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DETERMINATION OF FRICTION COEFFICIENT AT JOURNAL BEARINGS BY EXPERIMENTAL AND BY MEANS OF ARTIFICIAL NEURAL NETWORKS METHOD

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Abstract- Knowing friction coefficient is important for determination of wear loss conditions at journal bearings. Tribological events that influence wear and its variations affect experimental results. In this study, friction coefficient at CuSn10 Bronze radial bearings has been determined by a new approach as experimental and artificial neural networks method. In experiments, effects of bearings have been examined at dry and lubricated conditions and at different loads and velocities.

Key Words-Friction Coefficient, Journal Bearing, Artificial Neural Networks

1. INTRODUCTION

The force known as friction may be defined as the resistance encountered by one body in moving over another. This broad definition embraces two important classes of relative motion: sliding and rolling. The ratio between this frictional force and the normal load is known as the coefficient of friction and is usually denoted by the symbol μ: $\mu=F_f/F_n$ The magnitude of the frictional force is conveniently described by the value of the coefficient of friction. The Laws of Friction; the friction force is proportional to the normal load, the friction force is independent of the apparent area of contact and the friction force is independent of the sliding velocity. Friction coefficient (μ) is characteristic of tribological system but is not material characteristic [1, 2, 3].
The quantity known as the friction coefficient (or 'coefficient of friction') has long been used in science and engineering. It is easy to define, but not easy to understand on a fundamental level. The former is called the static friction coefficient, and the latter, the kinetic friction coefficient. In the case of solid-on-solid friction (with or without lubricants), these two types of friction coefficients are conventionally defined as follows:
$\mu=F_f/F_n$ and $\mu = F_k/F_n$ Where F_f is the force just sufficient to prevent the relative motion between two bodies, F_k is the forces needed to maintain relative motion between two bodies, and F_n is the force normal to the interface between the sliding bodies [4].
Friction of metals varies at different conditions. If metal surfaces are cleaned in high vacuum and then placed in contact, strong adhesion is usually observed. The coefficient of friction under these conditions has a very high value. Solid lubricants and thin soft metallic films can provide valuable protection. However, for most common materials sliding in air, the value of μ lies in the narrower range about 0.1 to 1. This value is ten times less at vacuum condition. This situation comes from oxide films in air. Oxide films are also important in the friction of dissimilar metals and alloys in air. In general, the coefficient of friction for an alloy tends to be rather less than that for its pure

components. When the temperature of a sliding metal is increased, several effects will occur: its mechanical properties will change, its rate of oxidation will increase, and phase transformations may take place. All these will influence its frictional behavior [1,2].

A lot of elements effect friction coefficient. One of them is lubrication. It has been determined by studies at sintered self-lubricating bronze bearings that additional oil at bearing considerably decreased friction coefficient especially at high velocities and pressures [5]. In addition, it has been seen that friction coefficient decreased more by additional additive [6].

In this study, friction coefficient has been determined by a new approach with a radial journal bearing test rig and artificial neural networks method. Bronze based materials have been used as bearing material. Effects of friction coefficient have been examined at different loads and velocities and at dry and lubricated conditions.

2. EXPERIMENTAL STUDIES

In experiments, bronze bearing of inner diameter d=10 mm, width B=10 mm, outer diameter D=15 mm has been used as basic friction element DIN 1705 CuSn10 and SAE 1050 steel journal of diameter d=10 mm has been used as opposing friction element. Chemical compositions of these materials have been illustrated in (Table 1). Experiments have been carried out for 2.5 hours, repeating every half an hour. Experiments have been repeated at 10 N, 20 N loads and 750 rpm, 1500 rpm at dry and lubricated conditions. Results of these experiments are v=392 m/s velocity, 3532.5 m sliding distance at n=750 rpm and v=785 m/s velocity, 7065 m sliding distance at n=1500 rpm.

The roughness of CuSn10 bronze is approximately R_a=1.5 μm and the roughness of 1050 steel journal is R_a=0.5 μm. The friction force and friction coefficient have been calculated for every half an hour, totally 2.5 hours.

Table 1: The chemical composition of SAE 1050 and CuSn10 (wt. %)

Material	C	Si	Mn	P	S	Fe	Cu	Sn
SAE 1050	0.51	0.29	0.82	0.040	0.050	Balance	-	-
CuSn10	-	-	-	-	-	-	89.8	10.2

3. MODELING WITH NEURAL NETWORKS

The artificial neural networks are a relatively new modeling technique. They are basically a ‘black box’ operation linking input data to output data in a very clever but indefinable way. Since the ANN’s are non-linear statistical technique, they can be used to solve problems that are not eligible for the conventional statistical methods. Apart from modeling, ANN’s are also applied for other tasks, such as classification, transformation, association and process control. In the past few years there has been a constant increase in interest of neural network modeling in different fields of materials science.

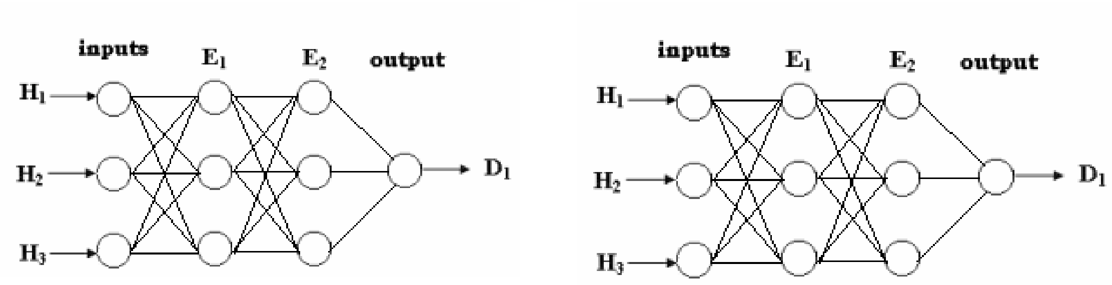

Figure 1. The ANN Architecture (a) dry (b) lubricated

If o_j^m represent the output of the *j*th neuron in the *m*th layer, and W_{ij}^m the weight on connection joining the *i*th neuron in the $(m-1)$th layer to the *j*th neuron in the *m*th layer, then:

$$o_j^m = f\left[\sum_i \left(W_{ij}^m o_j^{m-1}\right)\right], \qquad m \geq 2, \tag{1}$$

Where the function *f*(.) can be any differentiable function. In this study the sigmoid function defined below is used as the transfer function.

$$f(x) = \frac{1}{1+\mathrm{e}^{-x}} \tag{2}$$

This function limits the outputs o_j^m among 0 and 1. To achieve the required mapping capability, the network is trained by repeatedly presenting a representative set of input/output patterns, with a back-propagation error and weight adjustment calculation to minimize the global error e_{p} of the network, i.e.

$$E_P = \frac{1}{2}\sum_{j=1}^{n_0}\left(t_{pj} - o_{pj}^m\right)^2 , \tag{3}$$

Where t_{pj} is the target output of neuron *j* and o_{pj}^m is the computed output from the neural network corresponding to that neuron. Subscript *p* indicates that the error is considered for all the input patterns.

Minimization of this average sum-squared error is carried out over the entire training patterns. As the outputs o_{pj}^m are functions of the connection weights w^m and the outputs o_{pj}^{m-1} of the neurons in the layer $m-1$, which are functions of the connection weights w^{m-1}, the global error e_{p} is a function of w^m and w^{m-1}. Here, w with a superscript refers to the connection matrix. To accomplish this, w evaluates the partial derivative, $\partial e/\partial w_{ij}$ and supplies a constant of proportionality as follows:

$$\Delta W_{ij} = \varepsilon\, \delta_{\mathrm{p}j}\, o_{\mathrm{p}i} \tag{4}$$

Where ε refers to the learning rate, δ_{pj} refers to error signal at neuron j in layer m, and o_{pi} refers to the output of neuron i in layer m–1. δ_{pj} is given by

$$\delta_{pj} = \left(t_{pj} - o_{pj}\right) o_{pj} \left(1 - o_{pj}\right) \qquad \text{for output neurons,} \tag{5}$$

$$\delta_{pj} = o_{pj} \left(1 - o_{pj}\right) \Sigma_k \delta_{pk} w_{kj} \qquad \text{for hidden neurons,} \tag{6}$$

Where o_{pj} refers to layer m, o_{pi} refers to layer m–1, and δ_{pj} refers to layer m+1. The weights are adjusted in the presence of momentum by:

$$\Delta W_{ij}\left(n+1\right) = \varepsilon \left(\delta_{pj}\, o_{pi}\right) + \mu \Delta W_{ij}\left(n\right). \tag{7}$$

For this computation a PC (Pentium II- Intel MMX) was used. The input variables were H_1, H_2, H_3 represent the values of time (h), applied load (N) and period (rpm). Output variable was friction coefficient (D_1).
For dry condition, hidden layers were 3:3. Therefore, we have three input variables and an output variable in our application. In neural network applications, input or output values could be reduced to the values of 0-1, which is called the normalization process iteration number was selected as 8000. The learning rate and momentum values were selected as 0.7, 0.9 respectively. These values were found from the result of pre-trials. The training was made once for test phase. Microsoft Excel was used to calculate of mean error. The mean error was calculated as % 1.72 for friction coefficient. Iteration number versus mean square error (MSE) is shown in Figure 2. The ANN used architecture is a 3:3:3:1 multilayer architecture as shown in Figure 1a. Two values were selected for test phase.
For lubrication conditions, hidden layers were 3:3. Therefore, we have three input variables and an output variable in our application. In neural network applications, input or output values could be reduced to the values of 0-1, which is called the normalization process. Iteration number was selected as 5000. The learning rate and momentum values were selected as 0.7, 0.9 respectively. These values were found from the result of pre-trials. The training was made once for test phase. The mean error was calculated as % 6.4 for friction coefficient. Iteration number versus mean square error (MSE) is shown in Figure 7. The ANN used architecture is a 3:3:3:1 multilayer architecture as shown in Figure 1b. Two values were selected for test phase.

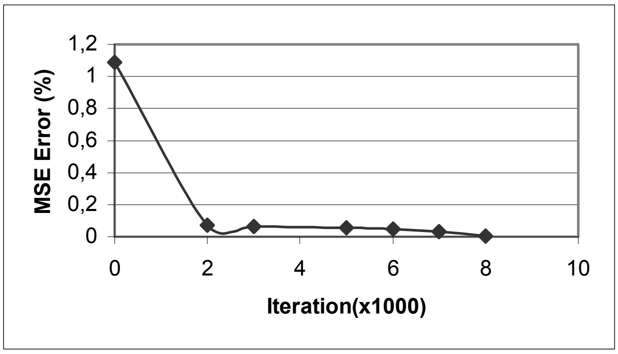

Figure 2. Iteration Number Versus Mean Square Error for Training Non-Linear Correction Coefficient (dry).

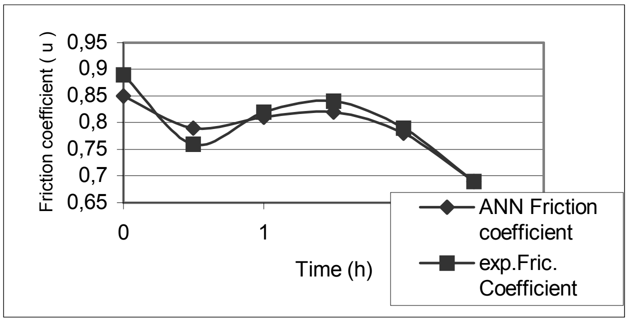

Figure 3 . The Comparison of Experimental and ANN Friction Coefficient Results at 750 rpm and 10 N load (dry)

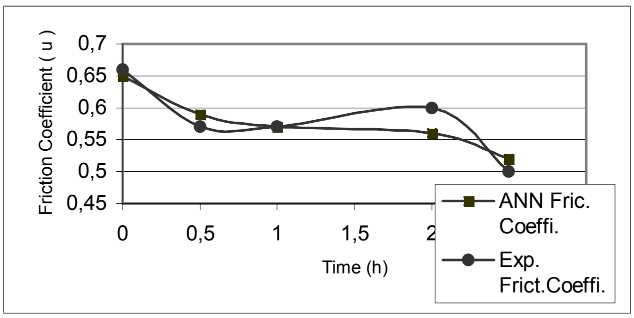

Figure 4. The Comparison of Experimental and ANN Friction Coefficient Results at 750 rpm and 20 N load (dry)

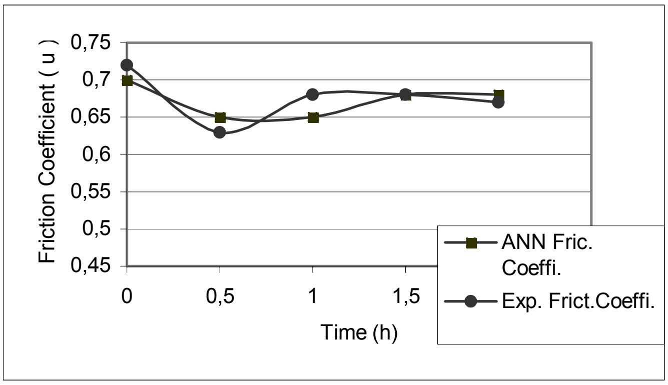

Figure 5. The Comparison of Experimental and ANN Friction Coefficient Results at 1500 rpm 20 N load (dry)

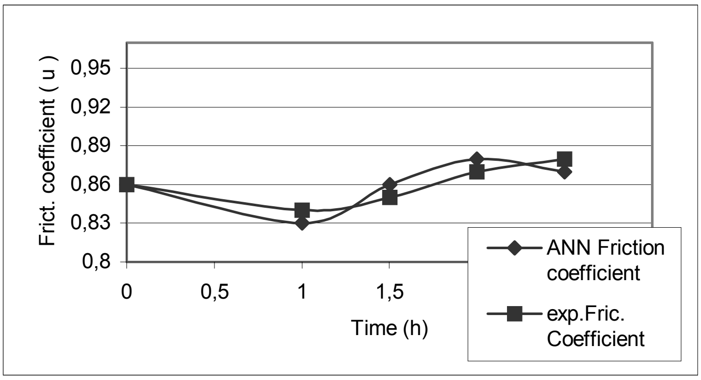

Figure 6. The Comparison of Experimental and ANN Friction Coefficient Results at 1500 rpm 10 N load (dry).

Table 1. The comparison of experimental and ANN tests results for dry conditions

n(rpm)	Load (N)	Time(h)	Friction Coeffic.(u) (Exp. Result)	Friction Coeffic.(u) (ANN result)
1500	10	0.5	0,79	0,80
750	20	1,5	0,58	0,567

% Mean error for test phase on dry conditions: %2.97

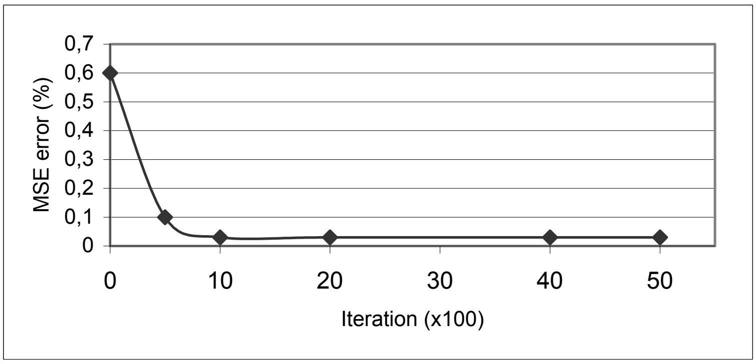

Figure 7. Iteration Number Versus Mean Square Error for Training Non-Linear Correction Coefficient (lubrication).

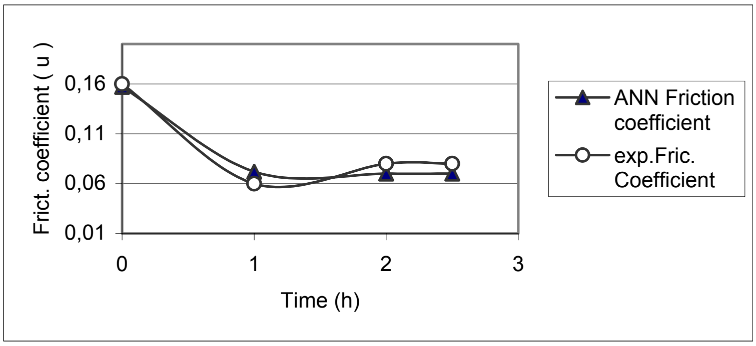

Figure 8. The Comparison of Experimental and ANN Friction Coefficient Results at 1500 rpm 10 N load (lub.)

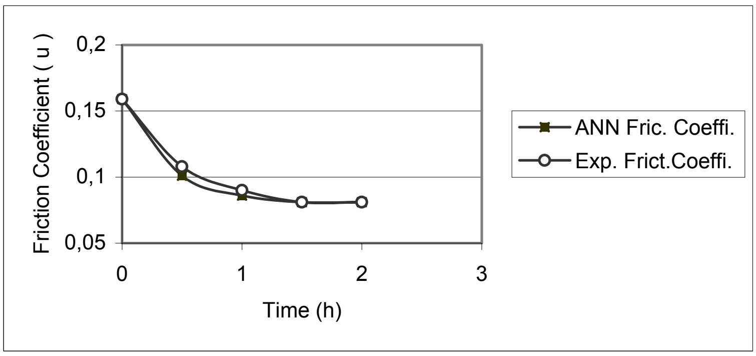

Figure 9. The Comparison of Experimental and ANN Friction Coefficient Results at 1500 rpm 20 N load (lub.)

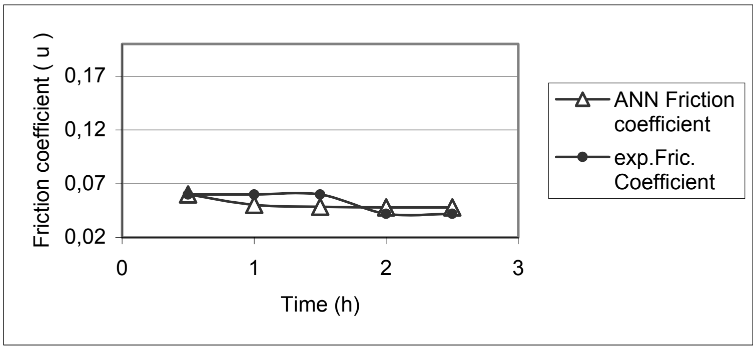

Figure 10. The Comparison of Experimental and ANN Friction Coefficient Results at 750 rpm 10 N load (lub.)

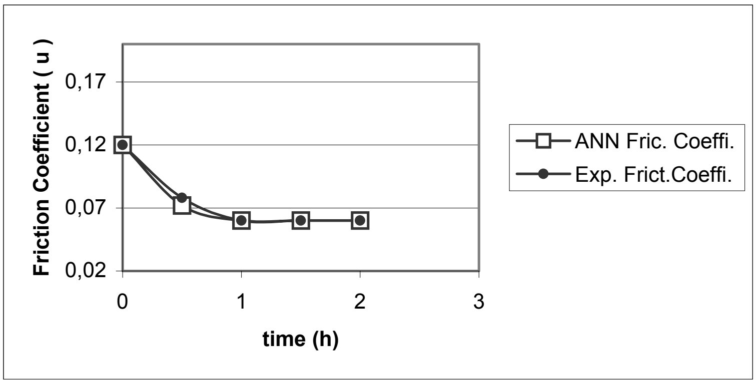

Figure 11. The Comparison of Experimental and ANN Friction Coefficient Results at 750 rpm 20 N load (lub.)

Table 2. The comparison of experimental and ANN tests results for lubrication condition.

n(rpm)	Load (N)	Time(h)	Friction Coeffic.(u) (Exp. Result)	Friction Coeffic.(u) (ANN result)
0	10	750	0,12	0,114
2,5	10	1500	0,08	0,084

% Mean error for test phase on lubricated conditions: %4.35

4. RESULTS AND DISCUSSION

Journal bearing samples were worn under 10 N, 20 N loads and at 750 rpm, 1500 rpm for every half an hour, totally 2.5 hours, at dry and lubricated conditions. When journal had began to rotate happens, friction force caused a movement at comparator. Friction coefficient was determined as a function friction force and applied load. Friction

coefficients under 10 N, 20 N loads, 750 rpm have been illustrated in (figure 3-4); friction coefficients under 10 N, 20 N loads, 1500 rpm have been illustrated in (figure 5-6) at dry conditions.
Quite higher friction coefficients μ = (0.6-0.9) were obtained at dry condition experiments. As a result excessive wears were observed at samples.
Lubrication has been done by SAE 90 gear oil. Friction coefficient under 10 N, 20 N loads, 750 rpm has been illustrated in (figure 11-12) and friction coefficient under 10 N, 20 N loads, 1500 rpm has been illustrated in (figure 9-10). It has been seen that friction coefficient decreased in lubricated conditions. As a result, fewer wears have been observed at samples.
D. Coupard et al. have determined friction coefficient as approximately 0.7 at AISI-54100 steel opposing to CuSn12 bronze on pin-on-disc at 5 N load, 235 mm/s velocity and 30 minutes [17]. In this study, similar results have been obtained at calculations.

5. CONCLUSIONS

In this study, a new test rig and method have been developed for measuring friction coefficient at journal bearings. By this method, friction coefficients have been calculated at different loads and velocities at journal bearings. Repeatability of the results shows the suitability of the test rig and the method.
As mentioned in the literature, high friction coefficients and high wears have been observed at dry test conditions. Low friction coefficients and low wears have been observed at lubricated test conditions.
In addition, friction coefficient has been determined as a function normal force and friction force. Friction force increases by increasing load and velocity. At the beginning of the motion because of the dry friction, friction coefficient increases later decreases. As the load increases, friction coefficient decreases at dry condition. But at lubricated condition, friction coefficient increases by increasing load because of decreasing oil film thickness.
These experimental results were compared with ANN results. Iteration number was selected 50000 for dry and 100000 for lubrication. The ANN used architecture is a 3:4:3:4:1 multilayer architecture for dry conditions and 3:4:4:1 multilayer architecture for lubrication conditions. The learning rate and momentum values were selected as 0.7, 0.6 respectively for dry conditions and as 0.7, 0.9 respectively for lubrication conditions. The trainings finished in 10 minute, whereas experimental study took a long time. The results obtained in ANN application are close to friction test results. Therefore by using trained ANN values, the intermediate results that were not obtained in the tests can be calculated.

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