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Prediction Models by Response Surface Methodology for Turning Operation

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Abstract This study is intended to develop a predictive model for surface roughness and temperature in turning operation of AISI 1020 mild steel using cemented carbide in a dry condition using the Response Surface Method (RSM). The values of the selected cutting speed, feed rate, and depth of cut are based on the preliminary trial experiments by design of experiments. The analysis of variance for the predictive model of second order for both models shows that the feed rate is the most significant parameter which affects the surface roughness and temperature followed by cutting speed. The goal is to monitor one response by other instead of using different techniques. Both models are convenient for predicting of the main effects of the machining parameters and are economical for determining the influence of various parameters in a systematic manner.

Keywords: *response surface methodology, machining parameters, surface roughness, AISI 1020 mild steel*

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1. Introduction

The commercial success of a new product is strongly influenced by time factor. Shorter product lead-times are of importance for industry in a competitive market. This can be achieved only if the product development process can be realized in a relatively shorter time frame. However, the development of new cutting inserts involve time consuming trial and error iterations, which mainly due to limited empirical knowledge of the mechanical cutting process [1-6]. The study of cutting process is further complicated by the fact that material removal occurs in a hostile environment with high temperature and pressure involved in the cutting zone [5,7]. A knowledge of these principles makes it possible to model, and thereby to predict the practical results of the cutting process and thus to select optimum cutting conditions for each particular case. One of the well known methods used for studying metal cutting is based on statistical modeling of the machining process to predict surface roughness, temperature and tool wear [1]. This model would have a great value in increasing the understanding of the cutting process and in reducing the number of experiments which are traditionally used for tool design, process selection, and machinability evaluation.

The objective of this study is to establish a predictive model that would enable us to predict cutting performance such as cutting temperature, and surface roughness. The ultimate objective of the metal cutting science is to solve practical problems associated with efficient material removal in the metal cutting process. To achieve this, the principles governing the cutting process should be understood.

1.1. Response of Surface Methodology (RSM)

By designing the experiments carefully, the objective of the present study is to optimize a response (output variable) which is influenced by several independent variables(input variables). An experiment is a series of tests, called runs, in which changes are made in the input variables in order to identify the reasons for changes in the output response [8,9]. In physical experiments inaccuracy can be due to measurement errors, whereas in computer experiments numerical errors are due to incomplete convergence of iterative processes, round-off errors or the discrete representation of continuous physical phenomena. In RSM, the errors are assumed to be random [8,9]. The Response Surface Method (RSM) is a methodology of constructing approximations of the system behavior using results of the response analyses calculated at a series of points in the variable space. Optimization of RSM can be solved according to the following three stages:

1. Design of experiment.
2. Building the model.
3. Solution of minimization problem according to the criterion selected.

Response surface method (RSM) is a combination of experimental, regression analysis and statistical inferences. The concept of a response surface involves a dependent variable y called the response variable and several independent variables x_1, x_2,. . . ,x_k called independent [8,9]. If all of these variables are assumed to be measurable, the response surface can be expressed as:

$$y = f(x_1; x_2; . . . ; x_k) \quad (1)$$

The goal of the present study is to optimize the response variable y. It is assumed that the independent variables are continuous and controllable by the experimenter with negligible error. The response or the dependent variable is assumed to be a random variable. In a milling operation, it is necessary to find a suitable combination of cutting speed ($x_1 = \ln V$), feed rate ($x_2 = \ln f$), and depth of cut ($x_3 = \ln d$) that optimize response. The observed response y as a function of the speed, feed, depth of cut can be written as [8,9]:

$$y = f(x_1, x_2, x_3) + \varepsilon \quad (2)$$

Usually a low order polynomial (first-order and second-order) in some regions of the independent variables is employed. The first-order model is expressed as [8,9]:

$$y = \beta_o + \sum_{i=1}^{k} \beta_i x_i + \varepsilon \quad (3)$$

and the second –order model [27,28],

$$y = \beta_o + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x^2_i + \sum_{i} \sum_{j} \beta_{ij} x_i x_j + \varepsilon \quad (4)$$

for i<j are generally utilized in RSM problems. The β parameters of the polynomials are estimated [8,9].

The RSM is a practical, economical and relatively easy to use and was employed by many researchers for modeling machining processes [10,11,12,13]. Mead and Pike [14] and Hill and Hunter [15] reviewed the earliest work on Response Surface Method (RSM). In order to institute an adequate functional relationship between the surface roughness and the cutting parameters (speed, depth of cut and feeds), a large number of tests are required, which in turn require a separate set of tests for each as well as a combination of cutting tool and workpiece material. Fuh and Wu [16] proposed a prediction models by using the Takushi method and the Response Surface Method (RSM). By using factors such as cutting speed, feed and depth of cut, Alauddin et al [17] developed surface roughness models and determined the cutting conditions for 190 BHN steel and Inconel 718. They found that the variations of both tool angles have important effects on surface roughness. In order to model and analyze the effect of each variable and minimize the cutting tests, surface roughness models which utilize response surface methodology and experimental design were carried out in this investigation. Mishra [18] has found out a relationship to study the residual stresses based on a moving heat source under various simulated cutting conditions, but the predicted trend was not in agreement with the results of actual machining. Response Surface Method (RSM) was then utilized for determining the residual stresses under different cutting conditions and for various tensile strengths presented by different materials [19]. Wu [20] was the first pioneer who used RSM in tool life testing. The number of experiments required to develop a surface roughness equation can be reduced as compared to the traditional one-variable-at-a-time approach. Based on RSM and 23 factorial designs, first- and second-order models have been developed in this project. Only twelve tests were required to develop the first-order model, whereas twenty four tests were needed for the second-order model. Reen [21] has pointed out that for accurate rating of machinability, three factors, namely, tool life, surface finish, and power consumed during cutting, must be considered. Similar views were expressed by Shaw [22], whereas Taraman [23,24] used RSM approach for predicting surface roughness. A family of mathematical models for tool life, surface roughness and cutting forces were developed in terms of cutting speed, feed, and depth of cut. Hasegawa et al., [25] conducted 34 factorial designs to conduct experiments for the surface roughness prediction model. They found out that surface roughness increased with an increase in cutting speed. Sundaram and Lambert [26,27] considered six variables i.e. speed, feed, depth of cut, time of cut, nose radius and type of tool to monitor surface roughness. Mital and Mehta [28] carried out a survey of surface roughness prediction models that influence surface roughness and found out that most of the models were developed for steels. Boothroyd [29] and Baradie [30] investigated the effect of speed, feed and depth of cut on steel and grey cast iron, and then emphasized the use of RSM in developing a surface roughness prediction model.

2. Selection of Cutting Data

After a preliminary investigation to find the suitable levels of the machining parameters, the researchers used Minitab software to deduce experiments based on Box-Behnken design. The generated levels of independent variables like: cutting speed, feed rate and depth of cut are given in Table 1.

Table 1. The values and levels selected for the variables.

Levels	Low -1	Medium 0	High 1
Speed-*v* (m/min)	250	300	350
Feed-*f*(mm/rev)	0.1	0.2	0.3
Depth of cut-*d* (mm)	1	2	3

All randomly designed experiments are based on three variables and three levels each. The experiments consist of 15 experiments and one central experiment that reflect the intermediate interval of the levels. This central experiment will be repeated twice to measure the environment change through giving lack of fit of the all experiments as shown in Table 2.

Table 2. Design values obtained from the Minitab.

Run	Cutting speed (m/min)	Feed (mm/rev)	depth of cut (mm)
1	300	0.3	3
2	300	0.2	2
3	300	0.3	1
4	350	0.2	1
5	300	0.2	2
6	250	0.3	2
7	350	0.3	2
8	250	0.2	3
9	300	0.1	3
10	350	0.1	2
11	300	0.1	1
12	250	0.1	2
13	250	0.2	1
14	350	0.2	3
15	300	0.2	2

2.1. Experiments Preparation

The Typical mild steel AISI 1020 used in this study as workpiece material is cheap and can be subjected to various heat treatments. Conventional insert type CNMG 12 04 08-PM 4225 with tool holder type PCLNL 2020K 12 is used. All experiments were carried out in a random manner on CNC turning machine and in adry cutting condition. Each experiment was stopped after 100 mm cutting length. Each experiment conducted by a new cutting edge every time used to obtain accurate readings of the surface roughness and temperature. Three measurements of surface roughness and temperature which were made and averaged for each test were accepted. Handheld infrared thermometer type (OS534E) for temperature measurement. Surface roughness is carried out using surface roughness tester model MahrPerthometer (MarSurf PS2, produced by Mahr PGK, Germany).

3. Results and Discussion

3.1. Development of Surface Roughness Model

The second order equation was established to describe the effect of the three cutting conditions investigated in this study on the surface roughness. The second order model can be

$$y = -9.6550 + 0.0816x_1 - 4.8375x_2 - 0.9037x_3 \\ -0.0001x_1^2 + 32.3750x_2^2 + 0.2087x_3^2 \quad (5)$$

Table 3. Experimental and predicted surface roughness by second order model.

Run	Responses		
	Exp. Surface roughness (um)	Predicted surface roughness (um)	Deviation of Exp.& Pred. %
1	2.95	2.905	1.525
2	1.63	1.63	0
3	3.22	3.0425	5.512
4	1.18	1.45625	-23.411
5	1.63	1.63	0
6	2.38	2.51875	-5.829
7	2.23	2.31375	-3.755
8	1.57	1.52375	2.945
9	1.1	1.2825	-16.590
10	0.96	0.69125	27.994
11	1.38	1.42	-2.898
12	0.85	0.89625	-5.441
13	1.8	1.66125	7.708
14	1.41	1.31875	6.471
15	1.63	1.63	0

Table 4. Estimated regression coefficients for second order predicted surface roughness.

Term	Coef.	*P*-value
Constant	-9.6550	0.026
Cutting speed	0.0816	**0.008**
Feed rate	-4.8375	**0.252**
Depth of cut	-0.9037	**0.050**
Cutting speed*Cutting speed	-0.0001	0.007
Feed rate*Feed rate	32.3750	0.010
Depth of cut*Depth of cut	0.2087	0.062

S = 0.3498, R^2 = 95.9.0%, (adj) R^2 = 92.8%

Where x_1 is cutting speed, x_2 is feed rate and x_3 is depth of cut. The surface roughness obtained experimentally and predicted values are given in Table 3, whereas the estimated regression coefficients for the second order predicted surface roughness is given in Table 4.

The analysis of variance as shown in Table 4 indicates that there is a significant difference between the factors. The small *p*-values for linear term also point out that their contribution is significant to the model. Moreover, the main effects can be referred as significant at an individual 0.05 of significant level. Cutting speed and depth of cut are significant to the response model at α = 0.05, on the other hand, feed rate insignificantly contributes to the response model at α = 0.05. From the value of R^2 (95.9 %), the fits of data can be measured from the estimated model. For instance, consider the regression calculated the R^2 and the adjusted-R^2 for the model are statistically significant for the surface finish. It suggests that the estimated regression equations for the Case Study of the second order fits the data very well.

The model (equation 5) shows that the surface roughness increases with an increase in the feed rate and would decrease if cutting speed is increased. Another observation from equation 5 is the square of the feed rate gives a very good indication that the feed rate played a major factor with the surface roughness. The analysis of variance shown in Table 5 indicates that the model is adequate as the *p*-value of the regression of the square is significant more than linear.

Table 5. Analysis of Variance for second order surface roughness model

Source	DF	P-value
Regression	6	0.000
Linear	3	0.013
Square	3	0.004
Residual Error	8	
Pure Error	2	
Total	14	

A good estimated regression model will explain the variation of the dependent variable in the sample. There are certain tests of hypotheses about the model parameters that can help the experimenter in measuring the effectiveness of the model. The first of all, these tests require for the error term ε's to be normally and independently distributed with mean zero and variances. To check this assumption, the normal probability, fitted values, and histogram of residuals for the experiments graphed are given in Figure 1.

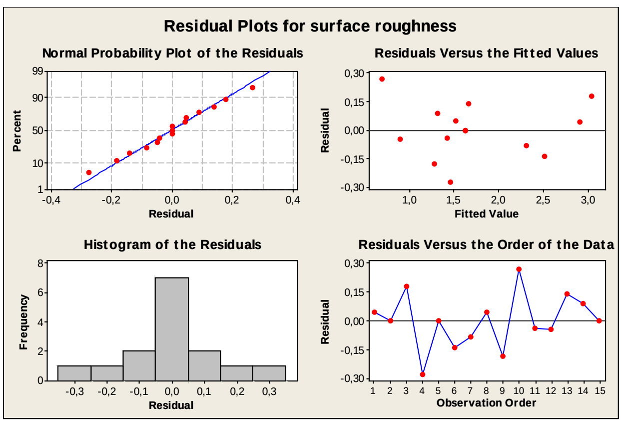

Figure 1. Residual plot of surface roughness by second order prediction model

The second order model (equation 5) was used to plot contours of the surface roughness for different values of cutting parameters. Figure 2 through Figure 4 shows the surface roughness contours of three different combinations of cutting parameters. It is clear that increasing of cutting speed with decreasing of feed rate will decrease the surface roughness dramatically. Figure 3, shows that surface roughness reaches its highest value when cutting speed is medium associated with low depth of cut. While, feed rate at its maximum values as shown in Table 4.

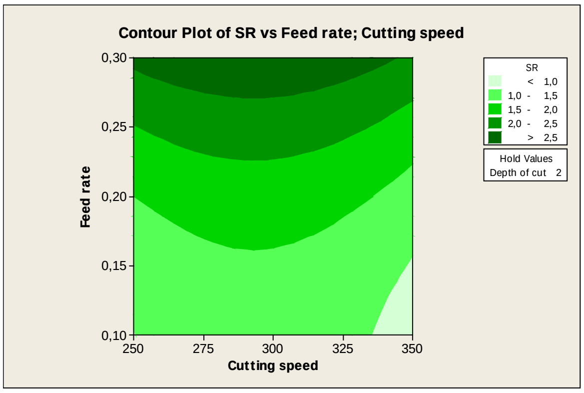

Figure 2. Surface roughness contours in the cutting speed-feed rate plane for depth of cut 2 mm

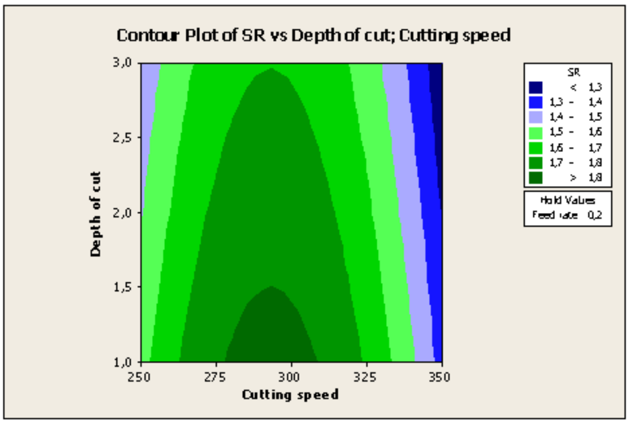

Figure 3. Surface roughness contours in the cutting speed-depth of cut plane for feed rate 0.2(mm/rev).

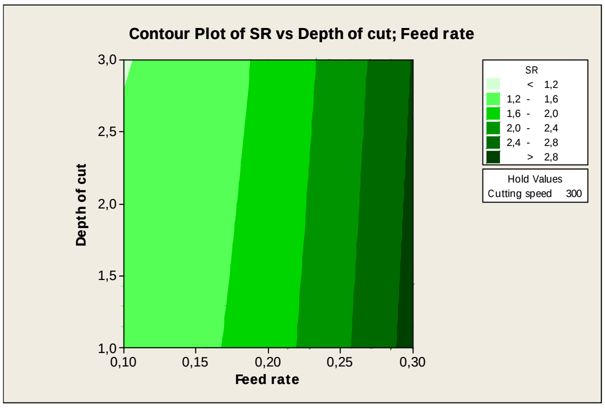

Figure 4. Surface roughness contours in the cutting speed-feed rate plane for cutting speed 300 m/min.

3.2. Development of Temperature Model

The second order equation was established to describe the effect of the three cutting conditions investigated in this study on the temperature. The second order model can be expressed as:

$$\begin{aligned} T &= -43.769 + 0.731x_1 - 274.038x_2 \\ &\quad -4.750x_3 - 0.001x_1^2 + 503.846x_2^2 \end{aligned} \tag{6}$$

Where x_1 is cutting speed, x_2 is feed rate and x_3 is depth of cut.

The temperature obtained experimentally and predicted values are given in Table 6.

Table 6. Experiment and prediction result for temperature from second order model.

Run	Experiments Temperature	Predicted temperature	Deviation of Experiment and Predicted %
1	48	46.2308	3.685
2	44	43.6923	0.699
3	36	36.7308	-2.03
4	38	36.9808	2.682
5	44	43.6923	0.699
6	37	37.5192	-1.403
7	39	39.5192	-1.331
8	43	44.4808	-3.443
9	63	60.7308	3.601
10	57	54.0192	5.229
11	47	51.2308	-9.001
12	51	52.0192	-1.998
13	38	34.9808	7.945
14	43	46.4808	-8.094
15	44	43.6923	0.699

The analysis of variance as shown in Table 7 indicates that there are significant differences between the factors. Moreover, the main effects can be referred to as significant at an individual 0.05 significant level. Cutting speed, feed rate and depth of cut significantly contribute to the response model at $\alpha = 0.05$.

Table 7. Estimated Regression Coefficients for temperature of the second order model.

Term	Coef.	P-value
Constant	-43.769	0.397
Cutting speed	0.731	0.052
Feed rate	-274.038	0.001
Depth of cut	4.750	0.001
Cutting speed*Cutting speed	-0.001	0.058
Feed rate*Feed rate	503.846	0.005

S = 2.623, R^2 = 92.3%, (adj) R^2 = 88.1%

From the value of R^2 (92.3 %), the fits of data can be measured from the estimated model. For instance, consider the regression calculated the R^2 and the adjusted-R^2 for the model are statistically significant for the response temperature. It suggests that the estimated regression equations for the Case Study of the second order fits the data very well.

The model shows that the temperature increases with an increasing in the feed rate and would decrease if the cutting speed increased. On the other hand, unlike in the case of the first order model, the cutting speed has a significant effect. Another observation from equation 6 is that the square of the feed rate gives a very good indication that the feed rate plays a major factor with the temperature. It can be inferred that the equation can produce values close to those obtained experimentally. The analysis of variance shown in Table 8 indicates that the model is adequate as the *p*-value of the regression second order is significant.

Table 8. Analysis of Variance for second order temperature model

Source	DF	Seq SS	Adj SS	Adj M S	F-value	P-value
Regression	6	6.45794	6.45794	1.076323	31.30	0.000
Linear	3	5.38688	0.71610	0.238699	6.94	0.013
Square	3	1.07107	1.07107	0.357022	10.38	0.004
Residual Error	8	0.27510	0.27510	0.034388		
Pure Error	2	0.00000	0.00000	0.000000		
Total	14	6.73304				

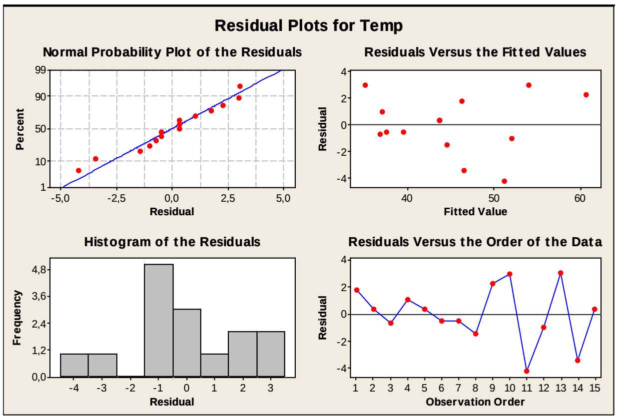

Figure 5. Residual plots for temperature for second order prediction model

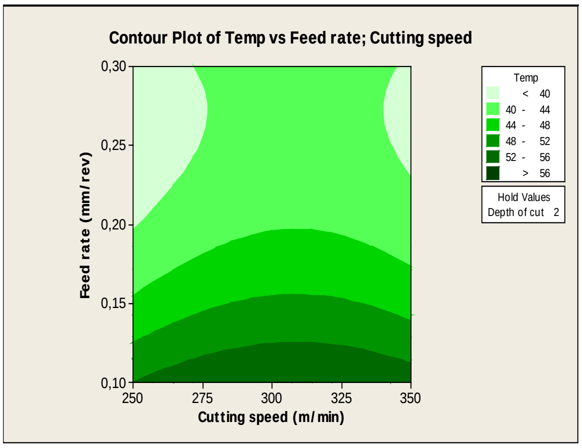

Figure 6. Temperature contours in the cutting speed-feed rate plane for depth of cut 2 mm

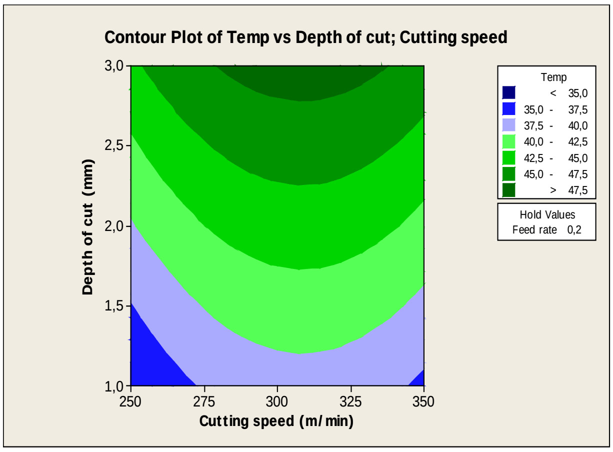

Figure 7. Temperature contours in the cutting speed-depth of cut plane for feed rate 0.2 (mm /rev)

A good estimated regression model shall explain the variation of the dependent variable in the sample. There are certain tests of hypotheses about the model parameters that can help the experimenter in measuring the effectiveness of the model. The first of all, these tests require for the error term ε's to be normally and independently distributed with mean zero and variances. To check this assumption, the normal probability, fitted values, and histogram of residuals for the experiments are graphed as shown in Figure 5.

Figure 6 through Figure 8 shows the temperature contours at three different combinations of cutting parameters. It is clear that the reduction in cutting speed and the increase in feed rate will cause the temperature decrease dramatically. From Figure 7 the temperature reaches its highest value when of depth of cut increases, except for feed rate, are at their maximum values.

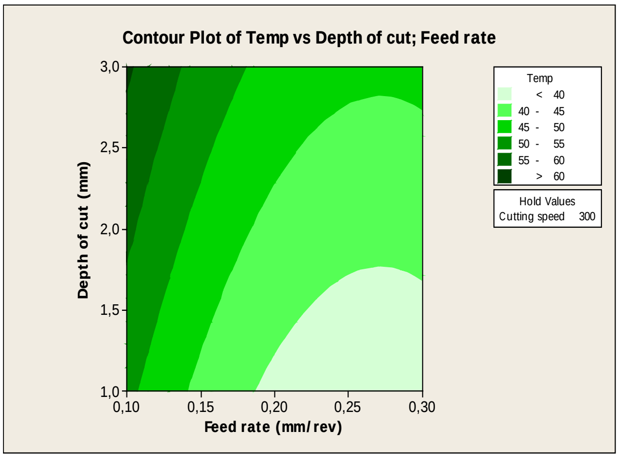

Figure 8. Temperature contours in the cutting speed-feed rate plane for cutting speed 300 m/min.

4. Conclusions

In this study, a second order of mathematical model used to predict the cutting parameters such as cutting speed, feed rate, and depth of cut for the turning process from the surface roughness values and temperature is based on response surface methodology (RSM). The results obtained from the mathematical model are then compared with the experimental results. It was found out that the feed rate, cutting speed, and depth of cut play a major role on the responses such as surface roughness and temperature when machining mild steel AISI 1018. The following are some important conclusions which are derived out from this study:

1. The response surface methodology (RSM) combined with the design of the experiments (DoE) is a useful technique for surface roughness and temperature tests. Relatively, a small number of designed experiments are required to generate information that is useful in developing the predicting equations for surface roughness and temperature. The analysis of variance for the second order for both models shows that the feed rate is the most significant parameter which affected the surface roughness and temperature followed by depth of cut, and lastly cutting speed. Hence, the feed rate parameter playeda significant role in controlling the surface roughness and temperature.
2. Both second order models are convenient in predicting the main effects and square effects of

different influential combinations of machining parameters. This procedure is economical in determining the influence of various parameters in a systematic manner.

3. Furthermore, this procedure can be used to predict the surface roughness and temperature for the turning of mild steel within the range of the studied variables. However, the validity of the procedure is mostly limited to the range of factors considered in the experiment.
4. Results of the developed predicted model are compared with those of the real experiments. The percentage of error obtained from the CNC turning machine is from 0% to 2% for both predicted models.

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