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MATHEMATICAL MODELLING OF SURFACE ROUGHNESS THROUGH MACHINING PARAMETERS AND MACHINING TIME DURING THE DRY MILLING PROCESS

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Abstract

This paper investigates the effects of milling parameters on the surface roughness and surface texture by applying RSM. The most important measures of surface quality during the machining process is the average surface roughness (Ra), and it is mostly caused by many machining parameters, such as true rake angle and side cutting edge angle, cutting speed, feed rate, depth of cut, nose radius, machining time etc.

In this work, an experimental investigation through mathematical modelling was carried out to study the effect of cutting parameters such as; cutting speed, feed rate and machining time on surface roughness during the dry end milling process of cold rolled steel C62D. The experiment is executed on the basis of a three level factorial design. The influences of all machining parameters on surface roughness have been analyzed based on the developed mathematical model. The developed prediction equation shows that the most significant parameter is cutting speed followed by feed rate and lastly machining time. The result from this research is useful to be implemented in industry to reduce time and cost in surface roughness prediction.

Keywords: Machining; cutting process; milling; roughness; tool; machining time

1. Introduction

Machinability is a fundamental technological feature of the machined metal and is an economic feature of the cutting operations. Machinability of metals and the tool cutting capacities are mutually related terms and are defined by the same method [11]

Metal cutting is one of the most significant manufacturing processes in the area of material removal. Black [2] defined metal cutting as the removal of metal chips from a workpiece in order to obtain a finished product with desired attributes of size, shape, and surface roughness [1]. One important parameter in the qualification of cut surfaces is their roughness, and its indexes. The roughness has great significance primarily at mating, sliding surfaces. This has been one more reason for the researchers' increased interest for a long time to predict these indexes for a given process within the specified cutting conditions. Several modeling procedures and techniques were worked-out, which essentially can be classified into four groups: l) analytical models, 2) experimental methods, 3) DoE (Design of Experiment)-based methods and 4) AI (Artificial Intelligence)-based methods [2, 3].

In order to establish an adequate functional relationship between the responses (such as surface roughness, cutting force, tool life/wear) and the cutting parameters (cutting speed, feed, and depth of cut), a large number of tests are needed, requiring a separate set of tests for each and every combination of cutting tool and work piece material. This increases the total number of tests and as a result the experimentation cost also increases. As a group of mathematical and statistical techniques, response surface methodology (RSM) is useful for modeling the relationship between the input parameters (cutting conditions) and the output variables. RSM saves cost
and time by reducing number of experiments required [4].

Surface roughness has received serious attentions for many years. It has formulated an important design feature in many situations such as parts subject to fatigue loads, precision fits, fastener holes and esthetic requirements. In additions to tolerances, surface roughness imposes the most critical constraints for selection of machines and cutting parameters in process planning [5].

The surface finish in milling is found to be influenced in varying amounts by a number of factors, such as cutting speed, feed rate, depth of cut, material characteristics, tool geometry, workpiece deflection, stability and stiffness of the machine tool - cutting tool - workpiece system, built-up edge, cutting fluid, etc. [6].

There are various parameters used to evaluate surface roughness. In the present research for surface finish characterization in turning operations, the average surface roughness (R_a) is selected. It is the most widely used surface finish parameter in industry. Many authors suggested linear and exponential empirical models for surface roughness as functions of machining parameters by the following.

The progress in the development of predictive models, based on cutting theory, has not yet met the objective; the most essential cutting performance measures, such as, tool life, cutting force, roughness of the machined surface, energy consumption, … etc., should be defined using experimental studies. Therefore, further improvement and optimization for the technological and economic performance of machining operations depend on a wellbased experimental methodology. Unfortunately, there is a lack of information dealing with test methodology and data evaluation in metal cutting experiments [7].

Various methodologies and practices are being employed for the prediction of surface roughness, such as machining theory, classical experimental design, the Taguchi method and artificial intelligence or soft computing techniques [6].

The aim of this research is to develop the model for predict the in-process surface roughness in ball-end milling process which can be used in practice. The in-process surface roughness models are developed under various cutting conditions by employing the exponential function with the aid of the multiple regression analysis and the use of the least square method[17].

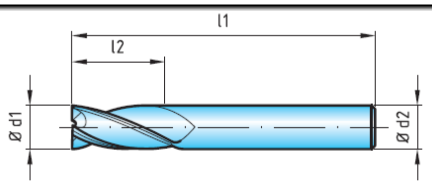
2. Nomenclature

R_a the average surface roughness
P power
n RPM
f feed rate
d_{max} workpiece diametër
L tail stock
N factorial design
K number of factors
N_0 number of additional tests
v cutting speed
T cutting time
c_0, c_1, c_2,c_3 constants
y logarithmic value of the measured surface roughness
β_0, β_1, β_2, β_3 regression coefficients
x_0 unit vector
x_1, x_2, x_3 logarithmic values of cutting speed, feed rate, cut of depth

3. Experimental conditions

Machine tool: Universal milling machine *GKA-3* motor power:8 kW, spindle speed range: 40 - 2000 rpm, feed rate range: 0,02 - 2,0 mm/rev, working are: X/Y/Z 400x2000x300 mm, max. tool diameter: 80 mm, max. tool length: 200 mm.

Workpiece was made of cold rolled steel C62D. Its chemical composition is as follows: (0.62-0.65)% C; (0.56-0.78)% Mn; 0.22% Si; 0.032% P, 0.03% S, and 98,28% Fe. Tensile strength is 230-247 N/mm2, and hardness 236-245 N/mm2. The workpiece dimensions are: the length 300 mm, the diameter 70 mm, and it is machined under dry turning conditions. Cutting tool: HSS-E Co10, with data in table 1. To guarantee the initial conditions of each test, a new tool is used in each experiment.



DIN 844	d_1 [mm]	d_2 [mm]	l_1 [mm]	l_2 [mm]	z
HSS-E Co10	20	20	104	38	3

Table 1. Cutting tool data

Roughness measuring equipment: HADRON, SRT-6210. Spectrometer Metorex Arcmet 930, Hardness meter Krautkramermic.10.DL.

4. Experimental setup

Experimental design. This work is an experimental study focused on the effect of cutting parameters and machining time on surface roughness, developing a correlation between them. The experimental design involves variation of three factors at three levels (low, medium and high), including cutting speed (v), feed rate (f) and machining time (T) as indicated in Table 2.

A design matrix was constructed on the basis of the selected factors and factor levels as shown on the table 2. The selected design matrix was a full factorial design N=2k+N0 (k=3 - number of factors, N0=4 – number of additional tests for three factors) consisting of 12 rows of coded/natural factors, corresponding to the number of trials. This design provides a uniform distribution of experimental points within the selected experimental hyper-space and the experiment with high resolution [7, 8].

The factor ranges were chosen with different criteria for each factor, aiming at the widest possible range of values, in order to have a better utilization of the proposed models. At the same time, the possibility of the mechanical system and manufacturer's recommendations are taken into account.

Machining conditions used in the experiment also are shown in Table 2 [9, 10, 11]. All of the trials have been conducted on the same machine tool, with the same tool type and the same cutting conditions.

Measured values of surface roughness, as the results of testing twelve experimental points defined by experiment plan matrix, are shown in Table 3. The mentioned values of surface roughness are input data for mathematical modeling of results, which was made by multiple regression analysis.

Cutting factors and their levels					
No.	Factors	Code level	High level	Middle level	Low level
			1	0	-1
1	v, m/min	X_1	94.20	72.96	56.52
2	f, mm/rev	X_2	0.3	0.18	0.1
3	T, s	X_3	1200	1049	900

Table 2. Experimental setup at three level factors.

a. Regression based modeling

The main task for regression analysis is to show relationship between the roughness and machining independent variables. Many authors suggested linear and exponential empirical models for surface roughness as functions of machining parameters [13, 14, 15, 16], by the following:

$$R_a = c_0 \cdot v^{c_2} \cdot f^{c_1} \cdot T^{c_3} \tag{1}$$

Coded factors	Performance measures

Test No.	X_0	X_1	X_2	X_3	Ra	Y = ln R a
1	+1	+1	-1	+1	2.783	1.023529483
2	+1	-1	+1	+1	2.985	1.093599747
3	+1	+1	+1	-1	1.982	0.684106436
4	+1	-1	-1	-1	1.524	0.421338457
5	+1	0	0	0	1.963	0.674473915
6	+1	0	0	0	1.882	0.632335041
7	+1	-1	-1	+1	1.479	0.391366184
8	+1	+1	-1	-1	1.256	0.227932068
9	+1	+1	+1	+1	1.145	0.135404637
10	+1	-1	+1	-1	3.182	1.15750993
11	+1	0	0	0	1.714	0.53882982
12	+1	0	0	0	1.825	0.601579987

Table 3. Experimental results.

Three parameters: cutting speed (v), feed rate (f), and cutting time (T), were selected for this study, which are based on experimental results of tool life in earlier stage for the same cutting conditions [12]. Ra is the surface roughness in µm, f - feed rate in mm/rev, r-nose radius in mm, T-cutting time in sec., and respectively c_0, c_1, c_2, and c_3 are constants.

Multiple linear regression models for surface roughness can be obtained by applying a logarithmic transformation that converts non-linear form of eq. (1) into following linear mathematical form:

$$\ln R_a = \ln c_0 + c_1 \ln f + c_2 \ln r + c_3 \ln T \tag{2}$$

The linear model of eq. (3) in term of the estimated response can be written as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x + \varepsilon \tag{3}$$

where y is the logarithmic value of the measured surface roughness, β_0, β_1, β_2, β_3 are regression coefficients to be estimated, x_0 is the unit vector, x_1, x_2, x_3 are the logarithmic values of cutting speed, feed rate, cut of depth and ε is the random error.
The above equation in matrix form becomes:

$$y = X\beta + \varepsilon \tag{4}$$

Thus, the least squares estimator of β is

$$\beta = (X'X)^{-1} X'y \tag{5}$$

The fitted regression model is

$$\acute{Y} = X\beta \tag{6}$$

The difference between the experimentally measured and the fitted values of response is:

$$e = y - \dot{y} \tag{7}$$

The regression analysis technique using least squares estimation was applied to compute the coefficients of exponential model. The following empirical exponential model for surface roughness was determined and is given, respectively:

$$R_a = 1.942\ v^{-05426} f^{0.250}\ T^{0.215} \tag{8}$$

5. Results and discussion

Table 3 presents experimental results of surface roughness criteria R_a for various combinations of cutting speed, feed rate and machining time to full factorial design. Minimal value of surface roughness criteria R_a was obtained at V = 94.20 m/min, f = 0,1 mm/rev, T=900 s, (test No. 8). That means increasing of cutting speed with the lowest feed rate and machining time lead to decreasing of surface roughness.

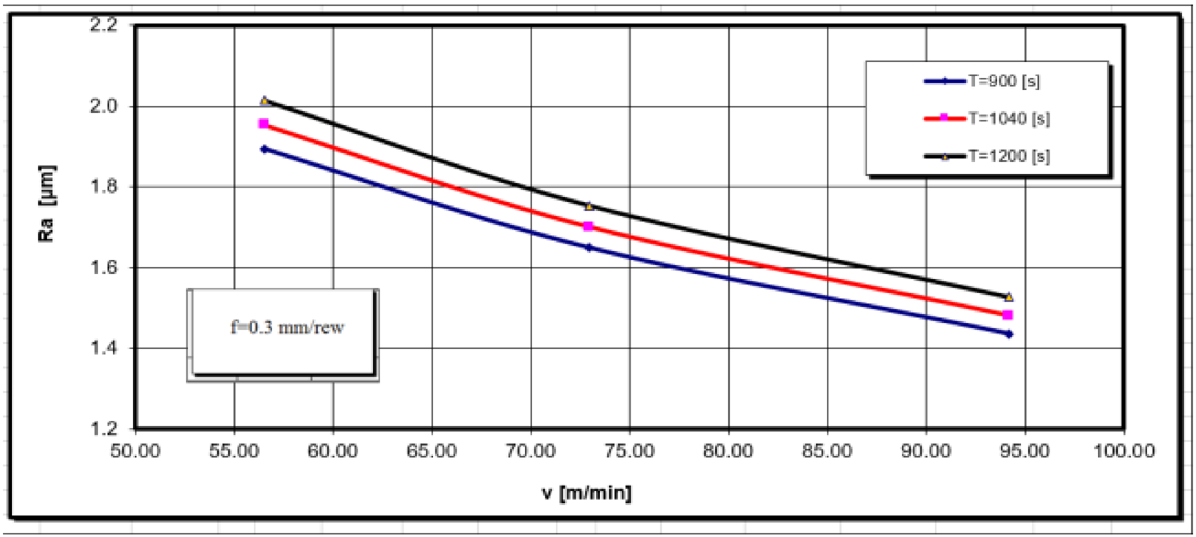
It is found that cutting speed has the most significant effect on surface roughness, followed by feed rate and machining time.

Maximal value of surface roughness criteria R_a was registered at V = 56.52 m/min, f = 0.3 mm/rev, T =1200 s, (test No. 2). In order to achieve better surface finish, the highest level of cutting speed, and the lowest level of feed rate and machining time, should be recommended.

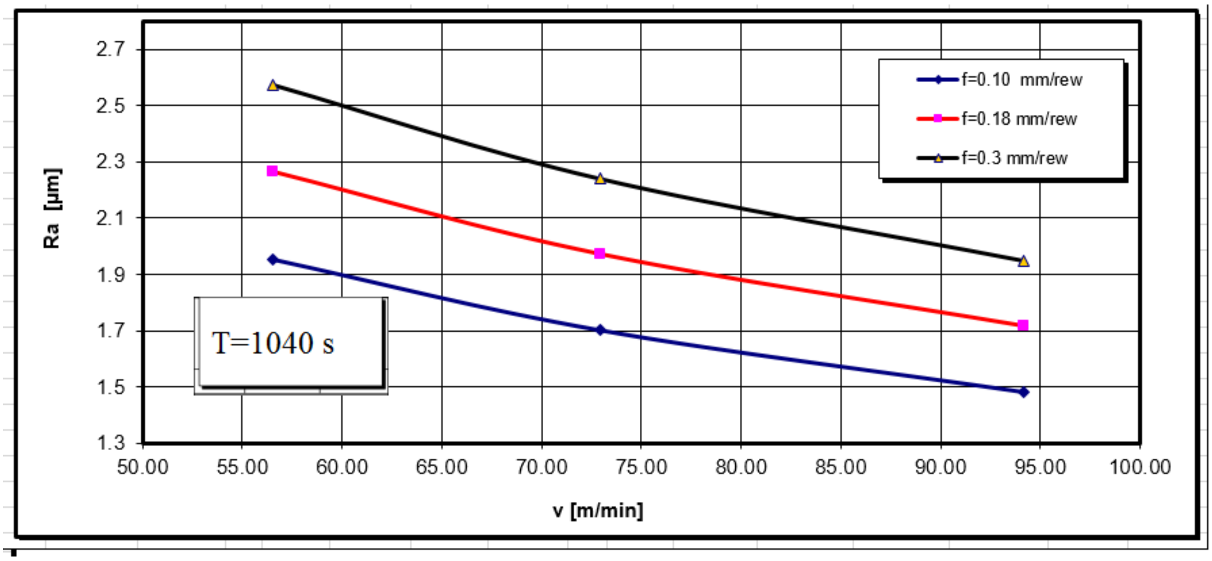
The analysis of obtained mathematical models and cutting data influence at surface roughness has been made using diagrams shown in Figures 4, 5, 6.

Fig. 1 which highlights the main factor plots for Ra appears to be an almost linear decreasing function of cutting speed and an increasing function of feed rate (f) and cutting time (T).

Figs. 2 a, b, c and d illustrate 3D surface plots of Ra according to the predictive exponential empirical model (9).



a)



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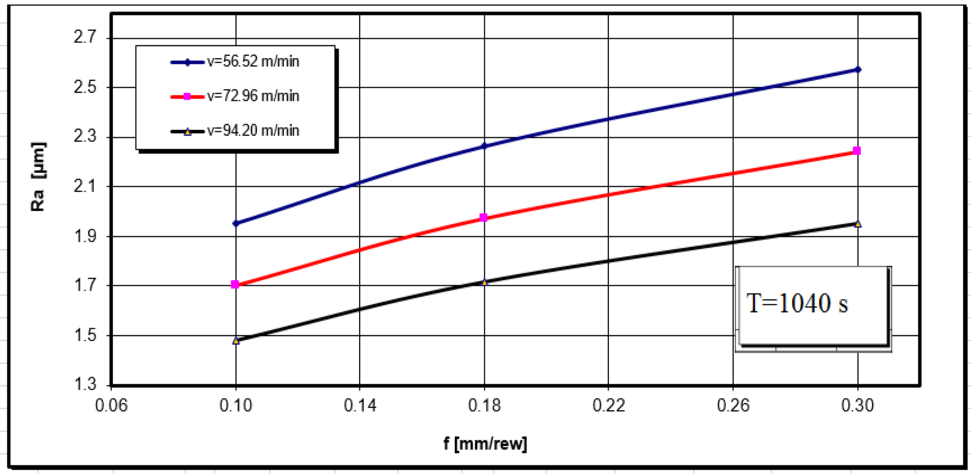
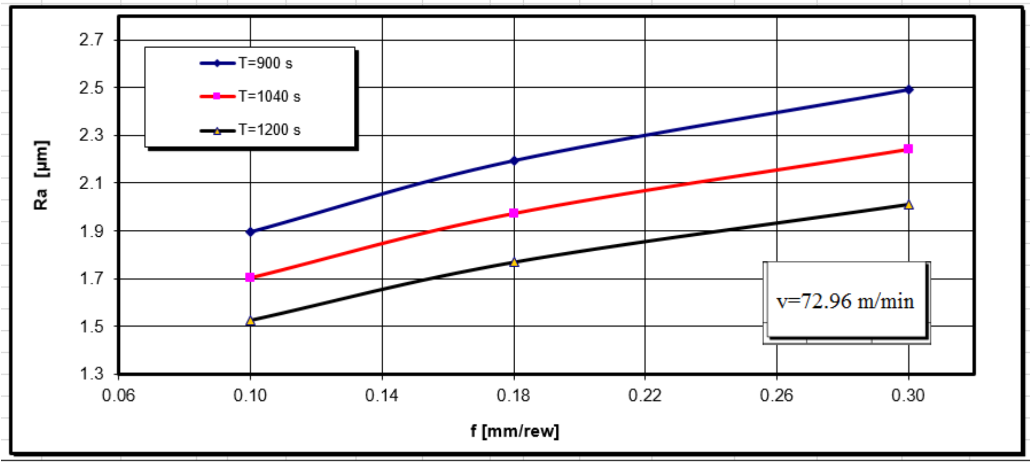
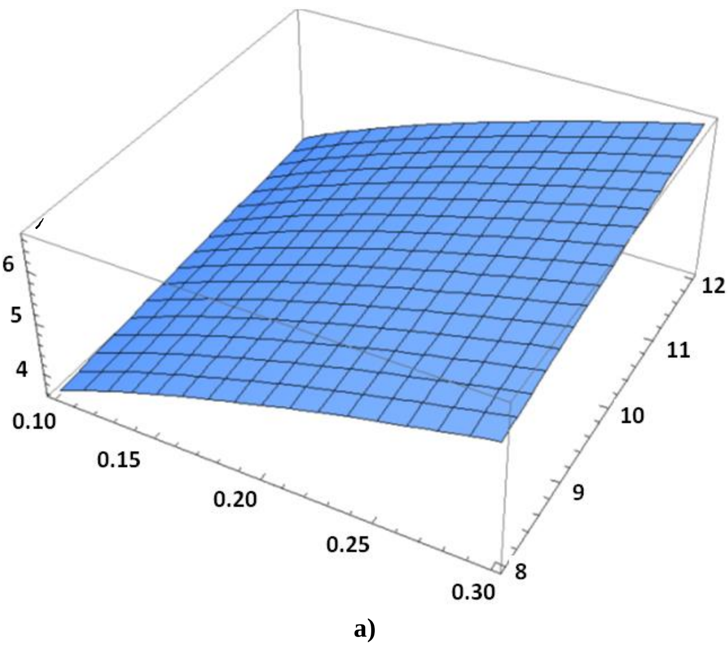


c)

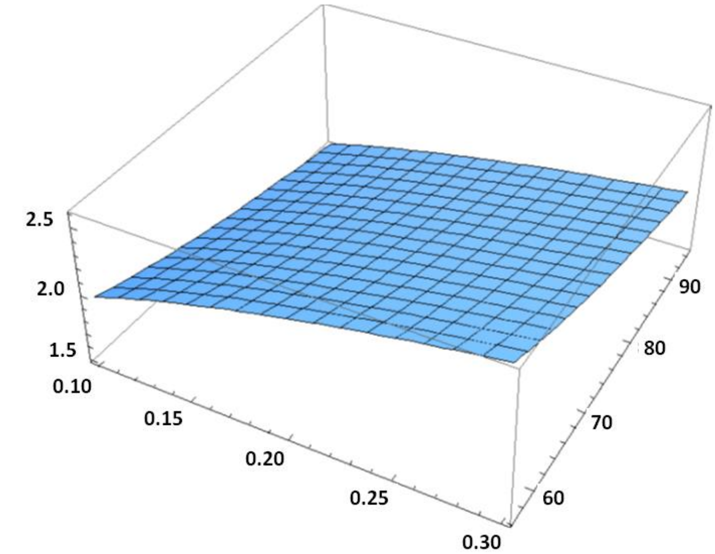


d)

Fig. 1. The dependence of surface roughness on: a) cutting speed and various values of cutting time, b) cutting speed and various values of feed rate, c) feed rate and various values of cutting speed, d) feed rate and various values of cutting time



a)



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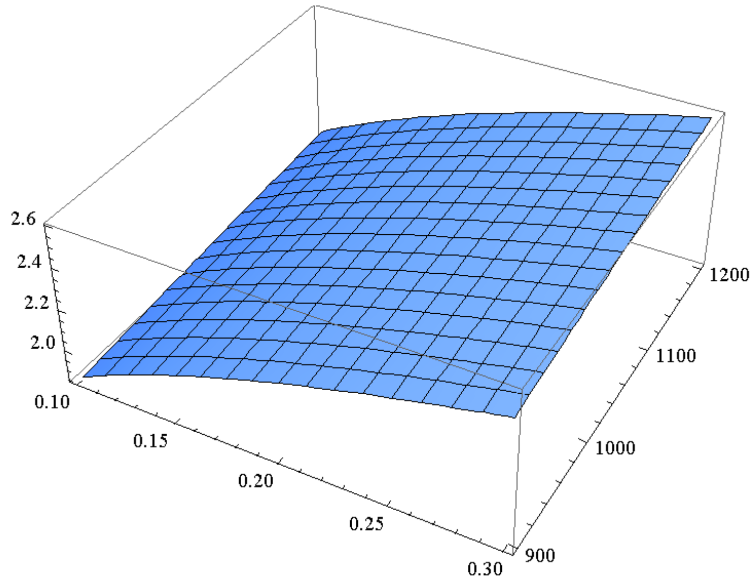

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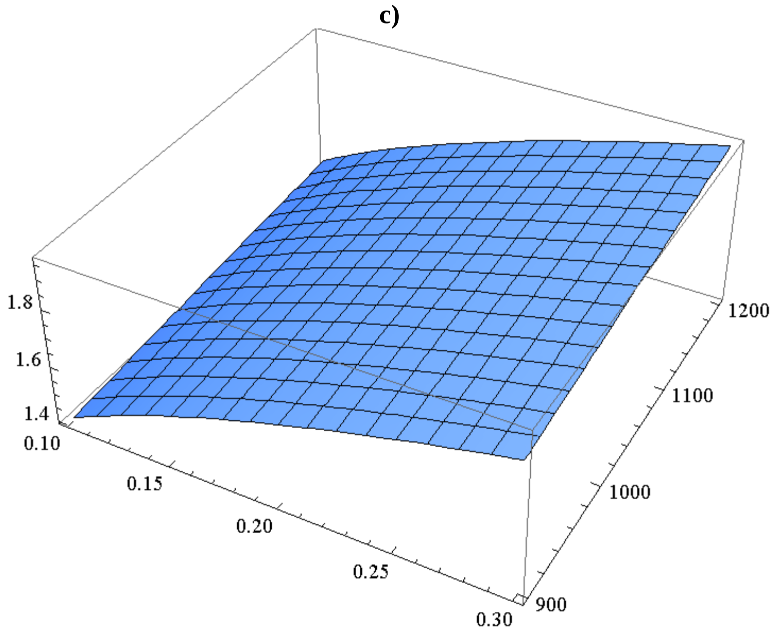

d)

Fig.2. 3D surface plots: Plot3D [6.795*(56.52^0.542)*(f^0.250)*(T^0.215),{f,0.1,0.3},{T,900,1200}]

6. Conclusions

This paper presents research of various cutting parameters affecting the surface roughness in dry milling of carbon steel using HSS cutters.The investigations of this study indicate that the cutting parameters like cutting speed and feed rate are the primary influencing factors, which affect surface roughness.

Statistical models deduction defined the degree of influence of each cutting regime element on surface roughness criteria. The results revealed that cutting speed seems to influence surface roughness (0.542) more significantly than feed rate (0.250). However, machining time is less significant (0.215). With the regression equation generated, the best combination of design independent variables for achieving the optimization of cutting processes.

The relations of the surface roughness, the cutting speed, the feed rate, and the cutting time are investigated to develop the prediction models of surface roughness. The exponential function is employed to represent the relation of the arithmetic average surface roughness, the cutting force ratio, and the cutting parameters. The multiple regression analysis has been utilized to calculate the regression coefficients of the in-process prediction of surface roughness model by using the least square method.

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