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Optimization of stir–squeeze casting parameters for production of metal matrix composites using a hybrid analytical hierarchy process–Taguchi-Grey approach

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ABSTRACT

A hybrid optimization approach using analytical hierarchy process (AHP) combined with Taguchi-Grey has been developed and tested for the first time to optimize the stir–squeeze casting process parameters in the production of aluminium metal matrix composites reinforced with alumina for automotive brake disc application. The AHP method was used for assigning a weight to the response variables, which was based on experts' opinion on the importance of the response variables for brake disc application. For producing brake discs, the optimum process parameters are found to be a squeeze pressure of 100 MPa, squeeze time of 45 s, die preheating temperature of 250°C and stirrer speed of 525 rpm. Also, a confirmatory analysis was carried out to validate these optimum process parameters, and the results indicated enhanced compressive strength of 433 MPa (18.5% increase) and reduced porosity of 5.29% (13.5% decrease) in the composite.

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1. Introduction

Industries such as aerospace and automobile utilize aluminium and its alloys because of their high strength-to-weight ratio, corrosion resistance, specific strength, good formability and recyclability (Gangil, Siddiquee, and Maheshwari 2017). However, to improve the properties and utilization of aluminium alloys further, materials scientists have developed aluminium metal matrix composites (AMMCs). AMMCs are a popular engineering material as they exhibit very high specific strength, compression and tensile strength, stiffness, corrosion resistance and wear resistance when compared with aluminium alloys. Incorporation of hard ceramic particles, called reinforcement, in the aluminium matrix improves the properties of AMMCs. Reinforcement factors such as the size of particles, shape of particles, volume fraction, homogeneous distribution, interfacial bonding between the matrix and reinforcement in the composite determine the mechanical behaviour of the composite (Park, Crosky, and Hellier 2008). However, the widespread adoption of particulate-reinforced metal matrix composites for engineering applications has been hindered by the high cost of producing components of even minimally complex shapes (Prabu *et al.* 2006).

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Among the several available processes for producing AMMCs, liquid state processing, specifically stir casting, is one of the most frequently used and established processes. Stir casting is the least expensive process available for composite materials among all methods, and also it offers a comprehensive option for the selection of materials and processing conditions (Shorowordi *et al.* 2003). However, the stir casting process produces high porosity in the substrate. To minimize casting defects such as porosity and to obtain better properties, stir casting is augmented with the squeezing process (squeeze casting), which is a combination of stir casting and hydraulic forging.

There are various process parameters in squeeze casting which greatly affect the quality of the produced composites, such as squeeze pressure, squeeze pressure holding time, stirring time, stirring speed, melt temperature, die preheating temperature and reinforcement preheating temperature. Among these, squeeze pressure, squeeze pressure holding time, die preheating temperature and stirring speed are identified as the most influential parameters determining the mechanical properties (Bahrami *et al.* 2016; Das *et al.* 2014; Dhanashekar and Senthil Kumar 2014; Gurusamy, Balasivanandha Prabu, and Paskaramoorthy 2015; Ravikumar, Amirthagadeswaran, and Senthil 2014; Senthil and Amirthagadeswaran 2012, 2014; Souissi *et al.* 2015; Vijian and Arunachalam 2007a; Yilmaz 2004). To optimize all these parameters, especially using full factorial experiments, is not only time consuming but also uses valuable resources that industry cannot afford. Hence, many researchers have attempted to optimize the squeeze casting process parameters using different techniques. Several approaches have been adopted, but most of them assign equal weights to all the parameters. However, for a specific application, assigning equal weights will not yield the optimum process parameters for a given application.

Vijian and Arunachalam (2007a) used the Taguchi technique and the Pareto analysis of variance (ANOVA) method to optimize the process parameters such as squeeze pressure, die preheating temperature and duration of pressure, and concluded that the squeeze pressure is the major contributing factor for improving tensile strength and hardness of materials. Senthil and Amirthagadeswaran (2012), using the ANOVA method, concluded that among the parameters, squeeze pressure, melt temperature, die preheating temperature and squeeze pressure holding time are the critical parameters. Most researchers have used the Taguchi technique with ANOVA for the optimization of process parameters in squeeze casting. Minimal research has been done using other techniques such as genetic algorithm (Arulraj and Palani 2018; Vijian and Arunachalam 2007b), multi-response optimization using response surface methodology (Saravanakumar *et al.* 2016) and statistical regression approach (Manjunath Patel, Krishna, and Parappagoudar 2016). Ezatpour *et al.* (2017) investigated and reported the optimal composite with the best combination of strength and formability properties using the analytical hierarchy process (AHP) method. Also, the AHP method revealed the desired combination (matrix A356 and 2 wt. % of alumina reinforcement) for nanocomposite produced by compocasting. Babu *et al.* (2018) used the AHP method to find a superior matrix material for enhancing the properties of aluminium hybrid metal matrix composites and identified that AA5083 and AA7075 are the best matrices in the process. Each optimization technique has its strength and weakness and so may not be capable of providing the best process parameters in all cases. A hybrid approach, on the other hand, can capitalize on the strengths of the techniques, thereby eliminating the weaknesses in the techniques.

In this research, a hybrid approach is used to optimize the process parameters in squeeze casting to produce AMMCs reinforced with alumina, targeting automotive brake disc application. The braking system acts as an essential critical safety component in any automobile industry (Belhocine and Ghazaly 2015; Razmi *et al.* 2016). The limitations with the existing brake disc are the frictional heat generated during braking application. The heat can cause several damaging effects on the brake disc, such as brake fade, premature wear and thermal cracks (Belhocine and Bouchetara 2012a). The heat distribution between the friction pads and the brake disc is mainly dependent on the material characteristics (Belhocine and Bouchetara 2012b). Metal matrix composites are rapidly replacing grey cast iron brake rotor/disc in automobiles because of their better strength-to-weight ratio and enhanced mechanical and tribological properties (Kumar and Megalingam 2019). Considering the advantages of MMCs, the present research focuses on optimizing the process parameters to produce composites targeting automotive brake discs. The novelty of this research is not only in the optimization approach but also in the composite itself, which is produced using scrap aluminium alloys from automobiles wheels (Kumar *et al.* 2019).

2. Hybrid optimization approach

The Taguchi method is a statistical approach that is widely used to optimize process parameters and to improve the quality of manufactured products. Genichi Taguchi proposed the method for designing the experimental setup to further investigate the effect of input parameter on output response (Sudhagar *et al.* 2017). The method has been employed with great success in experimental designs for problems with multiple parameters due to its practicality and robustness (Fei, Mehat, and Kamaruddin 2013). The method uses a unique design of orthogonal arrays to provide a reduced variance for the experiment with the optimum setting of process parameters (Ahmad *et al.* 2016). The advantage of Taguchi's optimization method is that it allows the optimization of the process parameter with a minimum number of experiments. Because of these advantages, as well as off-line quality control, the Taguchi method has been successfully used in the optimization of process parameters in several manufacturing processes (Jadoun *et al.* 2006). The traditional Taguchi technique can optimize only a single response variable under the effect of multiple parameters. Therefore, this technique is combined with grey relational analysis (GRA) to optimize multi-process parameters for multiple response variables that this research tends to address. GRA is widely used to convert multiple response variables into a single grey relational grade (GRG) (Sudhagar *et al.* 2017).

Further, in the GRA method, the outcome in the form of single GRG is generally calculated based on the assumption that the weight for all response variables is equal. The optimization approach generally assumes equal weight for all response variables, which practically is not realistic (Patel and Maniya 2015) as different applications demand a different degree of importance on response variables. Also, most researchers have assigned equal weights to the responses in their models and experiments for the multi-objective optimization problem, which in actual practice may not come out right. The approach of assigning equal weights is also valid for the production of AMMCs for various applications. In a real-life application, weight to the responses can be assigned according to need (Luthra *et al.* 2016) and can also be calculated based on the scientific method. Very few researchers have assigned different weights in their multi-objective optimization problem for the machining process. Kumar *et al.* (2013) optimized process parameters for a computer numerical control (CNC) turning operation using a multicriteria optimization and compromise solution (in Serbian: VIseKriterijumska Optimizacija I Kompromisno Resenje [VIKOR] method), and Nayak and Mahapatra (2013) used the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)-based Taguchi method to optimize process parameters for the wire electrical discharge machining (WEDM) machine. Both of them used the AHP method to identify the weight for the responses. Chalisgaonkar and Kumar (2015) optimized process parameters for trim-cutting WEDM operations based on a utility method in conjunction with adjacency matrix for assigning a weight to the response variables, which is based on differences of opinion from the end user's viewpoint. Patel and Maniya (2015) proposed the AHP and multi-objective optimization by ratio analysis (MOORA) method to optimize WEDM process parameters based on material removal rate, kerf width and surface roughness.

It is obvious that AHP combined with Taguchi-Grey has not been applied, especially for the stir and squeeze casting process. Thus it is assumed that this is the first attempt in the field of AMMCs production whereby the AHP method is combined with the Taguchi–GRA method to optimize process parameters such as squeeze pressure, squeeze pressure holding time, stirrer speed and die preheating temperature. This hybrid approach is capable of identifying the best process parameters to produce a composite with desirable properties for a specific application. In this research, the AHP method is used to identify the weights for the response variables based on experts' opinion. The result of AHP is then integrated with the Taguchi-Grey method to obtain the optimized value

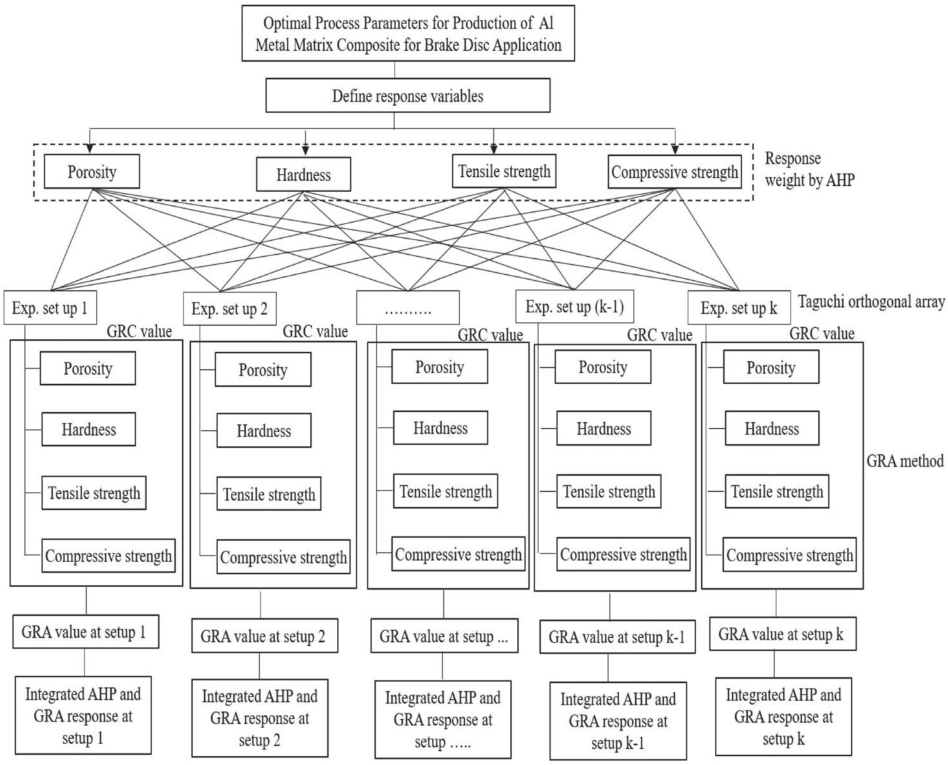

Figure 1. A conceptual framework to optimize multiple parameters using AHP and Taguchi-Grey approach.

of multiple-process parameters. The produced AMMC exhibited enhanced material characteristics and mechanical properties. The conceptual framework of the proposed hybrid approach is shown in Figure 1 and is described in the following subsections.

2.1. AHP method

The AHP method starts with the construction of a problem into a hierarchical structure, thereby defining the criteria to be assessed for the given objective. This hierarchical structure is illustrated in Figure 1. The following steps are executed in the AHP method:

2.1.1. Pairwise comparison

In this problem, the criteria refer to the responses that are supposed to be optimized. Once the responses are determined, and the problem is structured, the responses are compared in terms of the importance of one response over others concerning the objective. Experts' opinion is solicited for the comparison. The comparison results in a square matrix (V_l) obtained from an l^{th} expert ($l = 1, 2, \ldots., L$), the size of which is equal to $n \times n$, where n represents the number of responses. Each element (a_{ijl}) of matrix V_l represents a numeric value obtained from the comparison by an l^{th} expert on the response i and j according to the Saaty scale (Saaty 1990). The scale is as shown in Table 1. If $i = j$, then a_{ijl} will be equal to 1 in Equation (1).

$$V_l = \begin{pmatrix} a_{11l} & a_{12l} & \ldots & a_{1nl} \\ a_{21l} & a_{22l} & \ldots. & a_{2nl} \\ \ldots. & \ldots. & \ldots. & \ldots.. \\ a_{n1l} & a_{n2l} & \ldots.. & a_{nnl} \end{pmatrix} \text{ where, } a_{ijl} = 1/a_{jil} \text{ and } i = 1, \ldots, n, j = 1, \ldots, n, l = 1, \ldots, L \tag{1}$$

Table 1. Importance scale of criteria for pairwise comparison.

Value	Definition
1	'i' and 'j' are equally important
3	'i' is slightly more important than 'j'
5	'i' is important than 'j'
7	'i' is much important than 'j'
9	'i' is absolutely important than 'j'
2, 4, 6, 8	Intermediate values

2.1.2. Calculate the geometric mean of experts' opinion

In order to avoid the influence of point of view of one expert over the other, experts' opinion is solicited individually. In the next step, the aggregate score of experts is then calculated. As shown in Equation (2), the technique of geometric mean is used to calculate the aggregate score as it is the most common and widely used technique (Grošelj *et al.* 2015). The aggregate score matrix is shown in Equation (3).

$$b_{ij} = \sqrt[L]{\prod_{l=1}^{L} a_{ijl}} \quad \forall i, j \text{ and } i, j \in k \tag{2}$$

$$V = \begin{pmatrix} b_{11} & b_{12} & \ldots & b_{1n} \\ b_{21} & b_{22} & \ldots. & b_{2n} \\ \ldots. & \ldots. & \ldots. & \ldots.. \\ b_{n1} & b_{n2} & \ldots.. & b_{nn} \end{pmatrix} \tag{3}$$

2.1.3. Normalize the aggregate score matrix

The individual score obtained from the geometric mean is then normalized using Equation (4). Equation (5) represents a normalized matrix.

$$p_{ij} = \frac{b_{ij}}{\sqrt{\sum_{i=1}^{n} b_{ij}^2}} \forall i, j \tag{4}$$

$$W = \begin{pmatrix} p_{11} & p_{12} & \ldots & p_{1n} \\ p_{21} & p_{22} & \ldots. & p_{2n} \\ \ldots. & \ldots. & \ldots. & \ldots.. \\ p_{n1} & p_{n2} & \ldots.. & p_{nn} \end{pmatrix} \tag{5}$$

2.1.4. Calculate the weight of response variables

Finally, weight for response variables is calculated using Equation (6). Weight here represents the priority of one response over others such as compression strength, hardness, tensile strength and porosity to improve the material properties.

$$w_i = \frac{\sum_{i=1}^{n} p_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} p_{ij}} \forall i \in k \quad i = 1, 2, \ldots, K \tag{6}$$

2.1.5. Consistency check

Saaty (Grošelj *et al.* 2015) defined the consistency matrix as a matrix whose consistency ratio (CR) is lower than 0.1. CR value greater than 0.1 represents an inconsistency in the pairwise comparison. Inconsistency matrix violates the principle of transitivity (Khanna *et al.* 2015). Therefore, if an inconsistency exists, it is necessary to revise the pairwise comparison matrix.

$$CR = \frac{CI}{RI} \tag{7}$$

where,

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{8}$$

Random inconsistency index (RI) in Equation (7) represents the average consistency index (CI) for criteria n over several entries of the same order reciprocal matrices. $\lambda_{\max}$ in Equation (8) is the principal eigenvalue of the pairwise comparison matrix V of order n, which can be calculated using Equation (9).

$$\lambda_{\max} = \frac{\sum_{j=1}^{n} b_{ij} w_j}{w_i} \tag{9}$$

2.2. Taguchi-Grey relational analysis

The Taguchi methodology, developed by Genichi Taguchi, uses a unique design of orthogonal arrays to provide a reduced variance for the experiment with the optimum setting of process parameters and with a minimum number of experiments (Ahmad *et al.* 2016). In order to evaluate the process parameters, the Taguchi method uses the signal-to-noise (S/N) ratio, which is the ratio of the mean (signal) to the standard deviation (noise). Since the traditional Taguchi method cannot optimize the multi-objective optimization problem, it is combined with GRA to optimize the multi-process parameters this research is addressing.

GRA theory was proposed by Deng in 1982 based on grey set by combining concepts of system theory, space theory and control theory (Ju-long 1982). GRA calculates and unifies grey relational coefficients (GRCs) for all responses; either they are of 'larger the better or smaller, the better' category (Nelabhotla *et al.* 2016). It is one of the most widely used techniques for optimizing multiple-process parameters in many manufacturing processes (Khanna *et al.* 2015; Senthil and Amirthagadeswaran 2012; Srirangan and Paulraj 2016). The following steps are implemented to obtain GRG using the Taguchi–GRA method.

2.2.1. Calculate S/N ratio for response variables

Taguchi classifies the response function based on S/N ratio into three types, *i.e.* larger-the-better, smaller-the-better and nominal-the-better situation. Each of these types uses a different equation to convert response function into the S/N ratio. Since the responses considered in this research require both maximize and minimize options, Equations (10) and Equation (11) will be used to calculate S/N ratio for maximizing and minimizing, respectively.

$$x_k^o(i) = -10\log_{10}\left(\frac{1}{n}\sum_{k=1}^{n}\frac{1}{y_k^2(i)}\right) \tag{10}$$

$$x_k^o(i) = -10\log_{10}\left(\frac{1}{n}\sum_{k=1}^{n} y_k^2(i)\right) \tag{11}$$

In the above equations, 'n' represents the total number of experimental trials, $y_k(i)$ is the observed value on response variable i ($i = 1, 2, \ldots., h$) obtained from experiment k ($k = 1, 2, \ldots.., n$).

2.2.2. Normalize the value

Haq *et al.* (2008) recommended that the S/N ratio be used in normalizing the data in GRA. The normalized S/N ratio gives the dimensionless unit on response variables so that these units can be integrated into one single value. The normalized value is computed using Equation (12) and Equation (13) depending upon whether the response needs to be maximized or minimized.

$$x_k^*(i) = \frac{x_k^o(i) - \min x_k^o(i)}{\max x_k^o(i) - \min x_k^o(i)} \tag{12}$$

$$x_k^*(i) = \frac{\max x_k^o(i) - x_k^o(i)}{\max x_k^o(i) - \min x_k^o(i)} \tag{13}$$

In the above Equations, $\max x_k^o(i)$ and $\min x_k^o(i)$ represent the largest and smallest values for response variable i among the experiments.

2.2.3. Calculate the grey relational coefficient

The GRC helps to express the relationship between normalized data with the ideal result. It is expressed by Equation (14).

$$\gamma_k(i) = \frac{\Delta_{\min} + \zeta\,\Delta_{\max}}{\Delta_k(i) + \zeta\,\Delta_{\max}} \tag{14}$$

In Equation (14), ζ is a distinguishing coefficient value which varies in the range of 0–1. The value of ζ is preferred to be 0.5 when some parameter needs to be minimized, and others maximized (Kuo, Yang, and Huang 2008). It gives equal preference to the maximum as well as minimum absolute deviation. $\Delta_k(i)$ in the equation represents the distance between normalized value and reference sequence for an i^{th} response. $\Delta_{\max}$ and $\Delta_{\min}$ are the maximum and minimum values of $\Delta_k(i)$, respectively.

$$\Delta_k(i) = |x_o^*(i) - x_k^*(i)| \tag{15}$$

$x_o^*(i)$ in Equation (15) is the maximum value of $x_i^*(k)$and it represents the reference sequence.

2.2.4. Calculate grey relational grade

The GRG is a weighted average value of the GRC of all the response variables.

$$\delta_k = \sum_{i=1}^{h} w_i \gamma_k(i) \tag{16}$$

In Equation (16), w_i is the weight of response variable i obtained from AHP method.

3. Experimental design

The process parameters were selected based on the literature review and opinion of experts from relevant fields. The selected parameters are squeeze pressure, squeeze time, die preheating temperature and stirrer speed. Squeeze pressure is the most influential parameter that determines the strength of AMMCs. The squeezing pressure removes the gas bubbles and reduces the porosity in the casting, while grains are refined under pressure (Dhanashekar and Senthil Kumar 2014). Squeeze pressure of more than 125 MPa is not advisable since the compressive and tensile strength are decreased due to fracture of the reinforcement particles under higher pressure (Seo and Kang 1995). The squeezing pressure holding time is one of the factors that improve the heat dissipation rate as well as reducing porosity-related defects. The more heat that is dissipated during solidification, the better is the strength of the composite (Senthil and Amirthagadeswaran 2012); the die preheating temperature should not be more than 350°C. The squeezing pressure holding time is capped at 45 s, as the casting is almost solidified within this period. Stirrer speed is vital to obtain a homogenous mixture of the reinforcement particles (Prabu *et al.* 2006). For the given stirrer blade geometry, higher than 600 rpm results in turbulence, and this will lead to higher porosity in the castings. Lower rpm does not help

Table 2. Process parameters and their levels.

Parameters (units)	Level 1	Level 2	Level 3
Squeeze pressure '*P*' (Mpa)	75	100	125
Squeeze time 'T' (sec)	15	30	45
Die preheating temperature 'D' (°C)	250	300	350
Stirrer speed 'S' (RPM)	450	525	600

in mixing the reinforcement, and so the range was fixed between 450 and 600 RPM. Die preheating temperature is used to improve the elongation and tensile strength of the composites (Seo and Kang 1995). Three levels of each of these parameters are considered in the experiment, as shown in Table 2. Stirring time was kept constant at 5 min for all the experiments, as there was no improvement in the dispersion of the reinforcement particles once this time exceeds 5 min. Moreover, the stirrer blades wear out faster when they are exposed to higher stirring time because of the abrasive nature of the reinforcement particles. The effect of the four different process parameters is analysed in terms of four different response variables. The responses under consideration are porosity, hardness, tensile strength and compressive strength. Porosity is a significant issue in the production of AMMCs which seriously affects the hardness and strength of the products. Hence, porosity must be minimized unless there is a need to maximize porosity and all other responses. Therefore, the objective here is to identify the combination of experimental set up that minimizes porosity and maximizes other response variables such as hardness, and tensile and compression strength.

4. Experimental procedure

Scrap aluminium car alloy wheels (typically Al-Si7Mg) were cut into small pieces using a power saw and used as the matrix material in producing the AMMCs. The pieces were cleaned using a buffing wheel followed by acetone to remove the dirt, carbon deposits and grease before charging into the stir–squeeze casting furnace, shown in Figure 2. The reinforcement particle used in this research was alumina powder purchased from Alfa Aesar, with an average particle size of 50 µm. The reinforcement particles were preheated in the preheater chamber at a temperature of 300°C to eliminate dampness and to reduce particle agglomeration.

A split die with dimensions of a square cross-section of 50 and 250 mm in height was preheated to the required temperature. When the crucible reached 700°C, the matrix materials were charged into it, and the lid of the crucible closed to avoid heat loss. The wetting agent used was magnesium (1%), which was added into the melt after removing the slag using a scoop. The stirrer rod was then switched on and gently lowered into the crucible at the required rpm. The preheated reinforcement particles were slowly added to the vortex formed during stirring, and this lasted for 5 min. The molten mixture was then transferred through a bottom tapping mechanism into the preheated pathway pipe connected to the die of the squeeze casting setup. A required squeeze pressure was applied immediately to the hot mixture poured into the die. Finally, the sample was removed from the die after 1 h to maintain the cooling rate. As discussed in Section 3, with four process parameters and each parameter having three levels, the full factorial design would have resulted in 81 experiments. However, using the Taguchi optimization method, the number of experiments is reduced to nine. The experiments were conducted as per the L9 Taguchi orthogonal array generated using Minitab analytical software and shown in Table 3. The response variables obtained after subjecting the samples to various mechanical properties are also shown in the same table.

The density of the produced AMMCs was determined based on the Archimedes principle using a sample size of 50×25×10 mm cut from the cast sample. The hardness was measured using a Universal Hardness tester UH-250, and Rockwell B (HRB) scale was selected. The indentation force was 980N, and the dwell time was set to 15 s. The sample (mounted, ground, polished and etched) prepared for microstructure analysis was used for the hardness measurements. Five readings were

Figure 2. Stir–squeeze casting setup used for producing the AMMCs.

Table 3. Taguchi experimental plan and obtained response variables.

	Experimental setup				Response variable			
Exp.	Pressure 'P' (Mpa)	Time'T' (Sec)	Temperature 'D' (°C)	Speed'S' (RPM)	Porosity (%)	Hardness (HRB)	Ultimate Tensile Strength (MPa)	Ultimate Comp. Strength (MPa)
1	75	15	250	450	6.33	50.7	115.9	339.425
2	75	30	300	525	6.51	42.42	130.77	330.075
3	75	45	350	600	7.08	47.45	108.57	316.275
4	100	15	300	600	8.88	37.3	90.8	292.425
5	100	30	350	450	7.65	45.55	152	359.475
6	100	45	250	525	8.4	60.9	151.7	356.1
7	125	15	350	525	6.12	47.52	109.07	338.825
8	125	30	250	600	7.84	45.15	148.8	356.125
9	125	45	300	450	8.35	54.17	136.53	319.07

taken at different locations, and the average value is reported in Table 3. For the tensile and compression tests, four samples were cut from the cast block for each experiment as per American Society for Testing and Materials standards (ASTM) using a WEDM. The specimen was gripped at the two ends, and the tensile load was applied. The ultimate tensile and compressive strength obtained from the stress–strain curve is reported in Table 3. The strain rate used for both tensile and compression tests was 8.33×10^{-4} /s. A sample was also made at the optimal combination to validate the hybrid approach. The confirmation test samples were also evaluated for mechanical properties such as hardness, tensile and compressive strength. A 12 mm cube sample was cut and mounted using Bakelite for the microstructure analysis. The mounted samples were ground and polished progressively using an automatic grinding and polishing machine, and as such, highly polished scratch-free surfaces were obtained. After final polishing, Keller's reagent (2.5% HNO_3 (70% w/w), 1.5% HCl (50% v/v), 1% HF (40%), 95% H_2O) was used for 2 min to expose the grain boundaries. The microstructure analysis was carried out using both optical and scanning electron microscope (SEM). Elemental mapping images were also obtained using the SEM to analyse the distribution of the elements/particles in the sample produced using the optimized condition.

5. Results and discussion

Once the process parameters were identified and response variables determined, experts' opinion was solicited to rank the response variables in terms of their importance and also to identify the weight for each response. The objective was to optimize the stir–squeeze casting process parameters for the production of AMMC with alumina as reinforcement for automotive brake disc application. A total of eight experts were requested to compare the importance of one parameter over others for the given application based on the importance scale as defined in Table 1. These experts have vast experience, working in the area of producing AMMCs for more than 5 years. Weighted matrices received from the experts were then unified using the geometric mean approach (Equation 2). The unified weight matrix is shown in Table 4. The above matrix is further normalized (Equation 4), and the response variables were ranked based on the weight obtained (Equation 6). The ranking and weight of variables are as shown in Table 5. The consistency of pairwise comparison obtained from experts in Table 4 is also analysed. It was found that λ_{max} is 4.17 (Equation 9), and CI is 0.0567 (Equation 8). According to Khanna *et al.*, RI for $n = 4$ is 0.9. Therefore, from Equation 7, CR is equal to 0.063, which is lower than the acceptable value of 0.1. Therefore, pairwise comparison between response variables obtained from experts becomes consistent. From the result in Table 5, it is evident that the essential material property desirable for automotive brake disks is compressive strength, followed by hardness, tensile strength and porosity.

The obtained response variables, as shown in Table 3, are translated into the S/N ratio using Equation (10) and Equation (11) depending on whether the responses need to be maximized or minimized. The normalized value of the S/N ratio is then calculated using Equation (12) and Equation (13). Higher normalized S/N ratio represents better performance and vice-versa. Therefore, the individual best performance characteristic is represented by the normalized value of one and worst performance characteristic by zero. Table 6 shows the S/N ratio and the normalized values of all response variables.

GRC is then computed based on the normalized value. While computing GRC, the value of ζ in Equation (14) is assumed to be 0.5 to give equal importance to the maximum as well as minimum absolute deviation (Kuo, Yang, and Huang 2008). Finally, GRC values of response variables are integrated to calculate GRG by using weight obtained in Table 5. Table 7 below shows GRC, GRG and ranking of all the nine experiments based on GRG.

From the results, it is observed that the experimental number 6 represents the best-optimized combination (Squeeze pressure of 100 Mpa, squeeze time of 45 s, die preheat temperature of 250°C

Table 4. Experts' unified pairwise comparison matrix.

Response variable	1	2	3	4
Porosity	–	0.11	0.21	0.11
Hardness	9	–	2.56	1.0
Tensile strength	4.79	0.14	–	0.11
Compressive strength	9	1	9	–

Table 5. Weight of response variables and their ranking.

Response variable	Weight	Rank
Porosity	0.05	4
Hardness	0.37	2
Tensile strength	0.10	3
Compressive strength	0.48	1

Table 6. S/N ratio and the normalized value of the response variable.

	S/N ratio				Normalized value			
Exp.	Porosity	Hardness	Tensile strength	Comp. Strength	Porosity	Hardness	Tensile strength	Comp. Strength
1	−16.028	34.100	41.282	50.615	0.909	0.626	0.474	0.722
2	−16.272	32.551	42.330	50.372	0.834	0.262	0.708	0.587
3	−17.001	33.525	40.714	50.001	0.609	0.491	0.347	0.380
4	−18.968	31.434	39.162	49.320	0.000	0.000	0.000	0.000
5	−17.673	33.170	43.637	51.113	0.399	0.408	1.000	1.000
6	−18.486	35.692	43.620	51.031	0.147	1.000	0.996	0.954
7	−15.735	33.538	40.754	50.600	1.000	0.494	0.356	0.713
8	−17.886	33.093	43.452	51.032	0.332	0.390	0.959	0.955
9	−18.435	34.675	42.705	50.078	0.165	0.761	0.792	0.422

Table 7. GRC, GRG and Ranking of L9 experiments.

	Grey Relational Coefficient (GRC)				
Experiment	Porosity	Hardness	Tensile strength	Comp. Strength	GRG
1	0.846	0.572	0.487	0.643	0.611
2	0.751	0.404	0.631	0.547	0.513
3	0.561	0.496	0.434	0.446	0.469
4	0.333	0.333	0.333	0.333	0.333
5	0.454	0.458	1.000	1.000	0.772
6	0.370	1.000	0.992	0.916	0.928
7	1.000	0.497	0.437	0.636	0.583
8	0.428	0.450	0.924	0.917	0.720
9	0.374	0.677	0.706	0.464	0.562

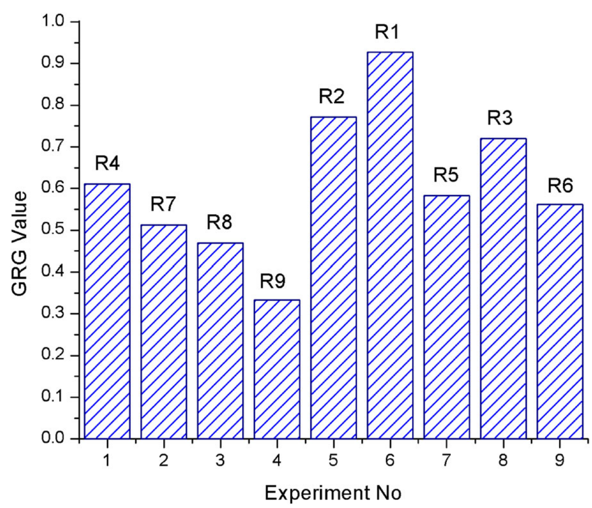

Figure 3. Ranking of experiments based on the GRG value.

and stirrer speed of 525 rpm) as the GRG value becomes the highest. This experiment is represented by P2-T3-D1-S2. On the other hand, the lowest GRG is obtained for the combination P2-T1-D2-S3. Figure 3 shows the ranking (R) of the L9 experiments.

Figure 4. Effect of process parameters on GRG at different levels.

Table 8. Response table for grey relational grade.

Response	L1	L2	L3	Best	Optimal condition	Max-min	Rank
Pressure (*P*)	0.531	**0.678**	0.622	0.678	P2	0.147	4
Time (T)	0.509	**0.668**	0.653	0.668	T2	0.159	3
Temperature (D)	**0.753**	0.470	0.608	0.753	D1	0.283	1
Speed (S)	0.649	**0.674**	0.508	0.674	S2	0.167	2

5.1. Significant process parameter

To estimate the effect of each process parameter on the responses, the interaction plot of average GRA is used in consideration with all the levels of other process parameters. The average response value at different levels of control parameters is shown in the interaction plot in Figure 4. From the interaction plot, it can be observed that the optimum value of process parameters is attained when squeeze pressure is at 100 MPa, squeeze time is 30 s, die preheating temperature is at 250°C, and stirrer speed is at 525 rpm, which is represented by the combination P2-T2-D1-S2. Furthermore, the average response value at a different level of parameters is also shown in Table 8. The parameter with the maximum difference of average GRG value in the table indicates the parameter with the highest influence. Therefore, die preheating temperature is the most dominant parameter on multiple performances, followed by stirrer speed, squeeze time and squeeze pressure.

5.2. Confirmation experiment

To validate the accuracy of the obtained optimized parameters and to determine the improvement in performance characteristics, the confirmatory experiment is an essential approach. For this purpose, it is necessary to first predict GRG based on the optimized processes parameters obtained from

Table 9. Confirmation experiment.

	Initial setting	Prediction	Experimental
Setting level	P2-T3-D1-S2	P2-T2-D1-S2	P2-T2-D1-S2
Porosity	8.4	–	5.29
Hardness	60.9	–	55.82
Tensile strength	151.7	–	132.87
Compressive strength	356.1	–	433.2
Grey relational grade	0.928	0.943	0.966
Percentage Improvement in GRG			3.93%

Table 8. The predicted GRG is calculated using Equation 17.

$$\delta_{pre} = \delta_{tot} + \sum_{i=1}^{n} (\delta_{opt} - \delta_{tot}) \tag{17}$$

In Equation (17), δ_{tot} represents the total mean of GRG, δ_{opt} is the mean of GRG at the optimum level of each process parameter and n is the number of parameters. Based on Equation (17), the predicted GRG is obtained as 0.943. Table 9 shows the results of the confirmation test using optimum process parameters estimated with the AHP-GRA method. From Table 9, it is seen that the GRG for the confirmation test is 0.966, which shows an improvement of around 4% from the initial optimal setting. The highest GRG obtained in the confirmation test, as compared with the other two settings in Table 9, shows that the process parameters estimated through the AHP-GRG method offer the most optimum performance characteristics among all the combinations of various levels of process parameters. AHP is used to identify the weight of responses based on expert opinion. The GRG value is significantly affected by the weight. It is possible that if the weight is different than what has been accomplished in this research for brake discs, then the optimal combination of process parameters will undoubtedly be different. Therefore, depending on the objective function or area of application of the product, the weight of the process parameters tends to be different, thereby having a different combination of process parameters to reach the optimal manufacturing process.

Figure 5 illustrates the optical microscope image of the microstructure obtained in the confirmatory experiment. The white regions are aluminium matrix, and black regions are the micro-pores. The porosity is quite low and very few pores can be observed in the focused region. Squeeze pressure is the leading cause for the reduction in porosity in the substrate. The applied pressure on the substrate during solidification removes all the gases, while the pores are eliminated (Dhanashekar and Senthil Kumar 2014). The porosity of 5.29% obtained for the confirmation experiment correlates with the microstructure, and it is the lowest among all the experiments that are desirable. Figure 6(a) shows the microstructure at a higher magnification obtained through SEM. The grey particles in the grain boundaries are a mixture of both the reinforcement and the eutectic phase of silicon. All microstructures exhibited an almost non-dendrite shape at the grain boundaries because of the squeeze pressure, which resulted in finer dendrites and decreased dendrite arm spacing (Singh *et al.* 2015).

The hardness value of 55.83 HRB and the ultimate tensile strength of 132.87 MPa are slightly lower than the one obtained at the L6 experimental condition. These slight variations are expected because of inhomogeneous properties caused by defects in the casting process itself. However, the obtained ultimate compressive strength (433.20 MPa), which is rank 1 in terms of the requirement for the brake disc application, is significantly higher than all other experiments. This will, therefore, enhance the AMMC performance, especially in brake disc applications. Figure 6 depicts the SEM morphology as well as the elemental mapping of the produced AMMC using the confirmation test process parameters. The porosity observed is consistent with the optical microscope image. The elemental mapping image for oxygen indicates that the reinforcements are distributed evenly throughout the entire sample. The alumina reinforcement particles are dispersed around the dendritic grains of the aluminium

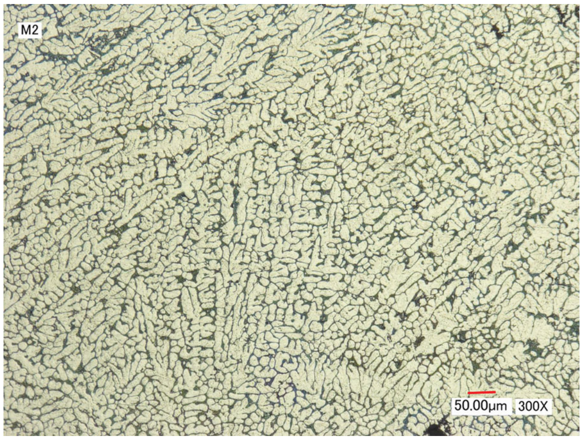

Figure 5. Microstructure obtained through an optical microscope for the confirmation test.

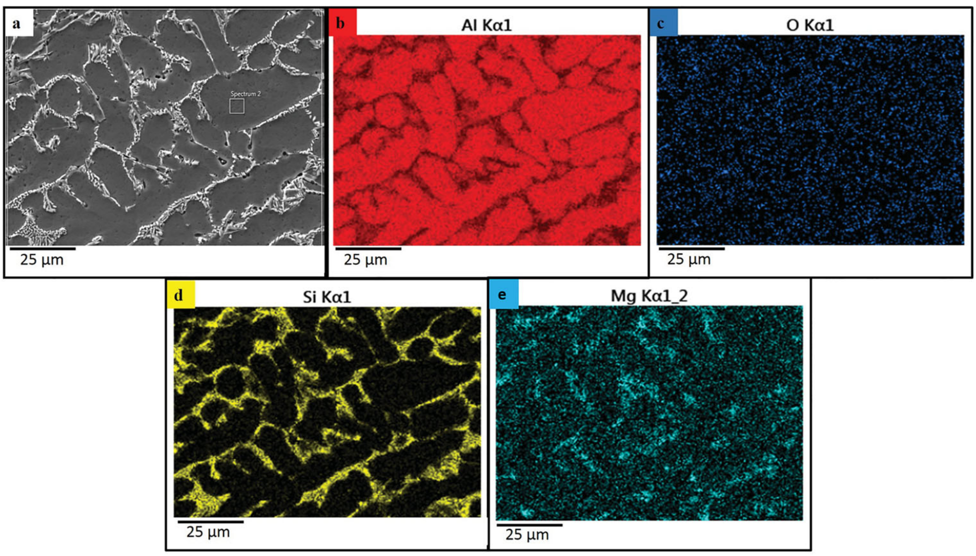

Figure 6. SEM and elemental mapping obtained for the confirmation test sample.

matrix, and this may be attributed to the optimal squeeze pressure (100 MPa) used during the production of the composite. The alumina particles have low thermal conductivity and heat diffusivity when compared with the aluminium matrix. During solidification, the reinforcement particles take more time to cool than the matrix; thus, the particles' temperature is somewhat higher. The hotter particles may have heated the surrounding melt, thereby delaying solidification of the surrounding liquid alloy. As an effect, nucleation of the matrix started in the liquid phase at a distance from the reinforcement, where the temperature was lower than the reinforcement particles. So, the microstructure of the composites contained primary Al dendrites and eutectic silicon, while the alumina particles are located in the interdendritic regions. As a result, this event occurs more easily with finer particles (Sajjadi, Ezatpour, and Beygi 2011).

6. Conclusions

The usefulness of the novel hybrid approach developed is successfully demonstrated to optimize the process parameters in the stir–squeeze casting process. The following are the salient conclusions from the investigations:

- The AHP method, integrated with Taguchi's grey technique, has been successfully utilized for the first time to handle the multi-response objective system for optimizing process parameters in the squeeze casting of AMMCs.
- The hybrid approach adopted in this research can determine the optimized condition with a minimal set of experiments, which is relevant in the stir–squeeze casting process as the experimental process including analysis is very time consuming and expensive.
- The optimum levels of process parameters are squeeze pressure of 100 MPa, squeeze time of 30 s, die preheat temperature of 250°C and stirrer speed of 525 rpm (P2-T2-D1-S2).
- Confirmation experiment shows an improvement of around 4% in GRG value as compared with the optimum process parameter (P2-T3-D1-S2) obtained from the L9 orthogonal array.
- Die preheating temperature is the most dominant process parameter, followed by stirrer speed, squeeze time and squeeze pressure, which influences the properties of the AMMC, especially for brake disc application.
- The quality of the AMMC is improved by reducing the casting defect, especially porosity. The average percentage of porosity obtained in the confirmation test is 5.29%, which is the lowest among all the experiments.
- Similarly, the ultimate compressive strength of 433 MPa obtained in the confirmation experiment is significantly higher, and so the AMMC will perform better for the brake disc application as this is the primary requirement, ranking at number 1 among the four response variables.
- Optical and SEM imaging showed that the composite produced in the confirmation experiment has lower porosity than the other composites, and the reinforcements are evenly distributed.
- The weight of responses obtained from the AHP method can significantly influence the GRG values, which in turn will affect the optimized process parameters. Therefore, depending on the application for the composite material, the optimal process parameters for stir–squeeze casting would be different.
- The hybrid approach has significantly improved the desirable properties expected for the brake disc application. This approach could be easily extended to optimize any manufacturing process with multiple responses where the weight of each response variable depends on the application.

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