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Experimental investigation of load behaviour of an industrial scale tumbling mill using noise and vibration signature techniques

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ABSTRACT

Mill load (i.e. the load level of coal powder), which is critical in improving the production capacity and energy efficiency of pulverizing system in thermal power plant, has not been effectively monitored and controlled industrially. This paper investigates the load behaviour in an industrial scale tumbling mill under practical working conditions. A microphone and an accelerometer were installed to pick up mill noise and inlet trunnion vibration signals, respectively. By analyzing the sensitivity distributions of mill noise energy and mill vibration energy, characteristic power spectra (CPS) of mill noise and mill vibration were obtained. The CPS energy, centroid frequency and frequency domain variance of the mill noise and mill vibration were then investigated and compared under various working conditions.

Experimental results show that the CPS energy of both mill noise and mill vibration can accurately represent the mill load. Moreover, the centroid frequency and frequency domain variance of mill noise can also be used to determine mill load. By combining these characteristics of mill noise and mill vibration, an improved estimation of mill load can be achieved.

1. Introduction

The tumbling mill is widely applied in thermal power plant as well as in the mineral and cement industries. The tumbling mill, as the most important mechanical installation in the pulverizing system, consumes a large amount of energy, being about 65–75% of the energy consumed by the pulverizing system and 15–20% of the energy consumed by the whole power plant. Therefore, improving the energy efficiency of the tumbling mill is critical. Most tumbling mills in power plants are poorly automated or run in an open-circuit mode, because some key process variables (such as mill load, ventilation rate and concentration of qualified coal powder in the pipe) cannot be measured accurately. The control strategies and manual operations are often based on other process variables (such as motor current, outlet temperature, and inlet–outlet pressure difference), which can be measured online and directly, resulting in poor mill performance. Mill load (i.e. the load level of coal powder) is the most important of the immeasurable key process variables. By monitoring and controlling mill load, it is possible to optimise the working conditions of the mill, in order to achieve significant improvement in production capacity, and to avoid the no-loading and over-loading faults. A thorough investigation into the load behaviour of coal powder is therefore needed, in order to enhance the energy efficiency of the tumbling mill.

Much research has been done to investigate the load behaviour of coal powder in mill. Kolacz (1997) studied mill load (powder filling) variations using a piezoelectric strain transducer. The transducer was installed midway along the length of the mill on the mill shell. By analyzing the strain changes during mill rotation, the coal powder filling conditions were obtained. Powell and Nurick (1996) studied particle motion in a laboratory mill using diagnostic X-rays from a bi-planar angioscope. This novel method is an accurate technique for tracking particle motion anywhere within a laboratory mill. Kiangi and Moys (2006) successfully studied the load behaviour in a dry experimental mill using an inductive proximity probe. However, these methods have not been used in industry. Recently, soft-sensing techniques have been applied to estimate the load level of coal powder (Wang and Song, 2001; Su et al., 2006). In soft-sensing models, the primary variable is mill load and the secondary variables are inlet–outlet pressure difference, outlet temperature, motor driver current, etc. Many data-driven models have been constructed using various intelligent algorithms to estimate the load level of coal powder. It is well known that the training set is the basis of these models. However, a perfect training set is difficult to obtain in practice and the secondary variables are often affected by the variations in working conditions, such as ventilation rate and coal properties.

Load behaviour has been studied by analyzing the mill vibration of laboratory and industrial mills. Zeng and Forsseberg (1993,

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1994, 1995) studied the mechanical vibration of an industrial scale tumbling mill. The vibration signals were first stored on a Digital-Audio-Tape recorder and then converted into digital format for further analysis. The empirical relationships between the vibration signal and grinding parameters (e.g. feed rate, power draw, and particle sizes) were investigated using multivariate statistical methods, such as principal component analysis and principal component regression. More recently, Behera et al. (2007) performed an in-depth analysis of the vibration signals of a laboratory scale mill with a diameter of 900 mm and a length of 150 mm. The possible effects of mill speed, powder filling, ball load and milling environment on the mill vibration were investigated and evaluated using the Fourier spectra method. However, there are visible differences between the laboratory scale and the industrial mill. Therefore, Su et al. (2008) implemented an experimental investigation on varying levels of coal powder in an industrial mill to interpret the vibration characteristics. On the basis of these vibration characteristics, they proposed a clustering method for diagnosing operating modes and a non-linear least square based model for online monitoring of the level of coal powder. Behera and Su's studies have laid a foundation for further investigation into the characteristics of industrial mill noise and vibration.

Since mill speed, ball load and milling environment (dry or wet condition) of industrial mill do not usually change in the pulverizing system of a power plant, this work focuses on the effects of mill load on mill noise and mill vibration. In this work, experiments were carried out on an industrial mill under practical working conditions. Mill noise and vibration signals under different working conditions were recorded and their sensitivity distributions were analyzed for the construction of the characteristic power spectra (CPS). CPS was constructed by removing the ineffective frequency components, which have less relation to mill load, from the original power spectra. Mill noise energy and mill vibration energy were calculated on the basis of CPS. Additionally, centroid frequency (f_c) and frequency domain variance (vf) were investigated. Then, the comparisons between the above-mentioned characteristics of mill noise and mill vibration were presented.

2. Noise and vibration signature techniques

A tumbling mill in the pulverizing system of a power plant is a rotating drum filled with balls and coal. When the mill is in operation, the balls are lifted up to a certain height, and subsequently collide with other balls, coal or liners in their descent, emitting noise and vibration. It is well know that these noise and vibration signals are mixtures of various source signals (such as background noise, inherent vibration of machinery, collision noise in the mill, and motor noise) and that only part of the source signals can describe load behaviour. Traditionally, noise and vibration signals are observed in a time domain, leading to difficulties in obtaining detailed information regarding these signals corresponding to various frequencies. However, these source signals have different characteristics in the frequency domain. Thus, we investigated the mill noise and mill vibration signals in frequency domain to extract the frequency components which are effective in describing load behaviour.

In this paper, mill load was defined as the volume fraction of the load voids occupied by coal powder, i.e. $L = V_{coal}/V_{voids}$, where V_{coal} and V_{voids} are the bulk of coal powder in the mill and the volume of load voids, respectively. According to this definition, the range of mill load is from 0% to 100%. This definition is more suitable for monitoring and controlling the tumbling mill in practice.

For the mill noise and mill vibration signals, a Hanning window, which acts like a predefined, narrowband, and low-pass filter (Behera et al., 2007) and reduces the errors introduced by leakage phenomenon, was used to process the time domain data. Then, the original power spectra of the mill noise and mill vibration were obtained using the Fourier transform technique (FFT). After that, a novel method was introduced to remove ineffective frequency components from the original power spectra and to construct the characteristic power spectra of mill noise and vibration. This method is described in detail in Appendix A. Moreover, the equations of CPS energy (E_f), centroid frequency (f_c), and frequency domain variance (vf) were also produced for subsequent investigation.

Commonly, relative variations are used to represent mill load. Therefore, in this paper, the energies of mill noise and vibration were transformed into normalized forms for the convenience of comparison. The normalizing algorithm adopted in this work is

$$x_u = (x_r - x_{min})/(x_{max} - x_{min}) \quad (1)$$

where x_u and x_r are the normalized energy data and the raw energy data, respectively. x_{min} and x_{max} are the minimum and the maximum values of raw energy data, respectively.

3. Experimental setup and data sources

3.1. Noise and vibration data acquisition system

The experiments were performed on an industrial tumbling mill (DTM350/700) of QinLing Power Plant in China with an outside diameter of 3.5 m and a length of 7.0 m, as shown in Fig. 1b. The mill, driven by two 900 kW motors, had a maximum ball load of 75 tonnes, a designed pulverizing capacity of 60.3 tonnes per hour and a rated revolution of 17.57 per minute. A belt feeder with a closed-loop controller was installed in the pulverizing system for coal feeding, as shown in Fig. 1c. The coal feeder controller adjusted the speed of the belt automatically to the pre-determined flow rate of the coal. The maximum feeding rate was set at about 120 tonnes per hour.

A data acquisition system (DAS) was designed to obtain mill noise and vibration data, as shown in Fig. 1a. The DAS consisted of a microphone, accelerometer, constant-current source unit (CCSU), signal conditioning unit (SCU), data acquisition card and human machine interface. In the DAS, 1/2 in. prepolarized condenser microphones (MPA206) and industrial accelerometers (M608A11) were used as front-end sensors, and their technical specifications are listed in Table 1. National Instruments data acquisition card (USB-9215A) was adopted to provide plug-and-play connectivity via USB for faster setup and measurement. The card offered four channels of simultaneously sampled voltage inputs with 16-bit accuracy to provide minimal phase delay when scanning multiple channels. The sampling frequency of each channel was 51,200 Hz. Data acquisition software, programmed in Borland C++, was developed to record the input signals of the first 200 ms in every 500 ms. The DAS was equipped with low-pass filters at each input channel for anti-aliasing. The frequency content of interest in mill noise and vibration signals under study did not exceed 10,000 Hz, and therefore, the sampling frequency was sufficient to recover the input analog signals from the recorded data. Moreover, motor current, inlet–outlet pressure difference and outlet temperature were simultaneously recorded every 0.5 s by a distributed control system (DCS).

The positioning of microphone and accelerometer is critical to the quality of acquired data. The final positions of the two sensors, shown in Fig. 2, were based on operator experience. The microphone was installed beside the mill with a 100 mm distance from the mill surface and a 2500 mm distance from the inlet side of the mill (i.e. about 1/3 length of the mill). In this position, where the coal has been well dried by the hot air, the influence of the coal moisture on the mill noise data is significantly reduced. The micro-