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TRIBOLOGICAL BEHAVIOUR ANALYSIS OF ELASTOMER-PLASTOMER COUPLES IN DRY FRICTION CONDITIONS

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Abstract

For couples working in dry friction conditions, the friction force is an important parameter, influencing both energy losses and wear of the components. In the elastomer-plastomer couples' case, the minimization of the friction force is a must, otherwise, the parts show a quick degradation. As previous studies have shown, there is the possibility to lower the friction force by choosing an optimal set of materials and functioning conditions, leading to a transferred material layer appearance. This layer stands as a lubricant, offering a prolonged life for the parts in contact. Taking into account that the relationship between materials and working conditions cannot be framed into a mathematical equation, artificial neural networks (ANN) are a valid alternative. The present work proposes a neural network model for friction force value evolution, in the case of pneumatic cylinders with rods made by plastomer and sealed with elastomeric gaskets. The model allows not only the identification of the most influencing parameters on the friction process both also the prediction and the optimization of friction force value.

Keywords: Dry friction, elastomer-plastomer couple, artificial neural networks-based modelling

1 Introduction

The dry friction is a challenge in the tribosystems design, as the lifetime of the parts can be dramatically reduced or improved following the accurate choice of the materials and working conditions. As a consequence, a model for dry friction force evolution can be very useful.

In the case of the pneumatic cylinder, the friction force shows a variation between two extreme values: one corresponding to the static friction - at strokes' ends and the other corresponding to the dynamic friction - during the rod displacement [1]. If an elastomer-polymer couple working in dry conditions (the rod made by plastomeric material and sealed with elastomeric gaskets), the solution for friction force decrease is the tuning of materials and working conditions as a way that the occurrence of a "third body" be possible. This one consists of a layer of transferred material on the rod (Figure 1), acting as a lubricant [2]. The only way to obtain this is to ensure an appropriate thermal working regime [3]. Taking into account that all the heat into the contact area is generated by the friction processes, a tight range of friction force values must be obtained in order to maintain the lubricant layer's existence.

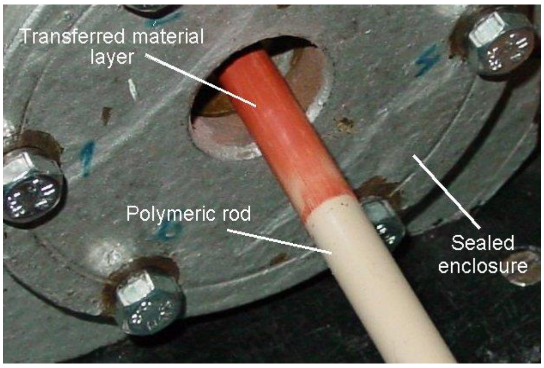


Figure 1. Transferred elastomeric material layer on the plastomeric rod

In the pneumatic drives case, the friction force values depend both by the rod-gasket couple of materials and by the working speed, as consequence, these should be the targets in an optimization attempt.

Taking into account that there is no mathematical equation available to link these parameters, the use of an experimental results-based method like the Artificial Neural Networks (ANN) modelling is appropriate.

2 Method and materials

2.1 Artificial Neural Network-based modelling

Artificial Neural Networks are computing systems composed of several units named artificial neurons (Figure 2) [4], interconnected by weighted links in a layered architecture working in two stages as the biological brains do. In the first stage, the ANN learns from presented known input-output data sets. In the second stage, the ANN provides predicted values (prior unknown) for the output corresponding to the present input values. Also, a reverse procedure is possible - find the optimal input values for the desired output values. Despite the fact that in both processes some controlled errors are accepted, this drawback is largely compensated by the main benefit - describing a phenomenon without mathematical support.

In order to build an ANN-based model, one needs a set of experimentally acquired data to train the ANN. There are several ANN architectures, each of these being suitable for solving a special range of problems: prediction, optimization, pattern recognition, classification, etc. [5]. For prediction and optimization, the feedforward architecture is most recommended (Figure 3) [6].

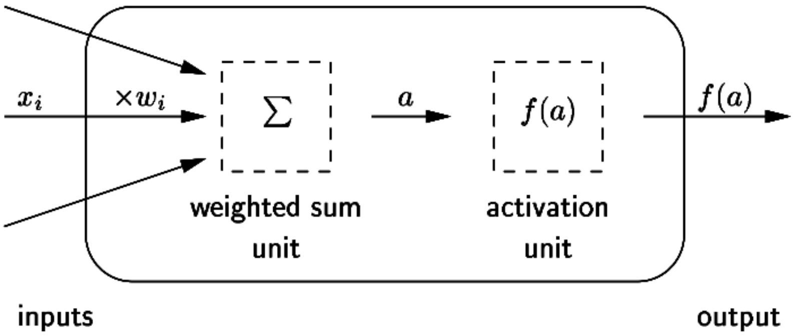


Figure 2. Basic unit for ANNs (Artificial Neural Networks) - the artificial neuron.

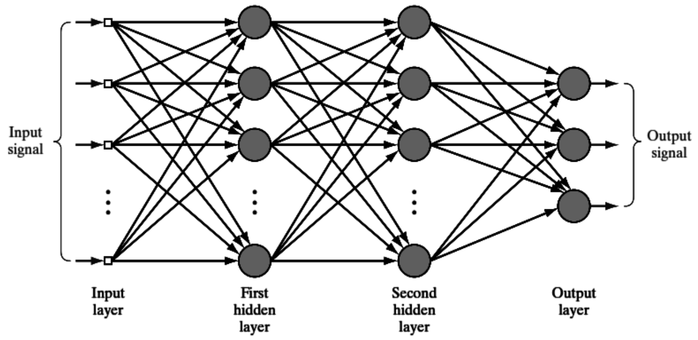


Figure 3. Feedforward ANN architecture.

Another characteristic of an ANN-based model is the training algorithm - the way that the training data are processed in order to obtain the specified training error value. One training algorithm, largely used for feedforward ANNs, is backpropagation. Here, the obtained error value comparing to the provided outputs with the desired ones is minimized by modifications of weight values [7].

2.2 Experimental setup

In order to obtain the necessary data sets for ANN model training, a test rig was used, simulating the pneumatic drives working in dry friction conditions. As rod materials, three polymeric materials were tested at several sliding speeds, monitoring the friction force value at different time intervals. In Figure 4 the schematic of experimental setup is presented.

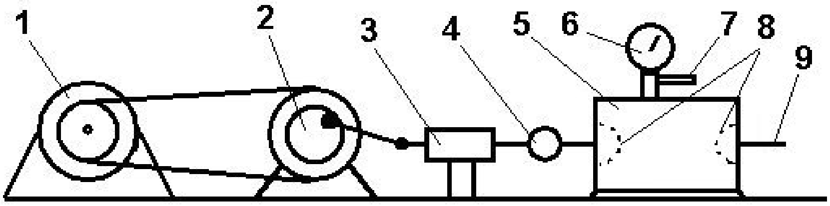


Figure 4. Experimental setup:
1-variable speed electric motor; 2-eccentric; 3-rigid guide; 4-force sensor; 5-pneumatic cylinder;
6-pressure gauge; 7-compressed air connector; 8-elastomeric gaskets; 9-plastomeric rod.

Table 1 presents the materials, conditions and range limits for the targeted properties. As rod materials, the POM (polyoxymethylene), PEEK (polyetheretheketone) and PA (polyamide) against silicone rubber gaskets were tested.

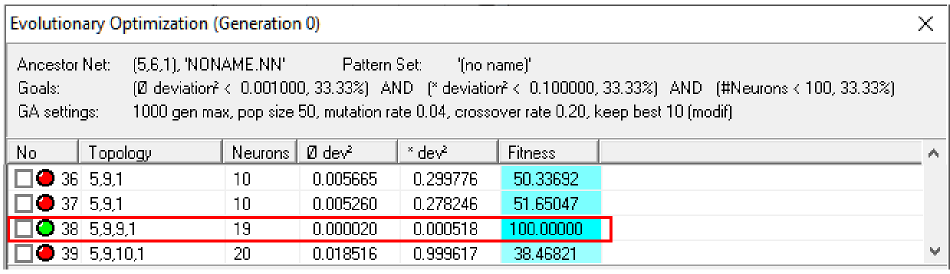
Table 1. Tested materials and working conditions.

Material and condition	**Value**	**Unit**
Rod material	POM, PEEK, PA	-

Sliding speeds	0.088 ÷ 0.307	m/s
Gasket material	silicone rubber	-
Working pressure	10	bar

3 Ann-based modelling of dry friction force evolution

In order to build an ANN-based model, one needs first to establish the appropriate network structure, meaning the number of neurons and hidden layers. This is an optimization problem too, for each problem corresponding to a unique best structure. The optimal ANN structure can be obtained by several methods, like try-and-error or by using dedicated software. In this work, the genetic algorithm-based software Pythia was used (Figure 5a). As inputs for the ANN model were chosen: the rod material (as Boolean value), the sliding speed and the functioning time until the sealing is compromised. As output, the friction force value was used. Starting from the experimentally acquired data set, a 5-9-9-1 structure for the ANN model was obtained (Figure 5b).

a) 

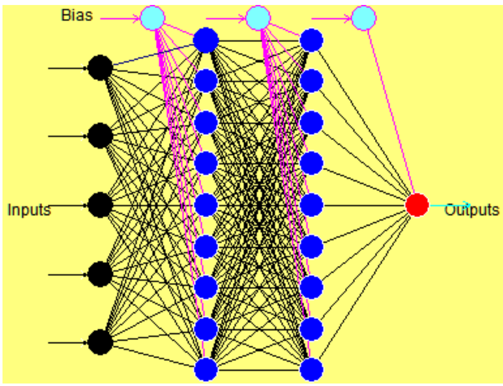
b) 

Figure 5. The ANN design: a) genetic algorithm result; b) ANN architecture.

After the ANN model's structure obtaining, a dedicated software, namely Neural Power was used for network training and interrogation. In order to stop the training, the correlation coefficient parameter (R) was chosen with a target value of R = 0.999 [8]. The obtained error after validating was RMS = 1.364, a better value than the one generally accepted for this type of ANNs, RMS < 3.0 [9], showing that the ANN model is ready for use.

4 Results and discussion

The obtained ANN model can be used for several goals: analysis - establishing the hierarchy importance of inputs over outputs, optimizing - establishing the inputs' values for a minimum friction force value, and prediction - estimation of friction force values for prescribed inputs.

4.1 Importance of analysis

The ANN model allows the investigation of the inputs' influences over the friction force evolution. The obtained results, as graph, are presented in Figure 6.

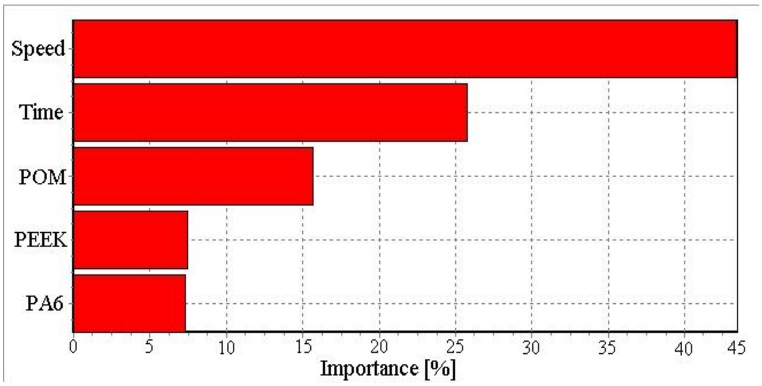


Figure 6. Inputs' importance over output.

As can be observed in Figure 6, the most influencing parameter is the sliding speed. This is in good correspondence with the observation presented by Myshkin *et al.* [2]. The appearance and stabilization of the transferred layer need thermal conditions, which can be obtained only if enough heat is generated during the friction processes.

In the second place, in Figure 6, the next important input is the functioning time. This is also in good concordance with the real working conditions: as the working time increase, the wear of the gasket is also increased, leading to a heating loss in the contact area. These losses affect the transferred layer structure due to both the air losses and tightening force, which decreases between rod and gasket; as consequence, a decrease in sealing quality is observed.

The last positions in Figure 6 are the rod materials type. Here, one can observe that the POM is the most influencing material on friction force. This is due to the fact that during the experimental measurements this material leads to the highest friction force values. In the case of the other two materials (PEEK and PA6) there are no important differences between them.

4.2 Friction force value optimization

In order to optimize the friction force, the appropriate input values must be established, in a way that the friction force values be minimum. Table 2 presents the obtained results for each rod's material. As can be observed in Table 2, there is a very tight link between sliding speed and friction force values for each tested material. In all cases, the highest friction force values were obtained at lower sliding speeds. This is due to the fact that at lower speeds, the friction generating heat it cannot ensure a continuously transferred layer.

Table 2. Optimized values for friction force versus rod material.

Rod material	Value	Friction force [N]	Sliding speed [m/s]
POM	Min	7.890	0.307
	Max	112.936	0.175
PEEK	Min	4.521	0.307
	Max	100.766	0.219
PA6	Min	3.581	0.153
	Max	78.921	0.110

At higher speeds, the quality of the transferred layer leads to a much lower friction force value (Figure 7). Looking at the friction force values, it can be observed that the largest difference between the minimum and maximum ones was obtained in the POM case. This is in good concordance with the observation presented in subsection 4.1, the second position of POM in hierarchy importance. Based on this optimization procedure, the best material can be chosen for a required sliding speed.

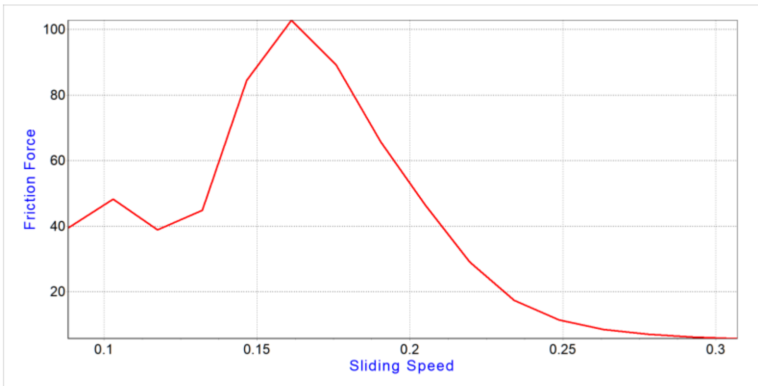


Figure 7. Friction force evolution versus sliding speed.

4.3 Friction force value prediction

The ANN model can be also used for friction force values prediction, when input data are provided. Looking for friction force values in a higher sliding speed case (0.5 m/s), in order to find how this affects the friction process, the obtained results were presented into the Table 3.

Table 3. Predicted values for friction force versus sliding speed.

Rod material	Friction force [N]	Sliding speed [m/s]
POM	3.753	0.5
PEEK	5.557	0.5

PA6	3.238	0.5

Comparing the values from Table 3 with those from Table 2, one can observe that each material shows a different behaviour: in the POM case, the friction force continuously decreases for higher speed; in the PEEK case, a friction force increase is visible; in the PA6 case, the friction force seems to be almost unaffected by the speed increase over the value, corresponding to the minimum value presented in Table 2.

Therefore, using the ANN prediction facility, the best rod material can be chosen even if the sliding speed overcame the limits presented in Table 1.

5 CONCLUSIONS

Taking into account all presented above some final conclusions can be drawn.

First, the ANN-based models can be successfully used for the investigation of complex processes, when there are no available mathematical equations or if these include a lot of experimentally established coefficients difficult to identify. The tribological processes are included in this category and ANNs stand as useful tools for the analysis and optimization of different tribo-parameters.

Second, in a pneumatic cylinder case with plastomeric rods sealed with elastomeric gaskets, working in dry friction conditions, the sliding speed is the most important factor that influences the friction force. Taking into account that a transferred layer occurs in the contact area, providing better sealing efficiency and lower wear components, the optimal couple rod material-sliding speed choice is imposed in the design stage.

Third, the ANN-based model presented in this work turned out to provide all information necessary for an optimal design of pneumatic drives with plastomeric rods and elastomeric gaskets, working in dry friction conditions.

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