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Multi response optimisation of CNC turning parameters via Taguchi method-based response surface analysis

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ABSTRACT

This study presents a new method to determine multi-objective optimal cutting conditions and mathematic models for surface roughness (*Ra* and Rz) on a CNC turning. Firstly, cutting parameters namely, cutting speed, depth of cut, and feed rate are designed using the Taguchi method. The AISI 304 austenitic stainless workpiece is machined by a coated carbide insert under dry conditions. The influence of cutting speed, feed rate and depth of cut on the surface roughness is examined. Secondly, the model for the surface roughness, as a function of cutting parameters, is obtained using the response surface methodology (RSM). Finally, the adequacy of the developed mathematical model is proved by ANOVA. The results indicate that the feed rate is the dominant factor affecting surface roughness, which is minimized when the feed rate and depth of cut are set to the lowest level, while the cutting speed is set to the highest level. The percentages of error all fall within 1%, between the predicted values and the experimental values. This reveals that the prediction system established in this study produces satisfactory results, which are improved performance over other models in the literature. The enhanced method can be readily applied to different metal cutting processes with greater confidence.

1. Introduction

Stainless steels have been widely used in the chemical, health, food production, pharmaceutical, textile, nuclear, biomedical, etc., industries for different applications. They exhibit high hardness and yield strength as well as excellent ductility and toughness over a wide range of temperatures and exhibit excellent corrosion and oxidation resistance.

Stainless steels are often considered as poorly machinable materials because of high strength and work hardening rates [1]. Austenitic stainless steels have properties that give them a different machinability compared to carbon steel or ferritic and martensitic stainless steels. The greatest difference is the high ductility of austenitic stainless steels, as well as their tendency to work hardening and form built-up edges on the cutting tool [2,3].

The surface roughness is of great importance for product quality and its function in manufacturing industries [4]. Minimal surface roughness is important due to increased consumer demands for quality, less costly products, minimum friction, maximum lubrication, and minimum wear. It is a characteristic that could influence the performance of mechanical parts and production costs.

Process modelling and optimization are two important issues in manufacturing products. The manufacturing processes are characterized by a multiplicity of dynamically interacting process variables [5]. Modelling of surface roughness is difficult because it is affected by different variables. Recently many surface roughness modelling, simulation and optimization systems were designed using

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different cutting parameters and methods. Some of the outstanding literature studies are given below:

Latha and Senthilkumar [6] carried out a prediction of surface roughness in drilling of composite materials using fuzzy logic rule–based modelling and ANOVA analyses. The experiments were conducted on a CNC drilling machine. The data for surface roughness were collected under different cutting conditions for various combinations of spindle speeds, feed rates, and drill diameters. They obtained good agreement between the model results and experimental values.

Palanikumar [7] modelled the delamination factor and surface roughness in machining of GFRP composites through response surface methodology. Three-factors five-levels central composite design was employed in his study. The results of analysis of variance indicated that the developed models were adequate at 95% confidence level within the limits of factors being considered.

Sun and Lee [8] concerned with the influence of design variables and different design conditions such as objective functions and constraints on the rotor performance. RSM based on D-optimal 3-level factorial design and genetic algorithm were applied to obtain the optimum solution of a defined objective function including the penalty terms of constraints.

Wiper inserts are increasingly being utilized in last years. The influences of the wiper inserts on the surface roughness were described in turning by Correia and Davim. Using with wiper inserts and high feed rate, was obtained machined surfaces with $Ra < 0.8$ μm [9].

Nowadays, many academicians and companies are interested in optimising manufacturing processes to reduce cost, improve quality, and obtain high efficiency. Unfortunately, most computational methods for complex machining systems require significant computational resources to evaluate each parameter of a multi-variable subject function. No method currently results in the same level of efficiency for all process.

The present work aims to use the surface roughness values (Ra and Rz) as multi objective functions, as an efficient method for the determining the optimal cutting parameters for multiple quality characteristics, via Taguchi method-based Response Surface Analysis for CNC turned AISI 304 austenitic stainless.

2. Design of experiments

2.1. Turning process parameters

Process parameter optimization has been widely used in turning operations. The process parameters affecting the characteristics of turned parts are: cutting tool parameters – tool geometry and tool material; work piece related parameters metallography, hardness, etc.; cutting parameters- cutting speed, feed, depth of cut, dry/wet cutting. Singh and Kumar [10] constructed a fishbone cause and effect diagram which was identified the process parameters that may affect the machining characteristics of turned parts and it is shown in Fig. 1.

2.2. Response surface methodology

Responce Surface Methodology (RSM) focuses a well-known up to date approach on the optimization of the input parameters models based on either physical experiments, simulation experiments and experimental observations. These approximated models need to be assessed statistically for their adequacy, and then they can be utilised for an optimisation of the initial model. RSM also quantifies relationships between the controllable input parameters and the obtained response surfaces [11]. The input parameters are sometimes called independent variables, and the performance measure or quality characteristic is the response. By using the results of a numerical experiment in the points of orthogonal experimental design, response surface analysis is computationally much less expensive than a solution using the traditional method. With this analytical model, the objective function problem can be easily solved and also a great deal of the time in computation can be saved [12]. At most, response surface methodology problems have a functional relation between responses and independent variables, and this relation can be explained using the second-order polynomial model in below [13,14].

$$\eta = \beta_0 + \sum_{i=1}^{k}\beta_i X_i + \sum_{i=1}^{k}\beta_{ii}X_i^2 + \sum_i \sum_j \beta_{ij}X_iX_j + \varepsilon \tag{1}$$

where η is the estimated response (surface roughness), β_0 is constant, β_i , β_{ii} and β_{ij} represent the coefficients of linear, quadratic, and cross-product terms, respectively. X reveals the coded variables.

The common approach in the RSM is to use regression methods based on least square methods. The method of least squares is typically used to estimate the regression coefficient, which is shown in the following equation [15].

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \cdots \\ \cdots \\ \beta_n \end{bmatrix} = \left(X^TX\right)^{-1}X^T\eta = \left[\frac{1}{k}\sum_{j=1}^{k}\eta_j, \frac{\sum_{j=1}^{k}X_{1j}\eta_j}{\sum_{j=1}^{k}X_{1j}^2}, \ldots, \frac{\sum_{j=1}^{k}X_{nj}\eta_j}{\sum_{j=1}^{k}X_{nj}^2}\right]^T \tag{2}$$

n is the number of objective function and k is the number of factors. The β terms comprise the unknown parameter set which can be estimated by collecting experimental system data. These data can either be sourced from physical experiments or from numeric experiments. The parameter set can be estimated by regression analysis based upon the experimental data. The process of the RSM and optimisation are shown in Fig. 2.

2.3. Taguchi design

The Taguchi method is a powerful and efficient design of experiment technique, which can improves process performance with a minimum number of experiments. It reduces, rework costs, manufacturing and cycle time costs in processes. The Taguchi design is to find optimal values of the objective function in manufacturing processes. Compared to traditional experimental designs, the Taguchi method makes use of a special design of orthogonal array

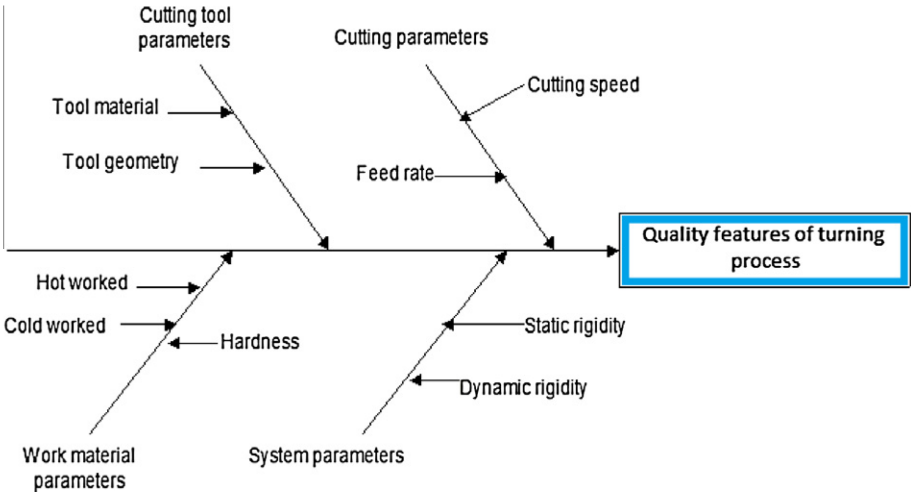

Fig. 1. Ishikawa cause effect diagram of turning process.

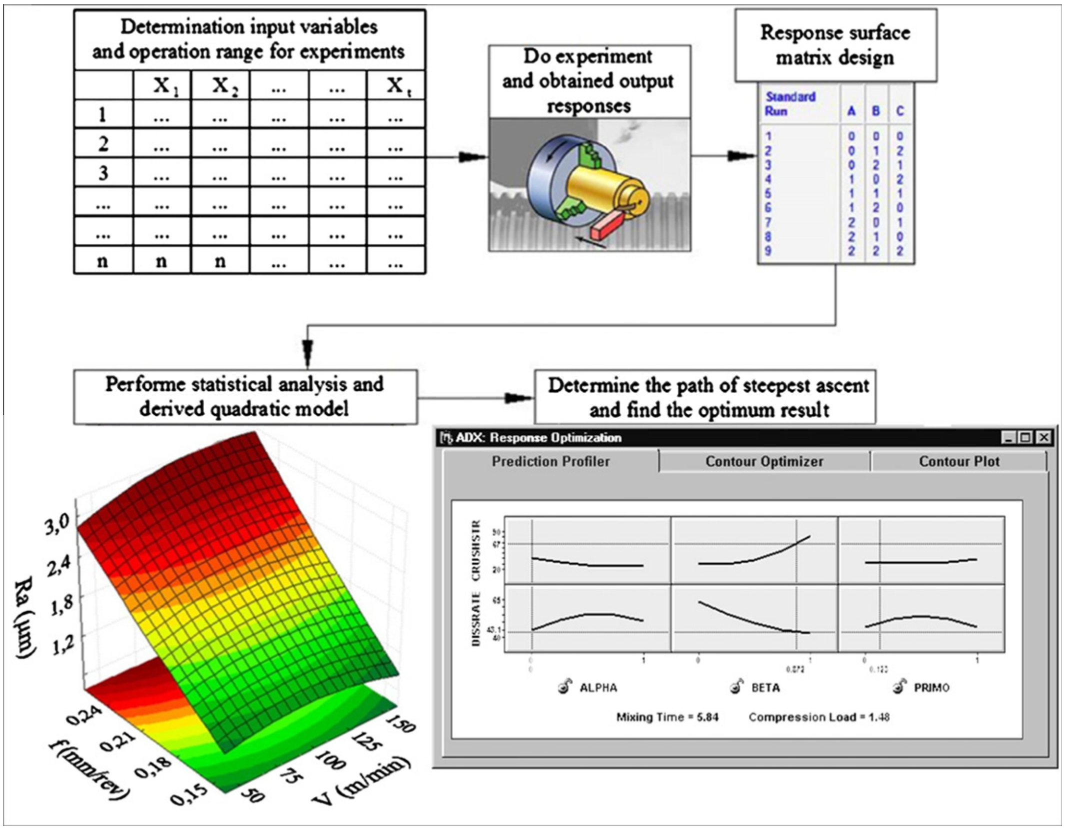

Fig. 2. Response surface methodology flowchart.

(OA) to examine the quality characteristics through a minimal number of experiments. The experimental results based on the OA are then transformed into S/N ratios to evaluate the performance characteristics. Therefore, the Taguchi method concentrates on the effects of variations on quality characteristics, rather than on the averages. That is, the Taguchi method makes the process performance insensitive to the variations of uncontrollable noise factors [16]. The optimum parameter conditions are then determined by performing the parameter design. Parameter

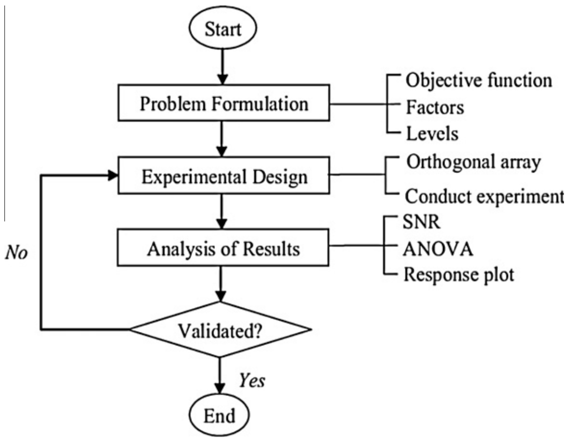

Fig. 3. Taguchi method flowchart.

design is also commonly referred to as robust design [17]. The flowchart of the Taguchi method is illustrated in Fig. 3 [18].

In this study, therefore, the Taguchi method is employed to determine the optimal turning process parameters. The configuration of the orthogonal array is based on the total degree-of-freedom (DoF_t) of the objective function. The most suitable array is $L_{27}(3^{13})$ (standart three-level orthogonal array), which needs 27 runs and has 26 DoF_t To check the DoF_t in the experimental design for the three levels of the test, the three main factors take 6 DoF_t s (3×2) and the remaining DoF_t s are taken by interactions.

3. Experimental procedure of turning

3.1. Selection of factors and their levels

The literature survey and accordance with ISO 3685 identified the turning parameters and their levels for the experiment. Finally, three parameters such as cutting speed, feed rate and depth of cut are selected and, the experimental conditions have been given in Table 1.

3.2. Material and method

The experimental work was carried out on the Taksan CNC turning machine (Oİ-TC-TTC 630). AISI 304 austenitic stainless steel rod (Ø 50 × 500 mm) was used for the experimentation. Its composition is 0.044%C, 1.47%Mn, 0.45%Si, 0.039%P, 0.026%S, 0.50%Cu, 0.38%Mo, 8.09%Ni, %0.073 N, 0.14%Co and 18.26%Cr. The Iscar's single insert tool holder (MULNR 2525 M–12 MW) and IC 3028 grade carbide inserts (SNMG 120408-PP) were selected for the study. The experimental setup is shown in Fig. 4.

After every experiment, the surface roughness values *Ra* and *Rz* were measured by a Mitutoyo SJ-201 surface roughness tester, and measurements were repeated 3 times. Using $L_{27}(3^{13})$ Taguchi standard orthogonal array, the experimental results are given in Table 2. This plan was developed for establishing the quadratic model of surface roughnesses using response surface analysis.

Table 1
Cutting parameters and their levels for Turning.

Symbol	Control factor	Unit	Level 1	Level 2	Level 3
V	Cutting speed	m/min	50	100	150
f	Feed rate	mm/rev	0.15	0.2	0.25
a	Depth of cut	mm	1	1.5	2

4. Analysis and discussion

4.1. Analysis of the signal-to-noise (S/N) ratio

The Taguchi method for robust design is a powerful tool. Two major tools used in robust design are S/N ratio and orthogonal array. Robust design is an important method for improving product or manufacturing process design by making the output response insensitive (robust) to difficult to control variations (noise). There are several types of quality characteristics, such as the lower-the-better, the higher-the-better and the nominal-the-better. In this study, since surface roughness should be a minimum the smaller-the-better type of the S/N ratio has been used and is defined as follows [19]:

$$S/N = -10\log\left[\frac{1}{n}(y_1^2 + y_2^2 \dots y_n^2)\right] \quad (3)$$

where $(y_1^2 + y_2^2 \dots y_n^2)$ are the responses of the machining characteristic, for a trial condition repeated n times. The negative sign in Eq. (3) is for showing the smaller-the-better quality characteristic. The S/N ratios were computed using Eq. (3) for each of the 27 trials, and the values are reported in Table 2 along with their experimentally measured values.

In this section, significance of controllable factors is investigated using S/N ratio approach. A smaller value of surface roughness is normally required in metal machining. Therefore, the smaller-the-better methodology of S/N ratio was employed for the aforesaid responses. Regardless of the category of the performance characteristics, the high value of S/N ratio corresponds to a better performance. Therefore, the optimal level of the process parameters is the level with the greatest S/N ratio [20].

Analysis of the influence of each control factor (*V*, *f*, *a*) on the surface roughness has been performed with a so-called signal-to-noise ratio response table. Response tables of S/N ratio for *Ra* and *Rz* are shown in Tables 3 and 4, respectively. They show the S/N ratio at each level of the control factors and how it is changed when settings of each control factor are changed from one level to another [21].

The influence of each control factor can be more clearly presented with response graphs (see Figs. 5 and 6, respectively).

These figures reveal the level to be chosen for the ideal cutting parameters (the level with the highest point on the graphs), as well as the relative effect each parameter has on the S/N ratio (the general slope of the line). As seen in the S/N ratio effects graphs (Figs. 5 and 6), the slope of the line which connects between the levels can clearly

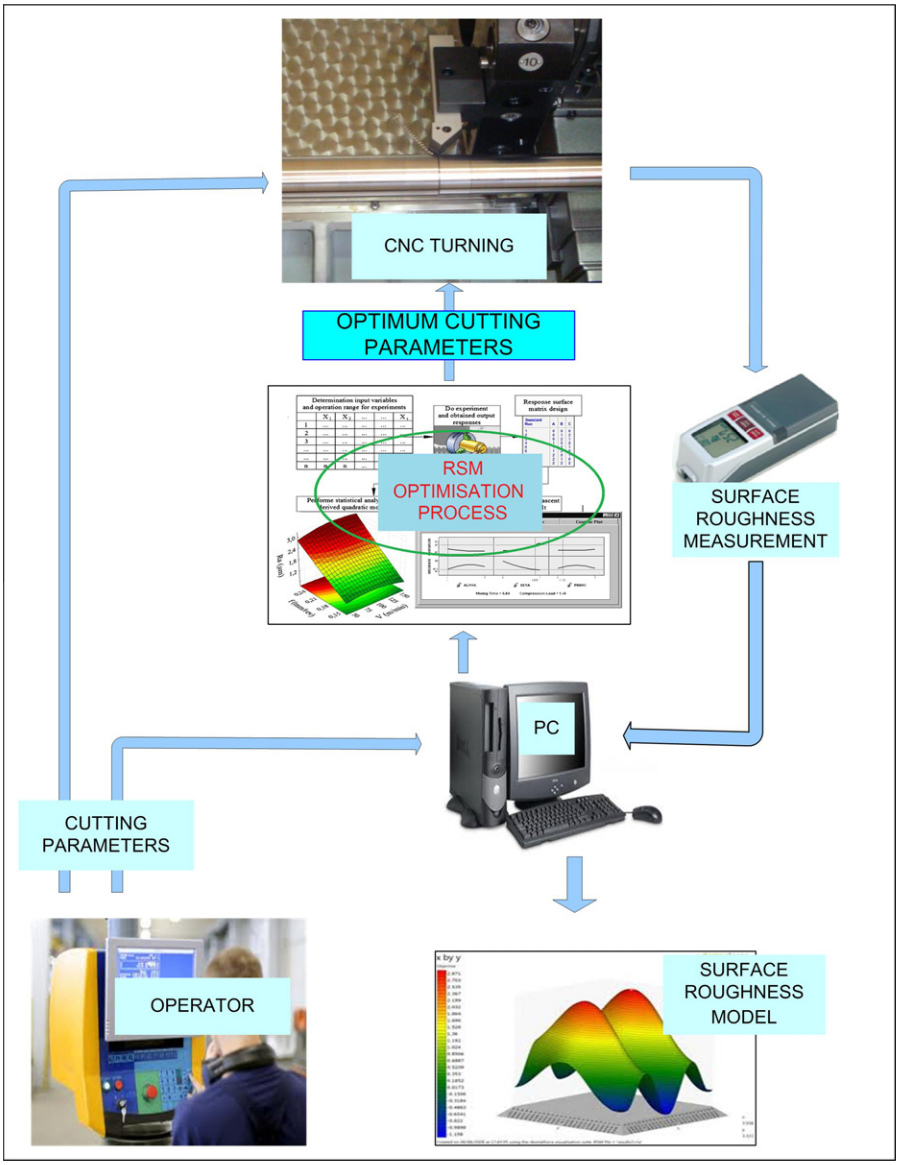

Fig. 4. Experimental set up to measure the vibration of the process.

show the power of influence of each control factor. Especially the feed rate is shown to have a strong effect on surface roughness and its S/N ratios. The cutting speed has a smaller effect, as evidenced by the shallow slope of the lines.

Table 5 shows the results of analysis of variance (ANOVA) for *Ra*. It can be found that workpiece revolution is the significant cutting factor for affecting the feed rate. The changes of the cutting speed and depth of cut in the ranges given in Table 5 have insignificant effects on *Ra*. Therefore, based on the S/N and ANOVA analyses, the optimal cutting parameters for *Ra* is $V_1f_1a_2$ i.e., V_1 = 50 mm/min, f_1 = 0.15 mm/rev and a_2 = 1.5 mm.

Table 6 shows the results of ANOVA for *Rz*. In this case feed rate is the significant cutting factor for affecting *Rz*. The optimal cutting parameters for surface roughness is $V_3f_1a_1$ *i.e.*, $V_3 = 150$ mm/min, $f_1 = 0.15$ mm/rev and $a_1 = 1$ mm.

4.2. Prediction optimal performance

The values of the significant factors for Surface roughness *Ra* and *Rz* were given in the Figs. 5 and 6 and Tables 5 and 6 can be used to estimate the mean surface roughness with optimal performance conditions. Two factors were found to be significant in both S/N and analysis of variance that is feed rate and depth of cut, which gave the smallest roughness values. When surface roughness *Ra* is considered, from Table 7, an estimated average when the two most significant factors are at their better level is at f_1a_2 level.

Table 2
$L_{27}(3^3)$ orthogonal array, experimental results and their *S/N* ratios.

Exp. No.	Control factor levels			Surface roughness *Ra* (µm)	Surface roughness *Rz* (µm)	S/N ratio for *Ra* (dB)	S/N ratio for *Rz* (dB)
	V Deep of cut	*f* Feed rate	*a* Workpi. rev.				
1	1	1	1	1.19	5.68	−1.51	−15.09
2	1	1	2	1.05	5.83	−0.45	−15.32
3	1	1	3	1.78	9.84	−5.01	−19.86
4	1	2	1	2.13	9.84	−6.57	−19.86
5	1	2	2	1.47	7.29	−3.33	−17.25
6	1	2	3	2.15	9.09	−6.65	−19.17
7	1	3	1	2.88	12.30	−9.19	−21.80
8	1	3	2	3.16	13.42	−9.98	−22.56
9	1	3	3	2.61	10.95	−8.32	−20.79
10	2	1	1	0.96	5.15	0.35	−14.24
11	2	1	2	1.10	5.18	−0.80	−14.29
12	2	1	3	1.48	7.47	−3.41	−17.46
13	2	2	1	2.54	9.48	−8.11	−19.54
14	2	2	2	2.30	9.68	−7.23	−19.72
15	2	2	3	2.60	10.97	−8.31	−20.80
16	2	3	1	2.81	11.88	−8.97	−21.50
17	2	3	2	3.22	14.45	−10.17	−23.20
18	2	3	3	3.14	13.68	−9.94	−22.72
19	3	1	1	1.10	5.11	−0.80	−14.17
20	3	1	2	1.26	5.66	−2.01	−15.06
21	3	1	3	1.55	6.27	−3.81	−15.95
22	3	2	1	1.92	8.24	−5.65	−18.32
23	3	2	2	1.90	8.56	−5.58	−18.65
24	3	2	3	2.12	10.74	−6.54	−20.62
25	3	3	1	2.84	11.90	−9.08	−21.51
26	3	3	2	3.00	12.87	−9.54	−22.19
27	3	3	3	3.73	14.27	−11.43	−23.09

Table 3
Response table for S/N ratios (smaller-is-better) for *Ra*.

Level	*V* (m/min)	*f* (mm/rev)	*a* (mm)
1	−5.668	−1.938	−5.503
2	−6.287	−6.44	−5.454
3	−6.048	−9.625	−7.046
Max–min	0.62	7.688	1.592
Rank	3	1	2

Table 4
Response table for S/N ratios (Smaller-is-better) for *Rz*.

Level	*V* (m/min)	*f* (mm/rev)	*a* (mm)
1	−19.08	−15.72	−18.45
2	−19.27	−19.33	−18.69
3	−18.84	−22.15	−20.05
Max–min	0.43	6.43	1.61
Rank	3	1	2

The estimated mean of the surface roughness *Ra* can be computed as [22]:

$$\begin{aligned}\bar{\mu}_{f_1 a_2} &= \bar{f}_1 + \bar{a}_2 - \bar{T}_{Ra} \\ &= 1.274 + 2.041 - 2.15 \\ &= 1.165\end{aligned} \tag{4}$$

where, $\bar{T}_{Ra} = 2.15$ was calculated from Table 2.

The 95% confidence interval for the surface roughness *Ra* and the confirmation experiment is

$$\mathrm{CI}_{Ra} = \sqrt{F_{\alpha,1,doferror} V_{error}\left(\frac{1}{n_{eff}}\right)} \tag{5}$$

$F_{0.05;1;26} = 4.23$ (tabulated)

$V_{error} = 0.0832$ (from Table 5)

$$n_{eff} = \frac{\text{Number of experiments}}{1 + \text{total dof in items in used in } \bar{\mu} \text{ estimate}} = \frac{27}{1+2+2} = 5.4$$

Thus, $\mathrm{CI}_{Ra} = 0.255$

$$[\bar{\mu}_{f_1 a_2}] - \mathrm{CI}] < \bar{\mu}_{f_1 a_2} < [\bar{\mu}_{f_1 a_2} + \mathrm{CI}] = 1.165 - 0.255 < \bar{\mu}_{f_1 a_2} < 1.165 + 0.255 = 0.91 < \bar{\mu}_{f_1 a_2} < 1.42$$

Likewise, when roughness parameter *Rz* is concerned, estimated average is at $f_1 a_1$ level.

Then,

$$\begin{aligned}\bar{\mu}_{f_1 a_1} &= \bar{f}_1 + \bar{a}_1 - \bar{T}_{Rz} \\ &= 6.245 + 8.843 - 9.47 = 5.618\end{aligned}$$

where, $\bar{T}_{Rz} = 9.47$ was calculated from Table 2.

The 95% confidence interval for the surface roughness *Rz* and the confirmation experiment is

$F_{0.05;1;26} = 4.23$ (tabulated)

$V_{error} = 1.438$ (from Table 6)

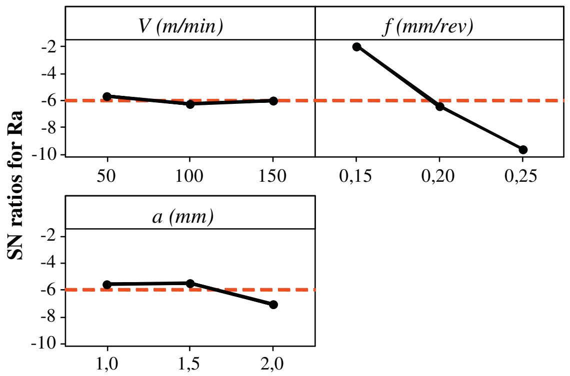

Fig. 5. Main Effects Plot for SN ratios for *Ra*.

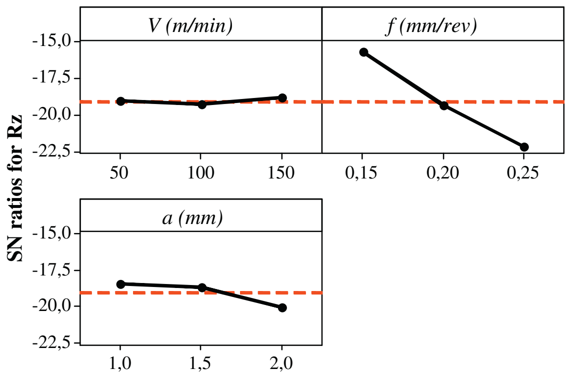

Fig. 6. Main Effects Plot for SN ratios for *Rz*.

Table 5
Analysis of Variance for *Ra*.

Symbol	DOF	SS	Variance	F	P	PC (%)
V	2	0.1702	0.0851	1.02[a]	0.378	1.03
f	2	14.0927	7.0463	84.71[a]	0.000	85.47
a	2	0.5606	0.2803	3.37[a]	0.055	3.4
Error	20	1.6636	0.0832			
Total	26	16.4871				

[a] At least 95% confidence.

Table 6
Analysis of variance for *Rz*.

Symbol	DOF	SS	Variance	F	P	PC (%)
V	2	1.209	0.605	0.42[a]	0.662	0.5
f	2	197.110	98.555	68.52[a]	0.000	82.67
a	2	11.322	5.661	3.94[a]	0.036	4.7
Error	20	28.767	1.438			
Total	26	238.408				

[a] At least 95% confidence.

Table 7
Means values for each factor at each level for *Ra* and *Rz* roughness parameters (Raw data).

Level	Roughness *Ra* (μm)			Roughness *Rz* (μm)		
	$\bar{V}$ (m/min)	$\bar{f}$ (mm/rev)	*a* (mm)	$\bar{V}$ (m/min)	$\bar{f}$ (mm/rev)	*a* (mm)
1	2.046	**1.274**	2.051	9.36	**6.245**	**8.843**
2	2.240	2.126	**2.041**	9.771	9.321	9.216
3	2.158	3.043	2.351	9.292	12.858	10.364

Bold values indicate the levels of the significant factors for which the best result is obtained and the optimal design are calculated.

Table 8
Factor effects and their optimum levels.

Factor	Effects surface roughness	
	Ra	*Rz*
V: Cutting speed		
f: Feed rate	Level 1	Level 1
a: Depth of cut	Level 2	Level 1

Table 9
ANOVA of quadratic response surface design for *Ra*.

Symbol	DOF	SS	Variance	F	p	R^2
V	1	0.056	0.056	0.675	0.423	91.39%
V^2	1	0.114	0.114	1.365	0.259	
f	1	14.086	14.086	168.848	0.000	
f^2	1	0.007	0.007	0.077	0.784	
a	1	0.434	0.434	5.196	0.036	
a^2	1	0.127	0.127	1.524	0.234	
$V \times f$	1	0.0913	0.091	1.094	0.310	
$V \times a$	1	0.122	0.122	1.463	0.243	
$f \times a$	1	0.032	0.032	0.384	0.544	
Error	17	1.418	0.083			
Total SS	26	16.48707				

Table 10
ANOVA of quadratic response surface design for *Rz*.

Symbol	DOF	SS	Variance	F	p	R^2
V	1	0.021	0.021	0.017	0.899	90.85%
V^2	1	1.188	1.188	0.927	0.349	
f	1	196.791	196.791	153.475	0.000	
f^2	1	0.319	0.319	0.249	0.624	
a	1	10.422	10.422	8.128	0.011	
a^2	1	0.899	0.899	0.702	0.414	
$V \times f$	1	3.719	3.719	2.900	0.107	
$V \times a$	1	1.320	1.320	1.03	0.325	
$f \times a$	1	1.931	1.931	1.506	0.237	
Error	17	21.798	1.282			
Total SS	26	238.408				

$$n_{eff} = \frac{\text{Number of experiments}}{1 + \text{total dof in items in used in } \bar{\mu} \text{ estimate}}$$

$$= \frac{27}{1+2+2} = 5.4$$

Thus, $CI_{Rz} = 1.061$

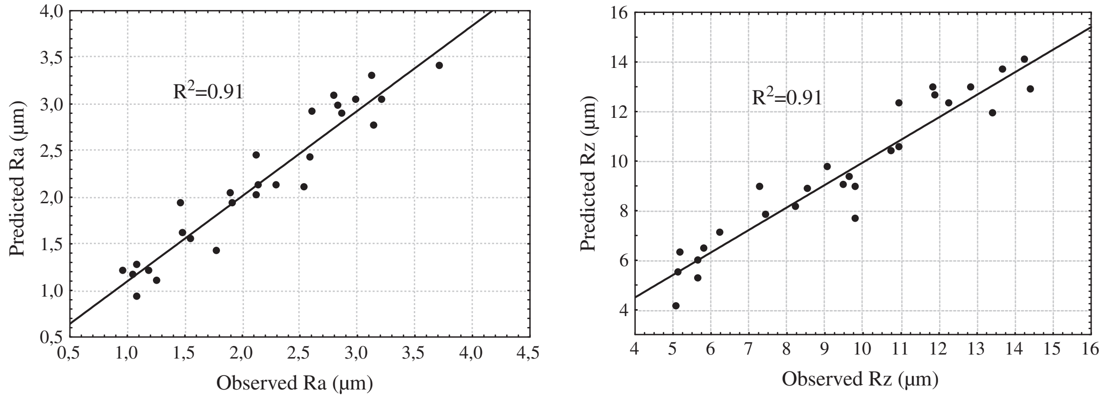

Fig. 7. Relationship between observed and predicted response values.

$$[\bar{\mu}_{f_1a_1} - \mathrm{CI}] < \bar{\mu}_{f_1a_1} < [\bar{\mu}_{f_1a_1} + \mathrm{CI}] = 5.618 - 1.061 < \bar{\mu}_{f_1a_1} < 5.618 + 1.061 = 4.557 < \bar{\mu}_{f_1a_1} < 6.679$$

Table 8 provides the comparative data of factors and levels which affect the various roughness responses. In this case, the different levels of two of the three significant factors provide a lower roughness response. As could be seen in Table 8, level 1 for factor *f* provides for the lowest roughness values. The same is true for factor *a*, where level 2 provides for lower roughness values *Ra* and level 1 provides for lower roughness values *Rz*. Factor *V*, however, has no significant effect on roughness values *Ra* and *Rz*.

4.3. Response surface analysis

The adequacy of the response surface quadratic model was further justified through ANOVA and the results are presented in Tables 9 and 10. It reveals that the first-order of feed rate (*f*) and depth of cut (*a*) have significant effects on the *Ra* and *Rz*. On the contrary, the first-order of cutting speed (*V*), quadratic and pairwise interactions of *V*, *f* and *a* have no significant effects on the roughness parameters.

Central composite design was used to develop a correlation between the cutting conditions and roughness parameters *Ra* and *Rz*. The quadratic response surface model

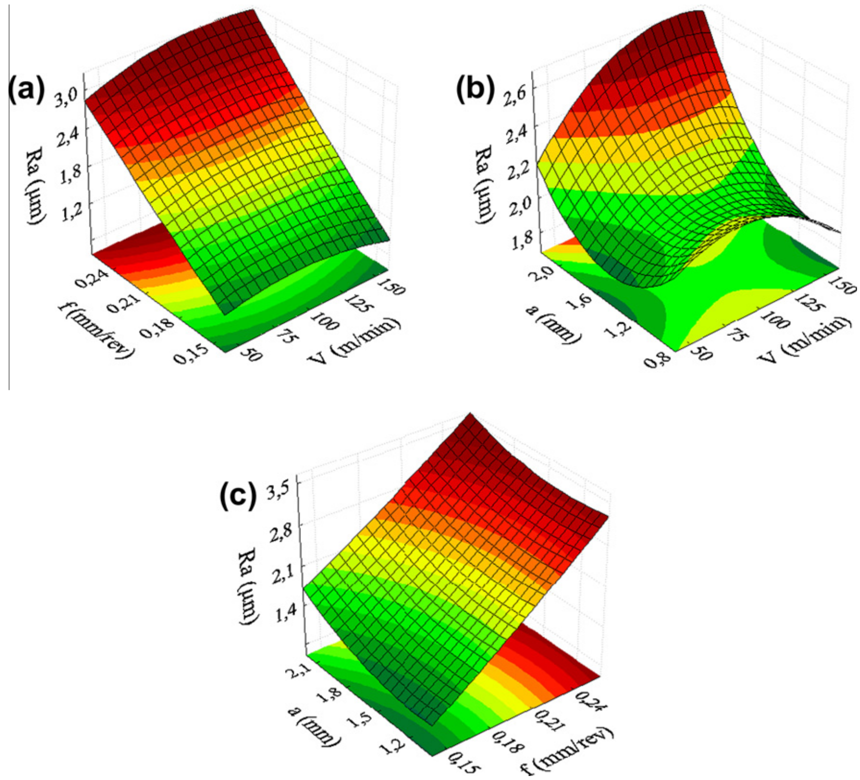

Fig. 8. Response surface plots showing the effect of two variables on *Ra* (the other variable is held at center level). *V*-Cutting speed; *f*-Feed rate; *a*-Depth of cut.

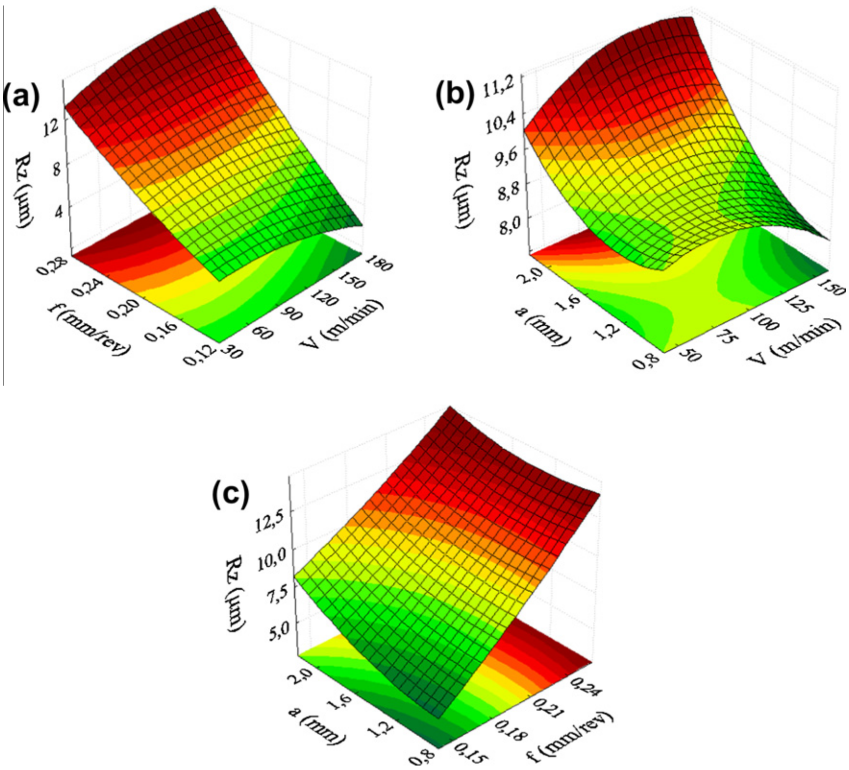

Fig. 9. Response surface plots showing the effect of two variables on *Rz* (the other variable is held at center level). *V*-Cutting speed; *f*-Feed rate; *a*-Depth of cut.

depicting the roughness parameters can be expressed as a function of turning factors such as *V*, *f*, *a*.

$$\begin{aligned} Ra = {} & -0,02907 - 0,00089V + 12,0593f \\ & - 1,42630a - 0,00006V^2 + 13,1111f^2 \\ & + 0,582222a^2 + 0,0348889Vf \\ & + 0,00403333Va - 2,06667fa \end{aligned} \tag{6}$$

$$\begin{aligned} Rz = {} & 0.9430 - 0.0295V - 0.0002V^2 + 31.0407f \\ & + 92.2222f^2 - 1.2426a + 1.5489a^2 + 0.2227Vf \\ & + 0.0133Va - 16.0444fa \end{aligned} \tag{7}$$

The above models can be used to predict surface roughness parameters at the particular design points. The differences between measured and predicted responses are illustrated in Fig. 7.

These figures indicate that the quadratic models are capable of representing the system under the given experimental domain.

In order to better understand the interaction effect of variables on roughness parameters, three-dimensional (3D) plots for the measured responses were created based on the model equations (Eqs. (6) and (7)). Since each model had three variables, one variable was held constant at the center level for each plot; therefore, a total of 6 response surface plots were produced for the responses (Figs. 8 and 9).

Fig. 8 gives the 3D surface graphs for the roughness parameter *Ra*. It reveals that *Ra* increases with increase in depth of cut, feed rate and cutting speed. Hence, a middle level of depth of cut, a minimum amount of feed rate and cutting speed equivalent to level 1 is required for minimum *Ra*.

The 3D surface graphs for the *Rz* are shown in Fig. 9. It is clear from Fig. 9a and c that *Rz* decrease with decrease in depth of cut and feed rate. From Fig. 9b, it is observed that if cutting speed reaches the higher level *Rz* is decreased. Therefore, the ideal combination of control factors for lowest surface roughness should consist of minimum depth of cut, minimum feed rate and maximum cutting speed.

5. Conclusions

This study presented a combined application of the Taguchi method and the RSM to develop a robust CNC turning. For this purpose, the first step in the optimisation process is to determine the S/N ratio for all the experimental tests using the Taguchi method. The next step is to find out the objective function. The objective function is formulated using the RSM. The three machining performance characteristics are optimised to meet the objective of the study. According to the results, the following summaries can be made:

- The optimised control factors settings for *Ra* are: V_1 (cutting speed 50 m/min), f_1 (feed rate 0.15 mm/rev), a_2 (depth of cut 1.5 mm).
- The optimised control factors settings for *Rz* are: V_3 (cutting speed 150 m/min), f_1 (feed rate 0.15 mm/rev), a_1 (depth of cut 1 mm).
- Both Taguchi and response surface statistical analyses indicated that the main effect of the feed rate is the most significant factor on the workpiece surface roughness (*Ra* and *Rz*) with the percent contribution of 85.5% in bringing down the average roughness values.
- The RSM was found to be effective for the identification and development of significant relationships between cutting parameters.
- Significance of interactions and square terms of parameter are more clearly predicted in RSM. The RSM shows significance of all possible combinations of interactions and square terms as depicted in Tables 9 and 10.
- As evident from Eqs. (6) and (7), RSM technique can model the response in terms of all parameters, their interactions and square terms. This facility is not provided by the Taguchi technique.

This results demonstrated that this optimisation method was efficient and greatly reduced the machining cost and the design process. The prediction models can be applied to determine the appropriate cutting conditions, in order to achieve desired surface roughness (<ceitalic>Ra</ceitalic> and <ceitalic>Rz</ceitalic>). Future empirical investigations will look into the impact of different cutting parameters on the surface roughness.

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