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Selective ensemble modeling load parameters of ball mill based on multi-scale frequency spectral features and sphere criterion

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ABSTRACT

It is difficult to model multi-frequency signal, such as mechanical vibration and acoustic signals of wet ball mill in the mineral grinding process. In this paper, these signals are decomposed into multi-scale intrinsic mode functions (IMFs) by the empirical mode decomposition (EMD) technique. A new adaptive multi-scale spectral features selection approach based on sphere criterion (SC) is applied to these IMFs frequency spectra. The candidate sub-models are constructed by the partial least squares (PLS) with the selected features. Finally, the branch and bound based selective ensemble (BBSEN) algorithm is applied to select and combine these ensemble sub-models. This method can be easily extended to regression and classification problems with multi-time scale signal. We successfully apply this approach to a laboratory-scale ball mill. The shell vibration and acoustic signals are used to model mill load parameters. The experimental results demonstrate that this novel approach is more effective than the other modeling methods based on multi-scale frequency spectral features.

1. Introduction

How to maintain an optimal grinding condition is a key and open issue in control and operation of the mineral industrial process [1]. Mill load has direct relationship with grinding production rate, product quality and energy consumption [2]. In order to quickly adjust current situation to optimized status, accurate detection of the mill load is one of the prime problems in the ball mill grinding process [3]. Communication mechanism of the ball mill is still far from understanding. Normally, there are millions of balls inside the mill, which arrange hierarchically. Theoretical analysis shows that the track of the ball's dropping point for different layers is a spiral line through the center of the mill shell. The impact forces and periods of different layer balls to mill shell differ. Thus, ball mills produce vibration and acoustic signals. They have non-stationarity and multi-scale characteristics. Studies show that these signals contain interesting information related to mill load [4]. They are always used to judge mill load parameters, such as mineral to ball volume ratio (MBVR), pulp density (PD) and charge volume ratio (CVR). So, we can adjust the feed ore, water and ball load to ensure optimized status of the grinding process [5].

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Most of the grinding mill circuits use dual microphones measured acoustic signals to detect volume of the mill load [1]. As vibration is a source of acoustics, a soft measuring method based on mill shell vibration signal has become a new focus [6,7]. However, most of the successful industrial applications are on dry ball mills in cement and coal-fire power plant [8], or on semi-autogenous (SAG) mill [9]. Studies on wet ball mill in the grinding process are mainly focused on laboratory-scale one. The published references include single model based on least squares support vector machines (LS-SVM) using shell vibration frequency spectral features [10], ensemble model based on kernel partial least squares (KPLS) using shell vibration frequency spectral segments [11], selective and online ensemble models based on the KPLS and adaptive weighting fusion (AWF) algorithm using shell vibration and acoustical frequency spectral feature sub-sets [5,12]. The first steps of above methods are to make fast Fourier transform (FFT) to the original shell vibration and acoustic signals. These methods are called single-scale frequency spectrum based soft sensor approaches in this paper. However, these single-scale frequency spectral feature sub-sets are difficult to explain. Moreover, FFT only can be used to process stationary and linear signal. Thus, these methods cannot reflect multi-scale, non-stationarity and non-linear characteristics of the shell vibration and acoustic signals.

Therefore, there are still many challenges on soft sensing mill load parameters, such as how to analyze components of these signals from production mechanism, how to split these signals into different sub-signals with physical meaning effectively, and how to explain them symmetrically. Fortunately, there are some new methods to deal with these multi-scale signals. Empirical mode decomposition (EMD) is one effective decomposition method based on partial characteristic of the original signal [13]. It can decompose the original signal into some intrinsic mode functions (IMFs) adaptively. Bearing fault diagnosis method based on EMD and power spectral density (PSD) was proposed in [14]. Tang et al. proposed an EMD, PSD and partial least squares (PLS) based approach to analyze the shell vibration signal [15]. Ensemble modeling methods based on multi-scale frequency spectra of the shell vibration signal were proposed in [16–18]. However, these methods do not analyze components of the shell vibration signal based on its production mechanism. They also do not fuse IMFs frequency spectral features of the acoustic signal. These problems are solved in [19]. However, modeling accuracy is still not as well as that of the single-scale frequency spectrum based soft sensor models.

Selective ensemble (SEN) modeling based on “manipulating input feature” is another technique for modeling multi-scale signals. It can be used to selectively fuse IMFs frequency spectral features based candidate sub-models. SEN has been proved as an NP-completed problem [20]. Optimization of the ensemble sub-models' weighting coefficients needs analytical solution. However, it is unrealistic for many practical problems. Genetic algorithm based selective ensemble (GASEN) approach accelerates the calculation process [21]. It uses back propagation neural networks (BPNN) to build candidate sub-models. Normally, BPNN needs many training samples and long learning time. It also causes over fitting problem. Simple average weighting method is used to combine ensemble sub-models in GASEN. Moreover, the contributions of these ensemble sub-models to SEN model differ; and the prediction outputs of these ensemble sub-models may be collinear. Studies show that PLS and KPLS algorithms are suitable to model high dimensional, small sample spectral data. Ref. [5] uses branch and bound (BB) and adaptive weighted fusion (AWF) algorithms to select and combine the ensemble sub-models. However, the co-linearity problem is still not solved. In [19], a universal BB based selective ensemble (BBSEN) approach was proposed, which improves versatility of the modeling problem based on multi-scale frequency spectral features. However, its prediction accuracy is still much lower than that of the former proposed single-scale frequency spectrum based models. The above modeling methods construct every candidate sub-model with high prediction accuracy. Thus, the diversities among them may be lost. Therefore, constructing candidate sub-models with different diversities may be one of the solutions.

Feature selection is important for building effective soft sensor model. Mutual information (MI) based feature selection method was used in our former study [19]. Such normally used feature selection methods scale the original modeling data into zero mean and unit variance. Thus, the measurement units' influence of different features can be eliminated. However, spectral data usually have same measurement unit, such as Raman spectra. The shape of spectral data is destroyed if we scale them. Feature selection method based on sphere criterion (SC) can overcome this problem [22,23]. This method has been used in single-scale spectral features selection. However, features' selection parameters have to be set manually. How to optimally select multi-scale frequency spectral features adaptively is still an open issue.

Therefore, an effective multi-scale frequency spectral features selection and modeling method is needed. Motivated by the above problems, a novel data-driven SEN modeling approach is proposed in this paper. It is based on adaptively multi-scale frequency spectral features selection method using SC. Firstly, the original shell vibration and acoustic signals are decomposed into a number of IMFs using EMD technique. Then, multi-scale IMFs frequency spectral features are adaptively selected using the proposed feature selection method. At the same time, candidate sub-models based on the PLS algorithm are constructed. Finally, BBSEN modeling approach is used to select and combine ensemble sub-models. The experiments are made on a laboratory-scale wet ball mill. The results show that this novel approach is more effective than the other modeling methods based on multi-scale frequency spectral features.

Compared with the former studies, the contributions of this paper are:

1) The threshold values of SC are adjusted automatically for different multi-scale frequency spectra. The modeling accuracy for multi-frequency signal is further improved. In [23], the spectral features' selection parameters are selected manually.
2) The features' selection parameters of candidate sub-models based on multi-scale frequency spectra are selected simultaneously. This overcomes the diversity problem of different candidate ensemble sub-models as in [19].