American Journal of Engineering Research (AJER)
e-ISSN: 2320-0847 p-ISSN : 2320-0936
Volume-11, Issue-06, pp-118-124
www.ajer.org
Research Paper Open Access

Prediction of Tribo-Behavior of Rice Husk Reinforced Epoxy Composite using an Artificial Neural Network (ANN) Model

Abdussalam Mamoon[1], Nazir Nasir Yunusa[2], Muhsin Abdussalam Ahmad[3]
[1]*Department of Mechanical Engineering, Kaduna Polytechnic, Kaduna, Nigeria*
[2] *Department of Mechanical Engineering, Kaduna Polytechnic, Kaduna, Nigeria*
[3] *Department of Computer Science, Kaduna Polytechnic, Kaduna, Nigeria*

ABSTRACT : *The potentials of using ANN in predicting the tribo-behavior of rice husk reinforced epoxy composite have been studied in the present work. Initially, varied percentage of rice husk was used in fabricating epoxy composite using hand layup method. The fabricated composites were subjected to wear test using the pin on disc apparatus and experimental results were noted. The experimental results data obtained were used to create a database for training and testing of the ANN model. Experimental and simulated data were compared satisfactorily with minimum differences. Validation of the proposed ANN shows a fair agreement with the actual experimental results. The obtained results indicated that the ANN model could be attractive as tribo behavior of rice husk reinforced composite estimator.*

KEYWORD: *ANN, Composite, Epoxy, Rice Husk, Regression.*

Date of Submission:01-06-2022 Date of acceptance: 14-06-2022

I. INTRODUCTION

Composites are emerging engineered materials as a result of a combination of two or more materials in which tailored properties can be achieved. Composites materials offer high strength to weight ratio, corrosion resistance, and good fatigue resistance which makes them highly competitive against conventional materials. Epoxy resins were widely used as a matrix in composites due to its good mechanical, outstanding adhesion to different substrates, low shrinkage upon cure, and the ability to be processed under various conditions (Parikh & Gohil, 2015).

In spite of these advantages, the widespread use of synthetic fiber-reinforced polymer composite has a tendency to decline because of their high-initial costs and also the production of synthetic composites requires a large energy and causes environment pollution (Ahmed Shubbar, 2018). In recent years, natural fiber reinforced with polymer matrix have received global attention of researchers because of their advantages such as low cost, lightweight, renewability, low density, biodegradability, environmentally friendly and abundantly available (Rout & Satapathy, 2012) (Shehu et al., 2014). The availability of these natural fibers and manufacturing have tempted researchers to study the feasibility of their usage as reinforcement in polymer composite technology for tribological applications (Debnath *et.al.*, 2013; Ahmad *et.al.*, 2015).

In many engineering elements, failure of parts is observed due to friction and wear between two contact surfaces; hence many researchers have made efforts to develop composites as a tribo-material. These researches reveal that mass loss of a composite depends on the selection of fiber (type, orientation, volume fraction, and length), resin, and filler material (size and shape). It also depends on operating parameters like load, speed, temperature, and sliding distance (Parikh & Gohil, 2019). Abhemanyu et al., 2019 conducted a research on the wear properties of natural fibre (NF) composite materials. They used hand lay-up method in fabricated these materials using banana, coconut sheath and jute fibres as reinforcements in epoxy resin. They reported that increase in amount of banana fibre increases the coefficient of friction as well as decreases the specific wear rate. Similarly, Acharya and Samantrai (2018) reported a research on the friction and wear behavior of modified rice husk filled epoxy composite. They concluded that the specific wear rate of the composite decreases with the addition of treated rice husk fibre.

Mechanical characterization of composite is a tedious task and highly sensitive to various external factors like manufacturing methods, personnel efficiency, environmental effects etc. Recently, these experiments are combined with analytical techniques like regression analysis, ANN and optimization tools to reduce the uncertainty (Gayatri *et al*., 2018). ANNs are basically a data-driven black-box model capable of solving highly non-linear complex problems. They have the ability to capture the relationship between input and output variables from given patterns (historical data or measured data on input and output variables of the system of the concern) and this enables them to solve large-scale complex problems (Seyhan *et al*., 2005).

ANN techniques have been reportedly used in literature to solve composite related issues. Zhang *et al*. (2003) and Hany El Kadi (2006) gave a comprehensive and elaborate review on the application of ANN for the modeling of a variety of composite materials. Similarly, Zhang *et al*., 2002 predicted the wear characteristics of short glass fiber reinforced polyamide composites using ANN. Another research by Seyhan *et al*. successfully applied ANN model for the prediction of compressive strength of polymer composites fabricated by VARTM process. Lastly, Keerthi *et.al* investigated the prediction of tensile properties of untreated coir reinforced polyester matrix composites using ANN. In this study, the effect of fiber volume fraction (VF) on the wear properties of rice husk reinforced epoxy composite is experimentally studied and predicted using ANN. The predicted values are compared with the experimental values to investigate the effectiveness of the above mentioned technique.

II. MATERIALS AND METHODS

2.1. *Materials*

2.1.1. Epoxy Resin

A premium blend, low odour epoxy clear resin (echenCHEM 885) and epoxy clear hardener (echenCHEM 995) were used as the matrix material. These resin and hardener were supplied by Galaxy Interior and Epoxy Ventures in Abuja, Nigeria, having negligible shrinkage, an excellent adhesion to different materials, high dimensional stability, and excellent mechanical properties, and negligible shrinkage.

2.1.2 Rice Husk

Rice husk was gotten as a by-product from a rice milling machine in IBB market Suleja, Niger State, Nigeria. The rice husk was chemically treated by soaking in a solution of 4% sodium hydroxide solution for about 3 hours in order to reduce its moisture absorption. A grinding machine was then used to grind the husk in to powder form. The powdered particle was screened in ASTM standard sieve shaker to obtain particles of less than 210µm size. The rice husk particles was characterised to determine its actual chemical composition at centre for solid mineral research and development (Step-B), Kaduna Polytechnic, Kaduna, Nigeria and is shown in the table 1 below. The particles were collected and stored in a desecrator to prevent them from absorbing moisture.

Table 1 : ***Chemical Composition of Rice Husk***

%SiO_2	**%V_2O_5**	**%Cr_2O_3**	**%MnO**	**%Fe2O3**	**%Co_3O_4**	**%NiO**	**%CuO**
59.37	0.051	0.016	0.380	0.375	0.026	0.03	0.17
%Nb_2O_3	**%MoO_3**	**%WO_3**	**%P_2O_5**	**%SO_3**	**%CaO**	**%MgO**	**%K_2O**
0.038	0.003	0.017	8.274	2.287	2.140	0.00	9.97
%BaO	**%Al_2O_3**	**%Ta_2O_5**	**%TiO_2**	**%ZnO**	**%Ag_2O**	**%Cl**	**%ZrO_2**
0.069	8.769	0.000	1.630	0.066	0.014	1.94	0.38

2.2. Methods

2.2.1 Preparation of Composites

The composites were fabricated by hand lay-up method. Moulds used for fabricating the composite were made up of 10mm thick aluminum sheets. They were cut to size designed in the form of an open mould. The design of the mould was based on predetermined samples sizes required for the various experiments.

The prepared rice husk particles were mixed with the epoxy resin by varying the mass weight of RH. They were mixed with a high speed mechanical mixer for about 5 minutes and were left to settle down in the container. The hardener was added with the recommended ratio (2:1 by weight) with gentle and short time mixing to avoid epoxy cross linking. The casting of the samples was done carefully and slowly so as to prevent bubble and flaws formation in the samples. The samples were kept in the moulds for curing at room temperature (33 °C) for 24 h. Cured samples were then removed from the moulds and used for experimentation. The composite samples were used to develop test specimen by cutting to stipulated ASTM and ISO standard sizes for various experiment.

2.2.2 *Tribo Test of Composites*

A pin on disk (POD) tribo testing machine was used to measure the wear rate of the epoxy-rice husk composites. The experiments were carried out according to ASTM G99 standard. The sample pin was fixed in a holder and was abraded under different applied loads (5N, 10N, and 20N). similarly, the sliding velocity and distance were varied with the values (2m/s, 3m/s, and 4m/s) and (500m and 1000m) respectively. After each run, the samples were removed from the machine and weighted accurately to determine the loss in weight. The experimental details are presented in table 2 below.

Table 2: Tribo Test Experimental Details

TEST PARAMETERS	UNITS	VALUES
Wt fraction of Fibre	%	0, 10, 20, 30
Load	N	5, 10, 20
Sliding Velocity	m/s	2, 3, 4
Sliding Distance	M	500, 1000
Track Radius	Mm	5.65
Temperature	°C	32

2.2.3 *Prediction using Neural Network*

An artificial neural network (ANN) helps in terms of creating relationships between variables for complex nonlinear relationships and including all the possible interactions between variables. An ANN can be used to predict behavior before preparing material, which may reduce the cost. To train and test the neural network, few samples of experimental data in table is taken as input. ANN uses the data to create a trend which can be used in predicting unknown values of the wear properties. A back propagation algorithm was used to calculate the optimal weights required to generate the output vector while minimizing the error function.

Wear test results from table with a total of 108 sets of tribo test data were obtained. In the present study 80 corrosion rate experiment results (74%) were used for training and 28 (26%) were used for testing. To test the network a test dataset was used. The accuracy of the prediction is identified by the root mean square error (RMSE) produced after training the test data. A lower value of RMSE gives higher prediction accuracy. To test the trained network 28 datasets were used. The trained network was used to predict the wear rate from a new dataset. New input parameters were selected, and conformation experiments were performed to simulate the network.

III. RESULTS AND DISCUSSION

3.1 Results

3.1.1 Wear Test Results

The wear tests were performed on the POD machine and the results noted. To obtain an acceptable result each experiment was repeated three times and the values of wear were noted. Table 3 shows the wear test results.

Table 3: Wear Test Result

Experiment No	L (N)	SD (m)	S (m/s)	Wear (µm)			
Materials				Epoxy	10% RH	20% RH	30% RH
1	5	500	2	36.50	40.00	45.00	56.30
2	5	1000	2	93.50	31.00	37.20	40.00
3	5	2000	2	50.00	42.00	44.00	28.90
4	5	500	3	53.00	28.00	29.10	29.00
5	5	1000	3	36.00	22.00	32.30	27.00
6	5	2000	3	39.50	33.80	36.70	40.00
7	5	500	4	90.00	65.00	60.40	30.00
8	5	1000	4	53.00	60.00	66.30	54.00
9	5	2000	4	47.00	52.30	50.21	51.30
10	10	500	2	42.00	35.00	49.80	43.00
11	10	1000	2	33.00	33.00	44.30	38.00
12	10	2000	2	38.90	38.00	35.70	43.1
13	10	500	3	36.00	28.00	29.80	20.10
14	10	1000	3	114.63	39.60	40.90	31.00
15	10	2000	3	54.36	51.70	50.10	40.80
16	10	500	4	37.6	31.70	28.30	29.00
17	10	1000	4	80.55	40.20	42.60	69.00
18	10	2000	4	38.90	37.10	38.20	34.00
19	20	500	2	60.50	30.90	55.30	53.26
20	20	1000	2	36.00	35.3	58.60	45.00
21	20	2000	2	63.20	53.30	44.40	40.80

22	20	500	3	51.00	21.90	29.80	30.90
23	20	1000	3	90.00	34.30	32.80	28.70
24	20	2000	3	53.20	43.30	38.20	39.00
25	20	500	4	65.00	39.10	41.80	48.30
26	20	1000	4	68.00	20.60	30.90	40.00
27	20	2000	4	56.00	55.00	40.90	42.00

3.1.2 Prediction Results

A feed forward neural network with four (4) neurons in one input layer, ten (10) neurons in one hidden layer and one (1) neuron in one output layer was created. The created network is illustrated in Figure 1 below.

The network uses the overall coefficient of determination R = 0.90567, shown in Figure 2 below. If the value of R is nearer to 1, the network gives better prediction results. From the coefficient of determination obtained (0.90567), it is expected that the network will give a considerably good prediction results.

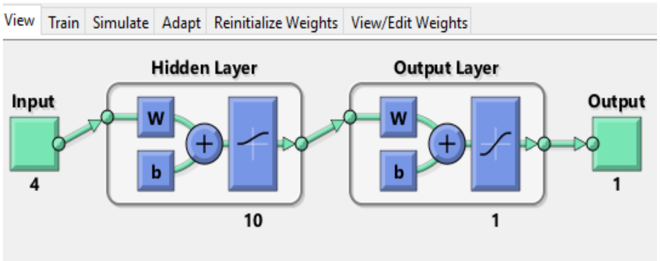

Figure 1: : Created Neural Network

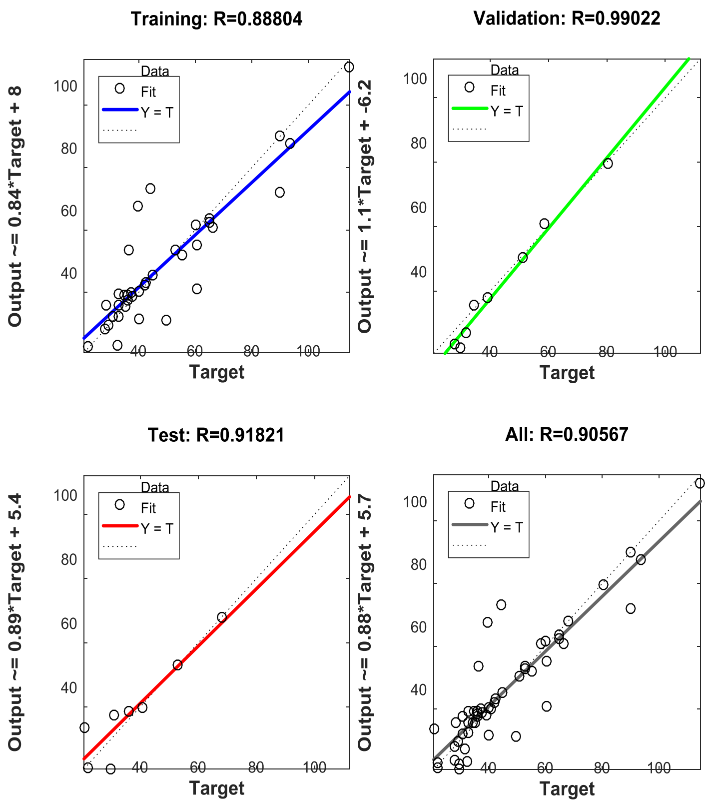

Figure 2: Regression Plot of the Network

The predicted corrosion rate from the network was compared with the actual corrosion rate obtained experimentally and is shown in table 3 below.

Table 4: Comparison btw experimental & predicted result

Exp. No	Exper Result	ANN Result	Difference
1	36.50	40.09	-3.59
2	43.50	38.45	+5.05
3	53.00	53.76	-0.76
4	36.00	34.49	+1.51
5	39.50	49.61	-10.11
6	28.00	29.42	-1.42
7	52.30	48.90	+3.40
8	35.00	31.09	+3.91
9	33.00	33.75	-0.75
10	37.10	38.79	-1.69
11	28.00	28.51	-0.51
12	43.00	41.19	+1.81
13	31.00	32.40	-1.40
14	35.30	36.95	-1.65
15	51.70	43.25	+8.45
16	60.00	58.33	+1.67
17	32.30	30.11	+2.19
18	50.21	41.28	+8.93
19	40.00	35.87	+4.13
20	39.00	38.27	+0.73
21	49.80	47.20	+2.6
22	20.10	23.33	-3.23
23	40.90	41.29	-0.39
24	56.00	59.16	-3.16
25	36.00	40.10	-4.1
26	33.00	30.99	+2.01
27	42.00	40.97	+1.03
28	47.00	48.69	-1.69

3.2 Discussions

The created network was executed with the experimental dataset obtained from wear resistance test conducted using Pin on Disc apparatus. The training stops on reaching maximum validation checks of 6 as indicated in the overall progress of the network as shown in figure 3a. From the figure, the number of epoch with 6 iterations and the performance (MSE) with 2.23, gradient decent of 6.23 and mu value of 1.0 was obtained. Similarly, a three (3) layer neural network training stat plot for network with 4 input nodes, 10 hidden nodes and one output nodes with a combination structure as (4-10-1) is shown in Figure 3b below. The training stops when the validation parameter max_fail reached maximum 6 validation checks at epoch 6 with the gradient decent value 6.2276 with reasonable Mu value 1.0.

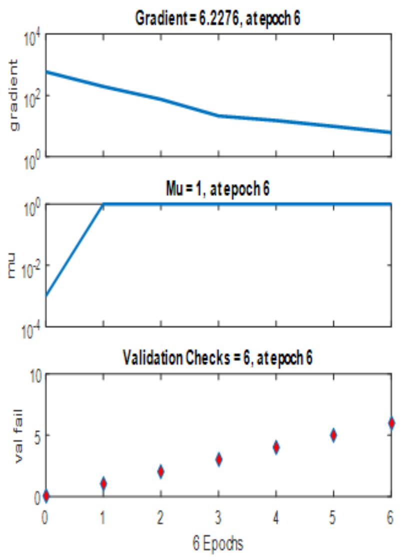

Figure 3a: Overall Progress Figure 3b: ANN training plot

The network training performance is shown in figure 4. The value of training, validation and test performance returned by the function train of the network was plotted. It can be seen that even though the training continues until 6 epochs, the best validation performance reached at epoch 0 with the value of 13.5396.

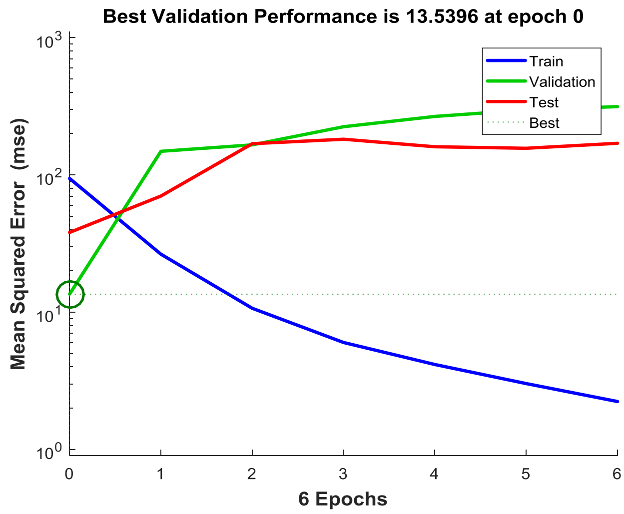

Figure 4: Network Training Performance Plot

The regression analysis was performed in ANN model after the network concludes training, testing and validation. It is a statistical process for estimating the relationships between the output and target of the network. The *plotregression* function takes two parameters (targets, outputs) values and plots the linear regression of targets relative to the outputs. Figure 2a shows the regression plot of training, test, validation and over all regression. The small circle shows the data representation in the model. After the regression plot has been constructed, the diagnosis of the model is important to confirm the goodness of fit. In our model the network shows significantly acceptable R values near to one. The Training R value was 0.88804, validation R value 0.99022, test R value 0.91821 and over all R value equals to 0.90567. This proves the developed model and the network procedure of training; testing and validation are significantly acceptable.

IV. CONCLUSION

It can be concluded from this research that:

1. In this work, an artificial neural network model has been selected and trained with corrosion rate data collected from the author's reported experimental values.
2. The best fitting training data were acquired with architecture of three layers, type 4:10:1 considering a Levenberg Marquardt learning algorithm, a tangent hyperbolic and linear transfer functions in the hidden and output layer respectively.
3. Experimental and simulated data were compared satisfactorily through a linear regression model with an overall correlation coefficient of 0.90567 and a mean square error, MSE, of 2.23 in the validation stage.
4. The ANN approach is useful to develop a neural network model to estimate the corrosion rate of low carbon steels.

Validation of the proposed ANN shows a fair agreement with the actual experimental results.

FUNDING STATEMENT

This work is sponsored under the Institution Based Research (IBR) research support scheme grants by Tertiary Education Trust Fund (Tetfund) Nigeria.

ACKNOWLEDGEMENTS

Acknowledgement goes to the Management of Kaduna Polytechnic and Specially the Chairman, Institution Based Research Committee in the Research Innovation and Technology Transfer Office (RITTO) Section for finding our research worthy of sponsorship

REFERENCES

[1]. Abdullahi I., Umar A. A. (2010). Potentials of Unsaturated Polyester – Groundnut Shell Composite as Material in Building Industry. *Journal of Engineering and Technology (Jet)* , 78-84.

[2]. Abhemanyu P. C., Prassanth E., Navin Kumar T., Vidhyasagar R., Prakash Marimuthu K. (2019). Wear Properties of Natural Fibre

Composite Materials. *AIP Conference Proceedings 2080* , 1-8.
[3]. Acharya S. K., Samantrai S. P. (2012). The Friction and Wear Behaviour of Modified Rice Husk Filled Epoxy Composite. *ACUN6 - Composites and NanoComposites in Civil, Offshore and Mining Infrastracture* , 1-6.
[4]. Ahmad Shubbar S. D. (2018). Experimental Investigation of Eice Husk Particles as Filler in Hybrid Composites. *Journal of University of Babylon, Engineering Sciences* , 307-315.
[5]. Ahmed Ali B.A., Sapuan S.M., Zainudin E.S., Othman M. (2015). Implementation of the expert decision system for environmental assessment in composite materials selection for automotive components. *Journal of Cleaner Production* , 10.1016/j.jclepro.2015.05.084.
[6]. El Kadi H. (2006). Modeling the mechanical behavior of fiber-reinforced polymeric composite materials using artificial neural networks — A review. *Composite Structures* , 1-23.
[7]. Gayatri V. M., Dave A., Chaganti P. K. (2018). Artificial Neural Network based Prediction of Tensile Strength of Hybrid Composites. *Materials Today: Proceeding* , 19908-19915.
[8]. Keerthi G. B. S., Easwara Prasad G. L., Velmurgan R. (2014). Prediction of Tensile Properties of Untreated Coir Reinforced Polyester Matrix Composites by ANN. *International Journal of Materials Science* , 33-38.
[9]. Parikh H. H., Gohil P. P. (2019). Experimental determination of Tribo Behaviour of Fibre-Reinforced Composites and its Prediction with Artificial Neural Network. *Durability and Life Prediction in Bio-, Fibre-Reinforced, and Hybrid Composites* , https://doi.org/10.1016/B978-0-08-102290-0.00013-1.
[10]. Parikh H. H., Gohil P. P. (2015). Tribology of Fibre Reinforced Polymer Matrix Composites - A review. *Journal of Reinforced Plastics and Composites* , 1340-1346.
[11]. Rout A., Satapathy A. (2012). Analysis of Dry Sliding Wear Behaviour of Rice Husk Filled Epoxy Composites Using Design of Experiments and ANN. *International Conference on Modeling Optimisation and Computing, Procedia Engineering* , 1218-1232.
[12]. Seyhan A.T., Tayfur G., Karakurt M., Tanoğlu M. . (2005). Artificial neural network (ANN) prediction of compressive strength of VARTM processed Polymer Composites. *Computational Materials Science* , 99-105.
[13]. Shehu U., Audu H. I., Nwamara M.,Shittu U. M., and Isa M. T. (2014). Natural Fibre As Reinforcement for Polymers: A review. *NO1* , 244-261.
[14]. Zhang Z., Friedrich K. . (2003). Artificial neural networks applied to polymer composites: a review. *Compos Sci Technol* , 2029-2044.
[15]. Zhang Z., Friedrich K., Velten K. (2002). Prediction on tribological properties of short fibre composites using artificial neural networks . *Wear* , 668-675.

Abdussalam Mamoon, et. al. "Prediction of Tribo-Behavior of Rice Husk Reinforced Epoxy Composite using an Artificial Neural Network (ANN) Model."*American Journal of Engineering Research (AJER)*, vol. 11(06), 2022, pp. 118-124.