ISSN: 0974-5823 Vol. 7 (Special Issue, Jan.-Feb. 2022)

*International Journal of Mechanical Engineering*

# Applying Grey Fuzzy logic to Optimization the stir casting process parameters of Al7075-$TiO_2$-BN-WC hybrid composite

***Kishorekumar.Nandyala[a], Dr Sanjeevreddy K Hudgikar[b],**

*a.Research scholar Department of Mechanical Engineering, VTU, Belagavi, India;*

*b Department of Mechanical Engineering, Sharnbasva University Kalaburagi, India;*

**Abstract**

This study examines the influence of the stir casting process parameters for developing hybrid AMMC Al7075/$TiO_2$/BN/WC. The design of experiments was developed according to Taguchi's L27 orthogonal array with process parameters stirring temperature, stirring speed, stirring time, the weight of reinforcements added, size of nanoparticles and type of nanoparticles added, for three levels. The output responses tensile test, hardness, compression and impact was performed on the samples and obtained optimum process parameters of the stir casting process. A soft computing technique, fuzzy logic (FL), is integrated with a multi-objective optimization method, grey relation analysis (GRA). The most influencing factors are investigated using ANOVA. The optimum stir casting process levels obtained are stirring temperature $800^0$ C, stirring time 10 min, stirring speed 800 rpm, the weight percentage of reinforcements added is 3%, size of nanoparticles 50, 90 nm and type of nanoparticles is $TiO_2$+BN.

## 1. Introduction

It is a great challenge to manufacture aluminium hybrid composite materials with a great strength-to-weight ratio for preset industrial uses. Stir casting is the most widely used casting technique to manufacture hybrid composite materials. The stir casting technique is used to overcome the strength-to-weight ratio by varying process parameters of the stir casting technique by applying soft computing techniques was discussed in this paper. M. Vignesh et al. This paper's stir casting method produced zircon sand (ZrSiO4)-reinforced aluminium (grade-LM25) matrix composites. Machining conditions (Dry/MQL), cutting speed (CS), depth of cut (DoC), feed rate and reinforcement are varied in the experiments. Fuzzy logic (FL), a soft computing technique coupled with a multi-objective optimization technique, grey relational analysis (GRA), was implemented to find the optimal cutting parameters. Statistical analysis is used to find the best levels for the experiments. In this case, MQL is the best cutting condition. The cutting speed is 200 m/min, the feed rate is 0.06 mm/rev, and the depth of cut is 0.5 mm [1]. K. Anand Babu et al. The purpose of this study is to look at how drilling parameters affect the Aluminum Metal Matrix Composite (Al7075/10 percentage - SiCp) that is made. It was done in a Taguchi L27 orthogonal array with uncoated and coated HSS tools on Al7075/10 percentage - SiCp composite under MQL. The variables used for the three cutting levels were speed, feed, tool material, point angle, and cutting environment. This composite is made by adding 53 m-sized SiC particles to an aluminium matrix material and stirring it together. The surface roughness is thought of as an experiment, and fuzzy logic is used to predict it. According to the results, the predicted surface roughness and experimental surface roughness are close, Which means that fuzzy logic modelling can predict surface roughness very quickly [2]. M.Vamsi Krishna et al. In this paper, an attempt is made to examine the effect of influential parameters such as type of reinforcement, size of reinforcing particle and weight percentage on mechanical properties. The stir casting technique has been employed to prepare the composites. The response parameters were tensile strength, impact strength and density. A fuzzy approach was used to investigate the optimal combination of influencing parameters on the mechanical behaviour. Optimum influencing parameter combination has been found at the size of 3μ, combined SiC/Graphite of 15% using the fuzzy logic technique [3]. R. Ambigai et al. Al-Gr, Al-Si3N4 nano and Al-Gr hybrid composites were cast by gravity die stir casting to investigate the wear and frictional characteristics under dry sliding conditions. The predominant wear mechanisms observed were abrasive for the nanocomposite and adhesive and abrasive mechanism for the hybrid composite. The hybrid composite's wear rate was optimized with fuzzy logic analysis and with low prediction errors of 4.27%. The results show that the Micro Vicker hardness of the Hybrid Composite is 16% more than that of the Nano Composite [4]. Logesh Kamaraj et al. The ultrasonic-assisted stir-casting technique improves the uniform dispersion of nano-reinforcements in aluminium hybrid metal matrix composites. Process parameters are optimized against the response factors such as porosity, ultimate tensile strength, and wear rate. An artificial neural network model is developed and validated for the given set of experimental data. The ANOVA results have revealed that the depth of ultrasonic vibration showed a significant contribution among the input factors [5]. Priyaranjan Samal et al. This study aims to determine the wear performance of AA5052 metal matrix composites (MMCs) reinforced with in-situ formed TiC particles using two methods: statistical-based non-linear regression and fuzzy logic. A pin-on-disc machine is used to get the wear data for the composites. It has been found that the sliding distance and the amount of weight being put on aluminium 5052 MMCs have a significant impact on the volumetric wear loss [6]. Jitendra M. Mistry et al., An experimental investigation was performed on Al7075 reinforced with Si3N4p by an electromagnetic stir casting process. Tensile strength was observed at 8% wt. Si3N4p was increased, and microhardness was improved while increasing the weight percentage. The wear rate decreased while the weight of the composition increased, and the wear rate improved by 31.17%

compared to the base alloy [7]. N. Ramadossa et al. the stir casting process developed the hybrid composites. Al7075 is the base alloy, with B4C and BN as reinforcements. In the present investigation, three samples were prepared using Al7075+3% B4C+3%, Al7075+9% B4C+3%, BN, and Al7075+9% B4C+3%, and tensile strength and hardness tests were performed. The tensile strength of Al7075+9% B4C+3% was increased by 22% compared to the base alloy. A Vickers hardness test was performed, and it was observed that the hardness increased by increasing the boron carbide. The wear rate was also decreased by 22.4% on the base alloy. The reinforcements were uniformly spread throughout the surface [8]. Kuldeep Ba et al. studied the mechanical and wear properties of Al7075 alloy reinforced with 3% BN and ZrO2 at three weights (2%, 4%, and 6%) and developed a hybrid composition. The hybrid composite Al7075+3% BN +6% ZrO2 recorded a high tensile strength of 187.585 MPa, and hardness also improved up to 92.6 BHN due to the uniformly distributed particles within the metal matrix. The wear rate also decreased while increasing the weight percentage of reinforcements. This limited ploughing activity resulted in a material loss from the sample surface [9].

## 2. Experimental Details

The present work optimizes stir casting process parameters for developing hybrid composite. Stirring temperature, stirring speed, stirring time, type of reinforcements added, the weight of reinforcements, and the size of nanoparticles added is considered the process parameters. The Taguchi design of experiments was developed with three levels and six process parameters shown in table 1; L27 experiments were obtained shown in table 2. Al7075 is considered as the base alloy, and $TiO_2$, BN, and WC are taken as reinforcements with three different weight percentages (3, 6, and 9 %), stirring temperatures are $750^0$ C, $800^0$ C, and $850^0$ C, stirring Time 10, 15 and 20 min, stirring speed 600, 800 and 1000 rpm, size of ($TiO_2$-80, BN-50, and WC-90 nm) and reinforcements added $TiO_2$+BN, BN+WC, and WC+$TiO_2$. The 27 samples were manufactured using the stir casting method to perform Tensile, compression, impact and hardness test to know effective process parameters.

### 2.1 Fabrication of Samples

The small pieces of base alloy Al-7075 are taken into a graphite crucible and heated to the required temperature; as per the set of experiments, the reinforcements were added to the molten metal and stirred for respective time and rpm. The nanoparticles were preheated up to $350^0$ C before pouring into the molten metal to remove the moister particles. Then the molten metal was transferred into a cast-iron mould and cooled to room temperature. And similarly 27, samples were fabricated as per the design of experiments and the prepared models were undergone for the mechanical test, and results were shown in table 2. Table 1. Factors and levels.

| Parameters | Symbol | Units | Levels | | |
|---|---|---|---|---|---|
| | | | 1 | 2 | 3 |
| Temperature | (T) | ºC | 750 | 800 | 850 |
| Stirring Speed | (S) | Rpm | 600 | 800 | 1000 |
| Stirring Time | (ST) | Min | 10 | 15 | 20 |
| Weight | (W) | % | 3 | 6 | 9 |
| Size of Nanoparticles | (SN) | nm | 80,50 | 50,90 | 90,80 |
| Nanoparticles | (N) | | TiO2+BN | BN+WC | WC+TiO2 |

Table 2. Design of Experimental by using orthogonal array L27 and responses

| Trial No. | T | S | ST | W | SN | N | Response of Mechanical properties. | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Tensile Strength(MPa) | Compressive Strength MPa) | Hardness (BHN) | Impact Test (J) |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 244.56 | 234.8 | 67.69 | 56.36 |
| 2 | 1 | 1 | 1 | 1 | 2 | 2 | 232.291 | 229.88 | 69.36 | 57.63 |
| 3 | 1 | 1 | 1 | 1 | 3 | 3 | 231.36 | 228.04 | 63.36 | 54.36 |
| 4 | 1 | 2 | 2 | 2 | 1 | 1 | 234.6 | 232.92 | 69.36 | 59.23 |
| 5 | 1 | 2 | 2 | 2 | 2 | 2 | 236.707 | 221.42 | 72.36 | 65.32 |
| 6 | 1 | 2 | 2 | 2 | 3 | 3 | 240.183 | 219.64 | 68.54 | 67.32 |
| 7 | 1 | 3 | 3 | 3 | 1 | 1 | 232.56 | 220.35 | 67.52 | 56.28 |
| 8 | 1 | 3 | 3 | 3 | 2 | 2 | 233.56 | 221.63 | 64.32 | 63.17 |
| 9 | 1 | 3 | 3 | 3 | 3 | 3 | 236.89 | 214.48 | 66.32 | 68.32 |
| 10 | 2 | 1 | 2 | 3 | 1 | 2 | 233.425 | 224.65 | 65.17 | 58.25 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 11 | 2 | 1 | 2 | 3 | 2 | 3 | 231.768 | 228.6 | 72.1 | 54.36 |
| 12 | 2 | 1 | 2 | 3 | 3 | 1 | 239.752 | 227.63 | 77.2 | 59.37 |
| 13 | 2 | 2 | 3 | 1 | 1 | 2 | 242.802 | 223.65 | 68.4 | 70.25 |
| 14 | 2 | 2 | 3 | 1 | 2 | 3 | 238.781 | 213.56 | 76.76 | 69.89 |
| 15 | 2 | 2 | 3 | 1 | 3 | 1 | 248.404 | 216.58 | 82.36 | 73.65 |
| 16 | 2 | 3 | 1 | 2 | 1 | 2 | 242.852 | 217.56 | 83.65 | 68.32 |
| 17 | 2 | 3 | 1 | 2 | 2 | 3 | 236.738 | 215.63 | 81.71 | 66.32 |
| 18 | 2 | 3 | 1 | 2 | 3 | 1 | 239.701 | 235.6 | 79.9 | 54.53 |
| 19 | 3 | 1 | 3 | 2 | 1 | 3 | 258.221 | 209.36 | 64.55 | 57.24 |
| 20 | 3 | 1 | 3 | 2 | 2 | 1 | 250.263 | 214.57 | 66.7 | 58.63 |
| 21 | 3 | 1 | 3 | 2 | 3 | 2 | 248.301 | 212.37 | 67.5 | 59.63 |
| 22 | 3 | 2 | 1 | 3 | 1 | 3 | 256.43 | 220.36 | 64.17 | 63.24 |
| 23 | 3 | 2 | 1 | 3 | 2 | 1 | 249.602 | 231.32 | 67.3 | 60.32 |
| 24 | 3 | 2 | 1 | 3 | 3 | 2 | 249.852 | 219.36 | 68.4 | 68.36 |
| 25 | 3 | 3 | 2 | 1 | 1 | 3 | 253.93 | 221.58 | 65.36 | 65.54 |
| 26 | 3 | 3 | 2 | 1 | 2 | 1 | 240.796 | 228.69 | 65.17 | 68.32 |
| 27 | 3 | 3 | 2 | 1 | 3 | 2 | 251.36 | 219.3 | 68.18 | 62.32 |

**2.2 Mechanical Test on Samples**

**2.2.1 Tensile Test**

The tensile test was performed on cylindrical samples fabricated as per ASTM E8/E8M measurements. The test was performed on the universal testing machine for 27 pieces, and the values were recorded. The test was conducted at normal room conductions shown in figure 1.

Figure 1 Tensile Tested samples

**2.2.2 Microhardness Test**

The Vickers Microhardness test was conducted on prepared samples as per ASTM E384 standards. Three values were taken at different places on each piece, with a 5 Kg load and 15 s dwell time, and the average value was taken.

**2.2.3 Impact Test**

The impact test was conducted on impact testing machine and the samples were prepared as per ASTM E23 standards. Shown in figure 2.

### 2.2.4 Compressive Strength

The specimens was prepared as per ASTM E9 standards and tested under computerized universal testing machine (UTM). Shown in figure 3.

Figure 3. Compression test Samples

## 3. Results and Discussions

The results of tensile strength, and microhardness test, were obtained from experimentation; these are considered inputs for the multi-response optimization method for the GRA method. The data attained experimentally are normalized as per GRA theory. The normalized values are taken and applied to the grey-fuzzy method and procedure shown in figure 4.

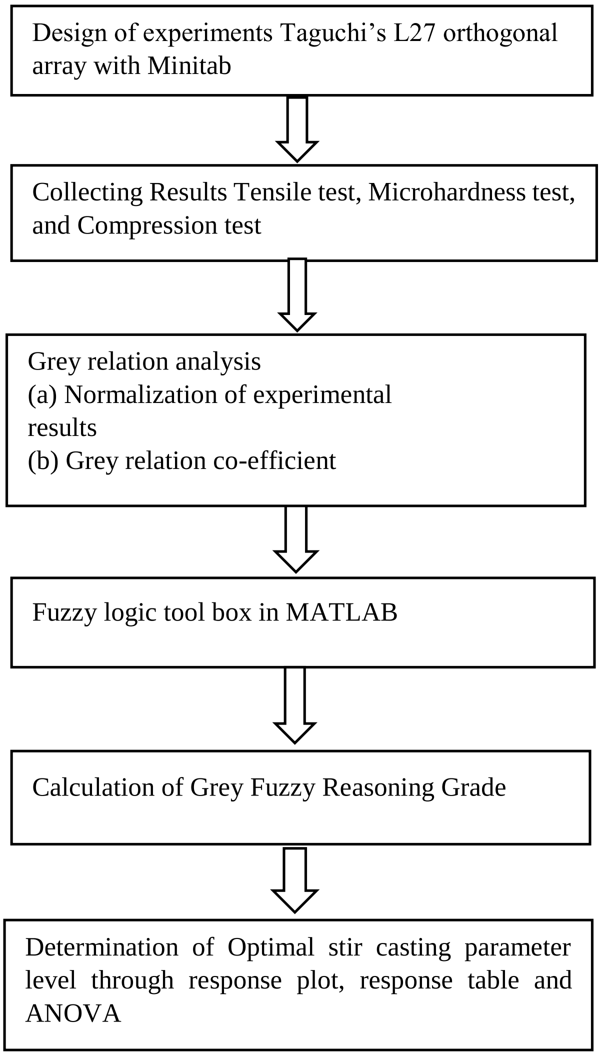



Figure 4. Workflow in the grey fuzzy method

### 3.1 The GRA has various steps for solving the multi-performances

Step 1: Normalization In this step, the output parameters tensile strength, microhardness, impact and Compression test was normalized first from range zero to one, and it is called Grey relation generation. These three methods for normalization, Larger-the-better, smaller-the-better, and nominal-the-better. In this work, the larger is better for mechanical properties, so consider the larger-the-better in Table 3. Equation no 1 is used for normalized.

$Y_i^*$(j) = $\frac{Y_i\text{(j)} - \min Y_i\text{(j)}}{\max X_i\text{(j)} - \min X_i\text{(j)}}$ (i)

Consider the lower-the-better characteristic of normalization equation no 2.

$Y_i^*$(j) = $\frac{\max Y_i\text{(j)} - Y\text{(j)}}{\max Y_i\text{(j)} - \min Y_i\text{(j)}}$ (ii) where $Y_i$ (j) is the value after the grey relational generation, max $Y_i$ (j) is the most significant value of $Y_i$ (j) , min$Y_i$ (j) is the smallest value of $Y_i$ (j), and $Y$ is the desired value.

Step 2 Calculation of the Grey relation coefficients and grey relation grade in this step, **GRC** expresses the relationship between the ideal (best) values and actual normalized values for all the combinations. GRC can be calculated using the following equation no 3.

$\xi_i$(j)=$\frac{\Delta\min+\zeta\Delta\max}{\Delta i(j)+\zeta\Delta\max}$ (iii) where ζ (ε 0,1)=distinguished coefficient, ζ =0.5 is generally used. $\xi_i$(j) is grey relational coefficient, $\Delta_{min}$ is the smallest value of $\Delta_{oi}$(j), $\Delta_{max}$ is the largest value of $\Delta_{oi}$(j), $\Delta_{oi}$(j) is the deviation sequence of the reference sequence $Y_i^*$(j), and the comparability sequence $X_i^*$(j),

$\Delta_{oi}$(k) = $|Y_i^*(j) - Y_i(j)|$ (iv)

$\Delta_{max}$ = max max$|Y_o^*(j) - Y_n^*(j)|$ (v)

∀jei ∀k

$\Delta_{min}$ = minx min$|Y_o^*(j) - Y_n^*(j)|$ (vi)

∀jei ∀j

The grey relation coefficient is obtained, and the grey relation grade is to be calculated by following equation (7)

$\gamma_i = \frac{1}{n} \sum_{n=1}^{n} \xi i(j)$ (vii)

Where $\gamma_i$ is the grey relation grade for the *i*th experiment and n is the number of performance characteristics.

Table 3. Normalization table of GRC and GRFC

| S.No | Normalizing | | | | GRC | | | | GRFC | Rank |
|---|---|---|---|---|---|---|---|---|---|---|
| | Tensile Test | Compression | Hardness | Impact | Tensile Test | Compression | Hardness | Impact | | |
| 1 | 0.4914 | 0.9695 | 0.2134 | 0.0800 | 0.4957 | 0.9425 | 0.3886 | 0.3521 | 0.5448 | 4 |
| 2 | 0.0347 | 0.7820 | 0.2957 | 0.1308 | 0.3412 | 0.6964 | 0.4152 | 0.3652 | 0.4545 | 17 |
| 3 | 0.0000 | 0.7119 | 0.0000 | 0.0000 | 0.3333 | 0.6344 | 0.3333 | 0.3333 | 0.4086 | 24 |
| 4 | 0.1206 | 0.8979 | 0.2957 | 0.1948 | 0.3625 | 0.8304 | 0.4152 | 0.3831 | 0.4978 | 12 |
| 5 | 0.1991 | 0.4596 | 0.4436 | 0.4384 | 0.3843 | 0.4806 | 0.4733 | 0.4710 | 0.4523 | 18 |
| 6 | 0.3285 | 0.3918 | 0.2553 | 0.5184 | 0.4268 | 0.4512 | 0.4017 | 0.5094 | 0.4473 | 20 |
| 7 | 0.0447 | 0.4188 | 0.2050 | 0.0767 | 0.3436 | 0.4625 | 0.3861 | 0.3513 | 0.3859 | 27 |
| 8 | 0.0819 | 0.4676 | 0.0473 | 0.3524 | 0.3526 | 0.4843 | 0.3442 | 0.4357 | 0.4042 | 26 |
| 9 | 0.2059 | 0.1951 | 0.1459 | 0.5584 | 0.3864 | 0.3832 | 0.3692 | 0.5310 | 0.4174 | 23 |
| 10 | 0.0769 | 0.5827 | 0.0892 | 0.1556 | 0.3513 | 0.5451 | 0.3544 | 0.3719 | 0.4057 | 25 |
| 11 | 0.0152 | 0.7332 | 0.4308 | 0.0000 | 0.3367 | 0.6521 | 0.4676 | 0.3333 | 0.4474 | 19 |
| 12 | 0.3124 | 0.6963 | 0.6821 | 0.2004 | 0.4210 | 0.6221 | 0.6113 | 0.3847 | 0.5098 | 10 |
| 13 | 0.4260 | 0.5446 | 0.2484 | 0.6356 | 0.4655 | 0.5233 | 0.3995 | 0.5784 | 0.4917 | 14 |
| 14 | 0.2763 | 0.1601 | 0.6604 | 0.6212 | 0.4086 | 0.3732 | 0.5955 | 0.5690 | 0.4866 | 15 |
| 15 | 0.6345 | 0.2752 | 0.9364 | 0.7716 | 0.5777 | 0.4082 | 0.8872 | 0.6864 | 0.6399 | 1 |
| 16 | 0.4278 | 0.3125 | 1.0000 | 0.5584 | 0.4663 | 0.4211 | 1.0000 | 0.5310 | 0.6046 | 3 |
| 17 | 0.2002 | 0.2389 | 0.9044 | 0.4784 | 0.3847 | 0.3965 | 0.8395 | 0.4894 | 0.5275 | 7 |
| 18 | 0.3105 | 1.0000 | 0.8152 | 0.0068 | 0.4204 | 1.0000 | 0.7301 | 0.3349 | 0.6213 | 2 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 19 | 1.0000 | 0.0000 | 0.0586 | 0.1152 | 1.0000 | 0.3333 | 0.3469 | 0.3611 | 0.5103 | 9 |
| 20 | 0.7037 | 0.1986 | 0.1646 | 0.1708 | 0.6279 | 0.3842 | 0.3744 | 0.3762 | 0.4407 | 21 |
| 21 | 0.6307 | 0.1147 | 0.2040 | 0.2108 | 0.5752 | 0.3609 | 0.3858 | 0.3878 | 0.4274 | 22 |
| 22 | 0.9333 | 0.4192 | 0.0399 | 0.3552 | 0.8823 | 0.4626 | 0.3424 | 0.4368 | 0.5310 | 6 |
| 23 | 0.6791 | 0.8369 | 0.1942 | 0.2384 | 0.6091 | 0.7540 | 0.3829 | 0.3963 | 0.5356 | 5 |
| 24 | 0.6884 | 0.3811 | 0.2484 | 0.5600 | 0.6161 | 0.4469 | 0.3995 | 0.5319 | 0.4986 | 11 |
| 25 | 0.8403 | 0.4657 | 0.0986 | 0.4472 | 0.7579 | 0.4834 | 0.3568 | 0.4749 | 0.5182 | 8 |
| 26 | 0.3513 | 0.7367 | 0.0892 | 0.5584 | 0.4353 | 0.6550 | 0.3544 | 0.5310 | 0.4939 | 13 |
| 27 | 0.7446 | 0.3788 | 0.2376 | 0.3184 | 0.6619 | 0.4460 | 0.3961 | 0.4232 | 0.4818 | 16 |

### 3.2 Fuzzy Logic Method

Fuzzy logic works on deciding the output based on assumptions and input set represents. A fuzzy system contains a fuzzifier, membership functions, fuzzy rule, inference engine and defuzzifier. In fuzzifier, crisp input values are converted into fuzzy values. In the present work, input parameters are GRC of tensile test, compression test, hardness test, and impact test design using Triangular membership function and output variables and GFRG using triangular membership function are used shown in figure no 5. The fuzzy inference engine undertakes fuzzy reasoning to produce the fuzzified values. A set of 27 'IF-THEN' rules are built between input and output variables are shown in figure no 6. The input and output variables are allocated to nine fuzzy subgroups very very low (VVL), very low (VL), low (L), medium low (ML), medium (M), medium high (MH), high (H), very high (VH), very very high (VVH). And rules are shown below in figure no 5, which was developed in Matlab software fuzzy logic tool.

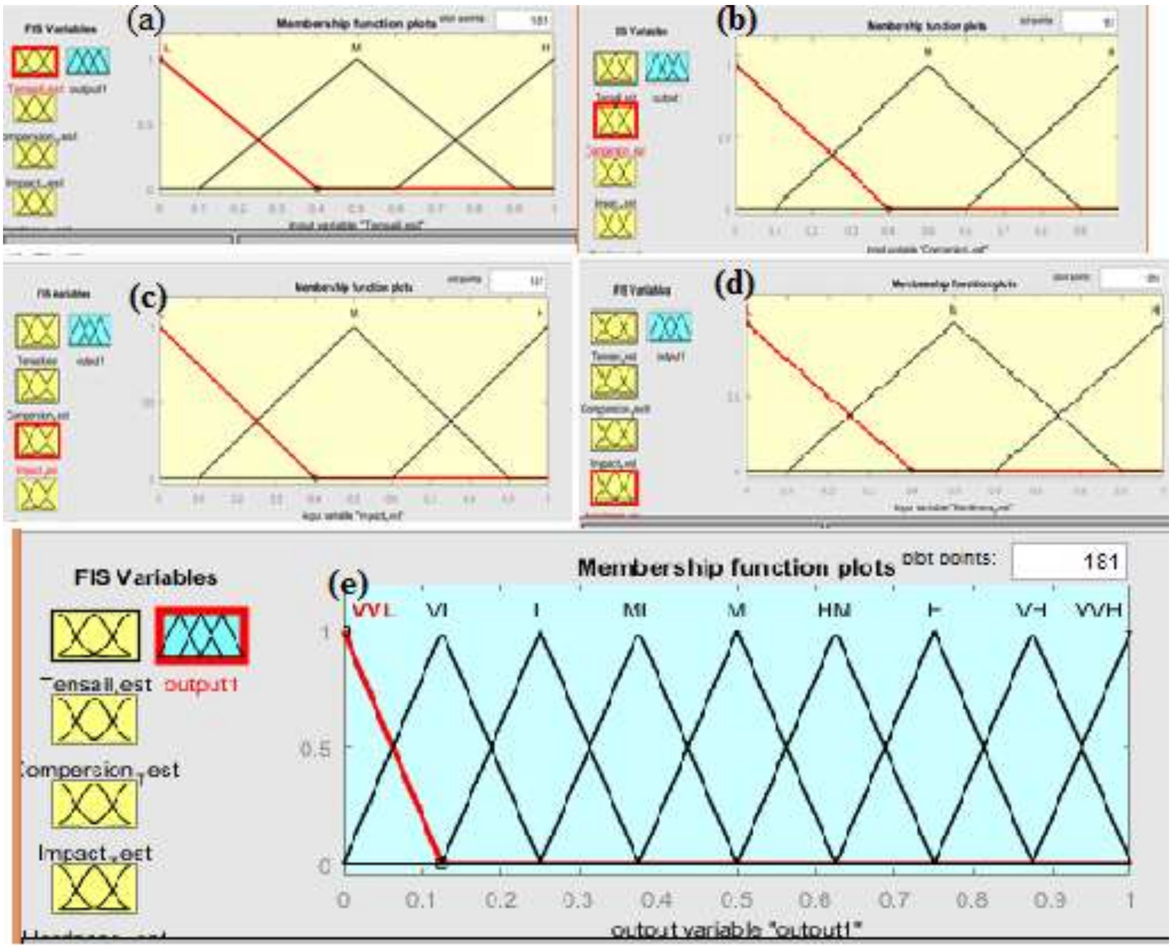



Figure 5. Input membership function of a. Tensile Test, b. Compression Test, c. Impact Test, d. Hardness Test, e. Output membership function GFRG

Rule 1: If (Tensail_test is M) and (Compersion_Test is H) and (Impact_Test is L) and (Hardness_Test is M) then (output1 is VH); else

Rule 2: 2. If (Tensail_test is L) and (Compersion_Test is H) and (Impact_Test is L) and (Hardness_Test is H) then (output1 is L); else………

Rule 27: If (Tensail_test is H) and (Compersion_Test is L) and (Impact_Test is M) and (Hardness_Test is M) then (output1 is ML) shown in figure no 7.

The defuzzification method is used to convert the fuzzy values to non-fuzzy values. In this method, a script file extinction with 'fis' was compiled in Matlab to get defuzzifier values. The program is shown in figure no 8. and finally defuzzifier converted the predicated fuzzy values to single GFRG values, and the highest GFRG gives the best performance characteristics.

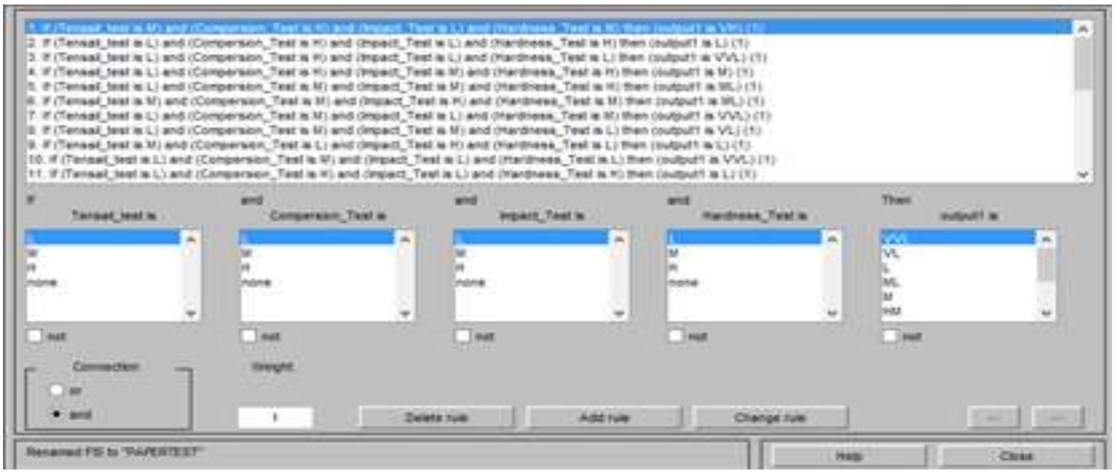


Figure 6. Fuzzy conductions

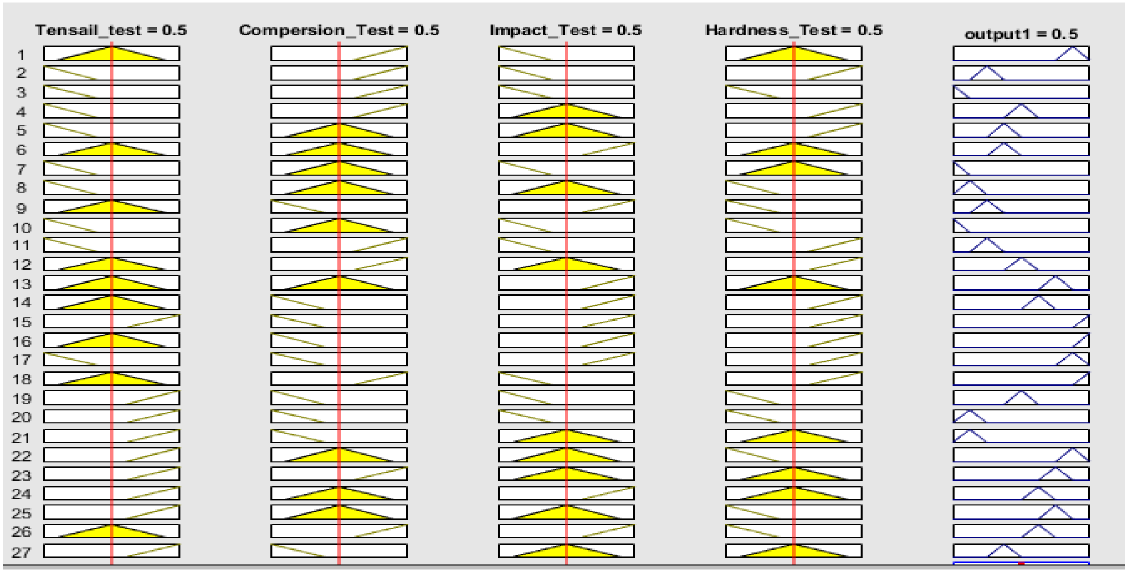
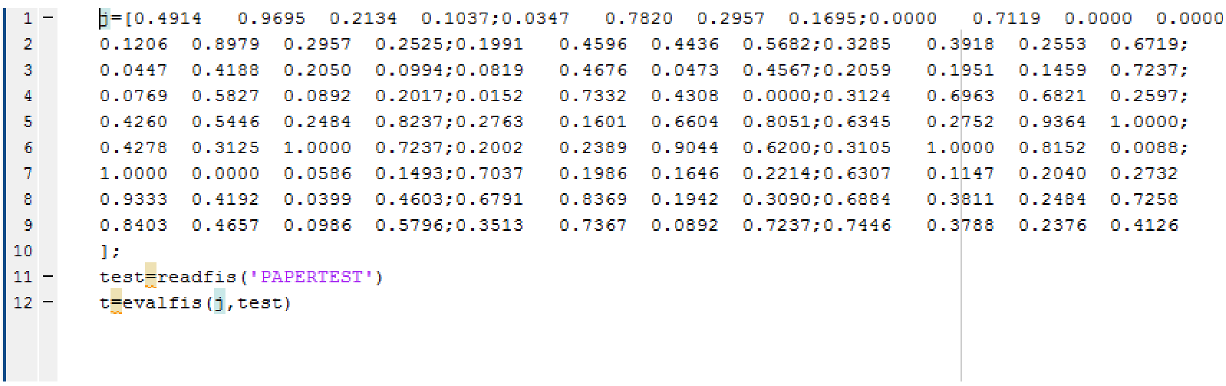



Figure 7. Fuzzy logic rules



```
j=[0.4914   0.9695  0.2134  0.1037;0.0347   0.7820  0.2957  0.1695;0.0000   0.7119  0.0000  0.0000
0.1206  0.8979  0.2957  0.2525;0.1991   0.4596  0.4436  0.5682;0.3285   0.3918  0.2553  0.6719;
0.0447  0.4188  0.2050  0.0994;0.0819   0.4676  0.0473  0.4567;0.2059   0.1951  0.1459  0.7237;
0.0769  0.5827  0.0892  0.2017;0.0152   0.7332  0.4308  0.0000;0.3124   0.6963  0.6821  0.2597;
0.4260  0.5446  0.2484  0.8237;0.2763   0.1601  0.6604  0.8051;0.6345   0.2752  0.9364  1.0000;
0.4278  0.3125  1.0000  0.7237;0.2002   0.2389  0.9044  0.6200;0.3105   1.0000  0.8152  0.0088;
1.0000  0.0000  0.0586  0.1493;0.7037   0.1986  0.1646  0.2214;0.6307   0.1147  0.2040  0.2732
0.9333  0.4192  0.0399  0.4603;0.6791   0.8369  0.1942  0.3090;0.6884   0.3811  0.2484  0.7258
0.8403  0.4657  0.0986  0.5796;0.3513   0.7367  0.0892  0.7237;0.7446   0.3788  0.2376  0.4126
];
test=readfis('PAPERTEST')
t=evalfis(j,test)
```

Figure 8. Script file in Matlab

### 3.3 Effects of GFRG analysis

The GFRG mean values are shown in table no 4, and the main effects plot for means and s/n are plotted in figure 9. From table 4 and figure 9, the optimal stirring process parameters are stirring temperature $800^0$ C, Stirring Speed 800 rpm, Stirring Time 10 min, Weight 3%, Size of Nanoparticles (50,90 nm) and Nanoparticles (TiO2+BN).

Table 4.The Response table for Gray Fuzzy Relational Grade means

| Parameter | L-1 | L-2 | L-3 | Delta(Max-Min) | Rank |
|---|---|---|---|---|---|
| Temperature(A) | 0.2715 | **0.4775** | 0.4640 | 0.2059 | 2 |
| Stirring Speed(B) | 0.3165 | **0.5021** | 0.3944 | 0.1856 | 4 |
| Stirring Time(C) | **0.4936** | 0.3389 | 0.3806 | 0.1547 | 5 |
| Weight(D) | **0.4771** | 0.4530 | 0.2829 | 0.1942 | 3 |
| Size of Nanoparticles(E) | 0.4146 | **0.4375** | 0.3609 | 0.0766 | 6 |
| Nanoparticles(F) | **0.5555** | 0.3040 | 0.3534 | 0.2515 | 1 |

### 3.4 Analysis of Variance (ANOVA)

By using ANOVA, the contribution of the individual process parameters can be determined. The confidence level GFRG of ANOVA is 67.89%, as per Taguchi ANOVA analysis, 50 % of confidence level is satisfactory. From table 5, the nanoparticles play a primary role is with a high contribution of 20.47% and followed by stirring temperature 15.34 %, weight % of nanoparticles are 12.92%, stirring speed 10.01% and stirring time and size of nanoparticle is recorded as less than 10%.

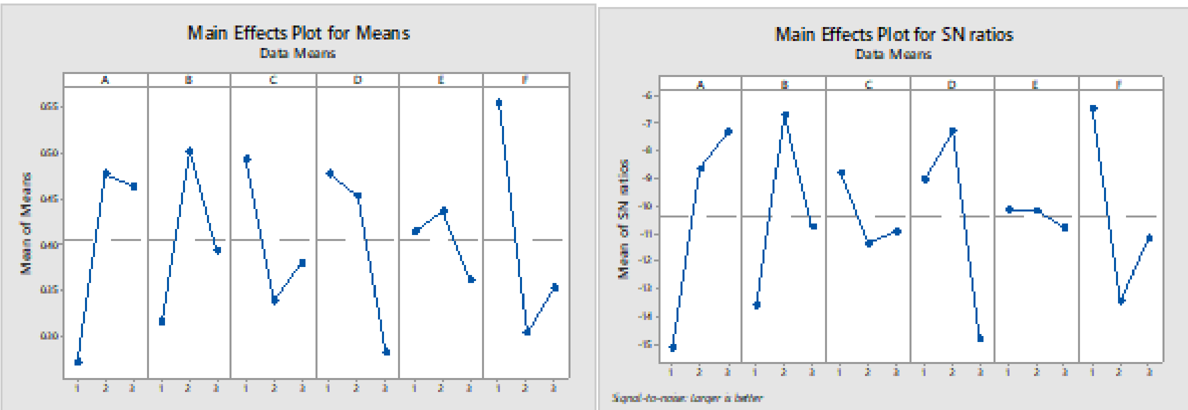



Figure 9. Main effects of GFRG means and Main efforts of S/N ratios for GFRG means.

Table 5. Analysis of Variance for Means for GFRG

| Source | DF | Seq SS | Adj SS | Adj MS | F | contribution |
|---|---|---|---|---|---|---|
| A | 2 | 0.23886 | 0.23886 | 0.11943 | 3.34 | 15.30418 |
| B | 2 | 0.15634 | 0.15634 | 0.07817 | 2.18 | 10.01698 |
| C | 2 | 0.11535 | 0.11535 | 0.05768 | 1.61 | 7.390678 |
| D | 2 | 0.20170 | 0.20170 | 0.10085 | 2.82 | 12.92327 |
| E | 2 | 0.02778 | 0.02778 | 0.01389 | 0.39 | 1.779914 |
| F | 2 | 0.31962 | 0.31962 | 0.15981 | 4.46 | 20.47862 |
| Residual Error | 14 | 0.50110 | 0.50110 | 0.03579 | | |
| Total | 26 | 1.56075 | | | | |

### 3.5 Predicting optimal value and confirmation test

The confirmation experiment was performed at these optimal process parameters levels. The experimental values of GFRG results were compared with predicted results, and the predicted GFRG is calculated using eq 8.

$\hat{\gamma} = \gamma t + \Sigma (\gamma i - \gamma)\, p \qquad i=1 \ (viii)$

Where $\gamma t$ is the total mean grey relation grade, $\gamma i$ Is the mean grey relation grade at the optimum level, and 'p' is the number of principal parameters that significantly affect the multiple performance characteristics

Table 6 Comparison between predicted and experimental results

| | | Setting level | Tensile Strength | Compressive Strength | Impact | Hardness | GRA | Improvement in GRA |
|---|---|---|---|---|---|---|---|---|
| Initial controllable parameters | | A2B2C3D1E3F1 | 248.40 | 216.58 | 73.65 | 83.2 | 0.7296 | |
| Optimal controllable parameters | Prediction | A2B2C1D1E2F1 | | | | | 0.9216 | |
| | Experiment | A2B2C1D2E2F1 | 250.36 | 231.25 | 82.36 | 79.36 | 0.8172 | 0.1044 |

**4. Conclusions**

This paper explains the grey-fuzzy logic approach to optimize the process parameters of the stir casting technique. Using Taguchi's orthogonal array, L27 experiments were performed, and conclusions were discussed.

1. The difference between the contributions of process parameters is very less; it shows that the contribution of every process parameter has a high influencing factor.

2. The confirmation test is performed, and the results are achieved better compared with all values

3. From ANOVA, statistics exposed that Nanoparticles ($TiO_2$+BN) add are the most influencing process parameter.

**5. References**


1. M. Vignesh , R. Ramanujam, G. Rajyalakshmi, and Sayantan Bhattacharya Application of Grey Theory and Fuzzy Logic to Optimize Machining Parameters of Zircon Sand Reinforced Aluminum Composites, Advances in Fluid Dynamics. Lecture Notes in Mechanical Engineering. Springer, Singapore. https://doi.org/10.1007/978-981-15-4308-1_51.

2. K. Anand Babu*, G. Vijaya Kumar and P. Venkataramaiah, Prediction of Surface Roughness in Drilling of Al 7075/10% - SiCp Composite under MQL Condition using Fuzzy Logic. Indian Journal of Science and Technology, Vol 8(12), 54074, June 2015s.

3. M.Vamsi Krishna, G.Bala Narasimha, N.Rajesh, Anthony M .Xavio, Optimization of InfluentialParameters on Mechanical behaviour of AlMg1 SiCu Hybrid Metal Matrix Composites using Taguchi integrated Fuzzy Approach, doi: 10.1016/j.matpr.2015.07.071.

4. R. Ambigai, S. Prabhu, Fuzzy logic algorithm-based Optimization of the tribological behaviour of Al-Gr-Si3N4 hybrid composite, Measurement, https://doi.org/10.1016/j.measurement.2019.07.025.

5. Logesh Kamaraj, P Hariharasakthisudhan and A Arul Marcel Moshi, Optimizing the ultrasonication effect in stir-casting process of aluminium hybrid composite using desirability function approach and artificial neural network, Journal Materials: Design and Applications, DOI: 10.1177/14644207211025706.

6. Priyaranjan Samal, Pandu R Vundavilli, Arabinda Meher and Manas M Mahapatra. Multi-response modelling for sliding wear behaviour of AA5052/TiC composites by stir casting: A comparative analysis using response surface methodology and fuzzy logic system, Journal Process Mechanical Engineering, DOI: 10.1177/09544089211037443

7. Jitendra M. Mistry and Piyush P.Gohil(2018), Experimental investigations on wear and friction the behaviour of Si3N4p reinforced heat-treated aluminium matrix composites produced using electromagnetic, Composites Part B: Engineering, https://doi.org/10.1016/j.compositesb.2018.10.074.

8. N. Ramadossa, K. Pazhanivelb and G. Anbuchezhiyanc (2020), ArticleSynthesis of B4C and BN reinforced Al7075 hybrid composites using stir casting method, Journal of Materials Research and Technology, https://doi.org/10.1016/j.jmrt.2020.03.043.

9. Kuldeep Ba, Ravikumar K.Pb, Pradeep Sc and Gopi K.Rd (2019), Effect of boron nitride and zirconium dioxide on mechanical behaviour of Al7075 metal matrix hybrid composite, Materials Research Express, https://doi.org/10.1088/2053-1591/aaf36b.

10. Swapnil V. Gosavi and M.D. Jaybhaye (2020), Microstructural studies on aluminium metal matrix composite (Al7075-SiC) fabricated through the stir casting process, MaterialsToday Proceedings, https://doi.org/10.1016/j.matpr.2020.05.094.

11. Sonagiri Suresh, G. Harinath Gowd and M. L. S. Deva Kumar (2018), Tribological Behavior of Al 7075/SiC Metal Matrix Nano-composite by Stir Casting Method, The Institution of Engineers (India), https://doi.org/10.1007/s40033-018-0167-2.

12. Himanshu Kumar and S. Shiva (2020), Experimental investigation on stir casting of a

metal matrix composite material, Journal of Micromanufacturing, DOI: 10.1177/25165984211015761.

13. Adeolu A. Adediran, Abayomi A. Akinwande, Oluwatosin A. Balogun, Bayode J. Olorunfemi and M. Saravana Kumar (2021), Optimization studies of stir casting parameters and mechanical properties of TiO2 reinforced Al 7075 composite using response surface methodology https://doi.org/10.1038/s41598-021-99168-1.

14. Tarun Kumar Gupta, Ashish Kumar Srivastava and Vishal Shankar Srivastava (2021), Microstructural and tensile behaviour of hybrid MMC Al7075/ SiC/B4C produced by mechanical stir casting, Materials Today: Proceedings, https://doi.org/10.1016/j.matpr.2021.06.430

15. Kuldeep Ba, Ravikumar K.Pb, Pradeep Sc and Gopi K.Rd (2019), Effect of boron nitride and zirconium dioxide on mechanical behaviour of Al7075 metal matrix hybrid composite, Materials Research Express, https://doi.org/10.1088/2053-1591/aaf36b.

16. Danappa G.T, Raghavendra C.R, Swamy R.P and Kishan Naik (2020), Dry sliding wear behaviour of Al7075/Gr/nano TiO2 MMC using RSM, Materials Today: Proceedings, https://doi.org/10.1016/j.matpr.2020.08.736.

17. K. Gurusami, S. Shalini, and T. Sathish (2020), Optimization of stir casting parameters for corrosion rate analysis of AA7068 – Boron carbide composites, Materials Today Proceedings https://doi.org/10.1016/ j.matpr.2020.08.302.

18. Poovalingam Muthu, Multi-objective optimization of wear behaviour of Aluminum MMCs using Grey-Taguchi method, published in Manufacturing Review in 2020, https://doi.org/10.1051/ mfreview/2020013.

19. Ashish K Srivastava, Amit Rai Dixit and Sandeep Tiwari, Investigation of microstructural and mechanical properties of metal matrix composite A359/$B_4C$ through electromagnetic stir casting. Indian Journal of Engineering & Material Sciences published in 2016. http://nopr.niscair.res.in/handle/123456789/35470.

20. M.Ravichandrana, M.Meignanamoorthy, G.P.Chellasivam, J.Vairamuthu, A.Senthil Kumar, B.Stalin, Effect of Stir Casting Parameters on Properties of Cast Metal Matrix Composite. Materials today 2606–2613, published in 2020, https://doi.org/10.1016/j.matpr.2020.03.391.

21. S. Suresh .G. Harinath Gowd .M. L. S. Deva Kumar, Mechanical Properties of AA 7075/Al2O3/SiC Nano-metal Matrix Composites by Stir-Casting Method. Journal of The Institution of Engineers (India): Series D, published in 2019. https://doi.org/10.1007/s40033-019-00178-1.

22. T. Pratheep Reddy, S. Jaya Kishore, P. Charan Theja, and P. Punna Rao, Development and wear behaviour investigation on aluminum-7075/B4C/fly ash metal matrix composites. Advanced Composites and Hybrid Materials published in 2020, https://doi.org/10.1007/s42114-020-00145-5.