JCARME
ISSN: 2228-7922
Journal of Computational and Applied Research in Mechanical Engineering
Vol. 2, No. 1, pp. 1-13, Sept. 2012
http://jcarme.srttu.edu

A study on tool wear and surface roughness in end milling of particulate aluminum metal matrix composites: Application of response surface methodology

R. Arokiadass*, K. Palaniradja and N. Alagumoorthi

Department of Mechanical Engineering, Pondicherry Engineering College, Puducherry- 605 014, India.

Article info:
Received: 02/05/2012
Accepted: 26/06/2012
Online: 11/09/2012

Keywords:
Metal matrix composites (MMC),
Response surface methodology (RSM),
Flank wear (VB_{max}),
Surface roughness (Ra),
Contour plots,
Optimization

Abstract

Metal matrix composites have been widely used in industries, especially aerospace industries, due to their excellent engineering properties. However, it is difficult to machine them because of the hardness and abrasive nature of reinforcement elements like silicon carbide particles (SiC_p).In the present study, an attempt has been made to investigate the influence of spindle speed (*N*), feed rate (*f*), depth of cut (*d*) and various %wt. of silicon carbide (*S*) manufactured through stir cast route on tool flank wear and surface roughness during end milling of LM25 Al-SiC_p metal matrix composites. Statistical models based on second order polynomial equations were developed for the different responses. Analysis of variance (ANOVA) was carried out to identify the significant factors affecting the tool flank wear and surface roughness. The contour plots were generated to study the effect of process parameters as well as their interactions. The process parameters are optimized using desirability-based approach response surface methodology.

1. Introduction

The Metal matrix composites (MMC) are the new class of materials and are being used to replace conventional materials 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 [1]. In the last decades, SiC/Al composites have been increasingly used in the aerospace industry and advanced arm systems such as satellite bearing, inertia navigation system, and laser reflector. 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

*Corresponding author.
Email address: raja_arokiadass@yahoo.com

surface quality and dimensional tolerance for efficient assembly [2].

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. [3] 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 better surface finish at high speed with low feed rate and low depth of cut.

Davim et al. [4] made a correlation between the chip compression ratios and shear plane angle or chip deformation during MMCs turning. The results showed shear angle decreased with the chip compression ratio. On the contrary, the chip deformation increased with chip compression ratio. The merchant model gives, in general, an overestimation of the shear plane angle value in cutting of aluminum matrix composites [5].

Kannan et al. [6] studied tool wear, surface integrity, and chip formation during machining of Al-MMC under both wet and dry condition. The turning results showed that the tool life was increased at higher cutting speeds in influence of coolant but the surface quality was deteriorated. Suresh Kumar Reddy et al. [7] studied quality of components produced during end milling of Al/SiC 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 aluminum alloy.

Tamer Ozben et al. [8] investigated the mechanical properties and the effects of machining parameters on tool wear and surface roughness of silicon carbide particulate (SiCp) reinforced aluminum MMC for different volume fraction. It was observed that the increase in reinforcement addition produced better mechanical properties, but the tool flank wear will be higher. The surface roughness was enerally affected by feed rate and cutting speed.

Ibrahim Ciftci et al. [9] studied the influence of different particle size of SiC and cutting speed on tool wear and surface roughness during machining of Al/SiC MMC using cubic boron nitride (CBN) cutting tool. The results showed that tool wear was mainly observed on flank side with a strong influence by abrasive reinforcement. Palanikumar [10] developed a model for surface roughness through response surface method (RSM) while machining GFRP (Glass Fibre Reinforced Plastics) 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.

Jenn-Tsong Horng et al. [11] made an attempt to model the machinability evaluation through the RSM while machining Hadfield steel. Results indicated that the flank wear was influenced by the cutting speed and the interaction effect of feed rate. Muthukrishnan et al. [12] developed two modeling techniques used to predict the surface roughness namely ANOVA and artificial neural network (ANN). Oktem et al. [13] 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).

From the literature it is found that the machining of Al MMC is an important area of research, but only very few studies have been carried out on optimization of tool flank wear and surface roughness while machining of particulate aluminum metal matrix composite (PAMMC). Hence, the main objective of the present work is to optimize tool flank wear and surface roughness while machining LM25 $AlSiC_p$ metal matrix composite using RSM approach.

2. Experimental planning

In the present experimental study, the material to be machined is LM25 Al alloy reinforced with SiC_p, at a various composition of 5%wt., 10%wt., 15%wt., 20%wt. and 25%wt. and of

5μm particle size manufactured through stir-casting route was used for experimentation.
Microscopic examinations of the specimens were carried out using a scanning electron microscope (SEM). The typical microstructures of the LM25Al alloy with different percentage weight of SiC_p composites are shown in Fig. 1. The dimensions of the specimens were of 100 mm × 50 mm × 40 mm.
The chemical composition of the LM25 Al alloy specimen is presented in Table 1. The cutting tools used were flat end uncoated solid carbide cutters, having diameter of 12 mm, helix angle of 45º, rake angle of 10º and number of flutes 4. The important factors influencing the tool flank wear and surface roughness and their levels are presented in Table 2.

Table 1. Chemical composition of LM25 aluminum alloy (%wt.).

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

The machining operations were carried out as per the conditions given by the design matrix at random to avoid systematic errors.
In the present study, the tool wear area was considered as the criterion that would affect the results of cutting process. The measurement of the width of the flank wear land of the cutting tool was used to evaluate the tool wear as shown in Fig. 2. The maximum value of flank wear (VB_{max}) was adopted as the machinability evaluation of machining MMC. Here, the tool flank wear (VB_{max}) was measured by using Metzer tool maker's microscope.
The surface roughness (Ra), which is mostly used in industries, is taken for this study. The surface roughness (Ra) of the machined test specimens was measured using a Talysurf tester with a sampling length of 10mm.

3. Design of experiment based on response surface methodology

In order to investigate the influence of process parameters on the tool flank wear and surface roughness, four principal process parameters such as the spindle speed (N), feed rate (f), depth of cut (d) and percentage weight of silicon carbide (S) were taken. In this study, these process parameters were chosen as the independent input variables. The desired responses are the tool flank wear and surface roughness which are assumed to be affected by the above four principal process parameters.
The response surface methodology is employed for modeling and analyzing the process parameters in the end milling process so as to obtain the machinability performances of VB_{max} and Ra. In the RSM, the quantitative form of relationship between the desired response and independent input variables are represented as follows:

$$Y = F\{N, f, d, S\} \tag{1}$$

where Y is the desired response and F is the response function (or response surface). In the procedure of analysis, the approximation of Y was proposed using the fitted second-order polynomial regression model, which is called the quadratic model. The quadratic model of Y can be written as follows:

$$Y = a_0 + \Sigma a_i X_i + \Sigma a_{ii} X_i^2 + \Sigma a_{ij} X_i X_j \tag{2}$$

where a_0 is constant, a_i, a_{ii}, and a_{ij} represent the coefficients of linear, quadratic, and cross product terms, respectively. X_i reveals the coded variables that correspond to the studied machining parameters. The coded variables X_i, i=1, 2, 3, 4 are obtained from the following transformation equations:

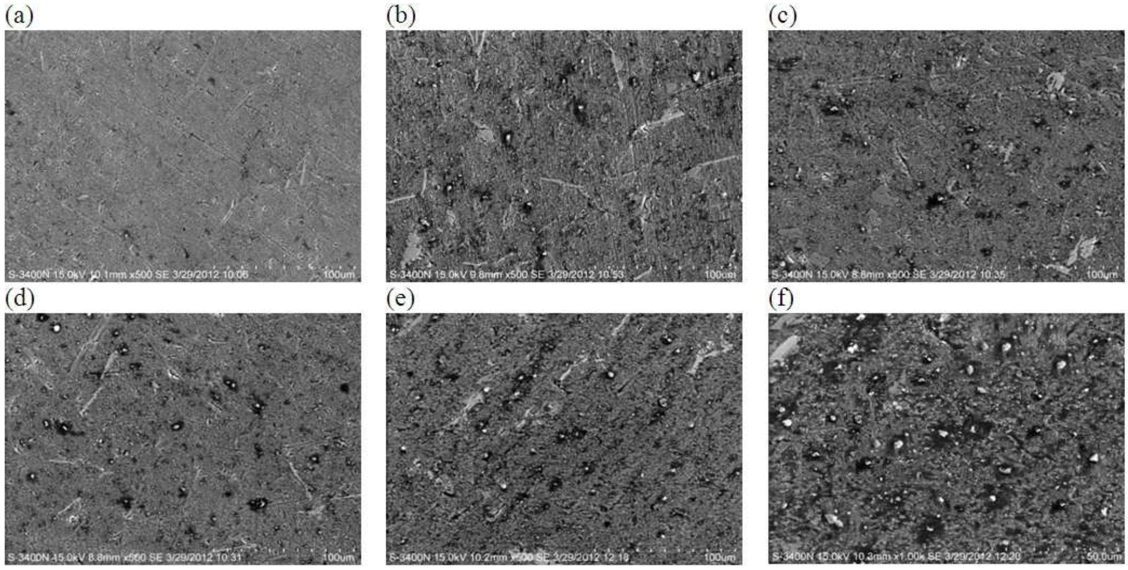

Fig. 1. SEM micrographs of LM 25 Al alloy reinforced with: (a) LM25 Al alloy; (b) 5% SiC; (c) 10% SiC; (d) 15% SiC; (e) 20% SiC and (f) 25% SiC (black regions SiC particles).

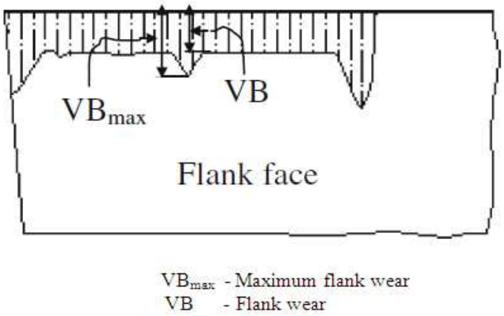

Fig. 2. Measurement of flank wear.

Table 2. Experimental parameters and their levels.

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

$$X_1= [N–N_0]/\Delta N \quad (3)$$
$$X_2= [f–f_0]/\Delta f \quad (4)$$
$$X_3= [d–d_0]/\Delta d \quad (5)$$
$$X_4= [S–S_0]/\Delta S \quad (6)$$

where X_1, X_2, X_3, and X_4 are the coded values of parameters N, f, d, and S respectively; N_0, f_0, d_0, and S_0 are the values of N, f, d, and S, respectively, at zero level. ΔN, Δf, Δd, and ΔS are the intervals of variation in N, f, d, and S, respectively. The purpose of using this quadratic model Y in this study was not only to investigate over the entire factor space but also to locate the region where the response approaches its optimum or near optimal value of the desired target. The necessary data for building the response models are generally collected by the experimental design.

The pertinent process parameter selected for the present investigation are spindle speed, feed rate, depth of cut and percentage weight of silicon carbide on the tool flank wear and surface roughness during the end milling process. For the four variables the design required 31 experiments with 16 factorial points, eight axial points to form central composite design with α=2 and seven center points for replication to estimate the experimental error. The design was generated and analyzed using MINITAB 15.0 statistical package. The levels of each factor were chosen as −2, −1, 0, 1, 2 in closed form to have a rotatable design [14]. Table 2 shows the factors and their levels in coded and actual values. The experiment has been carried out according to the designed experimentation based on central composite second-order rotatable design as depicted in Table 3.

Table 3. Experimental design matrix and results.

Ex.No	Coded factors				Actual factors				Flank wear, VB_{max} (mm)	Surface roughness, Ra (µm)
	X_1	X_2	X_3	X_4	N	f	d	S		
1	–1	–1	–1	–1	2500	0.03	1	10	0.224	4.406
2	1	–1	–1	–1	3500	0.03	1	10	0.284	3.812
3	–1	1	–1	–1	2500	0.05	1	10	0.258	6.034
4	1	1	–1	–1	3500	0.05	1	10	0.291	5.229
5	–1	–1	1	–1	2500	0.03	2	10	0.235	4.472
6	1	–1	1	–1	3500	0.03	2	10	0.294	3.802
7	–1	1	1	–1	2500	0.05	2	10	0.27	6.032
8	1	1	1	–1	3500	0.05	2	10	0.297	5.312
9	–1	–1	–1	1	2500	0.03	1	20	0.338	4.978
10	1	–1	–1	1	3500	0.03	1	20	0.407	4.395
11	–1	1	–1	1	2500	0.05	1	20	0.377	6.789
12	1	1	–1	1	3500	0.05	1	20	0.422	5.945
13	–1	–1	1	1	2500	0.03	2	20	0.358	5.071
14	1	–1	1	1	3500	0.03	2	20	0.413	4.402
15	–1	1	1	1	2500	0.05	2	20	0.384	6.804
16	1	1	1	1	3500	0.05	2	20	0.419	6.054
17	–2	0	0	0	2000	0.04	1.5	15	0.262	6.202
18	2	0	0	0	4000	0.04	1.5	15	0.361	4.638
19	0	–2	0	0	3000	0.02	1.5	15	0.314	3.679
20	0	2	0	0	3000	0.06	1.5	15	0.357	7.008
21	0	0	–2	0	3000	0.04	0.5	15	0.309	5.062
22	0	0	2	0	3000	0.04	2.5	15	0.341	5.299
23	0	0	0	–2	3000	0.04	1.5	5	0.211	4.334
24	0	0	0	2	3000	0.04	1.5	25	0.443	5.639
25	0	0	0	0	3000	0.04	1.5	15	0.322	5.183
26	0	0	0	0	3000	0.04	1.5	15	0.328	5.177
27	0	0	0	0	3000	0.04	1.5	15	0.319	5.221
28	0	0	0	0	3000	0.04	1.5	15	0.326	5.163
29	0	0	0	0	3000	0.04	1.5	15	0.323	5.155
30	0	0	0	0	3000	0.04	1.5	15	0.327	5.199
31	0	0	0	0	3000	0.04	1.5	15	0.329	5.229

4. Mathematical modeling

The Mathematical models based on second-order polynomial equations were developed for tool flank wear and surface roughness using the experimental results shown in Table 3 was obtained from planned set of experiments based on CCD. The coefficients of regression analysis for flank wear (VB_{max}) and surface roughness (Ra) is shown in Tables 4 and 5 along with their P value of the parameters, higher order, and interactions. The P value of regression analysis of VB_{max} in Table 4 indicates that linear effect of spindle speed, feed rate and percentage weight of SiCp are the most significant. In Square and interaction terms, spindle speed and feed rate are the most significant.

Similarly, the P value of regression analysis of Ra in Table 5 indicates that linear effect of spindle speed, feed rate and percentage weight of S_iC_p are significant.

In Square terms, spindle speed , feed rate and percentage weight of S_iC_p are significant. In interaction terms, spindle speed-feed rate and feed rate-%wt. S_iC_p are significant. Equations (7 and 8) represent the regression model equation for flank wear (VB_{max}) and surface roughness (Ra).

Table 4. Regression analysis of flank wears (VB_{max}).

Term	Coefficient	*P*- value
Constant	–0.2551	<0.001
X_1	0.0002	<0.000
X_2	2.4923	<0.042
X_3	0.0404	0.078
X_4	0.0084	<0.001
X_1^2	–0.0000	<0.011
X_2^2	34.4196	<0.001
X_3^2	0.0033	0.372
X_4^2	0.0001	0.158
$X_1 X_2$	–0.0013	<0.000
$X_1 X_3$	–0.0000	0.123
$X_1 X_4$	0.0000	0.207
$X_2 X_3$	–0.3125	0.207
$X_2 X_4$	0.0088	0.718
$X_3 X_4$	–0.0002	0.642

Table 5. Regression analysis of surface roughness (Ra).

Term	Coefficient	*P* value
Constant	4.716	<0.000
X_1	–0.002	<0.000
X_2	61.948	<0.000
X_3	0.050	0.810
X_4	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

$$VB_{max} = -0.2551 + (0.0002\,X_1) + (2.4923\,X_2) + (0.0404\,X_3) + (0.0084\,X_4) + (34.4196\,X_2^2) + (0.0033\,X_3^2) + (0.0001\,X_4^2) - (0.0013\,X_1 X_2) - (0.3125\,X_2 X_3) + (0.0088\,X_2 X_4) - (0.0002\,X_3 X_4) \tag{7}$$

$$Ra = 4.716 - (0.002\,X_1) + (61.948\,X_2) + (0.050\,X_3) + (0.099\,X_4) + (365.551\,X_2^2) - (0.017\,X_3^2) - (0.002\,X_4^2) - (0.008\,X_1 X_2) + (0.612\,X_2 X_3) + (0.789\,X_2 X_4) + (0.002\,X_3 X_4) \tag{8}$$

where X_1, X_2, X_3, and X_4 represent the decoded values of spindle speed (*N*), feed rate (*f*), depth of cut (*d*) and percentage weight of silicon carbide (*S*), respectively.

5. Analysis of the developed mathematical models

The ANOVA and *F* ratio test have been performed to justify the goodness of fit of the developed mathematical models. The calculated values of *F* ratios for lack-of-fit have been compared to standard values of *F* ratios corresponding to their degrees of freedom to find the adequacy of the developed mathematical models. The *F* ratio calculated from ratio of Mean Sum of Square of source to Mean sum of experimental error.

The fit summary recommended that the quadratic model is statistically significant for analysis of tool flank wear.

The value of R^2 is over 99.65%, which means that the regression model provides an excellent explanation of the relationship between the independent variables (factors) and the response (VB_{max}).

The associated P value for the model is lower than 0.05 (i.e., p=0.05, or 95% confidence) indicates that the model is considered to be statistically significant. The ANOVA table for the quadratic model for VB_{max} is shown in Table 6.

Similarly, the value of R^2 for surface roughness is 99.85%, which means that the regression model provides an excellent explanation of the relationship between the independent variables (factors) and the response (Ra).

The associated P value for the model is lower than 0.05 (i.e., p=0.05 or 95% confidence), which indicates that the model is considered statistically significant.

The ANOVA table for the quadratic model for surface roughness is shown in Table 7. The standard percentage point of F distribution for 95% confidence limit is 4.06.

As shown in Table 6 and 7, the *F* value is 2.15 and 3.58 for lack-of-fit is smaller than the standard value of 95% confidence limit. Thus, both the models are adequate in 95% confidence limit.

It is also seen that from the *P* values, for both tool flank wear (VB_{max}) and surface roughness (Ra), linear, square, and interaction effects are significant.

The plot of normal probability of the residual for tool flank wear and surface roughness are shown in Fig. 3 and 4.

From the normal probability plots of residuals (i.e error = predicted value from model – actual value) in Fig. 3 and 4, it is evident that the residuals lie reasonably close to a straight line implying that errors are distributed normally.

6. Results and discussion

6.1. Effect of machining parameters on flank wears (VB_{max})

Based on the mathematical model given by Eq. (7) developed through experimental observations and response surface methodology, studies have been made to analyze the effect of the various process parameters on the flank wear (VB_{max}). The contour plots were drawn for various combinations. The number represent in the plot is flank wear (VB_{max}). In Fig. 5, it is clear that the flank wear (VB_{max}) increases with the increase in the spindle speed (*N*). At lower spindle speed, flank wear is lesser extent, which can be attributed to formation of larger size unstable BUE due to high contact pressure and friction which protects the cutting edge from further wear [15].

But with increase in spindle speed, an increase in tool flank wear is observed which could be due to generation of higher temperature at higher spindle speed and associated thermal softening and deterioration of form stability of the cutting edge [16]; also, the flank wear increases with increase in feed rate. It is due to BUE formed on flank face that changes the geometry of the tool [17]. Fig. 6 shows the effect of spindle speed and %wt. of SiC_p on flank wear (VB_{max}). Increase in spindle speed, an increase in tool flank wear. Increasing the percentage of the SiC particles also increases the tool wear because of increasing the surface contact between the SiC particles and the cutting tool edge in higher percentage of the SiC particles [18].

The depth of cut (d) also has least influence factor on flank wear (VB_{max}) in machining of MMC. Fig. 7 show the effect of spindle speed and depth of cut on flank wear (VB_{max}). Increasing the depth of cut increases the flank wear (VB_{max}) due to increase in area of contact, normal load, and friction. This, in turn, increases temperature, which will cause work softening and thus results slight increase in flank wear (VB_{max}).

Table 6. Analysis of variance for tool flank wears (VB_{max}).

Source of variation	Degree of freedom	Sum of squares	Mean sum of squares	*F*- value	p-value
Regression	14	0.103963	0.007426	328.73	0.000
Linear	4	0.102512	0.000268	11.88	0.000
Square	4	0.000642	0.000160	7.10	0.002
Interaction	6	0.000809	0.000135	5.97	0.002
Residual Error	16	0.000361	0.000023		
Lack of fit	10	0.000283	0.000028	2.15	0.181
Pure Error	6	0.000079	0.000013		
Total	30	0.103963			

Table 7. Analysis of variance for surface roughness (R_a).

Source of variation	Degree of freedom	Sum of squares	Mean sum of squares	*F*- value	p-value
Regression	14	22.0127	1.572334	763.09	0.000
Linear	4	21.7361	0.078294	38.00	0.000
Square	4	0.2282	0.057041	27.68	0.000
Interaction	6	0.0485	0.008076	3.92	0.013
Residual Error	16	0.0330	0.002060		
Lack of fit	10	0.0282	0.002823	3.58	0.066
Pure Error	6	0.0047	0.000789		
Total	30	22.0456			

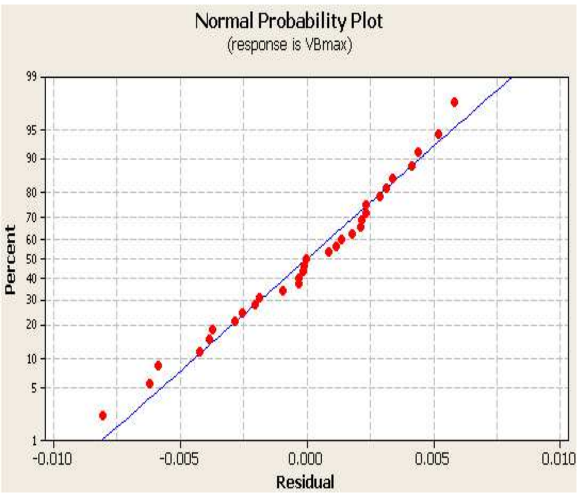

Fig. 3. Normal probability plot of residuals for VB_{max}.

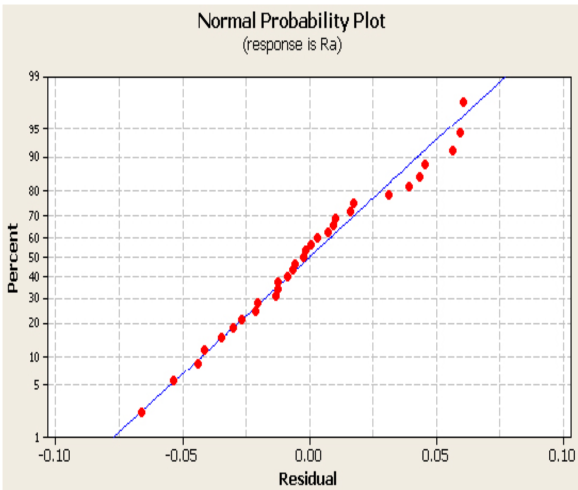

Fig. 4. Normal probability plot of residuals for Ra.

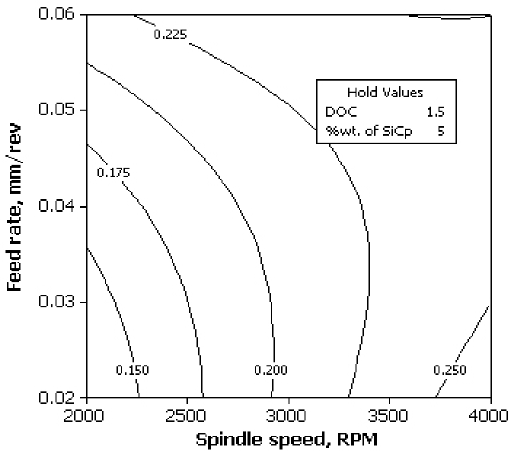

Fig. 5. Effect of spindle speed and feed rate on VB_{max}.

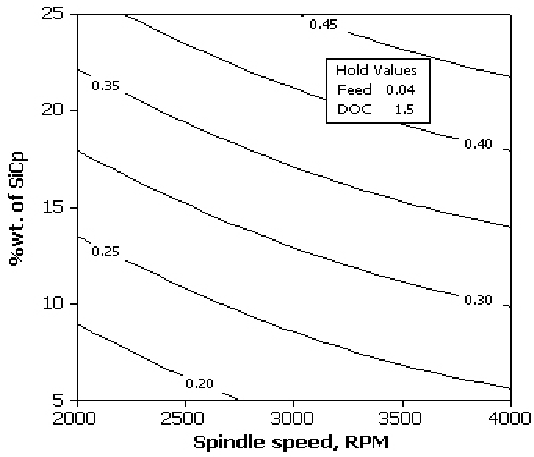

Fig. 6. Effect of spindle speed and %wt. of SiC_p on VB_{max}.

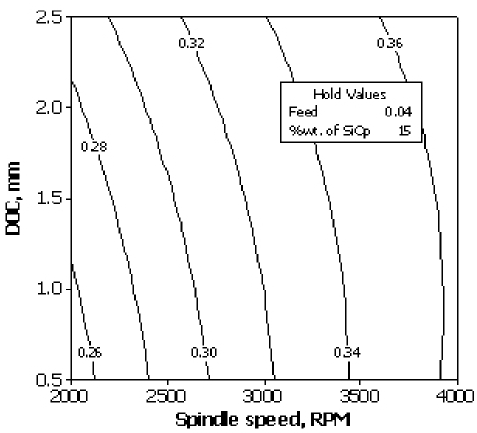

Fig. 7. Effect of %wt. of spindle speed and depth of cut on VB_{max}.

6.2. Effect of machining parameters on surface roughness (Ra)

Based on the mathematical model given by Eq. (8), the study of the effects of various process parameters on surface roughness (Ra) has been made so as to analyze the suitable parametric combinations that can be made for achieving controlled surface roughness. The contour plots were drawn for various combinations. The number represent in the plot is surface roughness (Ra).

From Fig. 8, the surface roughness (Ra) decreases as the spindle speed (*N*) increases. At low spindle speed (*N*), the unstable larger BUE is formed and also the chips fracture readily producing the rough surface. As the spindle speed (*N*) increases, the BUE vanishes, chip fracture decreases, and, hence, the roughness decreases [19].

Also, the increase in feed rate (*f*) increases the surface roughness (Ra). With the lower feed rates, the BUE forms readily and is accompanied by feed marks resulting in increased surface roughness.

With the increase in feed rate the rate of increase in surface roughness (Ra) is less due to the reduced effect of BUE [20]; the best surface finish was achieved at the lowest feed rate and highest cutting speed combination.

The effect of spindle speed and %wt. of SiC_p on the surface roughness (Ra) is shown in Fig. 9. The surface roughness (Ra) increases with the increase in the %wt. of SiC_p. Because 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 [21]. This result is observed commonly in all metal cutting processes.

Figure10 show the effect of spindle speed and depth of cut on surface roughness (Ra). Increase in depth of cut (d) results in high normal pressure and seizure on the rake face and promotes the BUE formation. Hence, the surface roughness (Ra) slightly increases along with increase in depth of cut (d).

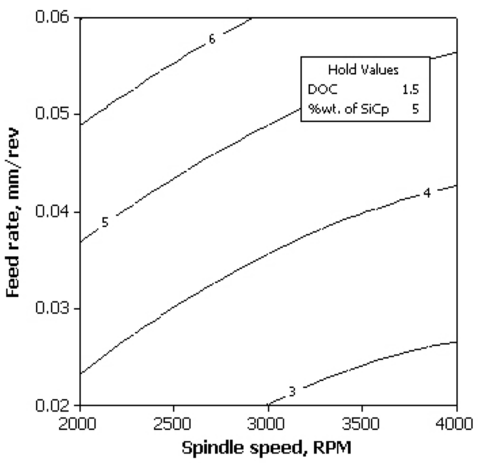

Fig. 8. Effect of spindle speed and feed rate on Ra.

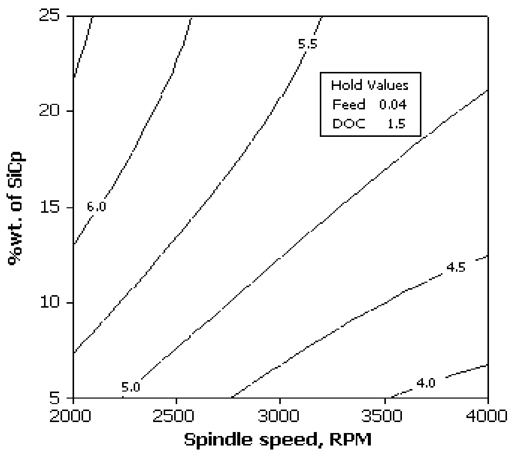

Fig. 9. Effect of spindle speed and %wt. of SiC_p on Ra.

7. Analysis for optimization of the responses

One useful approach to optimization of multiple responses is to use the simultaneous optimization technique popularized by Derringer and Suich [22]. Their procedure introduces the concept of desirability functions. The general approach is to first convert each response Y into an individual desirability function di that varies over the range.

$$0 \le d_i \le 1 \quad (9)$$

where if the response Y is at its goal or target, then d_i=1, and if the response is outside an acceptable region, d_i=0. The weight of the desirability function for each response defines its shape. For each response, one can select a weight (ri) to emphasize or de-emphasize the target. Finally, the individual desirability functions are combined to provide a measure of the composite or overall desirability of the multiresponse system [23]. This measure of composite desirability is the weighted geometric mean of the individual desirability for the responses. The optimal operating conditions can then be determined by maximizing the composite desirability. In the present investigation, the response parameters are chosen to maximize the overall desirability as follows:

$$D = (d_1^{i1}\ d_2^{i2})^{1/(i1+i2)} \quad (10)$$

where d_1 and d_2 are the desirability functions for flank wear (VB_{max}) and surface roughness (Ra), respectively, and i_1 and i_2 are the importance of transformed response parameters of d_1 and d_2. Usually, a reduced gradient algorithm with multiple starting points is employed that maximizes the composite desirability to determine the optimal input variable settings. 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.

Optimization plot for both the responses is shown Fig. 11. The objective is to minimize both responses considered at a time. As the composite desirability is close to 1, it can be concluded that the parameters are within their working range. The optimized values of process parameters are spindle speed (N) 3072.8597 RPM, feed rate (f) 0.020 mm/rev, depth of cut (d) 1.2450 mm, and %wt. of silicon carbide (S) 13.7250.

8. Conclusions

The experimental analysis highlights that the machining criteria like VB_{max} and Ra in composite machining are greatly influenced by the various predominant process parameters considered in the present study. Response

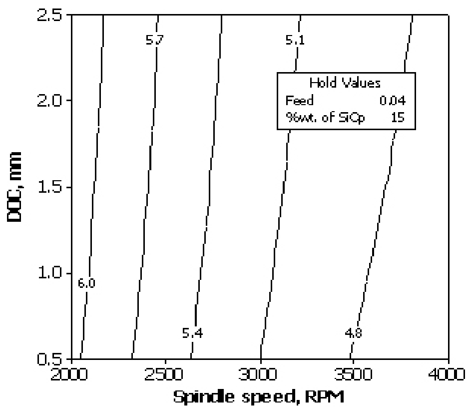

Fig. 10. Effect of %wt. of spindle speed and depth of cut on Ra.

surface methodology used in the present research work has proved its adequacy to be an effective tool for analysis of the composite machining process. From the investigation, the following conclusions are drawn:

1. Spindle speed and feed rate of the regression models are found to be more significant followed by percentage weight of silicon carbide and depth of cut. The proposed models for flank wear and surface roughness are found to be adequate and can be used to predict the characteristics within the experimental range.
2. Formation of BUE significantly affects the tool wear at low speeds whereas thermal softening plays important role at higher speeds and feed rates. Also percentage weight of silicon carbide increases tool flank wear also increases. Depth of cut increases the increase in tool flank wear.
3. The surface roughness is significantly affected by BUE formation at low speeds. The surface roughness is low at higher speed and lower feed rate ranges.
4. The optimal machining parametric combination is obtained using desirability function. Cutting conditions such as spindle speed (N) 3072.8597 RPM, feed rate (f) 0.020 mm/rev, depth of cut (d) 1.2450 mm, and %wt. of silicon carbide (S) 13.7250. can be used to achieve the minimum flank wear of 0.304mm and minimum surface roughness of 3.5854μm.

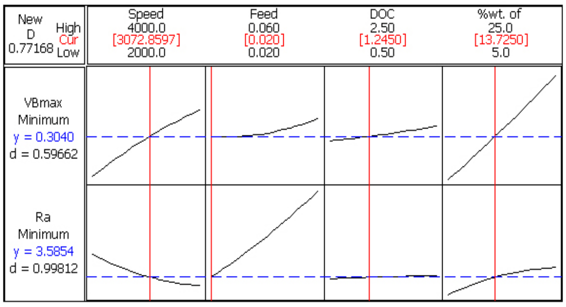

Fig. 11. Optimum results of minimum VB_{max} and Ra.

References

[1] Y. Quan and B. Ye, "The effect of machining on the surface properties of SiC/Al composites", *J. Mater Process Technol.*, Vol. 138, pp. 464–467, (2003).

[2] N. P. Hung, N. L. Loh and Z. M. Xu, "Cumulative tool wear in machining metal matrix composites part II: machinability", *J. Mater Process Technol.*, Vol. 58, pp. 114–120, (1996).

[3] A. Mannaa and B. Bhattacharya, "A study on machinability of Al/SiC-MMC", *J. Mater Process Technol.*, Vol. 140, pp.711–716, (2003).

[4] J. P. Davim, J. Silva and A. M. Baptista, "Experimental cutting model of metal matrix composites (MMCs)", *J. Mater Process Technol.*, Vol. 183, pp. 358–362, (2007).

[5] J. P. Davim, "Application of Merchant theory in machining particulate metal matrix composites", *Mater. Des.*, Vol. 28, pp. 2684–2687, (2007).

[6] S. Kannan and H. A. Kishawy, "Tribological aspects of machining aluminum metal matrix composites", *J. Mater Process Technol.*, Vol. 198, pp. 399–406, (2008).

[7] N. Suresh Kumar Reddy , K. S. Shin and Y. Minyang, "Experimental study of surface integrity during end milling of Al/SiC particulate metal–matrix composites", *J. Mater Process Technol.*, Vol. 201, pp. 574–579, (2008).

[8] T. Ozben, E. Kilickap and O. Cakır, "Investigation of mechanical and

machinability properties of SiC particle reinforced Al-MMC", *J Mater Process Technol*., Vol. 198, pp. 220–225, (2008).

[9] I. Ciftci, M. Turker and U. Seker, "CBN cutting tool wear during machining of particulate reinforced MMCs", *Wear*, Vol. 257, pp. 1041–1046, (2004).

[10] K. Palanikumar, "Modeling and analysis for surface roughness in machining glass fibre reinforced plastics using response surface methodology", *Mater Des*, Vol. 28, pp. 2611–2618, (2007).

[11] J. T. Horng , N. M. Liu and K. T. Chiang, "Investigating the machinability evaluation of Hadfield steel in the hard turning with Al2O3/TiC mixed ceramic tool based on the response surface methodology", *J. Mater Process Technol*., Vol. 208(1–3), pp. 532–541, (2008).

[12] N. Muthukrishnan and J. Paulo Davim "Optimization of machining parameters of Al/SiC-MMC with ANOVA and ANN analysis", *J. Mater Process Technol.*, Vol. 209, pp. 225–232, (2009).

[13] H. Oktema, T. Erzurumlu and H. Kurtaran, "Application of response surface methodology in the optimization of cutting conditions for surface roughness", *J. Mater Process Technol"*, Vol. 170, pp. 11–16, (2005) .

[14] P. Kuppan, A. Rajadurai and S. Narayanan, "Experimental investigation into electrical discharge deep hole drilling of Inconel718 using graphite electrode", *In: Proceedings of the 17th All India machine tool design and research conference*, pp. 923–927, (2006).

[15] K. Palanikumar, "Modeling and analysis for surface roughness in machining glass fibre reinforced plastics using response surface methodology", *Mater Des*, Vol. 28, pp. 2611–2618, (2007).

[16] J. Masounave, J. Litwin and D. Hamelin, "Prediction of tool life in turning aluminum matrix composites", *Mater Des*, Vol. 15, pp. 287–293, (1994).

[17] E. Kılıckap, M. Aksoy and A. Inan, "Study of tool wear and surface roughness in machining of homogenized SiC-p reinforced aluminum metal matrix composite", *J. Mater Process Technol*., Vol.164–165, pp. 862–867, (2005).

[18] N. P. Hung , F. Y. C. Boey , K. A. Khor ,Y. S. Phua and H. F. Lee, "Machinability of aluminum alloys reinforced with silicon carbide particulates", *J. Mater Process Technol.*,Vol. 56, pp. 966–977, (1996).

[19] R. Yousefi , M. A. Kouchakzadeh, J. Rahiminasab and M. A. Kadivar, "The Influence of SiC Particles on Tool Wear in Machining of Al/SiC Metal Matrix Composites Produced by Powder Extrusion", *Advanced Materials Research*, Vol. 325, pp. 393–399, (2011).

[20] K. Palanikumar and R. Karthikeyan, "Assessment of factors influencing surface roughness on the machining of Al/SiC particulate composites". *Mater Des* , Vol. 28, pp.1584–1591, (2007).

[21] I. A. Choudhury and M. A. El-Baradie, "Tool-life prediction model by design of experiments for turning high strength steel (290BHN)", *J. Mater Process Technol*., Vol. 77, pp. 319–326, (1998).

[22] G. Derringer and R. Suich, "Simultaneous optimization of several response variables", *J. Qual Technol.*, Vol. 12, pp. 214–219, (1980).

[23] S. Sarkar, M. Sekh, S. Mitra and B. Bhattacharyya, "Modeling and optimization of wire electrical discharge machining of γ-TiAl in trim cutting operation", *J. Mater Process Technol.*, Vol. 205, pp. 376–387, (2008).