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Research article

Multi-response optimization of reinforcement parameters of aluminum alloy composites by Taguchi method and grey relational analysis

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ABSTRACT

The present work describes the optimization of reinforcement parameters for hardness, thermal conductivity, and coefficient of thermal expansion while developing LM6 alloy/soda-lime glass particulate composite through Taguchi-based Grey Relational Analysis (GRA). Soda-lime glass particle weight % (1.5, 3.0 and 4.5 %), particle size (100, 150 and 300 μm) and pre-heat temperature (260, 380 and 500°C) are varied accordingly to explore the effect of reinforcement parameters on LM6 alloy/soda-lime glass composite properties. Composites are developed through stir casting based on the L9 Taguchi orthogonal array approach. The properties such as hardness, thermal conductivity and **c**oefficient of thermal expansion of developed composites are assessed. Signal to Noise Ratios (S/N ratios) are calculated and used for the optimization of parameters. GRA is employed for multi-response optimization to find the levels of parameters that affect the desirable properties of the composite. Thus, the reinforcement parameters are optimized for attaining the combined objectives of higher hardness, higher thermal conductivity and lower **c**oefficient of thermal expansion values considered in this investigation. The analysis shows that 4.5 wt %, particle size of 200 μm and pre-heat temperature of 380°C are optimal parameter levels. A confirmation test is carried out with the optimal parameter levels and the GRG value of 0.7778 is obtained. The GRG with the initial parameter settings is 0.4711, and the improvement of GRG is found to be 65.1 %. ANOVA is performed on GRG to find out significant parameters and the contribution of each parameter is identified. The wt.% of soda-lime glass is the most significant parameter and its contribution is 92.6 %.

1. Introduction

Metal Matrix Composites (MMCs) play a crucial role as they exhibit higher stiffness and specific strength than classic structural materials that are used in the aerospace and automotive industries [1,2]. MMCs usually consist of a light metal as the matrix and reinforcements are in the form of fibers, whiskers or particles of hard or strong materials. The mechanical properties of the composites can be modified by choosing the right matrix composites, the right reinforcement and quantity. MMCs show a significant improvement in stiffness, hardness, fatigue strength, etc. Compared to the matrix material [3]. They also have high creep resistance and adequate

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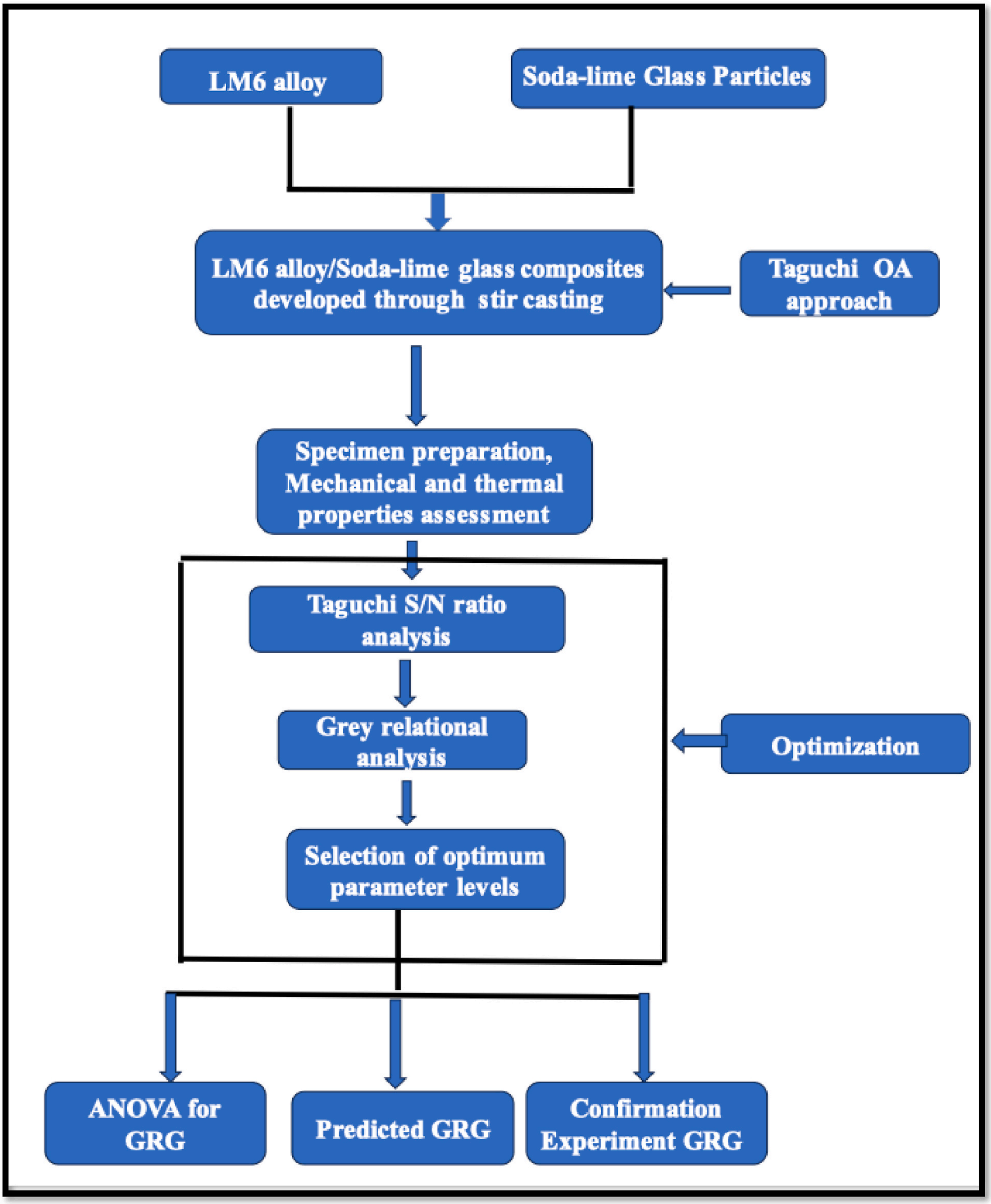
thermal shock resistance at elevated temperatures. Hence, lightweight, low-cost materials with excellent mechanical and tribological properties have been the focus of recent engineering applications [4]. Aluminium Metal Composites (AMCs) are widely used in various industries such as aerospace, marine, defence and automotive, where high stiffness, strength, fatigue resistance, low density and wear



Scheme 1. Flow chart of the process.

properties are required [5]. In addition, a high strength-to-weight ratio and adequate mechanical and thermal properties are also essential for the composites used in the industries [6] (see Scheme 1).

The hardness of the aluminium alloys can be improved by changing the composition, heat treatment, and developing composites of alloys [7–9]. The methodology for the improvement of hardness by composition modification and heat treatment techniques is almost saturated. However, it is difficult to realize all the requisite properties in a single alloy. The answer to this came with the advent of composite materials developed by incorporating a controlled amount of reinforcement. The properties of composites are also controlled by selecting appropriate parameters of reinforcement [10].

To improve the various aspects of industrial processes or products, various optimization techniques are available in the literature. Taguchi's orthogonal array approach is one such method used to design the experiments. This method reduces the experimental runs, optimizes one objective function at a time and uses the Signal-to-Noise ratio (S/N ratio) to reduce the effect of uncontrollable factors that result in the variation in the response [11].

Newly designed materials must possess many desirable properties to perform better in a complex environment. However, improvement in one property leads to the reduction of the other. Hence, there is a need to optimize various properties simultaneously, in a single material. In such situations, multi-response optimization methods are useful techniques to optimize the properties of the given material. Several multi-response optimization methods are used by researchers and documented in the literature to optimize the material properties, industrial processes and products. The most widely used methods are the Analytical Hierarchy Process (AHP), the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), VIekriterijumsko KOmpromisno Rangiranje (VIKOR) method, and Grey Relational Analysis (GRA) [12–14].

The AHP principle is based on pairwise comparison of hierarchical criteria. The advantages of using AHP are-it arranges complex and multi-criteria problems hierarchically, provides a flexible model and is easy to apply in almost every field. However, when some more criteria get added later, the whole process needs to be repeated from the beginning, which is time-consuming [15]. In the TOPSIS method, initially positive-ideal solutions and negative-ideal solutions are calculated and used as references. Then, alternatives are ranked as per closeness to the positive-ideal solution and farthest from the negative-ideal solution. Many decision-makers employed this approach because of its rationality and comprehensiveness, straightforward computations, pursuit of the best alternative and incorporation of weights. One of the drawbacks of TOPSIS is the rank reversal. When the alternatives are added or removed from the decision problem, order preference is changed. This phenomenon is called rank reversal [16].

VIKOR method is employed for the selection of a set of alternatives in the presence of conflicting criteria. However, TOPSIS and VIKOR approaches are similar; TOPSIS uses vector normalization and VIKOR uses linear normalization [17]. Many researchers use GRA for optimizing multi-objective functions simultaneously using the data that is limited. Other advantages of GRA are its simple calculations, it is based on original data and a straightforward method for the selection of decisions in the grey system [18].

Deng Jung a professor at Huazhong University of Science and Technology, China proposed the grey system theory. The word "Grey" in the name of the theory means "partially available information". That is, available information is in between "black" and "white". The "black" means no information and the "white" means complete information. The GRA is one of the models in grey system theory [19]. In GRA, desirable responses are normalized and Grey Relational Co-efficient (GRC) is calculated. Then, Grey Relational Grades (GRG) are determined by averaging the GRC for each alternative [20].

In Taguchi's method of Design of Experiments (DOE), only pairs of combination experiments are conducted, instead of all possible experiments, unlike full-factorial design. When limited data is available from the experimentation due to the reduced number of experiments, the primary strategy would be to use Grey Relational Analysis (GRA) [21]. Taguchi-based GRA was popularly used by many researchers; this technique reduces the experimentation efforts and optimizes two or more objective functions simultaneously [22–29]. Literature reveals that the Taguchi-based GRA is a crucial method in optimizing multiple responses simultaneously, with a minimum number of experiments.

Sufficient literature is available on glass fibre-reinforced aluminium composites [30]. However, the use of low-cost soda-lime glass powder as reinforcement in an aluminium alloy matrix is very limited [31]. Optimization of two or more material properties of the composites was not explored much. The present investigation aims to realize improved hardness of LM6 alloy/soda-lime glass powder composites, while soda-lime powder reduces the thermal conductivity and thermal expansion of the composites. These adverse effects can be minimized by selecting appropriate soda-lime glass parameter levels.

2. Materials and methods

2.1. Preparation of the composite

LM6 alloy is used in aerospace, automotive and other engineering sectors because of its high strength-to-weight ratio. It is a eutectic aluminum alloy and, silicon is the major alloying element. Its hardness range is from 50 to 55 BHN [32]. Industry-ready LM6 alloy was procured from the standard materials supplier. The commercially available soda-lime glass window sheets were procured and

Table 1
Composition of LM6.

Element	Al	Si	Cu	Mg	Fe	Mn	Ni	Zn	Pb	Sn	Ti	Other Elements
Wt. %	86.35	11.6	0.1	0.1	0.6	0.5	0.1	0.1	0.1	0.05	0.2	≤0.2

converted to the powder form of required fineness using a ball mill.

LM6 alloy composites were developed using soda-lime glass powder as reinforcement to enhance the hardness of LM6 alloy. The chemical compositions of LM6 alloy and soda-lime glass are shown in Table 1 and Table 2.

In this work, the stir-casting technique was used to produce the composites by varying reinforcement parameters and their levels as shown in Table 3 [33]. The methodology of composite production was optimized and maintained the same in all the trials of composite preparation. The processing parameters such as superheat temperature (750^{o}C) of melt, die temperature (300^{o}C), pouring temperature (640^{o}C), stirring speed (500 rpm), and stirring time (5 min) were kept constant for all composites. Nine sets of composites were produced with the combinations of 1.5, 3.0 and 4.5 wt per cent of soda-lime glass with 100-, 150- and 200-μm particle size, at pre-heat temperatures of 260, 380 and 500^{o}C [34].

Specimens were prepared as per ASTM E10 standards to assess the hardness of the developed composites. Brinell hardness tester with a steel ball indenter was used to test the hardness of the specimens as per the standard procedure of hardness test. The principle of the comparative cut bar method ASTM E1225 was used to the test thermal conductivity of the specimens. This method is most widely used for axial thermal conductivity assessment. ASTM E228-linear thermal expansion of solid material with a push-rod dilatometer was used to assess the coefficient of thermal expansion.

The Taguchi L9 orthogonal array was chosen, based on the three controllable parameters and at three levels each. Table 4 shows the Taguchi L9 orthogonal array-based experimental layout along with test results and S/N ratios. To convert the results into S/N ratios, the higher-the-better-quality characteristic was used for hardness and thermal conductivity, and smaller–the-better quality characteristic was used for the coefficient of thermal expansion.

2.2. *Taguchi's orthogonal array approach*

In this method, to reduce the effect of uncontrollable parameters on the response, the Signal to Noise ratio (S/N ratio) is calculated and used for optimization. Higher values of S/N ratios indicate improved quality and reduced variability. Higher-the-better and smaller-the-better S/N ratio equations are shown in Equations (1) and (2) respectively.

Higher-the-better:

$$\mathrm{S}\Big/\mathrm{N\ ratio} = -10\log_{10}\left(\frac{1}{\mathrm{n}}\sum\left(\frac{1}{\mathrm{y}_\mathrm{i}^2}\right)\right) \tag{1}$$

Smaller-the-better:

$$\mathrm{S}\Big/\mathrm{N\ ratio} = -10\log_{10}\left(\frac{1}{\mathrm{n}}\sum\left(\mathrm{y}_\mathrm{i}^2\right)\right) \tag{2}$$

('n' is the number of observations, 'y_i' is the observed data,' μ' is the mean of the observed data and 'σ^2' is the mean of the variance of the observed data)

2.3. *Grey relational analysis*

GRA is a method used to optimize multiple quality characteristics of a product or process [31,32]. In GRA, the experimental data are first normalized and then the Grey Relational Co-efficient (GRC) is calculated to express the relationship between the desired data and actual data. Then, the Grey Relational Grade (GRG) is computed by averaging the GRC. The selection of optimal parameter levels for the multiple responses is based on GRG. In GRA, the obtained data is normalized. Equations (3) and (4) are higher-the-better and smaller-the-better characteristics normalization equations respectively.

$$x_i\ (k) = \frac{y_i\ (k) - min\ y_i(k)}{max\ y_i(k) - min\ y_i(k)} \tag{3}$$

$$x_i(k) = \frac{\max\ y_i(k) - y_i(k)}{\max\ y_i(k) - \min\ y_i(k)} \tag{4}$$

The deviation sequence, $\Delta_{0i}(k)$, is used to calculate the GRC. It is the relationship between the ideal, $x_0(k) = 1$, and actual normalized experiment results. Equation (5) is used to calculate the deviation sequence.

$$\Delta_{0i}(k) = |x_0(k) - x_i(k)| \tag{5}$$

The GRC, $\zeta_i(k)$, of the data with the distinguishing factor (ξ) is calculated using Equation (6).

Table 2
Composition of soda-lime glass.

Element	SiO_2	Na_2O	CaO	MgO	Al_2O_3
Wt.%	72 %	14.5 %	9 %	2.5 %	1.5 %

Table 3
Reinforcement parameters and levels.

Factors	Unit	Level		
		1	2	3
A: Content	%	1.5	3.0	4.5
B: Particle size	micron	100	150	200
C: Pre-heat temperature	^{o}C	260	380	500

Table 4
Test results and S/N ratio.

Run No.	A	B	C	Test results			S/N ratio		
				BH (BHN)	TC(W/m^{o}C)	TE (/^{o}C)	BH (dB)	TC (dB)	TE (dB)
1	1.5	100	260	54.3	117.9	18.5×10^{-6}	34.6960	41.4303	94.657
2	1.5	150	380	57.0	115.6	17.4×10^{-6}	35.1175	41.2592	95.189
3	1.5	200	500	58.3	113.5	16.2×10^{-6}	35.3134	41.0999	95.810
4	3.0	100	380	64.6	107.1	15.4×10^{-6}	36.2047	40.5958	96.250
5	3.0	150	500	66.6	106.1	14.5×10^{-6}	36.4695	40.5143	96.773
6	3.0	200	260	66.3	105.0	13.6×10^{-6}	36.4303	40.4238	97.329
7	4.5	100	500	78.3	94.8	6.4×10^{-6}	37.8752	39.5362	103.876
8	4.5	150	260	80.6	93.2	6.2×10^{-6}	38.1267	39.3883	104.152
9	4.5	200	380	82.6	91.6	5.7×10^{-6}	38.3396	39.2379	104.883

$$\zeta_i(k) = \frac{\Delta_{\min} + \xi.\ \Delta_{\max}}{\Delta_{0i}(k) + \xi.\Delta_{\max}} \tag{6}$$

Further, the GRCs are converted into GRG, $\gamma_i(k)$, by using Equation (7). As a result, the different responses are converted into a single GRG. The GRG of all the experimental runs has been calculated and ranked as the highest GRG. The optimal level of parameters is determined from the response table of GRG.

$$\gamma_i(k) = \frac{1}{n}\left(\sum_{k=1}^{n}(\zeta_i(k))\right) \tag{7}$$

The next step is to predict the quality characteristic at the optimum parameters level using Equation (8).

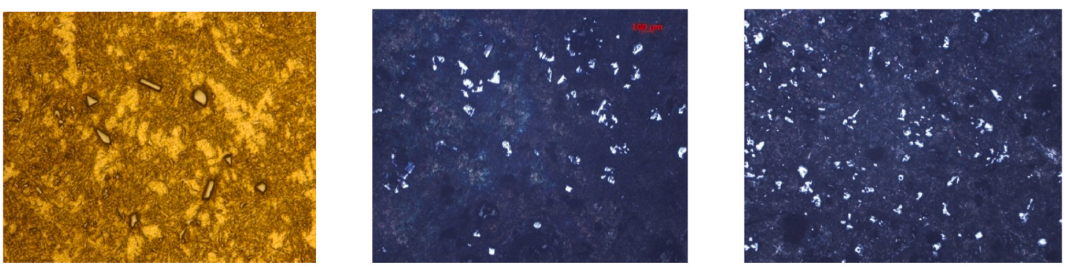
$$\gamma_{predicted} = \gamma_m + \sum_{i}^{q}(\gamma_o - \gamma_m) \tag{8}$$

Where γ_o represents the average GRG at the optimal levels of parameters and γ_m denotes the mean GRG. The quantity, q, is the number of parameters that affect the response.

3. Results and discussion

3.1. Microstructure examination

The test specimens were prepared for the micro-structural examination on optical microscope (Fig. 1). Micrographs show the



(a) (b) (c)

Fig. 1. Optical graph of 100 μm soda-lime glass reinforced in LM6 alloy matrix composite with wt.% of soda-lime glass reinforcement (a) 1.5 % (b) 3.0 % (c) 4.5 %.

uniformity in the dispersion of glass particles in the LM6 alloy matrix. Electron Scanning Microscope (SEM) micrograph (Fig. 2) evidences the proper bonding of glass particles with LM6 alloy and also shows the absence of any other phase at the interface.

3.2. Optimization using GRA

GRA was adopted to optimize the reinforcement content, particle size and pre-heat temperature of reinforcement for hardness, thermal conductivity and thermal expansion. Higher-the-better normalization was performed to transform S/N ratios on a 0 to 1 scale using Eq. (3). Subsequently, the deviation sequence of reference sequence was determined using Eq. (5). To compute GRC, Eq. (6) was used with distinguishing factor, $\xi = 0.5$. The GRC values were utilized to compute GRG using Eq. (7) and these values were ranked corresponding to the higher values and shown in Table 5. Accordingly, the first rank was assigned to experiment run 9.

The influence of the level of each parameter was observed independently through the response table for GRG. The response table was formed by averaging the GRG value with corresponding parameter levels. From the response table for GRG (Table 6), the maximum GRG exists at A3, B3 and C2. The delta value of the response table shows the extent of the influence of parameters on GRG. As per the delta value, the content of glass particles in the composite is the highly influencing parameter compared to glass particle size and pre-heat temperature. The main effects plot for means for GRG is shown in Fig. 3. The multi-response optimal parameter levels of LM6 alloy/Soda-lime glass composite are at 4.5 wt%, 200 μm particle size and 380$^{\mathrm{o}}$C pre-heat temperature. The optimum value of GRG, corresponding to parameter levels of A3, B3 and C2, is predicted using Eq. (8). The overall mean GRG obtained is 0.5716.

3.3. Confirmation tests

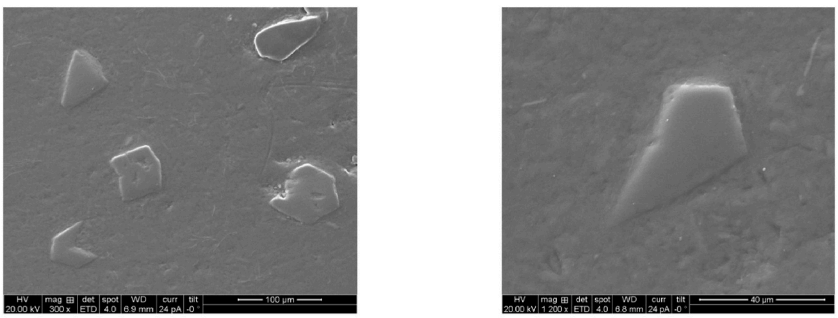
Confirmation tests were carried out at optimal parameter levels and results are presented in Table 7. The predicted value of GRG was calculated using Eq. (8) and compared with confirmation test GRG. The prediction error was found to be 4.2 %. Therefore, the accuracy and validity of the prediction model are supported by the confirmation test results. The study also showed that the optimal parameter levels improve the GRG from 0.4711 to 0.7778 by 65.1 %.

3.4. ANOVA on GRG

Analysis of Variance (ANOVA) is the statistical tool used to find the significant terms in response. From the ANOVA table, the contribution of each parameter to the response can be identified. ANOVA was performed for GRG with a 95 % confidence interval. When the p-value is less than 0.05 for a parameter, indicates its significant effect on the response [35]. ANOVA summary for GRG (Table 8) results show the contribution of reinforcement content is 92.6 %, the contribution of particle size is 0.6 % and the pre-heat temperature is 2.6 %. As the p-value of reinforcement content is 0.042 (less than 0.05) indicates the reinforcement content is a significant factor.

4. Conclusions

The primary objective of this investigation was to produce low-cost, light MMCs with the desired combination of properties. LM6 alloy/soda-lime glass powder composite was developed through stir casting, and Taguchi L9 orthogonal array was applied to minimize the experimentation efforts. GRA was performed to optimize the reinforcement parameters. As per GRA, the optimal levels are reinforcement content-4.5 wt%, particle size-200 μm and temperature-380$^{\mathrm{o}}$C. A confirmation test was carried out with the optimal parameter levels and a GRG value of 0.7778 was obtained. The GRG with the initial parameter settings was 0.4711, and with this study, an improvement in GRG by 65.1 % was observed. The accuracy of the prediction model was 4.2 %. The response values at the optimal parameter levels are - hardness-82.5 BHN, thermal conductivity-91.6 W/m$^{\circ}$C and coefficient of thermal expansion 5.7 $\times$ 10^{-7}/^{0}C. ANOVA was performed on GRG and the contribution of parameters was identified. ANOVA results showed that wt.% of soda-lime



(a) (b)

Fig. 2. SEM micrograph of 100 μm and 4.5 wt % soda-lime glass reinforcement showing (a) Distribution of reinforcement (b) interfacial bonding.

Table 5
Normalized values for S/N ratio, GRC, GRG and rank.

Run No.	Normalized values, $x_i(k)$			GRC, $\zeta_i(k)$			GRG, $\gamma_i(k)$	Rank
	BH	TC (W/m°C)	TE (/°C)	BH	TC	TE		
1	0.0000	1.0000	0.0000	0.3333	1.0000	0.3333	0.5556	4
2	0.1157	0.9220	0.0520	0.3612	0.8650	0.3453	0.5238	5
3	0.1694	0.8493	0.1128	0.3758	0.7684	0.3604	0.5015	6
4	0.4141	0.6194	0.1558	0.4604	0.5678	0.3720	0.4667	9
5	0.4867	0.5822	0.2069	0.4935	0.5448	0.3867	0.4750	7
6	0.4760	0.5409	0.2613	0.4883	0.5213	0.4036	0.4711	8
7	0.8725	0.1361	0.9015	0.7969	0.3666	0.8355	0.6663	3
8	0.9416	0.0686	0.9285	0.8954	0.3493	0.8749	0.7065	2
9	1.0000	0.0000	1.0000	1.0000	0.3333	1.0000	0.7778	1

Table 6
Response table for GRG.

Level	A	B	C
1	0.5270	0.5629	0.5777
2	0.4709	0.5684	0.5894
3	0.7169	0.5835	0.5476
Delta	0.2459	0.0206	0.0418
Rank	1	3	2

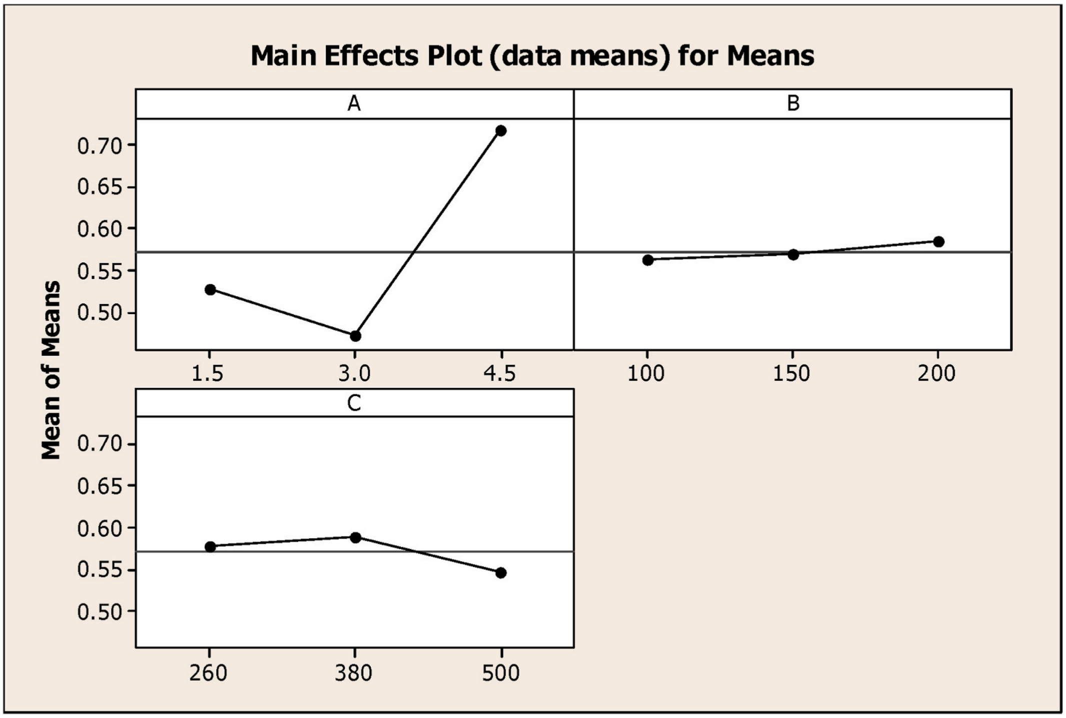


Fig. 3. Main effects plot for means for GRG.

content in composites was the most significant parameter and contributed 92.6 % to GRG. Based on the results, the composites developed through this investigation have found applications to increase hardness and appropriate thermal conductivity with lower thermal expansion.

CRediT authorship contribution statement

M.R. Shivakumar: Writing – original draft, Supervision, Resources, Investigation, Conceptualization. **Murali Krishna**

Table 7
GRG of confirmation experiments.

	Initial reinforcement parameters	Optimal reinforcement parameters		Improvement		Prediction Error
		Prediction	Experiment	Value	%	%
Level	A2B3C1	A3B3C2	A3B3C2			
GRG	0.4711	0.7466	0.7778	0.3067	65.1	4.2
HB (BHN)	66.3	–	82.6	–	–	–
TC **(W/m°C)**	105.0		91.6			
TE **(/°C)**	13.6×10^{-6}		5.7×10^{-6}			
Improvement in GRG = 0.3067						

Table 8
ANOVA for GRG.

Source	DF	Adj SS	Adj MS	F	P	Remarks	% of contribution
A	2	0.099685	0.049842	22.58	0.042	Significant	92.6
B	2	0.000681	0.000341	0.15	0.866	Not significant	0.6
C	2	0.002795	0.001397	0.63	0.612	Not significant	2.6
Error	2	0.004414	0.002207				
Total	8	0,107575					
$R^2 = 95.9$ %							

Panchangam: Writing – review & editing, Visualization, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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