

Monitoring of Grinding Burn by AE and Vibration Signals

Rodolpho F. Godoy Neto¹, Marcelo Marchi¹, Cesar Martins², Paulo R. Aguiar² and Eduardo Bianchi¹

¹*Mechanical Department, School of Engineering, Univ. Estadual Paulista - UNESP,
Av. Luiz E.C. Coube, 14-01, 17033-0360, Bauru – SP, Brazil*

²*Electrical Engineering Department, School of Engineering, Univ. Estadual Paulista - UNESP,
Av. Luiz E.C. Coube, 14-01, 17033-0360, Bauru – SP, Brazil*

Keywords: Neural Network Application, Monitoring, Acoustic Emission, Grinding Process, Burn.

Abstract: The grinding process is widely used in surface finishing of steel parts and corresponds to one of the last steps in the manufacturing process. Thus, it's essential to have a reliable monitoring of this process. In grinding of metals, the phenomenon of burn is one of the worst faults to be avoided. Therefore, a monitoring system able to identify this phenomenon would be of great importance for the process. Thus, the aim of this work is the monitoring of burn during the grinding process through an intelligent system that uses acoustic emission (AE) and vibration signals as inputs. Tests were performed on a surface grinding machine, workpiece SAE 1020 and aluminum oxide grinding wheel were used. The acquisition of the vibration signals and AE was done by means of an oscilloscope with a sampling rate of 2MHz. By analyzing the frequency spectra of these signals it was possible to determine the frequency bands that best characterized the phenomenon of burn. These bands were used as inputs to an artificial neural networks capable of classifying the surface condition of the part. The results of this study allowed characterizing the surface of the work piece into three groups: No burn, burn and high surface roughness. The selected neural model has produced good results for classifying the three patterns studied.

1 INTRODUCTION

Grinding is one of the most finishing processes used in the manufacture of precision mechanical components. It is the last stage in the manufacturing chain, which is why it affords a high added value to the end product. Despite its importance and popularity, grinding still remains as one of the most difficult and least understood processes in addition to the function of solving the problems of time and quality of the entire production sequence (Irani et al. 2005; Aguiar et al. 2010).

According to (Liao et al. 2008), grinding is one of the most complicated process, mostly due to the fact that a grinding operation is performed by a grinding wheel which is composed of many tiny, irregular shaped, and randomly positioned and oriented abrasives (also called grits) bonded by some medium. Thus, there are many variables that make it difficult to choose the optimal parameters in a simple way.

Since a reduction of the production costs and an increase in the quality of the machined parts are

expected, the automated detection of the machining process malfunctions has become of great interest among scientists and industrialists. By the use of a large variety of sensors, monitoring of machining processes represents the prime step for reduction of poor quality and hence a reduction of costs (Axinte et al. 2004).

One of the most critical problems in the intelligent grinding process implementation is the automatic detection of surface burn in the parts. The burn occurs during the cutting of the part by the grinding wheel when the amount of energy generated in the contact area produces an increase of temperature enough to produce a change of phase in the material. Such occurrence can visually be observed by the bluish temper color on the part surface (Aguiar et al. 2002). Grinding burn also has an adverse effect on component in-service strength and fatigue properties. When grinding becomes abusive the grinding temperature can easily rise to more than 800 °C. Due to the effects of elevated temperature, the surface of the workpiece may burn and the deterioration of the surface becomes evident. Workpiece burn during the grinding process is

essentially an irreversible change in the microstructure of a surface layer (Liu et al. 2005). Therefore, the grinding burn control and monitoring is of great interest to all industries dependent on the grinding process, thus leading to a reduction in scrap rate and production costs.

The main difficulty of controlling damages caused in the grinding process is the lack of a reliable method in supplying feedback in real time during the process. Since the grinding process causes intensive mechanical vibration and strong acoustic emission, these signals can be picked up easily and recorded by commercially available instruments.

According to (Babel et al. 2013), in light of its superior sensitivity to the multitude of fine dynamic interactions between the wheel and the workpiece, acoustic emission (AE) has emerged as a valuable tool in a host of monitoring applications in grinding. Typical examples include in-process wheel mapping, and the sensing of wheel-work contact, wheel loading, chatter and thermal damage. Still, the authors report that in many applications, it suffices to examine the signal in terms of time-averaged indices, while others necessitate frequency domain analyses of the raw AE signal, as the relevant information is embedded in the spectral components of the signal. In either case, due to the complex nature of grinding processes, the challenge in the effective and reliable application of AE lies in the identification and interpretation of signatures pertinent to the process responses that are of interest.

On the other hand, vibration is produced by cyclic variations in the dynamic components of the cutting forces, resulting from periodic wave motions. The nature of vibration signals arising from the metal cutting process incorporates free, forced, periodic, and random types of vibration. Direct measurement of vibration is difficult to achieve because the vibration mode is frequency dependent. Hence, related parameters are measured such as the rate at which dynamic forces change per unit time (acceleration) and the characteristics of the vibration are derived from the patterns obtained (Dimla, Snr. 2002).

Several investigations have been carried out to correlate vibration signals to the characteristics of machining processes. For example, Yamamoto *et al.* apud (Hassui & Diniz 2003) monitored the wheel vibration (they fixed the sensor on the wheel bearing) to detect the clogging of the wheel pores by chips. Aiming towards this goal, they used adaptive digital filters and created an index, based on the outputs of these filters, called index of the signal

pattern. This index showed to have a good relationship with the volume of chips clogged in the wheel. (Hassui et al. 1998) proved that the RMS signal of the workpiece vibration (they fixed the sensor on the workpiece tailstock) presents better relationship with wheel wear than acoustic emission. Besides, the sensitivity of the vibration signal to detect the wheel-workpiece moment of contact and the moment of spark out end is as good as acoustic emission sensitivity. (Hassui & Diniz 2003) tested the ability of the vibration signal to follow the changes of workpiece surface roughness and circularity, in order to verify the possibility of using it for the automatic definition of the dressing moment. The results showed good correlation of vibration signals with surface roughness and wheel condition.

According to (Teti et al. 2010), it is generally acknowledged that reliable process condition monitoring based on a single signal feature (SF) is not feasible. Therefore, the calculation of a sufficient number of SFs related to the tool and/or process conditions is a key issue in machining monitoring systems. This is obtained through signal processing methods that comprise pre-processing (filtering, amplification, A/D conversion, and segmentation) including, on occasion, signal transformation into frequency or time-frequency domain (Fourier transform, wavelet transform, etc).

One of the most used signal feature in machining monitoring systems is the root mean square (RMS) value, and it can be expressed as shown in equation 1.

$$f_{RMS} = \sqrt{\frac{1}{\Delta T} \int_0^{\Delta T} f_{raw}^2(t) dt} \quad (1)$$

where Δt is the integration time constant, and f_{raw} is the raw signal (Kim et al. 2001).

Thus, acoustic emission and vibration signals have their own and interesting characteristics, which adequately extracted and related to the studied phenomena can provide valuable information to the grinding process monitoring. This work aims at monitoring workpiece burn during the grinding process through neural modelling that uses features of the acoustic emission (AE) and vibration signals as inputs.

What makes this work distinguishable from others is the use of vibration signal along with AE signal. The former has not yet been employed in grinding burn detection. Besides, study on frequency domain for both signal that closely relates frequency bands to burn, non burn and high surface roughness

values has not been carried out either. The selection of frequency bands from the signal spectrum aims to better extract the signal features for the classes studied. Another contribution of this work is related to the types of classes, i.e., the models are able to classify parts with high surface roughness values (no visible burn), visible burn occurrence and normal operation. It is worth mentioning that thermal sensing, such as thermocouples inserted in the workpiece or tool could produce good results as well in monitoring the grinding burn. However, such techniques are genererally invasive and, therefore, infeasible in most practical implementation.

2 NEURAL NETWORKS IN MACHINING PROCESSES

According to (Teti et al. 2010), in monitoring and control activities for modern untended manufacturing systems, the role of cognitive computing methods employed in the implementation of intelligent sensors and sensorial systems is fundamental. A conspicuous number of schemes, techniques and paradigms have been used to develop decision-making support systems functional to come to a conclusion on machining process conditions based on sensor signals data features. The cognitive paradigms most frequently employed for the purpose of sensor monitoring in machining, including neural networks, fuzzy logic, genetic algorithms and hybrid systems able to combine the capabilities of the various cognitive methods.

Artificial neural networks (ANNs) are adaptive and have parallel information-processing structures with the ability to build functional relationships between data and to provide powerful tools for nonlinear, multidimensional interpolations. This aspect of neural networks makes it possible to capture and interpret the existing highly complex nonlinear relationships between input and output parameters that are frequently poorly understood. An ANN is a system consisting of processing elements (PE) with links between them. A certain arrangement of the PEs and links produce a certain ANN model, suitable for certain tasks (Ahmadzadeh & Lundberg 2013).

Anns have been accepted as a very good tool that can be applied to many nonlinear problems, where finding solutions using traditional techniques are cumbersome or impossible. Examples of applied areas of nns include robotics, control, and system identification. They have been successfully used in condition monitoring and fault diagnosis in

machining processes. These applications have usually used the pattern recognition approach combined with the classification ability of anns (marzi 2008).

Similar work on classification of grinding burn can be found in (Spadotto et al. 2008), where the authors perform only the classification of burn degrees (slight burn, medium burn, severe burn and non burn) of the part ground by using acoustic emission and power signals statistics as inputs to the neural network models. The results were good, reaching a success rate of 93.5 % for model II, which employs a statistic named DPO proposed by (Aguiar et al. 2002), composed of the multiplication between standard deviation of RMS AE and maximum value of grinding power in the grinding pass. Another similar work is presented by (Dotto et al. 2003) in which a neural network model having the RMS AE and grinding power as inputs is used to classify burn and non burn condition of the parts ground. Good response of the model can be observed in the regions charts, where burning and non burning occurrence were classified. The investigation in (Kwak & Ha 2004) proposed a diagnostic scheme of a grinding states (chatter, vibration and grinding burn) by the neural network using power and AE signals. The maximum successful diagnosis was about 95 %. Other investigations related to the topic of this work can also be found. However, none of them has used the vibration signal as well as verified the condition of high surface roughness values of the work piece ground.

3 MATERIALS AND METHODS

3.1 Experiments

The experimental tests were carried out in a surface grinding machine. Each test consisted of a single grinding pass across the workpiece length. Preceding each test, a single-point diamond dresser performed the dressing of the grinding wheel. Table 1 shows the grinding condition of each test.

An acoustic emission sensor and a processing signal unit, from Sensis manufacturer, model DM-42, were employed in the tests. Also, a vibration sensor, model 353B03 and a conditioning signal unit, from PCB Piezotronic, were used. An oscilloscope, model DL850, from Yokogawa, collected both raw signals, at a sampling rate of 2 MHz. The sensors were fixed on the workpiece holder and tested for good signal sensitivity and

without saturation.

Workpieces of SAE 1020 steel were ground with an aluminum oxide grinding wheel, model 38A150-LVH, from Norton, and cutting fluid was employed (Emulsion water-oil of 4 %). The following grinding parameters were used in the 13 tests: peripheral speed of the grinding wheel – 30.78 m/s; workpiece speed – 0.04 m/s; grinding wheel diameter – 326.64 mm; wheel width – 24.09 mm; workpiece dimensions – 152.64 mm length and 13.01 mm width. The schematic diagram in Figure 1 shows the experimental test setup used in this work.

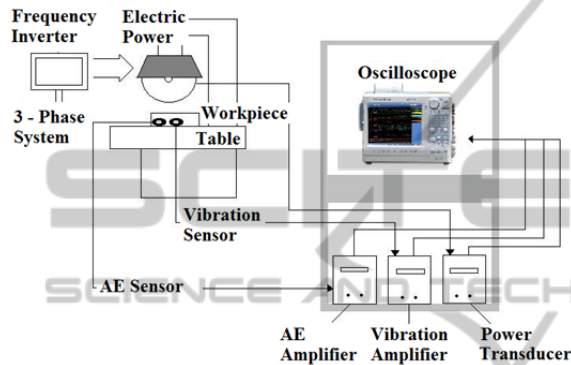


Figure 1: Experimental setup.

Following the experiments, the average surface roughness (R_a) for each workpiece was measured, using a Taylor Hobson Surtronic 3+ precision instrument. A sampling length of 1.6 mm and cut-off of 0.8 mm were used, following the recommendations of the ISO 4288-1996 standard. Each workpiece surface length was equally divided into 30 parts, where 3 surface roughness measurements were taken from each part. Thus, the mean value and standard deviation of each part were calculated, allowing the assessment of the ground workpiece regarding this important parameter. In addition to the surface roughness measurements, the visual inspection of each workpiece surface was carefully carried out as well as all workpiece surfaces were digitally photographed for further analysis.

Table 1 shows information of the 13 tests, where the cutting geometry means whether the grinding wheel cut the workpiece in the conventional way, i.e., flat geometry, or the workpiece was precisely inclined to allow a ramp-cutting geometry. The latter way, there are two cutting depths regarding the onset and the end of the cutting, respectively. In Table 1, HR stands for high surface roughness value, which was so considered workpieces with this value higher than 1.6 μm and with no visible burn. Workpieces

with visible burn was considered as burn, and those with no visible burn at all were classified as no burn.

Table 1: Information of the tests.

Test	Cutting Geometry	Depth of Cut (μm)	Surface condition
1	Flat	10	No burn
2		20	No burn
3		30	Burn
4		40	Burn
5		40	No burn
6		30	No burn
7		20	No burn
8		10	No burn
9		20	No burn
10		30	No burn
11			55
12	Ramp	20-70	HR
13		30-80	HR

3.2 Selection of Frequency Bands and RMS Vectors

The data acquisition produced vector of 20 million of samples for each machined workpiece. Subsets of 400,000 samples were selected from each test vector and for each surface condition (No burn, burn and high surface roughness) for further digital processing. The data sets from the tests were digitally processed in MATLAB. A study on the signals spectra was performed in order to identify frequency bands more strongly related to the burn phenomenon in surface grinding. The Fast Fourier Transform (FFT) algorithm was implemented in MATLAB routine for each surface condition. The RMS values of each signal (AE and vibration) were used as reference to pick the right position from which the 8192-block FFT, Hanning window, was performed. The spectra for AE and vibration signals are shown in Figure 2, where AE is within a frequency range of 20 kHz to 300 kHz and vibration of 1 kHz to 25 kHz, given by the sensors and process characteristics. Frequency bands were then selected from the spectrum of each signal, where nine frequency bands were chosen for the AE signal and six for the vibration signal, as shown in Figure 2 by the shade areas. The justification for frequency band selection is based on obtaining the best feature extraction that represents the classes studied (no burn, burn, high surface roughness). The criterion used in the frequency band selection was looking for the frequency windows on which the magnitudes of the signal for each class presented good differences.

Also, a minimum of overlapping among the three classes spectra was sought. These frequency bands, in kHz, are as following for AE: 40-51, 53-59, 62-68, 71-78, 80-87, 95-104, 128-135, 160-170, and 176-186. The frequency bands selected, in kHz, for vibration are: 1-3, 4-5, 6-8, 16-19, 20-21, and 22-25. It is worth mentioning that there are other frequency bands, which could be studied as well, but they will be considered for further study.

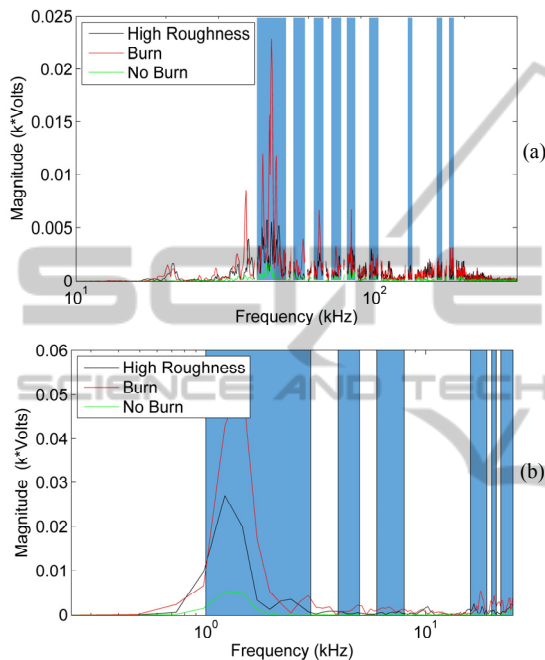


Figure 2: Frequency spectra of three conditions and the chosen frequency bands. (a) AE; (b) Vibration.

Three vectors of 400,000 samples each were extracted from the raw signals (AE and vibration) for each workpiece surface condition (no burn, burn, and high roughness). This procedure was based on three regions along a given ground workpiece, which represented a certain surface condition. Butterworth digital filters, order 6, for each frequency band previously selected, were applied to those vectors, and therefore new filtered vectors were generated. The RMS values were obtained using a block length of 2048 from the filtered vectors for each workpiece surface condition. Therefore, three RMS vectors were generated for each surface condition from which the mean value and standard deviation were calculated. Figure 3 depicts the procedure herein described. In this figure, B1 to Bn stand for the frequency bands selected for study.

3.3 Neural Network Models

Three types of MLP neural models were considered for comparison in order to choose the best classification model. Before building the NN models, the analysis of the RMS values in function of the frequency bands was carried out, and two frequency bands for each signal (AE and vibration) were selected for the models. Thus, the first NN model consisted of 1 input (RMS values) and 3 outputs (No burn, burn, and high roughness), and it was obtained by testing into the model each RMS vector filtered out for the 4 frequency bands selected previously. The second NN model was composed of 2 inputs (2 RMS values) and 3 outputs (as in the first model), and it was obtained by testing two RMS vectors into the model, as inputs, filtered out for the 4 frequency bands aforementioned. Finally, the third model comprised of four RMS vectors at each frequency band selected, as inputs, and 3 outputs (as in the first and second models). An algorithm for training and testing the models in MATLAB was developed, where the number of neurons (5, 10, 15, 20 and 25) and hidden layers (1 to 3) were varied. The Levenberg-Marquardt algorithm for training the neural models was used. In addition, sigmoid tangent activation function for the neurons of the hidden layers and linear activation function for the neurons of the output layer were found more suitable.

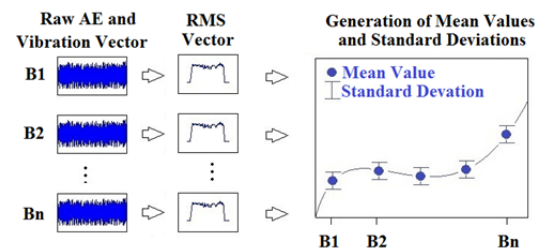


Figure 4: RMS values as a function of frequency bands; (a) AE; (b) vibration.

The input RMS vectors for training, testing and validating the neural models were obtained by dividing every RMS vector at each frequency band selected into 200 equally parts. This was done for both signals acquired (AE and vibration) in the 13 experimental tests. Therefore, a number of 2,600 samples for each RMS vector and for each frequency band was obtained, resulting in the total of 10,400 RMS values (4 frequency bands selected and further described). Of course, depending on the model considered, a different number of samples will be used in the training process, as described

previously. The total data obtained from the aforementioned procedure was then divided randomly, with 60 % used for NN model training and 20 % for validation. The remaining 20 % was used to test the ANN to confirm its satisfactory performance as well as to build the confusion matrices of the models.

To train the MLP networks, ranges representing the values 0 and 1 were defined. Thus, values between -0.50 and 0.50 represent the output 0, while values within the interval of 0.51 and 1.50 represent the output 1.

4 RESULTS AND DISCUSSION

Figure 4(a) and 4(b) depicts the curves of the RMS values for the nine and six frequency bands selected for AE and vibration, respectively.

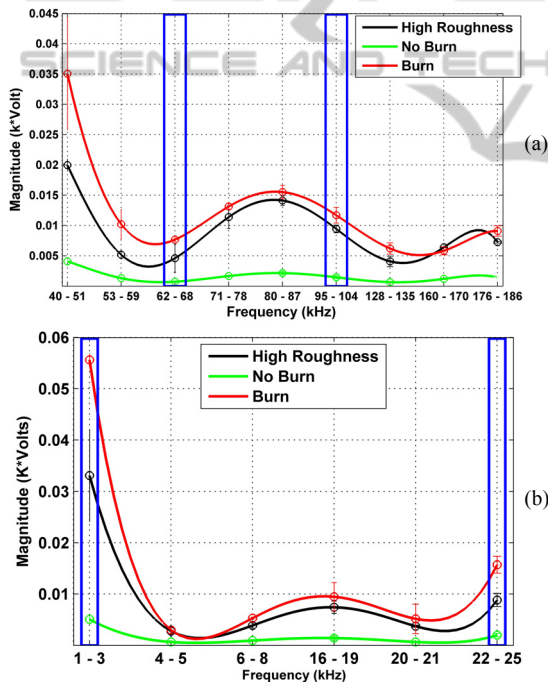


Figure 4: RMS values as a function of frequency bands; (a) AE; (b) vibration.

The choice of the best frequency bands was based on the observation of the signal magnitudes and standard deviations at each frequency band. In other words, a good situation was considered when the signal magnitude increased according to the following order of surface condition: no burn, high roughness and burn. Also, the proximity of the curves as well as the standard deviation were taken into account, i.e., a small standard deviation and

non-overlapping of the curves were sought. Thus, the frequency bands selected for the models were the following: 62-68 kHz (B2 – AE), 95 kHz – 104 kHz (B6 – AE), 1 kHz – 3 kHz (B1 – VIB), and 22 kHz – 25 kHz (B6 – VIB). These frequency bands are indicated in Figure 4 as blue rectangles.

The results of the best neural models are presented in Table 2, where it can be observed that the combination of the AE and vibration signals in the frequency bands selected (shown in Figure 4), produced the best classification result (98.3 %) in model A. Notwithstanding, the result of model 2 also shows a high level of classification (96.0 %). Besides, model B has only 2 inputs, i.e., AE at 62 kHz - 68 kHz and vibration at 1 kHz – 3 kHz, which is more suitable for hardware implementation.

Based on the results of models A and B, one can argue that frequency band of 62 kHz – 68 kHz for AE and 1 kHz – 3 kHz for vibration are good in the feature extraction for this work.

Model C, however, presented a low success rate of classification. That is due to the frequency bands used in this model are not much representative of the workpiece conditions.

Figure 5 shows the confusion matrix for model A, which was obtained from 20 % of data set not presented to the network-training phase.

Confusion Matrix

		Target Class			
		NB	B	HR	
Output Class	NB	100 33.3%	0 0.0%	0 0.0%	100% 0.0%
	B	0 0.0%	98 32.7%	3 1.0%	97.0% 3.0%
	HR	0 0.0%	2 0.7%	97 32.3%	98.0% 2.0%
		100% 0.0%	98.0% 2.0%	97.0% 3.0%	98.3% 1.7%

Figure 5: Confusion Matrix for Model A (B=burn, NB=No burn, HR=High roughness value).

It can be observed in the figure the good capacity of pattern classification of the network, especially in the class of no burn (NB) in which the success rate of 100 % was achieved. The network, however, has produced two false negatives for the burn class (B), which were classified as high roughness (HR). Also, three false negatives are observed for the high

Table 2: Results of the best neural models.

Name	Model A	Model B	Model C
Input Parameter	Mean RMS value of AE and Vibration signals		
Structure	10 – 10 – 5	25 – 0 – 0	3 – 3 – 0
Train. Function	<i>Levenberg-Marquardt Backpropagation</i>		
Max epochs	1000		
Inputs	4	2	2
Frequency Bands	AE: 62kHz – 68 kHz	AE: 62kHz – 68 kHz	AE: 95kHz – 104 kHz
	95kHz – 104 kHz	VIB: 1kHz – 3kHz	VIB: 22kHz – 25kHz
	VIB: 1kHz – 3kHz; 22kHz – 25kHz		
Overall Result	98.3 %	96.0 %	82.0 %

roughness class, which were classified as burn class. Both kinds of errors could not be of concern in the industrial environmental, since it would not compromise the quality of the part being manufactured.

The confusion matrix for model B is shown in Figure 6. In this model, a greater number of false negatives is observed for the same classes of model A. On the other hand, this model has only two inputs, which makes it more attractive for hardware implementation.

The confusion matrix for model C is presented in Figure 7, where one can clearly see the high number of false negatives for both classes of burn and high roughness. However, the success rate of 100 % for no burn class was similarly achieved.

The models with one input have shown high level of errors, and thus they were not presented.

Comparing the results of this work with the investigations of (Kwak & Ha 2004) and (Spadotto et al. 2008), it can be observed an improvement in classifying the burn occurrence, i.e., model A

presented a success rate of 98.3 % against 95 % and 93.5 %, respectively. In addition, this investigation adds an important class of high surface roughness to the neural models, which becomes the monitoring system even more effective.

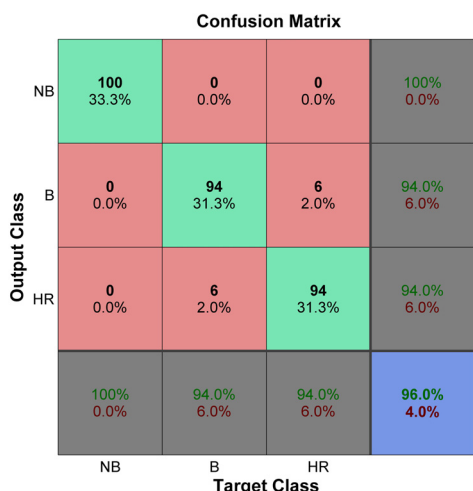


Figure 6: Confusion Matrix for Model B (B=burn, NB=No burn, HR=High roughness value).

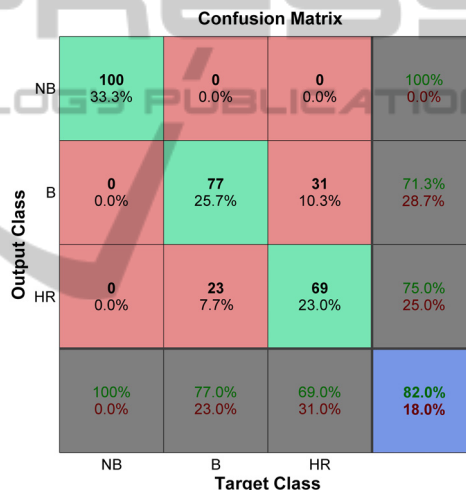


Figure 7: Confusion Matrix for Model C (B=burn, NB=No burn, HR=High roughness value).

5 CONCLUSIONS

The frequency content of the AE and vibration signals showed different behavior for the three surface conditions studied. Based on this analysis, frequency bands could be selected for the neural models, i.e., 62-68 kHz (B2 – AE), 95 kHz – 104 kHz (B6 – AE), 1 kHz – 3 kHz (B1 – VIB), and 22 kHz – 25 kHz (B6 – VIB).

The results showed that neural model A presented a success rate of 98.3 %, which had the four RMS inputs (2 AE and 2 VIB). However, a small number of false negatives were observed in the burn class as well as in the high roughness class, which would not necessarily compromise the quality

of the part being manufactured. Also, model B produced good results with a success rate of 96.0 %, but an increased number of false negatives. This model had only two inputs (1 AE and 1 VIB). Nonetheless, the hardware implementation of model B would be more interesting. Model C, however, presented low success rate of classification and must be discarded.

From model A and B, one can be argued that frequency band of 62 kHz – 68 kHz for AE and 1 kHz – 3 kHz for vibration are good in the feature extraction for this work.

As discussed in the previous section, the results of this work have proved superior when compared with the investigations of (Kwak & Ha 2004) and (Spadotto et al. 2008). The extraction of the best signals features from the spectra as well as the use of vibration signal along with AE produced better classification results.

Based on one of the best models obtained, it would be possible to implement it into a hardware that could provide information in real-time to operator in order to make adjustments and possibly avoid burning. In the case of burn classification has been made, the part should be discarded.

ACKNOWLEDGEMENTS

The authors are indebted to FAPESP, CNPq and CAPES, Brazilian agencies that have supported this work. Also, thanks go to the NORTON Company, from Saint Gobain Group, for donating the wheel.

REFERENCES

- Aguiar, P.R., Bianchi, E.C. & Oliveira, J.F.G., 2002. A method for burning detection in grinding process using acoustic emission and effective electric power signals. *Manufacturing Systems*, 31(3), pp.253–257.
- Aguiar, P.R. De, Paula, W.C.F. De & Bianchi, E.C., 2010. Analysis of Forecasting Capabilities of Ground Surfaces Valuation Using Artificial Neural Networks. *J. of the Braz. Soc. of Mech. Sci. & Eng.*, XXXII(2), pp.146–153.
- Ahmadzadeh, F. & Lundberg, J., 2013. Remaining useful life prediction of grinding mill liners using an artificial neural network. *Minerals Engineering*, 53, pp.1–8.
- Axinte, D. a et al., 2004. Process monitoring to assist the workpiece surface quality in machining. *International Journal of Machine Tools and Manufacture*, 44(10), pp.1091–1108.
- Babel, R., Koshy, P. & Weiss, M., 2013. Acoustic emission spikes at workpiece edges in grinding: Origin and applications. *International Journal of Machine Tools and Manufacture*, 64, pp.96–101.
- Dimla, Snr., D.E., 2002. The Correlation of Vibration Signal Features to Cutting Tool Wear in a Metal Turning Operation. *The International Journal of Advanced Manufacturing Technology*, 19(10), pp.705–713.
- Dotto, F. et al., 2003. Automatic detection of thermal damage in grinding process by artificial neural network. *Revista Escola de Minas*, 56(4), pp.295–300.
- Hassui, a. et al., 1998. Experimental evaluation on grinding wheel wear through vibration and acoustic emission. *Wear*, 217(1), pp.7–14.
- Hassui, a. & Diniz, a. E., 2003. Correlating surface roughness and vibration on plunge cylindrical grinding of steel. *International Journal of Machine Tools and Manufacture*, 43(8), pp.855–862.
- Irani, R. a., Bauer, R.J. & Warkentin, a., 2005. A review of cutting fluid application in the grinding process. *International Journal of Machine Tools and Manufacture*, 45(15), pp.1696–1705.
- Kim, H.. et al., 2001. Process monitoring of centerless grinding using acoustic emission. *Journal of Materials Processing Technology*, 111(1-3), pp.273–278.
- Kwak, J.-S. & Ha, M.-K., 2004. Neural network approach for diagnosis of grinding operation by acoustic emission and power signals. *Journal of Materials Processing Technology*, 147(1), pp.65–71.
- Liao, T.W. et al., 2008. Grinding wheel condition monitoring with boosted minimum distance classifiers. *Mechanical Systems and Signal Processing*, 22(1), pp.217–232.
- Liu, Q., Chen, X. & Gindy, N., 2005. Fuzzy pattern recognition of AE signals for grinding burn. *International Journal of Machine Tools and Manufacture*, 45(7-8), pp.811–818.
- Marzi, H., 2008. Modular Neural Network Architecture for Precise Condition Monitoring. *IEEE Transactions on Instrumentation and Measurement*, 57(4), pp.805–812.
- Spadotto, M.M. et al., 2008. Classification of burn degrees in grinding by neural nets. In *IASTED international conference on artificial intelligence and applications*. Innsbruck: ACTA Press, pp. 1–6.
- Teti, R. et al., 2010. Advanced monitoring of machining operations. *CIRP Annals - Manufacturing Technology*, 59(2), pp.717–739.