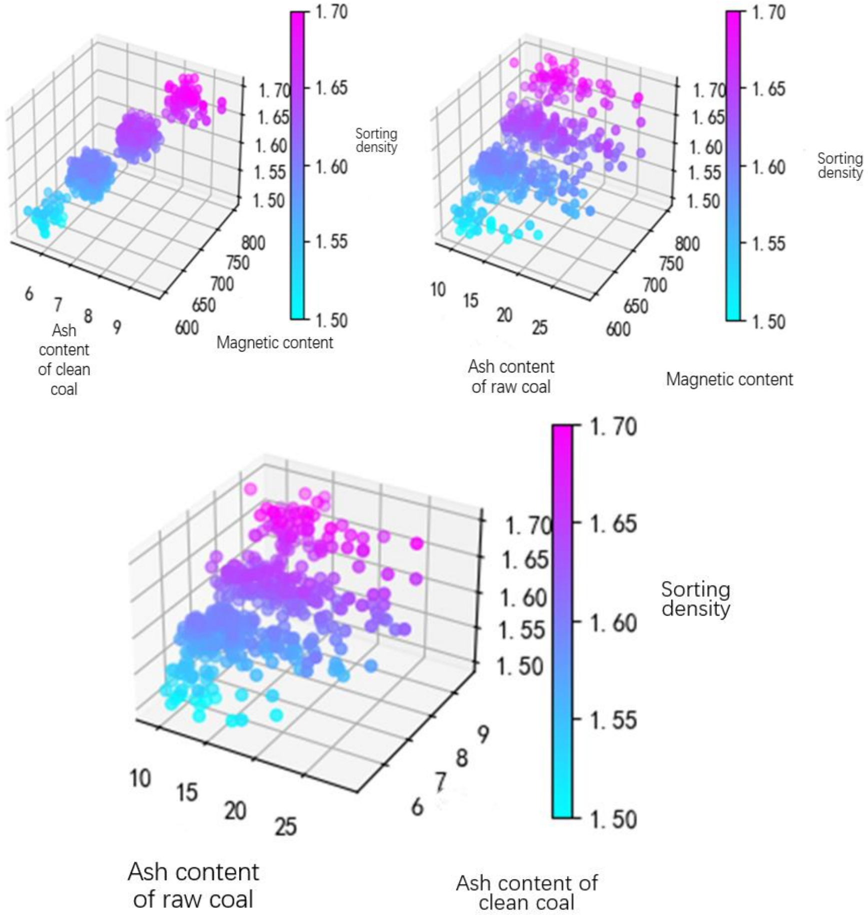

Fig. 3. Three dimensional graph of sorting density prediction effect

4 Prediction of Sorting Density Based on BP Neural Network

A BP neural network was designed to predict sorting density using parameters such as ash content of clean coal, ash content of selected raw coal, and magnetic content as inputs. Based on the order of the correlation coefficient between the input parameters and sorting density, three combinations of input parameters were used for comparison. The comparison of sorting density prediction results and prediction accuracy is shown in Figure 4-6.

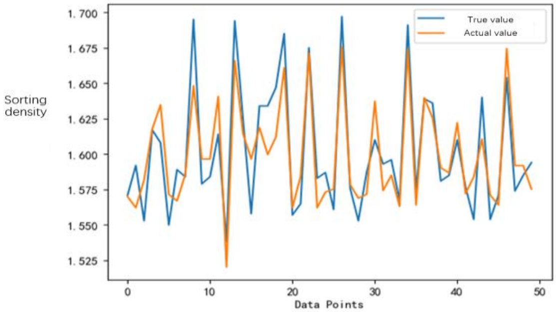

Fig. 4. Single parameter sorting density prediction

From Figure 4, it can be seen that when only using the magnetic content with the highest correlation coefficient to predict the sorting density, the predicted value deviates greatly from the actual value. When the sorting density is at its maximum and minimum values, the prediction error is significant.

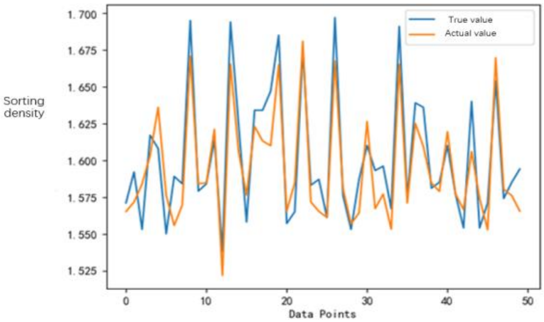

Fig. 5. Prediction of Two Parameter Sorting Density

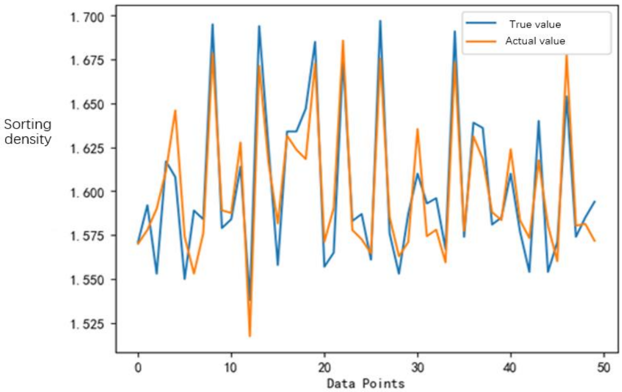

Fig. 6. Prediction of Three Parameter Sorting Density

From Figure 5, it can be seen that when using the magnetic content with the highest correlation coefficient and the fine coal ash fraction to predict the sorting density, the deviation between the predicted value and the actual value is small. When the sorting density is at its minimum, the prediction error decreases, but when it is at its maximum, the prediction error remains large.

From Figure 6, it can be seen that when using magnetic content, clean coal ash content, and selected raw coal ash fraction to predict the sorting density, the deviation between the predicted value and the actual value is the smallest. When the sorting density is at the maximum and minimum values, the prediction error is small, making it the optimal model.

Based on the prediction accuracy of different input parameter combination models mentioned above, the model with magnetic content, clean coal ash content, and selected raw coal ash as inputs and sorting density as output has the best prediction accuracy for all four indicators. R^2, MAE, MSE, and RMSE are 0.83, 0.1, 0.00, and 0.20, respectively.

5 Prediction of Sorting Density Based on LSTM

To establish a sorting density prediction model using LSTM, the parameters that need to be adjusted include the number of input layer nodes, output layer nodes, hidden layer nodes, hidden layer number, learning rate, time steps, etc. Due to the small predicted sorting density value, the learning rate parameter is set to 0.0005, with a focus on adjusting the number of hidden layer nodes, layers, and time steps. Select the optimal number of hidden layers and nodes based on empirical formulas:

$$l = \sqrt{m + n} + \alpha \tag{1}$$

In the formula, l is the number of hidden layer nodes, m is the number of input layer nodes, n is the number of output layer nodes, and α is any integer between 0-9. To determine the optimal network structure, models with different network structures were designed for comparison.

Through analysis, it was found that the number of hidden layers and hidden layer nodes is not necessarily better. Excessive number of hidden layers and nodes will increase model complexity, training time, and accuracy. Therefore, this article chooses an LSTM network structure with 6 hidden layers, each containing 12 neurons. After completing the training, the remaining 25% (50 groups in total) of the dataset was used as the test set, and some of the predicted results were extracted as shown in Table 1.

Table 1. Comparison of Prediction Results

Real density	Predict density	Absolute error	Relative error
1.642	1.649	0.007	0.402
1.636	1.635	0.001	0.066
1.652	1.649	0.003	0.190

Real density	Predict density	Absolute error	Relative error
1.655	1.656	0.001	0.082
1.657	1.645	0.012	0.724
1.635	1.643	0.008	0.478
1.641	1.638	0.003	0.202
1.652	1.654	0.002	0.141
1.663	1.653	0.010	0.598
1.648	1.646	0.002	0.107
1.634	1.635	0.007	0.428

From Figure 7, it can be seen that the predicted results of the LSTM model are basically consistent with the actual density trend. Figure 7 shows that the maximum absolute error is 0.012g · cm-3 and the minimum is 0.001 g · cm-3. The density predicted by the model can be kept below the percentile error. This indicates that using time series for deep mining of suspensions and selectively remembering the inherent patterns of input time over a certain period of time can effectively predict the trend of suspension density values, thereby further improving prediction accuracy. The application of this model to the on-site heavy medium sorting system can further improve the reliability of the online given sorting density. By analyzing real-time raw coal ash content, setting clean coal ash content, historical raw coal ash content, and clean coal ash content, the LSTM model can provide timely sorting density values for the next equidistant time, which can greatly improve the stability of on-site production.

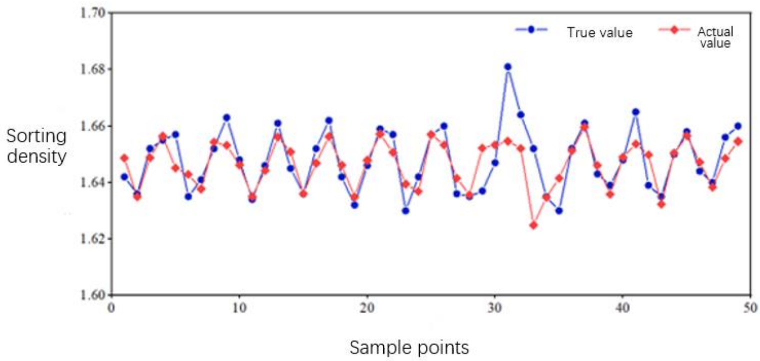

Fig. 7. Comparison of Prediction Results

6 Analysis of Production and Operation Status

Based on the completion status of the issued production plan, combined with scheduling records, delayed parking due to faults, equipment maintenance plans, raw coal quality data, and accumulated historical production and operation efficiency information, establish a product quality monitoring and early warning system to comprehensively analyze the production and operation effects. By reading online and offline data from the information center, organize and analyze the data for decision-making.

Based on online ash analyzer data and manual offline ash data, monitor the ash content of the refined coal product. When the ash content of the refined coal deviates from a certain threshold of the predicted ash content, issue warnings and control based on existing data: determine that the ash content deviation of the refined coal is greater than the threshold, conduct preliminary checks on the particle size and density composition of the raw coal. If the change in ash content of the raw coal is caused by changes in the properties of the raw coal, it is necessary to conduct screening, float and sink checks, update the raw coal quality information, and if there is no significant change, proceed to the next step; Fine tune the Ep value. If the actual ash content of the clean coal is close to the predicted ash content after adjustment, it indicates an increase in the fine particle size of the feed. Otherwise, it indicates a decrease in the fine particle size of the feed. If the Ep value needs to be adjusted too much to make it close, it is necessary to perform a single machine inspection and equipment inspection to analyze the current equipment Ep value and whether there are any faults. If there are no problems, proceed to the next step.

If the non-magnetic content of the suspension is too low, it indicates that the medium system is unstable and affects the sorting effect. If it is too high, it indicates poor concentration treatment effect, resulting in high viscosity of the suspension and inability to sort properly. It is recommended to check the coal slurry water treatment process.

7 Conclusion

A correlation model between sorting indicators and raw coal properties was established, and a genetic algorithm was used to optimize the ash content of clean coal that conforms to the principle of maximizing economic benefits; Based on big data analysis of production parameters in Xiaojihan Coal Preparation Plant, a neural network was used to construct a sorting density prediction model, achieving accurate and intelligent setting of sorting density. Based on the intelligent decision-making system for coal preparation, according to the properties of raw coal and the market price of clean coal, with the goal of maximizing the economic benefits of the enterprise, the optimized coal preparation product structure and sorting process are determined in real time; Since its operation, the system has been able to make quick and scientific decisions based on market demand, automatically adjust key production parameters, and achieve flexible production. With low coal quality fluctuations and the same operating conditions, the yield of clean coal has increased by 0.3%, increasing economic benefits by 12 million yuan per year.

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