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Comparison Between Artificial Neural Network And Multiple Regression For The Prediction of Superficial Roughness In Dry Turning

Comparación entre redes neuronales artificiales y regresión múltiple para la predicción de la rugosidad superficial en el torneado en seco

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Abstract

The simple regression and artificial neural network methods are techniques used in many industrial aplications. This work developed two models in order to predict the surface roughness in dry turning of AISI 316L stainless steel. In its implementation they were considered various cutting parameters such as cutting speed, feed, and machining time. The models obtained by both methods were compared to develop a full factorial design to increase reliability of the recorded values of roughness. The analysis can be corroborated by the values of coefficients of determination that the proposed models are able to predict for surface roughness. The obtained results show that the neural networks techniques are more accurate than the multiple regression techniques for this study.

Keywords: AISI 316L stainless steel, Analysis of variance and regression, Artificial neural network, Dry high-speed turning, Surface roughness.

Resumen

Los métodos de regresión múltiple y redes neuronales artificiales son técnicas usadas en muchas aplicaciones de la industria. En este trabajo se utilizaron dos métodos de predicción: regresión múltiple y redes neuronales artificiales (perceptrón multicapa) con el objetivo de predecir la rugosidad superficial en el torneado en seco del acero AISI 316l. En su implementación fueron considerados varios parámetros de corte como la velocidad, el avance y el tiempo de mecanizado. Las ecuaciones obtenidas por ambos métodos fueron comparadas desarrollando un diseño factorial completo para aumentar la fiabilidad de los valores registrados de rugosidad superficial. En el análisis se puede comprobar mediante los valores de coeficientes de determinación que los modelos propuestos son capaces de predecir la rugosidad superficial. Los modelos obtenidos demuestran que la técnica de redes neuronales artificiales tiene mejor precisión que la regresión múltiple para este estudio.

Palabras clave: acero inoxidable AISI 316L, análisis de varianza y regresión, redes neuronales artificiales, rugosidad superficial, torneado de alta velocidad.

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1. Introduction

Stainless steel is one of the most used metallic materials in the industrial sector, due to its favorable combination of mechanical properties, corrosion resistance and cost. This material has been widely used in the aerospace and military fields, where there is a growing demand and increasing surface quality requirements [1].

The characteristics of the machined surface directly affect fatigue resistance, corrosion resistance and the tribological properties of the machined components. Obtaining a high-quality surface increases the life of the product's fatigue capacity. Consequently, control of the machined surface is essential to ensure a correct cutting process. The most important aspect in manufacturing processes is the measurement and characterization of surface properties. In the turning pro-cess, surface roughness is a parameter that has a great influence on the behavior and functionality of me-chanical components and production costs [2].

Surface roughness is affected by several factors, such as: advance, the properties of the working material, cutting speed, depth, tip radius, the conditions of the machine, cutting fluids, the materials of the cutting tools, and the angles of the cutting tool, among others. Within them, it is easy to adjust cutting parameters in order to achieve the expected performance [3].

Austenitic stainless steels are considered difficult to machine, a characteristic related to their low thermal conductivity, high coefficient of thermal expansion, high ductility and high hardening by deformation. Fin-ishing operations carried out on these steels are com-monly executed with coated carbide inserts. The range of recommended speeds for the turning of these steels are very conservative (200-350 m/min) [4].

The use of low cutting speeds leads to a low efficiency in production and consequently high production costs [5]. As this range is unproductive in terms of current technological conditions, it is necessary to de-termine the behavior of surface roughness during the high-speed machining process (HSM).

Surface roughness generated in the machining processes has been studied since [6] by Sata and in [7] by Dickinson. The effect of the tool advancement, the tip radius and the angle of the edge on the surface roughness generated in the turning was described by Groover and named «ideal roughness», enunciated as the minimum roughness that is generated in a turned piece [8].

Surface roughness is one of the quality parameters most studied by researchers who analyze the machinability of austenitic steels. For example, Korkut et al. conducted a study of surface roughness and flank wear to determine the optimum cutting speed with the use of coated carbide inserts. The highest values of surface roughness during turning were achieved at low speeds (<180m/min) attributed to the presence of cut-ting edge growth [9]. A similar result was achieved by Ciftci during his experimental study to analyze the influence of cutting speed (between 120 m/min and 210 m/min) on surface roughness and cutting forces [9].

Four years later, Galanis and Manolakos developed an empirical mathematical model to predict surface roughness with the application of a surface response methodology. This investigation was developed during the machining of femoral heads with a tool coated with ($TiN/Al_2O_3/TiC$) [10].

In 2012, Çaydaş and Ekici implemented an artificial neural network to predict surface roughness. The validation of this model was developed through an experimental study that considered the cutting parameters involved in the dry turning of stainless steel AISI 304 [11].

That same year, Ahilan and others conducted an investigation with the purpose of developing a model based on artificial neural networks to predict cutting conditions on CNC lathes. They used the design of experiments (Taguchi method) to train and validate the proposed neural model [12]. In this case, the maxi-mum cutting speed used was 150 m/min.

Selvaraj and others developed a research to optimize cutting parameters in order to minimize surface roughness, cutting force and tool wear. The experiments are analyzed using the Taguchi method, the turning operation was performed dry and at a maximum cutting speed of 120 m/min [13].

Figure 1 shows a summary of the cutting speeds used in the main studies developed during the turning of austenitic steels. These investigations include not only the study of surface roughness, but also of wear of cutting tools, surface integrity, cutting forces, cut-ting power and chip formation.

The literature reveals (Figure 1) that there are few studies related to the dry turning of austenitic stainless steels at cutting speeds higher than 400 m/min. Only four authors exceeded this cutting speed.

Lin evaluates the wear behavior of the tool (flank wear) [14], Fernández-Abia and collaborators did not carry out dry machining [15], Maranhão and Darvim studied the influence of the friction coefficient of the tool-chip interface [16] and finally, Galanis and Manolakos studied the effect of cutting conditions on surface roughness during the machining of AISI 316L stainless steel femoral heads. The cutting length for this study was 28 mm [17].

The objective of this research is to compare two methods in order to predict surface roughness in AISI 316L stainless steel with speeds of 400 m/min and 450 m/min, one based on multiple regression and another in artificial neural networks of the multilayer percep-tron type.

For this purpose, it was necessary to implement a complete factorial design to investigate the effect of cutting conditions (speed, advance, time) on surface roughness. Multiple regression models are validated by basic assumptions.

A multilayer perceptron architecture with a back-propagation algorithm is used to develop the neural network and the criterion for updating the weights is a downward gradient. The effectiveness of both models is determined by comparing the coefficients of determination and the absolute average error.

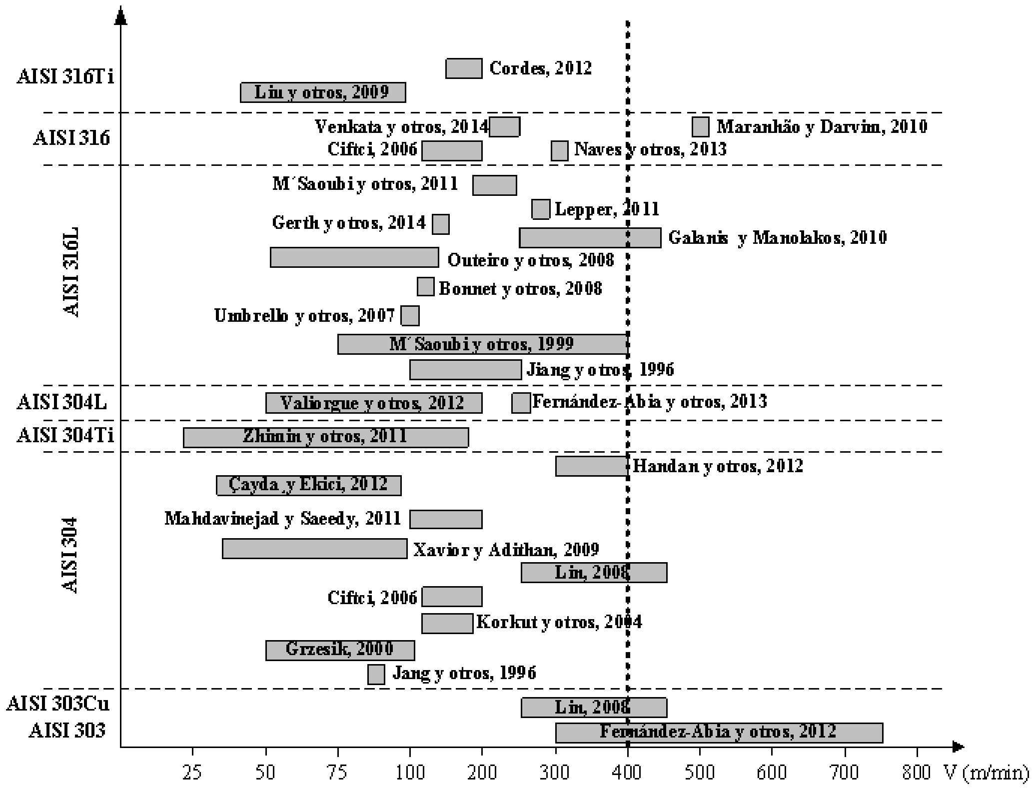


Figure 1. Main investigations in the turning of austenitic stainless steels

2. Materials and methods

2.1. Surface roughness models

In turning, there are many factors that affect surface roughness such as the cutting tool, the work material and the cutting parameters. The factors related to the tools include materials, tip radius, the angle of attack, the geometry of the cutting edge, the vibration of the tool, etc., while the variables related to the material of the piece of work include hardness, physical and me-chanical properties, among others. On the other hand, influential cutting conditions include cutting speed, advance and depth [18].

The appropriate selection of cutting parameters and the geometry of the tool to achieve the required surface quality is complex and difficult [19]. Therefore, it is clear that the selection and obtaining of a model that describes this process is essential for the machining of steels [20].

Surface roughness (Ra) is generally defined based on the ISO 4287 standard as the arithmetic mean of the deviation of the profile of the roughness from the centerline throughout the measurement. This definition is given in equation (1).

$$R_a = \frac{1}{L}\int_0^L |y(x)|dx \tag{1}$$

Where: L is the measurement length; y it is the distance between two points of the profile. The relationship between surface roughness and machining variables can be defined as (equation 2):

$$R_a = C \cdot V^n \cdot f^m \cdot d^p \cdot r^l \cdot \varepsilon \tag{2}$$

Where, Ra is surface roughness measured in μm; V, f, d, r are cutting speed (m/min), feed (mm/rev), depth (mm), radius of the tool tip (mm), respectively. C, m, n, l are constants and ε is the random error [21]. Equation (1) can be seen as equation (3) to facilitate the representation of constants and parameters. The arithmetic mean roughness (Ra) and the height of the maximum peak (Rt) of the turned surfaces can be de-termined by the following equations (3) and (4):

$$R_a \approx \frac{f^2}{32 \cdot r} \quad (3)$$

$$R_t \approx \frac{f^2}{8 \cdot r} \quad (4)$$

Where r is the tip radius (mm) and f is the cutting advance (mm/rev). Equations (3) and (4) show that surface roughness increases proportionally with the advance and, in addition, the increase in tip radius of the cutting tool reduces surface roughness in the turning.

2.2. Modelación por regresión múltiple

Multiple regression is a statistical technique that allows to determine the correlation that exists between independent variables and two or more dependent variables. Multiple regression can be used to analyze ordinal and categorical data [22]. Generally, a variance analysis (ANOVA) is carried out first to determine the important factors involved and then with the use of regression a quantitative model is obtained that relates the most important factors with the answer [23].

2.3. Prediction strategy using artificial neural networks

Artificial neural networks (ANNs) are widely used in many industry applications. These are very popular in the modeling of systems due to their high efficiency in adaptation and learning through pattern recognition [3].

The network installed in this research is a multilayer perceptronic network which is equivalent to multiple non-linear regression [24]. The multilayer perceptronic network is composed of the association of artificial neurons organized within the network forming levels or layers.

This case presents an input layer in which the patterns are introduced into the network (cutting parameters), a hidden layer with some neurons, and an output layer with the response variable (surface roughness). The structure of the ANN shown in Figure 2 was used to model and predict the dependent variable.

The determination of the optimal number of neurons of the hidden layer was carried out through a trial and error process in which different variants were tested. In any case, the objective was to provide the network with an adequate number of neurons in the hid-den layer to guarantee the ability to learn the characteristics of the possible relationships between the sam-ple's data.

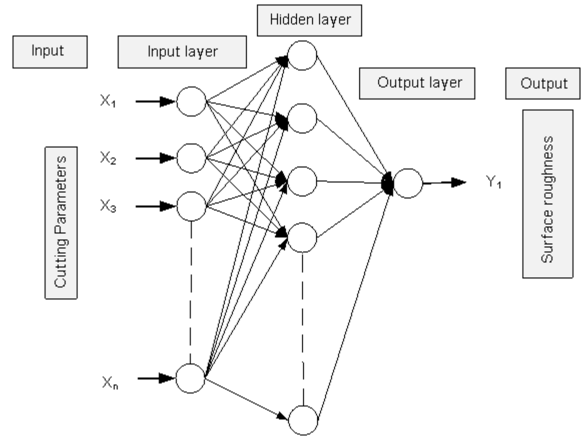


Figure 2. Structure of the multi-layer perceptronic network

2.4. Experimental tests

Experimental turning was executed in dry conditions, with the use of a multifunctional Okuma Multus B200-W type lathe with an engine power of 15 kW and a rotation of the spindle between 50 rpm and 5000 rpm (Figure 3).

Figure 3. CNC multifunctional lathe Okuma model Multus B-200W

AISI 316L stainless steel was the material selected for the test pieces. This steel is used in the manufacture of products resistant to corrosion and to high tem-peratures [25]. The chemical composition is C 0.015%, Si 0.58%, Mn 1.50%, Cr 16.95%, Mo 2.05%, Ni 10.08%, P 0.031%, S 0.029% and N 0.059%.

The specimens of 100 mm in diameter and 200 mm in length were turned with sandvik, GC1115 and GC2015 coated inserts. The coatings of (TiCN-A_2O_3-TiN) with a thickness of 15 µm corresponded to the GC2015 insert and, for the GC1115 insert, the coating was 5 µm thick TiN. After the turning operation, surface roughness (Ra) was measured with a CARL ZEISS rugosimeter model SURFCOM 1500SD2 (Figure 4).

The geometry of the inserts was CCMT 12 04 04-MF with chipbreaker, the Sandvik tool holder code C6-SCLCL-45065-12 and an adapter with code C6-391.01-63 060. The main incidence angle was 7°, the angle of attack was 0° and the radius of the tip of 0.4 mm.

Figure 4. CARL ZEISS rugosimeter model SURFCOM 1500SD2.

A complete factorial analysis was done to determine the relationship between the independent variables (cutoff parameters) and the dependent variable (surface roughness (*Ra*)). A total of 64 tests for two replicas were developed with two levels of cutting speeds (v), four levels of time (T), two levels of cutting advances (f) and two levels of tool material. Table 1 shows the variables studied.

Table 1. Factors and levels used in the development of the experiment

Factors	Symbols		Level 1	Level 2	Level 3	Level 4
Advanced (mm/rev)	f		0,08	0,16	-	-
Insert material	Ins		GC1115	GC2015	-	-
Speed (m/min)	v		400	450	-	-
Time (min)	T	400 m/min	2	3	4	5
		450 m/min	0,6	1,2	2	3

3. Results and discussion

Surface roughness is widely used as a parameter to indicate the quality of a product and in most cases, an important technical requirement in mechanical design.

Consequently, achieving the quality of the desired surface is of great importance for the functional behavior of a product [26]. It also has an impact on me-chanical properties, specifically on fatigue resistance and corrosion resistance [19].

Manufacturing industries are in charge of guaranteeing the consumer's increasing demands for superficial quality and availability of less expensive products. Therefore, knowing the effect of these parameters is important to evaluate the effectiveness and productivi-ty of the cutting process [27].

This section compares and discusses the results obtained through multiple regression and artificial neural networks.

3.1. Analysis of multiple regression

The models obtained as a result of the multiple regression analysis with the velocity of 400 m/min are shown in equations (5) and (6) for the GC1115 and GC2015 inserts respectively. The models with the speed of 450 m/min are shown in equations (7) and (8) for the GC1115 and GC2015 inserts respectively.

$$R_a = 0,358933 + 0,0188793 \cdot e^{T} \cdot f \qquad (5)$$

$$R_a = 0,27529 + 0,0109446 \cdot T^2 + 0,69 \cdot f \qquad (6)$$

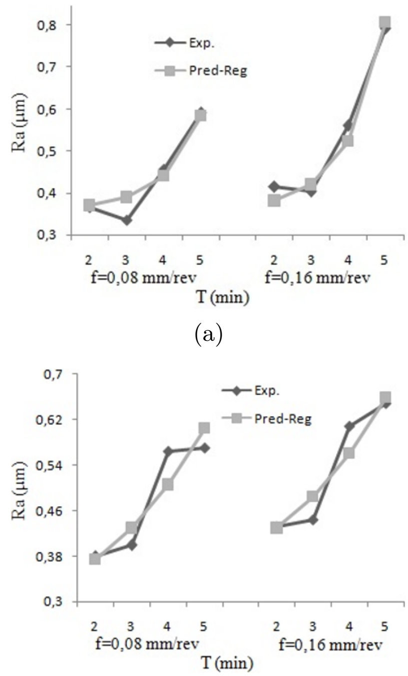
$$R_a = -2,75967 + 2,99435 \cdot e^{(T^3 \cdot f^2)} \qquad (7)$$

$$R_a = 0,219579 + 0,0201327 \cdot T^3 + 0,45625 \cdot f \qquad (8)$$

The coefficient of determination (R^2) represents the true measure of the correctness of the adjustment in the regression line determined by the model. For these cases the R^2 were at a speed of 400 m/min, 0.92 (GC1115) and 0.80 (GC2015) and for 450 m/min were 0.97 (GC1115) and 0.97 (GC2015).

In all cases, in order to validate the regression results obtained, compliance with the basic regression assumptions was verified, such as: homoscedasticity (White Test), non-autocorrelation of residues (Breusch-Godfrey Test), normality (Jarque-Bera Test) and no mean.

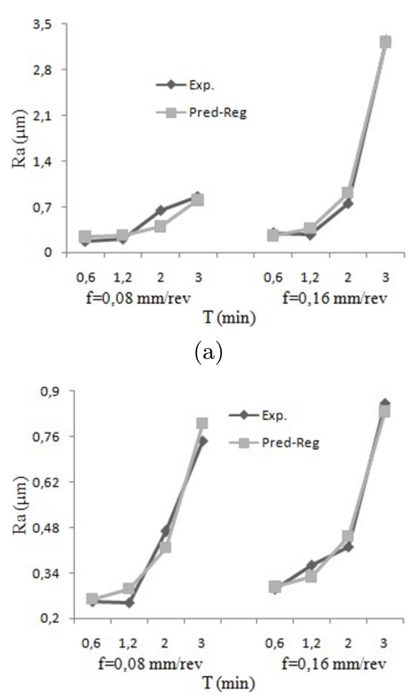
Figures 5 and 6 show the comparisons between the experimentally measured values and the estimated values of surface roughness by the models corresponding to the speeds of 400 m/min and 450 m/min, respectively. In these Figures we can observe a strong relationship between the estimated variables and the response variable.



(a)

(b)

Figure 5. Values measured and estimated by multiple regression for v = 400 m/min, a) GC1115 insert and b) GC2015 insert



(a)

(b)

Figure 6. Values measured and estimated by multiple regression for v = 450 m/min, a) GC1115 insert and b) GC2015 insert

3.2. Results of artificial neural networks

The structure of the network applied to model and predict surface roughness in the turning operation corresponds to the multilayer perceptron of the feedforward Backpropagations type. The experimental data were used to construct the model of artificial neural networks.

The training was developed through the Levenberg Marquardt algorithm. The best results were obtained with a 3-5-1 structure, three neurons in the input layer, 5 neurons in the hidden layer and one in the output layer. The neural network software was encoded using Matlab's Neural Networks Toolbox. The parameters of the proposed network structure are shown in Table 2.

The input data were divided by the speeds, therefore, only the machining time, the cutting advance and the type of cutting tool were considered. These data were randomly distributed in the following way: for the training 70% were selected (22 data), 15% (5 data) for the test stage and for the validation the remaining 15% (5 data).

Table 2. Parameters of the artificial neural network implemented in the study.

Number of layers	3
Number of neurons in the layers	Entrada: 3 Oculta: 5 Salida: 1
Activation function	Tansig-purelin
Number of iterations	10000

The results obtained were analyzed by statistical methods, the criteria used were the absolute average error (Emedio, (%)) and the coefficient of determination (R^2).

Equations 9 and 10 are used to calculate these criteria respectively.

$$E_{medio} = \left(\frac{1}{N} \sum_i \left| \frac{t_i - t_0}{t_i} \right| \times 100 \right) \tag{9}$$

$$R^2 = 1 - \left(\frac{\sum_i (t_i - t_0)^2}{\sum_i (t_0)^2} \right) \tag{10}$$

Where N, is the number of trials; t_i, experimental values and t_0, estimated values.

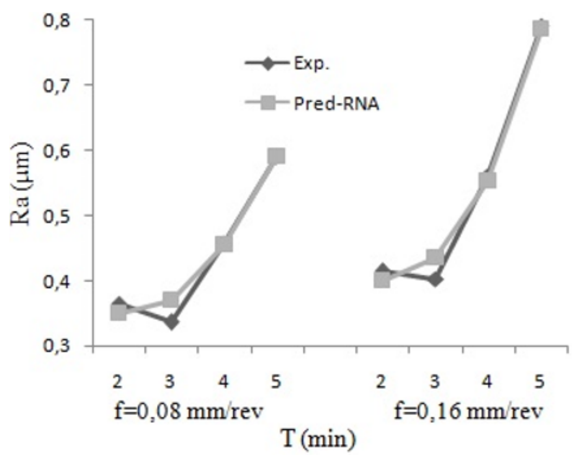
Figures 7 and 8 show a comparison between the experimental values and the estimated values of sur-face roughness by the model developed by artificial neural networks.

The results of the neural networks show that the models proposed in this study are suitable for the pre-diction of surface roughness.

The values of the coefficients of determination and of the absolute average errors are within acceptable ranges (Table 3).

Table 3. Values of coefficients of determination (R^2) and absolute mean errors for each developed neural network.

Parameter	Neural network 400 m/min	Neural network 450 m/min
Training	0,98134	0,99836
Test	0,99842	0,99026
General	0,98122	0,9973
$E_{average}$	2,869	6,946



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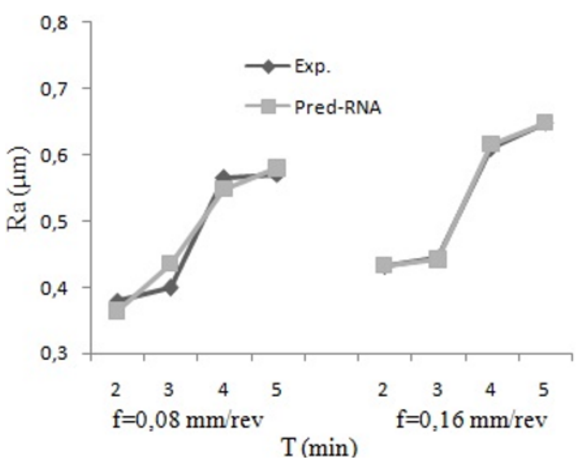
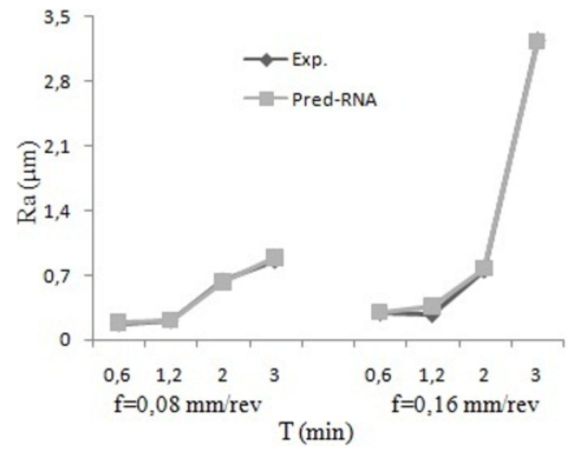


(b)

Figure 7. Values measured and estimated by artificial neural networks for v = 400 m/min, a) GC1115 insert and b) GC2015 insert

3.3. General evaluation

A complete factorial experiment design was applied to determine the effects of independent variables (speed, advance, time and cutting tools) of the dry turning process in surface roughness. After each turning test, surface roughness values were recorded for further analysis. In this research, models were developed us-ing artificial neural networks and multiple regression. Table 4 shows a comparison of the results according to the precision of the values obtained by means of multiple regression and by artificial neural networks. The results are close to those measured experimentally for all models. Therefore, the proposed models can be used to predict surface roughness in the dry turning of AISI 316L steel. However, as can be seen in the same table, the models obtained by artificial neural networks produce better results compared to the models using multiple regression.



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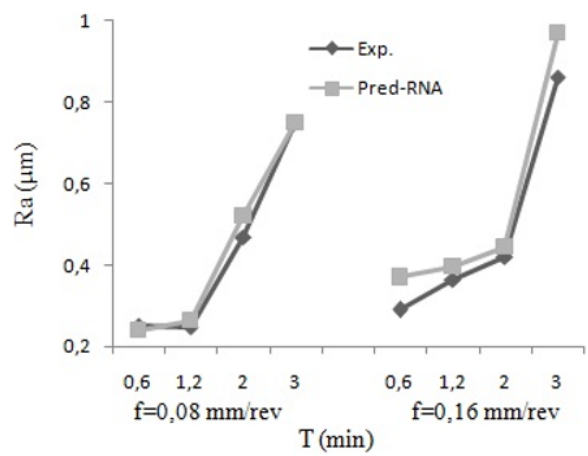

(b)

Figure 8. Values measured and estimated by artificial neural networks for v = 450 m/min, a) GC1115 insert and b) GC2015 insert

Table 4. Comparison of proposed methods

Method	Equation	$E_{average}$	R2
Multiple Regresión	-1	5,153	0,9
	-2	5,552	0,8
	-3	22,78	1
	-4	8,473	1
Artificial neural network	400 m/min	2,869	1
	450 m/min	6,946	1

4. Conclusions

In this research, a study has been carried out to predict surface roughness in the dry turning of AISI 316L steel. The influence of variables such as speed, ad-vancement and machining time were analyzed through a complete factorial design. The models to predict the surface roughness were developed from the experimental data. According to the results obtained in this work, the following conclusions are presented.

- The developed models were evaluated for their prediction capabilities with the values measured experimentally.
- The proposed models can be used to predict surface roughness in the dry turning of AISI 316L steel.
- The coefficient of minimum determination reached by the models was 80% and the maximum of 99%, indicating the proportion of variability of the data explained by the regression models, in the case of the absolute average error the minimum was of 2,869% and the maximum of 22.78.
- The lowest absolute mean errors were obtained with the models implemented with artificial neural networks.
- In future research, models based on neural networks and multiple regression could be developed to allow a study of the economy of the dry turning process.

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