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Statistical analysis and optimization of process parameters in development of metal matrix composite using industrial waste

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Abstract. Bauxite residue (BR) is the hazardous waste produced during extraction of alumina by processing of bauxite ore. BR has an adverse effect on humans and the environment due to its disposable problem. To minimize the environmental impact, BR must be effectively utilized. One such way is to use BR as a reinforcing for metal matrix composite. In this study, Taguchi's mixed fractional factorial experimentation (L18) approach is employed in the development of Al6063/BR composite through advanced stir casting process. The process parameters considered are stirring speed (rpm), reinforcement particle size (μm), reinforcement weight fraction (wt%) by weight of the matrix phase, pouring temperature (°C), and preheat temperature (°C). Later, ANOVA results indicate that particle percentage (wt%) is the major contributor in the development of porosity content. Moreover, the interaction of process parameters was also found to have an impact on porosity content. The outcome of the study reveals that the stirring intensity at 350 rpm, particle size at 80 μm, particle percentage at 2 wt%, pouring temperature at 730 °C, and preheat reinforcement temperature at 450 °C are the optimal conditions for fabricating defect free Al6063/BR composite.

Keywords. Bauxite residue; composite; porosity; process parameters; stir casting; Taguchi method.

1. Introduction

Bauxite residue (BR) is the hazardous residue produced during the extraction of alumina through Bayer's process [1, 2]. High caustic and alkalinity content, presence of radionuclides and toxic elements in BR causes environmental risk for fertile soil and ground water contamination [3, 4]. The high caustic content in BR leads to human health risks, like irritation to eyes and dermal problems [4]. Moreover, disposal of BR requires large area. Many countries like USA, India and China dumped BR into pools and constructed ponds. However, Japan, France, Greece dumped BR into sea water, causing harm to the aquatic life [1, 4, 5]. Such adverse effects can only be mitigated if we utilize bauxite residue effectively. Its major constituents like Al_2O_3, TiO and SiO_2 make it favorable for utilization as filler/reinforcement in development of metal matrix composites (MMC_s) [4, 5].

In the past two decades, numerous aluminum particulate metal matrix composites ($PAMMC_s$) were developed by various researchers using different reinforcement like Al_2O_3, SiC, B_4C, TiB_2, Zr_2O through conventional stir cast process [6–8]. Conventional stir cast process is an economical process, but the limitations include agglomeration/clustering of particles, poor wettablity, higher porosity content and void formation in composite [5, 9]. To overcome these problems it is essential to determine the optimal process parameters in fabrication of the PMMC through advanced stir cast process.

In the present investigation, different process parameters and their range was identified through extensive literature review [10–14]. Taguchi L18 (fractional factorial mix design) approach was used to obtain optimal process parameters in the development of robust Al6063/BR composite through advanced stir cast process. Porosity content is selected as output response characteristic. Further, a general linear model of ANOVA was performed to determine the major contribution of the selected process parameter on the output response characteristic. Confirmation experimentation was also performed to validate the obtained range of selected process parameters through Taguchi analysis.

Moreover, bottom pouring in vacuum environment is adopted (figure 1) to improve the quality characteristics of

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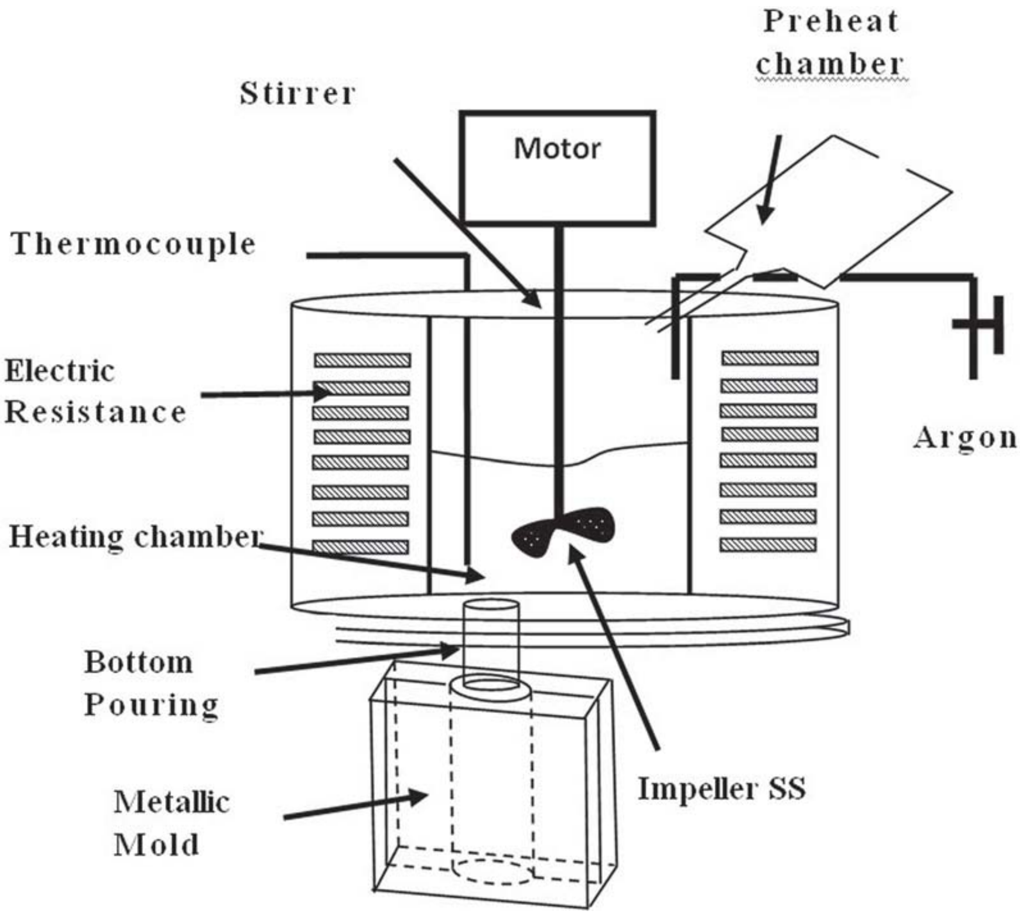

Figure 1. Advanced stir cast set-up.

Al6063/BR composite. The main advantage of the bottom pouring is that it minimizes the porosity content, which was the major drawback of conventional stir casting pouring process [5].

2. Materials and methodology

In the present study, an Al6063 (Al–Mg–Si) alloy is used as the base matrix and bauxite residue (BR) as the reinforcement to develop the particulate metal matrix composite (PMMC) through advanced stir cast process (figure 2). The BR was collected from Reenukoot HINDALCO. The elemental composition of the base matrix and reinforcement phase is listed in tables 1 and 2. An advanced stir cast process is chosen to develop Al6063/BR composite with defined set of process parameters with their ranges. The response characteristics i.e., porosity content was measured by comparing the theoretical and experimental densities of developed composite. The theoretical density of developed composite was measured through rule of mixture equation (1) and experimental density was calculated using microbalance (Denver Instruments ST 234 Summit Series Analytical Balance) which had an accuracy of 0.1 mg. Measurements of each sample were done thrice to determine the mean value. The deviation percentage between the theoretical and experimental observations was calculated to obtain the porosity percentage in cast Al6063/BR composite.

$$\rho_c = \frac{1}{\frac{W_m}{\rho_m} + \frac{W_r}{\rho_r}} \tag{1}$$

Where, W_m and ρ_m is the weight fraction and the density of base matrix respectively, W_r and ρ_r is the weight fraction and the density of the reinforcement phase, respectively, ρ_c is the density of the developed composite.

2.1 *Process parameters of advanced stir casting*

The present investigation is focused on the robustness of advanced stir cast process to develop PMMC. The following key elements were observed in achieving the target value.

Figure 2. Fabricated samples Al6063/BR composite through advanced stir cast process.

Table 1. Elemental composition of the base matrix.

Elements	Cu	Mg	Si	Fe	Ni	Mn	Zn	Pb	Sn	Ti	Cr	Al
(%)	0.03	0.417	0.478	0.151	0.003	0.072	0.005	0.022	0.01	0.016	0.007	98.76

Table 2. Elemental composition of bauxite residue

Elements	Fe_2O_3	Al_2O_3	TiO_2	SiO_2	Na_2O	CaO	P_2O_5	Others
(%)	35.26	21.89	15.11	12.46	11.82	1.83	0.40	1.63

1. To select the most significant factor that has dominant effect on the response characteristic.
2. To minimize the defects like porosity content and non-homogeneous distribution of reinforcement particles in cast samples considered as the most dominant quality characteristic in the development of sound PMMC through advanced stir cast process.
3. Develop the robust design using Taguchi orthogonal array experimental design for advanced stir cast process and collect the response characteristic data.
4. Generate the statistical significant parameter through ANOVA. Plot the graphs of response characteristics to determine the optimum levels of each process parameters.
5. Verify the optimal conditions in minimizing the defects (porosity content) in casting through confirmation experimentation test.

An Ishikawa diagram was drawn to identify the process parameters of stir casting route that may have impact on the performance of the composite (figure 3). In the present study, the process parameters are selected to observe the effect on response characteristics i.e., porosity content and homogeneous distribution of the reinforcement phase in development of robust Al6063/BR composite.

1. Stirring characteristics
2. Reinforcement characteristics
3. Processing characteristics
4. Types of base matrix
5. Pouring environment

For each process parameters except stirring intensity, three levels are selected in conducting the experiments (table 3). The first parameter i.e., stirring intensity, level is taken at two levels. The selection of levels for different process parameters was based on the trial run conditions. The trials were performed and limits were determined in analyzing the response characteristics. From trial runs, it was also observed that with increase in stirring intensity (parameter first) from 350 to 450 rpm the porosity content is increased. Particle size was chosen as the second parameter and different BR particle size was determined by sieve analysis. The BR particle size range was selected to avoid the agglomeration phenomenon of the particles. A decrease in particle size leads to increase in surface area and causes agglomeration phenomena in cast structure. During the trials no agglomeration is observed up to 6% of particle percentage (parameter third). Beyond this limit, agglomeration of the particles seen in cast structure has been earlier reported [5]. The pouring temperature was

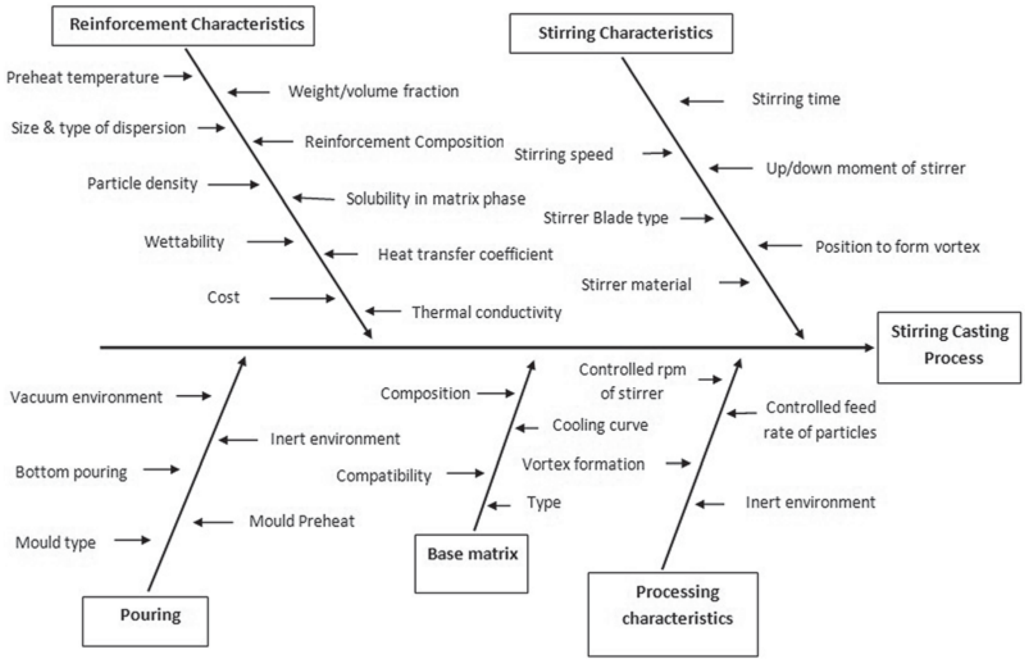

Figure 3. Ishikawa cause and effect diagram for stir casting process.

Table 3. Advanced stir cast process parameters and their levels.

Sl. No.	Labels	Process parameter	Range	Units	Level 1	Level 2	Level 3
1	A	Stirring intensity	350–450	rpm	350	450	–
2	B	Particle size	120–80	µm	120	100	80
3	C	Particle percentage	2–6	wt%	2	4	6
4	D	Pouring temperature	710–750	°C	710	730	750
5	E	Preheat temperature	250–450	°C	250	350	450

Mould preheat temperature: 300 °C

Magnesium : 1%

chosen as the fourth parameter in fabrication of metal matrix composite. Preheat temperature was chosen as the last parameter to predict the behavior of hydrous minerals present in BR which causes porosity in cast composite.

2.2 *Selection of orthogonal array*

In the present study, the L18 orthogonal array is used for conducting the experimentation. The extensive literature study reveals that porosity content occurs in cast composite is due to increase in reinforcement weight fraction and size, vigorous stirring speed, and preheat conditions of the reinforcement particles [5, 14–16]. Therefore, above said parameters are assumed to have significant influence on the porosity content and homogeneous distribution of BR in the base matrix. After selections of parameters, interactions between parameter, and their levels the required total degree of freedom (ν) comes to be 15 (number of level—1) (table 4). However, with L18 orthogonal array the available total degree of freedom (ν_{avl}) is 17 that is greater than the required degree of freedom (ν_{avl} > required, i.e., 17 > 15). Hence, 18 experimental runs were selected for the L18 orthogonal array by assigning of eight columns as shown in tables 4 and 5. Linear graph exhibits various columns to which parameters may be assigned and the columns subsequently evaluate the interaction of those factors [17].

2.3 *Experimental design statistical calculations*

The output response characteristic i.e., porosity content was obtained as per the defined experimental design in table 6. The experiments for each set of defined design were performed twice to minimize the variations in output response characteristic. For each set of experiment, the porosity

Table 4. Assignment of process parameters and interactions using L18 fractional factorial design.

Trail No.	A	B	AxB	C	AxC	BxC	D	E
1	1	1	1	1	1	1	1	1
2	1	1	2	2	2	2	2	2
3	1	1	3	3	3	3	3	3
4	1	2	1	1	2	2	3	3
5	1	2	2	2	3	3	1	1
6	1	2	3	3	1	1	2	2
7	1	3	1	2	1	3	2	3
8	1	3	2	3	2	1	3	1
9	1	3	3	1	3	2	1	2
10	2	1	1	3	3	2	2	1
11	2	1	2	1	1	3	3	2
12	2	1	3	2	2	1	1	3
13	2	2	1	2	3	1	3	2
14	2	2	2	3	1	2	1	3
15	2	2	3	1	2	3	2	1
16	2	3	1	3	2	3	1	2
17	2	3	2	1	3	1	2	3
18	2	3	3	2	1	2	3	1

content was measured thrice and the average was taken in response column. Porosity content was considered as "lower the better" output. Lower the better S/N ratios was also calculated and presented in table 6.

$$S/N_{LB}\text{ ratio} = -10\log[(\sum X^2 i)/n] \tag{2}$$

For the smaller is the better, the quality characteristic, S/N ratio can be calculated as [17, 18]:

$$S/N_i = -10\log\left(\sum_{u=1}^{N_i}\frac{X_u^2}{N_i}\right) \tag{3}$$

For example, for trial no. 1, the S/N ratio is:

$$\begin{aligned} S/N_{LB} &= -10\ \log[(\sum X^2 i)/n] \\ S/N\text{ratio} &= -10\log[(0.632)^2 + (0.501)^2]/2 \\ &= -4.875 \end{aligned}$$

2.3a *Statistical analysis of output response characteristics* The average value of the porosity content and S/N ratio for each parameter at different level is considered as mean value (table 7). The mean values of quality characteristics and S/N ratio are calculated by adding the response of all trial conditions at the selected level, and then dividing by the number of observations made (table 7).

Where, the response A (L_1) for parameter A are calculated as [19].

A (L_1) = (X_{11} + X_{12}) + (X_{21} + X_{22}) + (X_{31} + X_{32}) + (X_{41} + X_{42}) + (X_{51} + X_{52}) + (X_{61} + X_{62}) + (X_{71} + X_{72}) + (X_{81} + X_{82}) + (X_{91} + X_{92}) and similarly for A (L_2).

The calculated statistical output response characteristics for each parameter at their defined levels are plotted in figures 4 and 5. Minimum porosity content was observed at 350 rpm stirring intensity (parameter A-L_1), 80 µm particle

Table 5. Experimental L18 orthogonal array.

	Controlled Parameters				
Trial No.	A Stirring intensity (rpm)	B Particle size (µm)	C Particle percentage (wt.%)	D Pouring temperature (°C)	E Pre heat temperature (°C)
1	350	120	2	710	250
2	350	120	4	730	350
3	350	120	4	750	450
4	350	100	2	750	450
5	350	100	4	710	250
6	350	100	6	730	350
7	350	80	4	730	450
8	350	80	6	750	250
9	350	80	2	710	350
10	450	120	6	730	250
11	450	120	2	750	350
12	450	120	4	710	450
13	450	100	4	750	350
14	450	100	6	710	450
15	450	100	2	730	250
16	450	80	6	710	350
17	450	80	2	730	450
18	450	80	4	750	250

Table 6. Average response characteristic and their respective S/N ratio (dB).

	Porosity content in%			
Trail No.	Avg. R_1	Avg. R_2	Average	S/N ratio (dB)
1	0.632	0.501	0.5665	4.875
2	0.908	0.848	0.878	1.122
3	1.041	1.422	1.2315	−1.914
4	0.481	0.497	0.489	6.206
5	0.645	0.591	0.618	4.166
6	1.213	1.003	1.108	−0.931
7	0.491	0.515	0.503	5.963
8	1.209	1.311	1.26	−2.015
9	0.417	0.456	0.4365	7.184
10	1.938	1.909	1.9235	−5.682
11	0.712	0.619	0.6655	3.515
12	0.853	0.821	0.837	1.543
13	1.031	1.017	1.024	−0.208
14	1.735	1.769	1.752	−4.872
15	0.651	0.633	0.642	3.843
16	1.696	1.686	1.691	−4.563
17	0.546	0.582	0.564	4.964
18	1.275	1.24	1.2575	−1.991

size (parameter B-L_3), 2 wt% of particle percentage (parameter C-L_1), 730 °C pouring temperature (parameter D-L_2), and 450 °C preheat temperature of reinforcement (parameter E-L_3). The signal to noise ratio is also on higher side at above said parameter's level (figure 5), is the best value for getting minimum porosity content in the development of the robust Al6063/BR composite.

S/N ratio is signal to noise ratio where signals means response (output variable) and noise means uncontrollable variable like environmental temperature, humidity, human variation, etc. S/N ratio considers both target and variation in repetition of experiment. Target consists of experiment objectives i.e., higher is better, lower is better or nominal is best [13, 17, 20]. For example, mileage of an automobile is higher is the best, defects in cast products—lower is the better, diameter of cylindrical shaft—nominal is the best. Second, the variation in repetition of experiment for example experiments are repeated but produces different results, this is due to noise factor like environmental condition, human variation, etc.

The statistical analysis plots had shown in figures 4 and 5 gives the optimum mean value of the output response characteristics at level of their respective parameters rather than significant effect of the parameter. Hence, it is required to obtain the optimum process parameters that have impact on the porosity content. In present investigation, general linear model of ANOVA is applied to predict the optimum process parameter by analyzing the statistical total variation in the process (tables 8 and 9). The overall variation in the output response characteristics is broken up into following components:

1. Variation due to individual parameters A, B, C, D, and E
2. Variation due to parameter's interactions AxB, AxC, and BxC
3. Variation due to error

Total variation, $SS_T = [SS_A + SS_B + SS_C + SS_{D}$- $+ SS_E + SS_{AxB} + SS_{AxC} + SS_{BxC}]$ and Variation due to error, $SS_e = SS_T - [SS_A + SS_B + SS_C + SS_D + SS_E + SS_{AxB} + SS_{AxC} + SS_{BxC}] = 0.18$

Total degrees of freedom for error $Ve = V_T - [V_A + V_B + V_C + V_D + V_E + V_{AxB} + V_{AxC} + V_{BxC}] = 35 - 15 = 20$.

3. Results of ANOVA study

ANOVA identifies the significant process parameters and their interactions which significantly influence the output response characteristics i.e., porosity content (tables 8 and 9). However, some more information is required to determine the output response with an optimum setting of parameters [21].

Before interpreting and determining the output response through ANOVA, it is mandatory to check some assumptions like normality, independence, and constant variance. Normality of experimental data is checked by constructing each residual plot against its expected value under normality (figure 6). This plot is linear if these residuals are normally distributed. If plot does not appear linear through visual observation then there residual is further analyzed using coefficient of correlation of the plot [19]. Further, independence assumption on the residuals is checked by constructing the plot of residuals in time order of data collection (figure 7). The constructed plot should not contain any pattern. In the present study, Durbin–Watson test was adopted in checking the residual's independence assumption. If the statistic value of Durbin test is greater than its corresponding upper critical value then the assumption on residuals are independent. Moreover, F ratio test is incorporated rather than plotting residuals versus predicted assumption to determine residual variance constancy in the present study. The residuals have constant variance, if the statistical F ratio is less than or equal to its corresponding critical value (refer to table 8). Since all the assumption made in analysis were carefully checked and no violation of assumption was predicted. Therefore, the general leaner model of ANOVA is used in present study.

Statistical observation reveals that the F-ratio of parameters A, C, and E is greater than the significant value (table 8). Hence, the selected parameters have a significant effect on the output response characteristic. However, factor B is not significant due to F ratio test statistic is 2.33 that is less than the critical accepted value of F ratio i.e., 3.49. But its interaction AxB and BxC is in significant level because there statistic F ratio is greater than its critical F

Table 7. Mean value of porosity content and S/N ratio at different levels.

	Level 1		Level 2		Level 3	
Factors	Porosity (%)	S/N ratio	Porosity (%)	S/N ratio	Porosity (%)	S/N ratio
A	0.788	2.739	1.15	−0.383	–	–
B	1.017	0.576	0.939	1.367	0.952	1.59
C	0.56	5.098	0.853	1.766	1.494	−3.329
D	0.983	1.389	0.936	1.546	0.988	0.598
E	1.044	0.532	0.967	1.019	0.896	1.982

The mean values of the quality characteristic at A(L_1) & A(L_2) are $\bar{A}(L_1) = \frac{A(L_1)}{18}$ & $\bar{A}(L_2) = \frac{A(L_2)}{18}$

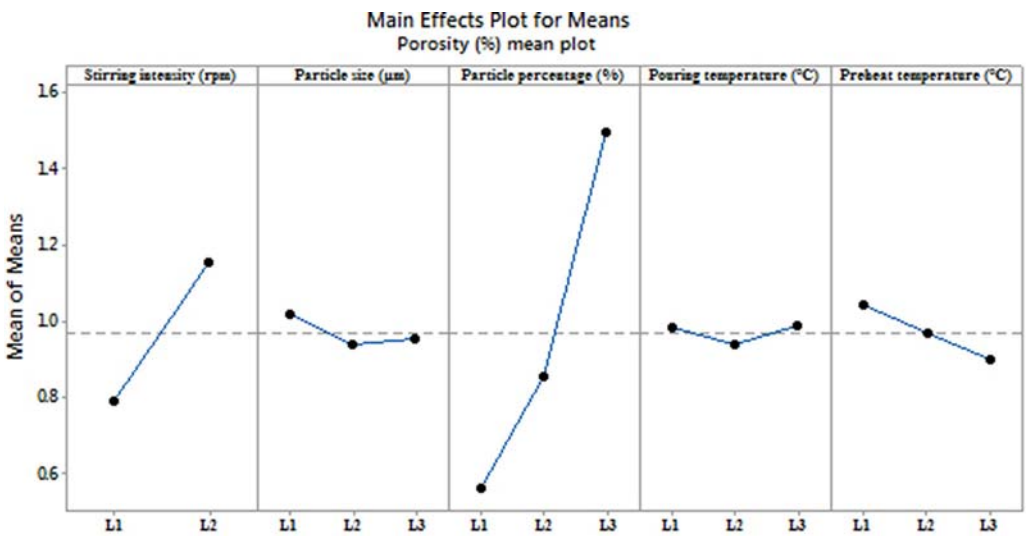

Figure 4. Main effect plots for the mean porosity (%).

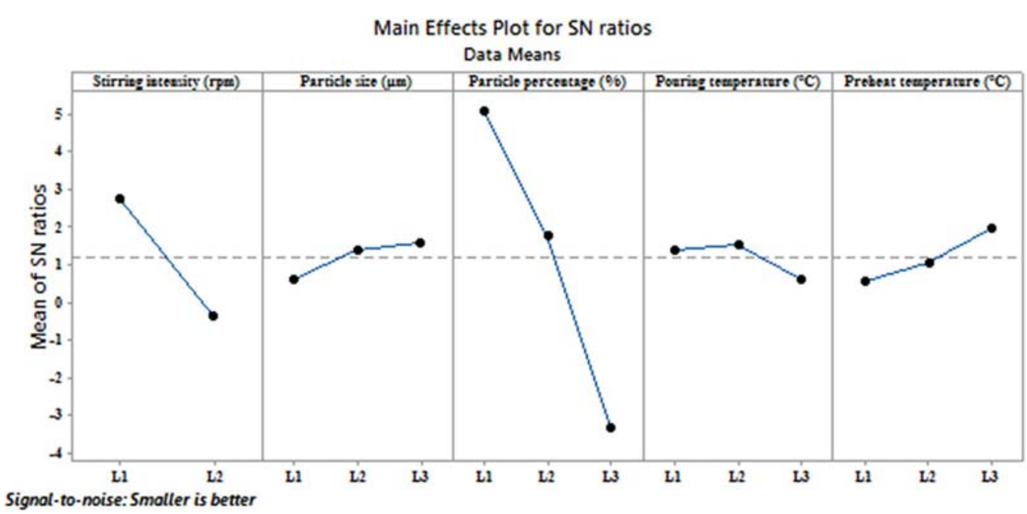

Figure 5. Main effect plots for S/N ratios of the mean porosity (%).

Table 8. ANOVA for mean porosity (%) at 95% confidence level.

Source	SS	DF	Variance	F ratio
A	1.185	1	1.185	131.77
B	0.042	2	0.021	2.33
AXB	0.082	2	0.041	4.51
C	5.474	2	2.737	304.43
AXC	0.00067	2	0.00033	0.04
BXC	0.424	2	0.212	23.59
D	0.02	2	0.01	1.08
E	0.132	2	0.066	7.36
Error	0.18	20	0.009	
Total	7.539	35		

Critical values of F ratio of factor A is 4.35 at (1, 20) & 3.49 at (2, 20) for factors B to E at 95% confidence level.

SS: sum of squares, DF: degree of freedom, V: Variance.

Table 9. Pooled ANOVA table of mean porosity (%).

Source	SS	DF	Variance	F ratio	SS'	P (%)
A	1.185	1	1.185	144.41	1.177	15.61
B	0.042	2	0.021	2.56	0.026	0.34
AXB	0.082	2	0.041	4.94	0.065	0.86
C	5.474	2	2.737	333.63	5.458	72.39
AXC	Pooled	2	Pooled	1.38	Pooled	Pooled
BXC	0.424	2	0.212	25.85	0.408	5.41
D	0.02	2	0.01	1.19	–	–
E	0.132	2	0.066	8.06	0.116	1.53
Error	0.18	22	0.0082			
Total	7.539	35				

Critical values of F ratio of factor A is 4.35 at (1, 20) & 3.49 at (2, 20) for factors B to E at 95% confidence interval.

SS: sum of squares, SS'; pure sum of error, DF: degree of freedom, V: Variance, P: percentage contribution

Where, $SS'_A = SS_A - (V_e * \nu_A)$, similarly for SS'_B, SS'_C, SS'_D, P (%) = $(SS'_A/SS_T)*100$

ratio value (table 8). Hence, the individual factors B (particle size in µm) has no significant effect on the porosity content but its interaction with factor A (stirring intensity in rpm) and factor C (reinforcement fraction in wt%) has significant effect on the porosity content. This indicates that factor B cannot be pooled. Moreover, interaction AxC is insignificant due to its F test statistic being less than the critical F ratio value. This indicates that the interaction of parameters A and C does not have an impact on the output response characteristics. However, factor A and C are of significant level.

3.1 *Pooling*

If the statistic F ratio to the corresponding parameter is less than tabulated F ratio (table 8) at the given confidence interval (95%), the parameter is insignificant and pooled the parameter [22]. The sum of square of pooled parameter in ANOVA calculation is added on the error sum of squares. In the present study, the interaction AxC is insignificant and pooled from the ANOVA calculation. The required ANOVA terms are advanced and presented in table 9.

$$SS_e(\text{pooled}) = SS_e + SS_{AxC}$$
$$f_e = f_e + f_A$$
$$V_e(\text{pooled}) = SS_e(\text{pooled})/f_e(\text{polled})$$

Where V_e is the error of variance, f_e and f_A degree of freedom due to error and parameter A, respectively.

The percent contribution (P%) of individual significant factor and/or interaction which is differed, is the part of the total deviation predicted in an experiment. The P% represents the relative power of a parameter and/or respective parameter's interactions to reduce the variation. The total variation could be reduced, if the levels of parameter/interaction are controlled precisely. The deviation due to a parameter/interaction has some value due to error and is represented by, $SS'_A = SS_A - (V_e \times \nu_A)$ if parameter A is significant.

Similarly, pure sum of squares for other significant parameters/interactions is determined. The total sum of square will remains same (SS'_e) after the subtracted amount of sum of squares that added to the error sum of squares.

$$SS'_e = SS_e + (\nu_e \times \nu_A)$$

Percentage contribution due to parameter A (P_A%)-= (SS'_A/SS_T) x 100. Similarly percentage contribution for parameter B, C, D, and E are calculated. The expected sums of squares (SS′) for each parameter is calculated by using P% (table 9).

3.2 *Optimization analysis of levels of their corresponding controlled parameters*

Once the experiments at their defined levels are performed and the optimal value within the experiment is predicted. Here, two possibilities exist: a) prescribed combination of parameters level is identical to one of those in the experiment and b) prescribed combination of parameters level is not included in the experiment.

In the present study, the second condition exists and estimation of mean for porosity content is achieved by following equation 4.

$$\mu = T + (A_1 - T) + (B_3 - T) + (C_1 - T) + (D_1 - T) + (E_3 - T) \tag{4}$$

Where, T is the mean value of the porosity content at different levels.

The above equation 4 is not good when the additivity of experimental observation is in 0 and 1 i.e., in percentage

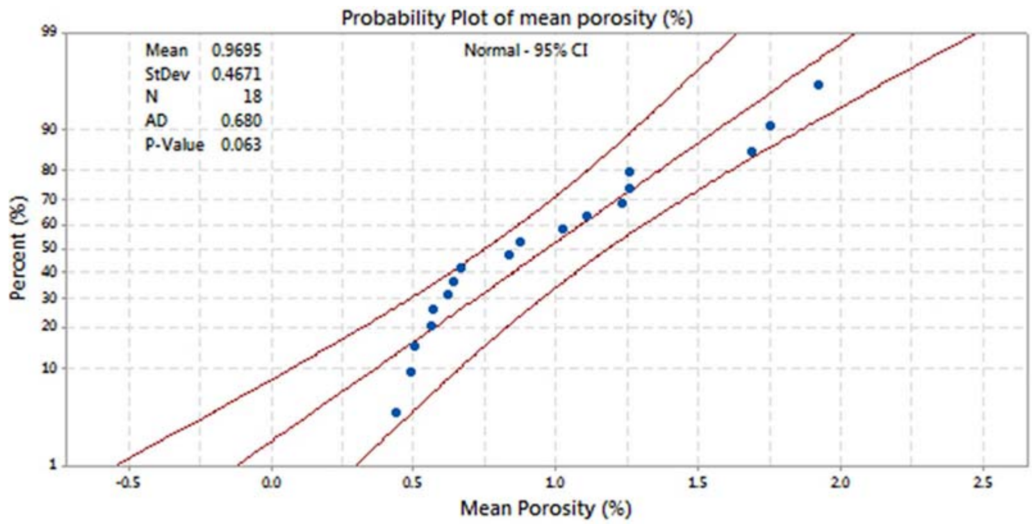

Figure 6. Normality plot of experimental data (mean porosity—%).

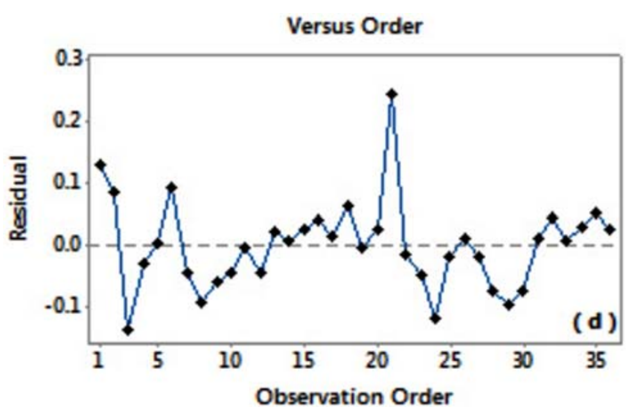

Figure 7. Residual Plot of the experimental observed data.

such as percent yield, percent loss or defect type output. This type of problem may lead to bad model's additive since the value being closer to 0 or 1. For this type of conditions the estimation of mean for the output response characteristic is determined through omega transformation [23, 24]. The following steps are involved for estimating the mean through omega conversion and presented in table 10.

1. Convert data percent values to db values using the omega tables or formula, $\Omega(db) = 10log\left[\frac{p}{1-p}\right]$.
   Where, p = fraction percentage value ($0 < p < 1$)
2. Use equation (4) to estimate the mean with substituted omega values.
3. Convert the obtained db value back to the percent value using the omega tables or formula

The omega transformation converts fractions between 0 and 1 to values between minus infinity and plus infinity. This transformation is most useful because percentage values are very small in the present investigation. In the present study, the porosity percentage is converted in db through omega transformation is represented in table 10. The mean for a selected trial condition for parameters at A_1, B_3, C_1, D_2, and E_3 is 0.4% (−23.982 db).

3.3 *Confidence intervals*

The optimum values of porosity (%) at the selected levels of significant parameters ((A_1, B_3, C_1, D_2, and E_3) through estimation mean (μ) is predicted (table 10). The estimate of the mean (μ) is the average of the results determined from the experiment run condition. Statistically, this gives a 50% chance of the true average being less or greater than mean (μ). The confidence level is the minimum and maximum value between which the true average should fall at some stated level. Hence, the expected value of true average should fall within the confidence interval. There are two types of confidence intervals (CI_{CE} and CI_{POP}) that are proposed by Taguchi for estimating the mean of optimal run conditions [23].

$$CI_{CE} = \sqrt{F_{\alpha}(1,f_e)V_e\left[\frac{1}{\eta_{eff}} + \frac{1}{R}\right]} \tag{5}$$

$$CI_{POP} = \sqrt{F_{\alpha}(1,f_e)V_e\left[\frac{1}{\eta_{eff}}\right]} \tag{6}$$

From tables 7 and 8, the CI is calculated from equations (5) and (6) as given under

Table 10. Average values of various responses at optimal level and respective omega transformation value (db).

Parameter	Optimal Level	Average porosity (%)	Db
Stirring intensity (rpm)	A_1	0.788	−21.00
Particle size (μm)	B_3	0.952	−20.172
Particle percentage (%)	C_1	0.56	−22.494
Pouring temperature (°C)	D_2	0.936	−20.246
Pr heat temperature (°C)	E_3	0.896	−20.438

$\Omega(db) = 10log\left[\frac{p}{1-p}\right]$ = 10 * log $\left[\frac{0.00788}{1-0.00788}\right]$, similarly rest of the response characteristics

Overall mean, T = 0.9695% = − **20.092** (from Table D.5 (Ross, 1996))

α—risk level = 0.05,
V_e—error of variance = 0.0082
η_{eff}—effective number of replication = $\frac{N}{1+\left[\begin{array}{c}\text{total DF associated with items}\\ \text{used in estimation of mean}\end{array}\right]}$
f_e—degrees of freedom for the error = 22
R—sample size for confirmation experiments = 2
N—total number of experimentation performed = 36
F_α—$F_{0.05}$ (1, 22) = 4.30 (tabulated)

Predicted optimal range (for a confirmation runs of two experiments) at 95% confidence interval is:

Mean (μ)—CI_{CE} < μ < Mean (μ) + CI_{CE}
$|\mu - CI_{CE}| < \mu < |\mu + CI_{CE}|$
0.234 < **0.4** < 0.566
The 95% confirmation interval of the predicted optimum of the porosity content value is
$|\mu - CI_{POP}| < \mu < |\mu + CI_{POP}|$
0.301 < **0.4** < 0.499.

3.4 *Confirmation experiments*

Confirmation experiments were used to verify that the response value through experimentation at defined optimal condition, predicted through estimation of mean is within the range described by the confirmation test. The confirming experiment defined for experiments at optimal conditions is highly recommended to verify the experimental results. If the average response characteristics from confirmation experiments are in the range of the confidence interval then the parameters and their corresponding levels predicted in obtaining the response are precisely selected. Moreover, if the average response characteristic from confirmation experiment is beyond the range of the confidence interval then the controlled parameters and their corresponding levels to control the output response value for a desired value are doubtful and it requires further experimentation [24]. Six confirmation experiments at defined optimal conditions were conducted as shown in table 11. The average output response characteristic (porosity content) in each experiment condition was found to be 0.512% which is within the limits of predicted value.

Table 11. Confirmation run for validate the results.

Confirmation experiments at optimal Parameters (A_1, B_3, C_1, D_2, E_3)	Porosity (%)
1	0.543
2	0.481
3	0.557
4	0.501
5	0.511
6	0.481
Average	**0.512**

Therefore, the selected process parameters and their corresponding levels are significant enough to obtain the desired response.

4. Conclusions

The hazardous waste (BR) is successfully utilized as reinforcing material with Al6063 alloy in development of robust particulate metal matrix composite (PMMC) through advanced stir cast process. The advanced stir cast process having the novelty in the present study. A bottom pouring arrangement is employed to pour the cast composite through bottom that restricts the dross and oxides at metal surface, from being a part of the cast. Moreover, the porosity content is also minimized by selecting the optimal settings at their corresponding process parameters through Taguchi analysis of cast PMMC. It also increases robustness of the advanced stir casting route. Before the implementation of Taguchi methodology, the process parameters and their levels were more arbitrary and it was difficult to select to appropriate level. Hence the defects like high porosity and void formation in cast composite had problems. Taguchi analysis yielded optimized process parameters, resulting in robust cast product. Through this analysis it can be observed that the maximum and minimum porosity content was observed to be 1.92% and 0.4%, respectively that was the worst and best condition for the cast composite. Hence, L18 mixed design approach gives the best suitable condition in the development of Al6063/

BR composite. The same is also confirmed through confirmation experiments.

From the present investigation, it can be reported that the output response characteristic can be improved by Taguchi analysis at the lowest possible cost. Moreover, to overcome from the limitation of the Taguchi, ANOVA methodology is adopted to predict the interaction and significant process parameter, and major contribution of the individual process parameter in the present investigation. Through ANOVA analysis, the optimized process parameters and their levels are with stirring intensity—350 rpm, particle size—80 μm, particle percentage—2 wt%, pouring temperature—730 °C, preheat temperature—450 °C for the output response characteristic i.e., porosity content. The experimentation also reveals that the every process parameter's of advanced stir cast process is responsible in variation in response characteristics and can be improved without additional cost.

List of symbols

BR	Bauxite residue
°C	Temperature in Celsius
USA	United state of America
PMMC	Particulate metal Matrix Composite
MMC_s	Metal Matrix Composite
W_m	Weight fraction of base matrix
ρ_m	Density of base matrix
W_r	Weight fraction of reinforcement
ρ_r	Density of the reinforcement
ρ_c	Density of the developed composite
rpm	Revolution per minute
ν	Total degree of freedom
ν_{avl}	Available total degree of freedom
S/N	Signal to noise ratio
S/N_{LB}	Signal to noise ratio lower is the better
db	Decibels
SS_T	Total Sum of Square
SS_A	Sum of square of parameter A
SS_e	Sum of square of error
Ve	Total degree of freedom due to error
V_T	Total degree of freedom
V_A	Total degree of freedom due to parameter A
μ	Mean
p	Fraction percentage
CI_{CE}	Confidence of interval due to confirmation of experiment
CI_{POP}	Confidence of interval due to population

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