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A New Hybrid Approach to Optimize the End Milling Process for Al/SiC Composites using RSM and GA

M. Vamsi Krishna[1*] and M. Anthony Xavior[2]

[1]Department of Mechanical Engineering, M.I.T.S, Madanapalle - 517325, Andhra Pradesh, India; vamsikrish.mits@gmail.com

[2]School of Mechanical and Building Sciences, VIT University, Vellore - 632014, Tamil Nadu, India; xavior_anto@hotmail.com

Abstract

The centre of research is to optimize the cutting Forces (F_R), surface Roughness (Ra) and Material Removal Rate (MRR) of end milling for Aluminium compositeusing Response Surface Methodology (RSM) and Genetic Algorithm (GA). The RSM L_{31} empirical model is conducted with Al/SiC composites of various compositions. The cutting forces and the surface roughness are measured using 3-axis milling tool dynamometer and MarTalk Profilometer respectively. The second order mathematical models in terms of machining parameters are developed for predicting responses with adequacy above 85%. The optimal configuration of end milling are 5 wt. % of reinforcement, 0.3 mm depth of cut, feed rate of 49.3 mm/min and cutting speed of 474.3 rpm to acquire minimum FR, Ra with maximum MRR is done by Genetic Algorithm (GA). From the estimated model, the responses are with the experimental deviation of 11% MRR, 13% Ra and 17% FR for the desirability of 98.7%. The optimization of three machining parameters with a advance hybrid approach brought a new scope for the researchers and manufactures to improve the standard of automated machining.

Keywords: ANOVA, Aluminium, Composites, Milling, Optimization

1. Introduction

The engineering ceramic composites with low density and high strength are mostly preferable for the industrial applications[1]. The distinctive properties like high specific stiffness and strength, high mechanical strength, good corrosive resistance and low thermal expansion of the particle reinforced composites have enabled their use in automotive, machine tool industries, aerospace, sporting equipment industries[2].

Generally, the engineering ceramic composites are Aluminium Metal Matrix Composite (AMMC)[3]. It is reinforced with different kinds of ceramic particles like Si_3N_4[4], $A1_2O_3$[5], B_4C[6,7], TiC[8] and the most commonly used particle is SiC[9,10].

However, it could be very difficult to machine AMMCs, because of their non-homogeneous, anistropic and reinforced by very abrasive materials. So, the machined composite may experience a significant damage and high wear rate of cutting tools. After all, the machining of composite materials is depending on several conditions like material properties, relative content of the reinforcement and the response to the machining process[11,12]. For machining these AMMCs for good machinability, the Poly Crystalline Diamond (PCD) tools were suggested well[13].

End milling is a vital and common machining process because of its flexibility and capability to produce various profiles even with curved surfaces. It has the ability to remove material faster with a good surface quality and milled surfaces are largely used to mate the aerospace, automobile, biomedical products, as well as in manufacturing industries applications[14].

The machining parameters optimization in an end milling process plays an important role in the practical manufacturing applications. The aims are to improve the surface roughness quality and maximize the Material Removal Rate (MRR) with optimal cutting force. Traditionally, trial-and-error and heuristic approaches are employed to obtain the optimal machining parameters. It

* Author for correspondence

is well recognized that these methods are time consuming and lead to long machining periods with large machining cost[15].

Design of experiments is a powerful analysis tool for modelling and analysing the influence of control factors on output performance. The traditional experimental design is difficult to be used especially when dealing with large number of experiments and when the number of machining parameter is increasing[16]. The most important stage in the design of experiment lies in the selection of the control factors[17]. The development of an effective methodology to determine the optimum cutting conditions leading to minimum surface Roughness (Ra) in milling by coupling Response Surface Methodology (RSM) with a developed Genetic Algorithm (GA)[18].

From the light of the review, it is inferred that there is a lack of study in predicting and optimizing the cutting force along with MRR and Ra for end milling process. In this work, the main objective is to develop the mathematical models for the MRR, Ra and cutting Force (F_R) with regards to machining parameters using RSM. The direct and interaction effect of each parameter are studied. The optimal machining parameters to obtain minimum Ra and cutting force with maximum MRRis done using Genetic Algorithm (GA).

2. Materials and Methods

2.1 Materials

The end milling tests were conducted with BATIBOI-NOMO universal milling machine shown in Figure 1a. In the milling experiments, Al 6061/SiC composite material were used as the work piece with varying reinforcement wt. % of 5, 10 and 15, which had a dimension of 100*100*10 mm^3. The stir casting method is the effectivemanufacturing mrthod for producingthe Al/SiC composites and the chemical composition of Al 6061 is tabulated in Table 1. The Poly Crstalline Diamond (PCD) coated tool shown in Figure 1b of thickness 0.6 mm and 12 mm in dia is used and its nomenclature is shown in Table 2.

Table 1. Chemical composition of Al 6061

Material	Mg	C	Cr	Zn	Fe	Si	Mn	Ti	Al
%	0.81	0.21	0.25	0.11	0.25	0.6	0.04	0.1	Balance

Table 2. Tool Nomenclature

d_1	d_2	l_1	l_2	l_3	l_4
6.0	6.0	57.0	8.0	21.0	36.0

The MRR is calculated using the Equation (1) and the cutting forces is measured using the 3-axis milling tool dynamometer. The force data was obtained through DAQ card and amplifier under Dynoware software. From this, the three Force components (F_x, F_y and F_z) are measured simultaneously and its resultant (F_R) is calculated using the Equation (2). The Surface Roughness (Ra) of the machined surface is measured using MarTalk Profilometer with the accuracy of 0.001 μm.

$$MRR = \frac{l * b * DOC}{Time} \quad (1)$$

$$F_R = \sqrt{F_x^2 + F_y^2 + F_z^2} \quad (2)$$

Where, l = length of the plate
b = breath of the plate
DOC = depth of cut
F_R = Resultant cutting force
F_x, F_y and F_z = Cutting force along x, y and z-axis respectively.

2.2 Design of Experiments (DOE)

The RSM involves the studying the response based on the combinations, estimating the coefficients, fitting the

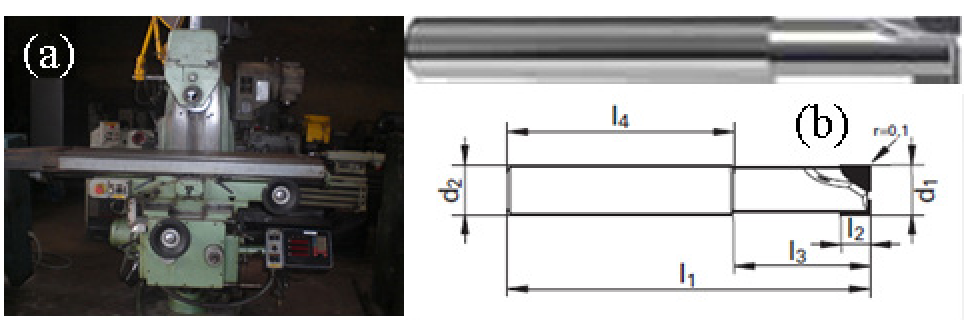

Figure 1. (a) Universal milling machine (b) PCD tool.

experimental data, predicting the response and checking the adequacy of the fitted model[20]. Here, the responses are MRR, Ra and FR for the independent variables (input parameters) are reinforcement %, Depth of Cut and Feed rate, Cutting Speed are shown in Table 3. For this DOE, the three levels RSM design with L_{31} array was done using MINITAB 16. The regression equations were formed for the individual responses based on the controlling parameters. From this mathematical model, the predicted models are estimated and the models are validated through ANOVA.

Table 3. Parameters and levels in end milling

S. No.	Variable	Parameter	Units	levels Low	levels High
1.	A	Material	(Wt. %)	5	15
2.	B	Depth of Cut	(mm)	0.3	0.6
3.	C	Feed	(mm/min)	30	90
4.	D	Cutting Speed	(rpm)	100	1000

2.3 Genetic Algorithm (GA)

GA is used to find the optimum configuration of input parameters to achieve the optimal response. In the GA many individuals construct a population to evolve based on described selection rules to state that the fitness gets maximized[21,22]. GA is of many coded types, here the real coded is used because the inputs are taken from RSM model. The values of initial parameters are tabulated in Table 4 for doing GA in MATLAB 14. The population was supervised by reproduction, which contained three main operators (selection, crossover and mutation) as shown in Figure 2.

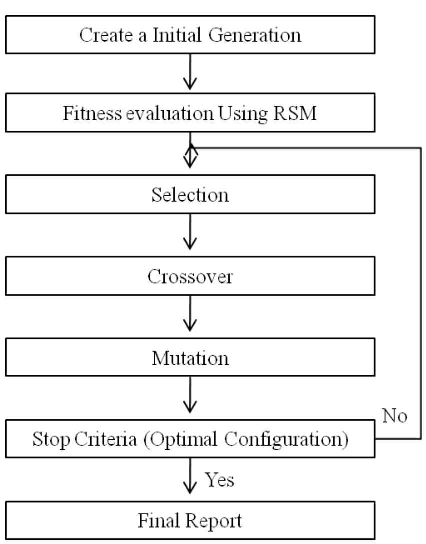

Figure 2. GA for optimization.

Table 4. Parameters of GA

Parameters	Value
Chromosome length	4
Population size	104
Mutation rate	0.2
Selection function	Tournament
Crossover fraction	0.8
Mutation function	Adaptive feasible
Crossover function	Single point

3. Response Surface Methodology

The results of the output parameters after machining process were consolidated for the mathematically model the input parameters. The experiment is designed according to the selected three factors with three levels, and it is given in Table 3 as explained[23]. The RSM trials of the randomized design Table are shown in Table 5.

3.1 Mathematical Models for the Responses

The mathematical models for the responses are derived from the uncoded data for the given input trails. The MRR in form of regression equation is stated in Equation (3), which states that the factor B influences more compared to other factors. In Equation (4) and (5) are the regression equations of Ra and F_R respectively, which also declare that the factors B (depth of cut) influences highly in all configuration results.

$$MRR = 1.25478 + 1.75719*A + 33.8615*B - 0.688283*C - 0.0103421*D - 0.0749221*A*A - 28.5895*B*B + 0.00425216*C*C + 1.27E-05*D*D - 1.09583*A*B + 0.0162917*A*C - 7.09E-04*A*D + 0.451806*B*C + 0.00682407*B*D + 2.78E-07*C*D \tag{3}$$

$$Ra = -1.26391 + 0.138958*A + 4.77893*B + 0.0573958*C - 0.00338567*D + 0.000519467*A*A - 1.41126*B*B + 0.00046443*C*C + 0.00000374314*D*D - 0.0154167*A*B - 0.0030125*A*C + 0.0000347222*A*D - 0.0132639*B*C - 0.00138426*B*D - 0.0000763426*C*D \tag{4}$$

$$F_R = 45.5807 + 2.53377*A + 50.2841*B + 10.8129*C - 0.653551*D - 1.23815*A2 - 71.7649*B2 - 0.0573376*C2 + 0.000460524*D2 + 11.2092*A*B - 0.03355*A*C + 0.0210617*A*D + 2.39389*B*C - 0.22425*B*D - 0.00468241*C*D \tag{5}$$

3.2 Checking of Data and Adequacy of Model

The normality of the data was assessed by means of the

Table 5. Analytical table of responses for the independent variables

S. No.	Material (wt. %)	Depth of Cut (mm)	Feed (mm/min)	Cutting Speed (rpm)	MRR (mm^3/s)	R_a (μm)	F_R (N)
1	15	0.3	30	1000	4.5	0.5	36.68
2	10	0.6	60	550	12.44	2.41	264.8
3	10	0.6	60	550	12.44	2.41	264.8
4	10	0.6	60	550	12.44	2.41	264.8
5	15	0.3	90	100	24.28	4.92	314.03
6	10	0.6	30	550	7.2	0.52	94.96
7	10	0.6	60	550	12.44	2.41	264.8
8	10	0.6	90	550	20.57	2.32	25.82
9	5	0.3	90	1000	10.29	0.69	49.33
10	15	0.9	90	1000	36	0.95	88.91
11	15	0.9	90	100	30.86	6.15	501.65
12	5	0.9	90	100	27	9.06	752.12
13	5	0.9	90	1000	31.76	0.77	49.83
14	10	0.6	60	550	12.44	2.41	264.8
15	10	0.9	60	550	11.37	1.13	122.16
16	10	0.6	60	100	12.13	3.51	365.64
17	10	0.6	60	1000	13.12	0.01	44.86
18	10	0.6	60	550	12.44	2.41	264.8
19	15	0.6	60	550	8	1.25	111.07
20	10	0.6	60	550	12.44	2.41	264.8
21	15	0.3	90	1000	8	1.25	111.07
22	10	0.3	60	550	3.6	0.62	88.91
23	15	0.3	30	100	3.6	2.76	35.62
24	5	0.6	60	550	8.37	0.78	51.01
25	5	0.9	30	1000	10.8	2.25	57.81
26	15	0.9	30	100	4.77	4.82	278.14
27	15	0.9	30	1000	4.25	0.78	7.28
28	5	0.3	90	100	1.87	7.57	501.65
29	5	0.3	30	100	2.4	1.84	373.07
30	5	0.3	30	1000	4	0.35	4.87
31	5	0.9	30	100	10.8	2.01	178.72

normal probability plot. The normal probability plot of the residuals for the MRR, Ra and F_R are shown in Figure 3 (a), (b) and (c) respectively. The normal probability plot for the responses reveals that the residuals fall in a straight line. This means the errors are distributed normally. The Independence of the data was tested, by plotting a graph between the residuals, and the run order for the responses confirms that there was no predictable pattern observed, because all the run residues lay on or between the levels, which agrees with the results[22].

Table 6. Adequacy of the models

S. No.	Response	Std. Deviation	R^2	$R^2_{(adj)}$
1.	MRR	3.308	92.7%	86.4%
2.	Ra	1.069	86.6%	84.9%
3.	F_R	108.9	89.4%	81.4%

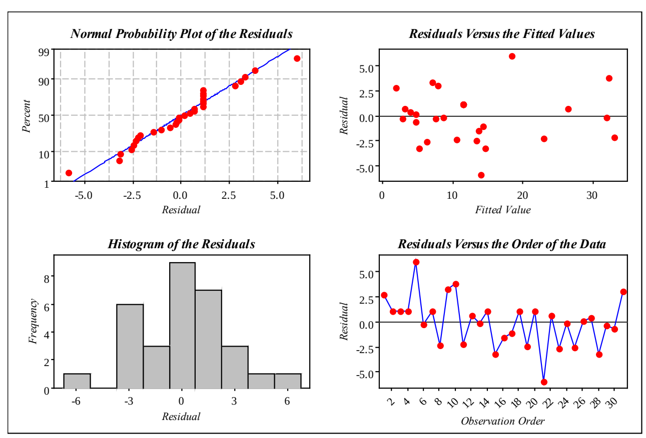

Figure 3. (a) Input data analysis of plot for MRR.

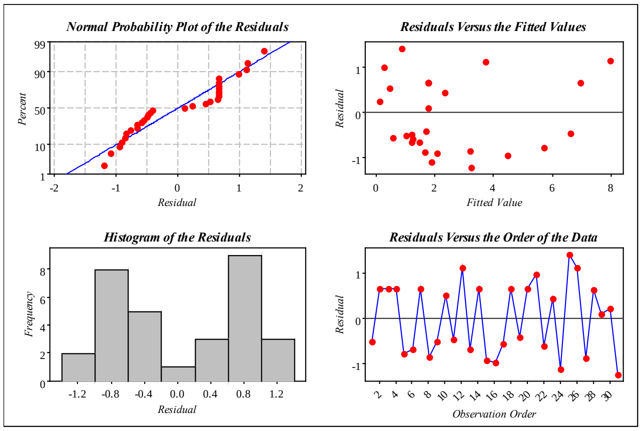

Figure 3. (b) Input data analysis of plot for Ra.

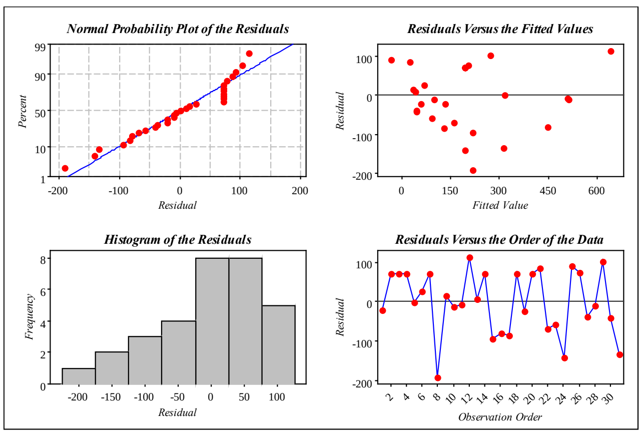

Figure 3. (c) Input data analysis of plot for F_R.

The adequacy of the responses are tabulated in Table 6 with R^2 and $R^2_{(adj)}$ values. These indicate that the model fits the data well and R^2 is in agreement with $R^2_{(adj)}$ which supports prediction power of the model. In all the models, both the values are good and above 80% which makes a fitness in predicted solutions.

3.3 ANOVA

The ANOVA for MRR, Ra and F_R are tabulated in Table 7 to 9 respectively. In all forms of regression, the P values of the responses are less than the F value and also it was less than 0.05 i.e. significant for 95% confidence limit. It confirms that the developed models are adequate, and the predicted values are in good agreement with the measured data.

Table 7. ANOVA for MRR

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	14	2234.93	2234.93	159.638	14.59	0
Linear	4	1693.47	1693.47	423.367	38.68	0
Square	4	83.78	83.78	20.944	1.91	0.157
Interaction	6	457.68	457.68	76.28	6.97	0.001
Residual Error	16	175.11	175.11	10.944		
Lack-of-Fit	10	175.11	175.11	17.511		
Pure Error	6	0	0	0		
Total	**30**	**2410.03**				

Table 8. ANOVA for Ra

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	14	118.318	118.3183	8.4513	7.39	0
Linear	4	89.375	89.375	22.3438	19.54	0
Square	4	7.788	7.7882	1.9471	1.7	0.198
Interaction	6	21.155	21.155	3.5258	3.08	0.033
Residual Error	16	18.293	18.2934	1.1433		
Lack-of-Fit	10	18.293	18.2934	1.8293		
Pure Error	6	0	0	0		
Total	**30**	**136.612**				

Table 9. ANOVA for F_R

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	14	731762	731762	52269	4.41	0.003
Linear	4	580060	580060	145015	12.23	0
Square	4	24819	24819	6205	0.52	0.22
Interaction	6	126884	126884	21147	1.78	0.166
Residual Error	16	189652	189652	11853		
Lack-of-Fit	10	189652	189652	18965		
Pure Error	6	0	0	0		
Total	**30**	**921414**				

3.4 Interaction Effect of the Controlling Factors

The contour plots were developed to study the interaction effect of controlling parameters on MRR is shown in Figure 4. The maximum MRR (Dark Green) is identified at high depth of cut and feed rate. The material and cutting speed factors doesn't influence much compared to others in MRR. This result confirms the results of Equation (3) and also it agrees with the results[24].

The interaction effect of controlling parameters on Ra shown in Figure 5 reveals that the minimum Ra (Dark Blue) is identified well with the maximum cutting speed[25]. Even though other parameters influence the Ra but the significant observation was found with the influence of cutting speed. The minimum F_R (Light Green) was noticed with less feed rate, reinforcement (wt. %) at high cutting speed as shown in Figure 6. The increase in F_R will leads to decrease in tool life but with minimum F_R configuration, the MRR is less. Therefore, it is essential to final an optimal configuration with minimal F_R with produce maximum MRR[26].

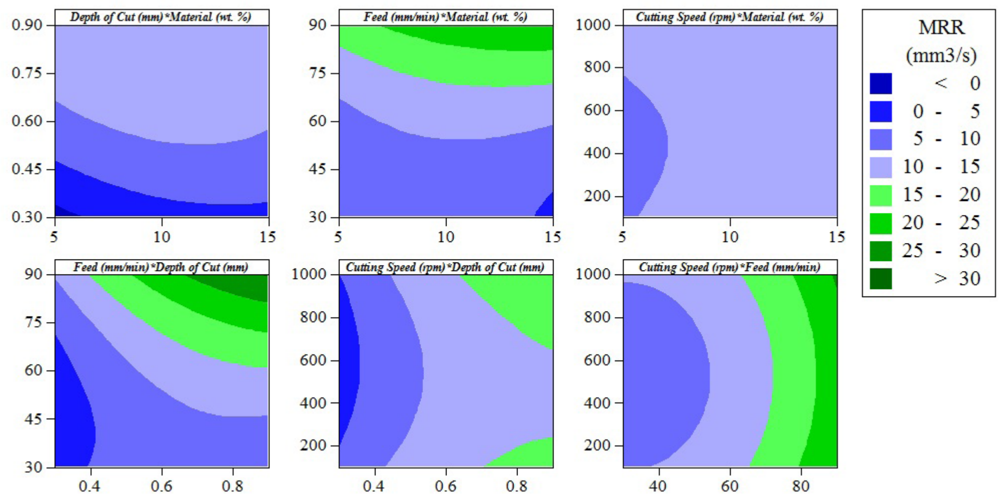

Figure 4. Contour plots for MRR.

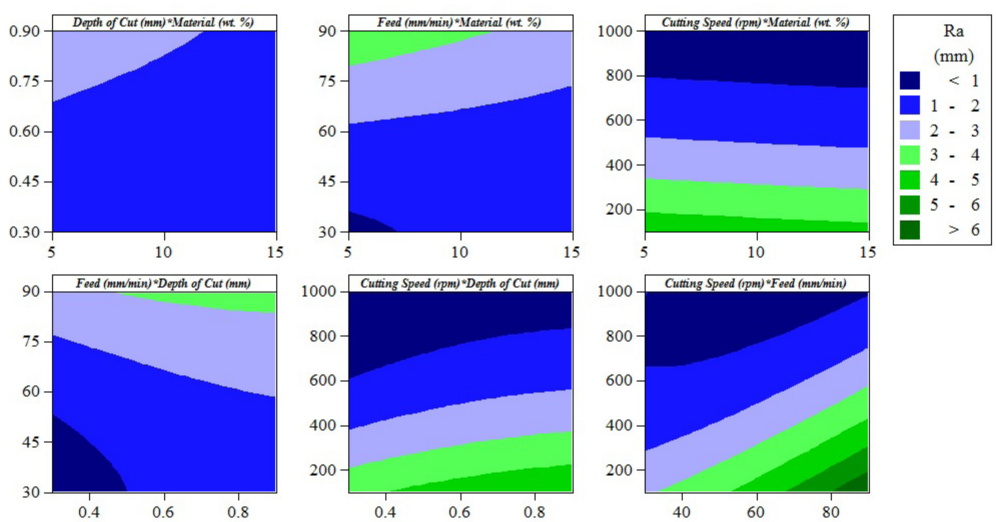

Figure 5. Contour plots for Ra.

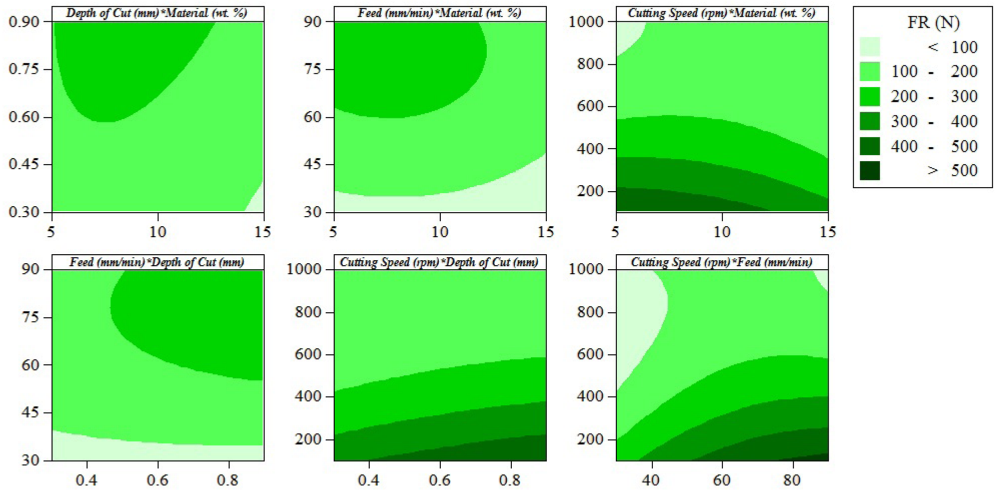

Figure 6. Contour plots for F_R.

4. Optimization of Machining Parameters

For finding the optimal end milling machining parameters, the generation was started with 0.5 of fitness value and it was increased with a 0.005 step to reach the final value. The generation plot was graphically represented in Figure 7 (a) and (b) against average spread and average distance respectively. This shows the average spread of 0.09 for the maximum generation of 104.

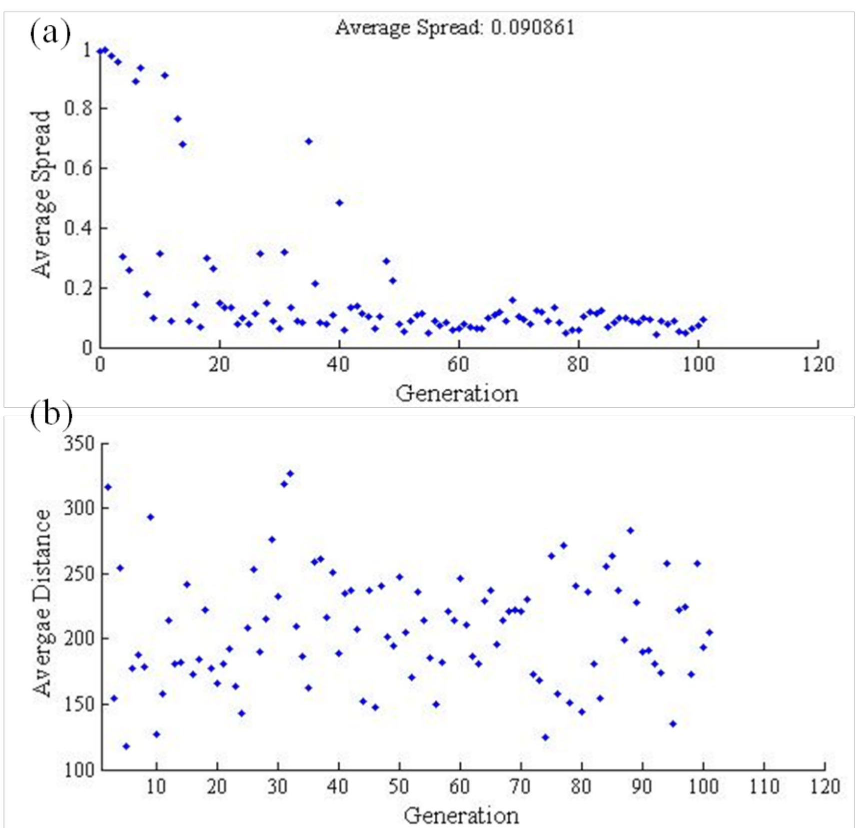

Figure 7. Generation plots.

Table 10. Optimal configurations of machining parameters

S. No.	Material (wt. %)	Depth of Cut (mm)	Feed (mm/min)	Cutting Speed (rpm)	MRR (mm^3/s)	R_a (μm)	F_R (N)
1	5	0.3	36.91679	474.5193	10.2476	0.560514	123.6861
2	5	0.3	49.03006	474.5217	11.52787	1.069799	174.7236
3	5	0.899979	35.31262	953.8406	12.96318	0.766906	188.81364
4	5	0.3	42.82476	474.5219	11.02791	0.791876	150.68
5	5	0.899983	42.83165	953.8375	13.9582	0.720817	20.15482
6	5	0.536115	35.31628	851.4056	8.099466	0.433402	37.33372
7	5	0.899983	35.31262	793.2725	10.64255	0.865503	8.980639
8	5	0.3	49.28599	793.2725	10.17886	0.239117	91.96585
9	5.000004	0.3	37.04314	793.2725	1.09412	0.020124	58.9226
10	5	0.3	37.04314	474.264	10.26745	0.565864	124.3951
11	5	0.3	49.03006	793.2739	10.16528	0.233112	91.45083
12	5	0.536115	35.64464	793.274	7.458711	0.464624	43.13715
13	5.00098	0.899003	42.83173	953.8379	13.95551	0.720581	20.30511
14	5.000002	0.3	42.82476	474.2643	11.02796	0.792738	150.7777
15	5	0.3	35.3153	851.4016	1.902908	-0.00929	51.51102
16	5.000004	0.42413	35.64464	851.4056	5.52074	0.244596	46.24067
17	5.000015	0.42207	35.64555	793.2736	4.891918	0.261781	49.41284
18	5	0.301469	42.8232	793.2754	0.387102	0.109374	76.64656
19	5	0.3	49.2869	474.2662	13.9582	1.083055	175.7282
20	5.00132	0.301389	35.3159	851.4036	1.949442	0.00614	51.46658
21	5	0.898026	35.64464	851.4025	11.44301	0.805968	1.622479

Among these configurations the possible optimal solutions are generated at 21 plots which are tabulated in Table 10. The optimal machining parameters of end milling which can provide minimum F_R, Ra and maximum MRR was found from Figure 8 i.e., reinforcement material of 5 wt. %, depth of cut 0.3 mm, feed rate of 49.3 mm/min and cutting speed of 474.3 rpm. From the estimated model, the responses for these input are MRR of 13.96 mm^3/s, Ra of 1.08 μm with the F_R of 175.73N. The same trail was practically executed to get the practically solution and it was MRR of 11.3 mm^3/s, Ra of 0.73 μm with the F_R of 211.47N which was 11%, 13% and 17% deviation from the predicted results but the optimal configuration remains well with the desirability of 98.7%.

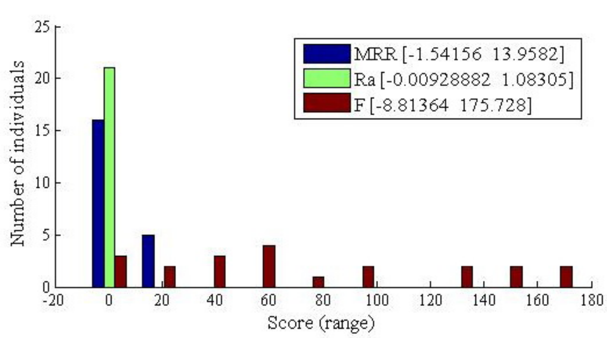

Figure 8. Optimized results of responses.

5. Conclusion

In this research, the engineering ceramic material Al/SiC was studied to machine through end milling process. The necessity of machining parameters control and its influences on quality also illustrated well. The second order polynomial mathematical models were generated to estimate the responses in a significant level using RSM with L_{31} array and it was optimized through GA. The optimal machining parameters of end milling were reinforcement of 5 wt. %, 0.3 mm depth of cut, feed rate of 49.3 mm/min and cutting speed of 474.3 rpm. From the estimated model, the responses for these input are MRR of 13.96 mm^3/s, Ra of 1.08 μm with F_R of 175.73N which were 11%, 13% and 17% deviation from the experimental results with the desirability of 98.7%.

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