Serbian Tribology Society

SERBIATRIB '15

14th International Conference on Tribology

University of Belgrade, Faculty of Mechanical Engineering

Belgrade, Serbia, 13 – 15 May 2015

NEURAL NETWORK BASED ANALYSIS OF TRIBOLOGICAL BEHAVIOR FOR AN EPOXY-ARAMID SYSTEM

Igor ROMAN[1,*], Sorin CIORTAN[1], Iulian Gabriel BIRSAN[1]

[1]"Dunarea de Jos" of University, Galati, Romania

*Corresponding author: igor.roman@ugal.ro

Abstract: *The aim of this paper is based on neural network model for tribological analyses of an Epoxy composite system. Created epoxy based composites with aramidic powders were tribological tested with diverse parameter in order to obtain follow properties: wear rate and friction coefficient. With all studied tribological properties were created a Neural Network (NN) model. The created NN model can perform optimisations for concentration of aramidic powder in final used composites for different domain of applications.*

Keywords: *epoxy composites, bloc on ring, friction coefficient, neural network analysis, optimisations.*

1. INTRODUCTION

It can surely be said that nowadays there are no branches of technology that don't use the effect of discoveries and researches about polymers development. The anisotropic character of filled polymers leads to more research in understanding how the properties are changed. There are a lot of mathematic model which are based on a theoretical and practical studies. These studies make the possibilities to predict the properties of composite material, even the created material don't work in real applications [1,2].

The aim of this research is to create high resistance epoxy composites for tribological applications by identifying how different volume ratios of fillers change the tribological behaviour. A neuronal network model was created, solving a highly nonlinear problem.

Due to their mechanical, chemical and electrical characteristics epoxy resins represents 72 % of the used thermosetting composites. On the second place is unsatured polyester resins (12 %) followed by phenolic resins (9 %) [3].

In order to obtain optimal performances with minimal expenses, some modifiers (additives) are used [4]. In the beginning, some powders were added to the composites in order to lower the final product price. The observation that the composite properties are improved by some of these materials led today to sophisticated additivation procedures with the aim to improve properties like dimensional and thermal stability, elasticity modulus, abrasion resistance etc. [5,6]. Comparing to fibres the powders are easier to obtain and to include in the composite matrix. The powders can be classified based on their source – organic or inorganic – or based on particle dimension – nano, micro and macro powders. The most used materials are carbon nanotubes, clay, starch, carbon black, talc, aluminium etc.

The main role in composite materials forming is played by resin matrix - reinforcing material interface. The best performances of composites are obtained when the adhesion between the phases is optimal [4]. Often some pre-treatments are applied to the components (in order to obtain chemical compatibility) leading to an improved adhesion [3]. This kind of treatments are expensive and time consuming leading to a increase of the filling materials price but also offering the possibility the increase their weight ratio in final composite without decreasing its properties values.

2. MATERIALS AND METHODS

2.1 Epoxy – aramidic composite system

For creating composite was used Epoxy system RE 4020 – DE 4020 as matrix and filled with aramidic powder.

The epoxy resin has been obtained by reacting epichlorohydrin (propylene chloride) with bisphenol A. The reaction proceeds in two steps, following first one which form diglycidyl ether bisphenol A (DGEBA), named component A, and second one was strengthening component A (DGEBA) with cycloaliphatic amine type nonylphenol named component B [3,4]. Aramadic powder (Twaron) was mixed in three concentrations as follow 5, 15 and 25 %. Used aramidic powder is actually a p-phenylene terephthalamide (PpPTA), the simplest form of the AABB para-polyaramide. The PpPTA is a product of p-phenylene diamine (PPD) and terephthaloyl dichloride (TDC). To dissolve the aromatic polymer it was used a co-solvent N-methyl pyrrolidone (NMP), and an ionic component (calcium chloride CaCl). In the first stage, the monomers are converted into a fine-grained powder polymer. This material has thermal and chemical properties typical of a para-aramid, still not acquired properties as a yarn or paste for reinforcement. The material in this state can be used to improve the properties of the composite materials. Aramidic powder (Twaron) is generally used to improve tribological properties. As it knows, tribological processes are very complex and to improve them is important do not loss other material properties.

For tribological properties assessment was used block-on-ring module on Universal Tribotester UMT2 (CETR®). Tests were done for 1500 m of sliding, at different sliding velocities and applied forces in order to identify their influence on friction coefficient and linear wear.

2.2 Epoxy – aramidic composite system

Tribological tests were performed on UMT-2 (CETR®, USA) device, using a block-on-ring module, with those block made by composite material and the ring made by stainless steel. Through device software loading force, rotation speed and testing time are controlled and friction force and linear wear are recorded.

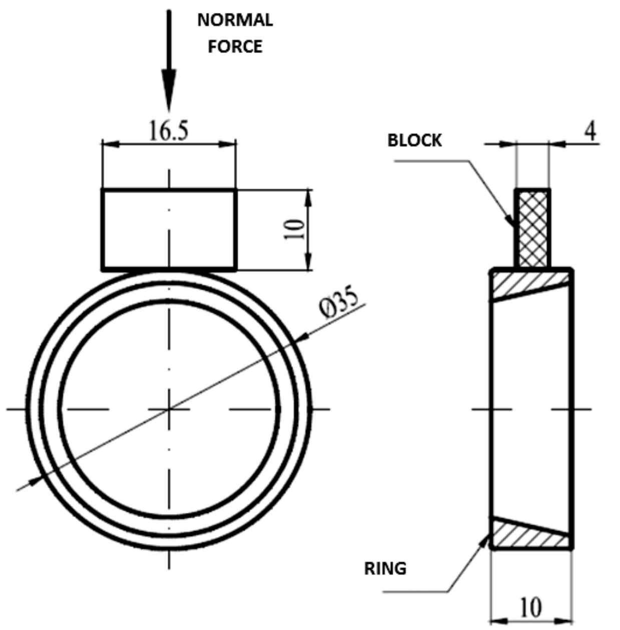

Figure 1. Shape and dimensions of linear contact friction couple (Timken type)

The composite sample block dimensions are 16.5 × 10 × 4 mm. The second triboelement of the couple was exterior ring of roller bearing KBS 30202 (DIN ISO 355.720) with dimensions Ø35 × 10 mm. The material of the ring is DIN 100Cr6 steel (60 – 62 HRC), with the roughness in contact area *Ra* = 0.8 µm.

The testing parameters are presented in Table 1. For each composite three samples were tested and results were averaged.

Table 1. Tribological testing parameters

Sliding speed [m/s]	Rotation speed [rot/min]	Loading force [N]		Time [min]	Sliding distance [m]
0.75	413	7.5	15	33	1500
1.11	620	7.5	15	22	

3. EXPERIMENTAL RESULTS AND DISCUSSIONS

All obtained data were analyzed through the influence of testing parameter and through the concentration of aramidic powder.

For *F* = 7.5 N and *v* = 0.75 m/s (Fig. 2) the lowest friction coefficient value was obtained for 5 % aramidic powder composite, followed by pure epoxy resin and 25 % aramidic powder composite, with a very similar evolution. The highest value was obtained for 15 % aramidic powder composite.

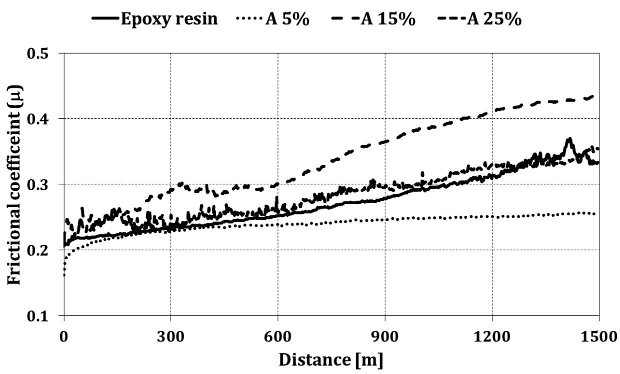

Figure 2. Frictional coefficient for epoxy/aramidic system *F* = 7.5 N, *v* = 0.75 m/s

In linear wear case, the lowest value was for pure epoxy resin and the highest value for 25 % aramidic powder composite (Fig. 3).

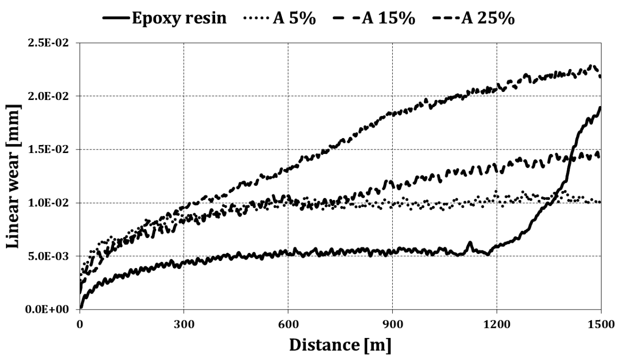

Figure 3. Linear wear for epoxy/aramidic system *F* = 7.5 N, *v* = 0.75 m/s

For *F* = 7.5 N and *v* = 1.1 m/s (Figs. 4 and 5) the lowest friction coefficient value was obtained for 25 % aramidic powder composite but with the highest linear wear value. The highest friction coefficient value was recorded for pure epoxy resin and the lowest linear wear value for 5 % aramidic powder composite. For 5 % aramidic powder composite the friction coefficient value is higher than that of 25 % aramidic powder composite but the linear wear is lower, indicating that the composite stability is higher at lower aramidic powder concentrations, due to higher epoxy resin volume.

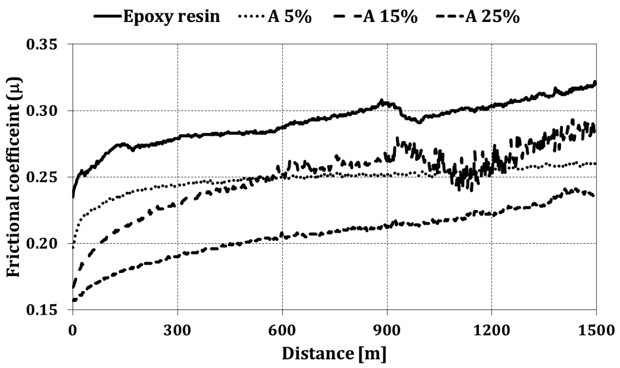

Figure 4. Frictional coefficient for epoxy/aramidic system *F* = 7.5 N, *v* = 1.1 m/s

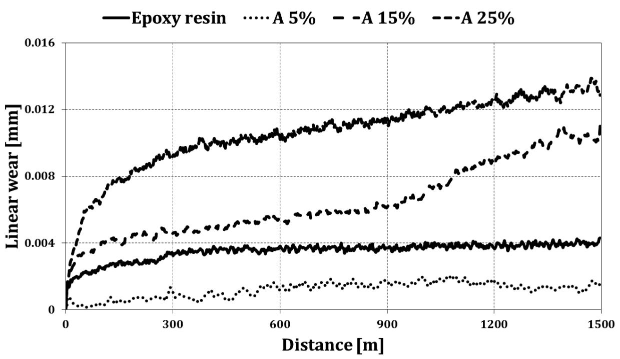

Figure 5. Linear wear for epoxy/aramidic system *F* = 7.5 N, *v* = 1.1 m/s

Yet, the friction coefficient value is lower than that of pure epoxy resin due to the lubricating properties of aramidic particles, leading that way also to a lower linear wear. In 15 % and 25 % aramidic powder composites, due to lower resin volume, the composite stability is lower leading to a higher linear wear. Due to the detached aramidic particles, during the wear processes, the friction coefficient values are lower than of pure resin.

For F = 15 N and v = 0.75 m/s, the friction coefficient evolution (Figs. 6 and 7) was very similar with that of pure epoxy resin and 5 % and 25 % aramidic powder composite. In 15 % aramidic powder composite the friction coefficient value was with 0.1 higher. A difference occurs in linear wear case. The lowest value was observed for 5 % aramidic powder composite, followed in order by pure epoxy resin and 15 % and 25 % aramidic powder composites, respectively. The explanation of tribological behavior in this case is similar with that for F = 7.5 N and v = 1.1 m/s.

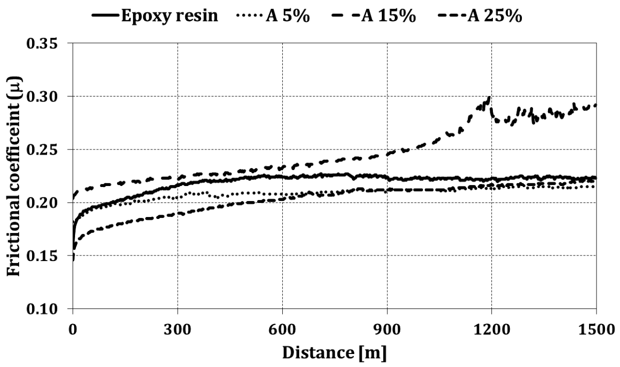

Figure 6. Frictional coefficient for epoxy/aramidic system F = 15 N, v = 0.75 m/s

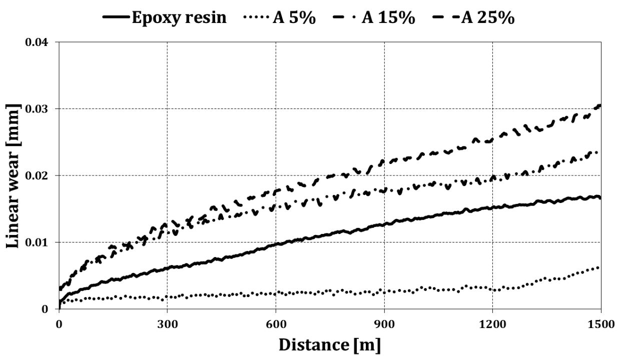

Figure 7. Linear wear for epoxy/aramidic system F = 15 N, v = 0.75 m/s

For the last set of testing parameters (F = 15 N and v = 1.1 m/s) the lowest friction coefficient value was measured in 5 % aramidic powder composite (Figs. 8 and 9). The pure epoxy resin friction coefficient value was with 0.1 higher than that of 5 % aramidic powder composite. The slopes of friction coefficient evolution for 15 % and 25 % aramidic powder composites are very similar, with a minor difference of 0.1. The same similarity is obtained also in linear wear case, with difference of 0.03 mm.

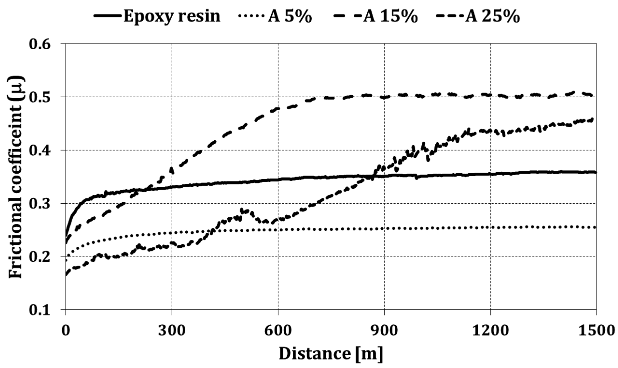

Figure 8. Frictional coefficient for epoxy/aramidic system F = 15 N, v = 1.1 m/s

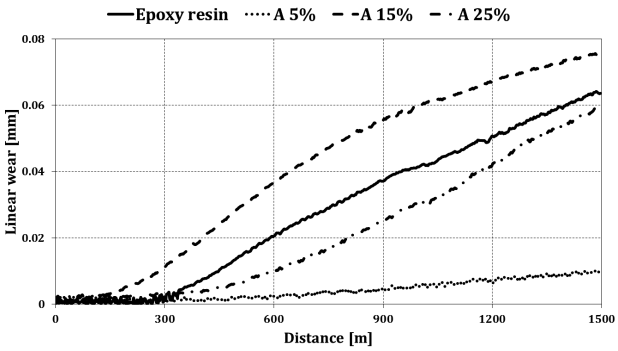

Figure 9. Linear wear for epoxy/aramidic system F = 15 N, v = 1.1 m/s

In Figure 10 is presented the worn surfaces of 15 % aramidic powder composite for F = 15 N, v = 0.75 m/s. Also in Figure 11 is presented the worn surfaces of 15 % aramidic powder composite for F = 15 N, v = 1.1 m/s. It can be observed the abrasive wear tracks, with thermally degraded particles (brown colour).

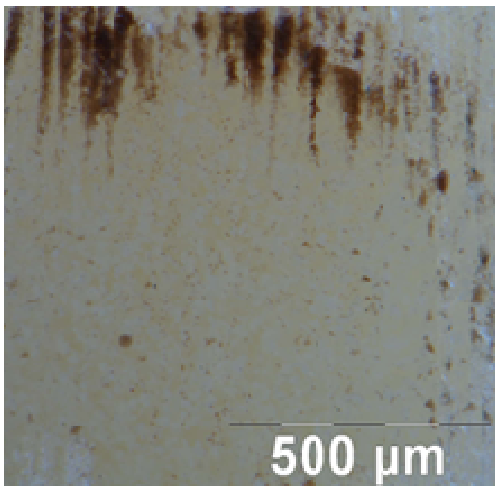

Figure 10. Worn surface for 15 % aramidic powder composite at testing parameter F = 15 N, v = 0.75 m/s

The analysis of loading force influence on friction coefficient evolution is presented in Figure 12. It be can observed that, for 0.75 m/s sliding speed value, the increase of loading force leads to a decrease of friction coefficient. This can be explained by wear detached particles, acting as a solid lubricant.

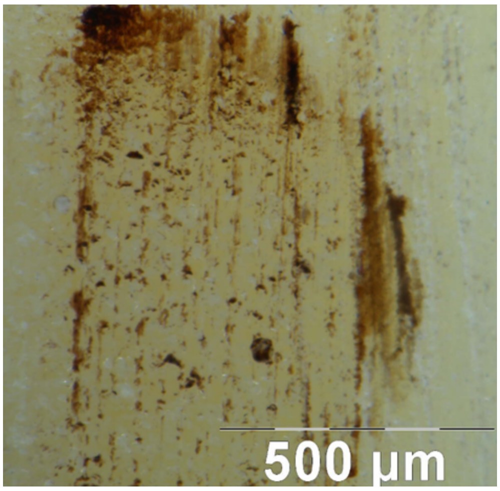

Figure 11. Worn surface for 15 % aramidic powder composite at testing parameter *F* = 15 N, *v* = 1.1 m/s

For 1.1 m/s sliding speed value, an increase of friction coefficient value with loading force can be observed for pure resin and for composites with 15 % and 25 % aramidic powder.

In 5 % aramidic powder composite case, the evolution of friction coefficient shows a very low dependency with loading force.

Analyzing the sliding speed influence on friction coefficient evolution, can be observed a decreasing tendency with sliding speed increasing, for 7.5 N loading force.

In 15 N loading force value, the friction coefficient values increase with sliding speed.

Looking to average of linear wear rate evolution (Fig. 13), a hierarchy can be observed for first three sets of parameters. For pure epoxy resin the wear intensity is higher than that of 5 % aramidic powder composite, increasing with the powder concentration.

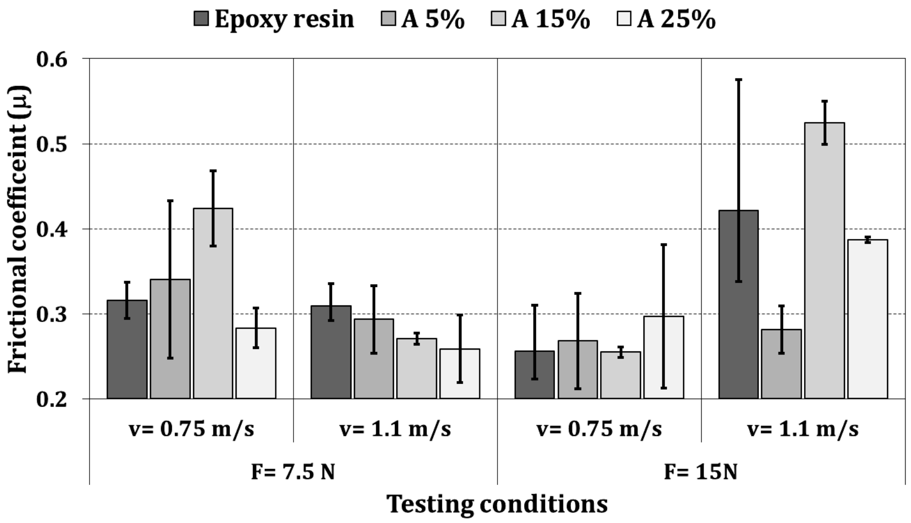

Figure 12. Average frictional coefficient for epoxy composites filled with aramidic powder

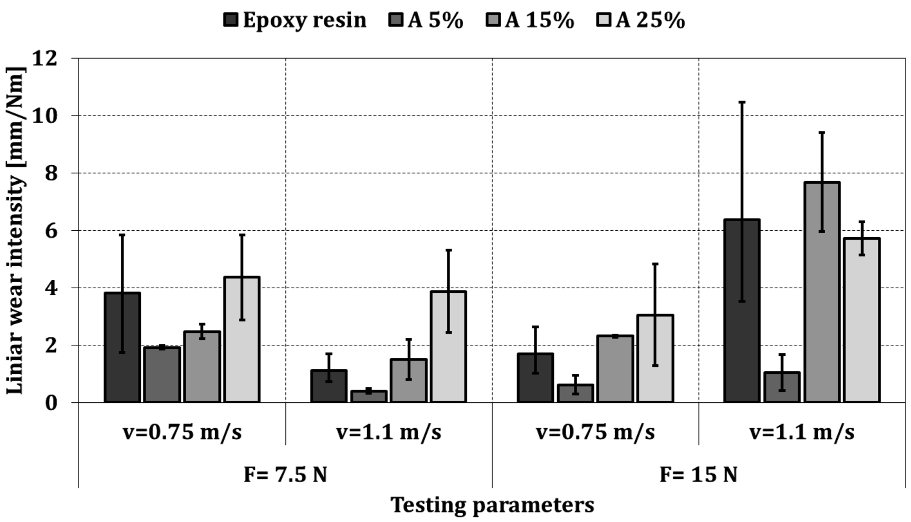

Figure 13. Average of linear wear rate for epoxy composites filled with aramidic powder

4. NEURAL NETWORK MODELING

The anisotropic character of filled polymers makes more difficult the understanding of the properties changing processes, requiring more researches on their behaviour. There are a lot of mathematical models, based on theoretical and experimental studies. Even these models allow the prediction of the composite material properties [3,4] the preliminary studies are as expensive and time consuming as high is the required prediction precision.

The neural networks based modelling methodology, wide used in case of processes with non-linear behaviour modelling [9], can be applied for both prediction and analyzing of properties evolution of composite polymers [10]. As consequence, a neural network model was created, in order to identify the relative influence on composite tribological properties of aramidic powder volume ratio and predict the properties values. As inputs value were used: aramidic powder concentration (*C*), loading force value (*L*) and sliding speed (*S*). As outputs value were used: friction coefficient (*FC*) and linear wear rate (*WR*). The numerical values used for training and validating the model were experimentally acquired. The chosen neural network was feed-forward back-propagation type.

Taking into account that, in case of neural network models, the network architecture has the highest influence on model's validity, being directly linked to the analyzed problem [11], three architectures were created and tested in EasyNN software framework, Fig. 14.

Analyzing the networks performances (Table 2) can be noticed that the increasing the number of hidden layers of the neural network leads to a higher training time so, from this point of view, the optimal architecture of the model is single hidden layered.

The neural model can be used both for investigate the inputs influences over outputs and for prediction of unknown output data for known input data sets.

Looking at the input importance over outputs, it can be observed in Table 2 that all tested architectures show the same hierarchy: the most influencing factor on tribological properties of the composite is aramidic powder concentration (*C*). On the second and third place are loading force (*L*) and sliding speed (*S*), respectively. This information, provided by the neural model, is in very good concordance with experimental results presented above, proofing that the neural networks succeeded to model the physical dependencies between the input-output factors.

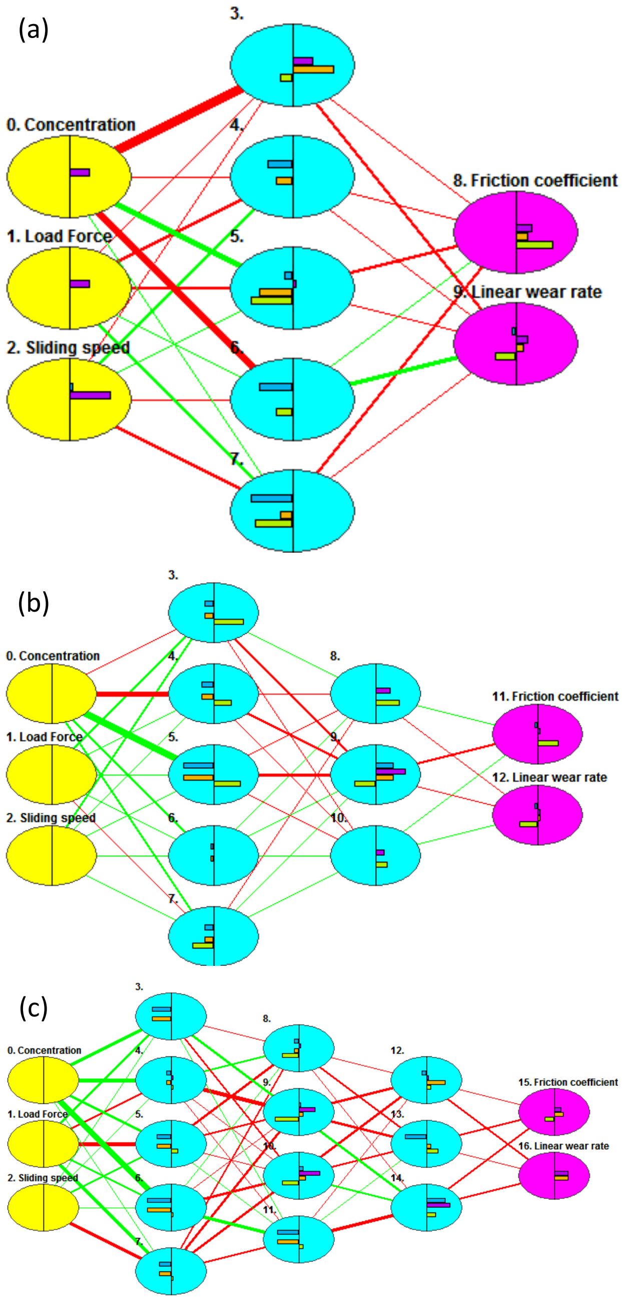

Figure 14. Neural networks architectures

Regarding the prediction of tribological properties of the composite based on known aramidic powder concentration, loading force and sliding speed values, the prediction error was computed by comparing the neural model outputs with the corresponding experimental acquired data. The results are different: for friction coefficient the lowest error is provided by three layered neural network while for linear wear rate the minimum error is obtained in the single layered network.

Table 2. Neural networks performances

Hidden layers / Parameter	1	2	3
Training cycles	405	500	3585
Input importance	*C L S*	*C L S*	*C L S*
Prediction error			
Friction coefficient	4.5 %	5.4 %	3.3 %
Linear wear rate	21.4 %	74.8 %	33.1 %

Taking into account the parameters values presented in Table 2 can be concluded that the best suitable network neural architecture for tribological properties analysis and prediction for studied aramidic powder composite is the single hidden layer one.

The neural model can be also used for optimization of aramidic powder concentration in order to obtain desired values (maximum or minimum) for friction coefficient and/or linear wear, for imposed functioning conditions (loading force and/or sliding speed), as is presented in Table 3.

Table 3. Aramidic powder concentration optimization

Input / Output			*C* [%]	*L* [N]	*S* [m/s]
FC	min	0.2557	5.75	15	0.75
	max	0.4880	17.75	11.77	0.91
WR	min	0.4339	7.25	15	0.75
	max	6.7069	19.25	11.85	0.91

In Table 3, it can be observed that the lowest/highest values for friction coefficient and linear wear are obtained for identical loading forces and sliding speeds values. The aramidic powder concentration values are slightly different.

5. CONCLUSIONS

Based on tribological analysis of aramidic powder additivated composites, following conclusion can be drawn:

- regarding the loading force influence on friction coefficient can be observed that in low speed case, the coefficient is decreasing with force increase. In higher speed case, the coefficient values are increasing with loading force values;
- regarding the sliding speed influence on friction coefficient evolution, can be observed a decrease with speed increasing, for low loading force values. At higher loading force values the friction coefficient is increasing with speed increasing;
- the neural network model can be build and trained with experimental acquired data;
- the neural model can be used for establishing which is the input that is most influencing over the outputs, for prediction of tribological values for known input data sets and for establishing optimal input data values for desired (minimum or maximum) output values.

ACKNOWLEDGEMENT

The work was supported by Project SOP HRD - PERFORM /159/1.5/S/138963.

REFERENCES

[1] M. Kawasumi: The discovery of polymer-clay hybrids, Journal of Polymer Science Part A: Polymer Chemistry, Vol. 42, No. 4, pp. 819-824, 2004.

[2] D. Lingaraju, K. Ramji, N.B.R. Mohan Rao, U. Rajya lakshmi: Characterization and prediction of some engineering properties of polymer - clay/silica hybrid nanocomposites through ANN and regression models, Procedia Engineering, Vol. 10, pp. 9-18, 2011.

[3] S. Mazumdar: Opportunities for thermoset resins in the composites industry, in: *Trends and Forecasts in Global Thermosets Resin Market 2008-2013*, pp. 50-62, 2010.

[4] D. Callister: *Materials Science and Engineering*, John Wiley & Sons, Inc., 2007.
[5] H. Zhang, Z. Zhang: Comparison of short carbon fibre surface treatments on epoxy composites: II. Enhancement of the wear resistance, Composites Science and Technology, Vol. 64, No. 13-14, pp. 2031-2038, 2004.
[6] K.S. Lee, S. Kobayashi (Eds.): *Polymer Materials, Block-Copolymers, Nano composites, Organic/Inorganic Hybrids*, Springer, 2010.
[7] T. Nasir, B.F. Yousif, S. McWilliam, N.D. Salih, L.T. Hui: An artificial neural network for prediction of the friction coefficient of multi-layer polymeric composites in three different orientations, Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science, Vol. 224, No. 2, pp. 419-429, 2010.
[8] R.N. Rothon (Ed.): *Particulate-Filled Polymer Composites*, Rapra Technology Limited, 2003.
[9] D. Michie, D.J. Spiegelhalter, C.C. Taylor (Eds.): *Machine Learning, Neural and Statistical Classification*, 1994.
[10] R.M. Hristev: *The ANN Book, Edition 1*, 1998.
[11] J. Šíma: *Introduction to Neural Networks*, Technical report No. V-755, 1998.