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Huizhon LIU (huizhon6@163.com)
Jiangxi University of Science and Technology
Keshun YOU
Jiangxi University of Science and Technology

Research Article

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Optimization of the dewatering process for concentrate pressure filtering by Support Vector Regression

*Huizhon LIU[1] Keshun YOU[1]

（1. School of Mechanical and Electrical Engineering, Jiangxi University of Science and Technology，Ganzhou 341000，China. *Email:huizhon6@163.com ）

Abstract: In order to better improve the efficiency of the concentrate filter press dehydration operation, this paper studies the mechanism and optimization methods of the filter press dehydration process. Machine learning models of RBF-OLS, RBF-GRNN and support vector regression (SVR) are constructed respectively, and Perform laboratory simulation and industrial simulation separately. SVR achieves the best accuracy in industrial simulation, the simulated mean relative error (MRE) of moisture and processing capacity are respectively 1.57% and 3.81%. Finally, a simulation model of the filter press dehydration process established by SVR, and the optimtical simulation results Obtained by optimization method based on control variables. The results show that the machine learning method of SVR and optimization methods based on control variables are applied to industry, which can not only ensure the stability of expected production indicators, but also shorten the filter press dehydration cycle to less than 85% of the original.

Key words: concentrate filter press dehydration; machine learning models; simulation accuracy; control variables; expected production indicators

1. Introduction

With the gradual exhaustion of easy-separation mineral resources, the amount of complex and low-grade ore increases, and the grain size of grinding becomes more fine, resulting in the dewatering and filtration of essential ore becoming more and more difficult. A high-efficiency pressure filter was developed and gradually applied to the concentrate filtration of the concentrator. Because the automatic control technology is pressure filter, this type of high-efficiency pressure filter is generally called an automatic pressure filter[1][2][3]. the forced dehydration process of "mechanical pressing" and "air drying" on the basis of the "feeding pressure" of the conventional filter press are applied in automatic pressure filter[4], so that it can not only obtain a filter cake with lower moisture, but also has a higher operating efficiency[5].

There are many kinds of automatic filter presses that have been successfully used in the mineral processing industry, such as the Larox-PF automatic filter press developed by Larox in Finland[7][8][9] and the BPF automatic filter press in China[10]. Simultaneously, a new design of bowl dehydrator with a spiral screen is built and developed by Zheng Gangfeng and his colleagues at Anhui University of Science and Technology in China, the effect of filter press dehydration of coal improved efficiently[11]. Since the dehydration process of the automatic pressure filter is relatively complicated, and the stability of the index and the efficiency of the dehydration process affected by the reasonableness of the control parameter setting of the dehydration process, the optimization research of the filter press dehydration process control has received more attention.

Research on dehydration optimization through chemical methods, Dewatering Aids and Flocculant to optimize the dehydration of mineral particles used by Firat Bura[13] and L. BESRA[13]. Several dewatering techniques of sedimentation thickening, filtration, centrifugation, dewatering on screens, and seepage-induced dewatering and consolidation even are studied by H. El-Shall[14] on dehydration optimization through big data methods, experimental data to characterize industrial dehydration performance also used by Shane P. Usher[15]. a mechanism model of the filter press process established by S.L.Jamsa-Jounela[16], striving to obtain the best operating control parameters of the filter press process to achieve process optimization. And Industrial Pressure Filtration with Process data analyzed andmodeled by F.D. Bähner[17].

Machine learning (ML) has recently gained in popularity[18] combined with big data applied to engineering practice. Combining machine learning with process control engineering can improve the accuracy of data-driven models[19]. A key issue is the optimization of process control through machine learning[20]. A large number of industrial production datas are used for establishing a machine learning model of pressure filter dehydration process control. By comparing the simulation and prediction accuracy of the three machine learning models of OLS and GRNN with RBF networks and support vector regression(SVR), it is found that support vectors regression (SVR) has the highest accuracy. In order to obtain the optimal control parameters in the control model, we study an optimization method of control variables, which aim to optimize another parameter while ensuring that one control parameter is qualified. In this way, the optimal control parameters in the industry are obtained, and finally the optimization of the industrial filter press dehydration process is realized.

2. Method and process of optimization

A complete working process of the automatic pressure filter includes: closing the filter plate-feeding and filtering, mechanical pressing, air-drying, opening the filter plate, unloading the cake, cleaning the filter cloth, etc. Determining the dehydration index are the three main dehydration processes of "feeding filter press", "mechanical pressing" and "air drying". Only a good under-standing of the filter press dehydration process and the purpose of optimization can better put forward the optimization method of the actual filter press dehydration process control parameters. Therefore, in this chapter, we first introduce the three-stage process of filter press dehydration, and then propose an optimization method based on the control variable according to the purpose of process optimization.

2.1. Feeding filter press process

The feeding filter press process, that is, the process of pressing the slurry into the filter chamber. This process starts the filtration operation when the slurry is hydraulically inserted into the filter chamber. It is a process of filter cake filtration and follows the following basic filtration equation proposed by Darcy[21].

$$Q = \frac{dV}{dt} = K\frac{A\Delta P}{\mu L} \tag{1}$$

Where: Q is the flow rate of the filtrate; A is the filtration area; t is the filtration time; V is the volume of the filtrate accumulated in time t; L is the thickness of the filter layer; K is the permeability coefficient of the filter layer; ΔP is the cross-filtration layer The pressure drop (the driving force of filtration); μ is the viscosity of the filtrate.

In the case of constant feed concentration and pressure, the length of feed time directly determines the thickness of the filter cake. With the extension of the

feeding time, the filter cake gradually thickens, but the thickening speed is rapidly decreasing. Although prolonging the feeding time can increase the thickness of the filter cake and increase the output of the filter cake per press filter cycle, if the feeding time is, it will significantly increase the filter press cycle, which in turn will reduce the cake output per unit time. Therefore, "feeding time" is one of the important factors that affect the dehydration index and efficiency. According to the nature of the material (filter cake thickness) to obtain a reasonable feeding time is the goal of this process optimization.

2.2. Press dehydration process

There are many ways to press dehydration, and the most widely used are mainly two methods: one is mechanical press dehydration with a pressing mechanism, and the other is hydraulic press dehydration. According to existing research, the comparison of the effects of these two pressing methods is shown in **Fig. 1**. It can be seen that the mechanical pressing curve is obviously steeper, which means that after the filter cake is mechanically pressed, the time to reach the same filter cake porosity is significantly shorter. Mechanical pressing can significantly shorten the dehydration time of the filter cake.

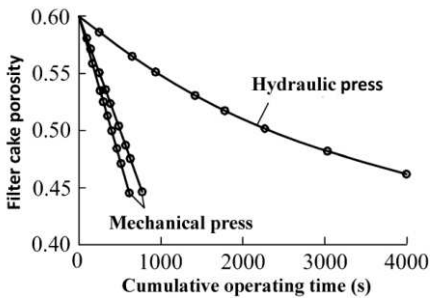

Fig. 1. Mechanical pressing and hydraulic pressing test curve

After the "feeding filter press" is completed, it enters the "mechanical press" stage. The automatic pressure filter uses a diaphragm press, which is a type of mechanical press. If the pressing time is not enough, and the water in the pores of the filter cake is not fully squeezed out and the pressing is stopped, it will inevitably cause the final moisture of the filter cake to increase, which will affect the efficiency of pressing. On the contrary, after a certain period of time of pressing of the filter cake, the porosity of the filter cake basically no longer decreases, and the water content basically does not decrease anymore. If the pressing time continues to be extended, the working cycle of the filter press will be prolonged and the pressing power will be consumed.

2.3. Air-drying process

After the pressing is completed, there is still some moisture remaining in the pores of the filter cake. At this time, if compressed air is passed into the filter chamber, through the filter cake, and further remove the residual moisture in the filter cake, air drying and dehydration can be realized. According to existing research, air drying can be divided into three stages: penetration stage, replacement stage and evaporation stage. The effect of each stage is shown in **Fig. 2.**

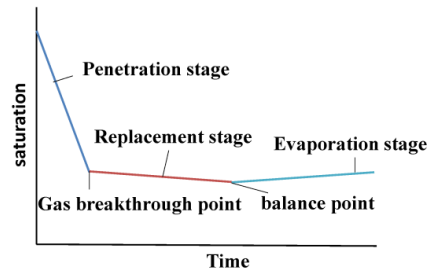

Fig. 2. Three stages of air drying and dehydration

It can be seen from **Fig. 2.** that the liquid discharge is the most in the penetration stage, and then enters the displacement stage and the evaporation stage is entered. After the penetration phase is over, the saturation of the filter cake drops very little, and the moisture of the filter cake is close to the final moisture. If you continue to blow and dry, it will only increase the consumption of compressed air. Therefore, under certain air-drying pressure conditions, reasonable control of the air-drying time, and timely termination of air-drying after the completion of

the penetration stage is the goal of air-drying process optimization.

2.4. Method of filter press dehydration optimization

For a fixed concentrate filter press dehydration system, the "feed pressure" is related to the feed pump and is relatively fixed, so we will not consider it. The size of the concentrate slurry is relatively fixed, and the viscosity is directly related to the concentration. Therefore, the filter press optimization process takes into account the two conditions of "feeding concentration" and "squeezing pressure". And "feeding time" and "press room"," Air drying time" are also the main optimization parameters of the filter press process[22].

The entire dehydration process is controlled by the automatic control system of the filter press. On the one hand, the automatic control system of the filter press realizes the precise control of the mechanical action of the filter press itself; on the other hand, it realizes the program control and auxiliary dewatering process of "feeding, pressing, air-drying, cake unloading and cloth washing",etc. Adjustment of control parameters, etc.

During the operation of the equipment, when slurry conditions such as "feeding concentration" or filtration index requirements change, the operator needs to modify the main control parameters in time through the man-machine interface to ensure the filter press dehydration index and work efficiency. However, the current setting and modification of the control parameters of the filter press dehydration process are mainly carried out by the operators based on their own experience and knowledge. Due to the different experiences of different operators, it is easy to cause fluctuations in the index and efficiency of the filter press dehydration operation. Obtaining the optimal value of the main control parameters of the filter press dehydration process is the key to ensuring the efficient operation of the dehydration operation. Obviously, it is impossible to get the optimal value only relying on the experience of the operator. Optimital parameters can be predicted by mechine learnig[23][24]. Therefore, we propose a precise machine learning model of filter press dehydration process that uses existing data samples, and then use the results of the machine learning model predicting to design a reliable optimization method to obtain the optimal value of the control parameters to achieve the filter press dehydration process Optimization of control. Through the study of the actual situation, we have proposed the following reasonable optimization principle (optimization methods based on the principle of controlled variables):

(1) Under the premise of ensuring that the filter cake with qualified water content is obtained, the optimized control of parameters is used to obtain the maximum processing capacity per unit filter area;

(2) Under the premise of ensuring the processing capacity per unit filter area, the filter cake with the lowest moisture can be obtained through optimized control of parameters.

As shown in **Fig. 3**, The principle of this optimization method based on the controlled variable is: "Under certain external conditions, within the reasonable value range of each control parameter, each control parameter is sequentially selected from small to large, and the value is cyclically selected at small intervals. The values obtained by the control parameters are arranged and combined to obtain a combination of control parameters under various conditions. For each combination, the machine learning model established is used to simulate the simulation results, and the simulation results are sequentially compared according to different optimization principles and optimization goals to find the optimal As a result, the control parameter group corresponding to the optimal result is the optimal control parameter. "

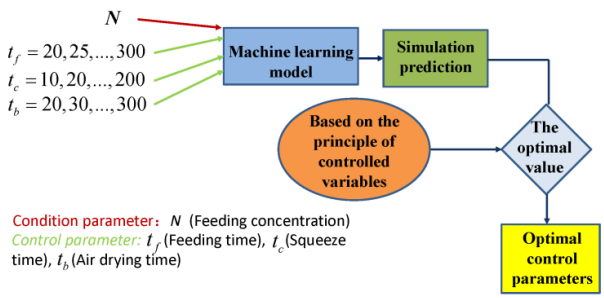

Fig. 3. Optimization process of filter press dehydration

3. Optimal model of filter press dehydration process control

Machine learning and artificial intelligence techniques increasingly promote the development of mineral processing[26]. According to the previously introduced filter press dehydration optimization principle and process, we know that in order to achieve the optimization of the filter press dehydration process, we need to build an accurate machine learning model. This paper uses the least squares method (OLS) and the generalized regression method (GRNN)) Based on Radial Basis Function (RBF) neural network and support vector regression(SVR) to construct an optimal control model for the filter press dehydration process.

3.1. RBF Machine learning model

Artificial neural network is a complex network system composed of many neurons intercon-nected. There are many kinds of neural network models. But we use the radial basis functions (RBF) neural network model based on orthogonal least squares (OLS) and generalized regression (GRNN) to establish a simulation model of the filter press dehydration process.

The energetic performance of SAH through the GRNN and RBF models of artificial neural network technology is predicted by Harish Kumar Ghritlahre, et [25]. The RBF neural network model structure of the filter press dehydration process established by us, which is showed in **Fig. 4.** The RBF network is a two-layer network with only one hidden layer in addition to the input and output layers. The transfer function in the hidden layer is a Gaussian function of the local response, while for other forward networks, the transfer function is generally a global response function. Due to this difference, to achieve the same function, RBF needs more neurons, which is why the RBF network cannot replace the standard forward network. But the training time of RBF is shorter. It is optimal for function approximation and can approximate any continuous function with arbitrary precision. The more neurons in the hidden layer, the more accurate the approximation.

As shown in **Fig. 5**, GRNN is an improvement of RBF with similar structure. The difference is that there is an extra layer of summation, and the weight connection between the hidden layer and the output layer (least squares superposition of Gaussian weights) is removed. Because GRNN has no model parameters to train, it converges quickly. Based on the radial basis network, it also has good nonlinear approximation performance. However, each test sample of GRNN needs to be calculated with all training samples, so its computational complexity is high. Furthermore, all training samples need to be stored, so the space complexity is also high.

In addition, we have also constructed a radial basis function (RBF) neural network model based on orthogonal least squares (OLS). This model is established on the basis of constructing the RBF model structure through the least squares method The optimization method of residual sum of squares is to optimize the parameters of the RBF network structure to minimize the sum of squares of the difference between the regression function and the actual value. The OLS method regresses the predicted response variable through a series of predictor variables. As shown in Eq. (2), OLS linear regression refers to a linear regres-

sion of the response variable *Yt* to the parameter . Among them, Yt is called the dependent variable, *Xt* is called the independent variable,which are the parameters that need to be determined by the least square method, also called regression coefficient, *t = 1, 2,3,4,* represents the number of observations.

$$Y_t = \alpha + \beta X_t + \mu_t \qquad (2)$$

As shown in Eq. (3), the purpose of OLS linear regression is to best fit the curve so that the sum of squares of the distances from each point to the straight line (ie, the residual sum of squares, *RSS* for short) is the smallest.

$$RSS = \sum_{t=1}^{T}\left(y_t - \hat{y}_t\right)^2 = \sum_{t=1}^{T}\left(y_t - \hat{\alpha} - \hat{\beta} x_t\right)^2 \qquad (3)$$

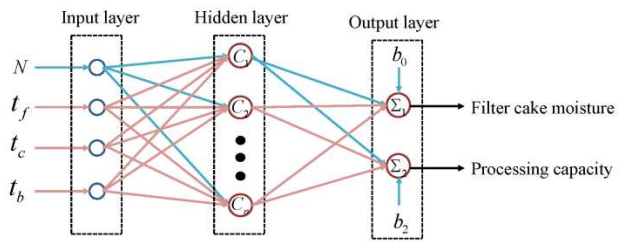

Fig. 4. RBF neural network model structure of filter press dehydration process

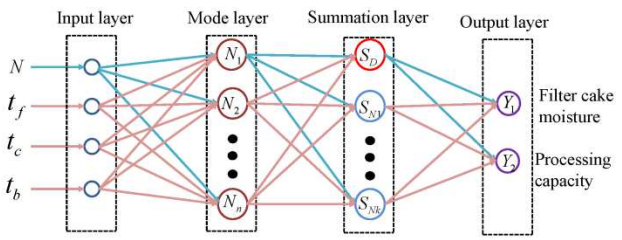

Fig. 5. GRNN neural network model structure of filter press dehydration process

3.2. Method of SVM and SVR

An excellent model will improve the accuracy of the industry[27]. The support vector mechaine(SVM) was proposed by Vapnik et al. in the 1990s, which is based on statistical learning theory [28][29]. SVM method is a machine learning method based on the VC dimension theory of statistical learning theory and the principle of structural risk minimization[30]. It is based on the complexity of the model based on limited sample information. Seek the best compromise between learning ability and learning ability in order to obtain the best generalization ability (Generalization Ability). Since neural network networks are based on the principle of empirical risk minimization, the number of samples is The requirements are high, and the SVM method is based on the principle of structural risk minimization, so under the condition of small samples, the model established by the SVM method has better generalization and promotion performance[31].

SVM is developed from the optimal classification surface in the case of linear separability. The basic idea can be illustrated by the two-dimensional situation in **Fig. 6.** The solid dots and the hollow dots represent two types of samples. *H* is the classification line. H_1 and H_2 are the lines that pass the closest samples to the classification line and are parallel to the classification line. The distance between them is called the classification interval (margin). The so-called optimal classification line requires that the classification line not only correctly separates the two categories, but also maximizes the classification interval. This type of classification line equation can be defined as Eq. (4)

$$wgx + b = 0 \qquad (4)$$

When SVM normalizes the data, it needs to make the linearly separable sample seted satisfy Eq. (5).

$$y_i\left[\left(wgx\right) + b\right] - 1 \geq 0 \qquad (5)$$

At this time, the classification interval is equal to $2/\|w\|$, so that the maximum interval is equivalent to the minimum $\|w\|^2$. The classification surface that satisfies the

condition(5). and minimizes $2/\|w\|^2$ is called the optimal classification surface.

A plane with the farthest distance from the point on the boundary to the plane is found by classification, and in order to minimize the distance from each point to the regression line, ς of an insensitive loss function as the loss function is introduced in the SVR.

$$\min_{w,b,\varsigma,\varsigma^*} \frac{1}{2} w^T w + C\sum_{i=1}^{n}(\varsigma_i + \varsigma_i^*) \tag{6}$$

$$\text{Subject to} \quad \begin{aligned} & y_i - w^T\Phi(x_i) - b \le \varepsilon + \varsigma_i \\ & w^T\Phi(x_i) + b - y_i \le \varepsilon + \varsigma^*_i \\ & \varsigma_i, \varsigma^*_i \ge 0, i = 1,\ldots,n \end{aligned} \tag{7}$$

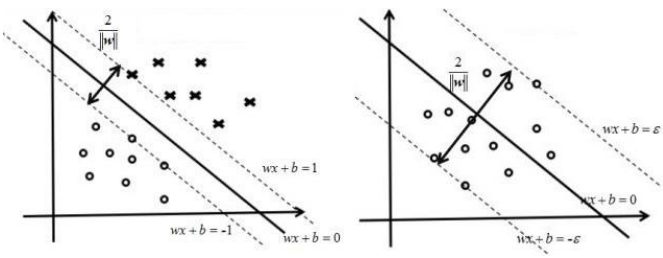

Fig. 6. Method of SVM(on the left) and SVR(on the right)

3.3. Laboratory simulation results of three machine learning model

After constructing three machine learning models for the control and optimization of the filter press dehydration process, we carried out the filter press dehydration experiment in the laboratory, and used the collected test data to explore the construction method of the filter press dehydration process simulation model. The samples were collected from the flotation gold concentrate of the Miaoling Gold Mine in Henan, China. A total of 31 sets of tests were carried out and 31 sets of data were collected. Excluding two sets of abnormal data, 20 sets of the remaining 29 sets of data are used as training samples, and the remaining 9 sets are used as test samples to verify the simulation accuracy of the built model. Take "feeding concentration", "feeding time", "squeezing time", and "air drying time" as the input of the model, and "filter cake moisture" and "processing capacity per unit area" as the output, respectively using OLS and GRNN neural networks Method and support vector regression (SVR) method for simulation model construction. The modeling and simulation program is designed in Matlab language. After the program is running, the simulation diagram and accuracy results of the model and test samples are obtained.

When regression model is used to predict, the common indicators used to analyze and evaluate model errors and accuracy, mean square error (MSE), mean absolute error (MAE) and mean relative error (MRE) are included. The mean square error refers to the expected value of the square of the difference between the estimated value of the parameter and the true value of the parameter; MSE can evaluate the degree of fluctuations of the data. The smaller the value of the MSE, the better the accuracy of the prediction model to describe the experimental data, but the average is generally used. The absolute error is the difference between the measured value (a single measured value or the average of multiple measured values) and the true value, and the relative error is the ratio of the absolute error to the true value. In other words, the credibility of the measurement can be better reflected by the mean relative error (MRE).

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} \tag{6}$$

$$MRE = \frac{1}{m}\sum_{i=1}^{m}\frac{|y_i - \hat{y}_i|}{y_i} \tag{7}$$

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|y_i - \hat{y}_i| \tag{8}$$

Where y_i is the true value, $\hat{y}_i$ is the estimated value or simulation value, and m is the number of test sample.

In ***Table 1***, for the simulation of moisture and processing capacity, the SVR method has the lowest MRE,. In general, the simulation errors are relatively considerable. We mainly consider the complexity and difficulty of data collection , As well as the small number of samples we have temporarily obtained, resulting in a large error in the entire experimental simulation, which inevitably leads to unreliable experimental simulation results. Therefore, after completing the exploration of the laboratory filter press dehydration process modeling method, the industrial production data directly collected from the industry to carry out the modeling and optimization research of the industrial filter press dehydration process.

Table 1

Laboratory simulation results of three machine learning models

Simulation parameters	Machine learning model	MRE /%	MSE/%
Simulation of moisture	RBF-OLS	7.30	10.56
	RBF-GRNN	8.24	5.65
	SVR	**6.47**	**0.94**
Simulation of processing ca-pacity	RBF-OLS	14.57	12.85
	RBF-GRNN	22.24	8.65
	SVR	**10.32**	**1.54**

4. Optimal model of filter press dehydration process control

The experimental simulation results of the industrial filter press dehydration process control model show that the accuracy of the simulation results of the three machine learning models with a small sample of experimental data is too small. Considering that the experimental simulation data samples are less, the overall experimental simulation accuracy is low. Therefore, we want to build a better machine learning model by appropriately adding some actual industrial production data samples, and to achieve good results in the actual industrial filter press dehydration process control, which is our goal.

4.1. Industrial simulation results of three machine learning model

Research is carried out by modeling and optimization of the industrial filter press dehydration system of the flotation gold concentrate of the Miaoling Gold Mine. the BPF-8 automatic filter press used in the system. The dehydration system is shown in **Fig. 7**.

We collected data samples from production for 7 working days and collected a total of 161 sets of industrial data. The size of the gold concentrate what we use is <0.074mm, which accounts for *75%* of the total, and the grade is *30g/t (AU)*. The first 100 sets of data were used as training samples to construct the simulation model of the filter press dehydration process, and then the last 61 sets of data were used as test samples to verify the simulation accuracy of the constructed model.

Take "feeding concentration" and "feeding time", "squeezing time" and "air drying time" as the input of the model, and "filter cake moisture" and "processing capacity per unit area" as the output, and OLS and GRNN neural networks and support vector regression (SVR) method respectively are also used for modeling and simulation. Matlab language is used for programming. The mean relative errors (MRE) of the three methods for the simulation of test samples are shown in ***Table 2***.

It can be seen from ***Table 2*** that the model constructed by the SVR method has the highest simulation accuracy and generalization performance. The simulation results of the SVR model on the test sample are shown in **Fig. 8**. The simulation of the SVR method can also be seen from the. The value has a good approximation to the actual industrial data value. The simulation accuracy of the SVR model for the industrial filter press dehydration process is *98.43%*, and the simulation accuracy of the industrial filter press dehydration process is *96.19%*. Therefore, at the end of this paper，the SVR model and the optimization method based on the control parameters of the filter press dehydration process is carried out.

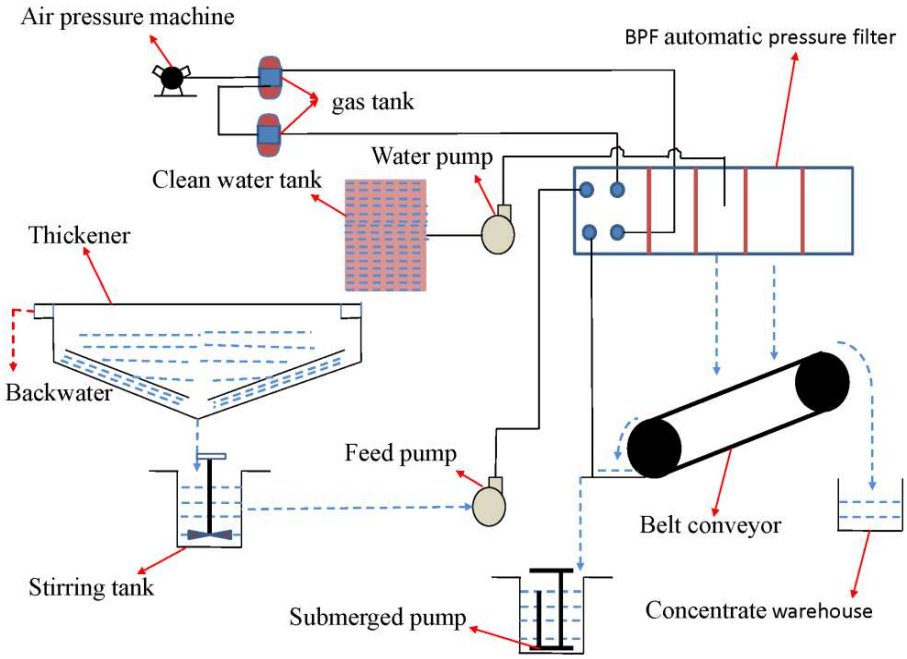

Fig.7. Dewatering system for industrial filter press

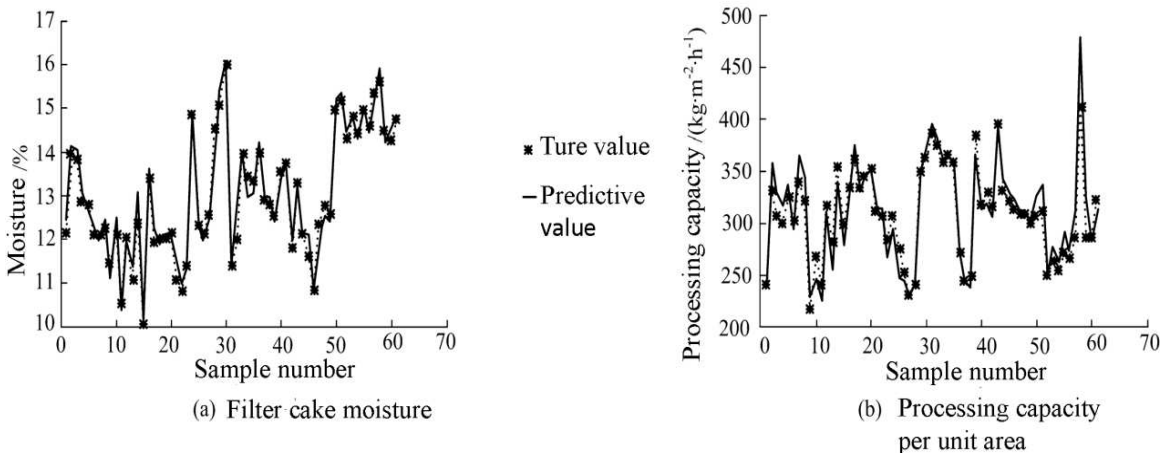

Fig. 8. Simulation results of industrial test samples

Table 2

Industrial simulation results of three machine learning models

Simulation parameters	Machine learning model	MRE / %

Simulation of moisture	RBF-OLS	4.92
	RBF-GRNN	4.68
	SVR	**1.57**
Simulation of processing capacity	RBF-OLS	8.19
	RBF-GRNN	7.12
	SVR	**3.81**

4.2. Industrial results of parameter optimization based on control variables

Section 2.4 introduces the optimization method of the filter press dehydration process, and adopts the optimization method based on control variables. In Chapter 3, we introduce three machine learning model laboratory simulations. In Section 4.1, we introduce the three machine model in the industrial experiment simulation, we finally adopted the SVR simulation model as the optimization model for the final filter press dehydration process control. After constructing the model, we can optimize the industrial filter press dehydration process control parameters accordingly. Therefore, in this section we focus on the actual results of the optimization method based on the principle of controlled variables in the industry. The optimization program is designed in Matlab language. After the program runs, the optimal control parameter table of each condition and predicted value is obtained.

We first control the expected moisture value to 12%, that is, in the industrial filter press dehydration process, the moisture value is required to be 12% or less to be qualified. Then, in the specific industrial experimental model simulation, the value (12% moisture value) is controlled and constrained, and finally we can get another corresponding simulation output value (processing capacity). Sorting the processing capacity value in ascending order, we get the top four processing capacity values. Group data, as shown in ***Table 3***. Through the optimization method based on control variables, we found that the optimal control parameter group in the industrial filter press dehydration process is the data group No. 4.

Table 3

Results of the optimization method based on the principle of controlled variables in the industry

number	Feeding concentration / %	Feeding time / s	Squeezing time /s	Air dryintime / s	Filter cake moisture / %	Processing capacity ($kg.m^{-2}.h^{-1}$)
1	40	35	15	90	**12.0**	280.3
2	45	40	20	85	**12.0**	304.2
3	50	35	35	75	**12.0**	325.8
4	**55**	**35**	**35**	**85**	**12.0**	**347.5**

4.3. Industrial application of filter press dehydration optimization control

After obtaining the optimization results of the control parameters, the optimal control parameters can be directly obtained according to the condition parameters and optimization goals to guide the setting and adjustment of the control parameters of the dehydration process, and realize the optimization of the process. Simultaneously, the optimization results obtained in this paper are used as training samples, and a support vector regression (SVR) simulation model with optimized parameters is constructed. This model can be used to achieve adaptive optimization control of the filter press dehydration process. The system configuration is shown in **Fig. 9**. In actual industrial applications, we first set the expected index of the filter press dehydration process through the computer, and then collect the working condition parameters through the computer in real time to obtain the corresponding work index. Finally, the computer compares the degree of gap between the work indicators and the expected indicators. Adjust the various parameters of the filter press in real time until it is closest to the expected index. In this way, adaptive control of the filter press dehydration process can be realized.

Industrial practice has proved that the optimization method proposed in this paper can not only ensure the stability of the filter cake moisture index, but also shorten the filter press operation cycle to less than 85% of the original, reducing the single-shift operation time of the filter press system, and correspondingly save production energy Consumption and cost, improve the efficiency of filter press operation.

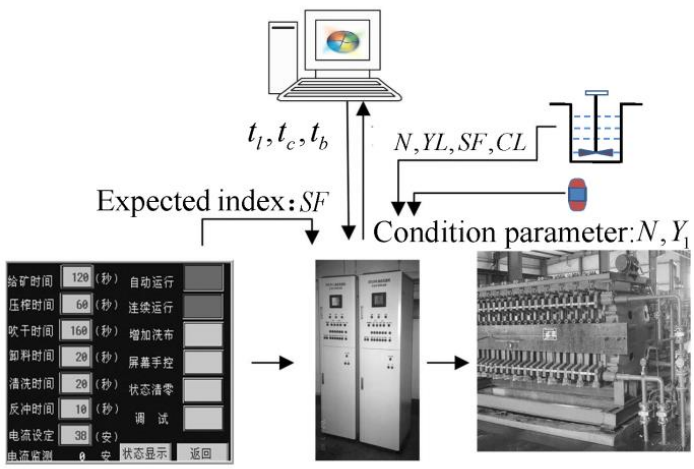

Fig.9. Adaptive control system of filter press dehydration process

5. Conclusions

The optimization ability of the entire filter press dehydration process control is determined by a suitable machine learning model. However, the model simulation data of the laboratory can only be used as a reference, and cannot serve the purpose of guiding the production. Only through industrial model simulation can it be practical, which has the ability to guide industrial production. Although the simulation results of the support vector regression (SVR) in the laboratory are relatively poor, it shows excellent performance in the industrial simulation results. Support vector regression (SVR) has better generalization performance than other algorithms, and has the nice simulation accuracy under small samples. The algorithm is

simple, but it can solve many nonlinear regression problems. The industrial filter press dehydration process simulation model established by the SVR method has the better simulation accuracy Compared with RBF-OLS, RBF-GRNN algorithm, and the simulation MRE of moisture and unit area processing capacity are 1.57% and 3.81%, respectively. Using the method of optimizing the control parameters of the filter press dehydration process based on the control variables, the optimal control parameter combination of the industrial filter press dehydration process was successfully obtained. Practice has proved that guiding the production with the obtained optimal control parameter combination can not only ensure the stability of the filter press production index, but also shorten the filter press cycle to less than 85% of the original. It reduces energy consumption and significantly improves the efficiency of filter press operations.

6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

References

[1] Townsend(2003).Automatic pressure filtration in mining and metallurgy.,16(2),165–173.doi:10.1016/s0892-6875(02)00266-2

[2] (1998). Automatic Pressure Filtration Systems . Metal Finishing , 96(5), 75–. doi :10.1016/S0026-0576(98)80134-7.

[3] (1998). Automatic pressure filtration . Metal Finishing, 96(6) , 152–. doi:10.1016/S0026-0576(98)80337-1.

[4] Leifson,E.(1931).A SIMPLE AUTOMATIC PRESSURE REGULATOR FOR FILTRATION. Science, 73(1904), 707–709. doi:10.1126/science.73.1904.707

[5] Z. H. Wu,Y. J. Hu,D. J. Lee,A. S.Mujumdar & Z. Y. Li (2010) Dewatering and Drying in Mineral Processing Industry: Potential for Innovation, *Drying Technology: An International Journal*, 28:7, 834-842, DOI: 10.1080/07373937.2010.490485.

[6] (1995).The development of automatic pressure filtration at Larox.,32(2),0–121.doi:10.1016/s0015-1882(97)84025-6

[7] (2019).Larox PF-DS pressure filter in wider applications. Filtration and Separation(6),.doi:10.1016/S0015-1882(20)30172-5.

[8] S-L. Jämsä-Jounela,et al."Operator Support System for the Larox Pressure Filter." *IFAC Proceedings* Volumes 36.24(2003):. doi:10.1016/S1474-6670(17)37637-1.

[9] SU Shou-gui. The applications of LAROX pressure filter in mineral processing plants[J]. Metallic OreDressing Abroad, 1999(3):31-32.

[10] LIU Hui-zhong, WANG Qing-fen. The research andde velopment of BPF auto-control pressure filter[J]. *Nonferrous Metals: Mineral Process*, 2003(6):30-35.

[11] Zheng Gangfeng, et al."Mining: Bowl dehydrator design for coal slurry processing." *Filtration and Separation* 51.3(2014):. doi:10.1016/S0015-1882(14)70105-3.

[12] Firat Burat, et al."Improved Fine Coal Dewatering by Ultrasonic Pretreatment and Dewatering Aids." *Mineral Processing and Extractive Metallurgy Review* 36.2 (2015):. doi:10.1080/08827508.2014.898637.

[13] L. BESRA, et al."Flocculant and Surfactant Aided Dewatering of Fine Particle Suspensions: A Review." Mineral Processing and Extractive Metallurgy Review 18.1(1998):.doi:10.1080/08827509808914153.

[14] H. El-Shall, and Patrick Zhang."Process for dewatering and utilization of mining wastes." Minerals Engineering17.2(2003):. doi:10.1016/j.mineng.2003.10.029.

[15] Shane P. Usher, et al."Characterisation of dewaterability from equilibrium and transient centrifugation test d

ata." Chemical Engineering Science 93.(2013):. doi:10.1016/j.ces.2013.02.026.

[16] S.-L. Jämsä-Jounela, et al."Operator support system for pressure filters." Control Engineering Practice 13.10 (2004):.doi:10.1016/j.conengprac.2004.11.019.

[17] F.D. Bähner, et al."Analysis and Modelling of an Industrial Pressure Filtration using Process Data * * The authors would like to acknowledge the Technical University of Denmark (DTU) and BIOPRO2. The project received financial support from Innovation Fund Denmark through the BIOPRO2 strategic research center (Grant number 4105-00020B).." IFACPapersOnLine 50.1(2017):.doi:10.1016/j.ifacol.2017.08.2152.

[18] Jay H. Lee, et al."Machine learning: Overview of the recent progresses and implications for the process systems engineering field." *Computers and Chemical Engineering 114*.(2018):. doi:10.1016/j.compchemeng.2017.10.008.

[19] Bikmukhametov,Timur; JÃ¤schke, Johannes (2020). Combning machine learning and process engineering physics towards enhanced accuracy and explainability of data-driven models. Computers & *Chemical Engineering,* 138(),106834–. doi:10.1016/j.compchemeng.2020.106834.

[20] E N Pistikopoulos, Ana Barbosa-Povoa, Jay H Lee, et al,Process systems engineering – The generation next?,*Computers & Chemical Engineering,*Volume 147,2021,107252.

[21] HEERTJES P M, HAAS H V. Studies in filtration. RecTravChim,1949,68:361-383.

[22] Ding Qisheng, Wang Weiyi. New practical filtration technology. Beijing: *Metallurgical Industry Press*, 2000: 120-126.

[23] Manfred Morari, Jay H. Lee, Model predictive control: past,present and future,*Computers & Chemical Engineering*,Volume 23, Issues 4–5,1999,Pages 667-682.

[24] Mihail Bogojeski, Simeon Sauer, Franziska Horn, Klaus-Rot Müller,Forecasting industrial aging processes with machine learning methods, *Computers & Chemical Engineering*, Volume 144, 2021, 107123.

[25] Harish Kumar Ghritlahre, Radha Krishna Prasad,Exergetic performance prediction of solar air heater using MLP, GRNN and RBF models of artificial neural network technique, Journal of Environmental Management, Volume 223,2018,Pages 566-575.

[26] J.T. McCoy, and L. Auret."Machine learning applications in minerals processing: A review." Minerals Engineering 132.(2019):. doi:10.1016/j.mineng.2018.12.004.

[27] Jaradeh Mohammad Amro, Suliman Saad M.A.,and Al Alawi Yaser."Improvement Model for the Proposal Accuracy of Security System Design at Industrial Facilities." Results in Engineering 8.(2020):. doi:10.1016/J.RINENG.2020.100186.

[28] Cortes, C., Vapnik, V., 1995. Support-vector networks. Mach. Learn. doi:10.1007/ BF00994018 Vladimir N.

[29] Vapnik.The Nature of Statistical Learning Thery.Springer,New York, NY,2000.

[30] Vapnik, V., 2000. The nature of Statistical Learning Theory, 2nd. ed. Springer doi:10. 1007/978-1-4757-3264-1.

[31] JIA Cun-liang, WU Hai-shan, GONG Dun-wei. Coal demand prediction based on a support vector machine model.*Journal of China University of Mining& Technology*,2007,36(1): 107-110.