ARTIFICIAL NEURAL NETWORK-BASED WEAR LOSS PREDICTION FOR A390 ALUMINIUM ALLOY

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ABSTRACT

Artificial neural networks (ANNs) are a new type of information processing system based on modeling the neural system of human brain. The potential of using neural network in prediction of wear loss quantities of A390 aluminium alloy has been studied in the present work. The material is subjected to dry sliding wear test using pin-on-disc apparatus at room conditions. Effects of load, sliding speed and time have been investigated by using artificial neural networks. The experimental results were trained in an ANNs program and the results were compared with experimental values. It is observed that the experimental results coincided with ANNs results.

KEY WORDS: *Wear; Artificial neural network; Neuron; Hidden layer, Sigmoid function*

1. INTRODUCTION

Aluminium alloys has been showing a successful trend in replacing cast iron and copper alloys in various technological applications due to their superior mechanical and tribological properties and better castability. A390 aluminium alloy has been utilized in high-tech structural and functional applications including aerospace, defence automotive and thermal management areas, as well as in sports and recreation [1-4]. The major advantages of this alloy over other alloys are its greater strength, good stiffness, reduced density, good corrosion resistance. Aluminium is the material of choice in many applications, especially those where weight and thermal conductivity are important.

In recent years, the application of artificial neural network (ANN) has attracted extensive interests in diverse fields. Durmus et al. [5] used ANN to predict wear loss and surface roughness of AA 6351 aluminium alloy, in this study, experimental and ANN results have been compared and they showed coincidence to large extent. Velten et al. [6] used back propagation ANN with Levenberg-Marquardt algorithm to predict and analyze the wear behaviour of short fiber reinforced polymer bearing materials. Cetinel et al. [7] used ANN based prediction technique for wear loss quanities determination when Mo coating was used. Artificial neural network modeling is inspired by the biological nerve system and is being used to solve a wide variety of complex scientific and engineering problems [8 – 14]. This mathematical technique is especially useful for simulations of any correlation that is difficult to describe with physical models because of 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.

In the present work, the ANN with back-propagation (BP) algorithm is applied to predict the wear properties of A390 aluminium alloy. Based on these databases, the neural network is trained. The well optimized and trained neural networks are used to predict the wear properties as a function of testing condition, according to the newly constructed input data sets.

2. MATERIALS AND WEAR TEST

A390 aluminium alloy having a composition of 15% Si 3.5% Cu 0.5% Mg 0.6% Mn 0.2% Cr 0.9% Ti 0.006% P 4% Fe and balance Al was used as the pin material having a dimension of 4 mm diameter and 25mm in length. The disc was made from stainless steel of 50 mm in diameter and 10 mm thickness.

The wear test specimens were studied under dry (unlubricated) and under ambient conditions using pin-on-disc wear testing machine. The test was carried out under varying loads, sliding speeds and time durations. After each test, the test machine was switched off, and the pin and rotating disc were taken out and the mass loss is measured using precision balance having 0.1 mg sensitivity. These mass losses of the tested pins were used to study the effect of load, sliding speed and time on the wear resistance of the alloy under consideration.

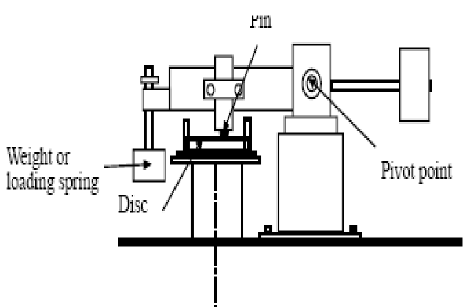


Figure.1 Schematic of the pin-on-disc apparatus.

3. MODELING WITH NEURAL NETWORKS

Artificial neural networks are considered as artificial intelligence modeling techniques. They have a highly interconnected structure similar to brain cells of human neural networks and consist of large number of simple processing elements called neurons, which are arranged in different layers in the network; an input layer, an output layer and one or more hidden layers.

One of the well known advantages of ANN is that the ANN has the ability to learn from the sample set, which is called training set, in a learning process. Once the architecture of network is defined, then through learning process, weights are calculated so as to present the desired output.

DATA SET AND PROCESSING

The inputs to individual ANN nodes must be numerical and in the closed interval [0, 1]. Because of this conversion method the normalization technique was used in the proposed ANN according to the following formula:

$$\text{Normalized value} = \frac{(\text{Input.value} - \text{Minimum.value})}{(\text{Maximum.value} - \text{Minimum.value})} \quad \ldots\ldots (1)$$

Output values resulted from ANNs are in the range [0, 1] and converted to their equivalent values based on reverse method of normalization.

LEARNING RULES AND TESTING

Neural networks are adaptive statistical devices. This means that they can change iteratively the values of their parameters (i.e., weights) as a function of their performance. These changes are made according to the learning rules of gradient descent method. Detailed description of the mathematical formulation of the back propagation algorithm has been covered extensively in literature [15 - 17].

Sigmoid function is the most common activation function in ANN because it combines nearly linear behaviour, curvilinear behaviour and nearly constant behaviour, depending on the value of the input [15, 16]. The sigmoid function is sometimes called a squashing function , since it takes any real valued input and returns an output bounded between (0, 1) [15, 16].

$$y = f(x) = \frac{1}{1 + e^{-x}} \quad \ldots\ldots (2)$$

Back propagation neural networks represent a supervised learning method, requiring a large set of complete records, including the target variables. As each observation from the training set is processed through the network, an output value is produced from output nodes. These values are then compared to the actual values of the target variables for this training set observation and the errors are calculated. Normalized root mean square error value (NSE) was used to evaluate the training performance of the ANN [18].

$$NSE = \sqrt{\frac{\Sigma(\theta-\theta_0)^2}{\Sigma\theta^2}} \qquad \text{...... (3)}$$

where θ is the experimental mass loss in wear and θ_0 represents the predicted output value for mass loss in wear.

It is important to evaluate the performance of the ANN model. This is done by separating the data into two sets: the training set and the testing set. The parameters (i.e., the value of weights) of the network are computed using the training set. When reaching the error goal, the learning process is stopped and the network is evaluated with the data from the testing set.

4. RESULTS AND DISCUSSION

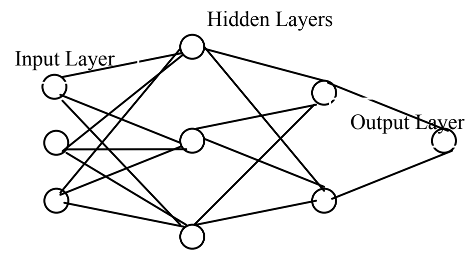
The test is a simulation of real life application. Where the test was done for specified conditions of load, rotational speed and time duration of counter face disk, however wear in contacted surfaces is primarily due to the material removal by cutting and plowing actions and in due course, wear grooves are generated. The depth and width of grooves generally control the amount of material removed from the specimen surface.

The ANN was constructed with three inputs: load, sliding speed and time; two hidden layers and one output node (mass loss). The determination of number of neurons in the hidden layer is given by [17] as

$$h = \frac{\text{Number of training cases}}{5(m+n)} \qquad \text{...... (4)}$$

where h is the number of neurons in the hidden layer, m is the number of neurons in the output layer and n is the number of neurons in the input layer. In this study, a trial and error method is performed to optimize the number of neurons in the hidden layer. It was found that the network with two hidden layers having three neurons in the first layer and two neurons in the second hidden layer fits well in the proposed ANN.

Architecture of ANN is shown in the Figure. 2.



3 Inputs: Load (N),
Sliding speed (m/s) and
Time (min)
1 Output: Mass loss (mg)

Figure. 2 The ANN architecture.

A data consists of 50 experimental data points were used to construct fully developed feed forward back propagation network. Among these 45 examples used as training examples and the residuals were used in the testing process.

For the training problem at hand the following parameters were found to give good performance and rapid convergence of neural network: sigmoid logistic is the activation function in both hidden and output layers, learning rate and momentum is set 0.6 and 0.25 respectively.

The training process is terminated after 100000 cycles and further iteration cycles had insignificant effect on the error deduction. Testing of the trained network was set to one testing cycle per 100 training cycles. Testing is used to examine if the network is good enough to do the prediction, if not testing still runs the training process to reach threshold error.

Once the optimal ANN was designed and trained efficiently, then it can be recalled to do the prediction of mass loss in wear test. Figure 3 illustrates the training process of the neural network, with averaged NSE reaches as low as 0.00085.

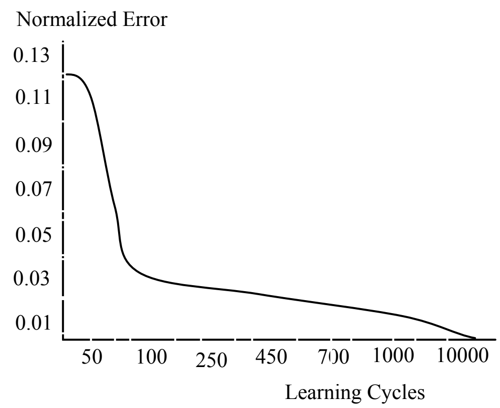


Figure. 3 Iteration number vs Normalized Error

To test the generalization performance of the trained network in training and testing processes, the experimental values were compared to the predicted values resulted from ANN as shown in Figure 4.

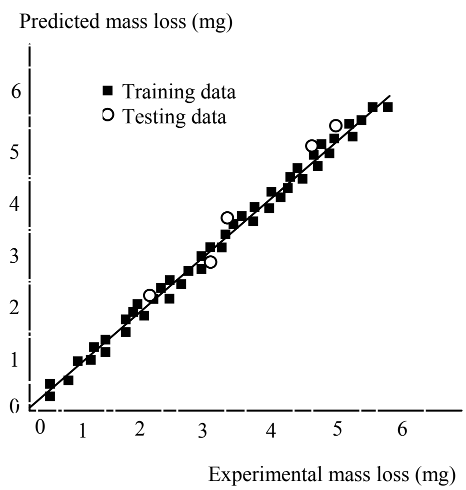


Figure. 4 Experimental vs Predicted mass loss in wear test.

After training and testing processes were finished, the ANN can be recalled to do prediction effectively.

5. CONCLUSION

In the present study, a feed-forward back propagation neural network was used to predict the mass loss quantities of A390 aluminium alloy. The experimental values of mass loss of the worn specimens were used for the training and testing of ANN. Satisfactory agreement between the experimental and ANN results was obtained from using this type of neural network. Hence it can be said that ANN can be used efficiently as prediction technique in the area of material characterization and tribology.

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