STUDY ON THE EFFECTS OF CERAMIC PARTICULATES (SIC, AL_2O_3 AND CENOSPHERE) ON SLIDING WEAR BEHAVIOUR OF ALUMINIUM MATRIX COMPOSITES USING TAGUCHI DESIGN AND NEURAL NETWORK

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Abstract

This paper investigates the sliding wear behaviour of three different composites. Three different reinforcements are under taken for this study namely SiC, Al_2O_3 and Cenosphere. Along with it percentage reinforcement is also varied from 8wt% to 16wt.%. Other factors applied normal load and sliding speed are also considered. Taguchi design of experimental technique is employed for the study of sliding wear. It is observed that SiC reinforced composites show better wear resistance than Al_2O_3 and Cenosphere reinforced composites. Regression and artificial neural network (ANN) is used to develop a model to predict the wear loss. It is observed that artificial neural network is more efficient than regression.

Keywords: *A. Metal-matrix composites (MMCs); B.Wear; C.Taguchi D. Nueral Network*

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1. INTRODUCTION

Aluminium matrix composites (AMC) have been an area of research since past decades due to its novel properties. These AMCs have better wear resistance than its base alloy. Hence these AMCs which are light in weight compared to steels and cast iron have found applications in cylinder blocks, cylinder liners, brake drum, connecting rods etc. where wear resistance is a matter of great concern [1,2]. Several attempts were made to study the wear behaviour of aluminium and AMCs [3-5]. In general, AMCs showed better wear resistance than aluminium alloys. Various soft and hard reinforcements are added to increase the wear resistance of aluminium alloys. Some reinforcement used are SiC, Al_2O_3, TiO_2, glass, WC, flyash etc [6, 7]. Many researchers have stated that the increase in the wear resistance of AMCs is attributed to the presence of hard particles [8] and the formation of mechanical mixed layer [9-12] which prevents the direct contact of the matrix alloy and the counter face.

Various factors which affect the wear rate are applied normal load, sliding speed, sliding distance, particle size etc. Various researchers have stated the influence of these factors on wear rate. Sahin [13] conducted an abrasive wear test on AMC with 5-10wt.% SiC_p content with 32-64µm reinforcement size. Factorial design of experiments was used to determine the contribution of applied normal load, sliding distance and abrasive size. It was concluded that wear rate of the composites increased with increasing abrasive size, applied normal load and sliding distance when SiC emery paper was used. When Al_2O_3 emery paper was used the wear rate increased with increasing abrasive size and applied normal load but decreased with increasing sliding distance. Mondal et al. [14] studied the two body abrasive wear behaviour of AMC with 10wt.% Al_2O_3 at different loads(1N-7N) and abrasive sizes (30-80 µm). They concluded that the dominating factor was applied normal load controlling the wear behaviour of composite. Basavarajapa et al. [15] studied the dry sliding wear behaviour of AMC reinforced with SiC and graphite particles using Taguchi technique. The wear parameters chosen for the experiment were sliding speed, applied normal load and sliding distance. They concluded that sliding distance and applied normal load are major factors determining wear. In the above studies either factorial design or Taguchi design was used. The number of test runs needed for a full factorial design increases exponentially that consumes much time and cost. Fractional design can substantially reduce the time needed to investigate the wear behaviour of composites. Taguchi design of experiments simplifies the fractional factorial design by the use of orthogonal array. Hence Taguchi method provides an efficient and systematic approach to optimize designs for quality cost and performance. For this reason Taguchi method has been used for wide range of industrial applications globally[16,17].

For the prediction of wear many models based on statistical regression techniques have been developed. The use of artificial neural network represents a new methodology apart from statistical regression technique. ANN was used extensively by many researchers to predict the mechanical, tribological and physical properties of metal matrix composites[18,19]. Altinkok and Koker [20] predicted the tensile strength and density of AMCs reinforced with SiC and Al_2O_3. The results shows that the properties of AMCs have been predicted with an acceptable accuracy by the use of neural network. Ganesan et al. [21] have demonstrated the application of neural network for obtaining the processing map for AMCs reinforced with 15 vol.% SiC in hot working process. The performance of neural network was found to be satisfactory as the flow stress were predicted with an accuracy of ±8%. Genel et al. [22] confirmed that the prediction through neural network could be feasible as there was a good correlation with experimental results. The degree of accuracy of prediction of specific wear rate and coefficient of friction were 94.2% and 99.4% respectively. In view of the above discussion it can be concluded that ANN is an excellent tool which could save considerably cost and time.

In this study, an attempt has been made to investigate the effects of different reinforcements (SiC, Al_2O_3 and Cenosphere), percentage reinforcement, applied normal load and sliding speed on the dry sliding wear behaviour of different composites using Taguchi design of experimental technique. The analysis of variance was employed to find out the percentage contribution of each factor and its interaction on dry sliding wear of composites. ANN was used to develop a model for the prediction of wear rate and was compared with regression models.

2. EXPERIMENTAL DETAILS

2.1 Experimental Method

Aluminium alloy 7075 composites with different reinforcement were fabricated using stir casting technique. In this technique the aluminium alloy was melted in the open mouth electric resistance furnace at a temperature between 800˚C- 850˚C. The mixing of the particle was attained by adding particles in the vortex formed in the melt by the help of mechanical stirrer. Stirring was done before and after mixing of particles to ensure uniform mixing throughout the melt. The particles were preheated in a muffle furnace upto 800˚C for 2hrs before adding it to the melt. After the mixing process the melt was cast into metal dies of dimensions Ø15x 150mm. The average size of reinforcement was 60 µm. Optical micrograph of 12wt.% SiC, Al_2O_3 and Cenosphere is shown in figure 1.

2.2 Sliding Wear Test

To study the dry sliding wear behaviour of aluminium alloy composites at room temperature, a pin-on-disc wear testing machine of Ducom was used. The wear tests were carried out as per ASTM G99-05 standard. The wear specimens of the composite were machined to dimensions of Ø8 x 50mm. The wear tests were carried out at applied normal load in the range of 35N to 75N in steps of 20N. The sliding speed was varied from 1.5m/s to 3m/s in the steps of 0.75m/s. The sliding distance was kept constant at 2500m. After each test the worn surfaces of the specimen were removed by facing operation to a depth of 0.5mm. The disc surface and the specimen were polished with 400,600, 800, and 1200 grit emery paper in sequence so as to expose a fresh surface for each test. This is to ensure uniformity for all test conditions. Before and after each test the specimens were weighed using an electronic balance of ±0.01mg accuracy. The wear rate was calculated in terms of volume.

3. DESIGN OF EXPERIMENT

For design of experiment Taguchi method has been employed as it is a powerful tool for design of high quality systems[23-25]. Taguchi's approach of optimum design is determined by using design of experiment principles which mainly has three phases: planning phase, designing experiments and analyzing results. Out of these planning phase is the most important phase. In this firsthand knowledge of the project is discussed and factors to be included in the study is carefully analyzed. The number of repetitions and factor levels are also decided in this phase. For conducting experiments Taguchi uses standard orthogonal arrays. The criterion for selecting an orthogonal array is that the degree of freedom of orthogonal array should be equal to or more than the sum of the degree of freedoms of factors and their interactions considered [26-28].

For this study four factors namely reinforcement(A), percentage reinforcement(B), applied normal load(C) and sliding speed(D) are being considered. Along with it three interactions viz (AxB), (AxC) and (BxC) are also being considered. For four factors and three degree of freedom the appropriate orthogonal array is L_{27} which has 26 degree of freedom and 13 columns. The factors and their levels are shown in table1. The linear graph for L_{27} array is shown in figure 2 . The plan of experiment is as follows: The first column was designated to reinforcement(A), the second column to percentage reinforcement(B), fifth column to load(C) and ninth column to sliding speed (D). For the study of interaction between reinforcement(A) and percentage reinforcement(B), third and fourth column was designated to (AxB)1 and (AxB)2 respectively. For the study of interaction between reinforcement(A) and applied normal load(C), sixth and seventh column was designated to (AxC)1 and (AxC)2 respectively. For the study of interaction between percentage reinforcement(B) and applied normal load(C), eighth and tenth column were designated to (BxC)1 and (BxC)2 respectively. The remaining columns were assigned to error columns. The L_{27} array has 27 runs compared to 81 runs in full factorial method. This brings out the efficiency of Taguchi method. The experimental layout using L_{27} array is shown in Table 2.

4. RESULTS OF TAGUCHI METHOD

Table 3 shows the experimental results of wear loss. Table 4 shows the response table for S/N ratio of wear. It is observed that the factor reinforcement (A) has the highest influence on the wear followed by applied normal load(C) and percentage reinforcement (B). The factor sliding speed(D) has the least influence on wear. Figure 3 shows the main effect plot for S/N ratio for wear. From the figure it can be concluded that factor combination $A_1B_1C_1D_2$ gives lowest wear rate. Figures 4, 5 and 6 show the interaction graph of AxB, AxC and BxC. The interaction AxC is the most influential as the S/N ratio is higher compared to other interactions. Table 5 shows the analysis of variance. It is observed that factor reinforcement (A) has the most influence on wear with percentage contribution of 53.64% followed by factor applied normal load(C) with percentage contribution of 21.85%. Factor percentage reinforcement(B) and sliding speed(D) has no significant effect as their percentage contribution is comparatively less. The interaction can be neglected as the percentage contribution is less than the residual error.

5. CONFIRMATION TEST OF TAGUCHI METHOD

The confirmation test is the final step in the Taguchi analysis. The purpose of this test is to validate the conclusions inferred from the analysis. The predictive equation is computed taking into consideration the interactions and ANOVA analysis. Based on the above discussions estimated optimal S/N ratio for wear considering factors can be computed as:

$$\bar{\eta}_w = \bar{A}_1 + \bar{B}_1 + \bar{C}_1 + \bar{D}_2 - 3\bar{T}_w \qquad (1)$$

Where $\bar{T}_w$ is the overall mean S/N ratio of the wear, $\bar{A}_1$, $\bar{B}_1$, $\bar{C}_1$, and $\bar{D}_2$ are average S/N values with parameters at optimal level. The S/N ratio value is found out to be -10.34 dB. Table 6 shows the experimental and the predicted values.

The confidence interval (C.I), for the predicted S/N ratio at optimum condition can be calculated using the following equation:

$$C.I. = \pm\sqrt{F(1,f_e) x V_e / N_e} \qquad (2)$$

$F(1,f_e)$ = the F ratio at 95% confidence level at DOF 1 and error DOF f_e

V_e= Variance of error term

$$N_e = \frac{\text{Total number of observation}}{1 + \text{DOF of all factors included in the estimate of S/N ratio}}$$

Using values V_e =6.72 (from the ANOVA table 5), f_e=6, N_e=3 and $F_{0.05}(1,6)$=5.9874(from F-table) the C.I. was calculated. The confidence interval C.I. = ±1.21. The predicted optimal S/N ratio for wear is -10.34dB. Therefore the optimum wear is -10.34 ±1.21 at 95% confidence level. This confirms that the predicted experimental value is within acceptable range.

6. REGRESSION ANALYSIS

Equations 3 4 and 5 show the regression equations for wear for SiC, Al_2O_3 and Cenosphere reinforced composites respectively. Where K_S, K_A and K_c are wear for for SiC, Al_2O_3 and Cenosphere reinforced composite respectively. The values of wear were normalized and a regression equations for the normalized values were developed. The R- value of the regression equation was 0.81. The regression equation had to be developed separately for each reinforcement as R-value for a common regression equation had a lower R-value. Following are the regression equations:

K_S= -0.189164 + 0.0146642*percentage reinforcement + 0.00666506*Load - 0.0277332*sliding speed (3)

K_A= -0.176652 + 0.0146642*percentage reinforcement + 0.00666506*Load - 0.0277332*sliding speed (4)

K_c= 0.222931 + 0.0146642*percentage reinforcement + 0.00666506*Load - 0.0277332*sliding speed (5)

7. MODELLING OF BACK PROPAGATION NEURAL NETWORK

In this paper multilayer feed forward network with back propagation learning algorithm is used.. The input layer consists of 4 neural cells, corresponding to material, percentage reinforcement, applied normal load and sliding speed. The output layer consisted of one neural cell corresponding to weight loss. The program code was generated using MATLAB software. The number of neurons in the hidden layer was chosen to be 10. The number of samples used for training validation and testing were taken to be 80%, 10% and 10% respectively. Figure 7 shows the mean squared error (MSE) of training, test and validation samples. Figure 8 shows regression plot for MSE of training, validation and test samples. Generally the R-value will be higher for the samples used for training, it is the R-value of test samples which determines whether the network is acceptable. The R-value is always desired to be closer to 1. The R-value for test samples was 0.93 and overall R-value for all samples was 0.94. This shows a good correlation between the experimental value and network response. Hence this trained network was used to predict the weight loss of the entire network. Figure 9 shows the regression plot for the same. It is seen that the R value is equal to 0.95 which is acceptable. It is suggested that the trained network could be used for the prediction of mass loss for dry sliding wear for the given parameters range. Graphs for the predicted normalized values of wear using both regression and artificial neural network was developed. Figure10 and Figure 11shows the predicted and experimental values for regression and ANN respectively. It is observed that ANN is more efficient in predicting the experimental value more efficiently.

CONCLUSIONS

The Taguchi method was applied to investigate the effects of different reinforcements (SiC, Al_2O_3 and Cenosphere), percentage reinforcement, applied normal load and sliding speed. ANOVA analysis was also employed of to find out percentage contribution of each factor considered. A model was also developed for the prediction of wear using ANN and compared with a model based on regression. From the above study following can be concluded:

i) The use of orthogonal array in Taguchi method is suitable to statistically analyze the wear behaviour of composites with various reinforcements namely SiC, Al_2O_3 and Cenosphere.

ii) SiC reinforced composite is the most efficient compared to Al_2O_3 and Cenosphere reinforced composite with regard to sliding wear.

iii) The optimal setting for minimum wear was found out using Taguchi Method. The factor combination for minimum wear are: SiC particles as reinforcement, with 8wt.% reinforcement, at 35N applied normal load and at 2.25m/s sliding speed.

iv) The deviations between actual and predicted S/N ratios for minimum wear lies within the confidence interval at 95% confidence level.

v) ANOVA analysis showed that the factor reinforcement and applied normal load were the most influential on wear with percentage contribution of 53.64% and 21.85% respectively.

vi) Both regression and ANN models were developed for the prediction of wear. It was observed that ANN model was more efficient than regression model.

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List of Tables:

Table 1 Factors and their levels

Factor	Unit	Symbol	Level 1	Level 2	Level 3
Reinforcement	-	A	SiC	Al_2O_3	CEN
Percentage reinforcement	%	B	8	12	16
Load	N	C	35	55	75
Sliding Speed	m/sec	D	1.5	2.25	3.00

Table 2 Experimental Layout of L_{27} orthogonal array

	A	B	$(AxB)_1$	$(AxB)_2$	C	$(AxC)_1$	$(AxC)_2$	$(BxC)_1$	D	$(BxC)_2$	-	-	-
Exp.No	1	2	3	4	5	6	7	8	9	10	11	12	13
1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2	2	2	2	2	2
3	1	1	1	1	3	3	3	3	3	3	3	3	3
4	1	2	2	2	1	1	1	2	2	2	3	3	3
5	1	2	2	2	2	2	2	3	3	3	1	1	1
6	1	2	2	2	3	3	3	1	1	1	2	2	2
7	1	3	3	3	1	1	1	3	3	3	2	2	2
8	1	3	3	3	2	2	2	1	1	1	3	3	3
9	1	3	3	3	3	3	3	2	2	2	1	1	1
10	2	1	2	3	1	2	3	1	2	3	1	2	3
11	2	1	2	3	2	3	1	2	3	1	2	3	1

12	2	1	2	3	3	1	2	3	1	2	3	1	2
13	2	2	3	1	1	2	3	2	3	1	3	1	2
14	2	2	3	1	2	3	1	3	1	2	1	2	3
15	2	2	3	1	3	1	2	1	2	3	2	3	1
16	2	3	1	2	1	2	3	3	1	2	2	3	1
17	2	3	1	2	2	3	1	1	2	3	3	1	2
18	2	3	1	2	3	1	2	2	3	1	1	2	3
19	3	1	3	2	1	3	2	1	3	2	1	3	2
20	3	1	3	2	2	1	3	2	1	3	2	1	3
21	3	1	3	2	3	2	1	3	2	1	3	2	1
22	3	2	1	3	1	3	2	2	1	3	3	2	1
23	3	2	1	3	2	1	3	3	2	1	1	3	2
24	3	2	1	3	3	2	1	1	3	2	2	1	3
25	3	3	2	1	1	3	2	3	2	1	2	1	3
26	3	3	2	1	2	1	3	1	3	2	3	2	1
27	3	3	2	1	3	2	1	2	1	3	1	3	2

Table 3 Experimental results for wear loss

Sl. No	A	B	C	D	Wear (mm^3)	S/N Ratio(dB)
1	SiC	8	35	2.25	2.87	-9.15
2	SiC	8	55	1.5	6.27	-15.94
3	SiC	8	75	3	4.11	-12.28
4	SiC	12	35	1.5	5.70	-15.12
5	SiC	12	55	3	5.54	-14.87
6	SiC	12	75	2.25	7.89	-17.94
7	SiC	16	35	3	6.35	-16.05
8	SiC	16	55	2.25	4.03	-12.10
9	SiC	16	75	1.5	11.66	-21.34
10	Al_2O_3	8	35	1.5	3.30	-10.36
11	Al_2O_3	8	55	3	7.49	-17.49
12	Al_2O_3	8	75	2.25	9.29	-19.36
13	Al_2O_3	12	35	3	4.07	-12.20
14	Al_2O_3	12	55	2.25	7.42	-17.41
15	Al_2O_3	12	75	1.5	6.26	-15.93
16	Al_2O_3	16	35	2.25	4.50	-13.06
17	Al_2O_3	16	55	1.5	5.59	-14.94
18	Al_2O_3	16	75	3	8.84	-18.93
19	CEN	8	35	3	5.76	-15.21
20	CEN	8	55	2.25	11.87	-21.49
21	CEN	8	75	1.5	20.78	-26.35
22	CEN	12	35	2.25	9.00	-19.09

23	CEN	12	55	1.5	12.42	-21.88
24	CEN	12	75	3	18.95	-25.55
25	CEN	16	35	1.5	15.33	-23.71
26	CEN	16	55	3	18.42	-25.30
27	CEN	16	75	2.25	18.96	-25.56

Table 4 Response table for signal to noise ratio for wear

Level	A	B	C	D
1	-14.98	-16.40	-14.88	-18.40
2	-15.52	-17.78	-17.94	-17.24
3	-22.68	-19.00	-20.36	-17.54
Delta	7.70	2.60	5.48	1.16
Rank	1	3	2	4

Table 5 Analysis of Variance for S/N ratio

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	2	332.874	332.874	166.437	24.77	53.65
B	2	30.345	30.345	15.173	2.26	4.89
C	2	135.596	135.596	67.798	10.09	21.85
D	2	6.496	6.496	3.248	0.48	1.05
A*B	4	22.414	22.414	5.603	0.83	3.61
A*C	4	13.842	13.842	3.461	0.51	2.23
B*C	4	38.571	38.571	9.643	1.43	6.22
Residual Error	6	40.319	40.319	6.720		6.50
Total	26	620.457				

Table 6 Predicted and experimental results for S/N ratio for wear

	Optimal Control parameters		
	Predicted	Experimental	% error
Level	$A_1B_1C_1D_2$	$A_1B_1C_1D_2$	
S/N ratio for wear	-10.34	-9.85	4.97

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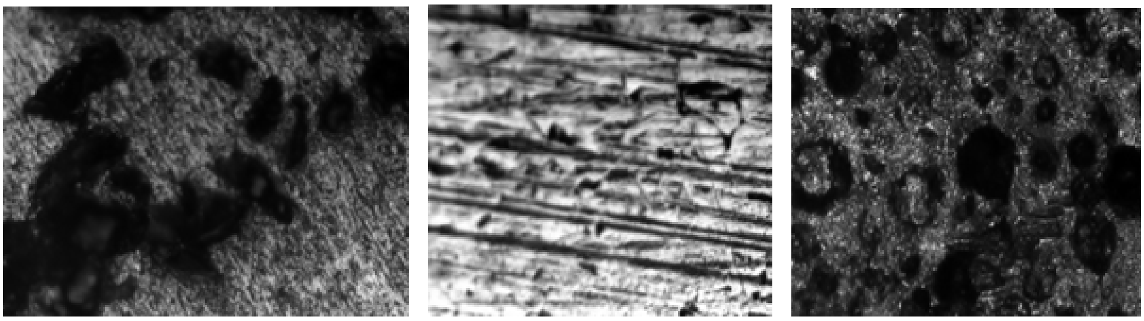


Fig.1 Optical micrograph of composite specimen (a) 12wt.% SiC (b)12wt.% Al_2O_3 (c) 12wt% Cenosphere

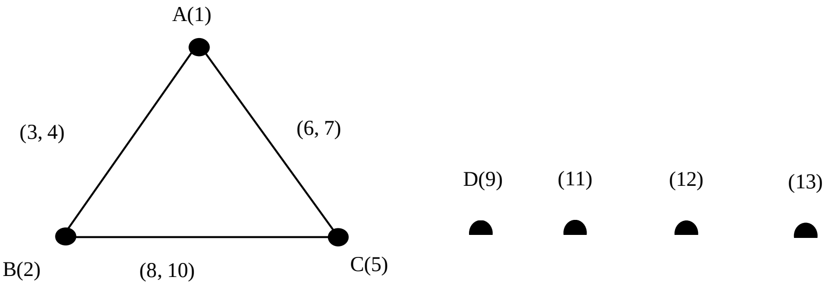
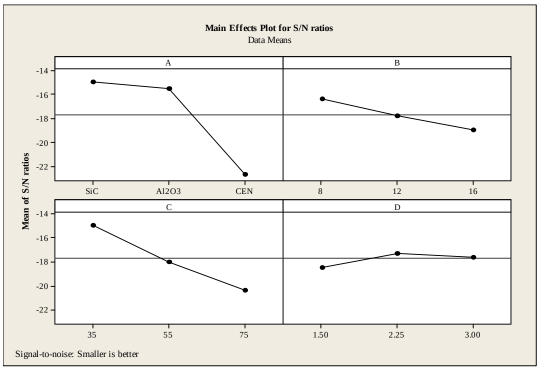


Fig 2 Linear Graph for L_{27} array



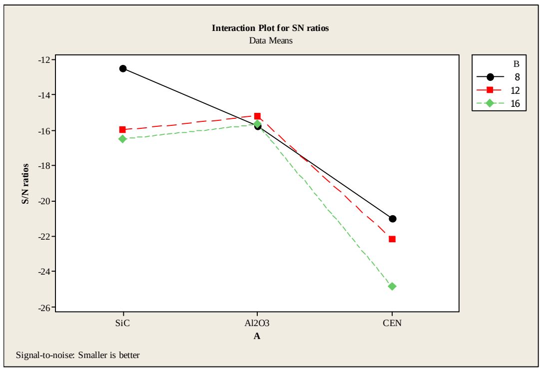
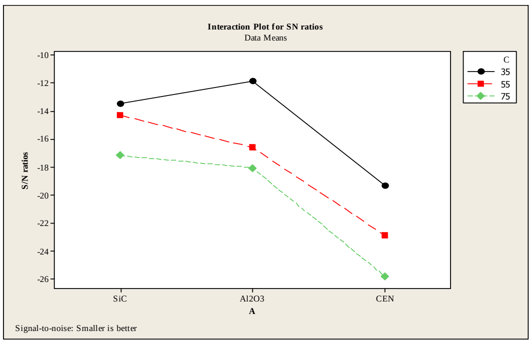


Fig.3 Main effect plot for S/N ratio for wear

Fig.4 Interaction graph (AxB)



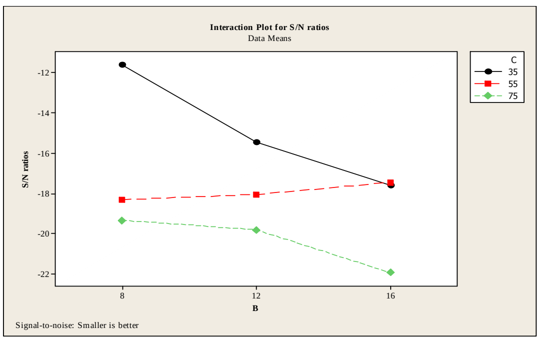
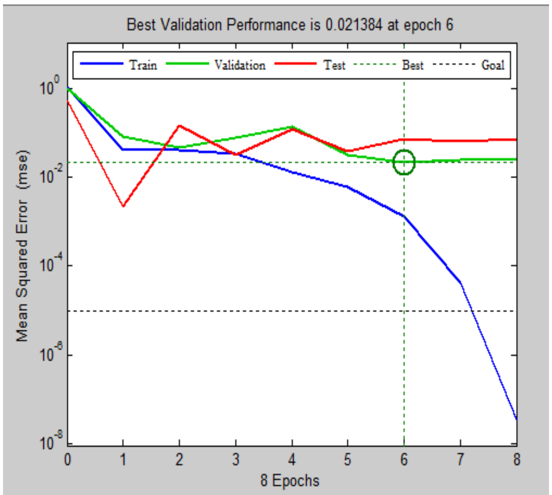


Fig.5 Interaction graph (AxC)

Fig.6 Interaction graph (BxC)



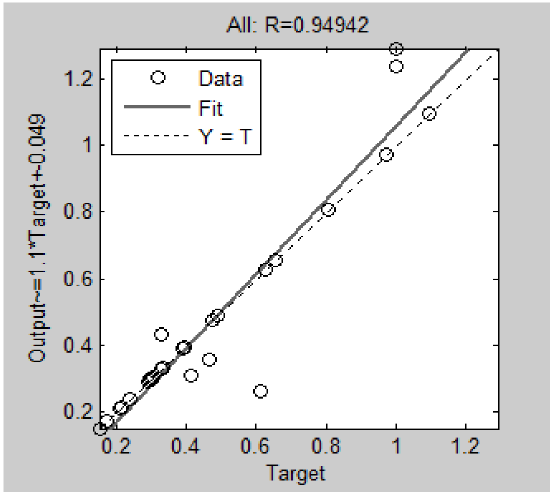


Fig.7 The variation of mean squared error (MSE) with number of epochs.

Fig.8 Overall Regression plot for trained network

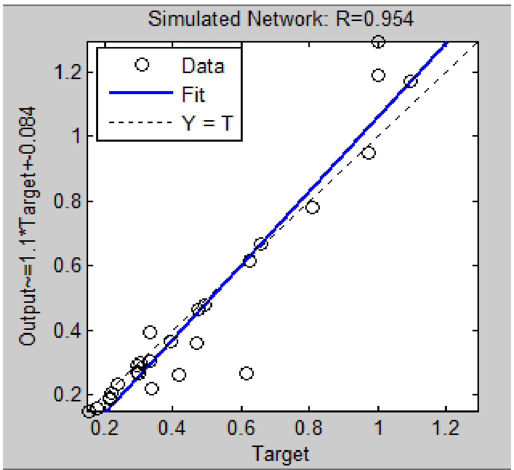


Fig.9 Overall Regression plot for simulated network

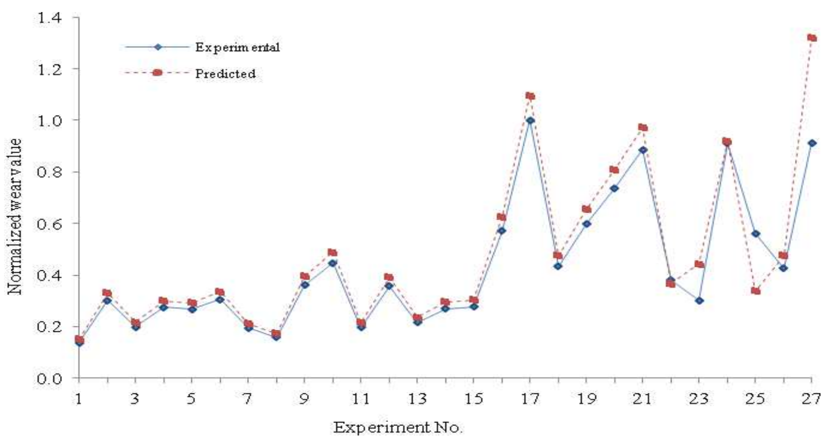


Fig.10 Comparison of experimental results with ANN predicted values

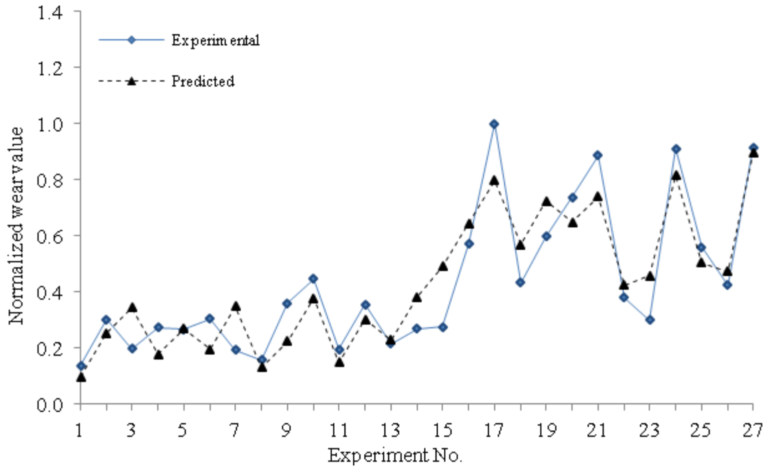


Fig.11 Comparison of experimental results with regression predicted values