Artificial neural network approach for the prediction of abrasive wear behavior of carbon fabric reinforced epoxy composite

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Artificial neural networks have emerged as a good candidate to mathematical wear models, due to their capabilities of handling nonlinear behavior, learning from experimental data and generalization. In the present work the potential of using neural networks for the prediction of abrasive wear properties of unfilled and graphite filled carbon fabric reinforced epoxy composite under various testing conditions is investigated. Back propagation neural network with 3-5-1 architecture has been used to predict the weight loss in abrasive wear situation. The network performance of different training algorithms is evaluated using the coefficient of determination B, sum squared error, mean relative error, mean squared error and regression as a quality measure. The results show that the performance of Levenberg-Marquardt (LM) training algorithm is superior to all other algorithms. Finally, the well-optimized and trained neural network with LM training algorithm is used to predict the wear properties as a function of testing conditions, according to the input data sets. The results show that the predicted data are perfectly acceptable when compared to the actual experimental test results. Hence, a well-trained artificial neural networks system is expected to be very helpful for estimating the weight loss in the complex three-body abrasive wear situation of polymer composites.

Keywords: Neural network, Back propagation, Carbon fabric, Epoxy, Graphite filler, Three-body abrasive wear

Metals have always been the first choice for engineering design since steel was invented. The need for improved materials with high specific mechanical properties, high stiffness to weight ratio, high strength to weight ratio, tailorability and damage tolerance led to the development of composites. A composite material is formed by the combination of two or more distinct constituents to create a new material with enhanced properties. In short, superior mechanical, physical and chemical properties are achieved by the combination of two or more distinct materials. The main advantages that drive the use of composites are weight reduction, improved wear and corrosion resistance, part-count reduction, thermal acoustical insulation, great specific strength, enhanced fatigue life and low thermal expansion.

Polymer composites are often used in places where they are subjected to different kind of wear situations. Wear is always undesirable and the effect of wear on the reliability of industrial components is very important and recognized widely. Vishwanath et al.1 studied the sliding wear behavior of three types of bidirectional reinforcements like, glass, carbon and Kevlar in phenolic matrix. It was reported that the glass fabric reinforced composite performed worst while Kevlar fabric reinforced composite exhibited the best performance. Also, at all velocities, coefficient of friction for Kevlar fabric reinforced composite is higher than the glass and carbon fabric reinforced composite. Suresha et al.2 and Basavarajappa et al.3 evaluated the mechanical and tribological properties of graphite filled glass-epoxy composites. Both of them reported that wear loss of the composites decreased with increase in filler content. Whereas Farag and Drai4 reported that the mechanical and tribological behavior of glass polyester composite system was improved up to 7.5% graphite filled composite and then decreased thereafter. Also, Harsha et al.5 reported that addition of PTFE and graphite fillers in glass and carbon fiber reinforced polyaryletherketones (PAEK) composites will increase the wear loss. Researchers have fabricated variety of composites and tested them for mechanical and tribological properties and further tried to model the wear behavior by using various techniques.

Artificial neural network (ANN) is inspired by the biological nerve system and is being used to solve a wide variety of complex scientific and engineering

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problems. This computational technique is especially useful for simulation of any correlation that is difficult to describe with physical model as ANN lay the ability to learn by example and to recognize patterns in a series of input and output values from example cases. This remarkable capability of modeling is useful in the study of complicated problems, which usually cannot be solved by existing physical theories or other mathematical approaches. ANN approach has been introduced recently into the field of study of wear behavior of polymers and composites. Velten and Zhang were among the earliest pioneers to explore this approach to polymer composites and they used ANN to predict the wear volume of short fiber/particle reinforced thermoplastics. The potential of ANN techniques to predict and analyze the wear behavior of short fiber (glass and carbon fibers, PTFE and graphite fillers) reinforced PA46-composites was investigated by Velten et al. They developed a multiple-layer feed-forward back-propagation neural network with non-linear differentiable transfer functions to analyze the wear data. A database, containing various testing details, i.e., material compositions, mechanical properties, measuring conditions and wear characteristics of PA46 composites, was used to train and test the neural network. From the analysis, they pointed out that the results of the neural network-based wear prediction looked very viable and promising for material design purposes, systematic parameter studies and the property analysis of the polymer composites. Zhang and Friedrich reviewed the application of various principles of ANN approach in predicting fatigue life, wear performance and dynamic mechanical properties of polymer matrix composite. Review showed that ANN is best suited for predicting mechanical behavior of polymer composite because of its resemblance to the complex biological network. A well-trained ANN is expected to be very helpful to predict the material properties before manufacturing / testing the real composites. LiuJie et al. used ANN to study the effects of pv (product of pressure and velocity) factor and contact temperature on the dry sliding tribological behavior of 30 wt% carbon-fiber-reinforced polyetheretherketone composite (PEEK-CF30) using a pin-on-disc wear testing machine. By the use of back propagation (BP) network, they built a non-linear relationship model for friction coefficient and weight loss of PEEK-CF30, pv factor and contact temperature being the inputs. From the study, they reported that a well-trained BP neural network model could precisely predict friction coefficient and wear weight loss in accordance with pv factor and contact temperature. The obtained results shown that friction coefficient was mainly influenced by the pv factor, and the weight loss was mainly influenced by the contact temperature. The tribological behavior of polyphenylene sulfide (PPS) composites filled with short carbon fibers (SCFs) (up to 15 vol%) and sub-micro-scale TiO₂ particles (up to 7 vol%) were investigated using an artificial neural network (ANN) approach by Zhenyu et al. They reported a synergistic effect of the incorporated short carbon fibers and sub-micro TiO₂ particles on improving the wear resistance. The lowest specific wear rate was obtained for the composition of PPS with 15 vol% SCF and 5 vol% TiO₂. A more optimal composition of PPS with 15 vol% SCF and 6 vol% TiO₂ was arrived at by ANN prediction. Finally, they concluded that, ANN prediction and the experimental observation showed a good agreement. Zhang et al. predicted the specific wear rate and frictional coefficient of short fiber reinforced polyamide 4.6 (PA4.6) composite using neural network. They adopted multilayer preceptor with back propagation method using different training algorithm (Bayesian regularization, Powell-Beale conjugate gradient, BFGS quasi-Newton method, adaptive learning rate and Levenberg-Marquardt) to predict the effect of type of algorithm. Study showed that ANN is a helpful mathematical tool in material design, parameters study and property analysis of polymer composites, being directly based on a limited number of measurement results.

From the literature, it is observed that there is a conflicting issue in inclusion of graphite filler in the composite system, i.e., increase or decrease in the wear resistance of the composites. In this context, the present work is proposed to predict the abrasive wear rate of unfilled and graphite filled carbon epoxy composite material using feed forward neural network model with back propagation (BP) training algorithm. Based on experimental database, the neural network is trained to minimize the error and to generalize these experimental data. The well-optimized and trained neural network is then used to predict the wear rate as a function of filler content, normal load and sliding distance.

**Experimental Procedure**

**Materials**

In this investigation, composites were fabricated using bidirectional plain-woven carbon fabric
(density 200 g/m$^3$), containing polyacryl nitrile (PAN)
based carbon fiber, supplied by CS Interglass AG,
BenzstraBe, as reinforcement. The matrix system
used is a medium viscosity epoxy resin (LAPOX -12),
and a room temperature curing polyamine hardener
(K5), both supplied by ATUL India Ltd, Gujarat,
India. The fillers that have been used are graphite
particulates supplied by Luba Chemie, Bombay.
Details of the fabrication method and the mechanical
properties of the carbon epoxy composites are given
in our earlier work$^{11}$. Four samples were prepared based
on the weight fraction of graphite filler in the composite.

Experimental set-up

The dry sand rubber wheel abrasion test setup as
per ASTM G65 is used to conduct the wear studies.
The schematic diagram of the set up is as shown in
Fig. 1. The abrasives are introduced between the test
specimen and the rotating wheel with a chlorobutyl
rubber tire. The test specimen is pressed against the
rotating wheel at a specified force by means of lever
arm while a controlled flow of grits abrade the test
surface. The rotation of wheel is such that its contact
face moves in the direction of grit flow. The pivot
axis of the lever arm lies within a plane, which is
approximately tangential to the rubber wheel surface
and normal to the horizontal diameter along which the
load is applied. The tests were carried out for different
loads and sliding distances.

Test procedure

The test samples were prepared by cutting the
composite laminates into 25 mm × 75 mm × 3 mm
size pieces. The samples were cleaned, dried and their
initial weights were determined in a high precision
digital electronic balance (0.0001 g accuracy) before
they were mounted in the sample holder. The silica
sand was used as abrasives in the present experiments.
The abrasive was fed at the contacting face between
the rotating rubber wheel and the test sample. The
tests were conducted at a rotational speed of 200 rpm.
The rate of feeding the abrasive was 250 g/min. Silica
sand with particle size of 200 µm were used in the
current study as dry and loose abrasives. The experiments
were carried out at normal loads of 11 N,
23 N, and 35 N, and the abrading distances chosen
were 300 m, 600 m and 900 m. The wear was
measured by the loss in weight.

Modeling with Neural Networks

In recent years, ANN has been applied in many
fields including function approximation and
prediction. ANN is a kind of information processing
technology, good at handling problems in which
complex nonlinear relations exist among the input and
output variables.

ANNs are based on the structure and functioning of
the biological nervous system. Neurons are the basic
unit or building blocks of the brain. A neuron receives
many input signals but it produces only one output
signal at a time. Inspired by these biological neurons,
ANN are composed of simple elements operating in
parallel. ANN is the simple clustering of the primitive
artificial neurons. This clustering occurs by creating
layers, which are then connected to one another. They
have been shown to exhibit many abilities, such as
learning, generalization, and abstraction. These networks
are used as models for processes that have input/output
data available. The input/output data allows the neural
network to be trained in a way that minimizes the error
between the real output and the estimated (neural net)
output. The model is then used for different purposes
among which are prediction and identification.

Back propagation network is made up of a large
number of interconnected neurons. The neurons are
arranged in layers: one input layer, one output layer,
and one or more hidden layer(s) between the input
layer and the output layer. Each neuron in the input
layer is connected to every neuron in the hidden layer,
which in turn is connected to the neuron in the output
layer. This topology results in a network commonly
known as the multi-layer perceptor (MLP) in which
there is no connection between neurons in the same
layer. Neurons in the input layer receive the input
signals from each training pattern. The neurons in the
hidden layer then receive the output of the input
neurons. This signal is then run through a nonlinear

Fig. 1—Dry sand rubber wheel abrasion test set-up
activation function to produce the output of each neuron of the hidden layer. The output of the neurons of the last hidden layer is in turn sent as an input to each output neuron. The predicted output is compared with the desired output and the error is sent back to the hidden layer for improving the prediction. The neural network architecture is described by the number of hidden layers, the number of neurons in each layer, the form of activation function used to nonlinearise the input-output relationship, training algorithms, the learning rate, momentum rate, and other pertinent parameters used in the network.

An artificial neural network mathematical model that represents the structure shown in Fig. 2 is written as:

\[ y = f(U) = W_o \tan h(W_i U + B_i) + b_o \quad \ldots (1) \]

where, \( y \) is the output of the neural network model, \( U \) is a column vector of size \( p \) that contains the \( p \) inputs of the process, \( W_o \) is a row vector of size \( n \) that contains the weights of the neural network model from the hidden layer to the output, \( W_i \) is a matrix that contains the weights of the neural network model from the inputs to the hidden layer. This matrix has \( n \) rows and \( p \) columns, \( B_i \) is a column vector of size \( n \) that contains the biases from the input to the hidden layer of the neural net model, \( b_o \) is the bias (scalar) from the hidden layer to the output of the neural net model.

Each input \( u_j, j=1,2,\ldots p \) has lower and upper bounds, \( Lb_j \) and \( Ub_j \), respectively. These bounds are calculated from the given input data. \( Lb_j \) is the minimum value of the \( j^{th} \) input over the given data whereas \( Ub_j \) is the maximum value of the \( j^{th} \) input over the given data.

In the present work ANN model with three neurons in the input layer (filler content, applied load and sliding distance), single hidden layer with five neurons and one output neuron (wear rate) has been constructed to predict the wear rate for various values of input parameters. The determination of number of neurons in the hidden layer is done by trial and error approach based on the mean square error criterion. It was found that the network with single hidden layer having five neurons fits well in the proposed neural network model as shown in Fig. 3 and it is a 3-[5]-1 architecture. Nonlinear tangent sigmoid activation function has been used for hidden neurons and linear activation function for output neuron. Experimental database consisting of 36 datasets are used to develop the ANN in order to understand the input-output correlation, it is shown in Table 1. These databases are then divided into three subsets: a training subset, which is used for computing the gradient to construct the neural network model, exclusively used to adjust network weights and biases; a validation subset which is required to compute validation error and testing subset.

The validation error is monitored during the training process. This error normally decreases during the initial phase of training, as does the training set error. However, when the network begins to over fit the data, the error on the validation set typically begins to rise. When the validation error increases for a specified number of iterations, the training is stopped and the weights and biases at the minimum of the validation error are returned. Finally, a test subset

![Fig. 2 — Structure of a back propagation neural network](image)

![Fig. 3 — The structure of back propagation neural network configuration used in the present study](image)
is used to compare different ANN models. 60% of the experimental data have been used for training the neural network model and 20% for validation and testing.

There are many variations of the back-propagation algorithm due to different ways of the gradient descent algorithm. In the present work, wear rate of the composites are predicted by the Neural Network Toolbox of MATLAB 7.3 using the training algorithms like batch gradient descent (traingd), gradient descent with momentum (traingdm), variable learning rate (traingda, traingdx), resilient back propagation (trainrp), Levenberg-Marquardt (trainlm), Bayesian regularization (trainbr), BFGS quasi-Newton method (trainbfg) and scaled conjugate gradient (trainscg) for comparison and the best algorithm giving the least error is used for prediction.

Then the network performance is evaluated for the test dataset, using the coefficient of determination \( B \), sum squared error, mean relative error, mean squared error and regression as a quality measure. The coefficient of determination \( B \) is calculated using the following formula.

\[
B = 1 - \frac{\sum_{i=1}^{M} [O_{pi} - O_{i}]^2}{\sum_{i=1}^{M} [O_{i} - O]^2} \quad \ldots (2)
\]

where \( O_{pi} \) is the \( i^{th} \) predicted wear characteristic, \( O_{i} \) the \( i^{th} \) measured value, \( O \) the mean value of \( O_{i} \), and \( M \) is the number of test data. The coefficient \( B \) describes the fit of the ANN’s output variable approximation curve with the actual test data output variable curve. Higher \( B \) coefficients indicate an ANN with better output approximation capabilities.

Sum squared error (SSE) is calculated by the following equation.

\[
\text{SSE} = \sum_{i=1}^{M} [O_{i} - O_{pi}]^2 \quad \ldots (3)
\]

Minimum value indicates that the better results. The mean relative error (MRE) is calculated as follows:

\[
\text{MRE} = \frac{\sum_{i=1}^{M} [O_{i} - O_{pi}]}{O_{i}} \quad \ldots (4)
\]

The value of mean squared error and regression is obtained directly from the neural network training session.

**Results and Discussion**

The abrasive wear loss of 0, 2, 4 and 6% graphite filled carbon epoxy composites under three loads 11, 23 and 35 N for sliding distances of 300, 600 and 900 m is given in Table 1. From the Table 1, it can be seen that the weight loss increases with increased percentage of graphite fillers. This is because the graphite particle is smooth and easily abraded by the silica particles. It reduces friction between the particles. As the sliding distance increases from 300 m to 900 m, the difference between the weight loss decreases for the composite samples. For obvious reasons, increased load resulted in increased wear.

<table>
<thead>
<tr>
<th>Test No.</th>
<th>Filler content wt%</th>
<th>Load N</th>
<th>Sliding distance m</th>
<th>Wear loss, g</th>
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<td>1</td>
<td>0</td>
<td>11</td>
<td>300</td>
<td>0.0843</td>
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<tr>
<td>2</td>
<td>0</td>
<td>11</td>
<td>600</td>
<td>0.1066</td>
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<td>3</td>
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<td>0.1576</td>
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<tr>
<td>4</td>
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<td>23</td>
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<td>0.2348</td>
</tr>
<tr>
<td>5</td>
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<td>23</td>
<td>600</td>
<td>0.3964</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>23</td>
<td>900</td>
<td>0.4923</td>
</tr>
<tr>
<td>7</td>
<td>0</td>
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<td>300</td>
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</tr>
<tr>
<td>8</td>
<td>0</td>
<td>35</td>
<td>600</td>
<td>0.5881</td>
</tr>
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</tr>
<tr>
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<td>11</td>
<td>600</td>
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<td>0.1909</td>
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<tr>
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<td>36</td>
<td>6</td>
<td>35</td>
<td>900</td>
<td>0.8354</td>
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</table>
Experimental data set given in Table 1 is used to train the constructed 3-[5]-1 neural network model. The network is trained for different training algorithms and the prediction qualities of these algorithms are compared, and it is shown in Table 2.

It can be noted from the Table 2 that for Levenberg-Marquardt (LM) algorithm the value of mean relative error is 9.5952, sum-squared error is 0.0356, mean squared error is 0.0002, regression is 0.9853 and coefficient of determination B is 0.9820. Therefore, it is clear that the performance of LM algorithm is superior to all other algorithms. Therefore, in the present work, LM algorithm is selected for prediction of wear loss. In the training session, validation is stopped after sixteen iterations at mean squared error value of 0.0002. Figure 4 shows performance plot, it is a plot showing the training, validation and test errors. Best validation performance occurred at iteration 10 (i.e. validation error is minimum at iteration 10 and increases thereafter) and the network at this iteration is returned. After iteration 10, the test set error and the validation set error have similar characteristics and no over-fitting occurred therefore validation stopped at 16 iterations.

A linear regression between the network output and the corresponding target is shown in Fig. 5. The output tracks the targets very well for training, testing, and validation and the correlation coefficient (R-value) is 0.98528 for the total response. It indicates good matching between the experimental data and prediction of the neural network model.

After neural network with LM training algorithm has been successfully trained, all domain knowledge extracted out from the existing samples is stored in weights associated with each connection between neurons. To test the prediction performance of the trained network, 12 data sets are used for testing the network. 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. The experimental values are compared with the predicted values from ANN and the same is given in Table 3. It is evident that error percentage lies in the range from 0.27% to 4.66% between experimental data and neural network prediction. Therefore, it can be concluded that neural network prediction has proceeded in correct manner.

<table>
<thead>
<tr>
<th>Training algorithm</th>
<th>MRE</th>
<th>SSE</th>
<th>MSE</th>
<th>Regression</th>
<th>B</th>
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<td>0.0356</td>
<td>0.0002</td>
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<td>0.0987</td>
<td>0.0066</td>
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</table>

Fig. 4—Performance plot for LM algorithm

Fig. 5—Regression plot for LM algorithm
Conclusions

An experimental approach to the evaluation of abrasive wear characteristics of carbon epoxy composites using back propagation neural network is proposed in the present study. Initially, the number of neurons in the hidden layer is optimized by trial and error method. Then the neural network 3-5-1 (three input neurons, five hidden neurons in one hidden layer and one output neuron) is trained using nine different training algorithms and the network performance is evaluated using the coefficient of determination B, sum squared error, mean relative error, mean squared error and regression as a quality measure. For Levenberg-Marquardt (LM) training algorithm, the value of mean relative error was found to be 9.5952, sum squared error 0.035616, mean squared error 0.00016, regression 0.98528 and coefficient of determination B 0.9820. The performance of LM algorithm was superior to all others. Finally, the well-optimized and trained neural network with LM training algorithm was used to predict the wear rate as a function of filler content, normal load and sliding distance. The results show that the predicted data are perfectly acceptable when compared to the actual experimental test results. Hence, a well-trained ANN system is expected to be very helpful for estimating the weight loss in the complex three-body abrasive wear situation of polymer composites and can be an alternative and practical technique to evaluate the wear loss.

References


Table 3—Test data and predicted values from neural network

<table>
<thead>
<tr>
<th>Test No.</th>
<th>Filler content % wt</th>
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