Modeling And Artificial Neural Network Based Prediction Of Wear Rate Of AA7075/Al_2O_3 Particulate Metal Matrix Composites

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Abstract: Particulate Metal Matrix Composites (PMMC) offers light weight, high wear resistance and high strength, which are attractive for automobile applications. Much of the earlier works on Aluminium 7075 (Al7075) based composite are either contains Silicon Carbide (SiC) as reinforcement or Alumina (Al_2O_3) in the fiber form. The Al7075/Al_2O_3 Particulate composite developed by liquid processing route needs to be studies with respect to its Mechanical and Tribological behavior in the context of processing route, volume fraction, particle size, compatibility of matrix and reinforcement for composite materials desired property. Further larger scope is available to establish the wear behavior of composite materials with mathematical models to evaluate its suitability for various applications. Al 7075/Al_2O_3 particulate MMC has been developed by stir casting process demonstrates improved Mechanical and Tribological property. Oxidative wear, delamination wear, adhesive wear, and small amount of Abrasive wear mechanisms are found to occur during the wear of MMCs. In the present work wear data and different wear mechanisms at various speed and load for the speed range of 0-1400 rpm and 1- 14kg load were evaluated. The nonlinear behavior of wear rate of composite controlled by more than 100 controlling parameter, but in the present work effect of limited parameters (13 parameters) are studied. Thirteen input parameter and eight output parameters are used and the ANN model with single hidden layer using feed forward back propagation neural network was developed. Based on the literature two algorithm are selected for the present work 1.Levenberg Marquardt 2.Bayesian Regularization The corresponding transfer functions are Trainlm and Trainbr are used for the network models. The Developed ANN model can be effectively extended to predict the nonlinear behavior of wear for any particulate MMC. Large amount of time, money and materials invested for the experiments can be reduced due to development of ANN models.

Index Terms: Artificial Neural Network, Al7075, Bayesian Regularization, Levenberg Marquardt, Particulate Metal Matrix composite, Stir casting, Wear rate

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1. INTRODUCTION

Aluminium alloys include Al-Zn, Al-Si, Al-Cu-Zn, Al-Zn-Cu-Mg etc., Aluminium alloy can be further modified by secondary process by heat treatment, ageing, rolling, forging, extrusion and drawing. 7XXX alloys are having highest strength when compared to all the alloy series. The Al-7075 (also represented as AA7075- American Association 7075) alloy was most popular in 7XXX series was introduced in 1943. Aluminium Alloy possess limited hardness and wear resistance which are to be addressed to make it suitable for Tribological applications. In the last three decades the material researchers around the world are shifting the attention from alloys to composite materials. The high strength and light weight properties have made the Al 7075 most widely researched matrix material [1]. The Al7075 alloy is precipitation strengthened alloy. The thermal treatment of the alloy containing high percentage of Zn and Mg forms Guinier Preston zones (GP zone) due to precipitation at grain boundary. The GP zone has strong interface with the Aluminium phase. The two phases (MgZn2) μ' and (MgZn2) μ has monoclinic and hexagonal crystal structure which imparts high strength to the Aluminium alloy. Wear behavior of the materials are studied to know the wear rate and wear coefficient [2]. Apart from this the mass loss and volume loss of materials are also studied. Tribolayers are studied to evaluate the mechanism of wear and to quantify the wear rate [3]. Adhesive wear mechanism can be identified by any one of the following phenomenon [4] Deformation of the contacting surfaces , Removal of the surface film, Formation of Adhering Junction, Transfer of softer material on harder material, Modification of the transferred debris, Formation of loose wear debris[5]. Adhesive wear is a common phenomenon in the metals and composites. It is also serious form of the wear which accounts for the high wear rate and higher coefficient of friction [6]. Neural Network gain popularity in the field of Pattern recognition, prediction of trend and behavior, date filtering to separate the noise, nonlinear data analysis and optimization. In the present work optimization and Predictions are employed for nonlinear system behavior. Artificial Neural network works on the set of input data developed experimentally which will be used to train the neurons. The input layer hidden layer and output layer are selected suitably [11]. The transfer function, Bias, Neurons and ANN architecture was developed to predict the output based on the trained neuron. The ANN models are developed with several training function and algorithm for the given problems and by trial and error the ANN will be optimized. Large amount of input data are used for the training and validated with remaining data set. Levenberg Marquardt with Feed forward Network are most popular ANN network [12].

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2 EXPERIMENTAL PROCEDURE

2.1 Matrix and Reinforcement

The alloy Al7075 contains 5.6% to 6.1 % Zinc, 2.1% to 2.5% Magnesium. The tensile strength of 276 MPa and maximum yield strength more than 145 MPa makes this alloy with highest strength used in air craft, marine and automobiles. The reinforcement used in the present work was Alumina (Aluminium oxide- Al_2O_3). Alumina has superior thermal, chemical and mechanical properties as compared to alloy. The density of both the material are close to each other and CTE of the alloy is higher than the reinforcement. The high melting temperature of the reinforcement regulates the stability of alumina during melting and solidification by controlling interface reactions of the alloy. For most of the composite material in the literature the maximum volume fraction is 80:20. But for the structural parts and packaging applications it is 50:50. The reinforcement in the present case is selected as 5%, 10%, 15% and 20%. The volume fractions are converted in to weight fractions of matrix and reinforcement for the fabrication process.

2.2 Developing Composite Material

Stir casting process involves heating the matrix material to its melting stage and addition of reinforcement with constant stirring before pouring in to the mold. The furnace used in the present work is Stir casting Furnace with bottom pouring arrangement Supplied by Swam Equip, Chennai, India is used for development of MMC.

2.3 Wear Testing

The rate of adhesive wear process are expressed as Specific wear rate, wear rate in volume loss, wear rate in weight loss, wear resistance and wear coefficient. The wear coefficient 'k' developed by Archard's is given by

$$\text{Wear Coefficient} \quad V = k.\,H/S.L \qquad (1)$$

Where k is wear coefficient, H is Hardness of Material, S is Sliding distance and L is applied load, V is volume loss. The wear mechanism with major part as adhesive wear, the k value is in the range of 10^{-4}. The value of k to be considered for acceptable wear of the material in Application is 10^{-5} or lower. The k value is considered as demarcation of the allowed wear rate for a particle application with adhesive wear. The factors affecting k are 1. Junction asperities, 2. Lubricants, 3. Type of Materials, 4. Load, Speed and Sliding Distance etc. The Pin on Disc testing machine used in the present study was supplied by Magnum Industries, Bangalore, India. The test are conducted at four different stages based on load and speed values. The load and speed are varied from low value of 1kg, 2kg, 3kg and 4kg to higher values of 10kg, 12kg, 14kg and 16 kg. The speed varied from low values of 200, 300, 400 and 500 rpm to 1000, 1200, 1300 and 1400 rpm. The speed was kept constant and the load was varied in steps of 1kg, similarly the speed was varied after conducting the test for all the load.

2.4 Artificial Neural Network Model

Three types of neural network Architecture are available 1. Feed forward network, 2. Feedback network, 3. Self-organizing Network. In the present work Feedback neural network with back propagation Algorithm was used [14]. It contains the output neuron to be feedback in the same layer or next layer for the weight adjustments. The primary function of Feed Back network is a) Forwarding the input to the hidden layer and then to the Output layer, b) Calculating the Error and back propagating the calculated error, c) Adjusting the weights in each layer with computation

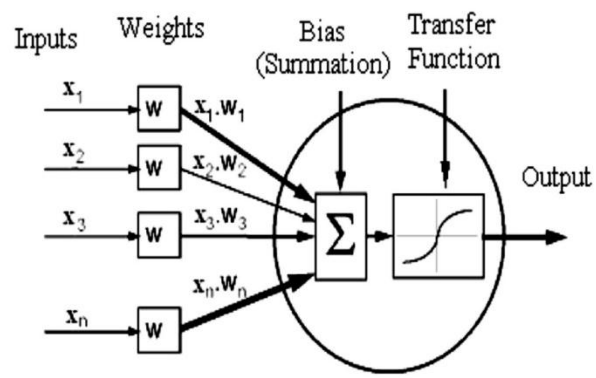

Fig 1. *Basic configuration and flow of Neuron*

These algorithms are capable of computing nonlinear behavior of the composite wear behavior. Also relatively large data set are handled by the algorithms. The sigmoid transfer functions used in the ANN are also used to account for nonlinear behavior. The representation of neuron work flow in the network is shown in figure 1. In the input layer the neuron receives the signal from training pattern. This signal will be sent to hidden layer containing the neurons. The neurons in the hidden layer containing the signal will be computed with nonlinear activation function to produce the output. This output will be sent to output layer [15]. The signal in the output layer neuron will be compared with that of input layer and the difference will be generated as an error. This signal will be sent to hidden layer for improvement with bias and adjustments in weight to improve the prediction. ANN has capability of predicting good accuracies for large training set. In Optimal model design the selection of transfer function, number of hidden layer, number of neuron and layer configuration are considered. The trial and error approach was used for arriving at optimal ANN model. The comparison of predicted and expected output are used to generate an error called Mean Square Error (MSE) [13]. If the performance of the system converges towards zero error for efficient ANN model. The selection of Transfer function and Training algorithm from the available list are selected suitably. Based on the literature two algorithm are selected for the present work 1.Levenberg Marquardt 2. Bayesian Regularization. The corresponding transfer functions are Trainlm and Trainbr are used for the network models.

TABLE 1.
INPUT/ OUTPUT PARAMETER FOR ANN MODEL

Sl No	Input Parameters	Output Results
1	Speed	Weight Loss
2	Load	Volume Loss
3	Sliding Distance	Wear rate
4	Pressure	Specific wear rate
5	Density	Wear resistance
6	Track radius	Wear coefficient
7	Hardness	Coefficient of friction
8	Tensile stress	Friction force
9	Compressive stress	

10	Young's modulus
11	CTE
12	Thermal Conductivity
13	Elongation

2.5 Prediction of Wear Rate by ANN

Artificial neural network structure and the algorithm as explained earlier are used for prediction of wear behavior. The ANN parameters as state earlier are used for designing the model. The Back propagation feed forward network was used with LM algorithm and BR algorithm. The input parameters and output parameter used for the ANN training is shown in table 1. A total of 13 parameters are used in training the ANN to predict 8 output parameters. The parameters like speed, load , hardness, density, track radius, pressure and sliding distance are also applied directly in the Pin on Disc wear test but the parameters like Tensile stress, Compressive stress, Elongation, CTE, Thermal Conductivity and young's modulus are calculated from the empirical relations. The training was carried out with two types of Algorithm (LM and BR) and three different hidden neurons as 10, 30 and 50. The network is represented as 13-[10]-1, 13-[30]-1, 13-[50]-1. The training will be started by using MATLAB R2016. The regression plot shows that for training the value of R is 0.99977 and it indicates the good agreement with the predicted and target value in the training part. Lowest value of The MSE was notices at 50 epoch for the wear rate during training. The similar trials are carried out for each of the outputs to be predicted with corresponding training result plots are generated. The procedure is carried out for 30 and 50 hidden neurons for LM algorithm. The best neuron obtained from the LM method was considered to be the bench mark for the BR method. The training was carried out with that particular neuron with BR and the error was compared with the LM method for generalization. The predicting capability of the ANN outside the domain are carried out for higher volume fraction. It can be approximately related to the experimental values for wear rate and coefficient of friction by superimposing both the data plots. The single layer ANN containing 10 hidden neuron and LM algorithm was identified as best network and this network was generalized for the prediction of the wear behavior, which was carried out for the parameters as shown in table 2.The wear rate was predicted for two set of parameters.

TABLE 2.
PARAMETERS OF ANN ALGORITHM AND MODEL

Particular	ANN Parameters	Remarks
Training Algorithm	Levenberg-Marquardt Method /Bayesian Regularization	Nonlinear, medium Data set
Number of Hidden layer	1	Best prediction capability
Number of Neuron in the hidden layer	10, 30, 50	For optimization of MSE
Transfer function	Trainlm, Trainbr	Commonly used for Prediction
Performance function	MSE	Best Error function

For varying Speed and Load for 0%, 5%, 10%, 15% and 20% volume fraction Alumina reinforcement. For varying Speed and Load for 25%, 30%, 35% and 40% and 50 % volume fraction Alumina reinforcement. The output results of the ANN are obtained for 8 parameters namely wear rate, wear coefficient, coefficient of friction etc. The predicted results are tabulated and analyzed with the experimental vales and compared. The training was carried out with 80% of the total available data and 20% for the testing and validation. The neurons selected are used for training separately for the output parameter. These process was carried out train the Network for each of the output. Training the ANN model carried out separately for LM and BR algorithm with 10, 30, 50 neurons for LM algorithm and 10 neuron for BR algorithm. Training data containing both input and output are used to modify the network weight according to the type of algorithm used (LM and BR algorithm). Initial value of the weight are set randomly between 0.5 to 1.0 by the network. The training data set are presented to ANN in an order to carry out training. The weights are updated as per the LM algorithm. After presenting all the data set to the model one epoch will be completed. Epoch is an iteration process of network in which entire data set is used. The epoch are continued with incrementing the weight each time and at particular epoch the computed mean square error will be minimum, with further increase in the epoch the error starts increasing. The number of epoch corresponding to minimum MSE is shown for one of the computations is shown in figure 4 which indicates at 25 epoch the minimum MSE was notices and for higher epoch the curve increases indicating the increase in MSE. This condition is called over shooting. The training has to be stopped at the minimum MSE with early stooping criterion. The training process will be optimized by two process 1. Early stopping 2 Regularization. Early stooping is advantageous as compared to other due to its simplicity and popularity.

4 RESULTS AND DISCUSSIONS

4.1 Microstructure

The distribution of reinforcement particles were established by optical micrograph, SEM Micrograph with EDS analysis. The grin size, secondary phase, interface reaction, intermetallic are identified by XRD spectrum analysis. The basic properties of composite like density and Porosity are estimated theoretically by rule of mixture and compared with experimental values. The Hardness and strength of the composite was evaluate by compression test and tensile test as per ASTM standards. The fracture surface were analyzed to estimate the interface bond strength and fracture morphology with the variations in volume fraction. The dispersion of the Al_2O_3 particles in the matrix are seen as dark particles. The microstructures also shows uniform dispersion of the particles in the aluminium matrix at all volume fractions by maintaining satisfactorily particle distance. The microstructure and grain boundary phase analysis of the composite explained above clearly indicates the incorporation of the reinforcement particles into the melt and establishes the strength of the composite by good interface bond strength and secondary phases of the Al 7075 alloy at the grain boundary.

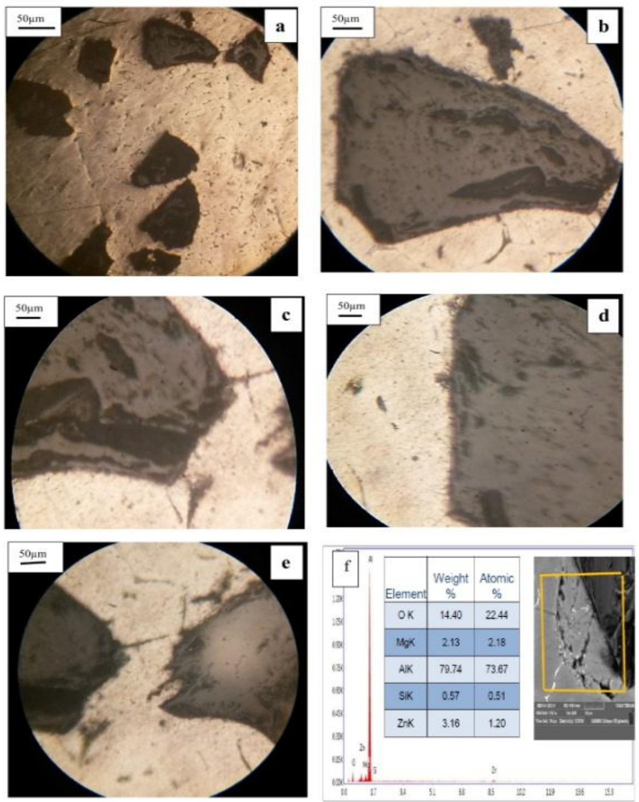

Fig 2. *Optical microstructure showing alumina particles in the composite under different magnification. a) 50x, b) 100x,c) 200x, d) 500x ,e) 500x, f) Energy Dispersive spectrum of Interface region.*

4.2 Wear Rate

Table 3.
Wear Rate selected for ANN prediction of

S. N	Load	Speed	Wear Rate mm^3/m Al7075	5%	10%	15%	20%
1	1	200	0.0023	0.0020	0.0013	0.0021	0.0012
2	1	300	0.0005	0.0008	0.0013	0.0013	0.00115
3	1	400	0.0011	0.0006	0.0009	0.0014	0.0004
4	1	500	0.0013	0.0007	0.0009	0.0008	0.0006
5	1	1000	0.0010	0.0008	0.0003	0.0008	0.0010
6	1	1200	0.0010	0.0014	0.0012	0.0006	0.0010
7	1	1300	0.0038	0.00119	0.0006	0.0007	0.0010
8	1	1400	0.0039	0.0008	0.0017	0.0010	0.0006
9	2	200	0.0028	0.0032	0.0028	0.0026	0.0022
10	2	300	0.0013	0.0020	0.0016	0.0016	0.0018
11	2	400	0.0017	0.0013	0.00118	0.0019	0.0007
12	2	500	0.0016	0.0014	0.0013	0.00112	0.0016
13	2	1000	0.0014	0.0013	0.0007	0.0010	0.0015
14	2	1200	0.0013	0.0028	0.0016	0.0013	0.00114
15	2	1300	0.0048	0.0020	0.0018	0.00114	0.0013
16	2	1400	0.0055	0.00211	0.0024	0.0012	0.0019
17	3	200	0.0033	0.0041	0.0035	0.0035	0.0028
18	3	300	0.0022	0.0024	0.0025	0.0017	0.0022
19	3	400	0.0025	0.0029	0.0018	0.0023	0.0022
20	3	500	0.0017	0.0017	0.0015	0.0021	0.0018
21	3	1000	0.0017	0.0022	0.0014	0.0017	0.0017
22	3	1200	0.0018	0.0050	0.0022	0.0016	0.0030
23	3	1300	0.0054	0.0029	0.0026	0.0033	0.0022
24	3	1400	0.0071	0.0032	0.0058	0.0021	0.0029
25	4	200	0.0044	0.0046	0.0040	0.0040	0.0037
26	4	300	0.0032	0.0032	0.0030	0.0030	0.0029
27	4	400	0.0028	0.0044	0.0020	0.0028	0.0027
28	4	500	0.0019	0.0027	0.0023	0.0033	0.0019
29	4	1000	0.0018	0.0050	0.0025	0.0038	0.0027
30	4	1200	0.0034	0.0057	0.0033	0.0033	0.0035
31	4	1300	0.0019	0.0043	0.0051	0.0034	0.0038
32	4	1400	0.0080	0.0037	0.0067	0.0033	0.0038
33	6	600	0.0029	0.0023	0.0043	0.0022	0.0017
34	6	800	0.0014	0.0044	0.0020	0.0027	0.0022
35	8	600	0.0033	0.0045	0.0055	0.0064	0.0022
36	8	800	0.0067	0.0033	0.0048	0.0033	0.0029
37	10	200	0.0052	0.0108	0.0041	0.0048	0.0045
38	10	300	-	0.0036	0.0060	0.0035	0.0052
39	10	400	0.0074	0.0052	0.0109	0.0052	0.0047
40	10	500	-	0.0055	0.0072	0.01168	0.0059
41	10	600	0.0038	0.0049	0.0086	0.0062	0.0121
42	10	800	0.0201	0.0091	0.0130	0.0133	0.0130
43	12	200	0.0054	0.01144	0.0047	0.0052	0.0005
44	12	300	-	0.0141	0.0076	0.0039	0.0065
45	12	400	0.0103	0.01132	0.0183	0.0059	0.0057
46	12	500	-	0.0100	0.0086	0.0033	0.0061
47	14	200	0.0071	0.0142	0.0054	0.0057	0.0008
48	14	300	-	0.0166	0.0107	0.0066	0.0072
49	14	400	0.0132	0.0124	0.0190	0.0120	0.0063
50	14	500	-	0.01112	0.0202	0.0046	0.0063
51	16	200	0.0079	0.0129	0.0092	0.0066	0.0010
52	16	300	-	0.0236	0.0134	0.0077	0.01311
53	16	400	0.0134	0.7637	0.0209	0.0014	0.0073
54	16	500	-	0.0187	0.0346	0.1967	0.0067

Wear test has been carried out very extensively for all the volume fraction of the composite developed in the present work. The complex phenomenon of the interacting surfaces are wear and friction. The absence of lubrication system shows the wear response which are evaluated at different parameters. Based on the dry sliding wear testing carried out as per ASTM G99 at various parameters like speed, load, and volume factions, the sample data presented in table 3. The wear rate found to increases with the normal load as seen from figure 3. At higher load the fracture of the surfaces are more and debonding occurs resulting in removal of the matrix material. At lower load the wear of alloy is less than the matrix material. Also at lower load the material transfer from disc to specimen can be observed as black deposits. The transfer layer begins at this stage. The transfer layer formation is delayed in composite material as compared to alloy. Also at higher load the wear rate the increase in speed and load the delamination wear occurs where matrix comes in contact with disc at low load and speed. Due to this wear rate increases as the hardness of matrix is lower than the disc. As the load increases the wear rate rapidly increased due to plastic deformation and temperature rise at the contact region. At this stage alumina particles comes in contact with the disc and control over the wear rate is governed by reinforcement particles.

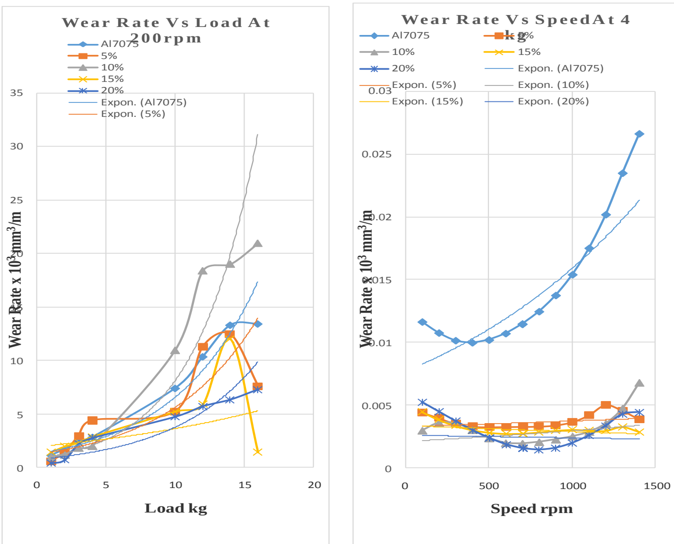

***Fig 3** Wear Rate variation of Al 7075/ Al2O3 with speed and load a) load vs wear rate b) speed vs wear rate*

4.3 ANN Predicted Wear Rate

The training carried out for all the models represented above with 80% of the dataset and the results of the training process are expressed in terms of MSE plot and Regression Plot are shown in figure 4 for clearly estimating the optimal model. Weight loss measured in the Pin on Disc wear test are converted in to wear rate using the wear rate equation. This calculated wear rate values are experimental values (Target) and wear rate predicted by ANN during the training stage are Predicted results (Output). The Mean Square Error calculated by tl ... each epoc ... an be conc ... for 10 hidd ... owest value

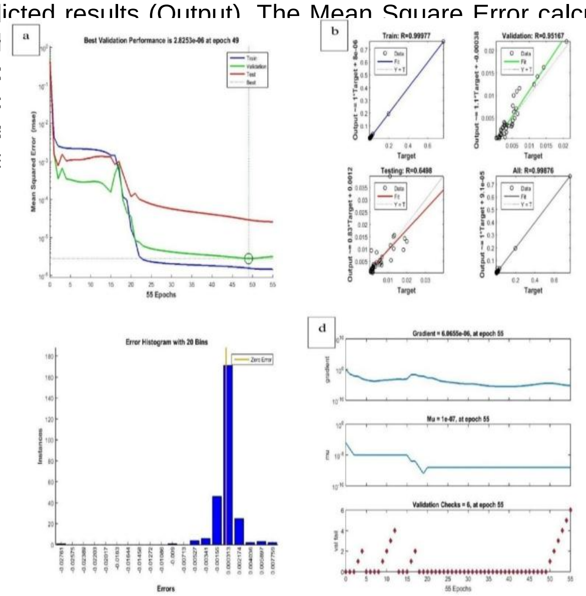

***Fig 4** Training results of ANN for Coefficient Of Friction a) Mean Square error plot, b) Histogram of Error, c) Comparison of regression plot of Training, Testing, validation and overall.d) Plot of gradient, mu and val fail.*

Total 125 data were predicted for 8 different wear parameters at 100 rpm and 1 to 25 kg load. A similar predictions are carried out at speed of 100 to 1400 rpm in steps of 100 rpm and 1kg to 25 kg for matrix material and all the composite material developed. Totally 2375 values for wear behavior are predicted for 0%, 5%, 10%, 15% and 20% volume fraction of the composite developed. A similar predictions are carried out for 25%, 30%, 35%, 40% and 50% Alumina reinforced composites. The validation of the ANN results with the experimental results are shown in the table 4 for varying load and varying speed conditions. The graph indicates two curves corresponding to ANN and Experimental values are close to each other with minimum error as seen in table 4. As per the comparison the predicted values of adhesive wear rate of the composite for various parameters varies within 10% and hence optimized values of the wear rate are acceptable.

TABLE 4.
ANN AND EXPERIMENTAL RESULTS COMPARISON

Sl No	Volume fraction	Load kg	Speed rpm	Experimental wear rate	ANN Predicted Wear rate	Relative Error of wear
1	20	14	400	0.00676072	0.006563558	0.0197
2	20	16	400	0.00177532	0.00238474	0.0609
3	20	1	500	0.00224633	0.003110499	0.0864
4	20	2	500	0.01215553	0.005360605	0.6795
5	20	3	500	0.0022418	0.002258998	0.00172
6	20	4	500	0.00296189	0.004793747	0.1832
7	20	10	500	0.01308395	0.0101457	0.2938
8	20	12	500	0.0010978	0.001558189	0.046
9	20	14	500	0.00157605	0.001547342	0.00287
10	20	16	500	0.00179344	0.001651402	0.0142
11	20	6	600	0.0027282	0.001995494	0.0733
12	20	8	600	0.00100541	0.001417435	0.0412
13	20	10	600	0.00114128	0.001627737	0.0486
14	20	6	800	0.00303435	0.002207681	0.0827
15	20	8	800	0.00350536	0.003350762	0.0155
15	20	10	800	0.00103677	0.001139678	0.0103
17	20	1	1000	0.0013294	0.001583551	0.0254
18	20	2	1000	0.00229092	0.002575673	0.0285
19	20	3	1000	0.00388788	0.004277665	0.039
20	20	4	1000	0.00067545	0.001291172	0.0616
21	20	1	1200	0.00194872	0.002002057	0.00533
22	20	2	1200	0.0029813	0.003377997	0.0397
23	20	3	1200	0.00388967	0.004445957	0.0556

The wear rate variation at the mild wear region for 5% volume fraction to 20% volume fraction of alumina is uniform in the range of 0.01 mm^3/m at 15 kg for 100 rpm corresponding to lower speed range and 5 kg at 1400 rpm at higher speed range as seen from figure 3. Once the speed and load increases this threshold value, the rapid change in the wear rate is noticed in which the ultra-mild wear will be transformed to mild wear. The corresponding load and speed above this value are considered as the transition load and speed for ultra-mild to mild wear mechanism. The oxidation wear and tribolayer formation will be reduced and the wear of composite takes place indicating increase in wear rate. The wear rate is higher for the composite with 25% volume fraction and beyond as compared to composite with 20% volume fraction reinforcement. The Shift in wear rate from the range of 0.002 to 0.04 mm^3/m for 20% volume fraction reinforcement to 0.3 to 0.6 mm^3/m was noticed in the ANN prediction. The increase in reinforcement beyond 20% volume fractions are not preferred for structural application due brittleness as clearly inferred by the data. The stir casting process involves stirring the mixture before pouring and any volume fraction beyond 20% the agglomeration increases which reduces the mechanical properties of the composite material. The isotropic property of Particulate MMC weakens beyond 20% which is strongly indicated by sharp increase in wear rate. Form 25% volume fraction onwards for every increment of 5% volume fraction reinforcement the wear rate becomes uncertain with maximum linear wear rate and corresponding load decreases by 2 kg as compared to previous case as seen in figure 6. The process of decrease in load values for linear region of wear rate with increase in speed continues till 50% volume fraction where it is the least value of 4kg at 1400 rpm.

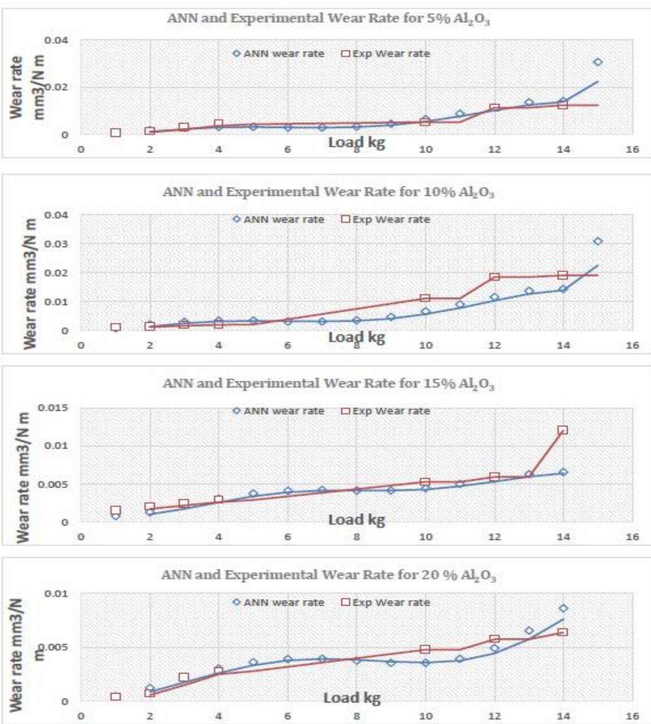

Fig 5 *Comparison of ANN Predicted and Experimental Wear rate variation with Load at 400 rpm speed*

The predicted values of wear rate response spectrum is shown in figure 5 and 6 against speed and load for each of the composite. The variation follows a trend where the increase in sliding speed and applied load influences the wear rate to increase. The wear rate variation at the mild wear region for 5% volume fraction to 20% volume fraction of alumina is uniform in the range of 0.01mm^3/m at 15 kg for 100 rpm corresponding to lower speed range and 5 kg at 1400 rpm at higher speed range. Once the speed and load increases this threshold value, the rapid change in the wear rate is noticed in which the ultra-mild wear will be transformed to mild wear. The corresponding load and speed above this value are considered as the transition load and speed for ultra-mild to mild wear mechanism. The oxidation wear and tribolayer formation will be reduced and the wear of composite takes place indicating increase in wear rate. Mechanical property of the composite influences the wear rate and the external factors like speed and load also influences the wear rate.

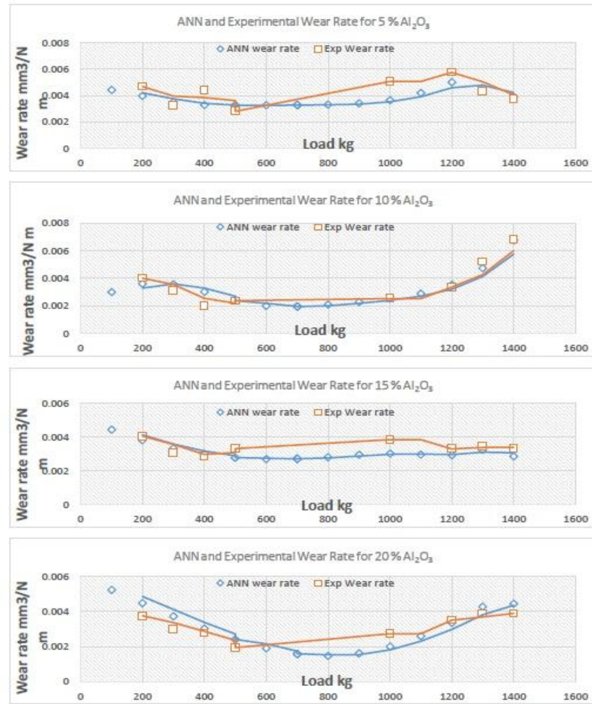

Fig 6 *Comparison of ANN Predicted and Experimental Wear rate variation with speed at 4kg load*

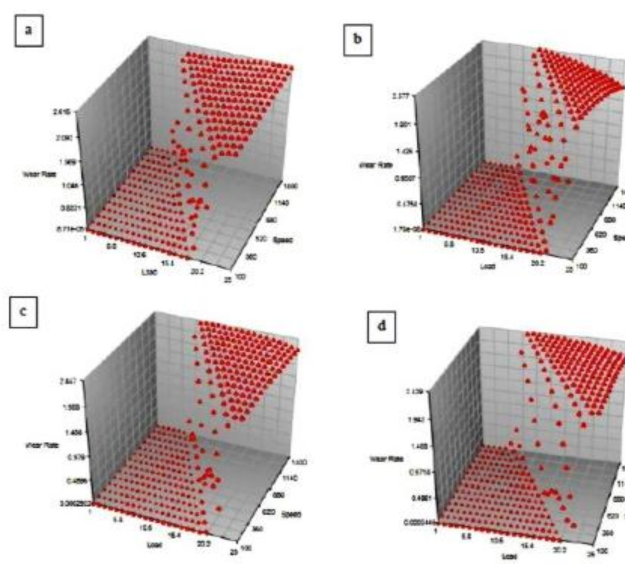

Fig 7 *ANN model predicted response surface plots for Wear rate against Speed and Load for a) 5% VF alumina, b) 10% VF alumina, c) 15% VF alumina, d) 20% VF alumina*

It can be observed in figure 7 the wear rate in vertical axis reduceses. This confirms with the increase in reinforcement volume fraction in the composite material the wear rate reduceses. Also load and speed for ultra-mild to mild wear reduces with increase in volume fraction. The wear rate generates uniform surface roughness due to wear of composite at all the load range. The developed ANN model is used for studying the performance parameters of Tribological behavior. The wear rate and wear coefficient can be effectively studied by simulating large set of results by the ANN model. The model in included with many parameters which is beyond the testing range can be predicted. The ANN will acts as a bridge between the Tribological parameter and material properties for Particulate MMCs. The limited number of test results can be used effectively to model the complete behavior of Particulate MMC over the wide range of operating conditions.

6 CONCLUSION

Wear behavior is Nonlinear and complex phenomenon and further the particulate composite exhibits unique tribological behavior at different operating parameters. The experimental burden of carrying out large number of test can be reduced with mathematical prediction tools. The Artificial Neural Network models can be used by incorporating large number of variables in the input to predict the output in terms of Tribological Properties. The ANN Models are well established tools for data prediction and simulation for material science application. The predicted data matches with the experimental values with minimum error. The ANN model can be developed for studying tribological behavior of Particulate composite material by incorporating as many controlling parameters. The developed model in this work utilizing the Levenberg Marquardt algorithm with 10 hidden neuron will perform effectively in prediction of wear rate at wide range of speed and load. The response plots of wear rate and coefficient of friction at lower and higher volume fraction of alumina reinforcement are used for analyzing the transition load and speed. At lower load the wear rate indicates ultra-mild wear mechanism and at higher load and speed mild and severe wear mechanisms. The coefficient of friction variation can be noticed at lower volume fraction of reinforcement but at higher volume fraction it is showing steady state behavior. The developed ANN model can be used for predicting the wear behavior of Particulate MMC with limited experimental data. ANN model developed by 10, 30 and 50 neurons in the hidden layer are trained with Levenberg Marquardt algorithm and Bayesian Regularization algorithm. The Model shows optimum results for 10 neurons in the training process. The Model has lowest MSE value and Regression value close to 0.9998 for Training, Testing and validation for Wear rate and Coefficient of friction. The developed Model shows satisfactory performance in predicting the wear rate and coefficient of friction at higher load, speed and volume fraction of reinforcement. The wear rate are found to be uncertain beyond 20% volume fraction of reinforcement due increase in brittleness and reduction in strength of the composite. Ultra mild wear of composite was noticed at lower speed and load and with increase in load the wear mechanism changes to mild wear with increments in wear rate. Higher volume fraction reinforced composite (above 20%.V F) has mild wear at lower load and speed. The developed ANN can be effectively used for creating wear data base which are further used for construction of wear map and wear behavior studies.

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