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Research paper

Prediction of Machining Characteristics of Hybrid Composites Using Response Surface Methodology Approach

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Abstract

This manuscript presents the influencing parameters of CNC turning conditions to get high removal rate and minimal response of surface roughness in turning of AA7075-TiC-MoS2 composite by response surface method. These composites are particularly suited for applications that require higher strength, dimensional stability and enhanced structural rigidity. Composite materials are engineered materials made from at least two or more constituent materials having different physical or chemical properties. In this work seventeen turning experiments were conducted using response surface methodology. The machining parameters cutting speed, feed rate, and depth of cut are varied with respect to different machining conditions for each run. The optimal parameters were predicted by RSM technique. Turning process is studied by response surface methodology design of experiment. The optimal parameters were predicted by RSM technique. The most influencing process parameter predicted from RSM techniques in cutting speed and depth of cut.

Keywords: *Hybrid composites; Material removal rate; ANOVA.*

1. Introduction

A Light weight metal matrix composite (MMC) imparts several advantages over alloys. The MMCs exhibit improved properties compared with monolithic alloy. They are particularly suited for applications that require higher strength, dimensional stability and enhanced structural rigidity [1]. Composite materials are engineered materials made from at least two or more constituent materials having different physical or chemical properties. In short, the composite materials are multi-functional systems that exhibit characteristics from all the individual components [2]. Aluminium based MMCs are the widely used matrix materials for MMCs. It was identified as conventional materials that can be used for several commercial and industrial applications. The reduction in the gross-weight of a component can reduce the fuel consumption and thereby reduce the dependence over fossil fuels. It helps to reduce the emission of greenhouse gases and thereby keeps the pollution under control. Replacing conventionally used material with MMCs can improve the fuel economy and can enhance the engine aspiration. The commercial exploitation of MMC is now becoming significant [3]. Literatures reported that just lowering the body weight without reducing the weight of the power train would not alter the fuel economy. Such that to enhance the fuel economy the engine material has to be replaced with lighter materials [4]. Though Al-based MMCs in automobiles enhances the efficiency of the engine, the higher processing cost does not recommend its usage over the steel counter parts. However, dramatic energy saving was observed when recycled Al parts were used. This suggests that the energy can be saved through the usage of recycled Al parts [5]. Response Surface Methodology has become a very powerful tool in the mathematical modeling of functional-relationships between the output responses and the input variables. Various studies have been carried out based on the prediction of mechanical and wear behavior of composites using RSM. The author analysed the various modeling methods that can be used to define the desired output variables through the development of mathematical models. One of the most widely used methods to solve this problem is RSM. It can be adopted to develop a suitable approximation method, which shows the functional relationship between the independent variables [6]. The specific wear rate among these response variables characterizes the nature of the Al-TiB2composite. Nalbanth have observed that RSM is helpful in developing a suitable approximation for the true functional relationship between the independent variables and the response variable that may characterize the nature of the machining [7]. It has been proved that efficient use of statistical design on experimental techniques allows the development of an empirical methodology to incorporate a scientific approach [8]. Ramanan et al have explained that RSM is a collection of mathematical and statistical techniques, which consist of experimental design for defining the range of independent input variables and empirical mathematical model [9]. The empirical mathematical model is used to explore an appropriate relationship between the output responses and the input variables. Author developed a numerical model to predict the abrasive wear rate of AA7075 alloy reinforced with SiC particles. This model was developed using RSM [10]. Baskaran et al have observed that RSM provides quantitative measurements for possible interactions between factors so as to obtain difficult information using other optimization techniques for composites [11]. So this research work is planned to predict the influencing parameters between various factors play a critical role especially for multivariable optimization in engineering problems and application of RSM in the prediction of characteristics process of composites.

2. Experimental Design

Experimentation and optimization of cutting parameters are done based on the response surface methodology. CNC turning machine is used for performing the machining operation. Experimental design is created by Minitab software followed by statistical analysis. Statistical studies of computer applications have some advantage like reliable, accurate and usually runs faster than other computing statistics and drawing graphs. Minitab is relatively simple to use when you know some fundamentals. Today, Minitab is frequently utilized along with Six Sigma and various statistics methods. Machining the metal matrix composite wire cutting operation using turning process in obtaining the required measurement of the work pieces. Then performing machining operation on the samples in different cutting environments connecting different grouping of process control parameters. MRR is calculated for the work piece during the machining operation. SR is calculated using a surface roughness profilometer. ANOVA analysis for regression test used to find the significant parameters. The process parameters affecting the turning process machining characteristics is given below. Cutting Speed (A), Feed Rate (B), Depth of cut (C). In the optimization design involving RSM, the initial task is to create the optimization model, like the system identification measures along with selection of the criteria which influence the scheme determines significantly.

Table.1. Variables and levels

Symbol	Cutting Parameter	Level 1	Level 2	Level 3	Units
A	Cutting speed	120	180	250	m/min
B	Feed rate	0.05	0.06	0.075	mm
C	Depth of Cut	1	1.25	1.5	mm

Input parameters of turning process were fixed from the machine setting. The tests were performed adapting standard procedure with process parameter depicted in the Table.1. A total of 17 tests (machining operations) need to be performed for 3 process parameters at 3 levels. The SR after each test was measured with the surface roughness profilometer SJ301. The observations are presented in the Table.1 which are further studied and analysed. The machining operations were followed as per the design matrix at random for avoiding systematic errors. Adapting RSM with a Box–Behnken design for 3 variables and 3 levels, the average number of tests carried out for machining process parameter are fixed.The corresponding MRR and SR recorderd are presented in Table.2.

Table.2. Design matrix of the experiments with the optimal model data

Experiment	Cutting speed	Feed	Depth of Cut	Material Removal Rate	Surface Roughness
	A	B	C	(mm3/min)	Ra(µm)
1	180	0.06	1.25	4.57	1.23
2	180	0.06	1.25	5.25	0.98
3	180	0.07	1.0	6.74	1.35
4	250	0.07	1.25	8.24	1.34
5	120	0.07	1.25	3.24	0.89
6	180	0.06	1.25	5.25	0.97
7	120	0.05	1.5	4.14	0.85
8	250	0.05	1.25	7.65	1.31
9	180	0.07	1.5	6.24	1.54
10	250	0.06	1.0	7.58	1.21
11	250	0.06	1.25	6.97	1.36
12	120	0.07	1.25	3.45	0.97
13	180	0.05	1.0	5.12	1.15
14	120	0.06	1.0	3.57	1.04
15	180	0.05	1.5	5.12	1.21
16	120	0.07	1.25	3.25	0.94
17	250	0.06	1.5	6.14	1.28

3. Modelling and Prediction

3.1. Multiple Regression Analysis

The experimental data is analyzed to create a multi-regression equation. The regression equations are used to generate sufficient data to train the proposed predictive networks along with the experimental data. The dependency of MRR and Ra asinput is developed using the multi-regression equation. The effect of machining parameters on the output variables of MRR and SR for MMC was performed by experiments as explained in Table 2. Minitab 17.0 version software is used to find the relationship between the input parameters and the output parameters of MRR and SR. To choose the degree of regression model, the values of coefficientof determination (R2) and adjusted R2-statistic (R2adj) are compared and recapped in Table 3 for MRR and Table 4 for SR. The full quadratic model for MRR and SR is the best and suitable among all models before the backward elimination, as listed in the Table 4 and 5, where R2 = 98.58% for MRR and R2 = 99.80% for SR indicates that 98.58% and 99.80% of total variation in the responses is elucidated by predictors or factors in the model. However, R2adj is 97.44% for MRR and 99.64% for SR, which accounts for the number of predictors in the model describe the significance of relationship. Hence, the full quadratic model is regarded for further analysis in the study.

Table 3. Result Obtained in RSM for MMC

Sl. No.	MRR (mm^3/min) Exp. Value	SR (µm) Exp. Value	MRR (mm^3/min) Predicted Value	SR (µm) Predicted Value	MRR Error	SR Error
1.	4.57	1.23	4.27	1.34	5.283361208	5.16249
2.	5.25	0.98	5.35	0.242	4.931776532	4.12654
3.	6.74	1.35	6.54	1.24	1.189348896	7.17271
4.	8.24	1.34	8.14	1.244	2.278342566	5.78388
5.	3.24	0.89	3.44	0.24	9.462217665	2.86921
6.	5.25	0.97	5.12	0.24	7.591042951	9.83644
7.	4.14	0.85	4.85	0.24	8.287360442	3.46337
8.	7.65	1.31	7.53	1.42	4.844714476	5.27183
9.	6.24	1.54	6.34	1.42	3.358626309	8.54918
10.	7.58	1.21	7.32	1.75	0.411428718	2.40341
11.	6.97	1.36	6.32	1.24	5.284973891	5.59303
12.	3.45	0.97	3.25	0.24	3.053457511	9.69701
13.	5.12	1.15	5.5345	1.425	2.172414068	6.05945
14.	3.57	1.04	3.425	1.425	7.653737188	7.58442
15.	5.12	1.21	5.42	1.24	3.505049632	3.13587
16.	3.25	0.94	3.42	0.24	0.475970987	4.95097
17.	6.14	1.28	6.42	1. 82	7.557121727	7.29921

It is observed that both the experimental values and predicted values using multiple regression models coincide each other and forms a straight line and the experimental values are fit for further analysis.

4. Results and Discussion

Table.4. ANOVA for MRR Estimated Regression Coefficients for MMC

Basis	DF	Adj SS	Adj MS	F value	P value
Model	9	0.574625	0.053847	5.05	0.0125
Linear	3	0.418725	0.109575	7.14	0.0127
A	1	0.180113	0.027013	18.17	0.0011
B	1	0.035000	0.045000	3.28	0.0128
C	1	0.013612	0.013612	1.14	0.0145
Error	5	0.067775	0.017755		
Lack of Fit	3	0.055375	0.015125	0.70	0.5850
Pure Error	2	0.033400	0.01700	0.70	0.3750
Total	14	0.493400			

ANOVA is used to ensure the sufficiency of second-order model, which comprises test for significance of the regression model, coefficients of the model and test for the lack of fit. Table 4 for MRR and Table 5 for SR summarize the ANOVA of the model that includes two sources of variation, i.e, regression and residual error. The variation due to the terms in the model is the summation of linear and the square terms whereas lack of fit and the pure error contribute to residual error. The Table 4 and 5 depicts the sources of variation, Degree of Freedom, Sequential Sum Square Error, Adjusted Sum Square Error, Adjusted Mean Square Error, F Statistic and p-values in columns. The p-value of lack of fit is ≤ 0.05, and certainly indicates that there is statistically significant at 95% confidence level. However, the p-value of regression model and it's all linear and square terms have p-value 0.000, hence they are statistically significant at 95% confidence and thus the model adequately represent the experimental data.

Table 5. ANOVA for SR Estimated Regression Coefficients for MMC

Basis	DF	Adj SS	Adj MS	F value	P value
Model	9	0.484625	0.053847	3.03	0.0117
Linear	3	0.328725	0.109575	6.17	0.0390
A	1	0.270113	0.027013	15.21	0.0110
B	1	0.045000	0.045000	2.53	0.0172
C	1	0.013612	0.013612	0.77	0.4210
Error	5	0.088775	0.017755		
Lack of Fit	3	0.045375	0.015125	0.70	0.6350
Pure Error	2	0.043400	0.01700	0.70	0.6350
Total	14	0.573400			

4.1 Effects of Machining Parameters on MRR and SR

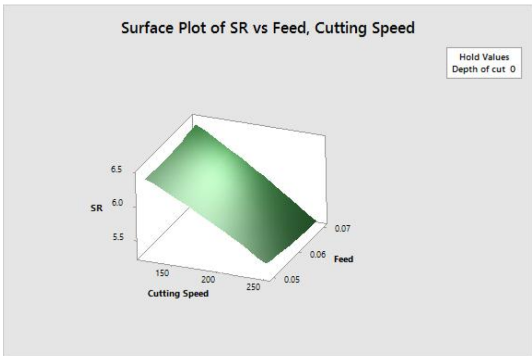

Fig 1. Effect of SR Vs. cutting speed and feed rate

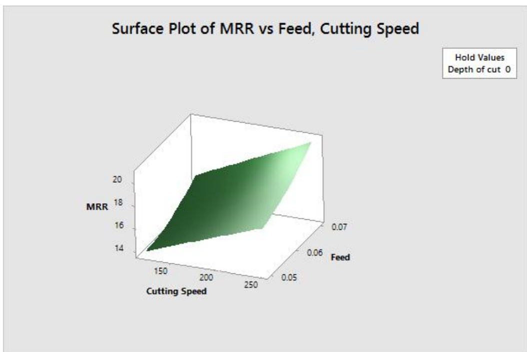

Fig 2. Effect of MRR Vs. cutting speed and feed rate

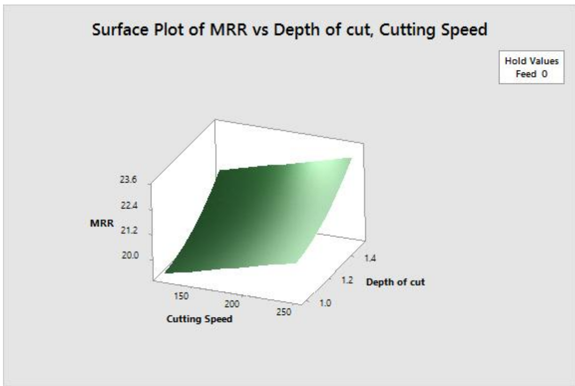

Fig 3. Effect of MRR Vs. Depth of cut and cutting speed

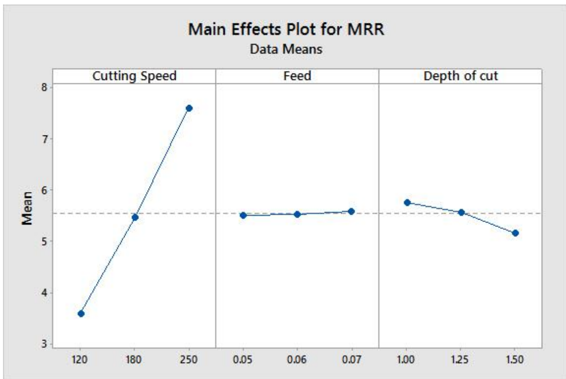

Fig 4. Main effect plot Effect of MRR

Fig 5. Main effect plot Effect of SR

The effects of process parameters ie, cutting speed, feed rate and depth of cut on MRR and SR are analysed by using the experimental values. Figure 1 and 2 explains the estimated response for SR and MRR with cutting speed and feed rate. This decreases when cutting speed at low level. It was observed that MRR exhibited improved values with higher cutting speed and feed rate. This is due to the high velocity of machine. The SR improves with higher feed rate and lower cutting speed Figure 3. The variation in SR exhibited a lower value with increased cutting speed and decreased depth of cut. Figure 4 and 5 shows the main effect plot of MRR and SR. this reveals cutting speed and feed rate ate most influencing parameter for this machining and depth of cut is insignificant process parameter for CNC machining of composites.

5. Conclusion

Turning process is done by response surface methodology design of experiment. The optimal parameters were predicted by RSM technique using experimental design. From concentrated response surface techniques on achieving a single quality characteristic at a time as a function of different appropriate levels of a number of input parameter settings. Improving one particular quality characteristic would possible lead to serious degradation of the quality characteristics. The optimal process parameter is predicted from RSM technique is 250m/min, 0.07mm, 1.5mm and responses are influencing process parameters are used to improve the machining characteristics.

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