Development of an AMMC through Identification of Influential Factors Combination Using Grey-Fuzzy Approach

G.Vijaya Kumar*, P.Venkataramaiah**

*Research scholar, department of mechanical engineering,S V University college of engineering, tirupati, andhra pradesh, India Ph: +91-9948012585,

**Associate professor, department of mechanical engineering,S V University college of engineering, tirupati, andhra pradesh, India Ph: +91-9291602889,

ABSTRACT

The present paper has focused on the development of an Alluminium metal matrix composite (AMMC) which posses good mechanical properties to meet the functional requirements as the materials of machine elements. The AMMC samples are prepared by mixing reinforcement materials like SiC, Al_2O_3, Al_3C_4 in different sizes and percentages with Alluminium base materials like Al6061, Al6063, Al7075 using stir casting furnace according to taguchi orthogonal array OA L9 for minimizing experimental cost. The properties (responses) like density, tensile strength, impact strength, and hardness are determined for the samples. These responses are studied and analyzed using grey-fuzzy approach, and the optimum combination of influential factors are identified. A new sample is prepared as per identified combination and tested for confirmation, and it is satisfactory.

KEYWORDS: Taguchi L_9 experimental design, mechanical properties, grey-fuzzy approach, optimum parameters, development of AMMC.

1. INTRODUCTION

Present days Automobile, Marine, and Aeronautical industries are looking for the materials of higher strength to weight ratio. Metal matrix composites can fulfill this requirement. Strength to weight ratio of MMC depends on the base material, reinforcement materials, and the amount of reinforcement. Most of the metal matrix composites are prepared with allminium alloys as base materials, and reinforcements are SiC and Al_2O_3 [12]. Using Taguchi method, the influence of parameters on responses, and an optimal combination of parameters are identified [1, 2]. So many researchers were used this method to analyze the machining of metals, composite materials and Metal Matrix Composites and succeeded in getting good results [3-6]. However, this method is not useful for analyzing the multi response problems. The grey system theory proposed by Deng [7] has been proven to be useful for dealing with poor, insufficient, and uncertain information. The grey relational theory is more useful for solving the complicated inter-relationships among multiple performance characteristics [8, 9] like Multi response optimization of drilling parameters of Al/SiC metal matrix composite, and Determination of optimum parameters for multi-performance characteristics in drilling.[10, 11].The fuzzy logics, is introduced by Zadeh, for dealing the problems with uncertain information [12]. So many researchers are succeeded by applying the fuzzy logics is dealing the multi response problems with uncertain data [13-16]. Stefanos investigated the effects of SiC particles on mechanical properties of MMCs [18]. He observed that the fatigue and tensile strength are increased with addition of SiC particles. Pai,et.al. [19], Muhammad Hayat Jokhio et.al [20] and Rajmohan and Palanikumar [21]were investigated and repoted that the stir casting is simple and low expensive when compared with other preparation methods, also reported the mechanical properties of Metal Matrix composites depends on distribution of particles throughout the matrix material, bonding of particles with base material. Many of the researchers are investigated the effect of SiCp reinforcement in various aluminum metal matrix composites [22, 23]. A.R.I.Khedera et.al. [24] Were investigated SiC, Al_2O_3 and MgO reinforced Al metal matrix composite and reported the improvements in the mechanical properties. And the effects of "Al2O3" particles reinforced in various aluminum matrix composites were observed by several researchers. And reported the effect of "Al_2O_3" particles on wear and Mechanical properties of Metal Matrix Composites [20, 24, 25, 26, 27].

The literature review reveals that the effect of the reinforcement of alluminium carbide is not investigated by the above researchers and no researcher used Taguchi experimental design in the development of AMMC by considering various influential factors. It is also reveals that optimization techniques have not been applied in the investigation of mechanical properties of AMMC.

To address the lack of research in this issue, the present work has focused on the development of a new AMMC based on optimum influential factors combination which is identified using Taguchi experimental design and grey-fuzzy approach. This is first of its kind to the best of authors’ knowledge.

2. INFLUENTIAL FACTORS AND EXPERIMENTAL DESIGN

The levels of the parameters, which influence the mechanical properties of AMMC shown in Table1. In the view of minimizing the experimental cost, fractional factorial design OAL9 is chosen for conducting experiments. In the present work nine different AMMCs have been prepared as per Taguchi L9 experimental design Table 2. using stir casting furnace as following.

Table 1. Influential factors and their levels

Sl no	Influential factors	Level1	Level2	Level3
1	Base material (BM)	Al 6061	Al 6063	Al 7075
2	Reinforcement material (RM)	SIC	AL2O3	AL4C3
3	Size of Reinforcement particles (SRP) (µm)	53	63	75
4	Percentage of Reinforcement material (PRM) (% vol)	5	10	15

Table:2 Experimental design

Expt. Runs (Samples no)	Influential factors			
	BM	RM	SRP (µm)	PRP (%)
1	Al6061	SIC	75	5
2	Al6061	AL2O3	63	10
3	Al6061	AL4C3	53	15
4	Al6063	SIC	63	15
5	Al6063	AL2O3	53	5
6	Al6063	AL4C3	75	10
7	Al7075	SIC	53	10
8	Al7075	AL2O3	75	15
9	Al7075	AL4C3	63	5

3. PREPERATION OF ALUMINIUM METAL MATRIX COMPOSITES

First the stir casting furnace with graphite crucible is switched on and allow it to raise the temperature up to 500^{O}C then the required amount of base material is poured into the crucible and the temperature is raised up to 850^{O}C and allow it to maintain the same up to complete melting of base material. At 675^{O}C, the wetting agent Mg of 1% is added to the base material. Then the reinforcement particles are added slowly to thew molten base material while the stirrer rotating. Before adding the reinforcement particles they are heated for 2 hrs upto 1000^{O}C to oxidise their surfaces. After mixing, the temperature of the slurry is raised upto 850^{O}C for getting improved fluidity and stirring is continued upto 5 minuits. Then the mixed slurry was poured in different preheated steel dies to produce the samples for testing.

4. TESTING OF ALUMINIUM METAL MATRIX COMPOSITE SAMPLES

Test specimens are prepared from above produced AMMC samples for testing of tensile, impact, and hardness properties and results are recorded (Table.3). The test details are presented in the following sections.

4.1. Tensile Properties of Metal Matrix Composition

Among the many mechanical properties of plastics as well as composite materials, tensile properties are probably the most frequently considered and evaluated. These properties are an important indicator of the materials behavior under loading in tension for different applications.The AMMC samples were machined to get dog-bone specimen for tensile test as per the ASTMD 3039-76 specifications. The computer interfaced universal testing machine was used for the tensile test and yield strength values of samples are recorded. The gauge lengths of the specimens were maintained at 100mm for this test.

4.2. Impact Strength and hardness Properties of Metal Matrix Composites

Impact tests data are used in studying the toughness of material. A material's toughness is a factor of its ability to absorb energy during plastic deformation. Brittle materials have low toughness as a result of the small amount of plastic deformation that they can endure. The test specimens with 24mmx16mmx17mm are cut as per ASSTM D 256-88 specifications. Impact strength is determined using IZOD impact tester and values are recorded. And also AMMC samples are tested for hardness using Brinell hardness machine and BHN are recorded.

Table:3 Experimental Results

Expt. Runs	Experimental Results			
	Tensile strength (N/mm^2)	Impact Strength (MN/m^2)	Brinell Hardness Number	Density (Kg/m^3)
1	80.84	307.63	133	2727.27
2	88.11	615.73	105	2786.4
3	94.21	186.55	150	2816.9
4	60.73	594.72	105	3097.3
5	66.52	184.62	95	2742.4
6	70.23	435.14	197.3	2855.1
7	58.34	632.9	229.5	3132.3
8	63.88	321.64	171	3007.5
9	67.47	589.65	171	2828.3

5. IDENTIFICATION OF OPTIMUM PARAMETER COMBINATION AND DEVELOPMENT OF AN AMMC

Using fuzzy logic, the test results are analyzed and optimum influential factor combination is identified for development of an AMMC which poses good mechanical properties

Step-I: Calculation of S/N ratios

S/N ratios for the corresponding responses are calculated for different cases according to the required quality characteristics as follows.

i). Larger - the – better

$$S/N\ Ratio(\eta) = -10log_{10}\left(\frac{1}{n}\right)\sum_1^n \frac{1}{y_{ij}^2} \text{ --------- } 1$$

ii) Smaller - the – better

$$S/N\ Ratio(\eta) = -10log_{10}\left(\frac{1}{n}\right)\sum_1^n y_{ij}^2 \text{ --------- } 2$$

Where n=number of replications, y_{ij}= Observed response value where i=1, 2 ...n; j=1, 2...k

Larger the better is applied for problem where maximization of the quality characteristic is sought and smaller the better is applied where minimization of quality characteristic is sought. For the responses, Tensile strength, impact strength, and Brinell Hardness larger the better is applicable and smaller the better is applicable for the response density. Hence, its S/N ratios are calculated using Eqs1&2 as shown in the Table 4.

Table 4: S/N Ratios for experimental Results

Expt. Runs	Tensile strength	Impact strength	Brinell Hardness Number	Density
1	-38.1525	-49.7606	-42.477	68.5465
2	-38.9005	-55.7878	-40.4238	68.7328
3	-39.4819	-45.4159	-43.5218	68.8276
4	-35.6681	-55.4863	-40.4238	69.6518
5	-36.459	-45.3256	-39.5545	68.5950
6	-36.9305	-52.7726	-45.9025	68.9432
7	-35.3193	-56.0267	-47.2157	69.7484
8	-36.1073	-50.1474	-44.6599	69.3964
9	-36.5822	-55.4119	-44.6599	68.8621

Step II: Normalization of S/N ratios

Data normalization is required where the range and unit in one data sequence may differ from the others. In data pre-processing, the original sequence is transformed to a comparable sequence. Depending on the quality characteristic of a data sequence, there are various methodologies of data pre-processing available for the grey relational analysis.

For quality characteristic of the "larger – the - better", the original sequence can be normalized as

$$x^*_i(k) = \frac{x^o_i(k) - min\ x^o_i(k)}{max\ x^o_i(k) - min\ x^o_i(k)} \text{ ---------- } 3$$

For quality characteristic of the "smaller – the - better" the original sequence, can be normalized as

$$x^*_i(k) = \frac{max\ x^o_i(k) - x^o_i(k)}{max\ x^o_i(k) - min\ x^o_i(k)} \text{ --------- } 4$$

Where i = 1..., m; k = 1..., n. m is the number of experimental data items and n is the number of parameters. x^o_i(k) Denotes the original sequence, x^*_i(k) the sequence after the data pre-processing, max x^o_i(k) the largest value of x^o_i(k), min x^o_i(k) the smallest value of x^o_i(k), and x^o is the desired value. For the S/N ratios of Tensile strength, impact strength, and Brinell Hardness, larger the better is applicable and smaller the better is applicable for the S/N ratios of density. Hence, its S/N ratios are normalized using Eqs3&4 as shown in Table5.

Step III: Determine the grey relational coefficient

After data pre-processing, the grey relation coefficient ξ_i(k) for the k[th] performance characteristics in the i[th] experiment can be determined using the Eq.5

Table 5: Normalized S/N Ratios for experimental Results

Expt. Runs	Tensile strength	Impact strength	Brinell Hardness Number	Density
1	0.3194	0.5856	0.6185	1
2	0.1397	0.0223	0.8865	0.845
3	0	0.9916	0.4821	0.7661
4	0.9162	0.0505	0.8865	0.0804
5	0.7262	1	1	0.9596
6	0.613	0.3041	0.1714	0.67
7	1	0	0	0
8	0.8107	0.5494	0.3336	0.2928
9	0.6966	0.0575	0.3336	0.7374

$$\xi_i(k) = \frac{\Delta_{min} + \zeta\ \Delta_{max}}{\Delta_{oi}(k) + \zeta\ \Delta_{max}} \text{ ---------- } 5$$

Where, Δ_{oi} is the deviation sequence of the reference sequence and the comparability sequence.

$\Delta_{oi} = \| x^*_o(k) - x^*_i(k)\|$

$\Delta_{min} = \underset{\forall j \epsilon i}{min}\ \underset{\forall k}{min} \|x^*_o(k) - x^*_j(k)\|$

$\Delta_{max} = \underset{\forall j \epsilon i}{max}\ \underset{\forall k}{max} \| x^*_o(k) - x^*_j(k)\|$

x^*_o(k) denotes the reference sequence and x^*_i(k) denotes the comparability sequence. ζ is distinguishing or identification coefficient and its value is between '0' and '1'. The value may be adjusted based on the actual system requirements. A value of ζ is the smaller and the distinguished ability is the larger. ζ = 0.5 is generally used. The Grey Relational coefficients of Density, Tensile strength, impact strength, and Brinell Hardness number are shown in the Table.6

Table 6 : Grey Relation Coefficients

Expt. Runs	Tensile strength	Impact strength	Brinell Hardness	Density
1	0.4235	0.5468	0.5672	1
2	0.3676	0.3384	0.815	0.7633
3	0.3333	0.9834	0.4912	0.6813
4	0.8565	0.3449	0.815	0.3522
5	0.6462	1	1	0.9252
6	0.5637	0.4181	0.3763	0.6024
7	1	0.3333	0.3333	0.3333
8	0.7254	0.526	0.4287	0.4142
9	0.6224	0.3466	0.4287	0.6556

Step IV: Determination of Grey-Fuzzy grade(GFG)

A fuzzy logic unit comprises a fuzzifier, membership functions, a fuzzy rule base, an inference engine and a defuzzifier. In the fuzzy logic analysis, the fuzzifier uses membership functions to fuzzify the grey relational coefficient first. Next, the inference engine performs a fuzzy reasoning on fuzzy rules to generate a fuzzy value. Finally, the defuzzifier converts the fuzzy value into a Grey-Fuzzy grade. The structure built for this study is a four input- one-output fuzzy logic unit as shown in Fig. 1. The function of the fuzzifier is to convert outside crisp sets of input data into proper linguistic fuzzy sets of information. The input variables of the fuzzy logic system in this study are the grey relational coefficients for

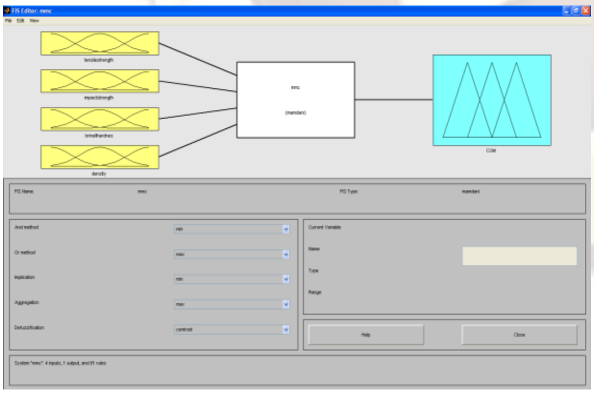

Figure.1 Four input- one-output fuzzy logic unit

Tensile strength, impact strength, Brinell Hardness number and density. They are converted into linguistic fuzzy subsets using membership functions of a triangle form, as shown in Fig. 2, and are uniformly assigned into three fuzzy subsets—small (S), medium (M), and large (L) grade. The fuzzy rule base consists of a group of if-then control rules to express the inference relationship between input and output. A typical linguistic fuzzy rule called Mamdani is described as

Rule 1: if x1 is A1, x2 is B1 ,x3 is C1 andx4 is D1 then y is E1 else

Rule 2: if x1 is A2 , x2 is B2 ,x3 is C2 andx4 is D2 then y is E2 else

Rule n: if x1 is An , x2 is Bn ,x3 is Cn andx4 is Dn then y is En else

In above Ai, Bi, Ci and Di are fuzzy subsets defined by the Corresponding membership functions i.e., α/4Ai, α /4Bi, α /4Ci, and α /4Di. The output variable is the Grey-Fuzzy grade yo, and also converted into linguistic fuzzy subsets

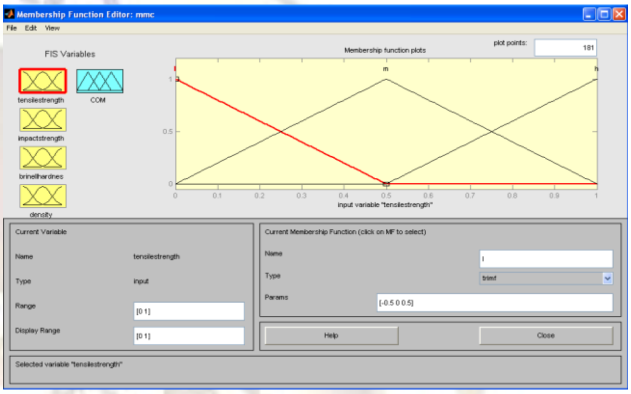

Figure 2. Membership functions for tensile strength, impact strength, brinell hardness, and density

using membership functions of a triangle form, as shown in Fig. 3. Unlike the input variables, the output variable is assigned into relatively nine subsets i.e., very very low (VVL), very low (VL), small(S) medium low(ML),medium (M), medium high(MH) high(H), very high (VH), very very high(VVH) grade. Then, considering the conformity of four performance characteristics for input variables, 81 fuzzy rules are defined and listed in Table 7. The fuzzy inference engine is the kernel of a fuzzy system. It can solve a problem by simulating the thinking and decision pattern of human being using approximate or fuzzy reasoning. In this paper, the max-min compositional operation of

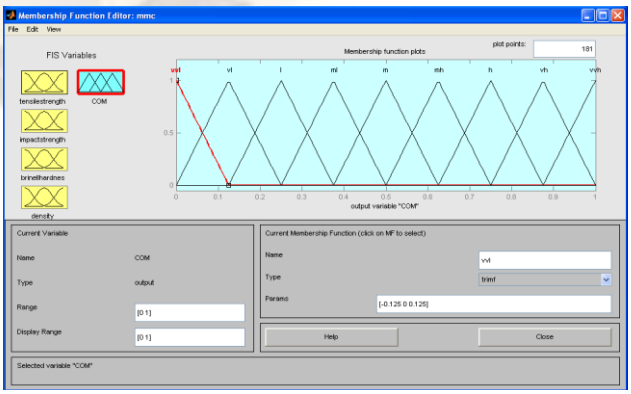

Figure 3. Membership function for Grey-Fuzzy Grade

Mamdani is adopted to perform calculation of fuzzy reasoning. Suppose that x1, x2, x3 and x4 are the input variables of the fuzzy logic system, the membership function of the output of fuzzy reasoning can be expressed as

$$\mu_{C_0}(y) = \left(\mu_{A_1}(x_1)\Lambda\mu_{B_1}(x_2)\Lambda\ \mu_{C_1}(x_3)\Lambda\mu_{D_1}(x_4)\Lambda\ \mu_{E_1}(y)\right) \vee \ldots \left(\mu_{A_n}(x_1)\Lambda\mu_{B_n}(x_2)\Lambda\ \mu_{C_n}(x_3)\Lambda\mu_{D_n}(x_4)\Lambda\ \mu_{E_n}(y)\right)$$

Where V is the minimum operation and Λ is the maximum operation. Hybrid Grade is shown in the Table 8.

Table 7. Fuzzy Rules

Rule no	Grey coefficients as input variables				GFG
	Tensile strength	Impact strength	Brinell Hardness Number	Density	
1	low	low	low	low	vvl
2	low	low	low	medium	vl
3	low	low	low	high	l
4	low	low	medium	low	vl
5	low	low	medium	medium	l
6	low	low	medium	high	ml
7	low	low	high	low	l
8	low	low	high	medium	ml
9	low	low	high	high	m
10	low	medium	low	low	vl
-	-	-	-	-	-
-	-	-	-	-	-
-	-	-	-	-	-
-	-	-	-	-	-
-	-	-	-	-	-
72	high	medium	high	high	vh
73	high	high	low	low	m
74	high	high	low	medium	mh
75	high	high	low	high	h
76	high	high	medium	low	mh
77	high	high	medium	medium	h
78	high	high	medium	high	vh
79	high	high	high	low	h
80	high	high	high	medium	vh
81	high	high	high	high	vvh

***Here: vvl-very very low, vl-very low, l-low, ml-medium low, m-medium, mh-medium high, h-high,**
vh-very high, vvh-very very high

Table8:Grey-Fuzzy Grade

Expt Run	Grey-Fuzzy Grade
1	0.6438
2	0.541
3	0.6167
4	0.5467
5	0.8568
6	0.4897
7	0.4704
8	0.5089
9	0.5157

5.3 Step V Development of AMMC

After determining the GFG, the effect of each parameter is separated based on GFG at different levels Fig4. The mean values of GFG for each level of the controllable influential factors and the effect of influential factors on multi responses in rank wise are summarized in Table 9. Basically, larger GFG means it is close to the product quality. Thus, a higher value of the GFG is desirable. From the Table 5, the best level of influential factors are base material at level 2 (Al6063), reinforcement material level 2 (Al_2O_3), size of reinforcement material at level 1 (53 μm), and percentage of reinforcement material at level 1 (5%). A new AMMC is prepared for this optimum level of influential factors and is tested for the responses. The responses are compared with AMMC of initial combination of influential factors (Table 10)

Table9: Grey-Fuzzy Grade for each level of influential factors

Influential factors	Level 1	level 2	level 3	max-min	rank
BM	0.600	**0.631**	0.498	0.132	**2**
RM	0.553	**0.635**	0.540	0.094	**4**
SRP	0.547	0.534	**0.647**	0.113	**3**
PRM	**0.672**	0.500	0.557	0.171	**1**

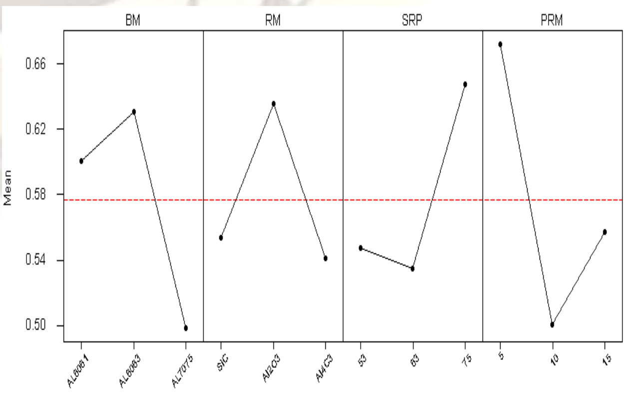

Fig4: **Grey-Fuzzy Grade for each level of influential factors**

7. CONCLUSIONS

After analyzing the data of developed AMMC, it is concluded that the percentage of reinforcement material and type of the base material highly influence the mechanical properties of metal matrix composites. Reinforcement material and size of reinforcement material have low influence on the mechanical properties. It is also concluded

Table.10: Comparison of responses between AMMC with initial combination and Developed AMMC

	Combination of Controllable Parameters	Tensile strength	Impact strength	Brinell Hardness Number	Density	Grey-Fuzzy Grade
AMMC with Initial Combination	BM2RM2SRP2PRP2	65	450	175	2816.9	0.530901
Developed AMMC	BM2RM2SRP3PRP1	125	700	200	2747.4	0.896867
Gain	N/A	60	150	25	69.5	0.365966
% of Gain	N/A	92.3	33.3	14.2	2.5	69

that aluminium oxide is the best reinforcement material of metal matrix composites among silicon carbide, aluminum oxide, alluminium carbide. This work may be extended by considering the other sizes of reinforcement material and percentages in the view of searching better properties of AMMC.

AKNOWLEDGEMENTS

The authors would like to acknowledge technicians and Mr. S.Gangaiah, PG student of Mechanical Engineering Department, SVUCE, Tirupati, for their help in conducting experiments.

REFERENCES

[1] P.J. Ross, Taguchi techniques for quality engineering, Mc Graw-Hill, New York. 1998.

[2] R.K. Roy, Design of experiments using the Taguchi approach, John Willey & Sons, Inc., New York. 2001.

[3] M. Villeta et.al. “Surface Finish Optimization of Magnesium Pieces Obtained by Dry Turning Based on Taguchi Techniques and Statistical Tests” Materials and Manufacturing Processes 2011 26:12, 1503-1510

[4] S. Basavarajappa, et.al. studies on drilling of hybrid metal matrix composites based on Taguchi techniques, journal of materials processing technology 2 0 0 8, 1 9 6 332–338

[5] Erol Kilickap, Modeling and optimization of burr height in drilling of Al-7075 using Taguchi method and response surface methodology, Int J Adv Manuf Technol 2010, 49:911–923

[6] N.Radhika, et.al, “Tribological behavior of Aluminium/Alumina/Graphite Hybrid Metal Matrix Composite using taguchi techniques” Journal of minerals and materials characterization and engineering 2011, 10(5) 427-443.

[7] J.L. Deng, Introduction to Grey System, Journal of Grey Systems 1/1 (1989) 1-24.

[8] C.P. Fung , Manufacturing process optimization for wear property of fiber-reinforced polybutylene terephthalate composite with grey relational analysis,Wear 254 (2003) 298-306.

[9] H.S. Lu, B.Y. Lee, C.T. Chung, Optimization of the micro-drilling process based on the grey relational analysis, Journal of the Chinese Society of Mechanical Engineerings 27 (2006) 273-278.

[10] Erol Kilickap, Modeling and optimization of burr height in drilling of Al-7075 using Taguchi method and response surface methodology, Int J Adv Manuf Technol (2010)49:911–923

[11] A. Noorul Haq, P. Marimuthu, R. Jeyapaul, Multi response optimization of machining parameters of drilling Al/SiC metal matrix composite using grey relational analysis in the Taguchi method, Int J Adv Manuf Technol (2008) 37:250–255

[12] L. Zadeh, Fuzzy sets, Information and Control 1965 (8) 338-353.

[13] Tian-Syung Lan, Fuzzy Deduction Material Removal Rate Optimization for Computer Numerical Control Turning, American Journal of Applied Sciences 2010 7 (7): 1026-1031,

[14] B. Latha and V. S. Senthilkumar ”Modeling and Analysis of Surface Roughness Parameters in Drilling GFRP Composites Using Fuzzy Logic” Materials

and Manufacturing Processes 2010 Volume 25, Issue 8, 817-827.

[15] R. Vimal Sam Singh, B.Latha, V.S.Senthilkumar Modeling and Analysis of Thrust Force and Torque in drilling GFRP Composites by Multi-Facet Drill Using Fuzzy Logic, International Journal of Recent Trends in Engineering 2009, 1/ 5 66-70

[16] Anil Gupta,et.al."taguchi-fuzzy multi output optimization in high speed CNC turning of AISI P-20 tool Steel"expert system with applications 2011, 38, 6822-6828

[17] Shivatsan, et.al,"Processing Techniques for Particulate Reinforced Metal Matrix Composites", Journal of Materials Science 1991, Volume 26, 5965-5978.

[18] Stefanos S., "Mechanical Behaviour of Cast SiC Reinforced with Al 4.5% Cu-1.5% Mg Alloy", Journal of Materials Science and Engineering 1996, Volume 210, 76-82.

[19] Pai, B.C et.al, , "Stir Cast Aluminum Alloy Matrix", Key Engineering Materials 1993, Volume 79-80, 117- 128.

[20] Rajmohan And Palanikumar " Artificial Neural Network Model To Predict Thrust Force In Drilling Of Hybrid Metal Matrix Composites " National Journal On Advances In Building Sciences And Mechanics, 2010 - 1(2), 11-16.

[21] Muhammad Hayat Jokhio et.al, "Manufacturing of Aluminum Composite Material Using Stir Casting Process", Mehran University research journal of engineering & technology, 2011 volume 30, no.1, 53-64.

[22] M. Rajamuthamilselvan and S. Raman than "Hot-Working Behavior of 7075 Al/15% SiC_p Composites" Materials and Manufacturing Processes 2012 Volume 27, Issue 3, 260-266.

[23] Venkatararaman, and Sundararajan, "Correlation Between the Characteristics of the Mechanically Mixed Layer and Wear Behavior of Aluminum AL-7075 Alloy and AL7075 Alloy and AL -MMCs", Journal of Wear, 2004 Volume 245, 22-28.

[24] A.R.I. Khedera et.al. " Strengthening of Aluminum by SiC, Al2O3 and MgO", Jordan Journal of Mechanical and Industrial Engineering 2011 Volume 5, Number 6, 533 – 541.

[25] Y. Sahina, V. Kilicli ()"Abrasive wear behavior of SiCp/Al alloy composite in comparison with ausferritic ductile iron", Journal of Wear 2011, 271, 2766– 2774.

[26] Nilrudra Mandal, et.al. "Mathematical Modeling of Wear Characteristics of 6061 Al-Alloy-SiCp Composite Using Response Surface Methodology", ASM International 2011, DOI: 10.1007/s 11665 - 011-9890-7 1059-9495

[27] N R Prabhu Swamy et.al." Effect Of Heat Treatment On Strength And Abrasive Wear Behaviour of Al6061–SiCp Composites" Bull. Mater. Sci., 2010 33,(1), 49–54.