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Comparison of two methods for predicting surface roughness in turning stainless steel AISI 316L

Comparación de dos métodos para la predicción de la rugosidad superficial en el torneado del acero inoxidable AISI 316L

Yoandrys Morales Tamayo[1]* Yusimit Zamora Hernández[2]
Roberto Félix Beltrán Reyna[3] KimberlyMagaly López Cedeño[4]
Ringo John López Bustamante[5] Héctor Cochise Terán Herrera[6]

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ABSTRACT

The present study aimed to explore various models to predict the surface roughness in dry turning of AISI 316L stainless steel. Multiple Regression Methods and Artificial Neural Networks Methods were implemented to study the effect of cutting speed, feed, and machining time. In order to increase the reliability and soundness of the registered surface roughness values, a complete Factorial Design was implemented. A statistical comparison of the resultant models was performed. The results produced by both methods show that the surface roughness can be predicted. Results of the Artificial Neural Networks models show a better accuracy than those derived from the Multiple Regression models.

Keywords: AISI 316L stainless steel, analysis of regression, artificial neural network, surface roughness, dry turning.

RESUMEN

El objetivo del presente estudio fue analizar varios modelos para predecir la rugosidad de la superficie en el torneado en seco de acero inoxidable AISI 316L. Los métodos de regresión múltiple y redes neuronales artificiales fueron aplicados para estudiar el efecto de la velocidad de corte, avance, y el tiempo de mecanizado. Con el fin de aumentar la fiabilidad y solidez de los valores de rugosidad superficial registrados fue implementado un diseño factorial completo. Se realizó una comparación estadística de los modelos resultantes. Los resultados producidos por ambos métodos muestran que la pueden ser utilizados para predecir la rugosidad superficial. Los resultados de los modelos de redes neuronales artificiales muestran una mayor precisión que los derivados de los modelos de regresión múltiple.

Palabras clave: Acero inoxidable AISI 316L, análisis de regresión, redes neuronales artificiales, rugosidad superficial, torneado en seco.

[1] Universidad Técnica de Cotopaxi. Av. Simón Rodríguez S/N, Sector San Felipe. La Maná. País: Ecuador.
E-mail: yoandrys.morales@utc.edu.ec
[2] Universidad de Granma. Carretera a Bayamo-Mzllo km 17 1/2. Bayamo. País: Cuba. E-mail: yzamorah@udg.co.cu
[3] Universidad de las Fuerzas Armadas. Av. General Rumiñahui s/n Ciudad: Sangolquí. País: Ecuador P.O.BOX: 171-5-231B.
E-mail: rfbeltrnr@espe.edu.ec
[4] Universidad de Guayaquil. Cdla. Universitaria "Salvador Allende". Malecón del Salado Guayaquil. Ecuador.
E-mail: kimberlylopezcedeno@hotmail.com
[5] Universidad Técnica de Cotopaxi. Av. Simón Rodríguez S/N, Sector San Felipe. La Maná. País: Ecuador.
E-mail: ringo.lopez@utc.edu.ec
[6] Universidad de las Fuerzas Armadas. Av. General Rumiñahui s/n Ciudad: Sangolquí. País: Ecuador P.O.BOX: 171-5-231B.
E-mail: hcteran@espe.edu.ec
* Autor de correspondencia.

INTRODUCTION

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

The characteristics of the machined surface directly affect the fatigue, corrosion resistance and tribology properties of the machined components. Obtaining a high value of quality surface increases the fatigue life of the product. Consequently, the control of machined surface is essential to ensure proper cutting operation.

The most important aspect of manufacturing processes is the measurement and characterization of surface properties [2]. In the process of turning, the surface roughness is a property that characterizes the quality of finished piece [2].

In turning, the surface roughness is affected by several factors which can be seen in Figure 1. Among them, they are easy to adjust the cutting parameters in order to achieve the expected performance [3].

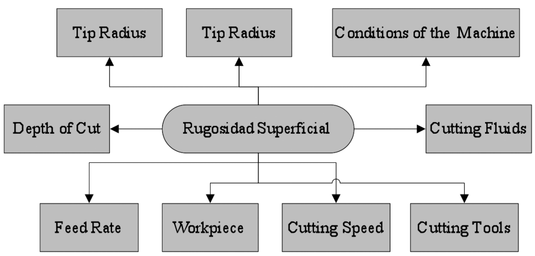

Figure 1. The major factors which affect the surface roughness.

The austenitic stainless steels are considered difficult materials to machine, a related feature with their low thermal conductivity, high thermal expansion coefficient, high ductility and high hardening by distortion. The finishing operations, in these kinds of steel, are carried out commonly with coated carbide inserts, the range of the recommended speeds are very conservative (200-350 m min^{-1}) [4].

Low speeds of cutting, lead to low production efficiency and consequently high production costs [23]. As this range is unproductive under current conditions of technology, it is necessary to determine the behavior of the surface roughness during high-speed machining (HSM).

The surface roughness generated in machining processes has been studied since 1963 by Sata and in 1968 by Dickinson. The effect of tool feed, the tip radius and the edge angle on the surface roughness generated in the turning has been described by Groover 2007 and has been called "ideal roughness", stated as minimum roughness generated in a turned part [5].

Galanis and Manolakos developed an empirical mathematical model to predict the surface roughness with the application of response surface methodology. This research was developed during machining of femoral heads at high speeds (264 m min^{-1}, 352 m min^{-1} and 440 m min^{-1}) with a covered tool (TIN / Al2O3 / TIC) [6].

In 2012, Çaydaş and Ekici implemented an artificial neural network to predict the surface roughness. Validation of this model was developed through an experimental study that will consider the cutting parameters involved in turning dry stainless steel AISI 304 [7].

By another side, Kuram and others conducted an analysis of the use of cutting fluids biodegradable in the process machining of steel AISI 304. Because these are considered less toxic, and biodegradable. The main objective of this research was to determine the optimum cutting conditions corresponding to the energy, the life of the tool and its surface roughness [8].

That same year, Ahilan and others conducted research in order to develop a system based on artificial neural networks to predict the cutting conditions in lathes CNC. They used the design of experiments (Taguchi Method) to train and validate the proposed neural model, back propagation neural network. In this case, the maximum cutting speed used was 150 m min^{-1} [9].

Selvaraj and others developed an investigation to optimize the cutting parameters in order to minimize the surface roughness, cutting force and wear of tool. The experiments are analyzed using the Taguchi method, the turning operation is in dry and at a maximum cutting speed of 120 m min^{-1} [10].

The literature reveals that there are few studies related to dry turning of austenitic stainless steels at speeds in excess of 350 m min^{-1}. The aim of this work is to develop two models for predicting surface roughness in stainless steel AISI 316L, one based on multiple regression and another on artificial neural networks.

For this purpose, it was necessary to implement a full factorial design to investigate the effect of cutting conditions (speed, advance, time) in the surface roughness. The multiple regression models are validated through the basic assumptions. A multilayer perceptron architecture with back-propagation algorithm is used to develop the neural network. The effectiveness of both models is compared by statistical methods.

MATERIALS AND METHODS

Models of surface roughness

In turning, there are many factors affecting the surface roughness such as cutting tool, work material and cutting parameters [11].

The factors related tools are:

a) The material, the tip radius.
b) The angle of attack, the geometry of the cutting edge.
c) The tool vibration.

The variables related to piecework:

a) Hardness.
b) The physical and mechanical properties.

The cutting conditions that influence:

a) Cutting speed.
b) Feed rate of cut.
c) Depth of cut.
d) Cutting Fluids

Proper selection of cutting parameters and geometry of tool is complex and difficult to achieve the required surface quality [12]. Therefore, it is clear that the selection and preparation of a model describing this process are essential for the machining of steels [13].

The surface roughness (Ra) is generally defined based on ISO 4287 as: the arithmetic average of deviation of the roughness profile from the center line along of the measurement. This definition is given in equation (1):

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

Where, ***L*** is the length measurement, and ***Y*** is the coordinate of the curved profile.

The relationship between the surface roughness and variables of machining can be defined as:

$$Ra = C \cdot V^n \cdot f^m \cdot d^p \cdot r^1 \cdot \varepsilon \tag{2}$$

Where ***Ra*** is the surface roughness measured in micrometer; ***V, f, d, r*** are the cutting speed (m min^{-1}), advance (mm rev^{-1}), the depth (mm), the tip radius of the tool (mm) respectively. ***C, m, n***, and ***l*** are constants $\mathcal{E}$ is random error. Equation 1 can be seen as equation 3 to facilitate the representation of constants and parameters [14].

The arithmetic mean roughness (Ra) and maximum peak height (Rt) of the sliding surfaces can be determined by the following equations:

$$Ra \approx \frac{f^2}{32 \cdot r} \tag{3}$$

$$Rt \approx \frac{f^2}{8 \cdot r} \tag{4}$$

Where ***r*** is the tip radius (mm) and ***f*** is the cutting advance (mm^{-1} rev). Equations 3 and 4 show that the surface roughness increases proportionally with the advance and the tip radius large reduces the roughness in turning.

Modeling by multiple regression

Multiple regression is a statistical technique to determine the correlation between independent and two or more dependent variables. Multiple regression can be used to analyze ordinal and categorical data [15]. Usually an analysis of variance (ANOVA) is first performed to determine the important factors involved and then using the regression getting a quantitative model relating the most important factors in the response [16].

Strategy prediction using artificial neural networks

Artificial neural networks (ANN) are widely used in many industry applications. These are very popular in modeling systems due to its high efficiency in adapting and learning by recognizing patterns [17-18]. The network implemented in this research is a multilayer perception network method which corresponds to multiple nonlinear regression [19]. The multilayer perception network composed of the association of artificial neural organized within the network to forming levels or layers.

In this case it corresponds to an input layer (two neurons) in which the patterns on the network (cutting parameters), a hidden layer with five neurons and an output layer (one neurons) with the response variable (surface roughness) the ANN structure that is shown in Figure 2, is used to model and predict the dependent variable. This neural network studied corresponds to a multilayer perceptron network.

Determining the optimal number of neurons in the hidden layer was performed by a process of trial and error in which different random variants were tested. In any case, the goal was to provide the network an adequate number of neurons in the hidden layer to ensure the ability to learn the characteristics of possible relationships between the data of the sample.

Experimental tests

The experimental turning was executed in dry conditions, with the use of the multifunctional turning

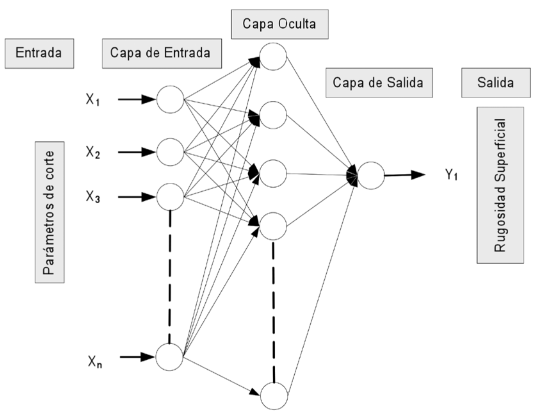

Figure 2. Structure of the multilayer perception network.

Okuma Multus B200-W with power output of 15 kW and spindle rotation between 50 rpm and 5000 rpm. The selected specimen was stainless steel AISI 316L, this steel is widely used in the manufacture of products resistant to corrosion and resistant to high temperatures [20]. 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 specimen of 100 mm diameter and 200 mm length was turning, with coated inserts quality GC2015 and GC1115 Sandvik. The coatings (TiCN-Al_2O_3-TiN) with a thickness of 15 μm corresponded to insert GC2015 and for the insert type GC1115 it coated was TIN 5 μm of thick (the thicknesses were measured on a scanning electron microscopy (SEM)). After the turning operation, the surface roughness (SR) was measured by a CARL ZEISS model SURFCOM 1500SD2.

The geometry of the inserts was TMCC 12-04-04-MF with chip breaker, the tool holder Sandvik code mark SCLCR-C6-45065-12 and an adapter. C6-391.01-63 060 main code, angle incidence was 7°, the angle of attack of 0° and the tip radius of 0.4 mm. The hardness of the inserts obtained a micro-hardness HV SHIMADZU mark was 1755 and 1404 for GC1115 HV for the insert GC 2015.

The full factorial analysis was the procedure used to determine the relationship between independent variables (cutting parameters) and the dependent variable (surface roughness (SR)). A total of 64 tests for two replicas were developed with two levels cutting speeds (v), four levels of time (T), two levels of advanced cutting (f) and two levels of tool material, in Table 1 lists the variables studied.

RESULTS AND DISCUSSION

The surface roughness is widely used as a parameter to indicate the quality of a product and in most cases, a technical requirement important in mechanical design. Consequently, achieving the desired surface quality is very important for the functional behavior of a product [21]. Also, it has an impact on the mechanical properties, specifically in the resistance and fatigue corrosion [12].

Manufacturing industries are responsible for ensuring the consumer increasing demands on the surface

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

Factor	Symbol		Level 1	Level 2	Level 3	Level 4
Advance (mm rev^{-1})	f		0,08	0,16	–	–
Material insert	Ins		GC1115	GC2015	–	–
Speed (m min^{-1})	v		400	450	–	–
Time (min)	T	400 m min^{-1}	2	3	4	5
		450 m min^{-1}	0,6	1,2	2	3

quality and in turn to obtain less expensive products. For this knowing the effect of these parameters is important to evaluate the effectiveness and productivity of the cutting process [22]. This section will be compared and discussed the results using multiple regression and artificial neural networks.

Analysis using multiple regression

The models obtained as a result of multiple regression analysis with the speed of 400 m min^{-1} shown in equations 5 and 6 for inserts GC2015 and GC1115 respectively. The models with the speed of 450 m min^{-1} are shown in equations 7 and 8 for inserts GC2015 and GC1115 respectively.

The coefficient of determination (R^2) represents the correct measure of the goodness of fit in the regression line determined by the model. For these cases, the R^2 were in the speed of 400 m min^{-1}, 0.92 (GC1115) and 0.80 (GC 2015) and 450 m min^{-1} were 0.97 (GC1115) and 0.97 (GC 2015). In all cases, in order to validate the results obtained was checked the compliance of the basic assumptions of regression like "homoscedasticity" and the not autocorrelation of waste, normalcy and zero mean.

$$Ra = 0,358933 + 0,0188793 * e^{T} * f \quad (5)$$

$$Ra = 0,275298 + 0,0109446 * T^{2} + 0,69 * f \quad (6)$$

$$Ra = -2,75967 + 2,99435 * e^{\left(T^{3} * f^{2}\right)} \quad (7)$$

$$Ra = 0,219579 + 0,0201327 * T^{3} + 0,45625 * f \quad (8)$$

In the figures 2 and 3 are shown comparisons between measured values in the experimentally way and values estimated of surface roughness by the corresponding models at speeds of 400 m min^{-1} and 450 m min^{-1} respectively. In these figures, we can see a strong relationship between estimated variables and the response variable.

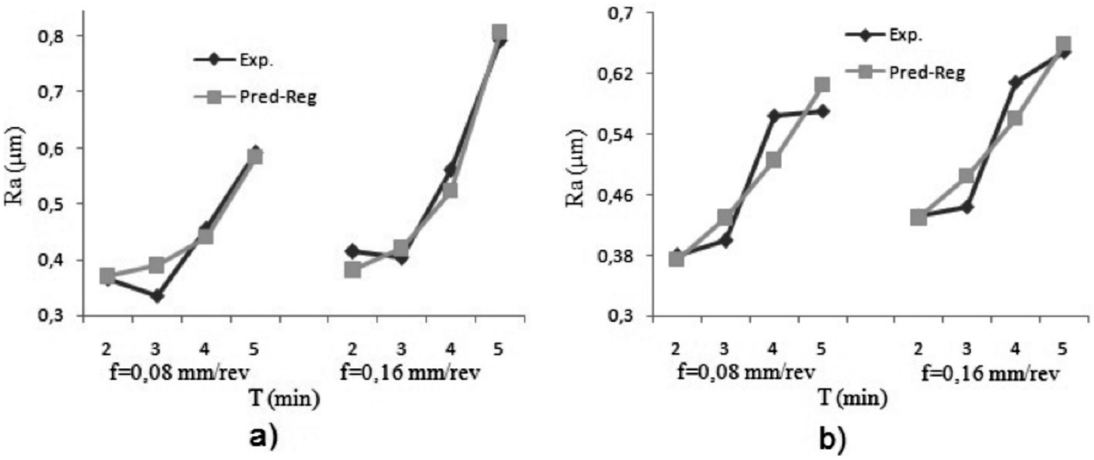

Figure 2a. Values measured and estimated by multiple regression for v = 400 m min^{-1}, a) was inserted GC1115; and b) was inserted GC2015.

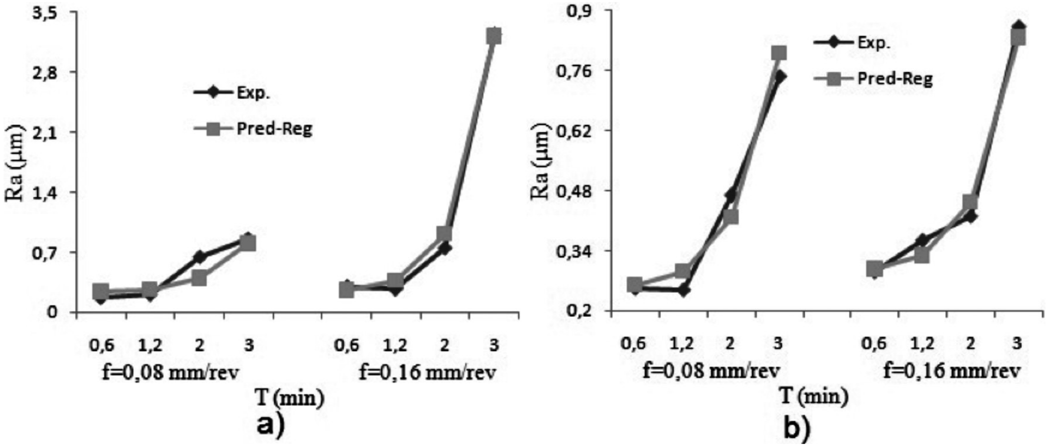

Figure 3. Measured values and estimated by multiple regression for v = 450 m min^{-1}, a) was inserted GC1115; b) was inserted GC2015.

Results of artificial neural networks

The structure applied for modeling and predict the surface roughness in turning is from Multilayer Perceptron to the feed-forward type Backpropagation. The experimental data were used to build the model of artificial neural networks.

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

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

Number of layers	3
Number of neurons in the layers	Input: 3, Hide: 5, Output: 1
Activation function	Tansig-purelin
Number of iterations	10000

Input data were divided by the speeds, therefore, only the machining time was considered, the cutting advance and the type of cutting tool. These data were randomly distributed as follows, for training, was selected 70% (22 data), 15% (5 data) for testing stage and for the validation, the remaining 15% (5 data). The percentages were assigned according to the software used for this case was MATLAB.

The results obtained were analyzed by statistical methods, the criteria used were the mean absolute error (E_{medio}, (%)) and the coefficient of determination (R^2). Equations 9 and 10 are used to calculate these criteria respectively.

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

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

Where N is the number of tests; $\boldsymbol{t_i}$ experimental values and $\boldsymbol{t_o}$, estimated values.

In Figures 4 and 5 shows a comparison between experimental and estimated values of surface roughness by the model developed by artificial neural networks values. The results show that models proposed in this study are suitable for prediction of surface roughness. The values of the coefficients of determination and absolute mean errors are in acceptable ranges (R>0,95 y E_{medio}< 15%) (Table 3).

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

Neuronal Network	Training	Test	General	E_{medio}
To 400 m min^{-1}	0,98134	0,99842	0,98122	2,869
To 450 m min^{-1}	0,99836	0,99026	0,99730	6,946

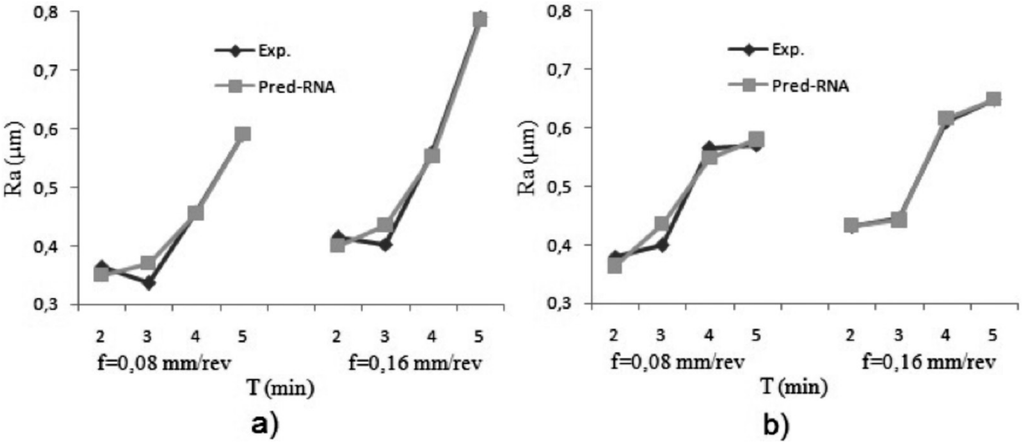

Figure 4. Measured values and estimated by artificial neural networks for v = 400 m min^{-1}, a) was inserted GC1115 and, b) was inserted GC2015.

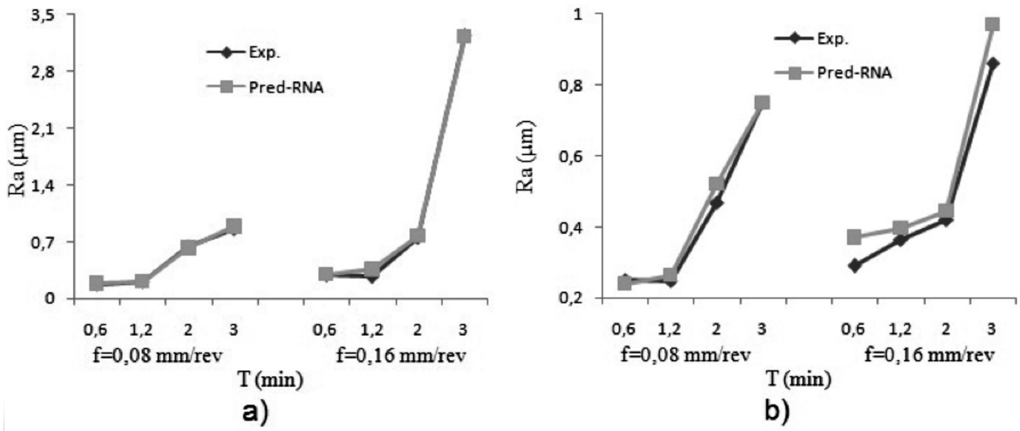

Figure 5. Measured values and estimated by artificial neural networks forv= 450 m min^{-1}, a) was insert GC1115 y b) was insert GC2015.

General evaluation

A full factorial design experiment was implemented to determine the effects of independent variables (speed, advance, time and cutting tools) the process of turning dry on the surface roughness. After each turning test, the surface roughness values were recorded for subsequent analysis. In this research, they have developed models using artificial neural networks and multiple regression. Table 4 shows a comparison of the results according to the accuracy of the values obtained by multiple regression and by artificial neural networks.The results are close to the experimental media for all models. Therefore, the proposed models can be used to predict the surface roughness in dry turning AISI 316L steel.

Table 4. Comparison of the proposed models.

Methods	Equation	E_{medio}	R^2
Multiple regression	(1)	5,153	0,92
	(2)	5,552	0,80
	(3)	22,781	0,97
	(4)	8,473	0,97
Artificial neural networks	To 400 m min^{-1}	2,869	0,98
	To 450 m min^{-1}	6,946	0,99

However, as it can be seen in the same table, the models obtained by artificial neural networks produce better results compared with multiple regression models.

CONCLUSIONS

This research has conducted a study to predict the surface roughness in dry turning steel AISI 316L. The influence of variables such as speed, advance and machining time were analyzed through a full factorial design. Models for predicting surface roughness were developed from experimental data. According to the results obtained in this work the following conclusions arise.

The models developed were evaluated by their prediction capabilities with values experimentally measured.

The proposed models can be used to predict the surface roughness in dry turning steel AISI 316L.

The minimum coefficient determination reached by the models was 80% and maximum 99%, indicating the proportion of the variability of the data explained by regression models, in the case of the minimum absolute average error was 2.869% and 22.78% maximum.

The smaller absolute mean errors were obtained with the models implemented with artificial neural networks.

In future researches models could be based on neural networks and multiple regressions to allow a study of the economics of the process of turning dry.

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