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## Optimization of soft-sensing model for ash content prediction of flotation tailings by image features tailings based on GA-SVMR

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**Abstract:** Ash content is one of the most important properties of coal quality and the ash prediction of coal slurry in floatation is urgent and important for automation of the floatation process. The aim of this paper is to propose a method of ash content prediction for flotation tailings by the use of image analysis. The mean gray value, energy, skewness and coal slurry concentration are highly correlated with coal slurry ash content by correlation analysis based on experiments while the particles' size has little effect on the ash. Single variable linear prediction model between coal ash content and mean gray value was developed by the LS and its prediction errors were below 7%. For improving the prediction results, an ash prediction model based on GA-SVMR was established with additional three input parameters: energy, skewness, coal slurry concentration. This model has a higher accuracy with predictive errors all below 5% and 80% of them less than 3%. Results indicate that GA-SVMR model has a higher precision compared with LS model and PSO-SVMR model and soft-sensing model based on image features of the slurry can be used as a new method for ash detection of floatation tailings in automatic control process of coal floatation.

**Keywords:** GA-SVMR, image feature, floatation, ash content

### 1. Introduction

Flotation is a very important issue in the coal cleaning industry. The ash contents of flotation products, i.e., froth products (clean coal) and tailings, are the most critical parameters that must be controlled to achieve an advanced flotation performance. Therefore, the development of online testing of ash content of flotation products becomes the key issue to enhance the automation of floatation (Shean et al., 2011; Wang et al., 2019).

Because of the danger of radiation in ash detection and its low accuracy (Chen et al., 2011; Wang and Chen, 2015), soft-sensing technology, as an industrial technology, provides a new method for detection of flotation feed properties. In the past few years, soft-sensing technology has been widely applied in the coal washing industry (Citir et al., 2004; Claudio et al., 2011; Sadr-Kazemi and Cilliers, 1997). Researches constructed the soft-sensing model for coal slurry ash content using the mean gray value of images of coal slurry based on a BP neural network and the least square method (LS), respectively (Zhang et al., 2014; Jorjani et al., 2009). A set of parameter measurement systems for an on-line flotation process was established by considering the texture and structure of froth images (Holtham et al., 2002). A relation model between the distribution of the bubble diameter and flotation reagents dosage was built using image technology (Perez et al., 2011). The ash content of clean coal was predicted using gray features of froth images (Hargrave et al., 1996).

A method was proposed for ash prediction of coarse coal by image analysis combined with GA-SVM (Zhang et al., 2014). In addition, some researchers analyzed the images of froth and extracted the feature parameters of a coal slime flotation process, ultimately established a mathematical model for the flotation process based on a neural network (Gülhan et al., 2008). To detect the ash content of solid-state

coal, an on-line coal ash analyzer, which avoids the harm of radiation, was developed using laser-induced breakdown spectroscopy (LIBS) technology (Adel and Luttrell, 1996; Ctvrtnickova et al., 2010). However, the analyzer is expensive, and the technology is not mature. It is necessary to conduct further studies before industrial applications.

The detection of the variables in the flotation process mainly focuses on the analysis of the froth properties. It cannot explain the whole flotation process only by the analysis of froth images. Therefore, the main approach of controlling the flotation process is to achieve on-line detection of flotation product quality and apply a stable feedback control strategy into the flotation process. Because of the low distinguishing of clean coal characteristics (Zhang et al., 2014), this paper mainly studies the characteristics of flotation tailings. By using the genetic algorithm and support vector machine regression (GA-SVMR) modeling theory (Patil et al., 2012), the soft-sensing modeling method for flotation tailings ash based on the image features is composed. A novel method for the on-line detection of coal ash is achieved by using this method.

In summary, there are few studies on the indirect measurement of coal slurry ash by image method. The detection accuracy and model adaptability of the established coal slurry ash detection model need to be further improved. Therefore, it is necessary to find a more suitable soft sensing model for coal slurry ash detection, in order to improve the accuracy of coal slurry ash detection and the applicability of the method.

## 2. Materials and Methods

### 2.1. Construction of soft-sensing model

The soft-sensing model for analyzing ash image features of flotation tailings consisted of the image acquisition, the image processing and the building of a linear prediction. Fig. 1 shows a schematic diagram of the collected feature values of gray images of flotation tailings. Sixty pictures of flotation tailings samples were continuously collected by the image acquisition system and these pictures were stored in the same folder. Bright spot characteristics in gray images were extracted by analyzing the pictures circularly. Once the largest bright spot area of the image was larger than the threshold value the image processing program will directly remove this defective picture from the folder. Otherwise, the program will extract statistical characteristic values including mean gray value, variance, smooth-

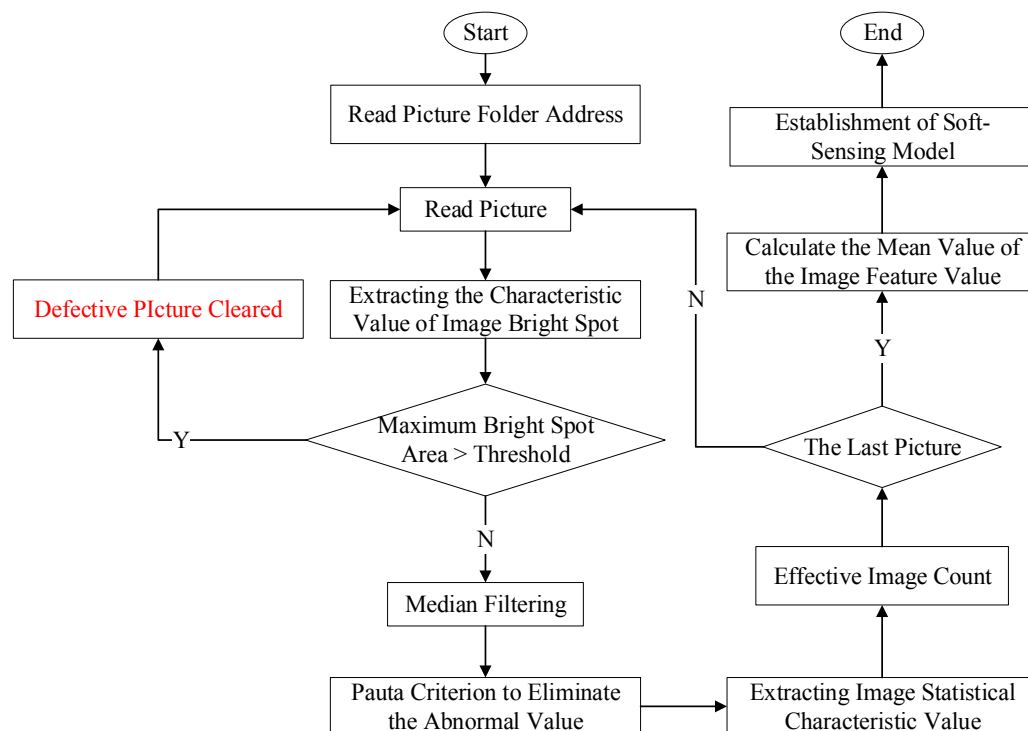


Fig. 1. Schematic diagram of extracting images feature values

ness, skewness, energy and entropy (Zhang et al., 2014). Then, the program continues by analyzing the next picture. Eventually, the average values of all the valid image features were obtained and a soft-sensing model between image feature values and ash content of flotation tailings was established by considering the optimization algorithm.

## 2.2. Image acquisition system

An experimental Image acquisition system is shown in Fig.2. The image acquisition system was built in a laboratory, and it mainly included a shading system, lighting system, mixing system, sample container, industrial camera and computer.

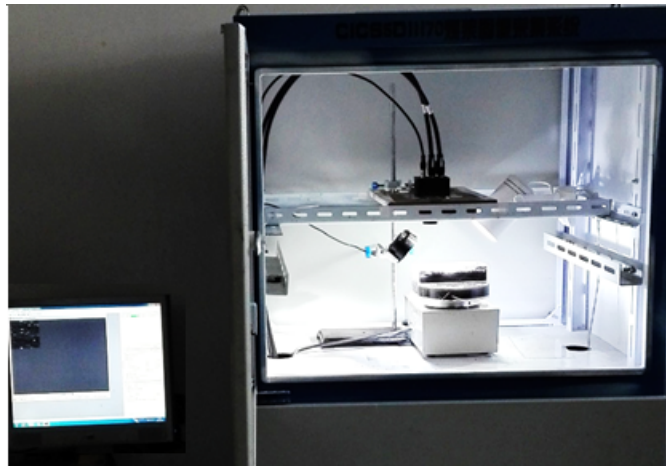


Fig. 2. Image acquisition system of coal slurry

The high speed camera VC-3MC was chosen as an image collector in this experiment. The lens aperture was F4 and lens focal length was 10 cm. The white light source has a higher identification performance for average gray level of coal slurry than others. That's why we chose the white light source. Due to the stability characteristic of the LED light source (Allen, T. 1969), its stability time, tested by an experiment, was 40 minutes. And the results show that the white light source is more suitable. The lighting system used a white LED light source with 130,000 lx light intensity. Illumination of light (45/0) and observation position was optimized before experimentation began. To avoid the sample precipitation in the acquisition process, the magnetic mixer was installed with a mixing speed of 800 r/min.

## 3. Results

### 3.1. Investigation of relevant factors

#### 3.1.1. Impact analysis of ash on image gray feature

We specially prepared six groups of experimental samples to study the influence of ash content on image characteristics. These six groups of samples with particle sizes of less than 0.5 mm and ash contents ranging from 40.63% to 66.37% were obtained using the mixture of clean coal and gangue at different mixture ratios. The ash content of clean coal is 10.9%, while that of gangue is 80.7%. Coal slurry with a concentration of 40 g/L was prepared with these dry samples. Images were collected using the image acquisition system and statistical features including mean gray value, variance, smoothness, skewness, energy and entropy were extracted by the image analysis program. Finally, the correlation between the ash and image features was conducted, and the results are shown in Table 1.

Table 1 show that the mean gray value and energy increase while the skewness decreases with increasing ash content of the samples. The correlation analysis indicates that mean gray value, energy and skewness are significantly related to samples ash contents with the correlation coefficients of 0.9818, 0.8372 and -0.9490, respectively. However, the other three statistical features have poor correlation with samples ash contents.

Table 1. Correlation analysis between ash and statistical features of images

Ash, %	Mean gray value	Variance	Smoothness	Energy	Skewness	Entropy
40.63	114.407	36.79	-4.90	0.040	0.057	-4.46
46.30	125.453	40.07	-5.08	0.040	0.050	-4.55
51.89	139.313	40.08	-5.19	0.043	-0.010	-4.50
56.62	143.810	43.05	-4.79	0.040	-0.033	-4.58
61.14	172.110	38.77	-5.42	0.050	-0.127	-4.49
66.37	183.883	40.65	-5.56	0.050	-0.103	-4.49
R <sup>2</sup>	0.9818	0.4736	-0.7081	0.8372	-0.9490	-0.0601

### 3.1.2. Impact analysis of concentration on image gray feature

Thirty groups of coal slurry samples, with ash contents of 10.9%, 40%, 80.7% and concentrations of 5 g/L~50 g/L, were prepared according to the method mentioned in 3.1. The particle size was controlled to below 0.5 mm in the prepared coal slurry. Finally, images were collected using the image acquisition system and image features were also extracted. The relation between mean gray value and concentration is shown in Fig.3.

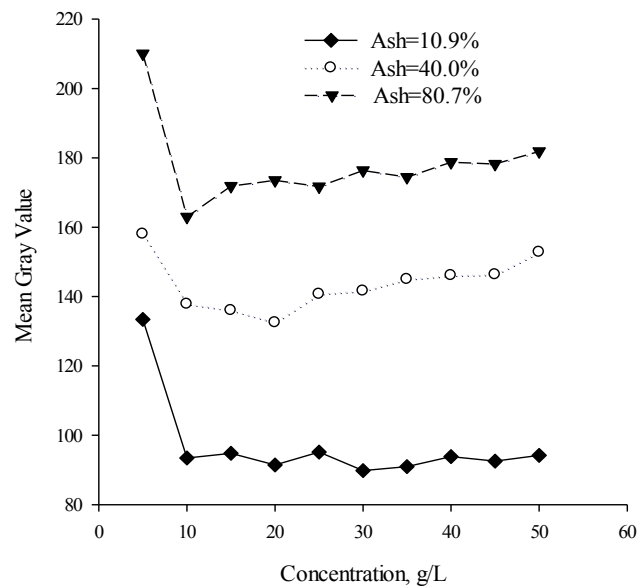


Fig. 3. Influence of concentration on image mean gray value

As shown in Fig. 3, the mean gray value of samples with different ash contents experienced a sudden change when the concentration increased from 5 g/L to 10 g/L. This may be attributed to the low sample concentration, which makes the slurry almost transparent, leading the color of collected images to be the same as that of the sample container and mixing device. As the sample concentration increased from 30 g/L to 50 g/L, the mean gray value of the two samples with ash content ranging from 10.9% to 40.0% grew slowly. Therefore, the sample concentration was an important factor affecting the ash prediction model.

### 3.1.3. Impact analysis of particle size on image gray feature

According to the previous method, four groups of samples with ash content of 40% and concentration of 40 g/L were prepared. The particle sizes of these four groups of samples were 0.5-0.25 mm, 0.25-0.125 mm, 0.125-0.074 mm, 0.074 mm size fractions. The mean gray values were extracted from the collected images and the relation between particle size and mean gray value is shown in Table 2. Table 2 indicates that the mean gray values of four samples are similar. Specifically, the average mean gray values of various size fractions were approximately 36.8, except for the second group which was 39.582. Overall, particle size has no significant effect on the mean gray value of sample images, which

indicates that it is not a primary factor affecting the image characteristics. Therefore, the particle size is excluded from the input variables for establishing a soft-sensing model using image analysis.

Table 2. Impact of particle size on feature values of gray images

Particle size, mm	Mean gray value
0.5-0.25	36.801
0.25-0.125	39.582
0.125-0.074	36.793
-0.074	37.110

### 3.2. Data preparation for model building and validation

Coal samples with particle sizes of less than 0.5 mm were taken from the Xuehu Coal Preparation Plant. Twenty-six groups of samples with different ash contents were prepared by changing the ratio of clean coal and gangue. The actual ash content of these samples was obtained by ash content analysis using burning tests. Furthermore, three concentrations of coal slurry, 35 g/L, 40 g/L and 45 g/L, were prepared, and 78 groups of mixed samples in slurry were obtained. Three characteristics, mean gray value, energy and skewness, were extracted. At this time, a total of 234 groups of data are obtained, of which 219 groups are randomly selected for model training and construction, and the remaining 15 groups are used for model accuracy test.

The variation range of actual ash, concentration, mean gray value, energy and skewness are 25.74(40.63%-66.37%), 10(35%-45%), 76.03(113.5-189.53), 0.01(0.04-0.05) and 0.263(-0.2-0.063), respectively. Five groups of parameters are distributed in a relatively stable region and there is no abnormal value.

### 3.3. Linear model for ash of flotation tailings based on mean gray value

As there are no acknowledged theory theories between regarding various characteristics of gray images and coal ash content in slurry, the image mean gray value, which is significantly related to sample ash, is chosen as the independent variable and the sample ash as the dependent variable. Sixty-three groups of sample data, including their ash contents and mean gray values, were obtained. Then, a linear prediction model between the mean gray value of the images and their ash contents was established in Eq. (1).

$$y = 0.3814x - 1.944 \quad (1)$$

where  $x$  represents the mean gray value of the sample images and  $y$  means represents the ash content of the sample. 15 Fifteen groups of data were used to test the accuracy of the linear model. The prediction results were shown in Fig. 4.

As shown in Fig. 4, the relative error of the linear model was all below the 7% line, where 60% of the relative errors were less than 5% while several individual sample errors were comparatively larger comparatively, at 6%. Poor accuracy may be attributed to the negligence of other characteristics of the tailings images. Thus, other 2 other image features, which have notable correlation with ash content, should also be considered in the formation of the prediction model. Besides, It has been proved proven that the sample concentration has a notable effect on the mean gray value of the sample in 3.1.2. It is better to take sample concentration into consideration when the prediction model is built.

As a result, the prediction model of for predicting ash content should be a multidimensional nonlinear model with four inputs, such as mean gray value, skewness, energy and the concentration of the coal slurry.

### 3.4. Establishment of soft-sensing model for ash content of coal tailings based on GA-SVMR

GA-SVMR has been widely used in multivariate modeling, especially in the case of small particle size. Fig. 5 shows the optimization process of the parameters of SVM. As shown in Fig. 5, the optimization process of parameters in GA-SVMR model can be divided into the following steps:

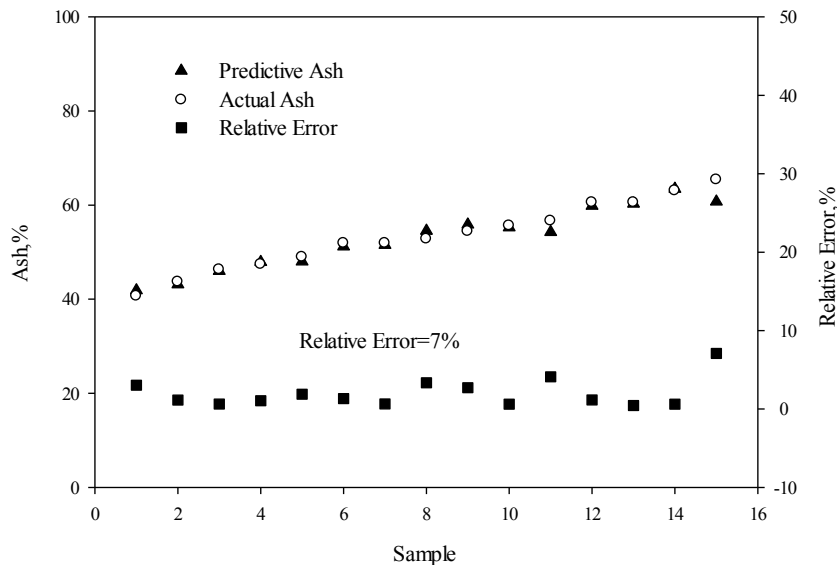


Fig.4. Error analysis of linear prediction model based on LS

- (1) Firstly, dividing divide sample data into a training set and test set by randomization and normalize the training data;
- (2) Initialize the penalty factor C and the kernel parameter G;
- (3) Take output error as indices of excellence and obtain optimal parameters, including penalty factor C and kernel parameter G, using the cross-validation method and GA algorithm;
- (4) Predict output variables with the optimal model and test data.

The soft-sensing model for predicting ash content of flotation tailings was established by GA-SVMR and the expression function was as follows:

$$[Q_{\text{ash}}] = f(P_{jz}, P_{n1}, P_{pd}, P_{nd}) \quad (2)$$

where  $Q_{\text{ash}}$  is the ash content of coal tailings;  $P_{jz}$ ,  $P_{n1}$  and  $P_{nd}$  are image features obtained from image analysis that and they stands for the mean gray value, energy and skewness, respectively.  $P_{nd}$  represents the concentration of the sample.

The four variables were used as the inputs of the model while the ash content was the output. Sixty-three groups of data were randomly selected as the input of the GA-SVMR algorithm to establish the soft-sensing model. The best C and G of the SVM model optimized by the GA algorithm with training data were 48.7008 and 0.07515, respectively. The remaining 15 sets of sample data were substituted into the optimal model to predict the ash content of the coal tailings. The predicted results and errors are shown in Fig. 6. It is obvious from Fig. 6 that the relative error between the actual ash contents and that of the prediction determined by GA-SVMR model are all below 5% and 80% samples' relative errors are less than 3%, which indicates that the predictive model for ash content of the coal tailings based on the GA-SVMR has a higher precision.

### 3.5. Comparison of different prediction model

To obtain the best performance of the prediction model, the particle swarm optimization (PSO) algorithm was used to optimize the parameters of the penalty factor C and kernel parameter G in supporting the vector machine (Patil et al., 2012). Finally, the prediction results of the three models, LS, PSO-SVMR and GA-SVMR, were shown in Tare shown in Table 3.

Table 3. Prediction effects of the three models

Model types	Eigenvalue number	RMSE	R2
LS	1	1.557	0.9375
PSO-SVMR	4	1.4671	0.9620
GA-SVMR	4	1.308	0.9661

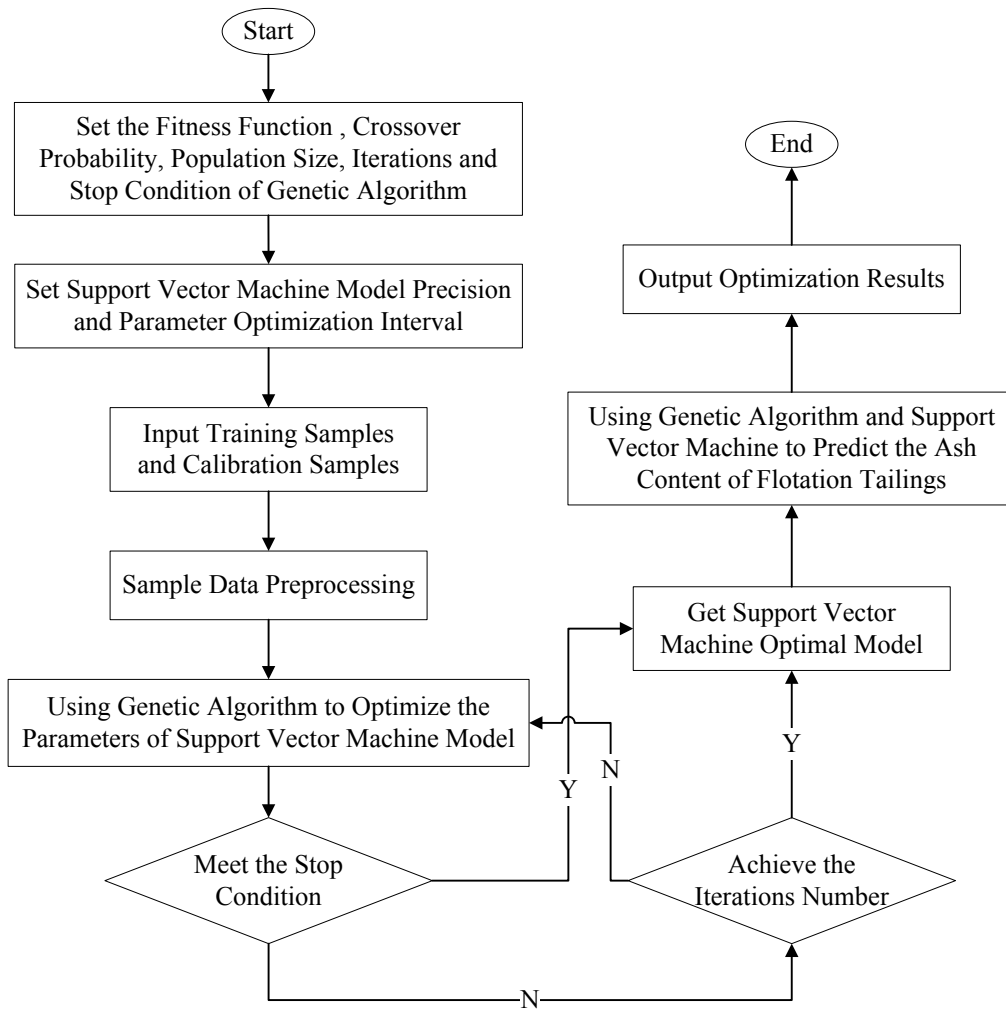


Fig. 5. Process of parameter optimization for GA-SVMR model

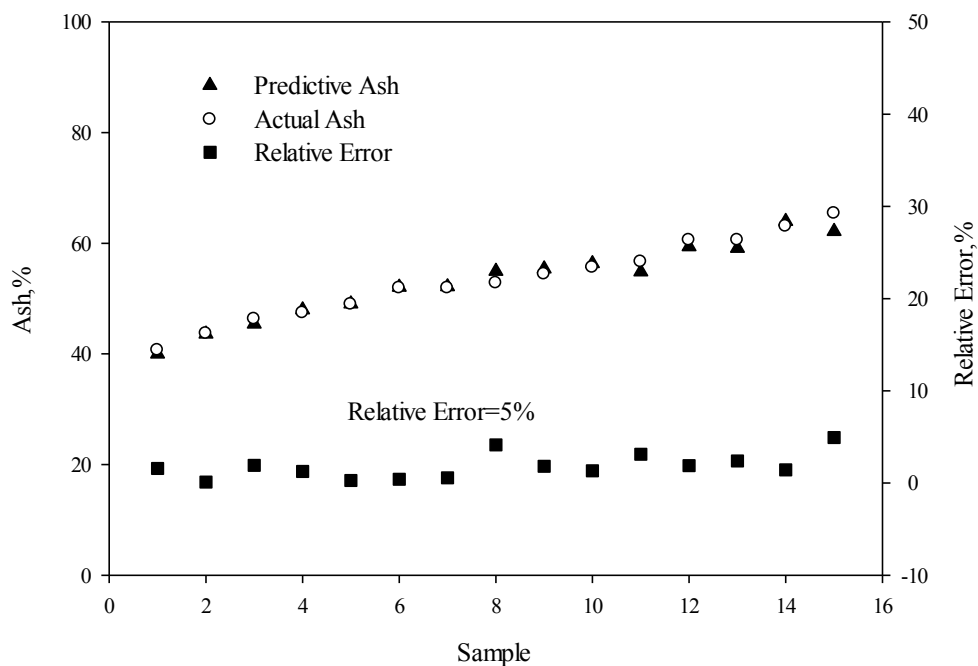


Fig. 6. Error analysis of soft-sensing model for ash of flotation tailings based on GA-SVMR

The Root Mean Squared Error (RMSE) in the Table 3 is the average variance of the predictive and actual ash contents (Diambomba et al., 2016). The lower this value is, the higher the prediction accuracy will be. R2 is an index to measure the correlation extent between the predictive ash contents and actual ash contents. According to the definition of correlation coefficient, the R2 value will always lie between 0 and 1 and the former value indicates that the model does not have predictive power while the latter shows the model has an accuracy of 100%.

It can be known seen from Table 3 that the accuracy of the prediction model based on LS is the worst when using one variable as the input. The performance of the prediction model based on GA-SVMR is better than that of PSO-SVMR. Above all, it can be concluded that the soft-sensing model based on GA-SVMR has the better best accuracy and provides a novel method to monitor the ash contents of tailings in the floatation process online.

#### 4. Conclusions

The effects of the slurry concentration and particle size of floatation tailings in images features were analyzed. The results showed that the ash content of the coal slurry had a positive effect on the mean gray value of the image, while the particle size had little influence on the mean gray value.

The linear prediction model between the mean gray value and the ash content of the coal tailings was established, and its prediction errors were all below 7%. To reduce the error, the soft-sensing model was established based on GA-SVMR, in which another three variable inputs were added: energy, skewness and concentration of coal slurry. By comparing the testing performance of the three models, LS, PSO-SVMR and GA-SVMR, it was concluded that the prediction model based on GA-SVMR had a higher accuracy with predictive errors all below 5% and 80% of predictive errors less than 3%. This investigation provides a novel and precise method for ash contents detection of floatation slurry online.

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