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Artificial Neural Network Prediction of Fretting Wear Behavior of Structural Steel, En 24 Against Bearing Steel, En 31

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In this study, artificial neural network (ANN) technique is used to predict the friction and wear behavior of various surface-treated structural steel (En 24) fretted against bearing steel (En 31). A three-layer neural network with a back propagation algorithm is used to train the network. Fretting wear volume and coefficient of friction obtained at different normal loads (ranging between 2.4 and 29.4 N) for various treated samples (hardened, thermo-chemically treated, MoS_2 coated) were used in the formation of training data of ANN. Results of the predictions of ANN are in good agreement with the experimental results. The degree of accuracy of predictions was 96.3 and 95.7% for fretting friction coefficient and wear, respectively.

Keywords artificial neural network, coefficient of friction, ferrous, fretting wear, surface treatments

1. Introduction

Fretting wear is a typical wear form caused by low-amplitude oscillatory movements between bodies in mechanical contact. Generally, fretting occurs at the contacting surfaces that are intended to be rigidly fixed, but actually undergo minute alternating relative motion that is usually produced by vibration. The displacement amplitude of such a relative motion is typically less than 200 μm. This process is a result of various wear mechanisms such as adhesion, abrasion, and oxidation-assisted wear. All quasi-static assemblies in the machinery experience fretting wear damage and some of the examples reported are keys and keyways, splines, bearing races, leaf springs, hub and shaft, pinned joints, flanges, flexible couplings, bolted and riveted joints, etc. Much research has been carried out to evaluate the fretting wear characteristics of different materials under various test conditions. The mild wear leads to the loss of press fit capability or it can cause unallowable clearances that affect the functionality of the mechanical system.

To mitigate fretting wear damage, the introduction of surface treatments or coatings is reported to be an ideal solution (Ref 1). Many experiments have been carried out to evaluate the effect of hard- and low-friction coatings (Ref 2, 3) and lubricants (Ref 4) on the fretting wear behavior of steels. Diffusion of nitrogen/boron on the steel surface results in the formation of beneficial compounds and plays a dominant role in combating wear under sliding wear conditions (Ref 5, 6). For better performance, a duplex surface treatment, one that combines nitriding and oxidation, was developed in recent years and found to be effective against both sliding wear and corrosion (Ref 7). Only limited experimental work has been done to evaluate the effects of such thermo-chemical treatments under various fretting conditions. Understanding the clear-cut deterioration mechanism under fretting conditions and finding an economical surface modification technique to combat fretting surface damage is very much needed by industry.

An artificial neural network (ANN) is a computational modeling tool that has emerged recently and found acceptance in tribology for modeling real-world problems. Artificial neural network is comprised of interconnected adaptive simple processing elements, called artificial neurons that are capable of performing parallel computations for data processing and knowledge representation. One of the distinct characteristics of ANN is its ability to learn and generalize from experience and examples, and then adapt to changing situations. Artificial neural network offers a fundamentally different approach to material modeling and material damage control than statistical methods. Artificial neural network modeling in the field of tribology has been investigated (Ref 8).

In the present study, ANN is implemented to evaluate the correlation between friction and wear under fretting conditions based on the results of various test conditions for different thermo-chemical and solid-lubricated coatings.

2. Test Materials and Experimental Methodology

The widely used structural steel En 24, for high-strength application and bearing steel En 31, were used in the current studies. Crossed-cylinder wear couple geometry, which results in a point contact, was used. The dimensions of the cylindrical specimens are 10 mm diameter and 15 mm length. As-received En 24 and En 31 steel rods of 12 mm diameter were turned and ground to the required dimensions. To improve the fretting wear resistance, various surface strengthening processes were

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selected which are confined to fretting wear characteristic behavior. En 24 steel specimens were subjected to hardening, various thermo-chemical treatments such as salt bath nitriding, boriding, and duplex treatment (post-oxidation of nitrided specimen) and bonded solid-lubricant coatings. The counter specimens made of bearing steel En 31 were hardened and tempered. The chemical compositions of steel specimens are shown in Table 1. Table 2 describes processing steps, the micro-constituent present at the surface, and the corresponding surface hardness values.

The principle of operation of the fretting wear test rig used in current studies is described elsewhere (Ref 9). Specimens were ultrasonically cleaned in acetone before testing. Tests were carried out at a constant slip amplitude of 60 ± 3 μm. Specimens were mounted rigidly in the specimen holder to avoid any slip during test. Fretting wear tests were conducted at different normal loads ranging from 2.4 to 29.4 N. Dead weight loading was used. At least two tests were conducted in each condition. All experiments were run at a constant test frequency of 5 Hz for up to 1×10^5 cycles. Tests were performed under dry sliding conditions without external lubrication at room temperature (303 ± 3 K; 60 ± 5% RH). Wear volume loss was calculated from the measured wear scar diameter using the approximate equation given by Halling (Ref 10). The fretting wear scar was observed using optical and scanning electron microscopy.

3. Neural Network Structure and Operation

The most popular ANN architecture, the multi-layer feed forward network with back propagation (BP) was used. Back propagation is one of the most effective training algorithms for multi-layer perceptions. It is a gradient descent technique used to minimize the error for a particular training pattern (Ref 11). The network has three layers of neurons: input layer, hidden layer, and output layer. The hidden layer aids in performing useful intermediary computations before directing the input to the output layer. The neuron in one layer is connected to other neurons in the succeeding layer by weights. The neuron consists of multiple inputs and a single output. The basic neuron model in a feed forward network is shown in Fig. 1. Each input is modified by a weight that multiplies the input value. The neuron will combine these weighted inputs, and with reference to a threshold value and activation function determine its output. The response of the neuron is a non-linear function of its weighted inputs.

From the difference between the desired response and actual response, the error is determined at the output layer and propagated backward through the network. At each neuron in the network, the error is used to adjust the weights and threshold values of the neuron, so that at the next time, the error in the network response will be less for the same inputs. After each cycle, the error between the ANN output (predicted) and desired values are propagated backward to adjust the weight in a manner mathematically guaranteed to assure convergence (Ref 12). Adjustments of the weights ΔW_{ji} can be calculated using

$$\Delta W_{ji}(t) = \eta \delta_{pj} O_{pi} \qquad \text{(Eq 1)}$$

where η is the learning rate, Opj is the actual output value of output neuron j for pattern p, and δpj is the output neuron error signal. The learning rate coefficient determines the size of weight adjustments made at during each iteration, and hence, influences the rate of convergence. From these equations, a predetermined set of weights, a set of threshold values, and a description of the network structure (i.e., the number of layers and the number of neurons in each layer) are determined. It is then possible to compute the response of the neural network to any set of inputs.

Table 1 Composition of test specimens

	Composition (wt %)					
Material	**C**	**Mn**	**Si**	**Cr**	**Ni**	**Mo**
En 24	0.40	0.70	0.30	0.80	1.80	0.45
En 31	1.00	0.30	0.25	1.50	0.20	0.05

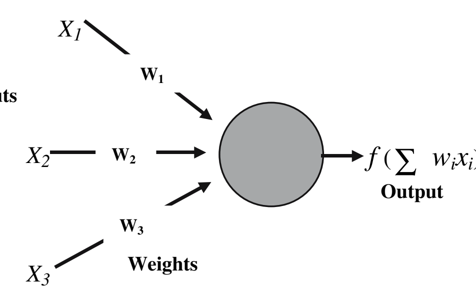

Fig. 1 Basic neuron model in a feed forward network

Table 2 Treatment conditions for various treated En 24 steel

S. No.	Process	Processing temp. (K)	Duration/holding time (min)	Subsequent process	Micro-phase constituent	Hardness (HV)
1	Hardening and tempering	1118	15	Quenching	Martensite and retained austenite	640
		853	60	Air cool		
2	Liquid nitriding	823	120	Air cool	Epsilon iron nitride	725
3	Liquid boriding	1173	240	Air cool	Iron boride	2050
4	Nitriding + post-oxidation	773	60	Air cool	Hematite + Magnetite	645
5	MoS_2 spraying and querying	305	30	Air cool	MoS_2	222
		423				

4. Neural Network Approach

MATLAB® tool functions are used for network modeling, training and testing of the present problem. The function *newff* creates a feed forward network. Four input function parameters were used to formulate the network object. Figure 2 shows the major steps followed for network modeling and training. Based on the command functions, a network model is created with initialized weights and biases. The friction and wear data of various treated steel samples, tested at different normal loads, were used as the source information for network training and testing. The data are split into a training set and a testing set. The testing data are from experiments and are used for validating the trained network. The experimental data sets consist of 35 pair of measurements, which include friction and wear data. (A total of 70 values are used for Network I training and testing, and for Network II training.) Among them, 20 data sets were used for training the network and 15 were selected to test the performance of the trained network.

4.1 Network Architecture Applied to Friction and Wear Behavior

Two networks were established for the prediction of friction and wear behavior under fretting condition. Figure 3 shows the neural network architecture applied to friction and wear behavior prediction (Network I and Network II). The number of neurons in the input layer represents the number of input parameters used in the network. The various treatments selected to combat the wear damage are considered as one input. Micro-hardness of treated samples is given as the input. The second input is the normal load applied during testing. The other testing conditions like frequency, number of cycles of operation, sliding velocity, and environmental condition are constant. The predicting parameter in Network I is the coefficient of friction. One hidden layer composed of four hidden neurons is used. The *tan sigmoid* function is used for the hidden layer and a linear function is used for the output layer. The training algorithm is a resilient BP algorithm.

For the prediction of wear behavior, another network architecture (Network II) is modeled. In this network, the input parameters are treatment type and normal load. The output parameter is total wear loss. The difference between this network and Network I is the additional effective hidden neurons in the hidden layer. To decide the structure of network, the rate of error convergence was checked by changing the number of hidden neurons and by adjusting the learning rate. The functions and optimized process parameters for Network I and Network II are given in Table 3.

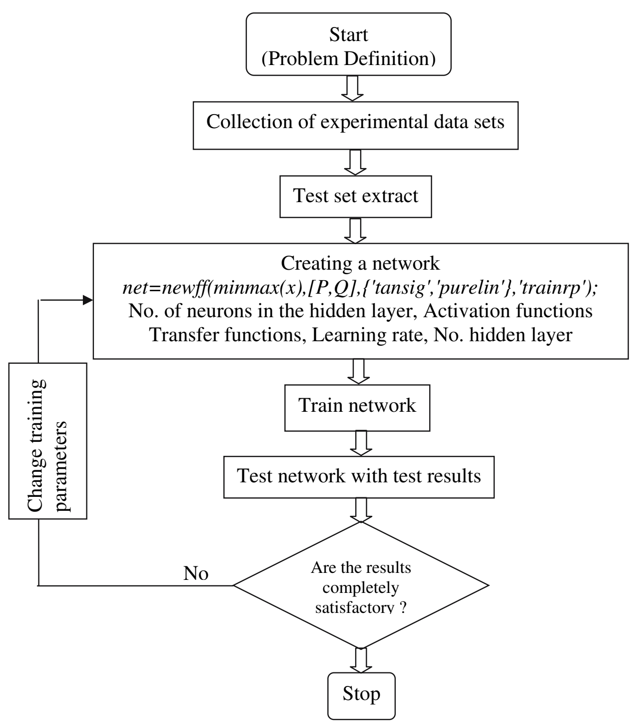

Fig. 2 Flow chart used for fretting wear data prediction

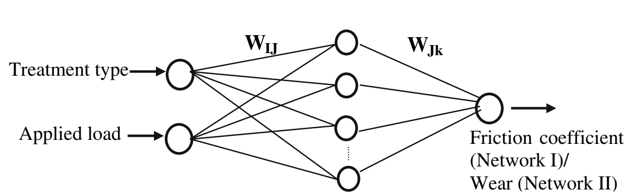

Fig. 3 The structure of three-layered network for the present study

4.2 Training and Testing of Network

Before presenting the training data set to the network, it is necessary to carry out normalization and randomization of input and corresponding output data for better performance and convergence. $X' = ((X - X_{\min})/(X_{\max} - X_{\min}))$ is the widely employed method in unification where $X_{\max}$ and $X_{\min}$ indicate the largest and smallest value of X, and X' is the unified value of the corresponding X. Figure 4 represents the tasks followed during the training phase. In Network I, the coefficient of friction obtained experimentally for various surface treatments was used as the target value. Surface hardness and normal load were used as input neurons and trained to achieve the target value. In Network II, similar inputs were considered in the training process. Wear loss data obtained from experiments were used as target values. Training is the act of continuously adjusting the connection weights until they reach unique values that allow the network to produce outputs that are close enough to the actual desired outputs. In order to finalize the optimum structure with minimum error response, the network training parameter is changed and validation of the training performed. The optimum training parameters for Network I and Network II are given in Table 3.

Table 3 Network architecture parameters for friction and wear behavior

Type	Network I	Network II
Architecture	Normal feed-forward MLP	Normal feed-forward MLP
Hidden layer number	1	1
Number of neurons	Input—2 Hidden—4 Output—1	Input—2 Hidden—6 Output—1
Transfer function	Tan-sigmoid	Tan-sigmoid
Training function	Resilient back propagation (Trainrp)	Resilient back propagation (Trainrp)

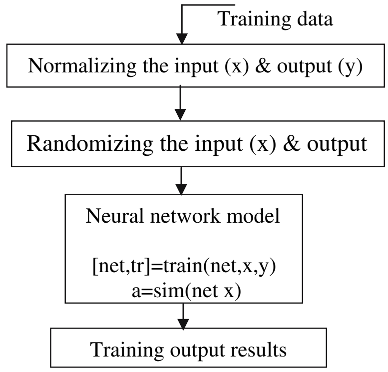

Fig. 4 Block diagram indicating tasks performed in training phase

In order to validate the network prediction capabilities, the test data was used. Test data are presented to the trained network, undergoes simulation and gives testing output results (predicted results). The error in the network response is calculated by comparing the predicted result with the actual result for the two different network parameters. The mean error (ME) is defined as the ratio of absolute error to number of data, and following form is used in the error analysis.

$$\mathrm{ME} = \frac{1}{n}\sum_{i=1}^{n} |T_i - P_i| \quad \text{(Eq 2)}$$

where T_i is the target value (desired value), P_i is the predicted value (output value), and n is the number of data.

5. Results and Discussion

5.1 Fretting Coefficient of Friction Prediction

The proposed model predicts the friction coefficient and wear loss at different normal loads for various surface-treated structural steel samples fretted against bearing steel. In Network I, the applied training data is in the form of coefficient of friction and shows the best results at the learning rate of 0.09 and 500 training cycles. The error goal fixed for the network is 1×10^{-4}. Figure 5 shows the convergence characteristics obtained during training phase for Network I. For every increase in the number of training cycles, the mean square error at the output neuron decreased and converged at 500th training cycle. The calculated relative error distribution as a function of test data derived from Network I is shown in Fig. 6. The level of relative error is satisfactory and well within the limit. The mean relative error between the experimental and predicted values is within 3.7%. Comparison of experimental coefficient of friction with the ANN predicted values for various surface-treated En 24 steel samples is shown in Fig. 7. The predicted ANN results are in line with the experimental data. The main quality indicator of the neural network is its generalization ability, and its ability to predict accurately the output of unseen test data. The predicted friction behavior of non-conducted test conditions was plotted for various treated samples. Figure 8 shows the predicted results at different normal loads. In the MoS_2 coated sample the coefficient of friction increases with increase in normal load. This trend is not similar for thermo-

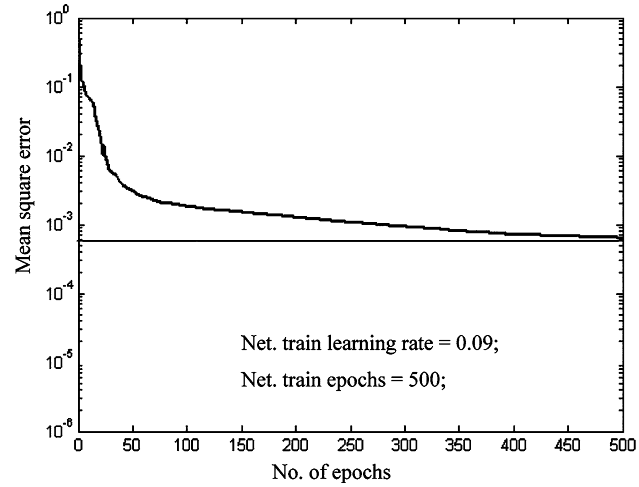

Fig. 5 Convergence characteristics during training phase applied to friction behavior prediction

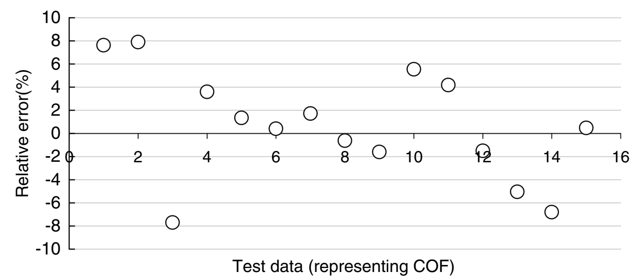

Fig. 6 The relative error distribution as a function of test data arrived from Network I

chemically treated samples and shows a decrease in coefficient of friction with increase in normal load. The predicted characteristic behavior is similar to experimental behavior and reasoning for such behavior under experimental conditions are discussed elsewhere (Ref 10, 13).

5.2 Fretting Wear Loss Prediction Behavior

Experimental test condition (input set) and corresponding wear loss (output data) presented to the Network II for training exhibit a good response at the following training parameter values. The learning rate and total number of epochs are 0.008 and 300, respectively. The error goal set was 1×10^{-4}. Mean square error convergence of the Network II for the mentioned training parameter value is shown in Fig. 9. The variation between experimental and predicted wear loss was estimated and mean relative error was calculated to be 4.3%. Figure 10 shows the distribution of relative error for each test data set and is well within the limit. Predicted wear loss is closer to the experimental results indicating the learning capability of the Network II (Fig. 11).

By applying the untested load condition at various intervals, the wear loss was predicted. Figure 12 shows the predicted wear loss as a function of normal load for various surface-treated samples. The wear loss is proportional to normal load up to particular load and then decreases with further increase in load. The change in the nature of contact under fretting

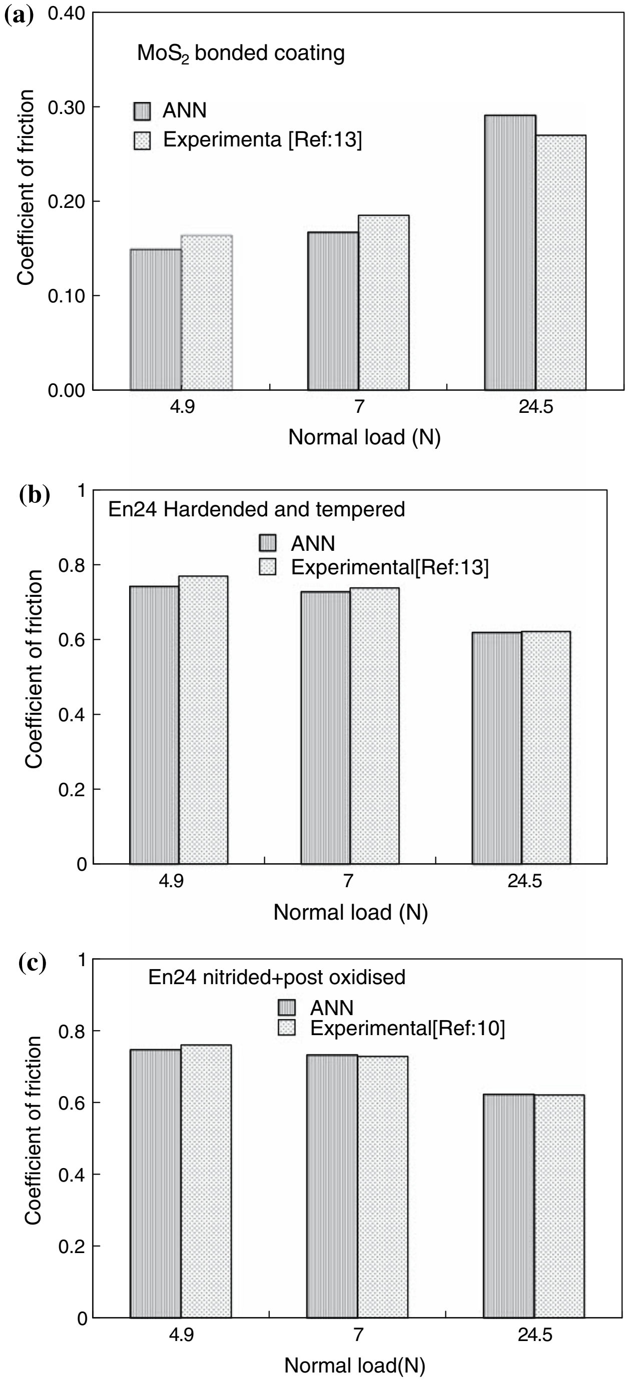

Fig. 7 Comparison of ANN and experimental coefficient of friction results for: (a) MoS_2 bonded En 24 steel, (b) hardened and tempered En 24 steel, and (c) liquid nitrided and post-oxidized En 24 steel

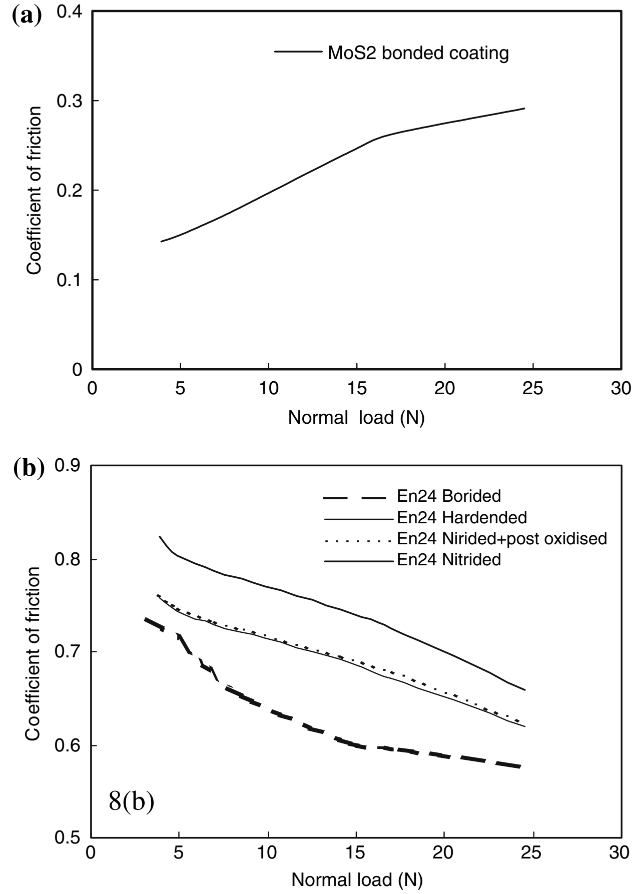

Fig. 8 Prediction of coefficient of friction as a function of normal load for: (a) MoS_2 (solid lubricant) coated samples and (b) various thermo-chemically treated En 24 steel

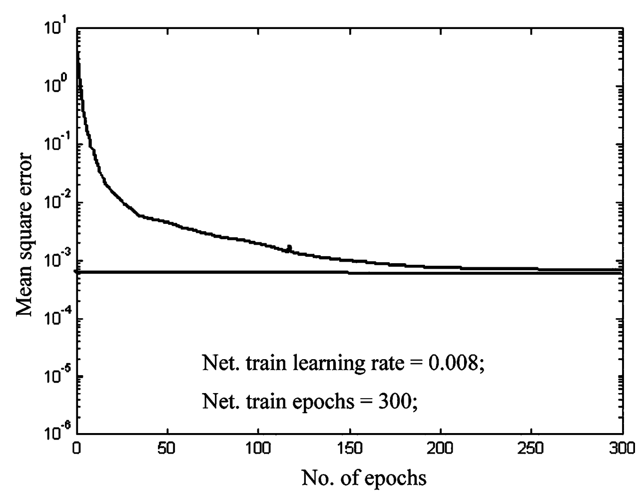

Fig. 9 Convergence characteristics during training phase applied to wear behavior prediction

conditions from gross slip (slip between the whole contact area) to stick-slip (partial slip) limits the wear. This behavior is similar for all types of treatments considered in the present study. However, the load at which transition occurs is different for each treatments. The chemical compatibility between the contacting surfaces affects the fretting wear resistance and also the transition conditions (Ref 10, 13). Table 4 shows the predicted transition loads observed for different palliative treatments. It facilitates evaluation of the change in wear mechanism taking place and the corresponding wear losses for various surface composition of En 24 steel fretted against bearing steel En 31. The evaluation of transition normal load is beneficial, because the change in contact condition to partial

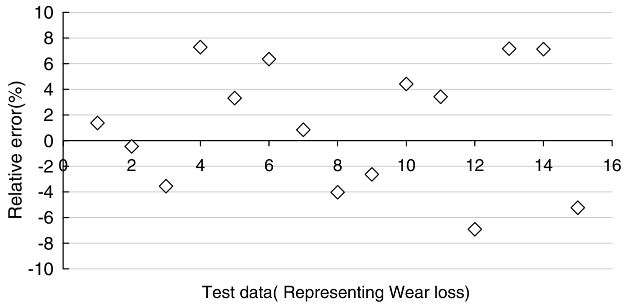

Fig. 10 The relative error distribution as a function of test data arrived from Network II

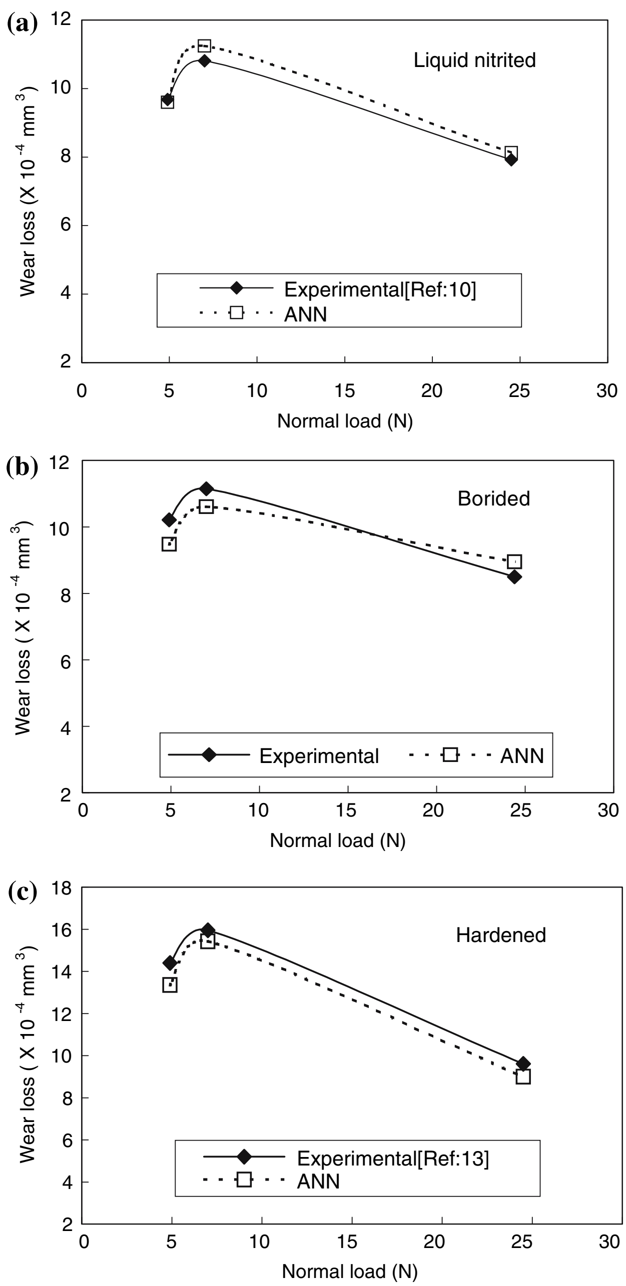

Fig. 11 Comparison of ANN and experimental wear results for: (a) liquid nitrided En 24 steel, (b) borided En 24 steel, and (c) hardened En 24 steel

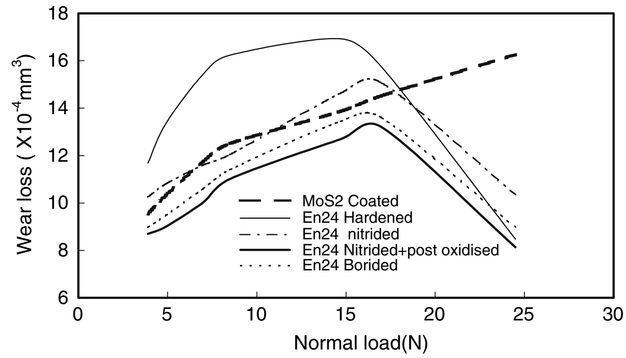

Fig. 12 Prediction of wear loss as a function of normal load

Table 4 Transition load for various surface-treated En 24 steel under fretting

Treatment	Transition load (N)	Change in operating conditions
MoS_2 coated	30	G.S → P.S
Hardened and tempered	8.5	G.S → P.S
Liquid nitrided	17.0	G.S → P.S
Liquid nitrided + post-oxidized	17.0	G.S → P.S
Borided	17.0	G.S → P.S

stick-slip condition has been proven to be the most dangerous regime for crack nucleation and service failure (Ref 14).

6. Summary

Artificial neural network was used to describe the friction and wear behavior under fretting conditions for various selected surface treatments. The proposed model predicts good agreement with experimental data. Neural network modeling provides useful information from relatively small experimental databases, leading to savings in cost and time.

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