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Investigations on Wear Behaviour of ADI using Artificial Neural Network

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Abstract

Austempered Ductile Iron (ADI) is emerging as an alternative material to forged steel in many applications. ADI possesses remarkable wear resistance properties with reasonable toughness and ductility combined in one. In the present investigation, ADI was obtained by solutionizing ductile iron at 870°C for 90 minutes and austempering at 345°C for 150 minutes. The present work aims at predicting the wear behaviour of ADI by using Artificial Neural Network (ANN). A feed forward back propagation algorithm was used for the analysis. Experiments were planned using Design of experiments by Taguchi method. L9 orthogonal array was selected and experiments were conducted as per the run order generated by Taguchi for the control factors at three levels. Applied load of 19.62, 29.43, 39.24N were selected for study at speeds of 1.047, 2.095, 3.142m/s for sliding distances of 1257, 2514 and 3770m. Finally 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 results. Hence a well trained artificial neural network system is expected to be very useful for estimating the weight loss of ADI under dry sliding wear test conditions at atmospheric temperature.

Keywords: *Austempered ductile iron, Dry sliding wear, Weight loss, Coefficient of friction artificial neural network*

INTRODUCTION

From the past few decades Austempered Ductile Iron (ADI) has emerged as an excellent engineering material with strength, toughness and ductility. When Ductile Iron (DI) is subjected to Austempering heat treatment, it results in ADI which brings in balanced mechanical properties [1,2]. The material is relatively inexpensive in comparison with steel [3]. The selection of heat treatment temperatures and times are based on desired microstructure and properties. ADI undergoes two stage reaction process during the cycle of heat treatment [4,5]. ADI has wide application areas such as in the manufacture of automotive components and machine parts such as camshafts, bearings and timing gears subjected to severe service conditions [6-9]. It is also used in the production of jaw crusher components, impact plates, hammers, excavator teeth, rolls and drills [10]. Wear is one of the mechanical phenomenons resulting in malfunctioning of component with subsequent material replacement resulting in huge loss to industries. The wear is not a material dependent property but depends on various factors such as process parameters (speed, load and time), external factors such as operating temperature, lubrication etc. and as well on the microstructure and its work hardening capacity. Thus weight loss for the material is studied with careful selection of these control factors. There are various ways of predicting weight loss of materials and many investigators have successfully used these techniques in their study.

In recent years, the application of artificial neural network (ANN) has attracted extensive interests in diverse fields. Durmus et al. [11] used ANN to predict weight 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. [12] 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. [13] used ANN based prediction technique for weight 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 [14-20]. 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.

EXPERIMENTAL PROCEDURE

1. Specimen preparation

DI with the chemical composition shown in Table 1 was produced in a commercial foundry using 500 kg medium frequency induction furnace. Specimens with dimensions ϕ10 mm and length 30 mm were machined from the cast test bar in shell mould. Specimens were subjected to austempering heat treatment to produce ADI.

Table 1: Chemical composition of DI (wt%)

C	Si	Mn	P	S	Mg
3.52	2.5	0.161	0.037	0.014	0.054

ADI was austenitised at 870 °C for 90 min. and austempered in salt bath at 345°C for 150 min.

2. Wear test

The dry sliding wear tests were carried out using DUCOM pin-on-disc apparatus, at room temperature and at a relative humidity between 28 and 37% as per ASTM standards. The pins, with a diameter of 10mm, were made by ADI and the counterface disc was EN-32 steel disc with 65 HRC. The sliding surfaces had an initial roughness of R_a=0.5μm. Tests were conducted at room temperature for applied loads of 19.62, 29.43 and 39.24N run for different sliding distances 1257, 2514 and 3770m at three sliding speeds of 1.047, 2.095 and 3.142 m/s. The weight loss was determined to a precision of 0.1 mg. The obtained values were converted into wear volumes by considering a density of 7.1 g/cm^3. At least three tests for each experiment were carried out to minimise the experimental error. Coefficient of Friction (COF) was also calculated for each of the test from the normal applied load. The pin-on-disc machine used for conducting the tests is shown in figure 1.

3. Artificial Neural Network (ANN)

MATLAB version 2011b is used for the design, implementation and simulation of the networks with feed forward back propagation algorithm. Back propagation networks are multi layer networks with hidden layers of sigmoid transfer function and a linear output layer. The linear transfer function were used as the activation transfer function, the back propagation function is used to train algorithm. The back propagation algorithm was used as the linear rule and mean square error was used as the performance function. In each parameter model, the training and testing were normalized (0, 1) due to the use of hyperbolic tangent sigmoidal function in the model and network.

RESULTS AND DISCUSSION

The experiments were conducted on the pin-on-disc machine as per the plan of experiments indicated generated by Taguchi method using L_9 array. The experimental results are depicted in table 2.

Figure 1: DUCOM pin-on-disc machine

Table 2: Experimental test results

Experiment no.	Load, L (N)	Speed, S (m/s)	Sliding distance, D (m)	Weight loss in gms.	Coefficient of friction
1	19.62	1.047	1257	0.0009	0.4485
2	19.62	2.095	2514	0.0011	0.5556

3	19.62	3.142	3770	0.0004	0.3772
4	29.43	1.047	2514	0.0028	0.4179
5	29.43	2.095	3770	0.0016	0.4315
6	29.43	3.142	1257	0.0005	0.2107
7	39.24	1.047	3770	0.0017	0.4918
8	39.24	2.095	1257	0.0006	0.4791
9	39.24	3.142	2514	0.002	0.5912

Modelling for predicting wear rate using Artificial Neural Network

The following procedure was employed to predict the wear rate using Artificial Neural Network.

- Define input and target (output)
- Import input and target data
- Create a new network by selecting network type, learning type, transfer function, number of layers and number of neurons.
- Training the network created
- Find out performance plot
- Many networks were created by changing the number of neurons and the corresponding performance plot was noted.

In the present work ANN model with three neurons in the input layer (load, speed and sliding distance), single hidden layer with 10 neurons and one output neuron (weight loss) has been constructed to predict the loss of weight by wear 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 ten neurons fits well in the proposed neural network model as shown in figure 2 and is a 3-[10]-1 architecture. Nonlinear tangent sigmoid activation function has been used for hidden neurons and linear activation function for output neuron. 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 [21, 22].

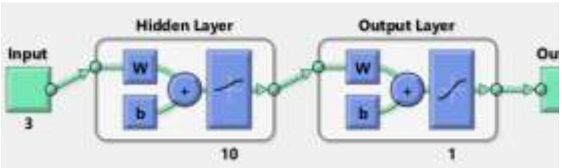

Figure 2: The structure of back propagation neural network configuration used in the present study

Here 17 networks is created by using the above procedure. Network one with 10 neurons gave the best results. Figure 3 shows the performance plot and figure 4 shows the regression plot for the analysis. The normalised output data is indicated in figure 5 from the output of the network performance results. The results were converted into the weight loss back from these normalised output data and are indicated in table 3. From figure 3 best validation performance is 0.029106 at epoch 1.

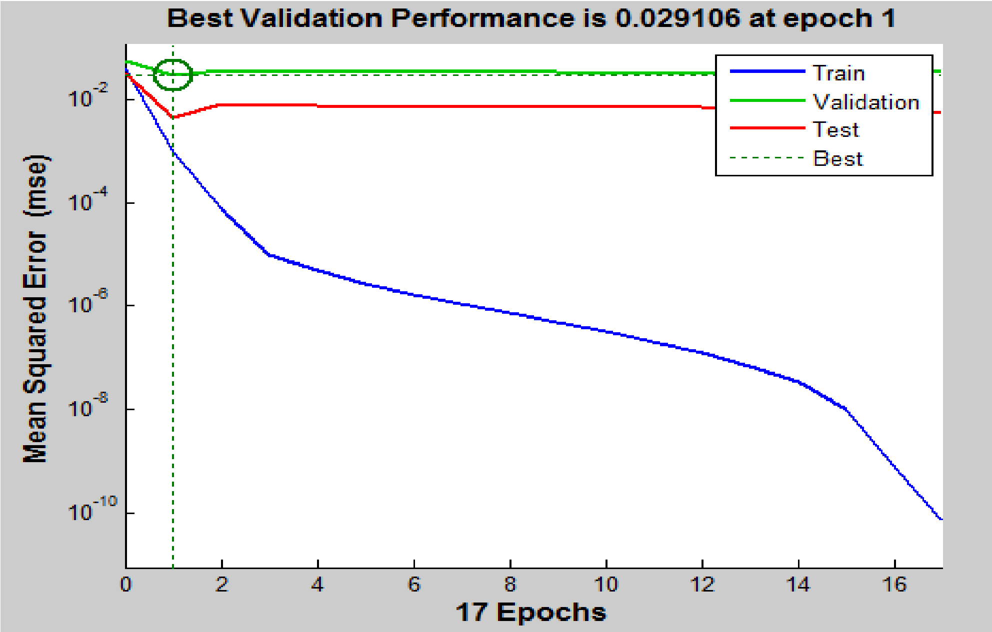

Figure 3: Performance plot for wear loss

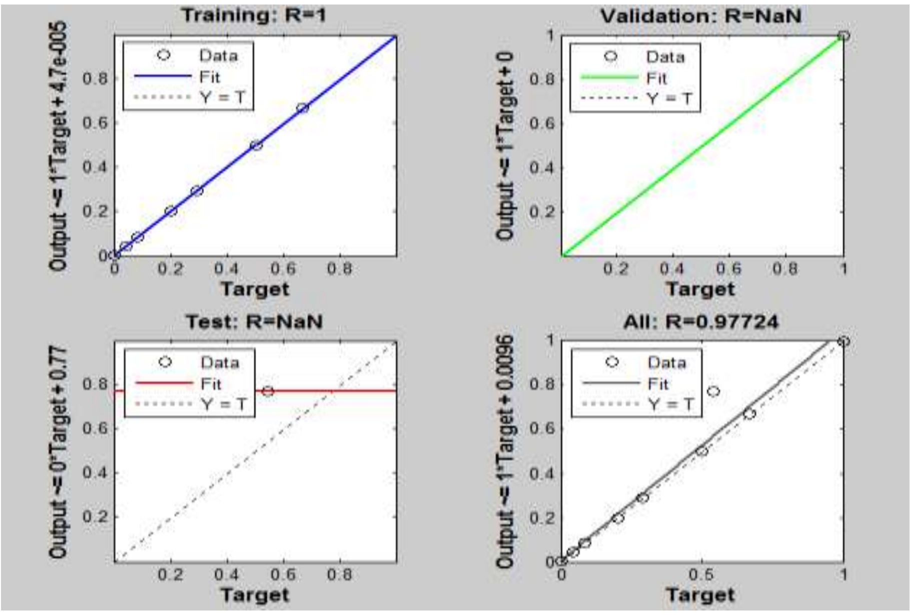

Figure 4: Regression plot for wear loss

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Plot regression (target, outputs) plots the linear regression of target relative to output. From figure 4 R=0.97724.

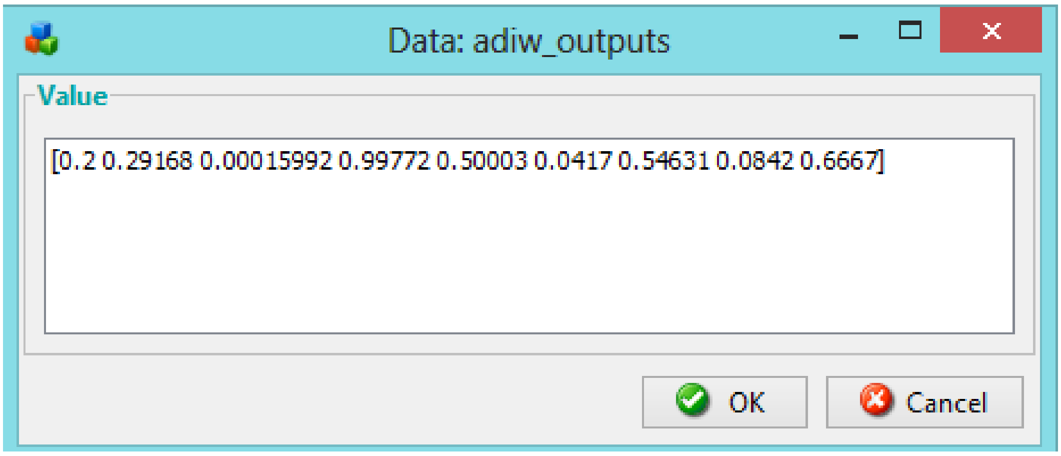

Figure 5: Normalised output results from ANN

Table 3 Wear rate predicted by Artificial Neural Network

Expt. No.	Load, L (N)	Speed, S (m/s)	Sliding distance, D (m)	Experimental weight loss	Weight loss predicted by ANN
1	19.62	1.047	1257	0.0009	0.00088
2	19.62	2.095	2514	0.0011	0.0011
3	19.62	3.142	3770	0.0004	0.0004
4	29.43	1.047	2514	0.0028	0.00279
5	29.43	2.095	3770	0.0016	0.0016
6	29.43	3.142	1257	0.0005	0.0005
7	39.24	1.047	3770	0.0017	0.00171
8	39.24	2.095	1257	0.0006	0.0006
9	39.24	3.142	2514	0.002	0.002

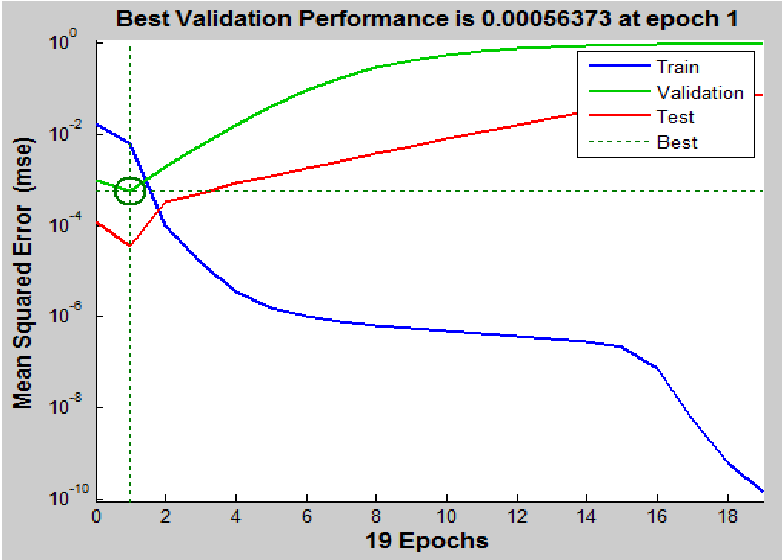

Figure 6: Performance plot for weight loss

Modelling for predicting coefficient of friction using Artificial Neural Network

Here 19 network is created by using the above procedure. Network one with 10 neurons gave the best results. Figure 6 shows the performance plot and figure 7 shows the regression plot for the analysis. The normalised output data is indicated in figure 8 from the output of the network performance results. The results were converted into the weight loss back from these normalised output data and are indicated in table 4. From figure 6 best validation performance is 0.00056373 at epoch 1.

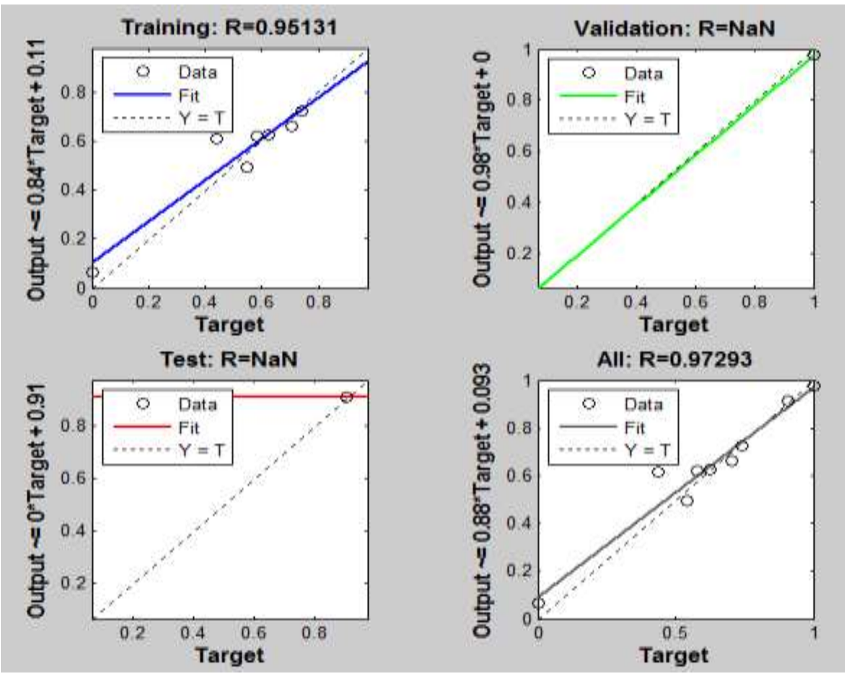

Figure 7 Regression plot for weight loss

Plot regression (target, outputs) plots the linear regression of target relative to output. From figure 4 R=0.97293.

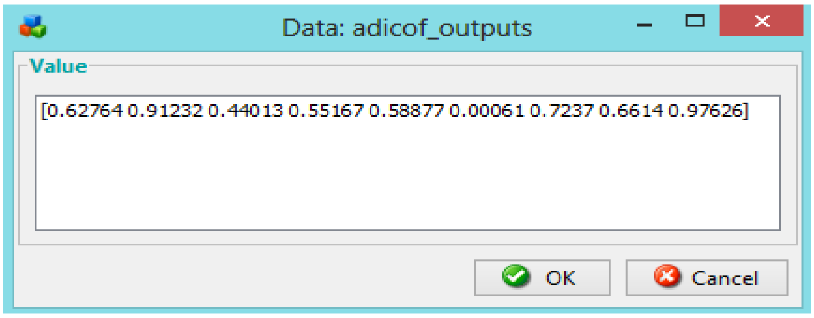

Figure 8 Normalised output results from ANN

Table 4 Coefficient of friction predicted by Artificial Neural Network

Expt. No.	*Load, L (N)*	*Speed, S (m/s)*	*Sliding distance, D (m)*	*Experimental COF*	*COF predicted by ANN*

1	19.62	1.047	1257	0.4485	0.44952
2	19.62	2.095	2514	0.5556	0.55784
3	19.62	3.142	3770	0.3772	0.37817
4	29.43	1.047	2514	0.4179	0.42061
5	29.43	2.095	3770	0.4135	0.43473
6	29.43	3.142	1257	0.2107	0.21093
7	39.24	1.047	3770	0.4918	0.48584
8	39.24	2.095	1257	0.4791	0.46236
9	39.24	3.142	2514	0.5912	0.58217

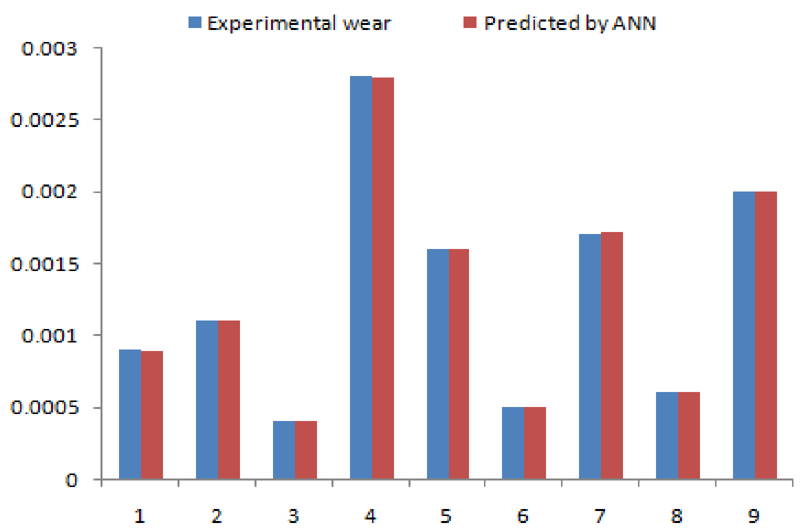

Figure 9: Comparison of Experimental weight loss with the predicted losses

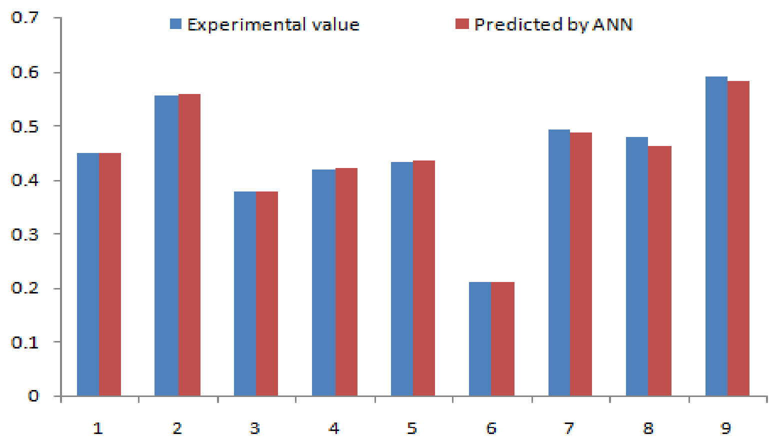

Figure 10: Comparison of Experimental COF with predicted COFs

A comparison of the experimental value with the value predicted by ANN is represented by figures 9 and 10 for weight loss and coefficient of friction. The comparison results show that the two results obtained are in good agreement indicating ANN as the best tool for predicting the performance results.

CONCLUSIONS

The following conclusions can be drawn from the above analysis of results;

- The weight loss was minimum for an applied load of 19.62N at the sliding speed of 3.142m/s for sliding distance of 3770m.
- The coefficient of friction was minimum for an applied load of 29.43N at a sliding speed of 3.142m/s for a sliding distance of 1257m.
- The maximum percentage error is 2.2% for the weight loss and 3.49% for the coefficient of friction between the experimental value and the predicted value.
- Satisfactory agreement results were obtained between the observed values and predicted values. Hence ANN can be efficiently used as prediction technique in the area of tribology and material characterization.

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