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SURFACE ROUGHNESS PREDICTED MODELING IN MACHINING OF TI 6AL 4V ALLOY USING NEURAL NETWORK AND LINEAR REGRESSION

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Abstract: Titanium alloys are attractive materials due to their unique high strength, excellent performance at elevated temperatures and exceptional corrosion resistance. The aerospace and military industries are the main users of this material. Titanium alloys are classified as difficult machining materials. The correct parameters of machining are a hard setting, actually researches are looking to develop new models to predict and optimize these parameters. The surface roughness (Ra) in turning of a titanium alloy machining Ti 6Al 4V was predicted using neural network and linear regression is shown. The machining tests were carried out using PVD (TiAIN) coated carbide inserts under different cutting conditions. Confidence intervals were estimated in the model to get correct results. There are various machining parameters and they have an effect on the surface roughness. A set of initial parameters in finished turning of Ti 6Al 4V obtained from literature have been used. These parameters are cutting speed, feed rate and depth of cut. The results showed the advantages of use a Neural –Statistical approach to analyze the variables and to model the machining process.

1. INTRODUCTION

Identifying and optimizing parameters in machining is a very important and critical process. Titanium alloys are extremely difficult materials to produce. The machinability of titanium and its alloys are generally considered poor because of the enormous inherent properties of the material. The titanium has low thermal conductivity and high chemical reaction with many materials tools. This is because the low thermal conductivity increases the temperature at the edge of the cutting tool (Che-Haron, 2005), which produces a bad quality in the workpiece. The titanium is one of the most expensive alloy to produce. Companies specializing in the machining of materials such as titanium techniques generally seek to maximize the surface integrity of titanium alloys. The surface quality is one of the customers' most specified requirements. (Ramesh, 2007).

At present the modern companies put great emphasis on the surface finish of the products (Meziane, 2000). There are important variables in the machining process, being able to predict and optimize the parameters are two important strategies in manufacturing. The surface finish and dimension of a piece is critical to control in order to obtain the correct fabrication of the piece and to know how it is going to work. Making predictive models of machining operations requires details of all the conditions of work, usually base in laboratory experiments, because it is very difficult in practice to keep under control all the factors for success (Morales, 2007).

Over the past 20 years, intelligent systems composed of Neural Networks, Fuzzy Logic, Evolutionary Computation, sometimes alone and other combinations have been applied in manufacturing and engineering analysis with big success (Pawadea, 2007), (Russell, 2003). This has enabled a extensive variety of applications in industry, such as control of manufacturing a product, the planning process, and so on. A large number of improvements have emerged using intelligent systems to predict, control and optimize manufacturing parameters, improving surface roughness in different materials (He, 2001).

This study proposes a neuro-statistical system to predict the roughness produced during the machining process of Ti64. Using a neural network backpropagation and statistical linear regression. The results can serve as support in making decisions for the betterment of the machining process, productivity and savings in the cost of the product.

This work is organized as follows: In section 1 a small introduction, section 2 a summary of previous work using an intelligent systems in the machining processes, introduction to the neural networks, statistical regression, and the finish or roughness. The experimental development is explained in section 3 which includes the methodology, test and finally the results and conclusions and future work are in Section 4 and 5 respectively

2. LITERATURE REVIEW

Ramesh in his article "Modeling for prediction of surface roughness in machining of Ti64 alloy using response surface methodology" (Ramesh, 2007), made a prediction model which included parameters such as feed rate, cutting speed and depth of cut to see their effects turning the titanium and to obtain the quality parameters on surfaces response, on the other hand Che-Haron (Che-Haron, 2005), worked in an investigation that determined the impact the machining of Ti64 has on the surface finish, checking metallographic alterations of material obtained in machining with a variety of types of tool used in the study.

Rico (Rico, 2005), used the methodology Surface Response and neural networks to predict the roughness. Developing a model for predicted temperature and roughness of the cutting tool on the machining of the steel 1018. Pawadea (Pawadea, 2007) shows in his article entitled "Effect of machining and cutting edge geometry parameters on surface integrity of high-speed turned Inconel 718" high-speed cutting and low advance, as well as the moderate depth of cut coupled with the use little angles of court can ensure the generation of residual compression efforts in the face of machining.

A. Molinari (Molinari, 2002) was devoted to comprehensive studies of chip produced at the milling Ti-6Al-4V, analyzing the process of cutting orthogonal produced at different speeds and the transformation of adiabatic shear banding. He found that the lower speeds chip becomes rougher; this is due to the limitation thermomechanical, which generates adiabatic shear banding, is different the conduct of high speeds.

Krain (Krain, 2007) evaluated the effect of varying feed rate/chip thickness, immersion ratio (radial depth of cut), tool material and geometry on tool life, tool wear and productivity obtained when end milling Inconel 718. The study showed that no single tool material or geometry gave the best overall performance. Kopac (Kopac, 2002) utilized a Taguchi experimental design to determine the optimal machining parameters for a desired surface roughness for traditional turning. The Taguchi designed method was used to identify the impact of various parameters on output and determine the combination of parameters for controlling them to reduce the variability in that output. They found that the surface roughness increased with an increase in cutting speed. Ocktem (Oktem, 2006) developed a model to determine the best cutting parameters leading to minimum surface roughness in end milling mold surfaces of an ortez part used in biomedical applications by coupling neural networks and genetic algorithms. It appears that a considerable amount of work is going on in the area of machining parameters optimization, based on different criteria such as tool wear, vibration, surface roughness, unit cost, etc (Pawadea, 2007), (Krain, 2007), (Kopac, 2002). Nowadays artificial intelligence (AI) based on modeling is a new trend in modeling for machining operations (Morales, 2007). It was found that the use of heuristic methods to model predictions of surface roughness was very limited, so emphasis was laid on the development of a surface roughness prediction model. New research using Neural Networks has appeared to improve and optimize the assembly and disassembly of products (Ramesh, 2007).

2.1 Artificial Neural Networks.

Neural networks are computational paradigms that simulate some of the human brain properties, such as some rational capacities like association, recognition of shapes and even behavior patterns. Prediction is an important property of neural networks.

Neural networks are non-linear mapping systems that consist of simple processors called neurons, linked by weighted connections. Each neuron has inputs and generates an output that is the result of the information that was stored and of the processes in the hidden layers. The output signal of a neuron is fed to other neurons as input signals via interconnections. Since the capability of a single neuron is limited, complex functions can be needed through the connection of many neurons. It is widely reported that the structure of neural network, the representation of data, the normalization of inputs outputs and the appropriate selection of activation functions have a strong influence on the effectiveness and performance of the trained neural network (He, 2001), (Hagan, 1996).

Some merits of ANN applications can be summarized as follows, (1) Fault tolerance and adaptability; (2) Data-driven nature; (3) Noise suppression capabilities

There are several neural networks (Morales, 2007), (He, 2001), (Pawadea, 2007), (Krain, 2007), This research shows that the perceptron with a back propagation learning rule is the one most used to predict parameters. To develop this research a multilayer perceptron with a back propagation learning rule was used.

2.2 Lineal Regression

Regression analysis is a technique used for modeling and numerical data`s analysis, consists of a number of independent and dependent variables. The model is a group of independent variables and one or more parameters. The parameters are adjusted to give more approximate value, it is using to obtain the best fit with the least-squares` method, but also may use other criteria. In the dependent variable is assumed that this is a random variable with observation`s errors.

The data consist of *r* values taken from *y* observations which are response or dependent`s variable. The dependent variable is subject to error. This error is assumed that a random variable with mean zero. The independent variable x, is called predictor o regressor´ variable. In a simple linear regression model is described by the following equation 1. (Montgomery, 2004)

$$y_i = \sum_{j=1}^{n} x_{ij}\beta_j + \varepsilon_i \qquad (1)$$

The constant`s coefficients are Xij or functions of the independent`s variable, x. And this is under the following scenarios

• Residual ε_i is normal with mean zero and unknown common variance σ^2; addition, these residual are independent.
• The number variables that explain the problem (*m*) is lower than observations (*n*); this hypothesis is called full range.
• There is not exact linear relationship between the variables used to explain.

Using linear regression is to decide if the response variable *y* is really linear function of the *x* variable.

2.3 Surface Roughness

In everyday life as well as in industry, the degree of surface finish is very important, sometimes is necessary to have very high values of it, other times it is unwanted because the product requires lowest friction of the surface when to be in contact with another, with this minimizing the wear materials` phenomenon. The roughness is the set of irregularities in the actual surface (González, 2005). To measure the parts roughness used sensitivity micrometer electronic instruments called roughness meter determining quickly the roughness of surfaces. There are several parameters that reflect the measurement of roughness, such as Ra, Ry, Rz. The most common is Ra (González, 2005), it is an arithmetic mean of the distance roughness` absolute values of the middle line of the length measurement.

3. EXPERIMENTAL DEVELOPMENT

3.1 Methodology

The methodology followed in this study is shown below. First data extraction, after classification of the data, analysis with intelligent system, prediction with Neural Network, prediction with Lineal Regression, comparation between the results, calculate the errors and the normality of them, select the best, calculate the confidence intervals, prediction with different parameters. The identification and optimization of variables involved in the process of manufacturing a product is not an easy task. New research using intelligent systems in manufacturing process show that integrating the knowledge of experts into these tasks is accomplished by having good results. To achieve this difficult feat, the global trend has been to adapt intelligent systems that are able to develop the ability to learn from these experts and their improvements.

3.2 Description Problem

The problem is identify, control and optimized the parameters that influence in the machining of Ti 64, with the propose to increase the productivity, dismiss the cost, first take the parameters use for the study which would be the input data both in the regression as well as the neural network, these are described in Table 1. The main focuses of this study is predicting the machine parameters and get the roughness to titanium 64 machining process and provide appropriate values in the machine to ensure obtain the roughness that want when machining this alloy

Table 1. Machining parameters used in the test

Conditions	*Units*	*Level 1*	*Level 2*	*Level 3*
Cutting Speed	m/min	40	60	80
Feed Rate	mm/rev	0.130	0.179	0.220
Depth of Cut	mm	0.500	0.750	1.000

The tests were extracted from the Ramesh`s article (Ramesh, 2007). The machining processes are carried out on a lathe NAGMATI-175. The insert tool used was PVD carbide cover with TiAlN. The workpiece`s dimension was 38mm in the diameter with 125mm long of a titanium alloy (Ti-6Al-4V) Annelead. The turning took place over a length of 110mm for each experiment. The roughness was measure with a surface roughness meter "Taylor Hobson Surtronic 3 +". The measurements were made on a granite table, and using pattern blocks to level the pieces. The information used to train the neural network and maximum sensibility are showed in the figure 1

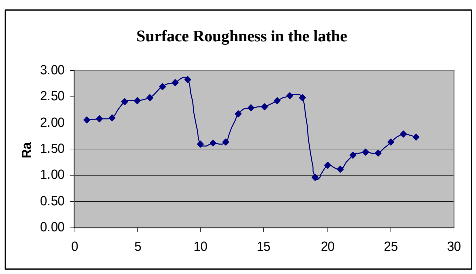

Figure 1. Surface roughness in the machining process.

3.2.1 Neural Network Back propagation Analysis.

To build the network it is important to identify the following parameters: (1) The set of training patterns, input and target (2) A learning rate value (3) A criterion that terminates the algorithm (4) A methodology to update weights (5) The nonlinearity function (6) Initial weight values (7) Learning moments. To develop this research a multilayer perceptron with a back propagation learning rule was used. Some of variables used are: Tinp = Neurons of the input layer and bias; Tmid = Neurons of the hidden layer; Tout = Neurons of the output layer; eta = Constant learning; alpha = Moment

The parameters values were obtained by a design of experiment. The following Table 2 shows the best results obtained in the tests to train the network. The input parameters are Speed, feed and depth cut; Output value: Surface roughness value. After make different test to train the network. With this parameters was trained the neural network and valid them, the results are shown in Fig. 2. The results shown that the network output data are reliable and close to the real data.

Table 2. Results with the best values for the variables used in the Neural Network

Tinp	Tmid	Tout	eta	alpha	Ntepochs	error4
3+1	25	1	0.600	0.250	5000	0.0039

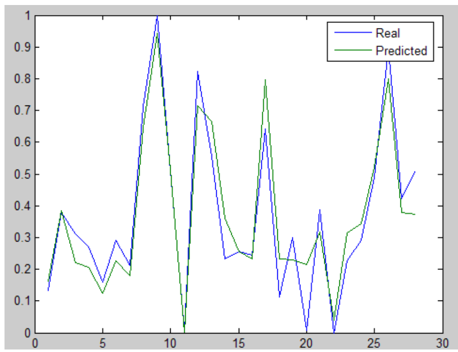

Figure 2. Graphic real values of the experimentation vs. trained obtain of Neural Network Back Propagation

3.2.2. Statistical Analysis.

The statistical study was conducted with a linear regression ($\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$) of the data obtained in the experiment shown in table 1 and figure 3, where the roughness is evaluate with each regressors, (machining parameters), the levels used for each regressors are shown in Table 1. Making the prediction model in a software called Minitab®, and obtain an analysis of variance show in the Table 3, with the results of the model for predicting the roughness generated, the model is as follows.

$$Ra = 1.96 - 0.0254(Speed) + 8.09(feed) + 0.162(depth) \quad (2)$$

Table 3. Analysis of variance of experiment data

Predictor	Coef	SE Coef	T	P	VIF
Constant	1.958	0.176	11.110	0.000	
Speed	-0.025	0.002	-16.790	0.000	1.000
Feed	8.093	0.671	12.060	0.000	1.000
Depth	0.162	0.121	1.340	0.019	1.000

S = 0.128276	R-Sq =	94.9%	RSq(adj)=	94.3%

In the linear regression model can see that the adjustment of the data obtained (R2), is very good and that the inflation factors for the variable (VIF) are within the range of work (between 1 and 10). After that made a comparison of real results beside predict with neural networks and statistical model and get the Figure 3. See that the adjustment between the network and real data obtained from the experiment is the closest that obtained through the regression.

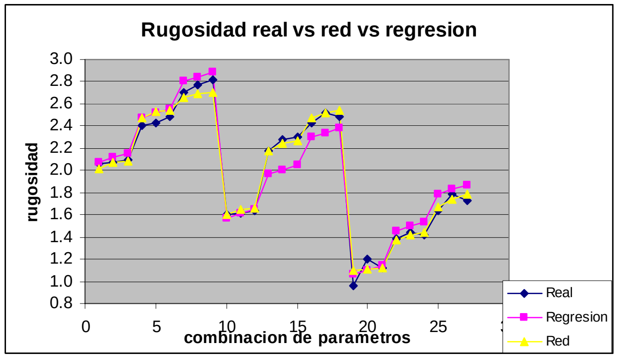

Figure 3. Real roughness vs predicted by the network and predicted regression.

3.3. Discussion

It's important to get the confidence intervals for the estimated values, first determine errors $\varepsilon = y - \hat{y}$, uses a Kolmogorov-Smirnov test, which evaluate the normality of the data, the results are presented in the figures 4, which notes that the network is normally because the p-value is greater than 0.05 but in case of errors of regression, there is no normally in the data. Only the normal data can be calculated confidence intervals (IC). For the network the data is shows in the Table 4. The next step was predicted parameters that have not been run in the machining process and obtain a roughness with confidence intervals, and its give a value very close to reality. In Table 5 shows the results of predictions with confidence intervals.

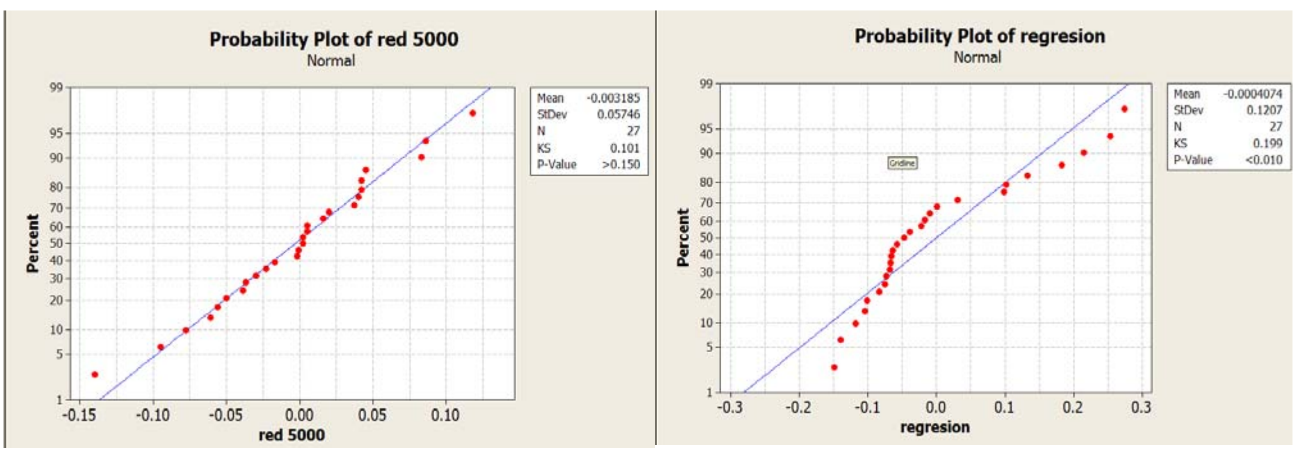

Figure 4. Tests of normality for the mistakes of the network (right hand) and back (left)

Table 4 .- Confidence Intervals for the network

IC max	IC min
0.01228947	-0.01232538

Table5 .- Intervals predicting the roughness with the neural network

Speed	Feed	Depth	Ra	IC min	IC max
40	0.13	0.5	2.066	2.053	2.078
40	0.13	0.6	2.062	2.049	2.074
40	0.13	0.7	2.060	2.047	2.072
40	0.13	0.8	2.066	2.053	2.078

4. CONCLUSIONS

Only the predicted results of the neural network include confidence intervals because it has normal errors with a standard deviation known. This shows that the neural network can help predict the roughness and this can be used as a complement to design parts. It is very important to find the best conditions for optimizing machining and reduce costs and the same time; this can be easy using an intelligent system. The problem for the use of regression is that can not get the confidence intervals to which the machine works because of the data´s characteristics. In conclusion is most convenient use of neural network because predicted the values with a confidence interval

5. FUTURE WORK

It should continue working on techniques to help optimizing these results such as algorithms (random search, hill climbing, genetic algorithms), also experiment with regression to the square polynomial complete. Search other material conditions affecting the machining of superalloys to evaluate most complete this process. Analyze machining process with other alloys with difficult machinability, materials such as Inconel, other titanium alloys, composites, or other expensive materials and actually being used in industry more frequently each time and it generate a lot time and economic waste

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