

# Model of Ball Mill Based on the CPS

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**Abstract.** With the development of the new technology of intelligent manufacturing and cyber physical system, a new scheme is proposed for designing of predictive production based on ball mill. First, physical model (PM) and the model based on data (cyber model, CM) are discussed. Then, the combination of physical model and cyber model (CPM) is realized. Physical model is established according to the volume balance formula and the material balance formula. Cyber model uses the algorithm of the extreme learning machine which introduces penalty function. CPM uses the least square method to realize the combination of PM and CM and gets the value of the coefficient. Compare the actual data on ball mill to the data of the model then the result shows that the mean square error of CPM is smaller than the mean square error of PM and CM. The experimental results validate the effectiveness of the proposed method, which can be effectively used in ball mill in our industry.

**Keywords:** cyber-physical systems, ball mill, cyber model, physical model, cyber-physical model

## 1. Introduction

Intelligent manufacturing is a core technology of the new industrial revolution. The core technologies converge at cyber-physical system (CPS)<sup>[1]</sup>. Cyber-physical systems (CPS) is a new type of intelligent system. Governments, academia and the business community attaches great importance to CPS.

CPS is a concentration of computing, communication and control in intelligent technology. CPS has many characteristics such as real-time, safe, reliable, high-powered and so on<sup>[2]</sup>. Building CPS models is a key technology for intelligent manufacturing. The system usually consists of cognitive layer, equipment layer, sensing layer and control layer. After sensing, collecting, transmitting, storing, mining and analyzing the information about the machine in physical space (PS), a digitalized machine mirroring the physical machine is set up in cyber space (CS) and referred to as the digital model of the physical machine on the CPS cognitive layer<sup>[3]</sup>. So CPS model need to master the knowledge about computing system and physical system. CPS involves content including the discrete calculating system and the continuous physical process. So it is difficult to establish a unified modeling architecture.

Ball mill is a key equipment which can smash materials. It is suitable for all kinds of ores and other materials and is widely used in mineral processing, building materials and chemical industry, etc. Materials after grinding are aspersed to engine body on the right side under the effect of rotary cylinder

in the overflow ball mill. Finally make products overflow from empty journal. Abrasive machining process is more compact which achieve classification operations and reduce the grinding cycle load effectively. Because ball mills are multi graded and the mechanism is more complex, cyber modeling and physical modeling is very difficult about ball mills.

WANG et al<sup>[4]</sup> put forward an inverse control strategy based on distributed NN (neural net-work) which used principle of inverse system control and property of the ball mill system. Yuan et all<sup>[5]</sup> proposed a nonlinear prediction model which used nonlinear partial least squares in the real ball mill pulverizing system. Discrete element method<sup>[6]</sup> allows modeling of internal steel in ball mill and the motion process of material particles in numerical simulation. Scholars at home and abroad<sup>[7]</sup> have been studying the fineness prediction model about ball mills. But these models do not reflect the influence directly about operating variables such as the feeding, add water. So these models are unable to real-time dynamically response changeable behavior of circuit operating conditions. This is the reason why these models are not control process models. Graded distribution prediction model is still worthy of further research in industrial ball mill modeling. If you can establish a dynamic model to predict grinding indicators according to water flow, additive amount of grinding ball, characteristics of ore and so on, which will have greater practical value.

Using physical methods establish the continuous physical model. Firstly, establish simple physical equation of a system, and then create a continuous system model based on time according to the property characteristics of the system and the parametric model in continuous system modeling. EA Lee<sup>[8]</sup> used Newton's law analysis to verify physical process and the system model was established. Formal modeling method based on mathematical theory simulates system behaviors. From the perspective of multi-agent systems, a high-confidence software formal model (HCSFM) of CPS based on two complementary formalisms, namely Petri nets and  $\pi$ -calculus was proposed by Yu<sup>[9]</sup>. A quantitative security analysis model based on the combination of Petri net and game theory was proposed by XU<sup>[10]</sup> to reflect not only the hybrid of cyber and physical world but the behaviors of attackers and defenders. Banerjee<sup>[11]</sup> proposed a Linear 1 space dimension Spatio-Temporal Hybrid Automata which modeling oriented object was discrete system.

This paper realizes the combination of physical model and cyber model (CPM) based on CPS. According to the volume balance formula and the material balance formula, physical model is established to predict the output of ball mill. Physical model is a dynamic model based on the parameters of water flow, additive amount of grinding ball, characteristics of ore and so on. Use extreme learning machine (one of the neural network algorithm) algorithm to build mathematical modeling of ball mill which can predict the output. Finally use the least squares method to combine physical model and cyber model. Experimental results demonstrate the effectiveness of the proposed method.

## **2. CPS Model**

### ***2.1 Physical Model: PM***

Figure 1 is a continuous grinding process of ball mill. Continuous grinding process is the rough ore crushed. When particles have been filtered, the material through belt transmit to ball mill, which is called undressed ore blanking. Overflow ball mills use wet grinding ways. So ball mills need to add a certain amount of water, which is named grinding water flux. A large number of steel ball is a medium. Ball mills

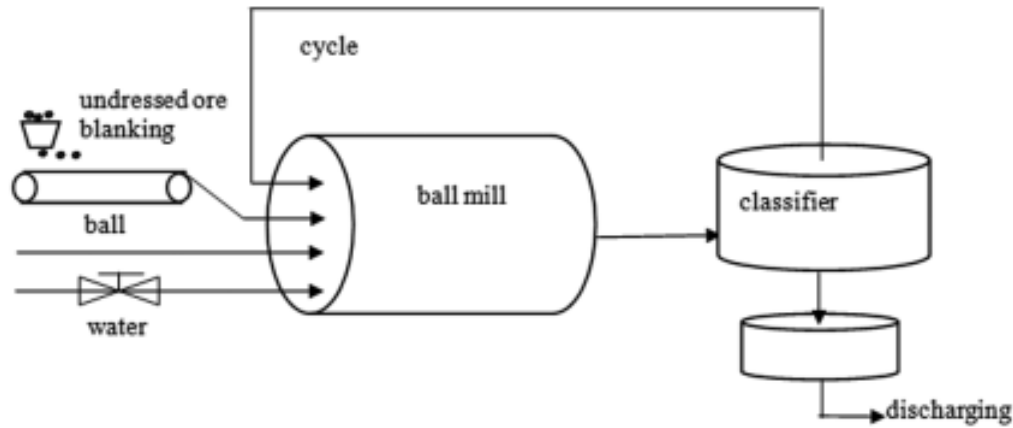


Figure.1 continuous grinding process of ball mill

of rotation grind pulp. After grinding, fine ore which is in the form of pulp overflow from discharging opening of ball mill. Coarse particles enter into the classifier and are recycled into ball mill until in the form of pulp overflow from discharging opening of ball mill. In the process of the experiment, this paper set parameters such as material grindability, cylinder speed, lining structure are invariable.

The input variables in physical model are grinding water flow which is recorded as  $R_{water\_flux}(t)$ , undressed ore blanking which is called  $R_{belt\_flux}(t)$ , Additive amount of grinding ball that is named  $R_{ball\_add}(t)$  and swirling flux that is regarded as  $R_{ore\_flux}(t)$ . The output variables are overflow concentration named  $C_{ovf\_con}(t)$  and overflow flux called  $R_{ovf\_flux}(t)$ . According to the overflow concentration and overflow flux, physical model predicts production which is the product of overflow concentration and overflow flux. The volume of pulp  $V$  and the length of ball mills  $L$  are invariable. Volume balance formula is expressed as:

$$\frac{d(V(t))}{dt} = R_{water\_flux}(t) + R_{belt\_flux}(t) + R_{ball\_add}(t) + R_{ore\_flux}(t) - R_{ovf\_flux}(t). \quad (1)$$

The expression of  $R_{ovf\_flux}(t)$  is formulated as follows:

$$R_{ovf\_flux}(t) = k\sqrt{V(t)/L}. \quad (2)$$

$k$  is a adjustive coefficient. Put formula (2) into formula (1) can get formula (3):

$$\frac{V(t+1) - V(t)}{\Delta t} = R_{water\_flux}(t) + R_{belt\_flux}(t) + R_{ball\_add}(t) + R_{ore\_flux}(t) - k\sqrt{V(t)/L}. \quad (3)$$

Formula 2 can obtained  $R_{ovf\_flux}(t)$ , Formula 3 can get volume of pulp  $V$ . Undressed ore blanking are solid mineral aggregate whose concentration is one. Concentrations of grinding water flux and additive amount of grinding ball are zero. Then the material balance formula is defined as:

$$\frac{d(C_{ovf\_con}(t)V(t))}{dt} = R_{belt\_flux}(t) - C_{ovf\_con}(t)R_{ovf\_flux}(t). \quad (4)$$

Formula (4) is also expressed as follows:

$$\frac{C(t+1) - C(t)}{\Delta t} V + \frac{V(t+1) - V(t)}{\Delta t} C(t) = R_{belt\_flux}(t) - C_{ovf\_con}(t)k\sqrt{V(t)/L}. \quad (5)$$

Formula (5) can get the value of  $C_{ovf\_con}(t)$ . As such the overflow concentration is:

$$C(t+1) = (R_{belt\_flux}(t) - C_{ovf\_con}(t)k\sqrt{V(t)/L} - \frac{V(t+1) - V(t)}{\Delta t} C(t)) * \Delta t + C(t). \quad (6)$$

Finally, physical model determine the production which is the product of overflow concentration and overflow flux.

## 2.2 Cyber Model: CM

This paper use cyber model which is extreme learning machine that is called ELM in short<sup>[12]</sup>. ELM is an algorithm of neural network and generic single-hidden layer feed forward network (SLFN). The input variables of cyber model is the same with the input variables of physical model. The output of the prediction is production.

The SLFN consists of input layer, hidden layer and output layer. Hidden layer has L hidden neuron. The output of output layer is an m-dimension vector. Output function expression is shown as in formula (7).

$$f_L(x) = \sum_{i=1}^L \beta_i G(a_i, b_i, x). \quad (7)$$

$a_i$  and  $b_i$  are respectively the center of the radial basis function (RBF) node and influencing factor.  $\beta_i$  is weight between neurons of hidden layer and neurons of output layer.  $\beta_i$  is an m-dimension weight vector. G is the output of hidden layer neurons and is also called as activation function. Y is output of prediction. The output function of neural network can be written as:

$$H\beta = Y. \quad (8)$$

$$H = \begin{pmatrix} h(x_1) \\ \dots \\ h(x_N) \end{pmatrix} = \begin{pmatrix} G(a_1, b_1, x_1) \dots G(a_L, b_L, x_1) \\ \dots \\ G(a_1, b_1, x_N) \dots G(a_L, b_L, x_N) \end{pmatrix}_{N \times L}. \quad (9)$$

$$\beta = \begin{pmatrix} \beta_1^T \\ \dots \\ \beta_L^T \end{pmatrix}_{L \times m}. \quad (10)$$

$$Y = \begin{pmatrix} Y_1^T \\ \dots \\ Y_L^T \end{pmatrix}_{N \times m}. \quad (11)$$

This paper uses optimized ELM<sup>[13]</sup> which is introduced penalty function and is called  $L_{ELM}$ . Objective function is shown as follows:

$$\text{Min} : \frac{1}{2} (\|\beta\|^2 + C \sum_{i=1}^N \|\varepsilon_i\|^2) \quad \text{s.t. } h(x_i)\beta = y_i^T - \varepsilon_i^T. \quad (12)$$

Lagrangian function is expressed as:

$$L_{ELM} = \frac{1}{2} (\|\beta\|^2 + C \sum_{i=1}^N \|\varepsilon_i\|^2) - \sum_{i=1}^N \sum_{j=1}^L \alpha_{i,j} (h(x_i)\beta - y_i^T + \varepsilon_i^T). \quad (13)$$

Solving process is defined as follows:

$$\frac{\partial L_{ELM}}{\partial \beta_j} = 0 \Rightarrow \beta_j = \sum_{i=1}^N \alpha_{i,j} h(x_i)^T \Rightarrow \beta = H^T \alpha. \quad (14)$$

$$\frac{\partial L_{ELM}}{\partial \varepsilon_i} = 0 \Rightarrow \alpha_i = C \varepsilon_i. \quad (15)$$

$$\frac{\partial L_{ELM}}{\partial \alpha_i} = 0 \Rightarrow h(x_i)\beta - y_i^T + \varepsilon_i^T = 0. \quad (16)$$

In formula (14),  $\alpha = (\alpha_1, \dots, \alpha_N)^T$ .

Put formula (14) and (15) into formula (16), the result is:

$$\left(\frac{I}{C} + HH^T\right)\alpha = Y. \quad (17)$$

By formula (14) and (17),  $\beta$  is ( $N \gg L$ ):

$$\beta = H^T \left(\frac{I}{C} + HH^T\right)^{-1} Y.$$

Finally, the output result is:

$$f(x) = H\beta = HH^T \left(\frac{I}{C} + HH^T\right)^{-1} Y. \quad (18)$$

### 2.3 Cyber-Physical Model: CPM

The output of physical model is  $y_p$ . The expression of  $y_p$  is the product of formula (2) and formula (6) at the same time.  $y_c$  is the output of cyber model in formula (18). Formula (19) is weighted summation to predict  $y$ .  $w_1$  and  $w_2$  are the coefficient values. The relationship between  $w_1$  and  $w_2$  is as shown in formula (20).

$$y = w_1 y_p + w_2 y_c. \quad (19)$$

$$w_2 = 1 - w_1. \quad (20)$$

By formula (19) and (20), ( $w_1$  is expressed by  $w$ ):

$$y = w y_p + (1 - w) y_c. \quad (21)$$

The parameters of  $y_p$  is  $k$ . The parameters of  $y_c$  is  $\phi$  which includes penalty coefficient  $C$  and the number of hidden layer nodes  $L$ .  $h$  is predicted output. This paper uses least square method and regular terms. The purpose of using regular terms is that restraining parameters to make it not too big can reduce the fitting.

$$\frac{1}{2} \min_w \sum_{i=1}^N (h_i - y_i)^2 + \lambda_1 \sum_{i=1}^N k_i^2 + \lambda_2 \sum_{i=1}^N \phi_i^2. \quad (22)$$

The process of solving the coefficient value  $w$  is as shown below.

$$\begin{aligned} J &= \frac{1}{2} \left( \sum_{i=1}^N (h_i - y_i)^2 + \lambda_1 \sum_{i=1}^N k_i^2 + \lambda_2 \sum_{i=1}^N \phi_i^2 \right) \\ &= \frac{1}{2} \left( \sum_{i=1}^N (w(y_p - y_c) + y_c - y_i)^2 + \lambda_1 \sum_{i=1}^N k_i^2 + \lambda_2 \sum_{i=1}^N \phi_i^2 \right). \end{aligned} \quad (23)$$

Partial derivative of formula (23) is expressed as:

$$\frac{\delta J}{\delta w} = \sum_{i=1}^N (w(y_p - y_c) + y_c - y_i)(y_p - y_c) = 0. \quad (24)$$

The value of  $w$  is:

$$w = \frac{\sum_{i=1}^N (y_c - y_i)(y_c - y_p)}{\sum_{i=1}^N (y_p - y_c)^2}. \quad (25)$$

Process of solving the parameters is shown as follows:

solving the parameter k, fixing  $\phi$ , w

Objective function:

$$\frac{1}{2} \min_w \sum_{i=1}^N (h_i - y_i)^2 + \lambda_1 \sum_{i=1}^N k_i^2.$$

solving the parameter  $\phi$ , fixing k, w

Objective function:

$$\frac{1}{2} \min_w \sum_{i=1}^N (h_i - y_i)^2 + \lambda_2 \sum_{i=1}^N \phi_i^2.$$

solving the parameter w, fixing k,  $\phi$

### 3. Realization and Validation Model

In the process of the experiment, this paper uses 253 data. Experiment selects 80% data as the training set and 20% as the test set. The experiment loops 20 times. The experimental results are average. Do the data cleaning before experiment. Because the magnitude of various parameters is different, data must be disposed. Before modeling normalization processing is carried out for meeting the input requirements of the model. The result of normalization is to make the value of the parameter between -1 and 1.

In the experiment, the value range of parameters: in the physical model, k is from 0.01 to 0.15, in the cyber model, C (punish coefficient) value is from  $2^{15}$  to  $2^{20}$ , L (the number of hidden layer nodes) is 50, 100, 200, 300, 500 or 1000. When the mean square error (mse) of CPM is minimum, the optimum combination parameters is that k is 0.14, C is  $2^{19}$ , L is 300. A parameter is variable and the rest of the two parameters is fixed. Observe effects on the model.

#### 3.1 PM

In physical model, adjust the parameter k which is in formula (2). k is from 0.01 to 0.15. When k is variational, Figure 2 and Figure 3 are the change of the mean square error (mse) in PM and CPM. As can be seen from Figure 3, mse is gradually convergent and the best value of k is 0.14.

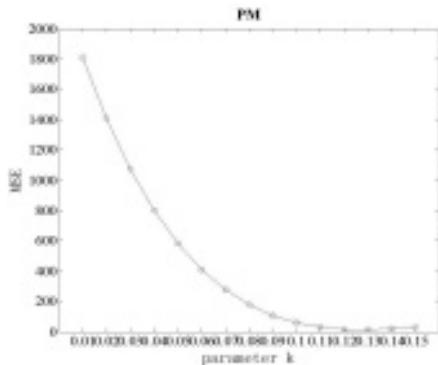


Figure.2 improve parameter k in PM

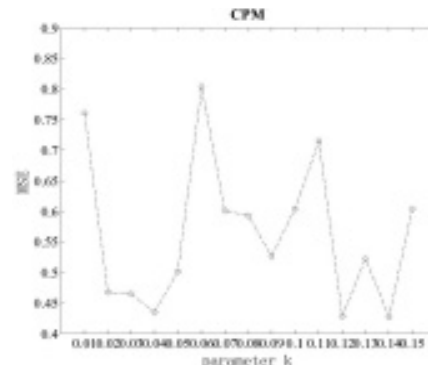


Figure.3 improve parameter k in CPM

### 3.2 CM

In cyber model, adjust the parameter C (punish coefficient). C is from  $2^{15}$  to  $2^{20}$ . Adjust the parameter L (the number of hidden layer nodes). L is 50, 100, 200, 300, 500 or 1000. When C is variational, Figure 4 and Figure 5 are the change of the mean square error (mse) in CM and CPM.

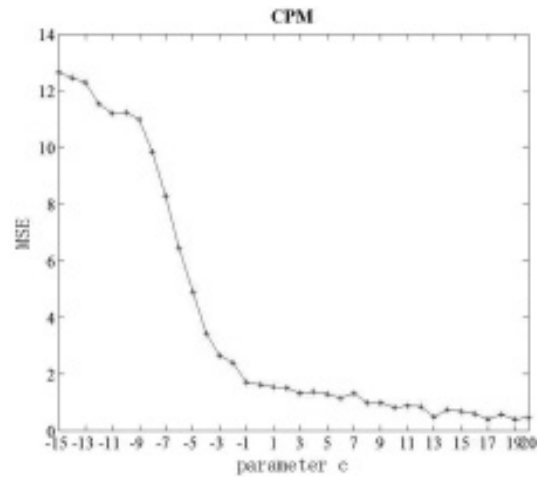
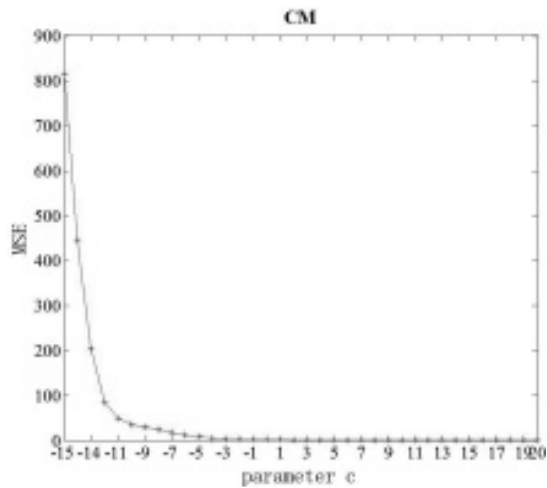


Figure.4 improve parameter C in CM

Figure.5 improve the parameter C in CPM

From Figure 4 and Figure 5, mse is gradually convergent in CM and CPM. Table.1 is the partial comparative result of mse between CM and CPM. When C is  $2^{19}$ , mse of CPM is minimum.

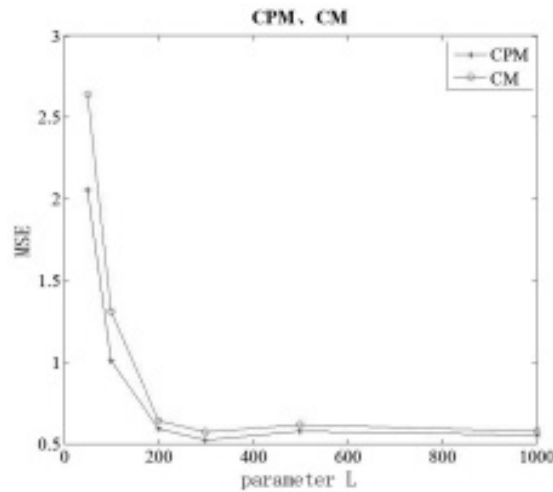


Figure.6 improve parameter L in CPM and CM

The best value of L is 300 from Figure 6. From the result, the conclusion is that mse of CPM is smaller than mse of CM and PM.

Table 1 improve parameter C, contrast mse in CM and CPM

Numbers of experiment	CM	CPM
1	1.8281	1.5291
2	1.7824	1.5032
3	1.4975	1.3073
4	1.5613	1.3616
5	1.4815	1.2907
6	1.3520	1.1646
7	1.5195	1.3138
8	1.1150	0.9884
9	1.1069	0.9908
10	0.9253	0.8316
11	0.9540	0.8650
12	0.9543	0.8602
13	0.5305	0.4948
14	0.8041	0.7353
15	0.7255	0.6851
16	0.6341	0.5924
17	0.4270	0.4087
18	0.5952	0.5628
19	0.4312	0.4083
20	0.4770	0.4577

When adjust parameter L, the change of mse in CM and CPM is shown in Figure 6. The result is stable convergence.

### **3.3 CPM**

Fix optimal parameter and change parameter w. The experiment loops 20 times. In Figure 7, when w is changeable, mse of CPM is also altered.



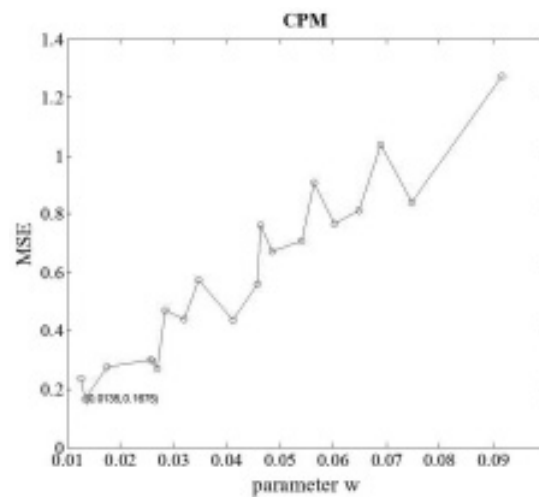


Figure.7 improve parameter w and change of Mean Square Error (mse) in CPM

From Figure 7, the changes of  $w$  have bigger influence on the predictive value of CPM. When  $w$  is 0.0135, mse of CPM is minimum.

### **3.4 Model Validation**

When parameter is determinate, test data is used to validate model, the predictive mse is shown in Figure 8. From Figure 8, in addition to the individual data points are abnormal, mse of predicted value are smaller. So model is credible.

### **3.5 Select Data Randomly**

This paper uses 253 data. Experiment randomly selects 80% data as the training set and 20% as the test set. The experiment loops 20 times which is same as above. The optimal parameters are fixed. Table.2 shows comparative results of mse in each model and each experiment.

Experimental results show that mse of CPM is smaller than mse of PM when data are selected randomly in each experiment. CPM is mostly smaller than mse of CM. As shown in Table 2, the results demonstrate the feasibility of the model.

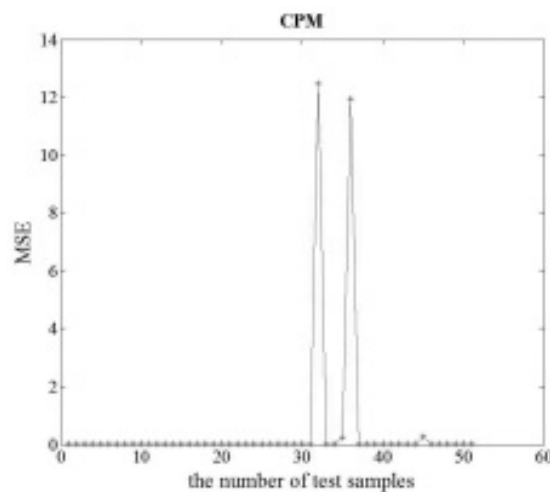


Figure.8 prediction of MSE in CPM

Table 2 comparative mse in CM, PM and CPM

Numbers of experiment	CM	PM	CPM
1	0.0238	21.6516	<b>0.0344</b>
2	0.4182	18.2764	0.4081
3	0.0217	19.0294	0.0215
4	0.7217	24.2934	0.6944
5	0.4233	16.2498	0.4064
6	0.00096	17.3997	<b>0.0036</b>
7	5.1209	16.5267	4.9692
8	1.0219	17.3815	<b>1.0059</b>
9	0.0204	15.7797	0.0200
10	14.9908	16.4463	14.6024
11	0.0015	16.0704	0.0035
12	0.1555	14.5969	<b>0.1647</b>
13	0.5444	23.4765	0.5167
14	1.2102	18.8124	1.1645
15	0.4937	17.8530	0.4720
16	0.1140	16.5295	0.1092
17	1.2052	20.4670	1.1643
18	0.2215	22.8540	0.2001
19	0.0976	13.7874	0.0912
20	0.5072	14.6934	0.4980

#### 4. Conclusion

This paper proposes a combining model of cyber model and physical model. The combining model is named CPM. CPM can make that production of ball mill predicts more accurate. At the same time, the experiment demonstrates the combination of computer and physics in CPS modeling. First of all, separate physical model is established. Then the model based on data is separately set up which is named CM. CM uses ELM with penalty function. Furthermore, get coefficients of physical model and cyber model by least square method. In the process of experiment, determine optimal parameters, then regulate various parameters respectively and compare the effects of various parameters on the model. In section 2.4, through the test figure can be seen that CPM model predicts accurate. Experimental results demonstrate effectiveness of the proposed method. Finally, Select data randomly and compare mean square error of the model. The experimental results show the feasibility of the model. So this method can be effectively applied in industrial ball mill.

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