Prediction of the abrasive wear behaviour of heat-treated aluminium-clay composites using an artificial neural network

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ABSTRACT
This work employs the T6 heat treatment process to aluminium-clay (Al-Clay) composite consisting of 15 wt% clay. The samples were solutionized at 500°C, 550°C and 600°C, and were quenched in air, oil and water. Selected samples of the heat-treated composite were subjected to wear tests using Denison T62 HS pin-on-disc wear-testing machine in accordance with ASTM: G99-05 standard. The effects of two different loads (4 and 10 N) and three sliding speeds (200, 500 and 1000 rpm) under dry sliding conditions were investigated. The potential of using back-propagation neural network with 4-10-1 architecture was explored to predict the wear rate of the heat-treated composites. The results show that the performance of Levenberg–Marquardt training algorithm is superior to all other algorithms used. The well-trained ANN system satisfactorily predicted the experimental results and can be handy for an optimum design and also an alternative technique to evaluate wear rate.

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1. Introduction
The wide use of composites materials for engineering applications has been hindered by the high cost of producing the component. Hence, much efforts have been geared towards the development of composites with low-cost reinforcements that can compete favourably with those composite reinforced with silicon carbide (SiC), aluminium oxide (Al₂O₃) and graphite in terms of strength and wear characteristics. Clay is readily available for commercial exploitation and it contains major constituents like Al₂O₃ and SiO₂ in addition to Fe₂O₃, TiO₂, and Na₂O as minor constituents giving it the potential to serve as a single source for multiple reinforcements in place of the monolithic reinforcements like SiC, Al₂O₃, etc. currently in use.

Obtaining the best strength for a metal matrix composites generally requires heat treatment as per the parent alloy. Although, the hardening curves are likely to be significantly different with respect to the matrix and the reinforcement components, hardening generally occurs much faster in the reinforced materials, owing to the higher dislocation densities associated with the presence of the reinforcing particles [2,3]. The mechanical and wear properties of aluminium metal matrix composite can be enhanced by as much as 40 times using suitable alloying and heat treatment, when compared to high-purity aluminium [4].

The two-stage T6 heat treatment (quenching and ageing) of aluminium alloy (AA) 6063 allows the precipitation of Mg₂Si intermetallic compounds that provide increased strengthening of the AA 6063 matrix phase. These intermetallic precipitates are incoherent with main structure and it affects mechanical and physical properties of the material. The mechanical and wear properties are further improved as a result of precipitation of a new precipitate due to time and heat from supersaturated solid solution [4,5].

Simulation of material properties involves the development of a mathematical model derived from experimental data. Simulation is helpful in the optimization, especially for fibre-reinforced composites [6]. The lack of good prediction methods is a barrier to a deep understanding of the processing fundamentals of particulate-reinforced composites. This is especially true for the complex conditions which exist in tribological test situations. Wear process is considered as a non-linear problem with respect to its variables: either materials or operating conditions. To obtain the minimum wear rate, appropriate combinations of operating parameters have to be planned [7].
For this reason, the method of artificial neural networks (ANNs) was introduced into the field of materials science [8]. ANN is a computational structure inspired by a biological neural system. ANN is composed of very simple and highly interconnected processors called neurons. The neurons are connected to each other by weighted links over which signals can pass. Each neuron receives multiple inputs from other neurons in proportion to their connection weights and generates a single output, which may be propagated to several other neurons [5]. Neural computation based on ANN is a technique that involves database training to predict input–output evolutions. Basically, this technology is suitable for some complex, non-linear and multi-dimensional problems because it can imitate the learning capability of human beings. This means the network can learn directly from the examples without any prior formulae about the nature of the problem and generalize by itself some knowledge, which could be applied for new cases. The network generally consists of three parts connected in series: input layer, hidden layer and output layer. The coarse information is accepted by the input in series: input layer, hidden layer and output layer. The network can learn directly from the examples without any prior formulae about the nature of the problem and generalize by itself some knowledge, which could be applied for new cases. The network generally consists of three parts connected in series: input layer, hidden layer and output layer. The coarse information is accepted by the input layer and processed in the hidden. Velten et al. [9] developed a multiple-layer feed-forward back-propagation neural network with non-linear differentiable transfer functions to analyse the wear behaviour of PA46 composites. The wear data were used to train and test the neural network. The results of the analysis showed that the neural-network-based wear prediction is viable and promising for material design purposes, systematic parameter studies and property analysis of the polymer composites. Rao et al. [10] investigated 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. They employed a back-propagation neural network with 3-5-1 architecture to predict the weight loss in abrasive wear situations. The network performance of different training algorithms was evaluated using the coefficient of determination R², sum squared error (SSE), mean relative error (MRE), mean squared error (MSE) and regression as a quality measure. The results showed that the performance of Levenberg–Marquardt (LM) training algorithm is superior to all other algorithms employed and this was used to predict the wear properties as a function of testing conditions, according to the input data sets. The results showed that the predicted data are perfectly acceptable when compared to the actual experimental test results. Hence, a well-trained ANNs system is expected to be very helpful for estimating the weight loss in the complex three-body abrasive wear situation of polymer composites.

2. Materials and methods

In this present research, AA 6063 matrix reinforced with 15 wt% aluminosilicate clay particles was heat treated using the T6 heat treatment process. The Al-Clay composite samples were solutionized at 500°C, 550°C and 600°C and quenched in air, oil and water to determine the effect of solutionizing temperature and quenching medium on the wear properties of the developed composites. The samples were artificially aged at 180°C for 6 h. The wear property of the composite was evaluated and compared with as-cast composites. The wear characteristics of the composites in dry sliding conditions were subjected to a series of wear tests on a Denison T62 HS pin-on-disc machine. The cylindrical pins of 5 mm diameter made from the composite were subjected to the action of two different loads (4 and 10 N), on AISI stainless steel disc at three sliding speeds of 1.05 m/s (200 rpm), 2.62 m/s (500 rpm) and 5.24 m/s (1000 rpm) based on the ASTM: G99-05 standard. The mass loss was measured by weighing the pins before and after the test. ANN model with four neurons in the input layer – quenching media (as-cast-1, air-2, oil-3, and water-4), solutionizing temperatures (500°C, 550°C and 600°C), sliding speeds (200, 500 and 1000 rpm), and normal load (4 and 10 N), single hidden layer with 10 neurons and 1 output neuron (wear rate) was developed to predict the wear rate for various values of input parameters. The determination of number of neurons in the hidden layer is done by a trial and error approach based on the mean square error criterion [8]. It was found that the network with single hidden layer having 10 neurons fits well in the proposed neural network model as shown in Figure 1 and it is a 4-[10]-1 architecture. Non-linear tangent sigmoid activation function was used for hidden neurons and linear activation function for output neuron.

The validation error is monitored during the training process. This error 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

![Figure 1. Structure of back-propagation neural network configuration](image-url)

Figure 1. Structure of back-propagation neural network configuration [10] used in the study.
biases at the minimum of the validation error are returned. Finally, a test subset is used to compare different ANN models. 80% 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 was predicted through the Neural Network Toolbox of MATLAB 8.3 using the training algorithms such as resilient back propagation (RBP), LM, Bayesian regularization (BR), BFGS quasi-Newton method (BFG) and scaled conjugate gradient (SCG) to compare the influence of the training algorithms on their predictive qualities. The network performance is evaluated for the test dataset, using the coefficient of determination ($B$), SSE, MRE, MSE and regression ($R$) as quality measures. The coefficient of determination $B$ is calculated using the expression in Equation (1).

$$B = 1 - \frac{\sum_{i=1}^{M} [O_i - O_i]^2}{\sum_{i=1}^{M} [O_i - \bar{O}]^2},$$

(1)

where $O_i$ is the $i$th predicted wear characteristic, $O_i$ is the $i$th measured value, $\bar{O}$ is 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 superior output approximation capabilities. SSE is calculated by the following equation:

$$SSE = \sum_{i=1}^{M} [O_i - O_i]^2.$$  

(2)

Minimum value indicates better results. The MRE is calculated as follows:

$$MRE = \sum_{i=1}^{M} \frac{|O_i - O_i|}{O_i}.$$  

(3)

The value of MSE and regression is obtained directly from the neural network training session.

3. Results and discussion

The design template of the ANN is presented in Figure 2. Table 1 shows the abrasive wear loss of the as-cast and heat-treated composites under normal loads of 4 and 10 N for sliding speed of 200, 500 and 1000 rpm.

The wear rate varies with the solutionizing temperature and quenching media with superior wear resistance properties exhibited by the water-quenched samples solutionized at 550°C. As the sliding speed increases from 200 to 1000 rpm, the wear rate increases by as much as 60%. The results of the spectrochemical and atomic absorption spectroscopic analyses of the AA 6063 and the clay are presented in Tables 1 and 2, respectively.

Experimental data set given in Table 3 was used to train the constructed 4-[10]-1 neural network model. The neural network was trained for different training algorithms and the prediction qualities of these algorithms are compared, as shown in Table 4.

Thus, the performance of LM algorithm is superior to all other algorithms. In the training session, validation is stopped after 43 iterations at MSE value of 0.00036 (see Figure 3).

Best validation performance occurred at iteration 37 (i.e. validation error is minimum at iteration 10 and increases thereafter) and the network at this iteration is returned. After iteration 37, the test set error and the validation set error have similar characteristics and no over-fitting occurred and the validation stopped at 43 iterations.

A linear regression between the network output and the corresponding target is shown in Figure 4. The output tracks the targets very well for training, testing, and validation and the correlation coefficient ($R$-value) is .98533 for the total response. This is an indication of

![Figure 2. Design template of the ANN.](image-url)
good and smooth agreement between the experimental data and prediction of the neural network model. The predicted values from ANN compared with experimental values can be seen in Figure 5. 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. Similar quality of prediction was also observed in previous literature [5,6,9,10].

4. Conclusions

The wear behaviour of aluminium-clay composites was predicted using a back-propagation neural network in this study. The well-optimized neural network 4-10-1 (4 input neurons, 10 hidden neurons in 1 hidden layer and 1 output neuron) trained with five different training algorithms were used to predict the wear rate as a function of quenching media, solutionizing temperature, sliding speed and normal load.

This novelty would assist design engineers for good wear prediction and its optimization. Quality measures
such as coefficient of determination $R^2$, SSE, MRE, MSE and regression ($R$) were used to evaluate the network performance.

The performance of LM algorithm was superior to all others algorithm used. The results show that the predicted data are perfectly acceptable when compared

Figure 4. Regression plot for LM algorithm.

Figure 5. Test data and predicted values from neural network.
to the actual experimental test results. Hence, the developed well-trained ANN system can be very helpful for estimating the wear rate in the complex three-body abrasive wear situation of AlMMC and this can be an alternative and practical technique to evaluate the wear rate.

Disclosure statement
No potential conflict of interest was reported by the authors.

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