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Procedia Engineering 100 (2015) 135 – 140

Procedia Engineering

www.elsevier.com/locate/procedia

25th DAAAM International Symposium on Intelligent Manufacturing and Automation, DAAAM 2014

Effect of Machining Parameters and Machining Time on Surface Roughness in Dry Turning Process

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Abstract

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. This paper a model of surface roughness was developed based on the response surface method to investigates the machining parameters such as feed rate, tool geometry, nose radius, and machining time, affecting the roughness of surface produced in dry turning process. The experiment has been designed and carried out on the basis of a three level factorial design. Obtained results are in good accordance with the published results in the field, validating the effectiveness of regression analysis in modeling of surface roughness in dry turning process.

Peer-review under responsibility of DAAAM International Vienna

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

1. Introduction

A good understanding of the material removal process in metal cutting is essential in selecting the tool material and design, and also in assuring consistent dimensional accuracy and surface integrity of the finished product. Metal cutting friction influences the cutting power, machining quality, tool life, and machining cost.

When tool wear reaches a certain value, increasing cutting force, vibration and cutting temperature, it causes deteriorated surface integrity and dimension error greater than tolerance [1].

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Peer-review under responsibility of DAAAM International Vienna
doi:10.1016/j.proeng.2015.01.351

One important parameter in the qualification of cut surfaces is their roughness, and its indexes. The roughness has great significance primarily at mating the 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, depth of cut, nose radius, cutting time, etc.), 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 turning 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.

There are various parameters used to evaluate surface roughness. In the present research the average surface roughness (R_a) is selected for characterization of surface finish during turning operations, which 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.

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, 7].

Objective of this research presents the development of mathematical model for surface roughness prediction before turning process in order to evaluate the effect of machining parameters such as feed rate, nose radius and cutting time. Multiple Regression Method was used to determine the correlation between a criterion variable and a combination of prediction variables.

Nomenclature

R_a	the average surface roughness
P	Power
n	RPM
f	feed rate
d_{max}	workpiece diameter
L	tail stock
N	factorial design
K	number of factors
N_0	number of additional tests
r	nose radius
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

ε	random error

2. Experimental conditions

Machine tool used for this investigation was the production lathe C10A, P = 10 kW with a speed range n = 18 - 2500 rpm, feed rate range f = 0,05 - 2,0 mm/rev, max. workpiece diameter d_{max} = 280 mm, and distance from chuck to the tail stock L = 2000 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/mm^2, and hardness 236-245 N/mm$^{2.}$ The workpiece dimensions are: the length 300 mm, the diameter 70 mm, and it is machined under dry turning conditions. Tensile strength is 70 - 75 N/mm^2.

Cutting tools are SNMM coated tungsten carbide inserts (Sintal), with a tool holder ISO PSDNN2525P12, as presented in table 1.

Table 1. Dimensions of cutting plates.

ISO	*l, mm*	*s, mm*	*r, mm*
SNMN120404	$12.7^{0.500}$	$4.76^{0.187}$	$0.4^{0.016}$
SNMN120408	$12.7^{0.500}$	$4.76^{0.187}$	$0.8^{0.031}$
SNMN120412	$12.7^{0.500}$	$4.76^{0.187}$	$1.2^{0.047}$

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

3. Experimental setup

It is obvious that the effects of factors on the selected target function are nonlinear. An experiment with factors at three levels was set up, 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 $N=2^k+N_0$ (k=3 - number of factors, N_0=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.

Table 2. Experimental setup at three level factors.

			Cutting factors and their levels		
No.	*Factors*	*Code*	*High level*	*Middle level*	*Low level*
		level	*1*	*0*	*-1*
1	*f, mm/rev*	X_1	0,285	0,214	0,178
2	*r, mm*	X_2	*1.2*	*0.8*	*0.4*
3	*T, s*	X_3	3950	*2590*	1700

Table 3. Experimental results.

Test	Coded factors				Performance measures	
No.	X_0	X_1	X_2	X_3	Ra	Y = lnR a
1	+1	+1	-1	+1	3.064	1.119721252
2	+1	-1	+1	+1	1.179	0.164666622
3	+1	+1	+1	-1	1.012	0.012620031
4	+1	-1	-1	-1	1.075	0.072320662
5	+1	0	0	0	1.961	0.673454547
6	+1	0	0	0	1.902	0.642905964
7	+1	-1	-1	+1	2.703	0.994362267
8	+1	+1	-1	-1	3.2963	1.192800627
9	+1	+1	+1	+1	1.957	0.671412688
10	+1	-1	+1	-1	2.227	0.800655388
11	+1	0	0	0	1.682	0.519983562
12	+1	0	0	0	1.804	0.590006422

3.1. 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 [5, 7, 9, 13, 14, 15], by the following:

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

Three parameters: feed rate (f), nose radius (r) 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:

$$ln\ R_a = ln\ c_0 + c_1\ ln\ f + c_2\ ln\ r + c_3\ ln\ T \tag{3}$$

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

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x + \varepsilon \tag{4}$$

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:

$$y = X\beta + \varepsilon \tag{5}$$

Thus, the least squares estimator of β is

$$\beta = (X'X)^{-1}X'y \tag{6}$$

The fitted regression model is

$$\acute{Y}=X\,\beta \qquad (7)$$

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

$$e=y-\dot{y} \qquad (8)$$

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

$$R_a = 1.329\, f^{0.513}\, r^{-0.943}\, T^{0.258} \qquad (9)$$

4. Results and discussion

Table 3 presents experimental results of surface roughness criteria Ra for various combinations of feed rate, nose radius and cutting time to full factorial design. Minimal value of surface roughness criteria Ra=1.0127 µm was obtained at f = 0,285 mm/rev, r=1.2 mm, T=1700 s (test No. 3). That means increasing of nose radius with the lowest feed rate and cutting time lead to decreasing of surface roughness.

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

Maximal value of surface roughness criteria Ra =3.296 µm was registered at f = 0.285 mm/rev, r =0.4 mm and T=1700 s, (test No. 12). In order to achieve better surface finish, the highest level of cutting speed, depth of cut, and the lowest level of feed rate should be recommended.

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

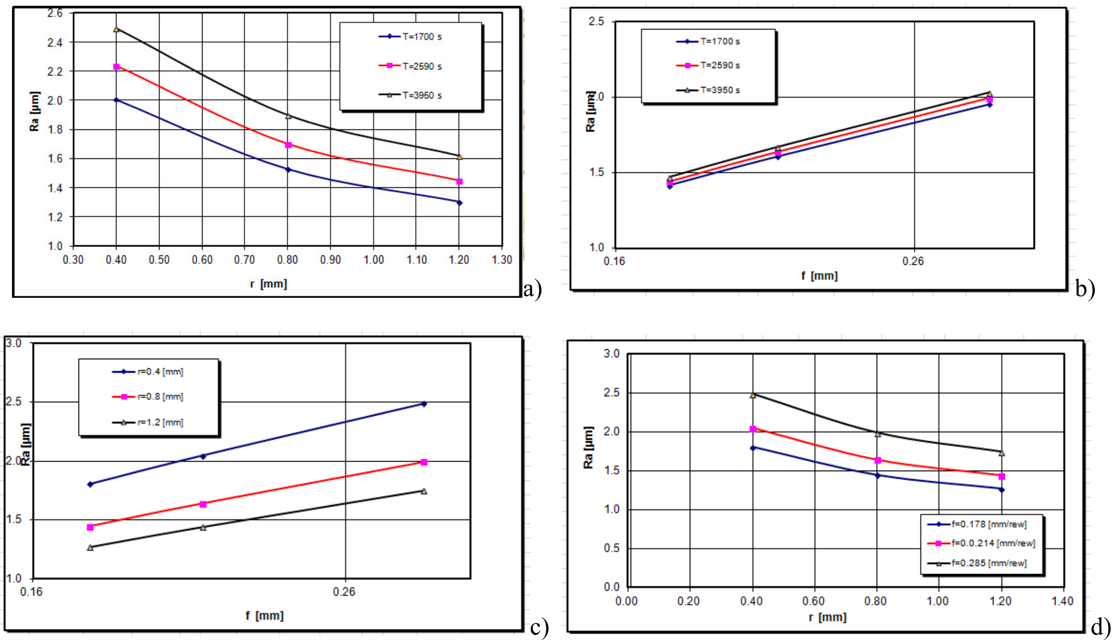

Fig. 1. The dependence of surface roughness on: a) nose radius and various values of cutting time, b) feed rate and various values of cutting time, c) feed rate and various values of nose radius, d) nose radius and various values of feed rate

Conclusion

This paper presents research of various cutting parameters affecting the surface roughness in dry turning of coated tungsten carbide inserts.
The investigations of this study indicate that the cutting parameters like feed rate, nose radius and cutting time 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 feed rate seems to influence surface roughness (0.513) more significantly than nose radius (0.394) and cutting time (0.258).
With the regression equation generated, the best combination of design independent variables for achieving the optimization of cutting processes was presented.

Further research should be aimed at harmonizing the size of nose radius on insert plate with a depth of cut and its impact on the quality of the machined surface.

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