Research Article

Optimization of end milling on Al–SiC-fly ash metal matrix composite using Topsis and fuzzy logic

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Abstract
Metal matrix composites are extensively used in aerospace, automobile and other engineering applications as an alternative to a wide range of elements. High strength–weight ratio, durability and high corrosion resistance are benefits of metal matrix composites. The study that exhibits adopts optimal cutting parameters (speed, feed and depth of cut). The initial study is to explore end milling process of alumina (AA6082 with SiC 3% and fly ash 2%) molted metal matrix composite. The technique for order preference by similarity to ideal solution and fuzzy logic for optimizing the cutting parameter values has been utilized in the MMC. The response surface methodology is being used to develop the numerical model between output responses and machining parameters. The second-order regression models are studied through analysis of variance. The experimental investigation exhibits that feed rate is the important factor on response variables.

Keywords Milling · Alumina · Optimum · Machining · Composites · Fuzzy logic

1 Introduction

Metal matrix composites (MMCs) have a rare mechanical property. Reinforced aluminum MMC has a notable design property. These materials have been recognized as hard-to-machine materials, due to their durability and abrasive nature of support components like silicon carbide particles [1]. The MMCs are most generally used in aviation and automotive industries [2]. End milling is one of the primary machining activities used in modern industries due to its ability to produce geometric surfaces, accuracy and surface finish. The surface roughness (SR) of the component highly depends on the exclusive cutting parameters. SR is the major parameter, used for assurance and the estimation of the quality characteristics. SR and material removal rate (MRR) are the measures of the quality of a product and have a significant impact on the product cost.

Although destruction has been used in this article, technique for order preference by similarity to ideal solution (Topsis) presented by Hwang and Yoon [3] has been utilized for evaluation of the alternatives. Vinodh et al. [4] have built up a tool with integrated fuzzy, analytical hierarchy process (AHP) and Topsis for doing execution assessment and distinguishing the best strategy for the reuse of plastics. Nayak and Mahapatra [5] utilized AHP with Topsis method for the optimization of various responses like MRR, surface finish and kerf angle. Dewangan et al. [6] examined the impact of different electro-discharge machining (EDM) parameters on the distinctive parts of surface integrity. A response surface methodology (RSM)-based design of experiment was treated in their research. Awasthi et al. [7] proposed a crossbreed approach in the light of the service quality model and fuzzy logic (FI)—Topsis for assessing the administration nature of urban transportation frame works. Fuzzy with Topsis is used to resolve the relative weights of decision criteria [8]. A fuzzy-Topsis-based system for appraisal and decision of vertical computer numerical control machining centers for an

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assembling unit is studied by Onut et al. [9]. Yurdalul and Lc [10] evaluate the advantages of utilizing fuzzy numbers instead of crisp numbers in a Topsis method based on instrument choice model. The conclusion was that fuzzy numbers should be preferred instead of crisp in the decision-making issues.

Sidhu et al. [11] investigated the effect of EDM process parameters on the surface properties of variant Al/SiC composites. Their result shows that microhardness of the machined surface is directly proportional to the concentration of reinforced (SiC) particulates. Gadakh [12] applied Topsis for taking care of various criteria enhancement issues in the wire-EDM procedure. Yurdakul and Cogun [13] have proposed a determination strategy for non-traditional machining processes (NTMPs) in the light of a gathering of AHP and Topsis techniques. Temucin et al. [14] built up a fuzzy-based choice help for demonstrating NTMPs choice through application of Topsis and fuzzy-Topsis strategies. Shivakoti et al. [15] used the triangular fuzzy member for ascertain the weight performance criteria, and fuzzy-Topsis. Kumar et al. [16] applied the Taguchi and Topsis techniques in the EDM machining process with conventional electrodes on M2 tool steel with aluminum power and without aluminum powder.

Sidhu et al. [17] studied the surface modification of three different types of metal matrix composite using powder mixed electrical discharge machining process and reported that microhardness increased primarily with increase in the density of reinforced particles in the matrix. Shunmugesh and Paneerselvam [18] studied the drilling parameter with carbon fiber reinforced polymer. The result shows that multi-objective technique has good agreement with Topsis technique. Arif Gok [19] studied the SR expectation dependent on the cutting parameters in turning operation. Tamiloli et al. [20] dealt with improvement in cutting parameters for end milling process dependent on gray-fuzzy logic for SR and MRR. The statistical methods of signal-to-noise ratio and analysis of variance are applied in their investigation. Sidhu and Yazdani [21] used lexicographic goal programming for investigating the better EDM machining parameters to optimize conflicting objectives such as induced residual stresses on the machined surface, tool wear rate and material removal rate. Makadia [22] studied the machining parameters and output response (SR). The outcomes revealed the feed rate is the main influencing factor of the machining parameter.

Sidhu [23] reports the optimal process conditions for machining of three different types of MMC's: 65 vol% SiC/A356.2; 10 vol% SiC-5 vol% quartz/Al; and 30 vol% SiC/A359 using powder mixed electric discharge machining process. MRR, TWR, SR and surface integrity were identified. The four responses were then collectively optimized using Topsis, and optimal process conditions were identified for each type of MMC. Roy and Dutta [24] studied about the multi-objective optimization of electrical discharge machining using integrated fuzzy AHP and fuzzy-Topsis method. A fuzzy-Topsis method was used [25] to optimize multiple responses, viz. SR, MRR and tool wear rate, in EDM based on various process parameters. Recast layer thickness and SR were optimized [26] using Taguchi-based fuzzy logic technique. This technique significantly improved multiple responses in WEDM. Topsis is a well-known application in many areas [27–31] and given a choice network and a basic leadership strategy.

Topsis finds an ideal choice elective that is at the closest partition to the positive ideal solution (PIS) and most remote division to the negative ideal solution (NIS). PIS is an ideal arrangement wail, and NIS is the most perceptibly horrendous game plan that is not of any interest. Based on the multi-regression analysis, a suitable mathematical model of the responses has been established. The prime objective of this research is to minimize the surface roughness and normal cutting force simultaneously. Thus, this case of an inconsistent condition requires multi-objective optimization tool for an optimum solution. In the second phase of analysis, the multi-optimization techniques such as technique for order preference by similarity to ideal solution and fuzzy logic have been adopted to optimal solution.

2 Materials and methods

The stir casting method is used to reinforce silicon, fly ash and aluminum alloy 6082T6. The chemical composition of AA6082T6, silicon carbide and fly ash is shown in Table 1. Initially, the silicon and sieved fly ash (50–75 µm) are preheated at 650 °C. Using the electrical furnace,

Table 1 Chemical composition of aluminum, silicon carbide and fly ash

Materials	Chemical compositions
AA6082T6	Si (0.7–1%), Fe (0.5%), Cu (0.1%), Mn (0.4–1%), Mg (0.6–1.20%), Cr (0.25%), Zn (0.20%), Ti (0.1%) and aluminum (remaining)
Silicon carbide	Sic (98.7%), Si (0.3%), Sio_2 (0.4%), Fe (0.08%), Al (0.1%) and C (0.3%)
Fly ash	SiO_2 (52.78%), Al_2O_3 (24.48%), Fe_2O_3 (6.25%), CaO (11.08%), MgO (2.58%), SO_3 (1.31%) and loss of ignition 1.3% by weight

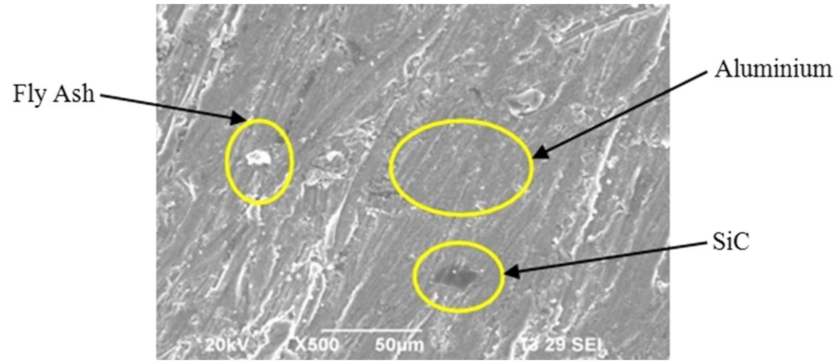

Fig. 1 Microstructure (aluminum 95% + Sic 3% + fly ash 2%)

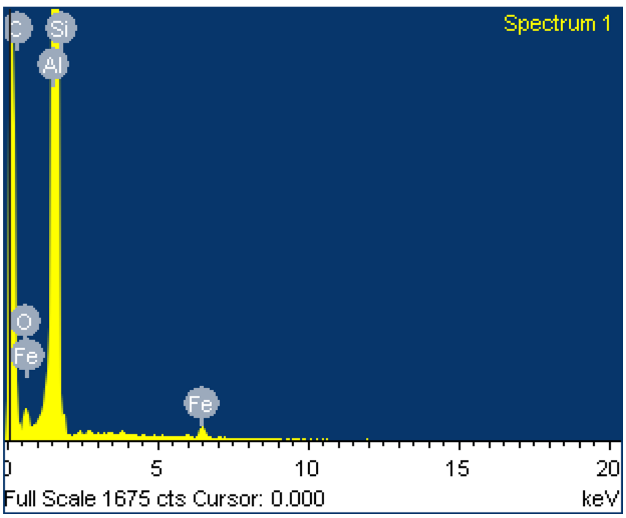

Fig. 2 EDAX (aluminum 95% + Sic 3% + fly ash 2%)

Fig. 3 Knee-type vertical milling machine

Table 2 Property of the workpiece

Peak stress (MPa)	Peak load (KN)	Hardness (BHN) (100 Kgf)	Modulus (GPa)	Flexural stress (MPa)
119.6	4.3	537	49.797	229.1

Table 3 Process variables with their limits

Parameters	Unit	Level 1	Level 2	Level 3
Spindle speed (A)	rpm	500	710	1000
Feed (B)	mm/min	40	63	100
Depth of cut (C)	mm	0.5	0.75	1.0

aluminum bars are melted to 650–800 °C and fried silicon and fly ash add the molten metal and continuously stirred 650 rpm for 10 min. In order to increase the wet ability, one weight percent of magnesium was added. The molten metal poured to 100 × 50 × 30 mm metal was mold and solidified. The scanning electron microscope image of the distributed composite is shown in Fig. 1, and energy-dispersive X-ray analysis (EDAX) image is exposed in Fig. 2. A property of the workpiece (aluminum 95% + SiC 3% + fly ash 2%) is shown in Table 2.

2.1 Process variables with their limits

The machining was carried out on a knee-type milling machine (model: UF-1) as shown in Fig. 3. The work material selected for the study was aluminum 95% + SiC 3% + fly ash 2%. Based on the Taguchi, orthogonal array (OA) was considered L27 experiments required for the determination of the optimal level. Speed (A), feed rate (B) and depth of cut (DOC) (C) as machining parameters and surface roughness and normal force were selected as a process performance. In Table 3, the levels of machining parameters are shown.

Table 4 Results of surface roughness and cutting force using L27 orthogonal array

S. no.	Speed (rpm)	Feed (mm/min)	Doc (mm)	SR R_a (μm)	F_z (N)
1	500	40	0.5	4.416	144.000
2	500	40	0.75	4.525	144.149
3	500	40	1	4.108	125.766
4	500	63	0.5	5.301	182.156
5	500	63	0.75	4.830	160.300
6	500	63	1	4.467	145.390
7	500	100	0.5	5.878	213.725
8	500	100	0.75	5.461	195.341
9	500	100	1	5.831	156.200
10	710	40	0.5	5.548	169.442
11	710	40	0.75	4.908	150.200
12	710	40	1	4.714	132.675
13	710	63	0.5	5.907	189.065
14	710	63	0.75	5.490	170.682
15	710	63	1	5.639	170.700
16	710	100	0.5	6.484	277.200
17	710	100	0.75	6.067	202.250
18	710	100	1	5.650	183.867
19	1000	40	0.5	6.385	178.983
20	1000	40	0.75	5.968	160.599
21	1000	40	1	6.610	164.100
22	1000	63	0.5	7.643	180.100
23	1000	63	0.75	6.327	180.223
24	1000	63	1	5.910	161.84
25	1000	100	0.5	7.321	230.175
26	1000	100	0.75	6.904	197.600
27	1000	100	1	6.487	193.408

2.2 Evaluation of surface roughness (SR) (R_a) and cutting force (F_z)

SR measurement was taken by portable stylus-type profilometer. The machining was carried out under dry cutting condition with tungsten carbide insert (single side). The arithmetic average values R_a (μm) were measured with the help of a surface roughness tester (Mitutoyo model SJ-210), and normal feed force (F_z) (N) was carried out with help of Kistler dynamometer. The L27 (full factorial) experimental values are shown in Table 4.

2.3 Topsis steps

The recommended optimization techniques of Topsis and FI procedure are shown in Fig. 4. The Topsis steps are summarized in Fig. 5. Normalized decision matrix, weighted normalized values, separation measures, average, fuzzy reasoning grade (FRG) and ranks are shown in Table 5.

2.4 Fuzzy rule-based modeling

During this analysis, the multi-objective responses were changed to single objective optimization utilizing the Topsis technique. The uncertainties in the output were condensed further by FI. The criteria acknowledged as the best executions with machining aluminum composites need aid for lower surface roughness and normal feed force.

Utilizing the Topsis technique, the original sequence data were converted into normalized decision matrix. After that all the machining parameters are manipulated. A more significant value of the average was indicative of the good performance characteristic equal to one. The parametric condition was corresponding to the highest cutting force and SR. However, there is a tendency of a certain level of a particular degree about the controversial matter to bring about shortage.

Uncertainties emerged mainly due to the imprecision and absence of the majority of the data. The FI approach appeared to offer a compelling result for controlling these averages. As a result, fuzzy thinking about various execution qualities was formed and suggest to the fuzzy thinking evaluation. The steps in the FI approach include fuzzification of input data, principle induction for more defuzzification procedure [22].

The fuzzy algorithm for deciding the ideal level about machining parameters and the steps included are summarized as follows.

- The extended parameters may be determined, and a suitable orthogonal show adjusted for leading examinations.
- Responses such as SR and F_z were considered for each trial. These responses were initially normalized during data preprocessing. Following this, normalized decision matrix weighted normalized values and separation measures, average and FRG determined are listed in Table 3. The input parameters and output values were normalized with help of Topsis.

The triangular membership function and fuzzy rule were established to fuzzify the speed $\xi(k)$ of every response. Three fuzzy subsets were assigned to the surface roughness and cutting force using the membership function. IF–THEN rule statement was used for formulating conditional statements. It has three machining parameters (speed, feed and DOC) ξ_1, $\xi_i(k)\xi_2$, ξ_3, and one multi-response output η; these are represented as follows:

$$\begin{aligned} &\text{Rule 1}: \quad \text{if } \xi_1 \text{ is } A_{11},\ \xi_2 \text{ is } A_{12} \text{ and } \xi_3 \text{ is } A_{1n},\ \text{then } \eta \text{ is } D_1,\ \text{else} \\ &\qquad \vdots \\ &\text{Rule } n: \quad \text{if } \xi_1 \text{ is } A_{31},\ \xi_2 \text{ is } A_{32} \text{ and } \xi_3 \text{ is } A_{33},\ \text{then } \eta \text{ is } D_3,\ \text{else} \ldots \end{aligned} \tag{1}$$

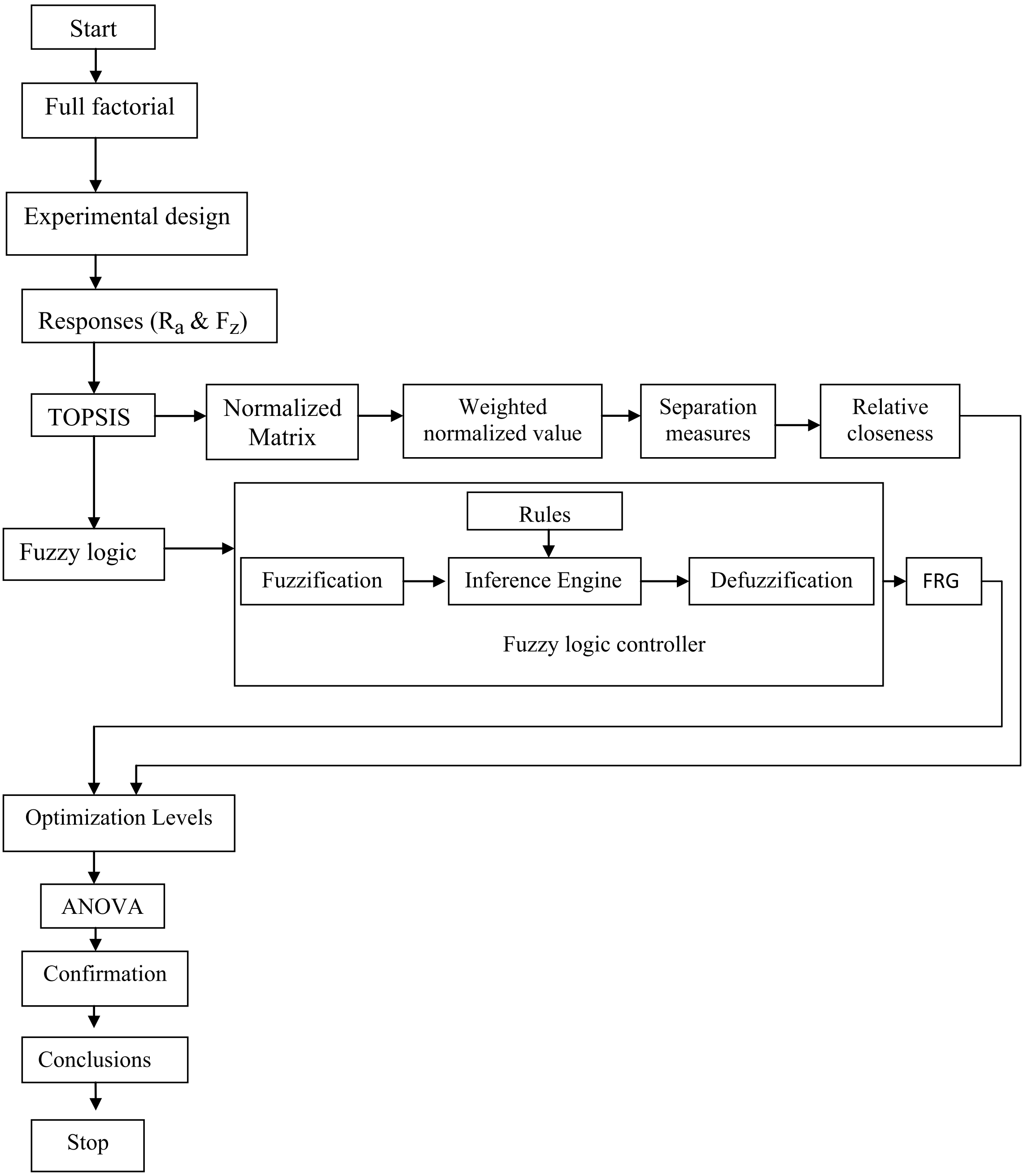

Fig. 4 Flowchart of the research

Nine fuzzy subsets were utilized for the multi-reactions output η. The scope of each fuzzy subset is exhibited in Table 5. In light of the exploratory arrangement, fuzzy rules were produced by the concurrence concept that a substantial parameter would be a superior procedure reaction.

- Fuzzy multi-reactions output (normal) $\mu D0(\eta)$ is figured with the maximum and minimum interface tasks. The inferential outcome in a fuzzy set with a participation work for the multi-reaction output η can be expressed as:

$$\mu D_0(\eta) = (\mu A_{11}(\xi_1) \wedge (\mu A_{12}(\xi_2) \wedge (\mu A_{13}(\xi_3) \wedge (\mu D_1(\eta) \vee (\mu A_{21}(\xi_1) \wedge (\mu A_{22}(\xi_2) \wedge (\mu A_{23}(\xi_3) \wedge \mu D_2(\eta) \vee (\mu A_{31}(\xi_1) \wedge (\mu A_{32}(\xi_2) \wedge (\mu A_{33}(\xi_3) \wedge \mu D_3(\eta) \quad (2)$$

where ∧ and ∧ are the mini–max operations, respectively.

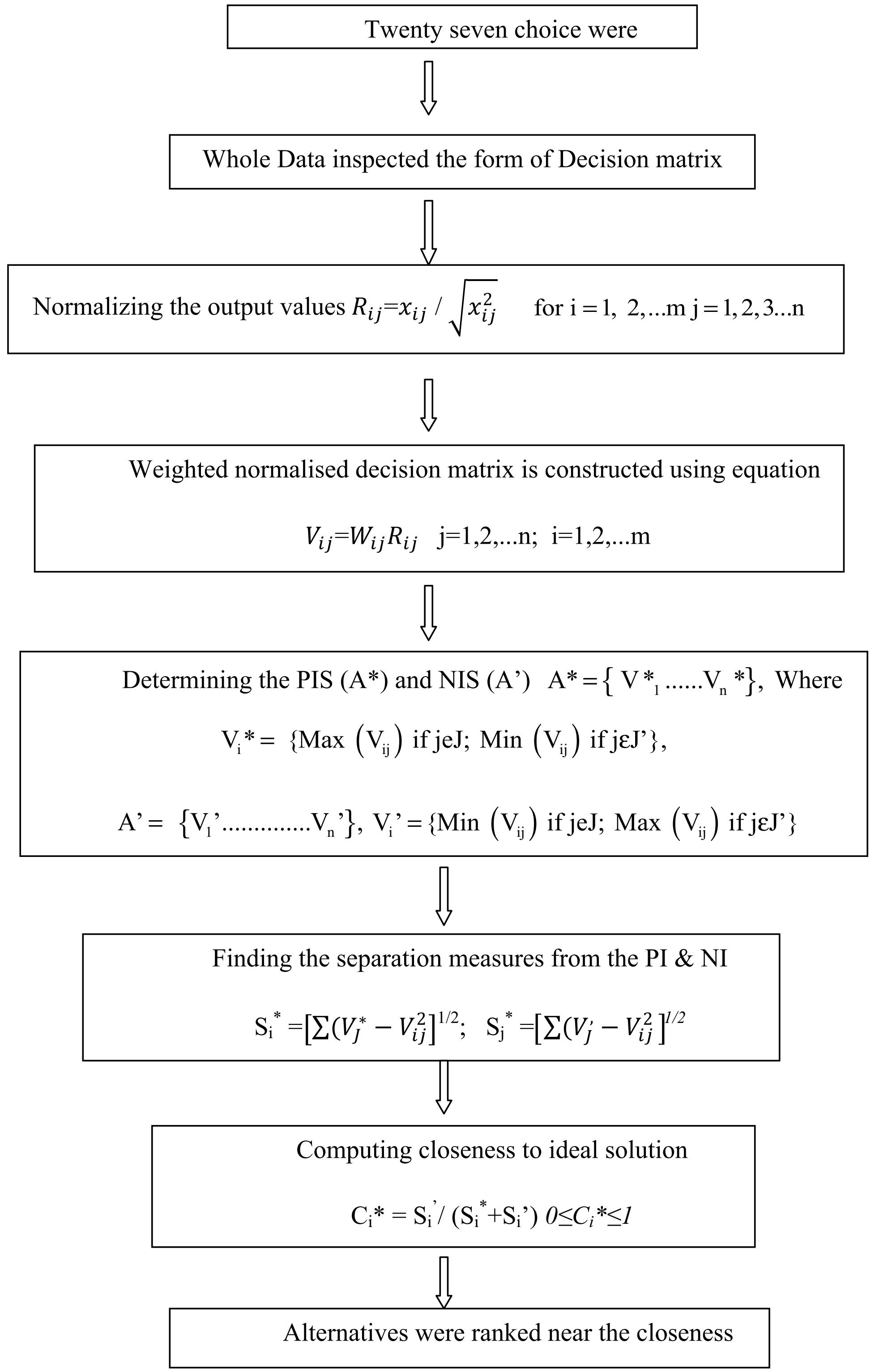

Fig. 5 Topsis steps

Table 5 Normalized decision matrix, weighted normalized values, separation measures, average, fuzzy reasoning grade (FRG) and rank

S. no.	Normalized decision matrix		Weighted normalized values		Separation measures		Average	Rank	FRG	Rank
	R_a	F_z	R_a	F_z	R_a	F_z				
1	0.1465	0.1555	0.073	0.078	0.011	0.090	0.890	3	0.888	2
2	0.1502	0.1556	0.075	0.078	0.012	0.089	0.880	4	0.878	3
3	0.1363	0.1358	0.068	0.068	0.000	0.101	1.000	1	0.950	1
4	0.1759	0.1967	0.088	0.098	0.036	0.064	0.639	14	0.629	14
5	0.1603	0.1731	0.080	0.087	0.022	0.078	0.780	7	0.781	7
6	0.1482	0.1570	0.074	0.078	0.012	0.089	0.879	5	0.875	5
7	0.1951	0.2308	0.098	0115	0.056	0.045	0.447	24	0.437	25
8	0.1812	0.2109	0.091	0.105	0.044	0.057	0.566	17	0.572	19
9	0.1935	0.1686	0.097	0.084	0.033	0.072	0.686	8	0.750	8
10	0.1841	0.1829	0.092	0.091	0.034	0.068	0.669	10	0.680	10
11	0.1628	0.1622	0.081	0.081	0.019	0.082	0.815	6	0.878	3
12	0.1564	0.1432	0.078	0.072	0.011	0.092	0.896	2	0.875	5
13	0.1960	0.2041	0.098	0.102	0.045	0.056	0.551	18	0.583	17
14	0.1822	0.1843	0.091	0.092	0.033	0.068	0.670	9	0.657	11
15	0.1871	0.1843	0.094	0.092	0.030	0.066	0.654	13	0.719	9
16	0.2152	0.2993	0.108	0.150	0.091	0.019	0.175	27	0.333	27
17	0.2013	0.2184	0.101	0.109	0.053	0.048	0.478	22	0.469	24
18	0.1875	0.1985	0.094	0.099	0.040	0.060	0.598	15	0.572	19
19	0.2119	0.1932	0.106	0.097	0.047	0.057	0.546	20	0.583	17
20	0.1980	0.1734	0.099	0.087	0.036	0.069	0.656	12	0.643	12
21	0.2193	0.1772	0.110	0.089	0.046	0.063	0.578	16	0.625	15
22	0.2536	0.1945	0.127	0.097	0.066	0.052	0.444	25	0.513	22
23	0.2100	0.1946	0.105	0.097	0.047	0.057	0.546	19	0.531	21
24	0.1961	0.1747	0.098	0.087	0.036	0.069	0.658	11	0.631	13
25	0.2429	0.2485	0.121	0.124	0.078	0.026	0.251	26	0.354	26
26	0.2291	0.1918	0.115	0.096	0.054	0.055	0.504	21	0.593	16
27	0.2153	0.2088	0.108	0.104	0.054	0.049	0.477	23	0.500	23

- Fuzzy reasoning grade η_0 is considered from fuzzy multi-responses output $\mu D_0(\eta)$ with the accompanying equation:

$$\eta_0 = \Sigma y \mu D_0(y) / \Sigma \mu D_0(y) \quad (3)$$

- Optimum level of parameters was resolved for the utilization of the data found in the response table and after that assessed.
- The results were obtained based on the confirmation test carried out for the optimum level of machining parameters.

Methodology for fuzzy logic

- Selection of the input parameters and their levels.
- To perform the experiments, values utilize a L_{27} design.
- Calculation of SR and F_z, ξ_i (k) for every response by utilizing Eqs. (1), (2) was utilized for the generation of the overall fuzzy reasoning grade γ_i.
- Fuzzification of the SR and F_z was obtained from every response and fuzzification of the general FRG by utilizing the membership function. Likewise, the rules in a linguistic form relating to SR, F_z and overall FRG were built up.
- Calculation of the fuzzy multi-response output $\mu D_0(\eta)$ utilizing the max–min interface operation (Eq. 3) was trailed by employment of centroid defuzzification and by computation of a fuzzy reasoning grade η_0.
- Selection of the optimum combination of parameters found in the response table and the graph. Interaction effects were determined with help of ANOVA for finding the contribution of each parameter.
- Finally, a confirmation test was conducted in the outcomes.

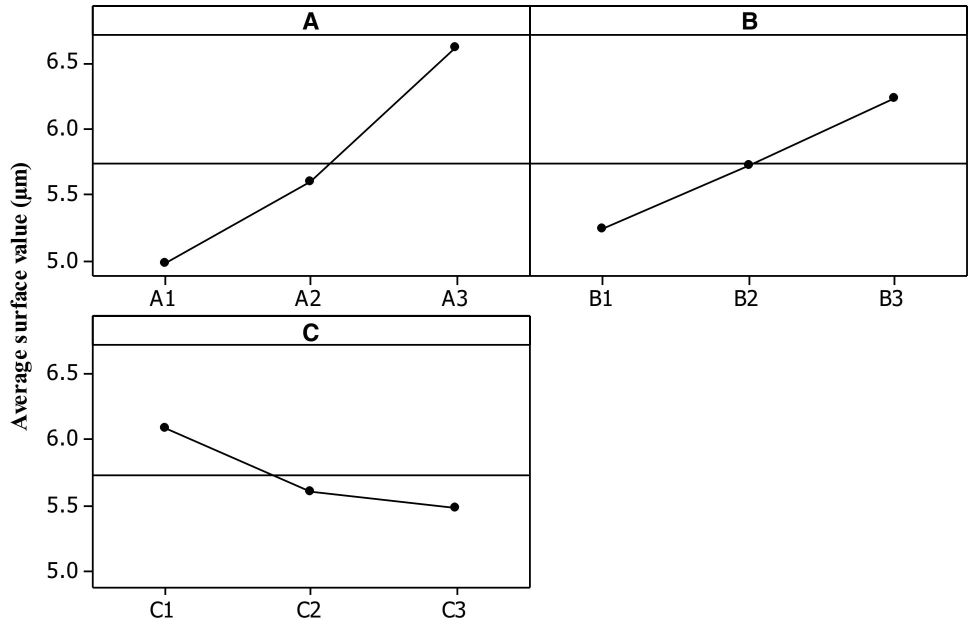

Fig. 6 Optimal level of surface roughness

Table 6 Average values of surface roughness

S. no	L1	L2	L3
1	4.980	5.601	**6.617**
2	5.242	5.724	**6.231**
3	**6.098**	5.609	5.491

Table 7 ANOVA for surface roughness

Parameters	DOF	SS	MSS	F_{cal}	% contribution
A	2	12.302	6.151	41.631	59.083
B	2	4.403	2.201	14.899	21.145
C	2	1.867	0.933	6.318	8.967
AB	4	0.555	0.139	0.939	2.664
BC	4	0.328	0.082	0.555	1.576
AC	4	0.185	0.046	0.313	0.889
Error	8	1.182	0.148		5.677
Total	26	20.821	0.801		100

3 Results and discussion

3.1 Effect of surface roughness

Figure 6 shows the main effect plots for the surface roughness. It is clear from the graph in Fig. 6 that with the increase in cutting speed, the surface roughness value first decreases to a substantial amount and then increases. As cutting speed increases, it minimizes the built-up edge development. In addition to this high-speed machining, more heat is produced which raises the temperature in the shear zone and makes the material removal easier for the cutting tool and ultimately decreases surface roughness [32]. From the graph, with the cutting speed of 500 rpm, the surface roughness starts increasing up to 1000 rpm; it might be due to some chatters or material flow on side of sample [33].

Figure 6 shows the optimal level as A3–B3–C1 (speed 1000 rpm, feed 100 mm/min and DOC 1 mm) in a single response. Huang et al. [34] and Das et al. [35] found that the surface roughness increases as the feed rate increases; it produces the thrust forces which act on the surface and also produces vibrations which ultimately increase surface roughness. This results in an increase in the values of surface roughness. As depth of cut increases, the SR was decreased due to thermal softening of the workpiece. Surface roughness average values are shown in Table 6 which indicates the maximum optimal value 6.617 speed, 6.231 feed and DOC as 6.098. Table 7 shows the ANOVA, the maximum contribution of speed 59.083%, feed 21.1455%, DOC 8.967% and the interaction which also studied shows the value of AB 2.664%, BC 1.576% AC 0.889% and error as 5.667%.

3.2 Effect of cutting force

The outcome of the cutting force in the end milling process was the optimal level of average cutting force as shown in Fig. 7. The optimal values are shown in Table 8. The optimal level was A3–B3–C1 (speed 1000 rpm, feed 100 mm/min and DOC 0.5 mm). Table 9 shows the maximum contribution as feed rate (50.373%) followed by the DOC, whereas at high cutting speed and feed, the

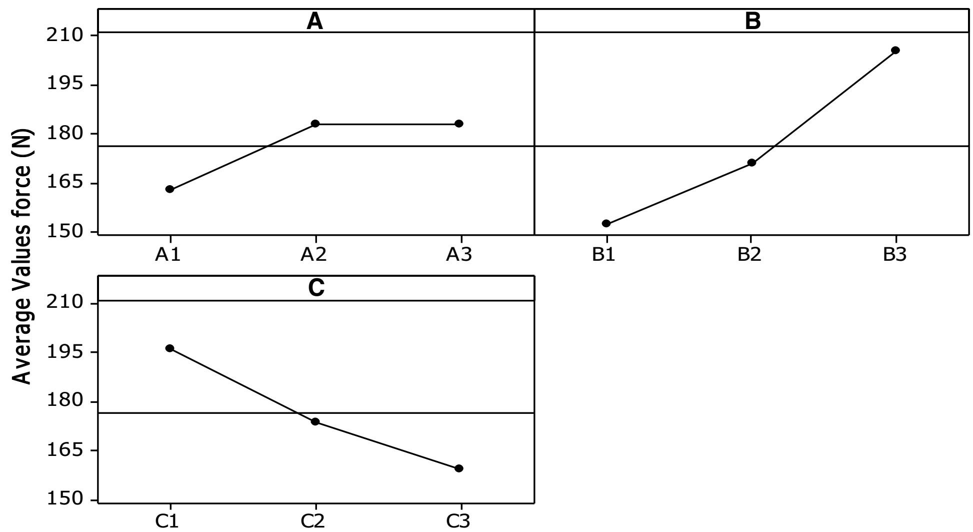

Fig. 7 Optimal level of cutting force

Table 8 Optimal values of cutting force

S. no	L1	L2	L3
1	163.003	182.898	**183.003**
2	152.213	171.162	**205.530**
3	**196.094**	173.483	159.327

Table 9 ANOVA for cutting force

Parameters	DOF	SS	MSS	Fcal	% contribution
A	2	2387.466	1193.733	9.669	9.146
B	2	13148.711	6574.355	53.250	50.373
C	2	6190.301	3095.150	25.070	23.715
AB	4	917.900	229.475	1.859	3.516
BC	4	1621.516	405.379	3.283	6.212
AC	4	849.083	212.271	1.719	3.253
Error	8	987.699	123.462		3.784
Total	26	26102.676	1003.949		100

cutting force required was higher due to the effect of the coefficient of friction between the tool and the workpiece. At the same time, there was an increase in the DOC and there was a decrease in the cutting force due to softness of aluminum.

3.3 Technique for order preference by similarity to ideal solution

The effect of the Topsis in the end milling process of the optimal level of average cutting force is shown in Fig. 8. The average optimal values are shown in Table 10. The optimal level is A1–B1–C3 (speed 500 rpm, feed 40 mm/min and DOC 1 mm). Table 11 illustrates the result of ANOVA for the average values. It shows feed as the most influencing parameter, affecting the average values and the percentage of contributions. The feed contribution was observed as 43.537%, speed as 25.664%, DOC as 19.876% and interaction effect of speed, feed (AB) as 3.617%, feed, DOC (BC) as 2.772%, followed by speed, DOC (AC) as 1.691%.

3.4 Fuzzy logic

The membership functions of input parameters are speed, feed and DOC with the output parameter as the Topsis value. The three input membership functions were: low (L), medium (M) and high (H). The nine output membership functions are: EL (extremely low), VVL (very very low), VL (very low), L (low), M (medium), H (high), VH (very high), VVH (very very high), EH (extremely high). The input and output membership function values are shown in Table 12 and Fig. 9. The fuzzy rules are shown in "Appendix", and maximum fuzzy rule viewer is shown in Fig. 10. The surface viewers of speed and feed and the average value of FRG are shown in Fig. 11. It shows the increase in speed and feed followed by an increase in the average values (output). Figure 12 shows surface viewers of feed and DOC increases the FRG values also get increased (output). The yellow color represents the maximum, and red color shows the minimum of the output values.

Table 13 shows the optimal values of the fuzzy reasoning grade values at level-1, feed at level-1 and DOC at level-3 (A1–B1–C3). Figure 13 shows the optimal level as identified by A1–B1–C3. The figure shows that as speed and feed increase, the fuzzy average values are decreased; similarly, when feed increases the fuzzy average values also decrease. Table 14 shows the fuzzy values

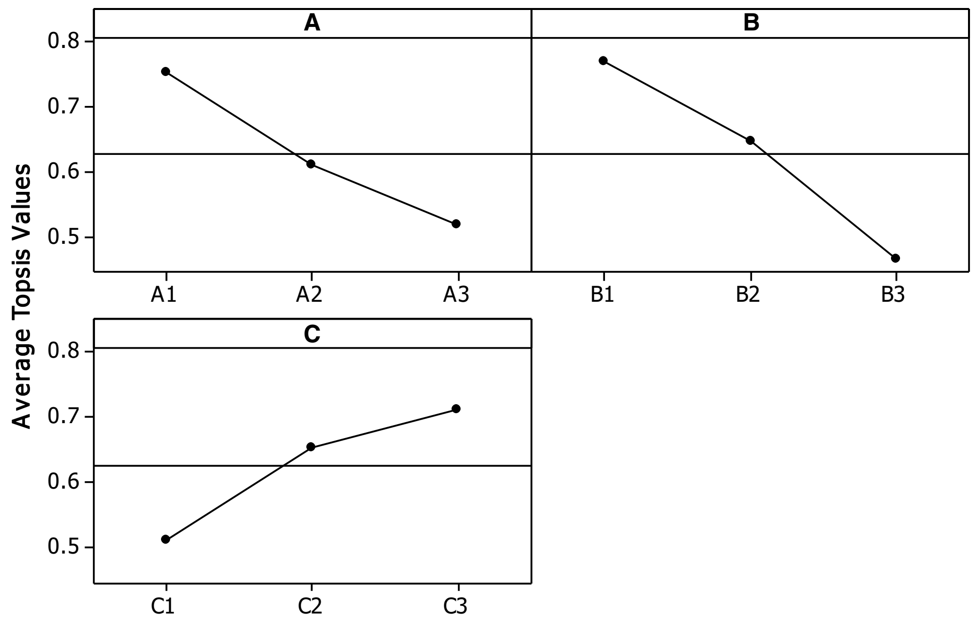

Fig. 8 Average levels of Topsis values

Table 10 Average of Topsis optimal values

S. no	L1	L2	L3
1	**0.751**	0.612	0.518
2	**0.770**	0.647	0.596
3	0.512	0.655	**0.714**

Table 11 ANOVA for average Topsis values

Parameters	DOF	SS	MSS	*F*	% contribution
A	2	0.250	0.125	36.115	25.664
B	2	0.424	0.212	61.266	43.537
C	2	0.194	0.097	27.970	19.876
AB	4	0.035	0.009	2.545	3.617
BC	4	0.027	0.007	1.950	2.772
AC	4	0.016	0.004	1.190	1.691
Error	8	0.028	0.003		2.842
Total	26	0.974	0.037		100

Table 12 Fuzzy input and output variables and ranges

variables	Parameters	Fuzzy set	Range
Input	Speed	L, M, H	500–1000
	Feed	L, M, H	40–100
	Depth of cut	L, M, H	0.5–1
Output	Average Topsis values	EL, VVL, VL, L, M, H, VH, VVH, EH	0–1

of feed contribution as 44.605% followed by speed as 24.333%. The maximum interaction for speed and feed is AB as 5.669%.

3.5 Response surface methodology (RSM)

RSM explores the relationship between the machining parameter and the output response of the quadratic form. The two responses, adjusted R^2 (SR) value 0.9369 and the R^2 (F) value of force are 0.9083. The R^2 values show the correlation with experimental values. The 3D relation of surface roughness, resultant force and cutting parameter is shown in Figs. 14 and 15.

The performance values were close to the numerical values. The mathematical equations are given in Eqs. 4–7.

$$\begin{aligned}\mathrm{SR} = {} & 2.39 + 0.17 * A + 0.10 * B - 0.064 * C \\ & - 0.048 * A * B - 0.014 * A * C - 6.238E - 003 * B * C \\ & + 7.415E - 003 * A^2 - 0.024 * B^2 + 0.036 * C^2\end{aligned} \tag{4}$$

$$\begin{aligned}\mathrm{Force} = {} & 13.48 + 0.33 * A + 0.94 * B - 0.69 * C \\ & - 0.20 * A * B + 0.17 * A * C - 0.32 * B * C \\ & - 0.45 * A^2 - 0.29 * B^2 + 0.20 * C^2\end{aligned} \tag{5}$$

$$\begin{aligned}\mathrm{Topsis} = {} & 0.76 - 0.056 * A - 0.011 * B + 4.047E \\ & - 003 * C - 0.020 * A * B - 0.043 * A * C + 0.044 * B * C \\ & + 0.020 * A2 + 0.056 * B2 - 0.046 * C2\end{aligned} \tag{6}$$

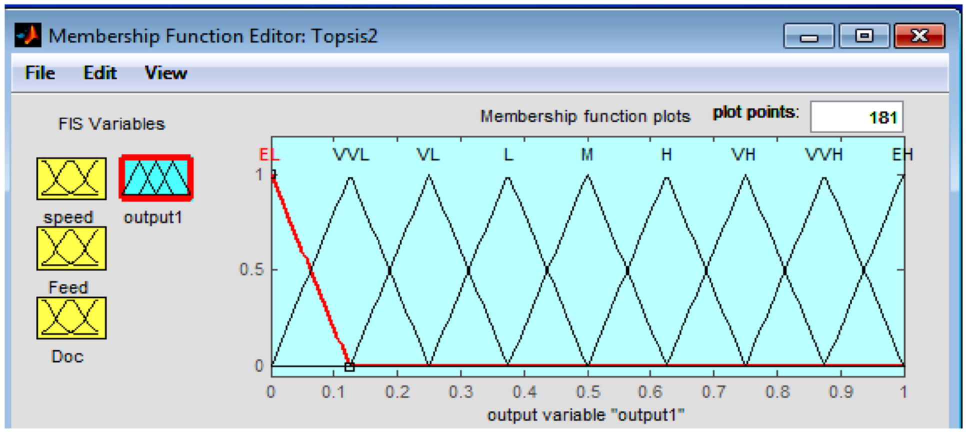

Fig. 9 Range of membership function

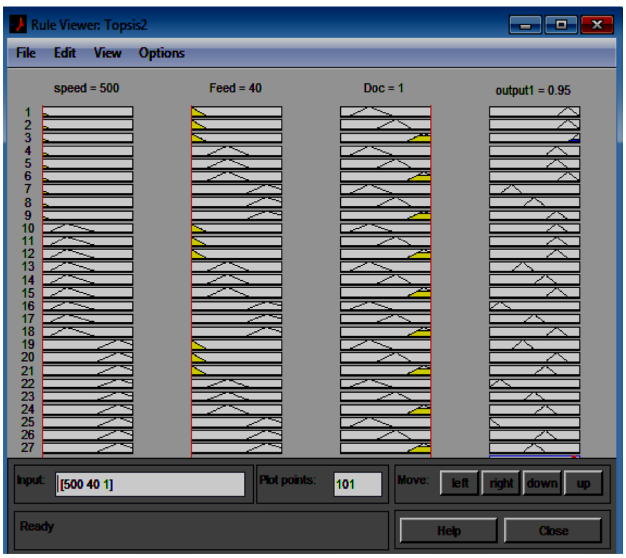

Fig. 10 Rule viewer of optimal value

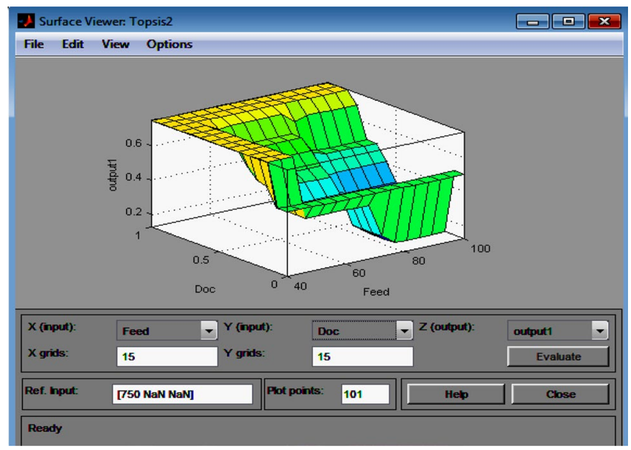

Fig. 12 Surface viewers of feed, DOC and output

Table 13 Optimal values of fuzzy

S. no	L1	L2	L3
1	**0.751**	0.641	0.553
2	**0.778**	0.658	0.596
3	0.556	0.667	**0.722**

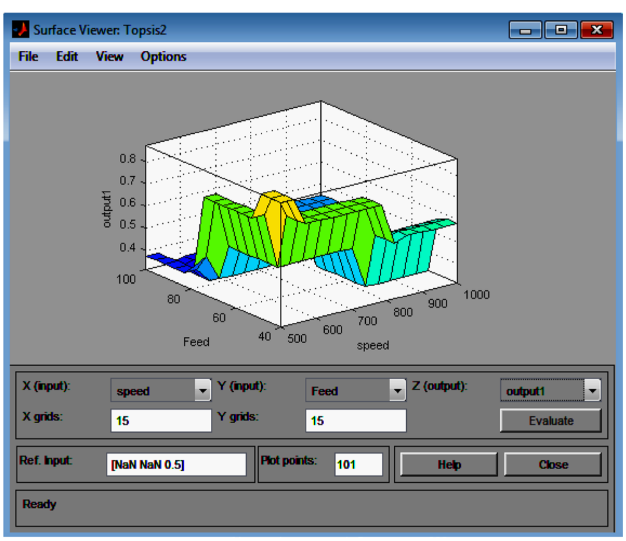

Fig. 11 Surface viewers of speed, feed and output

$$\begin{aligned} \mathrm{FRG} = {} & 0.79 - 0.058 * A - 0.084 * B + 0.055 * C \\ & + 0.026 * A * B - 0.014 * A * C + 0.027 * B * C \\ & + 0.018 * A2 + 5.372E - 003 * B2 - 0.021 * C2 \end{aligned} \tag{7}$$

The predicted values of R_a and F_z were acquired by using Eqs. 4 and 5, respectively, and compared with the measured values. In both the cases, the predicted values were observed to be statically similar to the actual values as appeared in Figs. 16 and 17. The wear is 0.012 µm, and the image of scanning electron microscope of tool wear is shown in Fig. 18a. The optimal machined surface

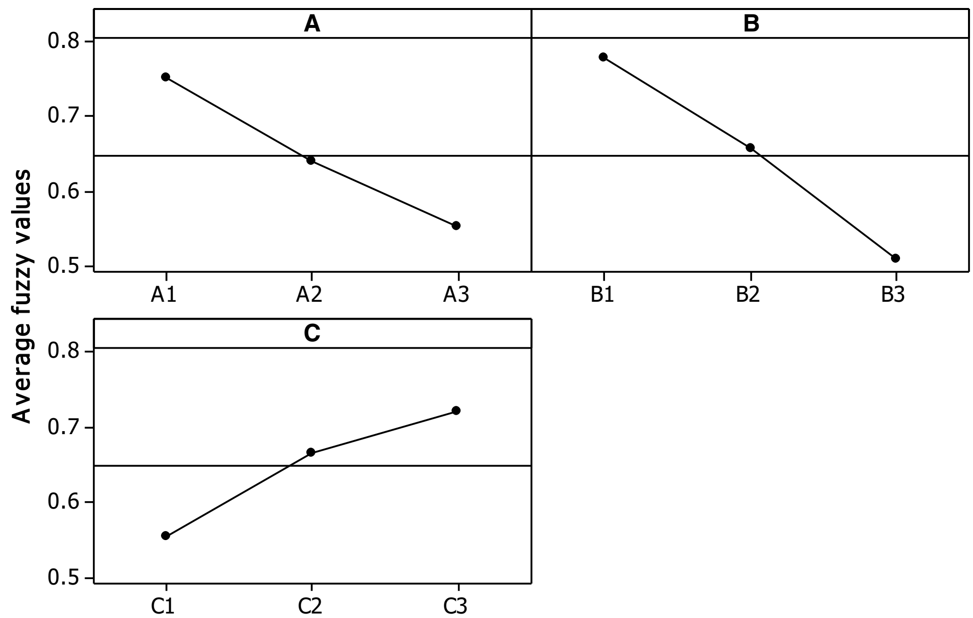

Fig. 13 Optimal level of fuzzy value

Table 14 ANOVA for fuzzy logic

Parameters	DOF	SS	MSS	F	% contribution
A	2	0.178	0.089	27.544	24.333
B	2	0.327	0.163	50.492	44.605
C	2	0.129	0.065	19.984	17.654
AB	4	0.042	0.010	3.208	5.669
BC	4	0.016	0.004	1.270	2.244
AC	4	0.014	0.004	1.110	1.961
ERROR	8	0.026	0.003		3.534
TOTAL	26	0.732	0.028		100

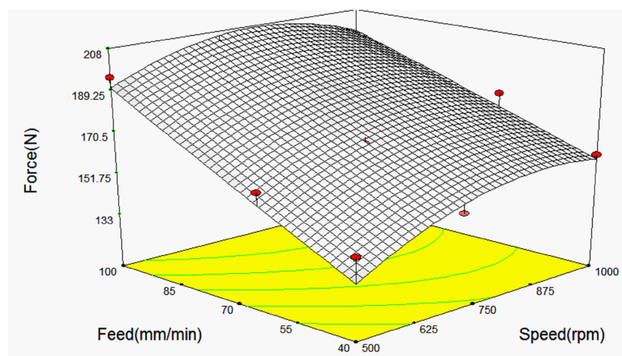

Fig. 15 3D relation of speed, feed and cutting force

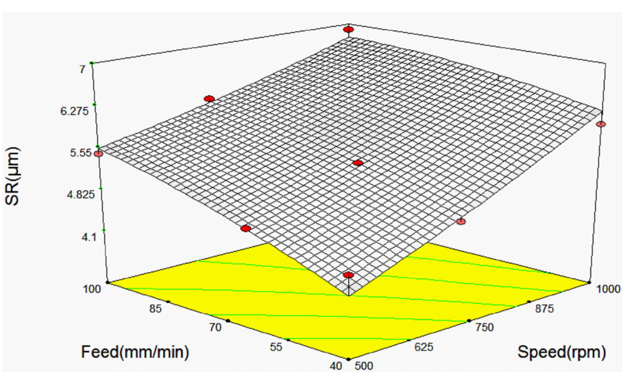

Fig. 14 3D relation of speed, feed and SR

(A1–B1–C3) is shown in Fig. 18b. The surface demonstrates a good finish, and great appearance is distinguished from other machining process.

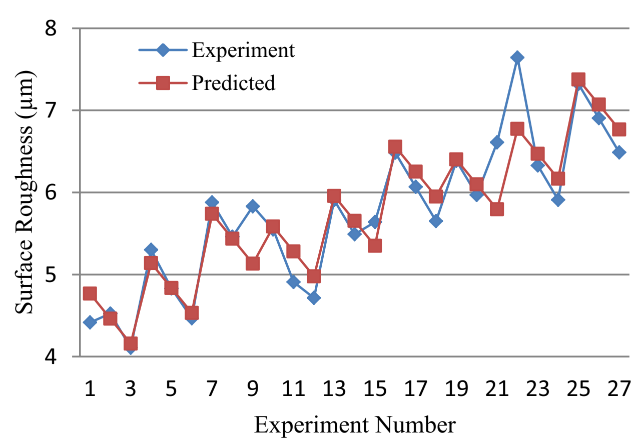

Fig. 16 Comparison of experimental and predicted values (SR)

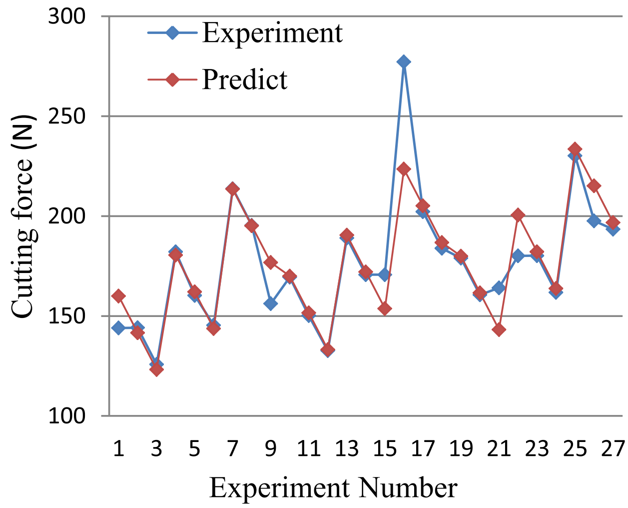

Fig. 17 Comparison of experimental and predicted values (CF)

$$\eta_{\text{Predicted}} = \eta_0 + \sum_{i=1}^{n} (\eta_m - \eta_0) \quad (8)$$

where η_0 is the fuzzy reasoning grade mean, η_m-mean of fuzzy reasoning grade at the optimal level of A, B and C, and *n*-number of significant parameters (n = 3). The confirmation results are shown in Table 15 and reveal that the surface roughness values decrease from 4.416 to 4.108 µm and force from 144 to 125.766 N. The improvement in technique for order preference by similarity to ideal solution is 12.36%, and a fuzzy logic value is 6.98% from the experimental value to the initial condition. A higher Topsis and Fl in an optimal setting confirm the enhancement in multi-performance characteristics. There was an improvement within the tool life of the insert beneath the optimum conditions.

4 Confirmation experiment

The confirmation experiment was the ultimate step to substantiate the advance in performance characteristics at the optimal level of machining parameters. An experiment was conducted based on the optimal condition. The predicted Topsis with fuzzy reasoning grade was calculated using Eq. (8).

5 Conclusions

End milling operations were conducted with tungsten carbide insert on aluminum metal matrix composite, and process parameters were analyzed regarding R_a and F_z through variation in the speed, feed and DOC. Multi-objective optimization was performed using Topsis and Fl. From the response, the machining conditions

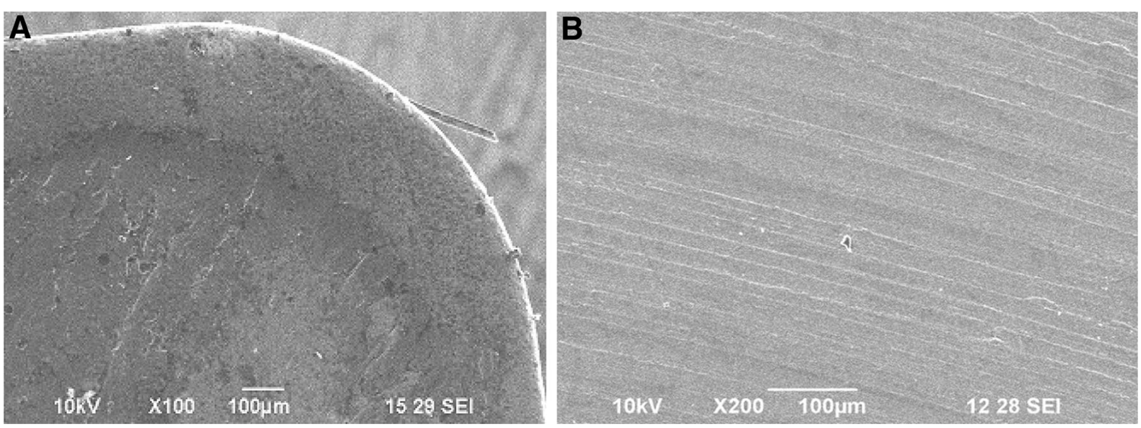

Fig. 18 **a** Tool wear (0.012 µm). **b** SEM image of milled surface (A1–B1–C3)

Table 15 Confirmation test results

Process	Initial (A1–B1–C1)	Predicted (A1–B1–C3)	Experimental	Variation	% improvement
SR (µm)	4.416	–	4.108	0.308	6.97
Force (*N*)	144	–	125.766	18.234	12.66
Topsis	0.890	0.981	1.000	0.11	12.36
Fuzzy	0.888	0.955	0.950	0.062	6.98
Improvement in Topsis is 12.36%					

were obtained. From the analysis, following points are concluded.

- The mathematical study of the influence of individual parameters demonstrates that speed (59.083%) is the important parameter which influences the SR, where the feed (50.373%) influences the cutting force.
- The ANOVA demonstrated the most influence factor for both Topsis and FI. This analysis indicates that the speed and feed rate are the dominant factors for surface roughness and cutting force.
- Topsis is used to reveal the effect of parameters influencing both R_a and F_z. Feed is found as the transcendent parameter that influences both R_a and F_z. Topsis is used to identify the optimum machining parameters such as cutting speed of 500 rpm, the feed rate of 40 mm/min and DOC of 1 mm from the third experiment.
- The relative closeness values of fuzzy logic are used to find the optimal levels in the experiments. The most extreme fuzzy reasoning grade is identified in the third experiment (A1–B1–C3). The optimal level found in the Topsis and FI is the same.
- According to Topsis and FI, the smallest values of speed, feed and depth of cut lead to R_a and F_z values as shown in Table 4.
- The response surface methodology is effectively used to create the numerical model between machining parameters.
- From the quadratic polynomial model, the obtained correlation coefficient R^2 values are 93.69% and 90.83%. The value indicates that the generated model can be used to predict R_a and F_z in milling operation.
- The total number of experiments in milling operations is reduced by using Topsis and FI for determining the optimum cutting conditions. The results acquired in this research would be useful in manufacturing sectors.

The methodology offered experimentally and statically during this study is often viewed as an applicable method for the improvement in milling processes.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix: Fuzzy rules

if (Speed is L) and (Feed is L) and (DOC is L) Then (output is VVH)
if (Speed is L) and (Feed is M) and (DOC is M) Then (output is VVH)
if (Speed is L) and (Feed is H) and (DOC is H) Then (output is EH)
if (Speed is L) and (Feed is L) and (DOC is L) Then (output is VH)
if (Speed is L) and (Feed is M) and (DOC is M) Then (output is VH)
if (Speed is L) and (Feed is H) and (DOC is H) Then (output is VVH)
if (Speed is L) and (Feed is L) and (DOC is L) Then (output is VL)
if (Speed is L) and (Feed is M) and (DOC is M) Then (output is M)
if (Speed is L) and (Feed is H) and (DOC is H) Then (output is VH)
if (Speed is M) and (Feed is L) and (DOC is L) Then (output is VH)
if (Speed is M) and (Feed is M) and (DOC is M) Then (output is VH)
if (Speed is M) and (Feed is H) and (DOC is H) Then (output is VH)
if (Speed is M) and (Feed is L) and (DOC is L) Then (output is L)
if (Speed is M) and (Feed is M) and (DOC is M) Then (output is H)
if (Speed is M) and (Feed is H) and (DOC is H) Then (output is VH)
if (Speed is M) and (Feed is L) and (DOC is L) Then (output is VVL)
if (Speed is M) and (Feed is M) and (DOC is M) Then (output is M)
if (Speed is M) and (Feed is H) and (DOC is H) Then (output is VH)
if (Speed is H) and (Feed is L) and (DOC is L) Then (output is L)
if (Speed is H) and (Feed is M) and (DOC is M) Then (output is VH)
if (Speed is H) and (Feed is H) and (DOC is H) Then (output is H)
if (Speed is H) and (Feed is L) and (DOC is L) Then (output is VVL)
if (Speed is H) and (Feed is M) and (DOC is M) Then (output is M)
if (Speed is H) and (Feed is H) and (DOC is H) Then (output is H)
if (Speed is H) and (Feed is L) and (DOC is L) Then (output is EL)

if (Speed is H) and (Feed is M) and (DOC is M) Then (output is H)

if (Speed is H) and (Feed is H) and (DOC is H) Then (output is M)

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