IN-PROCESS GRINDING MONITORING BY ACOUSTIC EMISSION

Paulo R. Aguiar[1], Paulo J. A. Serni[1], Eduardo C. Bianchi[2], Fábio R. L. Dotto[1]

University of Sao Paulo – Unesp – Electrical Engineering Department – Bauru-SP - Brazil
University of Sao Paulo – Unesp – Mechanical Engineering Department – Bauru-SP - Brazil

ABSTRACT

This work aims to investigate the efficiency of digital signal processing tools of acoustic emission signals in order to detect thermal damages in grinding process. To accomplish such a goal, an experimental work was carried out for 15 runs in a surface grinding machine operating with an aluminum oxide grinding wheel and ABNT 1045. The acoustic emission signals were acquired from a fixed sensor placed on the workpiece holder. A high sampling rate data acquisition system at 2.5 MHz was used to collect the raw acoustic emission instead of root mean square value usually employed. Many statistics have shown effective to detect burn, such as the root mean square (RMS), correlation of the AE, constant false alarm (CFAR), ratio of power (ROP) and mean-value deviance (MVD). However, the CFAR, ROP, Kurtosis and correlation of the AE have been presented more sensitive than the RMS.

1. INTRODUCTION

The market revolution in the last years has been demanded from industries more and more an effective cost reduction in connection with quality increase of the parts manufactured by the machining operation. This built-up need faces increasingly to the manufacturing problems, such as rapid setup and the wear of the cutting tools [4]. Moreover, by virtue of the changes in the production system characteristics, that is, increase of the small batches and high costs of qualified personnel, the use of production system fully flexible and automatic, capable of compensating the process variations became imperative. This implies in system developing and strategies for the process monitoring in a manner that the automation with safety and repeatability can be achieved. The grinding process is not known enough technologically yet. This may have origin at the wrong faith in which the process is very complex to be understood due to the multiplicity of cutting edges and their irregular geometries, high cutting speed and depth of cut that varies from grain to grain. Damages in the part are very expensive, since all the previous processes besides the grinding itself are lost when a part is scrapped in this stage. The need of effective reduction of costs associated with the increase of quality of the parts manufactured claim the implementation of more intelligent systems in the industrial environments. Hence, the damage control in grinding process is of great interest to every industry dependent on this process, leading to lower loss rates and, in turn, to a lower production cost. Thus, the present work aims to investigate new statistical tools to detect burn in grinding by digitally processing the acoustic emission signals generated during the process.

2. MONITORING AND PROCESS CONTROL

The implementation of intelligent processes in industries utilizing computer numerically controlled machining is increasing rapidly. However, computer numerically controlled systems is not enough reliable to operate without human interference so far. It is common to observe operators of those CNC machines simply to correct the process parameters or identify the end of the tool life [1]. According to Inasaki [5], there are three important goals to the grinding process monitoring: detecting problems, which occur during the process; providing information to optimize the process and contribute to the development of a database needed to determine the control parameters. Taking as an example the external plunging grinding process, where many parameters dwell and need to be determined, which are related to the choice of the grinding wheel and coolant. The wheel speed, work speed and feed rate are the parameters mentioned. Among these parameters, the feed rate is the most one that influences on the grinding results. The choice of the grinding cycle that consists of determining the desired roughness, the end of the operation and spark-out period is another important parameter to be considered. The information obtained during the system monitoring may be used to minimize the grinding cycle time and increase the process quality [5]. The use of acoustic emission (AE) to monitor and control the grinding process is a relatively recent technology [2], besides being more sensitive to the grinding condition variations compared with the force and power measurements [11], providing a promising technique to the process monitoring. The relatively easiness of digitally

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processing the root mean square (RMS) of the acoustic emission signal has led approaches in which this type of statistic is employed. However, the inherent average operation involved in determining the RMS of acoustic emission signal makes it to a certain extent insensitive to impulsive events such as cracks and burn on the part, although this kind of parameter carries a lot of useful information [2]. In this present work, tests results are presented for two types of metals – ABNT 1045 and VC131 steels; setup employed; and tests off-line to evaluate the superficial integrity of the parts ground. Furthermore, results from many digital signal processing tools are shown, where those with amplitude independent are stressed and then the power of the AE signal does not affect the signal characteristic. This is explained due to the fact that the power of the AE signal may undergo variations during the grinding process, which have nothing to do with the part condition than its geometry. The result analyses from the digital signal processing as well as a discussion of the investigation are presented.

3. EXPERIMENTAL TESTS

The experimental tests were carried out upon a surface grinding machine where raw acoustic emission signals were collected for fifteen (15) different runs at 2.5 million of samples per second rate. The ABNT 1045 steel has been used for the tests. The major parameters were kept constant during the runs. However, the depth of cut was varied from light and aggressive cutting. All the parts were essayed post-mortem and the burn marks were identified. The setup for these runs is shown in Figure 1.

The grinding parameters include: Grinding wheel Peripheral Speed: 27.94 m/s; Workpiece speed: 0.044 m/s; Coolant type: water-based fluid 4%; Grinding Wheel: Aluminum Oxide – 38A80-PVS– Norton; Grinding Wheel Diameter: 296.50 mm; Grinding Wheel Width: 40.21 mm; Workpiece Dimensions: 98.58 x 8.74 mm.

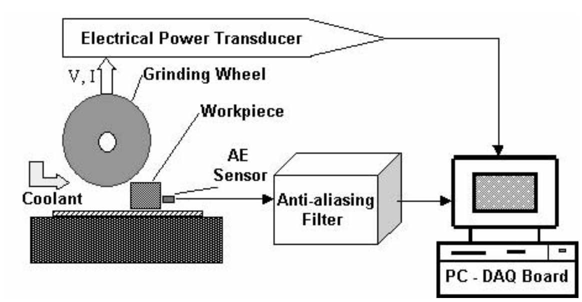

Figure 1 – Experimental Setup

Data was collected from a fixed acoustic emission sensor of the Sensis manufacturer; model PAC U80D-87, which was mounted on the part holder. The data acquisition board from National Instruments was set up to work at 2.5 million of samples per second with a 12 bits precision per sample. The table 1 shows details of tests carried out for the ABNT 1045 steel Besides the visual analysis, roughness and microhardness tests were performed on the parts essayed to better characterize the burn.

Table 1 – Tests with ABNT 1045 Steel

Test	**Depth of cut μm**		**Cutting Profile**	**Comments**
1	10			No burn
2	30			Slight burn
3	20			Severe burn
4	90	10		Severe burn
5	20	2,5		Severe burn
6	40	5		Severe burn
7	15			Burn at middle

4. SIGNAL PROCESSING

From the data of acoustic emission available on binary files, several programs developed in Matlab for digitally processing the signals was utilized, where many statistical correlations such as kurtosis, skew, autocorrelation, RMS among others were employed and are described as following.

4.1 RMS of Acoustic Emission Signal

For a given time t, the RMS value of a raw acoustic emission signal can be expressed by

$$AE_{rms} = \sqrt{\frac{1}{T}\int_{t-T}^{t} AE_{rms}^2(\tau)d\tau} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} AE_{rms}^2(i)} \qquad (1)$$

where T is the integration time and N is the discrete number of AE data within the interval T. In this work, T was considered equal to 1 ms [12].

4.2 CFAR Statistic

Nuttal [9] is a statistic tool employed in detection of events, which is described by

$$T_{pl}(X) = \sum_{k=0}^{M-1} X_k^{\upsilon} \qquad (2)$$

Where Xk corresponds to the kth FFT of x(t), υ is a variable exponent and 2M corresponds to the data base vector size to get the FFT calculated. Although υ between 2 and 3 provides a good performance for a wide band of frequency of the signal studied, this statistic needs of pre-normalized data. Thus, due to the acoustic emission signal variations during the process, the constant false alarm rate (CFAR) is utilized, Nuttall [8]. This statistic is based on the supposition of flatness of the acoustic emission signal. An alternative version of this tool was employed due to the system distortions and expressed by the equation 3 [10].

$$T_{bcpl}(X) = \frac{\sum_{k=n1}^{n2} X_k^{\upsilon}}{\left(\sum_{n1}^{n2} X_k\right)^{\upsilon}} \qquad (3)$$

Were M=1280 and the frequency range between 300 and 700 kHz was considered.

4.3 Kurtosis and Skew Statistics

The measurement if the distribution tail is longer than other is made by Skew. In case of kurtosis, the tail size is concerned. Both statistics are utilized in this work aiming to find an indicator to the acoustic emission variations. Thus, abrupt changes in the AE signal such as those in which burn occurs may result in spikes in these statistics. The equations 4 and 5 shows the way of calculating kurtosis and skewof an x signal.

$$K = \sum \frac{(x-\mu)^4}{N\sigma^4} - 3 \qquad (4)$$

$$K = \sum \frac{(x-\mu)^3}{N\sigma^3} \qquad (5)$$

where μ is the mean of x, N the number of samples in the range considered and σ the standard deviation.

4.4 Mean Value Dispersion Statistic – MVD

The form of MVD statistic is therein employed [3] but in a more convenient form used by Wang [10] as shown in equation 6.

$$MVD = \sum_{k=n1}^{n2} \log\left(\frac{\frac{1}{n_2 - n_1 + 1}\sum_{l=n1}^{n2} X_l}{X_k}\right) \qquad (6)$$

Where X has the same meaning as to CFAR statistic as well as n_1 e n_2.

4.5 Ratio of Power – ROP

It is instinctive to think about the different behaviors expected for a good part or bad one by observing the frequency spectrum of the acoustic emission signal. Hence, for each block of acoustic emission data ROP is given by equation 7.

$$ROP = \sum_{k=n_1}^{n_2} \frac{|X_k|^2}{\sum_{k=0}^{N-1} |X_k|^2} \qquad (7)$$

where N set to 1024; n_1 and n_2 in the range of 300 to 700 kHz were chosen.

4.6 Autocorrelation

The time correlation of a function Φ_{xy} is defined by Oppenheim [6] in Equation 8.

$$\phi_{xy}(t) = \int_{-\infty}^{+\infty} x(t+\tau)\, y(\tau)\, d\tau \qquad (8)$$

Φ_{xx} is commonly referred to as autocorrelation.

5. RESULTS AND DISCUSSION

The graphs for each workpiece tested were obtained from the digital signal processing of acoustic emission signals in which the statistics previously described were employed. The results from tests 1, 5 and 7 for ABNT 1045 steel are presented as shown in Figures 2 to 4 respectively.

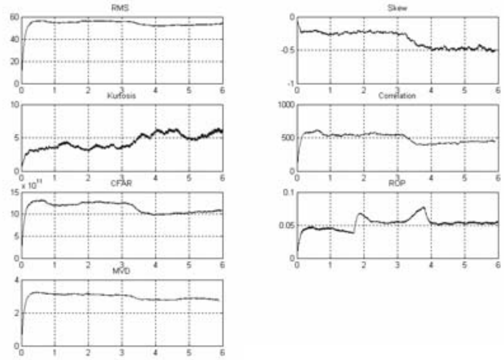

Figure 2 – Results for Test 1 –ABNT 1045 steel with no burn occurrence; Horizontal axis corresponds time in seconds and Vertical axis Volts multiplied by a constant

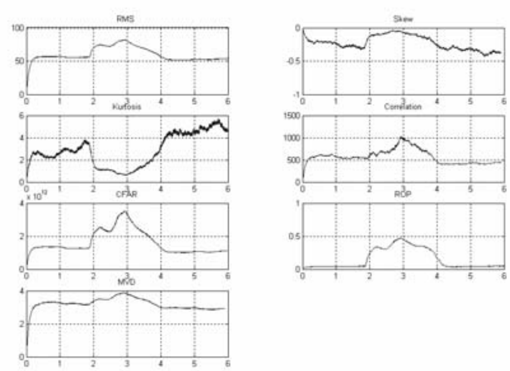

Figure 3 – Results for Test 5 – ABNT 1045 steel with severe burn from close to the beginning to the end of the workpiece; Horizontal axis corresponds time in seconds and Vertical axis Volts multiplied by a constant

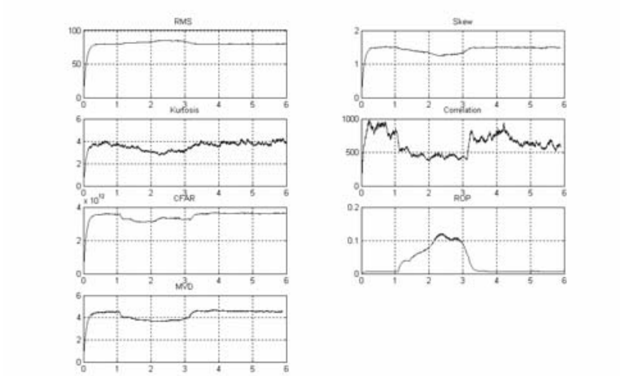

Figure 4 - Results for Test 7 – ABNT 1045 steel with burn in the midst of the part; Horizontal axis corresponds time in seconds and Vertical axis Volts multiplied by a constant

From the results for the ABNT 1045 steel it can be observed that the statistic RMS had its level pretty steady for the non-burning workpiece during all over the grinding pass while the signal had good variation when severe burn occurred such as in Figure 3. Skew and kurtosis presented variation when burn took place but positive amplitudes for some tests and negative ones for others were observed, which are not useful for an indicator parameter to burn. Surprisingly, the ROP turned out to be a good indicative to burn, since its behavior has shown quite sensitive to the studied phenomenon. Besides, its level is low to those non-burning parts and high to the burning ones. Additionally, it has well characterized the beginning of contact between the wheel and part as well as the end of the grinding pass. The MVD tool presented a behavior similar to the RMS statistic but not so good as RMS because the low level obtained for the test 7. The autocorrelation statistic was very sensitive to burn for the most tests performed but for a few it has shown useless by virtue of the decreasing observed when burn occurred.
Similarly to the autocorrelation, the CFAR tool has behaved quite well to burn detection for most of the tests carried out but with no decreasing of signal at all, except for test 7 where a decreasing was observed during the grinding pass. This behaviour, however, did not compromise the utility of CFAR tool, for the level of test 7 has kept higher than to the non-burning test.

6. CONCLUSIONS

From digital processing of the raw acoustic emission signal for the ABNT 1045 steel, the results show that several statistics have worked quite well to burn detection as is the case of RMS, CFAR, ROP e MVD. Nevertheless, skew and kurtosis statistics have presented an interesting behavior regarding the waveform of the signal and their variation along the grinding pass, though they are not effective to detect burn. These features may be better explored in further investigation. The autocorrelation has shown ineffective to detect burn.

7. ACKNOWLEDGMENT

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