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Research Article

Surface Roughness Models and Their Experimental Validation in Micro Milling of 6061-T6 Al Alloy by Response Surface Methodology

Jie Yi, Li Jiao, Xibin Wang, Junfeng Xiang, Meixia Yuan, and Shoufeng Gao

Key Laboratory of Fundamental Science for Advanced Machining, Beijing Institute of Technology, Beijing 100081, China

Correspondence should be addressed to Li Jiao; jiaoli@bit.edu.cn

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Due to the widespread use of high-accuracy miniature and micro features or components, it is required to predict the machined surface performance of the micro milling processes. In this paper, a new predictive model of the surface roughness is established by response surface method (RSM) according to the micro milling experiment of 6061-T6 aluminum alloy which is carried out based on the central composite circumscribed (CCC) design. Then the model is used to analyze the effects of parameters on the surface roughness, and it can be concluded that the surface roughness increases with the increasing of the feed rate and the decreasing of the spindle speed. At last, based on the model the contour map of the surface roughness and material removal rate is established for optimizing the process parameters to improve the cutting efficiency with good surface roughness. The prediction results from the model have good agreement with the experimental results.

1. Introduction

The aluminum and aluminum alloy, with its excellent inherent qualities such as small density, high intensity, good conductive thermal conductivity, and good corrosion resistance, can easily be processed. Aluminum and its derivatives have been widely used in the industries of national economy and defense, especially in light structure material, light weight, strength, air, sea, and land and all kinds of vehicles, especially aircraft, missile, rocket, and the artificial earth satellite, which need to use a lot of aluminum. The hardness of 6061-T6 Al alloy has a wider range of application and has gained favor over the years in the industry. Because of the 6061-T6 Al alloy excellent plasticity it can be molded into any particular shape of radiator, especially small engines.

Micro manufacturing is defined as a scaling-down of conventional technologies or process in order to manufacture micro products/features [1]. Micro milling is one of micro manufacturing processes that have the ability to produce micro products with complex shape. Surface and size effect begins to dominate material response and behavior due to the scaling-down effect [2]. The application of micro milling technology in complex precision three-dimensional small parts manufacturing has caused major technological change in the field of micro manufacturing. Compared with traditional milling method, MEMS and ultra-precision machining technology are effective means to manufacture micro and middle scale small parts with high efficiency and high precision. What is more, MEMS and ultra-precision machining technology can realize the unique advantages [3, 4] of the three-dimensional curved surface machining, so it received extensive attention of experts and scholars domestically and overseas.

Surface finish is an important measure of the technological quality of a product and a factor that greatly influences manufacturing cost. Surface roughness has received serious attentions for many years. It has formulated an important design feature in many situations such as parts subject to fatigue loads, precision fits, fastener holes, and aesthetic requirements. In addition to tolerance, surface roughness imposes one of the most critical constraints for selection of machines and cutting parameters in process planning [5]. For achieving the desired surface finish, it is necessary to understand the mechanisms of the material removal and

the kinetics of machining processes affecting the performance of the cutting tool [6].

Certain theories and principles have been proposed by the researchers who have used conventional macro-machine tools. In the recent years, micro machining became popular due to the development of miniaturized industries. The existence of the minimum cutting thickness, the influence of the scale effect, and the strengthening of the nonfree cutting give rise to a difference between conventional milling and micro milling. Therefore, further study of micro milling condition influences the process parameters on surface roughness and machining before the selection of cutting parameters, forecast, and control in order to achieve the goal of the surface roughness. Lou et al. examined the multiple regression models for finished surface prediction [7]. Taguchi statistical method was used by Yang and Chen [8] and Ghani et al. [9] for optimum milling parameters. Recently, Ben Fredj et al. developed surface roughness prediction model using design of experiment method and the neural network [10]. Thepsonthi and Özel [11] studied the chip flow and tool wear of Ti-6Al-4V titanium alloy in micro-end milling. Kopač et al. used signal-to-noise response method to analyze the surface roughness with turning [12]; Benardos and Vosniakos introduced the prediction method to predict surface roughness in machining [13]. Kiswanto et al. [14] researched about the effect of spindle speed, feed rate, and machining time to the surface roughness and burr formation of aluminum alloy 1100 in micro milling operation. Kant and Sangwan [15] used artificial neural network coupled with Genetic Algorithm for predictive modelling and optimization of machining parameters to minimize surface roughness. Campatelli et al. [16] used the response surface method to optimize the process parameters for minimizing power consumption in the milling of carbon steel. However, the research work mentioned above used the conventional machine tool. The results could not suit the micro machining. In this paper, new surface roughness prediction model is developed based on micro milling process. In the present work, a mathematical model has been developed to predict the surface roughness of milling 6061-T6 Al alloy using response surface method (RSM). Analysis of variance (ANOVA) is used to check the validity of the model and F-test is used to find the significant parameters. The surface roughness and the equivalent response of the surface can therefore be established. This model can be effectively used to predict the surface roughness of the milled 6061-T6 Al alloy. Some experiments have been conducted to find the proper important parameters to maximize material removal rate and minimize surface roughness.

2. Experimental Scheme and Design

2.1. Central Composite Designs (CCDs). Combination design is generally the test plan which is formed by putting one combination of regression design point and some specific sites together. Therefore, combination can greatly reduce the number of test designs and can make the secondary design on the basis of one design. The design can satisfy the orthogonal concept by adjusting the asterisk arm. The most well-known and recommended Central Composite Design is a repeat order strategy that is part of the experiment in the design of the second order. Central Composite Design has three types which are central composite circumscribed design (CCC), central composite inscribed design (CCI), and central composite face-centered design (CCF). Each variable of CCC and CCI requires 5 levels, but CCF only needs 3 levels. The comparison [17] of similarities and differences of CCC, CCI, and CCF is shown in Table 1. Compared with the CCF, the prediction error precision of CCC has good consistency and CCC improves the square effect estimates. Furthermore CCC is the most effective method in estimating model parameter. So the design of CCC is adopted in the experiment, and its diagram is shown in Figure 1.

Table 1: Similarities and differences of CCC, CCI, and CCF.

	CCC	CCI	CCF
Design domain shape	Sphere	Sphere	Cubic
Design level	5	5	3
Complexity	High	High	Low
Factorial points position	±1	±0.7	±1
Axial points position	$\alpha = \sqrt{k}$	$\alpha = 1.0$	$\alpha = 1.0$
Recommend the center number	3~5	3~5	1~2
Rotatability	Rotatable	Rotatable	Not rotatable
Uniformity of prediction error	Good	Good	Bad
Model based parameter estimation	Most effective	Worst	Second
Extrapolation of robustness	Second	Best	Second

Where k is the number of the variables and α is the axial distance.

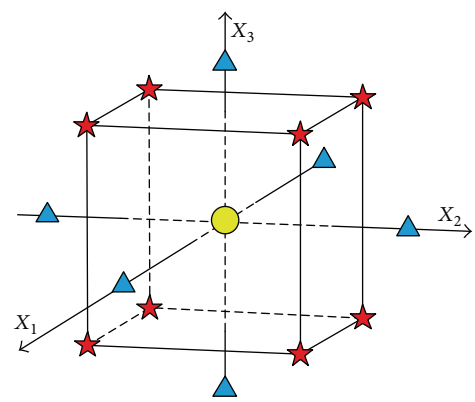


Figure 1: The sketch of CCC design.

2.2. Response Surface Modeling Method. Response surface method is a nonlinear regression which combines principles of mathematics, statistics, and experimental design technique; it also explores the mathematical relationship between influence factors and the response output. A process or system contains the response $y(x)$, which depends on the input factors $x_1, x_2, \ldots, x_p$, if there is a linear function

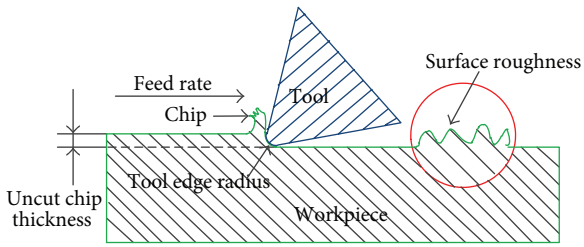


Figure 2: Schematic of tool-workpiece interaction.

relation between response and the independent variables; the approximate function is the first-order model:

$$y(x) = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \varepsilon, \tag{1}$$

where β_0 is constant and β_i is x_i the linear effect and ε is the error.

The studied relationship between response $y(x)$ and input $x_1, x_2, \ldots, x_p$ is called response surface research. The second-order response surface model considered the interaction effect and the second-order effect, which can be expressed as

$$y(x) = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \beta_{ij} x_i x_j + \sum_{i=1}^{n} \beta_{ii} x_i^2 + \varepsilon, \tag{2}$$

where β_{ij} is the interaction effect between x_i and x_j and β_{ii} is the second-order effect of x_i.

Spindle speed (x_1), feed rate (x_2), and depth of cut (x_3) will affect the value of the surface roughness. In order to accurately understand the effects of the processing parameters on surface roughness, response surface method is adopted to establish the relationship between the surface roughness and machining parameters. The model is as follows:

$$\begin{aligned} R_a = {} & \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 \\ & + \beta_{23} x_2 x_3 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{33} x_3^2 + \varepsilon, \end{aligned} \tag{3}$$

where R_a represents surface roughness.

The purpose of the test is to obtain a set of optimum processing parameters to get the best surface quality. Through the response of the surface method analysis, various factors regarding the response value in the regression model can eventually respond as a predictive value achieving optimization by determining reasonable level combination.

2.3. Micro Milling Mechanics. As shown in Figure 2, in micro scale cutting, a great number of critical issues, such as tool edge radius, negative rake angle, elastic deformation of machined surface, minimum chip thickness, and micro structure become prominent when uncut chip thickness becomes comparable to the tool edge radius or grain size of work materials. These issues may be categorized as size effect which can influence underlying cutting mechanisms by altering cutting forces, the chip formation process, burr formation, vibration and process stability, energy consumption, and generation of the machined surface.

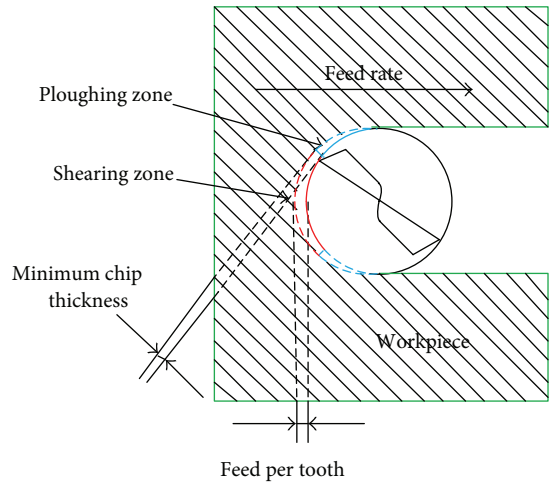


Figure 3: 2D view of full-immersion of ploughing and shearing mechanisms in micro-end milling.

Because of an intermittent cutting mechanism for micro milling, uncut chip thickness in the radial direction for each cutting passage varies from zero to the feed per tooth and then to zero. It is thus inevitable to encounter ploughing or rubbing in the minimum chip thickness effect. In cases where the feed per tooth is larger than minimum chip thickness, ploughing and shearing mechanisms are present in one cutting passage, as shown in Figure 3. The ploughing mechanism becomes dominant when the radial depth of cut is smaller than minimum chip thickness. However, once radial depth of cut is larger than minimum chip thickness, shearing of work materials takes place and chips can be formed. Ploughing dominant zones are located at the entrance and exit of the passage while the rest of the zone is dominated by shearing. In cases where feed per tooth is smaller than minimum chip thickness, there are probably no chips formed during several consecutive revolutions of cutting on account of the ploughing dominant mechanism and elastic recovery of work materials.

2.4. Experimental Process and Results. Because of the influence regarding the surface shape error and other factors, the workpiece zero cross section is not easy to directly determine. In order to eliminate the error, zero planes must be generated by milling in advance, and then micro groove structures whose length is 5 mm were milled on the datum plane. Diagram of micro milling process is shown in Figure 4. And Figure 5 shows the machining status of micro milling.

The workpiece 6061-T6 Al alloy was milled by a cemented carbide micro milling cutter with diameter being 1 mm and the number of teeth being 2, as shown in Figure 6. The material mechanical and physical properties of 6061-T6 Al alloy are given in Table 2. Test chose high spindle speed, small axial feed, and depth of cut. And three-factor five-level orthogonal test was designed. The orthogonal experiment factor level distribution is shown in Table 3. Assume that x_1, x_2, and x_3 represent the spindle speed (n), feed rate (f), and depth of cut (a_p), respectively. At the same time, the

Table 2: Typical mechanical and physical properties of 6061-T6 Al alloy.

Tensile strength σ_u(MPa)	Yield strength σ_s (MPa)	Hardness (HB)	Density (g/cm^3)	Young's modulus E (GPa)	Poisson ratio
310	276	95	2.7	70	0.33

Table 3: Important factors and their levels.

Parameter	Notation	Unit	Levels				
			−2	−1	0	1	2
Spindle speed n	x_1	r/min	10000	12000	14000	16000	18000
Feed rate f	x_2	μm/r	0.4	0.8	1.2	1.6	2.0
Depth of cut a_p	x_3	μm	10	20	30	40	50

Table 4: The test design matrix and results.

S. number	Design									R_a, average surface roughness (μm)
	x_1	x_2	x_3	x_1^2	x_2^2	x_3^2	x_1x_2	x_1x_3	x_2x_3	
1	−1	−1	−1	1	1	1	1	1	1	1.315
2	1	−1	−1	1	1	1	−1	−1	1	1.016
3	−1	1	−1	1	1	1	−1	1	−1	1.436
4	1	1	−1	1	1	1	1	−1	−1	1.001
5	−1	−1	1	1	1	1	1	−1	−1	1.503
6	1	−1	1	1	1	1	−1	1	−1	1.117
7	−1	1	1	1	1	1	−1	−1	1	1.402
8	1	1	1	1	1	1	1	1	1	1.301
9	−2	0	0	4	0	0	0	0	0	1.511
10	2	0	0	4	0	0	0	0	0	1.113
11	0	−2	0	0	4	0	0	0	0	1.008
12	0	2	0	0	4	0	0	0	0	1.349
13	0	0	−2	0	0	4	0	0	0	1.165
14	0	0	2	0	0	4	0	0	0	1.304
15	0	0	0	0	0	0	0	0	0	1.271
16	0	0	0	0	0	0	0	0	0	1.269
17	0	0	0	0	0	0	0	0	0	1.238
18	0	0	0	0	0	0	0	0	0	1.256
19	0	0	0	0	0	0	0	0	0	1.247

processing parameters ranges are determined: the range of parameter n is 10000~18000 r/min, f is 4~36 mm/min, and a_p is 0.01~0.05 mm. The milling test numbers are 19. According to statistical inference, the average surface roughness value can be measured and obtained by taking the average five groups of experimental data. In Figure 7, it shows the method to obtain the average surface roughness whose value is 1.271 μm with the cutting parameters $n = 14000$ r/min, $f = 1.2$ μm/z, and $a_p = 30$ μm, and test results are shown in Table 4 and Figure 8.

3. Experimental Results Discussion

From Figure 8, the range of the average surface roughness is different. Comparing the red I-shaped line ($R_a = 1.511$ μm) with the green I-shaped line ($R_a = 1.001$ μm), the range of the red one is obviously larger than the green one. This is because the cutting parameters in the green one are better than the red one.

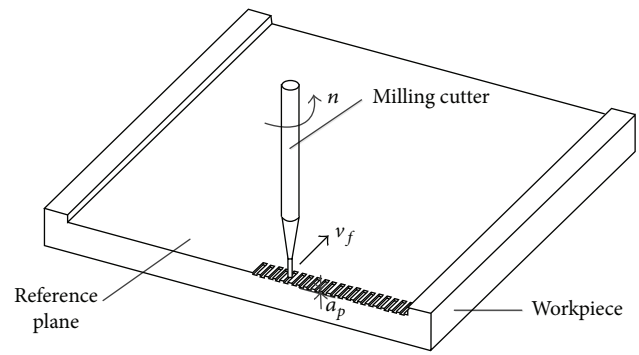


Figure 4: Diagram of micro milling 6061-T6 Al alloy process.

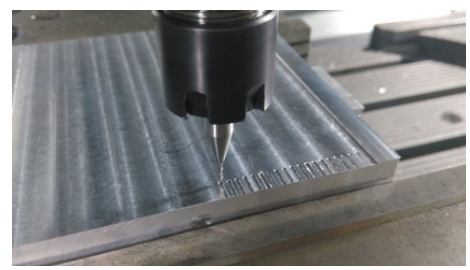


Figure 5: Machining status of micro milling.

From Table 3, the experimental factors of free variables and surface roughness are converted into matrix form through the test parameter transformation; then (3) coefficient can be found by using the least squares regression, so the multivariate regression empirical formula between surface roughness and cutting parameters is established. The final model was developed in coded values and is given as follows:

$$\begin{aligned} R_a = {} & 1.26 - 0.128x_1 + 0.0568x_2 + 0.0544x_3 \\ & + 0.0233x_1x_2 + 0.0356x_1x_3 - 0.0189x_2x_3 \\ & + 0.0149x_1^2 - 0.0185x_2^2 - 0.0045x_3^2. \end{aligned} \quad (4)$$

The adequacy of the model is checked by using the analysis of variance (ANOVA) technique. As this technique, if the calculated value of the F ratio of the developed model does exceed the standard tabulated value of F ratio for a desired level of confidence (say 99%), then the model is considered to be adequate within the desired limit. ANOVA and F-test results are presented in Table 5. The value of $F0.01$ (9, 9) equals 5.35 which is less than the fitting F-value that equals 7.06 in the present research, and hence the developed model may be accepted. The regression equation was analyzed

Table 5: Analysis of variance for surface roughness.

Source	DF^a	Sum of squares	Mean square	F-value	F-tab
Regression	9	0.376	0.041	7.06	5.35
Residual error	9	0.0532	0.006		
Total	18	0.675			7.06 > 5.35

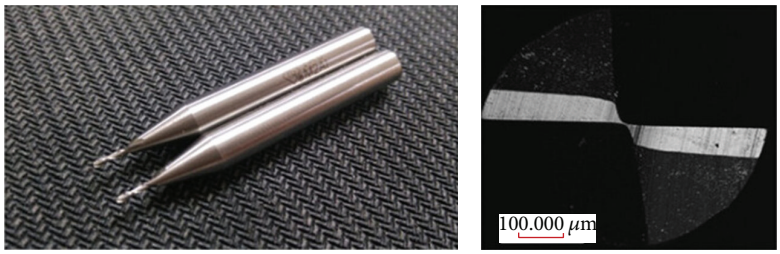


Figure 6: Micro milling cutter.

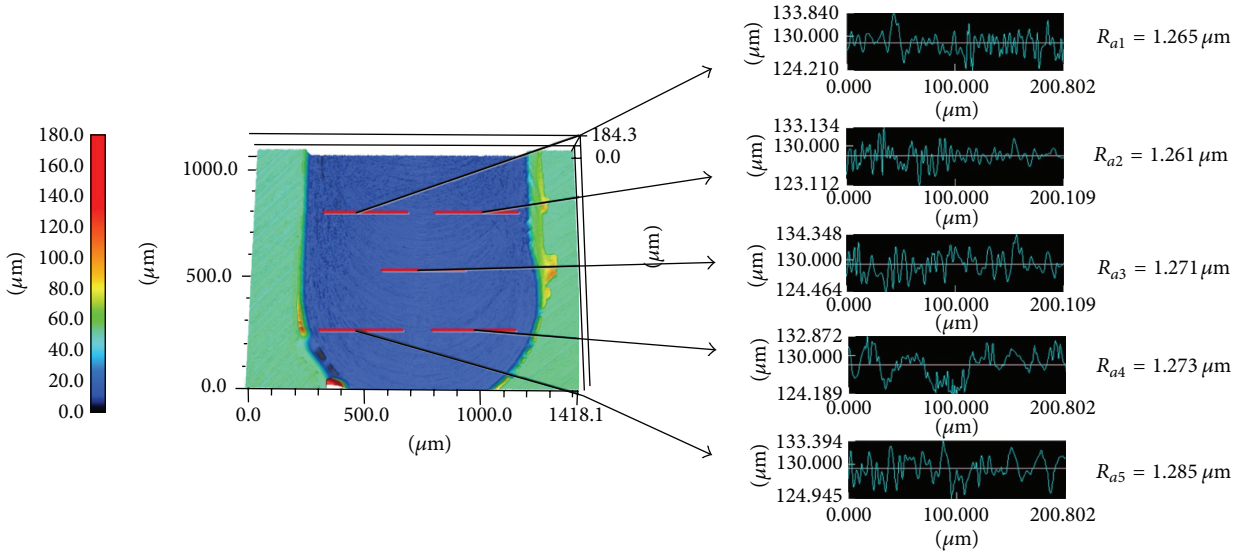


Figure 7: Schematic diagram of obtaining average surface roughness.

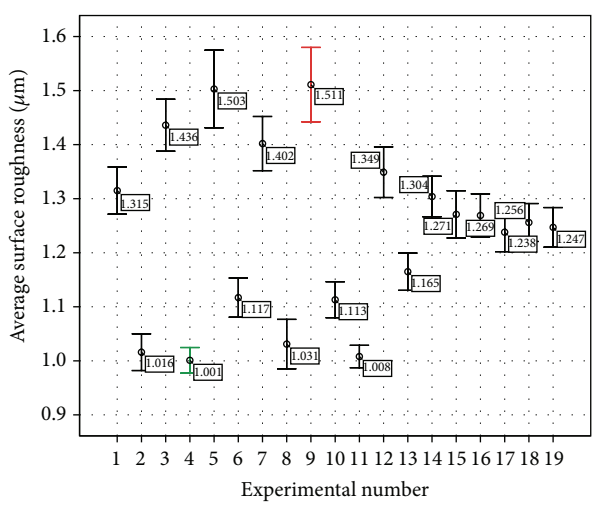


Figure 8: Plot of average surface roughness.

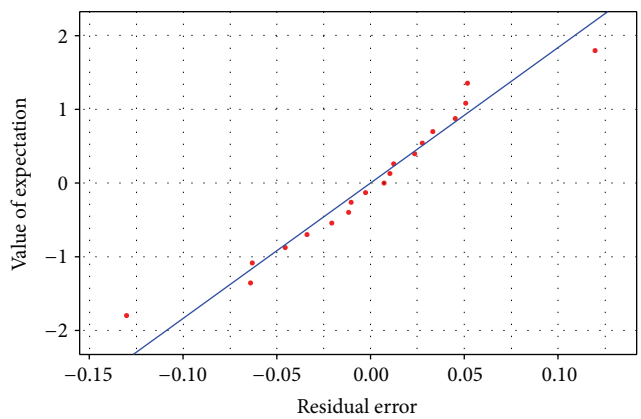


Figure 9: Rankit plot of the regression model.

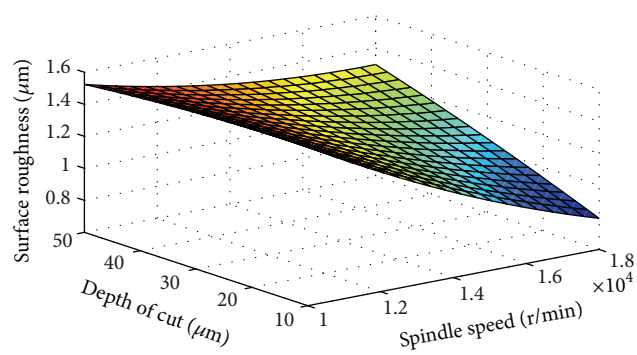


Figure 10: The influence of surface roughness by spindle speed and depth of cut ($f = 1.2\,\mu$m/r).

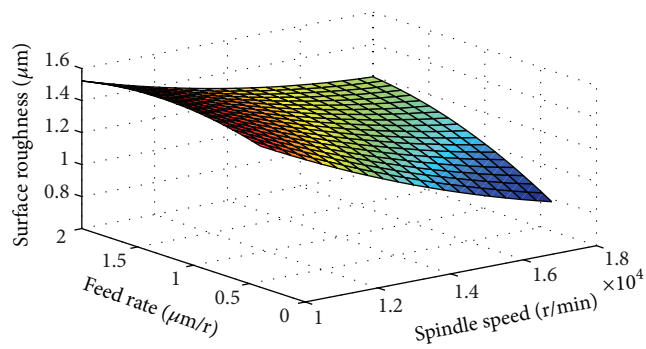


Figure 11: The influence of surface roughness by spindle speed and feeding rate ($a_p = 30\,\mu$m).

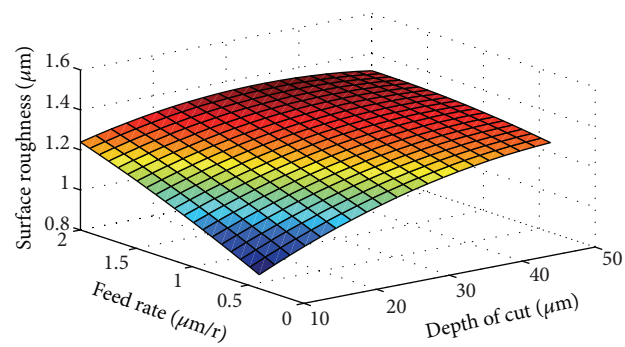


Figure 12: The influence of surface roughness by depth of cut and feeding rate ($n = 14000$ r/min).

by variance and F-tests that indicate the prediction model has significant state, fitting well with the actual situation. Micro milling predicted the surface roughness of hard 6061 aluminum alloy which has higher credibility.

Further, as shown in Figure 9 which is the model of residual analysis Rankit, residual error and the value of expectations have a near linear relationship. As a result, the regression equation model is suitable, the analysis of variance is credible, and the regression model is effective.

According to (4), the figures of the surface roughness model can be drawn, so the influence law of parameters on surface roughness is obtained, as shown in Figures 10~12:

(a) Figure 10 shows that the surface roughness value decreases obviously with increasing of spindle speed under the condition with $a_p = 10\sim50\,\mu$m and $f = 1.2\,\mu$m/r. And the surface roughness (R_a) is close to $0.8\,\mu$m when spindle speed is nearly 18000 r/min and depth of cut's value is the minimum. Therefore improving spindle speed has significant effect on reducing the surface roughness.

(b) In Figure 11, the change of surface roughness's value was not large with increasing of feed rate under the low spindle speed and depth of cut. But increasing feed rate has significant effect on surface roughness when the spindle speed reaches 16000 r/min, and the result is that surface roughness's value is increasing. When the spindle speed is between 15000 and 17000 r/min, it has a little influence on the surface roughness value. At this area, the relatively stable machining surface quality can be obtained ($R_a = 0.7\,\mu$m).

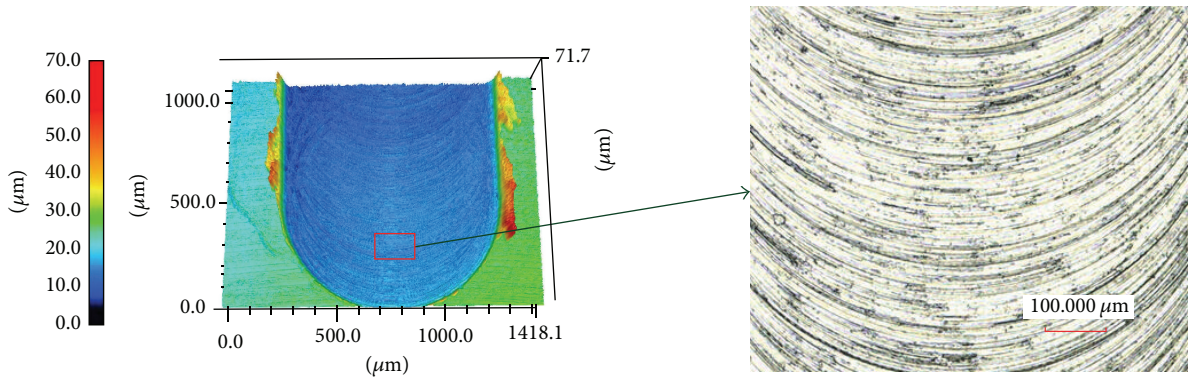
(c) Figure 12 shows that the value of surface roughness becomes large with increasing of feed rate and depth of cut with $n = 14000$ r/min. And the feed rate has greater influence on the surface roughness than depth of cut. The value of surface roughness is the minimum when depth of cut and feed rate are the minimum value.

The profile of machined surface mainly depends on the feed rate. The distance between two adjacent profiles becomes larger when the feed rate is increased as shown in Figure 13. And from Figure 13, there is another conclusion where the height of burr becomes smaller with increasing of the feed rate. Maybe this is because of size effect where the cutting edge radius is less than the grain size of 6061-T6 Al alloy. Another reason is the chips stick together for Al alloy's cohesive property. Hence the burr is high because the chip is difficult to remove.

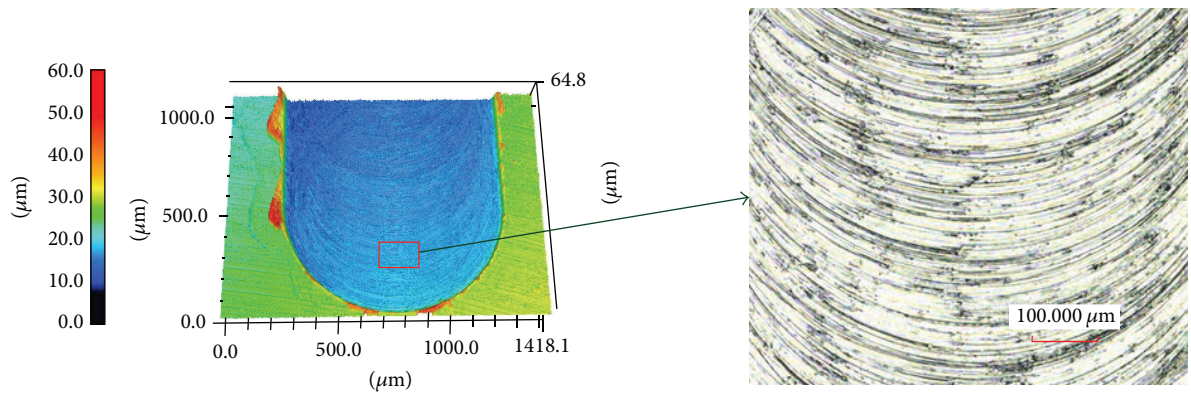
In regression analysis, the significance of regression equation does not mean that the influence of each independent variable on the dependent variable is important. Test of regression coefficients is needed where the purpose is to

Table 6: Significance test analysis of regression coefficient.

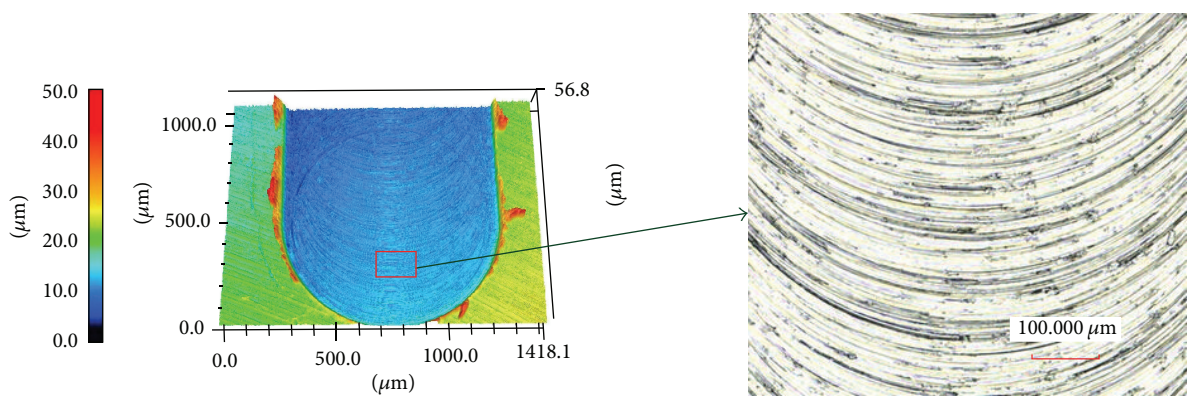
	β_1	β_2	β_3	β_{11}	β_{22}	β_{33}	β_{12}	β_{13}	β_{23}
P value	0.000	0.018	0.022	0.372	0.272	0.782	0.431	0.240	0.562
Significant degree	(1)	(2)	(3)	(6)	(5)	(9)	(7)	(4)	(8)



(a) Feed rate is 1.2 μm/r



(b) Feed rate is 1.6 μm/r



(c) Feed rate is 2.0 μm/r

Figure 13: The profile of machined surface by micro milling process with 1 mm milling cutter (n = 14000 r/min, a_p = 10 μm).

examine significant degree of each independent variable on the dependent variable and thereby test results can be better forecasted and controlled. Table 6 is the significance test analysis of regression coefficients.

From Table 6, the difference of influence on surface roughness prediction model by the spindle speed, depth of cut, and feed rate can be seen. Spindle speed and feed rate have significant influence on surface roughness. Improving the spindle speed and reducing feed rate and depth of cut can effectively reduce the micro milling surface roughness values under this experimental condition. The comparison of surface roughness between the predicted values which

Table 7: Results of verification tests.

Number	n [r/min]	f [μm/r]	a_p [μm]	Surface roughness R_a [μm]	
				Predicted value	Experimental value
1	10000	2.0	50	1.395	1.359
2	12000	1.2	40	1.417	1.400
3	14000	1.6	10	**1.209**	**1.248**
4	16000	2.0	30	1.233	1.195
5	18000	1.6	30	1.149	1.186

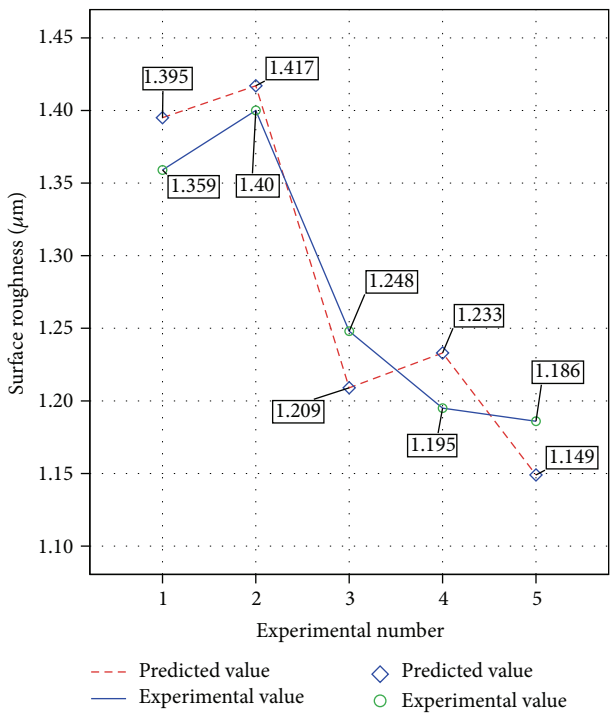


Figure 14: Comparison predicted with experimental value of surface roughness.

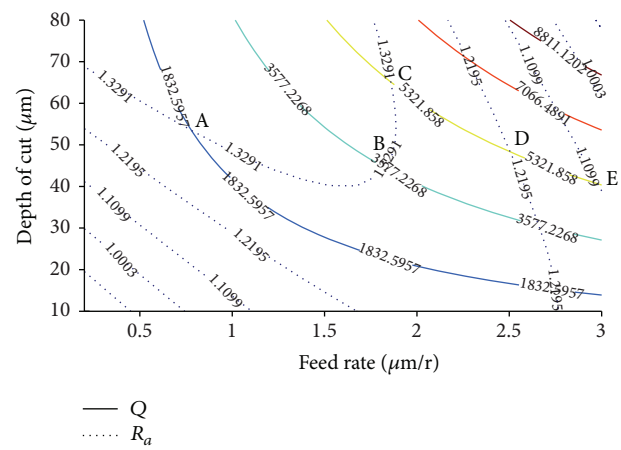


Figure 15: Contours of surface roughness and metal removal rate at n = 14000 r/min.

obtained by (4) through the quadratic response surface and experimental values is shown in Table 7 and Figure 14, and from Table 7, the error between predicted value and experimental value is less than 3.13%, so the error is allowable and the accuracy of the prediction model is proved.

In the optimization of cutting parameters, the value range of factors which have great effect must be determined to ensure the R_a value of the mechanical parts. And for the choice of small effect factors, improving the machining efficiency in relation to the parts should be considered. The material removal rate [18] can be defined as

$$Q = \frac{\pi D n f a_p}{1000}. \tag{5}$$

From Table 3 and (4), it can be concluded that

$$\begin{aligned} R_a = {} & 3.4123 - 2.5665 \times 10^{-4} n + 0.1535 f - 0.01111 a_p \\ & + 3.725 \times 10^{-9} n^2 - 0.115625 f^2 - 4.5 \times 10^{-5} a_p^2 \\ & + 2.9125 \times 10^{-5} n f + 1.78 \times 10^{-6} n a_p - 4.725 \\ & \times 10^{-3} f a_p. \end{aligned} \tag{6}$$

In the process of micro milling, the purpose of optimizing the cutting parameters is to improve cutting efficiency under the premise without increasing the surface roughness. Combining the above analysis, the determination of the scope of n can ensure the value of R_a. Then appropriate f and a_p are chosen to improve the value of Q. Assume that n = 14000 r/min and combine (5) and (6); the contour between R_a and Q can be drawn as shown in Figure 15.

From Figure 15, the contours of R_a = 1.3291 μm and Q = 1832.5957, 3577.2268, 5321.858 mm^3/min intersect at points A, B, and C which show that these three groups of processing parameters have the same R_a value. However, at point C the machining efficiency is much higher than A and B; therefore, the metal removal rate of C is larger than that of A and B. In addition, under the same processing efficiency, the best surface quality can also be acquired by selecting reasonable parameters. From the contour lines of Q = 5321.858 mm^3/min it can be seen that point E processing parameters of R_a value are smaller than C and D. Therefore, in the actual processing, the optimal processing parameters ultimately can be determined by a combination of the specific production conditions. The optimal method may be not precisely to show the better parameters which will make the minimum surface roughness and the maximum metal removal rate. However, it can give the manufacturing engineer the approximate value of surface roughness and metal removal rate which can effectively help them to choose the proper cutting parameters when machining the similar material. Because of the time and the length of the paper, in the long future, a lot of new

optimization techniques such as artificial neural network and Genetic Algorithm should be considered and made better use of to improve the surface finish.

4. Conclusion

A new mathematical model has been developed to predict the surface roughness of micro milling of 6061-T6 aluminum alloy. The experimental plan is based on the central composite circumscribed (CCC) design. The validity of the model is checked by ANOVA and F-test. The following conclusions can be drawn as follows:

(a) A new surface roughness model is built using the RSM method for micro milling process, in which feed rate, spindle speed, and depth of cut are considered. Upon examination, the model has high confidence and practicality in the test conditions. The model can be used to select proper cutting parameters in order to predict and control surface roughness before machining.

(b) The surface roughness increases with the increasing of feed rate and the decreasing of the spindle speed.

(c) With the increasing feed rate, the distance between two adjacent profiles becomes larger, and the height of burr becomes smaller.

(d) After determining the scope of the main factors, the contour map between the surface roughness and material removal rate can be obtained to optimize the process parameters under the specific production conditions.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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