Consideration of the use of artificial intelligence methods for determining the friction coefficient of lubricated sliding bearings

B R Andelković1, A Al-Sammarraie2, D Milčić1, D Stamenković1, M Banić1, J S Marinović1, B Đorđević1 and N Zdravković1

1University of Niš, Faculty of Mechanical Engineering, A. Medvedeva 14, 18000 Niš, Serbia
2University of Tikrit, Faculty of Engineering, Department of mechanical engineering, Tikrit, Iraq

E-mail: bandjel@gmail.com

Abstract. Sliding bearings’ main advantages over the ball bearings are it’s load capacity and longevity. If hydrodinamic lubrication conditions are met then the sliding bearings will work forever. This is especially important when dealing with high rotation rate environments, where ball bearings see very limited use due to their inferior load capacity and longevity. The focus of this study is the examination and determination of coefficient of friction values in sliding bearings made of tin based white metal alloys conditioned with hydrodinamic lubrication. A sliding bearing is based on a kinematic pair made of a steel axle and a braided alloy TEGOTENAX V840 made by Ecka Granules. The chemical composition of the this alloy is 88.7% Sn, 7.6% Sb and 3.7% Cu. The examination was performed using one oil lubricant. Experimental data has been used for creating an adaptive neuro-fuzzy inference system model. ANFIS model provides an estimation of coefficient of friction values in function of load. Based on the ANFIS model an analytical expression, used for connecting load values with coefficient of friction values, was defined. This analytical expression is suitable for engineering applications and purposes.

1. Introduction
Friction is a physics phenomenon that can have positive and negative effects on the manufacture and functional processes of mechanical construction designs. Sliding bearings are very commonly used as kinematic pairs. Friction coefficient of sliding is one of the basic parameters defining the quality of a sliding bearing. High quality sliding bearings have very low friction coefficients values. Friction is a phenomenon that, in this case, has a negative effect. With regards to both manufacture and design, project developers aim to diminish friction values as much as possible. In full-film lubrication conditions, film thickness should be enough to separate the peaks of rough contact surfaces. Experiments of R Đuriš [1] and Labašová [2] have shown that the friction coefficient values of an aluminum - steel sliding bearing can be much lower than the expected value of 0.8, and that it can even be as low as 0.1.

There are a large number of papers and publications on dealing with the problems of friction coefficient and sliding bearings. Numerous authors [2] and [3] have studied the friction coefficient of graphite notched bronze. Results show that the friction coefficient lowers with perpendicular load
increases. Some studies also observed friction coefficient values of groove slides with brass, aluminum and polyamide contact materials. Highest friction coefficient value drop was observed with aluminum contacts [1]. Friction coefficient value drops were also observed with brass and polyamide contacts.

This article’s purpose is to explore friction coefficient values of tin and steel based alloy kinematic pairs often used in heavy industry conditions.

2. Theoretical foundation

Journal bearings are also complete bearings that completely surround the journal by their contact surface. Mathematical theory of hydrodynamic lubrication is based on the work of Raynolds’ [1], [4]. The differential equation defining the law by which the pressure changes within the lubrication layer is called Raynolds’ equation (1)

$$\frac{d}{dx} \left( \frac{h^3}{\mu} \frac{dp}{dx} \right) + \frac{d}{dz} \left( \frac{h^3}{\mu} \frac{dp}{dz} \right) = 6 \cdot U \cdot \frac{dh}{dx}$$

where $p$ is lubricating film pressure, $U$ is the relative velocity of bearing surfaces, $h$ is variable film thickness, $x$ is coordinate in the direction of motion, $z$ is coordinate in the axial direction, $\mu$ is the absolute viscosity of the lubricating fluid and $B$ is axial bearing length. Finite length of bearings $B/D = 1$ has been studied by this paper.

The low axial pressure value can often be ignored and the equation (1) becomes [5]:

$$\frac{d}{dz} \left( \frac{h^3}{\mu} \frac{dp}{dz} \right) = 6 \cdot U \cdot \frac{dh}{dx}$$

Finite length bearing’s friction coefficient and the solution of Raynolds’ equation, according to Tao L. N. [6], are shown in equation (3):

$$f = \frac{F_f}{F_n} = \frac{2 \pi \mu U r^2 L}{c (1 - \eta^2)^2 W_2} + \frac{c \eta}{2r}$$

where $f$ is the friction coefficient of lubricated sliding bearings, $F_f$, $F_n$ are friction and normal forces respectively, $r$, $c$ are the radius and radial clearance of bearing respectively, $\eta = e/c$ is a ratio of eccentricity $e$ to radial clearance $c$, $L = l/d$ where $l$ and $d$ are the length and diameter of the bearing, $W_2$ is perpendicular component of load carrying capacity of the bearing projected to the line of center.

3. Experimental model

3.1. Experimental materials and conditions

Sliding bearing material is a white metal alloy with a chemical composition shown in Table 1, and the shaft material is steel composed as shown in Table 2. Sliding bearing brass is made in such a way that it’s interior is layered with white metal. Lubrication is achieved by adding lubricating oil through a 3mm diameter side hole perpendicular to the bearing axis (Figure 1). Oil then goes through a 2mm wide and 30 µm deep spiral groove on the inner surface of the bearing for an evenly distributed oil layer. Sliding brass outer diameter is 60 mm while the inner diameter is 40 mm. Sliding bearing length is 40 mm.

Observed specimen were, during the experiment, lubricated with oil under pressure. Lubrication oil used was ISO VG32 oil. Load was increased from 500 to 2500N and the rotation speed from 25 rpm to 75 rpm. Results processed in this document are for the rotation speed of 25 rpm.

The goal of this examination was to measure data regarding rotation speed, load, friction coefficient values in an even time interval, then to form a neuro-fuzzy model approximating friction coefficient values based on that data.
Table 1. Chemical composition of TEGOTENAX (V480).

|    | Sn  | Sb  | Cu  | As  | Bi  | Ni  | Pb  | Cd  | Fe  | Al  | Zn  |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| %  | 88.7| 7.6 | 3.7 | 0.009| 0.002| 0.003| 0.008| 0.010| 0.009| 0.002| 0.002|

Table 2. Chemical composition of AISI440C.

|   | C | Si | Mn | Ni | Cr | Mo | P | S |
|---|---|----|----|----|----|----|---|---|
| % | 1.2| 1  | 1  | 1  | 18 | 0.75| 0.04| 0.03|

3.2. Test procedure and analytical basis

Measuring friction coefficient values, for this specific purpose, was done using a constructed measuring system (Figure 2). Torque on a known length lever was measured, which was then used to calculate tangential force values of the outer diameter of the sliding bearing brass. The vertical component of the bearing’s force was measured using the force transducer from HBM. Judging by the $F_n$ lever force measurement and the appearance of transient mode inertia forces, special attention to possible occasional oscillatory changes and $F_f$ friction force direction changes was needed. This kind of dynamic system behaviour should be excluded from the experimental data base to avoid negative friction coefficient values. This analysis and assumption was deemed to be true, because when a data base was measured in transient mode while in shaft acceleration to nominal speed phase, negative friction coefficient values appeared due to friction force direction change. For a stationary state with constant angular velocity, the following equations (4 - 6) apply (Figure 3).

Figure 1. Sliding brass with oil spiral groove.

Figure 2. Hydrodynamic journal bearing test system.

Figure 3. Principle of friction coefficient value measurements.
\[ T_a = F_{pol} \cdot l_{pol} = F_f \cdot \frac{d}{2} \] (4)
\[ F_f = F_n \cdot f \] (5)
\[ f = \frac{F_{pol} \cdot l_{pol}}{F_n} \] (6)

According to D'Alembert's principle, the following equations (7, 8) apply:
\[ T_a - T_{in\_shaft} - F_f \frac{d}{2} = 0 \quad \text{and} \quad F_f \frac{d}{2} - T_{in\_brass} - F_{pol} \cdot l_{pol} = 0 \] (7)
\[ T_a - J_{in\_shaft} \dot{\varphi}_1 - F_f \frac{d}{2} = 0 \quad \text{and} \quad F_f \frac{d}{2} - J_{in\_brass} \dot{\varphi}_2 - F_{pol} \cdot l_{pol} = 0 \] (8)

where \( J_{in\_shaft}, J_{in\_brass} \) are body's moment of inertia of the journal and brass respectively, \( T_{in\_shaft}, T_{in\_brass} \) are moments of inertia of the journal and brass respectively and \( T_a \) is the active moment of the electromotor. A mathematical relation based on equation (8) can be used to calculate friction coefficient values in any given time, as in equation (9).
\[ f = \frac{2 F_{pol} \cdot l_{pol} + J_{in\_brass} \dot{\varphi}_2}{F_n} \] (9)

In a stationary state angular velocity \( \dot{\varphi}_1 \) is null thus equations (7) and (8) are reduced to equation (4, 10):
\[ T_a - F_f \frac{d}{2} = 0 \quad \text{and} \quad F_f \frac{d}{2} - F_{pol} \cdot l_{pol} = 0 \] (10)

4. ANFIS methodology
An adaptive neuro fuzzy iteration system (ANFIS) [7-10], a specific artificial neural network (ANN) family part, is used to determine the way of parameter approximation of friction coefficient modelling based on experimental data in this study. ANFIS has shown very good qualities in studying and approximation, which makes it an efficient tool for solving the uncertainty of any and all systems. ANFIS, a hybrid intelligent system that improves autonomous learning and adapting, was used by scientists in different engineering systems [11-16]. There are many current studies regarding ANFIS usage for approximation and identification of different systems in real time [17-22].

ANFIS structure contains 5 layers (Fuzzification, Rule, Normalization, Defuzzification, Output summation node). MATLAB software uses a fuzzy iteration system in its’ entire process of training and evaluation of ANFIS. Dual input ANFIS network is shown by Figure 4.

The fuzzy IF-THEN rules of Takagi and Sugeno’s class and one inputs for the zero-order Sugeno is employed for the purposes of this study, as in equation (11).
\[ \text{if} \ x \ \text{is} \ A \ \text{and} \ y \ \text{is} \ C \ \text{then} \ f_1 = c_1 \] (11)

The 1st layer is made up of input parameters MFS, and it provides the input values to the following layer. Each node here is considered an adaptive node having a node membership function (MF) \( \mu_{AB}(x) \) and \( \mu_{CD}(x) \). Gauss membership functions having the maximum value (1.0) and the minimum value (0.0) are selected, such as in equation (12):
\[ \mu(x) = \text{gauss} \ (x; \sigma, c) = e^{-\frac{(x-c)^2}{2\sigma^2}} \] (12)

where \((\sigma, c)\) is the set of parameters set. Here, \(x\) is the input to node.
Function `genfis1` generates the initial fuzzy inference system (FIS) based on the training data (Figure 5). Experimental data collected is separated into 2 subsets, one of which is used as training data, and the other used as a control subset - check data. A single input/output FIS is generated. The input variable has 5 Gauss membership functions (Figure 6). Sugeno FIS output function is a constant, it is zero order Sugeno. Inference result of every rule is a constant. FIS formed in such a way is trained to minimize errors of output values. Training is accomplished using the function `anfis`. Function `anfis` can have multiple input variables and only a single output variable. If a system has multiple outputs, multiple `anfis` functions are used for training, one for each of the outputs respectively with common input variables. The high accuracy, least amount of errors condition was met by a large number of iterations during the ANN training. The number of iterations was 10000. Any fewer number of iterations did not achieve satisfactory relative error values. The final ANFIS curve is shown in the Figure 7.
5. Results

For practical reasons, an analytical expression connecting input load data and output friction coefficient values was formed using approximation methods. This kind of an analytical interpretation allows swift use for engineering applications. Approximated analytical expressions are made for 2 types of data, one for load – measured coefficient values data (equation 13) and one for load – measured coefficient values based on ANFIS model data (Figure 8) (equation 14). Medium square root of error of RMSE was 0.0177 and 0.0980 while the regression coefficient value $R$ was 0.9985 and 0.9516 for experimental and ANFIS model data, respectively.

\begin{align*}
    f &= a \cdot F_n^b = 74.76 \cdot F_n^{-0.983} \\
    f &= a \cdot F_n^b = 71.18 \cdot F_n^{-0.9809}
\end{align*}

(13)  

(14)

Comparing modeling results with experimental data proved useful. Comparison was achieved in 2 ways:

- comparing ANFIS model values to measured values and
- comparing approximated expression values to measured values.

For simplicity, using experimental data 10 different, random, sliding bearing load values were chosen that were roughly evenly spread throughout a measurement interval of cca 500 – 2300N. First part of the measurement interval valued 0 – 500 N isn’t suitable for comparison since it’s considered to be a measurement system’s configuration phase and the electromotor acceleration phase. It is also mandatory to avoid the transient area analysis because of shaft and brass inertial force appearance. This period covers the first 10-20 seconds of measurement system’s work time. After establishing the

![Figure 6. Gauss membership functions.](image)

![Figure 7. ANFIS curve.](image)

![Figure 8. Approximation curve of the ANFIS model.](image)
stationary state and the final base load values, measured values reflect stationary state relations and allow the analysis of the phenomenon being researched. Table 3 shows friction coefficient values $f$ measured during the experiment, values calculated using the ANFIS model, ratio of relative errors of the ANFIS model and measured values, friction coefficient values approximated using experimental results and the ratio of relative errors and measured values.

| $F_n$ | $f$  | $f$ from ANFIS | Rel. error ANFIS [%] | $f$ from curve fit | Rel. error curve fit [%] |
|------|-----|---------------|----------------------|----------------|-----------------------|
| 1    | 433.11 | 0.195465      | -1.741600            | 0.193715       | -0.895240             |
| 2    | 674.23 | 0.118939      | 1.480950             | 0.125490       | 5.507587              |
| 3    | 920.59 | 0.083642      | 3.127740             | 0.092453       | 10.53408              |
| 4    | 1168.64 | 0.064649      | 3.291420             | 0.073160       | 13.16468              |
| 5    | 1348.90 | 0.058340      | -2.094930            | 0.063556       | 8.941132              |
| 6    | 1554.02 | 0.049666      | -3.497800            | 0.055316       | 11.37570              |
| 7    | 1781.95 | 0.039869      | -3.497800            | 0.055316       | 11.37570              |
| 8    | 1958.93 | 0.040125      | -11.15402            | 0.044076       | 9.845701              |
| 9    | 2068.03 | 0.038567      | -13.17401            | 0.041793       | 8.365863              |
| 10   | 2308.61 | 0.039662      | -0.041370            | 0.037516       | -5.40946              |

6. Conclusions
Examining the friction appearing due to hydrodynamic lubrication of a sliding bearing, made of a white metal brass and a steel shaft sleeve, showed that the artificial intelligence method based on neuro-fuzzy artificial networks can be used. By using this method, a highly accurate model was created for calculating friction coefficient values under known sliding bearing loads in given lubrication conditions. The final result is an analytical expression which is in fact an approximation of the created neuro fuzzy iteration system. The appearance of spikes on the measured data diagram (Figure 5) points to occasional irregularities and the signs of dynamic forces. This can be the result of a large number of causes and has stochastic characteristics. Possible causes would be: occasional loss of the lubricating oil film and the appearance of dry friction, particle accumulation as a result of wear, uncontrolled bearing load oscillations, as well as a disorder caused by the electromotor’s vibrations which are transferred to the measurement point via structures. These irregularities should be, judging by the rules, excluded from the measured data. This is commonly achieved by data filtering. Data filtering, although planned along with ANFIS model expansion, was not done for this model.

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