Soft sensor for parameters of mill load based on multi-spectral segments PLS sub-models and on-line adaptive weighted fusion algorithm

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A B S T R A C T

The parameters of mill load (ML) not only represent the load of the ball mill, but also determine the grinding production ratio (GPR) of the grinding process. In this paper, a novel soft sensor approach based on multi-spectral segments partial least square (PLS) model and on-line adaptive weighted fusion algorithm is proposed to estimate the ML parameters. At first, frequency spectrums of the shell vibration acceleration signals are obtained. Then the PLS sub-models are constructed with the low, medium and high frequency spectral segments. At last, the PLS sub-models are fused together with a new on-line adaptive weighted fusion algorithm to obtain the final soft sensor models. This soft sensor approach has been successfully applied in a laboratory-scale wet ball mill grinding process.

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1. Introduction

Comminution consumes about 2.8–3% of the world’s electrical energy production [1]. As one of the oldest comminuting devices, ball mills have been widely used in the mineral, cement and power plant industries. However, the ball mill is very inefficient, which uses no more than 1% of the supplied energy for comminution, and the rest is wasted in producing noise and heat [2]. According to the experimental studies, 10% electrical energy and 9% steel mineral consumption of the ball mill can be reduced at least. Sometimes, inappropriate operating status of the ball mill may cause costly damage of the grinding devices. Therefore, the ball mill plays a major role in maintaining the stability, improving the grinding production rate (GPR) and the quality of the products for the grinding process [3]. However, it is difficult to maintain an optimal grinding condition for the grinding process. One of the main reasons is the lack of sensors in the industrial plants to monitor the grinding and transportation mechanisms inside the mill. Despite tremendous research efforts, the understanding of ball mill’s comminution mechanism is still far from complete [4]. The real-time mill load (ML) measurement has not been accomplished completely [5]. Therefore, it is essential to develop a method to monitor the ML.

The ML of the industrial ball mill was previously controlled by measuring the power consumption of the mill motor, which cannot guarantee the optimal range of the mill filling [6]. The measure instruments based on the mill acoustic signals has been widely used to measure and control the ML of the dry ball mill [7,8]. To overcome the shortage of axis vibration signals in measuring ML, Kolacz studied the ML variations using a piezoelectric strain transducer, which was installed on the mill shell [9]. Recently, Gugel et al. measured the level of ML in cement industry using the mill shell vibration acceleration signals [10,11]. The results show that the on-contact vibration based system has at least twice the resolution of the traditional acoustical signal based system, and also has zero adjacent mill acoustical crosstalk. In order to study the correlation between the filling level and the position of the maximum vibration point, analysis of the mill shell vibration signal in power plant was done [12]. Su and Si also investigated the load behavior of industrial ball mill by inlet trunnion vibration and acoustic signals, respectively, the results show that the characteristic power spectral energy of both vibration and acoustical signals can represent the ML [13,14].

While most of research focus on the dry ball mill, very few studies on wet ball mill have been reported to date. This might be due to the difficulty in the expression the ML of wet ball mill for the slurry during milling [15]. In practice, the ML of wet ball mill in the mineral grinding process is mainly supervised by fusing the experience of the experts and information of multi-sensor to estimate its status [16,17]. However, due to their differences in experience and insufficient vigor, it is difficult to maintain the economical working conditions for a long time [12,18]. Little studies focus on the soft sensor of the ML parameters. Some key parameters of the wet ball mill can also be obtained by measuring...
the mechanical vibration of axis and mill acoustic signals, which shows that some characteristic frequency sub-bands relate to the operating parameters such as pulp density, particle size, etc. [19]. Zeng et al. constructed the partial least square (PLS) and principle component regression (PCR) models between the operating parameters and characteristic frequency sub-bands based on the spectrum of axis vibration and mill acoustical signals [20]. But the axis vibration signal is dispersed and disturbed by the transfer system of mill. Some studies also show that the acoustic signals contain more information of operating parameters than axis vibration signal, but the former has acoustical crosstalk with adjacent mill [19]. Moreover, using acoustic signal, only the mineral to ball volume ratio (MBVR) can be monitored [21]. The studies of the shell vibration signal for semi-autogenous (SAG) mill show that the shell vibration is the indicator of pulp density and viscosity [22]. Recently, Tang et al. proposed a genetic algorithm–partial least square (GA-PLS) approach to select different characteristic frequency sub-bands for different ML parameters based on the frequency spectrum of mill shell vibration acceleration signal [23]. However, this approach is difficult to explain the physical meaning of the selected sub-bands and may lead to loss of useful information because of some unselected sub-bands.

Experimental analysis of the shell vibration frequency spectrum shows that different vibration frequency spectral segments are caused by different grinding mechanism [23]. Comparison of the spectral segments at different grinding conditions such as zero, dry and wet milling, shows that these modes contain different ML information and have different physical meaning. Therefore, Tang et al. proposed another soft sensor approach based on the principal component analysis (PCA) and support vector machines (SVM) [24]. However, this approach cannot reflect the contribution of different frequency spectral segments on modeling ML. Moreover, principal components (PCs) do not take into account the correlation between inputs and outputs [25]. Even though the first several PCs might be able to properly explain the frequency spectrum, they may have little correlation with ML parameters. Furthermore, the PCs with higher prediction performance and lower correlation with frequency spectrum are used to construct ML soft sensor models, which may cause worse prediction performance [26].

Therefore, we can construct different sub-models for different frequency spectral segments using the PLS algorithm. The problem needs to solved is how to weight the sub-models effectively to obtain the final ML parameters models. As the inputs of the sub-models are the different segments of the same frequency spectrum, the weighting of several sub-models can be treated as fusing multi-sensor information. Adaptive weighted fusion algorithm based on minimum mean square error (MMSE) is generally used in multi-sensor system to obtain the optimal observation values [27,28]. This algorithm can be used to obtain the weighting coefficients of the PLS sub-models. Most of the industrial processes are slow time-varying. The frequent variations of the physical characteristics of the feed mineral or other uncertain factors affect the ML of the ball mill. In addition, the shell vibration signal is more sensitive than other signals, whose frequency spectrum has significant changes with different grinding conditions. Therefore, the on-line update of the weighting coefficients of sub-models is necessary.

In this paper a soft sensor approach based on multi-spectral segments PLS sub-models and on-line adaptive weighted fusion algorithm is proposed to estimate the ML parameters. First, spectrums of the shell vibration signals are obtained using Welch’s method. Then, in order to decrease the numbers of the input variables and fully reflect the contribution of different spectral segments, different PLS sub-models are constructed for low, medium and high spectral segments. Finally, the PLS sub-models are fused with a new proposed on-line adaptive weighted fusion algorithm, which can adjust the PLS sub-models’ weighting coefficients adaptively. This algorithm minimizes the mean square of the estimation error to achieve better prediction performance.

The paper is organized as follows: Section 2 describes the ML of the wet ball mill, which introduces the scheme of the grinding process and the ML, the relation between the ML and GPR, and why the shell vibration signals can represent the ML parameters. Section 3 gives the overall modeling strategy, involving data preprocessing, multi-spectral segments PLS sub-models and on-line adaptive weighted fusion algorithm. Section 4 discusses the experimental applications of the proposed soft sensing approach, followed by the conclusions in Section 5.

2. Description for the ML of the wet ball mill

2.1. Scheme of the grinding process

Two-stage closed-loop grinding circuit is usually adopted in the iron ore processing plants in China. The GPR is always decided by the load of the ball mill in the first stage [3]. Fig. 1 shows the grinding circuit of the stage one, in which \( L_{w}, L_{m}, \) and \( L_{b} \) represent ball, mineral and water loads in kg, respectively; \( L_{x} \) and \( L_{y} \) are the water load to be added to wet preconcentration and sump in kg, respectively; \( L_{lt} \) is mineral load from the feeder in kg; \( L_{mt} \) is mineral tailing from wet preconcentration in kg; \( L_{l} \) and \( L_{o} \) are the inlet and outlet load of ball mill in kg, respectively; \( L_{mc} = (L_{w}, L_{m}, L_{b}) \) and \( L_{lt} = (L_{w}, L_{m}, L_{b}) \) are the recycle load and overflow load in kg, respectively; \( x \) represents the shell vibration acceleration signal of ball mill.

The fresh mineral \( L_{mf} \) from an mineral bin is fed onto a conveyor belt through a vibratory feeder, and then is conveyed continuously...
into the wet preconcentration, along with certain amount of mill water $L_{w}$.

The wet preconcentration is used to select the useful mineral $(L_{b}-L_{m})$ by the magnetism. Then, together with the recycle of the hydrocyclone $L_{H}$, the mineral flows down continuously into the ball mill. Due to the knocking and tumbling action of the steel balls within the revolving mill, the mineral is crushed to finer particles. By means of fluidity, a continuous flow of the mixed mineral slurry $L_{m}$ is discharged from mill, and then flows into the sump. In order to maintain certain density, some water flow (called sump water $L_{w}$) is added into the sump. The slurry of the sump is pumped into the hydrocyclone at a constant pressure. The feed stream to the hydrocyclone is separated into an overflow stream $L_{o}$ containing the finer particles and an underflow stream $L_{u}$ containing the coarser particles (recycle). The underflow $L_{u}$ is recycled back to the mill for regrinding, while the overflow $L_{o}$ is the final product of the first stage, which is transported to the second stage grinding circuit.

ML is defined as the total amount of the mineral, water and balls in the ball mill. Fig. 1 shows that the inlet load of the mill includes fresh mineral, mill water, recycle of hydrocyclone and the periodically added balls, which can be represented as

$$L_{i} = (L_{b} + L_{w})L_{m} = (L_{b} + L_{w})(L_{m} + L_{o} + L_{u})$$

(1)

The outlet load is mineral slurry, which can be represented as

$$L_{o} = (L_{b} + L_{w})L_{m} = (L_{b} + L_{w})(L_{m} + L_{o} + L_{u})$$

(2)

Even if all the instruments to measure the process variables, such as levels of pump, power of mill drive motor, rotation speed of mill, slurry density, slurry pressure and slurry flow rate of the outlet of sump, are installed in the grinding circuit, we still cannot calculate the outlet load. The outlet slurry is added to the sump. In order to maintain certain density, some water flow (called sump water $L_{w}$) is added into the sump. The slurry of the sump is pumped into the hydrocyclone at a constant pressure. The feed stream to the hydrocyclone is separated into an overflow stream $L_{o}$ containing the finer particles and an underflow stream $L_{u}$ containing the coarser particles (recycle). The underflow $L_{u}$ is recycled back to the mill for regrinding, while the overflow $L_{o}$ is the final product of the first stage, which is transported to the second stage grinding circuit.

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Even if all the instruments to measure the process variables, such as levels of pump, power of mill drive motor, rotation speed of mill, slurry density, slurry pressure and slurry flow rate of the outlet of sump, are installed in the grinding circuit, we still cannot calculate the inlet load and outlet load of the ball mill accurately. One reason is that the abrasion and corrosion of the ball load $L_{b}$ and $L_{w}$ as well as the wear and tear of the mill liners cannot be correctly measured. Another reason is that the instruments used to measure the density, pressure and flow rate for the mineral slurry are not as precise as expected. Moreover, the grinding process contains intricately mixed minerals with randomly varying properties (grain size, mineral content and associations, micro-cracks and surface characteristics distribution) [29]. The balls’ size and its size distribution, and the pulp rheology are also extremely difficult to measure. These uncertain factors affect the ML and the grinding process. For example, the fluctuation in mineral hardness and size distribution of the feed mineral will cause the mill to be over-loaded [16].

2.2. Relationship between ML and GPR

The fundamental objective of a grinding circuit is not size reduction but rather to liberate valuable minerals in such a way that the subsequent separation process can be operated at its maximum economic efficiency. Occasionally, a circuit may be controlled at constant GPR trying to maximize the product fitness, but most of the time it is controlled at a fixed set point of the fitness, trying to maximize the GPR, i.e. minimizing the energy consumed per ton of mineral [30]. The maximization of the GPR is normally obtained by fixing an optimal value of the circulating load. That is to say, the GPR is always decided by the ML of the ball mill [3].

ML is one of the key parameters, which are affected by lots of factors. The representation of ML can be qualitatively described by the status of the ML or quantitatively described by the parameters inside the mill [13]. In this paper, the later is called ML parameters, which represent the ML more accurately. Three ML parameters, namely mineral to ball volume ratio (MBVR, $\phi_{mb}$), pulp density (PD, $\phi_{p}$) and ball charge volume ratio (BCVR, $\phi_{b}$), are normally used in the mineral grinding circuit of the wet ball mill [21]. In order to show the exact total filling volume of ball, mineral and water load in the mill, a new ML parameter, charge volume ratio (CVR, $\phi_{mbw}$) is defined in [23]. As BCVR remains constant in short time period, CVR is used to replace the BCVR to construct ML parameters soft sensor models. The relationship between the ML and the ML parameters can be found in [23].

Studies show that GPR is affected by the properties of mineral, BCVR, MBVR, PD, CVR, recycle ratio of the hydrocyclone and rotational speed of the mill shell, etc. [31]. With higher MBVR or PD, lower quality raw mineral such as higher hardness and bigger mineral particle size can cause the ball mill to be over-loaded, further lead to lower GPR [16]. The proper values of BCVR and MBVR with higher GPR in different PD are given in [32]. The relationship between GPR and ML parameters can be represented below and in Fig. 2 [31].

$$Q = \frac{\phi_{mbw} \exp[-1.32(\phi_{mbw}-1)]L_{m}}{\tau(1+C_{r})}$$

(3)

where $Q$ is the GPR; $\tau$ is the average stay time of $L_{m}$ in mill and $C_{r}$ is the recycle ratio of the hydrocyclone.

Fig. 2 shows that with the increase of BCVR from 30% to 42% (PD from 62% to 82%), the GPR increases as well. However, when further increasing BCVR (PD), the GPR decreases.

2.3. Relationship between the ML and shell vibration

The comminution of the mineral load mainly relies on the cyclical movement of the ball load inside the ball mill, which produces strong shell vibration when the ML colliding with the mill liners. The motion of the ball is shown in Fig. 3, in which only one of the outmost layer steel balls is analyzed.

Fig. 2. Relationship between GPR and operating parameters.

Fig. 3. Motion analysis of the ball load inside the mill. (For interpretation of the references to color in the text, the reader is referred to the web version of this article.)
The ball falls from the leaving point A with a parabolic trajectory. It impacts with the mill liners at the dropping point B. The ball ascends back to point A with the rotation of mill shell. Therefore, the motion of the ball can be divided into four parts: falling, impact, grinding and sliding, which is shown in Fig. 3 with red dotted line. The corresponding comminution zones are paola zone (I), impact and broken zone (II), grinding zone (III), sliding zone (IV) and dead zone (V) [31]. In practice, the motion of the steel ball is a three-phase hybrid movement, whose trajectory includes circular path, parabolic path and cataracting path. Therefore, the mill shell is impacted by a variety of impact forces. However, the shell vibration is mainly caused by the steel balls with parabolic movement.

The impact force with ball-only load to mill liners can be represented as a semi-sine function as follows [33]:

$$F_b(0,t) = \begin{cases} F_{h0} \sum \cos \left[ \frac{2}{T_{mill}} (t - N_{mill} T_{h0}) \right] & \quad \text{for } 0 < t < T_{mill} \frac{T_{h0}}{2} \\ \delta \left(0 - \theta_0\right) + F_{b1}, & \quad \text{for } T_{mill} \frac{T_{h0}}{2} < t < T_{mill} \frac{T_{h0} + T_{b0}}{2} \\ \text{others} \end{cases}$$

(4) where $T_h$ is the impact time of balls to mill liners; $T_{h0}$ is the impact period of balls; $N_{mill}$ is the rotational speed of the ball mill; $\theta$ is the rotational angle; $F_{h0}$ and $F_{b1}$ are the maximum and average of the impact force. The calculation of $F_{b0}$ is given by [34]

$$F_{b0} = \sqrt{\left(-\frac{4 \pi \rho \omega^2}{\rho_{b0}^2} \sin^2 \theta \cos \theta \sin \theta \cos \theta \sin \theta \cos d \theta \right)^2}$$

(5)

where $\omega$ is the angular velocity, $\omega = \pi N_{mill} / 30$; $\theta_1 = (\pi / 2) - \arccos(N_{mill} R/900)$; $\theta_2 = (\pi / 2) - \arccos(N_{mill} R/900)$; $\rho_b$ is the loose density of ball load; $L_{mill}$ is the length of the mill drum, and $R_1$ and $R_2$ are the maximum and minimum turning radius of ball load.

With the addition of the mineral and water load, the motion of the ball load are affected by the pulp rheology. The rheological properties of the mineral pulp mainly embodies in pulp viscosity in a grinding mill, affects the coating thickness of the balls, and also indirectly influences the impact force and impact time of the balls to the mill liners. In practice, the PD should be thick enough so that the ball surfaces are coated properly for maximum exposure to grinding action, yet it should not be too thick to act as a cushion between balls [35]. Low viscosity permits the ball to move with excessive speed and this combined with the thin protective film around the steel balls, may cause abnormal wear and heat build-up. With high viscosity free movement of the ball is impeded, which can cause a carrying over and “throw” of the ball resulting in inefficiencies. In effect, this merely increases the thickness of the film surrounding the ball thereby providing more cushion against impact. Therefore, pulp viscosity (rheological properties) will affect the movement of steel balls, which also has an effect on the shell vibration. The impact force in the wet ball mill can be represented as

$$F_{bmvw} = \Phi_{bmvw}(\eta, \delta, \varphi_{mvw}, T_{op}, \varphi_{mb}, \varphi_{bmvw}) F_b$$

(6) where $\Phi_{bmvw}$ is the unknown nonlinearity function, $T_{op}$ and $\eta$ are the temperature and relative viscosity of the mineral pulp, respectively, and $\delta$ is the coating thickness of the balls. The calculation of $\eta$ and $\delta$ can be given by [31,36]

$$\eta = 1 + K_1 \frac{\rho_w \varphi_{mvw}}{\rho_m (1 - \varphi_{mvw})} + K_2 \left( \frac{\rho_w \varphi_{mvw}}{\rho_m (1 - \varphi_{mvw})} \right)^2 + K_3 \left( \frac{\rho_w \varphi_{mvw}}{\rho_m (1 - \varphi_{mvw})} \right)^3$$

(7)

$$\delta = \delta_0 \exp \left( \frac{K_4 \rho_w \varphi_{mvw}}{\rho_m (1 - \varphi_{mvw}) \varphi_{w0}} \right)$$

(8)

where $K_1, K_2$ and $K_3$ are the coefficients; $\varphi_{mvw}$ are the maximum value of the coating thickness of the balls and PD; $\rho_m$ and $\rho_w$ are the density of the mineral and water, respectively.

The impact time of ball load to mill liners, other balls and mineral is around 0.1–0.2 ms. The shorter of the impact time $T_{b}$ the wider of the bandwidth of the impact force, which also causes wider bandwidth of the shell vibration signal. The impact time in the wet ball mill can be calculated by [37]

$$T_{bmvw} = \Phi_{bmvw}(\eta, \delta, \varphi_{mvw}, T_{op}, \varphi_{mb}, \varphi_{bmvw}) \times \sqrt{\frac{1}{R_b L_{b0}^2 \left(1 - \frac{1}{E_1} \left(1 - \frac{1}{E_2} \right)^2 \right)^2 \nu_b}}$$

(9) where $R_b$ and $L_{b0}$ are the diameter and quality of the single ball, respectively; $\nu_b$ is the speed of ball at the dropping point B; $\Phi_{bmvw}$ is the unknown nonlinearity function, which represents the affection of mineral pulp to impact time; $E_1$ and $E_2$ are the elastic modulus of balls and mill liners; $\mu_1$ and $\mu_2$ are the Poisson coefficient of balls and mill liners.

When we measure the vibration of a structure and decompose the vibration signal into frequency spectrum, the modes of vibration and the large cyclical excitation forces are evidenced by peaks in the spectrum [38]. Therefore, the shell vibration spectrum should contain at least two modes, which are the vibration mode of the new structure compared by mill shell and ML, and the impact mode caused by the cyclical impact of the load to the mill liners. The behavior of grinding mineral as a damping medium can be analyzed by considering various energy dissipation mechanisms. Under different grinding conditions, the impact force and impact time of balls to mill liners are different. Based on the mechanism analysis and experimental results in [23], we can conclude that the amplitudes and frequencies of the shell vibration spectrum contain information is related to ML parameters directly. Moreover, the correlation between different frequency spectral segments and ML parameters is different.

3. Soft sensing methodology for ML parameters

The grinding process of wet ball mill is a complex production process, which can be characterized as a process with large time-delay, strong nonlinear as well as other uncertainties. The shell vibration signal contains more ML information and is more sensitive than other signals. Therefore, based on the analysis of the previous sections, a new soft sensing methodology for ML parameters is proposed, whose structure is shown in Fig. 4. Here $X_j$ is the input of PLS sub-models; $y_i$ is the output of the PLS sub-models; $j = 1,2,3$, represents low, medium and high spectral segments, respectively, and $i = 1,2,3$, represents MBVR, PD and CVR, respectively.

Fig. 4 shows that the proposed approach consists of the data preprocessing module, multi-spectral segments PLS sub-models module and on-line adaptive weighted fusion algorithm module. The data processing module is used to filter and transfer the time domain signal to frequency domain, and partition the spectrum to different segments. The multi-spectral segments PLS sub-models module is used to construct ML parameters’ sub-models for every spectral segment. The on-line adaptive weighted fusion algorithm module combines the sub-models to produce the final models used for ML estimation.

3.1. Data preprocessing

Although the shell vibration signals of wet ball mill are stable and periodic over a given time interval, the interested signals from grinding are buried in a wide-band random noise signal
“white noise” in the time domain [20]. Because any waveform that exists in the real world can be generated by adding up sine waves in a unique manner, we can use these sine waves to represent the shell vibration signals in the frequency domain. Then, we can find the evident features, which are related to the ML information. In order to reduce computation time and increase the precision of the fast Fourier transform (FFT), the original sampled data needs to be converted into an equivalent signal with a different sampling rate. The data length to obtained power spectral density (PSD) should be one revolution of the ball mill. After data filtering and pre-processing, the classic Welch’s method is used to obtain the PSD of the vibration acceleration signal. Moreover, the final PSD should be averaged by several revolutions to overcome the fluctuation of the operating conditions. Every spectral segment represents one mode of the mechanical vibration [39]. The shell vibration modes are caused by different mechanism and contain different ML parameters information. Therefore, based on the prior knowledge, the vibration frequency spectrum is partitioned into several spectral segments which consist of many little peaks.

3.2. Multi-spectral segments PLS sub-models

One of the challenges in ML parameters modeling based on the spectrum is the correlation among the high dimension of the frequency spectrum. PLS has been proved to capture the maximal covariance between input and output data using the less latent variables (LVs), which decomposes the input and output space simultaneously while keeping the orthogonal constraint [40]. Assume predictor variables $X \in \mathbb{R}^{k \times p}$ and response variables $Y \in \mathbb{R}^{k \times q}$ are normalized as $E_0 = (E_{01}, E_{02}, \ldots, E_{0q}) \in \mathbb{R}^{k \times q}$ and $F_0 = (F_{01}, F_{02}, \ldots, F_{0q}) \in \mathbb{R}^{k \times q}$, respectively. Let $t_1$ be the first latent score vector of $E_0$, $u_1 = E_0w_1$, and $w_1$ be the first axis of the $E_0$. $|w_1| = 1$. Seemly, Let $u_1$ be the first latent score vector of $F_0$, $u_1 = F_0c_1$, and $c_1$ be the first axis of the $F_0$. $|c_1| = 1$. We want to maximize the covariance between $t_1$ and $u_1$, thus have the following optimization problem:

$$\begin{align*}
\text{Max}(E_0w_1, F_0c_1) \\
\text{s.t.} \quad w_1^Tw_1 = 1, \\
c_1^Tc_1 = 1
\end{align*}$$

By solving (10) with Lagrange approach

$$s = w_1^TE_0^TF_0c_1 - \lambda_1(w_1^Tw_1 - 1) - \lambda_2(c_1^Tc_1 - 1)$$

where $\lambda_1$ and $\lambda_2 \geq 0$. At last, we obtain that $w_1$ and $c_1$ are the maximum eigenvector of matrix $E_0^TF_0E_0$ and $F_0^TE_0F_0$. So, after the $t_1$ and $u_1$ is obtained, we have

$$E_0 = t_1p_1^T + E_1$$

$$F_0 = u_1q_1^T + F_1$$

where $p_1 = E_0^Tw_1/|w_1|^2$, $q_1 = F_0^Tw_1/|w_1|^2$, $r_1 = F_0^Tw_1/|w_1|^2$ and $E_1$, $F_1$ are the residual matrices. Then we replace $E_0$ and $F_0$ with $E_1$ and $F_1$ to obtain the second latent score vectors $t_2$ and $u_2$. Using the same method, we get all the latent score vectors until $E_0 = F_0 = 0$.

As the mapping between the vibration frequency spectrum and different ML parameters are different, PLS1 (single output variable PLS algorithm) is used in this paper. Assume $T_{ji}$ is the score matrix which is composed by the former $h_j$ score vector, the PLS1 models between the input frequency spectral segments $X_j^t$ and ML parameters $y_j$ can be represented as [41]

$$X_j^t = T_{ji}B_{ji}^1 + E$$

$$y_{ji} = T_{ji}q_{ji} + r = X_j^tB_{ji} + r$$

where $p_{ji}$ is the loading vector; $q_{ji}$ is the regression coefficient vector of the former $h_j$ score vector; $E$ and $r$ are the residual matrix and vector, respectively; $B_{ji}$ is the regression coefficient vector of ML parameters models. The numbers of the LVs $h_j$ are decided by leave-one-out cross-validation method.

3.3. On-line adaptive weighted fusion algorithm

Adaptive weighted fusion algorithm is often used for multisensor fusion, which makes the mean square error of the weighted fusion smaller than that of every sensor [42]. Here, we use adaptive weighted fusion algorithm to obtain the initial weighted coefficients of the PLS sub-models. We look at the outputs of the sub-models of different spectral frequency bands as outputs of different sensor system. Suppose there are $k$ samples to validate the original PLS models, then the estimate values for validation data are denoted by $(y_j^k(l)) (l = 1, 2, \ldots, k)$. We can calculate the means and variances of $(y_j^k(l)) (l = 1, 2, \ldots, k)$, which are denoted as $u_j^k$ and $\sigma_j^k$, respectively. According to MMSE-based adaptive weighted fusion algorithm [27], the initial weighted coefficients of low, medium and high spectral segments sub-PLS1 models $w_j^k$ with constraint $\sum_j=1 w_j^k = 1$ are obtained by

$$w_j^k = 1/\left(\frac{\sigma_j^k}{\sigma_j^k + \frac{1}{k}}\right)^3$$

where $k$ is the number of the samples for validation data.

When a new test sample comes, we use the PLS sub-models to predict. Then we get the estimation values $y_j^{k+1}$ of the PLS sub-models. The fusion results of the new test sample are calculated as follows:

$$y_j^{k+1} = \sum_j=1 w_j^k y_j^{k+1}$$

In order to on-line update $w_j^k$ to adapt to the time-varying characteristics of the grinding process, we need to update $u_j^k$ and $\sigma_j^k$ on-line first. Based on the updating method for means $u_j^k$ and variances $\sigma_j^k$ in [43], a new on-line adaptive weighted fusion
algorithm is proposed. The on-line updating of $w^k_j$ is shown in (19)–(21):

$$u^{k+1}_j = \frac{k}{k+1} u^k_j + \frac{1}{k+1} y^{k+1}_j$$

(19)

$$(\sigma^k_j)^2 = \frac{k-1}{k} (\sigma^k_j)^2 + y^k_j - u^k_j)^2 + \frac{1}{k} \| u^{k+1}_j - u^k_j \|^2$$

(20)

$$w^{k+1}_j = 1 - \left( \frac{1}{1 + \| \sigma^k_j \|^2} \right)$$

(21)

4. Application in a laboratory-scale ball mill grinding process

The experiments were performed on a laboratory scale ball mill (XMQ-L420 × 450), which is a continuous grinding grid mill. The mill drum is 460 mm in diameter and 460 mm in length. The vibration signal was picked up by an accelerometer located on the middle of the shell. The ball load, mineral load and water load were added to the mill. Then mill was started and run for a given period of time, the vibration signal was measured during the grinding process. Another test was performed by gradually changing the quantity of mineral and water. In order to find the influence of every possible load and every operating parameter of ML to the shell vibration at different grinding conditions, a lot of assumptions on the mill operating conditions were made. To avoid redundancy, experimental details as described in [23] are omitted here.

4.1. Data preprocessing

The following parameters are used to calculate the PSD using Welch’s method: the data length is 32,768, the section number is 4. The sensitivity of different ML parameters to different frequency spectrum more clearly than other soft sensor approach. But sub-models can explain the physical meaning of the frequency spectrum and ML parameters. The PLS algorithm cannot captures the nonlinear between frequency spectrum and ML parameters. The PLS sub-models can explain the physical meaning of the frequency spectrum more clearly than other soft sensor approach. But the PLS algorithm cannot captures the nonlinear between frequency spectrum and ML parameters.

4.2. Multi-spectral PLS sub-models

Estimation of ML parameters is carried out using 26 samples, 13 for training and 13 for testing. For every frequency spectral segment, three PLS sub-models for three ML parameters are constructed. Therefore, a total of nine PLS sub-models are constructed. The statistic results for the percent variance captured of the former 5 LVs are shown in Table 1 and Fig. 5. The prediction results of the sub-models are shown in Section 4.4.

Based on Table 1 and Fig. 5, we can conclude the following:

1. The contribution of different frequency spectral segments is different. The percent variance of the first LV to three ML parameters for LF, MF and HF are 79.99%, 96.47% and 99.83%, respectively. This shows that the MF and HF are more sensitive than the LF. The reason is that the former are caused by the cyclical impact force, while the latter is the vibration mode of the hybrid mechanical structure, which is composed of ML and mill shell. This also shows it is necessary to construct different models for different frequency spectral segments.

2. The sensitivity of different ML parameters to different frequency spectral segment is different. Fig. 5(a) shows that the first LV of every frequency spectral segments have little correlation with MBVR, such as sub-model of LF, 1.69% variance of the spectrum corresponding to 40.74% variance of MBVR. However, Fig. 5(b) and (c) show that the first LV of every frequency spectral segments, PD and CVR captures most of the variance simultaneously.

3. The PLS algorithm is suitable to build the soft sensor model between the frequency spectrum and ML parameters. The PLS sub-models can explain the physical meaning of the frequency spectrum more clearly than other soft sensor approach. But the PLS algorithm cannot captures the nonlinear between frequency spectrum and ML parameters.

4.3. On-line adaptive weighted fusion

After all the PLS sub-models have been constructed, the initial weighting coefficients are calculated with (17) based on the high frequency spectral bands to construct PLS models are 100–1600 Hz, 1600–3500 Hz and 3500–65000 Hz, respectively, which are abbreviated as LF, MF and HF, respectively.

Table 1 Percent variance captured by PLS sub-models.

<table>
<thead>
<tr>
<th>LV#</th>
<th>LF</th>
<th>MF</th>
<th>HF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>X-Block</td>
<td>Y-Block</td>
<td>X-Block</td>
</tr>
<tr>
<td></td>
<td>This LV</td>
<td>Total</td>
<td>This LV</td>
</tr>
<tr>
<td>MBVR</td>
<td>1</td>
<td>76.52</td>
<td>76.52</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>17.28</td>
<td>93.81</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1.69</td>
<td>95.50</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>2.25</td>
<td>97.75</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>0.69</td>
<td>98.44</td>
</tr>
<tr>
<td>PD</td>
<td>1</td>
<td>82.05</td>
<td>82.05</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>4.79</td>
<td>86.84</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>9.70</td>
<td>96.54</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.93</td>
<td>97.47</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>0.66</td>
<td>98.13</td>
</tr>
<tr>
<td>CVR</td>
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<td>81.40</td>
<td>81.40</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>12.05</td>
<td>93.45</td>
</tr>
<tr>
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<td>2.94</td>
<td>96.39</td>
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</table>
Fig. 5. Percent variance captured by PLS sub-model of ML parameters for different frequency spectral segments: (a) percent variance captured by MBVR PLS sub-model; (b) percent variance captured by PD PLS sub-model; and (c) percent variance captured by CVR PLS sub-model.

Fig. 6. Weights of ML parameters soft sensor models.
prediction values of the training data. Then, the on-line adaptive weighted fusion algorithm is used to obtain the weighing coefficients. In order to find the contribution of the different frequency spectral segments in details, the changes of the weights for different ML parameters' sub-models at LF, MF and HF are given in Fig. 6.

Fig. 6 shows that the weights of LF, MF and HF change evidently with different samples. One reason is that most of the grinding conditions of the experiments are made in the unrealistic production conditions. Another reason is that the initial weighted coefficients are calculated with the prediction values of the training data, which may cause the initial weighting coefficients unreasonable. More experiments should be done to validate this approach further.

4.4. Results of the final PLS models

In order to illustrate the effectiveness of our proposed approach, we compare it with PLS, PCR, GA-PLS [23], PCA-SVM [24], and PCA-least square SVM (PCA-LSSVM) [44] algorithms with full frequency spectrum. The results are shown in Table 2. The curves of the real and predicted values with the proposed approach are shown in Fig. 7.

In order to compare with the proposed method, the number of the LVs for GA-PLS method is 5, and the contribution ratio limit of the PCs for PCA-SVM and PCA-LSSVM method is 99%. Therefore, the number of PCs of LF, MF and HF are 5, 3 and 1, respectively. The results show that the soft sensor models based on the proposed multi-spectral segments PLS sub-models and on-line adaptive weighted fusion algorithm have the best prediction performance. Constructing the soft sensor models with PCR and PLS algorithm using the full frequency spectrum has similar prediction accuracy. However, the PLS approach has less LVs than PCR approach. The GA-PLS approach selects the useful characteristic frequency sub-bands for different ML parameters to build soft sensor models, whose performance is better than PCR and PLS method. Although the PCA-SVM approach uses the same PCs for different ML parameters models, the kernel functions are linear kernel, radial basis function (RBF) kernel and polynomial kernel. The PCA-LSSVM uses the same RBF kernel, but the radius of RBF is 11, 40 and 68, respectively. This shows that the mapping between vibration frequency spectrum and different ML parameters is different. Fig. 7 shows that the PLS sub-models of different spectral segments have different prediction accuracy, which shows that the contribution of different spectral segments to different ML parameters are different. This also illustrates the complexity of the grinding mechanism inside the wet ball mill. Table 2 also demonstrate that the average prediction accuracy of “PLS+Weighted” is lower than the proposed approach, further proving the on-line updating of sub-models weighting coefficients is effective. Future research would address how to update the PLS sub-models simultaneously to adaptive the time-varying nature of grinding process more effectively.

5. Conclusions

This paper presents an effective approach for modeling parameters of wet ball mill load based on the vibration spectrum of the mill shell. It has made the following contributions: the PLS algorithm is used to construct different frequency spectral sub-models for different ML parameters, which enables deeper understanding of the grinding mechanism; a new on-line adaptive weighted fusion algorithm based on means and variances on-line updating method is proposed; the on-line adaptive weighted fusion algorithm is used to fuse estimation value of sub-models to obtain the final model; the experimental results indicate that the proposed soft sensor approach produces higher fitting precision and better predictive performance. However, the PLS algorithm cannot capture the nonlinear characteristics between the frequency spectrum and ML parameters. The on-line adaptive weighted fusion algorithm updates the weighting coefficients with every new sample. In addition, the test of the model is based on a laboratory-scale wet ball mill grinding process with limited samples. Therefore, Future research and more experiments should be done on the industrial wet ball mill.
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