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ACOUSTIC SIGNAL CHARACTERIZATION OF A BALL MILLING MACHINE MODEL

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Introduction. A ball milling machine, is a cylindrical device used in grinding process. A ball mill rotates around a horizontal axis, partially filled with the material to be degradated and the grinding medium. Spherical balls are mostly used as the grinding media, these media cascade within a mill and impinge on the ore thus providing a crushing action. As the balls tumble within tubular mills, they provide a grinding action and forces of attrition, all of which result in further reduction of the size of the rock particles. Impact breakage occurs as balls drop into the toe of the charge and abrasion or attrition occurs as the layer of balls or rods slides over each other or against the mill liner. In designing a plant for size reduction material the two main features of interest are the power required for size reduction and the choice of crushers and grinders [1]. The power or energy required is the sum of the work required to crush or grind the rock as well as rotate the mill. The power required depends on the hardness of the rock, the initial size and the final product size required. In mining industry, the main objective consists in to achieve reasonable liberation of the mineral of interest from the host rock. Several efforts have attempted to determine the energy required for crushing rocks. It had been observed that in the process of size reduction, as the size of the particles diminishes the surface area of the particles increases. So a measure of size or surface area before and after size reduction would indicate the extent of energy expended in the comminution process. It is worth to mention that this kind of process consumes the 4% of the world energy, being responsible for the 50% of total costs in mining industry [2].

In this work a smaller scale ball mill machine, frequently used in construction industry, is analyzed. This particular machine covers procedures like testing material resistance of different types and sizes. This paper addresses the particular problem of acoustic signal processing, emitted by this type of ball mill, in order to estimate the material percentage of resistance to degradation. The traditional test procedure takes at least 26 hours, with 24 hours of intense energy consumption (by means of grinding, and drying procedures). Hence, an online resistance estimating algorithm is highly desired. An algorithm, based on the methodology proposed in this work, could result in savings of time, energy, and also, may determine a more precise estimative.

The Modeling Problem. The performance of a particular mill is determined by the system dynamics (or macrodynamics) involved in the milling process, such as the motion of the balls, impact velocity, collision frequency, and milling dynamics (or microdynamics) involved in individual collision events, such as powder deformation and microstructural evolution [3]. Therefore, system and milling dynamics are inter-related. Inside the ball mill, the particles are hit by mechanical charge of great power which leads to large plastic deformations and fractures. The particle motion is governed by impulsive forces acting on each collision, no analytical expression for the complete ball trajectory can be obtained. In addition, mechanical systems that exhibit impacts are highly nonlinear due to sudden changes of speed at the moment of impact. Many different types of periodic and chaotic impact motions exist indeed even for simple systems with external periodic excitation forces [4].

A simplified vibratory ball mill model, called Bouncing Ball, is presented in [5] to analyze the chaotic phenomena. This simple chaotic system could represent the ball mill chaotic behavior on a single axis of motion with a single particle [6]. Simulating this model will allow to capture the test data necessary to identify the coarse aggregate degradation pattern, avoiding time and material investments.

The Bouncing Ball system consists of a ball bouncing on a vibrating table. Its mathematical model is presented in equations (1) and (2), [7]. Where Îś is the restitution coefficient and varies in the interval 0- 1, where 1 means a completely elastic collision (no loss of speed), and 0 means a completely inelastic collision (kinetic energy lost). This model has been modified, so that the coefficient of restitution begins in 1 and after each collision it decreases by 0.01, simulating the coarse degradation.

$$\begin{aligned} 0 &= A[\sin(\theta_k)+1] + v_k\left[\frac{1}{\omega}(\theta_{k+1}-\theta_k)\right] \\ &\quad -\frac{1}{2}g\left[\frac{1}{\omega}(\theta_{k+1}-\theta_k)\right]^2 - A[\sin(\theta_{k+1})+1] \end{aligned} \tag{1}$$

$$v_{k+1} = (1+\alpha)\omega A \cos(\theta_{k+1}) - \alpha\left[v_k - g\left(\frac{1}{\omega}(\theta_{k+1}-\theta_k)\right)\right] \quad (2)$$

Methodology. The proposed method utilizes the chaotic model behavior in order to generate several time signals by change the initial conditions (velocity and phase) with a decreasing rate of the restitution coefficient. Thus, it is possible to emulate different signals considering different materials and operation conditions of the ball milling machine.

The ball displacement variable will provide the test necessary data to identify the degradation pattern. The frequency spectrum analysis of vibration or acoustic signals is considered an interesting and auspicious option in order to identify patterns [8], in this case, the degradation pattern. The proposed estimation strategy, consists of three functional units [6]: a) Time Analyzer; b) Characteristics extractor, which extracts a set of features that retain the essential frequency content; c) Patterns classifier, system trained to characterize the set of variables entry. The present work is focused on the units a) and b). The continuous wavelet transform (CWT) is considered optimal for intuitive purposes of feature extraction. Hence, using a standard routine of the discrete Fourier transform, it is computed the CWT for the whole signal simultaneously [9]. The Morlet wavelet is chosen, for feature extraction purposes, due to it provides an excellent balance in time-frequency localization.

Main Analysis Results. Fig. 1 presents the wavelet power spectrum (WPS), where x axis is time, y axis the frequency and z axis the WPS in dB. Thus, using this time-frequency diagram it is possible to identify the main characteristics components. More precisely, it is possible to observe that the higher WPS coefficients (positive dB) reduce over time, showing a basicthe coarse degradation pattern.

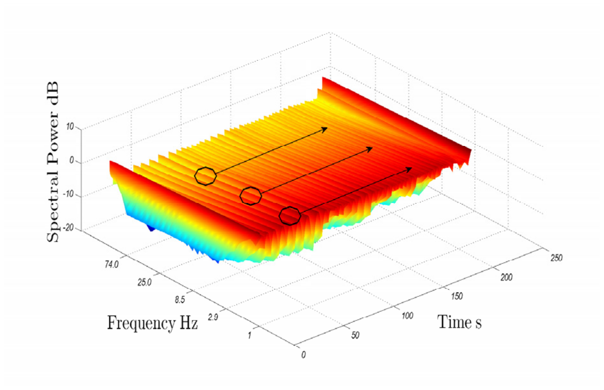

Figure 1 – Wavelet Power Spectrum 3D

After the feature extraction performed (CWT), a dimension reduction algorithm, through the global wavelet spectrum (GWS), is applied in order to provide a vector that summarizes the most important features. The GWS captures the power spectrum of the signal in a given time interval. So, splitting the signal in several intervals, it is possible to measure the WPS concentration in each one.

The signal characterization described was applied on two acoustic signals taken from the ball milling machine (blast furnace tin). The GWS is calculated at seven different time intervals during the fifteen minutes of milling. This result verifies the pattern found for the simplified model.

Conclusion. The main contributions of this work can be summarized as follows: i) The pattern found, by means of bouncing ball system model, describes a direct relationship between the WPS of the acoustic signal and the instantaneous restitution coefficient of the analyzed material. ii) The proposed method uses the global wavelet spectrum to successfully quantify the pattern in several time intervals. iii) The method was validated applying the GWS on two acoustic signals obtained from a real implementation of the Los Angeles machine. As future work, a neural network based estimator is objectified to obtain a resistance percentage to degradation instant value. Additionally, a real time implementation should be pursued by means of a Digital Signal Processor.

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