

# Predicting Surface Roughness in Grinding using Neural Networks

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## 1. Introduction

High rates of manufactured items have been machined by grinding at some stage of their production process, or have been processed by machines whose precision is a direct result of abrasive operations. However, even being the grinding process the most used in industry for obtaining high level of surface quality, it remains as one of the most difficult and least understood processes (Wang et al., 2005). That maybe has origin in the mistaken faith the process is extremely complex to be understood due to the large number of cutting edges and irregular geometry, high cutting speed, and very small depth of cut which varies from grain to grain. In addition, according to (Haussi & Diniz, 2003), grinding is the process indicated when the workpiece demands good surface, dimensional and geometrical quality. Thus, the grinding process is usually one of the last steps in the machining operations chain. When the workpiece reaches this point, it has high aggregated value, which makes a possible rejection very expensive.

Monitoring of machining processes is mandatory for their optimization and control. Acoustic emission (AE) has become an increasingly popular monitoring technique. The sensors are inexpensive, easy to mount, and analog signal processing is comparatively simple, but good techniques for extracting reliable process information from the signals are still lacking (Hundt et al., 1997; Aguiar et al., 2002).

Electrical power signals have also been largely used in grinding researches. The signal can be monitored either by the electric current of the electric motor or by the product between voltage and current signals, which gives the electrical power consumed by the electric motor. Thus, an estimate of the cutting force can be easily obtained if a model of the electric motor is available (Aguiar et al., 2002).

Some researchers have shown the acoustic emission and the cutting power signals combined can provide significant results for monitoring the grinding process phenomena (Aguiar et al., 2002; Dotto et al., 2006; Kwak & Ha, 2004; Aguiar et al., 2006).

Neural network has attracted a special interest in grinding research owing to its functions of learning, interpolation, pattern recognition, and pattern classification. Various examples of applications into the production engineering field have been reported (Wang et al., 2005; Dotto et al., 2006; Kwak & Ha, 2004; Aguiar et al., 2006; Wang et al., 2001).

According to (Wang et al., 2005), surface roughness is one of the most important factors in assessing and determining the quality of a part. In practical, predicting and controlling the

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roughness is difficult due to the fact that many variables are affecting the process and many of these variables are non-linear, interdependent, or difficult to quantify with crisp numeric precision. Still, taking into account that some grinding processes can only be represented by experimental data or linguistic descriptions, the usage of intelligent systems into the optimization of grinding processes appears to be inevitable.

The objective of this work was to use neural networks to predict the surface roughness of ground workpieces based on the analysis of several process output variables, such as acoustic emission, cutting power, and other statistics generated from these signals.

## 2. Literature review

Machining with grinding wheels is a very complex process affected by so many factors that a reproducible result is rarely obtained. The most important one is that the cutting ability of the grinding wheel changes considerably during the grinding time. In practice, the grinding process is carried out with cutting parameters which are safe but not optimal. The workpiece quality depends to a great extent on the experience of the operator (Lezanski & Rafalowicz, 1993).

The result of a grinding process can be subdivided into characteristics concerning the geometry and surface integrity of a ground component. The geometrical quantities are dimension, shape and waviness, as essential macro-geometric quantities; whereas the roughness condition is the main micro-geometric quantity. The surface integrity state can be described by residual stresses, hardness and structure of the material (Brinksmeier et al., 1998).

According to (Bhushan, 2001), solid surfaces, irrespective of their method of formation, contain irregularities or deviations from the prescribed geometrical form. The surfaces contain irregularities of various orders ranging from shape deviations to irregularities of the order of interatomic distances. No machining method, however precise, can produce a molecularly flat surface on conventional materials. Even the smoothest surfaces, such as those obtained by cleavage of some crystals, contain irregularities, the heights of which exceed the interatomic distances. For technological applications, both macro and micro-nanotopography of the surfaces (surface texture) are important.

A very general topology of a solid surface is seen in Figure 1. Surface textures that are deterministic may be studied by relatively simple analytical and empirical methods; their detailed characterization is straightforward. However, the textures of most engineering surfaces are random, either isotropic or anisotropic, and either Gaussian or non-Gaussian. Whether the surface height distribution is isotropic or anisotropic and Gaussian or non-Gaussian depends upon the nature of the processing method. Surfaces that are formed by cumulative processes (such as peening, electropolishing, and lapping), in which the final shape of each region is the cumulative result of a large number of random discrete local events and irrespective of the distribution governing each individual event, will produce a cumulative effect that is governed by the Gaussian form. It is a direct consequence of the central limit theorem of statistical theory. Single-point processes (such as turning and shaping) and extreme-value processes (such as grinding and milling) generally lead to anisotropic and non-Gaussian surfaces. The Gaussian (normal) distribution has become one of the mainstays of surface classification (Bhushan, 2001).

A typical parameter that has been used to quantify the quality of a surface topography is the surface roughness, which is represented by the arithmetic mean value,  $R_a$ , the root-mean-

square-average,  $R_q$ , and the maximum roughness height,  $R_t$ . In general, the longitudinal surface roughness has a lower value than the traverse surface roughness; therefore the latter is more frequently used in industry (Hecker & Liang, 2003). Still, according to (Kwak et al., 2006) the surface roughness obtained in grinding depends in a complex way upon the roughness of the wheel surface, the grinding parameters, and tribological interactions between the abrasive cutting points and the workpiece.

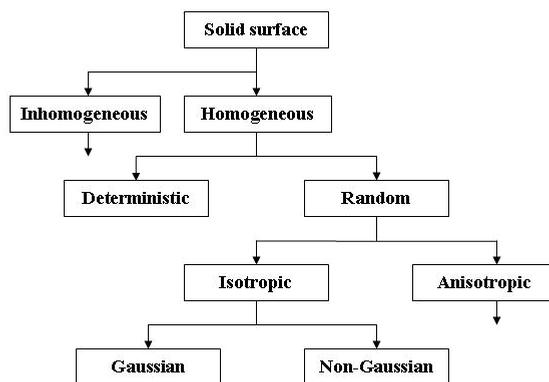


Fig. 1. General typology of surfaces (Bhushan, 2001)

Several sensing schemes for monitoring tool condition and cutting status in normal machining have been proposed and evaluated in the last two decades. However, the technique which involves monitoring the acoustic emission generated during the machining operation has been found to be very sensitive to elements of metal removal, such as sliding contact, plastic deformation, phase transformation, micro-cracking, fracture, impacts and so on (Dornfeld, 1985). The acoustic emission sensing technique uses the information contained in the transient elastic stress wave, which is generated by rapid release of energy within a material, to provide knowledge about the state of the process.

The application of signals from the cutting process became a more interesting tool when neural networks are used for their processing and interpretation. This tool has attracted interest of several researchers in the surface roughness prediction (Wang, 2005; Aguiar et al., 2006; Kwak et al., 2006; Fredj et al., 2002).

Artificial neural networks have been studied for many years in the hope of achieving the human-like performance in the field of the speech, image recognition and the pattern classification. These neural networks are composed of many non-linear computational elements operating in parallel. Neural Networks, because of their massive nature, can perform computations at a higher rate. Because of their adaptative nature using the learning process, neural networks can adapt to changes in the data and learn the characteristics of the input signals (Kwak & Ha, 2004). Still, according to the author, the ability to learn is a fundamental trait of the neural network. Although a precise definition of learning is difficult to formulate, the learning in a neural network means the finding an appropriate set of the weights that are connection strengths from the elements to the other layer elements.

What makes this work distinguished from others is the use of grinding parameters as input to the neural network, which have not been tested yet in surface roughness prediction by neural networks. Besides, a high sampling rate data acquisition system was employed to acquire the acoustic emission and cutting power.

### 3. Methodology

The materials, methods and equipments used for the development of the grinding tests, surface roughness measurements, training and validation of the neural networks will be presented in the next section.

#### 3.1 Experimental set-up and grinding parameters

The workpieces for the grinding tests consisted of laminated bars of steel SAE 1020 ground in the shape of a prism with 150mm length, 12.7mm width and 43mm height. A surface grinding machine from Sulmecânica manufacturer, Brazil, model RAPH-1055 was used in the grinding tests. The grinder was equipped with an aluminium oxide grinding wheel, from Norton Manufacturer, Model ART-FE-38A80PVH.

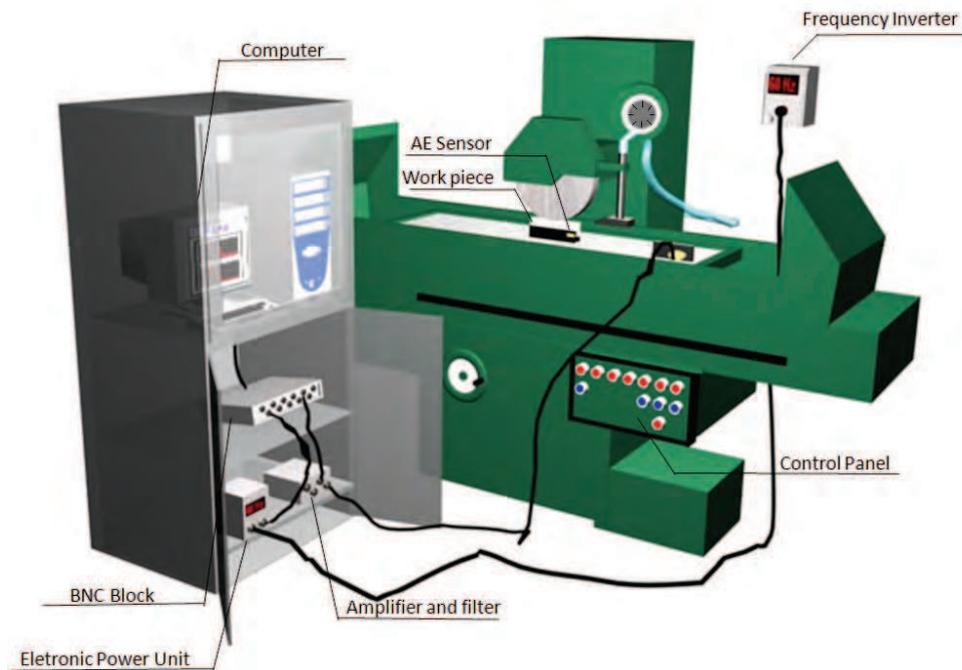


Figure 2. Schematic diagram of the grinding machine and instrumentation

A fixed acoustic emission sensor from Sensis manufacturer, model DM-42, placed near the workpiece and an electrical power transducer for measuring the electrical power consumed from the three-phase induction motor that drives the wheel were employed. The power transducer consists of a Hall sensor to measure the electric current and a Hall voltage sensor to measure the voltage at the electric motor terminals. Both signals are processed internally 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 as well as the power signal are further sent to the data acquisition board from National Instrument, model PCI-6011, which is installed into a personal computer.

The LabVIEW software was utilized for acquiring the signals and storing them into binary files for further processing and analysis. The acoustic emission sensor used 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 2 shows the schematic diagram of the grinding machine and instrumentation used.

The tests were carried out for 15 different grinding conditions, using  $5\mu\text{m}$  as the lowest depth of cut and  $50\mu\text{m}$  as the largest one. Dressing parameters, lubrication and peripheral wheel speed were adequately controlled in order to ensure the same grinding condition for the three repetitions of each test. The workpiece speed was set up at  $0.043\text{ m/s}$  and the wheel speed at  $30\text{ m/s}$ . The latter was maintained constant by adjusting the frequency of the induction motor on the frequency inverter, as the grinding wheel had its diameter decreased along the tests.

The dressing overlap ratio ( $U_d$ ), which determines the wheel sharp level (Malkin, 1989), was set to 1 for all the tests. To control this parameter, the width of the dressing diamond tip was measured before each test. The measurements have been done using a profile projector which allows micrometer precision. Figure 3 shows the scheme used to measure the dressing diamond tip.

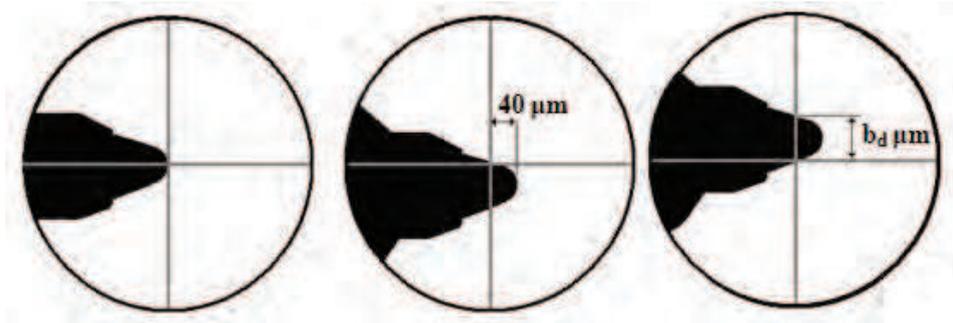


Figure 3. Method used to measure dressing tip width ( $b_d$ ) on a profile projector.

Using equation 1 is possible to determine the dressing speed

$$V_d = \frac{n \cdot b_d}{U_d \cdot 60} \quad (1)$$

Where:  $V_d$  is the dressing speed;  $L_r$  is the wheel width ( $31,75\text{ mm}$ );  $n$  the wheel rotation ( $1800\text{rpm}$ ). For a better understanding, figure 4 was built to show some details on the dressing operation used in this work. It can be observed the single-point diamond moving across the wheel surface with direction given by the speed vector  $v_d$ .

A water-based fluid was used with 4% concentration. Each run consisted of a single grinding pass of the grinding wheel along the workpiece at a given grinding condition to be analyzed. The acoustic emission and cutting power signals were measured in real time at 2.5 millions of samples per second rate, and then stored onto 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.

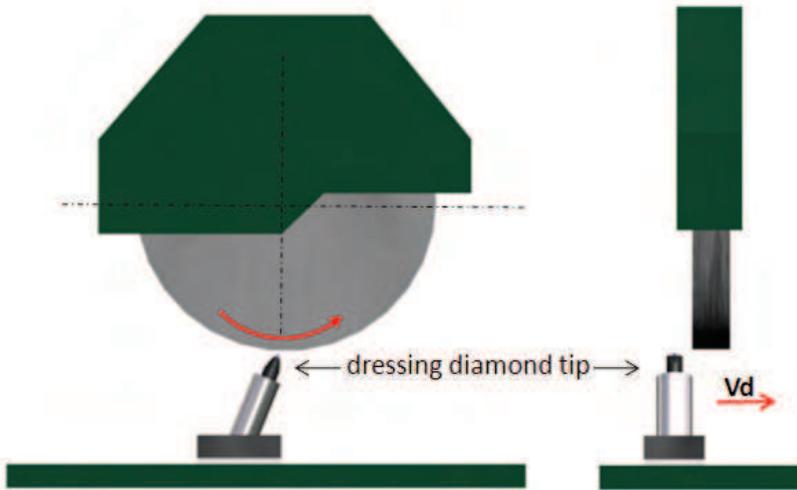


Figure 4. Dressing operation with single-point diamond.

### 3.2 Surface roughness measurements

Once all the grinding tests were done, surface roughness measurements were taken using a Surtronic 3+ tester and Taylor Hobson's TalyProfile software, version Lite 3.1.4, adjusted to a length of 8 mm sampling rate. Figure 5 shows the regions along the workpiece where the surface roughnesses were taken which accounted for 15 measurements. The surface roughness  $R_a$  was defined as the measurement parameter.

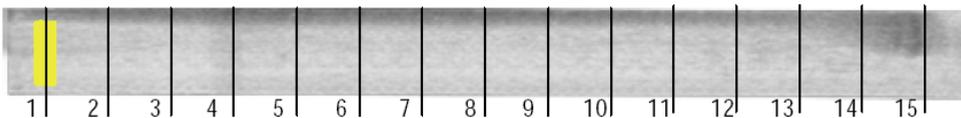


Figure 5. Lines showing the 15 regions along the workpiece where the surface roughness was measured

These data on surface roughness were naturally used in the neural networks, and they allow to verifying the magnitudes and efficiency of the system for prediction.

### 3.3 Statistical parameters used in the neural networks

Many parameters for monitoring fault in the grinding process have been studied. Two important parameters investigated by (Aguar et al., 2002) and (Dotto et al., 2006) are DPO and DPKS. The DPO is defined as the standard deviation of the root mean square of acoustic emission signal multiplied by the maximum value of electric power in the grinding cycle or pass. The DPKS is the sum of the difference to the fourth power between cutting power and standard deviation of the cutting power multiplied by the standard deviation of the root mean square acoustic emission in the grinding cycle or pass. The DPO and DPKS are shown by equations 2 and 3 respectively.

$$DPO = std(AE)Max(Power) \quad (2)$$

$$DPKS = \left\{ \sum_{i=1}^{i=m} [Power(i) - std(Power)]^4 \right\} std(AE) \quad (3)$$

Where Max is the maximum value; Power the cutting power; AE the acoustic emission; std the standard deviation, m was set to 1024 in this work.

Thus, DPO and DPKS parameters were obtained from the data files stored during the acquisition. As these parameters were efficient at detecting grinding burn, they were tested as being the inputs of the neural networks in this research.

### 3.4 Neural network and input sets

Among several well known techniques of artificial intelligence are artificial neural networks, which basically consist of computational models analogous to the human brain whose main characteristic is the capability of learning (Aguiar et al, 2006). They are composed of many non-linear computational elements operating in parallel fashion. Neural networks, because of their massive nature, can perform computations at a higher rate. Due to their adaptive nature in using the learning process, neural networks can adapt to changes in the data and learn the characteristics of input signals (Kwak & Ha, 2004). In this work, the back-propagation algorithm of neural networks, which is one of the learning models, was used. Three hidden layers composed of 60, 40 and 20 neurons were found to be the best configuration for the neural networks studied. The following parameters were also found more suitable: sigmoid tangent activation function for the neurons of the hidden layers; linear activation function for the neurons of the last layer, downward gradient training algorithm; all data in the neural networks were normalized; training for 10000 epochs; square mean error value of 10-5; learning rate of 0.3; and momentum coefficient of 0.4. Table 1 shows three different sets used for the neural networks.

Set	Neural Network Configuration
1	AE, Cutting Power and Depth of Cut
2	AE, Cutting Power, DPO, DPKS and Depth of Cut
3	DPO and Depth of Cut

Table 1. Neural Network Configurations

## 4. Results and discussion

The measurements of surface roughness have shown an increase in magnitude as the depth of cut was increasing, mainly after the test with 35  $\mu\text{m}$  depth of cut where grinding burn on the workpiece surface took place. In order to illustrate that increase in surface roughness, Figure 6 shows the mean values of surface roughness ( $\mu\text{m}$ ) calculated for each depth of cut used for 15 regions along the workpiece (Figure 5) and three repetitions for each grinding condition. It can be observed the high standard deviation values more easily visible to those conditions of greater depth of cut, due mostly to encompass the mean of surface roughness along the workpiece. This factor can be better explained by the difference of surface roughness along the workpiece length; mainly in the tests where in certain region of the workpiece burn occurred. Thus, there was a great difference between the surface roughness values for the region where burn took place and the region with no burn.

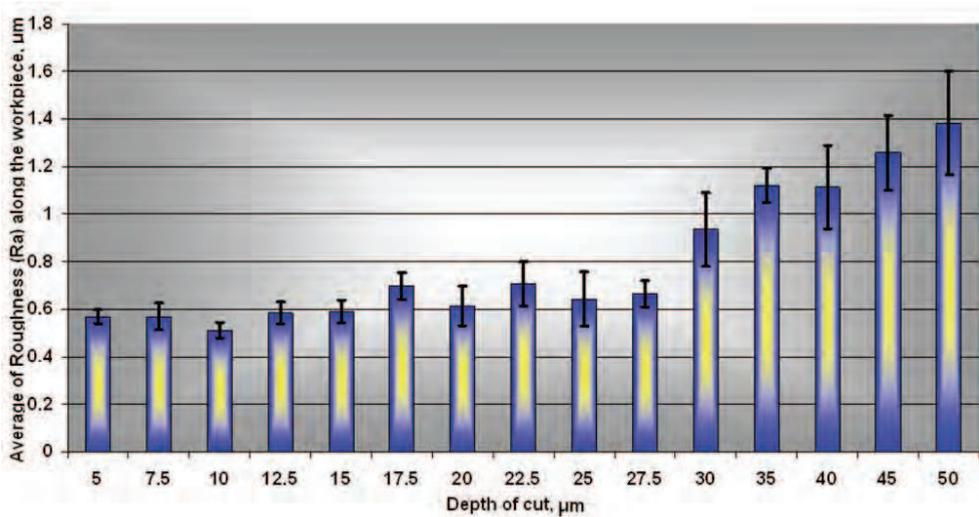


Figure 6. Average of Surface Roughness Ra ( $\mu\text{m}$ ) along the workpiece in function of the depth of cut ( $\mu\text{m}$ ) for 15 grinding runs.

It is important to point out that Figure 6 was built just for easily visualization of the surface roughness behaviour in relation to the depth of cut, provided the training and validation tests in the neural networks the surface roughness for each measured region was used. From the grinding tests acoustic emission and cutting power vectors were extracted. Following each test, the root mean square of AE and filtering of both signals were obtained in order to check the success of the test as shown in Figure 7.

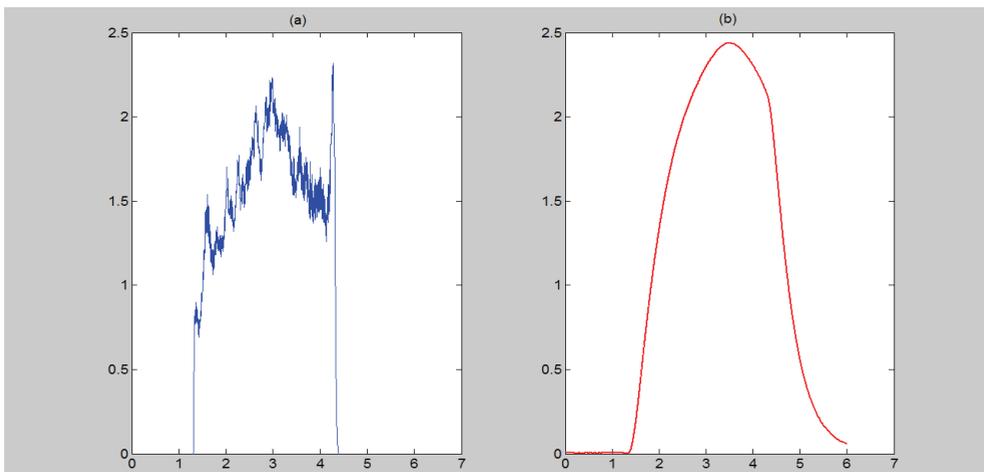


Figure 7. Acoustic Emission (a) and Cutting Power (b). Horizontal axis in seconds; Vertical axis in Volts.

These vectors were applied to the training of the neural networks, which provided surface roughness values and allowed the analysis of the system efficiency. The quantification of

errors was done point by point through the computation of the absolute value of the difference between the measured values of surface roughness and the values given by the neural network. That was done for each of the 15 regions along the workpiece and for each workpiece.

Figure 8 shows the average values of square errors for all 15 regions along the workpiece length and 3 repetitions of each grinding condition as well as the variation of the error in each of those conditions. The lateral bar exhibits the three groups of errors found, that is, the lowest one the success, errors about  $10^{-1}$   $\mu\text{m}$  in the middle in green, and errors equal to or greater than 1  $\mu\text{m}$  on the top in red.

Figure 8. Average values of square errors, maximum and minimum errors values for each of 15 workpiece regions and 3 repetitions of each grinding condition.

It can be seen in Figure 8 the set number 1 presented error quite high to those greater depths of cut studied, overreaching the value of 1  $\mu\text{m}$  for the last three grinding conditions. As mentioned previously, from the analysis of workpiece integrity it can be observed the grinding burn started at depth of cut of 35  $\mu\text{m}$ . Thus, acoustic emission, cutting power and depth of cut have not responded very well as inputs to the neural network in the surface roughness prediction. However, the error observed does not necessarily mean that those parameters are not adequate to monitor other grinding control parameters, for instance, the grinding burn. The set number 2 has also presented greater errors in the last three grinding conditions but they have not overreached in average value of 1  $\mu\text{m}$ .

Based on this information, the difference between the real measurements and the output of the neural networks can be classified in three groups: The first group for errors not greater than  $10^{-2}$   $\mu\text{m}$ , the second group for errors of about  $10^{-1}$   $\mu\text{m}$ , and the third group for errors equal to or greater than 1  $\mu\text{m}$ .

As the surface roughness measurement device used in this work allows measurements with precision of two decimal digits, the last digit of this equipment is concerned with the uncertainty of the measurement. Thus, all the errors in the range of  $10^{-2}$   $\mu\text{m}$  or inferior were considered to be successful in the prediction of the surface roughness. This remark is reinforced by the tolerances applied to the grinding process in industry, which in general has tolerances in the range of  $10^{-1}$   $\mu\text{m}$ .

In the second group, errors of about  $10^{-1}$   $\mu\text{m}$  was thought as bad ones, but it would be mostly fine in industry depending on the type of part ground. Finally, the third group of errors is in the range of 1  $\mu\text{m}$  or superior, which is classified as very bad ones.

Based on these analyses, we can see in Figure 8 that for many conditions, neural network had a hundred percent of success or almost that, mainly in the region from 5  $\mu\text{m}$  of depth of cut to 30  $\mu\text{m}$ , proving a total efficiency of the system for certain processes. These conditions are, for example, 10  $\mu\text{m}$ , 12.5  $\mu\text{m}$ , 15  $\mu\text{m}$  and 17.5  $\mu\text{m}$  for Set 1 and Set 2, and from 10  $\mu\text{m}$  to 30  $\mu\text{m}$  for Set 3.

It is important to point out that the great efficiency of the process occurred in the area of industrial application, since the largest rate of success was obtained exactly when burn on the workpiece doesn't succeed.

Comparing the values of surface roughness obtained in the tests and shown in Figure 6 it can be inferred that the studied process is optimized using 27.5 $\mu\text{m}$  depth of cut. This depth of cut represents the largest material removal rate employed before grinding burn takes place. Surface roughness values are similar to the grinding conditions before 27.5 $\mu\text{m}$  depth of cut.

Figure 9 was built in order to facilitate the comparison among the 3 input Sets and to show the general result of the values in all tested conditions.

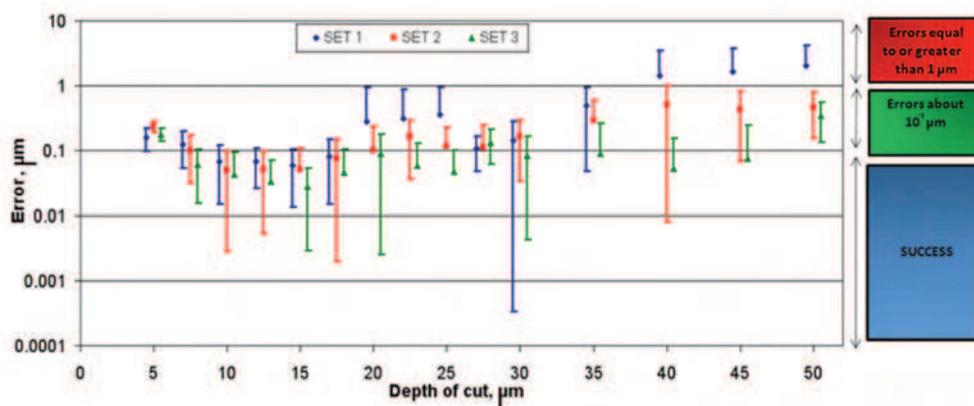


Figure 9. Percentage of errors and success of the neural network prediction for each set

Observing Figure 9 and other results from the neural network output as well as the comparison between the surface roughness values, the following remarks can be summarized. From the sets utilized in the neural network training, the set number 3 (DPO and depth of cut) has presented the best output values for almost every grinding condition tested. This set of inputs has provided about 70% of success in the prediction of surface roughness analyzed region by region. In addition, it has not presented any error classified as bad one for the grinding process control.

The set number 1, composed by acoustic emission, cutting power and depth of cut, has presented satisfactory performance in the vast majority of the grinding condition tested, showing however pretty high errors mainly in the conditions of high depth of cut. Burning of the workpieces has occurred in these conditions, which can be understood as if this set is sensitive to others parameters besides surface roughness.

In the same way as occurred with set number 1, set number 2 (AE, cutting power, DPO, DPKS and depth of cut) also had good performance. The values of prediction for these two sets have alternated themselves, either for better or for worse when they are compared to each other. It is important to highlight that the set number 1 has showed higher errors than those seen in the set number 3 for some conditions. However, it has obtained good performance in the analysis of bad errors, showing only 3.1% for this kind of error.

## 5. Conclusions

The technique of surface roughness prediction has been developed using multi-sensor method with AE sensor and power meter for grinding process. Based on the results presented in this research, it can be concluded that acoustic emission and cutting power signals are very good input parameters to the neural network for surface roughness prediction of ground parts. Thus, the implementation of these signals is feasible in the control of grinding process in industry, provided that very low percentage of “bad” errors presented by the neural network was found. From the sets used in the training of the neural networks, and for the grinding conditions and methods employed, the set number 3 composed only by the DPO parameter and depth of cut has presented the best results. This set has reached about 70% of success in the prediction and none “bad” error, and for the condition where workpiece burn didn’t occur success at prediction was almost 100%. In the comparison of errors generated by each set, set 3 was followed either by the set 1 or set 2. Because the level of errors found in the utilization of set number 3 as input to the neural network, the use of DPO parameter is highly attractive for predicting surface roughness in grinding. Therefore, an analog DPO output signal could be generated by an electronic circuitry with no need for further digital processing of AE and cutting power signals.

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The book presents an excellent overview of the recent developments in the different areas of Robotics, Automation and Control. Through its 24 chapters, this book presents topics related to control and robot design; it also introduces new mathematical tools and techniques devoted to improve the system modeling and control. An important point is the use of rational agents and heuristic techniques to cope with the computational complexity required for controlling complex systems. Through this book, we also find navigation and vision algorithms, automatic handwritten comprehension and speech recognition systems that will be included in the next generation of productive systems developed by man.

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