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Automatic detection of thermal damage in grinding process by artificial neural network

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Resumo

Esse trabalho tem por objetivo o desenvolvimento de um sistema inteligente para detecção da queima no processo de retificação tangencial plana através da utilização de uma rede neural perceptron multi camadas, treinada para generalizar o processo e, conseqüentemente, obter o limiar de queima. Em geral, a ocorrência da queima no processo de retificação pode ser detectada pelos parâmetros DPO e FKS. Porém esses parâmetros não são eficientes nas condições de usinagem usadas nesse trabalho. Os sinais de emissão acústica e potência elétrica do motor de acionamento do rebolo são variáveis de entrada e a variável de saída é a ocorrência da queima. No trabalho experimental, foram empregados um tipo de aço (ABNT 1045 temperado) e um tipo de rebolo denominado TARGA, modelo ART 3TG80.3 NVHB.

Palavras-chave: Redes neurais artificiais, aquisição de dados, processamento de sinais, automação, sistema de monitoramento e controle, ferramentas de software, processos de fabricação.

Abstract

This work aims to develop an intelligent system for detecting the workpiece burn in the surface grinding process by utilizing a multi-perceptron neural network trained to generalize the process and, in turn, obtnaing the burning threshold. In general, the burning occurrence in grinding process can be detected by the DPO and FKS parameters. However, these ones were not efficient at the grinding conditions used in this work. Acoustic emission and electric power of the grinding wheel drive motor are the input variable and the output variable is the burning occurrence to the neural network. In the experimental work was employed one type of steel (ABNT-1045 annealed) and one type of grinding wheel referred to as TARGA model ART 3TG80.3 NVHB.

Keywords: *Artificial neural networks, data acquisition, data processing, signal processing, automation, monitoring control system, software tools, manufacturing process.*

1. Introduction

In the metal mechanics industry, grinding is usually the final process of a precision component. This process is used for the production of parts of different materials, demanding low superficial roughness, control of dimensional and form errors of the parts, maximum tool life with minimum time and costs (Aguiar, 1997).

The superficial grinding process is still not very dominated technologically. This perhaps has origin in the erroneous faith that the process is very complex to understand, due to multiplicity of cutting edges and its irregular geometry, high speed of cut, and small depths of cut that vary from grain to grain.

According to Aguiar (1997), the chip removal in the superficial grinding process doesn't happen in the same way found in those more conventional operations such as milling and turning. In these operations the tool has defined geometry of cut, while in grinding the tool presents many cutting edges, that is, irregular cutting geometry. The great amount of variables involved in the process as well as the constant change of the cutting geometry make difficult the choice of the grinding conditions that facilitate the desired results.

Damages caused in the workpiece are of high cost, once every previous process, besides the own grinding is lost when a part is damaged in this stage. The damages most common in the grinding operation are burning, cracking and or undesirable residual stresses.

In the case of metals, the main cause of damages is the excessive thermal entrance into the ground surface of the part.

The need of effective reductions of costs aside the increase of quality of the manufactured parts, requires the implementation of more intelligent systems in industrial environments. Therefore, the control of the actual damages in the grinding process is of great interest of all dependent industries on this process, thus leading to a lower rate of scraps and consequently at a lower cost of production.

According to Malkin (1989), the high temperatures generated in the grinding zone can cause some types of thermal damages to the part, as for example burning (in the case of steel), excessive tempering of the superficial layer with possible re-hardening and increase of the brittleness, undesirable residual stresses of traction, reduction of the fatigue strength, and cracks. To attenuate the restriction of thermal damages, it is generally necessary to reduce the grinding power.

The coolant has also an important effect as a lubricant. Direct lubrication with grinding fluids becomes mainly important in the creep-feed grinding (Malkin, 1989). Some analysis of heat transference indicate that the use of a faster work speed, keeping the same removal rate would lower the temperature and reduce the thermal damage, but this is not always true in practice. The fundamental difficulty of controlling damages caused in the grinding process is the lack of a reliable method in supplying feedback in real time during the process. Acoustic emission and electric power signals together combined have successfully been used in determining indicative parameters when burn takes place. Once these signals are processed and combined properly, they allow the on-line implementation of a burn monitoring system, optimizing the grinding process. This would be of great benefit for the dependent companies on this process, once the quality demand and international competitiveness grow more and more with the world globalization (Aguiar, 1997).

In his doctorate thesis in 1997, Aguiar established the DPO parameter for detention of the superficial burning in surface grinding. This parameter is the multiplications of the standard deviation of the RMS acoustic emission signal for each grinding wheel pass by the maximum value of the power level in the current pass.

$$DPO = SEA \ x \ Maxpot \quad (1)$$

According to Aguiar (1997), the behavior of the DPO parameter revealed an increase along the passes of the grinding wheel until the moment of burning, thus presenting a more expressive characteristic to detect burn than acoustic emission and electric power signals alone. The DPO parameter demonstrated to be efficient in detecting the superficial burning and will be able to help the industries on the burning monitoring in superficial grinding process.

Aguiar et al. (2002) developed another important parameter to detect the superficial burning occurrence in the grinding, the FKS parameter. A lot of studies and researches have demonstrated that the association of statistical tools with the tangential cutting force and acoustic emission can help a lot in obtaining parameters and thus avoiding damages caused by burning. The FKS parameter is calculated by the ratio between the maximum cutting force and the multiplication of skew and kurtosis of the acoustic emission signal for each grinding pass.

$$FKS = \frac{Fc\max}{S(EA).K(EA)} \quad (2)$$

The FKS parameter has demonstrated to be very sensitive to the variations in the grinding conditions and, therefore, it revealed very efficient at detecting superficial burning of the part.

Although there are many parameters to detect burning occurrence as DPO and FKS, these ones were not successfully implemented in this work for the grinding conditions used. The existing parameters have shown very bad results, so a multi-perceptron neural network has been used to detect burning for the grinding conditions set in this work.

The use of neural networks on burning detection in grinding process is an alternative approach due to their capability of self-adjustment to new weights as well as to generalize results.

In this work, a perceptron neural network to classify pattern will be used. Thus, the burn and non-burn patterns will properly be classified from the correspondent values of electrical power and acoustic emission signals.

The ABNT 1045 is a steel of ductile-brittle transition that makes difficult any burning analysis by acoustic emission signal. In addition, the grinding wheel named Targa has a great capacity of self-sharpening, which in burning situation does not allow the cutting power to increase at high levels. As the DPO and FKS parameters depend on the acoustic emission change and the supposedly increase of the cutting power at the burning moment, it is not difficult to realize that burn detecting is not a simple matter to solve in those grinding conditions.

2. Concepts of superficial burning in grinding process

One of the most common types of thermal damages in grinding process is the burning of the part. When the superficial burning of the part is initiated, there is a trend of growth of the metallic particle adhesion in the abrasive grains of the grinding wheel, having as consequence the increase of the grinding forces. This increase of forces causes the deterioration of the superficial quality of the part, being able to lead to the increase of the diametrical loss of grinding wheel with the subsequently increase in its volumetric wear. According to Malkin, the superficial burning of the part influences on the alteration of the microstructure of the ground material (Malkin, 1989).

According to Malkin, the superficial burning of the part, observed for bearing steels brings an adverse aspect with regard to the limit of fatigue strength and consequent reduction of the number of cycles of these steels after grinding operation (Malkin, 1989). This behavior is attributed to the formation of non-annealed martensite generated in the burning superficial process, in function of the heating at the austenitization temperature and fast cooling without posterior relief of stresses (annealing).

There is another front of researches that defends the film-boiling phenomenon due to the increase of the temperature in the grinding zone.

Shafto postulated that the fast increase in temperature is characteristic to a phenomenon known as burnout, which occurs in boiling pipes (Shafto, 1975). At a critical temperature related to the burnout temperature, a collapse in the mechanism of heat transference takes place, which results in a fast increase of temperature. When the temperature reaches values around 100ºC, the water enters in boiling causing bubbles on the heater surface. An increase beyond the boiling temperature provokes the union of the bubbles, forming a vapor layer on the surface known as Film-boiling. The transference of heat through this film is much more difficult, thus causing a sudden increase of the temperature.

Yasui at al. (1983) measured the temperature in the surface of the part using oil and water as coolant and also dry grinding. He has observed that at temperature above of the boiling point of each fluid, the surface of the part reached the corresponding temperature to which was verified for dry grinding. In other words, the fluids were no longer effective. In a posterior study, Salmon experimentally observed the formation of a vapor film on the surface of the part, immediately below of the contact zone (Salmon, 1988).

3. Perceptron neural network and training algorithm

The growing interest in Artificial Neural Network (ANN) can be seen as a notable phenomenon in the 80's and occurred for its characteristic of big capacity in processing and its flexibility in the integration with other mathematics tools.

The ANN are being used in many applications, such as: Recognition in patterns (Widrow, et al. 1998), signals processing (Haykin, 1994), speaking processing (Waibel et al, 1989), Robotics (Van Der Smagt et al., 1991), Identification and control (Narendra et al., 1990), optimization in systems and many more.

There are consisted of group elements called artificial neurons that are organized into a very complicated intercommunicating network interlinked with other neuron groups through connections called artificial synapses in which are allowed the signal to run between the various groups or neurons layers. In general, a neuron consists of vector weight (W - weight), invariable (b- bias) and a determined function (F) applied in an input (P). The neuron output (a) is expressed by:

$$a = F(w \times p + b)$$

Each neuron performs a linear combination in its input followed by a use in a definite function and afterward transfers this datum to its subsequent. In practice the neural networks operates with mathematics operational sequences with data matrix being interpreted as a matrix structure.

The neural network's name was given to these mathematics structures according to its resemblance with the structure and functioning of the neuron cells.

A recent tendency is the implementation the ANN in digital systems seeking the maximization in its processing velocity. Usually the implementation through hardware is provided in development board that can be connected to computers or workstations.

In a broad idea you can classify the ANN according to two basic characteristics in its architecture, related to its neurons disposition and how is developed its training.

In the training the parameters of each neuron are modified iteratively in order to adequate the answer to the network and its input searching the behavior reproduction showed by the samples collected in the testing. After trained the network can be used to provide output values referred to the different inputs from that ones in which it was trained.

The ANN used in this work was a Perceptron Multilayer Network trained in the Levenberg Maquardt algorithm, which is constituted by:

- One input layer (with as much neurons as the inputs).
- At least one hidden neural layer.
- One output neural layer (with the same quantity of neurons as the desired outputs).

However, there is no connection between the neurons in the same layer.

The Perceptron Multilayer network main employments are:

- Function linear approximation.
- Temporal series prevision.
- Identification and control.
- Pattern recognition.
  - Non-linear boundary.
  - Convex and non convex sets.
  - Disconected sets.

The Perceptron architecture showed itself adequated to the problem found in this work, in which was intended to classify into two output categories (burn and non burn) the various combinations between the two used inputs (power and acoustic emission), defining boundaries. The completion used in the Perceptron Network and its result can be visualized in the Figures 1, 4 and 5 in simulations and results.

Other similar works used this kind of ANN as Aguiar (2002).

The multilayer NN can be trained by Back propagation algorithm or improved algorithm based in the same. Amongst these detaches the Levenberg-Maquardt algorithm considered the most utilized (Hagan, 1994).

In the apprenticeship in back propagation there are two training fazes: the forward step and the backward step. The first is consisted of the signals propagation process from the input layer to the output one. The second refers to the inverse process, in a brief way, from the output layer to the input one.

In the forward step the network collects the input data and then this information is going to be processed flowing from layer to layer resulting in an output answer. This output answer is compared to the wanted answer to this specific stimulus. Subsequently the error is calculated and in case this result is not satisfactory according to predetermined criterion, the algorithm is going to the backward step, back propagating, layer to layer updating all the synaptic weight needed from the output to the input.

The Levenberg-Maquardt algorithm is based in the minimum square method for the non-linear models that can be incorporated to the back propagation algorithm having as objectivity the improvement in the efficiency of the training process.

The back propagation algorithm is a methodology of decreasing in the gradient related to the quadratic error function, on the other hand, the Levenberg-Maquardt algorithm is an approaching to the Newton's method for non-linear systems.

4. Simulations and results

As mentioned previously, the detection of burn during the grinding process was modeled through the use of a multi-layer perceptron network. The electric power and acoustic emission, which are the input variables were acquired and measured by a data acquisition system. On the whole, 9.5×10^6 samples were collected during the grinding process at 0.075mm depth of cut and 2.25×10^6 samples at 0.110mm depth of cut. Hence, the total pattern set was of 11.75×10^6 samples from which 10×10^6 samples constituted the training set and the rest of it the test set for validation and generalization of the network results.

As can be seen in Figure 4 and Figure 5, the sets regarding the burn and non-burn are comprised of disconnected regions and non-linear boundaries. Thus, there is a great complexity on identifying grinding burn during the grinding of metals.

Several architectures of artificial neural networks were tested in order to properly classify those patterns. The perceptron network with one hidden layer and 30 neurons provided the best classification among the networks tested.

The algorithm of Levenberg Marquardt was employed due to the complexity of identification and the great number of experiment data. The experiment data and respective

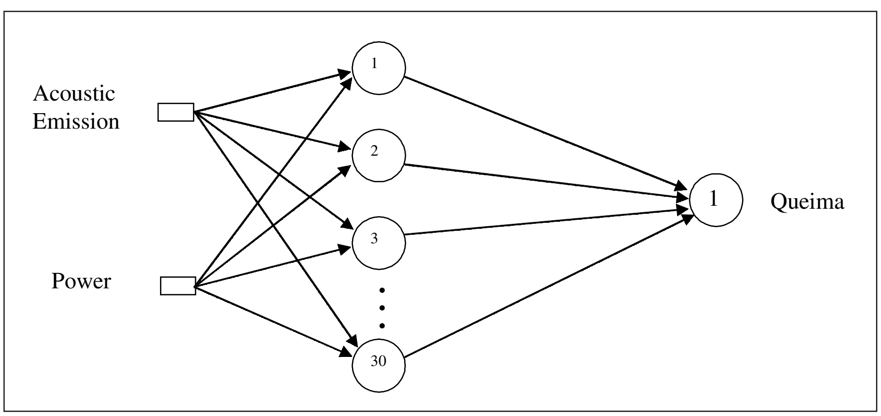

Figure 1 - Perceptron Network using Levenberg-Marquardt training.

Table 1 - Grinding Conditions.

ABNT 1045 Steel ART 3T680.3 NVHB Wheel	
a = 20μm	a = 30μm
V_w=0.123m/s	V_w=0.123m/s
V_s = 32.6m/s	V_s = 32.6m/s
h_{eq}=0.075μm	h_{eq}=0.110μm

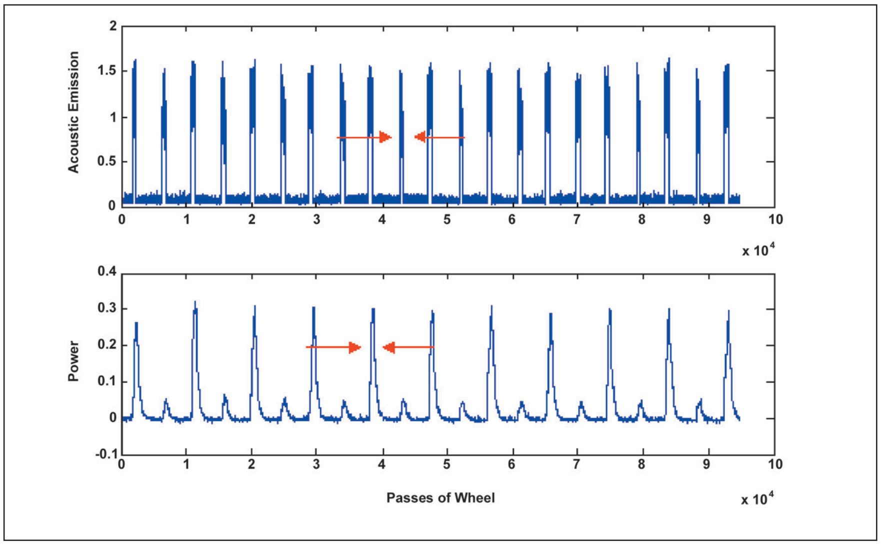

Figure 2 - Acoustic Emission and Electric Power of the motor drive for the ABNT 1045 steel, heq=0.075μm.

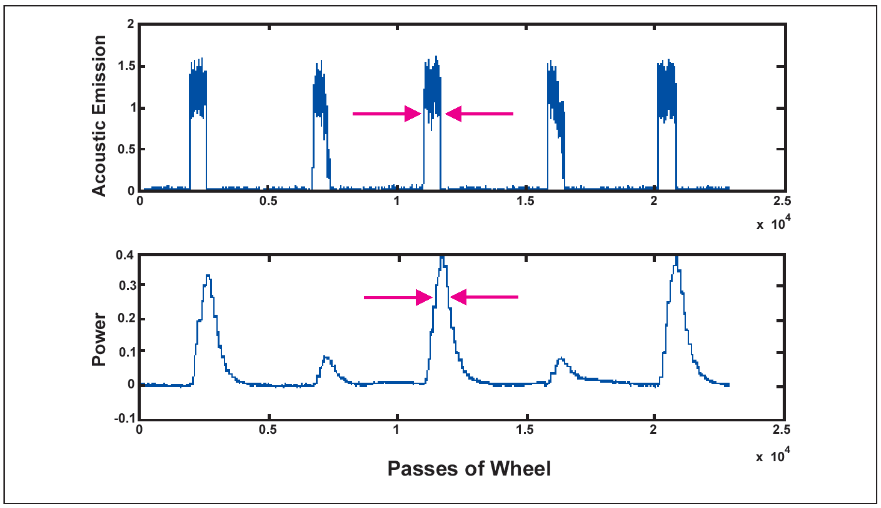

Figure 3 - Acoustic Emission and Electric Power of the motor drive for the ABNT 1045 steel, heq=0.110μm.

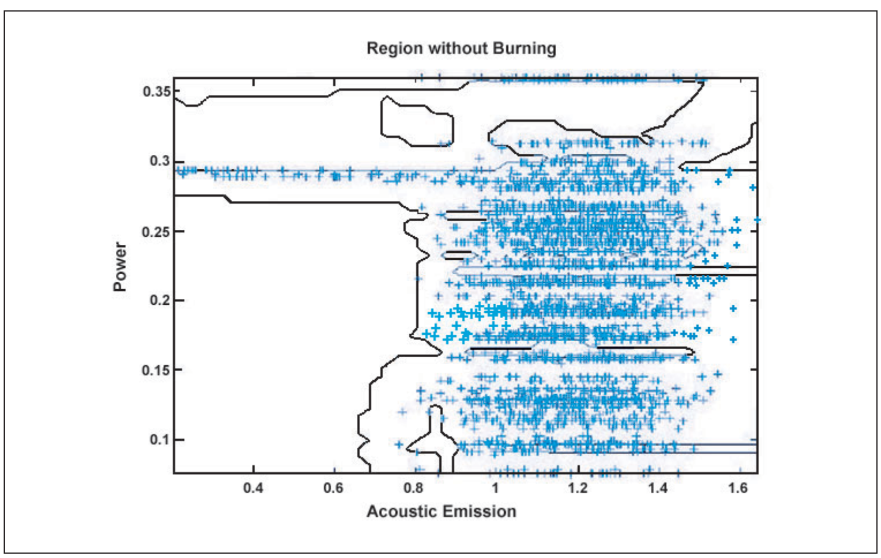

Figure 4 - Regions with no burning.

boundaries of decision for the burn and non-burn sets are presented in Figure 4 and Figure 5.

Table 1 shows the grinding conditions utilized in the neural network training. The network was trained for heq=0.075μm e heq=0.110μ m.

The input variable used in the neural network training is shown in Figures 2 and 3. It is possible to observe in these figures the grinding pass where burning did not occurr. The red arrows indicate where the burning took place.

A set of points with heq=0.094μm was utilized in order to validate the neural network. The results obtained are shown in Figures 4 and 5.

The region containing the points where the burning did not happen is shown in Figure 4 where as Figures 5 shows the regions with points where burning took place. It can be observed that, in general, the points tested are correctely classified in both graphs and then provide a good response to determining the burning occurrence.

5. Conclusions

Based on the tests carried out in this work it can be observed that the neural network presents a great

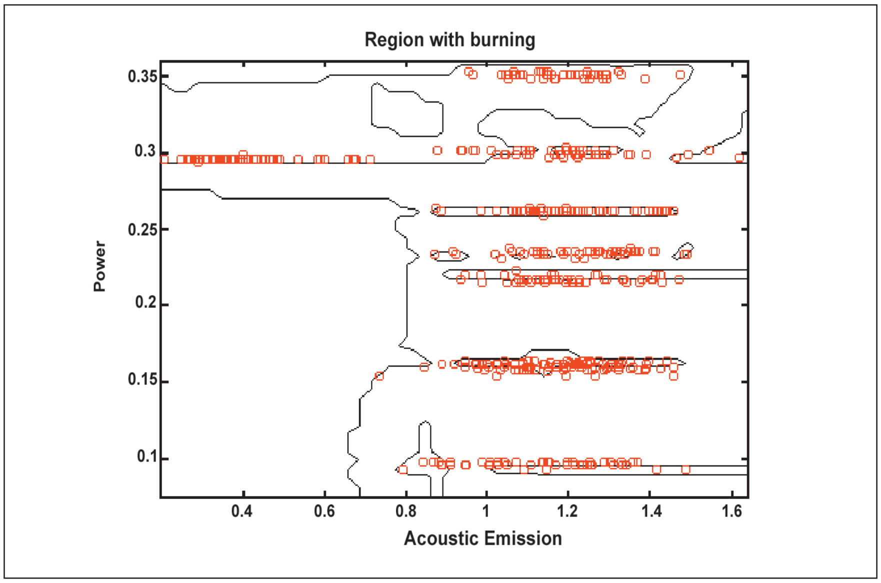

Figure 5 - Region where burning took place.

response, that is, it converges about 82% of the points. A previous validation was accomplished by using the data with depth of cut of 25μm and the same level of convergence was noted.

A set of input pairs will be tested in the secong stage of this work instead of the one used (Acoustic Emission and Electric Power) to validate the output. The occurrence or not of burning with a higher level of convergence may be reached through the analysis of those responses.

The tests performed during this work have shown perfectly directed to those applications in which the surface grinding process is involved, for according to the previous analysis better results have been successfully achieved than those obtained for DPO and FKS parameters. However, the computational effort has considerably increased as well and this system implementation in microcontrollers would be more expensive than that carried out with the FKS and DPO parameters.

Other tests will be further put into practice in order to obtain better results but other input parameters will be accounted such as depth of cut, cutting speed etc.

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