Research on Intelligent Operation of Coal Preparation Heavy Medium Separation System

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Abstract. This paper introduces the research and application of intelligent operation of dense medium separation system in coal preparation. A valve opening prediction model was built based on support vector mechanism to achieve intelligent control of water replenishment valve, diversion valve, and medium addition amount. Since the application of the intelligent heavy medium sorting system, the system has operated stably and achieved good results.

Keywords: intelligent operation; heavy medium; separation

1 Introduction

The construction of intelligent coal preparation plants has become a key development direction for the national washing industry [1-2].At present, Xiaojihan Coal Mine Coal Preparation Plant has two sets of heavy medium shallow groove systems, and density adjustment requires manual setting of sorting density and manual operation for density adjustment [3]. Moreover, the current pressure difference density meter detection accuracy is not accurate enough. The composite density is tested every 2 hours on site and feedback is sent to the scheduling for density adjustment, but the density adjustment lags behind. Adjusting the density through the water replenishment valve above the mixing tank takes a longer time. The flexibility and error in controlling the density of qualified media are poor, making it difficult to accurately ensure the stability of the composite density [4]. The density fluctuation range is large, resulting in fluctuations in product quality. The scheduling personnel adjust the density based on the laboratory test results, but there is a significant lag, and production is under passive control [5-6]. To solve the existing problems of the heavy medium separation system in Xiaojihan Coal Preparation Plant, this chapter conducted research on intelligent control of the coal preparation heavy medium separation system [7-8].

2 Xiaojihan Intelligent Dense Medium Control System

Develop an intelligent heavy medium control system that utilizes digital twin technology to construct a three-dimensional digital twin model of all elements involved in

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production activities in a virtual environment at a 1:1 ratio, mapping the entire production process environment to the virtual model. At the same time, the 3D digital twin environment connects the data involved in the real production line through interfaces and deeply integrates it with heterogeneous data from multiple sources, enabling it to accurately simulate the production process and behavioral characteristics of the working face, achieve real-time collection of working face data, and achieve the mapping from reality to virtuality.

The intelligent heavy medium system can display various equipment and related important parameters (such as composite density, magnetic content, composite barrel position, diversion valve opening, and water replenishment valve opening) on the interface, and real-time display on-site data. By controlling the values of each parameter, the heavy medium system can operate intelligently and achieve stable density in heavy medium sorting.

3 Establishment of Re Mediation System Model

3.1 Research on the Coupling Characteristics of Density Control Variables in Heavy Media

Determine the sorting density of the heavy medium shallow trough based on the original coal flotation experiment, draw the raw coal selectivity curve, and obtain the sorting density setting value according to the ash content of the clean coal required for production. The selection density setting value is obtained based on the ash content requirement range and other production data, which is called ash closed-loop control. In actual production, due to the significant fluctuations in coal quality from different sources, the selectivity of raw coal varies, and the density setting value changes greatly. A single sorting density cannot meet production requirements.

The traditional ash closed-loop control strategy is to read the ash content data of clean coal measured by the ash analyzer online and perform corresponding control. When the ash content of clean coal exceeds the reasonable range, the sorting density is changed by adjusting the opening of the water replenishment valve and diversion valve. In addition, water replenishment and diversion will also have an impact on the position of the blending tank, the content of magnetic substances, and the ash content of raw coal, and the process variables will exhibit strong coupling characteristics. When the coal quality changes and the sorting density does not change, the fine coal ash will exceed the reasonable range. At this time, adjusting the sorting density again will lead to a strong coupling between variables, which will result in a poor control effect of the heavy medium shallow groove and a lag in adjustment, which is not conducive to controlling product quality.

By studying the coupling relationship between various variables in the production process of heavy medium shallow trough and combining it with the production data of Xiaojihan Coal Preparation Plant, a suspension density prediction model can be constructed to achieve real-time prediction of suspension density for different sources of raw coal, thereby achieving closed-loop control of ash content and improving product quality and production efficiency.

3.2 Sorting Density Prediction Algorithm and Model

Based on the floating and sinking experiments of raw coal, clean coal, and gangue under different working conditions, corresponding selectivity curves and distribution curves were drawn. Combined with the production data of Xiaojihan, a multivariate long short-term memory network prediction model was constructed. This model is trained using production data from Xiaojihan, with raw coal ash content, refined coal ash content, etc. as inputs for training the model, and actual suspension density as the model output. By using the sorting effect prediction module, optimize the sorting density predicted by the model based on the principle of maximizing the yield of clean coal or maximizing economic benefits.

3.3 Model Construction of Multi Parameter Heavy Medium Control System

The density of heavy medium suspension is the core objective of heavy medium sorting control, mainly maintained through diversion, water replenishment, and medium addition to maintain stability. The most traditional method is manual control, where operators rely on experience to control valve opening based on product quality. This method has strong lag and low accuracy. To stabilize the control of suspension density, data-driven analysis is adopted for heavy medium control systems with strong hysteresis and coupling, and appropriate opening values for diversion valves and makeup valves are given. When the quality of raw coal changes, the density prediction model constructed based on big data analysis can provide suitable sorting density and achieve intelligent control through the constructed prediction model such as valve opening. The density of the suspension is measured in real-time by an online density meter, and its error value is used for feedback adjustment to achieve stable suspension density and ensure product quality.

Using the LSTM model, intelligent prediction of suspension density is achieved based on production data of raw coal ash content and refined coal ash content. The popular algorithm in the field of machine learning, support vector machine, is used to predict parameters such as valve opening. This algorithm has the advantages of strong robustness and high prediction accuracy.

In the construction of the SVM model, the suspension density r, the position of the mixing tank h, and the magnetic content c are used as inputs, and the opening degrees of the diversion valve Q_f and the replenishment valve Q_b are used as outputs. The established model functions are as follows:

$$\begin{cases} Q_f = f(\rho, h, c) \\ Q_b = f(\rho, h, c) \end{cases} \tag{1}$$

The specific steps are as follows:

(1) Determine input and output data, standardize data;
(2) Model regression training to obtain model parameters;
(3) Algorithm optimization, parameter optimization;
(4) Output the results of anti standardization and conduct error evaluation analysis.

Using production data from Xiaojihan Coal Preparation Plant, a valve opening SVMR prediction model was established by training 75% of the data. The remaining 25% (125 sets) of test set data were used to evaluate the model. The evaluation method is as shown in Equation 2.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i' - y_i)^2}{\sum_{i=1}^{n} (\bar{y}_i - y_i)^2} \tag{2}$$

The molecule represents the sum of the squared differences between the true value and the predicted value; The denominator represents the sum of the squared differences between the true value and the mean. Based on the value of R^2, the quality of the model can be judged within the range of [0,1]. The larger the calculation result, the better the fitting effect of the model, and vice versa.

Using the R^2 evaluation criteria, the SVMR model parameters were first trained. The training results are shown in Figure 1. It can be seen from the figure that as the penalty coefficient C increases, R^2 continues to increase, while as the gamma increases, R^2 continues to decrease. Therefore, the optimal model parameters determined are C=198, gamma=0.001, and R^2=0.885.

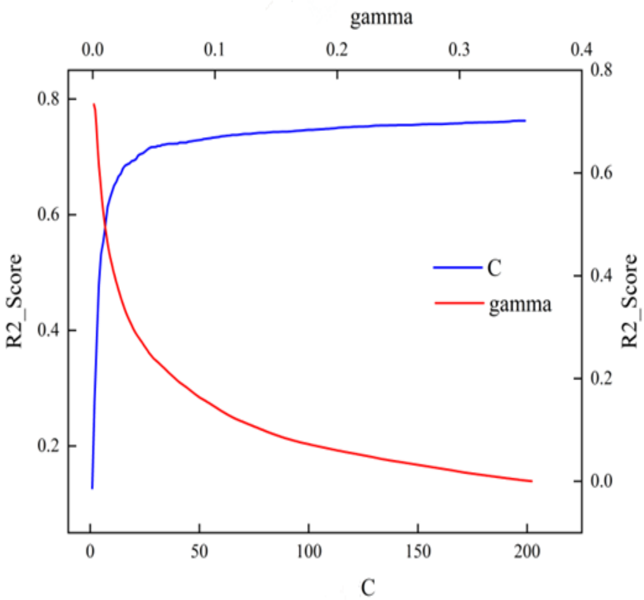


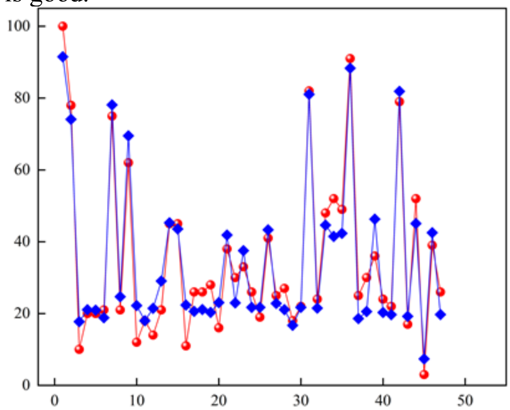
Fig. 1. SVMR parameter optimization

After determining the model parameters, the model is used to predict the data in the test set and compare it with the true values. The predicted results are shown in Table 1, and the prediction effect is shown in Figure 2.

Table 1. Prediction results and errors of water replenishment valve opening

Actual opening of the water replenishment valve	Predicted opening of water replenishment valve	Relative error
78	74.10	0.05
10	17.74	0.77
20	21.07	0.05
20	20.93	0.05
39	44.00	0.13
21	18.84	0.10
75	78.10	0.04
15	20.19	0.35
21	24.69	0.18
98	90.11	0.08
62	69.48	0.12
92	84.51	0.08
18	18.00	0.00
14	21.45	0.53
21	29.04	0.38
45	45.28	0.01
45	43.55	0.03
26	20.61	0.21
26	21.13	0.19
28	20.32	0.27
16	23.06	0.44

From Table 1, it can be seen that the maximum relative error between the predicted and actual opening of the water replenishment valve is 0.53%, and the minimum relative error is 0.01%. The prediction effect is shown in Figure 2, and it can be seen that the prediction effect is good.



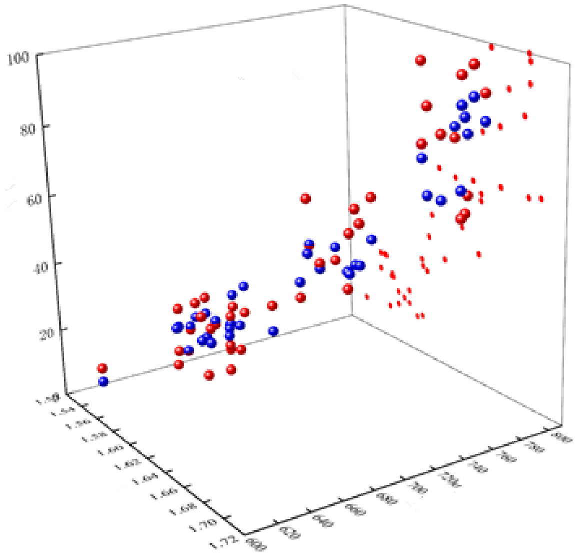


Fig. 2. Comparison between predicted and actual values of water replenishment valve

3.4 Prediction of Diversion Valve Opening

The optimal model parameter for predicting the opening of the diversion valve is C=36, gamma=0.001, R^2=0.819.The partial data of the prediction results are shown in Table 2, and the prediction effect is shown in Figure 3.

Table 2. Prediction Results and Errors of Diverter Valve Opening

Actual opening of the water replenishment valve	Predicted opening of water replenishment valve	Relative error
5.00	5.85	0.17
2.00	2.81	0.40
46.00	43.03	0.06
1.00	4.61	3.61
6.00	4.09	0.32
10.00	11.90	0.19
39.00	40.74	0.04
36.00	32.00	0.11
22.00	21.65	0.02
18.00	19.16	0.06
37.00	40.73	0.10
10.00	11.82	0.18
43.00	45.27	0.05
26.00	25.33	0.03

36.00	42.65	0.18
44.00	41.69	0.05
47.00	41.60	0.11
5.00	4.48	0.10
38.00	39.16	0.03
46.00	51.37	0.12

From Table 2, it can be seen that the maximum relative error between the predicted and actual opening of the diversion valve is 3.61%, and the minimum relative error is 0.03%. The prediction effect is shown in Figure 3, and the prediction effect is good.

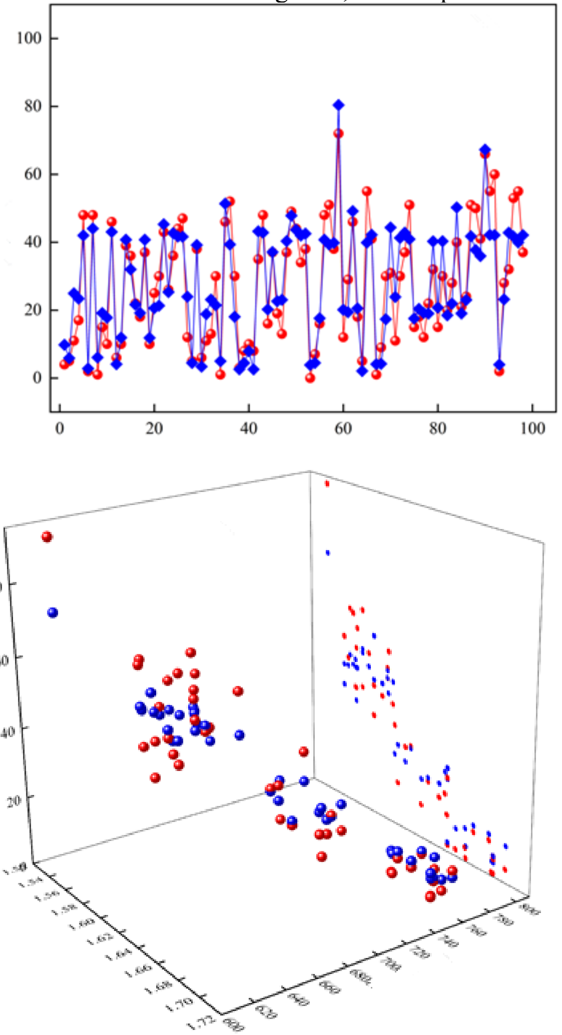


Fig. 3. Comparison between predicted and actual values of diversion valve

3.5 Prediction of Add Time

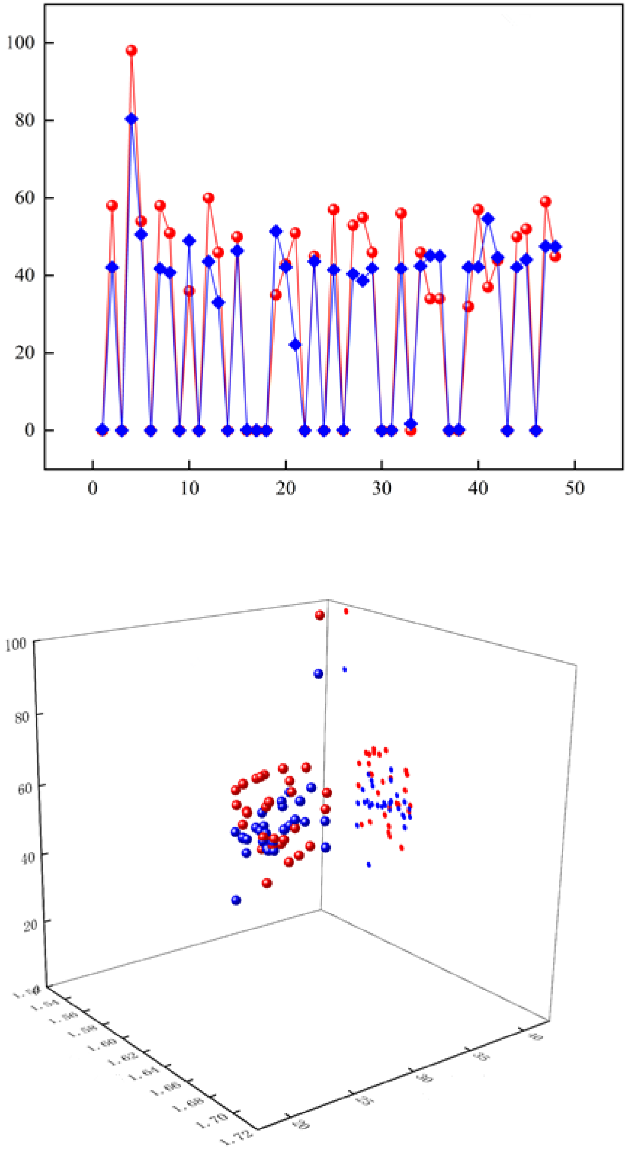


Fig. 4. Comparison chart between predicted and actual values of time addition

When the level of the concentrated medium tank is too low, the actual production will stop adding medium to maintain the level of the concentrated medium tank, and the model predicts the correct result. As shown in Figure 4, when it is necessary to add a medium, the model's prediction performance is close to the actual value, indicating that the model can provide real-time and correct medium addition time prediction, which can improve the stability of suspension density.

4 Conclusion

A valve opening prediction model was built based on support vector mechanism to achieve intelligent control of water replenishment valve, diversion valve, and medium addition amount. Since the application of the intelligent heavy medium sorting system, the system has operated stably and achieved good results. The density fluctuation range of the heavy medium suspension is ± 0.01g/cm^3.

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