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Carlos Danilo G. Euzebio[2], carlos.danilo@uol.com.br
Paulo R. Aguiar[1], aguiarpr@feb.unesp.br
School of Engineering – FEB, UNESP - Universidade Estadual Paulista
Department of Electrical[1]/Mechanical[2] Engineering
Av. Luiz Edmundo Carrijo Coube, 14-01, Vargem Limpa, Cep 17033-360, Bauru-SP, Brazil

Hugo I. C. Miranda[1], hugo_iounchan@hotmail.com
Eduardo C. Bianchi[2], bianchi@feb.unesp.br
School of Engineering – FEB, UNESP - Universidade Estadual Paulista
Department of Electrical[1]/Mechanical[2] Engineering
Av. Luiz Edmundo Carrijo Coube, 14-01, Vargem Limpa, Cep 17033-360, Bauru-SP, Brazil

MONITORING OF GRINDING BURN BY FUZZY LOGIC

The grinding process is of high dimensional accuracy and provides a high degree of finish. Damages on the workpiece are of high cost, since all previous process besides the grinding itself is lost. In the case of metals, the most common cause of damage is excessive thermal input on the ground surface. One of the critical problems in implementing an intelligent grinding process is the automatic detection of workpiece surface burn. This work aimed to develop two models using fuzzy logic to predict the various levels of burning surface of the workpiece in the grinding process. Most engineering applications of fuzzy logic belong to "Linguistic Mathematics". It deals with engineering problem where variables cannot be assigned crisp numeric values or can be assigned context-dependent linguistic values. This is exactly applicable to a grinding process. For example, in the context of grinding, grain size cannot be specified by, say, diameter in micron. In practice, words like "coarse", "medium", and "fine" are found very vague but yet very expressive of the main characteristics. The workpieces for the grinding tests consisted of SAE 1020 laminated steel bars with dimensions of 150mm length, 10mm width and 60mm height. The grinding was performed along the length of the workpiece. The samples were inspected visually registering any change of color of the ground surface. Based on acoustic emission signals, cutting power, and the mean-value deviance (MVD), linguistic rules were established for the various burn situations (slight, intermediate, severe) by applying fuzzy logic using the Matlab Toolbox. Two practical fuzzy system models were developed. The first model with two inputs (root mean square of acoustic emission signal and the power signal from the electric motor that drives the wheel) resulted in a simple analysis process. The second model has an additional statistic input (MVD), associating information and precision. The two models differ by the number of association rules and the MVD input in the second model. The two developed models presented valid responses, proving effective, accurate, reliable and easy to use for the determination of ground workpiece burn. In this analysis, fuzzy logic translates the operator's human experience associated with powerful computational methods. The models may be attractive to the practicing engineer who would like to get quick answers for on-line intelligent control and/or 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 steels and grinding wheels.

***Keywords**: Fuzzy Logic, Grinding, Burn Monitoring*

1. INTRODUCTION

In the metal and mechanical industry, grinding is usually the final finishing process of a precision component. This process is used in the fabrication of parts of a wide variety of materials, requiring results such as low surface roughness, control of dimensional errors and shape of the workpiece, maximum tool life and time, and minimum costs.

Damage of the workpiece is costly, since the entire preceding process, as well as the grinding itself, is lost when a workpiece is damages in this stage. The most common types of damage in the grinding operation are burning, cracking, and or undesirable residual stresses. In the case of metals, the most common cause of damage is excessive thermal input on the ground surface.

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

The combination of acoustic emission signals and cutting power have been used successfully to determine parameters indicative of burning (Kwak *et al.,* 2004). These signals, treated and combined, allow for the implementation of a burn control system in real time, optimizing the grinding process (Dotto *et al., 2006)*. This would be highly beneficial for companies that 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 modeling, and usually require human intelligence (Pham *et al.,* 1999*)*.

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 (Pham *et al.,*1999).

Fuzzy logic has numerous applications in engineering, where the command of knowledge is usually imprecise. Interesting results have been achieved in the area of machine 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 *et al.,* 1995); prediction of surface roughness of ground components Ali *et al.,* 1999); control of grinding burn (Ali *et al.,* 2004); among others.

The development of an intelligent system for burn detection, prediction and classification still poses a challenge for researchers. Therefore, this work 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 Wang *et al.* (2001) demonstrated to be efficient in grinding burn detection, grinding power, and root mean square (RMS) of the acoustic emission signal used by Dotto *et al.* (2006).

2. BURN AND FUZZY LOGIC 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 to cause a localized phase change in the workpiece material. This occurrence can be observed visually from the discoloration of the workpiece surface (Malkin, 1989 e Kwak, 2001).

Malkin (1989), burning is expected when a critical temperature (~720°C) is exceeded in the grinding zone.

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 (Aguiar 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 (Ali et al., 2004). In addition, according to Ali et al. (2004), the production operation does not require a high precision "absolute" model because such precision is not reproduced in practice. What is needed, as Shaw (1996) points out, 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 a relative model will be a good starting point.

Based on these practical aspects, Ali et al., (2004) proposed a fuzzy model with 37 absolute rules and eight relative rules for predicting burn of ground workpiece surfaces. The model is designed for practical application, i.e., an operator can infer from the model, engineers can use it in planning the process, or the model can be part of an intelligent adaptive control, without the need for additional information.

Ge et al. (2002) proposed a fuzzy clustering method for evaluating the degree of grinding burn damage using burn color spots on a specimen's side surface. The method can replace the complicated wet grinding thermometry method. The results can be used as an index to evaluate the performance of cutting fluids for restricting grinding burn damage.

Liu et al. (2005) 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.

Other works employing fuzzy logic in the area of manufacturing can be found, including estimation of residual stress induced by grinding (Ali et al., 1997), prediction of surface roughness of ground components (Ali et al., 1999), classification of the condition of the grinding wheel's cutting ability (Lezanski et al., 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.

3. STATISTICAL PARAMETERS FOR BURN DETECTION

According to (Aguiar et al., 2001 e Tönshoff et al., 2000), acoustic emission and grinding power signals provide a variety of information about the grinding process.

However, more rigorous analyses can be obtained by treating signals with the help of statistical parameters.

With the help of mathematical manipulation software these signals can be treated to obtain information such as the RMS value, standard deviation, autocorrelation, FFT, etc.

Acoustic emission (AE) can be defined as elastic stress waves generated by the rapid release of deformation energy inside a material subjected to an external stimulus.

These stress waves produce displacements on the surface of the material that can be detected by a piezoelectric sensor that 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, 2000 e Liu, 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, 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 by Wang et al. (2001) in burn detection, 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 X is the mean value of { }k X ; 2M is the total number of FFT bins, and k X is the kth magnitudesquared FFT bin.

4. METHODOLOGY

4.1. Test bench

The grinding tests were carried out with a surface grinding machine (Sulmecânica RAPH-1055, Brazil) equipped with an aluminum 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's 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 the electric current and a Hall voltage sensor to measure the voltage in the electric motor terminals. Both signals were processed in the power transducer module by an integrated circuit, which delivers a voltage signal proportional to the electrical power consumed by the electric motor. The acoustic emission and power signals are then sent to the data acquisition board (National Instrument, 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 has 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 1 shows a schematic diagram of the grinding machine and instrumentation used.

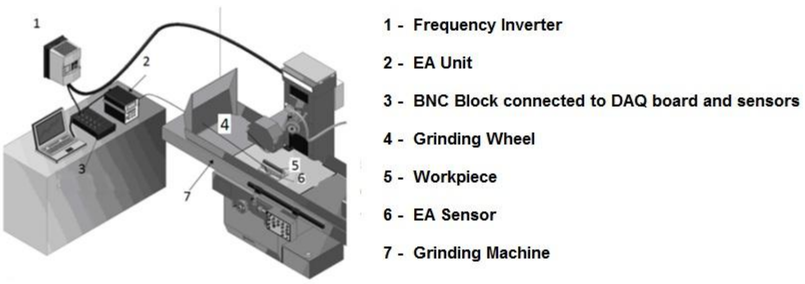

Figure 1 – Test bench layout

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

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tests progressed. The overlapping ratio, which is the relationship between the effective cutting width and the axial dressing feed rate, was set to 1, and the dressing condition was the same in all the tests. A water-based fluid was used with 4% concentration. Each run consisted of a single grinding pass of the grinding wheel along the workpiece length at a given grinding condition to be analyzed. 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 for further processing. 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 digital signal processing of acoustic emission generated the statistics previously described, i.e., the RMS value and MVD of acoustic emission.

4.2. CONSTRUCTION OF INPUT VECTORS

The percentage of burn and the degree of burn of each workpiece were determined using software developed by 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 software. 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 to define differences in the degrees of burn observed. 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 contain 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 (RMS, MVD and power) without distortions occurring among points in the comparisons.

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.

5. 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. Zadeh (1965) defined linguistic variables as "variables whose values are words or sentences in natural or artificial language". 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 2 shows a general model of a fuzzy inference system (FIS).

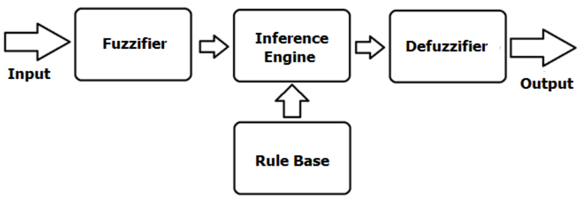

Figure 2 – Block diagram of a fuzzy inference system

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.

5.1. 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. The graph in Figure 3 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.

A clustering process (Ge et al., 2002) was applied to each numerical input, which consisted of determining 4 subclusters.

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 4 shows the fuzzified acoustic emission RMS input into the system by means of membership functions. The axis of the abscissas 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.

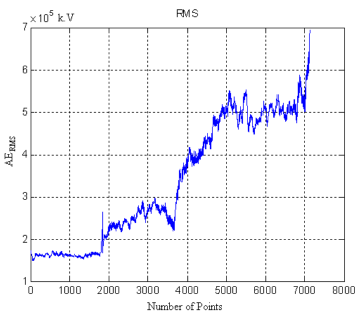

Figure 3 – Acoustic emission RMS graph

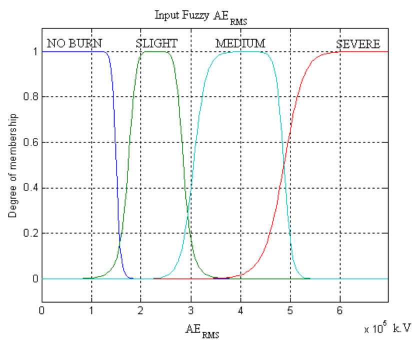

Figure 4 – Fuzzified Input of the RMS Acoustic Emission signal

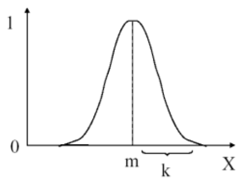

Figure 5 – Gaussian function

$$A(X) = e^{-k(x-m)^2}$$

where k > 0

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Estas funções de associação ajudam na conversão de valores numérico e variáveis em termos linguísticos.

The key features of a typical fuzzy set is defined by its pertinence function. This function, normalized between 0 and 1, expresses the gradual transition of pertinence to the non-pertinence. There are many ways to characterize this transition mathematically, both analytically and graphycally. Data normalization is necessary to transform the crisp values into fuzzy. This conversion was done with the help of mathematics, but not exclusively. The fuzzyfication was made by crisp graphics, observing the resulting values of subclusters for each group firing, normalizing the data to fuzzy.

The figure 5 represents the pertinence function used in this work. The gaussiana function is the one that best represents the fuzzy set due to its greater smoothness between the gradual changes in amplitude.

5.2. 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, very slight, slight, medium, severe, very severe, and total damage.

This scope is due to the fact that the model is not restricted to only 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. The axis of the abscissas is represented from 0 to 100, representing the percentage of burn of the workpiece in relation to the entire analyzed workpiece.

5.3. Inferences and Rule Base of Fuzzy Models

Based on the inputs and a fuzzified output, an inference was established between input and output (Hu et al., 2003). First, 2 logic system models were created. The first model had two inputs: the RMS of AE and the grinding power (GP). The second model has 3 inputs: the RMS of AE, the GP, and the MVD statistic. 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 1. Each input analyzed in all the models had the same weight relative to the system, i.e., all the inputs affect the system equally.

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 2

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

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

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

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

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5.4. Defuzzification of the Proposed Systems

Two 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. 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 3.

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$$COG = y_{crisp} = \frac{\sum_{i=1}^{n} \mu_A(y_i).y_i}{\sum_{i=1}^{n} \mu_A(y_i)} \quad (3)$$

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.

6. 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's toolbox.

6.1. Model 1: Two-Input Control

Based on the rules, a 3D surface was generated which allows one to visualize the effects of the rules on the system's inputs and output. Figure 6 shows this surface for the first model. This surface indicates how regular the newly developed rule base is. If the rule base is not completely consistent, disproportions and coarse irregularities are visible on the generated surface.

Continuity, transition and symmetry are characteristics well expressed in Figure 6. 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.

Once the consistency of the system's domain of inference has been verified, one can then predict the burn level of the workpiece surface based on values of the applied RMS signal and on the system's electric power. The simulation expressed in Figure 7, was carried out in Matlab and 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.

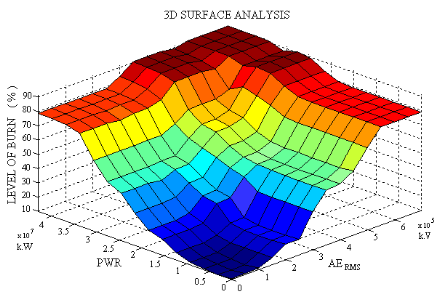

Figure 6 – 3D analysis of the surface generated by the rule system of model 1

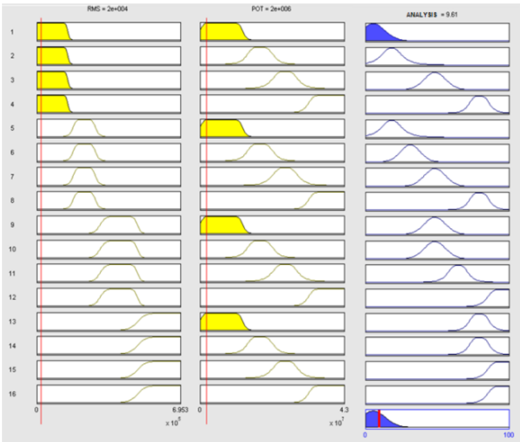

Figure 7 – Simulation of model 1.

6.2. Model 2: Three-Input Control Combined in Pairs

Model 2 was created to minimize this error an input variable containing an incorrect value of the system. As mentioned earlier, this second model has three fuzzified inputs. The idea of this model is that its rule base be combined in pairs, generating a total of 48 rules. The rule set is listed in 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 8. This analysis indicates that the rule base continues to be logically valid. As can be seen from the generated surface, the

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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.

The simulation of model 2 is performed following the same standard as model 1. A very high RMS value, 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.

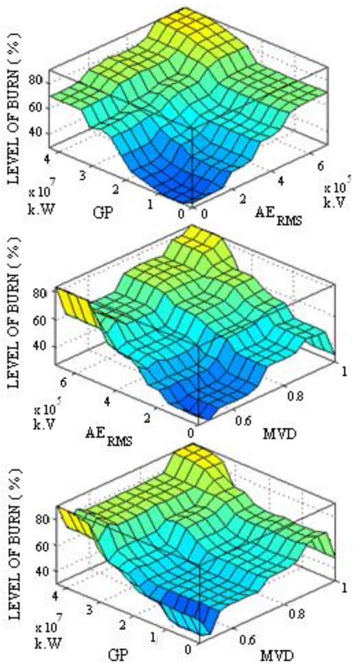

Figure 8 – 3D analysis of the surface generated by therules system of model 2.

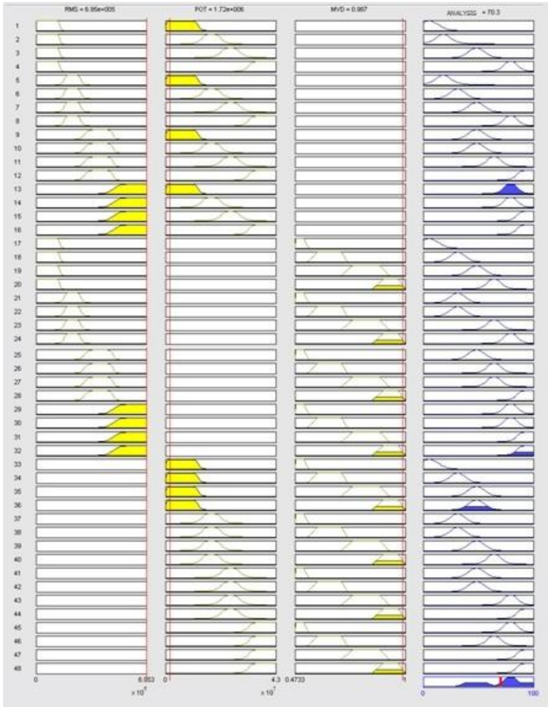

Figura 9 – Simulation of model 2.

7. CONCLUSION

The use of fuzzy logic in the process of predicting the burning of rectified piece is a great resource to be exploited. With the whole process of artificial intelligence, the fuzzy logic is capable of simulating systems associated with a very human experience. The propositions of simple logic models to more complex should be analyzed according to the degree of necessity of the required system.

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 and 2 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 quick answers for on-line intelligent control and/or 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 steels and grinding wheels. The figure 9 represents the output of fuzzy inference, having as a result a value close to 70,3 %.

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10. RESPONSIBILITY NOTICE

Carlos Danilo G. Euzebio[2], carlos.danilo@uol.com.br
Paulo R. Aguiar[1], aguiarpr@feb.unesp.br
Hugo I. C. Miranda[1], hugo_iounchan@hotmail.com
Eduardo C. Bianchi[2], bianchi@feb.unesp.br
School of Engineering – FEB, UNESP - Universidade Estadual Paulista
Department of Electrical[1]/Mechanical[2] Engineering
Av. Luiz Edmundo Carrijo Coube, 14-01, Vargem Limpa, Cep 17033-360, Bauru-SP, Brazil

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