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USING OF ARTIFICIAL NEURAL NETWORKS FOR MODELLING WEAR BEHAVIOUR OF AGED 2024 and 6063 ALUMINIUM ALLOY

Ahmet Meyveci[1], İsmail Karacan[1], Hülya Durmuş[2], Uğur Çalıgülü[3]

[1] Karabuk University, Faculty of Technical Education, Department of Machine Education, Karabuk-Turkey. ahmetmeyveci@hotmail.com, iskaracan@gmail.com

[2]Celal Bayar University, Turgutlu Technical Vocational School of Higher Education, Turgutlu-Manisa, Turkey. hulya.kacar@bayar.edu.tr

[3] Fırat University, Faculty of Technical Education, Department of Metal, 23119 Elazığ, Turkey. ucaligulu@firat.edu.tr

Abstract

This paper reports on the effectiveness of a back-propagation artificial neural network model that predicts the wear loss of 2024 and 6063 Al Alloy samples which have been aged different temperatures (140°C, 180 °C, 220 °C) and different aging time. Artificial Neural Networks (ANNs) have the capacity to eliminate the need for expensive and difficult experimental investigation in testing and manufacturing processes. This paper shows that ANNs can be employed for optimizing the process parameters of aluminum alloys. Predicted values from the model and experimental values are in close agreement and this indicates the usefulness of applying ANNs in predicting wear loss results.

Key words: Wear Loss, ANN, 2024 Al alloy, 6063 Al Alloy, Aging.

1. Introduction

The wear behavior of aluminium alloys has received substantial (Ghazali et al, 2007). By most estimates, improved attention to friction and wear would save developed countries up to 1.6 % of their gross national product, or over $ 100 billion annually in the USA alone (Gavgali et al, 2003).

Aluminium and its alloys find a wide variety of uses in industrial areas and daily life because of its remarkable combination of characteristics such as the low density, the high corrosion resistance, high strength, easy workability and high electrical and heat conductivity (Totik et al, 2004). However, low surface hardness and low wear resistance often limit their engineering applications (Liao et al, 2004).

Precipitation strengthening is applied to the some aluminium alloys. Precipitation hardening is one of the most important hardening methods used to increase strength in aluminium alloys (Kaçar et al, 2003).

Heat treatable Aluminium alloys are being used increasingly in automotive industry (Hirth et al, 2001).The 6xxx and 2xxx series alloys have recently found increased application in automotive, construction and aerospace industries. (Dutkiewicz et al, 2002; Troeger et al, 2000). 6xxx and 2xxx Aluminium alloys are of particular interest to both the aerospace industry (for fuselage skins and other applications) and automotive industry (for body panels and bumbers) because of their attractive combinations of properties (Troeger et al, 2000). The precipitation hardenable aluminium alloy 6063 is widely used in the structural applications, in which the wear behavior is a fundamental design requirement (Gavgali et al, 2003) and Alloy 2024 is used in engineering applications such as aeroplane constructions, orthopaedic soles, rivet and pulling wheels (Kaçar et al, 2003).

An ANN can be considered as a black box that has the capacity to predict an output pattern when it recognizes a given input pattern. Neural networks are basically connective systems, in which various nodes called neurons are interconnected. A typical neuron receives one or more input signals and provides an output signal depending on the processing function of the neuron (Fig. 1) (Anijdan et al, 2007). The neural network must first be ‘‘trained’’ by processing a large number of input patterns and evaluating the output that results from each input pattern. Once trained, the neural network is able to recognize similarities when presented with new input patterns, and is able to predict an output pattern. The ANN models are composed of various nonlinear computational elements interrelated through a network of connections (Jia and Davalos, 2006; Su et al, 2005).

Back-propagation networks consist of an input layer, one or more hidden layers and an output layer (Fig.1). This ANN incorporates a hidden layer that is used to establish the interrelationships between the input variables and their relationship with the output to minimize the error between the actual and predicted output (Sterjovski et al, 2005).

In the past few years there has been a steady increase in interest in neural network modeling in different fields of materials science. The basic unit in an ANN is the neuron. The neurons are connected to each other by a weight factor. A network is usually trained using a large number of inputs with corresponding to output data (Durmuş et al, 2006; Taskin et al, 2008).

S. Dhanasekaran and R. Gnanamoorthy investigated the abrasive wear characteristics of sintered steels containing molybdenum di sulphide powders and they developed the artificial neural network model predicts the wear volumes (Dhanasekaran and Gnanamoorthy, 2007). Satpathy et al (2006), reports implementation of ANN for analysis and prediction of wear behaviour of plasma sprayed fly ash coating. Song, Zhang, Tseng and Zang investigated the application of artificial neural networks on ageing dynamics in AA 7175 aluminum alloys. Several authors used ANNs for comparing with experimental results (Şahin, 1999).

The use of ANN will reduce the calculation times and it is aimed at eliminating the full-size experiments that have to be carried out prior to actual production processes (Bajimaya et al, 2007).

The present work aimed to develop an artificial neural network model that could predict the wear loss of aged 2024 Al alloy and 6063 Al alloy depending on aging temperatures, aging time and applied loads. Furthermore, it was showed that the wear loss could be predicted using the trained network. Hence, the main objective of the current work is to employ neural networks to model the obtained results from the wear loss of aged 2024 Al Alloy and 6063 Al Alloy on process temperatures, loads and process time, an area not tackled to date by ANN modelling approaches.

2. Experimental Procedure

In this study, AA 2024 ($AlCuMg_2$) and AA 6063 ($AlMg_2Si$) wrought alloys were used as test material and the test materials were provided from SEYDISEHIRALUMINUM and ACAMETAL (Turkey). The chemical composition of the material used is given in Table 1. For adhesive wear and hardness test specimens of 10 mm in diameter and 6 mm in height from AA 2024 and AA 6063 aluminium alloys were machined by CNC lathe machining.

AA 2024 and AA 6063 aluminium alloys were solution treated at two different temperatures of 490 and 520 ±5 °C for 2 hours in a furnace. Then both specimens were cooled to room temperature. After this process, the specimens were aged at three different temperatures (140, 180, 220 °C) for ten different periods of time (2, 4, 6, 8, 10, 12, 14, 16, 18, 20 hours.) for artificial ageing (T6). Wear lost has been aged AA 2024 and AA 6063 aluminium alloys, under the 10 gr load and hardness measurement AFFRI SYSTEM.

2.2. Wear tests

Wear tests were carried out on the pin-on-disk model wear test apparatus (Fig. 2). The disk was driven by an electrical motor with a constant speed of 0.08 ms^{-1} at loads of 10 N, 20 N and 30 N. The experiments were performed in the atmospheric condition where the relative humidity of 55% and temperature of 20 ^{0}C. Experimental data, i.e coefficient of friction and time, were recorded continuously during the wear tests. After 0.08 ms^{-1} speed, which result in after the distance of 400 m, 800 m, 1200 m and 1600 m were taken, the experiment was stopped, wear specimens were removed and the worn surfaces were measured using a sensitive scale with the accuracy of 0.001 mg.

2.3. Microstructural analysis

Microstructures of AA 2024 and AA 6063 alloys with as-cast and artificial aging were charasterised using a Jeol Jsm-6060 Scanning Electron Microscope (SEM) and an Energy Dispersive Detector (EDS). Figure 3 (a) and (b) shows the secondary phases in matrix, which were obtained from SEM image of the AA 2024 and AA 6063 aluminium alloys.

3. Artificial neural network Modelling

An ANN is a computational system that simulates the microstructure (neurons) of biological nervous system. The most basic components of ANN are modeled after the structure of the brain. By inspired 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. It may also vary how these layers connect. Basically, all ANN have a similar structure of topology. Some of the neurons interface the real world to receive its input, and other neurons provide the real world with the network's output. All the rest of the neurons are hidden from view (Satpathy, 2006).

Neural elements of a human brain have a computing speed of a few milliseconds, whereas the computing speed of electronic circuits is on the order of microseconds. The ANNs are parallel process elements which has characteristic in below.

-ANN is a mathematical model of a biological neuron.

-ANN has very process elements which are related another.

-ANN keeps knowledge with connection weights (Taskin and Caligulu, 2006).

In this study, a database of 39 values was used to train the ANNs. The momentum and learning rate values are taken as 0.9 and 0.7, respectively. These values were found from the result of pre-trials. A back-propagation algorithm is used in the optimization in which the weights are modified. In the trials, neural networks with having different structures are employed. For his study, suitable network obtained is 3:4:4:1. The ANNs architecture is illustrated in Fig. 1, and comprises many simple processing neurons organized in a sequence of layers: input, hidden and output layers. The training process finished in one minute approximately. A very good agreement between the predicted values from the trained neural network and the validating data is achieved.

4. Results and Discussion

The measured wear loss for the aged samples was plotted as a function of the applied load and aging time. The results were presented in Fig.3. The wear tests were performed directly onto the surface at loads of 10, 20 and 30 N. It is clear that the obtained wear loss values are independent from the aging time, aging temperature and applied load.

The prediction of wear loss is performed using the ANN model. An ANN model with 2 hidden layers and 4 neurons in hidden layers is an appropriate method for prediction of wear loss in aged 2024 Al alloy and 6063 Al alloy, where aging temperature, aging time and applied load are input parameters (Fig.4). The wear loss value is found by trial and calculation (Fig. 5). The mean errors were 0.49% for the 2024 Al alloy learning phase and 1.32 % for the 6063 Al alloy learning phase.

Wear loss is considered as an output. A step-by-step method was carried out on the trained ANN by differing iteration numbers and different hidden neurons. For every input parameter, the percentage was changed in the output as a result of the change in the input parameter.

Results obtained from the neural models are given in Fig. 6. As seen from the figures, neural network models are able to establish a high correlation between ANN and experimental values. Fig. 7 shows the predicted wear loss and measured values.

For the testing phase of aged 2024 Al alloy and 6063 Al alloy, six samples were selected. In Fig. 8, ANN and experimental wear loss values are shown. The mean error was 5 % for the testing phase for aged 2024 Al alloy, 1.74 % for the testing phase for aged 6063 Al alloy. This degree of agreement is very pleasing. For different hidden neurons, the test mean errors were calculated, and for 3:4:4:1 ANN architecture and 10000 iteration, the lowest test mean error was obtained (Fig.9, 10 and 11).

Very good performance of the trained neural network was achieved. The predictions were in good agreement with the experimental values. ANN has the potential to minimize the need for expensive experimental investigation and/or inspection of aluminum alloys used in various applications, hence resulting in large economic benefits for organizations. The training phase finished in 1 min. whereas the experimental study lasted a number of days.

As an explanation, the effect of ageing temperature, ageing time and ageing load on wear loss should be expressed clearly as shown in figures. The maximum wear strength was found to be that of aged specimen at 140 and 180 C temperatures. At these temperatures, with increasing ageing time, wear strength were increase. Over aged was observed at 220 ^{o}C, so wear strength was decreasing these specimens. Both experimental results and ANN results have confirmed it.

5. Conclusion

In this study, neural network was used for calculation of the wear loss in aged 2024 Al alloy and 6063 Al Alloy. An ANN model with 2 hidden layers and 4 neurons in hidden layers was proven to be powerful tool for prediction of wear loss in aged Al alloys, where aging temperature, aging time and applied load were input parameters. The overall performance of the model was quite satisfactory. The results showed that the ANN approach could be considered an alternative and practical technique to evaluate the wear loss in aged Al alloys (Table 2 and 3). These features enable the use of ANNs in aged Al alloys and will assist studies in this field. Hence, experimental studies can be reduced to a minimum in situations where the use of ANNs is appropriate. Given and predicted values of the ANN system can also be employed at no cost. This can be handled as a cost saving item at advanced production planning. This method, in the future, may be applied further to other manufacturing processes as well.

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FIGURES

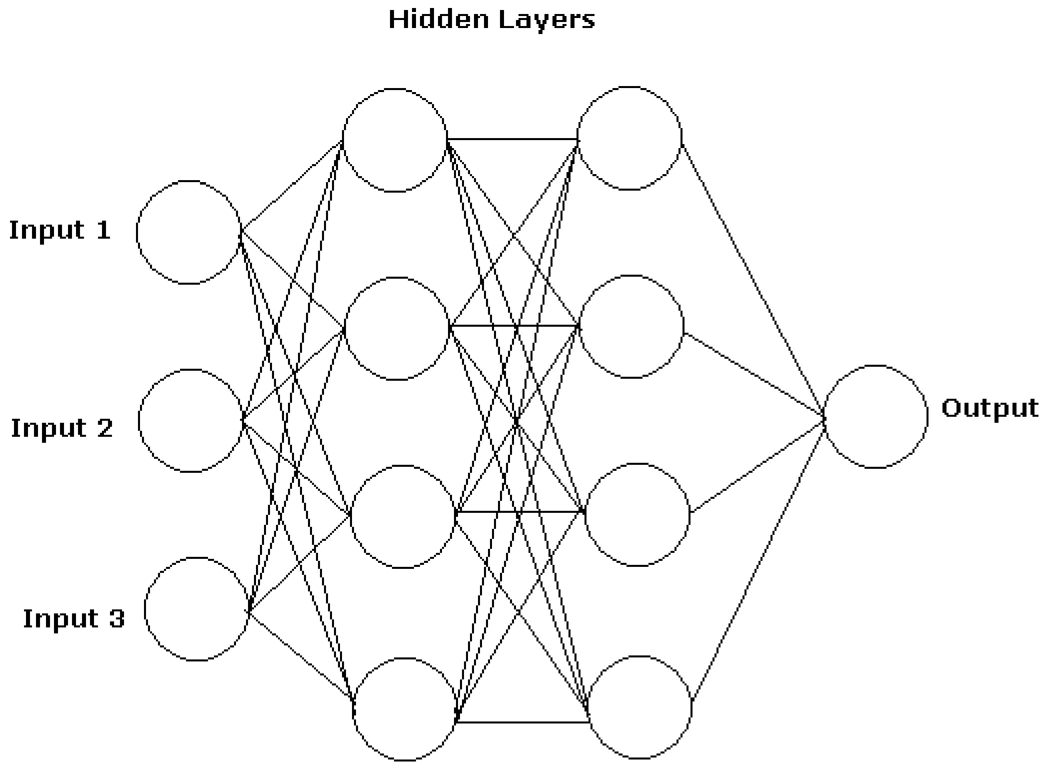

Figure 1. The structure of ANN used in this study for aged 2024 Al alloy and 6063 Al alloy.

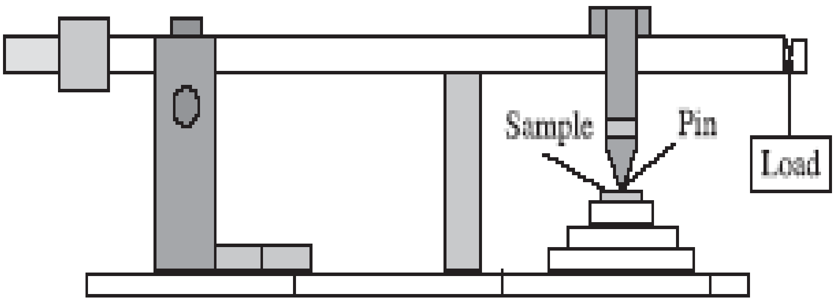

Figure 2. Schematic representation of the pin-on-disc test configuration [Gavgali et al].

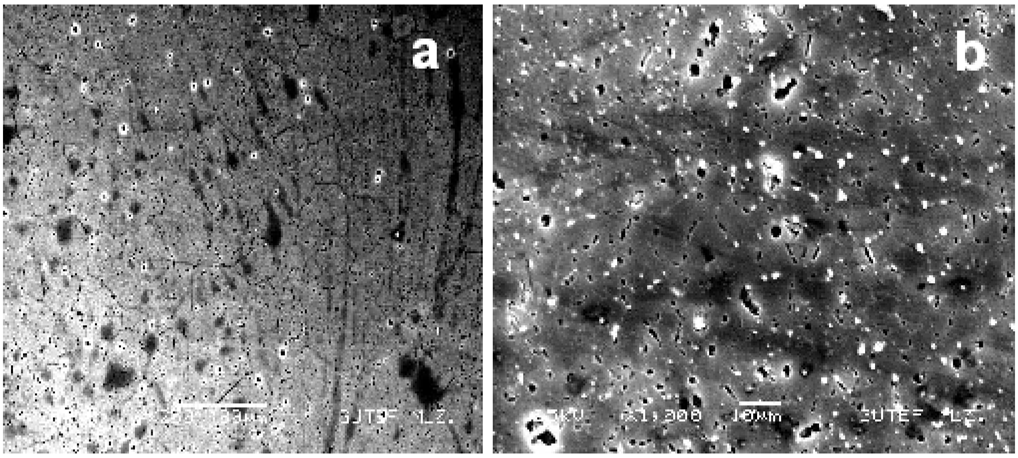

Figure 3. SEM images of the AA 6063 and AA 2024: (a) at 140 °C aged for 10 h of AA 6063; (b) at 180 °C aged for 2 h of AA 2024.

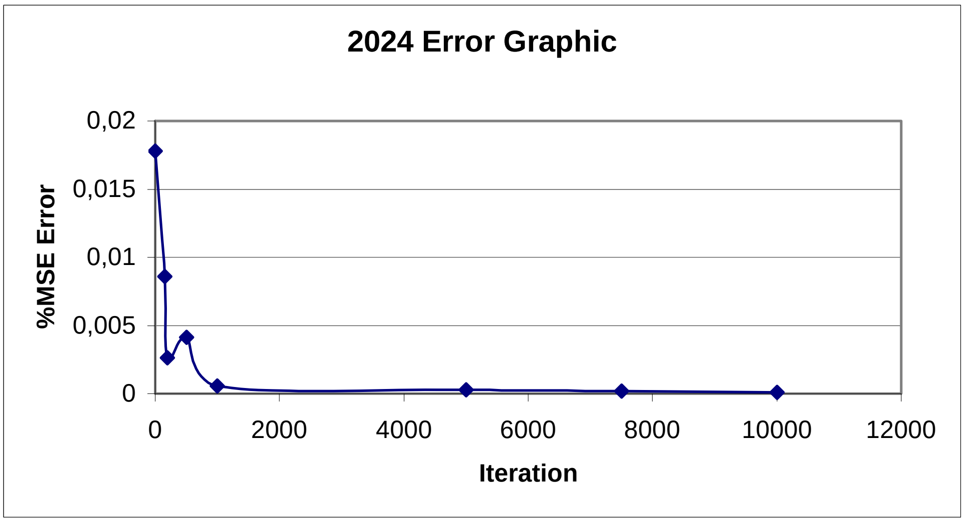

Figure 4. Iteration number versus mean square error for training nonlinear correction coefficient for aged 2024 Al alloy.

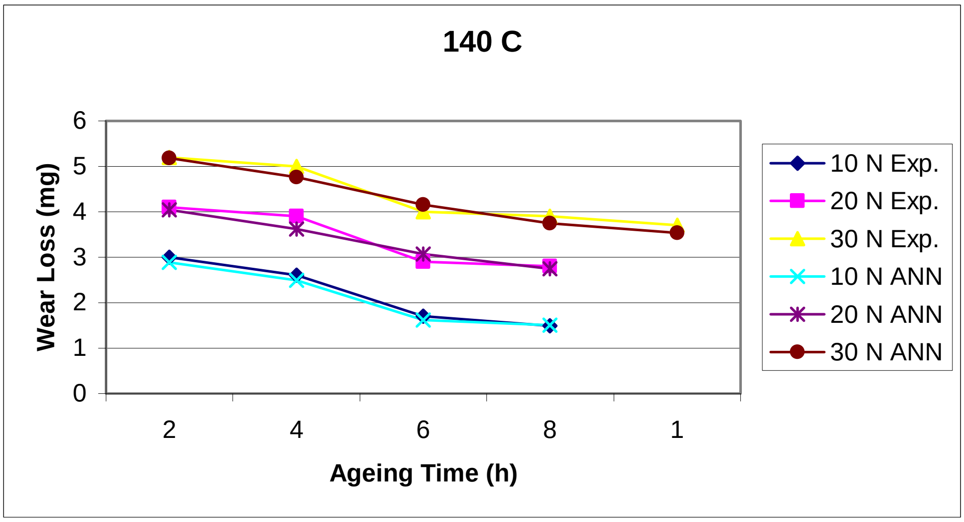

Figure 5. The comparison of experimental wear loss values with ANNs results of 2024 Al alloy at 140 ^{o}C ageing temperature and different applied loads.

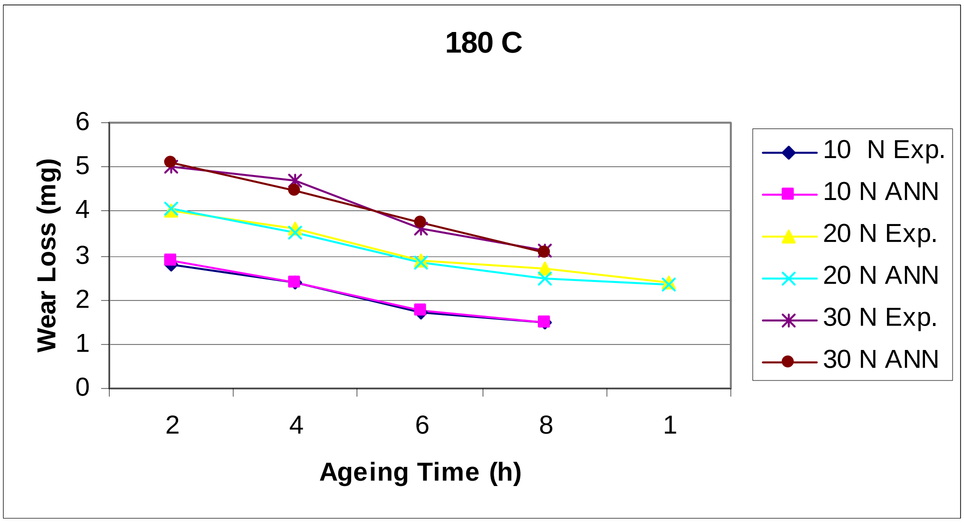

Figure 6. The comparison of experimental wear loss values with ANNs results of 2024 Al alloy at 180 ^{o}C ageing temperature and different applied loads.

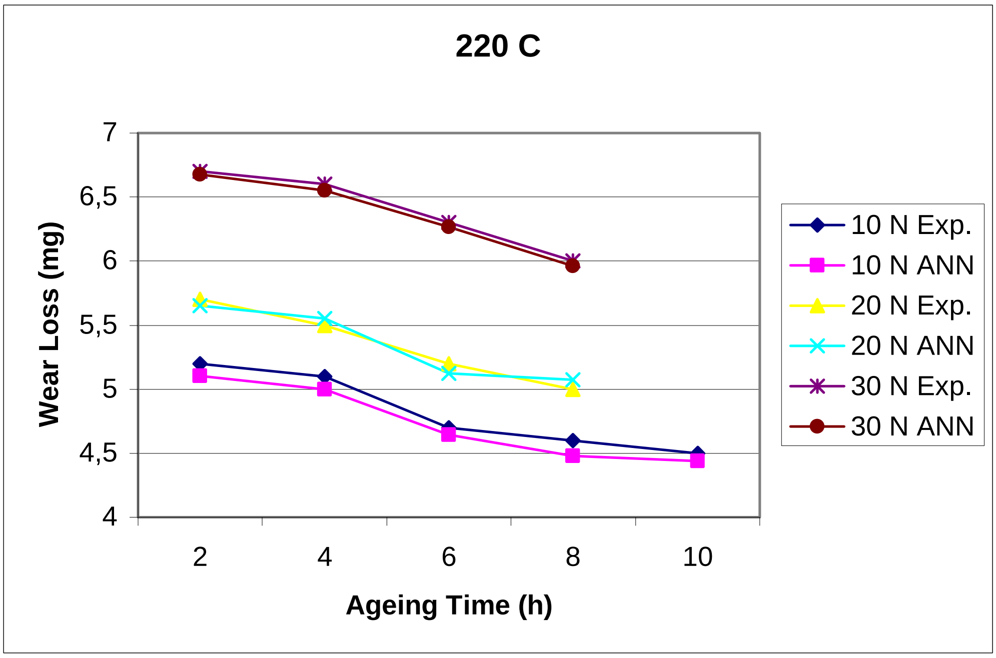

Figure 7. The comparison of experimental wear loss values with ANNs results of 2024 Al alloy at 220 ^{o}C ageing temperature and different applied loads.

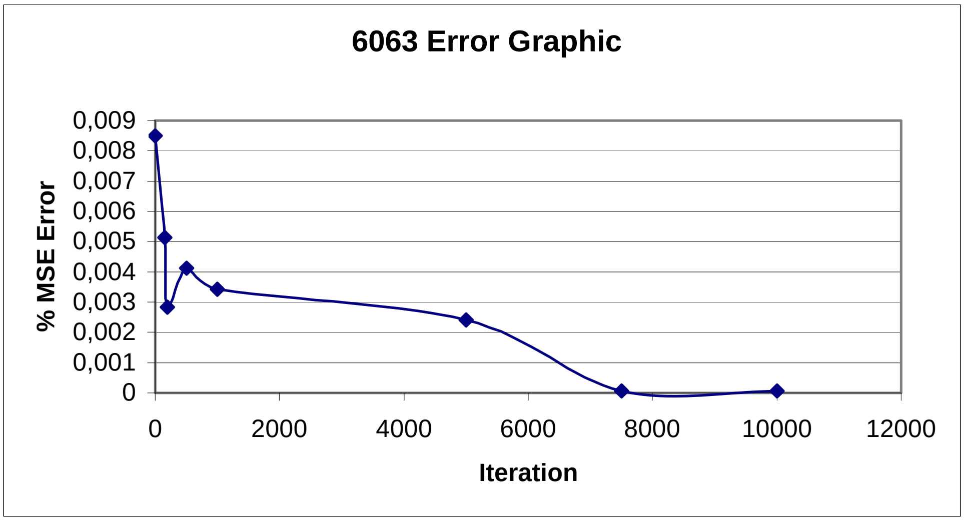

Figure 8. Iteration number versus mean square error for training nonlinear correction coefficient for 6063 Al alloy.

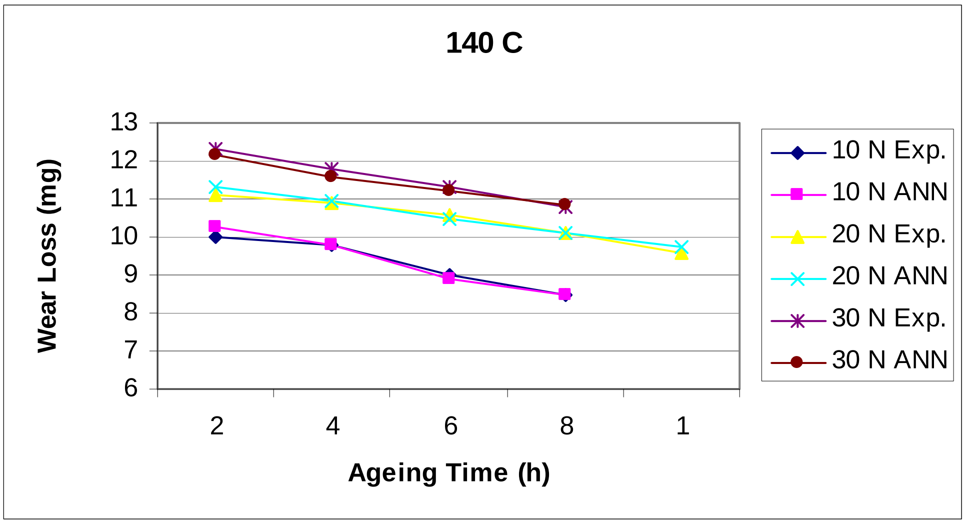

Figure 9. The comparison of experimental wear loss values with ANNs results of 6063 Al alloy at 140 °C ageing temperature and different applied loads.

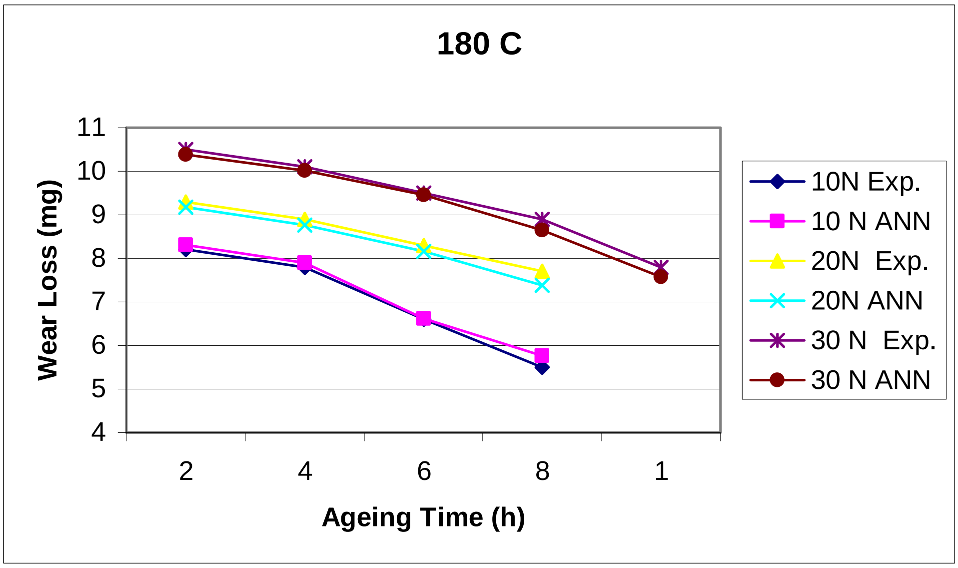

Figure 10. The comparison of experimental wear loss values with ANNs results of 6063 Al alloy at 180 °C ageing temperature and different applied loads.

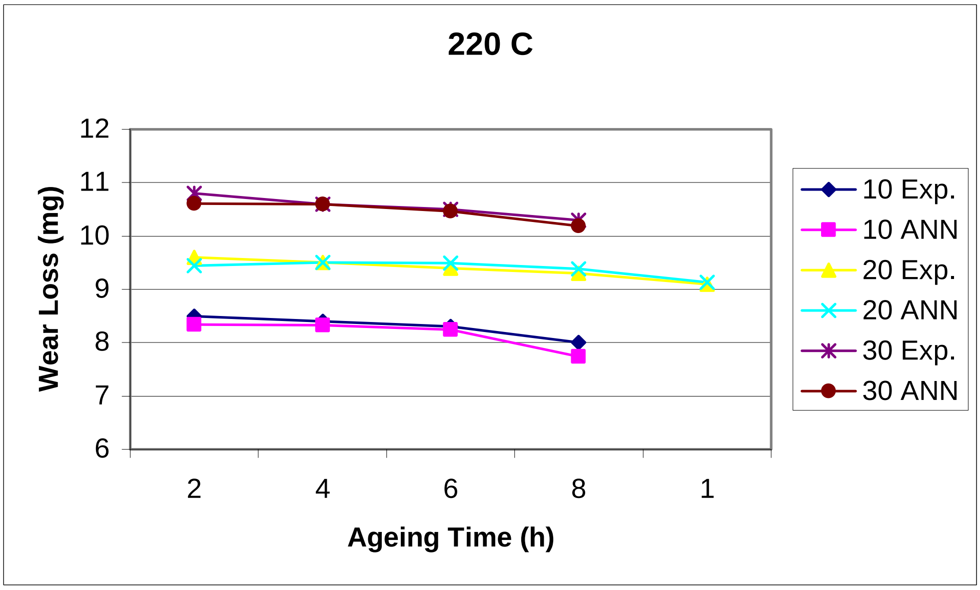

Figure 11. The comparison of experimental wear loss values with ANNs results of 6063 Al alloy at 220 ^{o}C ageing temperature and different applied loads.

TABLES

Table 1. Chemical composition of materials used in the experiments

Element	Si	Fe	Cu	Mn	Mg	Zn	Cr	Ti	Al
AA 2024	0.37	0.38	4.28	0.43	1.45	0.18	0.016	0.019	Balance
AA 6063	0.52	0.3	0.08	0.1	0.82	0.1	0.03	0.06	Balance

Table 2. Comparison of test phase and experimental results for ged 2024 Al alloy.

Ageing Temperature (°C)	Ageing Time (h)	Load (N)	Wear Loss (Exp) (mg)	Wear Loss (ANN) (mg)
140	6	10	1,8	1,92
140	10	20	2,6	2,624
180	10	10	1,2	1,44
180	8	30	3,3	3,296
220	6	20	5,3	5,28
220	8	30	6,2	6,08

Table 3. Comparison of test phase and experimental results for aged 6063 Al alloy.

Ageing Temperature (°C)	Ageing Time (h)	Load (N)	Wear Loss (Exp) (mg)	Wear Loss (ANN) (mg)
140	6	10	9,5	9,30
140	4	30	12,1	11,91
180	6	10	7,2	7,34
180	10	20	6,6	6,42
220	8	10	8,2	8,07
220	4	30	10,7	10,64