Paper – 489

LOAD TORQUE ESTIMATION FOR MONITORING BALL MILL FILLING

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ABSTRACT

The purpose of the research is to monitor ball mill filling by means of signals usually measured in its electrical drive. The method is based on the mill torque estimated from rotor speed and induction motor stator voltage and currents. New signal processing is presented in both time and frequency domain for measurements in a dry laboratory ball mill. Statistical analysis is applied to time series resulting in good correlation to mill filling. Fast Fourier Transform (FFT) and power spectral density (PSD) also resulted in an accurate filling indicator. The proposed method does not need any sensor to be installed directly on the mill and requires only sensors usually available for motor control purposes. The experimental results showed that the method have potential to be used to construct an automatic system for monitoring operational variables in ball mills. The aim of this monitoring is to improve energy efficiency, reliability and productivity.

KEYWORDS

Ball Mill, Charge Monitoring, Estimated Torque, Indirect monitoring

INTRODUCTION

Recently, a great number of papers have pointed the importance of ball mill filling monitoring and also of grinding control (Lu, et al., 2014) (Ramasamy, et al., 2005) (Tsamatsoulis, 2014) (Zhou, et al., 2009). Additionally, great amount of control techniques have also been presented with several complexity degrees (Tsamatsoulis, 2014). According to Eremenko (2015) the lack of effective and accurate methods for fill level measurement is the main reason that makes mill optimal control so complicated. It happens because nonlinearity, long time delay and time varying features of the ball mill turns difficult to develop a truly efficient method for monitoring filling.

At the same time, fill level has a determining role in charge motion and consequently on particle breakage. For low levels of filling many energy is expended in impacts with very low breakage efficiency. Those impacts can also damage mill liner. In contrast, high levels of filling causes damping effects that reduces breakage and can also affect energy consumption. Based on this it is conclusive that fill level measurement of ball mills is an important issue for grinding efficiency. This fill level information can be used for operators to control ball mills and also for engineers to run simulations and improve confidence levels of circuit designs (Shi, 2016).

Although fill level measurement of ball mills is still a necessity in mineral industry, many methods have already been proposed to meet this need, among which the electronic ear (Kang, 2006) (Xing, 2004), strain analysis (Kolacz, 1997) and vibration signature (Behera, et al., 2007) (Das, et al., 2011) (Gugel & Moon, 2007) (Mohanty, et al., 2015) (Peng, et al., 2009) (Si, et al., 2009) (Tang, et al., 2010) (Tang, et al., 2012) (Zeng & Forssberg, 1994) (Zhi-gang, et al., 2008). Each one of these methods has some drawbacks which are described in the related literature (Pedrayes, et al., 2018) (Esteves, et al. 2014, 2015, 2016).

Esteves et al. (2014, 2015) proposed the use of estimated torque signal for monitoring ball mill filling. By applying a technique called Load Torque Signature Analysis (LTSA) the estimated torque was obtained based on electrical motor variables. By comparing, in frequency domain, torque signal and mill mechanical vibration it was proven that torque spectral components are clearly affected by mill filling. Recently, Pedrayes et al. (2018) obtained a good correlation between torque in frequency domain and mill filling. The method is based on computational simulations using Discrete Element Method (DEM) and presented good results for a laboratory ball mill used for dry grinding.

This paper proposes a new approach for estimated torque signal processing with the aim to obtain an accurate measurement of ball mill filling. It is a continuation of a previous work presented in the IMPC 2014 in Chile (Esteves, et al. 2014).

Torque Analysis

Mill torque is disturbed by charge motion, which produces vibration in mill shell (Behera et al. 2007). Mill torque oscillations and/or vibrations are transmitted to the driving motor through a coupling device. Those torque oscillations affects current, rotor speed and position. Such variables can be used as inputs to a load torque estimator.

A block diagram illustrating the structure is shown in Figure 1. First, motor stator currents, stator voltages and rotor speed are measured. Then, signal conditioning applies anti-aliasing filters and adequate gains. These data feed the torque estimation stage. It consists of a load torque estimator based on a Luenberguer observer. The reader interested in additional information about the load torque estimator such as equations, transfer functions derivation, frequency response, gain adjustment, parametric changes effects and others detail can find it in (Stopa, 2011) (Stopa & Cardoso Filho, 2012). Than signal processing is divided into two stages: time and frequency domain. After that, filling indicators are obtained and can be combined to guarantee an accurate filling measurement.

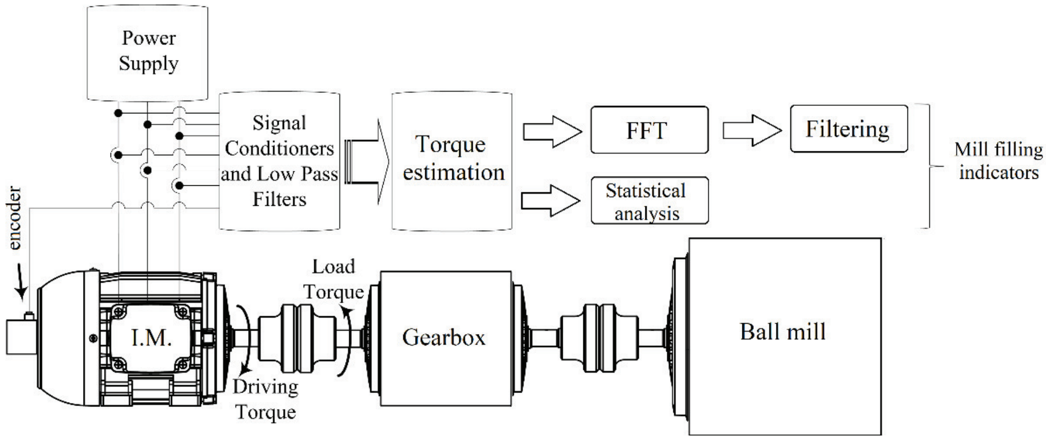

Figure 1 - Functional block diagram of torque energy calculation

Signal processing in time domain

Salehi-Nik et al. (2009) proposed applying statistical analysis of acoustic emissions to determine hydrodynamic behavior of gas-solid fluidizes beds. The obtained results presented good correlation to the physical phenomena. Later the method was applied by Esteves (2018) to indirectly estimate screw wear in vertical stirred mills. Standard deviation, kurtosis and skewness are analyzed. Standard deviation is a measure of dispersion that quantifies how spread is the data. Skewness and kurtosis are measures of shape that quantifies data flatness and symmetry. Details of the method can be found in the related literature.

Signal processing in frequency domain

The torque signal contains several harmonics that are related to driving system, rotating elements and the electric motor. In frequency domain it is possible to eliminate those components in order to obtain the torque energy that is directly related to mill load. To apply this method the torque signal is first converted to frequency domain by applying Fast Fourier Transform (FFT). In frequency domain the peak frequencies can be identified. Energy associated with those peaks are obtained based on power spectral density (PSD) techniques. Peaks energy that cannot be correlated to mill filling are eliminated and, finally, torque energy related to charge motion is obtained.

MATERIALS AND METHODS

In order to validate the proposed methodology, tests were performed at Industrial Applications Laboratory – UFMG (Universidade Federal de Minas Gerais), with the assistance of the Mining Processing Laboratory - UFMG. The ball mill is driven by a three phase, four poles, 220V, 1,5 hp, induction motor. The motor is supplied by a frequency inverter, which allows varying the velocity from 0 to 1800rpm. The mill is coupled to the motor by means of a 15:1 reduction ratio gearbox. Mill length is 360mm, mill diameter is 460mm and ball top size is 40mm. The laboratory set is shown in Figure 2. Details about data acquisition and signal conditioning can be found in Esteves (2014).

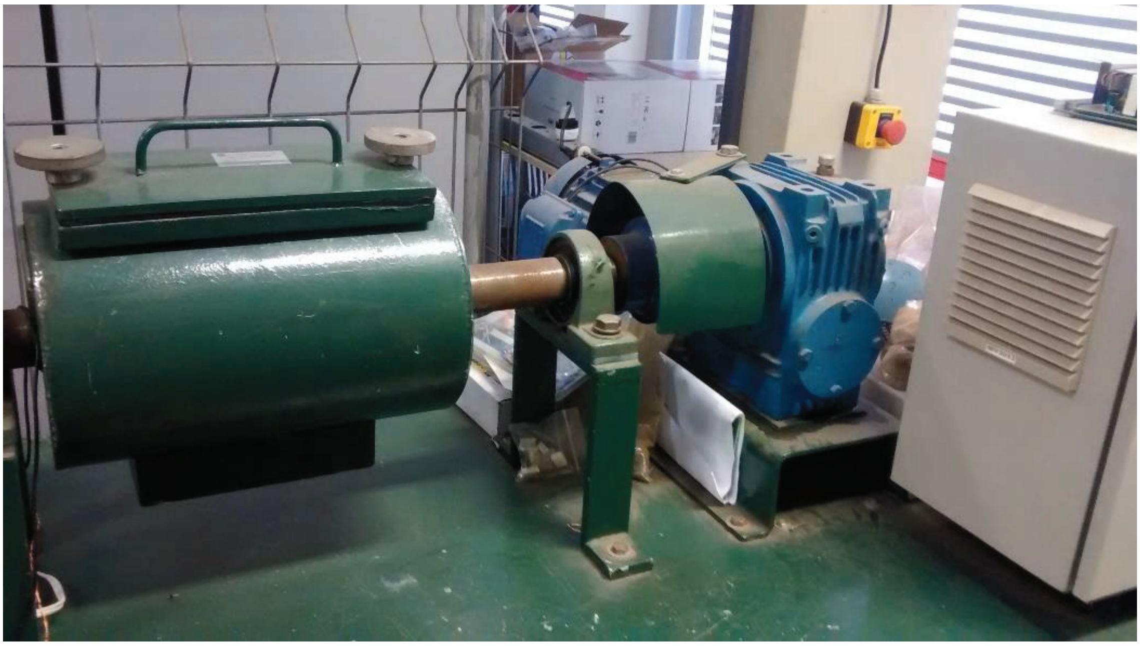

Figure 2 - Experimental setup

Two speeds were tested: 68% and 78% of critical velocity. Mill charge was 2kg, 4kg, 6kg and 8kg that respectively represents 14%, 20%, 27% and 33% of filling. Grinding was tested under dry conditions.

RESULTS AND DISCUSSION

Figure 3 presents torque results in time domain at 68% of critical speed. For 78% of critical speed the behavior is similar. Statistical analysis was applied to test time series data, as can be seen in Figure 3, for the two tested velocities. Standard deviation is clearly affected by ball charge. It is very low for the case of the empty mill and increases with ball addition for both tested speeds. However, standard deviation tends to stabilize for bigger amounts of balls. Mill velocity also increases this indicator, indicating that torque values are spreader when rotational speed gets closes to its critical value. On the other hand, torque signal skewness is null for the case of the empty mill, indicating that it presents a Gaussian distribution. As ball charge increases, the absolute value of skewness increases, in negative values. It shows that median and mean of the signal are smaller than mode of the Gaussian distribution. It means that torque signal tends to smaller values in an asymmetrical distribution. This can be explained because of the presence of big negative torque peaks. Finally, kurtosis tends to increase with ball charge, indicating the presence of big peaks in torque signal. Kurtosis is bigger for the lower speed, indicating that at 68% of critical velocities torque peaks are bigger than at 78%. One possible explanation is that the lower speed favored the occurrence of very energetic impacts. Increasing mill speed a bigger amount of balls starts to centrifuge, so impact energy tends to decrease and consequently torque kurtosis is lower. Finally, total torque energy is analyzed in the range of 0 Hz to 500 Hz. Torque energy increases with ball addition and then tends to stabilize. For the case of low velocities torque energy is bigger, for the same reason explained for the increase in kurtosis. Sensitiveness of torque energy can be improved after eliminating torque peaks that are not directly related to mill filling.

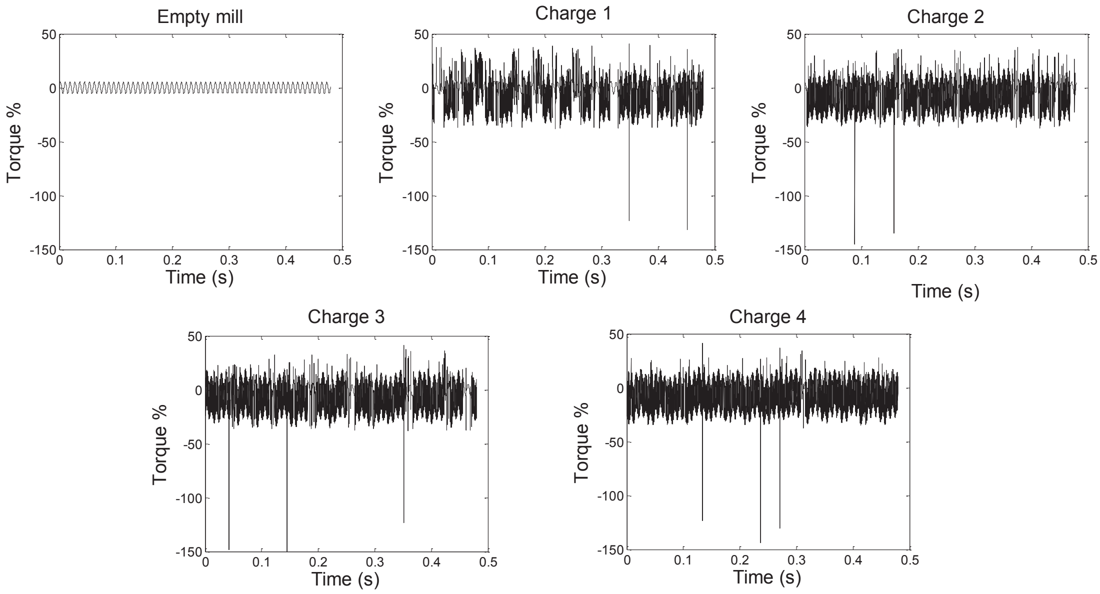

Figure 3 - Time series data of the estimated torque

Figure 4 shows estimated torque in frequency domain. The torque spectrum of the empty mill is characterized by the presence of only a few peaks of torque. All peaks are harmonics of the first small peak, located around 29 Hz. Those peaks that appears in the empty mill spectrum are mechanical features, once mill filling is null. After charge addition a great amount of energy appears in the spectrum, including harmonic components. Correlation between those harmonics and ball charge was tested.

Figure 5 shows PSD of harmonic peaks versus ball charge. As can be seen it is not possible to establish a direct correlation between energy of harmonics from 1 to 12 and the mill filling. There are no clearly tendencies that can be correlated to mill filling and velocity. Because of this lack of correlation, PSD associated with those peaks is subtracted of the total torque PSD. In this way, the remaining torque energy can be correlated to mill filling for the two tested velocities.

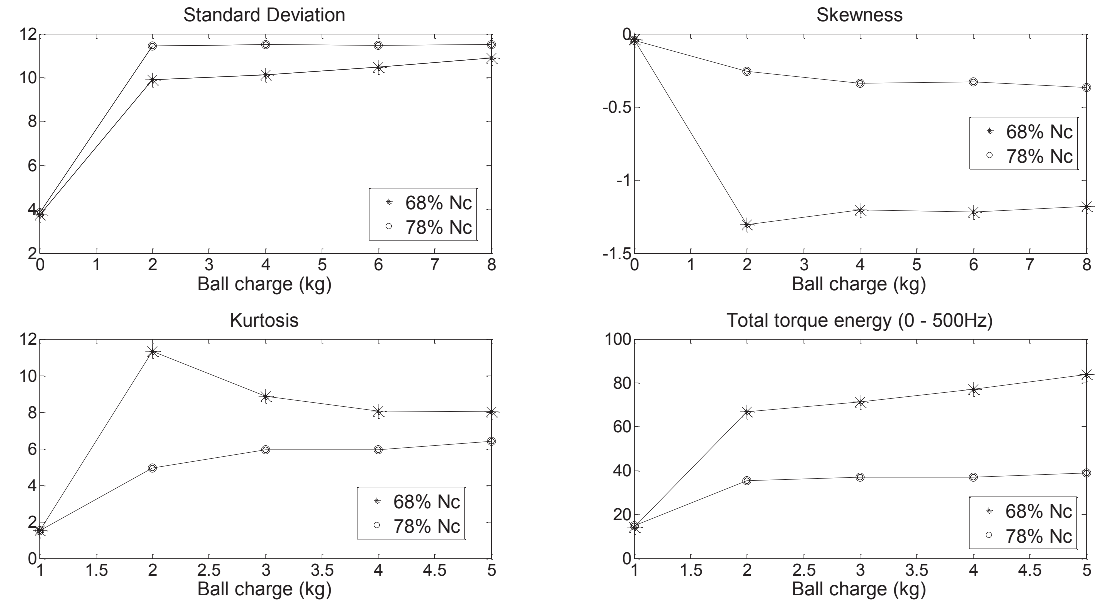

Figure 4 - Statistical analysis of estimated torque time series data

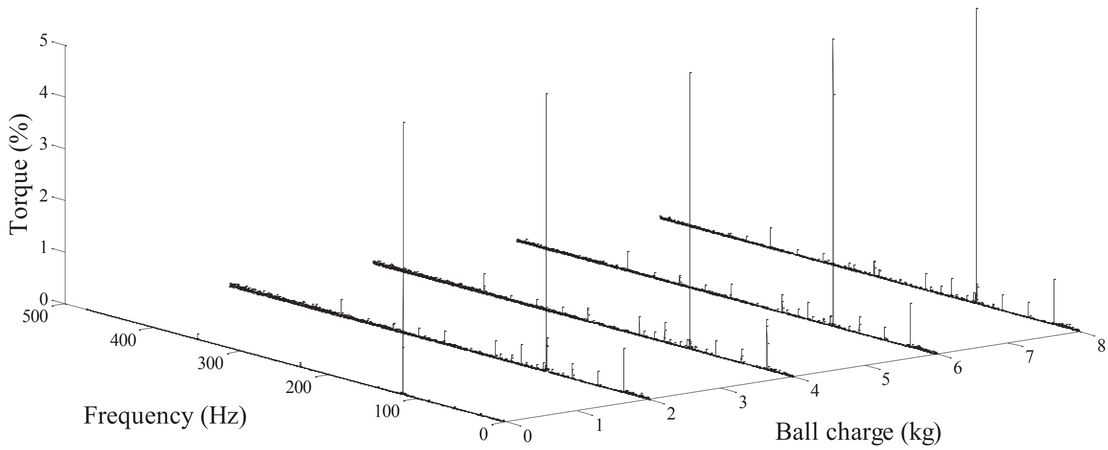

Figure 5 – Torque spectrum of 68% of critical velocity

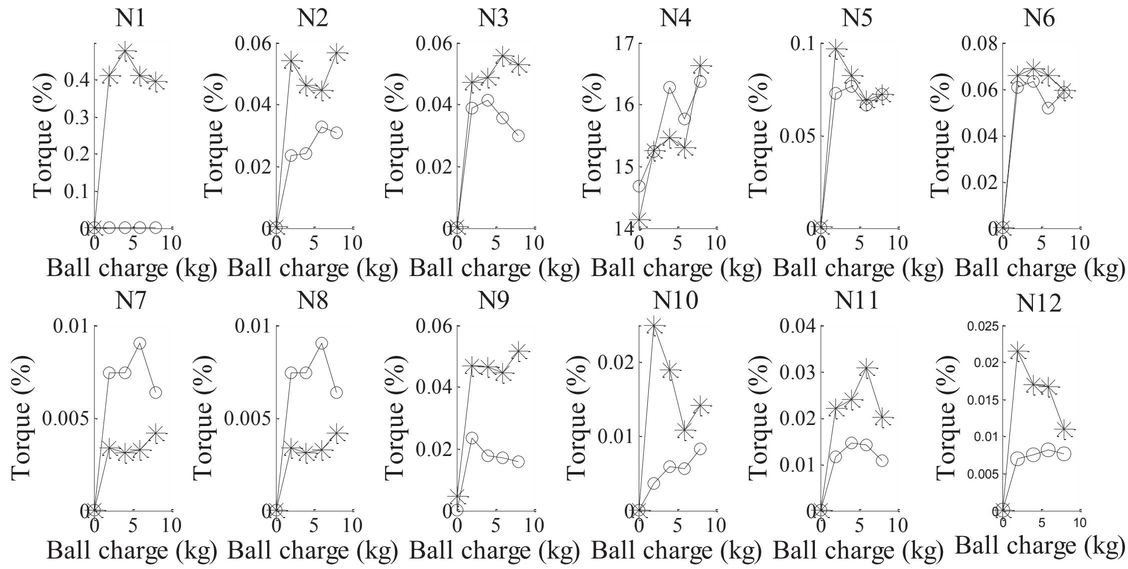

Figure 23 – Harmonic peak components x Ball charge

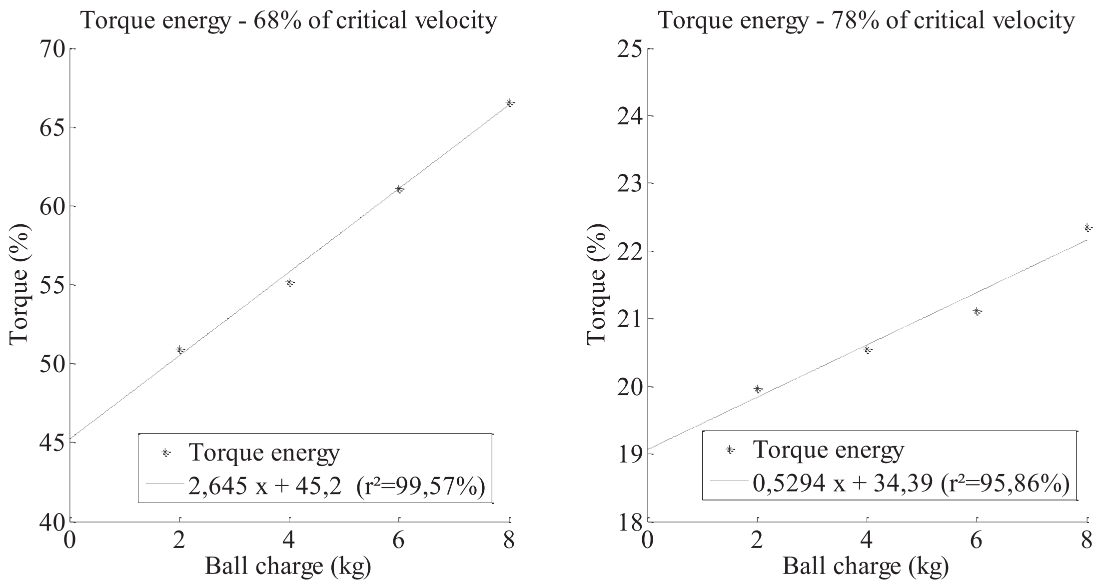

Figure 6 - Mill filling indicator

The results are shown in Figure 6. It is possible to note that there is no remaining energy in the empty mill torque signal. This confirms the supposition that all energy associated with mechanical components were eliminated in the previous step. The developed indicator resulted in a linear relation between torque and mill filling. It is also possible to note that the obtained torque energy is bigger for the lower mill velocity. One possible explanation is that at this velocity impacts of great energy predominates inside the mill. As the mill velocity increases the amount of impacts decreases and consequently torque energy is lower. Another interest feature is that line slope also decreases when velocity increases. It indicates that bigger velocities disadvantage the occurrence of great energy impacts. As a great amount of charge starts to centrifuge inside the mill, torque varies only slightly with ball addition. The same conclusion was obtained based on statistical analysis of torque time series, as explained for skewness and kurtosis results.

CONCLUSIONS

Torque was estimated based on electrical motors variables, such as currents, voltages and velocity. Statistical analysis of time series data proved that torque signal can be correlated to mill charge. The obtained indicators presented good correlation to mill filling. The changes in torque data can also be physically explained by charge motion. However, for bigger charge fillings those indicators tends to stabilize and are not very sensitive. This problem was solved by performing frequency domain analysis of torque signals. Peak frequencies related to mechanical mill components did not presented good correlation to mill charge. Those peaks were eliminated and then torque energy was recalculated. The results presented good correlation and sensitiveness to mill charge, indicating that they can be successfully used as a filling indicator. To guarantee the accuracy of the method statistical analysis and frequency analysis can be used together. The biggest advantage of this method is that is low cost, low intrusiveness and of easy development. The method can be perfectly applied to other laboratory and industrial ball mills, after applying some level of customization.

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