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Vibration feature extraction and analysis of industrial ball mill using MEMS accelerometer sensor and synchronized data analysis technique

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Abstract

The use of advanced technologies such as Micro-electromechanical system (MEMS) sensors and low power wireless communication hold a great promise for optimal performance of industrial wet ball mill. The direct translation of the natural phenomena of the batch mill in a lab setup to a continuous process mill in the industry is quite perplexed in the nature of their intent and operating conditions. In this paper, the vibration signatures are analyzed for industrial wet ball mill using a MEMS accelerometer sensor. The signals are acquired using two wireless accelerometer sensors; mounted at feed and discharge end of the ball mill to validate the grinding status of the copper ore. The vibration spectrum before and after feed are compared to estimate the actual grinding status of the ore inside the mill. A limiting threshold level for the intensity is identified from the spectral analysis to monitor the desired grinding status of the ore. The high frequency (ZigBee) transmission loss due to diffraction is also compensated by the novel arrangement of the sensor transceiver. Finally, Pearson correlation technique is used to analyze the effect of sample length and its dependency with the rpm of the mill in determining the actual vibration signature.

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1. Introduction

Ball mills are used in mineral processing industries to grind ores to desired size (from mm to micron size). Comminution in ball milling is a complex phenomenon. The delineation of the process behavior is an important step to understand the actual physical process taking place within the mill. The utilization of energy for grinding is
generally 1-2% of the supplied energy, so it is necessary to effectively monitor the process behavior to increase the production efficiency.

In the past, diverse works have been borne out by many researchers to study the process behavior of the ball mill. Different approaches have been attempted to supervise the performance of ball mill, i.e., power drawn of the mill, acoustic data analysis, vibration data, etc [1-2]. Performance also can be enhanced by analyzing and monitoring the behavior of the ball mill using wireless acoustic sensor [3]. These analyses have certain advantages and disadvantages. Only acoustic and vibration cannot be the source of information, even though correlations between these two phenomena are quite tough in an industrial noisy environment. The power drawn by the mill is an easy way to understand the load parameter in ball mill, but it fails to analyze in an efficient manner [4-6]. These analyses are easily suited in a laboratory batch mill. The real phenomena in the laboratory mills are quite dissimilar from that of an industrial continuous mill in the nature of their conception and process parameters used in the output flow [7]. The vibration signal analysis for lab model sag mill is same as that of ball mill, but the frequency of operation of vibration signal and impact strengths are different [8]. Sag mill will require a higher value of $g$ and BW of the sensor due to higher stiffness compared to that of ball mill (as the length of the mills is accounted). The kinetics of the industrial wet mill varies due to its significant run length and the material characteristic changes due to pulp density variation. The uses of sensors technology can benefit, but as per as the piezo based sensor are concerned they require external power supply, which is really difficult for the rotating machinery. To benefit from the advanced technology, the authors have used wireless MEMS based capacitive (having both static and dynamic response) Zigbee based three axes wireless accelerometer sensor to monitor the impact signature of the mill.

2. Experimental setup & Methodology

The actual behavior of the MEMS sensor is tested in different systems i.e., the industrial mill, lathe machine, and the lab experimental setup prior to the final experimentation performed for the vibration data acquisition [9-11]. The observational results are used to determine the impact phenomena (impact statistic) of the ball mill with settling time of the sensors. After successful verification of these sensors, they are used in the ball mill to acquire the vibration signals [12-13].

For experimental studies, two wireless accelerometer sensors are mounted (stud mounting); one at feed (node-1) and other at discharge end (node-2) as shown in the Figs. 1(a) & (b). The node positions are selected to differentiate the vibration signature, which interns depend on coarse (at feed end) and fineness (at discharge end) of the ore. The data packet transmission losses due to diffraction in the high shielded metallic environment are compensated by mounting the transceiver at the side wall of the mill as shown in Fig. 1(a) [14-16]. The process parameters used for these experiments of a typical industrial wet ball mill is specified in the Table 1.

![Position of accelerometer sensors on industrial Ball mill](image1.jpg)
Table 1. Parameters of Industrial Ball Mill

| Parameters                  | Value                  |
|-----------------------------|------------------------|
| Feed type                   | Copper ore             |
| Feed rate                   | 110-130 MT/Hr          |
| Feed size                   | -6 mm                  |
| Discharge particle size     | -75 Micron             |
| Diameter of mill            | 11.6 Ft (3.5 m)        |
| Length of the mill          | 18 Ft (5.49 m)         |
| R.P.M                       | 17.47                  |
| Power rating of motor       | 10 MW                  |
| Power required for grinding | 700-800 KW             |
| Temperature                 | Ambient                |
| Ball diameter               | 65 mm                  |
| Pulp density                | 75% ore & 25% Water    |

3. Experimental results and analysis

The experimental results are evaluated in steps to validate the vibration signature, with proper justification as per the mill condition during grinding.

3.1. Vibration feature extraction using mill rpm and sampling rate synchronization

Here, the authors have tried to synchronize the mill speed and sensor data acquisition rate to produce a better auto and cross-correlation between the vibrations signals acquired at feed and discharge end. The proposed method is based on the principle of synchronicity between the mill angular rotation and data acquisition rate matching of the sensor. Once the sensors are mounted permanently on the mill shell, it is very difficult to know the exact location of sensor at every run. Referable to the centrifugal action of the balls, the impact phenomena and its actions are observed only in the half section of the mill. The other half section of the mill is free from both attrition and impact. During motion of the sensor, it encompasses the full circumference of the mill, i.e., it covers the impact zone and non-impact zones [19]. The FFT for the synchronized discrete sampled signal $x(n)$ is defined in (1);

\[
X(k) = \frac{2}{N} \sum_{n=0}^{N-1} x(n)e^{-j2\pi kn/N}
\]

Where $N=158000$, the sample length for 23 revolutions.

![Fig. 2. The synchronized data sample for the feed end (node 1), without feed (a) Composite vibration signal in time (b) frequency of vibration for 0-10 mins.](image)
The experimentations are performed for total time duration of 140 minutes. For the first twenty minutes, the data are acquired using sensor without any feed. Later, the experiments are performed for the rest of 120 minutes with feed as shown in Table 2. The signal and its spectrum obtained for the first 0-10 minutes, without feed, are as shown in Figs. 2 & 3. The vibration signatures of the mill, once the material is fed are shown in the Figs. 4 & 5.
3.2. Vibration feature extraction

The data obtained from the Figs. 2, 3, 4 & 5 are extracted for the discrete values of amplitudes and frequencies (where the strength of the signal is maximum), and are shown in Figs. 6 (a) & (b). It is observed from Fig. 6 (a) that, the initial intensity for both feed (marked as blue star) and discharge end (marked as green triangle) are almost same for first 20 mins., but once the material is fed into the mill, the intensity of vibration for the feed end started falling, whereas, the intensity of the discharge end maintain the value of an almost constant level as that before the feed. In general, the intensity should fall to a lower level as compared to the feed end due to the increase in the pulp density, as it happens in case of batch process mill. But, the same is not true in case of industrial mill. The reason could be the increase in ball to ball contact, or the numbers of balls participating in the impact process are more to sustain the oscillation to a higher value as compared to that of feed end. Frequency of vibration in Fig.6 (b) follows a constant pattern, because of the residual balls present in the mill surface remains constant.

| Feed of materials | Time in Mins. | Frequency in Hz (Feed end, node-1) | Magnitude in 'g' (Feed end) | Frequency in Hz (Discharge end, node-2) | Magnitude in 'g' (Discharge end) |
|-------------------|--------------|-----------------------------------|----------------------------|--------------------------------------|-------------------------------|
| No                | 0-10         | 174                               | 0.13                       | 238                                  | 0.16                          |
|                   | 10-20        | 175                               | 0.16                       | 243                                  | 0.20                          |
| Yes               | 20-30        | 175                               | 0.08                       | 243                                  | 0.16                          |
|                   | 30-40        | 175                               | 0.08                       | 243                                  | 0.16                          |
|                   | 40-50        | 180                               | 0.07                       | 244                                  | 0.14                          |
|                   | 50-60        | 179                               | 0.07                       | 242                                  | 0.14                          |
|                   | 60-70        | 180                               | 0.06                       | 243                                  | 0.13                          |
|                   | 70-80        | 180                               | 0.06                       | 238                                  | 0.12                          |
|                   | 80-90        | 181                               | 0.05                       | 245                                  | 0.12                          |
|                   | 90-100       | 179                               | 0.06                       | 240                                  | 0.13                          |
|                   | 100-110      | 181                               | 0.065                      | 245                                  | 0.14                          |
|                   | 110-120      | 177                               | 0.06                       | 240                                  | 0.13                          |
|                   | 120-130      | 178                               | 0.065                      | 243                                  | 0.13                          |
|                   | 130-140      | 179                               | 0.08                       | 243                                  | 0.14                          |

Fig. 6. (a) Magnitude in g variation at every time step after FFT (b) Frequency variation for each time step of 10 min

To get the threshold level of operation of the mill, the feed and discharge end intensities are subtracted and a threshold level is set as shown in Fig. 6 (a) (marked with red circle). The range of $g_{TH}$ (m/sec²) threshold range must be well within 0.04 < $g_{TH}$ < 0.10; to have stable operation of the mill during grinding. The remarkable observation can also be drawn from the threshold level that the variation is still well below the threshold set and the product size at the discharge end continues to be -75 microns [17-18]. Any deviation in threshold indicates the improper product size and there could be a problem in the running condition of the mill.
3.3. Statistical analysis before and after data sample length synchronization

The objective of this analysis is to validate the final conclusion drawn from the Figs. 6 (a) and (b) using statistical technique.

The statistical analysis is initially carried out for a sample length 2000 samples; the rate at which the sensor is acquiring the data (the time varying impact phenomena is not taken into account, simply the sensor acquisition rate is considered). The formulation of correlation coefficient using Pearson correlation is as in (2);

\[
 r_{xy} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{(n-1)s_x s_y}
\]  

(2)

Where mean for \(x\) and \(y\) can be represented using (3);

\[
 \bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i
\]

(3)

Standard deviation can be used to depict the distribution pattern of the data from the mean and can be formulated for \(x\) and \(y\) using (4);

\[
 s_x = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (x_i - \bar{x})^2}
\]

(4)

It is observed from the Figs. 7 (a) & (b), that the mean and standard deviation (SD) for the feed end are 0.5960 and 0.1809; and for discharge end they are 0.8545 and 0.3047; when no material is fed into the mill. Figs. 8 (a) & (b) show the mean and standard deviation (SD) for the feed end are 0.3180, 0.1080; and 0.7319, 0.3448 at discharge end; when the material is fed into the mill. For better prediction, standard deviation should be low for perfect distribution of impact energy. The standard deviations for the Figs. 7 & 8 are very high due to the significant change in the intensity level of the signal. As the sample length is considered for every second, i.e., 2000 samples/sec, at which the sensor is acquiring data. The calculated Pearson coefficients for the intensity variation at each second without and with the feed are - 0.379 and 0.229 respectively. It can be observed that the data are not highly correlated due to significant mismatching in the sampling rate at which the sensor is acquiring the signal and the angular rotation of the mill. Here, the authors have proposed a method to monitor the vibration signature of industrial ball mill with a better correlation and minimal SD in the signals when the data acquisition rate of the sensor and the impact phenomena of the mill are taken into consideration as in (5).

\[
 P = f(DAQR, RPM)
\]

(5)

Where, DAQR is the data acquisition rate of the sensor and RPM is the revolution per minute of the mill and \(P\) is actual data sample length required for vibration feature extraction.

![Fig. 7. Probability and standard deviation distribution of ‘g’ without feed (a) Feed end (b) Discharge end](image-url)
The previous analyses are carried out for un-synchronized data sample length of 2,000 samples. Due to the data synchronization, for a sample length of 1,58,000; the standard deviation for both feed end and discharge end fall to a lower value of 0.03046 and 0.02128 respectively as shown in Figs 9 (a) & (b). It means, the data are highly correlated and the Pearson cross correlation coefficient is found to be 0.912. It signifies the data at both the ends follows a regular pattern. This is the reference exact grinding status of the mill when the output particle size is of -75 microns. If the cross correlation coefficient decreases below 0.8, it means that the grinding in the mill is not happening properly and the mill should be checked to control its feed rate, pulp density, liner and lifter conditions etc.

4. Conclusion

The sensor node with inbuilt transmitter is highly prone to fading, and is overcome by connecting the sensor with separate transmitter mounted on side wall of the mill. It is observed that the sensitivity of the sensor is sufficient enough to acquire the data in an effective manner as the intensity of vibration fall within ±10g. It is also observed, even though impact produced is high due to the centrifugal action of the balls, but the intensity of vibration gets dampened by the balls present on the bottom surface of the mill, the rubber liner and the mill shell. As a result external vibration effect is less outside the mill. As per the sensor selection is concerned for a heavily loaded ball mill, the sensitivity of the sensors should be high as compared to the ‘g’ value required, and the BW of operation can be limited by the mass of the balls present on the surface of the mill during grinding. The typical frequency of operation of the mill is well below 1000Hz. The mass of the balls present will control the operational frequency band of the mill (even though mass of the balls, ore and the liner affect the frequency of operation). It is noticed that the synchronization of mill's angular speed and sampling rate of the sensor, determine a threshold level for optimal
grinding with a product size of -75 microns, as per the industrial requirement of the KCC, Khetri. For controlled grinding of the copper ore, the $g$ value falls within $0.04 < g_{TH} < 0.10$ range and the correlation coefficient should be as high as possible i.e., more than 0.8. Any deviation in this range would indicate an improper output product size of the copper during grinding. Finally, it can be concluded that the sample length selection has a dramatic effect in the grinding status analysis of the ball mill. Significant data analysis in ball mill can be done when the sensor data acquired rate and the rpm of the mill are synchronised to nullify the effect of impact dead zone.

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