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Intelligent Control System Design for Vertical Mill Based on Data Mining

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Abstract—It is difficult to effectively control the vertical grinding process of raw materials due to its characteristics of strong coupling, non-linearity and large hysteresis. This paper proposes a vertical mill intelligent control system based on data mining to predict the operating conditions of the slag grinding system. Taken into consideration corresponding shortcomings of each algorithm, we combine several algorithms to propose a feature extraction method for analyzing operating conditions and determining the indicators that affect the operation. Next, we clustered the healthy operating conditions to get the distribution of health conditions, and based on this, established a healthy operating condition library. The operational data are compared with the reference conditions, and the prediction model is trained using the ARIMA algorithm to predict the trend of the corresponding indicators. To verify the effectiveness and practicability of the method, we developed a software system and applied it to the actual case analysis. It is concluded that the vibration of the control group is decreased by an average of 10%, and the average power consumption per ton is decreased by 6.05%. According to the total number of vertical mills of 350,000 tons, the average power consumption per ton is 43.5 degrees. Therefore, the total annual power consumption will be 1.5225 million kilowatt hours, which can save 921,100 kilowatt hours. According to the average industrial price of 1.5 yuan / kWh, the annual saving will be 1,381,700 yuan.

Keywords—Data mining, Vertical mill, Health operating conditions, Clustering analysis, Intelligent control

I. INTRODUCTION

Vertical mill is a kind of complex equipment commonly used in grinding large slag particles and other materials into fine particles. It mainly grinds the waste generated from building materials, chemical engineering, steel and other industries to realize the reuse of the waste residue. The ground powder is usually used as raw materials for cement production[1, 2]. However, the slag grinding systems possess the disadvantages of complicated process, poor working environment and long-term high-load operation. The vertical grinding process features strong coupling, nonlinearity and large hysteresis, along with physical and chemical changes [3,4]. At the present stage, the variable setting in the practical grinding process is generally adjusted by operators based on experience, resulting in high subjectivity and arbitrariness. Therefore, it is an urgent problem to be solved how to accurately establish the model of raw material grinding process in vertical mill to optimize the control of key parameters during the process[5].

The model of raw material grinding process for vertical mill has been studied in-depth both at home and abroad. Cai X[6] established a soft- sensing model of the material thickness by using the method of least square support vector machine to achieve the indirect measurement of material thickness and the adjustment of parameters in the vertical grinding system. Lin X[7] established a vertical mill grinding model using wavelet neural network and realized the optimal parameter setting through ant colony algorithm. Umucu Y[8] built the model of cement granularity by using multilayer perceptron neural network and radial basis function neural network and obtained a higher prediction accuracy. Wang Kang[9] constructed a recursive neural network model of slag powder production process with data-driven idea, based on which, using adaptive dynamic programming, the tracking controller with control constraints was designed and applied to the production process of slag powder. Lin Xiaofeng[10] established the production target prediction model of vertical mill raw material grinding process using wavelet neural network, and then combined the case-based reasoning technology with the particle swarm optimization algorithm and the target prediction model to achieve the optimal setting of key parameters during the grinding process. Yan Wenjun [11] constructed the vertical mill control loop model by using least square method, extracted multi-loop switch control rules according to the field operation experience and the abnormal operating condition characteristics and finally achieved the optimization control for the circuits.

Summarizing various models of the vertical mill grinding process described above, we find that most researchers only explored the interrelationship between single indicators of vertical mill operation. However, vertical mill is a multivariable coupled and nonlinear system, and the variables affect each other, which makes it difficult to establish a complete mechanism model of the production process. With the development of information and automation technology, especially the wide application of sensors and data acquisition devices on complex products, life cycle data of vertical mill equipment can be recorded in real time and feature 4V characteristics of big data. Among them, the data during operation have the largest growth rate. These data have implied product characteristics of service performance and evolution in time and space[12]. Big data analysis focuses on improving the efficiency of processing massive data with existing data mining methods through distributed or parallel algorithms. It has already been usefully explored and initially applied in many fields[13].

CHEN Jianhong[14] analyze the characteristics and research method of data-mining and give some typical applications of data-mining system based on power plant real-time database on intranet. Wei Huang[15] use the multi-objective design optimization approach to optimize quantitative indicators of transverse injection flow fields in supersonic crossflows, and then those optimized results that lie in the Pareto front are dealt with and visualized using data mining theory. It provides more design ideas for researchers to choose the optimal configuration for engineering application. From the data mining cases mentioned above, we find that although the big data analysis and the data mining technology have been widely adopted in the health status evaluation and prediction for the mechanical structures, the practical application in the vertical mill field is scarce and needs more attention and urgent studies.

In this paper, an intelligent control model of vertical mill based on data mining is proposed. The health status evaluation indicator is determined, and the health status cluster analysis is finally compared to get the instantaneous and predicted health evaluation of vertical mill system, which results in the optimal control of slag grinding system. In addition, through system development, the engineering application value of the vertical mill intelligent control system is verified.

II. VERTICAL MILL INTELLIGENT CONTROL MODEL

A. Determination model of health status indicators

Health status indicators refer to a series of equipment operating parameters that can characterize the health status of the system. The housing vibration is an important factor to reflect the stable operation and good production condition of vertical grinding system, which is the parameter indicator under key monitoring in practical system operation. Therefore, the vertical mill system health status can be described as a continuous status in which the vertical mill housing vibration amplitude maintains at a reasonable range within a certain time period under the premise of unchanged rated output.

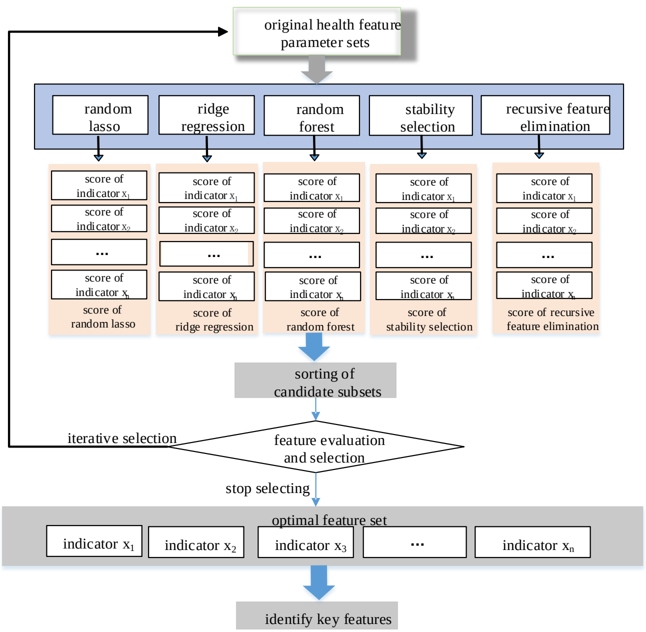

Fig.1. Key feature mining process model

Vibration amplitude of the housing is a monitoring variable, the stability of which needs to be achieved by adjusting other adjustable parameters. Moreover, vertical mill system is a high coupling system so the vibration will change with a variety of factors. In order to find key parameters that have great influence on the vibration and determine characteristics related to the steady status, the feature selection is necessary. Common feature selection methods include random lasso, ridge regression, random forest, stability selection, recursive feature elimination, etc. These methods have their own advantages and disadvantages. Ridge regression and random lasso need to adjust the parameters to achieve the control of the sparseness of model coefficients. Random forest often emerges overfitting problem. Stability selection is based on subsampling so the results obtained through different samplings are different. The stability of the recursive feature elimination depends on the choice of the underlying model.

To optimize the accuracy of the steady status judgment results, this paper combines the above five algorithms to avoid limitations and disadvantages of certain single method. The principle is, by solving the relationship between input and output, to apply five methods respectively to obtain stable features. And then, the importance of each feature will be scored, according to which the degree of feature importance will be assessed. The feature selection process model is shown in Fig.1. Finally, obtained key parameters and corresponding numerical ranges together constitute the health status of the system.

B. Clustering analysis model

The operating condition clustering of healthy operation status refers to the clustering analysis of different operating modes for the sample data based on determined health status indicators to obtain possible operating mode categories. At the very start, according to the parameter value distribution and practical production experience, the sample data is pretreated and screened, and then the screening result is taken as the input of the cluster calculation. The K-means method is used to obtain operating conditions cluster in the dataset. The centroids of K clusters in the dataset are found respectively, and the points in the dataset are assigned to the centroid nearest to it, which determines their categories according to corresponding centroids. The iteration method needs to be adjusted constantly according to running results to determine the value of K. After confirming the cluster of operating conditions, all the operating conditions in the sample data need to be marked to establish a healthy operating condition library.

C. Stable operating condition library establishment model

According to the definition of data status in the clustering grouping, the category annotation of the existing operating condition record will be completed. The stable operating condition label is set to 0 while the unstable label is set to 1. The stable operating conditions are extracted to establish a stable operating condition library.

The process of establishing the stable operating condition library is shown below in Fig.2: Every operating condition contains the controllable variables X, the stable characterization variables Y and the category labels. For each operating condition, we calculated the similarity distance between the parameters of X and existing operating conditions in the operating condition library. If the distance equals zero, the condition is seemed to have already been stored and no longer needs to be recorded repeatedly. Otherwise, the condition will be stored in the stable operating condition library in the form of vectors along with corresponding time stamp. Obviously, the stable operating condition library is not fixed and needs to be regularly trained and updated.

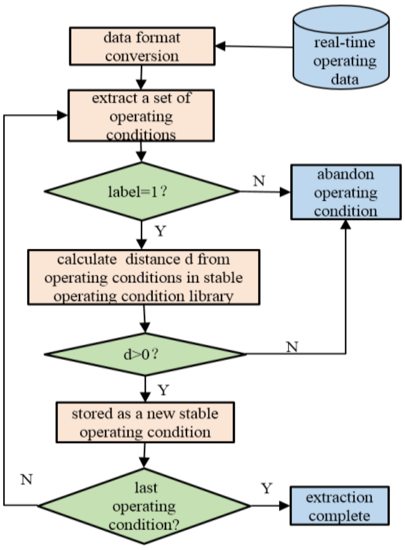

Fig.2. Establishment process model of stable condition library

D. *Real-time health status evaluation model*

Real-time health status evaluation refers to the process of obtaining health status evaluation results in real time based on the comparison between the real-time system operating data and healthy operating condition library. In the practical production process, it is reasonable not to directly use transient single-point data as a basis for judgments but to clean null values and abnormal values from the operating data, and then perform evaluation after a certain period of average calculation. According to determined indicators of health characteristic, the average value, the variance and the number of outliers of real-time running data of each parameter in the collection window are calculated respectively. The results are taken as characteristic variables of the stable operating condition judgment to be compared with the status in the healthy operating condition library. Real-time health evaluation process is shown in Fig.3：

Step 1 Take T as a starting time at some point and take Δt seconds as sampling interval (based on computer performance in the production site) to collect the real-time operating data of each parameter of the health characteristic indicators.

Step 2 Clean null values and abnormal values for the collected data of each parameter and record the frequency of occurrence respectively. Perform the successive technical accumulation.

Step 3 Calculate the mean value and the variance of the data after processing null values and abnormal values of each parameter with n*Δt seconds as a period. (Where n is the multiple of the sampling window period).

Step 4 Determine the number of occurrences of null values and abnormal values in the judgment cycle (where outliers refer to values exceeding the critical range of the health characteristic parameters). If it is greater than the preset counting threshold, the current operating condition will be considered as abnormal or not suitable for real-time evaluation of health status. Therefore, it is necessary to remind production staff on site of inspection.

Step 5 Respectively take the mean and the variance of each parameter in the sampling period as characteristics of instant operating condition and compare them with the healthy operating condition library. When there is one status similar to the abnormal operating conditions or not in line with healthy conditions, it is necessary to remind production staff on site of inspection.

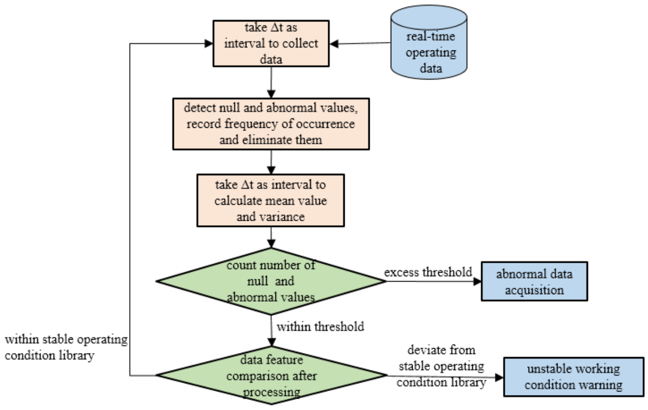

Fig.3. Real-time health status evaluation model

E. *Health status prediction evaluation model*

Health status prediction evaluation refers to the operating condition prediction and the health status evaluation within one certain period in the future based on the real-time operation data evaluation. One concept is here to be clear firstly -- stationary sequence. For a sequence {X (t)}, if its values fluctuate within a finite range, the mean and the variance are both constant while the autocovariance and the autocorrelation coefficient of sequence variables also keep unchanged after a k-period delay, it can be defined as a stationary sequence, otherwise, as a non-stationary sequence.

Due to the harsh operating conditions of the vertical mill system, the housing vibration is affected by external environmental factors and other attribute parameters. The operating condition sequence belongs to non-stationary sequence. Therefore, the Autoregressive Integrated Moving Average (abbreviated as ARIMA) Model Algorithm is used for time series modeling of vertical mill system operating condition prediction in this paper. The essence of ARIMA model is to add a difference operation before the Autoregressive Moving Average Model (ARMA) operation as shown below:

$$x_t = \phi_0 + \phi_1 x_{t-1} + \phi_2 x_{t-2} + \ldots + \phi_p x_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} \tag{1}$$

The model indicates that the value of variable x at time t is a multivariate linear function of the x-value of previous p periods and the disturbance ε of previous q periods. The error term is the current random disturbance ε_t, which is a zero-mean white noise sequence. Therefore, based on the real-time operating data, the historical time series can be used to predict system operating conditions at a certain time t in the future and to further achieve the predictive evaluation of the operating health status.

III. SYSTEM COMPOSITION AND ANALYSIS

In this paper, an intelligent control system of vertical mill is designed and developed based on the vertical mill intelligent control model. The overall structure of the system is shown in Fig.4. The system mainly includes seven major functional modules: data preprocessing, indicator mining of health evaluation, cluster analysis of health status, stable operating condition mode library establishment, status evaluation indicator feature acquisition, real-time feature parameter prediction and vertical mill grinding operation intelligent control.

The data preprocessing module mainly aims to achieve the pre-processing of sample data. The module first implements the cleaning of abnormal and null values, then discretizes and normalizes the data, and finally obtains the complete data set for mining analysis.

The health evaluation indicator mining module is used to determine types of parameters that determine the steady state of the system and their numerical boundaries. The health condition judgment indicator determination model is adopted to excavate and analyze the operating condition data. And then key parameters that characterize the system health status are obtained in turn.

The health status cluster analysis module achieves classification and mining of the system operating data. It obtains the cluster of the operating condition which is composed of numerical values of stable characteristic parameters in different time windows, and finally forms an operating mode library for recognizable running status. The operating condition clustering analysis model of healthy operating status is adopted to get the characteristics of each operating condition cluster and the status distribution in operating condition. The operating status categories in historical operating condition are defined. Finally, the status of each operating condition is labeled and screened to form the operating condition mode library.

The stable operating condition mode library establishment module, according to the definition of data status in clustering grouping, is responsible for the category annotation of existing operating condition record. The stable operating condition label is set to 0 while the unstable label is set to 1. The stable operating conditions are extracted to establish a stable operating condition library.

The real-time health status evaluation module realizes the system health evaluation in time. Real-time health status evaluation model is used to analyze the real-time running data of stable characteristics indicator to assess and judge whether the system is in healthy operation or not.

The health status prediction module achieves the prediction of system operating health status within one certain period in the future with the use of the analysis of real-time operating data. The principle is to perform the health predictive model training with using health status prediction model.

The vertical mill grinding operation intelligent control module takes effect when the parameter in the stability indicator is abnormal. The control program will start and search the control target from the stable mode library and return the point closest to the current status as the candidate operating condition. Next, it will compare the difference between the current status and the candidate operating condition, and then count the parameters, the required control range and the number of control parameters to be adjusted when the current status is transferred to the target to be selected. Taken these three dimensions in consideration, a control target is determined from the candidates. The target selection principle is to keep control parameters as few as possible and control range as small as possible. When the target is determined, the parameters of controllable variables will be adjusted according to the preset control range until they reach the target values. In the process of control, the trend of changes will be monitored. If the indicator does not return to normal, the system can cut off the control process at any time and proceed to the manual control stage.The seven main modules mentioned above take the historical sample dataset and real-time operating dataset as input respectively, and achieve vertical mill intelligent control through the data processing together with mining analysis.

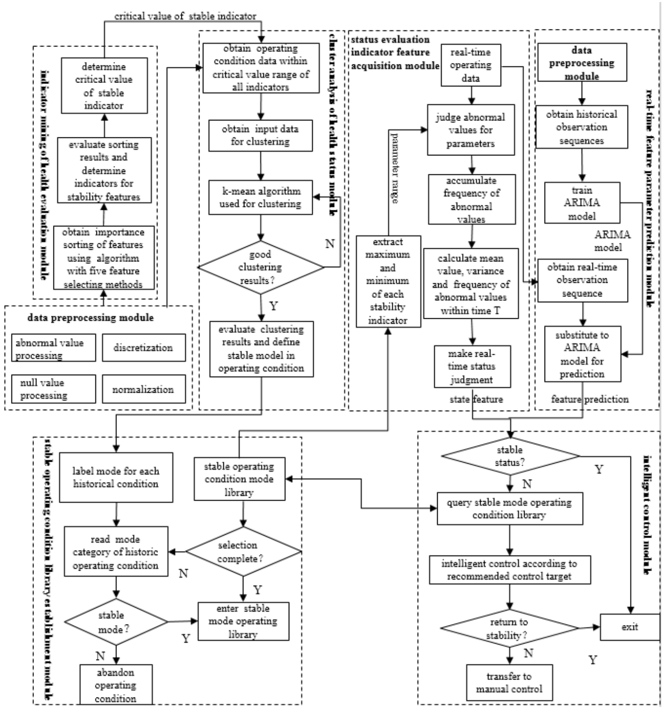

Fig.4. System general structure

IV. APPLICATION CASES AND ANALYSIS

The system has been put into operation in a powder factory in Henan province. The field application proves that the system provides more economical and effective decision-making for the intelligent control of the vertical mill and it runs stably.

A. Data acquisition and preprocessing

The system adopts OPC protocol to realize data communication and sends the connection requests to the vertical mill central control system server for real-time data collection. The system can set the type of parameter collected and sampling interval.

There are 65 kinds of data signal parameters collected in the practical operation of the field system. After attribute screening, data outlier processing and null processing, a subset of 30 attributes of main process and performance parameters of vertical mill systems are obtained. Taking into account process conditions, manual settings of production staff and controllability of parameters in actual operation of the vertical mill system, the data are processed by further simplification and dimensionality reduction. Finally, the remaining 12 main characteristic parameters are as follows: feeding amount, powder specific surface area, material layer thickness, mill outlet temperature, mill inlet temperature, mill inlet pressure, separator revolving speed, mill pressure difference, main ventilator revolving speed, cold air valve opening, hot air valve opening, circulating air valve opening. Some features and values are shown in Table 1:

TABLE 1 FEATURE SELECTION OF PARTIAL DATA

Feeding amount (t/h)	**Powder specific surface area**	**Housing vibration(mm)**	**Host current(a)**	**Material layer thickness (mm)**	**Mill inlet pressure (pa)**	**Mill inlet temperature (℃)**
176	431	5.6	284.9	151.3	-510	199.9
164	425	5.7	254	153.8	-510	189.2
180	391	5.2	251.2	151.9	-484	177.7
180	404	4.8	275.2	151.1	-438	180
170	416	6.5	254.1	145.3	-410	201.7
180	411	5.8	290	149	-599	182

TABLE 2 PARTIAL DATA AFTER NORMALIZATION

Feeding amount	**Powder specific surface area**	**Housing vibration**	**Host current**	**Material layer thickness**	**Mill inlet pressure**	**Mill inlet temperature**
1.24	1.57	-1.55	-0.14	1.13	-0.21	0.26
-0.47	1.17	-1.46	-1.61	1.24	-0.21	-0.41
1.81	-1.07	-1.95	-1.75	1.16	0.14	-1.13
1.81	-0.21	-2.34	-0.6	1.13	0.75	-0.98
0.38	0.58	-0.67	-1.61	0.88	1.13	0.38
1.81	0.25	-1.36	0.1	1.04	-1.41	-0.86

TABLE 3 SCORE RESULTS OF CANDIDATE CHARACTERISTICS

Feature name	**Random lasso**	**Ridge regression**	**Random forest**	**Stability selection**	**Recursive feature elimination**	**Average**
Feeding amount	0.1	0	0.03	0.08	0.18	0.08
Powder specific surface area	0.31	0.39	0.07	0.0	0.09	0.17
Material layer thickness	0.6	1.0	1.0	0.8	0.71	0.82
Mill outlet temperature	0.21	0.45	0.32	0.66	0.42	0.41
Mill inlet temperature	0.0	0.0	0.23	0.0	0.14	0.07
Mill inlet pressure	0.11	0.0	0.43	0.24	0.13	0.18
Separator revolving speed	0.06	0.0	0.27	0.0	0.59	0.18
Mill pressure difference	0.5	0.79	0.67	0.95	0.95	0.77
Cold air valve opening	0.29	0.0	0.0	0.0	0.09	0.08
Hot air valve opening,	0.21	0.0	0.01	0.12	0.0	0.07
Circulating air valve opening	0.6	0.21	0.14	0.24	0.33	0.3
Main ventilator revolving speed	0.01	0.1	0.01	0.0	0.0	0.02

It can be seen from the table that dimensions of parameters are inconsistent and ranges of values vary greatly. In order to eliminate the influence of the range of values and the dimensional differences on the analysis results, the data needs to be normalized. To avoid existence of a maximum or a minimum in the data that affects subsequent analysis, zero-mean method is adopted as normalization method, which is more stable than min-max normalization. Part of data after normalization are as shown in Table 2:

B. *Health characteristics indicator determination*

In the application filed, 12 main parameters of the vertical mill system under operation status are collected for 15 working days with 2 seconds as the sampling period.

The operation data of three working days were randomly selected as the sample, and the score of attribute indicator of each parameter was obtained by using the health evaluation indicator mining module. The comprehensive score record is shown in Table 3. In addition to the vibration amplitude of housing, the outlet temperature of the mill, the thickness of the material layer and the pressure difference of the mill are finally determined to be the health status characteristics of the vertical mill system.

V. COMPARATIVE ANALYSIS OF INTELLIGENT CONTROL SYSTEM OPERATING EFFECTS

A. *Field operation data selection*

The vertical mill may occur violent vibration during the operation, which may result in abnormal situations. As an uncontrollable factor, the violent vibration will affect the evaluation of the control data. Therefore, the data of continuous operation without violent vibration are selected as the evaluation data to exclude the influence of the vibration on this evaluation.

The vertical mill intelligent control system is used in a grinding production line in ZD Group. After three days of commissioning operation, working conditions data are obtained. Two sets of data in the process of intelligent control are randomly taken as the control group and another four sets of data under manual control are taken as the comparison group. The time window of the data is one hour, and the control effect of the intelligent system is analyzed.

B. *Characteristics evaluation of power consumption*

Fig.5 shows the energy consumption of each group of vertical mill within 1 hour as time period, with blue and orange as the control group and others as the comparison group. Unit consumption = total current / feed. Fig.6 shows the average value of unit consumption of each group: the average value of unit consumption of the control group is slightly less than that of the comparison group, and the average value of unit consumption of the control group 1 is 6.05% lower than that of the comparison group. Taking the vertical mill of 350,000 tons per year for calculation, with 43.5 kWh consumption per ton, it can save 9211000 kWh every year, which means, in accordance with the average price of industrial electricity 1.5 yuan / kWh, 1381700 yuan will be saved every year.

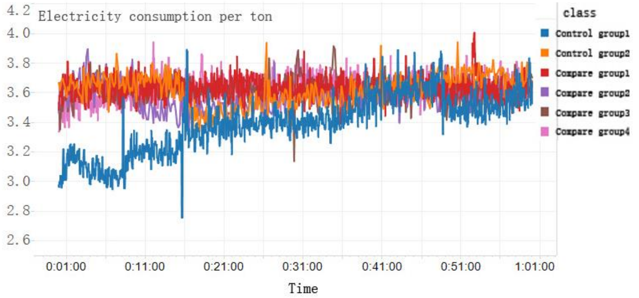

Fig.5. Operation data of power consumption per ton

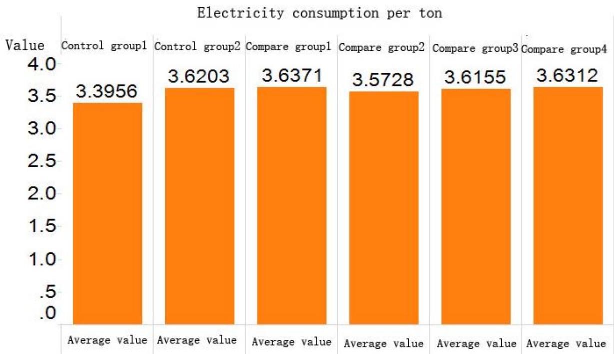

Fig.6. Comparison results for average of power consumption per ton

VI. Conclusion

In this paper, firstly we present a model and a system for the health status identification and intelligent control of the vertical mill based on data mining, and use a comprehensive feature selection method to excavate and analyze the operating condition data to get key parameters that affect the stable operation of the vertical mill, which are determined as health status evaluation indicators. Next, we perform cluster analysis of operating conditions to obtain the state distribution in the historical operating conditions and define the healthy operating condition categories in the historical conditions. Finally, we make use of ARIMA algorithm to establish the system healthy status feature training model to predict the changing trend of the system operating parameters, realizing the health status identification. When the value of the stable judgment indicator deviates from the normal range, the steady status automatic control is triggered. The system has been put into operation in a slag mill in Henan Province. It indicates that the system is stable, flexible and efficient, and shows obvious operation effect. The mean value of the vibration of the control group is reduced by 10% compared with that of the comparison group, and the average power consumption per ton of the control group is decreased by 6.05% compared with that of the comparison group. Taking the vertical mill of 350,000 tons per year for calculation, with 43.5 kWh consumption per ton, it can save 9211000 kWh every year, which means, in accordance with the average price of industrial electricity 1.5 yuan / kWh, 1381700 yuan will be saved every year.

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