Research Article

Optimization Of Wear Behaviour Of LM26-Gr Composite Using Taguchi Based Grey Relational Analysis

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Abstract: The progression in present manufacturing technology created the need of developing new materials for superior wear resistance. The objective of this paper is to optimize the three process parameters wear loss, wear rate, specific wear at three different levels with Taguchi technique in L9 Orthogonal array. A multi-response optimization technique Grey relational analysis is used to obtain the single process parameter setting for both the responses. LM26 metal matrix composite is fabricated by stir casting technique with Almandine garnet particles as reinforcement in different weight percentages with two different particle sizes. Analysis of Variance (ANOVA) was conducted to recognize the prevalent factor and found all the three factors as being critical. The above process was validated by Linear regression technique after conformation tests has been performed.

Keywords: LM26, Tribological Properties, Taguchi method, Grey Relational Analysis

I. INTRODUCTION

LM26 is an Aluminium-based alloy that is wide utilized in automotive engine applications because of their exceptional wear resistance, low coefficient of thermal expansion and its retention of strength and hardness at elevated temperatures.

The relatively poor wear resistances of Al alloys have limited their use in certain tribological applications. Aluminum Metal Matrix Composites (AMCs) have superiorproperties compared with the monolithic alloys and can be tailored to suitable specificapplications [1]. The presence of hard reinforcement phases, particulates,fibres, whiskers or flakes has endowed these composites with good Tribological characteristics. This metal alloy will structure properly as a metal matrix composite by correct reinforcements, the ensuing material will offer minimum wear rate beneath the precise loading conditions.

The priority of present work in predicting theTribological behaviour of Aluminium alloy LM26 was done by considering process parameters like Reinforcement, Sliding velocity, Load applied however moderate analysis is done for two particle sizes(250μm& 400μm) within the space of study. The present work furnishes the Taguchi based Grey Relational Analysis (GRA) to analyse the process parameters at three different levels using L9 orthogonal array.

2.PARAMETERS AND DESIGN OF EXPERIMENTS (DOE):-

We areconsidering the three process parameters for conducting the experiments by varying them for three levels. The three process parameters are Reinforcement, Sliding velocity and Load applied.

Table-1:- Control factors and their levels

Parameters	Level1	Level2	Level3
Reinforcement (%)	3	6	9
Sliding velocity (m/sec)	3	6	9
Load applies (N)	20	40	60

Design of Experiments is a systematic method to determine the relationship between factors affecting a process and the output of that process. It was used for analysing the various input parameters on a given output. DOE approach uses Taguchi technique to seek out the optimum combination of parameters for a given set of response [2].

2.1TAGUCHI'S ORTHOGONAL ARRAY

It is a sort of general fractional factorial design. It is a highly fractional orthogonal design i.e. based on a design matrix and permits you to think about a specific set of combinations of multiple factors at multiple levels. Taguchi represents an orthogonal array as $L_N(S^K)$

Where S = Number of levels for each factor

K = Maximum number of factors

N = Total number of trials during experimentation

A standard orthogonal array is based on the number of parameters and the effect of parameters on the target value. The experimental design might also determine control variables that have to be held constant to prevent external factors from affecting the results [3].

The minimum level to urge the accurate result is three. Normally, for the three factors and three variables we haveto do 3^3 = 27 experiments but we are using Taguchi orthogonal array to seek out the minimum number of experiments to be done within the possible limit of factors and levels. Here$L_9(3^3)$ orthogonal array minimises the overall experiments to nine and also gives the clear idea to process the model design by doing nine experiments. This orthogonal array was done by using Minitab 19 Software.

Table-2:- Experimental design for L9 orthogonal array

Run No	A	B	C
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

2.2 Wear properties

Wear Loss is a factor that increases with the increase of applied load.

Wear Rate is that the volume loss per unit distance and is independent of load applied [4].

Wear Rate = (wear loss) (sliding distance or time) (m^3/m)

Specific Wear is that the volume loss per unit meter per unit load and depends on applied on to cause wear [5].

Specific Wear = (wear rate)(normal force)(m^3N-m)

Experimentation work accordance to orthogonal array to find out wear rate was accomplished on pin-on disk machine.

Table3:- Wear properties of 250µm particle size samples

Table4:- Wear properties of 400µm particle size samples

S No	Wt (%)	Velocity (m/sec)	Load (N)	Wear Loss (gm)	Wear rate×10^{-3} (mm^3/m)	Specific Wear×10^{-4} (mm^3/m)
1	3	3	20	0.021	2.869	1.434
2	3	6	40	0.023	3.142	0.785
3	3	9	60	0.027	3.689	0.614
4	6	3	40	0.024	3.279	0.819
5	6	6	60	0.032	4.372	0.728
6	6	9	20	0.026	3.552	1.776
7	9	3	60	0.031	4.235	0.705
8	9	6	20	0.022	3.005	1.503
9	9	9	40	0.026	3.522	0.889

S. No	Wt (%)	Velocity (m/sec)	Load (N)	WearLoss (gm)	Wear rate×10^{-3}(mm^3/m)	Specific Wear×10^{-4}(mm^3/m)
1	3	3	20	0.031	3.770	1.885
2	3	6	40	0.035	4.256	1.064
3	3	9	60	0.037	4.502	0.749
4	6	3	40	0.03	3.566	0.891
5	6	6	60	0.036	4.280	0.713
6	6	9	20	0.034	4.042	2.021
7	9	3	60	0.033	3.872	0.645
8	9	6	20	0.031	3.637	1.819
9	9	9	40	0.032	3.755	0.938

2.3Linear Regression Technique:

Linear Regression is a statistical approach for modelling the relationship between a dependent variable and one or more independent variables. Simple Linear Regression is the process of having one independent variable whereas having more than one independent variable is called Multiple Linear Regression [6].Regression Analysis is used to estimate the coefficients for all factors in each experiment. It is based on the random process of the probability theory and focuses on the grouped values of the random variables [7].

2.3.1Regression Analysis: Wear loss versus Reinforcement (A), Velocity (B) and Load (C)

Regression Equation:- Wear loss = 0.0292 - 0.001167A + 0.001510B + 0.00166C

Table5:- Analysis of Variance for 250µm Samples

Source	DOF	SS	MS	F-value	P-value
Regression	3	0.000038	0.000013	6.93	0.031
A	1	0.000008	0.000008	4.43	0.089
B	1	0.000014	0.000014	7.32	0.043
C	1	0.000017	0.000017	9.04	0.030
Total	5	0.000009	0.000002		
Error	8	0.000048			

2.3.2Regression Analysis: Wear loss versus Reinforcement (A), Velocity (B) and Load (C)

Regression Equation:- Wear loss = 0.01511 + 0.000444A + 0.000167B + 0.000175C

Table6:- Analysis of Variance for 400µm Samples

Source	DOF	SS	MS	F-value	P-value
Regression	3	0.000086	0.000029	4.78	0.063
A	1	0.000011	0.000011	1.78	0.239
B	1	0.000001	0.000001	0.25	0.638
C	1	0.000073	0.000073	12.30	0.017
Total	5	0.000030	0.000006		
Error	8	0.000116			

2.3.3Regression Analysis: Wear Rate versus Reinforcement (A), Velocity (B) and Load (C)

Regression Equation:- Wear Rate = 3.620 - 0.2104A + 0.1818B + 0.2008C

Table7:- Analysis of Variance for 250µm Samples

Source	DOF	SS	MS	F-value	P-value
Regression	3	0.7067	0.23556	9.12	0.018
A	1	0.2663	0.26628	10.31	0.024
B	1	0.1984	0.19838	7.68	0.039
C	1	0.2420	0.24200	9.37	0.028
Total	5	0.1291	0.02582		
Error	8	0.8358			

2.3.4Regression Analysis: Wear Rate versus Reinforcement (A), Velocity (B) and Load (C)

Regression Equation:- Wear Rate = 2.081 + 0.0590A + 0.0211B + 0.02392C

Table8:- Analysis of Variance for 400µm Samples

Source	DOF	SS	MS	F-value	P-value
Regression	3	1.58486	0.52829	4.62	0.066
A	1	0.18797	0.18797	1.64	0.256
B	1	0.02407	0.02407	0.21	0.666
C	1	1.37282	1.37282	12.00	0.018
Total	5	0.57183	0.11437		
Error	8	2.15668			

2.3.5 Regression Analysis: Specific Wear versus Reinforcement (A), Velocity (B) and Load (C)

Regression Equation:- Specific Wear = 2.401 - 0.0493A + 0.0478B - 0.6030C

Table9:- Analysis of Variance for 250µm Samples

Source	DOF	SS	MS	F-value	P-value
Regression	3	2.20998	0.73666	14.91	0.006
A	1	0.01460	0.01460	0.30	0.610
B	1	2.18165	0.01373	0.28	0.621
C	1	0.24703	2.18165	44.16	0.001
Total	5	2.45702	0.04941		
Error	8	1.57824			

2.3.6 Regression Analysis: Specific Wear versus Reinforcement (A), Velocity (B) and Load (C)

Regression Equation:- Specific Wear = 1.722 + 0.0147A + 0.0178B - 0.02222C

Table10:- Analysis of Variance for 400μm Samples

Source	DOF	SS	MS	F-value	P-value
Regression	3	1.21338	0.40446	9.01	0.018
A	1	0.01162	0.01162	0.26	0.633
B	1	0.01717	0.01717	0.38	0.563
C	1	1.18459	1.18459	26.40	0.004
Total	5	0.22436	0.04487		
Error	8	1.43774			

From the given parameters and levels, the experimental results of output responses using Taguchi's orthogonal array is given as 0.03 of wear loss, 4.502 of wear rate , 2.021 of specific wear for 250μm samples and 0.021of wear loss, 4.372 of wear rate, 1.776 of specific wear for 400μmsamples. These values show the decrease in wear rate by increasing the wt % of reinforcements from 3% to 6%. The reinforcements of 3%, 6% and the load applied of 60N had a huge impact on the Wear rate[8].

After Taguchi's experiments, we have done Regression Analysis using Analysis of Variance (ANOVA) for the wear parameters and observed that this technique has a drawback for finding the optimal combination for the output responses[9]. The experimental values are nearly same as in the regression analysis and therefore the values don't seem to be as correct as GRA values.

Therefore we tend to approached Grey Relational Analysis for finding the best combination for the output responses.

3. GREY RELATIONAL ANALYSIS

Grey Relational Analysis was proposed by Deng in 1989 is widely used for measuring the degree of relationship between sequences by Grey Relational Grade [10]. Grey Relational Analysis is applied by the researchers to optimize control parameters having multi-responses through Grey Relational Grade [11].The use of Taguchi method with Grey Relational Analysis includes following steps.

1. Identify the method parameters to be evaluated.
2. Number of levels for the process parameters is to be determined.
3. Choose and assign the parameters to the relevant orthogonal array.
4. Perform the experiments based on the arrangement of the orthogonal array.
5. Normalize the experimental results of wear loss, wear rate and specific wear.
6. Evaluate the grey relational coefficients and grey relational grades by averaging the coefficients.
7. Analyse the experimental results using the grey relational grade.

3.1 Data Pre-Processing:-

Data Pre-Processing is the initial stage for Grey Relational Analysis performed to formalize the random grey data with various measurement units to change them to dimensionless parameters. Thus, the data pre-processing converts the original sequences to a set of comparable sequences. Different approaches may be enforced to pre-process grey data relying upon the quality characteristics of the original data. The original reference sequence and pre-processed data (comparability sequence) are represented by $x_o^{(o)}(k)$ and $x_i^{(o)}(k)$, i=1,2….m; k=1,2…n respectively, where m is the number of experiments n is the total number of observations of data.The three main categories are employed for normalizing the original sequence depending upon the quality characteristics are identified as follows:

If the original data has quality characteristic as 'larger-the-better' then the original data is pre-processed as 'larger-the-better':

$$x_i^*(k) = \frac{x_i^{(o)}(k) - \min x_i^{(o)}(k)}{\text{Max} x_i^{(O)}(k) - \min x_i^{(O)}(k)} \quad (1)$$

If the original data has quality characteristic as 'smaller-the better' then the original data is pre-processed as 'smaller-the-better'.

$$x_i^*(k) = \frac{\text{Max } x_i^{(O)}(k) - x_i^{(O)}(k)}{\text{Max } x_i^{(O)}(k) - \min\ x_i^{(O)}(k)} \quad (2)$$

However, if the original data has a target optimum value (OV) then quality characteristic is 'nominal-the-best' and the original data is pre-processed as 'nominal-the-best'

$$x_i^*(k) = \frac{|x_i^{(O)}(k) - OV|}{\max\{\max x_i^{(O)}(k) - OV, OV - \min\ x_i^{(O)}(k)\}} \quad (3)$$

Also, the original sequence is normalised by a simple method in which all the values of the sequence are divided by the first value of the sequence.

$$x_i^*(k) = \frac{x_i^{(o)}(k)}{x_i^{(o)}(1)} \quad (4)$$

Where max $x_i^{(O)}(k)$ and min$x_i^{(O)}(k)$ are the maximum and minimum values respectively of the original sequence $x_i^{(o)}(k)$. Comparable sequence $x_i^*(k)$ is the normalized sequence of original data.

3.2 Grey relational Grade:-

Next step is that the calculation of deviation sequence, Δoi(k) from the reference sequence of the pre-processed data $x_o^*(k)$ and the comparability sequence $x_i^*(k)$. The Grey Relational Coefficient is formulated from the deviation sequence using the following relation

$$\gamma(x_o^*(k),x_i^*(k)) = \frac{\Delta min+\varepsilon\,\Delta max}{\Delta oi(k)+\varepsilon\,\Delta max} \quad 0< \gamma(x_o^*(k),x_i^*(k)) \leq 1 \quad (5)$$

where Δoi(k) is the deviation sequence of the reference sequence $x_o^*(k)$ and the comparability sequence $x_i^*(k)$.

$\Delta oi(k) = |x_o^*(k) - x_i^*(k)|$

$$\Delta max = \max |x_o^*(k) - x_i^*(k)|; \qquad \Delta min = \min |x_o^*(k) - x_i^*(k)|$$

ε is the distinguishing coefficient ε ε [0,1]. The distinguishing coefficient (ε) value is chosen to be 0.5. A grey relational grade is the weighted average of the grey relational coefficient and is defined as follows:

$$\gamma(x_o^*,x_i^*) = \sum_{k=1}^{n} \beta k\gamma(x_o^*(k),x_i^*(k)), \sum_{k=1}^{n} \beta k = 1 \quad (6)$$

The grey relational grade $\gamma(x_o^*,x_i^*)$ represents the degree of correlation between the reference and comparability sequences. If two sequences are same, then grey relational grade value equals to one[12]. The grey relational grade implies that the degree of influence related between the comparability and reference sequences. In case, if a comparability sequence has a lot of influence on the reference sequence than the other ones, the grey relational grade for comparability and reference sequence will exceed that for the other grey relational grades[13].

4. EXPERIMENTAL DETAILS AND RESULTS

Experiments have been carried out on pin-on-disc apparatus and the work piece material used was LM26 Aluminium Cast alloy. Specimens of size 8mm diameter and 30mm length were cut from the cast samples. The pin is held pressed during the test against a rotating EN32 steel disc. The Chemical composition of Aluminium Cast Alloy LM26 is shown in table 10 whereas the mechanical properties are shown in the table 11 respectively were shown in fig1. Before the test, the outside of the pin tests was cleaned utilizing emery paper to ensure a complete contact of the level surface with steel circle. The pins and wear track were purified with $(CH_3)_2CO$ and Gauged (to exactness of 0.0001g utilizing microbalance) before and after each test. The pin is put in the throw and is held against a turning circle (EN31 steel plate) with track distance across of 60 mm. The load is applied on the samples through a fixed slidingdistance and speed. At that point the pins were taken out from the holder, scrubbed with $(CH_3)_2CO$, dried and weighed to discover the weight reduction because of wear[14].Machine as demonstrated in Fig. 1

Fig. 1: Pin on disc machine

Table-10:- Chemical composition of LM26

Al	Cu	Si	Fe	Mg	Mn	Zn	Ti	Ni
84.6	2.0	8.5	1.2	0.5	0.5	1.0	0.2	1.0

Table-11:- Mechanical properties of LM26

Property	Value
Tensile stress (N/mm^2)	210
Elastic modulus ($*10^3$ N/mm^2)	71
Hardness (HRC)	65
Density (g/cm^3)	2.9
Thermal conductivity at 25°C (W/mK)	0.25
Coefficient of Thermal expansion (per °C at 20-100°C)	0.000021

In full factorial design, the number of experimental runs exponentially increases with increase in the number of factors as well as their levels. This results in huge experimentation cost and considerable time period[15]. To search for the optimal process, Taguchi's L9 orthogonal array is used for conducting experiments. This data is used for the analysis and evaluation of the optimal parameter combination.

Table12:- Orthogonal array $L_9(3^3)$ of the experimental runs and results250μm Samples

Parameter Level				Experimental Level		
Run no	Reinforcement (%)	Velocity (m/sec)	Load applied (N)	Wear Loss (gm)	Wear rate$\times10^{-3}$ (mm^3/m)	Specific Wear$\times10^{-4}$ (mm^3/m)
1	3	3	20	0.031	3.770	1.885
2	3	6	40	0.035	4.256	1.064
3	3	9	60	0.037	4.502	0.749
4	6	3	40	0.03	3.566	0.891
5	6	6	60	0.036	4.230	0.713
6	6	9	20	0.034	4.042	2.021
7	9	3	60	0.033	3.872	0.645
8	9	6	20	0.031	3.637	1.819
9	9	9	40	0.032	3.755	0.938

The response variables measured were wear loss, wear rate and specific wear.

Table13:- Orthogonal array $L_9(3^3)$ of the experimental runs and results400μm Samples

Parameter Level				Experimental Level		
S No	Reinforcement (%)	Velocity (m/sec)	Load applied (N)	Wear Loss (gm)	Wear rate$\times10^{-3}$ (mm^3/m)	Specific Wear$\times10^{-4}$ (mm^3/m)
1	3	3	20	0.021	2.869	1.434
2	3	6	40	0.023	3.142	0.785
3	3	9	60	0.027	3.689	0.614
4	6	3	40	0.024	3.279	0.819
5	6	6	60	0.032	4.372	0.728
6	6	9	20	0.026	3.552	1.776
7	9	3	60	0.031	4.235	0.705
8	9	6	20	0.022	3.005	1.503
9	9	9	40	0.026	3.522	0.889

5.ANALYSIS OF RESULTS

5.1 Best Experimental Run:-

The experimental results for wear loss, wear rate and specific wear are given in the table6. Smaller values of wear loss, specific wear and larger values of wear rate are desirable. Thus the data sequences have the 'smaller-the-better' characteristic, the 'smaller-the-better' methodology i.e. equation 2 is employed for data processing[16]. The values of the WL, WR and SW are set to be the reference sequence $x_o^{(o)}(k)$, k=1-3. Moreover the results of nine experiments were the comparability sequence $x_i^{(o)}(k)$, i=1,2….9; k=1-3. The below table listed all of the sequences after implementing the data pre-processing using equation (2). The reference and the comparability sequences were denoted as $x_o^*(k)$ and $x_i^*(k)$ respectively.

Table-14:- Data Pre-Processing Results

Run No	Wear loss 1.000	Wear rate 1.000	Specific wear 1.000
1	0.857	0.218	0.099
2	0.286	0.737	0.695
3	0.000	1.000	0.924
4	1.000	0.000	0.821
5	0.1429	0.763	0.951
6	0.426	0.509	0.000
7	0.571	0.327	1.000
8	0.857	0.076	0.147
9	0.714	0.202	0.787

Table-15:- Data Pre-Processing Results

Run No	Wear loss 1.000	Wear rate 1.000	Specific wear 1.000
1	1.000	0.000	0.294
2	0.818	0.182	0.853
3	0.455	0.546	1.000
4	0.727	0.273	0.824
5	0.000	1.000	0.902
6	0.545	0.454	0.000
7	0.091	0.909	0.922
8	0.909	0.091	0.235
9	0.545	0.454	0.763

Also, the deviation sequence Δ_{oi}, Δ_{oi}max (k) and Δ_{oi}min(k) for I = 1-9, k=1-3 can be calculated. The deviation sequences $\Delta_{01}(1)$ using equation (6) can be calculated as follows:

$$\Delta_{01}(1) = |x_0^*(1) - x_1^*(1)| = |1.00-0.857| = 0.143$$

The distinguishing coefficient can be placed for the Grey relational coefficient in equation (5). If all the process parameters have same weighting, then it is set to be 0.5. The grey relational coefficients and grey relational grades for all nine comparability sequences are listed below.

Table16:- Calculated Grey Relational Coefficient and Grey Relational Grade

Orthogonal array $L_9(3^3)$				Grey Relational Coefficients				
Exp run	Reinforcement	Velocity	load	Wear loss	Wear rate	Specific wear	Grey relational Grade	Grey Order
1	1	1	1	0.778	0.389	0.977	0.715	2
2	1	2	2	0.412	0.655	0.621	0.563	8
3	1	3	3	0.333	1.000	0.867	0.733	1
4	2	1	2	1.000	0.333	0.737	0.690	3
5	2	2	3	0.368	0.678	0.910	0.652	5
6	2	3	1	0.467	0.504	0.333	0.435	9
7	3	1	3	0.538	0.426	1.000	0.655	4
8	3	2	1	0.778	0.674	0.369	0.607	6
9	3	3	2	0.636	0.385	0.701	0.574	7

Table17:- Calculated Grey Relational Coefficient and Grey Relational Grade

Orthogonal array $L_9(3^3)$				Grey Relational Coefficients				
Exp run	Reinforcement	Velocity	load	Wear loss	Wear rate	Specific wear	Grey relational Grade	Grey Order
1	1	1	1	1.000	0.333	0.415	0.569	3
2	1	2	2	0.733	0.379	0.773	0.382	6
3	1	3	3	0.478	0.524	1.000	0.333	9
4	2	1	2	0.647	0.408	0.739	0.392	5
5	2	2	3	0.333	1.000	0.836	0.366	7
6	2	3	1	0.524	0.478	0.333	0.667	1
7	3	1	3	0.355	0.846	0.865	0.359	8
8	3	2	1	0.846	0.355	0.395	0.588	2
9	3	3	2	0.524	0.478	0.678	0.413	4

This investigation employs the response table of the Taguchi method to calculate the average grey relational grades foreach factor level given within the above table. Since the grey relational grades represents the connection between the reference and the comparability sequences[17]. The larger grey relational grade means the comparability sequence showing a high degree correlation with the reference sequence.

Table18:- Response Table for grey relational grade250μm Samples

Levels	Reinforcement (A)	Velocity (B)	Load (C)
1	0.6703	0.6866	0.647
2	0.5923	0.6073	0.551
3	0.612	0.5806	0.6766

Average of Grey relational Grade= 0.625

The responses of A_1, B_1 and C_3 show the absolute best value of Grey Relational Grades for the factors A, B and C respectively. Therefore $A_1B_1C_3$ with a reinforcement of 3%, sliding velocity of 3m/s and the load applied of 60N is the best optimum parameter combination [10].

Table19:- Response Table for grey relational grade400μm Samples

Levels	Reinforcement (A)	Velocity (B)	Load (C)
1	0.428	0.44	0.449
2	0.475	0.445	0.469
3	0.453	0.471	0.438

Average of Grey relational Grade= 0.452

The responses of A_2, B_3 and C_2 show the absolute best value of Grey Relational Grades for the factors A, B and C respectively. Therefore $A_2B_3C_2$ with a reinforcement of 6%, sliding velocity of 9m/s and the load applied of 40N is the best optimum parameter combination.

6. CONCLUSION

The application of Taguchi based Grey Relational Analysis to optimize the process parameters of LM26 Aluminium Cast alloy is presented in this paper work. The conclusions are:

1. The DOE considerably reduces the number of experiments to mobilize the relevant experimental data. Taguchi's orthogonal array design is obtained to get the best combination of factors and levels. From the given parameters and levels, the experimental results of output responses using Taguchi's orthogonal array is given as 0.03 of wear loss, 4.502 of wear rate , 2.021 of specific wear for 250μmsamples and 0.021of wear loss, 4.372 of wear rate, 1.776 of specific wear for 400μmsamples. These values show the decrease in wear rate by increasing the wt % of reinforcements from 3% to 6%. The reinforcements of 3%, 6% and the load applied of 60N had a huge impact on the Wear Rate.

2. Regression Analysis is done for the responses using Analysis of variance (ANOVA) with the process parameters using Minitab Software to estimate the coefficients for all factors in each experiment. But it doesn't give an optimal combination for the output responses. So we approached GRA for best solution.

3. The Highest Grey Relational Grades of 0.733 and 0.667 was obtained in the experimental run 3 and experimental run 6 as shown in the response table (table 18& 19) of the grey relational grades which gives the optimal combinations of parameters and levels for 250μmSamples and for 400μmSamples.

4. Grey Relational Analysis mainly investigates the dynamic process of the system whereas regression analysis studies the static behaviour of the system. But GRA gives the most accurate optimal combination and is superior over the other obtained results. We obtained the optimal combinations for the output responses from the response tables 4.7 & 4.8 for the Grey Relational Grades as 0.6703 for 3% wt of reinforcement, 0.6866 for 3m/s sliding velocity and 0.6766 for 60N of load applied for 250μmsamples and 0.475 for 6% wt of reinforcement, 0.471 for 9m/s sliding velocity and 0.469 for 40N of load applied for 400μmsamples.

7. REFERENCES

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