Investigation of tribotechnical characteristics of epoxy composites using neural networks

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Abstract

The main focus of this work is to research the tribotechnical characteristics of epoxy composites. The main ingredient of this material is structurally modified by plastification dispersed polyethylene. The composite was obtained at the stage of heat treatment during its forming. In this work, the tribotechnical characteristics of the epoxy binder were modeled. The intensity of linear wear, the coefficient of friction, and the temperature in the friction zone were researched depending on the load. Neural networks were used to improve the accuracy of the test results. The results of the study of modeling the characteristics of composites are in good agreement with the experimental data of other authors. It is proved that the correlation coefficient in the presented test sample is 0.98. For these characteristics in the test samples, the prediction error when using neural networks is 0.15% for wear intensity, 0.12% for friction coefficient, and 0.23% for temperature. It is shown that neural networks are capable of analyzing data and learning from it. Therefore, modeling the properties of materials by neural networks allows achieving high accuracy in researching the properties of composites.

Keywords

Machine learning, neural networks, friction, intensity of linear wear, tribotechnical

1. Introduction

Increasing the durability of mechanisms and machines for various purposes while reducing their energy and metal consumption during creation and operation is a prerequisite for the development of modern industry. Since the units, in most cases, comprise friction units, improving tribotechnical characteristics is an important task of increasing their operational reliability. In this area of research, the use of composite materials is promising [1-4], including those for antifriction purposes [5,6]. From a practical and scientific point of view, it is important to research the effect of dispersed polyethylene on the coefficient of friction, the intensity of linear wear, and the temperature in the friction zone under conditions of reversed motion of the counterbody. It should be noted that it is effective to create polyethylene particles in the epoxy matrix with surface plasticization with mineral oil [5,6]. This was achieved by combining dispersed polyethylene with a lubricant introduced into the epoxy

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composition at the stage of its formation into a product, followed by mandatory heat treatment at 125-130^{0}C. In addition, it is also important to research the load characteristics of composites in a friction pair. In this context, the use of automation systems for research processes will significantly increase the accuracy and reduce the time of tribotechnical research. Automated systems, in particular neural networks, make it possible to scientifically and predictably control the antifriction characteristics of materials at the stage of their formation and processing of test results. In this area of research, neural networks are an effective tool when used to process experimental data of polymer composites on wear resistance, friction coefficient, and temperature in the friction zone. Automation of experimental data processing, including the use of neural networks, during the process of experimental research provides intelligent data analysis, which allows establishing significant relationships between the composition of the material and its characteristics [7]. This approach is especially effective in the research of polymer composite materials (reactoplastics) based on epoxy diane binder [8]. The accuracy of the systems depends on the settings of the neural networks. In general, the properties of polymer composites can be modeled with high accuracy using machine learning algorithms, in particular neural networks [9-13]. One of the advantages of this approach is the possibility of non-destructive testing, which allows obtaining the results of experimental studies without affecting the structure of the composite.

The modern technology for creating polymer composites, including epoxy composites, is mainly aimed at studying the influence of structure on material characteristics. This approach is based on theoretical concepts of controlling the processes of structure formation in a composite material [14-20] and the analysis of empirical data on their performance properties. To obtain composites with optimal characteristics, a set of requirements for the polymer matrix is established, such as high physical, mechanical, adhesive, and thermal characteristics, as well as the necessary tribotechnical properties [21]. This is achieved by selecting ingredients in the polymer binder, such as modifiers, plastifiers, catalysts, and fillers. In addition, one of the promising areas for improving the properties of heterogeneous composite systems at the present stage of development of materials science is the modification of compositions by introducing fillers and their plastification at the molding stage during heat treatment. It is proved that such an approach will ensure the creation of epoxy composite materials with predetermined performance characteristics due to the targeted control of the structural organization of the filler itself in the process of forming the material into products.

It is known that the improvement of tribotechnical characteristics was achieved by introducing low-melting polyolefins into a rigid matrix. Under increased loads, a thin layer of this polymer, which is a more fusible component, is formed. This contributes to the formation of transfer films on the friction surface, reduces the wear rate, the coefficient of friction of the material and the temperature in the friction pair. Therefore, the study of changes in the conditions of frictional interaction during friction contact is a complex process that depends on many factors: different loads, conditions for the formation of transfer films, changes in the structural characteristics of fillers and their plasticization, etc. However, not enough attention has been paid to the study of tribotechnical characteristics, especially in the conditions of changing the dynamics of the process of frictional interaction of surfaces in a friction pair, by using neural networks. In connection with the above, the use of neural networks in the study of composite properties is an urgent task of modern materials science.

2. Research methods

The binder material for the experimental studies was chosen based on the operating conditions of friction units for antifriction purposes. Epoxy-diane resin ED-20 was chosen as a binder, and polyethylene polyamine was used as a curing agent. Dispersed polyethylene was used as a filler. The oil and powdered polyethylene were mixed, then introduced into the epoxy composition and cured with subsequent heat treatment at 443 K. The process of plastification of the surface layers of polyethylene particles placed in a rigid epoxy matrix was provided.

The tribotechnical characteristics of the epoxy coatings were studied during friction on the MI-1M friction machine according to the shaft-partial sleeve scheme at a relative sliding speed of 0.5 m/s in the load range of 0.1-3.0 MPa. The friction force was determined by the value of the deformation of the elastic element, which was measured using strain gauges connected in a bridge scheme. The wear intensity was found using the formula:

$$I=\frac{\Delta m}{L\rho S}\cdot 10^{-8}$$

where Δm - is the mass wear, mg; L is the friction path, km; ρ is the density of the material, g/cm; S is the friction area, cm^2.

The temperature is measured by thermoelectric thermometers with an error of no more than ±2 K.

In modern studies of the tribotechnical characteristics of epoxy composites, one of the most promising analysis methods is the use of neural networks. Neural networks, due to their ability to model complex nonlinear relationships, are becoming an indispensable tool in predicting and optimizing the properties of materials [22]. In this study, a multilayer perceptron was used to analyze and predict the tribotechnical characteristics of epoxy composites, the architecture of which is shown in Fig. 1 [23-25].

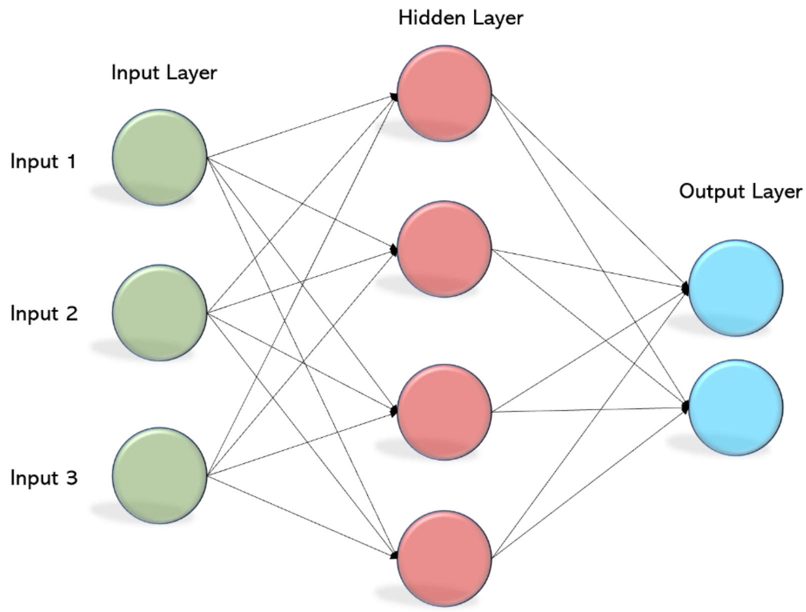

Figure 1: Architecture of the multilayer perceptron.

A multilayer perceptron is a type of artificial neural network consisting of three main types of layers: input, hidden, and output [26]. Each neuron in the network interacts with the neurons of the next layer through weighted connections, which allows the network to learn and find patterns between input and output data.

To analyze the tribotechnical characteristics, a multilayer perceptron model with the following architecture was developed:

- Input layer: the number of neurons corresponds to the number of parameters describing the properties of the composite (e.g., filler content, temperature, sliding speed, etc.).
- Hidden layers: the optimal number of layers and neurons in each layer is selected based on experimental data and by selecting hyperparameters.
- Output layer: one neuron responsible for predicting a target tribotechnical property, such as friction coefficient or wear.

To train the model, an experimental data set was used, including various combinations of composite parameters and corresponding tribotechnical characteristics [27]. The data were divided into training and test samples to ensure reliable model quality control.

The multilayer perceptron was trained using a back-propagation algorithm with gradient descent [28]. To prevent overtraining, regularization and early stopping methods were applied [29-30].

In terms of solving a regression problem, a multilayer perceptron has a number of advantages:

- A multilayer perceptron is able to approximate any complex nonlinear relationships between input and output data. This is especially useful in cases where the dependencies between variables are difficult to express analytically.

- With the right architecture and hyperparameters, a multilayer perceptron can achieve high prediction accuracy in regression tasks.
- Neural networks can adapt to new data and detect hidden patterns, which allows the model to be improved based on additional information.
- A multilayer perceptron can work with large data sets containing many input variables without losing efficiency.
- Neural networks are well suited for implementation on modern hardware, such as graphics processing units (GPUs), which can significantly speed up computations.

However, this architecture is not without its drawbacks, which should be taken into account when solving the problem:

- For effective training, a multilayer perceptron requires a significant amount of training data. In the case of limited data, the model may not achieve the desired accuracy.
- The choice of the number of layers, neurons in each layer, learning rate, and other hyperparameters is critical to the success of the model. Incorrect settings can lead to overtraining or undertraining. To solve this problem, various approaches are used to determine the set of hyperparameters under which the network produces the best results.
- Neural networks are often viewed as "black boxes" because it is difficult to interpret how the model makes decisions. This can be problematic in tasks where it is important to understand the decision-making process.
- Training a multilayer perceptron, especially on large datasets, requires significant computational resources and time, but this problem can now be solved by running it on multiple GPUs simultaneously.
- If the network architecture is too complex, there is a risk of overfitting, when the model performs well on training data but poorly on test data.
- Neural networks can show instability during training, especially if the data contains noise or if an inappropriate optimization algorithm is used.

A multilayer perceptron is a powerful tool for regression problems, but its effectiveness largely depends on the correct model setup and the amount of available data.

In particular, in this study, we built such types of networks as MLP 2-8-1 for the study of the friction coefficient and for linear wear, and, accordingly, MLP 2-9-1 for the temperature in the friction zone of the friction pair. The training algorithm was BFGS, the error function was SOS, and the hidden layer activation functions were logarithmic for the friction coefficient and temperature in the friction surface contact zone. Whereas the activation functions of the outer layer were logarithmic for the friction coefficient and wear rate, and tangential for the temperature in the friction zone.

3. Experimental analysis

It has been found that the introduction of dispersed plastified polyethylene into epoxy oligomers (ED-20) leads to a more significant reduction in the wear rate of coating materials compared to other known antifriction fillers for coating materials. Experimentally, it was found that a minimum was observed on the curve of the wear resistance-filler concentration dependence. This extreme dependence is typical for certain concentrations of additives in the epoxy matrix. It should be emphasized that the coating material made of unfilled epoxy resin, without dispersed polyethylene, has a two orders of magnitude higher wear rate under the same test conditions [32].

It has been experimentally established that the use of dispersed polyethylene increases the wear resistance of the composite due to the formation of transfer films from a more fusible ingredient, polyethylene, in the friction zone. This effect of frictional separation of the components leads to the appearance of self-lubrication by the polyethylene melt. It should be noted that this process is not long-lasting due to the destruction of the transfer film under the action of frictional contact, mainly due to their destruction during its interaction with air oxygen.

The introduction of dispersed polyethylene, pre-mixed with mineral oil, into the epoxy matrix, followed by heat treatment, causes plasticization of the surface layers of polyethylene particles. In this case, the mobility of polyethylene molecules increases. During frictional contact, films 5-10 microns thick of plasticized polyethylene are formed on the friction surfaces. It has been established that the formation of films occurs at loads of 0.05-0.25 MPa and at a temperature much lower than the melting point of polyethylene. In this case, the improvement of the tribotechnical properties of the coatings is due to the formation of polyethylene films plasticized with mineral oil and the migration of the oil by friction into the friction contact zone from the volume of the filler itself. It has been experimentally proven that the lubricant protects polyethylene films, significantly reducing destructive processes in them.

At the next stage of research, tests were conducted on the load capacity of epoxy composites containing the optimal ratio of ingredients. The effect of load on the wear resistance of the coating material under friction was investigated [33]. Increasing the load causes a monotonous increase in the intensity of linear wear of the material of the studied coatings (Fig. 5). Epoxy coatings based on materials filled with dispersed partially plastified polyethylene have the highest wear resistance and the lowest friction coefficient (Fig. 6) at loads of 0.25-3.0 MPa. It was experimentally established that increasing the heat treatment temperature to 433 K increased the load capacity of epoxy coatings [33-34]. It has been proven that this is due to an increase in the degree of crosslinking in the matrix, which in turn reduces the deformation component of the friction force. The increase in loads leading to catastrophic wear of polyethylene-filled composites can be explained by the formation of effective protective transfer films on friction surfaces that have low shear resistance. This is apparently due to the low values of the cohesion energy of polyethylene and the effect on its reduction of plasticization by lubricant and an increase in the temperature of the friction contact (Fig. 7). The filling of the epoxy matrix leads to a decrease in the wear resistance of coating materials by an order of magnitude compared to the wear resistance of similar materials that have not been modified. This is due to the lower shear energy of the transfer films compared to polyethylene. This is also facilitated by an increase in the temperature of the surface layers during frictional contact [35-37]. This, in turn, leads to a decrease in the wear of the epoxy matrix due to an increase in the yield of the gel fraction, which reduces the adhesive component of the friction force during the frictional interaction of surfaces in a friction pair.

Thus, the studies show that in order to increase the wear resistance of coatings, epoxy materials need to be modified with dispersed partially plastified polyethylene to improve the tribotechnical characteristics of the material in a friction pair. The research results show that the filling with dispersed polyethylene allows to realize the effect of frictional distribution of mixtures at relatively low loads of 0.1-0.25 MPa. It should be noted that the volume temperature in the friction zone at these loads is significantly lower than the melting point of polyethylene. The manifestation of the effect of frictional separation of composite components, in this case, is associated with an increase in the mobility of filler macromolecules, which is primarily due to the plasticization of polyethylene.

The friction coefficient, linear wear intensity, and temperature in the friction zone were modeled using neural networks based on experimental data. In particular, in the process of training neural networks, the data were divided into two parts - training and test samples[38-39]. That is, 22960 elements for each epoxy polymer filled with plasticized polyethylene. Of this data, 80% was randomly selected for the training set, and the remaining 20% was left to evaluate the quality of the prediction. Here, the initial parameters were the following characteristics: wear intensity $I \cdot 10^{10}$, friction coefficient $f_{тр}$, and temperature in the friction zone T(K). Filler concentration ω(wt%) and load P(MPa) were considered as input parameters. Discrete and distributed time delays are considered in the article [40] in the form of results of a qualitative study of a neural network. A method for calculating the exponential decay rate for a neural network model based on differential equations with a discrete delay was developed and used [41], [42].

The dependences of the experimental data of tribotechnical characteristics of materials and temperature in the friction zone on the predicted ones obtained by the neural network method are shown in Figs. 2-4.

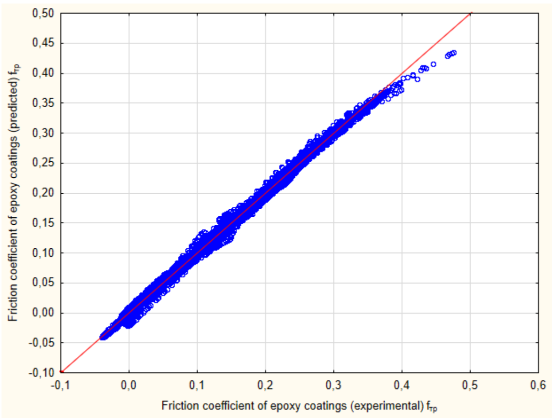

Figure 2: Predicted and experimental dependences of the friction coefficient.

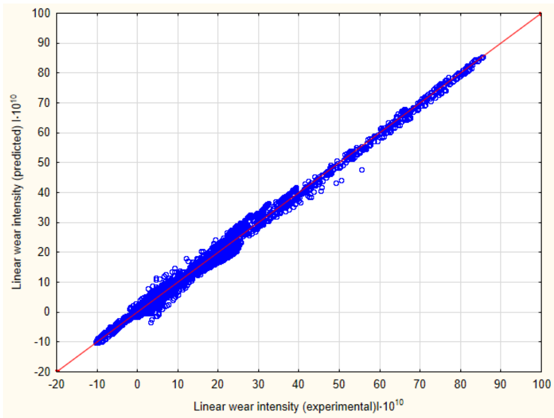

Figure 3: Predicted and experimental dependences of linear wear intensity.

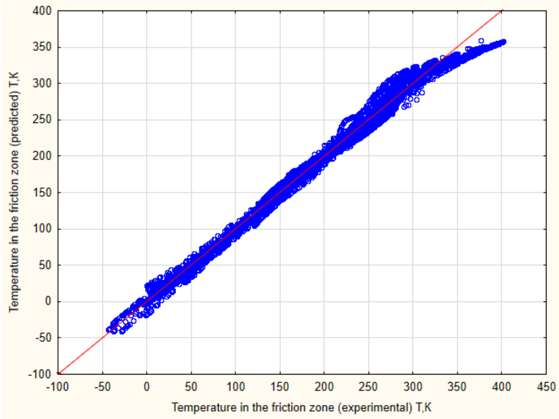

Figure 4: Predicted and experimental temperature dependences in the friction zone.

Dependencies of tribotechnical characteristics of materials and temperature in the friction zone on load are shown in Figs. 5-7.

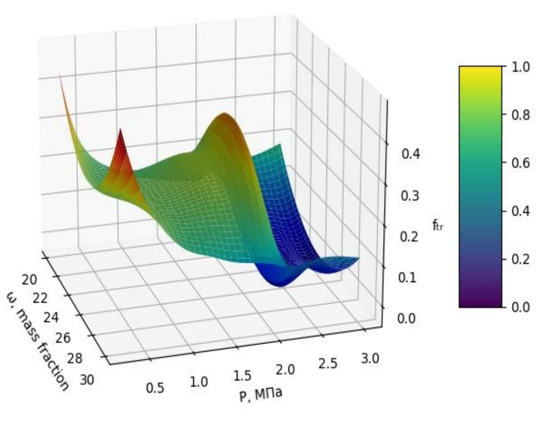

Figure 5: Dependence of the coefficient of friction of epoxy coatings on load.

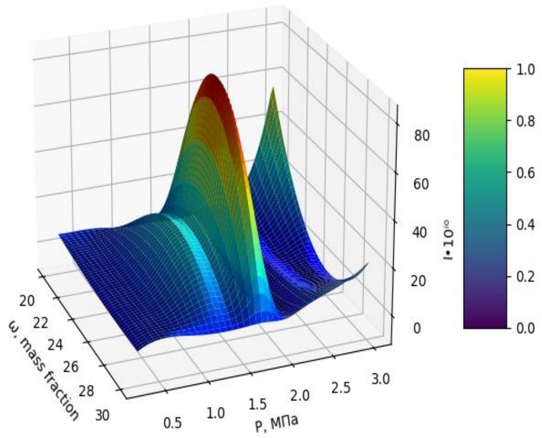

Figure 6: Dependence of linear wear rate of epoxy coatings on load.

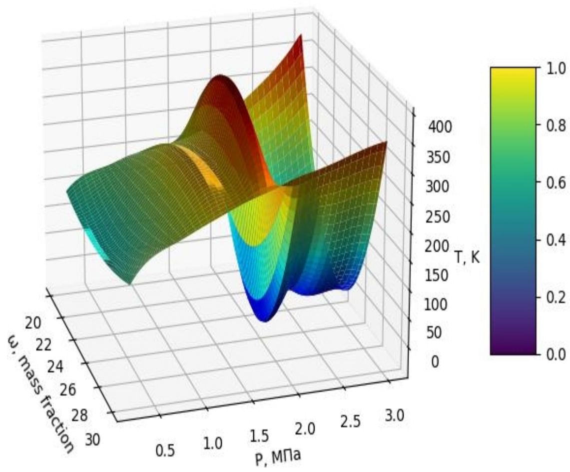

Figure 7: Dependence of temperature in the friction zone of epoxy coatings on load.

To analyze the data, a statistical graph in the form of residuals diagrams was used. It was found that the residuals have a normal distribution[43-45].

The diagrams of residual values for composites filled with plasticized polyethylene, respectively, the friction coefficient, linear wear intensity, and temperature in the friction zone are shown in Figs. 8-10 .

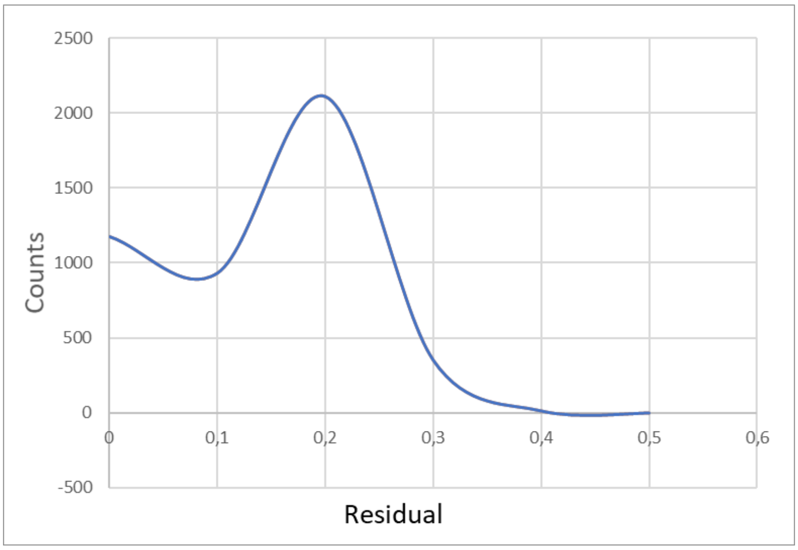

Figure 8: Diagram of residual values of the coefficient of friction.

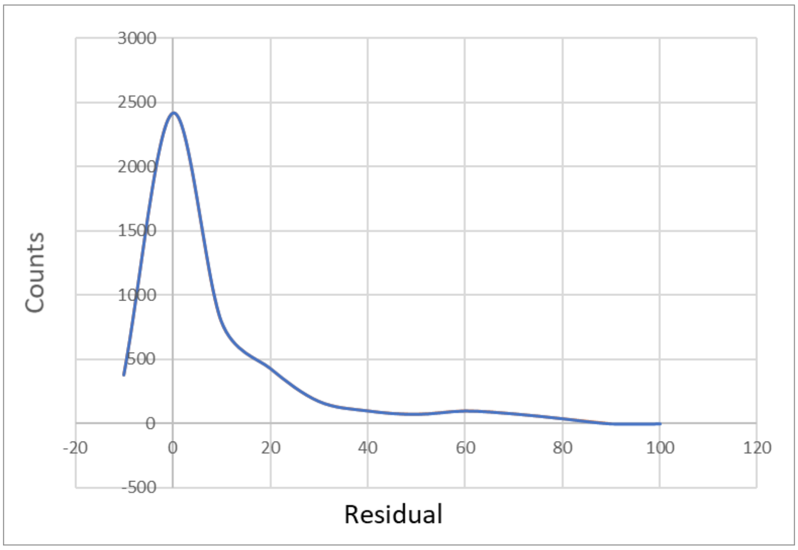

Figure 9: Diagram of residual values of linear wear intensity.

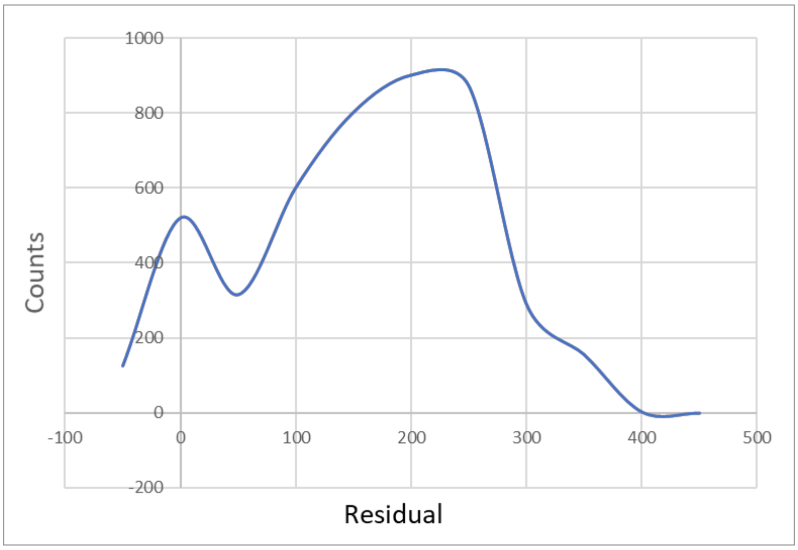

Figure 10: Diagram of residual temperature values in the friction zone.

4. Conclusion

In this work, we modeled the processes of changes in tribotechnical characteristics: friction coefficient, linear wear intensity, and temperature in the friction zone of epoxy materials as a function of the ratio of ingredients and the content of partially plasticized polyethylene in the composite and the load in the friction pair using neural networks. The results are in good agreement with the experimental data. The prediction error of the research results by neural networks is 0.15, 0.12, and 0.23 % in the test samples. The results obtained will allow creating conditions for targeted regulation of tribotechnical characteristics and adjusting technological parameters at the stage of their formation.

In the future, studies are planned to optimize the composition of antifriction ingredients in the composite to use the developed materials as coatings for friction pairs.

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