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THE EFFECTS OF MILLING PARAMETERS ON SURFACE ROUGHNESS OF STAINLESS STEEL X22 CR MO V 12 1

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ABSTRACT

Stainless Steels have several uses in different industries and include an extensive area of steels, and because of many differences between mechanical and physical properties of different kinds of stainless steels, it is still necessary to study this type of steels. The surface roughness has been regarded by many researchers since many years ago, because of its high importance in the efficiency of final product, and also because it is considered as a main parameter in examining machinability of metals. In this paper, the experimental reports about optimizing roughness of final surface in milling stainless steel X22 Cr MoV 12 1, has been carried out using multiple regression technique and ANN(Artificial Neural network). The second order mathematical model has been attained from input parameters of process including cutting speed; Feed rate, radial and axial depths of cut. Each of these inputs of the research has been studied in 3 levels and for this purpose totally 81 experiments have been performed. After measuring the surface roughness caused by milling, the obtained model has been used for scrutinizing the effects of different parameters, and also for predicting the optimal milling parameters in order to obtain ideal surface Roughness.

KEYWORDS: Stainless Steel, Milling Parameters, Multiple Regression, Artificial Neural Network, Surface Roughness.

The reason for choosing stainless steels in industry is usually their high strength and resistance against impact, and also unique capability of these steels in resistance against corrosion and heat. Machinability of different kinds of stainless steels varies diversely in different usages of them and this fact is a ground for machining these steels. Since physical and mechanical properties of each type of these steels differ with those of each other, so their machinability are different too

Martensiticstainless steel X22 CrMoV 12 1 is a Ferromagnetic steel and belongs to the group of stainless steels resistant against heat and creep which is used in pressure pipes, boilers, airspaceequipment, manufacturing reactors, components of turbines, and also in screws and nuts which work in high temperatures. Because of high toughness, low heat transfer, and high degree of work hardening, stainless steels are known as hardlymachinable materials(Paro, 2001). The most important features which influence the behavior of machining stainless steels are:

- Stainless steels have higher tensile strength and higher median between yield strength and failure strength, comparing with low and medium carbon steels. Hence the needed energy for machining stainless steels is more than that for cutting ordinary steels.
- Austenitic stainless steels have high work hardening rate and low heat transfer. High hardening work rate results in increment of consumed energy in comparison with carbonic non-hardened steels, and also low heat transfer of these steels causes increasing the heat slope of chips, and increasing produced heat in the region of secondary transformation leads toincrement of temperature in common interface of chip and tools which consequently raises the rate of wear (wear is considerably function of temperature).
- Some groups of high carbon stainless steels which contain remarkable amount of free particles of carbide are hardly machining, since because of existence these particles, the ground hardness increases and also results in rigorous wear of the cutting tool.

Surface roughness of stainless steels 304 and 316 using two carbide tools coatedby Titanium Nitride and Aluminum Oxide has been studied (Ciftici, 2006). His report showed that in both cases by increasing cutting speed the surface roughness and machining force reach to a minimum measure and then by more increment of this speed they increase. The cause of decrement of surface roughness is that the built-up edge did not form, and the cause of decreasing the force is decrement of contact area and shear strain in the Flowing area as a result of raising temperature. Increasing in both roughness and force are caused by tool wearing.

(Razfar,Zinati,2011) have studied the optimization of surface roughness resulted from process of turning and milling (facemilling) Martensitic stainless steel 420 (X20Cr13). Through performing 81 examinations, which were implemented for three levels of four input parameters __ insert edgeradius, cutting speed, Feed rate and cutting depth__, (Suresh et al) have predicted and

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optimized machining parameters in order to achieve to minimum measure of surface roughness. (Oktem, 2009) have accomplished a comprehensive study on surface roughness during milling process with the purpose of optimization and modeling.His studied materials were AISI 1040 and carbide tool with TIALN coating. (Korkut et al, 2004) studied machinability of Austenitic stainless steel 304 by multi-layer coatedcemented carbide tool. They reported in their researches that by increasing cutting speed the surface roughness decreases and described the failure in forming built-up edge and softening the workpiece as causes of this decrement. (Hasan et al, 2008) investigated surface roughness of stainless steel 440C in turning process and declared that because of special nature of this steel, during machining its function is unpredictable. In turning Martensitic stainless steel, one should consider that by choosing medial cutting speed and high Feed rate and cutting depth, the measure of produced heat is so little that does not result in wearing. (Bruni et al, 2006) studied effects of using three cooling methods __i.e. MQL technique, dry technique and applying cooling __ on the stainless steel 420B. They observed that these three methods have no meaningful difference with together in their influences on wearing, but using cooling liquid leads to minimal surface roughness. They explained that why cooling liquid and MQL technique have no effect on wearing: when dry machining is applied, the resulted heat leads to softening the transformation zone and so to decreasing roughness and tool wear, and on the other hand increment in temperature causes more tool wear (since heat softens the tool). But if cooling takes place, heat caused softening does not occur and also easier material flowing, which causes more roughness and tool wear, does not happen. (Alauddin et al, 1995)offered a mathematical model for predicting surface roughness during milling process, based on response surfaces methodology. (Shaoo et al)implemented a research on machining by end milling tool and optimization surface roughness using response surface methodology. (Chen J. C.)Studied the effects of cutting speed, Feed rate, and cutting depth on surface roughness in machining by end milling on aluminum worked piece.

Reviewing the literature of modeling surface roughness showed that numerous studies on this parameter have been implemented. In this paper a second order model on the basis of various experimental measurements has been developed, in order to introduce a model for scrutinizing the effects of different parameters on the surface roughness. Cutting speed, Feed rate, axial and radial depths of cut have been considered as input parameters, and surface roughness as output one.

SURFACE ROUGHNESS

Surface roughness is an important parameter of quality of workpiece surface and has so much effect on final function and production cost of pieces, and also on mechanical properties such as fatigue life, corrosion resistance, creep resistance and …, and on the other features of the piece like as friction, lubrication, electrical conductivity and so on. Hence, many researches have been carried out on modeling surface roughness and optimizing and controlling the parameters in order to find ideal surface roughness through choosing correctly the machining parameters.

Surface roughness is one of the irregular aspect of workpiece which is resulted from machining processes. There are different ways for explaining surface roughness. One of them is mean roughness which is shown commonly byR_a. $R_a$is defined as the difference value calculated according to mean line.

R

Or (1)

R

METHODOLOGY

Multiple Regression

The multiple regression is an expansion of regression analysis which predicts several independent variables in equation. In other words,formodeling and analyzing the problems whose answersare influenced by several variables, and their goal is optimizing the output, one can determine the relationships between independent and dependent variables by using this method. In most problems the form of relationship between response and independent variables is unknown. So, the first step is finding a proper approximation for correct functional relationship between response Y and a group of controllable variables $(X_1, X_2, \dots, X_n)$. Commonly when the response function is unknown or nonlinear, a second order model such as following one is applied:

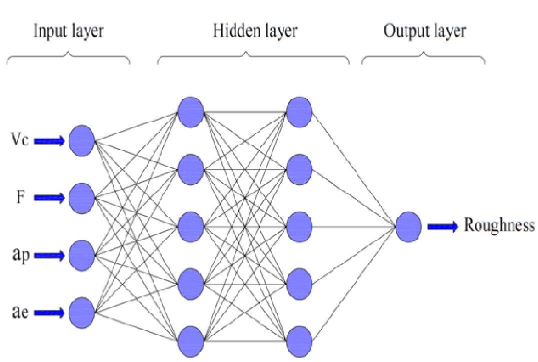
where ε represents error and is the difference between response Y and expected answer.   is the constant value of regression formula. For curve fitting a formula containing input variables by minimizing residual error measured by sum of squares of deviances between real and expected answers, the minimum mean squares technique is used. After modeling, the regression should be formed, and checked according to calculated coefficients orequations of the model or, ultimately, statistical meaningfulness.

Artificial neural network

An ANN is an algorithm that can learn and remember experiential knowledge. The massively simple and connected artificial neurons are used to simulate the ability of a biological brain. The architecture of ANN is made of an input layer, a hidden layer and an output layer. Each layer has a set of neurons that has the same function. A neuron is an information process unit. The basic aspects of the neuron model are illustrated in below. The mathematical model of a neuron is represented in Eq.(3).

(3)

Where $x_1,x_2,\ldots,x_p$ are the input information, w_{k1}, $w_{k2},\ldots,w_{kp}$ are weight for neurons k, u_k the combiner, $\theta_k$the threshold value, f the activation function, and y_k the output of neuron. As has been said there are three layers in an ANN; that is, an input layer, a hidden layer and an output layer. Each layer has a set of neurons that has the same function. The activation functions used in this study are the logsig-logsig-logsig transfer function. The weights and threshold values will be modified as the network input one training sample. The back-propagation neural network (BPN) that is a kind of ANN has been used in this paper because of its good agreement behavior in prediction for complex problems. The structure of BPN is illustrated in *Fig. 1*.



(2)

Figure 1: BPN that used in this paper

The BPN includes two phases. The first one is called the training process that can update the weight values and threshold values for each neuron by giving the training patterns obtained from experiments. The second one is called the recalling process that can read the well-trained weight values and threshold values from the training process and has the prediction ability.

PROCEDURE OF EXPERIMENT

Design of Experiment

There are many factors for machining a specific material in milling process with end milling which one can suggest. Anyway, reviewing the literature shows that four machining factors have significant effect on output parameters of process. In order to study effects of input parameters on milling process perfectly, each of cutting rate, Feed rate, radial and axial depths of cut were changed in three levels in full factorial manner, and so 3^4=81 experiments have been considered and the tests have been executed in this research. In *table 1* design levels of the experiment are shown.

Table 1: Design levels of Experiment

	Level 1	Level 2	Level 3
Vc	40	100	160
f_z	0.02	0.04	0.06
a_p	0.5	1	1.5
a_e	1	2.5	4

EQUIPMENT

For executing experiments we have used HARTFORD-VMC1000 milling machine CNCwith the controller FANUC-OM. This machine CNC has maximum spindle speed 6000 (rpm) and maximal Feed rate 10000 (mm/min). Through reviewing the literature of itwas found that the TiN coated tools lead to lesser machining forces due to lower friction coefficient of this coating, and so the selected tool wasflathead two-lip end milling with TiN coated carbide insert with diameter 16 mm which, in order to be sureof correctness of results,after every three machining passes were replaced. It should be noticed that because of high quality of used inserts, during removal of chips, they were not struck by nicking or wearing. Measuring the roughness was performed by roughness tester Mahr model Pocket Surf PSI. Roughness testing of each test was implemented three times and their average was considered as roughness measure used in regression.

Figure 2:Mahr Roughness tester

Materials

Experimental tests were performed on cubic blocks with dimensions mm, made of Martensitic stainless steel. Chemical composition and properties of this steel are shown in *tables 2 and 3*, respectively.

Table 2: Chemical composition of stainless steel X22 CrMoV 12 1

	C	Cr	Mo	V	Ni
Min	0.18	11	0.8	0.25	0.3
Max	0.24	12.5	1.2	0.35	0.8

Table 3: Properties of stainless steel X22 CrMoV 12 1

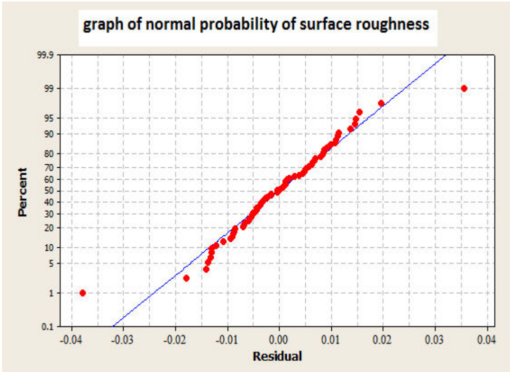
Yield Stress [MPa]	Tensile Stress [MPa]	Haedness	Density (kg/dm^3)
600-700	800-1050	302 HB	7.7

RESULTS AND DISCUSSION

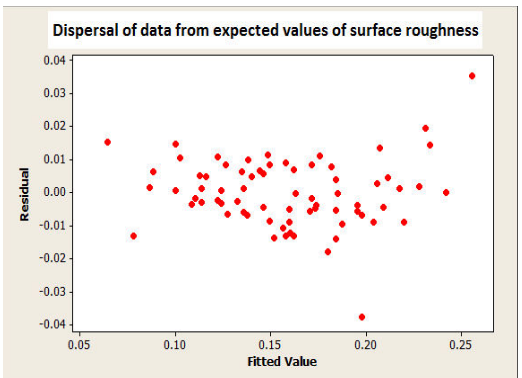
The effects of cutting parameters on the response variable were discovered. From 81 designed experiments, surface roughness was measured and its mean value was used to obtain regression model.In order to develop second order model between input and output parameters, the software Minitab was applied.71 tests were selected randomly for developing model and remaining 10 tests were used to examine efficiency of prepared model. This second order model is as following:

$$Ra = 0.07974 - (0.0002186\ Vc) + (1.29\ fz) + (0.0569\ ap) + (0.00560\ ae) - (0.00280\ Vc\times fz) - (0.000162\ Vc\times ap) - (0.000055\ Vc\times ap) + (4.54\ Vc^2) + (4.54\ fz^2) \quad (4)$$

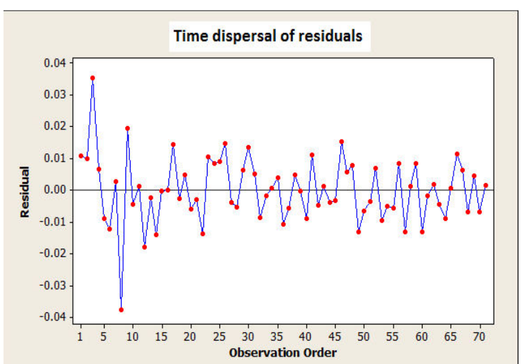
Generally all results of regression analysis are authentic if the premises of regression, i.e. the condition that variance of residuals is normal, independent and constant, be true. The most common method for examining this premises, is to probe different kinds of graphs of residuals. For examining normality of distribution of residuals one can the normal probability graphs. If distribution is normal, values of residuals lie in a straight line direction; else, some regular deviances would be observed. In specifying straightness of pattern of points around a straight line, the emphasis is on the central values of the graph and the modest deviances are not commonly significant. The graph of residuals' dispersal from expected values or from input variables was used for scrutinizing the condition ofunchangeability of variance of residuals. If these graphs have a specific pattern or structure too, the condition of unchangeability of variance of residuals will be disproved. Also, the graph of residuals' dispersal according to time periods in which they have been collected is used to investigate the independence of residuals. Existence of a specific pattern and structure in this graph means the refusal of independence condition. Before offering the results of analysis, in order to be sure of credibility of premises of regression, three introduced graphs would be overviewed. As one can see in normal probability graph there is no significant deviance and also the graph of dispersal of residuals' values in time intervals in which they are collected lacks a given pattern or structure. Consequently the normality and independence conditions of residuals are authentic. Dispersal of residuals versus expected values does not have a specific structure and so we can declare that the condition that the variance of residuals is a constant value is correct too.



Graph 1: Normal probability of residuals



Graph 2: Dispersal of residuals for regression of surface roughness



Graph 3: Time dispersal of residuals

In this paper, trying various types of networks, a multilayer perceptron back propagation neural network was adopted for predicting surface roughness. As such, a database including sufficient number of data was collected from milling process. In the back propagation algorithm, in a forward pass inputs are processed throughout the network and network output is computed. Then the computed output is compared to the actual measured value and the difference (error) is calculated. At this time, in a backward pass the error is back propagated throughout the network and the connection weights are updated. This computational loop is repeated until the network error is converged to a minimum.

The experimental tests were considered as the network inputs. A database including 71 data was prepared for model construction. From the collected database, 10% of datasets was selected for testing the model using a sorting system to ensure consistency of the selection. To recognize the optimum model usually the root mean squared error (RMS) or summed squared error (SSE) can be utilized. The optimum model architecture (4-5-5-1) is shown in *Fig 1*.

After investigation examinations, for an assessment of regression model and ANN model used three statistical coefficients VAF, RMSE, R^2. The values of these coefficients were derived from following relations.

$$VAF = 100(1 - \frac{var(T_i - O_i)}{var(T_i)}) \tag{5}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(T_i - O_i)^2} \tag{6}$$

$$R^2 = 100\left[\frac{\sum_{i=1}^{N}(O_i - \overline{O_i})(T_i - \overline{T_i})}{\sum_{i=1}^{N}(O_i - \overline{O_i})^2 \sum_{i=1}^{N}(T_i - \overline{T_i})^2}\right]^2 \tag{7}$$

Ti, Oi and N are real output value, model expected output value, and the number of pair data, respectively.$\overline{O}_i$and$\overline{T}_i$ are the averages of real and expected values. Resulted values of these coefficients for test's data in regression model are shown in *table 4*.

Table 4: Evaluation of regression model

Coefficient	Regression Model	ANN
VAF	93	95.5
RMSE	0.0092	0.0079
R^2	0.93	0.96

The relationship between real and expected values for test data which have been applied in regression modeland ANN model are shown in *Fig.3 and 4*.

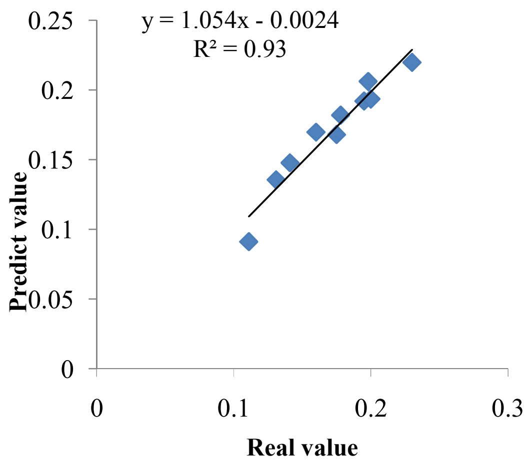


Figure 3: Comparing real and expected value of test data (Regression)

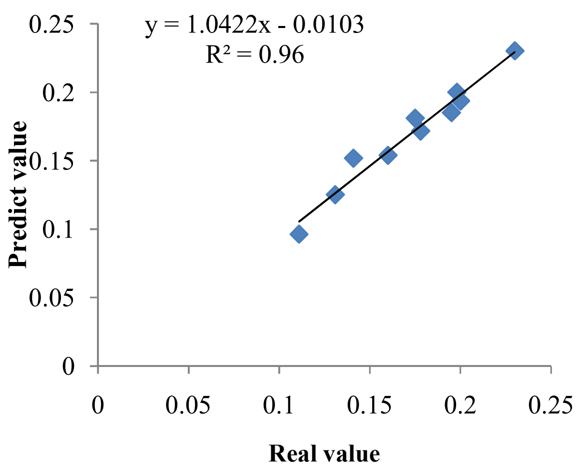


Figure 4: Comparing real and expected value of test data (ANN)

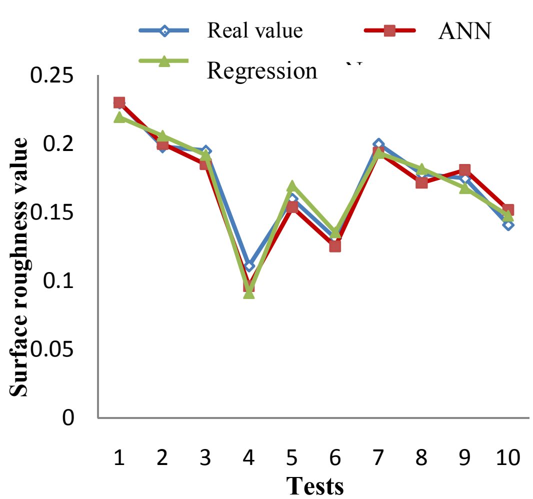
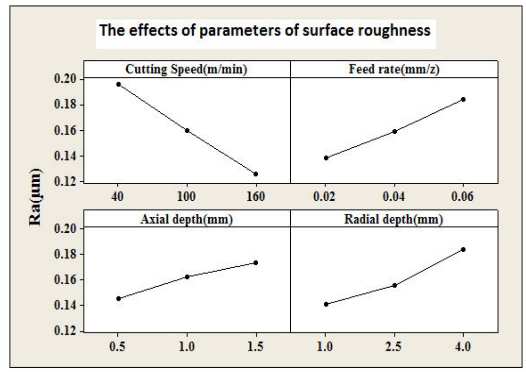
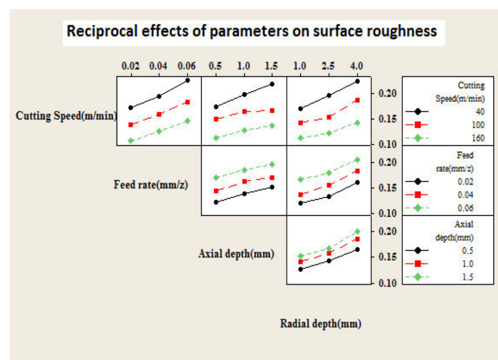


Figure 5: Comparing outputs of different models and real values

Finally can say that surface roughness is an important factor and different parameters have effect on it; it is also one of the significant parameters of machinability and has high influence on function of final piece. The effects of different parameters on surface roughness due to machining are shown in graphs 4 and 5.



Graph 4: The effects of input parameters on surface roughness



Graph 5: Effects of different parameters on each other resulted from findings of surface roughness

Decreasing surface roughness by increasing cutting speed couldbe seen as a result of easing plastic transformation and decreasing friction due to increment of temperature. On the other hand increasing cutting speed leads to decreasing formation of built-up edge; hence by more increasing cutting speed the formation of built-up edge would be decreased and the surface roughness will be improved. Indeed,in high cutting speeds its effect on roughness will become venial, since in this case it approaches to theoretical value of surface roughness.By increasing Feed, due to incrementundeformed chip thickness, the height of inquality and, consequently, the roughness increase. The values of axial depth of cut have no significant effect on surface quality and increasing radial depth of cut results in increment of roughness of machining surface and so its effect is more considerable than that of axial depth of cut.

CONCLUSION

In milling operation, scrutinizing and predicting surface roughness is an important factor. A second order model and ANN model were developed according to experimental data and regression tests (normal probability, data dispersal and data time dispersal) endorse its correctness. Moreover, in order to examine the ability of regression and Artificial neural network in predicting and modeling, by calculating indices VAF,RMSE and R^2, the accuracy of curve fitting was approved. These indices for the regression model and ANN were derived 93, 0.0091,0.93 and 95.5, 0.0079, 0.96 respectively. This results show that ANN model is effective than Regression Model. And finally on the basis of results of roughness testing, effects of different parameters on the surface roughness were determined. Cutting speed, Feed, radial and axial depths of cut have maximal effects of surface roughness of studied stainless steel, respectively

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