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Monitoring of Grinding Burn by Acoustic Emission

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1. Introduction

In the metal and mechanical industry, grinding is usually the last step of the manufacturing chain, when it comes to precision components. This process is used in the fabrication of parts of a wide variety of materials, which require low surface roughness, strict dimensional and shape tolerances, while maintaining maximum tool life and the shortest operation time, along with minimum costs.

Damage of the workpiece during grinding is very costly, since it has already a high aggregated value from the previous manufacturing processes. The most common types of damage in grinding are burning, cracking, and undesirable residual stresses. In the case of metals, the most common cause of damage is excessive heat generation on the ground surface.

The high temperatures generated in the grinding zone may cause several types of damage to the workpiece, e.g., burns (in the case of metals), excessive hardening of the surface layer, with possible rehardening and increased brittleness, undesirable residual tensile stresses, reduced fatigue strength, and cracking (Malkin, 1989).

The combination of acoustic emission signals and cutting power have been used successfully to determine indicative parameters of burning (Kwak & Ha, 2004). These signals, properly manipulated, allow for the implementation of a burn control system in real time, optimizing thus the grinding process (Dotto et al., 2006). This would be highly beneficial for companies that strictly depend on this process, since the requisite of quality and international competitiveness increases continually with globalization (Brinksmeier et al., 2006).

On the other hand, the growing interest in the use of artificial intelligence for the solution of engineering problems is visible from the considerable number of articles published in the last decade. These problems are normally difficult to solve analytically or through mathematical modelling, and usually require human intelligence (D.T. Pham & P.T.N. Pham, 1999).

Thus, the present chapter aims to present results of statistical tools and fuzzy modelling 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, these systems are not enough reliable to operate without human interference so far. It is common to observe operators of CNC machines correct the process parameters or identify the end of the tool life (Aguiar et al., 1999).

When it comes to grinding, there are three main goals related to process monitoring: detection of problems during machining; provision of information necessary to optimize the process; and the contribution to the development of a database needed to determine the control parameters (Inasaki, 1999). For example, in external plunging grinding, many parameters are involved and need to be determined, which are related to the choice of the grinding wheel and coolant. The wheel and work speeds, and feed rate are one of these aforementioned parameters. Among these, the feed rate is the most critical in influencing the results.

The choice of the grinding cycle, the satisfactory end of the operation and spark-out time are other important parameters to be considered, in order to obtain the desired surface quality. The information obtained during monitoring may be used, thus, to minimize the grinding cycle time and increase the overall process quality (Inasaki, 1999).

The use of acoustic emission (AE) to monitor and control the grinding process is a relatively recent technology (Bennett, 1994), besides being more sensitive to the grinding condition variations, when compared with the force and power measurements (Webster et al., 1994), standing as a promising technique to the process monitoring.

The relatively easiness of digitally processing the root mean square (RMS) of the acoustic emission signal has led to approaches in which this type of statistic is employed. However, the inherent average operation involved in determining the RMS makes it to a certain extent insensitive to impulsive events, such as cracks and burn of the workpieces, although this kind of parameter carries a lot of useful information.

2.1 Burn control in grinding

Grinding burn occurs during the cutting process when the amount of energy generated in the contact zone produces a sufficiently high increase in temperature in order to cause a localized phase change in the workpiece material. This occurrence can be observed visually from the discoloration of the part surface (Nathan et al., 1999; Kwak & Song, 2001). Also, burning is expected when a critical temperature (approx. 720°C for steels) is exceeded in the grinding zone (Nathan et al., 1999).

The root mean square (RMS) value of the acoustic emission signal has been the main parameter studied in previous researches on grinding over a carefully selected frequency band. This signal has provided a reasonable parameter, because it is rich in sound waves carrying a lot of useful information (Spadotto et al., 2008).

Thermal models for grinding can be taken as an example of the theory of a moving heat source with various boundary conditions for estimating the distribution of temperature inside the grinding zone. This distribution is used to predict the generation of residual stresses, the onset of burning of the workpiece surface, or other characteristics related to surface integrity. However, these models require parameters that are often not readily known in the production environment. Moreover, several properties of many materials and of the cutting fluid are not known exactly in the predominating grinding conditions. In addition, the production operation does not require a high precision "absolute" model, because such precision is not reproduced in industrial practice (Ali & Zhang, 2004). What is needed, is a "relative" model that can guide the user about what should be done and how to do it, because there will always be a certain degree of trial and error on the shop floor, and this relative model will be a good starting point (Shaw, 1996).

2.2 Statistical parameters for burn detection

Acoustic emission and grinding power signals provide a variety of information about the grinding process. However, more rigorous analyses can be obtained by the signal processing with the help of statistical parameters. Using mathematical manipulation software, these signals can be processed to obtain information such as the RMS value, standard deviation, autocorrelation, FFT, etc. (Wang et al., 2001; Tönshoff et al., 2000).

Acoustic emission (AE) can be defined as the elastic stress waves generated by the rapid release of deformation energy, inside a material subjected to an external stimulus. These stress waves produce surface displacements that can be detected by a piezoelectric sensor, which transforms the displacements into electrical signals (Tönshoff et al., 2000). Their frequency range varies from 50 kHz to 2MHz, which is above the range of many noises originating from sources outside the grinding process. Thus, it is a sensitive and adequate method to monitor the grinding process (Tönshoff et al., 2000; Liu et al., 2006).

The parameter that has been studied predominantly in previous researches using acoustic emission has been the root mean square (RMS) of the AE signal (AERMS), filtered over a carefully selected frequency band. This signal has been a reasonable study parameter, since the grinding process is very rich in sound waves, thus containing a lot of available acoustic information (Aguiar et al., 1999).

The RMS value of AE can be expressed by equation (1) (Kim et al., 2001).

$$AE_{RMS} = \sqrt{\frac{1}{\Delta T}\int_{0}^{\Delta t} AE^2(t).dt} \tag{1}$$

where Δt is the integration time constant.

The mean-value deviance (MVD) statistic was used successfully in burn detection (Wang et al., 2001), and is defined by equation (2).

$$T_{mvd}(X) = \frac{1}{M}\sum_{k=0}^{M-1}\log\left[\frac{\bar{X}}{X_k}\right] \tag{2}$$

where $\bar{X}$ is the mean value of $\{X_k\}$; $2M$ is the total number of FFT bins, and X_k is the kth magnitude-squared FFT bin.

3. In-process grinding monitoring by acoustic emission

In the following sections, results are presented for the evaluation of the surface integrity of AISI 1045 steel parts during grinding, using properly processed acoustic emission signals. Furthermore, results from several 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.

3.1 Materials and methods

The experimental tests were carried out upon a surface grinding machine (Sulmecânica RUAP H 1055-E - Brazil) where raw acoustic emission signals were gathered for fifteen (15) different runs, at 2.5 million of samples per second rate. The AISI 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 low to severe material removing. All workpieces were evaluated after machining, and the burn marks were then identified. The setup for these tests is shown in Figure 1.

The grinding parameters include: wheel peripheral speed: 27.94 m/s; tool: aluminium oxide grinding wheel (38A80-PVS) manufactured by Norton Abrasives, with dimensions of: 296.50 mm external diameter, 40.21 mm width; workpiece speed: 0.044 m/s; workpiece dimensions: 98.58 x 80.12 x 8.74 mm; and coolant type: oil emulsion (4% concentration on water).

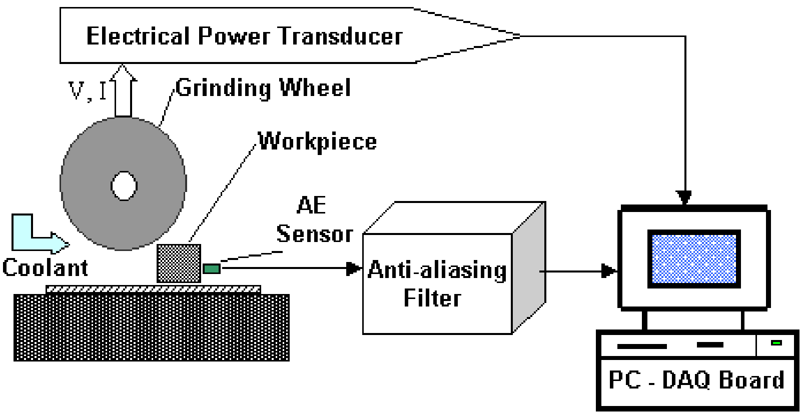


Fig. 1. Experimental setup

Data was gathered from a fixed acoustic emission sensor (Sensis PAC U80D-87), which was fixed on the part holder. The data acquisition board (National Instruments, PCI-6011) was set up to work at 2.5 million of samples per second, with 12 bits precision per sample. Table 1 shows details of carried out tests.

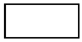
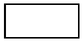
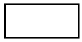
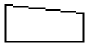
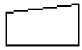
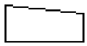
Test	Depth of cut [µm]		Cutting Profile	Comments
1	10			No burn
2	30			Slight burn
3	20			Severe burn
4	90	10		Severe burn
5	20	2,5		Severe burn
6	40	5		Severe burn
7	15			Burn at middle

Table 1. Tests with AISI 1045 Steel

3.2 Signal processing

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

3.2.1 Root mean square (RMS) of acoustic emission signal

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

$$AE_{rms} = \sqrt{\frac{1}{T}\int_{t-T}^{t} AE_{raw,t}^{2}.dt} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} AE_{raw,i}^{2}} \tag{3}$$

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 (Webster et al., 1996).

3.2.2 Constant false alarm rate (CFAR)

Constant false alarm rate (CFAR) is a statistic tool employed in detection of events, which is described by (Nuttal, 1997):

$$T_{pl}(X) = \sum_{k=0}^{M-1} X_k^{\upsilon} \tag{4}$$

Where X_k 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 frequency band of the studied signal, this statistic needs pre-normalized data. Thus, due to the acoustic emission signal variations during the process, the constant false alarm rate (CFAR) is utilized (Nuttal, 1996). This statistic is based on the supposition of flatness of the acoustic emission signal. An alternative version of this tool was employed due to system distortions, which is expressed by the following equation (Wang, 1999).

$$T_{bcpl}(X) = \frac{\sum_{k=n1}^{n2} X_k^{\upsilon}}{\left(\sum_{n1}^{n2} X_k\right)^{\upsilon}} \tag{5}$$

Values for M=1280, and a frequency range between 300 and 700 kHz were considered.

3.2.3 Kurtosis and skewness statistics

The measurement, if the distribution tail is longer than other, is made by skewness. 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 peaks for these statistics. Equations 6 and 7 show the way of calculating kurtosis and skewness of an x signal, respectively.

$$K = \sum \frac{(x-\mu)^4}{N\sigma^4} - 3 \tag{6}$$

$$K = \sum \frac{(x-\mu)^3}{N\sigma^3} \tag{7}$$

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

3.2.4 Mean value dispersion (MVD) statistic

The form of MVD statistic is also employed, but in a more convenient form (Wang et al., 1999), as shown in equation 8.

$$MVD = \sum_{k=n1}^{n2} \log\left(\frac{\frac{1}{n_2 - n_1 + 1}\sum_{l=n1}^{n2} X_l}{X_k}\right) \tag{8}$$

where X has the same meaning as to CFAR statistic, as well as n_1 and n_2.

3.2.5 Ratio of power (ROP)

It is instinctive to think about the different behaviours expected for a satisfactory or non satisfactory part by observing the frequency spectrum of the acoustic emission signal. Hence, for each block of acoustic emission data, ROP is given by equation 9.

$$ROP = \sum_{k=n_1}^{n_2} \frac{|X_k|^2}{\sum_{k=0}^{N-1} |X_k|^2} \tag{9}$$

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

3.2.6 Autocorrelation

The time correlation of a function ϕ_{xy} is defined in equation 10 (Oppenheim et al., 1997).

$$\phi_{xy}(t) = \int_{-\infty}^{+\infty} x(t+\tau)y(\tau)d\tau \tag{10}$$

where ϕ_{xx} is commonly referred to as autocorrelation.

3.3 Results and discussion

The figures 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. In all figures below, the horizontal axis corresponds to time (in seconds), and the vertical axis to Volts (multiplied by a constant).

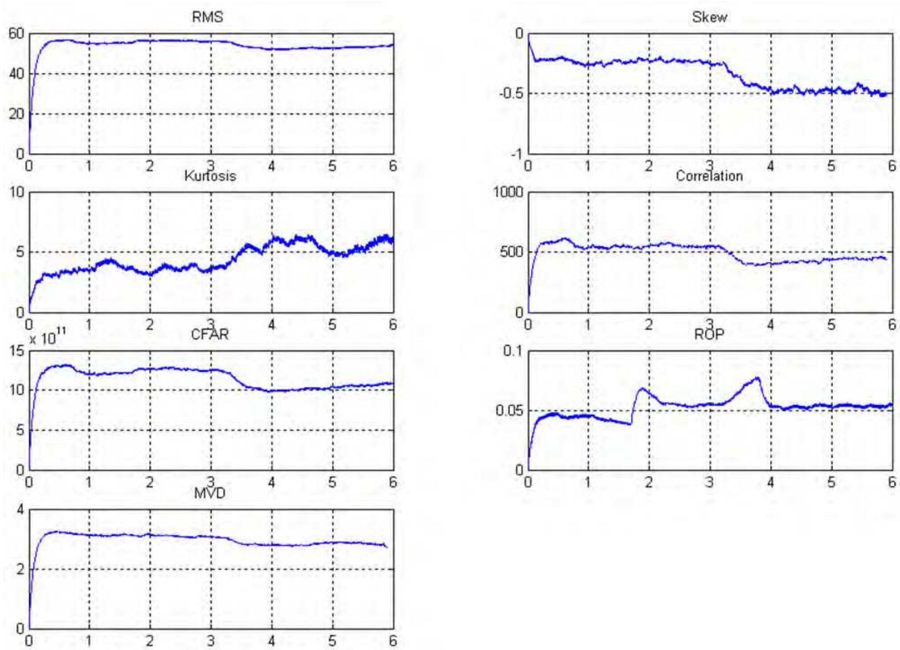


Fig. 2. Results for test 1 – AISI 1045 steel with no burn

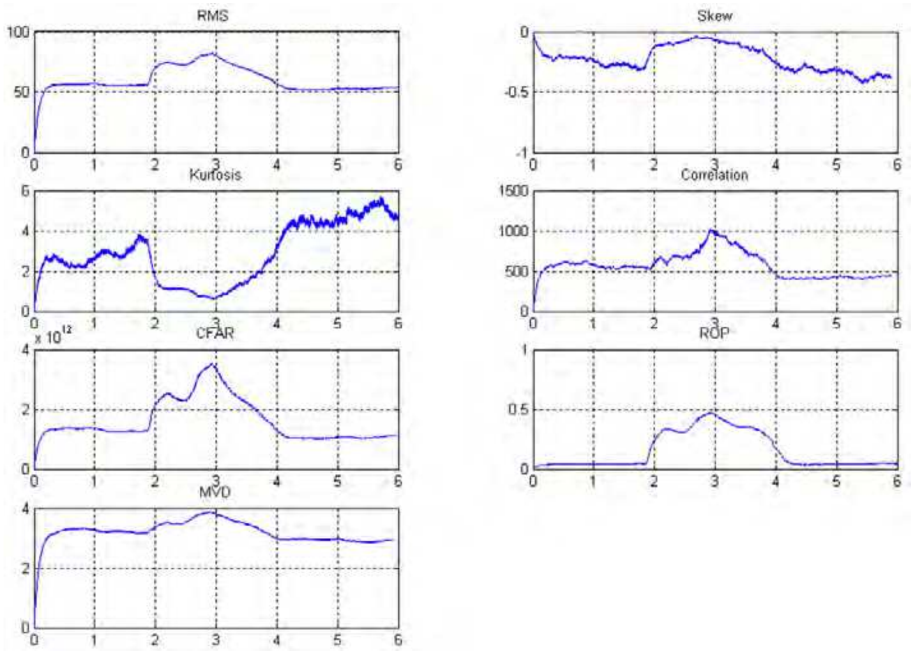


Fig. 3. Results for test 5 – AISI 1045 steel with severe burn in practically the whole workpiece

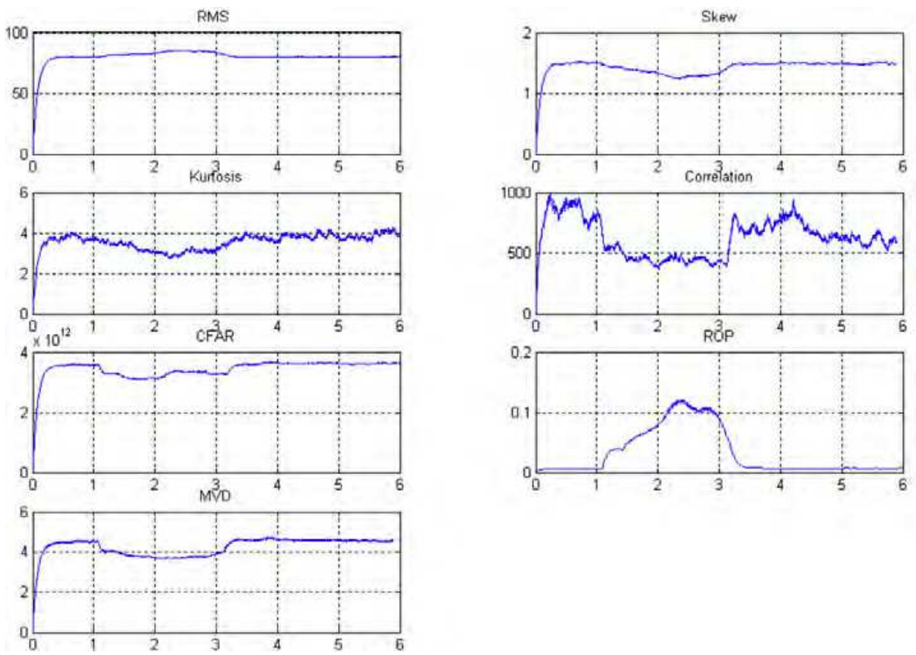


Fig. 4. Results for test 7 – AISI 1045 steel with burn in the midst of the part;

From the results for the ABNT 1045 steel, it can be observed that RMS providade a pretty steady level 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. Skewness and kurtosis presented variation when burn took place, but positive and negative amplitudes 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 as satisfactory as RMS, due to the low level obtained for test 7. The autocorrelation statistic was very sensitive to burn, for the most tests performed, but for a few it has shown itself useless, by virtue of the decrease observed when burn occurred.

Similarly to the autocorrelation, CFAR has behaved quite satisfactory to burn detection, for most of the tests, not providing signal decreases at all, except for test 7, where a decrease 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 the non-burning test.

4. Acoustic emission and fuzzy logic to predict grinding burns

The use of fuzzy logic, which reflects the nature of qualitative and inexact reasoning of humans, enables specialist systems to be more flexible. With fuzzy logic, the precise value of a variable is substituted by a linguistic description represented by a fuzzy set, and inferences are made based on this representation (D.T. Pham & P.T.N. Pham).

Fuzzy logic has numerous applications in engineering, where the command of knowledge is usually imprecise. Interesting results have been achieved in the area of machining processes and control, although other sectors have also benefited from this tool. Several engineering applications can be cited, such as welding arc height control (Bigand et al., 1994); control of robotic hands with multiple fingers (Bas & Erkmen, 1995); prediction of surface roughness of ground components (Ali & Zhang, 1999); control of grinding burn (Ali & Zhang, 2004), among others. However, the development of an intelligent system for burn detection, prediction and classification still poses a challenge for researchers.

Based on these practical aspects, a fuzzy model was proposed with 37 absolute rules and eight relative rules for predicting burn of ground workpiece surfaces. This model is designed for practical application, i.e., an operator can infer from the model, engineers can use it in process planning, and the model can be part of an intelligent adaptive control, without the need for additional information (Ali & Zhang, 1999).

A fuzzy clustering method was proposed for evaluating the degree of grinding burn damage using burn colour spots on the workpiece side surface. This method can replace the complicated wet grinding thermometry method. The results can be used to evaluate the performance of cutting fluids for restricting grinding burn damage (Ge et al., 2002).

Others presented a new method of grinding burn identification using a wavelet packet transform to extract features from acoustic emission signals and employing fuzzy pattern recognition to optimize features and identify the grinding status. Experimental results showed that the accuracy of grinding burn recognition was satisfactory (Liu et al., 2005).

Other works employing fuzzy logic in the area of manufacturing can be found, including estimation of residual stress induced by grinding (Ali & Zhang, 1997), prediction of surface roughness of ground components (Ali & Zhang, 1999), classification of the condition of the grinding wheel's cutting ability (Lezanski, 2001), etc. However, only few researches have been published about grinding burn using fuzzy logic. Therefore, this work explores not only the application of fuzzy logic but also the fusion sensors and grinding burn parameters not used to date.

Therefore, the next sections represent the work which aimed to investigate burning in the grinding process based on a fuzzy model. The inputs of the models are obtained from the digital processing of the raw acoustic emission and cutting power signals. The parameters to be obtained and used in this work include the mean-value deviance (MVD), which proved efficient in grinding burn detection (Wang et al., 2001), grinding power, and root mean square (RMS) of the acoustic emission signal (Dotto et al., 2006).

4.1 Materials and methods

The grinding tests were carried out with a surface grinding machine (Sulmecânica RUAP-H1055-E, Brazil) equipped with an aluminium oxide grinding wheel (Norton ART-FE-38A80PVH). A fixed acoustic emission sensor (Sensis DM-42) was placed near the workpiece, and the electric power consumed by the wheel three-phase induction motor was measured with an electrical power transducer.

The workpieces for the grinding tests consisted of SAE 1020 laminated steel bars with dimensions of 150mm length, 10mm width and 60mm height. Grinding was performed along the length of the workpiece.

The power transducer consisted of a Hall sensor, to measure both the electric current and the voltage in the electric motor terminals. Both signals were processed in the power transducer module by an integrated circuit, which delivered a voltage signal proportional to the electrical power consumed by the motor. The acoustic emission and power signals were then sent to the data acquisition board (National Instruments, PCI-6011) installed in a personal computer. The signals were captured by LabVIEW software and stored in binary files for further processing and analysis. The acoustic emission sensor had a broad-band sensitivity of 1.0 MHz. Its amplifier also filtered the signal outside the range of 50 kHz to 1.0 MHz. Figure 5 shows a schematic diagram of the grinding machine and instrumentation used.

The tests were carried out in 12 different grinding conditions, and the degrees of burn (no burn, slight burn, medium burn, and severe burn) were evaluated visually on each workpiece surface. Dressing parameters, lubrication and peripheral wheel speed were controlled to ensure the same grinding condition in the three repetitions of each test. The workpiece speed was set at 0.033 m/s and the wheel speed at 30 m/s. The latter was kept constant by adjusting the frequency of the induction motor on the frequency inverter, since the diameter of the grinding wheel decreased as the tests progressed.

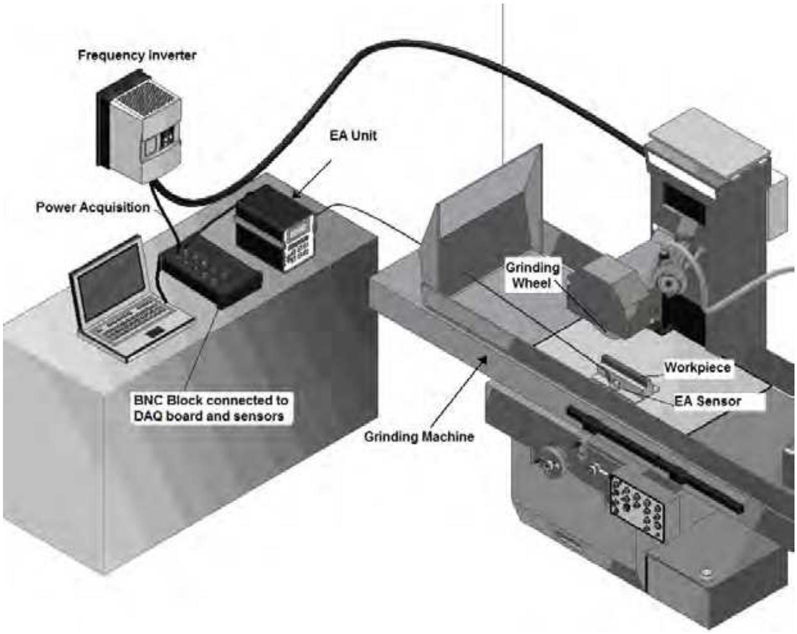


Fig. 5. Test bench layout

The overlapping ratio (U_d), which is the relationship between the effective cutting width and the axial dressing feed rate, was set to 1, and the dressing conditions were kept constant in all the tests. An emulsion oil (4% concentration on water) was used. Each run consisted of a single grinding pass of the grinding wheel along the workpiece length, at a given grinding condition. The acoustic emission and grinding power signals were measured in real time at a rate of 2.0 million samples per second, and stored in binary data files. It is important to mention that the raw acoustic emission signal was acquired instead of the root mean square, generally used.

The digital signals were processed after the 12 tests were carried out, and the data files stored. The processing of acoustic emission signals generated the aforementioned statistics, i.e., RMS and MVD.

4.2 Construction of input vectors

The percentage of burn and the degree of burn of each workpiece were determined using a software previously developed (Dotto et al., 2006). This software analyzes the surface condition of a workpiece, based on a photograph of the machined workpiece. Thus, aided by this software, reliable input data were extracted to represent the levels: no burn, slight burn, medium burn, and severe burn.

The signals were processed using MATLAB. RMS and MVD statistics were generated based on the raw acoustic emission signals and the grinding power signals, which served to build the input vectors for the fuzzy models.

This procedure was carried out for all the tested workpieces. However, it should be noted that among the inputs considered in this work (RMS, MVD and power), some were better than others, in order to define differences in the degrees of burn. Therefore, the use of fuzzy logic is attractive for this application, since it is based on the levels of imprecision generated by these inputs.

The files contained a set of burn data associated with the processed inputs. For example, the RMS signal of acoustic emission is represented by the level no burn, slight burn, medium burn and severe burn. The same situation applies to the MVD and grinding power statistics. The data vectors were standardized, i.e., all the vectors contained the same number of collected points. This allows comparisons to be made always among the same points of the input variables without distortions occurring among points.

Subsequently, the data that had been separated by level of burn were combined in a single file of a given input. To exemplify, the file of the RMS signal of AE, which previously consisted of separate files of no burn, slight burn, medium burn and severe burn, now had a single vector containing the data of the aforementioned files. This new vector is in the order of burn of the workpiece, i.e., the vector contains the no burn, slight burn, medium burn and severe burn data, respectively, in this position of the vector. The vectors for the MVD statistic and grinding power were constructed in the same way.

4.3 Fuzzy modeling

One of the advantages of using fuzzy logic is the possibility of transforming natural language into a set of numbers, allowing for computational manipulation. Linguistic variables can be defined as “variables whose values are words or sentences in natural or artificial language” (Zadeh, 1965). Linguistic variables assume values called linguistic values, e.g., the values of no burn, slight burn, medium burn and severe burn are relative to the burn variable of the workpiece. Figure 6 shows a general model of a fuzzy inference system (FIS).

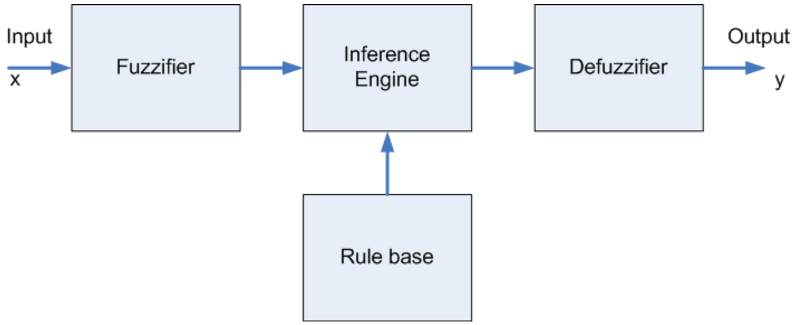


Fig. 6. Block diagram of a fuzzy inference system

It can be observed from the figure that the FIS includes four components: the fuzzifier, inference engine, rule base, and defuzzifier. The rule base contains linguistic rules that are provided by experts. It is also possible to extract rules from numeric data. Once the rules have been established, the FIS can be viewed as a system that maps an input vector to an output vector. The fuzzifier maps input numbers into corresponding fuzzy memberships.

This is required in order to activate rules that are in terms of linguistic variables. The fuzzifier takes input values and determines the degree to which they belong to each of the fuzzy sets via membership functions.

The inference engine defines mapping from input fuzzy sets into output fuzzy sets. It determines the degree to which the antecedent is satisfied for each rule. If the antecedent of a given rule has more than one clause, fuzzy operators are applied to obtain one number that represents the result of the antecedent for that rule. It is possible that one or more rules may fire at the same time. Outputs for all rules are then aggregated. During aggregation, fuzzy sets that represent the output of each rule are combined into a single fuzzy set.

The defuzzifier maps output fuzzy sets into a crisp number. Given a fuzzy set that encompasses a range of output values, the defuzzifier returns one number, thereby moving from a fuzzy set to a crisp number. Several methods for defuzzification are used in practice, including the centroid, maximum, mean of maxima, height, and modified height defuzzifier. The most popular defuzzification method is the centroid, which calculates and returns the center of gravity of the aggregated fuzzy set.

4.4 Input vectors

The aforementioned vectors of RMS, MVD and grinding power represent the numerical inputs of the fuzzy system. These inputs were transformed into fuzzy inputs. Figure 7 shows the RMS vector of acoustic emission (expressed in k*Volts), containing all the levels of burn and no burn observed in the tests. The k constant is a conversion constant that depends on the number of bits of the data acquisition board.

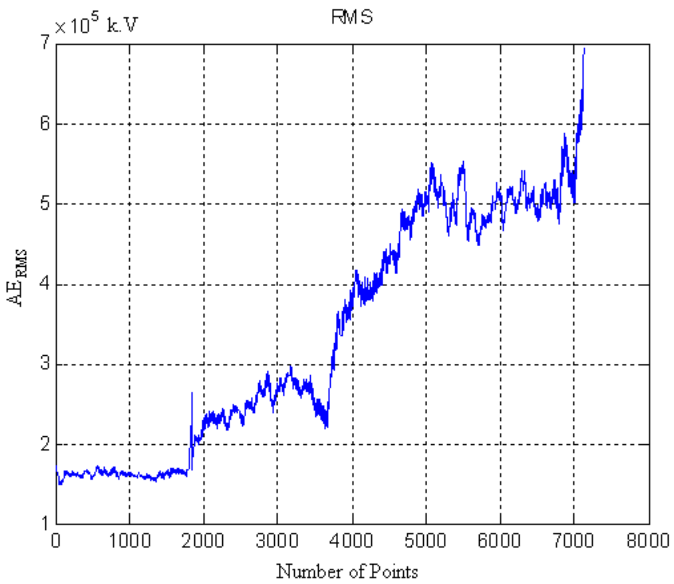


Fig. 7. Acoustic emission (RMS)

A clustering process was applied to each numerical input, which consisted of determining 4 subclusters (Ge et al., 2002). Clustering serves to group input vector data into 4 major groups that represent the burn levels of the workpiece. Each group thus determined contains a cluster center which best represents the group. For the statistics or signals employed here, the clusters were very close to the mean values of each group. Thus, the point that best represents a burn group is the mean value of the range of points of a burn level.

After this representative point was attributed and determined, the data vectors were normalized with values of 0 to 1. The numerical data vectors were then transformed in fuzzy system vectors, and the value of 1 was attributed to the cluster center. This value diminishes as the statistic values move away from this cluster point. With this process, the further away from the cluster center, the lower the relevance of the information and the lower the value attributed to the normalization of the data.

Figure 8 shows the fuzzified acoustic emission RMS input into the system by means of membership functions. The horizontal axis refers to the value of the amplitude of the statistic. In other words, the higher the amplitude of the statistic the greater the scope of the burn level in the fuzzified set.

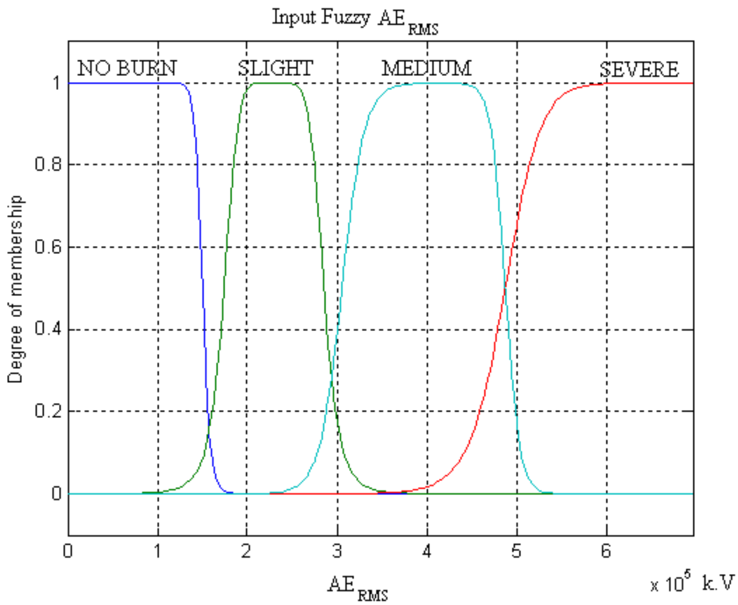


Fig. 8. Fuzzified input of the RMS acoustic emission signal

These membership functions help in converting numeric variables into linguistic terms.

4.5 Output vector

A single output vector was then created with the fuzzified input vectors to the fuzzy system. This output vector was created according to the various burn levels the workpiece would undergo. The fuzzy output has a totally encompassing set of burn levels of a surface. The output set contains the following levels: no burn, super slight, very slight, slight, slight +, almost medium, medium, medium +, almost severe, severe, severe +, and total damage.

This scope is due to the fact that the model is not restricted only to 3 or 4 burn levels. By extending these levels, the result was decentralized to a broader and strongly detailed vision of the problem. The fuzzified output vector represents the fuzzy output set.

4.6 Inferences and rule base of fuzzy models

Based on the inputs and the fuzzified output, an inference was established between both (Hu & Tzeng, 2003). First, 3 logic system models were created. The first model had two inputs: the RMS of AE and the grinding power (GP). The other two models had 3 inputs: the RMS of AE, the GP, and the MVD statistic. What differentiates these two models is the inference of the rules used.

The rule sets extracted for all the models were based on the experience of specialists in the subject, and are therefore based on a typically fuzzy system. The first model is a simple control of two inputs. The rule base is shown in Table 2. Each input analyzed in all the models had the same weight relative to the system, i.e., all the inputs affect the system equally.

GP\AE RMS	NO BURN	SLIGHT	MEDIUM	SEVERE
NO BURN	NO BURN	VERY SLIGHT	MEDIUM	SEVERE
SLIGHT	VERY SLIGHT	SLIGHT	MEDIUM	SEVERE
MEDIUM	MEDIUM	MEDIUM	VERY SEVERE	TOTAL DAMAGE
SEVERE	SEVERE	SEVERE	TOTAL DAMAGE	TOTAL DAMAGE

Table 2. Rule base for model 1. Combination of GP and the RMS value

The second model is based on an inference system of three inputs, combined in pairs. This system is widely valid, since, if one of the inputs has an incorrect value, it will not affect the output to any appreciable degree. The rules for this model are shown in Table 3.

The third and last model developed here is a fuzzy control with three fuzzy inputs, namely: the RMS value of the acoustic emission signal, the grinding power (GP), and the MVD statistic of the signal. What differentiates this model from the second one is the part of rule inference. The rule set was developed from a triple combination of inputs, thus providing a total of 64 well distributed rules. Table 4 shows the rule set for model 3.

4.7 Defuzzification of the proposed systems

Three models of fuzzy systems were presented. Fuzziness helps us to evaluate the rules, but the final output of a fuzzy system has to be a crisp number. The input for the defuzzification process is the aggregate output fuzzy set and the output is a single number.

GP\AE RMS	NO BURN	SLIGHT	MEDIUM	SEVERE
NO BURN	NO BURN	VERY SLIGHT	MEDIUM	SEVERE
SLIGHT	VERY SLIGHT	SLIGHT	MEDIUM	SEVERE
MEDIUM	MEDIUM	MEDIUM	VERY SEVERE	TOTAL DAMAGE
SEVERE	SEVERE	SEVERE	TOTAL DAMAGE	TOTAL DAMAGE
AE RMS \MVD	**NO BURN**	**SLIGHT**	**MEDIUM**	**SEVERE**
NO BURN	NO BURN	SLIGHT	MEDIUM	VERY SEVERE
SLIGHT	SLIGHT	SLIGHT	VERY SEVERE	SEVERE
MEDIUM	MEDIUM	VERY SEVERE	VERY SEVERE	TOTAL DAMAGE
SEVERE	SEVERE	SEVERE	TOTAL DAMAGE	TOTAL DAMAGE
GP\MVD	**NO BURN**	**SLIGHT**	**MEDIUM**	**SEVERE**
NO BURN	NO BURN	SLIGHT	MEDIUM	MEDIUM
SLIGHT	SLIGHT	SLIGHT	MEDIUM	VERY SEVERE
MEDIUM	MEDIUM	MEDIUM	SEVERE	TOTAL DAMAGE
SEVERE	SEVERE	VERY SEVERE	TOTAL DAMAGE	TOTAL DAMAGE

Table 3. Rule set of model 2, paired combination of the fuzzy inputs

The center of gravity (COG) or centroid defuzzification method was used in each model. It finds the point where a vertical line would cut off the aggregate set into two equal masses. A reasonable estimate can be obtained by calculating it over a sample of points and expressed by equation 11.

$$COG = y_{crisp} = \frac{\sum_{i=1}^{n} \mu_A(y_i) y_i}{\sum_{i=1}^{n} \mu_A(y_i)} \tag{11}$$

where $\mu_A(y_i)$ is the membership function and y is the variable to be defuzzified.

It is the most widely used technique because, when it is used, the defuzzified values tend to move smoothly around the output fuzzy region.

4.8 Results and discussion

The proposed models were developed using the "Fuzzy Logic" toolbox of MATLAB. Initially, a model was built with only two fuzzy inputs. Its rule base was edited and placed in the software toolbox.

RMS	GP	MVD	OUTPUT
NO BURN	NO BURN	NO BURN	NO BURN
NO BURN	NO BURN	SLIGHT	SUPER SLIGHT
NO BURN	NO BURN	MEDIUM	VERY SLIGHT
NO BURN	NO BURN	SEVERE	SLIGHT
NO BURN	SLIGHT	NO BURN	SUPER SLIGHT
NO BURN	SLIGHT	SLIGHT	SLIGHT
NO BURN	SLIGHT	MEDIUM	SLIGHT +
NO BURN	SLIGHT	SEVERE	ALMOST MEDIUM
NO BURN	MEDIUM	NO BURN	SLIGHT +
NO BURN	MEDIUM	SLIGHT	ALMOST MEDIUM
NO BURN	MEDIUM	MEDIUM	MEDIUM
NO BURN	MEDIUM	SEVERE	MEDIUM +
NO BURN	SEVERE	NO BURN	MEDIUM
NO BURN	SEVERE	SLIGHT	MEDIUM +
NO BURN	SEVERE	MEDIUM	ALMOST SEVERE
NO BURN	SEVERE	SEVERE	SEVERE
SLIGHT	NO BURN	NO BURN	SUPER SLIGHT
SLIGHT	NO BURN	SLIGHT	VERY SLIGHT
SLIGHT	NO BURN	MEDIUM	SLIGHT
SLIGHT	NO BURN	SEVERE	SLIGHT +
SLIGHT	SLIGHT	NO BURN	VERY SLIGHT
SLIGHT	SLIGHT	SLIGHT	SLIGHT +
SLIGHT	SLIGHT	MEDIUM	SLIGHT +
SLIGHT	SLIGHT	SEVERE	ALMOST MEDIUM
SLIGHT	MEDIUM	NO BURN	ALMOST MEDIUM
SLIGHT	MEDIUM	SLIGHT	MEDIUM
SLIGHT	MEDIUM	MEDIUM	MEDIUM
SLIGHT	MEDIUM	SEVERE	MEDIUM +
SLIGHT	SEVERE	NO BURN	ALMOST MEDIUM
SLIGHT	SEVERE	SLIGHT	MEDIUM
SLIGHT	SEVERE	MEDIUM	MEDIUM +
SLIGHT	SEVERE	SEVERE	SEVERE
MEDIUM	NO BURN	NO BURN	SLIGHT
MEDIUM	NO BURN	SLIGHT	SLIGHT +
MEDIUM	NO BURN	MEDIUM	ALMOST MEDIUM
MEDIUM	NO BURN	SEVERE	MEDIUM +
MEDIUM	SLIGHT	NO BURN	SLIGHT +
MEDIUM	SLIGHT	SLIGHT	ALMOST MEDIUM
MEDIUM	SLIGHT	MEDIUM	MEDIUM
MEDIUM	SLIGHT	SEVERE	SLIGHT +
MEDIUM	MEDIUM	NO BURN	ALMOST MEDIUM
MEDIUM	MEDIUM	SLIGHT	MEDIUM
MEDIUM	MEDIUM	MEDIUM	MEDIUM +
MEDIUM	MEDIUM	SEVERE	ALMOST MEDIUM
MEDIUM	SEVERE	NO BURN	MEDIUM +
MEDIUM	SEVERE	SLIGHT	ALMOST SEVERE
MEDIUM	SEVERE	MEDIUM	SEVERE
MEDIUM	SEVERE	SEVERE	SEVERE +
SEVERE	NO BURN	NO BURN	ALMOST MEDIUM
SEVERE	NO BURN	SLIGHT	MEDIUM
SEVERE	NO BURN	MEDIUM	MEDIUM +
SEVERE	NO BURN	SEVERE	ALMOST SEVERE
SEVERE	SLIGHT	NO BURN	MEDIUM
SEVERE	SLIGHT	SLIGHT	MEDIUM +
SEVERE	SLIGHT	MEDIUM	ALMOST SEVERE
SEVERE	SLIGHT	SEVERE	SEVERE
SEVERE	MEDIUM	NO BURN	MEDIUM +
SEVERE	MEDIUM	SLIGHT	ALMOST SEVERE
SEVERE	MEDIUM	MEDIUM	SEVERAL +
SEVERE	MEDIUM	SEVERE	TOTAL DAMAGE
SEVERE	SEVERE	NO BURN	SEVERE
SEVERE	SEVERE	SLIGHT	SEVERE +
SEVERE	SEVERE	MEDIUM	TOTAL DAMAGE
SEVERE	SEVERE	SEVERE	TOTAL DAMAGE

Table 4. Third fuzzy model. Triple combination of inputs

4.8.1 Model 1: Two-input control

Based on the rules, a 3D surface was generated, which allowed to visualize the effects of the rules on the system inputs and output. Figure 9 shows this surface for the first model. This surface indicates how regular the newly developed rule base is. If it is not completely consistent, disproportions and coarse irregularities are visible on the generated surface.

Continuity, transition and symmetry are characteristics well expressed in Figure 9. As can be seen, as the values of the RMS signal and grinding power increase, a prediction of high burn level on the surface is generated.

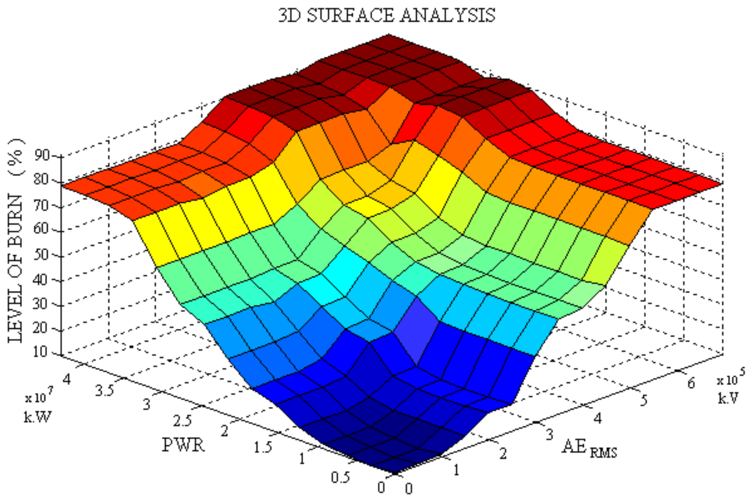


Fig. 9. 3D analysis of the surface generated by the rule system of model 1

Once the consistency of the system inference domain has been verified, it is possible to predict the burn level of the workpiece surface, based on values of the applied RMS signal and on the system electric power. The simulation was carried out in MATLAB, and is based on a low RMS signal and GP. The analysis resulted in a no burn prediction with a maximum value of 9.61% of surface burn. This simulation can be made with varied values, presenting different levels of prediction.

The advantage of model 1 is its simplicity. With only two fuzzified inputs having the same weight, model 1 produces a reliable and stable prediction in the system. However, if one of the variables presents an incorrect value originating from innumerable real factors such as reading errors, etc., it will affect the prediction of the control.

4.8.2 Model 2: Three-input control combined in pairs

Model 2 was created to minimize the aforementioned error, i.e., an input variable containing an incorrect value of the system. This second model, on the other hand, has three fuzzified inputs. The idea of this model is that its rule base be combined in pairs, generating a total of 48 rules (Table 2). With the two main inputs of RMS and GP, the MVD statistic added to this model served to aid the system by increasing its robustness.

If one of the input variables were to present an incorrect value, the combinations of the other two would ensure a logical result for the control. To exemplify, if the RMS is very high, the GP is very low and the MVD statistic is also very high, the result will indicate a prediction of high burn. The simulation will assume that the GP value, which is outside the standard, is incorrect. Thus, the incorrect value will exert little influence in the analysis.

The three-dimensional analysis of the surface generated by the rules system of this model is shown in Figure 10. This analysis indicates that the rule base continues to be logically valid. As can be seen from the generated surface, the inputs of the RMS value of the acoustic emission signal and the grinding power (GP) exert a stronger influence on the system than the MVD statistic that was introduced.

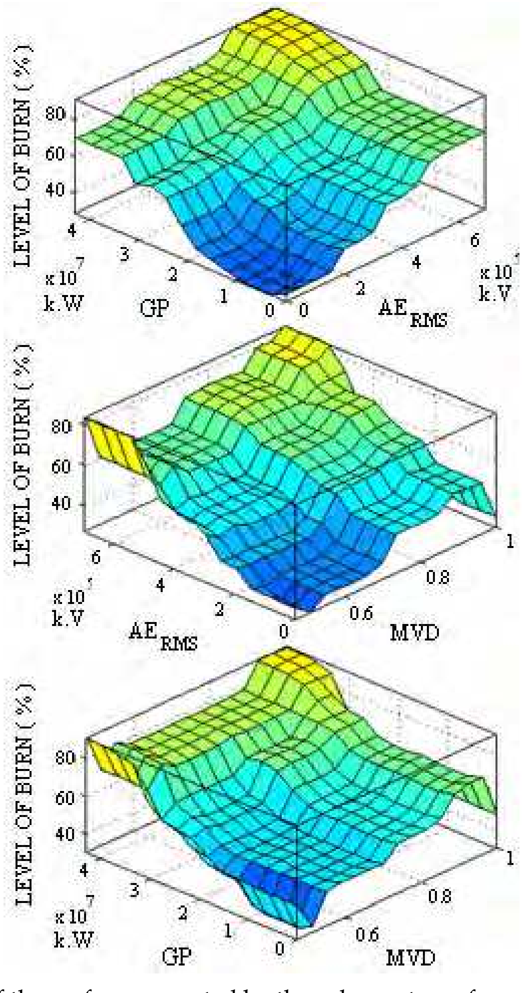


Fig. 10. 3D analysis of the surface generated by the rules system of model 2

The simulation of model 2 is performed following the same standard as model 1. A very high RMS value, a very low GP value, and a high MVD value result in a prediction of severe burn of the workpiece, with a value of 70.3% burn.

4.8.3 Model 3: Three-input control combined in triplets

The third model is based on the same three inputs described earlier, RMS, GP and MVD. The difference between this model and model 2 is the rule system. Its rules are based on the combination of three variables, i.e., all the inputs affect the resulting level of prediction. With a total of 64 rules described in Table 3, the third model possibly offers the best contribution of input signals in relation to the output. The advantage of this system in relation to that of model 1 is its more comprehensive complexity, which enhances its capacity to predict the burn level.

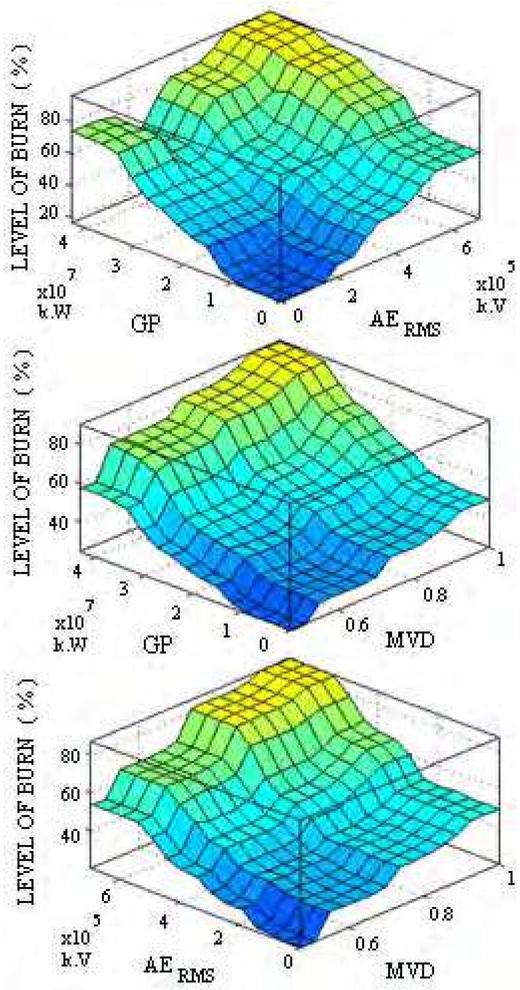


Fig. 11. 3D surfaces generated by the rules of model 3

Figure 11 depicts the 3D surfaces generated by the rules. As can be seen, the rules bases are valid due to their symmetry and flexibility. The main change in these surfaces compared to those of model 2 in Figure 11 is with respect to the RMS vs. MVD and GP vs. MVD analysis.

Previously, there was a high value in the prediction analysis with high RMS and low MVD. Now there is a value that provides equality, i.e., low RMS and low MVD generate a low value in the prediction analysis.

This model is simulated in the same way as the previous processes. A high value of RMS, GP and MVD generate an output with a prediction of 97% of burn of the workpiece, resulting in total damage of the machined material.

4.9 Conclusions

As can be seen, acoustic emission signals can be widely applied in monitoring grinding burn. The undeniable significance of this phenomenon stimulated the researchers to study different methods predict and even to quantify burn.

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

In terms of fuzzy modeling, the results of the proposed models were substantially validated. The imprecise information about statistical values of acoustic emission and electric power signals was transformed into reliable burn prediction values. Models 1, 2 and 3 differ from each other, enabling them to adapt to different circumstances.

The models may be attractive to the practicing engineer who would like to get fast answers for on-line intelligent control and optimization. In its current state, the models are limited to SAE 1020 steel and oxide grinding wheel, but they can easily be extended to other types of workpiece and tool materials.

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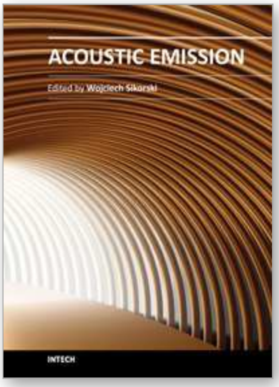

Acoustic Emission

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Acoustic emission (AE) is one of the most important non-destructive testing (NDT) methods for materials, constructions and machines. Acoustic emission is defined as the transient elastic energy that is spontaneously released when materials undergo deformation, fracture, or both. This interdisciplinary book consists of 17 chapters, which widely discuss the most important applications of AE method as machinery and civil structures condition assessment, fatigue and fracture materials research, detection of material defects and deformations, diagnostics of cutting tools and machine cutting process, monitoring of stress and ageing in materials, research, chemical reactions and phase transitions research, and earthquake prediction.

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