Modelling Wear Behaviour of Aluminium-Silicon Alloys Using Generalized Feed Forward Neural Network

A.Nagaraj[1*], S.Gopalakrishnan[2]

[1] *Assistant Professor, Department of Mechanical Engineering, Hosur Institute of Technology and Science, Hosur, Tamilnadu, India.*

[2] *Professor, Department of Mechanical Engineering, K.S.Rangasamy College of Technology, Thiruchengode, Tamilnadu, India.*

* *Corresponding author E-mail:* naga.nagaraj.raja@gmail.com

Abstract

Artificial Neural Network (ANN) is a new technic of information processing Artificial Intelligence (AI) system based on modelling the neural system of the human brain. The possibility of using neural networks in the prediction of wear reduction quantities of Aluminium-Silicon (Al-Si) 6%, 9%, and 14% AS (Aluminium Silicon) alloys were prepared Liquid Metellugy route by stir casting method has been examined in the present work. The Aluminium- Silicon alloys material is subjected to dry sliding wear behaviour using pin-on-disc equipment in the room atmosphere. Effects of load, Sliding Time, sliding Speed, and sliding distance on the wear loss and Specific Wear Rate of the alloy have been investigated. The results of experimental tests showed that the specific wear rate of Al-Si alloys were significantly decreased by the increase of Si percentage and load as well as sliding speed. Through the use of Artificial Neural Network, these experimental results were trained Generalized Feed Forward (GFF) network in an ANN plan, as well as the results, were compared with experimental values. All the experiments were performed as per ASTM standards. The experimental results were used to train the ANN model GFF successfully with standard mean square error (MSE) of 0.0033 and testing MSE of 0.090. The ANN forecasts reveal quite good agreement with experimental values with a correlation coefficient of 0.87. It is found that the experimental results and ANNs results coincided. ANN could be considered an exceptional tool for modeling complex procedures that have many variants. The experimental Specific Wear Rate is compared with the ANN desirable output signal as well as the error is reduced. This work is primarily is determined by supervised learning using the Generalized Feed Forward backpropagation algorithm.

Keywords: *Wear, Artificial Neural Network, Generalized Feed-Forward Network, backpropagation algorithm.*

1. INTRODUCTION

1.1. Aluminium-Silicon Alloys

Aluminium-Silicon (Al-Si) alloys are of greater relevance to engineering sectors as they show high strength to weight ratio, high wear resistance, low density, low coefficient of thermal expansion, etc. Silicon imparts high fluidity and low shrinkage, which results in weldability and excellent castability. Al-Si alloys are designated 4000 alloys in compliance with the Aluminium Association Wrought Alloy Designation System. The cast aluminium alloy system that is key is Aluminium-Silicon, where the high levels of silicon lead to give great casting features.

Where lightweight or corrosion resistance is needed, aluminium alloys are extensively used in engineering constructions and parts [1].

The important options that come with the 4000 series are: [2]

- → Heat treatable
- → Good flow characteristics, medium strength
- → Easily joined, especially by brazing and soldering

The two important major uses of the 4000 series – for weld and hammering filler alloy. Both applications are due to the exceptional flow features supplied by comparatively high silicon content [3]. Aluminium-Silicon (AS) alloy was utilized in high technology practical and structural applications, including automotive, defense, aerospace, and thermal management areas, as well as in recreation and sports. The significant benefits of this alloy over other alloys are its greater durability, good corrosion resistance, high rigidity, reduced density. Aluminium is the material of preference in several applications, particularly those where thermal conductivity and weight are essential.

1.2 Wear

Wear of alloys is among the very critical yet understood facets of tribology. It is undoubtedly the most youthful of the tri of issues, lubrication, friction, and wear, to bring scientific focus, although its practical value has understood through the years. The findings of Guillaume Amontons in 1699 [4] creating scientific studies of friction are nearly 300 years ago, While Tower [6], Petrov[5] and Reynolds [7] brought enlightenment in the frantic 1880 100 years past to the subject of lubrication.

1.3 Adhesive Wear

This type of wear is caused between two metallic parts, which are sliding under an applied load against each other as well as within an environment where no abrasives are present. The name “adhesive” is given due to the forming of a powerful metallic bond involving the asperities at the top of the contacting materials [9]. In the present work, studies have been performed to assess the Friction and Wear behavior of Al-Si alloy under a controlled laboratory state. An all-inclusive image of wear under different working conditions continues to be presented by running lab tests in pure sliding mode using a pin-on-disc machine.

1.4 Wear Test– an overview

Pin-on-disc wear testing machine shown in figure 1. having incorporated applications for data collection, was likely to be used to run the wear test [8]. The wear test specimens were examined under dry (unlubricated) and under ambient conditions using a pin-on-disc wear testing machine. The evaluation was performed under changing loads, sliding speed and time durations. After every evaluation, the test machine will probably be switched off, as well as the pin and the rotating disc is going to be taken out as well as the wear loss is quantified using precision equilibrium having 0.1 mg sensitivity. These wear reduction of the pins that are tested will likely be utilized to examine the impact of load, sliding speed and time under consideration on the wear resistance of these alloys that will used to measure the wear behavior of the Al-Si alloys, against hardened ground steel disc (En 32) having hardness 65 HRC and surface roughness (Ra) 0.5 μm.

Figure 1. Pin on disc wear Test Machine

1.5 Artificial Neural Network

Artificial Neural Network (ANN) is a brand new kind of information processing system based on modeling the neural system of the human brain. A sensitivity analysis that is normally performed in neural network modeling for discovering the contributory effect of inputs to outputs in a neural network model in neural network controls is discussed [10].

Artificial Neural Network (ANN) or Neural Network (NN) has supplied an exciting alternative way of solving a wide variety of difficulties in different areas of science and engineering.

ANNs are parallel information processing system. A neural network consists of a set of neurons or nodes arranged in layers, and in the case that weighted inputs are used, these nodes provide suitable inputs by conversion functions [11]. Any layer consists of pre-designated neurons and each neural network includes one or more of these interconnected layers. Figure 2. represents a three-layered structure that consists of one input layer, I, one hidden layer, H, and one output layer, O. The operation process of these networks is so that the input layer accepts the data and the intermediate layer processes them, and finally the output layer displays the resultant outputs of the model application. During the modeling stage, the coefficients related to the present errors in the nodes are corrected by comparing the model outputs with the recorded input data [12].

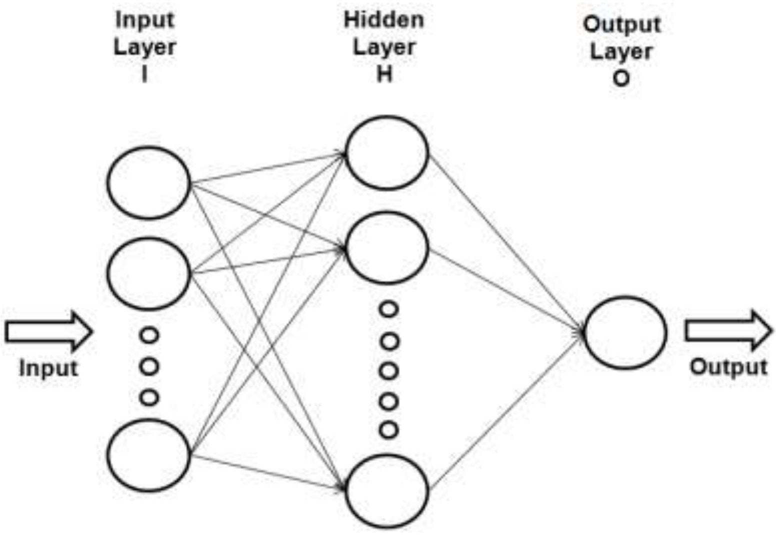


Figure 2. Neuron Layout of Artificial Neural Networks (ANN)

Some nodes (units, neurons, processing components)

- Each node has an output signal and input
- Each node performs a computation that is simple by its own node function

Considering that the ANN is a nonlinear statistical technique, it could be used to solve issues that are not eligible for the standard statistical methods.

2. MATERIALS AND METHODS

The Aluminium-Silicon alloys, Al06%Si, Al09%Si, and Al14%Si were prepared through liquid Metallurgy route by stir casting. The wear test specimen was made by using a lathe machine with a dimension of diameter 6 mm x 25 mm length. From Figure 3. specimens from each casting were prepared for the test.

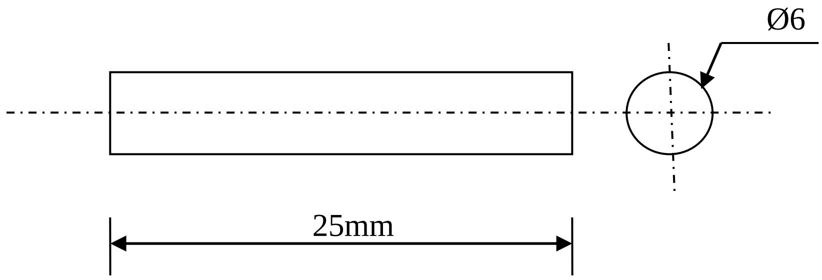


Figure 3. Cylindrical Pin Al-Si Alloys Specimen

3. TRAINING USING GENERALIZED FEED FORWARD NEURAL NETWORK

Generalized Feed Forward (GFF) networks are a generalization of the MLP such that connections can leap over a lot more than one layer. The input signals, as mentioned before, for this network are wanted to use load and sliding speed, while wear reduction from the experimental value is the output signal.
The dataset is randomized to reach even distribution. Subsequently, the columns are labeled as output signals and input signals. 70% of the data set (exemplars) is set apart (labeled) for training, 15% for testing, and another 15% for cross-validation. 5 exemplars are kept as generation data for generation testing.

The generalized feed-forward network design consists of 4 inputs (Al-Si %, Load, Sliding Time and Sliding Speed) signals processing components, 1 output (Specific wear Rate) signal processing component, exemplars that were 39, 3 hidden layers, with first hidden layer composed of 16 processing components, TanhAxon transfer function, with impetus learning rule. The 2nd hidden layer is made up TanhAxon transfer function 8 processing components and impetus learning rule. The 3rd hidden layer consists of TanhAxon transfer function 5 processing components and impetus learning rule additionally. The output layer contains the BiasAxon transfer function, one processing element, and the conjugate gradient learning rule. 2000 epochs are defined for the training iterations. The created (GFF) structure design, revealing output, and input files with transfer functions and the hidden layers are presented in Figure 4.

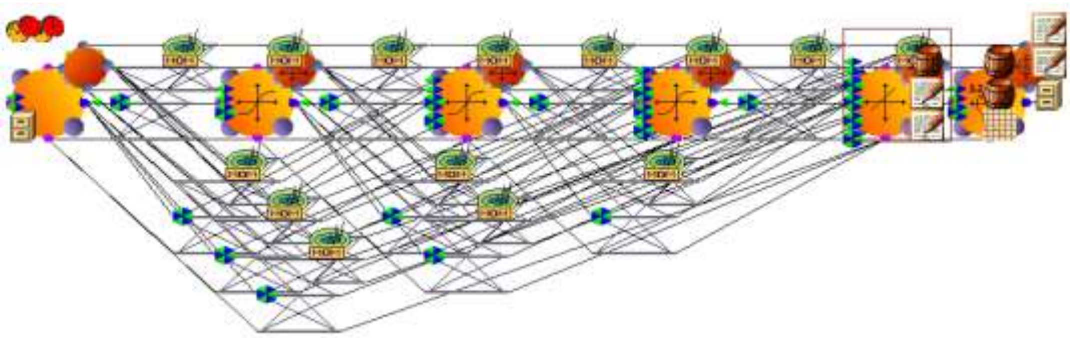


Figure 4. Generated Generalized Feed forward (GFF) Network Architecture Design

4. RESULTS AND DISCUSSION

Several runs of the Specific Wear Rate were performed, and a wide range of alloys was measured. The measured data have been statistically analyzed. To improve specific wear rate prediction, ANN was used. The following sections present these parts of the research program. The evaluation is a simulation of real-life use. The ANN was built with 4 input signals: Al-Si %, Load, Sliding Time and Sliding Speed, two hidden layers and one output node SWR (Specific Wear Rate).

4.1 Effects of Load and Sliding Velocity

Figures 5 and 6 for different (Al-6%Si, Al-9%Si, and Al-14%Si) alloys under different test conditions. Figure 5. shows the variation of Specific wear rate with a normal load. It can be observed from the plots that the specific wear rate decreases with an increase in normal load. This is because at higher load, the frictional thrust increases, which results in increased debonding and fracture. Al-Si alloy having 14% silicon is showing a lower specific wear rate.

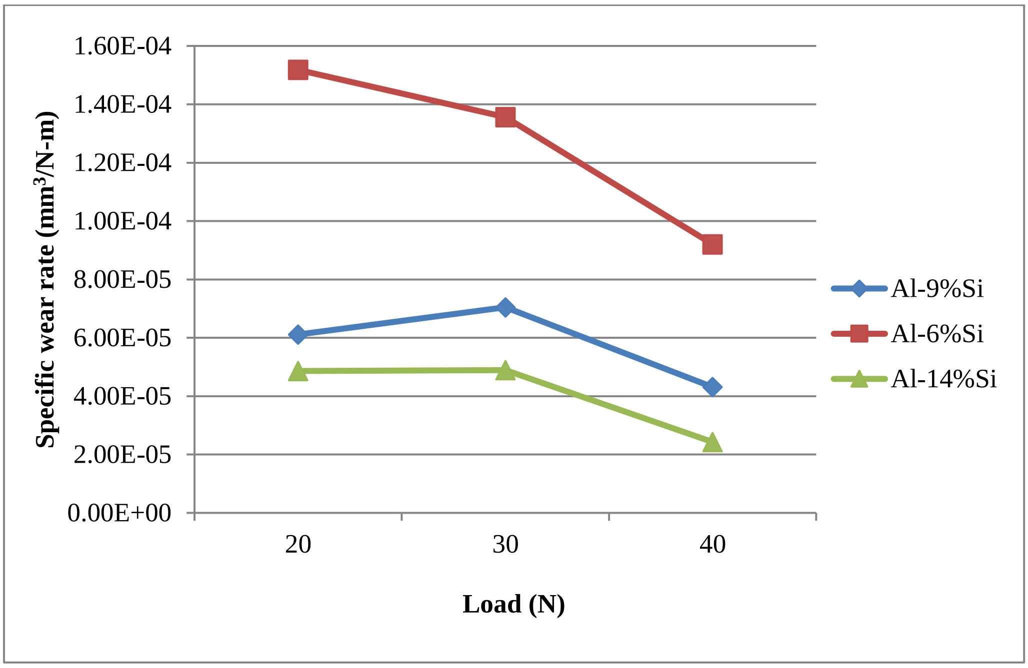


Figure 5. Variation of Specific Wear Rate with Normal Loads

Figure 6. shows the variation of specific wear rate with sliding velocity. The specific wear loss gradually decreases with increasing sliding velocity, and Aluminium-Silicon alloys having 6% Silicon is shows lower specific wear rate.

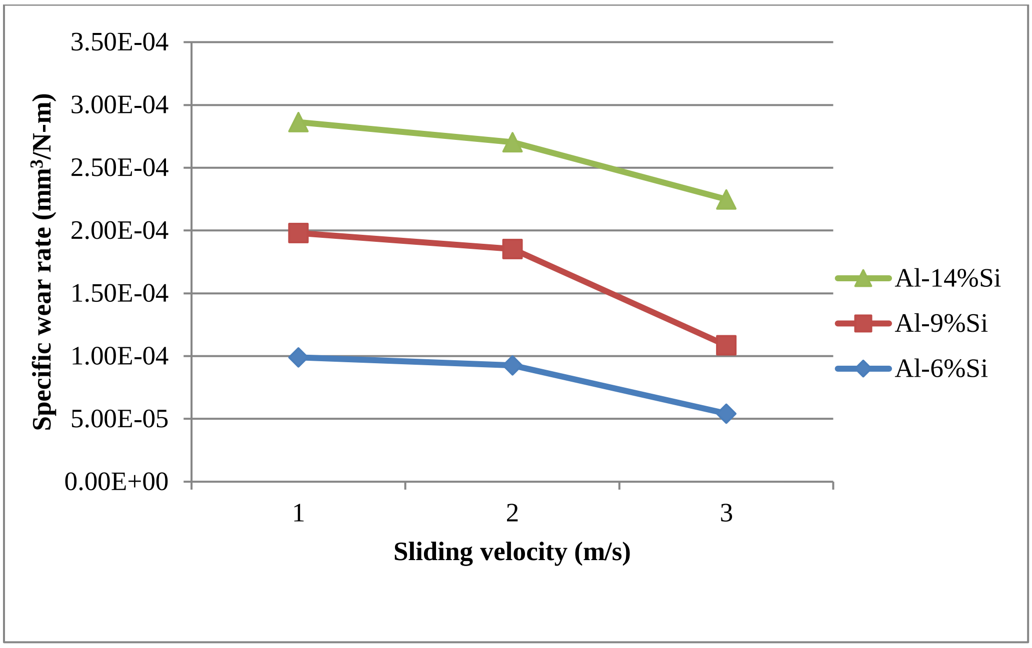
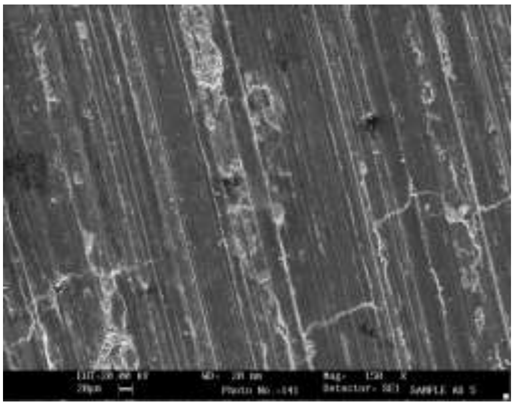


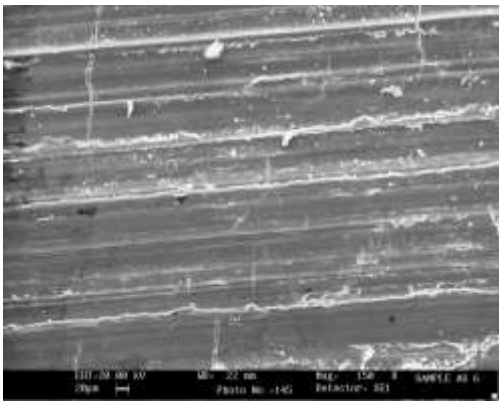
Figure 6. Variation of Specific Wear Rate with Sliding Velocity

4.2 Wear Mechanism

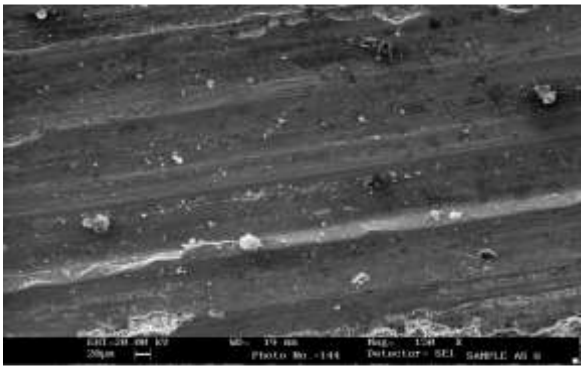
The test is a simulation of real-life applications. Where the test was done under specified conditions of load and rotational speed of counterface disc, however, wear in contacted surfaces is primarily due to the material removal by cutting and plowing actions, and in due course, wear grooves are generated. Wear cracks that would propagate in the sliding direction were detected as indicated by arrows in the photograph. These appearances suggest that large wear particles were possibly formed, resulting in wear grooves. Al-Si alloys showed a worn surface on which there were many small irregular cracks. Yoshiro Iwai et al. These cracks would possibly connect and detach small wear particles [13]. Al-14% Si alloy in Figure 7(c), it can be seen that the abrasive and adhesive wear approximately are absent. This behavior may be attributed to protrusions of the Silicon particles that prevent the steel disc (counterbody) asperities from reaching to the Aluminium Alloys, i.e., preventing metal to metal contact, thus decreasing wear loss, wear rate and increasing hardness. Mohammed.T et al. In aluminium alloy with a low number of clusters. Also, good bonding between silicon particles and an Aluminium-silicon alloy is confirmed [14]. Furthermore, the presence of low porosity and cracks is approximately absent.



(a) Al-6%Si



(b) Al-9%Si



(c) Al-14%Si

Figure 7. SEM Micrographs Showing Worn Surfaces of Sample Al-Si Alloys at 150 X Magnification

The 150 X magnification SEM micrographs, Figure 7. shows excellent scoring marks. The scoring depth in the case of 7(a) Al-6%Si alloy is more as compared to 7(b) Al-9%Si and is lowest in 7(c) Al-14%Si. It indicates the sliding wear is highest in Al-6%Si and lowest in Al-14%Si. The presence of scoring marks may be due to abrasion by entrapped debris, hard asperities on the hardened steel counterface, or work hardened deposits on the counter face [15].

4.3 ANN Training and Testing

The results of the training performance demonstrate an excellent functionality as well as a little error of about 0.0033 at training epochs of 1991. The training is so ceased in 1991 epochs. The Mean Square Error MSE curve reveals a down pitch (weight decay) indicative of great functionality. The network is further analyzed to validate the uniformity of the operation.

The outcomes of the training and cross-validation are presented in Figure 8.

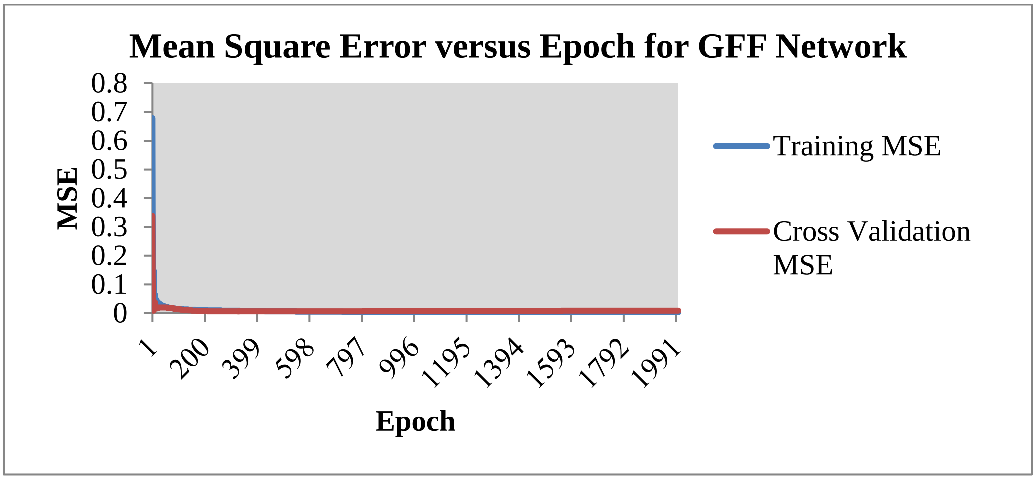


Figure 8. Training Performance of the Generalized Feedforward Network

The linear correlation coefficient quantifies the testing error (r), mean absolute error (MAE), normalized mean squared error (NMSE), and mean squared error (MSE). These statistical parameters give an acceptable measure of the amount of functionality and control the quality of the network. How closely the predicted resistance lines are after the specific wear reduction is, as demonstrated in Figure 9 and is established.

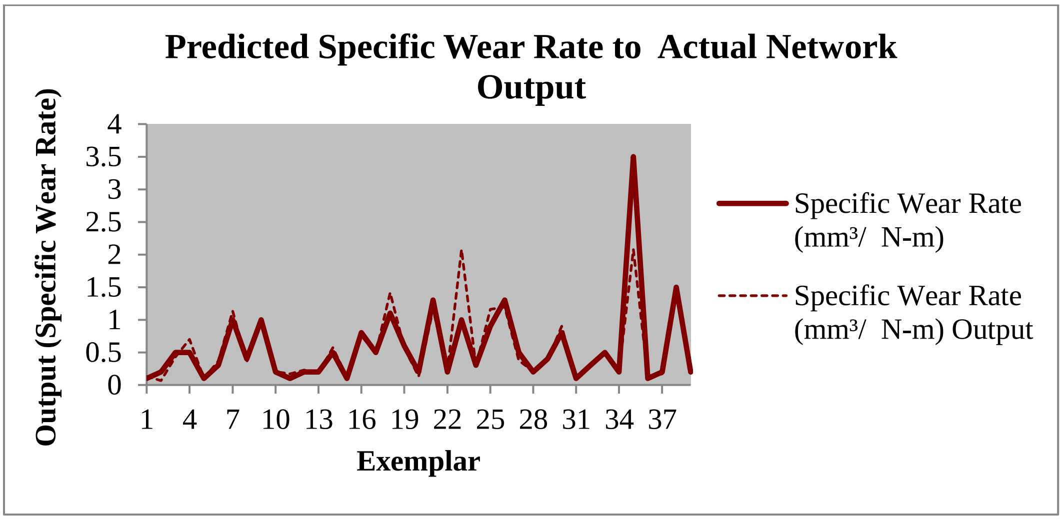


Figure 9 Testing Performance of the Generalized Feedforward Network

The results of the examining operation provide Mean Square Error (MSE) of 0.0904, and Mean Absolute Error (MAE) of 0.1257. This suggests an excellent performance. The Normalized Mean Squared Error (NMSE) is about 0.2422, and the linear correlation coefficient (r) value is 0.8705. The linear correlation coefficient of 0.8705 demonstrates that the set of items is close to a straight line, which suggests a strong correlation coefficient. Figure 9 reveals that the estimated Specific Wear Rate is closely following the Specific Wear Rate value. Table 1. shows the ANN Predicted Specific Wear Rate that is foreseen to the experimental, as well as the Generalized Feed Forward neural network being used by the actual prediction.

Table 1. Predicted Specific Wear Rate to Actual Specific Wear Rate Using Generalized Feed Forward (GFF) Neural Network

Sl. No	Al-Si alloy (si%)	Load (N)	Sliding Time (Sec)	Sliding Speed (RPM)	Actual Specific Wear Rate (mm³/N-m)	Predicted Specific Wear Rate (mm³/N-m)	Difference	% Difference
1	AS14	20	1800	480	0.1	0.13	-0.030	-30.4
2	AS9	30	1000	320	0.2	0.07	0.133	66.7
3	AS6	30	1000	320	0.5	0.43	0.068	13.7
4	AS9	20	600	320	0.5	0.70	-0.198	-39.6
5	AS14	20	1000	480	0.1	0.10	-0.002	-2.3
6	AS14	30	600	160	0.3	0.36	-0.064	-21.3
7	AS9	30	600	160	1	1.13	-0.133	-13.3
8	AS14	30	1000	320	0.4	0.36	0.043	10.9
9	AS9	40	600	160	1	0.96	0.040	4.0
10	AS14	40	1000	320	0.2	0.20	-0.003	-1.4
11	AS9	30	1800	480	0.1	0.17	-0.070	-70.4
12	AS6	20	1800	480	0.2	0.23	-0.031	-15.5
13	AS14	40	600	480	0.2	0.19	0.014	7.2
14	AS6	40	1000	160	0.5	0.57	-0.072	-14.4
15	AS14	40	1800	480	0.1	0.12	-0.019	-19.3
16	AS9	20	1800	160	0.8	0.75	0.046	5.8
17	AS14	40	600	160	0.5	0.49	0.010	1.9
18	AS9	20	1000	160	1.1	1.41	-0.314	-28.6
19	AS6	20	1000	320	0.6	0.57	0.034	5.6
20	AS14	20	1800	480	0.2	0.13	0.070	34.8
21	AS6	30	600	160	1.3	1.16	0.138	10.6
22	AS9	40	1000	320	0.2	0.23	-0.030	-15.0
23	AS9	20	600	160	1	2.08	-1.076	-107.6
24	AS6	40	1000	320	0.3	0.29	0.007	2.3
25	AS6	30	600	160	0.9	1.16	-0.262	-29.1
26	AS6	40	600	160	1.3	1.19	0.106	8.1
27	AS9	20	1000	320	0.5	0.38	0.124	24.9
28	AS6	40	1800	480	0.2	0.21	-0.010	-5.2
29	AS6	30	1800	480	0.4	0.38	0.015	3.8
30	AS6	20	600	320	0.8	0.90	-0.100	-12.5
31	AS9	40	1800	480	0.1	0.08	0.019	18.8
32	AS14	20	1000	320	0.3	0.31	-0.011	-3.6
33	AS14	20	600	160	0.5	0.48	0.021	4.1
34	AS14	30	1800	480	0.2	0.20	-0.003	-1.4
35	AS9	20	600	160	3.5	2.08	1.424	40.7
36	AS14	20	1800	480	0.1	0.13	-0.030	-30.4

Sl. No	Al-Si alloy (si%)	Load (N)	Sliding Time (Sec)	Sliding Speed (RPM)	Actual Specific Wear Rate (mm^3/N-m)	Predicted Specific Wear Rate (mm^3/N-m)	Difference	% Difference
37	AS9	20	1800	480	0.2	0.17	0.030	14.9
38	AS6	20	600	160	1.5	1.41	0.086	5.7
39	AS6	20	1800	320	0.2	0.18	0.015	7.6
Mean					**0.57**	**0.57**	**0.00037**	**-4.45**
St Dev					**0.62**	**0.53**	**0.30**	
St Dev %					**2.62**	**1.75**	**15.22**	

Table 1. shows the marked differences in between the Specific Wear Rate that was foreseen with a prediction error of about 1.9% to 14.9%, to the real. The prediction output signal of this network using real data for training the network, not used, is presented in Figure 8. That is to further assess how well the network is in a position to generalize. The mean values of ANNcoincide with experimental values and less standard Deviation 2.62, 1.75, and the difference Absolute Error percentage is 15.22% matched with observed values of prediction error very close to 1.9% to 14.9%.

The graph demonstrates the generalization is shown in figure 10. ANN with Two hidden layers has enough accuracy and GFF network architecture 4-11-5-1 (input layer having four neurons, two hidden layers with 11, 5 neurons; one output neuron) have minimum RMS and maximum (r). So architecture 4-11-5-1 with the TanhAxon transfer function could be selected in this case. It seems that using ANNs for Specific Wear Rate or similar problems is due to researchers interesting to check how ANNs, work for nonlinear problems. In this way, we have also tried to handle ANNs capability in nonlinear problems. As shown in Figure 10. the result is acceptable in estimating Specific Wear Rate (SWR). The trained network was able to predict the response with (r) and RMSE, respectively. This ANN model is capable of predicting the values of Specific wear Rate in Aluminium-Silicon alloys and was in close agreement with experimental results.

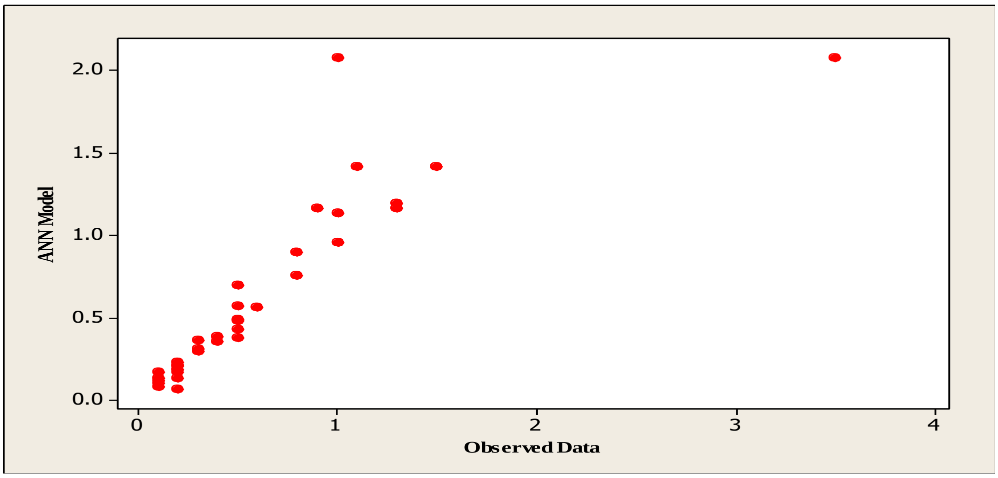


Figure 10. Plot of Specific Wear Rate as predicted by ANN and observed data

4.4 Sensitivity Analysis

The data were further analyzed for sensitivity to identify the impact of the varied input process parameters on the properties of the output. The results obtained were shown in Figure 11. The Al-Si, (AS6) had the highest influence, and the applied load is less on the Specific Wear Rate, followed by the AS9 and AS14. Results showed that the amount of Specific Wear Rate is dependent Silicon percentage, Load, Sliding Time and Sliding Speed, respectively. Therefore it is suggested to minimizing wear loss. If this loss not normal, the Percentage of silicon must increase and load. Sliding speed may be decreased. In other words (if wear loss is high, to change other fillers to the addition of material should be considered. Figure 12. shows the effect of each input variables (Load, sliding Time, Sliding speed and Al si% alloys) individually on Output (Specific wear Rate). Network input, output results, while the increase in Load, sliding Time, Sliding speed, and increasing Si% decreases Specific Wear Rate. It can be observed from the plots that the specific wear rate decreases with an increase in all the inputs. The ANN results were accurately analyzed with experimental results.

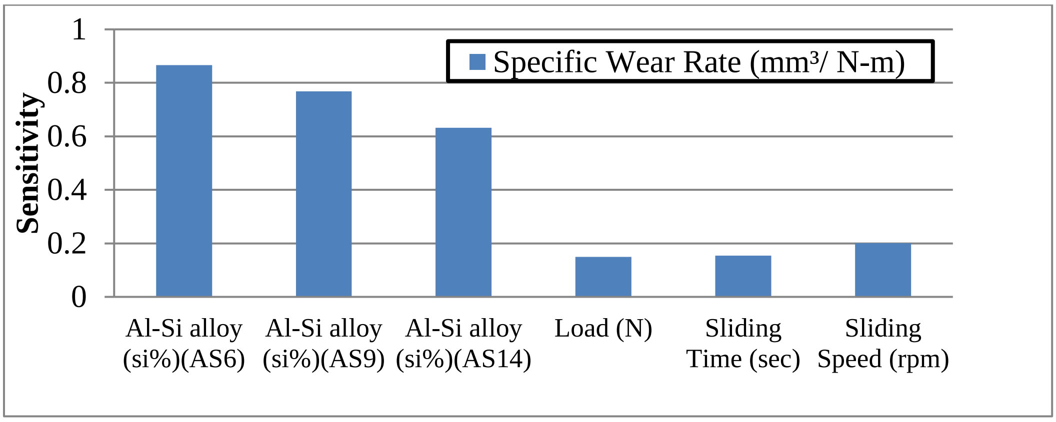
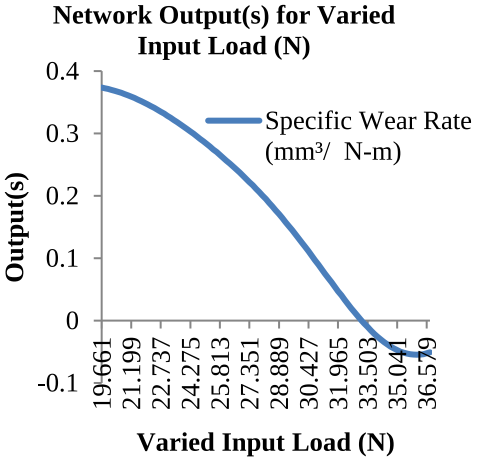
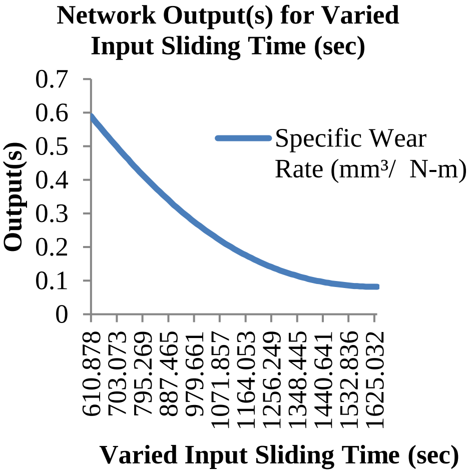


Figure 11. Sensitivity Analysis of Output to Input Variables





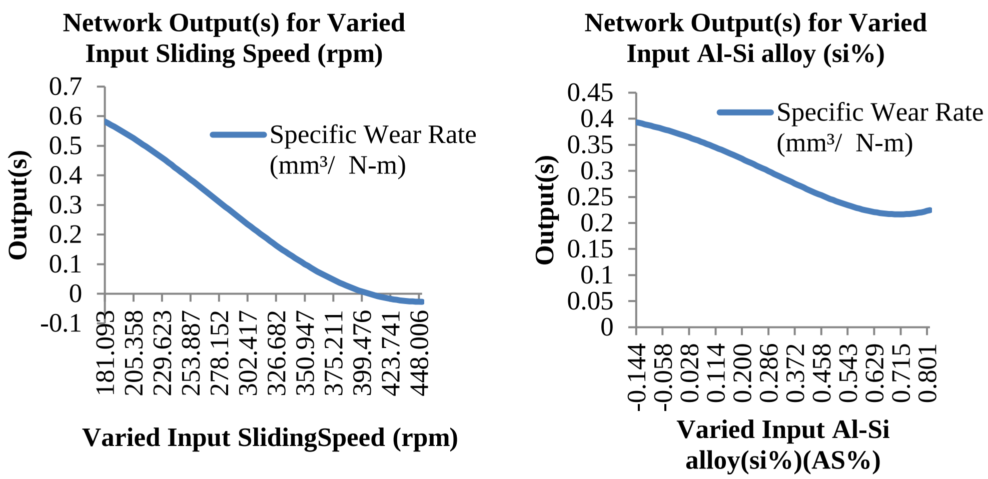


Figure 12. Effects of independent variables on Specific Wear Rate

According to Table 2. the coefficient of determination equal to 0.76 was obtained. It shows the existence of high dependency of the dependent variable on the independent variables included in this study. In other words, the 0.87 amount of Specific wear Rate in Al-Si alloys is related to the changes in four variables, and only the remaining 0.09 is related to other factors that are not considered in this study.

Table 2. Network Performance

Network Performance	Grain separation
Mean Square Error (MSE)	0.09
The Correlation Coefficient (R)	0.87
Coefficient (R^2)	0.76

5. CONCLUSION

In the present study, A Generalised Feed Forward (GFF) backpropagation neural network technique was used to predict the wear reduction amounts Specific Wear Rate of Al-Si alloys.

The results obtained led to the following conclusions:

- The specific wear rate for alloys decreases gradually with an increasing amount of silicon, sliding velocity, and normal load.
- The GFF network structure for predicting the specific wear rate was found at 4-11-5-1, i.e., four nodes in the input layer, two hidden layers with 11, 5 nodes, and one node in the output layer.

- The experimental values of wear reduction of the specimens that were distressed were used for testing and the training of ANN. A reasonable understanding between the ANN and experimental results was obtained from applying this kind of Generalised Feed Forward neural network.

- The correlation coefficients for testing data sets for the optimum ANN were 0.87 for Specific Wear Rate, which was acceptable and confirmed the feasibility of ANN to effectively model and predict the Al-Si alloys properties.

- The ANN model showed the excellent capability to study the sensitivity of the Aluminium Silicon (AS) Percentage is the highest influence and applied load was less influence of Al-Si alloys.

- ANN model is capable of predicting the values of Specific Wear Rate in Al-Si alloys and was in close agreement with experimental results. Thus, ANN could be utilized economically as a prediction technique in the section of tribology and a feasible study of all the material characterization.

References

[1] *Darel E. Hodgson, ASM Metals Handbook Vol. 2, "Properties and Selection of Nonferrous Alloys and Special Purpose Materials", ASM International, p. 222, **(1990).***

[2] *Degarmo, E. Paul. Black, J T. Kohser, Ronald A, "Materials and Processes in Manufacturing", (9th ed.). Wiley. p. 133 **(2003).***

[3] *Polmear, I.J. Arnold, "Light Alloys", Metallurgy of the Light Metals **(1995).***

[4] *Amontons. G, Mem. Acad, T. Ser, A, **(1699),** pp. 257-282.*

[5] *Petrov, N.P. "Friction in machines and the effect of the lubricant", Inzh.Ah, **(1893),** pp 71-140, Vol. 2, **(1983),** pp. 227-279.*

[6] *Tower. B, "First report on friction experiments", Proc., Inst. Mech. Eng., London, **(1983),** pp. 632-659.*

[7] *Renolds. O, "On the theory of lubrication and it's application to Mr. Beauchamp Tower's experiments", Plilos. Trans. T. Soc. London, Vol. 177, **(1886),** pp. 157-234.*

[8] *Holm. R, "The frictional force over the real area of Contact", Wiss. Vereoff. Siemens Werken, Vol. 17 (4), **(1938),** pp. 38-42.*

[9] *Dr. George E. Totten, FASM, Editor, ASM Handbook. 18, 713 "Friction, Lubrication, and Wear Technology", U.S.A, **(1992).***

[10] *Agrawal, g. and frost, j.d. and chameau, c.l.a, "Data Analysis and Modeling Using Articial Neural Network", Proceedings of XIII International Conference of Soil Mechanics and Foundation Engineering , New Delhi,* ***(1994),*** *pp. 1441–1444.*

[11] *K. Ozgu, "Daily River Flow Forecasting Using Artificial Neural Networks and Auto-Regressive Models", Turkish J. Eng. Env. Sci., 29,* ***(2005),*** *pp.9-20.*

[12] *G. R. Rakhandehroo, M. Vaghefi, and M. M. Shafiee, "Flood forecasting in similar catchments using neural networks", Turkish J. Eng. Env. Sci., 34,* ***(2010),*** *pp.57-66.*

[13] *Iwai Yoshiro Iwai a Weiya Hou a, Tomomi Honda a, Hidetomo Yoneda b, "Wear behaviour of high tensile strength aluminium alloys under dry and lubricated conditions", Wear, 196,* ***(1996),*** *pp.46-53.*

[14] *Mohammed T. Hayajneh*, Mohammed A. Almomani, and Mu'ayyad M. Al-Shrida, "Mechanical and Tribological Properties of Green Metal Matrix Composite", Sci Eng Composite Material, 26,* ***(2019),*** *pp.423–434. DOI:https://doi.org/10.1515/secm-2019-0027.*

[15] *Pramila Bai. B.N, Biswas. S.K, "Effect of magnesium addition and heat treatment on mild wear of hypoeutectic aluminium-silicon alloys", Acta Metall. Mater., Vol. 39:5,* ***(1991),*** *pp. 833-840.*