Optimization of Tribological Properties Using Grey Relational Analysis and Artificial Neural Network

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Abstract—**In the field of engineering application metal contact surfaces are subjected to friction and wear. It is essential to suggest a modeling method to predict and analyze theeffectiveness of parameters of specific wear rate.In the present work the wear responsible in ball bearing used in conveyors while conveying powder, granular material and solid was assessed.The wear parameters were optimized by way of pin-on-disk.We are going to analyze wear characteristics of bearing material with the help of experimental work and advance optimization tools (non-traditional optimization technique) e.g. grey relational analysis, neural network etc. This study focuses on evaluation and prediction of wear behavior of various types of bearing materials depending on various boundary conditions. We have developed a standardize model for the wear of bearing materials which will be applicable for variety of bearings.**

It is found from grey relation analysis that 3 kg load, 2 km sliding distance, 2.199 m/s velocity and PTFE + 20% Bronze bearing material (A3B1C2D2) provide the optimal parameters condition. From ANN it is found that the optimum set (A3B1C2D2) value by grey relational analysis i.e. 0.8588 is closer to the ANN predicted value i.e. 0.78015. This study also focuses on optimization of wear parameters and reduces number of trial and error.

Keywords—**Specific Wear Rate, COF, GRA, ANN,PTFE, ANOVA**

I. INTRODUCTION

Generally, small bearings are used in applications where rotational accuracy and low torque are primary requirement with low load. Therefore the operating lifetime of the bearing is relatively long, and, if properly operated, failure is rare. Nevertheless, all bearings have a finite life under use and will eventually fail to perform satisfactorily due to an increase in noise and vibration, loss of running accuracy, deterioration of lubricant, or fatigue flaking of the rolling surfaces. Such failure modes are considered normal and can be predicted using standardized techniques. In addition to normal deterioration, b

earings may fail due to excessive heat, fracture, scoring of the rings and other conditions caused by improper use, selection or maintenance of the bearing. Such failures are not normal and can only be avoided by careful handling and correct operation of the bearing in a given application. There are various bearing damages like wear, indentation, smearing, surface distress, corrosion, electric current, flaking, cracks, cage damage etc.

Wear of rolling bearings appears in many different forms. Wear occurs when surfaces slide against each other and there is insufficient or no lubrication to keep them apart. If a full hydrodynamic lubricant film can be maintained at all times, wear will not occur. However, in reality, this is very rarely the case and so wear is almost always unavoidable. Unlike other causes of rolling bearing failure such as fatigue, corrosion and overloading, wear appears in many different forms that cannot all be dealt with in this article. Instead, this article will discuss the four principle types of rolling bearing wear: abrasive wear, adhesive wear and fretting wear/corrosion.

Simulation of tribological properties generally involves the development of mathematical models derived from experimental data. Numbers of these models were derived to simulate wear behavior of materials under limited conditions. However, no unique model generalized to express wear properties of polymers, especially under fluctuating loading condition. Recently, Artificial Neural Networks (ANNs) have emerged as good tools to such models, due to their capabilities of nonlinear behavior, learning from experimental data and generalization. The pioneering investigations of neural network (NN) techniques to predict tribological parameters have been presented. Subsequently, a lot of research workers investigated the potential on neural networks to predict and analyze the wear behavior under various parameters.

In the simulation of wear tests, known sliding properties of rubbing material are input to the ANN model and the expected wear responses of the virtual case are determined. The principle benefit of neural network modeling compared to other approaches is in its capability for accurate predictions when significant non-linearity and hysteresis are present simultaneously. The latter is not easy to attain with conventional curve fits. Furthermore, the neural networks will

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readily handle irregular or random inputs. Several articles illustrated that the prediction accuracy of ANN models is satisfactory, but the dependence of it on the number of training data indicates that the accuracy could be further improved by expanding the experimental database for network training. On the other hand, a well-trained neural network provides more useful data from a relatively limited database obtained by experiments. Lots of techniques have introduced to improve the predictive capabilities of the artificial neural network by automatically identifies the optimal size of the network or by increasing available database. The optimization of artificial neural network configuration is not an easy task; it was studied by many researchers. However, there is lack of definite rules or methods to attain a most appropriate configuration of the ANN, which significantly determines the performance of network. The parameters of the network itself, including architecture of the hidden layer, training algorithm etc. can only be optimized mainly by comparisons between practical instances at present. By expanding the number of training datasets and further optimizing the ANN configuration, the predictive accuracy would be improved.

II. Literature Review

In the field of engineering application metal to metal contact occurs during the relative motion of rotating parts. This contact surfaces are subjected to friction and wear. We are going to analyze wear characteristics of bearing material with the help of experimental work and advance optimization tools (non-traditional optimization technique) e.g. grey analysis, neural network, fuzzy logic etc. Many authors worked on this,Jayapalan S. et.al. [1], reported the work on mechanical and tribological behavior of ABS/TiO_2polymer composites and optimization oftribological properties using grey relational analysis.A. Dhinakar et.al. [2], reported the work on optimization of sliding wear parameters for Mg/Grp composites by grey relational analysis. Grey relational analysis is used to optimize the wear reducing parameters and analysis of variance is performed to identify the significance of the parameters. M. K. Gupa et.al. [3], reported the work uaing grey relational analysis for optimization of machining parameters for turnig AISI 4340 steel. R. Singh et.al. [4], reported work on ptimization of control parameters for mechanical and wear properties of carburized mild steel using grey relational analysis.Zhang et.al. [5], reported that an artificial neural network (ANN) approach was applied to the erosive wear data of the polymers.Zhenyu J. et.al. [6], reported as, an artificial neural network (ANN) technique is applied to predict the wear properties of polymer-matrix composites.Zhenyu J. et.al. [7], reported that the artificial neural network technique was applied to predict the mechanical and wear properties of short fiber reinforced polyamide (PA) composites. A. Abdelbary et.al. [8], reported that Artificial Neural Networks (ANNs) have emerged as a good candidates to mathematical wear models, due to their capabilities of nonlinear behavior, learning from experimental data and generalization. K. V.Rao et.al. [9], reported as, tool wear, surface roughness and vibration of work piece were studied in boring of AISI 316 steel with cemented carbide tool inserts.The neural network can help in selection of proper cutting parameters to reduce tool vibration and tool wear and reduce surface roughness. A.K. Singh et.al. [10],reported the work which deals with drill wear monitoring using an artificial neural network. O. Gencelet. al. [11], worked on comparison of artificial neural networks and general linear model approaches for the analysis of abrasive wear of concrete. R. J. Kuoet. al. [12] reported work on multi-sensor integration for on-line tool wear estimation through artificial neural networks and fuzzy neural network. D. M. D'Addonuet. al. [13] reported work on image data processing via neural networks for tool wear prediction. K. N. Prasad et. al. [14] worked on tool wear evaluation by stereo vision and prediction by artificial neural network. O Palavaret. al. [15] reported work on artificial neural network prediction of aging effects on the wear behavior of in706 superalloy.

The main objective of this paper is to investigate the influence of the wear parameters, such as load, sliding distance, velocity and material of bearing using Grey relational analysis and Artificial neural network. The analysis of experimental results is carried out using main effect graph by Grey relation analysis and from ANN prediction values by Artificial neural network.This study focuses on evaluation and prediction of wear behavior of various types of bearing materials depending on various boundary conditions. We want to develop a standardize model for the wear of bearing materials which will be applicable for variety of bearings. This study also focuses on optimization of wear parameters and reduces number of trial and error.

III. Objective and Scope

A. *Objectives of Experiment*

1. To Study the wear behavior of the selected materials and the effect of various parameters such as loads, sliding distance, sliding velocity on wear.
2. To develop mathematical model for wear which includes load, sliding distance, sliding velocity and PTFE content.
3. To find the effect of PTFE content on wear behavior of ball bearing.
4. To conduct confirmation tests to check the validity of developed model.
5. To develop a standardized neural network model to optimize wear parameters of bearing.
6. To reduce number of trial and error for optimization.

B. *Future Scope*

In future, this study can be extended to learn the wear behavior of similar multiphase metal alloy composites and polymer composites. It is possible to conduct same work in following different way
1. The same work can be repeated for different variables such as erosive wear, surface roughness, vibration, cutting tool life and drill wear etc.
2. The microstructures analysis of different material by XRD, EDS or XEDS, EDXMA etc. can be studied.
3. By changing the polymer elements or by changing chemical composition of polymers.

4. By using other network type than feed-forward-backpropagation.
5. By different training functions.
6. For different number of neurons in the different layers.

IV. METHODOLOGY

In the present investigation the wear responsible in ball bearing used in conveyors while conveying powder, granular material and solid was assessed. In mechanical conveying devices wear is of paramount importance which needs immediate attention to reduce the wear irrespective of bearing make and material. The wear parameters were optimized by way of pin-on-disk. The results obtained were further analyzed by using Grey relation analysis and Artificial neural network with three (PTFE + 10% Bronze, PTFE + 20% Bronze and PTFE + 30% Bronze) different materials with three replications. In this study four parameters were used for control factor and each parameter was design to have three levels which are shown in Table I.

TABLE I LEVEL VALUES OF INPUT FACTORS

Sr. No.	Factors	Level		
		1	2	3
1	Load (Kg)	1	2	3
2	Sliding Distance (Km)	2	4	6
3	Velocity (m/s)	1.09	2.199	3.29
4	Material	PTFE + 10% Bronze	PTFE + 20% Bronze	PTFE + 30% Bronze

A. Grey Relational Analysis

Grey relational theory is very much applicable to a system in which the model is unsure or the information is incomplete. The process of preprocessing of all the data is called as Grey relational generating. Wear factor corresponds to lower-the-higher criterion [1].

Normalized value $X_k(k)$ criterion can be expressed as:

$$X_k(k) = \frac{\max Yi(k) - Yi(k)}{\max Yi(k) - \min Yi(k)} \quad (1)$$

The grey relational coefficient $\xi_i(k)$ can be expressed as follows:

$$\xi_i(k) = \frac{\Delta \min + \xi * \Delta max}{\Delta oi(k) - \xi * \Delta max} \quad (2)$$

After averaging grey relational coefficient, the grey relational gradeYi is computed as:

$$Yi = \frac{1}{n}\sum_1^n \xi i(k) \quad (3)$$

Optimization of the complicated multiple process responses is converted into optimization of single grey relational grade.

B. Artificial Neural Network

Artificial neural networks are computational systems that simulate the microstructure (neurons) of a biological nervous system.A simple process element of the ANN is shown in Figure 1. The network has three layers; the input, hidden, and output layers. The input and output layers are defined as nodes, and the hidden layer provides a relation between the input and output layers [5].

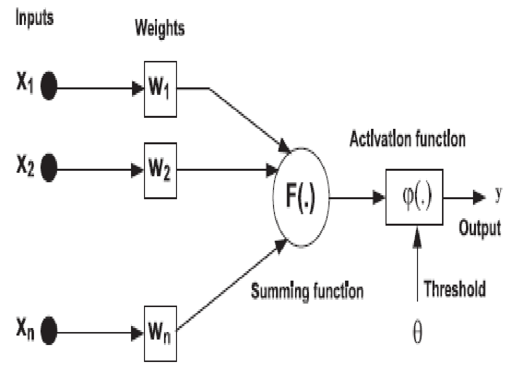

Fig. 1. Mathematical model of neural network [5]

The network performance is evaluated by using the test dataset. The quality of the prediction can normally be characterized by the root mean square error (RMSE) of the predicted values from the real measured data. Smaller the RMSE of the test dataset higher is the predictive quality. As an improvement, the coefficient of determination B (also called R^2 coefficient in some publications) has been introduced to evaluate ANN's quality, defined by

1. Mean relative error R:

$$R = \frac{1}{M}\sum_{j=1}^{M}\sum_{i=1}^{N}\frac{|Op(i) - O(i)|}{O(i)} \quad (4)$$

2. Coefficient of determination B:

$$B = 1 - \frac{\sum_{i=1}^{N}[Op(i) - O(i)]^2}{\sum_{i=1}^{N}[O(i) - Oavg]^2} \quad (5)$$

Steps to evaluate ANN predicted wear loss and percentage error in the experimental and predicted value of ANN in Matlab tool [16]:

- The script assumes that the input vectors and target vectors are already loaded into the workspace. If the data are not loaded, you can load them as follows:
- Nntool> import > load house_dataset; inputs = houseInputs; targets = houseTargets;
- Create a network. The default network for function fitting (or regression) problems, fitnet, is a feedforward network with the default tan-sigmoid transfer function in the hidden layer and linear transfer function in the output layer. The network has one output neuron, because there is only one target value associated with each input vector.
- Set up the division of data. With these settings, the input vectors and target vectors will be randomly divided, with 70% used for training, 15% for validation and 15% for testing.
- Train the network. The network uses the default Levenberg-Marquardt algorithm (trainlm) for training. For problems in which Levenberg-Marquardt does not produce as accurate results as desired, or for large data problems, consider setting the network training function to Bayesian Regularization (trainbr) or Scaled Conjugate Gradient

(trainscg), respectively.

- Stop Training. If you click Performance in the training window, a plot of the training errors, validation errors, and test errors appears.

In this study ANN is used to verify the optimized result of Grey relation analysis.

V. MACHININGPERFORMANCE MEASURE

The present study, Specific wear rate and friction coefficient were the output factor affecting the result of machining process by varying load, sliding distance, velocity and material of ball bearings. Table II shows orthogonal array (L_{27}) experimental design, input and output parameters of ball bearing.

TABLE II ORTHOGONAL ARRAY (L_{27}) EXPERIMENTAL DESIGN, INPUT AND OUTPUT PARAMETERS

Sr.no.	Load	SD	Velocity	Material	Wear	COF
1	1	2	1.090	10	22.37	0.2120
2	1	2	2.199	20	11.69	0.1451
3	1	2	3.290	30	14.08	0.1880
4	1	4	1.090	20	32.98	0.1710
5	1	4	2.199	30	18.94	0.1431
6	1	4	3.290	10	29.69	0.1131
7	1	6	1.090	30	27.72	0.2325
8	1	6	2.199	10	15.57	0.2880
9	1	6	3.290	20	18.93	0.3140
10	2	2	1.090	20	16.04	0.0840
11	2	2	2.199	30	14.51	0.0930
12	2	2	3.290	10	15.65	0.0760
13	2	4	1.090	30	18.34	0.1590
14	2	4	2.199	10	27.71	0.2230
15	2	4	3.290	20	22.94	0.1810
16	2	6	1.090	10	31.60	0.1210
17	2	6	2.199	20	25.15	0.0980
18	2	6	3.290	30	20.62	0.0790
19	3	2	1.090	30	20.26	0.0610
20	3	2	2.199	10	22.78	0.0710
21	3	2	3.290	20	14.31	0.0460
22	3	4	1.090	10	31.71	0.0530
23	3	4	2.199	20	16.39	0.0340
24	3	4	3.290	30	17.96	0.0710
25	3	6	1.090	20	17.81	0.0230
26	3	6	2.199	30	17.07	0.0540
27	3	6	3.290	10	19.13	0.0301

VI. RESULT AND DISCUSSION

The experiments were carried out on the bases of L_{27} orthogonal array. Specific were rate and friction coefficient were analyzed on changing load, sliding distance, velocity and material. The input parameters were optimized by using Grey Relational Analysis (GRA) for determining the optimal input parameters. The normalized results for specific wear rate and friction coefficient are calculated and are shown in Table III.

TABLE III NORMALIZED VALUE AND GREY RELATIONAL COEFFICIENT

Exp No.	Wear	COF	Normalized Wear	Normalized COF	Grey coefficient Wear	Grey coefficient COF
1	22.37	0.2120	0.498	0.286	0.499	0.434
2	11.69	0.1451	1	0.539	1	0.543
3	14.08	0.1880	0.887	0.377	0.816	0.468
4	32.98	0.1710	0	0.441	0.333	0.495
5	18.94	0.1431	0.659	0.546	0.594	0.547
6	29.69	0.1131	0.154	0.660	0.371	0.617
7	27.72	0.2325	0.247	0.209	0.399	0.409
8	15.57	0.2880	0.817	0	0.732	0.354
9	18.93	0.3140	0.659	-0.098	0.595	0.333
10	16.04	0.0840	0.795	0.769	0.709	0.704
11	14.51	0.0930	0.867	0.735	0.790	0.675
12	15.65	0.0760	0.813	0.800	0.728	0.732
13	18.34	0.1590	0.687	0.486	0.615	0.516
14	27.71	0.2230	0.247	0.245	0.399	0.421
15	22.94	0.1810	0.471	0.403	0.486	0.479
16	31.60	0.1210	0.064	0.630	0.348	0.597
17	25.15	0.0980	0.367	0.716	0.441	0.659
18	20.62	0.0790	0.580	0.788	0.543	0.722
19	20.26	0.0610	0.597	0.856	0.553	0.792
20	22.78	0.0710	0.479	0.818	0.489	0.751
21	14.31	0.0460	0.876	0.913	0.802	0.863
22	31.71	0.0530	0.059	0.886	0.347	0.829
23	16.39	0.0340	0.779	0.958	0.693	0.929
24	17.96	0.0710	0.705	0.818	0.629	0.751
25	17.81	0.0230	0.712	1	0.634	1
26	17.07	0.0540	0.747	0.883	0.664	0.824
27	19.13	0.0301	0.650	0.973	0.588	0.953

Grey relational grade was found out and ranked for obtaining the optimal condition and are shown in Table IV.

TABLE IV GREY RELATIONAL GRADE AND ITS ORDER

Exp No.	Grey relational grade	Order
1	0.467078	23
2	0.771861	4
3	0.642623	12
4	0.414537	25
5	0.571338	16
6	0.494595	20
7	0.404461	27
8	0.54366	19
9	0.464262	24
10	0.707252	9
11	0.732871	7
12	0.730929	8

13	0.566185	17
14	0.410171	26
15	0.482795	21
16	0.472962	22
17	0.550737	18
18	0.632945	13
19	0.673455	11
20	0.620851	14
21	0.832995	1
22	0.588099	15
23	0.811712	3
24	0.690631	10
25	0.817477	2
26	0.744319	6
27	0.771041	5

The mean response for each factor and the ranks are determined from the loss function as shown in Table V.

TABLE V GREY RELATION GRADE RESPONSE

Level	Load	SD	Velocity	Material
1	0.530491	0.686657	0.567945	0.566598
2	0.587427	0.558896	0.639724	0.650403
3	0.727842	0.600207	0.638091	0.628759
Delta	0.197351	0.127761	0.071779	0.083805
Rank	1	2	4	3

From the rank it was observed that the load is the most significant factor for grey relational grade. After that sliding distance followed by material and velocity.From the grey relation grade response table the effect plot is plotted, which is shown in Figure 2.

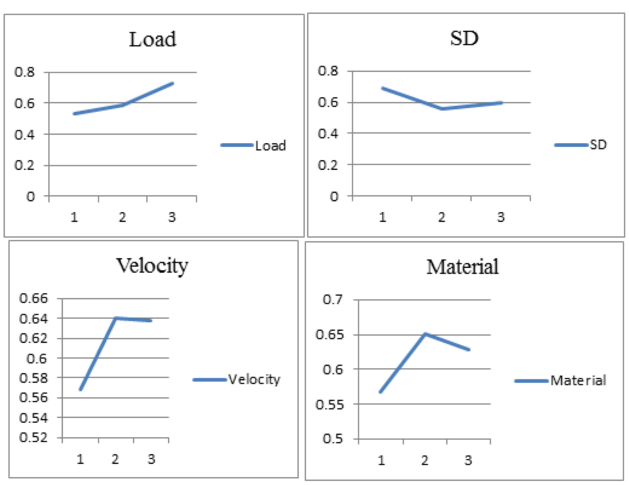

Fig. 2 Grey relational grade response plot

It was observed from Fig 2 that the optimal combination of the factors for Group-I which gives minimum specific wear rate and friction coefficient is 3 kg load, 2 km sliding distance, 2.199 m/s velocity and PTFE + 20% Bronze material (A3B1C2D2).In order to understand contribution of the design parameters load, sliding distance, velocity and material on the experimental results analysis of variance were carried out. The results of ANOVA for grey relational grade are shown in Table VI.

TABLE VI ANOVA TABLE FOR GREY RELATIONAL GRADE

	DOF	Sum of square	Mean square	F value	% contribution
Load	2	0.1857	0.0928	11.1487	38.9799
SD	2	0.0765	0.0382	4.5929	16.0585
Velocity	2	0.0302	0.0151	1.8144	6.34409
Material	2	0.0340	0.0170	2.0450	7.15025
Error	18	0.1499	0.0083		31.4671
Total	26	0.4764	0.1715		100

It was observed from the Table VI that load (A) has most significant effect on grey relational grade followed by sliding distance (B), material (D) and velocity (C) for this analysis. Now confirmation test is carried out to verify the accuracy of the analysis. The confirmation test results for the analysis of are shown in Table VII.

TABLE VII CONFIRMATION TEST

	Initial parameter	Optimal parameter	
		Theoretical	Experimental
Level	A2B2C2D3	A3B1C2C2	A3B1C2C2
Wear	14.51		
COF	0.093		
Grey grade	0.7328	0.8589	0.8483

From the confirmation test it was observed from Table VII that the theoretical value of grey grade (0.8589) for optimum parameters is closer to the experimental value of grey grade (0.8483) for optimum parameters.

To verify the optimized results of Grey Relation Analysis (GRA), Artificial Neural Network (ANN) is used. Grey relational grade was computed by ANN. The network is trained for different training algorithms and prediction qualities of these algorithms are compared. Prediction qualities for different training algorithm are shown in Table VIII.

TABLE VIIIPREDICTION QUALITIES OF DIFFERENT TRAINING ALGORITHM

Training algorithm	MRE	SSE	MSE	Regression	B
LM	0.0028	0.0176	0.0029	0.9844	0.9820
BFG	0.0056	0.0196	0.0065	0.8781	0.8544
BR	0.0268	0.2234	0.0059	0.7343	0.6816
GD	0.0382	0.0564	0.0254	0.8153	0.7998
GDM	0.0944	0.0811	0.0118	0.7211	0.7127
GDA	0.0090	0.0984	0.0153	0.6799	0.6537
GDX	0.0653	0.0343	0.0124	0.9443	0.9225
RP	0.0382	0.0263	0.0017	0.8831	0.8711
SCG	0.0129	0.0591	0.0038	0.9026	0.9012

It was observed from Table VIII that theLevenberg-Marquardt (LM) algorithm is significant than other algorithms. The LM algorithm shows relatively lowest values of MRE (0.0028), SSE (0.0176), MSE (0.0029) and relatively highest values for R (0.9844), B (0.9820) than other statistical values. Therefore, LM algorithm was selected for training the network to estimate the values of ANN predicted output and percent error.Test dada and predicted values from the neural network are shown in Table IX.

TABLE IX TEST DADA AND PREDICTED VALUES FROM THE NEURAL NETWORK

Exp No.	Grey relational grade		% Error
	Experimental	ANN predicted	
1	0.4670	0.4268	4.0228
2	0.7718	0.7113	6.0510
3	0.6426	0.6457	-0.3106
4	0.4145	0.4268	-1.2342
5	0.5713	0.5854	-1.4122
6	0.4945	0.4829	1.1645
7	0.4044	0.4268	-2.2379
8	0.5436	0.4266	11.7030
9	0.4642	0.4060	5.8212
10	0.7072	0.4270	28.0181
11	0.7328	0.7712	-3.8408
12	0.7309	0.7044	2.6458
13	0.5661	0.4333	13.2804
14	0.4101	0.4316	-2.1449
15	0.4827	0.5086	-2.5874
16	0.4729	0.4302	4.2702
17	0.5507	0.6255	-7.4763
18	0.6329	0.6849	-5.2044
19	0.6734	0.6772	-0.3815
20	0.6208	0.6320	-1.1159
21	0.8329	0.8318	0.1154
22	0.5880	0.5845	0.3599
23	0.8117	0.8123	-0.0638
24	0.6906	0.7032	-1.2629
25	0.8174	0.8111	0.6356
26	0.7443	0.7702	-2.5911
27	0.7710	0.7524	1.8571

From the test results, it can be observed from Table IX that the predicted values are very close and follow almost the same trend as the experimental values and are showing the minimum percentage error. To test the prediction performance of trained network, 4 data sets including optimum parameters setfrom grey relation analysis are used for test the network. From the test results, it can be observed that the predicted values are very close to the optimum parametersset values from grey relational analysis. The prediction values for optimum set are shown in Table X.

TABLE X THE PREDICTION VALUES FOR OPTIMUM SET

Sr. No.	Load	SD	Velocity	Material	ANN predicted
1	3	2	1.09	30	0.67727
2	3	2	2.199	10	0.63201
3	3	2	2.199	20	0.78015
4	3	2	3.29	20	0.83184

It was observed from Table X that the optimum set (A3B1C2D2) i.e. 3 Kg load, 2 Km sliding distance, 2.199 m/s velocity and PTFE + 20% Bronze bearing materialvalue by grey relational analysis i.e. 0.8588 is closer to the ANN predicted value i.e. 0.78015.The linear regression between network output and corresponding target is shown in Figure 3.

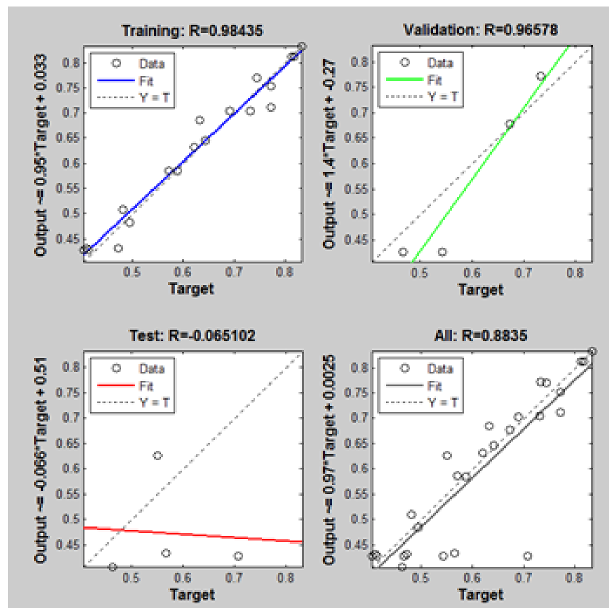

Fig. 3 Regression plot for LM algorithm

VII. CONCLUSION

The specific wear rate and friction coefficient of the bearing material were optimized using grey relational analysis and that was verified by artificial neural network.

1. It was found that 3 kg load, 2 km sliding distance, 2.199 m/s velocity and PTFE + 20% Bronze bearing material (A3B1C2D2) provide the optimal condition from the mean response effect plot.
2. From ANOVA, it was observed that load (A) has most significant effect on grey relational grade followed by sliding distance (B), material (D) and velocity (C).
3. Simultaneously wear and friction coefficient characteristics of bearing material using back propagation neural network were proposed in the present study.

4. From the test results, it can be observed that the predicted values are very close and follow almost the same trend as the experimental values.
5. It was observed that the optimum set (A3B1C2D2) value by grey relational analysis i.e. 0.8588 is closer to the ANN predicted value i.e. 0.78015.
6. The results shows that the predicted data are perfectly acceptable when compared with the experimental test dada.

Hence ANN is expected to be very helpful for estimating weight loss in complex situation of composite material. It can be expected to be an alternative and practical technique to evaluate wear loss.

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