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# Evaluation of the tribological behavior of a brake disc-pad friction pair using a fuzzy inference model based on an adaptive network (ANFIS)

1st George Ipate
Department of Biotechnical Systems
Politehnica University of Bucharest
Bucharest, Romania
george.ipate@upb.ro

2nd Andreea Catalina Cristescu
Department of Biotechnical Systems
Politehnica University of Bucharest
Bucharest, Romania
catalina.cristescu@stud.isb.upb.ro

3rd Constantin Daniel Cotici
Department of Biotechnical Systems
Politehnica University of Bucharest
Bucharest, Romania
constantin.cotici@stud.isb.upb.ro

4th Nelus Evelin Gheorghita
Department of Biotechnical Systems
Politehnica University of Bucharest
Bucharest, Romania
nelus.gheorghita@upb.ro

5th Andrei Florin Hristache
Department of Biotechnical Systems
Politehnica University of Bucharest
Bucharest, Romania
florin.hristache@stud.isb.upb.ro

Daiana Alina Ionescu
Department of Biotechnical Systems
Politehnica University of Bucharest
Bucharest, Romania
alina.ionescu1007@upb.ro

***Abstract*** **— The purpose of this research is to forecast the tribological behavior of the materials used in the field of braking systems using an Artificial Neural Network (ANN) based on the experimental data obtained by measuring the friction between the friction linings and the brake disc of a bicycle in the translational movement. The data analysis results from this research show that the estimates and forecasts with the proposed model (ANFIS) of the dynamic friction coefficient (COF) between the pads and the disc in translational motion using the ANN have been confirmed to be powerful and useful. The experimentally determined average value of the dynamic COF was 0.2003 with a standard deviation of 0.0233 in the range of values of 0.1244-0.3013.**

***Keywords — tribology, friction coefficient, adaptive neuro-fuzzy system, model.***

## I. Introduction

Over time, the field of brake system materials has evolved significantly as the need to meet more demanding operational requirements has increased. With the increasing weight of the bodies involved in the braking process and their traveling speeds, the operating conditions are becoming more and more demanding. [1,3,5,7,8].

The current requirements for fully safe operation require maintaining properties such as the highest possible friction coefficient, good resistance to wear and corrosion, good thermal conductivity, etc., when applying a load to the braking pair in motion at a certain speed sliding, at temperatures varying in the range [-20 .. 300]°C. Iron-based and copper-based friction materials are two classes of materials used in the manufacture of friction coupling components [2].

The materials used to manufacture the brake system that form the friction pair must ensure the conversion of the kinetic energy of the system into heat through the frictional surfaces. The brake disc is the part used to slow down or stop the rotation of the wheel. These brake discs are made of cast iron-carbon alloy, but in many cases they can be made of composite (reinforced, carbon-carbon, ceramic compounds) material. [1, 2, 4, 12].

The materials to be used in the future for the formation of friction materials must necessarily take into account the fact that they must be non-toxic. Even if in the not too distant past, the role of asbestos was inevitable in the creation of these materials, it was still practically replaced by different synthetic fibers or organic materials (fig.1). Brake pads could also be composed of metal-free and copper-free matrices [6].

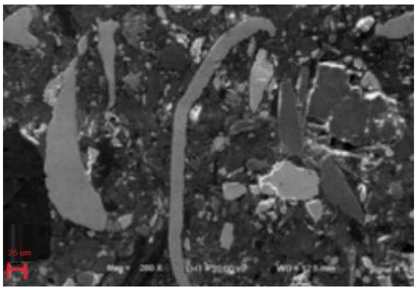

Fig. 1. Asbestos-free organic brake pad microstructure [6]

The upper COF for the brake pads, the extra braking capability will be generated. The COF can differ depend on the category of material utilised for the brake disc. Commonly, brakes refer to the dynamic COF, or the COF quantified while the vehicle is in motion. If a material with a very high COF is used, the brake disc will wear out more quickly. In this sense, a vehicle must be equipped with its own braking system, one that does not prematurely wear out the other components of the system.

Many of the problems that occur in the braking system of vehicles belong to the tribological field [2, 6, 8]. In the bicycle braking system, the braking speed between the disc and the pads is variable, so that, in the range of low and very low speeds, the stick-slip phenomenon appears, which can be one of the causes of the noises and vibrations that occur during braking.

Both the number and the variety of fuzzy logic applications have experienced a fantastic process of expansion in recent years. The field of applications includes consumer goods such as industrial process regulation, medical instruments, decision-making systems [10,16,17].

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Adaptive neuro-fuzzy inference system (ANFIS) is an increasingly used pattern for prediction, prognostic or classification in diagnostic systems, and findings indicate superior outcome of machine training techniques (like as ANN ) than sophisticated statistical techniques [13]. The biggest point of view to consider on one ANFIS model is through this aggregate model can use the accuracy of neural networks and fuzzy inference simultaneously. In addition, the synergy of fuzzy logic and neural network removes the incertitude of statistical consideration [14, 15].

The current research aims to develop and test an ANFIS model for fifteen real sliding friction coefficient data sets. The main purpose of the research is to gain in-depth knowledge through advanced research methods about the friction properties, heat transfer and corrosion resistance of the materials for the discs that are part of the braking system in order to be able to improve them.

The work is carried out according to the following format. The experimental equipment and ANFIS strategy is reflected in Section 2. Section 3 presents the results of the proposed method applied to our experimental data to demonstrate its effectiveness. Finally, section 4 provides some conclusions.

## II. Material And Methods

The experimental tests presented in this paper were carried out on a Hounsfiled 1Ks universal mechanical test stand and had as their main purpose the determination of the evolution of the COF of the friction material pair of the bicycle disc brake system. For these tests, a friction table for linear motion was mounted on the Hounsfield equipment. This test method involves a friction pad coming into contact with the brake disc mounted on the friction table under a series of predetermined conditions. A body of known mass sits on the plate thus creating the normal loading force, while the plate has a linear movement in the horizontal plane, thus realizing the frictional force (fig. 2).

Fig. 2. Experimental stand used to measure the dynamic COF

The brake pad used in the research have semi-metallic friction linings with a copper grooved plating base for better heat dissipation, and contain aluminum and ceramic particles to improve wet braking. The brake disc with a radius of 70 mm, a mass of 155 g and six mounting holes is made of high-quality, heat-resistant stainless steel.

As far as friction measurement is concerned, there are still some prejudices that sure enough had their excuse in the former time, but which can now be overcome due to the high level of precision of the equipment used. In spite of the fact that frictional strength is connected to the applied normal load, on this point is not always direct proportionality among these specific feature. However, it is usual to address to a COF, the ratio of the frictional force to the normal force, in agreement with established apply during the last three hundreds of years. The necessary requirements for any friction testing apparatus are well summarized in the paper [7].

The neural-fuzzy combination transfers the learning capabilities and parallel computing force of neuronal networks to fuzzy methods and the ability of upper level reasoning, close to the human one, from fuzzy systems to neural networks [16,18,19,20]. In the neuro fuzzy network structure, presented in the study, the rules are built regularly, while the off-line running.

For ANFIS training, the system needs friction coefficient data provided by a physical model. ANFIS enables accurate modeling of poorly defined or unreliable data systems. [14,19].

The development of the ANFIS model is done taking into account the four input quantities, and the effect is the estimated value of the COF (vezi fig. 3).

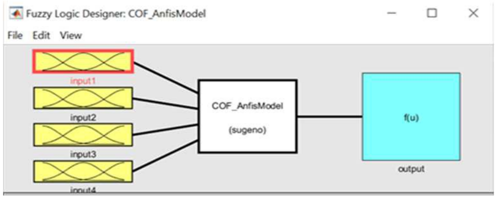


Fig. 3. Sugeno Fuzzy inference system

The goal is to acquire the straightforward model, so the selection of frame is: the number of membership functions is 4 for the 4 Gaussian-shaped inputs (fig. 4). In this stage, the developed model utilizes a hybrid learning iterative procedure to keep the past, and purposeful parameters of a Sugeno-type fuzzy inference system.

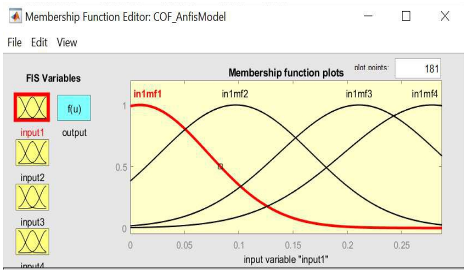


Fig. 4. Membership functions for the purposed model

In the learning process, two phases are used concurrently: learning the structure and learning the parameters. Learning the organization involves training the preconditions, the consequences and identifying the feedback structure of the fuzzy dynamic rules. Next, the type and functions of the neurons that compose each level of a neuro-fuzzy type network with layers without reverse connections are presented.

At the first level, every node is named a linguistic node and agree to a variable. The neuron just passes the input values to the following layer [16].

$$a^{(1)} = u_i^{(1)} \tag{1}$$

At the second level, every node is named an input node and agree to a single linguistic value (hot, warm, cold) of an input parameter. If a Gaussian membership function is utilized, then the function achieved by each node is [16]:

$$\mathrm{a}^{(2)} = \exp\left\{-\left(\mathrm{u}_{\mathrm{ij}}^{2} - \mathrm{m}_{\mathrm{ij}}\right)^{2} / \sigma_{\mathrm{ij}}^{2}\right\} \tag{2}$$

where, $\boldsymbol{m_{ij}}$ represents the midpoint and $\boldsymbol{\sigma_{ij}}$ the range of the membership function of the linguistic term $\boldsymbol{j}$ for the input variable $\boldsymbol{x_i}$.

At the third level, the nodes are called rules and calculate the "match" of the precondition of a rule. Every node has inputs from the previous level, which represent the degree of spatial fulfillment of the rule, and inputs from the reaction layer, which represent the degree of temporal fulfillment. In each node, the rule is used by the following "single input" operator, which represents the algebraic product from fuzzy logic [16]:

$$a^{(3)} = a^{(6)} \prod u_i^3 = a^{(6)} e^{-[D_i(x-m_i)]^T [D_i(x-m_i)]} \tag{3}$$

where, $D_i = diag\left(\frac{1}{\sigma_{i1}}, \ldots, \frac{1}{\sigma_{in}}\right)$, $m_i = (m_{i1}, m_{i2}, \ldots, m_{in})^T$, and $a^{(6)}$ represents the exit of a neuron from the reaction layer.

At the fourth level, called the consequence level, the nodes represent an output term. To integrate the activated rules, which have the same consequent part, each output term node performs a processing similar to the fuzzy OR operation [16]:

$$a^{(4)} = \sum u_i^4 \tag{4}$$

In the input-output partitioning phase, the amount of rules is based on how the input area is split up. Here, as it were spatial data is utilized for clustering, and the concentrated of spatial enactment is utilized as a measure.

$$\mathrm{F}^i(x) = \prod u_i^3 = e^{-[D_i(x-m_i)]^T [D_i(x-m_i)]} \tag{5}$$

where, $\mathrm{F}^i$ is in range 0..1. The exponent represents the distance between variable $\boldsymbol{x}$ and the midpoint of cluster $\boldsymbol{i}$. On the base of this degree, the algorithm can be built to generate a new fuzzy rule in which the following notations are considered: $\mu = (m_i, \sigma_i)$ - Gaussian membership function with midpoint $\boldsymbol{m_i}$ and breadth $\boldsymbol{\sigma_i}$, and $\boldsymbol{E(A,B)}$ - fuzzy measure of two fuzzy sets $\boldsymbol{A}$ and $\boldsymbol{B}$. The initial working hypothesis is that there are no rules and the algorithm is implemented to generate fuzzy regulations and fuzzy groups for every input changeable parameters.

## III. Results And Discussion

The tests to determine the coefficient of sliding friction on the steel disc (COF) were carried out for pressing forces between 4 N and 8 N, the travel speed in the translation movement in the range of 1 - 10 mm/min, the ambient temperature of 25ºC. The average value of the dynamic friction coefficient was 0.2003 with a standard deviation of 0.0233 in the range 0.1244-0.3013, and the coefficient of variation 11.63%. Fig. 6 shows the friction force measured between the brake pad and disc ($F_f$), at the ambient temperature of 25ºC, for the pressing force of 8 N, depending on the sliding speed of 10 mm/min.

To see if the sliding friction phenomenon is a stable phenomenon and to demonstrate that the experimental results are repeatable, a statistical analysis of them is necessary. The determination of the statistical parameters and also the repeatability of the experimental results was carried out by repeating a test 15 times under the same conditions, with the same normal load and the same relative sliding speed, for the specific values of the coefficient of friction [8, 9, 11].

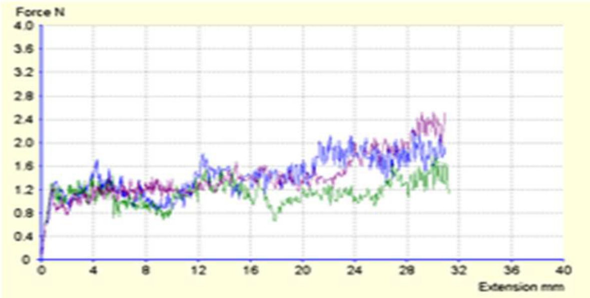


Fig. 5. Measuring the friction force in the brake disc-pad pair with the Hounsfield equipment

The fifteen tests were performed at a normal loading force of 4 N, resulting in a contact pressure between the two specimens of 0.0085 MPa, and at a sliding speed of 0.0167 mm/s. The results for the fifteen tests are shown in fig. 6, where the time variation of the COF can be observed.

The results show an increase in the friction between the brake pads and the disc proportional to the contact area and load, and also to the decrease in the sliding speed. The trends are slightly inconsistent with the theoretical models and are due to the variation of the contact surface between the elements [8]. Differences between experimental and theoretical results were analyzed, confirming that the experimental evaluation of friction in the braking system as a whole was performed correctly.

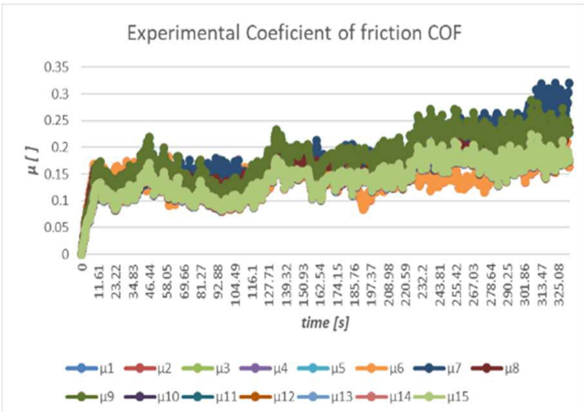


Fig. 6. Experimental results for COF as a function of time

*Development of the ANFIS model.* The goal of our study is to create a method that allows estimating the friction coefficient with a much simpler method. Only the experimental data of the COF for the translational movement between the brake pads and the disc were taken into account. The experimental data records were divided into three groups, each with 5 data sets; the first group was utilised for training the model, and the second, for validating the model; the third group, is was used to verify the ANFIS model.

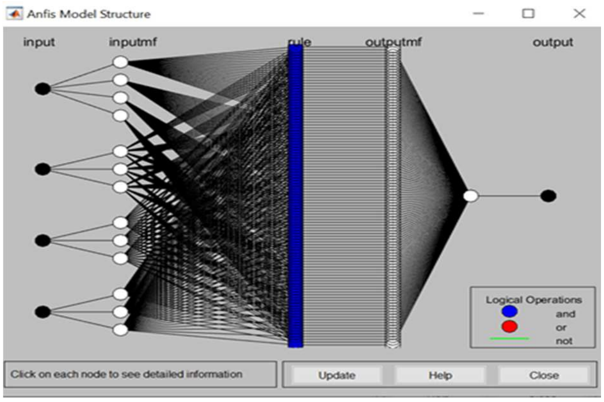


Fig. 7. Structure of the ANFIS model

For this research, a 6-layer neuro-fuzzy network without reverse connections was created for a set of 774 data. Figure 7 shows the architecture of the neural network structure. At level 1, every node has a particular linguistic name like input node and corresponds to a variable. The neuron just passes the input values to the next layer. At level 2, every node has a particular name as input node and corresponds to terms resulting from fuzzification. A Gaussian membership function is utilised in this stage. At level 3, a fuzzy rule is activated in each node which can be divided into two parts: an internal rule and an external rule. The neural network of the designed ANFIS model consists of 249 nodes by an overall number of 134 parameters, whit 108 linear and 26 nonlinear parameters. To the 774 training data values of the ANFIS model, the network uses just 108 fuzzy regulations.

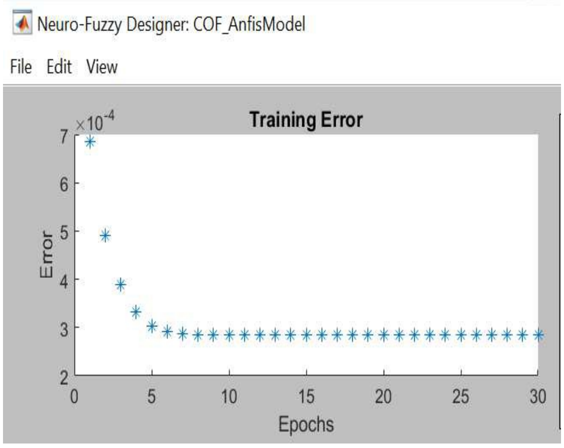


Fig. 8. Convergence of ANFIS model learning

A combination of least squares and gradient descent backpropagation, called the hybrid optimization method, was chosen to train the neuro-fuzzy model. The diagram in fig. 8, shows how to monitor the training process of deep learning networks. This graph shows the error curve for 30 training epochs (cycles) of the model. The curve formed (by the blue stars) shows the training errors. The minimum training error is produced at about epoch 7. We note that the validation set error curve increases after 2 epochs, specify that additional post-training outgrows the domain of the input data and produces progressively worse generalization.

The testing of the data obtained with the designed ANFIS model in comparison with the data from the training, validation and verification groups is presented in figure 9.

The output surface, shown in fig. 10, is non-linear and monotonic and show how the adaptive neuro-fuzyy model reply to different values of the input data. To see possible discrepancy in the input data which could provoke this counterintuitive result, it is recommended to plot the data distribution [20].

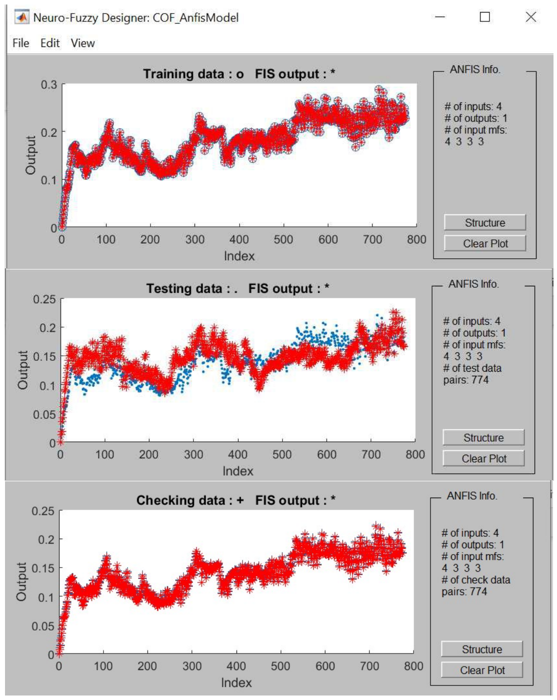


Fig. 9. Testing the output data from the model with the data from the 3 groups of experimental data

The results obtained with the ANFIS model indicate that the first two data sets give the ideal combination of two input factors. In the fact, because the difference between the data training and checking errors is not greater than the difference for any of the input variables, show that greater model complexity (i.e. including more variables), would increase overfitting [21].

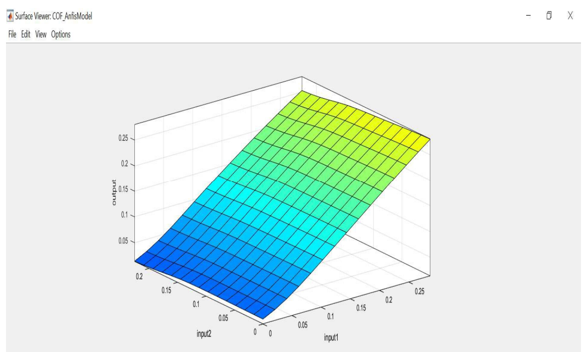

Fig. 10. Visualization of the output surface from the model

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Even though the hypothetical models for calculating specific friction parameters are extensive, developed with years of experiments, and can be implemented to the friction pad-disc pair, they cannot be considered highly accurate. In the opinion of the authors, performing the experimental measurements of the friction pairs in contact in operating conditions as close as possible to the real physical environment and processing the data with advanced research methods close to the field of artificial intelligence give the accuracy of the results.

## IV. Conclusion

In this paper, the tribological behavior of a disc brake system for a bicycle is studied. A methodology for estimating the sliding friction coefficient using a new method based on an adaptive neural fuzzy inference model (ANFIS) was proposed. The presented results are real data obtained for friction between semi-metallic friction pads with a steel disc. Highly accurate evaluation of friction is difficult. For an existing construction (the type and dimensions of the friction seals, the type and dimensions of the disc, the type of the actuation system and the loads) the rest of the parameters involved in the friction of the elements are: the values of the external loads; sliding speed and temperature depending on the dynamic viscosity of the material brake pads.

Aspects of friction pairs deformations, time-dependent parameters, measurement conditions and applied loads are of utmost importance. The experimental measurements presented in this paper show the influence of the contact surface and the speed on the friction pairs of the braking system. This is only a first step in the relative evaluating friction in disc brake systems with disc and brake pads.

Both the proposed experimental method for measuring the COF during the translational sliding movement between the pads and the brake disc, as well as the data analysis method resulting from these experiments, prove to be of real help in the study of the tribological properties of the friction materials.

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