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Analysis of Forecasting Capabilities of Ground Surfaces Valuation Using Artificial Neural Networks

Industry worldwide has been marked by intense competition in recent years, placing companies under ever increasing pressure to improve the efficiency of their product processes. In addition to efficiency, precision is an extremely important factor, allowing companies to maintain standards and procedures aligned with international standards. One of the finishing processes most widely utilized for the manufacturing of mechanical precision components is grinding, and one of the principal criteria for evaluating the final quality of a product is its surface, which is influenced mainly by thermal and mechanical factors. Thus, the objective of this work was to investigate the intrinsic relationship between the surface quality of ground workpieces and the behavior of the corresponding acoustic emission and grinding power signals in the surface grinding processes, using artificial neural networks. The surface quality of workpieces was analyzed based on parameters of surface grinding burn, surface roughness and microhardness. The use of artifice-al neural networks in the characterization of the surface quality ground workpieces was found to yield good results, constituting an interesting proposal for the implementation of intelligent systems in industrial environments.
Keywords: grinding, burn detection, surface roughness, hardness, artificial neural networks

Introduction

Grinding is a high specific energy finish machining process that is used widely in the manufacture of components requiring fine tolerances and smooth finishes. Grinding is the last stage in the manufacturing process, which is why it affords a high added value to the end product. Despite its importance and popularity, grinding still remains as one of the most difficult and least understood processes (Wang et al., 2005; Aguiar et al., 2002).

The need for effective cost reduction, allied to the enhanced quality of workpieces produced, requires the implementation of intelligent monitoring and control systems that are adaptable to industrial environments. Thus, controlling damage caused in the grinding process is of direct interest to all the sectors that depend on this process, favoring a lower rate of workpiece loss and, hence, lower production costs. Given the importance of the process, the development of this area is indispensable for the metal and mechanical industry.

Researchers have used a variety of techniques aimed at effectively controlling the grinding process, including acoustic emission (AE) and grinding power signals. These signals have been successfully used to determine parameters that indicate burn, and predict surface roughness, circularity, microhardness, etc.

Several researchers have demonstrated that, when treated and combined, acoustic emission and grinding power signals can allow the implementation of control systems in real time, thus optimizing

the grinding process (Aguiar et al., 2002; Dotto et al., 2006; Kwak and Ha, 2004; Aguiar et al., 2006).

The capability of a machine to perform functions generally associated with human intelligence is referred to artificial intelligence (AI). Grinding and other machining processes are suited to the application of AI techniques, because industrial practice relies strongly on skilled operators to achieve good results. In the artificial intelligence field, artificial neural networks have attracted a special interest in grinding research owing to its functions of learning, interpolation, pattern recognition, and pattern classification.

In this work, the surface quality of workpieces ground by the surface grinding method was evaluated based on three parameters: burn detection, surface roughness and microhardness. Three different structures were analyzed, using artificial neural networks as a tool to evaluate the results. The greatest challenge of this work was to devise a single structure that would be able to predict the occurrence of the burn phenomenon and provide predictions of the parameters of surface roughness and microhardness for given grinding conditions.

Thermal Damage and Monitoring of Grinding

Unlike manufacturing processes using tools with defined geometries, such as milling and turning, in grinding the chips, are removed by a very great amount of geometrically undefined cutting edges. The abrasive is composed of cutting grains that remove tiny chips of material, which is why the surface finish of a workpiece is usually superior to that obtained through other machining processes.

Damage on the surface of workpieces during the grinding operation can be caused by thermal, mechanical or chemical effects.

One of the most common types of thermal damage in the grinding process is burn of the workpiece. Burn in steels is characterized by a visible bluish temper color on the ground surface. In steel, due to the burning phenomenon, the temper color changes from light brown to dark brown to violet to blue, in that order, depending on the severity of burn. Grinding burn is best-detected by optical microscopic examination of the ground surface or by appropriate metallographic etching of the surface. However, this is only an off-line, destructive technique for burn detection to avoid wastage, to save time and to improve productivity; an in-process technique for burn identification is needed (Nathan et al., 1999).

Two important properties of materials are surface roughness and hardness. Surface roughness is characterized by geometric microirregularities on the surface of machined material. Surface roughness is generated by the interaction between the topography of the grinding wheel surface and the workpiece under the kinematic movements imposed by the machine. The morphological analysis of ground surfaces presents an additional complexity due to the innumerable phenomena involved in the process, such as slipping, attrition, plastic deformations without removal of material, and cutting of the material itself. The surface roughness requirement is often a consequence of dimensional tolerance requirements and the product's final quality, and both these factors can be similarly affected by grinding conditions. Controlling surface roughness in a machining process is extremely important and should be done through the management and optimization of the machining processes and conditions. Hardness, in turn, is an important mechanical property of materials, and is a measure of its resistance to localized plastic deformation. These are therefore important parameters for characterizing the final quality of products originating from machining processes.

According to Tonshoff et al. (2000), international competitiveness requires increased throughput and reduced innovation time in combination with high product quality. In the last few years, the use of monitoring systems for production processes has been increased to improve workpiece quality. There are a number of requirements which lead to the installation of a monitoring system in manufacturing. Cost intensive machines have to maintain reliability in order to ensure economical and ecological advantage. Systems for in-process quality assurance offer the possibility of reacting quickly to measured defects. Especially for processes located at the end of the value chain, such as hard turning and grinding, continuous process control is necessary to avoid rejects and refinishing.

The rapid development of methods and tools involved in artificial neural networks has generated enormous interest in finding solutions for manufacturing-related problems.

One of the most well known computational intelligence techniques are artificial neural networks (ANN), which are computational models analogous to the human brain and whose most outstanding characteristic is their ability to learn (Aguiar et al., 2006). In situations where the variables to be studied have complex or nonlinear relationships, neural networks are an efficient tool when compared with other classical prediction methods.

According to Brinksmeier et al. (2006), ANN models are distinguished by several properties, which make them suitable for modeling of complex, nonstationary processes that depend on many input variables. To obtain an ANN model of a process no analytical expressions for the underlying physical phenomena are required. The ANN model is constructed automatically through a training procedure based on process data. Also, ANN models are able to simultaneously process information from different sensors and physical quantities, which need not to be related. Such processing of information from various sources is called sensor fusion. Finally, the authors reported that ANN models can be effectively combined with physical models to further improve the modeling performance. Due to these properties, the ANN models continue to be considered as a tool suitable for modeling of grinding processes.

Using artificial neural networks, Nathan et al. (1999) monitored the power and temperature in the cutting region in a cylindrical grinding process. In their study, the artificial neural networks successfully predicted the moment of the onset of burn.

Kwak and Song (2001) used artificial neural networks trained with the backpropagation algorithm to predict problems frequently found in the cylindrical grinding process. They analyzed the occurrence of burn and of induced vibration in ground workpieces. The network they utilized proved efficient at predicting these patterns, showing success rates of 95% in the diagnosis of burn and vibrations.

In a similar study conducted by Saravanapriyan et al. (2001), the burn temperature was studied as a function of the AE signal, normal cutting force, vibration, and the number of grinding cycles. The data from their experimental tests were applied to an artificial neural network structure. The method proved effective for the purpose of their study, reinforcing the effectiveness of the use of AE signals and of artificial neural networks in monitoring grinding processes.

Wang et al. (2001) proposed artificial neural network structures to detect the occurrence of burn in grinding and collected AE signals for subsequent use in the networks they studied. Their results indicated that the use of neural networks led to an effective performance in the prediction of burn.

Aguiar et al. (2006) presented a study which involved the use of artificial neural networks to predict surface roughness and circularity parameters of workpieces ground in the cylindrical grinding process. To carry out this study, they used parameters from experimental tests, using AE and cutting force signals, DPO parameter, etc. Their results confirmed the successful prediction of surface roughness and circularity, with the neural networks showing results very similar to the experimental ones.

Spadotto et al. (2007) reported in their study that the artificial neural network structure was implemented using AE and grinding power signals as inputs, aiming to quantify the percentage of surface burn on workpieces ground in the surface grinding. The results showed the neural networks can provide reliable information about the workpiece integrity when properly trained.

Aguiar et al. (2007) conducted a study to analyze the surface roughness of ground workpieces based on various statistical parameters obtained by monitoring acoustic emission and grinding power signals applied to artificial neural networks. In their work, the networks achieved success rates of approximately 70% in the predictions of surface roughness.

Experimental Set-up and Measurements

The experimental set-up for this work is illustrated in Fig. 1. The workpieces used in the tests were taken from SAE 1020 steel, with final dimensions of 160 mm length, 12.7 mm width and 43 mm height. The tests were carried out with a Sulmecânica, model RAPH-1055, surface grinding machine equipped with a conventional aluminum oxide grinding wheel (NORTON, model ART-FE-38A80PVH) of medium granulometry and high hardness. The acoustic emission signals were acquired using a Sensis, model DM-42 sensor positioned close to the base of the grinding table so as to cover all the machining conditions without saturation of the signals. A signal amplifier with a filter was used to accommodate the acoustic emission signals within a range of 50 kHz to 1 MHz. To measure the grinding power in grinding, sensors were used to measure the electric power of the three-phase induction motor which drives the grinding machine main spindle. According to Malkin (1989), the net power available in the grinder is a little less than its

total evaluated power due to the inefficiency of the transmission system. The effective power of the main motor was determined by measuring the electric current and voltage transducer (Hall Effect). The electric current and voltage of the motor frequency inverter were monitored by a power module. The acoustic emission and power signals were captured by a National Instruments data acquisition board (model PCI-6111) with 12 bits precision, with maximum sampling frequency of 5 million samples per second, installed in a computer dedicated to the tests. LabVIEW software (National Instruments) was used to acquire the signals and store them into binary files for subsequent processing and analysis.
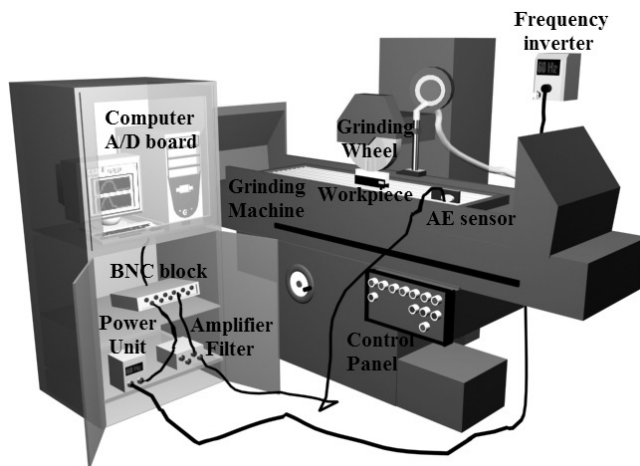

Figure 1. Experimental setup.

The tests were carried out through a previous selection of 15 cutting depths, adopting 3 repetitions for each depth, with the cutting depth ranging from 5 μm to 50 μm. The dressing, lubrication and grinding wheel peripheral velocity parameters were properly controlled in order to ensure the same grinding conditions in the 3 repetitions of each test. The velocity of the workpiece was set to 0.044 m/s, and the grinding wheel's peripheral velocity to 30 m/s; the latter kept constant by adjusting the frequency of the induction motor in the frequency inverter. This step was necessary due to the diametric loss the wheel underwent during the tests. The dressing overlap ratio (U_d) as being the relation between the dressing width and the dressing feed rate was kept unitary, thus maintaining the dressing conditions for all the tests executed. The cutting fluid employed was an emulsion containing 4% in volume of lubricant oil. The tests consisted of a single pass of the grinding wheel along the workpiece for each condition analyzed. The AE and grinding power signals were measured in real time at a rate of 2.5 million samples per second, and were stored onto binary files for each test. The machining parameters used in the preparation of the test bench are summarized and presented in Table 1.

Table 1. Machining parameters.

Machining Parameters of the Test Bench	
Peripheral grinding wheel velocity (V_s) (m/s)	30
Workpiece velocity (V_w) (m/s)	0.044
Number of passes	1
Type of cooling fluid	Water-oil 4% emulsion
Type of grinding wheel	38A80PVH – Norton
Original grinding wheel diameter (mm)	203.2
Original grinding wheel width (mm)	31.75
Workpiece dimensions (mm)	160 x 12.7 x 43

The collected signals were processed using MATLAB software to generate the DPO and DPKS parameters (described hereafter) utilized to feed the artificial neural networks. After the grinding tests, the workpieces were tested to quantify parameters such as burn, surface roughness and microhardness.

Statistical Parameters used in the Artificial Neural Networks

Various failure monitoring parameters have been studied in grinding processes. Two important parameters investigated by Aguiar et al. (2002) and Dotto (2006) are the DPO and DPKS parameters. These parameters were employed in this work because the authors reported that they were effective in detecting the grinding burn. Both parameters take advantage of the relatively unpredictable level of the acoustic emission signal, mainly due to the mechanical interfaces conditions of the signal transmission from the workpiece to the sensor. On the other hand, the grinding power signal is directly related to the grinding wheel cutting capacity. As the burning instant approaches, momentary softening of the workpiece material causes sudden variation of the acoustic emission signal, increasing its dispersal along the grinding pass, but no sudden variation of the grinding power signal is observed. Therefore, a combined analysis of RMS acoustic emission signal dispersal with the electrical power signal level is expected to be useful about grinding burn phenomenon (Aguiar et al., 2002).

The DPO parameter is defined as the standard deviation from the root mean square value of the acoustic emission signal multiplied by the maximum value of the mean grinding power signal per grinding wheel pass. The DPKS parameter is calculated by the standard deviation of the acoustic emission multiplied by the sum of the grinding power subtracted from its standard deviation raised to the fourth power. DPO and DPKS can be represented, respectively, by Eqs. (1) and (2).

$$DPO = std(AE).Max(Pot) \tag{1}$$

$$DPKS = \left\{ \sum_{i=1}^{i=m} \left[Pot(i) - std(Pot) \right]^4 \right\}.std(AE) \tag{2}$$

where *Max* is the maximum value, *Pot* is the grinding power, *AE* is the acoustic emission, *std* is the standard deviation, and *m* was selected as being 1024 in this work.

It should be noted that the DPO and DPKS parameters were obtained from the files stored during the acquisition of data from the experimental tests.

Classifying Burn

Besides visual inspection on all ground workpieces, the *Grinding Analysis* software developed by Dotto (2004) was used in order to better classify the occurrence of thermal damage on the ground workpiece. This software employs the digital picture of each ground workpiece to analyze the level of burn occurred on its surface based on a gray scale previously established. A reference value of 10% burn of the ground surface was adopted. Thus, all the workpieces showing a threshold above 10% burn of the ground surface were classified as "with burn", while values below that limit were classified as "without burn". This procedure was adopted to prevent the burn analysis from only following a subjective pattern through visual analysis.

Measuring Surface Roughness

The surface roughness of each tested workpiece was measured with a portable Taylor Robson surface roughness tester, model Surtronic 3+, adjusted to a sampling length of 8 mm. The mean arithmetic surface roughness (R_a) was the standard used in the reading. After selecting the measurement parameters, the readings were taken transversal to the cut, on 15 subdivisions of the workpiece spaced 1 cm apart, with three repetitions for each measurement. Figure 2 illustrates the 15 divisions made on the workpieces.
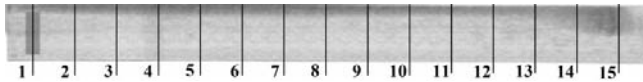
Figure 2. Division of the workpiece for mean surface roughness measurements.

The mean values of surface roughness for each cutting depth were used in the training stages of the artificial neural networks, and also served to verify the prediction efficiency of the networks under study.

Measuring Microhardness

The microhardness was measured with an M-Testor microhardness tester (Otto Wolpert-Werke, Baujahr, 1962), using the Vickers scale since this was the most appropriate scale for the type of metal and hardness involved. The weight utilized was 100 grams and the spacing between the points along the workpiece was approximately 10 mm. These tests consisted of measuring the microhardness along the surface of the workpiece in order to identify the behavior of the metallurgical transformation of the material, when burn of the workpiece occurred. To minimize measuring errors due to variations in the microhardness of the material's surface, three measurements were taken along the same perpendicular strip of the workpiece, as illustrated in Fig. 3.
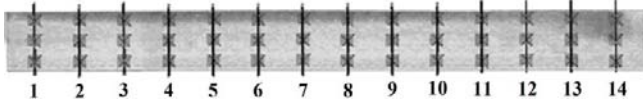

Figure 3. Divisions of the workpiece to measure microhardness.

Structures of the Artificial Neural Networks

The neural network (NN) chosen for the training and validation of the data was Backpropagation, due to the excellent characteristics of this ANN model for the purpose of this research. The set of networks were implemented with MATLAB software. The training was based on the traingdx criterion, which is a network-training function that updates the weight and bias values according to the moment of the descending gradient and the adaptive learning rate.

Sigmoidal tangent transmission functions were used in the network's architecture, since the network's input and output data were normalized between -1 and +1 values. The number of training cycles was set at 10,000 epochs. This number was adopted to avoid presenting the training set to the network too many times, leading to a loss of generalization, or insufficient times to enable it to reach its optimal performance. Another parameter set for all the networks was the mean square error. The estimated value, which presented good generalization and convergence in preliminary tests, was set to 10^{-2}. Thus, the training of the networks was concluded when any of the above criteria were met.

In this research, three different configurations were studied to dimension the neural networks in order to determine which configuration would present the best results in predicting the parameters adopted as output data. The set of input variables utilized to feed the neural networks was selected from the parameters established in the design of the experimental tests, in addition to parameters from the workpiece grinding process. The set of output variables from the neural networks was adopted to provide a good characterization of the surface quality of the workpieces subjected to the grinding tests. Figure 4 shows a diagram of the methodology along with the three NN configurations defined according to the input set employed. Thus, configuration 1 is that one with RMS acoustic emission, grinding power and depth of cut as inputs to the neural network; configuration 2 with DPKS and depth of cut as inputs; and configuration 3 with DPO and depth of cut as inputs. All configurations have the same output variables: burning detection, surface roughness, and microhardness.
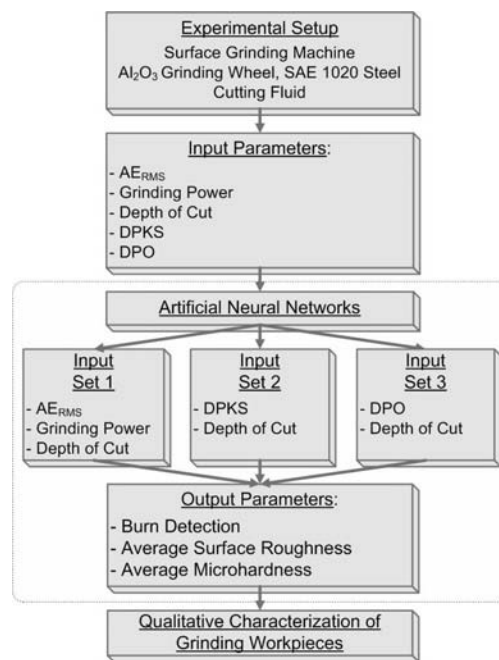

Figure 4. Diagram of the methodology showing the three NN configurations.

To determine the parameters of the neural networks, several structures were constructed. For each of the three configurations studied here, networks with distinct parameters were generated in order to determine the structure that would present the best generalization of the problem. The principal varied parameters were: number of intermediary layers, number of neurons of the intermediary layers, learning rate (lr), and momentum coefficient (mc).

The number of intermediary layers was set first, after which the variation in the number of neurons comprising them was defined. For each proposed structure, training cycles were generated with diverse learning rates and momentum values. The learning rate was tested for an interval of 0.1 to 0.9, and for each value, the momentum was also varied from 0.1 to 0.9. Training tests were carried out for each combination of learning rate and momentum coefficient. Upon conclusion of the training, the result was validated using 9 preselected workpieces.

One of the points worth mentioning in the conception of dimensioning the neural networks is the sensitivity of parameters such as the learning rate, momentum coefficient, number of intermediary layers, and number of neurons in the intermediary layers to influence the network's performance. The selection of the

optimal parameters for the network requires an empirical process in the quest for satisfactory results.

The data collected for the design of the experimental tests were separated into two categories: training data (used for training the networks), and validation data (used to verify the performance of the predictions).

Out of the 45 workpieces obtained in the tests, 31 were selected to make up the neural network training set. These workpieces were kept invariable in order to allow performance comparisons of each structure implemented.

Nine workpieces were selected for the validation stage, taking care of selecting workpieces with different cutting depths. These workpieces represented a significant sample of the process, covering the entire domain of the tests and considering the most diverse samples obtained in the experimental stage.

The choice of the workpieces for training and validation stages was based on the suggestion given by Prechelt (1994), that is, 75% of the total of workpieces meant for the training stage and 25% for the validation stage.

Results and Discussion

The acoustic emission and grinding power signals were monitored to track the phenomena resulting from the grinding process of the workpieces used in the experimental tests. These signals also served as the basis that originated the statistical parameters DPO and DPKS, which, together with the AE and grinding power signals, comprised the set of inputs into the artificial neural networks used for the qualitative evaluation of the implemented process. AE and grinding power signals were collected for all the workpieces used, and the behavior of the signals was analyzed through graphs generated from the stored data. The signals were processed with Matlab software, after calculating the root mean square (RMS) value of the raw acoustic emission and power signals. The graphs in Fig. 5 illustrate the acoustic emission (RMS) and grinding power signals from the workpieces ground at a cutting depth of 35 μm. A low-pass filter implemented in Matlab software was used to render the graphs more understandable, since the signal's high frequency would confuse its average behavior. The cutting frequency, which consists of the 3 dB point, was 5 kHz, and this parameter was used in the implementation of the digital filter for generating the graphs.
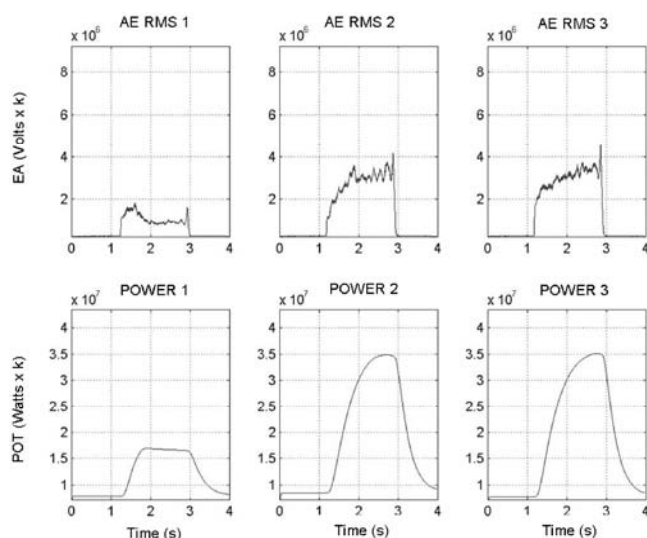
Figure 5. AE and POWER signals for the three tests at a depth of 35 μm.

The graph of Fig. 6 presents the burn classification results obtained with the *Grinding Analysis* software (Dotto, 2004), considering a 10% burn of the ground surface as the standard reference. As can be seen, for the experimental conditions adopted, i.e., type of steel and grinding wheel, dressing characteristics, velocity, cutting fluid, and grinding machine, there was a cutting depth range from which burn began to occur. Note that the burn phenomenon began at a cutting depth of 35 μm. At this cutting depth, burn results were obtained for two of the three workpieces tested. The only case when burn occurred at a cutting depth of less than 35 μm was in a workpiece cut at a depth of 22.5 μm, which presented burn on 13.17% of its surface. This may have been caused by non-controlled parameters in the grinding process or by self-excited vibration of the machine-tool set.
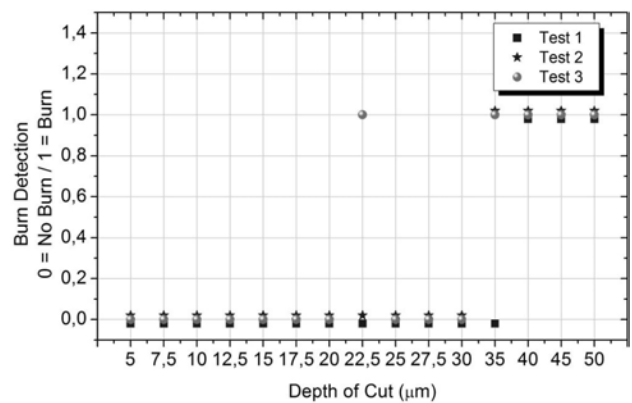
Figure 6. Burn classification of the ground workpieces.

Figure 7 shows the mean value of all the surface roughness values along the workpieces. Note that the most significant increase in surface roughness began at a cutting depth of 30 μm. This depth also represents the onset of burn of the workpiece, as discussed earlier herein. An analysis of Fig. 7 reveals that the variation in surface roughness along the workpieces increased at greater cutting depths, a fact that was also reflected in the values of the standard deviations around the mean value. Lower cutting depths tend to generate surfaces with a more uniform surface roughness.
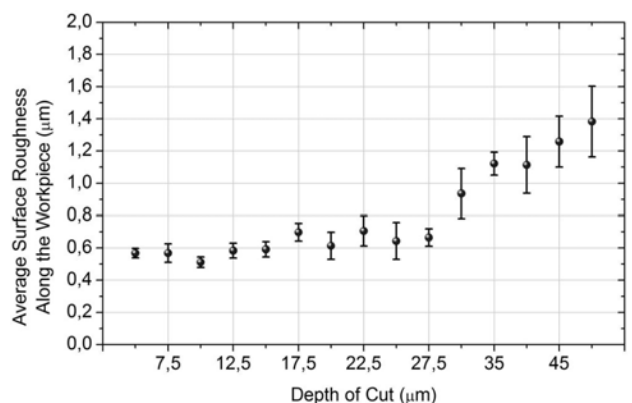
Figure 7. Mean surface roughness obtained for the adjusted cutting depths.

Figure 8 depicts the overall mean value of all the values of microhardness along the workpieces. Note that the microhardness values increase significantly in the workpieces ground at cutting depths of 35 μm and deeper, where the burn phenomenon occurs.
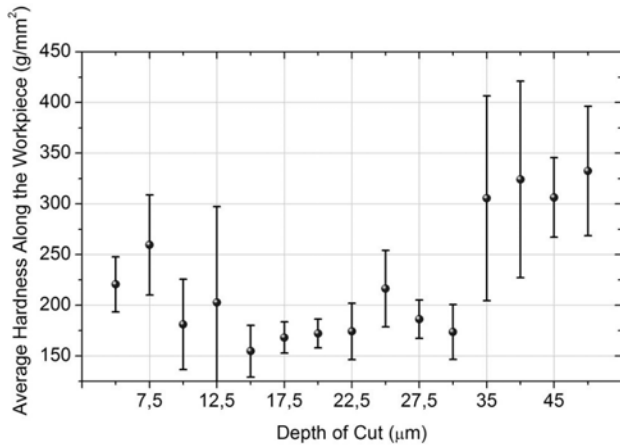
Figure 8. Mean values for microhardness obtained for adjusted cutting depths.

Tables 2, 3 and 4 show some of the results obtained by the ANNs, highlighting the combinations of parameters that generated the smallest errors of prediction by the structures implemented in the neural network architecture. These results represent a sample selected from the various networks studied. Note that the prediction results obtained by the networks were extremely satisfactory, since the mean error attained by all the parameters was 6.2%.

Table 2. Results of the neural networks for Configuration 1.

Structure	Epochs	lr	mc	Mean Prediction Error (%)
3-10-3	2878	0.5	0.4	6.03
3-20-3	1233	0.3	0.4	5.54
3-5-10-3	1848	0.4	0.3	6.42
3-10-15-3	2099	0.4	0.3	6.51

Table 3. Results of the neural networks for Configuration 2.

Structure	Epochs	lr	mc	Mean Prediction Error (%)
2-10-3	4096	0.5	0.4	6.31
2-20-3	519	0.4	0.3	6.12
2-5-10-3	5804	0.5	0.4	5.96
2-10-15-3	1004	0.4	0.3	6.08

Table 4. Results of the neural networks for Configuration 3.

Structure	Epochs	lr	mc	Mean Prediction Error (%)
2-10-3	5725	0.5	0.4	6.55
2-20-3	298	0.4	0.3	6.43
2-5-10-3	1601	0.4	0.6	6.37
2-10-15-3	2634	0.4	0.3	6.08

The comparative graph in Fig. 9 is based on the analysis of the trained structures, which showed the lowest prediction errors. The graph indicates the evolution of the performance of the networks as the number of intermediary layers and/or the number of neurons was modified. Note that the networks whose input signals used configurations 1 and 2 presented an excellent performance in predicting the output parameters. The results for configuration 3 were also good, albeit inferior to those obtained with configurations 1 and 2. It was also found that configuration 1 presented a loss in performance for networks composed of two intermediary layers, which was not the case of configurations 2 and 3.
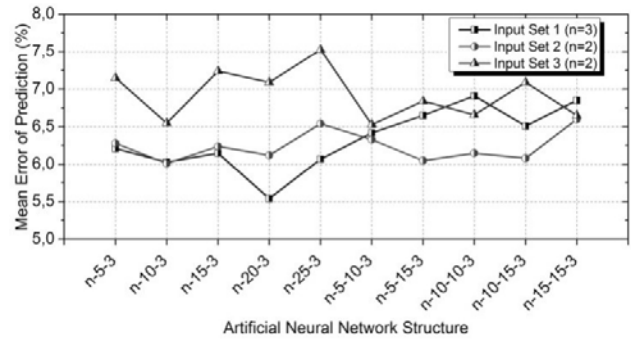

Figure 9. Performance comparison of the configurations developed for different NN structures.

In general terms, the structure that presented the best performance in predicting the parameters of burn detection, surface roughness and microhardness was that of the neural network with one intermediary layer composed of twenty neurons, configuration 1, where the set of input data are the parameters RMS acoustic emission, grinding power and cutting depth. The mean prediction error obtained at the output of this network was 5.54%.

Figure 10 illustrates the prediction performance of network 3-20-3 obtained by configuration 1. These graphs show the mean errors of each workpiece used in the validation stage for each of the output parameters. The prediction of the occurrence of workpiece burn shows the best rates of correct prediction, with the mean value of prediction error of 0.16%, thus ensuring, for practical purposes, a 100% rate of correctness. As can be seen, the detection of the occurrence of burn was obtained very accurately through the neural network implemented.
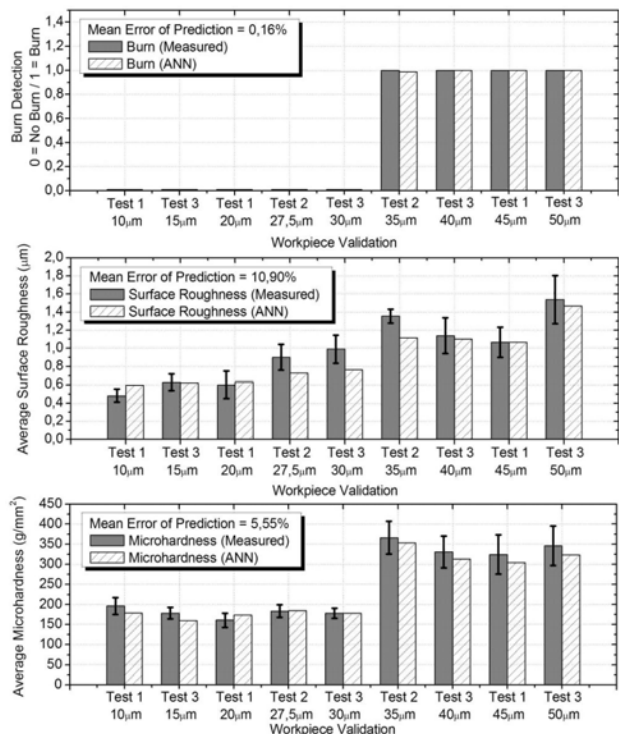

Figure 10. Performance of network 3-20-3 obtained by configuration 1.

An analysis of the network behavior in the validation tests indicates that the highest errors obtained involved the prediction of

the surface roughness parameter. The mean error attained for this parameter was 10.90%, and the highest error was obtained for the validation test #1 at a depth of 10 μm, with a prediction error of 23.87%. This fact may be explained by the small range of variation obtained in the surface roughness tests.

The network showed a high degree of precision in predicting microhardness, with a mean error of only 5.55%. The highest microhardness prediction error was that of the validation test #3 at a depth of 15 μm, with a correctness rate of 10.49%. Since this is a prediction of quantitative values, the error obtained can be considered low when compared with the values obtained in the tests.

The errors generated by the neural networks in the prediction of the surface roughness and microhardness parameters lay within the standard deviation range calculated from the respective values obtained in the experimental tests, highlighting the good performance achieved in the approximation of the values expected by the process. Because approximation functions are involved, the correctness rates attained in the prediction of results can be considered satisfactory. The classification of burn occurrence was also highly reliable, showing a high accuracy in the classification of thermal damage generated in the workpieces.

The measurement of the results obtained by the artificial neural networks was based on a comparison of the values provided by the networks and the values obtained through the experimental tests. The average rates of correctness of the network were good, as shown in Fig. 11, ensuring percentages for burn classification in the order of 99.84% and predictions of the estimated values of surface roughness and microhardness of 89.10% and 94.45%, respectively.
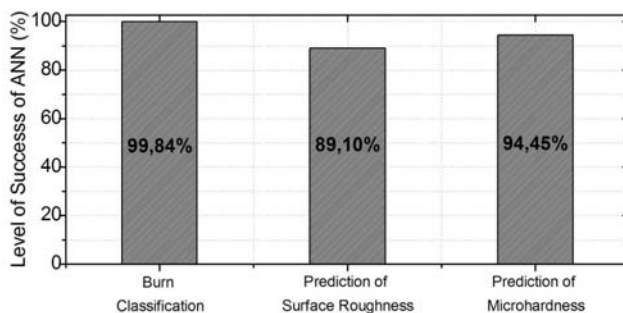

Figure 11. Correctness rate of the artificial neural networks.

Conclusions

Acoustic emission (RMS) and grinding power signals allied to the values of cutting depth of machined workpieces supply an excellent set of neural network input data for predicting parameters that indicate burn, surface roughness and microhardness. Even with structures that are little refined, i.e., without adjustment of the most optimized parameters of the network, it is possible to obtain good indicators of the quality of ground surfaces with the help of this powerful tool.

The use of artificial neural networks in the analysis of the quality of surfaces ground by the surface grinding process, as proposed and implemented in this work, provided excellent results with respect to both performance and precision attained in the classification of surface burn occurrence and in the approximation of surface roughness and microhardness values.

The configuration 1 whose input data set was composed of RMS acoustic emission, grinding power and cutting depth has presented the best performance among the configurations studied, with a correctness rate of 94.45%. That was accomplished by the neural network structure with 3 neurons in the input layer, 20 neurons in the intermediary layer and 3 neurons in the output layer.

Configurations 2 and 3, which were composed, respectively, of the input data of the cutting depth and DPKS parameter and of the cutting depth and DPO parameter, also performed reasonably well in predicting the indicators of the surface quality of ground workpieces, with the lowest mean prediction error of 5.96% given by configuration 2.

Therefore, RMS acoustic emission and grinding power signals are very good indicators for the characterization of workpiece surface quality. Allied to artificial neural networks, these signals are important parameters in machining processes such as grinding, adding value to productive processes through the qualitative characterization of the end product.

References

Aguiar, P.R., Bianchi, E.C., Oliveira, J.F.G., 2002, "A method for burning detection in grinding process using acoustic emission and effective electrical power signal", *CIRP Journal of Manufacturing Systems*, Paris, Vol. 31, No. 3, pp. 253-257.

Aguiar, P.R., Cruz, C.E.D., Paula, W.C.F., Bianchi, E.C., Thomazella, R., Dotto, F.R.L., 2007, "Neural network approach for surface roughness prediction in surface grinding", Proceedings of the 25th IASTED International Conference on Artificial Intelligence and Applications, Innsbruck, pp. 549-803.

Aguiar, P.R., França, T.V., Bianchi, E.C., 2006, "Roughness and roundness prediction in grinding", Proceedings of the 5th CIRP International Seminar on Intelligent Computation in Manufacturing Engineering – CIRP ICME´06, Italy, pp. 183-188.

Brinksmeier, E., Aurich, J.C., Govekar, E., Heinzel, C., Hoffmeister, H.-W., Klocke, F., Peters, J., Rentsch, R., Stephenson, D.J., Uhlmann, E., Weinert, K., Wittmann, M., 2006, "Advances in modeling and simulation of grinding processes", *Annals of the CIRP*, Vol. 55, No. 2, pp. 667-696.

Dotto, F.R.L., 2004, "Online Automatic Detection System of Thermal Damages in Grinding Process with Internet Monitoring", M.Sc. Dissertation, Unesp-Bauru, Sao Paulo.

Dotto, F.R.L., Aguiar, P.R., Bianchi, E.C., Serni, P.J.A., Thomazella, R., 2006, "Automatic system for thermal damage detection in manufacturing process with Internet monitoring", *Journal of the Brazilian Society of Mechanical Science & Engineering*, Vol. 28, No. 2, pp. 153-160.

Kwak, J.S., Ha, M.K., 2004, "Neural network approach for diagnosis of grinding operation by acoustic emission and power signals", *Journal of Materials Processing Technology*, Vol. 147, pp. 65-71.

Kwak, J.S., Song, J.B., 2001, "Trouble diagnosis of the grinding process using acoustic emission signals", *International Journal of Machine Tools & Manufacture*, Vol. 41, pp. 899-913.

Malkin, S., 1989, "Grinding Technology – Theory and Applications of Machining with Abrasives", Ellis Horwood Limited, England.

Nathan, R.D., Vijayaraghavan, L., Krishnamurthy, R., 1999, "In-process monitoring of burn in the cylindrical grinding of steel", *Journal of Materials Processing Technology*, Vol. 91, pp. 37-42.

Prechelt, L., 1994, "PROBEN1 – A Set of Neural Network Benchmark Problems and Benchmarking Rules". Technical Report 21, Fakultät für Informatik Universität Karlsruhe, 76128 Karlsruhe, Germany.

Saravanapriyan, A., Vijayaraghavan, L., Krishnamurthy, R., 2001, "On-line detection of grinding burn by integrated sensing". Sensors for Industry Conference – SICON'01, Illinois, pp. 89-94.

Spadotto, M.M., Paula, W.C. F., Aguiar, P.R., Bianchi, E.C., 2007, "Classification of Burn Degrees for Steel Parts in Grinding Process by Neural Nets", 6th Brazilian MRS Meeting, Natal, Vol. 1.

Tonshoff, H.K., Jung, M., Mannel, S., Rietz, W., 2000, "Using acoustic emission signals for monitoring of production processes", *Ultrasonics*, Vol. 37, pp. 681-686.

Wang, J.Z., Wang, L.S., Li, G.F., Zhou, G.H, 2005, "Prediction of surface roughness in cylindrical transverse grinding based on ALS algorithm", Proceedings of the 4th International Conference on Machine Learning and Cybernetics, Guangzhou, pp. 549-554.

Wang, Z., Willett, P., Aguiar, P.R., Webster, J., 2001, "Neural network detection of grinding burn from acoustic emission", *International Journal of Machine Tools & Manufacture*, Vol. 41, pp. 283-309.