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Integrated estimation model of clean coal ash content for froth flotation based on model updating and multiple LS-SVMs

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Abstract: Clean coal ash content, a prominent product index describing coal froth flotation, is difficult to be measured online. This constraint leads to a lack of timely guidance during operation and impedes the optimal operation of the coal flotation process. To solve this problem, considering the fluctuation of working conditions, the heterogeneity of raw coal and the variation of feed coal classes, an integrated estimation model of clean coal ash content for coal flotation based on model updating and multiple least squares support vector machines (LS-SVMs) is proposed. First, a single estimation model for a single class of coal based on LS-SVM is built, and the internal parameters are optimized by gravitational search algorithm (GSA). Second, the model updating strategy is designed to solve the problem of the decline in single model accuracy. Furthermore, a multiple LS-SVMs model formed by several single models for different classes of coal is studied along with the model switching mechanism to address the problem of model mismatch. Finally, an industrial experiment and evaluation are conducted. The mean relative error between the estimated and actual values is 3.32%, and the correlation coefficient is 0.9331. The estimation accuracy and adaptability of the integrated model can meet the industrial requirements.

Keywords: flotation, clean coal ash content, integrated estimation model, multiple LS-SVMs

1. Introduction

In the process of coal preparation, flotation is used to separate the ash-forming mineral matter and the carbonaceous materials of the fine coal below 0.5 mm in size (Bu, et al., 2016). The clean coal ash content is an important index of flotation product quality. The flotation froth is a gas-liquid-solid three-phase mixture; thus, it is difficult to obtain online measurements of the clean coal ash content. With the development of automation instrument technology, online ash content sensors of coal slurry had been developed; however, these sensors were expensive and place substantial constraints on the measurement environment (Abbott, 1994; Yang et al., 2000; Yang, et al., 2001). In addition, these sensors were typically based on the radioisotope principle. Accordingly, they are not widely used in coal preparation plants due to their high cost and the potential risk of radioactive sources. Numerous mathematical models based on flotation kinetics were developed to express the flotation product index (Tao, et al., 1999; Koh, et al., 2003; Zhang, et al., 2013). These mechanistic models can reasonably express the flotation process. However, their formulations are typically complex and contain many variable parameters. In addition, most of these models are based on differing hypotheses of flotation. Therefore, it is difficult to apply these mathematical models to the practical flotation process. In the practical implementation of coal flotation process, clean coal is sampled and the ash content is analysed every hour, resulting in high worker labour intensity. Moreover, the time delay is so long that the ash content obtained from the assay cannot guide the actual operation of flotation process in a timely manner. The manipulated variable of the flotation process cannot be adjusted in time, which affects the quality and stability of the products.

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In recent years, soft sensor technology has developed rapidly. González et al. (2003) established the soft sensor model of copper flotation concentrate grade based on partial least squares (PLS). Jorjani et al. (2009) developed a coal flotation concentrate prediction model of the combustible value and combustible recovery that was based on artificial neural network (ANN) and group maceral analysis. Another prediction model was established by Ding et al. (2011), who combined a linear model and nonlinear compensation to predict the iron flotation concentrate grade; the optimal parameters were selected by probability density estimation. Li et al. (2012) proposed a soft sensor model based on the kernel principal component analysis (KPCA) and an extreme learning machine (ELM) to predict the concentrate grade for iron flotation. Nakhaei et al. (2012), Nakhaei and Irannajad (2013) used various techniques (e.g., linear regression, nonlinear regression, back propagation neural network (BP-NN), and the radial basis function) to estimate the Cu grade and recovery values in a flotation column with variables including the reagents dosage, froth depth, and air. The Back-Propagation Neural Network (BP-NN) models performed the best. Besides, Zhang et al. (2014) proposed a method of ash content estimation of coarse coal by the support vector machine (SVM). Ren et al. (2015) also designed a static estimation model of copper concentrate grade based on least squares support vector machine (LS-SVM). Ding et al. (2015) presented a predictive model of the production rate of the hematite ore beneficiation process based on LS-SVM with mixtures of kernels.

In summary, these methods have shown that soft sensor technology has good applicability in the estimation of flotation product quality. The neural network (NN) is a good tool for establishing an estimation model; however certain problems still remain to be considered, such as the large amount of required training data and "over-fitting". In recent years, LS-SVM proposed by Suykens and Vandewalle (1999) has been widely used in pattern recognition and regression estimation (Jonsson et al., 2002; Zhang et al., 2013; Langone et al., 2015). SVM also features better estimation accuracy and stronger generalization ability than NN in the context of small sample sets (Subasi, 2013; Leng et al., 2017). In addition, because of its use of structure risk minimization principle, SVM can effectively avoid the over-fitting and local minimum in classical learning algorithms. In this research, the LS-SVM is introduced for the estimation of clean coal ash content in the coal flotation process. Additionally, there are still some problems that have direct impact on the accuracy, stability and applicability of the estimation model and need to be considered; for instance, the fluctuations of working conditions, heterogeneity of raw materials and change in the class of raw materials, etc.

Flotation is a complex nonlinear process involving multiple variables and a large time delay. The clean coal quality is affected by various influencing factors, including the feed properties, feed concentration, flow rate, froth depth, reagent dosage, and air rate, etc. Of these, the feed properties are particularly important. When the coal is consistent during a certain period of time, namely a relatively stable feed, the clean coal ash content is influenced primarily by the operating conditions. The single static estimation model typically achieves satisfactory results.

However, the accuracy of the single static estimation model may decrease over time due to various disturbances in the process, the heterogeneity of raw materials, and fluctuations of working conditions, among other factors. This problem is summarized as a decline in single model accuracy. Model updating is a valuable tool in engineering applications for minimizing the error between the actual and estimated values (Sarmadi et al., 2016; Xiong et al., 2016). Here, a model updating strategy is designed to improve the estimation accuracy of the single LS-SVM model.

In addition, the raw coal of a coal preparation plant usually comes from different coal seams of the same coal mine or even different coal mines. Once the source of raw coal has changed, the floatability of coal slime may change substantially, and then the operating conditions are quite different. At that time, it is challenging to use the single estimation model to track variations accurately; the accuracy is reduced considerably, and the estimation results may even be invalid. That is, the model is mismatched. The multiple model approach is an ideal framework for a complex nonlinear system (Hosseini et al., 2012). Each sub-model can describe the complex process accurately over a limited operating range (Domlan et al., 2011). The multiple model consisting of several sub-models includes a wide operating range and has shown satisfactory performance in various fields (Ahmad and Zhang, 2005; Gao et al., 2015; Sharifi, et al., 2017). In the process of coal flotation, considering the variety of raw coal sources and the limitation of a single model, a multiple LS-SVMs model formed by several single models for different classes of coal is studied along with the model switching mechanism to address the problem of model mismatch.

Drawing on the above analysis, an integrated estimation model of clean coal ash content for coal flotation based on model updating and multiple LS-SVMs is proposed in this research. First, the coal flotation process is described in Section 2. Then, the establishment of the integrated estimation model is introduced in Section 3, which describes the building of the single estimation, the model updating strategy, the multiple LS-SVMs and the model switching mechanism. In Section 4, the industrial test and evaluation are conducted on this integrated model. Section 5 presents the conclusions of this research.

2. Process description

In order to study the ash content estimation model of coal flotation, we chose a cyclonic micro-bubble flotation column (abbreviated as FCMC), which was developed and patented by Liu, J.T. (Liu, 2000) and is widely used in China's coal preparation plants. A schematic illustration of the FCMC flotation column is shown in Fig. 1. The FCMC flotation column is divided into three working zones: the froth zone, the collection zone and the scavenging zone. The washing device and overflow groove are located on the top of the column. The inlet is located at a position of approximately one third the column height. The concentrate is discharged from the overflow groove, and the tailings are discharged from the underflow port. The circulating pump is connected to the air bubble generator and is situated outside the column body. When the circulating pump jets the slurry, the bubble generator inhales air and mixes air with a frother in the coal slurry; then, a large number of micro bubbles are released in the pressure reduction process. Micro-bubbles enter the column along the tangent direction and move rotationally under centrifugal force. The bubbles and mineralized gas-solid aggregates move upward through the rotational flow centre and enter the collection zone. The unmineralized tailing moves downward and discharges through the underflow. The opposing movements of the feed and air bubbles promotes the mineralization and formation of gas-solid aggregates.

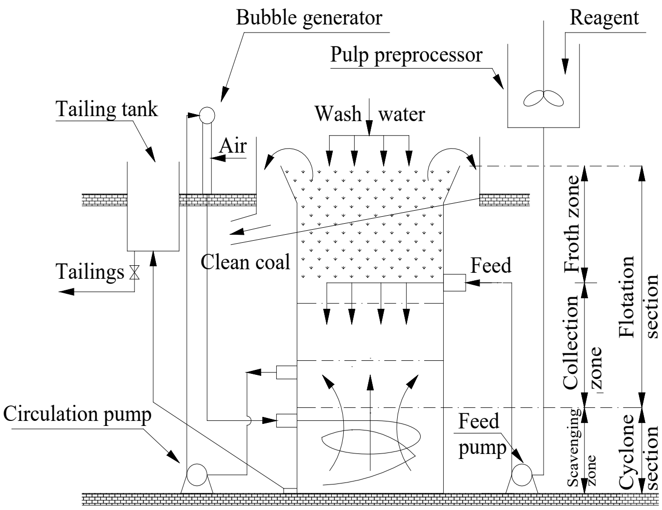

Fig. 1. Schematic illustration of the FCMC flotation column

The separation process of the FCMC flotation column is subject to various influencing factors, such as the column height, particle size distribution, feed ash content, concentration, flow rate, air rate, wash water rate, reagent dosage, and froth depth (pulp level) (Yang et al., 2008). When the feed property is stable, the clean coal ash content is influenced primarily by the working conditions, as shown below.

Feed flow rate: When the feed flow rate increases, the treatment capacity of the flotation column increases correspondingly. The reagent dosage and froth depth need to be adjusted to ensure a normal flotation process.

Feed concentration: The greater the feed concentration, the more coal particles per unit volume of slurry, thereby reducing the merger probability and the rising velocity of the bubbles. In contrast, the particle collision probability is increased. This configuration is prone to cause mechanical entrainment and increase the clean coal ash content.

Froth depth: With increasing froth depth, the secondary enrichment effect of the froth is strengthened, and the clean coal ash content decreases. In addition, the height of the collection zone decreases, thus decreasing the recovery.

Collector dosage: The collector can selectively act on the surface of coal particles to improve their hydrophobicity. Thus, the coal particles can be more strongly attached to the bubbles.

Frother dosage: The frother can disperse air into small bubbles in the pulp, preventing bubble merging. This process can also prolong the residence time of bubbles in the column. The collision probability between bubbles and coal particles is increased, and the separation effect is improved. However, if the dosage is excessively large, mechanical entrainment can easily occur, increasing the clean coal ash content (Yang et al., 2008).

Air rate: The air rate directly affects the state of the froth layer as characterized by the froth depth, bubble quantity and bubble diameter. This factor has a strong influence on the clean coal ash content and recovery.

Wash water rate: The wash water can strengthen the secondary enrichment effect and reduce the amount of fine coal slime with high ash content. This process reduces the ash content of clean coal.

Circulating pressure: The circulating pressure provides power for the concentrating and scavenging of the flotation column. With increasing circulating pressure, the air rate increases, the number of bubbles in the pulp per unit time increases, the collision probability of the coal particles increases, and the clean coal recovery increases. However, an excessive increase in the number of bubbles will lead to the mechanical entrainment of useless minerals (gangue); thus, the ash content of clean coal increases (Ge, 2013).

As shown above, flotation is a complex three-phase process involving gas, liquid and solid. The analysis indicates that many factors affect the flotation product quality and coupling exists between the factors. It is difficult to measure the clean coal ash content of flotation online, but soft measurement technology can be appropriately implemented to solve this problem. However, current researches on clean coal ash content estimation model concentrate predominantly on the establishment of a single model, which cannot fully adapt to the fluctuations of working conditions and the variety of coal classes. Therefore, an integrated estimation model of clean coal ash content for coal flotation based on model updating and multiple LS-SVMs is proposed. This approach is effective in improving the intelligent control level and achieving closed-loop optimal control of the coal flotation process.

3. Establishment of the integrated estimation model

3.1 Single estimation model based on LS-SVM

In the actual coal flotation production, when the feed is relatively stable, the clean coal ash content is influenced primarily by the operating conditions. Therefore, the estimation model of clean coal ash content for the single class of raw coal is established first.

3.1.1 Least squares support vector machine

In LS-SVM, the equality constraints are used to replace the inequality constraints of SVM; thus, the computational complexity is reduced, and calculating speed is greatly accelerated. Therefore, the LS-SVM modelling method can meet the actual requirement of the industrial process.

The training set is S: S: $\{(x_{1,}y_1)\ldots(x_{i,}y_i)\} \in R^n \times R$, where i=1,2…N, N is the number of samples, $\{x_i\}$ indicates the input vector and y_i represents the corresponding output vector. The input data are mapped into high dimensional feature space by the nonlinear mapping function $\varphi(\cdot)$, and the following regression model is established:

$$g(x) = \omega^T \cdot \varphi(x) + b \quad (1)$$

where ω represents the weight vector, b is the bias, $\omega \in R^n$, and $b \in R$. According to the principle of structural risk minimization, the regression problem can be transformed into a constrained quadratic optimization problem:

$$\begin{cases} Min\ J(\omega, e) = \frac{1}{2}\omega^T\omega + \frac{\gamma}{2}\sum_{i=1}^{l} e_i^2 \\ y_i = \omega^T \cdot \varphi(x_i) + b + e_i\,;\ i = 1,2,\dots,l \end{cases} \tag{2}$$

where γ is the regularization parameter and e_i is the slack factor. To solve the above optimization problem, the Lagrange multiplier is introduced to obtain the objective function:

$$L(\omega, b, e; \alpha) = J(\omega, e) - \sum_{k=1}^{N} \alpha_i \{\omega^T \cdot \varphi(x_i) + b + e_i - y_i\} \tag{3}$$

According to the Karush–Kuhn–Tucker (KKT) conditions of the optimal system theory, the optimal conditions can be obtained as follows.

$$\omega = \sum_{i=1}^{l} \alpha_i \varphi(x_i);\ \sum_{i=1}^{l} \alpha_i = 0;\ \alpha_i = \gamma e_i;\ \omega^T\varphi(x_i) + b + e_i - y_i = 0 \tag{4}$$

The following linear equations are obtained:

$$\begin{bmatrix} 0 & -Y^T \\ Y & \Omega + \gamma^{-1} I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ I \end{bmatrix} \tag{5}$$

where $\Omega = K(x, x_i) = \varphi(x)^T\varphi(x_i)$ and $K(x, x_i)$ represents the kernel function that satisfied Mercer's condition.

Finally, the regression function can be expressed as

$$f(x) = \sum_{i=1}^{l} \alpha_i K(x, x_i) + b \tag{6}$$

In this study, the RBF function with simple structure, nonlinear mapping ability and generalization ability is chosen as the kernel function (Vanny et al., 2013):

$$K(x, x_i) = exp(-\|x - x_i\|^2/2\sigma^2) \tag{7}$$

3.1.2 Data pre-processing and auxiliary variables selection

To accelerate the convergence rate and improve the accuracy of the LS-SVM model, the sample data need to be normalized. In this paper, the min-max method is adopted.

$$x'_{ij} = \frac{x_{ij} - min\, x_i}{max\, x_i - min\, x_i} \tag{8}$$

where x'_{ij} represents the normalized value, x_{ij} represents the *j-th* sample value of the *i-th* variable, $max\, x_i$ represents the maximum value of the *i-th* variable, and $min\, x_i$ represents the minimum value of the *i-th* variable.

Flotation is a complex process with various variables affecting the quality of clean coal. It is challenging to estimate which features are more sensitive to the estimation model. To remove redundant information and reduce the computational complexity of the LS-SVM while retaining maximal data information, principal component analysis (PCA) (Dong and Luo, 2013) is used to extract features, fuse the correlation between variables and reduce the dimensions of the input data. The procedure can be described as follows:

Given a sample set X, where m is the number of samples and t is the number of sample features, $x_{i,j}$ is the *j-th* feature of the *i-th* sample, where $i = 1,2 \cdots m, j = 1,2 \cdots t$.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1t} \\ x_{21} & x_{22} & \cdots & x_{2t} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mt} \end{bmatrix}$$

Step 1: Calculate the covariance matrix R of X, and get the eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_t$ of covariance matrix R.

Step 2: Arrange the eigenvalues in decreasing order to get a diagonal matrix $\lambda = \mathrm{diag}(\lambda_1, \lambda_2, \dots, \lambda_t)$, where $\lambda_1 \geq \lambda_2 \cdots \geq \lambda_t$. And $V = [v_1, v_2, \cdots, v_t]$ is a matrix consist of eigenvectors v_j $(j = 1,2 \cdots t)$ corresponding to the eigenvalues λ_j $(i = 1,2 \cdots t)$.

Step 3: Compute the contribution rate of the *j-th* principal component ρ_j and the cumulative contribution rate of the previous k $(k = 1,2 \cdots t)$ principal components ρ according to the following formulae. In general, the first *k* principal components (PCs) with a cumulative contribution of more than 85% are selected, it means that the selected PCs contain more than 85% of the total amount of information (Wang, 2010).

$$\rho_j = \frac{\lambda_j}{\sum_{j=1}^{t} \lambda_j} \tag{9}$$

$$\rho = \rho_1 + \rho_2 + \cdots + \rho_k = \frac{\lambda_1+\lambda_2+\cdots+\lambda_k}{\sum_{j=1}^{t}\lambda_j} \tag{10}$$

Step 4: A new feature space $P = [v_1, v_2, \cdots, v_t]^T X = [\mathrm{PC1}, \mathrm{PC2}, \cdots, \mathrm{PC}t]$ can be obtained and the first k principal components PC1, PC2,…,PCk with a cumulative contribution of more than 85% are selected as the input variables of LS-SVM.

In this research, when the feed of flotation is relatively stable, the main influencing variables of the coal flotation, shown in Table 1, are selected as the input variables of PCA. The principal components $\mathrm{PC1}, \mathrm{PC2}, \cdots, \mathrm{PC9}$ are the outputs. The first k principal components with more than 85% cumulative contribution rate are chosen as the input variables of the estimation model. The input / output relationship of the estimation model can be expressed using Eqs. (11).

$$y = f(\mathrm{PC1}, \cdots, \mathrm{PC}k);\ \ 1 < k < 9 \tag{11}$$

Table 1. Input variables of PCA

Variable	Name	Unit	Variable	Name	Unit
x_1	Feed flow rate	m^3/h	x_6	Air rate	m^3/h
x_2	Feed concentration	kg/m^3	x_7	Wash water rate	m^3/h
x_3	Collector dosage	L/h	x_8	Circulating pressure	KPa
x_4	Frother dosage	L/h	x_9	Raw coal ash content	%
x_5	Froth depth	mm			

3.1.3 Model parameters optimization

In the process of LS-SVM modelling, the model parameters have an important influence on the accuracy of model regression. In this paper, the gravitational search algorithm (GSA) is used to optimize the parameters of the LS-SVM model. GSA, a heuristic optimization algorithm based on the law of gravity, was proposed by Rashedi et al. in 2009 (Rashedi et al., 2009). GSA does not require evolutionary operators such as crossover and mutation, and it also has the advantages of fast convergence, resistance to falling into local minima and strong global search ability (Sarafrazi et al., 2013).

GSA is described as follows:

The agent position is X_i, $X_i = (x_i^1, \cdots, x_i^d, \cdots, x_i^n)$, where i=1,2…N, N is the number of agents and x_i^d represents the position of the *i-th* agent in the d-dimension space. At the *t-th* iteration, the gravity between the *i-th* and *j-th* agent is defined as follows:

$$F_{ij}^d(t) = G(t)\frac{M_i(t)\times M_j(t)}{R_{ij}(t)+\varepsilon}(\,x_j^d(t) - x_i^d(t) \tag{12}$$

where G(t) is the gravitational constant at *t-th* iteration, $G(t) = G_0 exp(-\alpha\frac{t}{t_{max}})$, G_0 is the initial value of gravitational constant, α is the attenuation index, and t_{max} is the maximum number of iterations. $R_{ij}(t)$ is the Euclidean distance between the *i-th* and *j-th* agent. $R_{ij}(t) = \|X_i(t), X_j(t)\|_2$, and ε is a small constant.

$M_i(t)$ represents the inertial mass of the *i-th* agent, which can be calculated by the following formulae:

$$\begin{cases} m_i(t) = \frac{fit_i(t)-fit_{worst}(t)}{fit_{best}(t)-fit_{worst}(t)} \\ M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \end{cases} \tag{13}$$

where $m_i(t)$ represents the gravitational mass, $fit_i(t)$ represents the fitness value of the i-th agent at the t-th iteration, $fit_{best}(t)$ is the best fitness value of the swarm and $fit_{worst}(t)$ is the worst fitness value of swarm.

In the d dimension, the sum of the external forces of the *i-th* agent is $F_i^d(t)$.

$$F_i^d(t) = \sum_{j\in k_{best}, j\neq i} rand_j\, F_{ij}^d(t) \tag{14}$$

k_{best} is a function of time, and its value gradually decreases from N to 1 with the iteration process. $rand_j$ is a random number between [0,1].

According to Newton's second law, the acceleration $a_i^d(t)$ of the *i-th* agent at the *t-th* iteration in the *d* dimension space can be calculated by the following formula:

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} \tag{15}$$

The position and speed of the *i-th* agent are updated according to the following formulae:

$$v_i^d(t) = rand(i)\, v_i^d(t) + a_i^d(t) \tag{16}$$

$$x_i^d(t) = x_i^d(t) + v_i^d(t+1) \tag{17}$$

In this paper, GSA is used to optimize the internal parameters γ and σ^2 as follows:

Step 1: Initialize the population size *N* = 30, maximum number of iterations $t_{max} = 200$, initial value of gravitational constant $G_0 = 100$, attenuation index $\alpha = 20$, small constant $\varepsilon = 10^{-6}$ and dimension *d* = 2. Randomly initialize the position of agents.

Step 2: The new parameters γ and σ^2, namely, the position of the agents, are adopted to train the LS-SVM model with the normalized training set. The root mean square error (*RMSE*) of the estimated value and the actual value is used as the objective function.

$$f_{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{18}$$

where n is the number of training samples, y_i is the actual value, and $\hat{y}_i$ is the estimated value.

Step 3: The minimum value of the objective function is taken as the optimization objective, the fitness value is calculated, and the inertial mass $M_i(t)$ is calculated according to Eq. (13).

Step 4: Calculate the sum of the external forces $F_i^d(t)$ and acceleration $a_i^d(t)$ according to Eqs. (14) and (15).

Step 5: Update the agents' position according to Eqs. (16) and (17). The new agents' position is the new LS-SVM parameter value.

Step 6: When the maximum iteration is reached or the fitness value satisfies the target value, stop the optimization process to obtain the optimal parameters of the LS-SVM; otherwise, return to step 2.

Step 7: The optimal parameters γ and σ^2 are obtained, and the estimation model is established according to Eqs. (6) and (7).

3.2. Model updating strategy

For a single class of coal, the single static estimation model based on LS-SVM can achieve acceptable results during a certain time. However, as time goes on, the fluctuation of the working conditions, the heterogeneity of the raw coal and the fact that training samples cannot cover all possible conditions all tend to decrease the adaptability and accuracy of the single estimation model. To enhance the generalization ability and accuracy of the single model, this paper combines the method of offline training and online learning. The model updating strategy, which consists of automatic retraining and parameters updating, is designed.

The coal flotation process is a nonlinear system with k step delay. When the system input is x(T), the estimation value of the LS-SVM model is $y(T+k)$, and the corresponding actual output (clean coal ash content), which is assayed every hour, is $\hat{y}$ (T+ k). Then, the relative error between the actual output and the estimated output is described as follows:

$$RE(T+k) = \left|\frac{y(T+k) - \hat{y}\,(T+k)}{\hat{y}(T+k)}\right| \tag{19}$$

In addition, the feedback error $RE(T+k)$ is compared with the setting relative error RE_{set}. If $RE(T+k) > RE_{set}$, it means that the estimation capability of the model has decreased, and the retrain procedure is activated. Then, the LS-SVM model is retrained using the new samples, and the parameters γ and σ^2 are updated using GSA, which is described in Section 3.1.3.

In this paper, the sliding time window method is adopted to determine the number of samples used to train and test the model. It is assumed that the sliding time window size is L and that the sliding step length is P. The main procedures are as follows:

Step 1: Train the single model based on LS-SVM using the L group sampling data.

Step 2: If $RE(T+k) > RE_{set}$, go to Step 3; otherwise, exit.

Step 3: The retraining and updating procedure is activated. Select the latest P group sampling data before activation time, remove the oldest P group data from the original L group data, and add the new latest P group data. The new L group data are obtained.

Step 4: Use the new L group data to retrain the LS-SVM model, and use the GSA to optimize the parameters γ and σ^2.

Step 5: Update the internal parameters γ and σ^2 of the LS-SVM.

3.3 The multiple LS-SVMs

In a coal preparation plant, the source of coal often changes from different coal seams of the same coal mine or even different coal mines. For different classes of coals, the floatability of coal slime may be different, and considerable differences also exist in the operating conditions. When the source of raw coal is changed, the floatability of coal slime may change greatly. To ensure the quality of flotation products, the operators will adjust the set-points of the operating variables, including the reagents dosage, froth depth, and air rate, enabling the coal flotation process to run at a new steady state. However, the estimation model based on a single LS-SVM cannot adapt to the new conditions at this moment, the model mismatch is easily occurred, which can easily lead to failure estimation. Consequently, the estimation should include a wide operating range. Considering this factor, the multiple LS-SVMs approach is proposed. For each class of raw coal, a corresponding estimation model based on LS-SVM is established according to Section 3.1. Then, several single LS-SVM models are constructed into a multiple LS-SVMs model. Combining the multiple LS-SVMs is similar to establishing a large model in which the corresponding trained estimation models based on LS-SVM are sub-models operating with a selection, thus a wide operating range is included. In other words, the combination can be thought of as the way of administrating the single models, each is known to be the best for its corresponding class of coal, but they may not be the best for others. The next problem is that which single model needs to run at the right time, therefore, a reasonable model switching mechanism needs to be studied.

For a coal preparation plants whose raw coal come from different sources, there are typically two preparation modes: preparation of single raw coal and preparation of blended raw coal. Reasonable coal blending can guarantee the quality of products and increase the economic benefits. Actually, different classes of raw coal are typically stored in different raw coal bunkers, and the coal feeders are installed under each bunker. Then, different classes of raw coal are mixed together and transported into the raw coal preparation workshop. The process of raw coal blending is shown in Fig. 2. For a single class of coal washing, it is straightforward to evaluate the coal class through the corresponding belt running status. For blended coal washing, coal is usually blended with no more than 3 classes, and the proportion is determined according to the product quality requirements and controlled by adjusting the coal feeders. Here, blended raw coals with different proportions are considered different coal classes. Therefore, in this paper, the model switching mechanism is designed based on coal blending schemes. Through the analysis, the running state signal of conveyor belts "I" and the number of running coal feeders "m" can be used to describe the coal blending process, and S is the corresponding coal class. The switching mechanism is described in Table 2. If the class of the raw coal changes, the estimation model will switch to the corresponding single LS-SVM model. It is noteworthy that coal preparation is a continuous process; when the class of raw coal changes, the model switching should be completed after a period of time "t", which is the running time of raw coal from the raw coal belt to the flotation pre-processor.

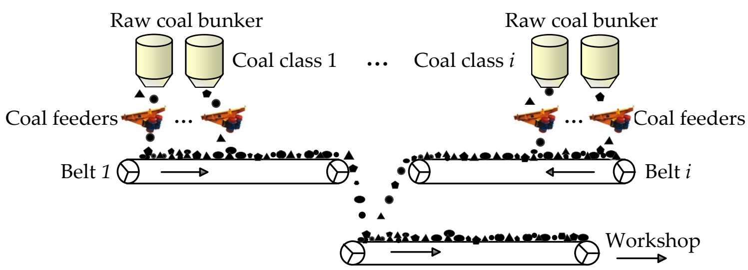

Fig. 2. Schematic illustration of coal blending process

Table 2. Description of the switching mechanism based on coal blending schemes

`Condition						Conclusion
I_1	$\cdots$	I_i	m_1	$\cdots$	m_i	S

In summary, in the process of establishing the integrated model, several single estimation models for each class of coal based on LS-SVM are built firstly. Principal component analysis (PCA) is applied to extract features as the model input, and each PCA performed on a single class of data separately. Gravitational search algorithm (GSA) is used to optimize the internal parameters of LS-SVM. Model updating strategy is designed to improve the accuracy of the single estimation model, and the model switching mechanism is established to address the problem of model mismatch. The structure of the proposed method is shown in Fig. 3.

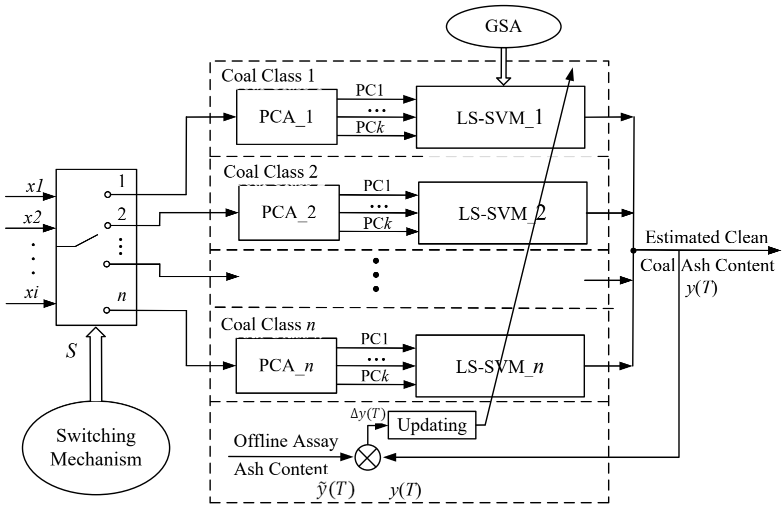

Fig. 3. The structure of the proposed integrated model

4. Experiment and evaluation

To evaluate its efficacy, the integrated model has been tested on an industrial FCMC flotation column of the Xingtai Coal Preparation Plant in Hebei Province, China. The flotation column is used for the separation of the fine coal slime between 0 and 0.25 *mm* in size. The experimental data are generated from the industrial flotation process.

The raw coal of the Xingtai Coal Preparation Plant includes Xingtai raw coal and Xingdong raw coal, which comes from different coal mines. The two classes of raw coals are transported to the raw coal preparation workshop through their respective transportation belts and joined together on the raw coal feed belt. There are substantial differences in the properties of the two coals, and the differences are clearly displayed in the ash content of raw coal, which is measured by a raw coal ash-measuring instrument with a sampling time interval of 2 min, as shown in Fig. 4. It can be seen from in Fig. 4 that the ash content of Xingtai raw coal is relatively higher than that of Xingdong. In order to further verify the differences in the properties of the two classes of coals on the flotation, the coal floatability is evaluated, and the results are compared in Table 3.

Based on the optimal operating parameters, the floatability of Xingtai and Xingdong coal slime is evaluated according to the Chinese standard MT259-1991. Table 3 indicates that under the same requirement of clean coal ash content, the floatability of Xingtai coal slime is poorer than that of Xingdong coal slime. In addition, when the Xingtai coal and Xingdong coal are washed separately with the same operating condition, the flotation effects are shown in Table 4. It can be seen that the feed ash content of Xingtai coal slime is higher, and the clean coal ash content of Xingtai coal flotation is also higher under the same flotation conditions, whereas the tailing coal ash content, extraction rate and combustible recovery rate are lower.

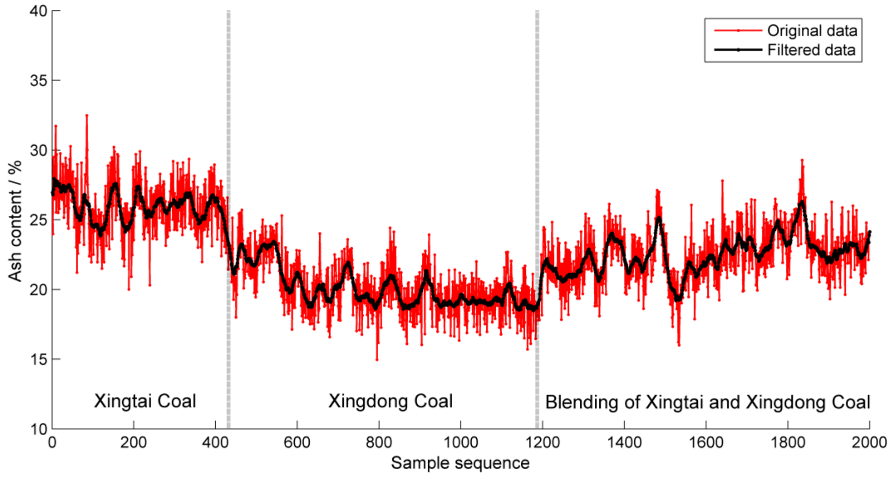

Fig. 4. Ash content of the different classes of raw coals

Table 3. Degree of flotation difficulty comparison between Xingtai and Xingdong coal slime

	Required clean coal ash content / %	Clean coal recovery / %	Tailing coal ash content / %	Combustible recovery / %	Degree of flotation difficulty
Xingtai coal slime	10	21.9	30.1	26.4	Extremely difficult
	11	51.3	40.7	61.15	Moderate
	12	65.4	50.2	77.08	Moderate
	13	78.3	53.6	91.23	Extremely easy
Xingdong coal slime	8	35.1	30.5	41.63	Difficult
	9	66.1	48.5	77.54	Moderate
	10	74.2	58.2	86.09	Easy
	11	76.4	60.1	87.66	Easy
	12	78.8	62.2	89.4	Easy

Table 4. The flotation effects of the Xingtai and Xingdong coal slime

Coal class	Feed ash content/ %	Clean coal ash content/ %	Tailings ash content/ %	Extraction rate/ %	Combustible recovery rate / %
Xingtai	27.19	12.43	44.41	53.85	64.67
	28.31	11.08	50.64	56.45	70.01
Xingdong	19.14	9.55	48.12	75.14	84.05
	19.87	10.37	63.76	82.21	91.95

Through the screening of Xingtai coal slime, the proportion of coal slime whose particle size is below 0.045 mm in the Xingtai coal reaches 68.51%, and the ash content is as high as 40.19%. These characteristics are the leading cause of the high ash content and poor floatability of Xingtai coal slime.

In summary, the above analysis indicates that there is a significant difference in the floatability between different classes of coal. The flotation effects are also significantly different under the same flotation conditions. In the actual production process of the Xingtai Coal Preparation Plant, the feed consists primarily of four classes of coals, including the single Xingtai coal, the single Xingdong coal and blended coals with different proportions of Xingtai and Xingdong, as shown in Table 5. There are four raw coal bunkers used for storing Xingtai coal and two bunkers used for storing Xingdong coal. Eight and four coal feeders are installed under the Xingtai and Xingdong coal bunkers, respectively, to control the coal feed quantity and the blending proportion. The number of coal feeders, which are running under the Xingtai and Xingdong coal bunkers, is m_1 and m_2, respectively. The running state signals of transport belts for Xingtai and Xingdong coals are I_1 and I_2, respectively. The condition I=1 indicates that the belt is running, and I=0 indicates that the belt is in a stopped state. S is the classification result. Therefore, in this paper, a switching mechanism based on the coal blending schemes shown in Table 6 is designed. In addition, through the analysis of actual production process of the Xingtai Coal Preparation Plant, the delay time of switching "t" is defined here as 12 min.

Table 5. The proportion of two classes of raw coal

	Xingtai raw coal	Xingdong raw coal
Proportion #1 (coal class 1)	100%	0%
Proportion #2 (coal class 2)	67%	33%
Proportion #3 (coal class 3)	50%	50%
Proportion #4 (coal class 4)	0%	100%

Table 6. Model switching mechanism

Rules	Conditions	Conclusion
Rule 1	I_1=1, I_2=0	S=1
Rule 2	I_1=1, I_2=1, m_1=4, m_2=2	S=2
Rule 3	I_1=1, I_2=1, m_1=3, m_2=3	S=3
Rule 4	I_1=0，I_2=1	S=4

In this research, the modelling data are derived from the actual industrial flotation process of the coal preparation plant. To ensure the stability and accuracy of the model, it is necessary to detect and remove the outliers from the industrial signal and then to filter the signal. The Pauta criterion is selected as the outlier detection and elimination method, and the filtering method adopts the improved queue average filter, as shown below.

$$\begin{cases} A = Initial\ value \\ Sum = A * N \quad (Initialization) \\ Sum = Sum - A + C \\ A = Sum/N \end{cases} \tag{20}$$

where N is a constant (here N = 20), C is the latest sampling value, and A is the filtered value.

Take coal class 1 as an example. After the flotation process is stable, the data are collected. The Pauta criterion is used to eliminate outliers from the data collected in steady state, and 100 groups of samples are selected, among which 70 groups are randomly selected as the training set; the remaining 30 groups are the test set. According to the selection criteria of PCs which has been mentioned in section 3.1.2, due to the result that the cumulative contribution rate of the first six principal components reaches 88.32%, the principal components "PC1,…, PC6" extracted by PCA are used as the input variables of the LS-SVM estimation model of coal class 1, and the clean coal ash content is the output variable. The internal parameters of LS-SVM are optimized by GSA, and the optimization results are γ =1.37 and σ^2 =14.72. The above parameters values are used for LS-SVM modelling. In order to verify the effect of the single estimation model based on LS-SVM, Back Propagation Neural Network (BP-NN) is also used for the modelling with the same training set of coal class 1. The root mean square error (*RMSE*), the mean relative error (*MRE*) and the maximum relative error (*MaxRE*) are chosen as the performance evaluation indicators of the estimation models, as shown in Eqs. (21a), (21b) and (21c), respectively. The comparisons between the estimated and actual values of the test set of the two models are shown in Fig. 5 and Table 7.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{21a}$$

$$\mathrm{MRE} = \left(\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right| * 100\%\right)/n \tag{21b}$$

$$\text{MaxRE}=\max\left(\left|\frac{y_i-\hat{y}_i}{y_i}\right| * 100\%\right) \tag{21c}$$

where n is the number of samples, y_i is the actual value, and $\hat{y}_i$ is the estimated value.

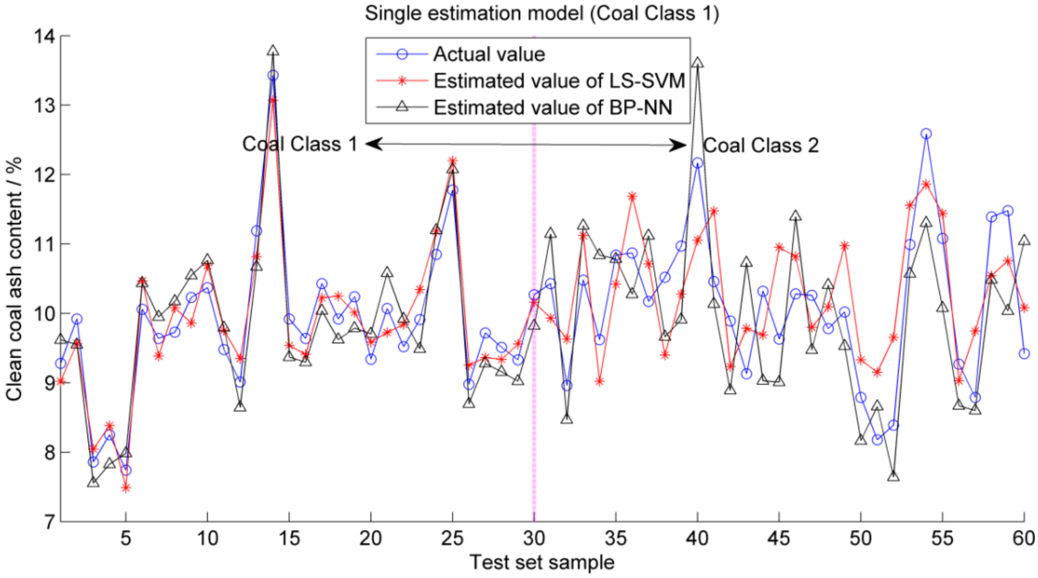

Fig. 5. Comparison of the estimated values and actual values (Coal class 1)

Table 7. Comparison results of the evaluation indicators (Coal class 1)

Single estimation model of coal class 1	Coal class 1-test set			Coal class 2-test set		
	RMSE	*MRE/%*	*MaxRE/%*	*RMSE*	*MRE/%*	*MaxRE/%*
LS-SVM	0.3063	2.98	4.38	0.7658	7.16	15.06
BP-NN	0.3830	3.54	5.57	0.9341	8.28	17.50

Fig. 5 and Table 7 indicate that both the single model based on LS-SVM and BP-NN fit the test data well, but the LS-SVM, which shows a lower *RMSE*, *MRE*, and *MaxRE* than the BP-NN, proves to be a better choice. These results may be due to the fact that the SVM has strong generalization ability in the case of a small sample set. In addition, it is clear that if the single estimation model of coal class 1 is applied to coal class 2, then the estimation accuracies of both LS-SVM and BP-NN are significantly reduced, making the estimated result invalid.

For further evaluation, the relative errors between the estimated and actual values for both classes of coal using the single estimation model of coal class 1 based on LS-SVM are calculated, as shown in Fig. 6. Using the single estimation model of coal class 1 based on the LS-SVM, the relative error of coal class 1 is limited within 5%, and the maximum relative error is 4.38%; however, the relative error of coal class 2 is significantly large, and the maximum relative error reaches 15.06%. From the above analysis, it is notable that a single estimation model based on LS-SVM can achieve satisfactory estimated results for the corresponding class of coal; however, the model is not suitable for a different class of coal, and thus the corresponding single estimation models for different classes of coals are quite necessary.

Therefore, in this paper, according to the above modelling method, the different single estimation models based on LS-SVM are established for different classes of coal. 100 groups of sample data are selected from each flotation process of coal class 2, coal class 3 and coal class 4 respectively. In this research, each single model consists of a respective PCA and LS-SVM which deal with the data of the corresponding class of coal, it means that each PCA performed on a single class of data separately. According to the selection criteria of PCs which has been mentioned in section 3.1.2, the number of selected PCs of the four single models are summarized in Table 8. The values of internal parameters and evaluation indicators are summarized in Table 9. The comparisons between the estimated values and the actual values of the 30 groups of test sets are shown in Figs. 7-9.

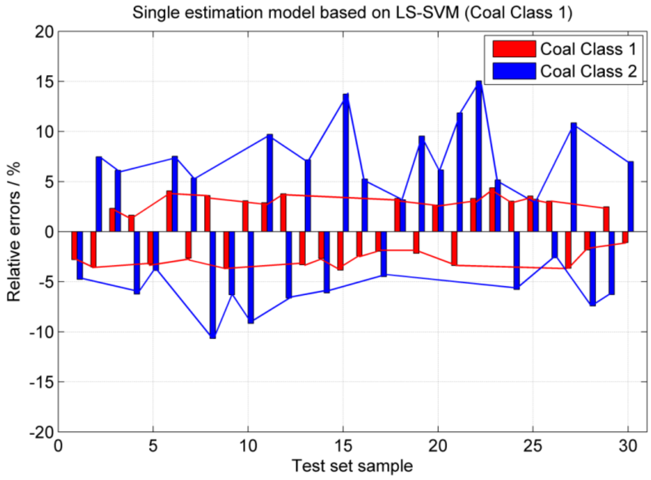

Fig. 6. Comparison of the relative errors

Table 8. the number of selected PCs

	Coal class 1	Coal class 2	Coal class 3	Coal class 4
Number of selected PCs	6	6	6	5

Table 9. The internal parameters and evaluation indicators values of the 4 single models

	γ	σ^2	RMSE	MRE/%	MaxRE/%
Single model (coal class 1)	1.37	14.72	0.3063	2.98	4.38
Single model (coal class 2)	53.03	11.26	0.3322	3.19	4.11
Single model (coal class 3)	16.72	2.68	0.3301	3.22	4.64
Single model (coal class 4)	113.64	32.37	0.3101	3.06	4.52

In summary, the main running procedures of the integrated model can be described as follows.

Step 1: Train the four single models based on LS-SVM using the corresponding offline sampling data.

Step 2: The integrated model runs online; the filtered industrial signals are input into the model.

Step 3: Through the model switching mechanism, determine the class of the current coal, and switch to the corresponding single estimation model.

Step 4: According to the model updating strategy, if needed, retrain the corresponding single model, and update the internal parameters γ and σ^2; otherwise, exit.

Step 5: Output the estimated clean coal ash content.

For further validation of the integrated estimation model proposed in this paper, this model was tested in an industrial experiment of the coal flotation process in the Xingtai Coal Preparation Plant. Samples of the flotation's clean coal were collected every hour, and the ash content was assayed. During the experimental period, the feed raw coal includes the four classes of coal which are mentioned above. Comparisons were made between the estimation results and operators' assay results during the 15 days of the industrial experiment period, as shown in Fig. 10. The relative errors are shown in Fig. 11. The mean relative error is 3.32%, while the maximum relative error is 5.46%. The results of the industrial experiment indicate that the proposed integrated model features a satisfactory estimation effect and industrial applicability.

Table 10 shows that the RMSE, MRE and MaxRE of the integrated model are all lower than that of the single static estimation model based on LS-SVM and that the proposed model shows a high correlation coefficient R value. This finding indicates that the estimation values are able to track the ash content trend and that the prediction accuracy and generalization ability of the integrated model proposed in this study are superior. This capability is primarily due to the following points: first, for a single class of coal, the accuracy of the static estimation model may decrease as time goes on because of the various disturbances in the process; therefore, a model updating strategy is designed in this research

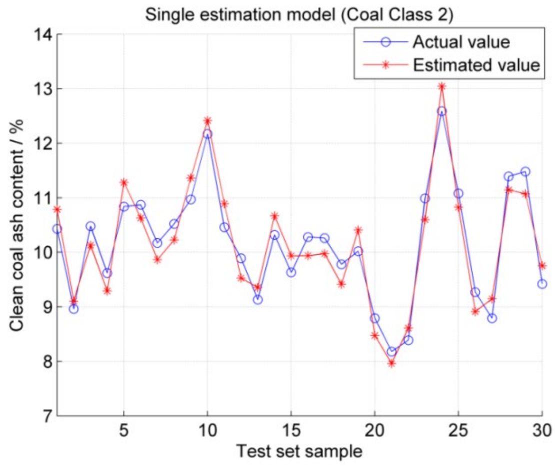

Fig. 7. Comparison of the estimated values and actual values (Coal class 2)

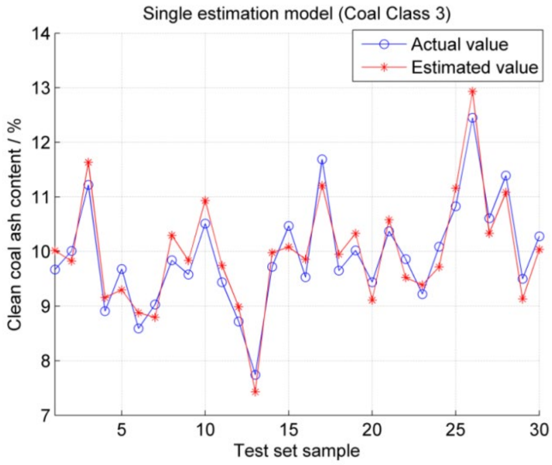

Fig. 8. Comparison of the estimated values and actual values (Coal class 3)

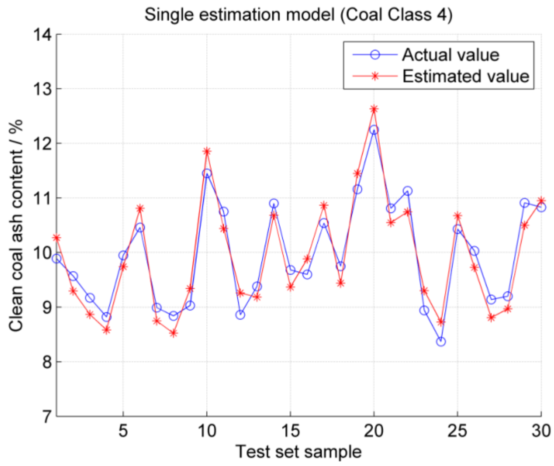

Fig. 9. Comparison of the estimated values and actual values (Coal class 4)

to solve the problem of decline in single model accuracy. Second, floatability of different classes of coal is considerably different as well as the operating conditions; thus, a multiple LS-SVMs model is developed by combining several single models for different classes of coal to address the problem of model mismatch. The above methods improve the estimation accuracy of the integrated estimation model.

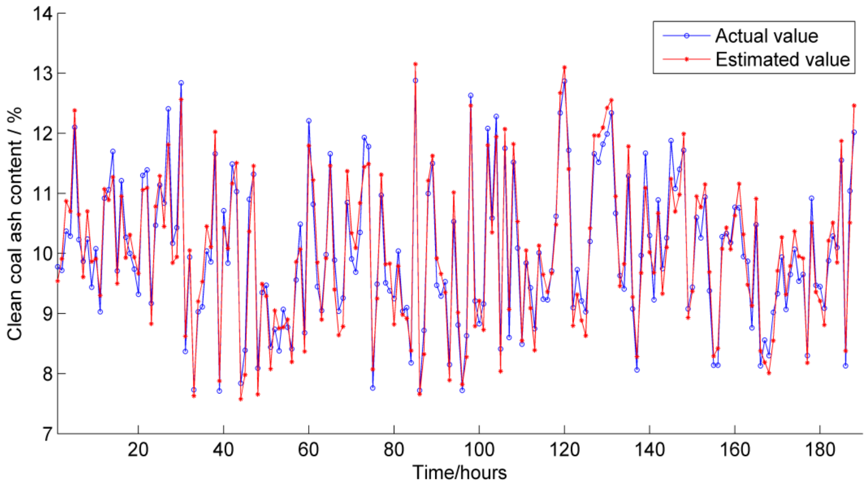

Fig. 10. Comparison of the estimated values and actual values in the industrial experiment

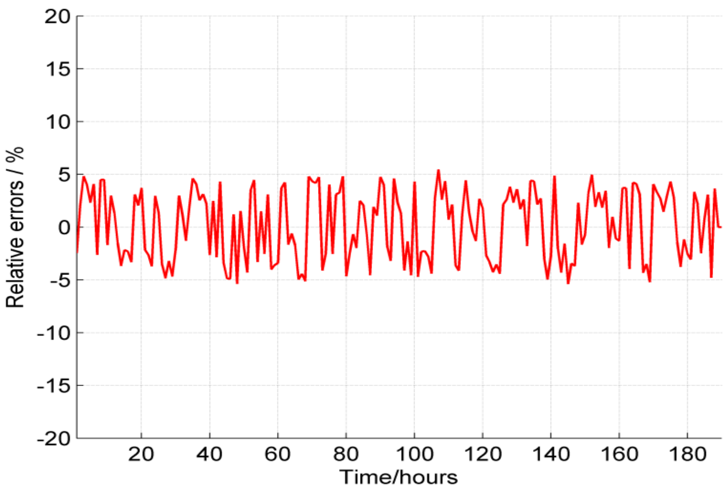

Fig. 11. Relative errors in the industrial experiment

Table 10. Comparison of the proposed model with a single estimation model

Model	*RMSE*	*MRE/%*	*MaxRE/%*	*R*
Single static estimation model	0.5747	8.62	17.33	0.7163
Integrated model proposed in this study	0.3540	3.32	5.46	0.9331

5. Conclusions

This paper proposes a new integrated model, based on model updating and multiple least squares support vector machines (LS-SVMs), to estimate the clean coal ash content for coal flotation. The single estimation model for the single class of coal based on LS-SVM is discussed first, and gravitational search algorithm (GSA) is used to optimize the internal parameters. The comparison with Back-Propagation Neural Network (BP-NN) verifies the better performance of LS-SVM with small sample sets. Furthermore, the model updating strategy is studied to enable the single model to adapt to the fluctuations of working conditions and the heterogeneity of coal. In addition, it is found that the single estimation model of the single class of coal is not suitable for a different class of coal. In the actual production process, the raw coal comes from different sources, and the floatability is substantially different as well as the operating conditions. Considering these factors, a multiple LS-SVMs model is proposed, which is formed by several single models for the different classes of coal and includes a wide operating range. Meanwhile a model switching mechanism based on coal blending schemes is designed.

The simulation results verify the accuracy, and an industrial experiment indicates that the integrated model has good industrial applicability. Compared with the single static estimation model, the integrated model shows better estimation results. The future work is to optimize the operating parameters of coal flotation process, such as the reagents dosage, air rate and froth depth by using the estimated clean coal ash content, so as to reduce the production cost and improve the quality of the flotation products. Besides, it might be better if a functional parameter which expresses the effects of feed size during flotation is added, and it is possible to realize that through some advanced technologies, such as machine vision, etc.

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