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Improvement of cutting performance of aluminium alloy 6061

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ABSTRACT

Purpose: Surface irregularities can result in the formation of nucleation sites for wear and cracks. Roughness is considered one of the important predictors when it comes to the performance of mechanical instruments or components. The study aimed to establish prediction models using response surface methodology (RSM) to optimise surface roughness (SR) when turning aluminium alloy 6061 with carbide insert TiCN/TiN using RSM.

Design/methodology/approach: RSM is a well-established method utilised by many studies in the literature to predict the machining outcomes and to choose the ideal machining parameters of specific machining processes and materials. It is an economical, practical, and relatively easy method. Moreover, it is a common method utilised in machining process modelling. Therefore, the study used RSM to develop prediction models and optimise the machining parameters to achieve the optimal surface roughness when turning aluminium alloy 6061 with carbide insert TiCN/TiN.

Findings: Both first and second-order models were developed and were found to be adequate according to the analysis of variance. The most contributing factor to the surface roughness was cutting speed. The contour plots have been generated and show different cutting parameter plots and how they influence the surface roughness (SR) values. Surface roughness reached its highest value when the feed rate increased, cutting depth increased, and cutting speed decreased. High cutting speed, low feed rate, and low cutting depth should be used to obtain the lowest surface roughness.

Research limitations/implications: Further development of contours generated by the RSM models will facilitate the selection of the ideal combination of cutting speed, feed rate, and depth to achieve optimal surface roughness. RSM is considered an efficient and convenient method, requiring little experimentation and giving highly crucial inputs and information.

Practical implications: Surface roughness equations clearly explain that the cutting speed and cutting feed rate are major contributors to surface roughness. Low cutting speed, high cutting depth, and feed rate correspond to a higher surface roughness.

Originality/value: In conclusion, reliable models for the prediction of surface roughness were developed and used to optimise the machining efficiency of aluminium alloy 6061. RSM is considered an efficient and convenient method, requiring little experimentation and giving highly crucial inputs and information.

Keywords: Surface roughness, RSM, Cutting speed, Feed rate, Cutting depth, Optimisation

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ANALYSIS AND MODELLING

1. Introduction

Surface irregularities can result in the formation of nucleation sites for wear and cracks [1]. Roughness is considered one of the important predictors when it comes to the performance of mechanical instruments or components [2]. Not only is surface finish considered one of the most important performance indicators that can potentially impact other machined parts' mechanical properties, It can also have an impact on the functional characteristics of the machined part, which include light reflection, wear, friction, electrical conductivity, and heat transfer [3-5]. Therefore, a good surface quality is required in most machining applications [6]. However, controlling roughness in manufacturing can be expensive and difficult; i.e. reducing surface roughness will often increase the manufacturing costs [7].

Material machinability refers to the adaptability of the material to be produced by a machining process. Ultimately, an optimal combination of parameters such as good surface finish, high material removal rate, low tool wear rate, low cutting force, and accurate geometrical characteristics of the workplace will produce better machinability [3]. Subsequently, surface roughness is rendered as one of the most important factors that can be used in determining the machinability of materials and the quality of products [8]. Besides, machining parameters can significantly influence surface roughness, including cutting depth, cutting speed, and feed rate [9].

Response surface methodology (RSM) goes back to 1951, as Box and Wilson developed it to help improve manufacturing processes. The method's main aim was to optimise chemical reactions to obtain good product characteristics at much lower costs (e.g. high purity, high yield, and low cost), which was accomplished after using sequential experimentation involving different factors (e.g. temperature and pressure). A similar methodology can be utilised to predict any response affected by different factor levels [10]. RSM is a well-established method used by many studies in the literature in many applications, including predicting the machining outcomes and optimising the machining parameters of specific machining processes and materials [11-17]. In addition, RSM is considered an economical, practical, and relatively easy method that provides important inputs with minimal experimentation [18].

Moreover, it is a common method utilised in modelling machining processes [19,20]. RSM combines experimental, statistical inferences, and regression analysis [21]. However, some studies have evaluated the influence of cutting parameters on surface roughness in the turning process of aluminium alloys. However, those studies have been conducted on different aluminium alloys and using different types of inserts. For instance, Chowdary et al. (2019) conducted an experimental study to optimise the surface roughness when aluminium alloy 6061 using titanium aluminium nitride (TiAlN) coated carbide inserts [22]. Furthermore, surface roughness RSM was developed by Musavi et al. (2020) for the turning process of aluminium alloy 2024 using an uncoated cemented insert [23]. In this study, an RSM model was developed to optimise the machining parameters of the turning process of aluminium alloy 6061 using titanium carbonitrate-coated carbide inserts.

Given that turning is considered one of the most commonly utilised machining processes [24], and the establishment of a thorough understanding of how each of these variables affects the surface roughness will help the selection of the optimal machining parameters that will produce the optimal surface roughness when turning aluminium alloy 6061. Understanding the impact of those independent factors on the surface roughness can guide the turning process of aluminium alloy 6061 to identify the right machining parameters' combination that can achieve optimal roughness. Therefore, in the given study, different cutting parameters, such as speed, feed rate, and axial depth, have been considered in predicting surface roughness when turning aluminium alloy 6061. The article aimed to establish RSM models for the prediction of surface roughness for the turning process of aluminium 6160 via the utilisation of response surface methodology.

2. Methodology

2.1. Response model

The RSM model contains a dependent variable (i.e. *y*), referred to as the response variable, and other independent variables that can influence the dependent variable, which can be identified as $x_1, x_2, ..., x_k$, Given that those variables can be measured. Therefore, the expression of the response variable can be as the following Equation No. 1:

$$y = f(x_1, x_2, \ldots x_k) \tag{1}$$

The goal of using the model is to optimise the response variable, i.e. y. The independent variables are assumed to be continuous and can be controlled experimentally with a negligible error, assuming that the dependent response variable is random. For example, in a turning operation, it is required to find an optimal combination of cutting speed, feed rate and cutting depth (x_1 = ln v), (x_2 = ln f), and (x_3 = ln cp) respectively, to achieve the most optimal surface roughness (y = ln Ra). Were ε is assumed to be normally distributed and correlated random error with constant variance and zero mean, the observed response y (i.e. surface roughness) can be expressed as a function of the speed, feed rate, and depth as the following Equation No. 2:

$$y = f(x_1, x_2, x_3) + \varepsilon \tag{2}$$

Usually, a first- or second-order low-order polynomial is used in some regions of the independent variables. The first-order model can be expressed in the following Equation No. 3:

$$y = \beta_o + \sum_{i=1}^{k} \beta_i x_i + \varepsilon \tag{3}$$

and the expression of the second-order model can be as the following Equation No. 4:

$$y = \beta o + \sum_{i=1}^{k} \beta_i\, x_i + \sum_{i=1}^{k} \beta_i\, x^2{}_i + \sum_i \sum_j \beta_{ij}\, x_i\, x_j + \varepsilon \qquad \text{for } i < j \tag{4}$$

Those functions are normally utilised in RSM problems. The estimation of β parameters of the polynomials is done using the least squares method Equation No. 5.

$$\mathrm{Ra} = \mathrm{C}\,(\mathrm{V}^{m} f^{n}\ \mathrm{C}_P\ \mathrm{y})\ \acute{\varepsilon} \tag{5}$$

where surface roughness is Ra and V, f and C_p are the cutting speed (m s-1), feed rate (mm rev-1) and cutting depth (mm), respectively, while C, m, n and q are constants, the logarithmic form of Equation (5) can be written as the following Equation No. 6:

$$ln\,Ra = ln\,C + m\,ln\,V + n\,ln\,f + q\,\ln C_{Px} + ln\,\acute{\varepsilon} \tag{6}$$

The linear form of Equation 2 can be expressed as the following Equation No. 7:

$$y = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon \tag{7}$$

where y is surface roughness, x_0 = 1 (dummy variable), x_1 = ln V, x_2= ln f, x_3 = ln CP, and ε = ln ε, where ε is considered to be uncorrelated, the normally distributed random error along with constant variance and zero means, β_0 = lnC while β_1, β_2, and β_3 are the model's parameters, the expression of the second model can be as the following Equation No. 8:

$$y^n = \beta_0\, x_0 + \beta_1\, x_1 + \beta_2\, x_2 + \beta_3\, x_3 + \beta_{11}\, x^2{}_1 + \beta_{22}\, x^2{}_2 + \beta_{33}\, x^2{}_3 + \beta_{11} x_1 x_2 + \beta_{12}\, x_1 x_3 \tag{8}$$

Using the least squares method to estimate values of β_1, β_2, and β_3. Its basic formula can be expressed as the following Equation No. 9:

$$(\mathrm{x^T\, x})\,\beta = \mathrm{x^T\ y}\ \ \beta = (\mathrm{x^T\ x})^{-1}\,\mathrm{x^T y} \tag{9}$$

where x^T is the transpose of the matrix x and $(x^T\ x)^{-1}$ is the inverse of the matrix (x^T x). The solution details by the matrix approach are thoroughly explained in the literature [25].

2.2. Experimental set-up

An arrangement consisting of fifteen experiments was implemented for first-order model development. The Box Behnken design (BBD) is frequently used when performing non-sequential experiments. Utilising such design, i.e. Box Behnken, allows sufficient assessment of coefficients for both the first and second-order models. BBD also has fewer design points, making it a less expensive method to implement than the central composite design with the same number of factors. Moreover, because BBD lacks axial points, this ensures that all design points are within the safe operating point. BBD also ensures that factors are not set at their highest values simultaneously. A 3-factor Box Behnken is shown in Figure 1. Preliminary tests were done to identify a suitable cutting speed, feed rate and cutting depth, as indicated in Table 1.

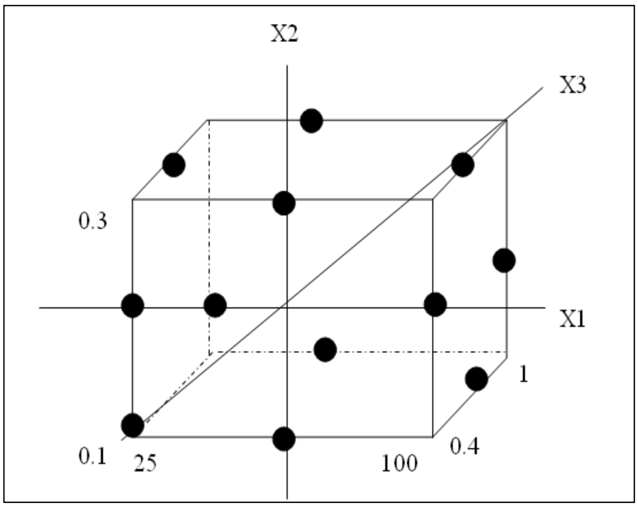

Fig. 1. BBD with three variables

Table 1.
Coding of independent variables and their corresponding values

Levels	Low	Medium	High
Coding	-1	0	1
V	415	642.5	870
F	1	2	3
CP	1.5	3	4.5

V: speed meseaured in m/min; F: feed rate measured in mm/rev; CP: cutting depth measured in mm

Aluminium alloy 6061 workpieces, each with a size of 30 mm in diameter and 100 mm in length, were used in this study. The cutting tool used is a tool holder section 25 x 25 mm with carbide insert TiCN/TiN.

The cutting test was performed after each run (cutting stroke) of 50 mm. To ensure accurate results, the same experiment was run multiple times.

BBD of the experiment is one of the most commonly utilised RSM designs that focuses on optimising the response variable.

In order to obtain the desired target, fifteen experiments were conducted at different levels of machining parameters as suggested by the box Behnken design of the experiment to collect the response (i.e. surface roughness) at different levels of machining parameters, i.e. at low, medium, and high levels.

Table 2 presents the experiments done at different levels of cutting parameters during the experiment along with the experimental measured surface roughness.

Table 2.
Experiment conditions and results

Experiment No.	Cutting speed	Feed rate	Cutting depth	(Exp.) Ra, nm
1	415	1	3	380.2
2	870	1	3	239.1
3	415	3	3	668.8
4	870	3	3	234.2
5	415	2	1.5	451.3
6	870	2	1.5	140.2
7	415	2	4.5	598
8	870	2	4.5	260.5
9	642.5	1	1.5	288.4
10	642.5	3	1.5	365.6
11	642.5	1	4.5	269.8
12	642.5	3	4.5	346
13	642.5	2	3	336.7
14	642.5	2	3	306.9
15	642.5	2	3	291.4

Ra: Surface roughness in nm

3. Results and discussions

The generated surface roughness's first-order model equation was as shown in Equation No.10:

$$Ra = 315.7 + 6.6\,depth + 0.141\,speed - 38.5\,rate \quad (10)$$

Tables 1 and 2 demonstrate the coding identifications of the independent variables and the experimental conditions, respectively. Each independent variable's equation can be transformed and expressed as the following Equation No. 11:

$$x_1 = \frac{\ln(V)-\ln(v)centre}{\ln(v)high-\ln(v)centre}$$
$$x_2 = \frac{\ln(f)-\ln(f)centre}{\ln(f)high-\ln(f)centre} \quad (11)$$
$$x_3 = \frac{\ln(C_P)-\ln(C_p)centre}{\ln(C_P)high-\ln(C_P)centre}$$

Table 3 shows the predicted versus experimental results of the first-order model. Table 4 displays the analysis of the variance. The p-value for the first-order model's lack of fit was 0.092, indicating that the model was adequate.

Table 3.
Comparison of experimental and predicted results according to the first-order model

Run order	Cutting speed	Feed rate	Cutting depth	Measured Ra, nm	Predicted Ra, nm
1	415	1	3	380.2	443.504
2	870	1	3	239.1	137.437
3	415	3	3	668.8	552.824
4	870	3	3	234.2	246.757
5	415	2	1.5	451.3	469.573
6	870	2	1.5	140.2	163.506
7	415	2	4.5	598	526.756
8	870	2	4.5	260.5	220.688
9	642.5	1	1.5	288.4	261.879
10	642.5	3	1.5	365.6	371.199
11	642.5	1	4.5	269.8	319.062
12	642.5	3	4.5	346	428.382
13	642.5	2	3	336.7	345.131
14	642.5	2	3	306.9	345.131
15	642.5	2	3	291.4	345.131

Ra: Surface roughness in nm

By inspecting the analysis of variance (ANOVA) results for the first-order model, feed rates and cutting speed were identified to impact surface roughness significantly, i.e. both significantly explain the variance in surface roughness. In addition, cutting speed was the most contributing factor to the surface roughness, followed by feed rate.

Table 4.
First-order model's analysis of variance

Source	DF	Seq SS	Contribution	F-Value	P-Value
Model	3	217796	81.37%	16.02	0.000
Linear	3	217796	81.37%	16.02	0.000
Cutting speed	1	187355	70.00%	41.34	0.000
Feed rate	1	23902	8.93%	5.27	0.042
Cutting depth	1	6540	2.44%	1.44	0.255
Error	11	49853	18.63%		
Lack-of-Fit	9	48793	18.23%	10.24	0.092
Pure Error	2	1059	0.40%		
Total	14	267649	100.00%		

DF: Total degree of freedom, SS: Sums of squares, F: F-value, P: p-value

Equation No. 10 was used to develop surface roughness contour plots at selected cutting depth values. It can be seen from Figure 2 (A) to (C) that to obtain the lowest surface roughness, a combination of high cutting speed, low feed rate, and low cutting depth should be used.

Such contour plots potentially make it easier to predict surface roughness at any of the experimental zone points. Figure 2 (D) illustrates the normality of the residuals. In addition, from Figure 2 (A) to (C), the surface roughness reaches the highest value, i.e. more than 500 nm at low cutting speed, high cutting depth and feed rate; also, it can be seen that reasonable surface roughness values can also be obtained at mid cutting depth, low feed rate, and high cutting speed values. The contour plot facilitates the selection of surface roughness's safety zone for any experiment.

By postulating the second-order model, obtain the impact of the machine's independent variables (i.e. machining parameters) and the response (i.e. surface roughness). According to the BBD method, the expression of the model's equation is as the following Equation No. 12:

$$Ra = 1055 - 2.088\,Cutting\ speed + 7\,Feed\ rate + 35.5\,Cutting\ depth + 0.001101\,Cutting\ speed * Cutting\ speed + 11.9\,Feed\ rate * Feed\ rate - 2.7\,Cutting\ depth * Cutting\ depth \quad (12)$$

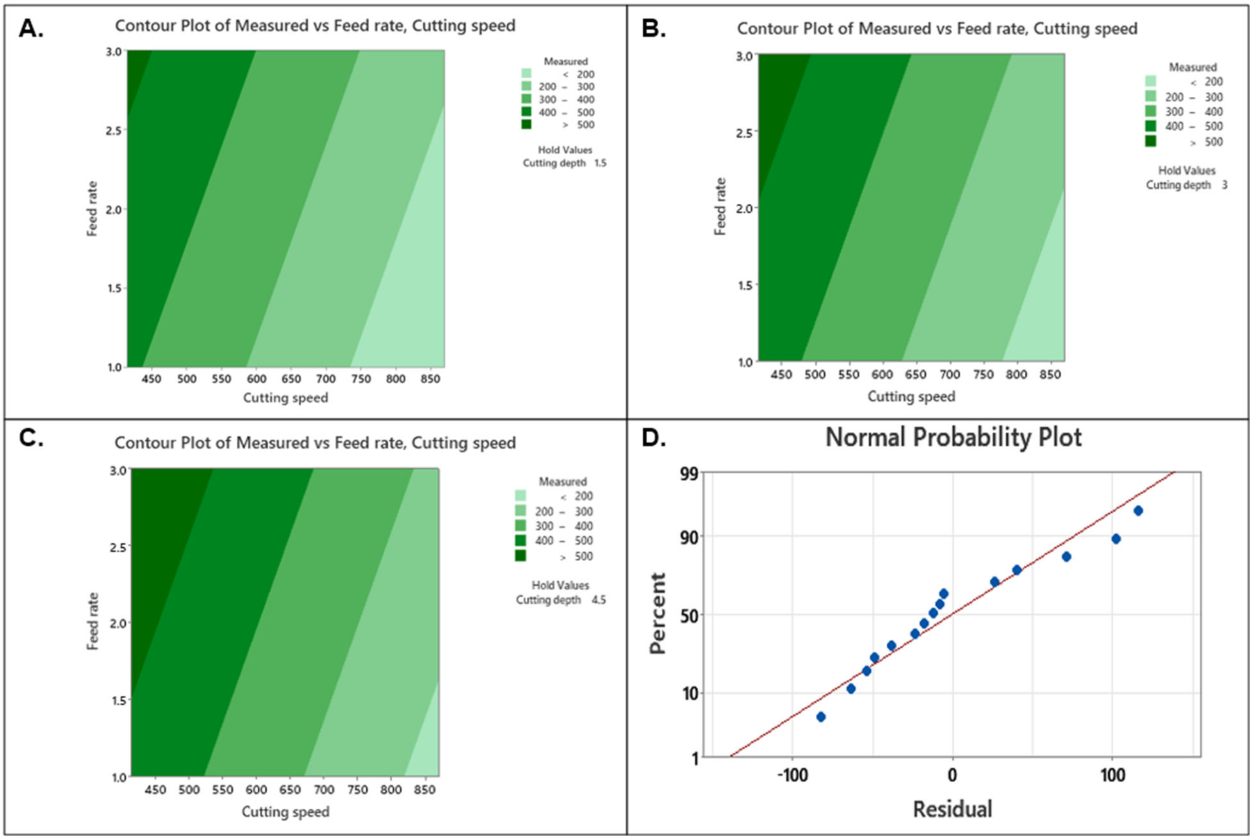

Fig. 2. (A) Contour plot of surface roughness at low cutting depth; (B) Contour plot of surface roughness at moderate cutting depth; (C) Contour plot of surface roughness at high cutting depth; (D) Normal probability plot of model's residuals

Table 5.
Comparison of experimental and predicted results according to the second-order model

Run order	Cutting speed	Feed rate	Cutting depth	Measured Ra, nm	Predicted Ra, nm
1	415	1	3	380.2	478.951
2	870	1	3	239.1	172.884
3	415	3	3	668.8	588.271
4	870	3	3	234.2	282.204
5	415	2	1.5	451.3	486.933
6	870	2	1.5	140.2	180.865
7	415	2	4.5	598	544.115
8	870	2	4.5	260.5	238.047
9	642.5	1	1.5	288.4	234.176
10	642.5	3	1.5	365.6	343.496
11	642.5	1	4.5	269.8	291.359
12	642.5	3	4.5	346	400.679
13	642.5	2	3	336.7	311.660
14	642.5	2	3	306.9	311.660
15	642.5	2	3	291.4	311.660

Ra: Surface roughness in nm

The data presented in Table 5 shows predicted results generated from the second-order model versus experimental values. ANOVA for the second-order model results shows that the second model's lack of fit *p* value was 0.083, indicating that the model was adequate, as described in Table 6.

By inspecting the second-order model's ANOVA results, cutting speed was identified to be significantly associated with surface roughness; in other words, cutting speed explains the variance in surface roughness. In addition, cutting speed was the most contributing factor to the surface roughness, followed by feed rate.

Equation No. 12 was utilised to develop surface roughness contour plots at the selected values of cutting depth. It can be seen from Figures 3 (A) to (C) that a combination of high speed, low feed rate, and low cutting depth should be used to obtain the lowest surface roughness. Such a contour plot potentially facilitates the prediction of the surface roughness at any point in the experimental zone. Figure 3 (D) illustrates the normality of the residuals.

In addition, Figures 3 (A) to (C) indicates that the surface roughness reaches the highest value, i.e. more than 600 nm at the lowest cutting speed, highest cutting depth and feed rate, where the value of surface roughness at its reasonable value at low cutting depth, and feed rate values from 1-2 and high cutting speed values of more than 700. Figure 3 (B) shows low surface roughness values can also be obtained using moderate cutting depth, high cutting speed and low feed rate. The contour plot facilitates the selection of surface roughness's safety zone for any experiment. In addition, when compared with the first-order model, the second-order model was more accurate as the root of the mean squared error of the second-order model was lower (49.7) versus (57.6) in the first-order model Table 7. Also, the r-squared value of the second-order model was (0.86), which is higher when compared with the first-order model (0.81), indicating that the second-order model was more efficient in explaining the variance in the surface roughness Table 7.

Furthermore, by inspecting Figure 4, predicted surface roughness values by the second-order model are more consistent with the actual surface roughness compared with the first-order predicted values. Second-order models are often selected to yield more accurate predictions [26]. It is because the second-order model includes more explaining variables, i.e. the second-order model includes linear terms and a second-order term for each dependent variable.

Table 6.
Second-order model's analysis of variance

Source	DF	Seq SS	Contribution	F-Value	P-Value
Model	6	230458	86.10%	8.26	0.004
Linear	3	217796	81.37%	15.62	0.001
Cutting speed	1	187355	70.00%	40.30	0.000
Feed rate	1	23902	8.93%	5.14	0.053
Cutting depth	1	6540	2.44%	1.41	0.270
Square	3	12662	4.73%	0.91	0.479
Cutting speed*Cutting speed	1	11951	4.47%	2.58	0.147
Feed rate*Feed rate	1	571	0.21%	0.11	0.745
Cutting depth*Cutting depth	1	140	0.05%	0.03	0.866
Error	8	37191	13.90%		
Lack-of-Fit	6	36131	13.50%	11.37	0.083
Pure Error	2	1059	0.40%		
Total	14	267649	100.00%		

DF: Total degree of freedom, SS: Sums of squares, F: F-value, P: p-value

Table 7.
Performance of first order RSM model compared with second order RSM model

Parameter	Linear RSM model	Second-order RSM model
RMSE	57.6	49.7
R^2	0.81	0.86

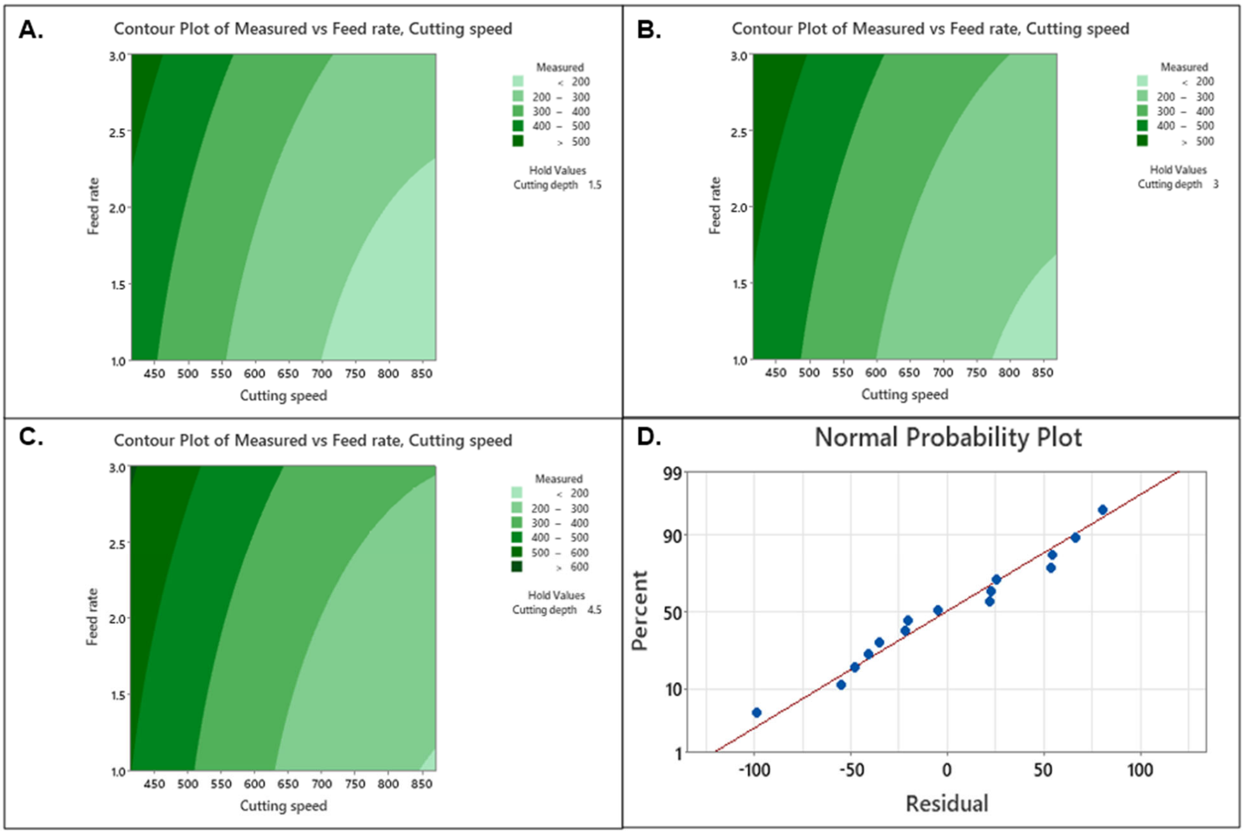

Fig. 3. (A) Contour plot of surface roughness at low cutting depth; (B) Contour plot of surface roughness at moderate cutting depth; (C) Contour plot of surface roughness at high cutting depth; (D) Normal probability plot of the residuals

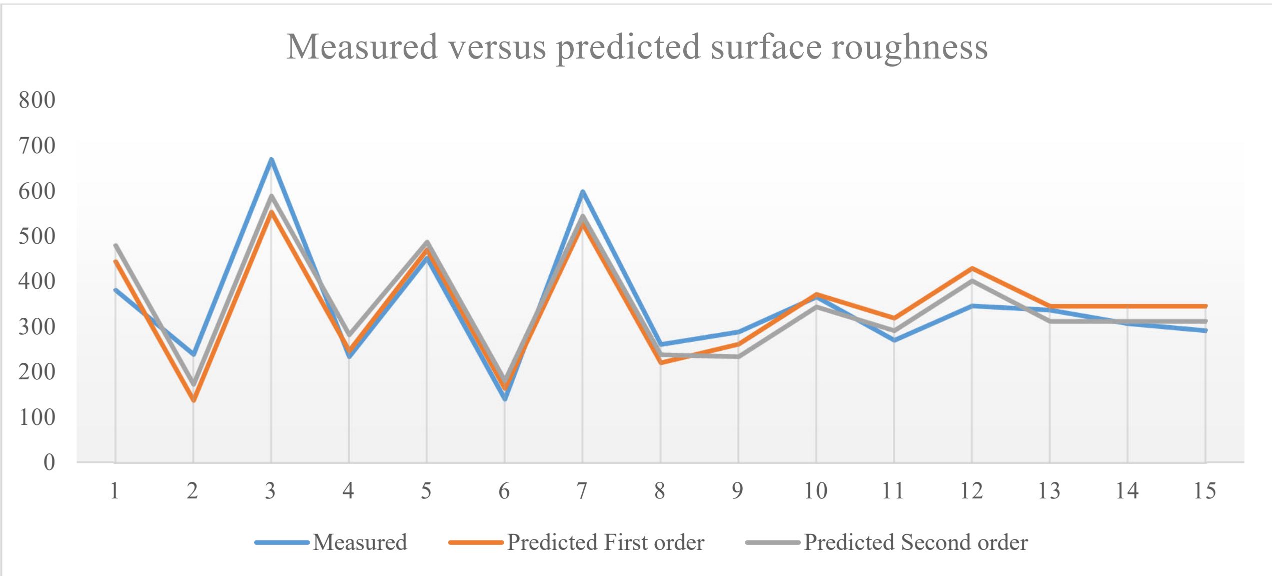

Fig. 4. Measured versus predicted surface roughness

4. Conclusions

In the given study, reliable models for surface roughness prediction were developed and used to optimise the machining efficiency of Aluminium alloy 6061. The surface roughness equation clearly explains that the cutting speed and cutting feed rate are major contributors to the surface roughness. Low cutting speed, high cutting depth, and feed rate correspond to higher surface roughness. Surface roughness output contours were built in planes containing two of the variables (independent variables). The usage and further development of contours generated by RSM models will facilitate the selection of the ideal combination of speed, feed rate, and depth to optimise surface roughness. RSM is considered an efficient and convenient method, requiring little experimentation and giving highly crucial inputs and information.

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