Application of Multi-dimensional Linear Fitting Method in the Establishment of the Semi-autogenous Grinding Mill Model

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Abstract. In order to build the semi-autogenous grinding mill model more accurately and efficiently, a large-scale concentrating mill in China was studied and its daily production data were analyzed. By combining the field experts experience and utilizing the multi-dimensional linear fitting methods, the semi-autogenous grinding mill axial pressure prediction model was built through various methods. Meanwhile, the advantages and disadvantages of different multi-dimensional linear fitting methods were compared to determine the most appropriate method. Then the multi-dimensional linear fitting model for the axial pressure of semi-autogenous mill was successfully achieved, via analyzing the influence of different parameters on the axial pressure model of semi-autogenous mill, and comparing the predicted results of the model with the measured values of the field production. It is demonstrated that this method has high accuracy and calculation speed simultaneously, which is significant to the establishment of semi-autogenous grinding model.

1. Introduction
It is well known that the semi-autogenous grinding mill has been widely used since its appearance in the 1950s, due to its advantages such as large processing capacity, large grinding particle size and low specific power consumption, etc. The semi-autogenous grinding mill was used to process non-metallic ore at first, and then gradually expanded to ferrous metals, non-ferrous metals, rare metals and other mines. With the extensive application of semi-autogenous grinding mills and the improvement of technology related to it, there will be more room for the development of semi-automatics [1].

Therefore, the research of semi-autogenous grinding mills and the technology related to it is more and more important. Based on the typical process engineering of semi-autogenous grinding mills--SABC (semi-autogenous grinding-ball grinding-crushing) process in a domestic concentrator, and combined with the field production data, this paper builds the model of semi-autogenous grinding mills by using multi-dimensional linear fitting method, and the final modelling method is determined by comparing multiple methods and parameters. Field practice proves that this method is effective in the model building of semi-autogenous grinding mills. At the same time, this method has important guiding significance for the realization of SABC process optimization control of semi-autogenous grinding mills [2].
2. The Modelling Strategy of Semi-autogenous Grinding Mills

In this study, a semi-autogenous grinding mill of 8.8 m x 4.8 m in SABC process of a mine is taken as the research object. The daily ore handling capacity of this series is 15,000 tons. The rated working power of the semi-autogenous grinding mills is 6,000 kW, the axial pressure is about 24 kPa, and the processing capacity is 1,800 t/h per machine-hour.

According to the field and previous control experience of semi-autogenous grinding mills, it is known that the axial pressure control of semi-autogenous grinding mills plays an important role in semi-autogenous grinding mills. Therefore, this paper takes the establishment of the axial pressure model of semi-autogenous grinding mills as the research object, and establishes a variety of semi-autogenous grinding mills axial pressure models. Please follow these instructions as carefully as possible so all articles within a conference have the same style to the title page. This paragraph follows a section title so it should not be indented.

2.1. Semi-autogenous Grinding Mills Model Considering Basic Parameters

According to the field experience and the working principle of semi-autogenous grinding mills, the main factors affecting the axial pressure of semi-autogenous grinding mills include: the ore feed of semi-autogenous grinding mills, the amount of lump ores, steel balls, hard rock weight (the amount on the screen after the linear screening of semi-automatic mills), the grinding concentration, power in the internal mill and other factors.

In this part, we consider that the influence factors of the front and the rear axle pressures are the same. Considering the four factors of feeding amount, lump ores amount, hard rock weight and power, and setting other influence factors as constants, the following axle pressure model can be established as:

\[ p_1 = k_{11}m_f + k_{12}m_b + k_{13}m_w + k_{14}W + \delta_1 \]  

\[ p_2 = l_{11}m_f + l_{12}m_b + l_{13}m_w + l_{14}W + \delta_2 \]  

In the formula, \( p_1 \) represents the front axle pressure of the semi-autogenous grinding mills; \( p_2 \) represents the rear axle pressure of the semi-autogenous grinding mills; \( m_f \) represents the ore feed of the semi-autogenous grinding mills; \( m_b \) represents the amount of lump ore; \( m_w \) represents hard rock weight; \( W \) represents the power sum of the semi-autogenous grinding mills; \( k_{11}, k_{21}, k_{31}, k_{41} \) represents the model coefficients of the front axle pressure; \( l_{11}, l_{21}, l_{31}, l_{41} \) represents the rear axle shaft pressure; \( \delta_1 \) represents the compensation coefficient of the front axle pressure; \( \delta_2 \) represents the compensation coefficient of the rear axle pressure.

2.2. Semi-autogenous Grinding Mills Model Considering Various Parameters

In the field test, it is found that in 1.1 there are limitations in considering only single factor on the influence of semi-autogenous grinding mills, and according to the field experience, it is found that the influence factors of the front and rear axle pressures of semi-autogenous grinding mills are different. Therefore, the influence of different parameters on the front and rear axle pressures will be discussed in this section.

2.2.1. Considering the influence of ore quantity on the front and rear axle pressure.

This part takes into account the influence of ore quantity on the front and rear axle pressure of semi-autogenous grinding mills. On the one hand, the ore feed quantity of semi-autogenous grinding mills has obvious influence on the front and rear axle pressure, on the other hand, the ore put quantity of semi-autogenous grinding mills has obvious influence on the rear axle pressure. Because the ore put cannot be detected, this paper replaces it with hard rock. At the same time, the change rate of ore quantity and
concentration and the influence of grinding sound on the axle pressure are considered. The axial pressure model of semi-autogenous grinding mills is obtained.

\[ p_1 = k_{12}w_\delta + k_{22}m_c + k_{32}m_y + k_{42}W + \delta_{22} \]  

\[ p_2 = l_{12}w_\delta + l_{22}m_y + l_{32}m_w + l_{42}W + \delta_{22} \]

In the formula, \( p_1 \) represents the front axle pressure of the semi-autogenous grinding mills; \( p_2 \) represents the rear axle pressure of the semi-autogenous grinding mills; \( w_\delta \) represents the ore quantity (the ore feed + hard rock) / concentration of 2 # scale; \( m_c \) represents the ore quantity of 1 # scale (the ore feed); \( m_y \) represents grinding sound; \( m_w \) represents the hard rock weight; \( W \) represents the power sum of the semi-autogenous grinding mills; \( k_{12}, k_{22}, k_{32}, k_{42} \) represents the model coefficients of the front axle pressure; \( l_{12}, l_{22}, l_{32}, l_{42} \) represents the rear axle pressure; \( \delta_{12} \) represents the compensation coefficient of the front axle pressure; \( \delta_{22} \) represents the compensation coefficient of the rear axle pressure.

2.2.2. Considering the influence of fragmentation on the front and rear axle pressure. The influence of fragmentation, especially large ore, on the semi-autogenous grinding mills is obvious. Considering the internal structure and working principle of the semi-autogenous grinding mills, it is considered that the influence of small ore on the front axle pressure is obvious, and the influence of large ore on the back axle pressure is obvious. At the same time, the change rate of ore volume and concentration and the influence of grinding sound on the axle pressure are also considered. The axial pressure model of semi-autogenous grinding mills is obtained.

\[ p_1 = k_{13}w_\delta + k_{23}m_c + k_{33}m_y + k_{43}W + k_{53}\alpha_{53} + \delta_{13} \]  

\[ p_2 = l_{13}w_\delta + l_{23}m_y + l_{33}m_w + l_{43}W + k_{53}\beta_{53} + \delta_{23} \]

In the formula, \( p_1 \) represents the front axle pressure of the semi-autogenous grinding mills; \( p_2 \) represents the rear axle pressure of the semi-autogenous grinding mills; \( w_\delta \) represents the ore quantity (the ore feed + hard rock) / concentration of 2 # scale; \( m_c \) represents the ore quantity of 1 # scale (ore feed); \( m_y \) represents the grinding sound; \( m_w \) represents hard rock weight; \( W \) represents the power sum of the semi-autogenous grinding mills; \( k_{13}, k_{23}, k_{33}, k_{43}, k_{53} \) represents the model coefficients of the front axle pressure; \( l_{13}, l_{23}, l_{33}, l_{43}, l_{53} \) represents the rear axle pressure; \( \alpha_{53} \) represents the specific gravity of small ore; \( \beta_{53} \) represents bulk ore specific gravity; \( \delta_{13} \) represents compensation coefficient of the front axle pressure; \( \delta_{23} \) represents the compensation coefficient of the rear axle pressure.

2.3. Semi-autogenous Grinding Mills Model Considering Series

Due to the on-site process, there are two series of separation operations in the follow-up of SABC grinding process. It is found that the prediction error of only one series of operation periods is very large. So, in this part, whether the on-site Series 1 and 2 are opened at the same time is considered. If the data needed to be predicted are judged to be two series, just normal to train and predict; but if only
one series of data need to be predicted, then a series of data samples are used to train and the model is obtained and predicted.

2.4. Semi-autogenous Grinding Mills Model Considering Liner Wear

After a long time of research and testing, it is found that the liner wear has a great influence on the axial pressure model of semi-autogenous grinding mills. In order to make the model more adaptable and intelligent and avoid the times of correction, this part will consider the liner wear of semi-autogenous grinding mills. The liner wear is shown in the material wear curve (approximate indication liner wear) of the following figure. Combining with the liner wear curve and field data fitting, the liner wear function is obtained as shown in Formula 7. According to formula 7, the axle pressure model of semi self-grinding machine considering liner wear is obtained as follows [3]:

\[ Y = 1.964X^2 \pm 0.000107X + 2.12375 \]  
(7)

\[ p_1 = k_{14}w_\delta + k_{14}m_c + k_{14}m_y + k_{44}W + k_{54}\alpha_{53} + \eta_{14} + \delta_{14} \]  
(8)

\[ p_2 = l_{14}w_\delta + l_{24}m_y + l_{44}m_w + l_{44}W + k_{54}\beta_{53} + \eta_{14} + \delta_{24} \]  
(9)

![Figure 1. Material wear (approximate indication of liner wear) curve](image)

In the formula, \( p_1 \) represents the front axle pressure of the semi-autogenous grinding mills; \( p_2 \) represents the rear axle pressure of the semi-autogenous grinding mills; \( w_\delta \) represents the ore quantity (ore feed + recalcitrant return) / concentration of 2 \# scale; \( m_c \) represents the ore quantity of 1 \# scale (ore feed); \( m_y \) represents the grinding sound; \( m_w \) represents the hard rock weight; \( W \) represents the power sum of the semi-autogenous grinding mills; \( k_{14}, k_{24}, k_{34}, k_{44}, k_{54} \) represents the model coefficients of the front axle pressure; \( l_{14}, l_{24}, l_{34}, l_{44}, l_{54} \) represents the rear axle shaft pressure; \( \alpha_{53} \) represents the specific gravity of small ore; \( \beta_{53} \) represents bulk ore specific gravity; \( \eta_{14} \) represents liner wear; \( \delta_{14} \) represents the compensation coefficient of the front axle pressure; \( \delta_{24} \) represents the compensation coefficient of the rear axle pressure.

3. Introduction of Core Algorithm

This section will introduce the core algorithms studied in this paper. There are mainly two methods of multi-dimensional linear fitting, namely fminsearch(simplex search method) and regress (multiple linear regression) and a neural network method ESN (state echo network).
3.1. Introduction of Fminsearch

Fminsearch uses the simplex search method of Lagarias et al. This is a direct search method that does not use numerical values or analytic gradients. [4][5] The algorithm uses \( n+1 \) points of \( n \)-dimensional vector \( x \). First, the algorithm increases each initial value \( x_0 \) from \( x_0(i) \) to \( x_0 \) by 5\%, and uses the \( n \) vectors divided by \( x_0 \) as a single element (if \( x_0(i) = 0 \) uses 0.00025 as component), the modification of the algorithm can follow the following procedure simply and effectively.

1. Let \( x(i) \) denote the current single point set, \( i = 1, 2, \cdots, n+1 \);

2. These single points are iterated from the minimum function value \( f[x(1)] \) to the highest \( f[x(n+1)] \). In each step of the iteration, the algorithm discards the current bad point \( x(n+1) \) and accepts another point in the single point. (Or, in the case of step 7 below, it changes all \( n \) points above the value off \( x(1) \));

3. Generate reflection points, \( r = 2m - x(n+1) \), where \( m = \sum_{i=1}^{n} \frac{x(i)}{n}, i = 1, 2, \cdots, n \), so as to calculate \( f(r) \);

4. If \( f[x(1)] \leq f(r) < f[x(n)] \), accept \( r \) and terminate this iteration;

5. If \( f(r) \geq f[x(1)] \), calculate the expansion point \( s \), \( s = m + 2[m - x(n+1)] \), and calculate \( f(s) \). If \( f(s) < f(r) \), accept \( s \) and terminate the iteration; otherwise, accept \( r \) and terminate the iteration;

6. If \( f(r) < f[x(n+1)] \) ( \( r \) is better than \( x(n+1) \) , calculate \( c = m + \frac{r - m}{2} \) and \( f(c) \). If \( f(c) < f(r) \), accept \( c \) and terminate the iteration. Otherwise, continue step 7 (contraction). If \( f(r) \geq f[x(n+1)] \), calculate \( cc = m + \frac{x(n+1) - m}{2} \) and calculate \( f(cc) \). If \( f(cc) < f[x(n+1)] \), accept \( cc \) and terminate the iteration, otherwise, continue step 7 (contraction);

7. Calculate \( n \) point \( v(i) = x(1) + \frac{x(i) - x(1)}{2} \) and calculate \( f[v(i)] \), \( i = 1, 2, \cdots, n+1 \), next iteration single point \( x(1), v(2), \cdots, v(n+1) \) is contracted.

The following figure shows the points in the fminsearch calculation process and every possible new single form. The original single shape has an obvious outline, and the iteration has been carried out until it meets the stop criterion.

Figure 2. Fminsearch computing process
3.2. Introduction of Regress

Regress is multivariate linear regression. In the multivariate geographic environmental system, there are many (more than two) elements that interact and correlate with each other. Therefore, the multivariate geographical regression model has the universal significance.

Assuming that some dependent variable \( y \) is affected by \( k \) independent variables, the observed value of \( n \) group is 
\[
y_a = \beta_0 + \beta_1 x_{1a} + \beta_2 x_{2a} + ... + \beta_k x_{ka} + \epsilon_a
\]

(10)

In the formula, \( \beta_0, \beta_1, ..., \beta_k \) are the undetermined parameters; \( \epsilon_a \) is a random variable.

If \( b_0, b_1, ..., b_k \) is the fitting value of \( \beta_0, \beta_1, ..., \beta_k \), then the regression equation is
\[
\hat{y} = b_0 + b_1 x_1 + b_2 x_2 + ... + b_k x_k
\]

(11)

In the formula, \( b_0 \) is a constant; \( b_1, b_2, ..., b_k \) is called the partial regression coefficient. The meaning of partial regression coefficient \( b_i \) \((i = 1, 2, ..., k)\) is that when other independent variables \( x_j \) \((j \neq i)\) are fixed, the value of the average change of the dependent variable \( y \) when the independent variable changes one unit.

According to the principle of least squares, the estimate of \( \beta_i \) \((\beta_i = b_i, i = 0, 1, 2, ..., k)\) should be made
\[
Q = \sum_{a=1}^{n} (y_a - \hat{y}_a)^2 = \sum_{a=1}^{n} \left[ y_a - (b_0 + b_1 x_{1a} + b_2 x_{2a} + ... + b_k x_{ka}) \right]^2 \rightarrow \min
\]

(12)

By the necessary conditions to evaluate the extremum
\[
\begin{align*}
\frac{\partial Q}{\partial b_0} &= -2 \sum_{a=1}^{n} (y_a - \hat{y}_a) = 0 \\
\frac{\partial Q}{\partial b_j} &= -2 \sum_{a=1}^{n} (y_a - \hat{y}_a) x_{ja} = 0(j = 1, 2, ..., k)
\end{align*}
\]

(13)

The expansion of equation group (13) can be summarized as follows:
\[
\begin{align*}
\sum_{a=1}^{n} x_{1a} b_0 + \left( \sum_{a=1}^{n} x_{1a}^2 \right) b_1 + \left( \sum_{a=1}^{n} x_{1a} x_{2a} \right) b_2 + ... + \left( \sum_{a=1}^{n} x_{1a} x_{ka} \right) b_k &= \sum_{a=1}^{n} y_a \\
\sum_{a=1}^{n} x_{2a} b_0 + \left( \sum_{a=1}^{n} x_{2a}^2 \right) b_1 + \left( \sum_{a=1}^{n} x_{2a} x_{1a} \right) b_2 + ... + \left( \sum_{a=1}^{n} x_{2a} x_{ka} \right) b_k &= \sum_{a=1}^{n} x_{2a} y_a \\
\sum_{a=1}^{n} x_{ka} b_0 + \left( \sum_{a=1}^{n} x_{ka}^2 \right) b_1 + \left( \sum_{a=1}^{n} x_{ka} x_{1a} \right) b_2 + ... + \left( \sum_{a=1}^{n} x_{ka} x_{2a} \right) b_k &= \sum_{a=1}^{n} x_{ka} y_a \\
\end{align*}
\]

(14)

The equation group (14) can be further written into matrix form by transformation.
Solving equation (15), we can obtain:

\[ b = A^{-1} B = (X^T X)^{-1} X^T Y \]  

(16)

Introducing signs:

\[ L_y = L_{\mu} = \sum_{a=1}^{n} (x_{ia} - \bar{x}_i)(x_{ja} - \bar{x}_j) (i, j = 1, 2, ..., k) \]

\[ L_{\bar{y}} = \sum_{a=1}^{n} (x_{ia} - \bar{x}_i)(y_a - \bar{y}) (i = 1, 2, ..., k) \]

The equation group can also be written as follows:

\[
\begin{align*}
L_{11} b_1 + L_{12} b_2 + ... + L_{1k} b_k &= L_{1y} \\
L_{21} b_1 + L_{22} b_2 + ... + L_{2k} b_k &= L_{2y} \\
&\cdots\cdots\\nL_{k1} b_1 + L_{k2} b_2 + ... + L_{kk} b_k &= L_{ky} \\
b_k &= \bar{y} - b_1 \bar{x}_1 - b_2 \bar{x}_2 - ... - b_k \bar{x}_k
\end{align*}
\]  

(17)

3.3. Introduction of ESN

ESN Echo state network (Echo state network ESN) is a new type of dynamic neural network, so it has all the advantages of dynamic neural network. At the same time, because the concept of "reserve pool" is introduced into the Echo state network, this method has a fundamental change in the identification of non-linear system compared with general dynamic neural network. It can be better adapt to nonlinear system identification. "Reserve pool" is actually a randomly generated large-scale recursive structure, in which neurons are sparsely interconnected. Generally, SD is used to represent the percentage of interconnected neurons in the total neuron N [8] [9].

\[
\begin{align*}
W_{in} & = f(W x(n) + W_{in} \mu(n) + W_{\text{back}} y(n)) \\
y(n+1) &= f_{\text{out}} \left( W_{\text{out}} \left[ x(n+1), \mu(n+1), y(n) \right] + W_{\text{bias}} \right) 
\end{align*}
\]  

(18)

In the formula, \( W \) represents the state variable of the neural network, \( W_{in} \) represents the input variable of the neural network, \( W_{\text{back}} \) represents the connection weight matrix of the output state variable of the neural network, \( x(n) \) represents the internal state of the neural network, \( W_{out} \) represents the weighting matrix between the reservoir of ESN echo state network, the input of neural network and the output of the neural network; \( W_{\text{bias}} \) denotes the output deviation of the neural network or can represent noise; \( f = f\left[ f_1, f_2, \cdots, f_n \right] \) denotes n activation functions of neurons in the "reservoir", in which \( f_i (i = 1, 2, \cdots, n) \) is a hyperbolic tangent function generally; \( f_{\text{out}} = \left[ f_{\text{out}1}, f_{\text{out}2}, \cdots, f_{\text{out}e} \right] \) denotes \( e \) output functions of ESN Echo State Network, \( f_{\text{out}} (i = 1, 2, \cdots, e) \) usually uses the identity function.

4. Simulation and Result Comparison

In this section, the above algorithms, fminsearch (simplex search method) and regress (multiple linear regressions) and a neural network method ESN (echo state network) are compared through a large number of field data and long-term field tests. Firstly, a better method of modelling the axle pressure of semi-autogenous grinding mills is selected through comparison in this section, and then through the
method to validate the precision of the first section of each model finally, the most suitable multi-dimensional linear fitting method is obtained.

Through field massive data analysis and data processing, this paper first chooses the data of November 2016 with better working conditions to test the whole month. Through comparison, it is found that the three algorithms in the second section which are more suitable for the axle pressure model of semi-autogenous grinding mills. This simulation adopts the axle pressure model of 1.2.1 section which considers the influence of ore volume on the front and back axle pressure model, here the fitting of axle compression sum is obtained by calculating the front axle compression and the rear axle compression separately and then adding them together. The calculation process uses the data of the previous day as training samples. After calculating the model, the axle compression sum of the next day is predicted. Because of the large amount of data and the large number of results, Any comparison of test results is given below. Figure 3 predicts the axial pressure sum of November 21 with the data of November 19 by ESN method, Figure 4 predicts the axial pressure sum of November 21 with the data of November 19 by fminsearch method, and Figure 5 predicts the axial pressure sum of November 21 with the data of November 19 by regress method.

![Figure 3. ESN prediction results](image1)

![Figure 4. Fminsearch prediction results](image2)
Figure 5. Algorithm regress prediction results

Comparing with Figure 3, Figure 4 and Figure 5, it is found that ESN obviously has a prediction misalignment of the model, which may be due to the lack of generalization of the training samples. The predicted values of the fminsearch and regress methods can track the actual detection values well, but the tracking accuracy of fminsearch is obviously inferior to the regress method. Although the above results are listed only once, the phenomenon still exists in the comparison of the rest of the days, which is not listed in this paper.

After determining the regress method, this paper uses the method to simulate and validate four kinds of semi-autogenous grinding mills axle pressure models given in the first section, which consider the influence of ore quantity on the front and rear axle pressure, the influence of fragmentation on the front and back axle pressure, the series of semi-autogenous grinding mills models, and the liner wear model respectively. The results are as follows. It is shown that:

Figure 6. Consider the influence of ore volume on the axial compression
Figure 7. Consider the effect of block size on the axial compression

Figure 8. A series of semi autogenous mill model

Figure 9. Model of semi autogenous mill considering liner loss

From Fig.6 to Fig.9, it is obvious that the semi-autogenous grinding mills model considering liner wear has high accuracy. The difference between Fig.6 and Fig.7 is not much, but in the other data listed in this paper, sometimes the model considering the influence of the ore quantity on the front and rear axle pressures is good, and sometimes the influence of fragmentation on the front and rear axle pressure is good. Therefore, both of them are considered to affect the parameters of the semi-autogenous grinding mills axial pressure model. As for the difference between Fig. 8 and Fig. 6 and Figure 7 are not too big, because there is no series of changes in this test. The model considering series changes in the case of the series changes still had great anti-interference ability, and its accuracy is
significantly better than the former two. In other tests this month, show no exceptions, the semi-autogenous grinding mills model considering liner wear has the strongest accuracy, and the error is within 10%, and most of the errors are below 1%, and the trend match degree is over 95%.

5. Conclusion
Based on the background of a large-scale concentrator in China, this paper combines the daily production data and combines the experience of field experts to establish a variety of semi-autogenous grinding mills models. At the same time, the above models are compared through various algorithms. Finally, through the simulation results, it is found that regress multi-dimensional linear fitting semi-autogenous grinding machine axial pressing die considering liner wear has strong adaptability and high accuracy, and the prediction trend is almost completely consistent with the actual situation. At the same time, through field practice and subsequent testing, the method can be used in the establishment of axial pressure model of semi-autogenous grinding mills. The predicted results can participate in the control, which is of great significance for the optimization control and research of semi-autogenous grinding mills.

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