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ITJ

ISSN 1812-5638

# INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 8 (3): 398-402, 2009
ISSN 1812-5638


# Artificial Neural Networks Modelling of Non-Asbestos Brake Lining Performance Boric Acid in Brake Pad

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**Abstract:** In this study, the friction coefficient-temperature and time experiments are carried out for the produced non-asbestos brake linings. For the evaluation of brake linings with different ingredients the mean value the friction coefficient and the standard deviation which gives the variation of the friction coefficients are calculated experimental. Recently, the ANN is successfully implemented for the prediction of experimental results in many areas. This is due to the capability of ANN in modeling of non-linear relation. The prediction of experimental results is advantageous for time and cost. In this study the ANNs are used for the prediction of mean value of friction coefficient and standard deviation for produced brake linings with different amount of organic dust and barite. The values of samples not included in education are compared with real values.

**Key words:** Artificial neural networks, brake pad, composite, friction, wear

## INTRODUCTION

Asbestos shows good friction characteristics in brake linings (Kim and Jang, 2001). On the other hand, asbestos has cancerogenic effect and the use of asbestos in brake lining is forbidden from 2000. So, novel materials for the substitution of asbestos are investigated. In this context, many natural and synthetic materials are used together for the production of friction materials. These materials are tested to determine the frictional properties (Ho *et al*., 2005).

It is well known that huge amount of technical importance of the friction systems and their significant deviations from most other tribological contact situations motivate a study on the particular nature of the tribological contact in automotive brakes (Eriksson *et al*., 2002). A major reason for the lack of publications on the surface characteristics of brake pads is the fact that the analysis is a difficult task to perform. The composition of the pad, the rough surface structure and the differences in mechanical properties of the different ingredients all constitute obstacles for different measurement techniques (Eriksson and Jacobson, 2000). Friction materials differ in many respects from most other tribomaterials. They are designed to show a high coefficient of friction, but are not allowed to seize. The friction must keep a relatively stable level over a wide range of temperatures, speeds, normal loads and environments. Their friction characteristics must not change dramatically if exposed to water, dirt or long time exposure to corrosive atmospheres. They have to be inexpensive and must not cause much wear to the discs. Due to these special demands, friction materials have evolved into very complex structures (Eriksson *et al*., 2001; Cho *et al*., 2003).

The friction element for an automotive brake system is one of the most concerned composite materials and usually contains about 10 ingredients. This is because of the friction materials that have to be considered to protect steady friction force, trustworthy strength and good wear resistance at a broad variety of braking circumstances. Manufacturing process of brake lining is very time consuming and has to be repeated many times in order to find the optimum friction coefficient of these materials (Mutlu *et al*., 2007).

During the last two decades a great deal of striving was made concerning different manners of friction performance of automotive brake systems (Jacko *et al*., 1984). A large part of the striving was given to the influence of asbestos replacement on friction performance (Gopal *et al*., 1996; Kato and Magario, 1994). Mechanical analysis of brake-induced phenomena has been advanced to understand noise, vibration and harshness during brake applications by using various computational techniques and advanced new apparatus (Lee and Barber, 1994). Anyhow, confined numbers of studies were reported about the role of ingredients on the friction performance. Especially, the investigation of friction modifiers such as abrasives, solid lubricants and other additives are relatively few although they act crucial roles in determining friction performance (Jacko and Lee, 1992). A part of the aim for the limited amount of information about ingredient study is because the results are normally categorized as proprietary information.

ANNs are good for some tasks while lacking in some others. Specifically, they are good for tasks involving incomplete data sets, fuzzy or incomplete information and for highly complex and ill-defined problems, where humans usually decide on an intuitional basis. ANNs have been applied successfully in various fields of mathematics, engineering, medicine, economics, meteorology, psychology, neurology and many others (Sozen *et al*., 2004). Some of the most important ones are; in pattern, sound and speech recognition, in the analysis of medical signatures, in the identification of military targets and of explosives in passenger suitcases (Kalogirou, 2000). They have also being used in weather and market trends forecasting, in the prediction of mineral exploration sites, in electrical and thermal load prediction, in adaptive and robotic control and many others (Sencan, 2007).

Artificial neural networks differ from the traditional modeling approaches in that they are trained to learn solutions rather than being programmed to model a specific problem in the normal way. They are usually used to address problems that are intractable or cumbersome to solve with traditional methods. They can learn from examples, are fault tolerant in the sense that they are able to handle noisy and incomplete data, are able to deal with non-linear problems and once trained can perform predictions at very high speed (Kalogirou and Bojic, 2000; Kalogirou, 2001). Recently, the ANN was used to predict the cold performance of the automotive friction material for two cases: (i) before and (ii) after fading and recovery tests (Aleksendric and Duboka, 2006).

In this study, it is described how to use the experimental data in order to create predictive tools based on artificial neural networks, to predict ratios of ingredient of brake pad materials subject to friction coefficient of brake pad for without a need to perform lengthy experiments. Firstly, the friction characteristic of a newly designed brake lining material with organic additive is obtained by usual tribological techniques. Secondly, the experimental data are used in the ANNs. For this reason six samples are educated for two inputs and six hidden and three samples are tested.

## MATERIAL AND METHODS

Friction materials investigated in this study were non-asbestos organic (NAO) type materials. The ingredients in the friction material comprise binder resin, friction modifiers, space filler and organic dust. Friction material specimens were produced by a conventional procedure for an NAO dry formulation following dry-mixing, pre-forming and hot pressing. The ingredients of the friction materials used in experiments are shown in Table 1.

Table 1: The ingredients of specimens used in experiment (all wt%)

| Material code | Phenolic resin | Cu (size 225-300 μm) | $Al_2O_3$ | Graphite | Brass particles | Organic dust | Barite |
|---|---|---|---|---|---|---|---|
| Tr1 | 20 | 15 | 5 | 5 | 2.5 | 2.5 | 50.0 |
| Tr2 | 20 | 15 | 5 | 5 | 2.5 | 7.5 | 45.0 |
| Tr3 | 20 | 15 | 5 | 5 | 2.5 | 10.0 | 42.5 |
| Tr4 | 20 | 15 | 5 | 5 | 2.5 | 15.0 | 37.5 |
| Tr5 | 20 | 15 | 5 | 5 | 2.5 | 17.5 | 35.0 |
| Tr6 | 20 | 15 | 5 | 5 | 2.5 | 25.0 | 27.5 |
| Ts1 | 20 | 15 | 5 | 5 | 2.5 | 5.0 | 47.5 |
| Ts2 | 20 | 15 | 5 | 5 | 2.5 | 12.5 | 40.0 |
| Ts3 | 20 | 15 | 5 | 5 | 2.5 | 20.0 | 32.5 |

Table 2: Experimental data for training session of artificial neural networks

| Specimen No. | Mean of friction coefficients | SD of friction coefficients |
|---|---|---|
| Tr1 | 0.55 | 0.06 |
| Tr2 | 0.57 | 0.11 |
| Tr3 | 0.4749 | 0.13226 |
| Tr4 | 0.512355 | 0.15001 |
| Tr5 | 0.41 | 0.1 |
| Tr6 | 0.454511 | 0.08519 |
| Ts1 | 0.544591 | 0.124755 |
| Ts2 | 0.49 | 0.15 |
| Ts3 | 0.477126 | 0.10833 |

In the present study, nine different samples were used, six of which for training ($Tr_1...Tr_6$) and three of which for testing ($Ts_1...Ts_3$). Braking tests carried out under 10.5 MPa pressure and at temperatures from 50 to 400°C for 500 sec. The temperature and friction coefficient values are stored in a databank. The tests are repeated three times for each sample. Table 2 shows the mean value of friction coefficients and the standard deviations for each material code.

## ARTIFICIAL NEURAL NETWORKS

A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use (Dony and Haykin, 1995). A neural network consists of a number of processing elements called neurons each of which have many inputs but only one output. As shown in Fig. 1 in a typical network there are three layers of neurons, i.e., input layer which receives input from the outside world, hidden layer or layers which receive inputs from the input layer neurons and the output layer which receives inputs from the hidden layers and passes its output to the outside world and in some cases back to the preceding layers.

Various network architectures have been investigated to find the one that could provide the best overall performance. The architecture, among those

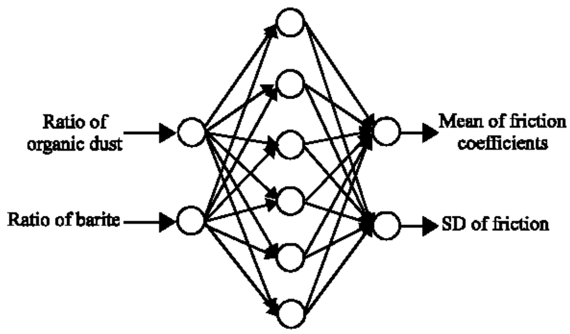


Fig. 1: Used neural network architecture

Table 3: ANN parameters

| Parameters | Value |
|---|---|
| No. of neurons for the input layer | 2 |
| No. of neurons for the output layer | 2 |
| Layer number | 1 |
| Layer cell number | 6 |
| Activation function | Sigmoid |
| Maximum iteration number | 150000 |
| Error limit | 0.0001 |
| Learning-rate | 0.7 |
| Momentum coefficient | 0.9 |

tested, that gave the best results and was adopted for the present study is shown in Fig. 1.

This architecture has been used in a number of engineering problems for modeling and prediction, with very good results. It is a feed forward architecture. Activation function using in nodes is sigmoid function. The same activation functions are used for both hidden layer and output layer. These characteristic parameters are shown in the Table 3.

In the study, generalized delta rule was used to adjust of ANN's weights and bias. This rule explained below: The output $O_j$ of each unit ij is defined by:

$$O_j = f\,(net_j),\ net_j = \sum_i w_{ij} O_i + \theta_j \quad (1)$$

where, $O_i$ is the output of unit i, $w_{ij}$ is the weight of the connection from unit i to unit j, $\theta_j$ is the bias of unit j, $\Sigma_i$ is a summation of every unit ij whose output flows into unit j and f (x) is equal to 1/(1+exp(-x)) is sigmoid function. When the set of m-dimensional input patterns $\{i_p = (i_{p1}, i_{p2}, ...., i_{pm});\ p \in P\}$ where, P denotes set of presented patterns and their corresponding desired n-dimensional output patterns $\{t_p = (t_{p1}, t_{p2}, ...., t_{pm});\ p \in P\}$ are provided, the neural network is taught to compute ideal patterns as follows. The squared error function $E_p$ for a pattern p is defined by:

$$E_p = \frac{1}{2} \sum_{j \in output} (t_{pj} - O_{pj})^2 \quad (2)$$

The purpose is to make $E = \sum_p E_p$ small enough by choosing appropriate $w_{ji}$ and $\theta_j$. To realize this purpose, a pattern $p \in P$ is chosen successively and randomly and then $w_{ji}$ and $\theta_j$ are changed by:

$$\Delta_p w_{ji} = -\,\varepsilon\,(\partial E_p / \partial\, w_{ji}) \quad (3)$$

$$\Delta_p \theta_j = -\,\varepsilon\,(\partial E_p / \partial \theta_j) \quad (4)$$

The factor ε is called the learning-rate parameter. This coefficient is a small positive constant. By calculating the right hand side of Eq. 3 and 4, it follows that:

$$\Delta_p w_{ji} = \varepsilon\, \delta_{pj}\, O_{pI} \quad (5)$$

$$\Delta_p \theta_j = \varepsilon\, \delta_{pj} \quad (6)$$

Where:

$$\delta_p = \begin{cases} f'(net_j)(t_{pj} - O_{pj}) \\ f'(net_j) \sum_k w_{kj} \delta_{pk} \end{cases} \quad (7)$$

Note that k in the above summation represents every unit k whose output follows into unit j. In order to accelerate the computation, the momentum terms are added on Eq. 5 and 6:

$$\Delta_p w_{ji}(n+1) = \varepsilon\, \delta_{pj}\, O_{pi} + \alpha \Delta_p\, w_{ji}\,(n) \quad (8)$$

$$\Delta_p \theta_j\,(n+1) = \varepsilon\, \delta_{pj} + \alpha\, \Delta_p\, \theta_j\,(n) \quad (9)$$

where, n represents the number of learning cycles and α momentum coefficient is a small positive value.

**Training of tribological property data of substrate and treated specimens:** The general aim in the training process is to teach the relations between input and output values to the program and get the results with the possible lowest errors. The input variables are the ratio of organic dust and ratio of barite in the produced specimens. The output variables are mean of friction coefficients and standard deviation of friction coefficients of produced analyzed brake linings. Therefore, there are two input variables and two output variables in this training session as shown in Fig. 1.

In neural network applications, real output values which used in training process are reduced to values between 0 and 1, which is called the normalization process. This is carried out by dividing the output values by the same integer numbers. Experimental values were

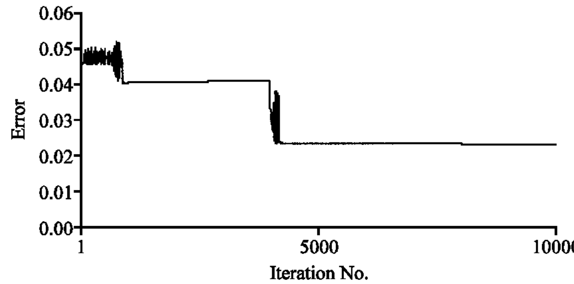


Fig. 2: Percentage error change due to the iteration No.

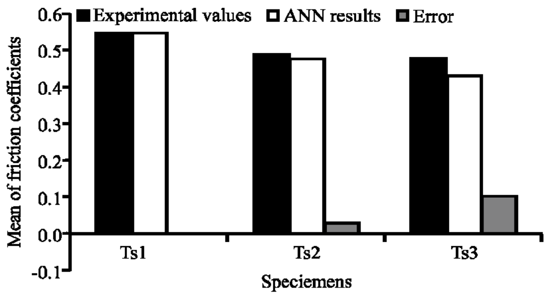


Fig. 3: Mean of friction coefficients for experimental value and ANN result of specimens used in test

set as input and output values. Some of the input and output values were kept for use in the testing process after the training was complete. The training process is always performed by 'trial and error method'. Training iteration are made by the learning-rate and momentum value obtained by prior experiences ($\varepsilon = 0.7$ and $\alpha = 0.9$). However, node numbers of hidden layers was changed so that error can be minimized value. In the result of trials, hidden layer node numbers is obtained as 6. In Fig. 2, percent error has been reduced to reasonable values after 5000 iterations.

**Testing:** Testing the designed neural networks is the final and most important step. The program was tested using different input and output values that were not given for training previously. The test results were compared with the output values that were experimentally obtained and kept for testing Table 1. The testing results were compared with the experimental values as seen in Fig. 3 and 4.

As can be seen in Fig. 3 the experimental and ANN values are very close and maximum error is lower than 10%. Figure 4 shows the standard deviations of friction coefficients and error rate. For this variable, however the values for Ts2 sample is very close but for the other two samples the error rates are higher. This may be due to the

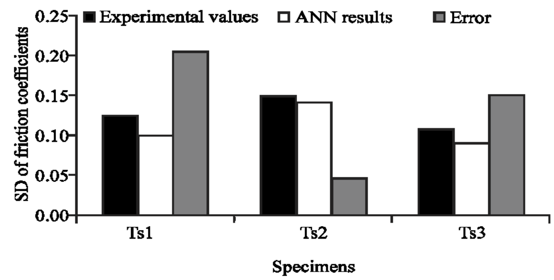


Fig. 4: SD of friction coefficients for experimental value and ANN result of specimens used in test

very low standard deviation of Tr1 sample (Table 2). This may be affected the training of ANNs and caused the very big error rate.

## CONCLUSIONS

In this study, determination of tribological properties such as mean of friction coefficients and standard deviations values of friction coefficients has been achieved by using artificial neural networks. The experimental results for various specimens were used for training the neural network programs and these programs were tested by the different inputs that were not used for training. The testing results were found to be reasonably good.

The calculated mean of friction coefficients and standard deviations values of friction coefficients were found to be highly satisfactory in comparison with the experimental results. Therefore, it is possible to predict the mean of friction coefficients and standard deviations values of friction coefficients without long time consuming tests.

It can finally be concluded that the neural networks are able to predict mean of friction coefficients and standard deviations values of friction coefficients at different ingredient ratios with less experimental studies. Calculations done by the testing process of the neural network programs took only milliseconds. Therefore, it can be reasonably assumed that the neural network programs provide a quick means of calculations conducted in this study.

The dependence of accuracy on the number of training data indicates that the accuracy could be further improved by expanding the experimental database for network training. Furthermore, a well-trained neural network provides more useful data from a relatively limited database obtained by experiments.

## ACKNOWLEDGMENTS

This research is funded by the Scientific and Technological Research Council of Turkey (TÜBİTAK) (Grant Reference No. 106M006). The author wishes to acknowledge the TÜBİTAK for the support.

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