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Optimization of Turning Bearing Steel Parameters for PCBN Tools Based on RSM

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Abstract: *Aiming at the bearing steel material brittleness, low thermal conductivity and easy to produce excessive cutting force during machining caused by machine vibration, resulting in reduced machining accuracy of the difficult problem, it is proposed to use the response surface method to establish the bearing steel turning process surface roughness and cutting force of the regression model, the constructed regression model as an adaptive function; according to the adaptive function and the constraints of the optimal combination of the cutting amount of superior The results show that: the optimal combination of the cutting tools is selected. The results show that the optimal combination of cutting dosage can reduce the surface roughness to 1.39065μm and the cutting force to 29.9846N.*
Keywords: *cutting force; surface roughness; cutting performance; RSM; parameter optimization*

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I. Introduction

Bearing steels are used to make balls for rolling bearings, precision gauges and precision parts for diesel engine pumps because of their high and uniform hardness and wear resistance and high elastic limit [1-3]. High-quality machined surfaces are critical to the performance of bearing steel precision parts, so high-speed hard cutting has become an important machining method for processing bearing steel. And cutting force as a high-speed hard cutting process control of the important indicators, research predicts the rule of change to optimize the cutting process, thus helping to reduce or eliminate cutting vibration. At this stage, how to reduce the cutting force generated by cutting bearing steel, improve the surface quality of the workpiece has become a hot issue in today's research [4-6].

At the present stage, the methods for optimization and prediction of bearing steel machining process tend to utilize orthogonal experiments, polar analysis, multiple linear regression, Monte Carlo methods and artificial neural networks [7-10]. And Response Surface Methodology (RSM), as a powerful statistical and mathematical technique, has many advantages in experimental design and optimization. Xu et al. used RSM to optimize the main process parameters of minimum trace lubrication assisted cutting, and obtained a set of optimum process parameters with an error of only 2.91% between the experimental value and the predicted value [11]. Faisal M.H et al. used CBN coated tool to cut aluminum alloy under different cutting parameters to enhance the tool life, RSM test analysis was carried out to obtain a set of optimum combination of turning parameters under which the cutting test was carried out and the tool life was enhanced by more than 20 min [12].

After the above analysis, it can be seen that previous research often focuses on the optimization of a single objective, while for cutting, the enhancement of machining quality and machining efficiency is jointly determined by a number of factors. Therefore, this paper uses the response surface method to establish the regression model of surface roughness and cutting force in the turning process of bearing steel, and the constructed regression model is used as an adaptive function, and the optimal combination of cutting dosage is preferred according to the adaptive function and constraints.

II. Materials and Methods

2.1. Experimental setup

In this paper, the object of study for the GCr15 bearing steel, according to the experimental conditions to determine the specifications of the workpiece is: Φ50X150 round bar, both ends of the processing of the top hole, the surface of the pre-turning. Lathe selection CA6140A ordinary lathe, and in the tool holder installed Kistler 9527B type force gauge for cutting force measurement. Figure 1 shows the machine tool used in this study and the sensor system used to measure the cutting forces. Table 1 illustrates the chemical composition and physical properties of the bearing steel bar stock used in this study. The tool was made of polycrystalline cubic boron nitride (PCBN) inserts embedded in the shank of the tool model MCLN2525M12.The PCBN inserts had a forward angle of -6^{o}, a backward angle and a main deflection angle of 91^{o}, a tip radius of 0.4mm and a thickness of 4.76mm.

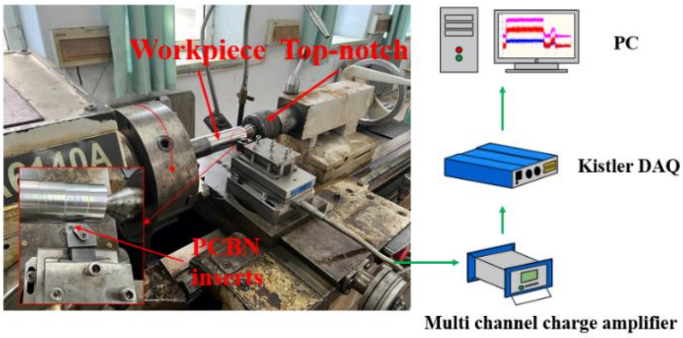


Figure 1. Machine tools and force measurement systems.

Table 1. Chemical elements and physical properties of GCr15.

Chemical element	Content (%)	Chemical element	Content (%)	Physical properties	Values
C	0.95-1.05	Ni	≤0.3	Poisson's ratio	0.277
Si	0.15-0.35	Mo	≤0.1	Young's modulus【Gpa】	201
Mn	0.2-0.4	Cu	≤0.25	Specific heat capacity【J/(kg • ℃)】	340
Cr	1.3-1.65	P	≤0.027	Thermal conductivity【W/ (m • ℃)】	52.5
S	≤0.02	Ni+Cu	≤0.5	Coefficient of thermal expansion【/℃】	11.5×10^{-6}

The equipment used to measure the surface roughness of the workpiece in this study is the Zegage Pro HR optical profilometer, when using the Zegage Pro HR optical profilometer for surface roughness measurement, in order to minimize the surface roughness measurement error, the roughness measurement is carried out at intervals of 72^{o}, and the whole outer circle is measured for a total of five times, and the average of the five roughness measurements is calculated.

2.2. Experimental Design

Response surface methodology (RSM) based on Box-Behnken design (BBD) was used to design cutting parameter optimization experiments [13,14]. RSM is a multivariate statistical analysis method used to study the relationship between independent and dependent variables, which can visualize complex multivariate relationships into simple two-dimensional or three-dimensional graphs, and can intuitively explain the relationship between variables. In the field of machining, RSM is used to optimize the process and improve product quality by studying the effect of cutting parameters on cutting forces and surface roughness. To achieve this goal, the cutting parameters are designed as variable parameters. The cutting parameter levels are shown in Table 2.

Table 2. Levels of cutting parameters.

Symbol	Factors	Unit	level		
			-1	0	1
v	Spindle speed	r/min	1000	1250	1600
f	Feed rate	mm/r	0.1	0.15	0.2
a_p	Depth of cut	mm	0.1	0.15	0.2

A total of 17 groups of experiments were designed using BBD, and the cutting experiments were carried out in the same cutting environment, and the tool was replaced after each cutting, and the experimental parameters and results are shown in Table 3. From Table 3, it can be seen that the surface roughness increases with the increase of feed and the cutting force increases with the increase of depth of cut. Therefore, in order to obtain better surface roughness and smaller cutting force, it is necessary to optimize the cutting parameters with the optimization objective of reducing surface roughness and cutting force.

Table 3. Experimental layout and measurement results.

No.	Cutting Parameter			R_a(μm)	F_x(N)
	v(r/min)	f(mm/r)	a_p(mm)		
1	1000	0.1	0.15	1.303	35.12
2	1600	0.1	0.15	1.318	35.927
3	1000	0.2	0.15	1.54	39.26
4	1600	0.2	0.15	1.652	40.98
5	1000	0.15	0.1	1.423	21.5505
6	1600	0.15	0.1	1.599	23.007

7	1000	0.15	0.2	1.439	50.29
8	1600	0.15	0.2	1.365	50.61
9	1250	0.1	0.1	1.418	27.722
10	1250	0.2	0.1	1.686	20.035
11	1250	0.1	0.2	1.317	46.34
12	1250	0.2	0.2	1.605	55.64
13	1250	0.15	0.15	1.396	37.09
14	1250	0.15	0.15	1.436	38.48
15	1250	0.15	0.15	1.412	38.63
16	1250	0.15	0.15	1.388	38.46
17	1250	0.15	0.15	1.451	38.37

2.3. RSM Modeling

The RSM model can be expressed as a polynomial function. Among them, the first-order regression prediction model lacks accuracy and adaptability, has a large fitting error, and cannot effectively respond to the effect of the cutting parameters on the surface roughness (cutting force) between the cutting parameters, although the fitting error can be reduced by increasing the order of the regression prediction model, the overfitting phenomenon leads to an increase in the model's prediction instability, and the increase in the coefficients to be determined makes the model to the number of samples demanded also increased dramatically. increase, leading to a decrease in modeling efficiency and an increase in the cost and burden of experimentation. Although the use of artificial neural networks produces good results in terms of quality and accuracy of the model, they are subject to problems such as overfitting, poor interpretability, the need for a large number of parameters and sensitivity to initial weights. Therefore, in this study, a quadratic polynomial regression prediction model was developed with the expression shown in equation (1).

$$y = a_0 + \sum_{j=1}^{3} a_j x_j + \sum_{j=1}^{3} \sum_{k=1}^{3} a_{jk} x_j x_k + \sum_{j=1}^{3} a_{jj} x_j^{\,2} + \varepsilon \qquad (1)$$

Where: y is the expected response, a_0 is a constant, a_j, a_{jj} and a_{jk} are the coefficients of the linear, quadratic and cross product terms, respectively, ε is the fitting error, and x_j is the input factor to the model.

III. Results and Discussion

3.1. Analysis of Experimental Results Based on RSM

In this study, the response surface correlation analysis was carried out using data analysis software, and the following model was obtained by establishing the regression equation of the RSM model for surface roughness and cutting force based on the data in Table 3 and equation (1).

$$\begin{aligned} R_a &= 1.42 + 0.0286v + 0.1409f - 0.05a_p + 0.0242vf \\ &-0.0625va_p + 0.005fa_p - 0.0067v^2 + 0.0433f^2 + 0.0466a_p^{\,2} \end{aligned} \qquad (2)$$

$$\begin{aligned} F_x &= 38.21 + 0.5379v + 1.35f + 13.82a_p + 0.2282vf \\ &-0.2841va_p + 4.25fa_p - 0.7271v^2 + 0.3428f^2 - 1.11a_p^{\,2} \end{aligned} \qquad (3)$$

In this study, the credibility of the model was assessed from both statistical and experimental perspectives through ANOVA and experimental validation, and the results of the ANOVA for R_a and F_x are presented in Tables 4 and 5, respectively.

As can be seen from Table 4, the F-value of the R_a model is 55.7 and the P-value of the model is less than 0.0001, which indicates that the established R_a model is extremely significant. The P-value of the primary terms v, f, a_p, interaction term $v \times a_p$, and secondary terms f^2, a_p^2 is <0.01, which indicates that the effect on the surface roughness R_a is extremely significant and the other factors are not significant. The C.V. is 1.44% <10%, which indicates that the experiments are highly credible and accurate. The Adeq Precision, which is the ratio of the effective signal to the noise, is considered to be reasonable for a value greater than 4. The R^2 and Adjusted R^2 of R_a model are 98.62% and 96.85% respectively, and the difference between them is only 1.77%, which is negligible, indicating that the polynomials established can adequately respond to the relationship between the design variables and the response with good adaptability.

From table 5 it is clear that the F-value of F_x model is 134.44 and the P-value of the model is less than 0.0001. primary term a_p, P-value of interaction term $f \times a_p$ <0.01 indicates extremely significant effect on cutting force F_x, P-value of primary term f <0.05 indicates significant effect on cutting force F_x and other factors are not significant. c.v. is 4.09% <10% and Adeq Precision has a value greater than 4. The R^2 and adjusted R^2 of F_x model are 99.42% and 98.69% respectively and the difference between them is only 0.73%.

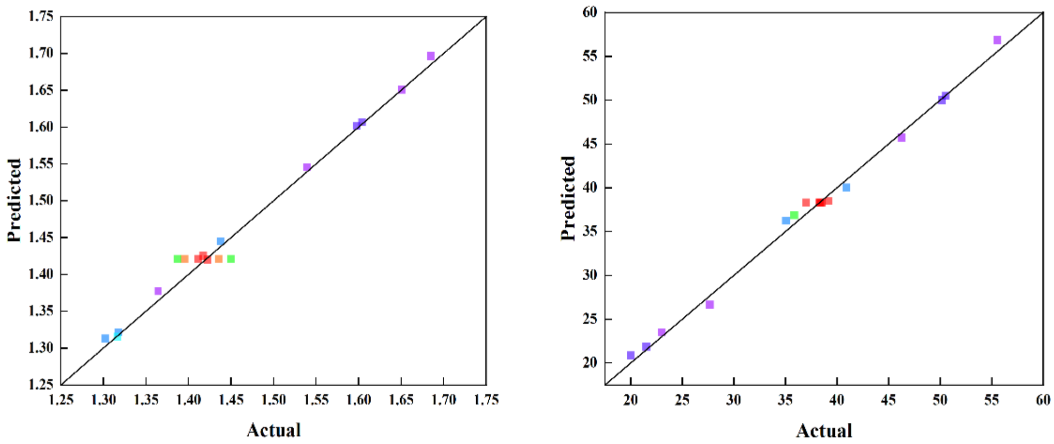
Table 4. ANOVA for cutting R_a.

Source	Sum of Squares	Degrees of Freedom	Mean Square	F-value	P-value	Remarks
Model	0.2214	9	0.0246	55.7	<0.0001	Significant
v	0.0066	1	0.0066	14.84	0.0063	Significant
f	0.1588	1	0.1588	359.5	<0.0001	Significant
a_p	0.02	1	0.02	45.29	0.0003	Significant
$v\times f$	0.0024	1	0.0024	5.33	0.0544	
$v\times a_p$	0.0156	1	0.0156	35.38	0.0006	Significant
$f\times a_p$	0.0001	1	0.0001	0.2264	0.6487	
v^2	0.0002	1	0.0002	0.4248	0.5354	
f^2	0.0079	1	0.0079	17.9	0.0039	Significant
$a_p^{\ 2}$	0.0091	1	0.0091	20.68	0.0026	Significant
Residual	0.0031	7	0.0004			
Cor total	0.2245	16				
R^2	0.9862				Std. Dev.	0.021
Adjusted R^2	0.9685				Mean	1.46
Predicted R^2	0.9612				C.V.%	1.44
Adeq Precision	22.8478					

Table 5. ANOVA for cutting F_x.

Source	Sum of Squares	Degrees of Freedom	Mean Square	F-value	P-value	Remarks
Model	1625.76	9	180.64	134.44	<0.0001	Significant
v	2.32	1	2.32	1.72	0.2307	
f	14.6	1	14.6	10.86	0.0132	Significant
a_p	1528.09	1	1528.09	1137.25	<0.0001	Significant
$v\times f$	0.2084	1	0.2084	0.1551	0.7054	
$v\times a_p$	0.3229	1	0.3229	0.2403	0.6390	
$f\times a_p$	72.14	1	72.14	53.69	0.0002	Significant
v^2	2.23	1	2.23	1.66	0.2390	
f^2	0.4948	1	0.4948	0.3683	0.5631	
$a_p^{\ 2}$	5.23	1	5.23	3.89	0.0891	
Residual	9.41	7	1.34			
Cor total	1635.16	16				
R^2	0.9942				Std. Dev.	1.16
Adjusted R^2	0.9869				Mean	37.50
Predicted R^2	0.9220				C.V.%	3.09
Adeq Precision	40.6447					

The distribution of predicted and actual values of surface roughness R_a and cutting force F_x are plotted in Figure 2. From Figure 2, it can be seen that the distributions of predicted and actual values of R_a and F_x are approximately on a straight line, indicating that the model fitted using RSM is well adapted.



(a) R_a Predicted vs. Actual (b) F_x Predicted vs. Actual

Figure 2. R_a and F_x Predicted vs. Actual.

In order to verify the reliability of the constructed model, experimental validation was also carried out in this study. Cutting parameters within the experimental interval were randomly selected, and the experimentally measured R_a and F_x values were compared with the calculated results of the constructed model. The relative errors of the experimental parameters, experimental results and predicted results are shown in Table 6. As can be seen from Table 6, the maximum relative errors of R_a and F_x are 2.59% and 3.749%, respectively, which are within the acceptable range of error, indicating that the model has good prediction results.

Table 6. Results of confirmation experiments and their comparison with predicted values.

Exp.No.	Design Parameters			R_a (μm)			F_x (N)		
	v (r/min)	f (mm)	a_p (mm/r)	Exp.	Predicated	Error (%)	Exp.	Predicated	Error (%)
1	1000	0.2	0.1	1.541	1.574	2.14%	19.16	18.95	1.096%
2	1000	0.15	0.15	1.364	1.385	1.54%	36.24	36.95	1.959%
3	1250	0.2	0.15	1.588	1.604	1.01%	40.09	39.91	2.872%
4	1250	0.15	0.2	1.398	1.417	1.36%	49.53	50.92	2.806%
5	1600	0.2	0.1	1.852	1.804	2.59%	21.87	21.05	3.749%
6	1600	0.15	0.15	1.429	1.442	1.62%	38.42	38.02	1.041%

The normal probability distributions of the R_a and F_x residuals are plotted in Figure 3. From Figure 3, it can be seen that most of the residuals are tightly clustered around a straight line, which indicates that the model is well adapted. Figure 4 depicts a perturbation plot showing the effect of cutting parameters on R_a and F_x. The results show that the feed has a significant effect on the surface roughness and the spindle speed has the least effect on the surface roughness; this is mainly due to the fact that too large a feed will lead to increased friction, heat generation and a decrease in the surface roughness, and the change in feed will also affect the size and shape of the chips produced during the cutting process, and the optimum chip formation is essential for obtaining a smooth surface roughness. The depth of cut has the most significant effect on the cutting force, while the spindle speed and feed have less effect on the cutting force. The main reason for this is that as the depth of cut increases, the contact area between the tool and the material increases, resulting in greater cutting forces.

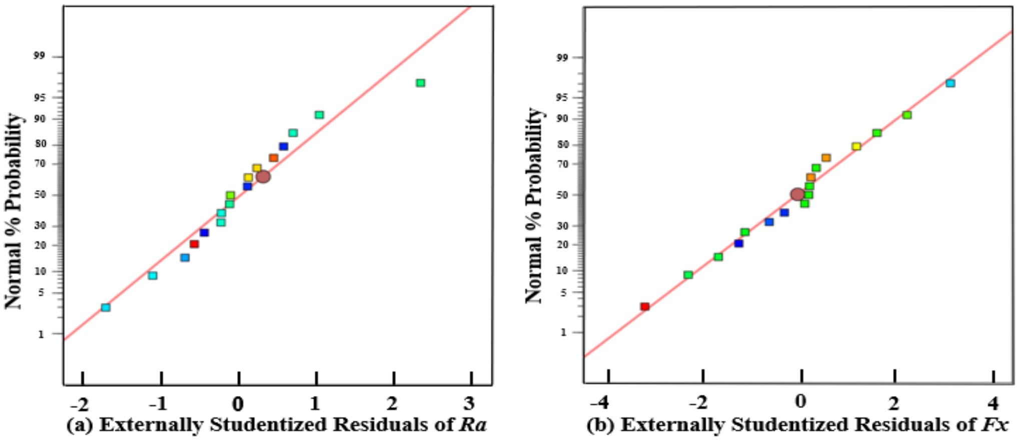
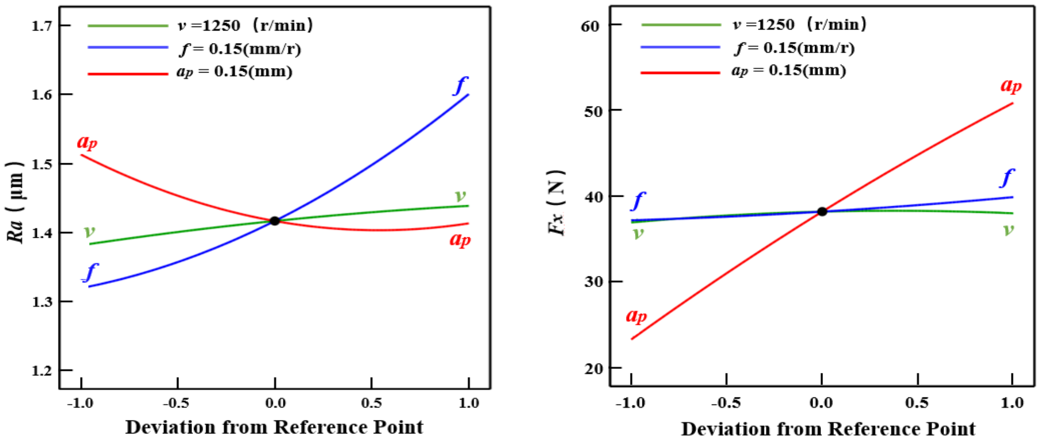


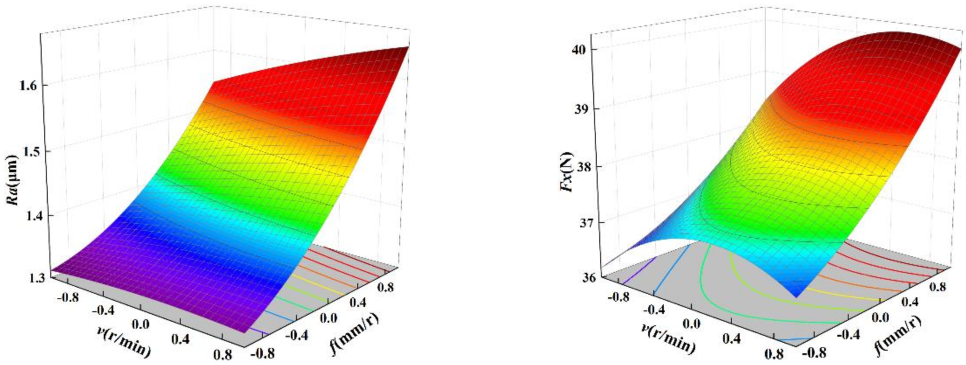
Figure 3. Normal plot of R_a and F_x .



(a) Perturbation plots of R_a (b) Perturbation plots of F_x

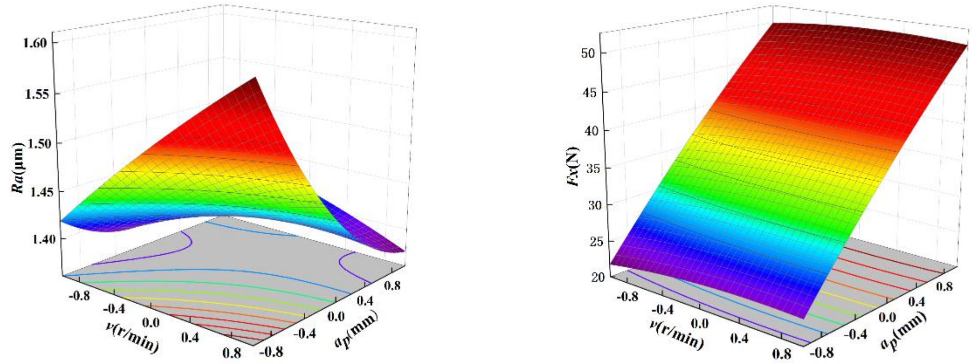
Figure 4. Perturbation plots of R_a and F_x .

The three-dimensional stereo response surface of the effect of cutting parameters on surface roughness (cutting force) is shown in Figures 5-7. Examining the cutting parameters of a factor fixed in the center value of the case of constant, the interaction of the other two factors on the surface roughness (cutting force). Figure 5 shows the effect of spindle speed and feed on the surface roughness (cutting force) while the depth of cut is kept at the center level. From Figure 5(a), it can be seen that surface roughness increases with increase in feed and spindle speed and from Figure 5(b), it can be seen that cutting force increases with increase in feed and spindle speed. Figure 6 shows the effect of spindle speed and depth of cut on surface roughness (cutting force) with feed kept at intermediate level. From Figure 6(a), it can be seen that when the spindle speed is higher and the depth of cut is smaller, the surface roughness is larger, but with the increase of depth of cut, the surface roughness decreases gradually. From Figure 6(b), it can be seen that the cutting force increases with the increase of spindle speed and depth of cut. Figure 8 shows the effect of feed and depth of cut on surface roughness (cutting force) with spindle speed kept at intermediate level. From Figure 7(a), it can be seen that the surface roughness increases when the feed is larger and the depth of cut is smaller, and from Figure 7(b), it can be seen that the cutting force increases with the increase of feed and depth of cut.



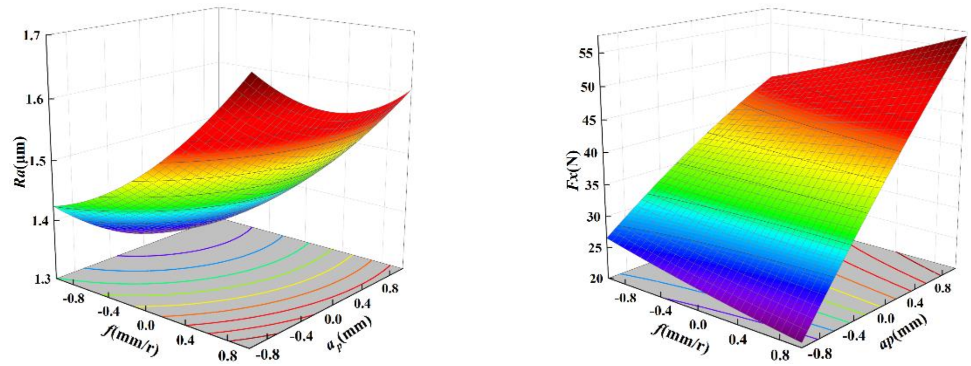
(a) RSM interaction surface plot between *Ra* Vs *v* and *f* (b) RSM interaction surface plot between F_x Vs *v* and *f*

Figure 5. Influence of feed rate and Spindle speed on R_a and F_x .



(a) RSM interaction surface plot between *Ra* Vs *v* and a_p (b) RSM interaction surface plot between F_x Vs *v* and a_p

Figure 6. Influence of depth of cut and Spindle speed on R_a and F_x.



(a) RSM interaction surface plot between *Ra* Vs *f* and a_p (b) RSM interaction surface plot between F_x Vs *f* and a_p

Figure 7. Influence of feed rate and depth of cut on R_a and F_x .

The optimum combination of turning parameters is derived from the three-dimensional response surface. The schematic representation of the optimum parameters is shown in Figure 8, which shows that in order to obtain a surface roughness of 1.39065μm and a cutting force of 29.9846 N, a spindle speed of 1280 r/min, a feed of 0.106 mm/r, and a depth of cut of 0.185mm are recommended.

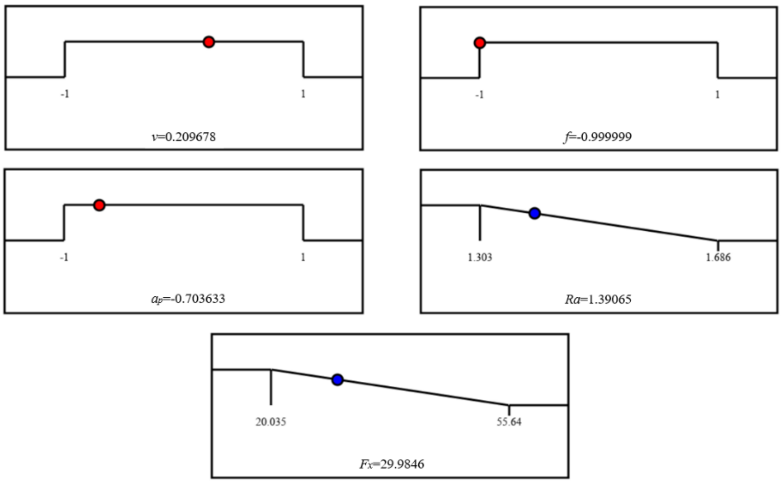


Figure 8. Optimum conditions for R_a and F_x.

IV. Conclusions

In this paper, the response surface method is used to establish the regression model of surface roughness and cutting force in the turning process of bearing steel, and the constructed regression model is used as an adaptive function, and the optimal combination of cutting dosage is preferred according to the adaptive function and constraints. It is found through the study:

1. The effect of cutting parameters on cutting force and surface roughness was analyzed by RSM and it was found that the feed had the most significant effect on surface roughness followed by depth of cut and spindle speed had the least effect on surface roughness. The most significant effect on cutting force is depth of cut followed by feed and spindle speed has the least effect.
2. In this paper, the response surface method (RSM) is used to establish a quadratic polynomial regression model of cutting parameters and surface roughness (cutting force). Through ANOVA analysis and experimental verification, the constructed regression model can respond to the relationship between the cutting parameters and the surface roughness (cutting force), and improve the machining efficiency as much as possible under the premise of guaranteeing the machining accuracy, which provides a theoretical basis for the subsequent production of parts.

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