MultiCraft

International Journal of Engineering, Science and Technology
Vol. 3, No. 6, 2011, pp. 78-87

INTERNATIONAL JOURNAL OF ENGINEERING, SCIENCE AND TECHNOLOGY
www.ijest-ng.com

Surface roughness prediction model in end milling of Al/SiC$_p$ MMC by carbide tools

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Abstract

The advancement in automation and accuracy of machine tool made it possible to produce high quality industrial products. One of the main perceptions of quality in mechanical products is its physical appearance. One of the most important factors in physical appearance is the surface roughness. A number of research publications addressed this issue of surface roughness measurement and analyses. This research focuses on study and analyses of surface quality improvement in end milling operation of Al/SiC$_p$ metal matrix composite. These materials are selected as they are most widely used in automobile and aerospace industry. This research paper develops an improved mathematical model for surface roughness (Ra) prediction in end milling of Al/SiC$_p$ MMC. The impacts of spindle speed, feed rate, depth of cut and various percentage weight of silicon carbide are studied on surface roughness. The result obtained using Response Surface Methodology (RSM) gives a good prediction of surface roughness when compared with actual surface roughness.

Keywords: Surface roughness (Ra), Response surface method (RSM), End milling, Metal matrix composites.

DOI: http://dx.doi.org/10.4314/ijest.v3i6.7

1. Introduction

The recent advancements in the CNC machine tool technology and the wide availability in manufacturing of mechanical components made it possible to produce high quality products. The factors defining "quality of a component" are generally its geometrical and dimensional tolerance, material specification, optimal design efficiency and good surface finish. The surface operations during manufacturing are affected by these factors directly or indirectly. They not only affect the surface quality but also influence the tool wear, fracture and work piece rejection, which leads to economic losses, Groover (2000).

Metal-matrix composites (MMC$_s$) have been increasingly used in industries because of their improved properties over those of non-reinforced alloys. Among the various types of MMC$_s$, aluminium-based composites have been found in various engineering applications such as the aerospace and automobile industries. The most popular reinforcements are silicon carbide (SiC) and alumina (Al2O3). Aluminum, titanium, and magnesium alloys are commonly used as the matrix phase. The density of most of the MMCs is approximately one third that of steel, resulting in high-specific strength and stiffness, Quan and Ye (2003). It is possible to produce high-quality MMC components to near-net shape through various manufacturing techniques, but additional machining is unavoidable to achieve the desired surface quality and dimensional tolerance for efficient assembly, Hung et al. (1996).

Several studies have been done in order to examine the efficiency of different cutting tool materials, such as carbide, coated carbide, and diamond in turning, milling, drilling, reaming, and threading of MMC materials. The main problem while machining MMC is the extensive tool wear caused by the very hard and abrasive reinforcements. Manna et al. (2003) investigated the machinability of Al/SiC MMC and found that no built-up edge (BUE) is formed during machining of Al/SiC MMC at high speed and low depth of cut and also observed a better surface finish at high speed with low feed rate and low depth of cut. Kumar Reddy et al. (2008) studied quality of components produced during end milling of Al/SiC particulate metal matrix composites (PMMCs).

The results showed that the presence of the reinforcement enhances the machinability in terms of both surface roughness and lower tendency to clog the cutting tool, when compared to a non-reinforced Al alloy.

Palanikumar (2007) developed a model for surface roughness through response surface method (RSM) while machining GFRP composites. Four factors five level central composite rotatable design matrix was employed to carry out the experimental investigation. Analysis of variance (ANOVA) was used to check the validity of the model. Muthukrishnan et al. (2009) developed two modeling techniques used to predict the surface roughness namely ANOVA and ANN. Oktem et al. (2005) developed an effective methodology to determine the optimum cutting conditions leading to minimum surface roughness while milling of mold surfaces by coupling RSM with a developed genetic algorithm (GA). Alauddin et al. (1995) predicted the surface roughness of 190 BHN steel after end milling using a mathematical model depending on cutting speed, feed rate and depth of cut. They used the response surface methodology (RSM) to explore the effect of these parameters on surface roughness. C-olak et al. (2007) predicted surface roughness of milling surface related to cutting parameters by using the genetic expression programming method. They considered cutting speed, feed rate and depth of cut of end milling operations for predicting surface roughness and predicted a linear equation for surface roughness related to experimental study.

The researchers also used response surface methodology (RSM) to explore the effect of such cutting parameters as cutting speed, feed rate and depth of cut on surface roughness. Alauddin et al. (1997) also established a mathematical model for predicting the tool in the end milling process of 190 BHN steel under dry cutting conditions. The model included the following variables: cutting speed, feed rate and axial depth of cut. It also verified the suitability of the prediction model via ANOVA.

This paper focuses on machining of Al/SiC_p metal matrix composites which is widely used in engineering applications. The chemical composition of the LM25 aluminum alloy is shown in Table-1.

Table 1. Chemical composition of LM25 aluminum alloy

Material	Si	Mg	Mn	Fe	Cu	Ni	Ti
LM25 Al alloy	7	0.33	0.3	0.5	0.1	0.1	0.2

2. Surface roughness

The surface roughness parameter used to evaluate surface roughness in this study is the Roughness average (Ra). This parameter is also known as the arithmetic mean roughness value, Arithmetic Average or Centerline Average. Within the presented research framework, the discussion of surface roughness is focused on the universally recognized Ra. Ra is recognized universally as the commonest international parameter of roughness. The average roughness is the area between the roughness profile and its centre line, or the integral of the absolute value of the roughness profile height over the evaluation length as shown in Figure 1, Yang and Chen (2001).

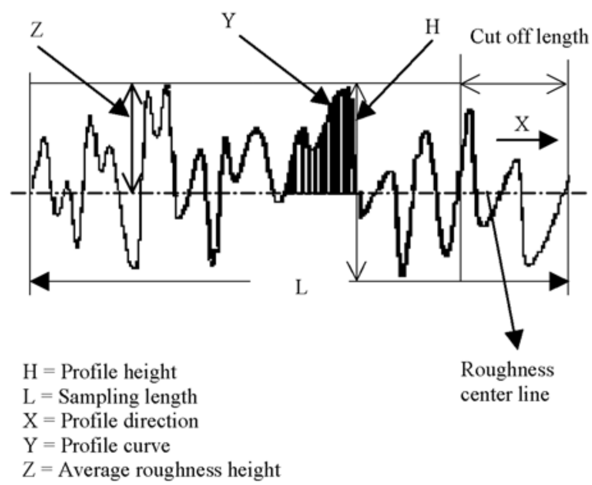

Figure 1. Surface roughness profile

Table 2. Process parameters and their limits

Factors / Coding of levels	-2	-1	0	+1	+2
Spindle speed, *N* (RPM)	2000	2500	3000	3500	4000
Feed rate, f (mm/rev)	0.02	0.03	0.04	0.05	0.06
Depth of cut, d (mm)	0.5	1	1.5	2	2.5
Silicon Carbide, S (%wt.)	5	10	15	20	25

Table 3. Experimental design matrix and results

Ex. No.	Coded values				Surface roughness (R_a) (μm)		
	X_1	X_2	X_3	X_4	Experimental values	Predicted values	
						Initial model	Improved model
1.	-1	-1	-1	-1	4.406	4.418	4.413
2.	1	-1	-1	-1	3.812	3.768	3.758
3.	-1	1	-1	-1	6.034	6.035	6.036
4.	1	1	-1	-1	5.229	5.234	5.231
5.	-1	-1	1	-1	4.472	4.468	4.483
6.	1	-1	1	-1	3.802	3.823	3.828
7.	-1	1	1	-1	6.032	6.098	6.106
8.	1	1	1	-1	5.312	5.301	5.301
9.	-1	-1	-1	1	4.978	4.998	4.997
10.	1	-1	-1	1	4.395	4.334	4.342
11.	-1	1	-1	1	6.789	6.773	6.778
12.	1	1	-1	1	5.945	5.958	5.972
13.	-1	-1	1	1	5.071	5.070	5.066
14.	1	-1	1	1	4.402	4.410	4.412
15.	-1	1	1	1	6.804	6.857	6.847
16.	1	1	1	1	6.054	6.046	6.042
17.	-2	0	0	0	6.202	6.143	6.140
18.	2	0	0	0	4.638	4.682	4.679
19.	0	-2	0	0	3.679	3.709	3.706
20.	0	2	0	0	7.008	6.962	6.959
21.	0	0	-2	0	5.062	5.103	5.115
22.	0	0	2	0	5.299	5.242	5.254
23.	0	0	0	-2	4.334	4.316	4.313
24.	0	0	0	2	5.639	5.641	5.638
25.	0	0	0	0	5.183	5.189	5.185
26.	0	0	0	0	5.177	5.189	5.185
27.	0	0	0	0	5.221	5.189	5.185
28.	0	0	0	0	5.163	5.189	5.185
29.	0	0	0	0	5.155	5.189	5.185
30.	0	0	0	0	5.199	5.189	5.185
31.	0	0	0	0	5.229	5.189	5.185

3. Response surface modeling

Response surface modeling was used to establish the mathematical relationship between the response (Y_u) and the various machining parameters. The general second order polynomial response surface mathematical model, which analyses the parametric influences on the various response criteria, can be described as follows:

$$Y_u = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{j>1}^{k} b_{ij} x_i x_j \quad (1)$$

where, X_i (1, 2, k) are coded level of k quantitative variables. The coefficient b_o is the free term, the coefficients b_i are the linear terms, the coefficients b_{ii} are the quadratic terms, and the coefficients b_{ij} are the interaction terms. Applying the least square technique, the values of these coefficients can be estimated by using the observations collected (Y_1, Y_2, Y_n) through the design points (n). To establish the initial model and refined model, a software package MiniTab was used to determine the coefficients of mathematical modeling based on the response surface regression model.

4. Experimental Work

In this investigation LM 25 Aluminum with various %wt.of silicon carbide are used. The test sample dimensions were 100 mm × 50 mm × 40 mm. In total 5 work pieces (Al reinforced with 5%, 10%, 15%, 20% and 25% weight of SiC_p) are prepared. The machining is done on HASS CNC milling machine. The tools used are carbide having diameter 12 mm and number of flutes: 4. CNC programs for the experiment were generated on FANUC software. The level of parameters selected for the experiments were given in the Table.2. Thirty one experiments are carried out according to the central composite design (CCD).The surface roughness (Ra) of the machined test specimens was measured using a Talysurf tester with a sampling length of 10mm.

5. Result and Discussion

5.1 Modeling and statistical analysis: The data given in the Table 3 is analysed by using a software package MiniTab ver 15. The regression analysis presented in Table 4. Model in Table 4 is the initial model and includes all the linear, square and interactions terms.

Table 4: Statistical Analysis of all linear, square and interaction terms

Estimated Coefficients for Ra (Un coded Units)

Predictor	Coefficient	*P* value
Constant	4.716	<0.000
X_1 (N, rpm)	-0.002	<0.000
X_2 (f, mm/rev)	61.948	<0.000
X_3 (d, mm)	0.050	0.810
X_4 (S, %wt.)	0.099	<0.000
X_1^2	0.000	<0.000
X_2^2	365.551	<0.001
X_3^2	-0.017	0.628
X_4^2	-0.002	<0.000
$X_1 X_2$	-0.008	<0.004
$X_1 X_3$	0.000	0.927
$X_1 X_4$	-0.000	0.758
$X_2 X_3$	0.612	0.791
$X_2 X_4$	0.789	<0.003
$X_3 X_4$	0.002	0.638

S = 0.0450746 R-Sq = 99.85% R-Sq(adj) = 99.72%

Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	14	22.0127	22.013718	1.572334	763.09	0.000
Linear	4	21.7361	0.313339	0.078294	38.00	0.000
Square	4	0.2282	0.228666	0.057041	27.68	0.000
Interaction	6	0.0485	0.048455	0.008076	3.92	0.013
Residual Error	16	0.0330	0.032508	0.002060		
Total	30	22.0456				

The empirical equation for predicting the surface roughness (Ra) is:

$$R_a = 4.716 - (0.002\, X_1) + (61.948\, X_2) + (0.050\, X_3) + (0.099\, X_4) + (365.551\, X_2^2) - (0.017 X_3^2) - (0.002\, X_4^2) - (0.008\, X_1 X_2) + (0.612\, X_2 X_3) + (0.789\, X_2 X_4) + (0.002\, X_3 X_4) \quad (2)$$

Analysis of variance (ANOVA) is given at the end of the Table 4. It shows the value of $p < 0.05$ for all linear, square and interactions terms. i.e. all these effects are significant on the surface roughness (Ra). The initial model also indicates that the DOC is insignificant factor, but it has less influence on surface roughness. In the light of above initial model, the insignificant square and interaction terms can be removed to generate a more precise model. Table 5 shows an improved model in which only significant terms ($p < 0.05$) from Table 4 are considered.

5.2 Improved modeling and statistical analysis: Table 5 takes into account only major factors, factor square and factor interactions that are influencing on the surface roughness. Based on 5 % confidence interval i.e. the value of $p < 0.05$, in linear terms spindle speed, feed rate, depth of cut and %wt. of SiC_p; in square terms spindle speed, feed rate and %wt. of SiC_p; in interaction terms spindle speed-feed rate and feed rate-%wt. of SiC_p plays an important role in affecting surface roughness. R-Sq(adj) is 99.78% indicating that our model can predict within 99.78% accuracy.

Table 5: Statistical Analysis of improved model

Estimated Coefficients for Ra (Uncoded Units)		
Predictor	Coefficient	*P* value
Constant	4.736	<0.000
X_1 (N, rpm)	-0.002	<0.000
X_2 (f, mm/rev)	62.509	<0.000
X_3 (d, mm)	0.070	<0.000
X_4 (S, %wt.)	0.097	<0.000
X_1^2	0.000	<0.000
X_2^2	370.013	<0.000
X_4^2	-0.002	<0.000
$X_1 X_2$	-0.008	<0.001
$X_2 X_4$	0.789	<0.001
S = 0.0404235 R-Sq = 99.84% R-Sq(adj) = 99.78%		

Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	22.0113	22.011329	2.445703	1496.70	0.000
Linear	4	21.7361	0.396642	0.099161	60.68	0.000
Square	3	0.2277	0.227661	0.075887	46.44	0.000
Interaction	2	0.0476	0.047611	0.023805	14.57	0.000
Residual Error	21	0.0343	0.034315	0.001634		
Total	30	22.0456				

The empirical equation for predicting the surface roughness Ra is:

$$R_a = 4.736 - 0.002X_1 + 62.509X_2 + 0.070X_3 + 0.097X_4 + 370.013X_2^2 - 0.002X_4^2 - 0.008X_1X_2 + 0.789X_2X_4 \quad (3)$$

The normal probability plot, given in Figure 2, shows a clear pattern (as the points are almost in a straight line) indicating that all the factors and their interaction given in Table 5 are affecting the surface roughness. Also the errors are normally distributed and the regression model is well fitted with the observed values. Figure 3 indicates that the maximum variation of -0.15 to 0.10, which shows the high correlation that exists between fitted values and observed values. This plot is the typical testing for the assumption of constant variance. If the assumption is satisfied, the residual plot should be structureless. It is obvious that it is subjective and difficult to determine whether the plot is structured. To get rid of this ambiguity, in this paper, the assumption of constant variance was checked by Brown–Forsythe test. At 95% confidence level, the critical value of Brown–Forsythe test is 4.06. In this study, Brown–Forsythe test statistic was 3.58. With the smaller value of the test statistic than its critical value, it can be concluded that the assumption of constant variance of residuals is satisfied. After the validity of the assumptions was carefully checked, no assumption was violated. Therefore, the ANOVA of this screening experiment was sufficiently reliable, Kanlayasiri et al. (2008)

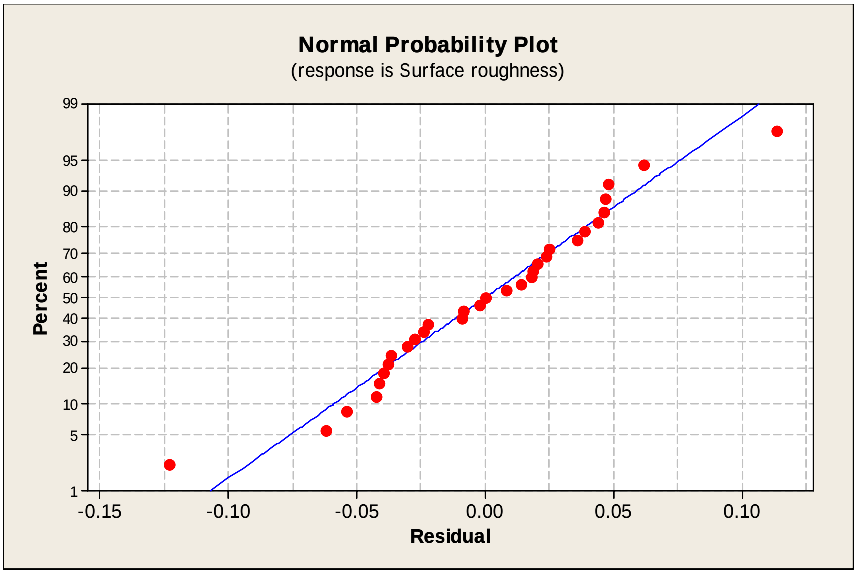

Figure 2. Normal probability plot for surface roughness

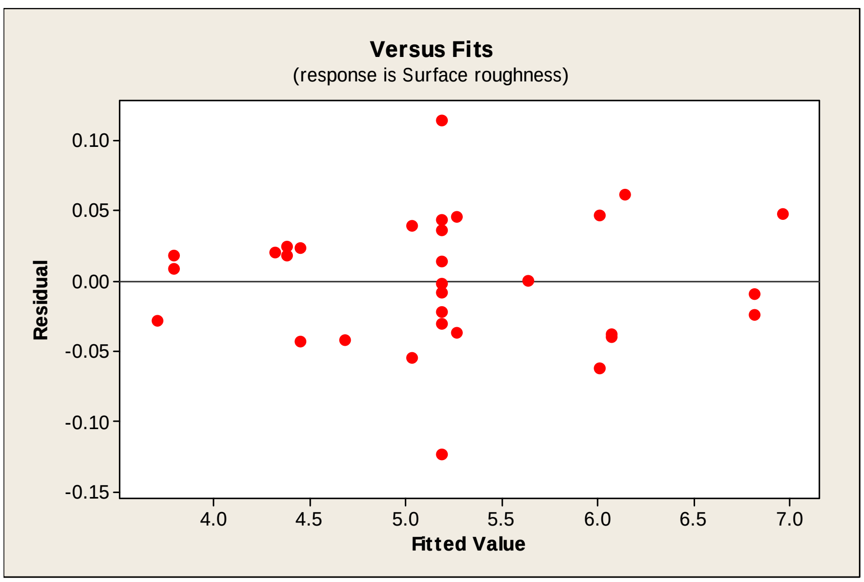

Figure 3. Residual Vs fitted values for surface roughness

Following conclusions can be deduced from Figure 4.

Speed: An increase in speed will significantly reduce the surface roughness. At low cutting speed (s), the unstable larger BUE is formed and also the chips fracture readily producing the rough surface. As the cutting speed (s) increases, the BUE vanishes, chip fracture decreases, and, hence, the roughness decreases, Palanikumar K et al.(2007). This conclusion is also supported by practically obtained values.

Feed: An increase in feed will increase surface roughness. Increase in feed rate increases the chatter and heat generation, which increases the surface roughness. This conclusion is also supported by observation.

DOC: Increasing the depth of cut would slightly increase the surface roughness.
%Wt. Of SiC_p: An increase in %wt. of SiC_p will increase surface roughness. This conclusion is also supported by observation.

Spindle speed - feed rate: From experience we know that spindle speed and feed rate interaction effects the surface roughness. Figure 5 shows that increasing the spindle speed decrease the surface roughness but increase feed rate will decrease the surface roughness. With the lower feed rates, the BUE forms readily and is accompanied by feed marks resulting in increased roughness and the surface roughness (Ra) decreases as the cutting speed (s) increases. At low cutting speed (s), the unstable larger BUE is formed and also the chips fracture readily producing the rough surface. As the cutting speed (s) increases, the BUE vanishes, chip fracture decreases, and, hence, the roughness decreases. The best surface finish was achieved at the lowest feed rate and highest cutting speed combination, Choudhury et al.(1998) and Palanikumar et al.(2007).This conclusion may be very useful as for mass production, optimal values for spindle speed and feed rate can be set hence reduce the manufacturing time without losing surface finish.

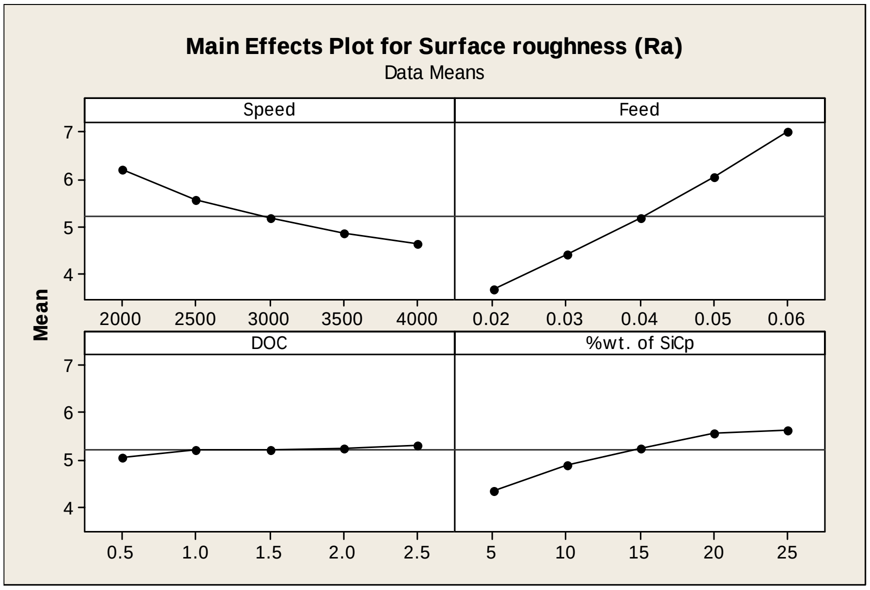

Figure 4. Main effects plot for surface roughness

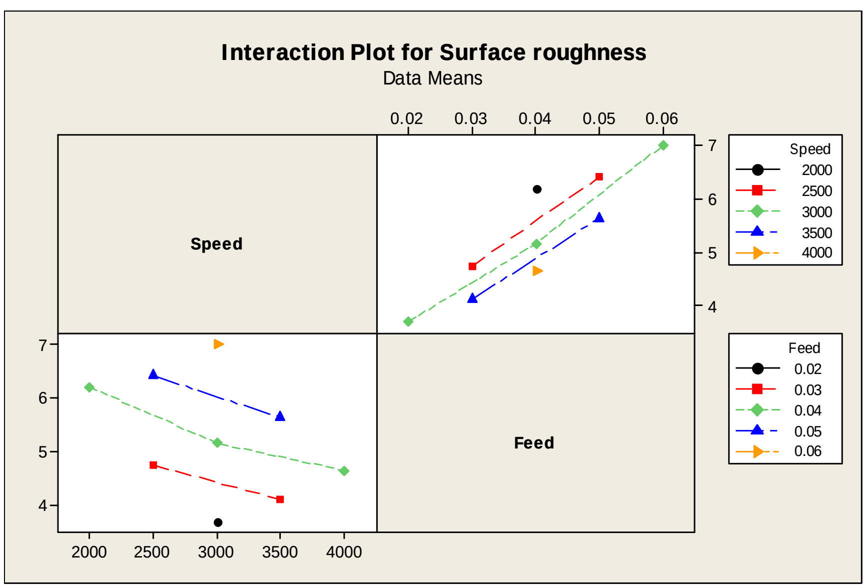

Figure 5. Spindle speed-Feed rate interaction plot for surface roughness

Feed rate - %wt. Of SiC$_p$: From experience we know that feed rate and %wt. of SiC$_p$ interaction effects the surface roughness. Figure 6 shows that increasing the feed rate will increase the surface roughness. Also increasing the %wt. of SiC$_p$ will increase the surface roughness. The reason being, addition of reinforcing materials which are normally harder and stiffer than the matrix, machining becomes significantly more difficult than in the case for conventional materials. The best surface finish is achieved at the lowest feed rate and lowest %wt. SiC_p combination,.Quan and Zehua (2000).

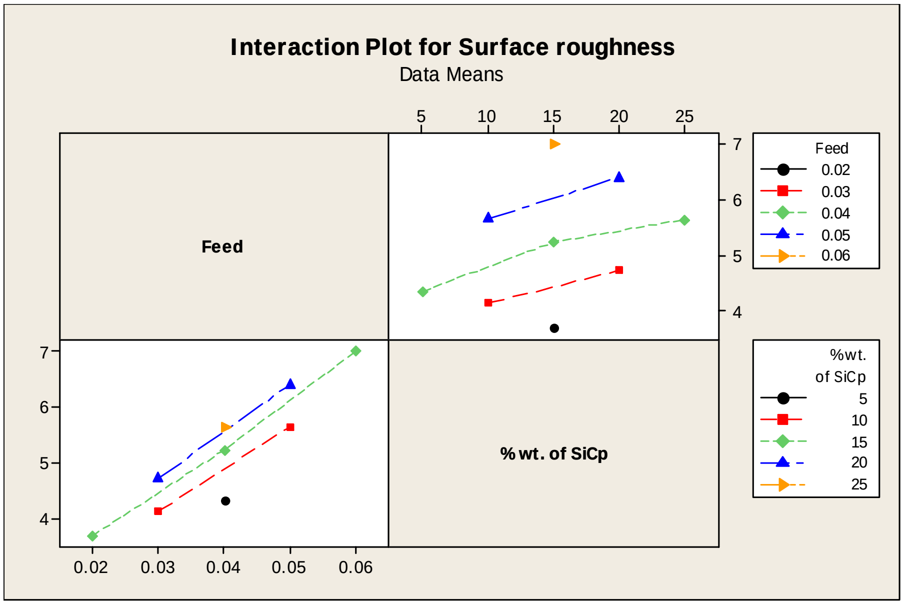

Figure 6. Feed rate-%wt. of SiCp interaction plot for surface roughness

6. Analysis for optimization of the responses

The After building the regression model, a numerical optimization technique using desirability functions can be used to optimize the response. The objective of optimization is to find the best settings that minimize a particular response, Myers RH, Montgomery DC. (2002). A desirability value, where $0 \leq d \leq 1$. The value of d increases as the "desirability" of the corresponding response increases. The factor settings with maximum desirability are considered to be the optimal parameter conditions. Most of the standard statistical software packages (Minitab, Design, Expert, etc.) employ this popular technique for response optimization. In the present case, Minitab was used to optimize the response parameters.

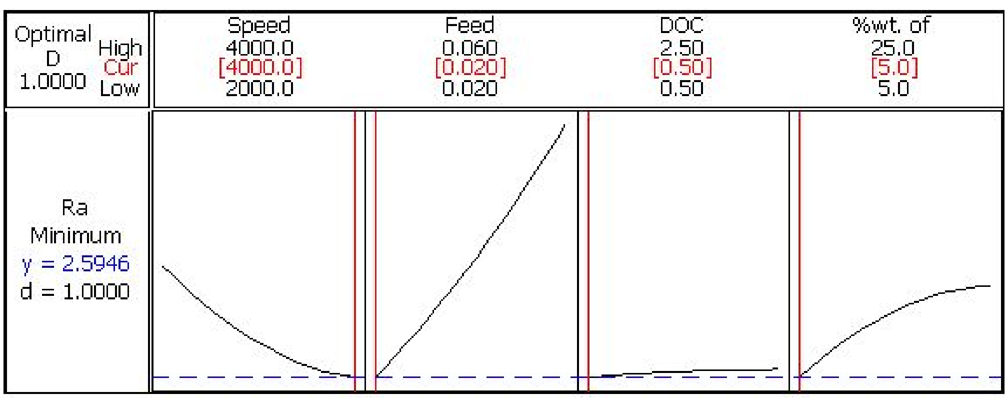

Figure 7. Optimum results for minimum surface roughness

The optimization plot for surface roughness has been shown in Fig. 7. It is revealed that highest desirability could be obtained at high cutting speed, low feed rate, low depth of cut and high cutter diameter. The goal was to minimize the surface roughness. The upper value and target has been fixed at 7.008 and 3.678 μm, respectively. The parameter setting for achieving a surface roughness as low as of 2.5946 μm has been predicted as spindle speed (N) 4000 rpm, feed rate (f) 0.020 mm/rev, depth of cut (d) 0.50 mm, and weight of silicon carbide (S) 5%. The desirability of optimization has been calculated as 1.0000, i.e., all the parameters are within their working range.

7. Conclusions

1. In this research the effect of process parameters spindle speed, feed rate, depth of cut and various percentage weight of silicon carbide were studied statistically on surface roughness for LM25 Al/SiC$_p$ MMC.
2. Response surface methodology is used to study the effect of these parameters and their interaction on surface roughness.
3. An empirical equation is formed by using RSM in MiniTab software to predict the surface roughness LM25 Al/SiC$_p$ MMC. The predicted value of improved model gives better result when compared with the actual measured values.
4. In the order of their influence, Feed rate, Spindle speed, % wt. of SiC$_p$, Feed rate-Spindle speed interaction and Feed rate-% wt. of SiC$_p$ interaction has most influence on surface roughness.
5. The study also concluded that the effect of depth of cut on surface roughness is negligible based on 95 % confidence level ($p > 0.05$).
6. From the developed mathematical model, the optimal machining parametric combination, i.e., spindle speed (N) 4000 rpm, feed rate (f) 0.020 mm/rev, depth of cut (d) 0.50 mm, and weight of silicon carbide (S) 5%. was found out to achieve the minimum surface roughness as 2.5946 μm.

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Received April 2011
Accepted August 2011
Final acceptance in revised form September 2011