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Optimization of machining parameters in turning of Al−SiC−Gr hybrid metal matrix composites using grey-fuzzy algorithm

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Abstract: Metal matrix composites reinforced with graphite particles provide better machinability and tribological properties. The present study attempts to find the optimal level of machining parameters for multi-performance characteristics in turning of Al−SiC−Gr hybrid composites using grey-fuzzy algorithm. The hybrid composites with 5%, 7.5% and 10% combined equal mass fraction of SiC−Gr particles were used for the study and their corresponding tensile strength values are 170, 210, 204 MPa respectively. Al−10%(SiC−Gr) hybrid composite provides better machinability when compared with composites with 5% and 7.5% of SiC−Gr. Grey-fuzzy logic approach offers improved grey-fuzzy reasoning grade and has less uncertainties in the output when compared with grey relational technique. The confirmatory test reveals an increase in grey-fuzzy reasoning grade from 0.619 to 0.891, which substantiates the improvement in multi-performance characteristics at the optimal level of process parameters setting.

Key words: hybrid composite; turning; optimization; grey-fuzzy algorithm

1 Introduction

Metal matrix composites (MMCs) offer interesting opportunities for new product design due to enhanced properties. Some of the beneficial properties of MMCs are high strength and stiffness, increased wear resistance, lower coefficient of thermal expansion and dimensional stability at a higher temperature. In aluminium metal matrix composites (AMCs), the matrix material is aluminium/aluminium alloy and the other phases are reinforcement which are Gr, SiC, Al_2O_3, B_4C, etc [1,2]. The incorporation of ceramic particles in Al alloy increases both mechanical strength and wear resistance of the composite. The hard abrasive SiC particles in Al−SiC composite complicate the machining operation. Thus the machinability of particulate MMCs is improved by reinforcing soft particles like graphite along with hard ceramic particles [3]. The composites with combined reinforcement of SiC and Gr particles are referred to Al−SiC−Gr hybrid composite. The superiority of Al−SiC−Gr composite is self-lubricating property, enabled by the presence of graphite and its strength is enhanced by SiC ceramic phase. This hybrid composite substitutes materials for pistons, cylinder liners, brake drums in automotive and aerospace applications [4,5].

Although most composite materials are molded or formed to near net shape, the machining process could not be eliminated entirely because it provides the preferred dimensions, shape and surface finish. PALANIKUMAR and KARTHIKEYAN [6] indicated that on machining Al−SiC composite, the surface roughness is influenced by the feed rate, cutting speed and volume fraction of SiC particles. BASHEER et al [7] reported that in precision machining of MMCs, the roughness of the machined surface is significantly influenced by the size of particles. It is been known that its magnitude depends on feed rate and tool nose radius. LIN et al [8] observed that the material removal rate of aluminium composite seems to be high when the feed rate is higher and cutting speed is lower. The tool wear normally occurred on flank and rake surfaces, with flank wear being most dominant. HOCHENG et al [9] observed the machining characteristics such as discontinuous chips, low cutting forces, less tool wear and low power consumption during machining of

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Al−graphite composite. KRISHNAMURTHY and SRIDHARA [10] obtained considerably reduced cutting forces in machining of Al−SiC−Gr hybrid composite when compared with Al−SiC composite. This is due to the presence of graphite particles in Al−SiC−Gr hybrid composite, which reduces friction at the machining interface. BASAVARAJAPPA et al [11] reported that the subsurface deformation extends up to a maximum of 150 μm below the machined surface in Al−2219/15SiC composite. However, in the case of Al−2219/15SiC/3Gr hybrid composite, it is only about 120 μm. RAJMOHAN et al [12] indicated that wear loss of Al/10SiC−3mica composite is reduced at the higher mass fraction of mica.

The most commonly applied techniques in optimization are Taguchi technique, artificial neural network (ANN), response surface methodology (RSM), genetic algorithm, scatter search technique, grey relational approach and fuzzy logic approach [13]. ANKITA et al [14] applied fuzzy based desirability function for optimizing multiple bead geometry parameters of submerged arc weldment. KOVAC et al [15] predicted surface roughness using fuzzy and regression model analysis. DENG [16] proposed a grey system to deal with poor, incomplete and uncertain output. This system also seemed to solve the complicated inter relationships among multiple responses. Grey relational analysis is used primarily for multi response optimization to obtain corresponding level of input parameters for better performance characteristics [17,18]. This technique is used for optimization in various applications such as drilling [19], turning [20], milling [21,22], EDM [23,24] and welding [25−27].

The present study uses grey-fuzzy algorithm to optimize the machining parameters in turning of Al−SiC−Gr hybrid composite. For a given work piece and machine tool combination, the performance characteristics such as surface roughness, material removal rate and flank wear of the tool are influenced by the process parameters such as cutting speed, feed rate, depth of cut and mass fraction of reinforcement. In order to minimize the surface roughness and flank wear of the tool and to maximize the material removal rate, an optimal setting of input turning parameters is required. Grey-fuzzy logic approach provides a viable solution to determine optimum setting of machining parameters with multi-performance characteristics.

2 Materials and their characteristics

2.1 Materials used

Aluminium alloy LM25 was used as the matrix material and its chemical composition included 7%Si, 0.35%Mg, 0.45%Fe, 0.13%Cu, 0.08%Zn, 0.01%Ni, 0.16%Mn, 0.01Pb, 0.05%Ti, and 91.76%Al. The presence of silicon content between 7% and 15% in aluminium alloy will inhibit the detrimental reaction product Al_4C_3 from SiC. The silicon carbide and graphite particles with combined equal mass fraction of 5%, 7.5% and 10% were used as the reinforcement materials. SEM micrographs of silicon carbide and graphite particles are shown in Fig. 1. The silicon carbide particles exhibit in the form of solid crystal whereas the graphite particles appear to be flakes. The average size and density of silicon carbide and graphite particles are 20 μm, 3210 kg/m^3 and 40 μm, 2090 kg/m^3 respectively. Al−SiC−Gr composite specimens required for the investigation were fabricated through compo-casting method. The hardness values of aluminium hybrid composites with 5%, 7.5% and 10% of SiC−Gr particles are BHN67, BHN 80, BHN 76 and their corresponding tensile strength values are 170, 210, 204 MPa, respectively. The higher mass fraction of graphite results in decreased hardness and tensile strength of Al−SiC−Gr hybrid composite.

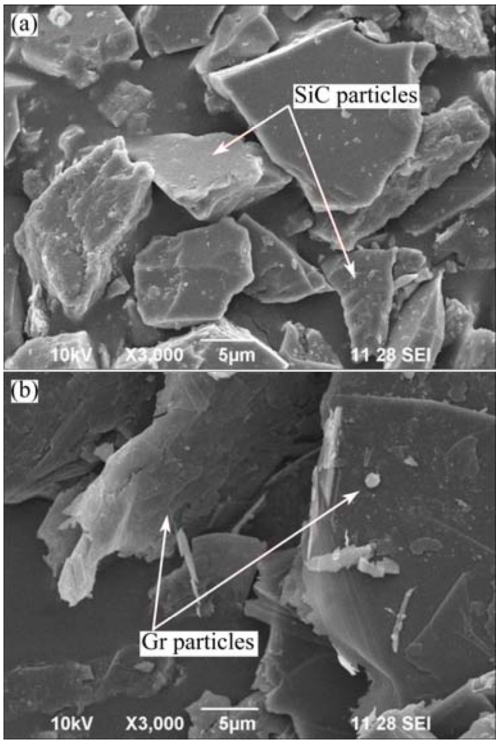

Fig. 1 SEM micrographs: (a) SiC particles; (b) Gr particles

2.2 Microstructure analysis

The optical micrographs of Al−SiC−Gr hybrid composites are shown in Fig. 2. SiC−Gr reinforcement particles influence the solidification pattern of composite melt and also lead to the refinement of grains. In solidification process, the inclusion of SiC−Gr particles resists the growing of α(Al) grains and acts as a grain nucleation site. The higher the content of SiC−Gr particles is, the more the number of nucleation sites is and the more the aluminium grains solidify on it. The intra-granular distribution of SiC−Gr particles can be seen from the micrographs of Al hybrid composites, which seems to provide better mechanical and tribological properties. The distribution of SiC−Gr particles in the aluminium matrix is based on the solidification process. Since the densities of matrix and reinforcement particles are different, the semi-solid state of stirring gives a homogenous dispersion of particles. In semi-solid state of stirring, the tendency of particles to sink or float is retarded due to enhanced viscosity of the composite slurry. It is evident from Fig. 2 that the SiC−Gr particles are dispersed nearly homogeneously in the aluminium matrix. The common casting defects such as porosity, shrinkages or slag inclusion are not visible in micrographs, which reveals the quality of castings.

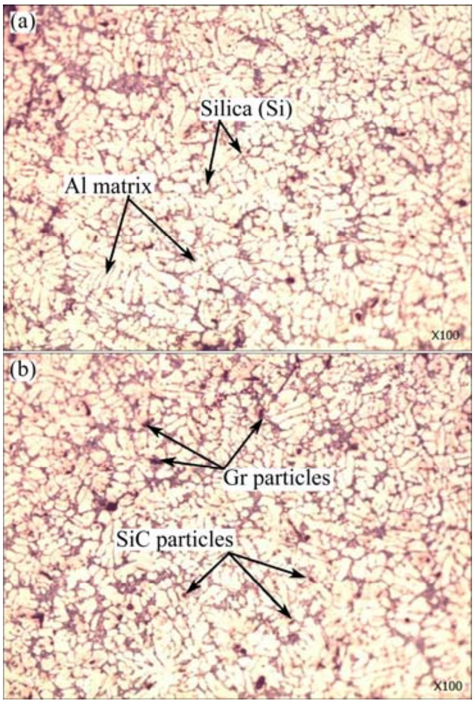

Fig. 2 Optical micrographs of Al−SiC−Gr hybrid composites: (a) Al−5%(SiC−Gr); (b) Al−10%(SiC−Gr)

3 Experimental design and procedure

The experiments were designed based on Taguchi's L_{27} orthogonal array with 27 experimental runs. The process parameters such as cutting speed, feed rate and mass fraction of SiC−Gr were selected for conducting experiments. The depth of cut was maintained constant in all experiments and its value was equal to 1 mm. Table 1 represents the machining parameters and their levels. The castings of Al−SiC−Gr composite specimens were machined and reduced to a standard sample with 30 mm in diameter and 250 mm in length. The machining tests were conducted using an ACE LT2 type of CNC lathe under dry turning condition. The tool holder MTJNL 2525M16 and tungsten carbide tool insert TNMG 120408 were used. The turning operation was performed on Al−SiC−Gr hybrid composites at different levels of machining parameters, as per the Taguchi's L_{27} orthogonal array.

Table 1 Machining parameters and their levels

Parameter	Symbol	Level 1	Level 2	Level 3
Cutting speed/(m·min^{-1})	A	100	150	200
Feed rate/(mm·r^{-1})	B	0.075	0.100	0.125
Combined equal mass fraction of SiC−Gr/%	C	5.0	7.5	10.0

The surface roughness (R_a) was determined using Mitutoyo Surf test SJ−201 with a cut-off length of 0.8 mm and a traverse length of 5 mm. The surface roughness values given in this study are the mathematical average of two measurements taken from the same machined surface. The material removal rate (MRR) was determined from the amount of material worn during the period of machining. The high precision digital balance meter was used to weigh the samples, thus ruling out the possibility of errors. For each experiment, a new insert tip was used for the turning operation. Further, the flank wear of the tool was measured with an optical microscope of 1 μm resolution. The experimental results are summarized in Table 2.

4 Grey-fuzzy analysis

Grey-fuzzy analysis combines both the grey relational approach (GRA) and fuzzy logic theory. In this analysis, the multi-objective problem is converted into a single-objective optimization using GRA technique and further uncertainties in the grey output are reduced by fuzzy logic theory.

While machining Al−SiC−Gr hybrid composites, the criteria considered for the best performance are lower surface roughness and flank wear, and higher material removal rate. Using grey relational approach, the original sequence data are first transformed into a comparability sequence. Subsequently, grey relational coefficients and grey relational grades are determined for all experimental runs. In this study, all machining parameters influence the responses, so equal weights are assigned to parameters. A larger value of grey relational coefficient is indicative of a better performance characteristic and would be equal to one. The parametric condition corresponding to the highest grey relational grade represents a minimum value for surface roughness and flank wear, and a maximum value for material removal rate. However, there is a possibility of certain degree of uncertainty in the obtained grey relational grades. These uncertainties arise primarily due to vagueness, imprecision and lack of information. Fuzzy logic

Table 2 Experimental results using L_{27} orthogonal array

Exp. No.	Level A	Level B	Level C	Actual value: Cutting speed/(m·min^{-1})	Feed rate/(mm·r^{-1})	Mass fraction of SiC−Gr/%	Response: R_a/μm	MRR/(g·min^{-1})	F_b/mm
1	1	1	1	100	0.075	5.0	3.8	9.51	0.20
2	1	1	2	100	0.075	7.5	3.4	10.91	0.13
3	1	1	3	100	0.075	10.0	3.1	12.32	0.16
4	1	2	1	100	0.100	5.0	4.4	16.68	0.15
5	1	2	2	100	0.100	7.5	4.2	18.55	0.17
6	1	2	3	100	0.100	10.0	3.9	20.43	0.19
7	1	3	1	100	0.125	5.0	4.9	23.85	0.17
8	1	3	2	100	0.125	7.5	4.5	26.19	0.21
9	1	3	3	100	0.125	10.0	4.4	28.54	0.23
10	2	1	1	150	0.075	5.0	3.5	20.26	0.14
11	2	1	2	150	0.075	7.5	3.0	22.37	0.16
12	2	1	3	150	0.075	10.0	2.5	24.48	0.17
13	2	2	1	150	0.100	5.0	4.0	31.01	0.16
14	2	2	2	150	0.100	7.5	3.8	33.83	0.17
15	2	2	3	150	0.100	10.0	3.5	36.64	0.19
16	2	3	1	150	0.125	5.0	4.6	41.77	0.17
17	2	3	2	150	0.125	7.5	4.4	45.29	0.19
18	2	3	3	150	0.125	10.0	3.9	48.8	0.22
19	3	1	1	200	0.075	5.0	3.0	31.01	0.19
20	3	1	2	200	0.075	7.5	2.8	33.83	0.21
21	3	1	3	200	0.075	10.0	1.6	36.64	0.18
22	3	2	1	200	0.100	5.0	3.5	45.35	0.2
23	3	2	2	200	0.100	7.5	3.2	49.10	0.24
24	3	2	3	200	0.100	10.0	2.9	52.86	0.25
25	3	3	1	200	0.125	5.0	4.4	59.69	0.25
26	3	3	2	200	0.125	7.5	4.1	64.38	0.27
27	3	3	3	200	0.125	10.0	3.9	69.07	0.30

approach seems to offer an effective solution to control these uncertainties in grey relational grade. Therefore, a fuzzy reasoning of multiple performance characteristics is developed and referred to grey-fuzzy reasoning grade. The steps in fuzzy logic approach involve fuzzification of input data, rule inference and defuzzification process [28].

The proposed grey-fuzzy algorithm for determining the optimal level of machining parameters is illustrated in Fig. 3 and the steps involved are summarized below.

1) The range of parameters is determined and an appropriate orthogonal array is adopted to conduct experiments.

2) Responses such as surface roughness, material removal rate and flank wear are measured for each experiment. These responses are first normalized through data pre-processing. Following this, grey relational coefficients and grey relational grades are determined and listed in Table 3.

3) Triangular membership function and fuzzy rule are established to fuzzify the grey relational coefficient $\xi_i(k)$ of each response. Three fuzzy subsets are assigned to the grey relational coefficient of surface roughness, material removal rate and flank wear using triangular membership function. If−Then rule statement is used to formulate conditional statements. It has three grey relational coefficients ξ_1, ξ_2, ξ_3, and one multi-response output η, which is represented as follows:

Rule 1: if ξ_1 is A_{11}, ξ_2 is A_{12} and ξ_3 is A_{1n}, then η is D_1, else

Rule 2: if ξ_1 is A_{21}, ξ_2 is A_{22} and ξ_3 is A_{23}, then η is D_2, else

⋮

Rule n: if ξ_1 is A_{31}, ξ_2 is A_{32} and ξ_3 is A_{33}, then η is D_3, else

(1)

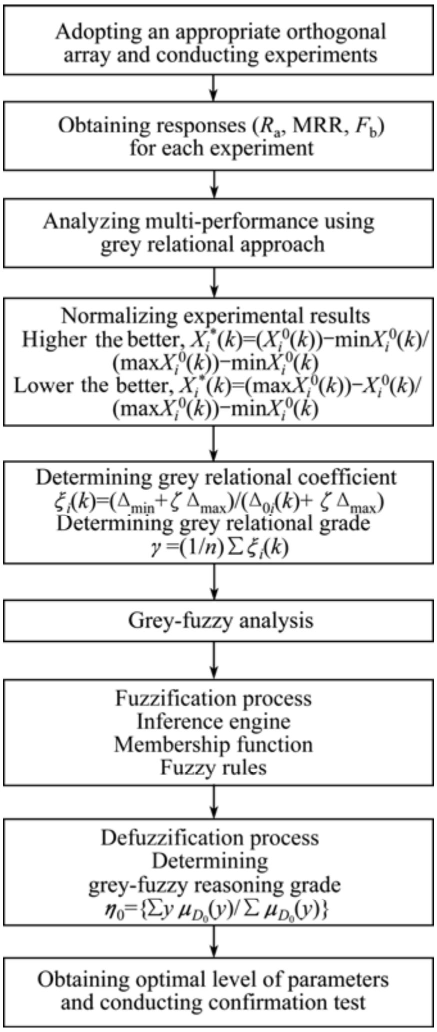

Fig. 3 Structure of grey-fuzzy integrated algorithm

For the multi-response output η, nine fuzzy subsets are used. The range of each fuzzy subset is presented in Table 4. Based on the experimental plan, 27 fuzzy rules are developed according to the concurrence that a large grey relational coefficient would be a better process response.

4) Fuzzy multi-responses output $\mu_{D_0}(\eta)$ is calculated using the max–min interface operation. The inferential result in a fuzzy set with a membership function for the multi-response output η can be expressed as follows:

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

where $\wedge$ and $\vee$ are the minimum and the maximum operations, respectively.

5) The grey-fuzzy reasoning grade η_0 is calculated from fuzzy multi-responses output $\mu_{D_0}(\eta)$ using the following formula:

$$\eta_0=\sum y\mu_{D_0}(y)/\sum\mu_{D_0}(y) \quad (3)$$

6) The optimal levels of parameters are determined from the response table and then evaluated.

7) The confirmation test is conducted at the optimal setting of machining parameters and results are verified.

Table 3 Grey relational coefficients and grey relational grade for each machining experiment

Exp. No.	Grey relational coefficient			Grey relational grade	Grey-fuzzy reasoning grade	Order
	R_a	MRR	F_b			
1	0.759	0.663	1.000	0.607	0.619	16
2	0.747	0.608	0.945	0.767	0.771	4
3	0.674	0.494	0.805	0.658	0.674	13
4	0.371	0.362	0.704	0.479	0.512	22
5	0.400	0.383	0.625	0.469	0.474	25
6	0.418	0.380	0.543	0.447	0.481	23
7	0.339	0.403	0.619	0.454	0.476	24
8	0.363	0.410	0.487	0.420	0.467	26
9	0.371	0.424	0.442	0.412	0.439	27
10	0.675	0.589	0.970	0.745	0.750	8
11	0.750	0.598	0.864	0.738	0.747	9
12	0.866	0.619	0.832	0.772	0.786	3
13	0.501	0.533	0.749	0.595	0.624	14
14	0.510	0.539	0.694	0.581	0.596	17
15	0.530	0.544	0.608	0.560	0.566	19
16	0.426	0.593	0.684	0.567	0.592	18
17	0.387	0.572	0.559	0.506	0.563	21
18	0.470	0.647	0.515	0.544	0.565	20
19	0.641	0.539	0.643	0.608	0.621	15
20	0.769	0.648	0.677	0.698	0.714	12
21	1.000	0.839	0.802	0.880	0.891	1
22	0.668	0.760	0.717	0.715	0.724	10
23	0.708	0.799	0.622	0.710	0.72	11
24	0.773	0.862	0.618	0.751	0.768	5
25	0.579	0.968	0.612	0.720	0.753	7
26	0.660	0.991	0.635	0.762	0.767	6
27	0.718	1.000	0.633	0.784	0.795	2

Table 4 Range of fuzzy subsets used

Condition	Range	Membership function
Ultra small	−0.125−0.125	
Very small	0−0.25	
Small	0.125−0.375	
Low medium	0.25−0.5	
Medium	0.375−0.625	Triangular
High medium	0.5012−0.7512	
Low	0.625−0.875	
Very low	0.75−1	
Ultra low	0.8762−1.126	

5 Results and discussion

5.1 Grey-fuzzy reasoning analysis

The process of obtaining grey-fuzzy output by integrating grey relational coefficients with fuzzy approach is represented as grey-fuzzy reasoning analysis and a MATLAB tool was used for this analysis. Each grey relational coefficient of surface roughness, material removal rate and flank wear is assigned with three triangular membership functions, thus amounting to a total of nine membership functions for the grey output. For activating fuzzy inference system, a set of rules is written and evaluated. The grey-fuzzy reasoning grades for all 27 experiments are predicted and their order is shown in Table 3. A comparison of grey relational grade and grey-fuzzy reasoning grade in Table 3 indicates that there is a definite improvement in grey-fuzzy reasoning grade. This improvement is achieved because of the reduced uncertainty in data obtained from grey relational approach. Since the fuzziness is reduced, the value of grey-fuzzy reasoning grade obtained is found to be higher when compared with grey relational grade and shows an increase towards the reference value 1.

The improvement in grade values by applying grey-fuzzy analysis is also similar to that by other researchers'. LIN et al [23] used grey-fuzzy relational analysis for optimizing EDM process with multiple responses and concluded that grey-fuzzy relational analysis is a direct method when compared with fuzzy-based Taguchi method. CHIANG et al [29] reported that using grey-fuzzy algorithm, the required performance characteristics in die casting process were significantly improved.

In order to find the optimal condition of machining precisely, a response table (Table 5) using grey-fuzzy reasoning grade has been developed. The values in response table are the average sum of grey-fuzzy reasoning grade for each level of machining parameters. The variation of average fuzzy reasoning grade with respect to different levels of machining parameter is shown in Fig. 4. The steep slope in the response plot indicates that the machining parameter influences the performance characteristics to a larger extent. In this experimental result, the feed rate is indicated by a steep slope with a fuzzy reasoning grade and it has a comparatively greater influence when compared with other parameters. The grade value increases in proportion to the cutting speed up to the second level, after which the grade value shows only a gradual increase towards multi-performance. At high cutting speed even though surface roughness is reduced, it results in increased flank wear of the tool. The heat produced at the machining interface is more at high cutting speed and this in turn, softens the tool tip. An increase in mass fraction of SiC−Gr shows an increase in fuzzy reasoning grade. Therefore, machining Al−SiC−Gr hybrid composite with a higher mass fraction of SiC−Gr

Table 5 Response table for grey-fuzzy reasoning grade

Parameter	Level 1	Level 2	Level 3
Cutting speed (*A*)	0.5673	0.6429	0.6900
Feed rate (*B*)	0.7518	0.6771	0.6013
Mass fraction of SiC−Gr (*C*)	0.6212	0.6466	0.6624

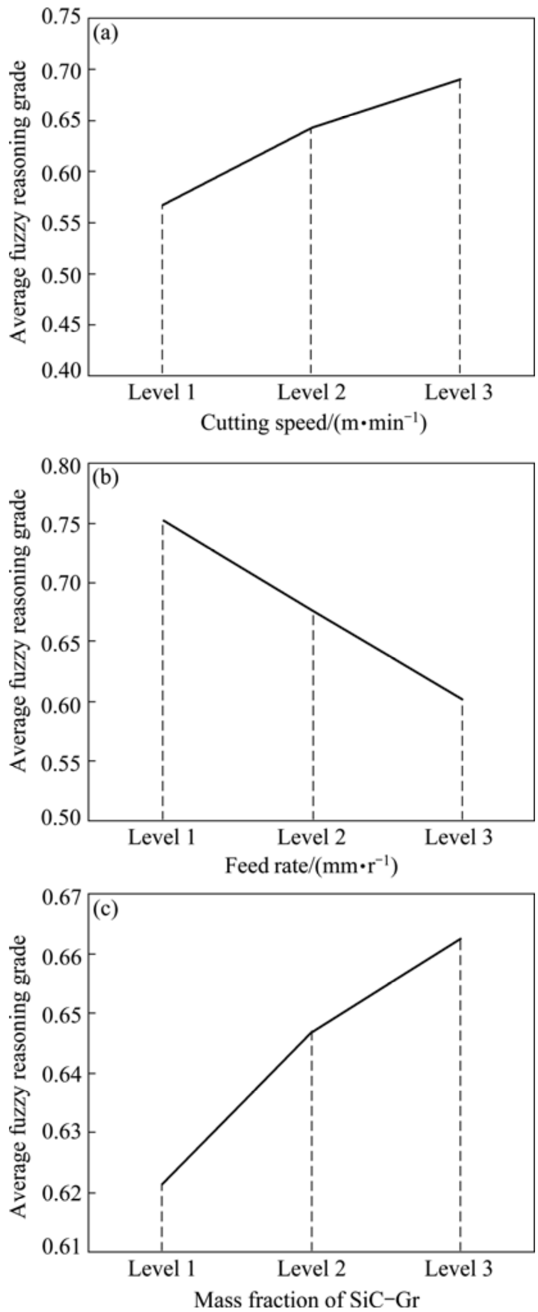

Fig. 4 Response graphs for different levels of machining parameters: (a) Cutting speed; (b) Feed rate; (c) Mass fraction of SiC−Gr

particles results in better multi-performance characteristics.

The highest value of grey-fuzzy reasoning grade η_0 in the response table indicates the optimal level of machining parameters. Since grey-fuzzy reasoning grade represents a level of relationship between reference sequence and objective sequence, a greater value of grey-fuzzy reasoning grade indicates the existence of strong correlation among them. The optimal parameter setting can be specified as follows: cutting speed at level 3 (200 m/min), feed rate at level 1 (0.075 mm/r) and mass fraction of SiC−Gr at level 3 (10%).

5.2 Effect of machining parameters and responses on grey-fuzzy reasoning grade

The influence of machining parameters and grey relational coefficients of responses on the grey-fuzzy reasoning grade is shown in Figs. 5 and 6, respectively. It can be observed from Fig. 5 that the highest and lowest values of grey-fuzzy reasoning grades are obtained at

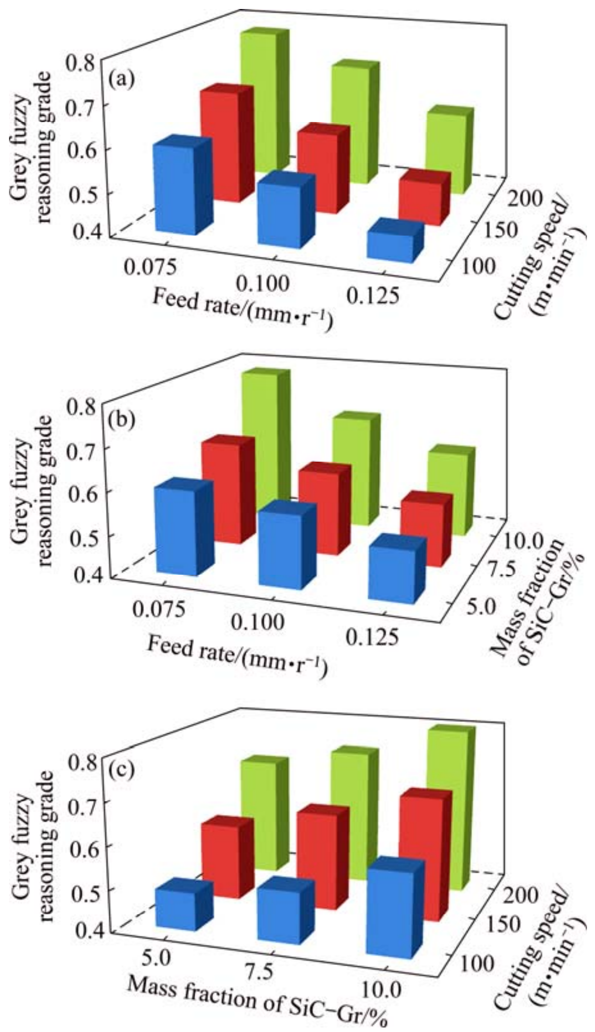

Fig. 5 Effect of grey-fuzzy reasoning grade on machining parameters: (a) Feed rate and cutting speed; (b) Feed rate and mass fraction of SiC−Gr; (c) Mass fraction of SiC−Gr and cutting speed

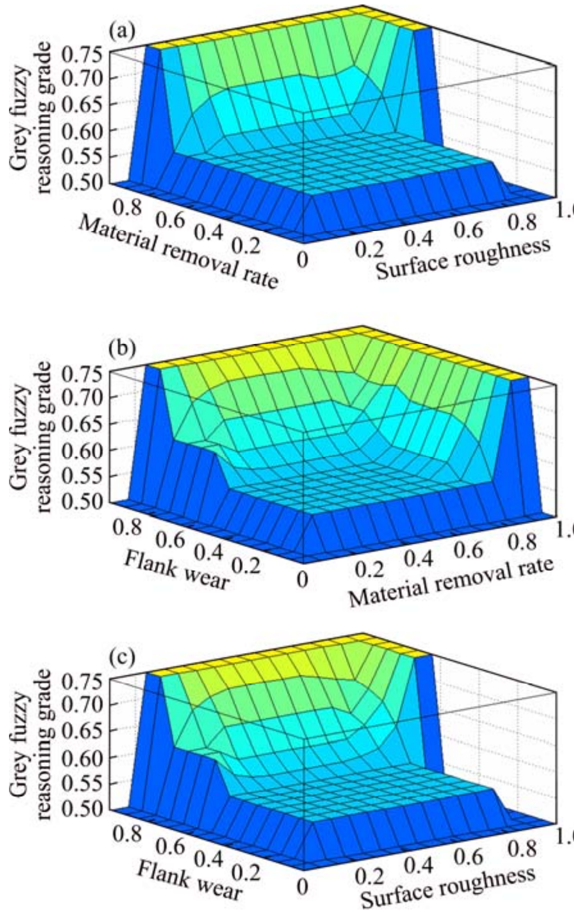

Fig. 6 Variation of grey-fuzzy grade based on grey relation coefficient of responses: (a) MRR and R_a; (b) F_b and MRR; (c) F_b and R_a

interaction levels A_3B_1, B_1C_3, A_3C_3 and A_1B_3, B_3C_1, A_1C_1 respectively.

Based on the results, it can be inferred that surface roughness reduces with an increase in cutting speeds; however, an increase in feed rate results increases surface roughness. The surface roughness is mostly affected by build-up edge formation (BUE) at the tip of insert. The BUE and chip fracture are developed at low speeds, which readily induces roughness. The surface roughness decreases as the speed increases due to the disappearance of BUE and chip fracture. The result is in agreement with results of PALANIKUMAR and KARTHIKEYAN [6]. Normally, at a high cutting speed, the force induced in machining increases which cuts the hybrid MMCs smoothly and results in lower surface roughness. In machining of hybrid Al−SiC−Gr composite, a low level of feed rate is preferred because an increase in feed rate increases the tangential force and heat generation during turning operation. This increase in tangential force bends the material to a great extent before the interfacial bond crack progresses, finally resulting in a higher surface roughness. Similar resulting have also been obtained by PAULO DAVIM [30] during turning operation; the surface roughness value is directly proportional to an increase in feed rate and is inversely proportional to cutting speed. From Figs. 5(b) and (c), it can be observed that an increase in mass fraction of SiC−Gr increases grey-fuzzy reasoning grade which represents decrease in surface roughness. This can be attributed to the increase in brittleness of hybrid composite and subsequently the build-up edge disappears.

The material removal rate increases with an increase in cutting speed, feed rate or mass fraction of SiC−Gr particles. The inclusion of SiC in metal matrix was reported to increase the hardness, tensile strength and heat resistance of the aluminium alloy. A higher mass fraction of SiC induces more flank wear of the tool, simultaneously resulting in a minimum material removal rate [6]. The MRR of the graphite particulate composite is better than that of the ceramic particles reinforcement. The increase in mass fraction of Gr particles reduces the ductility and hardness of Al−SiC−Gr hybrid composites. Therefore, machining of Al−SiC−Gr hybrid composites with a higher mass fraction of graphite is easy with a maximum MRR and less tool wear.

When cutting speed and feed rate are increased, the rubbing action between the tool and work piece also tends to become faster. This produces more heat during minimum period of tool contact. The generation of heat on flank side softens the edge, leading to increased wear. The addition of graphite particles reduces flank wear of the tool due to the formation of tribo-layer. Some of the crushed or removed graphite particles trapped between flank face of the tool and machining surface, and reduced friction at the machining interface.

Al−10%(SiC−Gr) has better machinability with a minimum surface roughness, flank wear and a maximum MRR under all cutting conditions when compared with MMC with 5% and 7.5% of SiC−Gr reinforcement. At the cutting speed of 200 m/min, feed rate of 0.075 mm/r and 10% of SiC−Gr, the overall machining performance is better which also reflects higher grey-fuzzy reasoning grade.

5.3 Confirmation experiment

The confirmation experiment is the final step to verify the improvement of performance characteristics at optimal level of machining parameters. After determining the optimum conditions, a new experiment was conducted. The predicted grey-fuzzy reasoning grade is calculated as follows:

$$\eta_{\text{predicted}} = \eta_0 + \sum_{i=1}^{n} (\eta_{\text{m}} - \eta_0) \tag{4}$$

where η_0 is the total mean of grey-fuzzy reasoning grade; η_{m} is the mean of grey-fuzzy reasoning grade at the optimal level of significant parameters A, B and C; n is the number of significant parameters that affect the performance characteristic and is assigned as 3. The confirmation test results are shown in Table 6, and reveal that the surface roughness reduces from 3.8 to 1.6 μm, and the flank wear of the tool from 0.20 to 0.18 mm, while the material removal rate improves from 9.51 to 36.64 g/min. The predicted grey-fuzzy reasoning grade is the nearest to the experimental value. A higher grey-fuzzy reasoning grade in optimal setting, confirms the enhancement in multi-performance characteristics. The increase in mass fraction of graphite in the composite avoids sticking of Al alloy with insert tip and in turn increases the tool life. Under optimum machining condition, the tool life is also found to be improved.

An examination of the machined surface (Fig. 7) under the optimum machining condition ($A_3B_1C_3$) reveals the presence of few micro cracks, particle pull-out and shearing of particles which normally induce surface roughness. The deformation and micro cracks seem to multiply at those regions of dislocation pile-up. The micro cracks thus form, tend to progress and finally end as they meet the reinforcement particle in their path. In machining process, plastic deformation occurs and graphite particles tend to smear over the machined surface due to low interfacial strength. This smeared graphite particles over the machined surface improve the surface finish. The micrograph in Fig. 8 reveals distinct abrasive wear grooves on the flank face while turning hybrid AMCs with 10% of SiC−Gr at a cutting speed of 200 m/min and feed rate of 0.075 mm/r. This abrasive wear is caused by the presence of hard abrasive SiC particles in the hybrid aluminium composite. The ridges and grooves are also induced by this particle on the flank face of tool. The grooves formed on the flank face are deposited with Al matrix material, which acts as a shield and prevents further major abrasive wear.

Table 6 Results of machining performance with initial and optimal setting of parameters

Item	Setting level	Surface roughness/μm	Material removal rate/(g·min^{-1})	Flank wear of tool/mm	Tool life/min	Grey-fuzzy reasoning grade	Grade improvement
Initially	$A_1B_1C_1$	3.8	9.51	0.20	38	0.619	
Predicted	$A_3B_1C_3$	–	–	–	–	0.882	0.263
Experimental	$A_3B_1C_3$	1.6	36.64	0.18	43	0.891	0.272

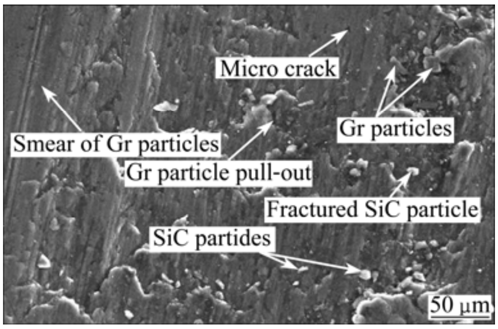

Fig. 7 SEM micrograph of machined surface under optimum machining condition ($A_3B_1C_3$)

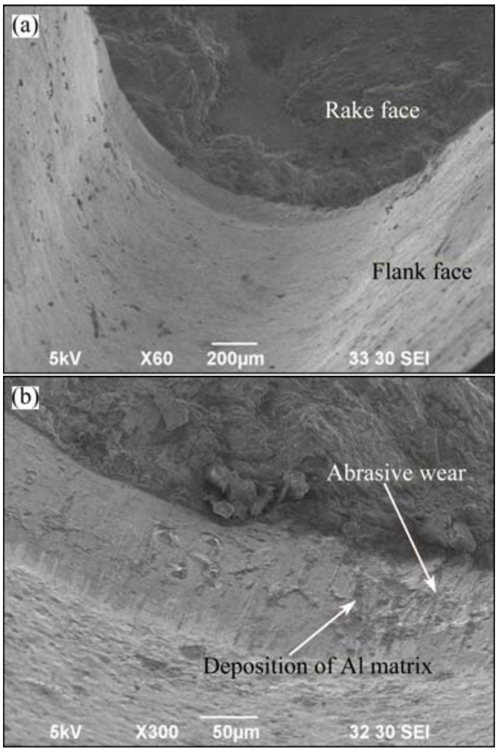

Fig. 8 SEM micrographs of flank wear under optimum machining condition ($A_3B_1C_3$): (a) Lower magnification; (b) Higher magnification

6 Conclusions

1) The semi-solid state of processing allows uniform distribution of SiC and Gr particles in aluminium matrix. The hardness of aluminium hybrid composite with 5%, 7.5% and 10% of SiC−Gr particles are BHN67, BHN80, BHN76 and their corresponding tensile strength values are 170, 210, 204 MPa, respectively. Al−10%(SiC−Gr) provides better machinability with a minimum surface roughness and flank wear, and a maximum MRR under all cutting conditions when compared with AMCs with 5% and 7.5% of SiC−Gr.

2) Implementation of fuzzy logic approach in a grey system offers improved grey-fuzzy reasoning grade and minimizes uncertain output. The recommended levels of turning parameters to minimize surface roughness and flank wear, and to maximize material removal rate are: cutting speed of level 3 (200 m/min), feed rate of level 1 (0.075 mm/r) and mass fraction of SiC−Gr of level 3 (10%) and at a constant depth of cut of 1 mm. An increase in grey-fuzzy reasoning grade from 0.619 to 0.891 confirms the improvement in performance characteristics at optimal level of process parameters. By increasing the number of process parameters and experiments, accuracy and effectiveness of grey-fuzzy approach could be further improved.

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灰度模糊算法优化 Al−SiC−Gr 混合金属基复合材料的加工参数

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摘　要：石墨颗粒增强金属基复合材料能够提供更好的切削加工性能和摩擦性能。用灰度模糊算法优化 Al−SiC−Gr 混合金属基复合材料的加工参数，以获得到具有优秀综合性能的材料。当混合金属基复合材料中 SiC−Gr 的质量分数分别为 5%、7.5% 和 10%时，对应的拉伸强度分别为 170、210 和 204 MPa。另外，与另外 2 种材料相比，Al−10%(SiC−Gr) 复合材料具有更好的切削加工性能。与其他的灰度技术相比，灰度模糊逻辑算法在输出方面提高了推理的合理性，降低了不确定性。实验结果表明，在设置的相同加工参数下，与其他的灰度技术相比，灰度模糊逻辑算法的推理合理性从 0.619 提高到 0.891，且同时保证材料具有更好的综合性能。

关键词：混合金属基复合材料;切削; 优化; 灰度模糊算法

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