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ISSN: 0976-3031

International Journal of Recent Scientific Research
Vol. 3, Issue, 5, pp.378 -381, May, 2012

International Journal of Recent Scientific Research

MODELING AND PREDICTING ADHESIVE WEAR BEHAVIOUR OF ALUMINIUM-SILICON ALLOY USING NEURAL NETWORKS

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ARTICLE INFO

Article History:

Received 12th March, 2012
Received in revised form 20th March, 2012
Accepted 28th April, 2012
Published online 28th May, 2012

Key words:

Dry sliding wear; Al-Si alloy; Artificial neural network; Hidden layer.

ABSTRACT

Knowing friction coefficient is important for determination of wear loss conditions at Al-Si alloys. Tribological events that influence wear and its variations affect experimental results. Artificial neural network (ANN) is a new information processing system based on the neural system of human brain. The potential of using feed forward backpropagation neural network in prediction of some physical properties of aluminium–silicon alloys synthesized by compocasting method has been studied in the present work. Al-Si alloys specimens were subjected to dry sliding wear tests using pin-on-disc apparatus at room conditions. Effects of load, sliding velocity and sliding duration on the wear loss of the alloy have been investigated. The experimental results were used to train the ANN program and the results were compared with experimental values. It was observed that the experimental results are very close to ANN's results.

INTRODUCTION

Aluminium-Silicon alloys are of greater importance to engineering industries as they exhibit high strength to weight ratio, high wear resistance, low density, low coefficient of thermal expansion etc. Silicon imparts high fluidity and low shrinkage, which result in good castability and weldability. Al-Si alloys are designated 4000 alloys according to the Aluminium Association Wrought Alloy Designation System. The most important cast aluminium alloy system is Al-Si, where the high levels of silicon (6.0%, 9.0% and 14%) contribute to give good casting characteristics. Aluminium alloys are widely used in engineering structures and components where light weight or corrosion resistance is required. The addition of silicon to aluminium also makes it less viscous when liquid, which together with its low cost (both component elements are relatively cheap to extract), makes it a very good casting alloy and a fresher metal. It is also used on 3 phase motors to allow speed regulation. Another use is rifle scope mounts and camera mounts.

Archard in 1953 and Archard and Hirst in 1956 developed the adhesion theory of wear and proposed a theoretical equation identical in structure with Holm's equation. In most basic wear studies where the problems of wear have been a primary concern, the dry frictions have been investigated to avoid the influences of fluid lubricants. Dry sliding wear involves sliding of one surface over other under the application of a load normal to the plane of motion (Genel *et al.,* 2003, ASM Handbook, 1992). The dry sliding wear test performed on Al-Si alloy is a type of Adhesive wear. This type of wear is caused between two metallic components which are sliding against each other under an applied load and in an environment where no abrasives are present. Adhesive wear involves material transfer from one surface to another due to direct contact and plastic deformation. In recent years artificial neural networks (ANNs) have emerged as a new branch of computing, suitable for applications in a wide range of fields. Artificial neural networks have been recently introduced into tribology by Jones *et al.,*In this study, experimental and ANNs results have been compared. A lot of studies have been published in which the prediction of various parameters on aluminum alloys was investigated systematically. Song, Zhang, Tseng and Zang inves-Artificial neural network (ANN) has provided an exciting alternative method for solving a variety of problems in different fields of science and engineering. Since the ANN is non-linear statistical technique, they can be used to solve problems that are not eligible for the conventional statistical methods (Liujie *et al.,* 2008, Rashed and Mahmoud, 2009). ANN static backpropagation algorithm is applied to predict the wear properties of Al-Si alloy in the present work. Based on these databases, the neural networks are used to predict the wear loss as a function of wear testing parameters, according to the newly constructed input data sets.

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MATERIALS AND METHODS

The aluminium-silicon alloys, AS06%, AS09% and AS14% were prepared through liquid Metallurgy route. The wear test specimens (cylindrical pins) were prepared wire cut as per the required dimensions of diameter 8 mm x 30 mm length. The specimen pins were studied under dry (unlubricated) and ambient conditions using pin-on-disc type Friction and Wear monitor (DUCOM; TL-20) wear testing machine (Fig. 1).Al-Si alloy pins were tested against hardened ground steel disc (EN-32) having hardness 65 HRC and surface roughness (Ra) 0.5 µm. All the tests were carried out as per ASTM standards.

Fig. 1 Pin-on-disc wear testing machine

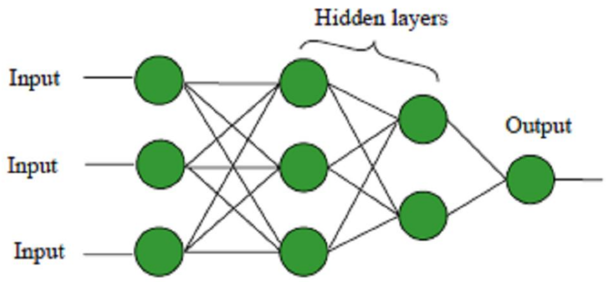
The tests were carried out under varying loads, sliding velocity and time durations. After each test, the test machine will be switched off, and the pin on the rotating disc will be taken out and the wear loss was measured using precision balance having 0.1 mg sensitivity. These wear losses of the tested pins will be used to study the effect of load, sliding speed and time on the wear resistance of the alloy under consideration.

ARTIFICIAL NEURAL NETWORK

Neural network architecture made up of inputs, network layers with hidden layers and output is shown in Fig. 2. At the training stage, the data was given to the network. The network computes an output which is compared to the desired output. Based on the level of error (difference between computed output and desired output) referred to as cost in neural network terms, the network weights are modified (adapted) to reduce the error. The weight modification is done by passing the epoch through an iteration process. An epoch is a complete set of input/output data made up of elementary. The weight modification is done by passing epoch through an iteration process (Sivanandam and Sumathi, 2009, Liujie *et al.*, 2008, Rashed and Mahmoud, 2009).

TRAINING USING MULTILAYER PERCEPTRON NEURAL NETWORK TYPE

Multilayer perceptrons (MLP) are layered feedforward network architecture which is typically trained with static backpropagation.



3 Inputs : Load (N)
Sliding Velocity (m/s)
Sliding Distance (m)
1 Output : Specific Wear rate

Fig. 2 A neural network architecture [adapted]

In this network architecture there are 5 input processing elements (Sliding velocity and applied load, Time, Sliding distance, and speed), 1 output processing element (Wear loss), 487 exemplars and 1 hidden layer. The hidden layer has 16 processing elements, TanhAxon transfer function with momentum learning rule. The output layer uses BiasAxon transfer function with conjugate gradient learning rule. The hidden layer and the process elements were determined by trial and error and by comparing the error output. The generated network architecture is shown in Fig. 3

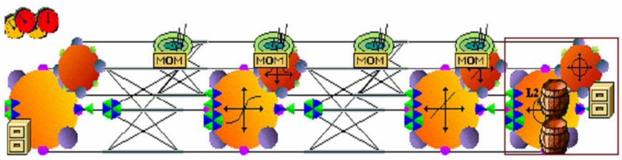


Fig. 3 Generated multilayer perceptrons (MLP) network architecture design

These values were 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.

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

Where θ is the experimental mass loss in wear and θ_0 represents the predicted output value for wear loss in wear. It is important to evaluate the performance of the ANN model. This was 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 were computed using the training set. When reaching the error goal, the learning process was stopped and the network was evaluated with the data from the testing set (John and Kingsly, 2008).

RESULTS AND DISCUSSION

Wear tests were conducted for specified conditions of load, sliding velocity and time duration of counter face disk, however wear in contacted surfaces is primarily due to adhesive wear and in due course, wear grooves were generated (ASM Handbook, 1992, John and Kingsly, 2008). The depth and width of grooves generally control the amount of material removed from the specimen surface. The ANN was constructed with five inputs: load, sliding velocity and time duration, speed, Sliding distance of counter face disk; one hidden layers and one output node (wear loss).

The determination of number of neurons in the hidden layer is given by John Presin Kumar and Kingsly Jeba Singh (2008). In their study, a trial and error method was performed to optimize the number of neurons in the hidden layer. Obtained from dry sliding wear test, having eight neurons fits well in their proposed ANN. A data consists of 45 experimental readings was used to construct fully developed static back propagation network. Among these 45 training exemplars and the residuals were used in the testing process (Fig.4). 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 0.4 and 0.23 respectively.

Table 1 Predicted Resistance to Actual Resistance using Multilayer perceptron with more input parameters

Al-Si alloy (si%)	Load (N)	Time (sec)	Speed (rpm)	Sliding Velocity (m/s)	Sliding Distance (m)	Wear loss Actual (mm^3/ N-m)	Wear loss Predicted (mm^3/ N-m)	Difference	% Difference
AS9	20	600	160	1	600	9.71	9.77	0.06	0.618
AS9	20	600	320	2	1200	9.09	8.62	-0.47	-5.171
AS9	20	600	480	3	1800	5.33	4.47	-0.86	-16.135
AS9	30	600	160	1	600	1	1.35	0.35	35
AS9	30	600	320	2	1200	3.97	4.18	0.21	5.29
AS9	30	600	480	3	1800	4.25	4.05	-0.2	-4.706
AS9	40	600	160	1	600	9.87	9.8	-0.07	-0.709
AS9	40	600	320	2	1200	3.84	4.29	0.45	11.719
AS9	40	600	480	3	1800	2.66	2.95	0.29	10.902
AS9	20	600	320	2	1200	5.01	4.95	-0.06	-1.198
AS9	30	600	320	2	1200	3.97	3.83	-0.14	-3.526
AS9	40	600	320	2	1200	3.84	3.99	0.15	3.906
AS9	20	960	160	1	1000	1.1	0.89	-0.21	-19.091
AS9	20	1200	160	1	1200	1.13	1.14	0.01	0.885
AS9	20	1500	160	1	1500	1.39	1.31	-0.08	-5.755
AS6	20	600	160	1	600	1.49	1.61	0.12	8.054
AS6	20	500	320	2	1000	1.2	1.63	0.43	35.833
AS6	20	600	480	3	1800	5.07	5.44	0.37	7.298
AS6	30	600	160	1	600	8.66	8	-0.66	-7.621
AS6	30	600	320	2	1200	8.34	7.81	-0.53	-6.355
AS6	30	600	480	3	1800	1.14	0.97	-0.17	-14.912
AS6	40	600	160	1	600	1.25	1.22	-0.03	-2.4
AS6	40	600	320	2	1200	4.52	4.91	0.39	8.628
AS6	40	600	480	3	1800	6.55	6.28	-0.27	-4.122
AS6	20	600	160	1	600	1.49	1.46	-0.03	-2.013
AS6	30	600	160	1	600	1.33	1.41	0.08	6.015
AS6	40	600	160	1	600	9.03	8.57	-0.46	-5.094
AS6	20	500	320	2	1000	1.2	1.41	0.21	17.5
AS6	20	600	320	2	1200	7.13	7.42	0.29	4.067
AS6	20	750	320	2	1500	6.59	6.84	0.25	3.794
AS14	20	600	160	1	600	5.17	4.92	-0.25	-4.836
AS14	20	600	320	2	1200	4.41	4.41	0	0
AS14	20	600	480	3	1800	4.76	3.2	-1.56	-32.773
AS14	30	600	160	1	600	2.84	2.25	-0.59	-20.775
AS14	30	600	320	2	1200	7.1	6.68	-0.42	-5.915
AS14	30	600	480	3	1800	4.8	5.21	0.41	8.542
AS14	40	600	160	1	600	5.17	4.64	-0.53	-10.251
AS14	40	600	320	2	1200	4.11	3.37	-0.74	-18.005
AS14	40	600	480	3	1800	3.55	4.19	0.64	18.028
AS14	20	600	480	3	1800	4.76	4.46	-0.3	-6.303
AS14	30	600	480	3	1800	4.8	4.8	0	0
AS14	40	600	480	3	1800	2.38	2.22	-0.16	-6.723
AS14	20	333.6	480	3	1000	4.19	4.41	0.22	5.251
AS14	20	400.2	480	3	1200	3.5	3.26	-0.24	-6.857
AS14	20	499.8	480	3	1500	3.41	3.77	0.36	10.557

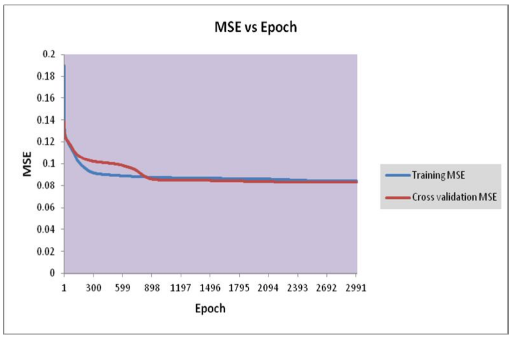


Fig. 4 Training performance of the multilayer perceptron (MLP) network

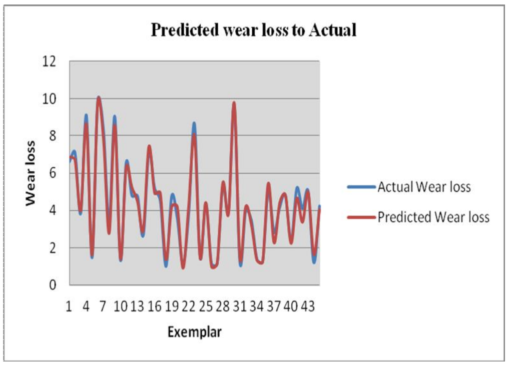


Fig. 5 Comparison of predicted wear loss and actual wear loss for various number of experiments

The training process is terminated after 3000 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 wear loss in wear test. Fig. 4 illustrates the training performance result of this multilayer perceptron architecture is better than the previous. The training mean square error output was 0.0004 at a training epoch of 3000 and similar values were obtained for at an epoch of 3000. Also, very good downward slope is observed in the multilayer perceptron (Fig.4). The network was further tested to confirm overall performance. The testing performance of the multilayer perceptron with more number of input parameters is presented in Fig. 5.On general, if more number of inputs are taken in multilayer perceptron, the network output performance will be very good and the same is observed in Fig. 5. To test the generalization performance of the trained network in training and testing processes, the experimental values were compared with the predicted values resulted from ANN and the same is shown in Fig. 5 and table 1. After training and testing processes were finished, the ANN can be recalled to do prediction effectively.

CONCLUSION

The wear property of the Al-Si alloy depends on many factors, such as sliding velocity, sliding distance and load. Computation through neural networks is one of the recently growing areas of artificial intelligence. Neural networks are promising due to their ability to learn highly non-liner relationship. It can also be gainfully employed to simulate property-parameters corelationship in a space larger than the experimental domain. It is evident from the present study that the artificial neural technique has the potential to predict and analyze the wear behaviour of Al-Si alloy if it is properly trained. Furthermore, The Multilayer perceptron (MLP) neural network type used in the present study outperformed the others.

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