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Optimization of Machining Parameters Based on Surface Roughness Prediction for AA6061 Using Response Surface Method

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Abstract
Surface roughness is strongly affected by machining parameters. In the past few decades, many researchers have established the relationship between the surface roughness and the machining parameters. But less attention has been paid to the sensitivity of the surface roughness to the parameters. In addition, the number of tool flutes was ignored, which affects the vibration period and values of the machining system and consequently influences the surface roughness of the machined parts too. Therefore, this study first-time includes the tool flutes in addition to cutting speed, depth of cut and feed rate as independent input variables. Firstly, a set of machining tests were conducted using AA6061 aluminum alloy as work piece material to provide original data, and Response Surface Model (RSM) was adopted to establish the relationship model between the surface roughness and the parameters using Minitab 16. Then, based on analysis of variance (ANOVA), the sensitivities of the surface roughness to the parameters were analyzed. The results show that cutter flutes has high significant influence on surface roughness followed by feed rate and depth of cut, while cutting speed has less significant influence. Finally, the parameters were optimized according to desired surface roughness, and the optimization error (residual) has limited values between -0.02 and 0.02μm.

1. Introduction

Quality of products is very much concerned in manufacturing industry. Surface roughness is one of the crucial performance parameters that have to be controlled within suitable limits for a particular process. Therefore, prediction or monitoring of the surface roughness of machined components is an important area of research.

Previous researches have indicated that cutting parameters such as cutting speed, feed rate and depth of cut strongly influence the surface roughness of the machined product [3-5, 8-11]. Researchers are trying to develop a robust and accurate model, which can describe correlations between the cutting parameters and the surface roughness of the machined products. Many researchers made quite good efforts on controlling the surface roughness using different type of techniques. However, the tool flute is not taken into account. In this work, we consider the tool flute, cutting speed, feed rate and depth of cut as machining parameters to study their relationship (sensitivity) with the surface roughness in end-milling. An experimental work was conducted by using full factorial design. Response Surface Methodology (RSM) was adopted to establish the relationship model between the parameters and corresponding surface roughness by Minitab 16. Based on analysis of variance (ANOVA), the sensitivities of the surface roughness to the parameters were analyzed to show that cutter flutes has high significant influence on surface roughness followed by feed rate and depth of cut, while cutting speed has less significant influence. Based on the prediction model, the parameters were optimized according to the desired surface roughness.

In this study, full quadratic model is applied based on response surface method (RSM) to express the surface roughness in term of cutting parameters including linear, interaction and squares of the cutting parameters. The result shows that interaction and squares of cutting parameters are insignificant, only linear model is significant. Therefore, linear model is adopted in this work. The verification test of the linear model gives good results, and the error is so limited. Hence we can judge that this model is so accurate and reliable. Verification of cutting parameters optimization gives very good results, the residuals of optimization is so limited, which indicates the robust techniques used.

2. Literature Review

Surface roughness is affected by many factors such as; machining parameters, cutting tool properties, work piece properties and cutting phenomena [1] as show in fish bone diagram Fig.1. Surface roughness is known to be significantly affected by depth of cut, spindle speed, and feed rate [2]. Therefore, surface roughness can be optimized if the appropriate cutting conditions are selected. Statistical prediction methods, such as the response surface methodology (RSM), are frequently utilized to model the surface roughness, so that the desired levels of machining parameters are achieved.

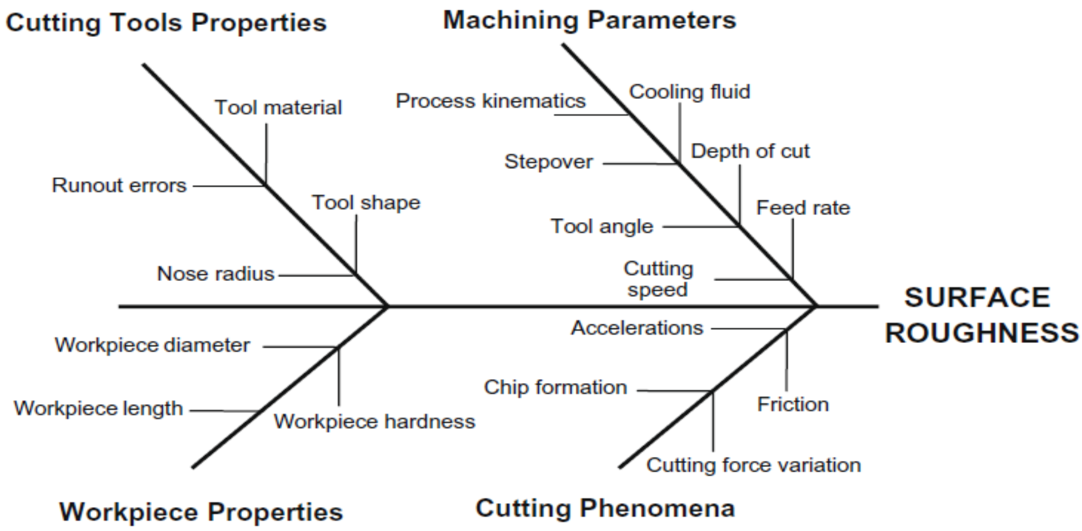

Fig. 1. *Fish bone diagram for surface roughness.*

There are many works reporting the success of implementing different techniques to predict surface roughness. Ahmed Murat [3] studied the effects of cutting speed, feed rate, tool path and depth of cut process parameters on the surface roughness in the pocket machining of AA5083 aluminum alloy materials by Taguchi method. It is found that surface roughness correlates positively with feed rate and depth of cut, but negatively with cutting speed while the tool path pattern factor is not significant. Noordin et al. [4] conducted an experiment on the turning process of AISI 1045 steel, investigated the effects of cutting speed, feed rate and side cutting angle on the multi-responses (tangential force and surface roughness) using the RSM, and finally built a second order regression model to predict these two responses. Singh and Rao [5] conducted an experiment to determine the effects of cutting conditions and tool geometry on the surface roughness in the finish hard turning of the bearing steel (AISI 52100).

Advance manufacturing technology offers effective means to achieve good quality, quality and productivity are two important measures that are conflicting criteria in any machining operations. Surface roughness is not only a quality indicator but also determines the machining performance and the operation cost [6]. In modern manufacturing, the end-milling is one of the most widely used metal removal operations in industry because of its ability to remove material faster and giving reasonably good surface finish [7].

Several researchers have studied the effect of machining parameters on the surface roughness in end milling of steels and aluminum. Huang and Chen [8] studied an empirical approach to investigate surface roughness in controllable and uncontrollable factors in end milling operation, the effect of cutting tool geometry on milling of AISI 1045 steel for surface roughness model has been studied, and then several studies were also carried out to predict surface roughness based on artificial neural networks (ANN) model. Öktem [9] has developed an integrated study of surface roughness model and optimization of the cutting parameters for end milling with AISI1040 steel material. Kim and Kang [10] investigated the machining of AA2024 alloy with polycrystalline diamond end mill using the criteria of surface roughness, as a result of the experiments conducted at different values of cutting speed, axial and radial depths of the cut, and feed per tooth parameters, it was found that, axial depth of cut is the most significant factor affecting surface roughness while radial depth of cut has a low effect. Yang and Chen [11] studied the effects of depth of cut, spindle speed, feed rate and tool diameter factors on surface roughness in the milling of AA6061 via Taguchi method, the experiments based on L18 orthogonal array were evaluated with analysis of variance (ANOVA) and S/N ratio analysis and it was seen that all the factors except tool diameter were significant. In addition, optimal factor levels with lowest surface roughness were determined and predicted. Lo et al. [12] investigated the high speed milling of AA6061 in two parts. In the first part, an experimental model was developed for the quick measurement of surface roughness using laser speckle method and digital image processing. In the second part, the effects of feed rate, spindle speed, depth of cut and tool material process parameters on surface roughness were evaluated via Taguchi technique. The tests based on L9 orthogonal array (OA) were analyzed with signal to noise (S/N) ratio and ANOVA, based on the results achieved, it was seen that depth of cut has the most dominant effect (40 %) followed by tool material (30 %) and spindle speed (21 %) in terms of order of significance, while feed rate does not have a significance effect. Sahin and Motorcu [13] utilized RSM to construct a surface roughness model for the turning process of AISI 1040 mild steel coated with TiN, three machining parameters, depth of cut, cutting speed and feed rate, were included in the predicted model based on central composite design (CCD). Öktem et al. [14] studied the surface roughness of the mould surfaces obtained by machining AA7075-T6 material with AlTiN-coated solid carbide end mill. The effects of cutting speed, feed per tooth, radial/axial depth of cut and machining tolerance were evaluated with Taguchi and full factorial methods. The surface roughness was modeled by regression analysis with a correlation coefficient of 0.96. The effects of factors and optimal surface roughness were determined by assessing the experiments based on L18 OA with S/N ratio and ANOVA. Finally, it was observed that the machining tolerance is the most dominant factor (96 %) followed by radial depth of cut (2.5 %), axial depth of cut (1.5 %), feed per tooth (0.177 %) and cutting speed (0.09 %).

Recently, some other factors were added to simulation models, such as; vibration and cutting forces during machining as well as cutting geometry. These parameters made the models more realistic and accurate. Lou and Chen [15] studied the effects of spindle speed, feed rate, depth of cut and vibration on surface roughness during the end milling of AA6061. The analysis of data and modeling were achieved via a neural fuzzy method; they predicted surface roughness with 96 % accuracy by the use of the proposed system. Chen and Savage [16] predicted the effects of feed rate, spindle speed, tool material type, work piece diameter and vibration factors on surface roughness in the milling of AA6061 and AISI 1018 steel materials. The proposed neural fuzzy approach modeled the surface roughness during milling operation with 90% accuracy. Yang et al. [17] proposed an adaptive system that can modify the table feed during machining to obtain the desired surface roughness in the face milling of AA6061. The system was constructed by combining two subsystems as fuzzy-nets in process surface roughness recognition and fuzzy-nets adaptive feed rate control. As a result of the 25 test experiments, the desired surface roughness was obtained by modifying the feed rate of the CNC machine tool instantaneously by the use of the proposed system. Zhang and Chen [18] developed an in process surface roughness adaptive control system in the end milling of AA6061 alloy. They conducted experiments in all combinations of spindle speed, feed rate and depth of cut factor levels by the use of full factorial experimental design method. The surface roughness was predicted with 91.5% accuracy with the system that can recognize cutting force signals collected during machining and the feed rate was modified in terms of desired surface roughness.

Brezocnik et al. [19] predicted the effects of spindle speed, feed rate, depth of cut and vibrations on surface roughness via genetic programming method, the specimens were obtained by machining AA6061 aluminum with four-flute high speed steel, they observed that high vibration increases the prediction accuracy and feed rate has the most influence on surface roughness. In this paper the author used only four-flute tool. New idea is come to my mind, what is the effect of the tool-flute number in the surface roughness.

To answer this question, an experimental work is carried out based on selected cutting parameters: cutting speed, depth of cut, feed rate and tool flute number. Tool flute number is selected as a new factor in this study to express its affect on surface roughness quality with other machining parameters which known as control factors.

3. Overall Scheme

Fig.2 shows the overall scheme of this work. At the first, a series of physical experimental works are carried out based on full factorial design with four cutting parameters (spindle speed, depth of cut, feed rate and cutter flutes). Each cutting parameter has three levels. Carry out cutting test under each parameters combination, and measure the surface roughness of the work piece. Then, according to the experimental data, on one hand, the sensitivities of the surface roughness to each parameter are analyzed though analysis of variance (ANOVA); on the other hand, surrogate model (RSM) is adopted to establish the mathematical model between the four cutting parameters and the surface roughness. Based on the model, the surface roughness can be predicted with cutting parameters as inputs. Inversely, the cutting parameters can be optimized with given desired surface roughness.

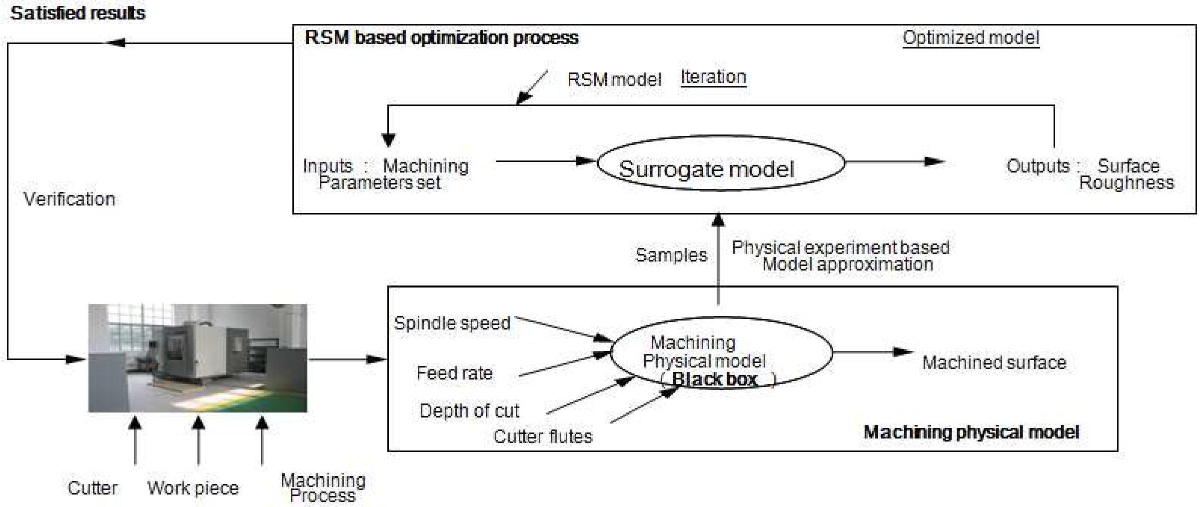

Fig. 2. *Flow diagram of the overall scheme.*

4. Experimental Work

The experimental work was conducted on a vertical machining center (DMC 635V) based on full factorial design. Four cutting parameters, cutting speed (*v*), feed rate (*f*), depth of cut (*d*) and tool flutes number (*z*) were taken into account as inputs, with three levels as shown in Table (1). According to the full factorial rule, (level parameters) there are (3^4) = 81 cutting tests are carried out. The levels of the cutting parameters are selected based on shop floor after valuable preliminary works.

The work piece material used is AA6061 aluminum alloy in cubic shape, dimensions 60mm x 60mm x 60mm. CNC vertical milling has spindle speed up 14000 rpm, and motor drive power 40kw with air coolant. Calculations of cutting speed are selected based on the work piece material and cutting tool type. High speed steel (HSS) tool with diameter 16 mm and flutes 2, 3 and 4 perform cutting speed (150 – 250 m/min) with corresponding (3000 – 5000 rev/min). Arithmetic surface roughness Ra is measured in this work according to widely used in industry and manufacturing field, the measuring device is portable TR200 with display range: 0.005-16μm and maximum display resolution 0.001μm.

Table 1. *Cutting parameters and levels.*

No.	Cutting parameter	Low level	Medium level	High level
1	Cutting speed (v). rev/min	3000	4000	5000
2	Feed rate (f). mm/rev	0.05	0.10	0.15
3	Depth of cut (d). mm	0.4	0.6	0.8
4	Tool flutes number (z)	2.0	3.0	4.0

Physical experimental work is carried out in institute's workshop (Advance Design and Manufacturing Institute) at southwest jiaotong university. Table *2* shows 27 experimental results of the tool has 2 flutes, measuring the surface roughness three times and calculates the average values. There are other two tables for 3 & 4 tool flutes (not attached) with total 54 experiments.

Table 2. *An experimental result of the tool has 2 flutes.*

Std Order	Run Order	cutting speed (*v*)	depth of cut (*d*)	feed rate (*f*)	tool flute (*z*)	Reading (1)	Reading (2)	Reading (3)	average surface reading
1	5	4000	0.6	0.05	2	0.429	0.393	0.4270	0.416
2	7	5000	0.6	0.15	2	0.606	0.589	0.5980	0.598
3	11	3000	0.6	0.15	2	0.590	0.538	0.5560	0.561
4	13	5000	0.6	0.10	2	0.471	0.479	0.4830	0.478
5	17	5000	0.4	0.05	2	0.550	0.526	0.5290	0.535
6	19	5000	0.4	0.10	2	0.492	0.600	0.5870	0.560
7	20	3000	0.6	0.05	2	0.234	0.233	0.2400	0.236
8	21	4000	0.4	0.15	2	0.613	0.603	0.6120	0.609
9	22	4000	0.4	0.05	2	0.438	0.466	0.4540	0.453
10	23	5000	0.6	0.05	2	0.276	0.290	0.2600	0.275
11	28	5000	0.8	0.05	2	0.526	0.503	0.5410	0.523
12	30	5000	0.8	0.15	2	0.742	0.742	0.7620	0.749
13	33	3000	0.4	0.10	2	0.304	0.332	0.2970	0.311

Std Order	Run Order	cutting speed (*v*)	depth of cut (*d*)	feed rate (*f*)	tool flute (*z*)	Reading (1)	Reading (2)	Reading (3)	average surface reading
14	34	5000	0.8	0.10	2	0.511	0.528	0.4940	0.511
15	35	4000	0.8	0.10	2	0.392	0.381	0.3400	0.371
16	38	4000	0.4	0.10	2	0.275	0.261	0.2480	0.261
17	46	4000	0.6	0.10	2	0.231	0.236	0.2500	0.239
18	48	5000	0.4	0.15	2	0.298	0.259	0.2790	0.279
19	52	3000	0.6	0.10	2	0.328	0.341	0.3000	0.323
20	55	3000	0.8	0.15	2	0.546	0.539	0.5450	0.543
21	65	4000	0.8	0.05	2	0.246	0.238	0.2200	0.235
22	69	3000	0.4	0.05	2	0.288	0.244	0.2410	0.258
23	70	3000	0.8	0.10	2	0.306	0.262	0.2990	0.289
24	76	4000	0.8	0.15	2	0.601	0.686	0.6040	0.630
25	77	3000	0.4	0.15	2	0.440	0.498	0.4930	0.477
26	79	3000	0.8	0.05	2	0.336	0.344	0.3690	0.350
27	80	4000	0.6	0.15	2	0.384	0.375	0.3900	0.383

5. Surrogate Model Establishment

General model of Response surface method (RSM) is defined as a procedure to express the quantitative form of the relationship between the desired response (dependant) and independent variables using statistical and mathematical model [20-23], general model of response surface can be express as equation (1).

$$R_a = f(x_1, x_2, x_3, ..., x_n) \quad (1)$$

Where R_a is surface roughness; x_1, x_2, x_3, ...x_n are independent variables.

Full quadratic model equation (2) is selected in this study (include first and second order equation with interaction), to express the real mathematical model to the response and cutting parameters. Investigation of the cutting parameters to the surface roughness is carried out based on independents parameters.

$$\hat{y} = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} b_{ii} x_i^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} b_{ij} x_i x_j + \varepsilon \quad (2)$$

Where $\hat{y}$ is predicted surface roughness value; b_0, b_i, b_{ii} and b_{ij} are regression coefficients; x_i, x_j are independent variables; ε is the error.

Experimental data fitted to the Minitab based on response surface method (RSM) full quadratic model. The estimation model for prediction is appear as equation (3), this equation include all the parameters in equation (2), which is not practical model. Based on statistical analysis, ANOVA technique is used to modify it. Modification of the parameter depends on the significant of each component.

$$\begin{aligned} R_a = &-0.95 + 1.7\times10^{-6} v + 0.019d - 0.026f + 0.0001413z + 1.96\times10^{-10} v^2 + 0.01044d^2 + 0.116f^2 \\ &+ 0.00046z^2 - 2.45\times10^{-6} vd - 5.7\times10^{-6} vf - 2.49\times10^{-7} vz + 0.0045df - 0.004dz + 0.003fz \end{aligned} \quad (3)$$

Some component of this equation may be not significant, to investigate the significant of all cutting parameters and their interaction, ANOVA analysis is adopted, then modification of this model is obtained. Sensitivity analysis shows the regression modification.

6. Sensitivity Analysis

It is well known that the cutting parameters affect the surface roughness. But little is known about the degree of influence of each parameter on the roughness, which has great practical significance for process planning. In this study, according to the experimental data, ANOVA is adopted to determine the significant cutting parameters. In table (3), ANOVA analysis shows that linear regression is significant, while square and intersection of cutting parameters are insignificant. In intersection state, only cutting speed with tool flutes is significant at 95% confidence interval.

Table 3. *Analysis of Variance (ANOVA) for surface roughness.*

Source	DF	Seq. SS	Adj. SS	Adj. MS	F- value	P- value
Regression	14	0.74672	0.746721	0.053337	3.81	0.000[a]
Linear	4	0.59882	0.598824	0.149706	10.69	0.000[a]
cutting speed - v	1	0.03375	0.033750	0.033750	2.41	0.125
depth of cut - d	1	0.04559	0.045588	0.045588	3.25	0.076
feed rate - f	1	0.09601	0.096013	0.096013	6.85	0.011[a]
tool flutes - z	1	0.42347	0.423473	0.423473	30.23	0.000[a]
Square	4	0.02431	0.024314	0.006079	0.43	0.784
cutting speed × cutting speed- v^2	1	0.00080	0.000800	0.000800	0.06	0.812
depth of cut × depth of cut - d^2	1	0.01243	0.012429	0.012429	0.89	0.350
feed rate × feed rate - f^2	1	0.00420	0.004201	0.004201	0.30	0.586
tool flutes × tool flutes - z^2	1	0.00688	0.006884	0.006884	0.49	0.486

Source	DF	Seq. SS	Adj. SS	Adj. MS	F- value	P- value
Interaction	6	0.12358	0.123582	0.020597	1.47	0.202
cutting speed × depth of cut- $v \times d$	1	0.00147	0.001469	0.001469	0.10	0.747
cutting speed × feed rate - $v \times f$	1	0.00011	0.000114	0.000114	0.01	0.928
cutting speed × tool flutes - $v \times z$	1	0.07803	0.078027	0.078027	5.57	0.021[a]
depth of cut × feed rate - $d \times f$	1	0.00540	0.005402	0.005402	0.39	0.537
depth of cut × tool flutes - $d \times z$	1	0.00853	0.008525	0.008525	0.61	0.438
feed rate × tool flutes - $f \times z$	1	0.03004	0.030044	0.030044	2.14	0.148
Residual Error	66	0.92458	0.924576	0.014009		
Total	80	1.67130				

a:significant at 95% confidence interval.
DF: degree of freedom
Seq.SS: sequential sum square
Adj.SS: adjusted sum square
Adj.MS: adjusted mean square

ANOVA Summary table (4) shows the regression analysis of full quadratic model equation (3). Modification is carried out, only significant parameters will be analyzed again to perform new model.

Table 4. *ANOVA summary analysis.*

Source	DF	Seq. SS	Adj. SS	Adj. MS	F- value	P- value
Regression	14	0.74672	0.746721	0.053337	3.81	0.000[a]
Linear	4	0.59882	0.598824	0.149706	10.69	0.000[a]
Square	4	0.02431	0.024314	0.006079	0.43	0.784
Interaction	6	0.12358	0.123582	0.020597	1.47	0.202
Residual Error	66	0.92458	0.924576	0.014009		
Total	80	1.67130				

a: significant at 95% confidence interval.

New regression is obtained after remove all insignificant parameters. ANOVA table (5) shows the analysis of the modified regression, cutting speed is insignificant, but it selected because of its interaction with the tool flute. To build the new model, Table (6) shows the coefficients of the cutting parameters. New model for surface roughness prediction estimation is adopted, as show in equation (4).

$$R_a = -0.577 + 0.165\times10^{-3}v + 0.145d + 0.843f + 0.257z - 4.66\times10^{-5}vz \quad (4)$$

Table 5. *ANOVA analysis of variance (modify model).*

Source	DF	Seq. SS	Adj. SS	Adj. MS	F-value	P- value
Regression	5	0.67685	0.676851	0.135370	10.21	0.000[a]
Linear	4	0.59882	0.598824	0.149706	11.29	0.000[a]
cutting speed	1	0.03375	0.033750	0.033750	2.55	0.115
depth of cut	1	0.04559	0.045588	0.045588	2.55	0.068
feed rate	1	0.09601	0.096014	0.096014	7.24	0.009[a]
tool flutes	1	0.42347	0.423473	0.423473	31.94	0.000[a]
Interaction	1	0.07803	0.078027	0.078027	5.88	0.018[a]
cutting speed × tool flutes	1	0.07803	0.078027	0.078027	5.88	0.018[a]
Residual Error	75	0.99445	0.994446	0.013259		
Total	80	1.67130				

a: significant at 95% confidence interval.

Table 6. *ANOVA regression coefficients.*

parameters	coefficient	SE. Coefficient	T-value	P-value
Constant	-0.576574	0.01279	40.585	0.000a
cutting speed -v	0.000165	0.01567	1.595	0.115
Depth of cut-d	0.145278	0.01567	1.854	0.068
Feed rate-f	0.843333	0.01567	2.691	0.009a
Tool flutes-z	0.274778	0.01567	5.651	0.000a
Cutting speed × tool flutes –v × z	-4.66E-05	0.01919	-2.426	0.018a

a: significant at 95% confidence interval.

Equation (4) includes significant parameters and cutting speed, as mentioned before cutting speed cannot be deleted from the model, because it has interaction with tool flute. Based on ANOVA analysis, correlations of regression R square has value 90.8% for analysis. This value shows the correlation of regression is good. According to the ANOVA analysis table (5), tool flutes has highest significant value (P = 0.000), then feed rate, depth of cut and cutting speed has lowest significant.

The new model equation (4) predicts good results. Fig.3 shows the residual plots of surface roughness after modification, the normal probability plot is very close to straight line, histogram of residual and frequency has normal distribution shape. Predicted value and residuals plot show scatter distribution points, since the scatter points didn't make specific shape, this indicates to the good model.

In order to investigate the sensitivity analysis, contour plot shows interaction of cutting parameters and their effect in machining process. Fig.4 shows interactions between cutting parameters to the surface roughness. From the results of feed rate and depth of cut plot, minimum surface roughness can be achieved (0.44 – 0.48) if the depth of cut in the rage of 0.4 to 0.6mm, with feed rate less than 0.1mm. In the second plot tool flute with depth of cut, minimum surface roughness obtained, if depth of cut less than 0.6 and tool has 2 flutes. In the last plot tool flute with feed rate, minimum surface roughness can be achieved, if the feed rate less than 0.1 with and 2 flutes tool.

From the results of contour plots, low levels of the cutting parameters lead to the minimum surface roughness, while high levels produce high surface roughness (positive relation). The minimum surface roughness < 0.4 is achieved only with minimum tool flutes, this is indicates to the significant of the tool flutes.

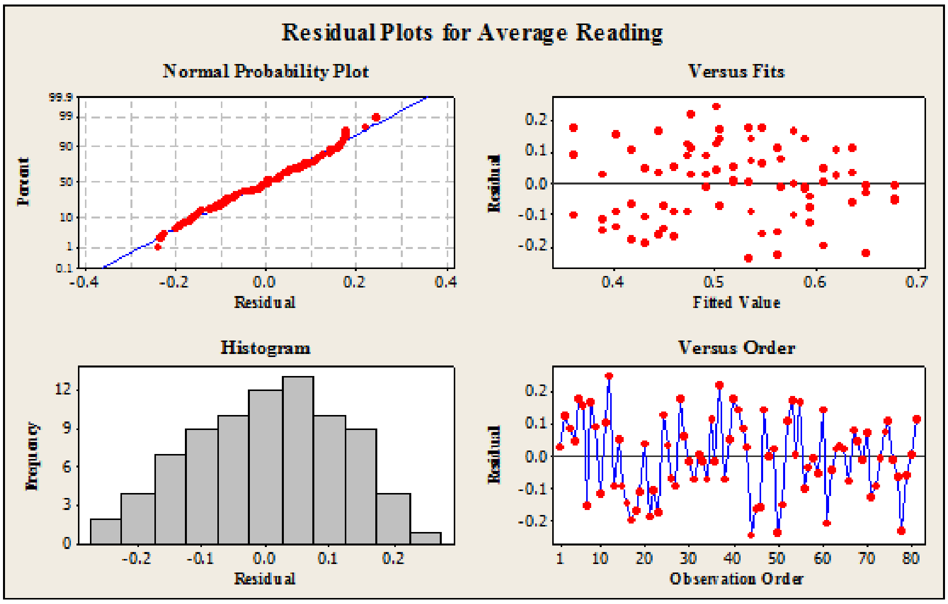

Fig. 3. Residual plots for surface roughness.

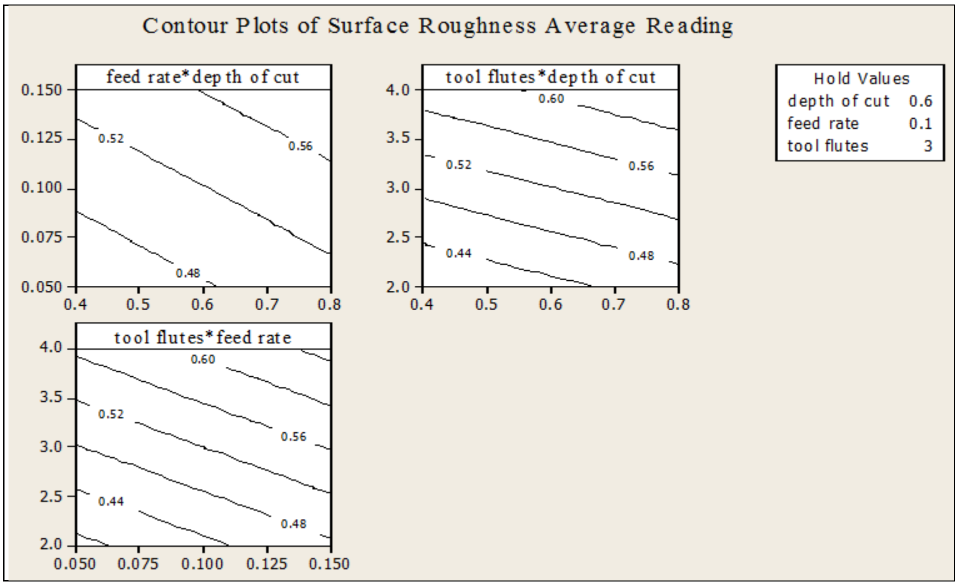

Fig. 4. Contour plots of cutting parameters.

In surface plots, Fig. 5-7 show machining parameters interactions results. Fig. 5 shows the effect of tool flutes and feed rate, tool flute has great effect in surface roughness, while feed rate has less. Fig. 6 shows the effect of tool flute to the surface roughness has big change than depth of cut. In Fig 7 effect of feed rate and depth of cut, feed rate has more effect in the surface roughness than the depth of cut. From all surface plots, it is very clear that tool flute has great influence in surface roughness machining, followed by feed rate and depth of cut.

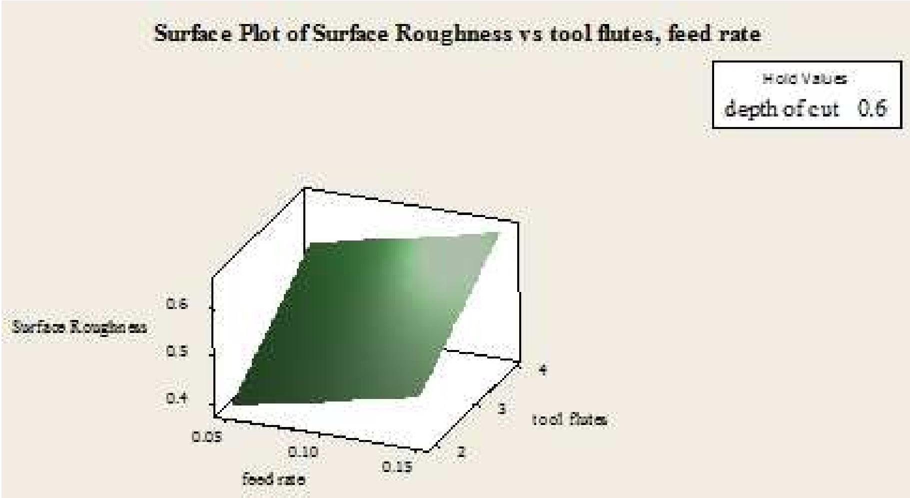

Fig. 5. *Surface plots of tool flutes and feed rate.*

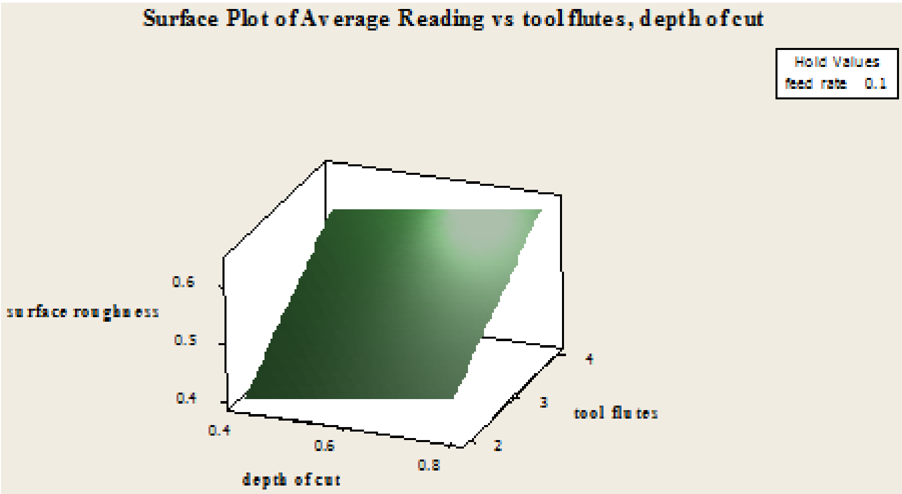

Fig. 6. *Surface plots of tool flutes and depth of cut.*

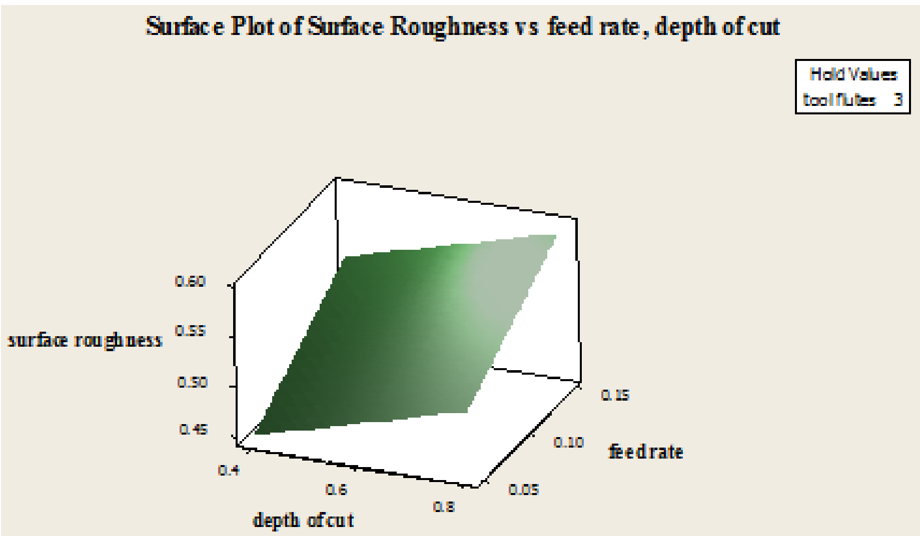

Fig. 7. *Surface plots of feed rate and depth of cut.*

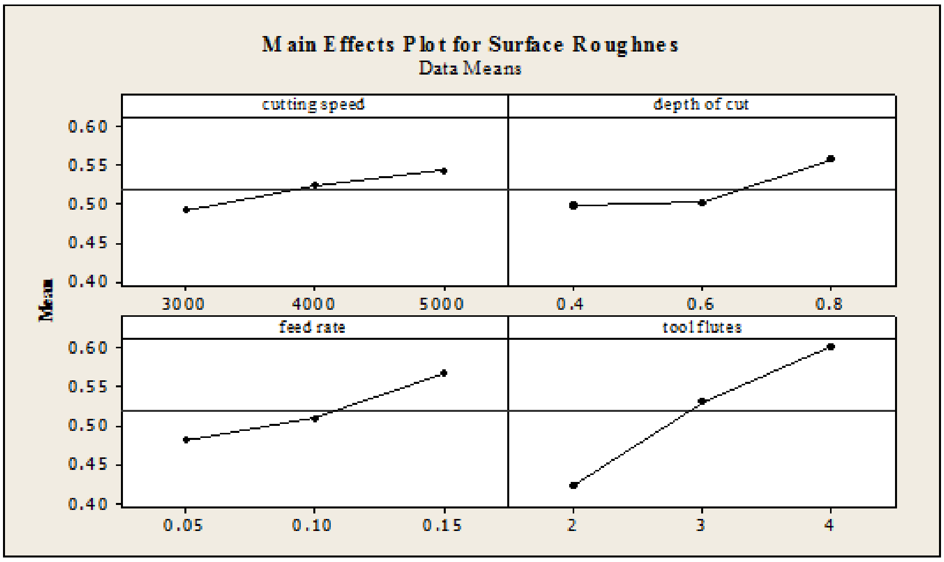

Fig. 8. *Main affects plots for surface roughness.*

Fig. 8 shows the main effect of machining parameters in surface roughness. Tool flute number has highest significant effects in surface roughness, hence the low number of tool flutes lead to low surface roughness, while higher number of flutes produces high values of surface roughness (positive relation). Feed rate and depth of cut are also affecting the surface roughness but less than tool flutes effects. Finally from the plots observations cutting speed has less effect in surface roughness.

From surface, contour and main effect plots. Tool flute has higher effect in surface roughness machining. Therefore; high attention should be consider in tool selection for machining process. Contribution of this paper is highlighting new factor to the surface roughness (tool flute). Paper results show the tool flute is very important factor in surface finish machining process, this work study gives more options to compare tool flutes to the other factors affecting in surface roughness, in order to express the rate factor of each parameters.

7. Cutting Parameter Optimization

Optimization of the machining parameters has been great concerned in manufacturing environments, where economy of machining operation plays a key role in competitiveness in the market. In this study, based on aforementioned model, the machining parameters (cutting speed, depth of cut, feed rate and tool flutes) were optimized using Minitab based on response surface method. The goal of the optimization is to find the optimal machining parameters combination to ensure desired surface roughness. Minitab displays the design parameters (cutting variables) for the response (surface roughness) by checking the target, lower and upper values for response, and gives the cutting parameters in optimized values by its inner algorithm.

Experimental work shows the maximum and minimum observation data for surface roughness are 0.751µm and 0.235µm respectively. Optimization strategy implemented in this study is to divide the surface roughness range into three levels: low (<0.3µm), medium (0.4 - 0.5µm) and high (>0.5µm). Table 7 shows optimization results of surface roughness and corresponding cutting parameters in three levels. The low level Fig. 9 has minimum surface roughness value 0.2545µm with corresponding cutting parameters (3000rpm cutting speed, 0.4525mm depth of cut, 0.05mm feed rate and tool has 2 flutes).

In optimization figures 9-11, the vertical red lines on the graph represent the current factor settings (cutting parameters), horizontal blue dotted lines represent the current response values, and gray regions indicate to factor settings where the corresponding response has zero desirability. Desirability function translates each response scale to (zero-to-one) in desirability scale. The most desirable values of the response have desirability is one, which means very close to the target, while zero means very far from target. Figure 10 and 11 shows the medium and high surface roughness optimization values respectively. Optimization results obtained should be tested physically to verify the validity of these results and to confirm the robust degree of the technique used in this work.

In order to test and verify the optimization result, experimental work was carried out based on the optimized cutting parameters. In each cutting test, the surface roughness was measured three times and the mean of the readings is registered. Table 8 shows optimization and experimental results, the error values is so limited, it varied approximately between +0.02 and -0.02µm, which express the efficient and robust of the technique used in this work.

8. Results and Discussion

From the results obtained for the machining parameters used in this study, tool flute has higher significant followed by feed rate, depth of cut and cutting speed. From contour and surface plots, optimization of surface roughness could be carried out based on surface roughness values. Residual plots of the errors show the normal distribution shape with 95% confidence intervals values. Sensitivity analysis of the machining parameters is carried out based on ANOVA results with 95% confidence intervals.

Table 7. *Optimizations results.*

Parameter Name	Low level	Medium level	High level
Predicted Surface roughness in μm	0.2545	0.4977	0.5299
Cutting speed (v) in *rpm*	3000	5000	5000
Depth of cut (d) in *mm*	0.4525	0.570	0.40
Feed rate (f) in *mm*	0.05	0.05	0.15
Tool flutes (z)	2.00	3.00	2.00

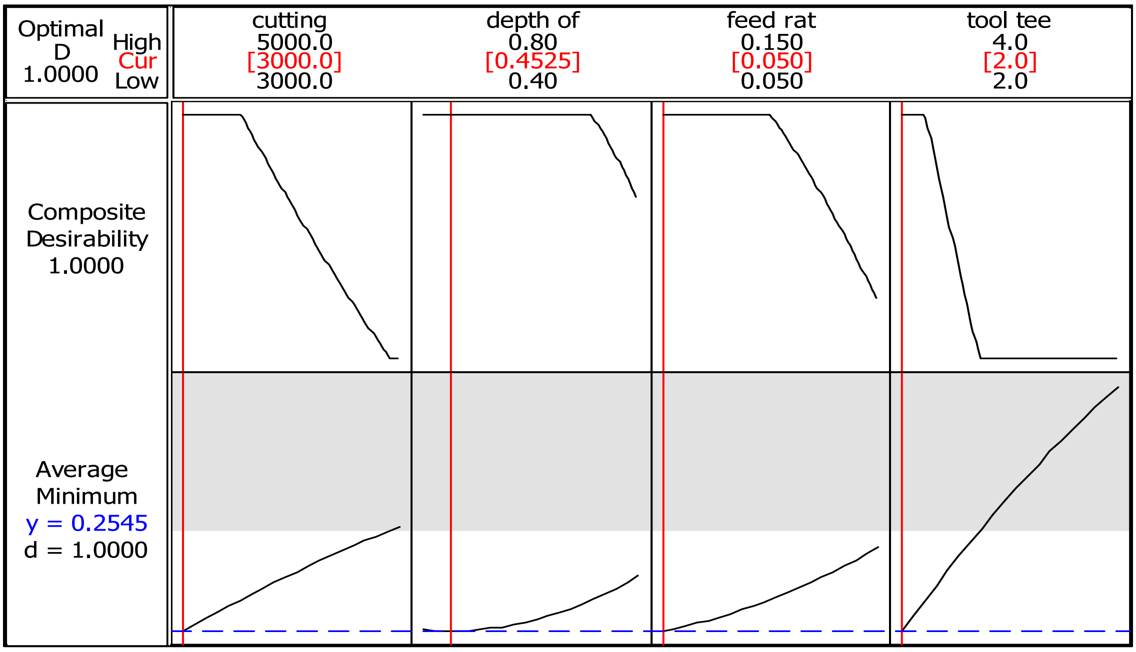

Fig. 9. *Optimization results in low level of surface roughness (R_a < 0.3).*

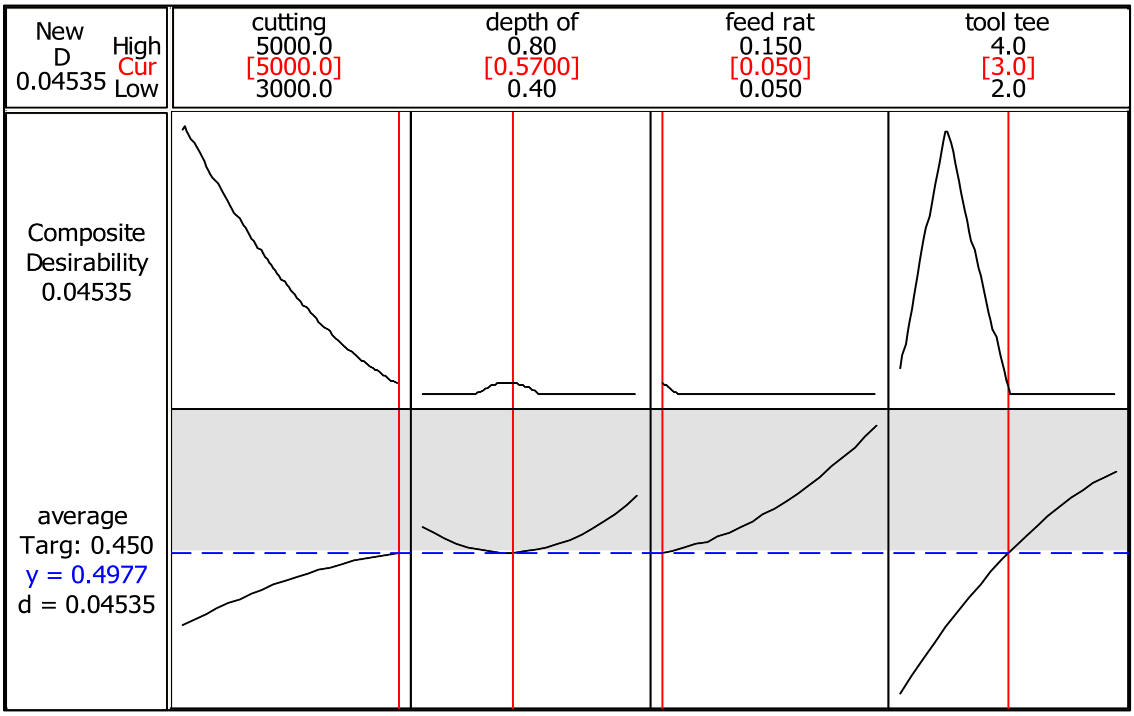

Fig. 10. *Optimization results in medium level of surface roughness (0.4 < R_a < 0.5).*

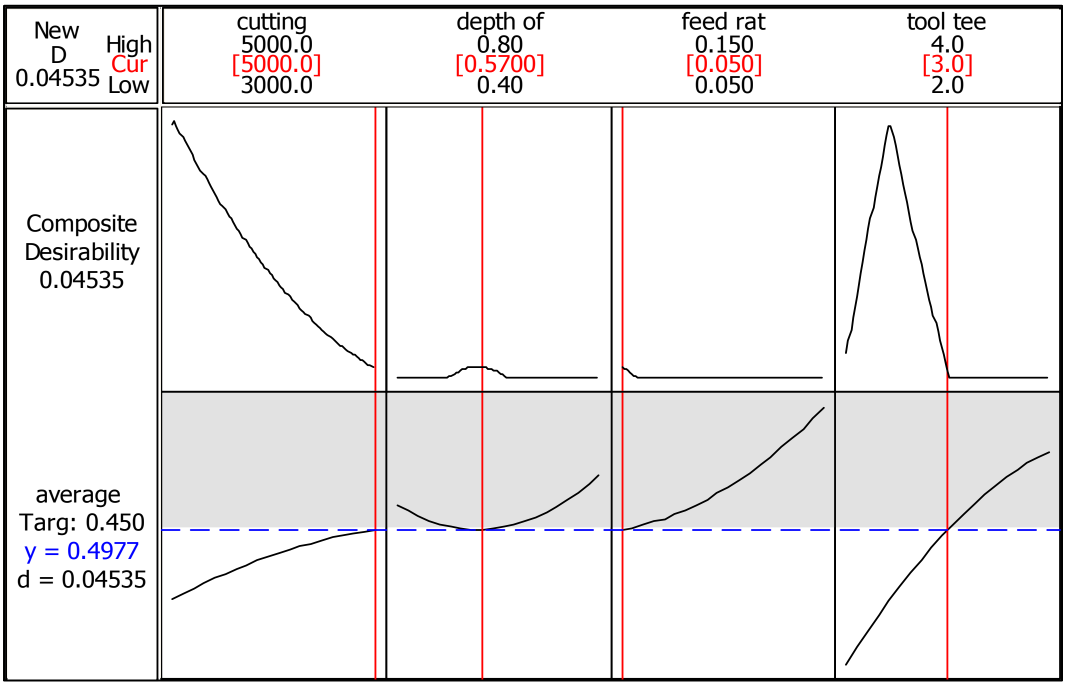

Fig. 11. *Optimization results in high level of surface roughness (R_a > 0.5).*

Table 8. *Experimental and optimization results.*

No. of test	Cutting speed (*v*) - rpm	Depth of cut (*d*) - mm	Feed rate (*f*) - mm	Tool flutes (*z*)	Optimization results - (µm)	Experimental results - (µm)	Error (µm)
1	3000	0.453	0.05	2	0.2545	0.2350	- 0.0195
2	5000	0.570	0.05	3	0.4977	0.5170	+ 0.0193
3	5000	0.400	0.15	2	0.5299	0.5410	+ 0.0111

Optimization of machining parameters used in this study is carried out based on surface roughness values, the values are divided in to three ranges. The optimization strategy implemented in this study is to divide the surface roughness range into three levels: low (<0.3µm), medium (0.4 - 0.5µm) and high (>0.5µm). Optimization results obtained in each range in verified. Verification results obtained in this study show the errors are very limited, hence we can say the technique used in this study is reliable and robust.

9. Conclusions

This paper presents an experimental investigation of surface roughness, based on response surface methodology (RSM) and sensitivity analysis, which describes the relationship between the cutting parameters (cutting speed. depth of cut, feed rate and tool flutes number) and surface roughness. According to the results analysis, tool flutes has highest significant, followed by feed rate, depth of cut while cutting speed has less significant. Modified regression model achieved in this study is reduced to first order equation. Regression correlation R square were 90.8% for analysis, which indicates that the correlation of regression has high value and the residuals plot is much closer to straight line. Residual plots follow normal distribution shape, with scatter residual plots which indicate to the good results. In contour plots, tool flute, feed rate and depth of cut all these parameters have positive relation affect to the surface roughness. Paper results show the tool flute is a very important factor in surface finish machining process, therefore, this study gives more options to compare tool flutes with other factors affecting in surface roughness to express their effect levels. Verification test show the optimization results obtained are useful and reasonable, and from the observations, optimization error has limited values -0.02 to 0.02. From the results achieved we can judge that RMS is an efficient and robust technique.

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