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TAGUCHI AND RESPONSE SURFACE METHODOLOGIES ENGAGED FOR SURFACE ROUGHNESS IN CNC TURNING AISI 316 BY MULTILAYERED COATED TOOL

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ABSTRACT

This paper examines about the utilization of Taguchi and reaction surface techniques (RSM) for minimizing the surface roughness (SR) in CNC turning austenitic stainless steel (AISI 316) by multilayered coated with $TiCN/Al_2O_3$ tool. The trials have been led utilizing Taguchi exploratory outline system. The cutting parameters utilized are cutting pace, encourage and profundity of cut. The impact of cutting parameters on SR is assessed and the ideal cutting condition for limiting the SR is resolved. In the first place and second request demonstrate are built up between the cutting parameters and SR utilizing RSM. The test comes about uncover that the most huge tuning parameter for SR is sustain trailed by cutting rate. The predicted values and measured values are fairly close, which indicates that the developed model can be effectively used to predict the SR in turning of AISI 316. Analysis of variance (ANOVA) is used for identifying the significant parameters affecting the responses. Finally the residual analysis is employed for verify the regression model.

***Keywords**: CNC tuning, surface roughness, Taguchi technique, Response surface method and ANOVA.*

1. Introduction

Machining process is very important in manufacturing technology. These processes are applied for manufacturing the mechanical parts because of these processes have efficient and economical. There are many parameters to be considered for affecting the surface quality [1, 2]. SR is one of the imperative reactions for machined item quality. SR is influencing the useful conduct of the mechanical items. The mechanism of SR formation depends on various uncontrollable parameters that make its estimation difficult [3, 4]. AISI 316 are generally regarded as being more difficult to machine material compare to carbon and other alloy steels due their high strength, ductility and high work hardening tendency [5]. Stainless steels are having different grades and different properties under variation of chemical compositions. Therefore, these variations in their properties have an influence on their machinablities [6]. Tool wear is broadly viewed as a standout amongst the most difficult part of causing poor surface quality in machining. Coated carbides are essentially an established carbide coated with at least one daintily layers of wear safe materials, for example, titanium nitride, titanium carbide and aluminum oxide [7, 8]. It is outstanding that covering can diminish tool wear and enhance the SR [9, 10]. Hence, a large portion of the carbide apparatuses utilized as a part of the metal cutting enterprises is covered while covering realizes an additional cost [11, 12].

In order to get good SR and dimensional properties, it is necessary to employ optimization techniques to find optimal cutting parameters and theoretical models to do predictions. Taguchi and RSM can be conveniently used for these purposes [13]. Taguchi and RSM are applied for optimizing geometric errors in surface grinding process [14]. RSM is more practical, economical and relatively easy to use [15]. Researcher have used many methods to predict responses, but combination of these methods not been done for CNC turning on AISI 316 by multilayered tool. In this paper Taguchi method is used to optimize the performance characteristics of process parameters and first and second order models are developed for predicting the SR. The predicted and measured values are fairly close to each other.

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2. Material and methods

The work material used for the present investigation is AISI 316. The diameter of the material is 32 mm and machined length is 60mm for all trials. The chemical composition of the work material is given in Table 1.

Table 1 Chemical composition of AISI 316.

C	Si	Mg	P	S	Ni	Cr	Mo
0.04	0.49	1.56	0.03	0.01	10.4	16.7	2.11
0	8	0	6	7	5	1	2

2.1 Taguchi method

This paper uses Taguchi method for optimization of machining parameters in turning AISI 316, which is very attractive and effective method to deal with responses influenced by number of variables. In this method, main parameters are assumed to have influence on process results, which are located at different rows in a designed orthogonal array. With such an arrangement completely randomized experiments can be conducted. This method is useful for studying the interactions between the parameters, and also it is a powerful design of experiments tool, which provides a simple, efficient and systematic approach to determine optimal cutting parameters. Compared to the conventional approach of experimentation, this method reduces significantly the number of experiments that are required to model the response functions [16, 17].There are three categories of quality characteristic in the analysis of the S/N ratio, (1) the-lower-the-better, (2) the-higher-the-better and (3) the-nominal-the-better. Since the quality characteristic is to be minimized, the-lower-the-better category is used to calculate the S/N ratio for SR. Equation (1) shows the smaller the better characteristic.

$$\eta = -10\log_{10}\left\{\frac{1}{n}\sum_{i=1}^{n} y_i^2\right\} \quad (1)$$

Where:
η = Signal to noise ratio
n = Number of repetitions of experiment
y = Measured value of quality characteristic

Minitab14 statistical software has been used for the analysis of the experimental work. The software studies the experimental data and then provides the calculated results of signal-to-noise ratio. In this work, the software has given the signal-to-noise ratio for SR.

2.2 Response surface methodology

The surface finish of machined AISI 316 part is critical in assembling applications which have extensive impact on a few properties, for example, superb corrosive resistance. While machining, quality of the parts can be achieved only through proper cutting conditions. Keeping in mind the end goal to know the surface quality and dimensional properties ahead of time, it is important to utilize hypothetical models making it conceivable to do expectation in capacity of operation conditions. RSM is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response. In many engineering fields, there is a relationship between an output variable of interest ‘y’ and a set of controllable variables $\{x_1, x_2. \ldots x_n\}$. In some systems, the nature of the relationship between y and x values might be known. Then, a model can be written in the form

$$Y = f(x_1, x_2 . x_n) + \varepsilon \quad (2)$$

Where ε represents noise or error observed in the response y. If we denote the expected response be f $(x_1, x_2. \ldots x_n) = \hat{y}$ then the surface represented by

$$\hat{Y} = f(x_1, x_2. \ldots x_n) \quad (3)$$

In most of the RSM problems, the form of relationship between the response and the independent variable is unknown. Thus the first step in RSM is to find a suitable approximation for the true functional relationship between y and set of independent variables employed. Usually a second order model is utilized in response surface methodology [18].

3 Experimental details

The experiments are planned using Taguchi’s orthogonal array in the design of experiments, which helps in reducing the number of experiments. The experiments were conducted according to orthogonal array. The three machining parameters selected for the present investigation is cutting speed (v), feed (f) and depth of cut (d). Since the considered factors are multi-level variables and their outcome effects are not linearly related, it has been decided to use three level tests for each parameter. The machining parameters used and their levels chosen are given in Table 2. Taguchi's orthogonal array of L_{27} is most suitable for this experiment. This needs 27 runs and has 26 degrees of freedoms. It can conduct three levels of parameters. To check the degrees of freedom (DOF) in the experimental design, for the three levels test, the three main factors take 6 (3× (3−1)) DOFs. Square effects and interaction between parameters take the remaining DOFs. The values of machining parameters and S/N ratio for SR are presented in Table 3. The experiments were conducted on Fanuc CNC lathe. Multilayered CNMG 120408 coated with $TicN+Al_2O_3$ of 14 µm is used as the insert for all machining operation. The range of cutting parameters were selected based on past experience, data book and available resources. SR is measured by the mitutoyo surface roughness tester.

Table 2 Machining parameters and levels.

Process parameter	Level 1	Level 2	Level 3
Cutting speed (m/min)	110	160	210
Feed(mm/rev)	0.1	0.2	0.3
Depth of cut (mm)	0.7	1.4	2.1

4 Results and discussions

4.1 Effect of control parameters on SR

In Taguchi method, the term signal represents the desirable value and noise represents the undesirable value. The objective of using S/N ratio is a measure of performance to develop products and processes insensitive to noise parameters. The S/N ratio indicates the degree of the predictable performance of a process in the presence of noise parameters. Table 4 shows the S/N ratios obtained for different parameter levels. The calculated S/N ratio for three factors on the SR in turning of AISI 316 for each level is shown in Fig. 4. As shown in Table 4 and Fig. 4 feed is a dominant parameter on the SR followed by depth of cut. The cutting speed had a lower effect on the SR. Lower SR is always preferred. The quality characteristic considered in the investigation is lower-the better characteristics. The SR observed at low cutting speed is more than the SR observed at higher cutting speed. In the present investigation, when the cutting speed is set at 110 m/min is applied the SR is minimized. From the experimental results, it is observed that at high depth of cut the SR is minimal. Here feed is increased with head generation and tool wear so the SR is increased. The increase in feed also increases the chatter, and it produces incomplete machining of work piece, which led to higher SR. The results shown prove that the roughness of the machined surface is highly influenced by the feed, based on the above discussion and also evident from Fig. 4.

It is emphasized that these conditions only provide best SR among the cutting conditions tested. From Table 6 ANOVA for SR. It can be found that depth of cut and feed are the significant cutting parameters for affecting SR. The change of the cutting speed range given in Table 3 has an insignificant effect on SR (p-value = 0.98).

Table 3 Experimental results for SR versus v,f,d.

Trial	v	f	d	SR(µm)	S/N for SR
1	110	0.1	0.7	0.64	3.87
2	110	0.1	1.4	0.61	4.29
3	110	0.1	2.1	0.56	5.03
4	110	0.2	0.7	1.39	-2.86
5	110	0.2	1.4	1.14	-1.13
6	110	0.2	2.1	1.11	-0.90
7	110	0.3	0.7	1.66	-4.40
8	110	0.3	1.4	1.44	-3.16
9	110	0.3	2.1	1.02	-0.17
10	160	0.1	0.7	1.49	-3.46
11	160	0.1	1.4	0.92	0.72
12	160	0.1	2.1	0.7	3.09
13	160	0.2	0.7	1.33	-2.47
14	160	0.2	1.4	1.43	-3.10
15	160	0.2	2.1	1.38	-2.79
16	160	0.3	0.7	1.17	-1.36
17	160	0.3	1.4	1.23	-1.79
18	160	0.3	2.1	1.33	-2.47
19	210	0.1	0.7	1.83	-5.24
20	210	0.1	1.4	0.64	3.87
21	210	0.1	2.1	0.74	2.61
22	210	0.2	0.7	1.51	-3.57
23	210	0.2	1.4	1.43	-3.10
24	210	0.2	2.1	1.23	-1.79
25	210	0.3	0.7	1.7	-4.60
26	210	0.3	1.4	1.47	-3.34
27	210	0.3	2.1	1.39	-2.86

Table-4 Taguchi Analysis: SR versus v,f,d.

Level	v	f	d
1	0.06220	1.64526	-2.68090
2	-1.51796	-2.41895	-0.75213
3	-2.00636	-2.68843	-0.02909
Delta	2.06856	4.33369	2.65180
Rank	3	1	2

Table-5 Analysis of Variance for SR versus v,f,d.

Source	DF	SS	MS	F	P
v	2	0.315	0.15790	2.62	0.098
f	2	1.226	0.61338	10.17	0.001
d	2	0.635	0.31774	5.27	0.015
Error	20	1.206	0.06034		
Total	26	3.384			

S = 0.245637 R-Sq = 64.35% R-Sq (adj) = 53.65%

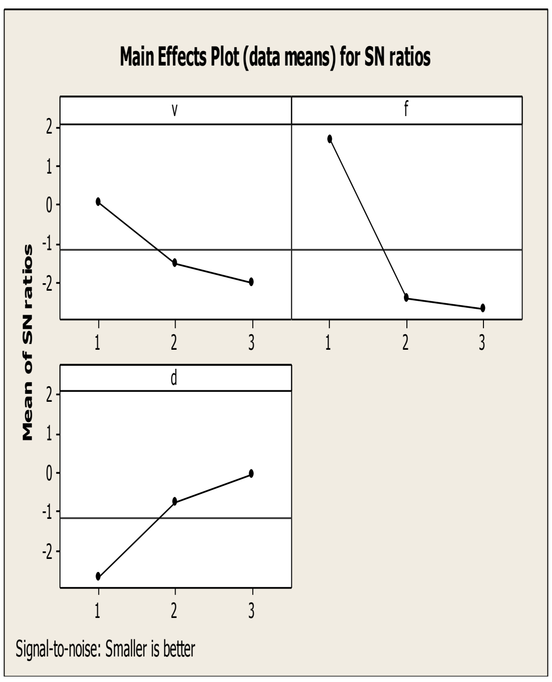

Fig.1 The main effect of plot for S/N ratio for SR

4.2 Response surface analysis

4.2.1 First order regression model

The first order response surface representing the SR can be expressed as a function of cutting parameters. The relation between the SR and machining parameters has been expressed as follows

$$SR = \beta_0 + \beta_1 (v) + \beta_2 (f) + \beta_3 (d) + \beta_7 (v\ f) + \beta_8 (v\ d) + \beta_9 (f\ d) \quad (4)$$

From the observed data for SR, the response function has been determined is un coded unit as

$$SR = 0.941 + 0.132\ v + 0.238\ f - 0.181\ d + 0.0372\ vf - 0.0228\ vd - 0.0717\ df \quad (5)$$

The β coefficients, used in the above model can be calculated by means of using least square method. The relationshipbetween S/N ratio and SR is given in the graphical plot in Fig.1. The first -order model is normally used when the response function is not known or nonlinear. The estimated first order regression coefficient the least squares method is as shown in table 6. Result of ANOVA for the function SR is presented in table 7. The analysis is carried of 5%, ie, for a level of confidence of 95%. To verify the regression model, we performed residual analysis. The normal plot and residual histogram from this analysis are depicted in Fig 2 and 3 respectively. As shown in Fig 2, the departures are scattered. It indicates the abnormalities in the residual distribution. Alternatively, the residual histogram shows that frequency of the residual is not satisfied with the normal distribution.

Table 6 First order regression coefficient

	Coef.	Coef.SE	T	P
β_0	0.9411	0.3028	3.11	0.006
β_1	0.13167	0.06096	2.16	0.043
β_2	0.23778	0.06096	3.90	0.001
β_3	-0.18111	0.06096	-2.97	0.008
β_4	0.03722	0.06096	0.61	0.548
β_5	-0.02278	0.06096	-0.37	0.711
β_6	-0.07167	0.06096	-1.18	0.254

Table 7 ANOVA for first order regression model

Source	D	SS	MS	F	P
Regression	6	2.04689	0.34115	5.10	0.003
Residual Error	20	1.33791	0.06690		
Total	26	3.38480			

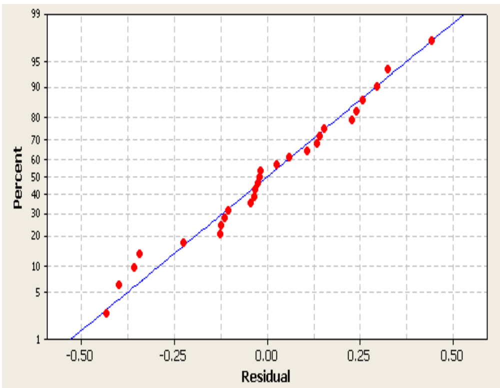

Fig 2 Normal probability plot for the residuals

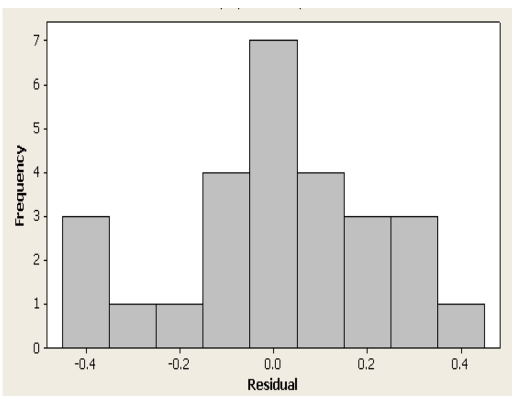

Fig. 3 Histogram of the residuals

4.2.2 Second order regression model

The second order response surface representing the SR can be expressed as a function of machining parameters. The relation between the SR and machining parameters has been expressed as follows

$$SR = \beta_0 + \beta_1 (v) + \beta_2 (f) + \beta_3 (d) + \beta_4 (v^2) + \beta_5 (f^2) + \beta_6 (d^2) + \beta_7 (v\ f) + \beta_8 (v\ d) + \beta_9 (f\ d) \quad (6)$$

From the observed data for SR, the response function has been determined is un coded unit as

$$SR = 0.889 + 0.132v + 0.238f - 0.181d + 0.0372v^2 - 0.0228f^2 - 0.0717d^2 + 0.0800vf + 0.0200vd - 0.0739fd \quad (5)$$

The second order estimated coefficient is shown in table 8. Result of ANOVA for the second order regression model is shown in table 9. Fig 2 and 3 show the results of normal probability and histogram of the residuals. As shown in Fig 4, the result is enhanced more than the first order regression model. Also, the frequency of the residual was satisfied with the normal distribution as shown if Fig 5 and the second order regression model is suitable for explaining the machining errors.

Table 8 The second order regression coefficient

	Coef.	Coef.SE	T	P
β_0	0.8889	0.3659	2.43	0.026
β_1	0.13167	0.06042	2.18	0.044
β_2	0.23778	0.06042	3.94	0.001
β_3	-0.18111	0.06042	3.00	0.008
β_4	0.03722	0.06042	0.62	0.546
β_5	-0.02278	0.06042	-0.38	0.711
β_6	-0.07167	0.06042	-1.19	0.252
β_7	0.08000	0.06042	1.32	0.203
β_8	0.02000	0.06042	0.33	0.745
β_9	-0.07389	0.06042	-1.22	0.238

Table 9 ANOVA for second order regression model

Source	DF	SS	MS	F	P
Regression	9	2.2675	0.25195	3.83	0.008
Residual Error	17	1.1172	0.06572		
Total	26	3.384			

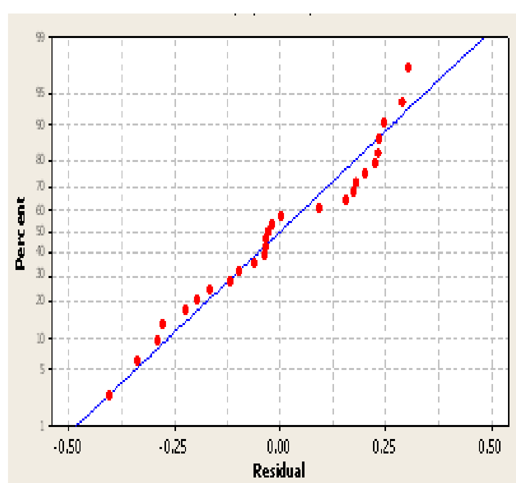

Fig. 4 Normal probability plot for the residuals

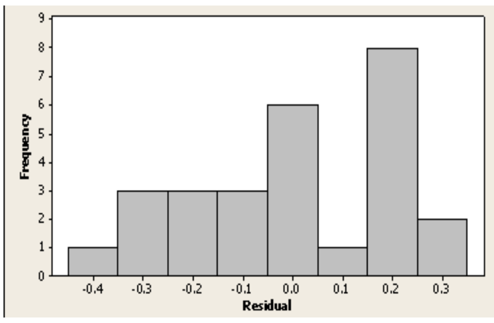

Fig. 5 Histogram of the residuals.

5 Conclusions

The SR in the turning procedure is measured for machining of AISI 316 under various cutting conditions with multilayer of TiCN/Al2O3 tool utilizing Taguchi orthogonal array. In view of the trial and diagnostic outcomes, the accompanying conclusions drawn.

- The impact of machining parameters on the SR has been assessed the assistance of Taguchi strategy and ideal machining conditions to limit the SR have been resolved.
- The feed is the predominant parameter for SR took after by the depth of cut. Cutting speed demonstrated negligible impact on SR contrasted with different parameters.
- For accomplishment of good SR on AISI 316 low cutting speed, low feed and high depth of cut are favored.
- The second order regression model demonstrate is more appropriate than the primary order regression model show for portraying the turning procedure, from the view purpose of ANOVA and residual analysis.
- The second order response surface model for SR is created from the watched information the anticipated and measured esteem are genuinely close, which shows that the created model can be adequately used to foresee the SR.

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