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Tool condition monitoring of single-point dressing operation by digital signal processing of AE and AI

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Abstract

This work aims at determining the right moment to stop single-point dressing the grinding wheel in order to optimize the grinding process as a whole. Acoustic emission signals and signal processing tools are used as primary approach. An acoustic emission (AE) sensor was connected to a signal processing module. The AE sensor was attached to the dresser holder, which was specifically built to perform dressing tests. In this work there were three types of test where the edit parameters of each dressing test are: the passes number, the dressing speed, the width of action of the dresser, the dressing time and the sharpness. Artificial Neural Networks (ANNs) technique is employed to classify and predict the best moment for stopping the dressing operation. During the ANNs use, the results from Supervised Neural Networks and Unsupervised Neural Networks are compared.

Keywords: Dressing; Acustic emission signal; Vibration signal; Tool wear; Artificial neural networks

1. Introduction

Grinding processing are generally one of the last operation on the workpiece. These processes are not necessarily limited to surface finishing or removal of small quantities of material. They can be used to remove large amounts of material and can compete in economic terms with processes such as milling and turning. The wear of the grinding wheel is more important because it adversely influence the shape and accuracy of the surfaces machined with this process [1]. A solution for this problem is the online monitoring of the grinding wheel conditions [2]. For the online monitoring of the grinding wheel, it is necessary to use sensors that acquire information about the performance of the grinding wheel. Such sensors can be sensors of force, vibration, current, acoustic emission (AE), etc. The sensors can control the dressing process. This is the process of grinding wheel surface restoring and it consists in eliminating worn grains in order to expose new sharp grains. Dressing is necessary when excessive friction wears the grinding wheel [1].

It is possible to correlate the AE produced by the dressing process to the exact point in which to stop the process. To do this, it is possible use Artificial Neural Networks (ANNs) to decisions making. ANN models have already been employed to predict the dressing wear of grinding operations on the basis of the measured AE signals and, furthermore, working parameters of cutting operations [3, 4].

2. Material and equipment

According to the dressing conditions established for this test and considering the need to ensure the digital processing of the signals, analysis and discussion of the results, several preliminary tests were carried out to determine the best parameters to be used. Thus, an experimental test setup was assembled and configured to allow process output variables to

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be acquired with quality. In the tests, an aluminum oxide grinding wheel was used, from NORTON, model 38A150LVH, with dimensions of 355.6x25.4x127mm, where it was mounted on a surface tangential grinding machine, model RAPH 1055, from Sulmecânica. An acoustic emission (AE) sensor was connected to a signal processing module, model Sensis DM-42. The AE sensor was attached to the dresser holder, which was specifically built to perform dressing tests. The DM-42 module was connected to an oscilloscope from the company Yokogawa, model DL850, and the AE signals were acquired at a sampling frequency of two million samples per second. The dressing tool used was the CVD single-point diamond, where the parameter b_d, which is the width of action of the dresser for a given depth of dressing (a_d), was measured before the beginning of each dressing test.

The method proposed by Nakayama et al. [5] and later adapted by Coelho [6], was used to measure the sharpness of the grinding wheel. This method consists in using a weight balance scale (an equipment similar to a seesaw) so that at one end is held fixed (without rotation) a cylindrical disc, which due to the force F_N, equal 1N, of known weights fixed on the opposite side equipment, the disc remains in constant contact with the cutting surface of the grinding wheel. Thus, by putting the grinding wheel in movement, a wear on the disc is generated, which consequently causes a displacement over a given contact time. This displacement in time is recorded by a TESATRONIC, model TT60, from Tesa Technology, and collected by serial communication using MatLAB software. The sharpness of the grinding wheel is determined at various times of the test; at each time four displacement curves are obtained as a function of time at 4 points along the cutting face of the grinding wheel. Equation (1) is used to determine the sharpness values (K) for each displacement curve and, afterwards, the standard deviation and the average of the sharpness of the grinding wheel are calculated from these values.

$$K = \frac{2b\sqrt{8r}}{3F_N} \cdot a^{2/3} \qquad (1)$$

where b and r are the width and radius of the disc, respectively, F_N is the normal force applied on the opposite end of the disc, and a is the gradient of the regression line obtained from the characteristic of displacement curve versus $(t)_{2/3}$, where t is the experiment time or contact time. The cylindrical discs used in the process of acquiring the sharpness curves, with external diameter of 24 mm, internal diameter of 7.8 mm and with of 2 mm, were made from a cylindrical bar of SAE 1020 steel.

Figure 1a presents the sharpness curves for two distinct grinding wheel conditions. A magnification of the gray region of figure 1a is shown in figure 1b, from which the sharpness of the grinding wheel was computed. According to [7], sharpness is the measure of a body's capacity to remove material from another. It can be observed in Figure 1a that the sharpness curve for the undressed and uneven grinding wheel condition makes a small α angle with respect to the time axis. That happens because the grinding wheel has its sharpness degraded, and thus its capacity to remove material from the workpiece is low. This characteristic occurs due to the clogging (with chips) of the cutting face of the grinding wheel and to the wear of the abrasive grains underwent during the grinding process. On the other hand, for a fully dressed and even grinding wheel, the sharpness curve forms a high β angle with the time axis, indicating that the grinding wheel is sharp because of its high capacity to remove material.

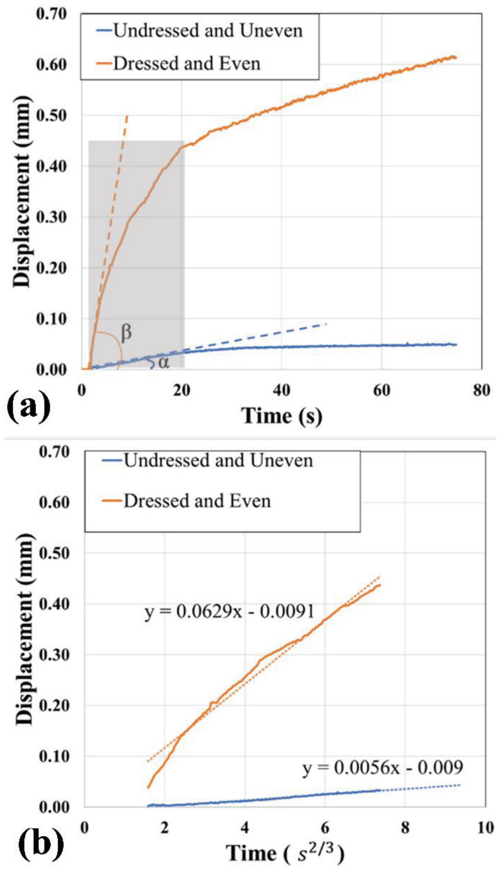

Fig. 1. DISPLACEMENT CURVE vs T(2/3)

3. Clogging and dressing tests

In this work, the process of clogging and dressing of the grinding wheel is divided into three steps:

- Dressing was performed with an overlap ratio (Ud) of 1.5 and a_d equals to 10 µm, consisting of 10 consecutive passes from the moment when the wheel surface was already cleaned, and after the last pass, the sharpness was measured;
- Aiming at clogging the grinding wheel, grinding of an SAE 1020 steel workpiece was performed, with dimensions of 150x48x12 mm. The grinding process consisted of 20 passes with cutting depths of 20 µm, and constant peripheral speed of the grinding wheel and workpiece speed equal to 33m/s and 0.098m/s, respectively. After the grinding, the sharpness of the grinding wheel was measured by the system described above;

- After the grinding operation on the wheel, dressing was performed with *Ud* equals to 1.5 and ad equals to 10 µm, which consisted of 24 consecutive passes. The signals of raw AE were collected throughout the test, and the sharpness measured after the last pass.

The dressing tests as well as the grinding test were performed without the use of cutting fluid.

In Table 1 and Table 2 are presented the parameters of each dressing test, in which (v_d) is the dressing speed, (b_d) is the width of action of the dresser, (t_d) is dressing time, K_0 is the sharpness measured before the start of the dressing test, and K_f is the sharpness at the end of the dressing test (last dressing pass).

Table 3 shows the classifications of the different grinding wheel conditions achieved during the tests 1, 2 and 3.

Table 1. Parameters of dressing test.

N° TEST	Passes	v_S (m/s)	v_d (m/s)	b_d (µm)	t_d (s)	U_d
TEST I	24	33	0.0098	520	2.6	1.5
TEST II	10	33	0.0098	520	2.6	1.5
TEST III	17	33	0.0069	365	3.7	1.5

Table 2. Parameters of dressing test.

N° TEST	Passes	Sharpness (K_0) (mm^3/N*s)	Sharpness (K_f) (mm^3/N*s)
TEST I	24	0.569	2.854
TEST II	10	2.437	2.796
TEST III	17	1.987	2.695

Table 3. Classification of the different grinding wheel conditions.

Condition	TEST I	TEST II	TEST III
Undressed and Uneven	Passes 1-9	-	Passes 1-9
Dressed and Uneven	Passes 10-14	Passes 1-4	Passes 10-14
Dressed and Even	Passes15-24	Passes 5-10	Passes 15-17

4. Digital signal processing

The raw AE signal was initially analysed to select only the period corresponding to the dressing process (dressing pass only). Then, the signal was analysed in the frequency domain in order to identify specific frequency bands that best characterized the behaviour of the process. The spectrum was obtained for two different conditions of the grinding wheel (dressed and even; undressed and uneven).

The discrete Fourier transform (DFT) was obtained for 9 points equidistant from the dressing pass. Thus, 9 vectors of 32768 points were processed in the MatLAB by means of the fft command and Hanning window and then the mean of the spectra was obtained, representing the spectral behaviour of the dressing pass.

From the analysis of the spectra referring to two conditions of the surface of the grinding wheel, a band of frequencies was selected using the criterion of non-overlap between the spectra. After analysing the signals, the band from 25 kHz to 40 kHz was selected for study. A 2048-point window, corresponding to 1 ms, as suggested by [8], was used. The ROP statistic was determined from the non-filtered signals, since this statistic uses a "self-filtering". For obtaining the Counts statistics, the raw AE signal was filtered by using a Butterworth digital filter, bandpass of order 30, in the selected band of 25 to 40 kHz. A threshold of 100mV was used to calculate the statistics Counts for all the tests.

5. Study of the frequencies

The results from the digital processing of the AE signals show that the spectral content changes, which depend on the shape and sharpening characteristics of the grinding wheel. In the spectrum presented in figure 2, two different conditions of shape and sharpening of the grinding wheel are presented: (1) undressed and uneven grinding wheel and (2) dressed and even grinding wheel.

It is observed in figure 2 that the spectrum of each condition of the grinding wheel express different energy levels. The grinding wheel without cutting capacity and uneven surface generates low energy levels over the entire significant frequency range, which are in the range of 0-250 kHz. As described by [9], this is due to the low friction between the dressing tool and the grinding wheel, which has its abrasive grains worn in that condition. On the other hand, the dressed and even grinding wheel produces higher energy levels, because in this condition the cutting edges of the grinding wheel are exposed, and therefore the contact between the dresser and the grinding wheel is full, causing a high friction and a higher level of AE. These characteristics can best be observed for the 25-40 kHz band in the magnification shown in figure 2.

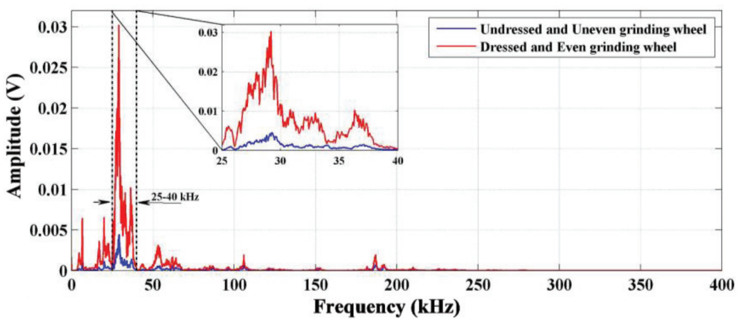

Fig. 2. SPECTRUM OF FREQUENCY FOR TWO CONDITIONS OF THE GRINDING WHEEL

6. Sensor signal feature extraction

The results obtained from the application of the ROP and COUNTS statistics for the 25-40 kHz frequency band are presented in figures 3 and 4, respectively, for two different conditions of the grinding wheel: (1) undressed and uneven and (2) Dressed and even. It is observed for a worn and dull grinding wheel, figure 3, there are great variations of peaks and valleys in the ROP and COUNTS values and an uneven behavior of these signals.

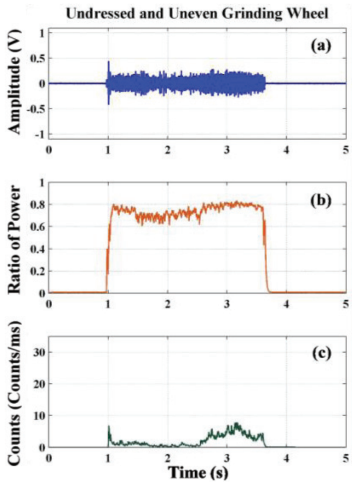

Fig. 3. UNDRESSED AND UNEVEN GRINDING WHEEL CONDITION

This is due to the clogging rate by chips, in addition to the uneven cutting surface and the abrasive grain wear of the grinding wheel directly influence on the acoustic activity generated during the dressing operation. On the other hand, the ROP and COUNTS values for the dressed and uneven grinding wheel occur uniformly, in other words, the statistics maintain a virtually constant energy level throughout the dressing pass. This occurs because at this stage the grinding wheel is conditioned and its contact with the dresser is full and uniform, generating more acoustic activity.

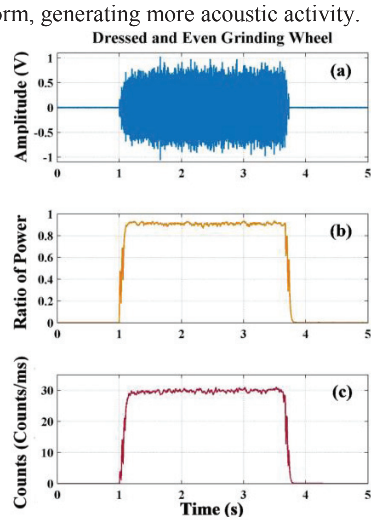

Fig. 4. DRESSED AND EVEN GRINDING WHEEL CONDITION

7. Neural networks models

The performances of a neural network might sensibly change according to the input parameters, network function, training function, number of nodes and epochs [2]. Every single points of AE waves and the passes number are used to construct the ANN model. The algorithm used as ANN is the Self-Organizing Map (SOM). It is an algorithm that show a topographic map of input data [10]. The supervised neural network used is the Back Propagation offered by MatLAB by a specific tool. This tool is called "*Neural Net Clustering*" and can be used by the APP software's section or by the command "*nctool*". The tool needs to input matrix and output matrix with a specific form.

7.1. Supervised Neural Network

Input matrix

The data from digital signal processing phase are composed by AE wave data vector of a single pass. For every single pass there is a vector with COUNTS and ROP information. This partition is the same for each test.

The Neural Net Clustering APP needs to a matrix containing all vectors of a test. This means that is necessary to make two matrix for every test: one matrix for COUNTS and one matrix for ROP.

A script MatLAB is used to make these matrices. The script use *for loop* for open all vectors and save them in a matrix. At the end of process, the script make a folder in the main directory containing the vectors and it save the generated matrix in this folder as *.mat* file. The generated matrix is characterized by having passes as rows and the points value of the wave of the passes as column.

Table 4 shows TEST 1 COUNTS matrix used for the Neural Net Clustering APP. Table 5 shows TEST 1 ROP matrix used for the Neural Net Clustering APP.

Output matrix

The output matrix is characterized by the number of condition as rows and the number of passes as column. The condition are Undressed and Uneven (UU), Dressed and Uneven (DU) and Dressed and Even (DE). Every condition in this matrix are indicate with 1 value. The reason of all this is related to Boolean value (1 is true and 0 is false). Table 6, 7 and 8 show respectively TEST 1, TEST 2 and TEST 3 output matrix used for the Neural Net Clustering APP.

Table 4. TEST 1 COUNTS matrix.

N° Passes	Point n°1	Point n°2	Point n°3	…	Point n°2570
Pass n°1	0	0	0	…	0
Pass n°2	0	0	5	…	0
Pass n°3	0	8	13	…	0
…	…	…	…	…	…
Pass n°24	0	0	0	…	0

Table 5. TEST 1 ROP matrix.

N° Passes	Point n°1	Point n°2	Point n°3	…	Point n°9727
Pass n°1	0.0083	0.0063	0.0099	…	0.0081
Pass n°2	0.0103	0.0078	0.0048	…	0.9318
Pass n°3	0.0088	0.0062	0.0129	…	0.0097
…	…	…	…	…	…
Pass n°24	0.0013	0.0015	0.0018	…	0.0034

Table 6. TEST 1 output matrix.

Condition	Pass n°1	Pass n°2	Pass n°3	…	Pass n°24
Undressed and Uneven	1	1	1	…	0
Dressed and Uneven	0	0	0	…	0
Dressed and Even	0	0	0	…	1

Table 7. TEST 2 output matrix.

Condition	Pass n°1	Pass n°2	Pass n°3	…	Pass n°10
Dressed and Uneven	1	1	1	…	0
Dressed and Even	0	0	0	…	1

Table 8. TEST 3 output matrix.

Condition	Pass n°1	Pass n°2	Pass n°3	…	Pass n°17
Undressed and Uneven	1	1	1	…	0
Dressed and Uneven	0	0	0	…	0
Dressed and Even	0	0	0	…	1

Figures 5 - 10 show respectively the confusion matrices for TEST 1 COUNTS, TEST 1 ROP, TEST 2 COUNTS, TEST 2 ROP, TEST 3 COUNTS and TEST 3 ROP. In the matrices, the diagonal represents the classification success carried out by the neural network, which is represented by the green colour. In those cells, the superior number represent the number of samples classified for each given class, and the inferior number represents the percentage of those samples related to the total of samples.

The error of the ANN models is represented by the red cells in the matrixes and it might be considered (false positive or false negative) for each given class. [2]

7.2. Unsupervised Neural Network

Input matrix

The matrices used in tool for SOM are characterized by the complete matrix without one row. The reason of the form of these matrices is related to use of the tool. Indeed the tool works in a different way from Neural Net Clustering APP and the user must insert manually a row in the matrix.

A script been made for recreate n-matrix, where n is the passes number of the selected test, with the respective rows. This script use two for loop to select the matrix and row and it make n-matrix and n-rows. The files made are saved as .mat file in a folder made by the script.

Output matrix

The output matrices for SOM tool are the vector extracted from the general matrix. Figures 11 and 12 show respectively TEST 1 COUNTS Self-Organizing Map and its labels. In Figure 12 it is possible to see where the Neural Network arrange a DE row called DE_TEST.

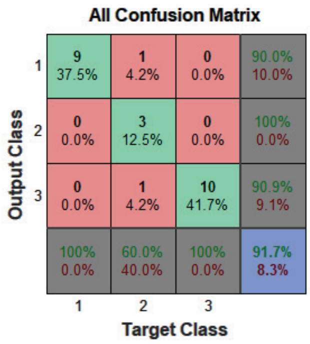

Fig. 5. TEST 1 COUNTS confusion matrix.

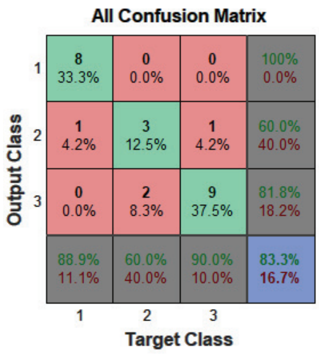

Fig. 6. TEST 1 ROP confusion matrix.

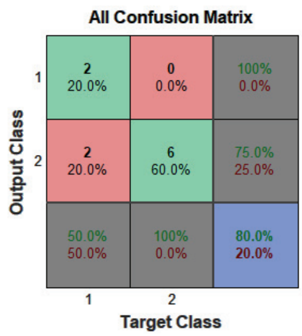

Fig. 7. TEST 2 COUNTS confusion matrix.

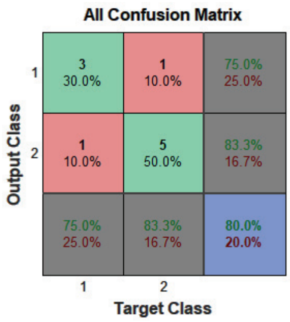

Fig. 8. TEST 2 ROP confusion matrix.

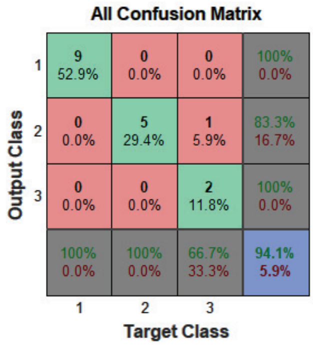

Fig. 9. TEST 3 COUNTS confusion matrix.

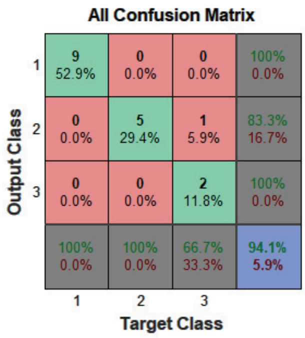

Fig. 10. TEST 3 ROP confusion matrix.

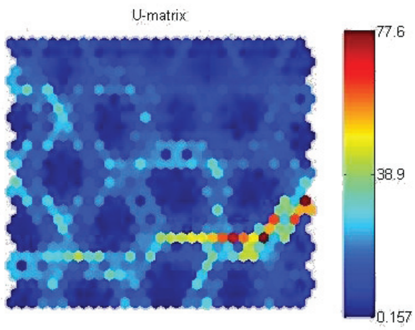

Fig. 11. TEST 1 COUNTS Self-Organizing Map.

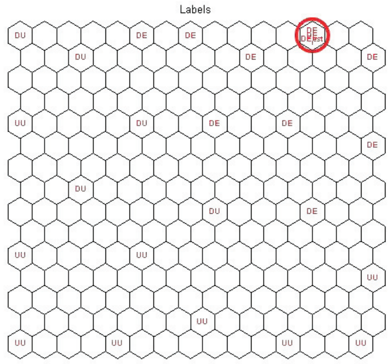

Fig. 12. TEST 1 COUNTS Labels of Self-Organizing Map

8. Conclusions

This paper analyze the possibility of find the right moment to stop single-point dressing the grinding wheel. The ANNs used to determinate this moment are the SOM and the Back Propagation Neural Network. It is possible to see that Back Propagation works very well for COUNTS and ROP. The percentage of success is between 80% and 94,1%.

The SOM offer us the possibility to see where the Neural Network puts a row inside a matrix. The efficiency is high with all rows insert in the right area of main matrix.

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