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Research Paper

PREDICTION OF THE FRICTION COEFFICIENT BASED ON THE HYSTERESIS VALUE OF SHOE SOLE RUBBER

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Abstract. *This paper present research focused on the prediction of the friction coefficient of shoe sole rubber by utilizing its measured hysteresis values, along with other influencing factors such as hardness, tile surface roughness, sliding speed, and surface conditions. Previous authors research determined that rubber hysteresis is an important property of rubber (among other mechanical and physical properties) to consider when performing tribological research of contact between rubber soles and a hard substrate (tiles, laminate, vinyl, concrete). Data required for design and training of a neural network were gathered by friction coefficient testing conducted on a specially designed test apparatus. Additionally, rubber hysteresis data were obtained using a uniaxial tensile testing machine. Given the role of rubber hysteresis in determining its properties, this study identifies it as a parameter that influences the friction coefficient and aids friction coefficient prediction through artificial neural networks (ANN). The research results showed a high correlation between the friction coefficient values predicted by ANN and actual experimental results, confirming that designed ANN can be used to predict the values of friction coefficient when the rubber hysteresis value is known.*

Key words: *Friction coefficient prediction, hysteresis, neural network, shoe sole rubber.*

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1. INTRODUCTION

Neural networks, inspired by biological neural systems, represent one of the most significant approaches in the field of artificial intelligence (AI). These networks have become a fundamental tool for solving complex problems in various domains, such as pattern recognition, natural language processing, and predictive analytics [1, 2]. Among other things, they are also used for predicting the friction coefficient based on various parameters. Chen et al [3] uses GA-BP neural network for friction prediction in bearing surface friction coefficient in bolted joints. They collect data for the friction coefficient and then use it for training the neural network. Zhang et al work [4] is interesting as it discusses the prediction of the friction coefficient between a car tire and asphalt. They use Mind Evolutionary Algorithm optimized Back-Propagation (MEA-BP) neural network model for the prediction of the tire-road friction coefficient and compare with the extreme learning machine (ELM) and BP neural network algorithms. Another work with similar research uses the Elman neural network for identification of the road friction coefficient [5]. In that paper, an identification method of road friction coefficient based on the Elman neural network was proposed.

Another study that deals with Artificial Neural Networks (ANN) to optimize time and cost in developing new friction brake systems, is a study which employed a Gate Recurrent Unit (GRU) algorithm enhanced by an improved Particle Swarm Optimization (PSO) method for predicting the coefficient of friction (COF) in braking applications [6].

In article [7], a genetic-algorithm-improved neural network (GAI-NN) was developed. Tree-dimensional (3D) point-cloud data of an asphalt pavement surface was obtained using a smart sensor (Gocator 3110). The friction coefficient of the pavement was then obtained using a pendulum friction tester.

Authors [8] make prediction models of the friction coefficient of asphalt pavement considering traffic volume and road surface characteristics. They use different pavement and tire parameters to make a model for friction coefficient prediction.

Also, authors [9] explore the prediction of the friction coefficient using 3D texture parameters of pavement surfaces by ANN.

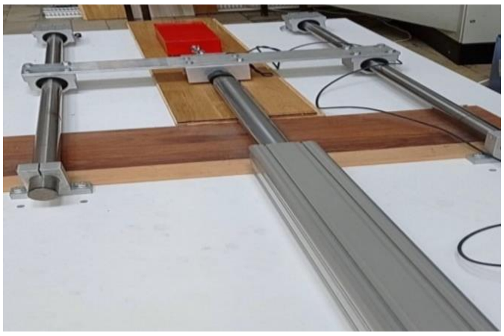
Paper [10] presents a trained novel predictive model developed for the measurement of road surface friction considering a big dataset of 18 months with daily records through novel intelligent road-based passive sensor measurement, on a Spanish highway section. The trained predictive model is developed on the machine learning (ML) approaches, namely support vector machine (SVM), and validated with the K-Fold cross-validation (CV) algorithm considering various kernels.

Authors [11] develop a model that classifies footwear outsoles based on how slip resistant they are on icy surfaces. They applied a transfer learning technique where the best classification model used the DenseNet169 pre-trained model and obtained an accuracy and F1-score of 0.93 ± 0.01 and 0.73 ± 0.03, respectively.

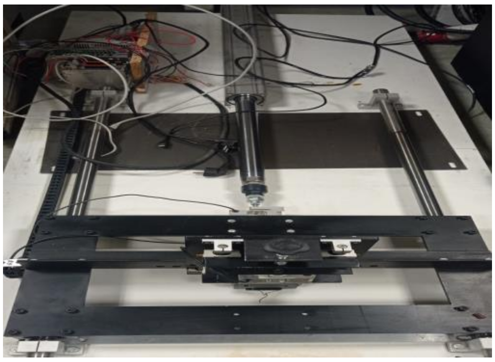
In previous research, most authors have focused on the influence of rubber hardness on its tribological characteristics, neglecting its hysteresis properties, even though the hysteresis component is part of the friction mechanism in viscoelastic bodies. Authors who have studied the influence of hysteresis have concentrated on determining the contribution of the hysteresis component under different tribological conditions, without determining the actual hysteresis value as a property of rubber or its impact on the coefficient of friction. For the reasons noted above, the subject of scientific research in this paper is the predicting the friction coefficient of shoe sole rubber by utilizing its measured hysteresis values along with other factors such as hardness, tile surface roughness, sliding speed, and surface conditions. The study employs an artificial neural network (ANN) to analyze data gathered from friction coefficient testing and rubber hysteresis measurements. The new approach in this research is the use of hysteresis as a parameter for predicting the friction coefficient of shoe sole rubber, which has not been previously utilized for this purpose.

2. EXPERIMENTS

Gathering data and performing experiments for this study took two months. A total of 240 data points for the friction coefficient were obtained. The dataset used for the artificial neural network to predict the friction coefficient based on rubber hysteresis included the following parameters: static and kinetic friction coefficients, rubber hysteresis, rubber hardness, substrate roughness, sliding speed, and surface condition (categorized as dry, wet, or soap-lubricated). Friction coefficient was measured on the testing device developed on Mechanical Faculty in Niš.



(a)



(b)

Fig. 1 Tribometer (a) and (b)

Figure 1(a) illustrates the friction coefficient testing device. This device was designed to support a wide range of speeds, accommodate various surface conditions (dry, wet, or lubricated), test different materials (rubber, tiles, metals…), and perform tests at a constant speed. Figure 1(b) shows a modified version of the testing device, equipped with the capability to adjust the normal force.

The device includes a holder for rubber sliders, which acts as a weight to define the normal force, a force sensor, an electric linear actuator with a servo drive, and a base for placing different floor samples. The testing setup and some parameters (speed, stroke, normal force, slider dimension and arrangement) are based on the EN 13893:2011 [12] standard method for measuring the coefficient of friction. Also, the tests are conducted on high-hardness granite tiles to eliminate the influence of the substrate hardness on the value of the coefficient of friction at the footwear-floor contact. Surface condition (dry, wet, soap) were selected from previous similar researches.

The electric actuator (SMC) uses a ball screw mechanism and features a linearly integrated AC servo motor (Mitsubishi). For testing, the normal force was set to 100 N, resulting in a contact pressure of 83 kPa. The sliding speeds were 50 mm/s and 300 mm/s for kinetic friction and 1 mm/s for static friction tests, with a total travel distance of 600 mm for measuring the friction coefficient. Friction force measurements were taken using an HBM S2 sensor, capable of handling forces up to 200 N.

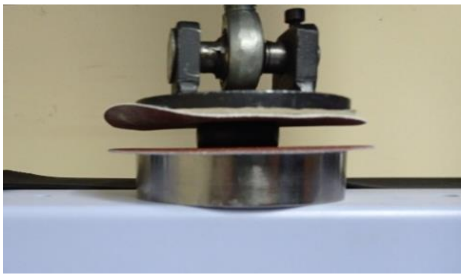


Fig. 2 Hysteresis testing

The samples for determining the hysteresis of the rubber are cylindrical shape, with a diameter of Φ35.7 mm and a height of 18 mm (shown on Fig. 3)

Fig. 3 Hysteresis rubber samples

The hysteresis testing of the rubber samples, shown in Figure 2, was conducted at the Faculty of Mechanical Engineering in Niš using a Shimadzu AGS-X uniaxial testing machine with a maximum load of 10 kN.

Hysteresis refers to the property of a material to expand and contract in the same manner, following an identical path during expansion and contraction on a force-displacement graph. This behavior is commonly observed in rubber and similar polymers. For instance, car tires heat up not due to friction but because of hysteresis in the rubber, as the tires deform momentarily upon contact with the road surface. This energy loss, which converts kinetic energy into heat, is described as the rolling resistance [13].

Rubber hysteresis plays a crucial role in determining the friction and energy absorption of shoe soles. It can be classified into thestatic hysteresis (examined in this study) and the dynamic hysteresis, such as Yearsley Hysteresis. The results obtained through this method closely align with those from the Yearsley method, showing a minimal result variance. This simpler method does not require specialized equipment and uses a uniaxial testing machine.

For the experiment, rubber compounds with hardness levels of 65 ShA (Method A) and 60 ShA were tested. Samples were cylindrical with a diameter of 35.7 mm and a height of 18 mm, produced by a local shoe sole manufacturer (Figure 3). The internal labels for these samples included OB202, OB290, OB2280, and OB221, among others.

Before testing, the rubber samples were conditioned at the testing temperature for at least 24 hours to stabilize the polymer chains. Once conditioned, their dimensions were verified. To increase the friction coefficient between the machine plates and the rubber sample, the samples were placed between two sheets of sandpaper. The applied axial pressure caused the cylindrical rubber samples to deform, pushing outward into a barrel-like shape.

For accurate rubber hysteresis testing, the samples underwent a conditioning process, which aimed to break weak bonds formed during vulcanization, stabilizing the rubber. The conditioning involved five cycles of applying vertical pressure at 0.25 mm/s until 9 mm of deformation (half the sample's height), followed by a 20-second hold and then a release at the same speed. This process was repeated for all samples, with three test samples per rubber mixture.

After conditioning, the samples rested for 30 minutes. The hysteresis test itself applied a vertical pressure force at 5 mm/min until 9 mm of deformation was reached and then released at the same speed. Force and deformation data were collected during the test to analyze the mechanical response of the samples.

3. Artificial Neural Network for Prediction of Coefficient of Friction

For predicting the friction coefficient, a standard artificial neural network with backpropagation was used. The ANN was designed to have four layers: an input layer, two hidden layers, and an output layer. The variables used in the input layer of the network are the kinetic friction coefficient, hysteresis, hardness, substrate roughness, sliding speed, and surface condition. The variable in the output layer of the network is the kinetic friction coefficient.

The ANN was created using the MATLAB software tool. The input layer of the artificial neural network consists of 5 neurons because there are 5 input parameters, while the output layer has 1 neuron, output is 1 dependent variable (friction coefficient). The hidden layer consists of 10 neurons. The scheme of ANN is shown on figure 4.

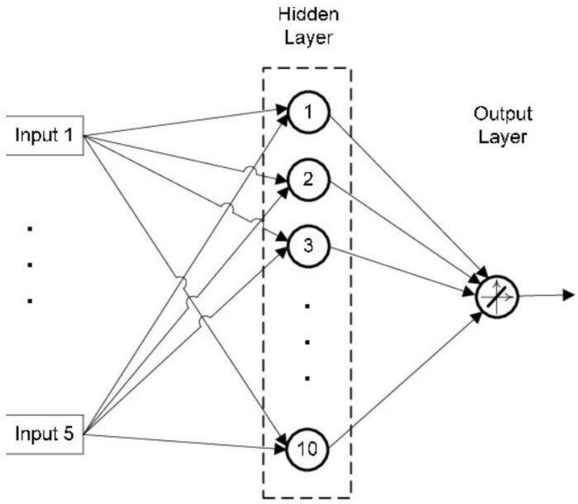


Fig. 4 Scheme of ANN

An artificial neural network was trained using the Levenberg-Marquardt backpropagation algorithm. The mean squared error was used to measure performance. The dataset consisted of 5 variables. Trial-and-error approach was used for determining the number of hidden layers and hidden neurons in these layers.

Table 1 presents input parameters for ANN, there are 5 input parameters: rubber hysteresis, rubber hardness, tile roughness (*Ra*), sliding speed and surface condition.

Table 1 Experimental inputs

No	Rubber hysteresis	Rubber hardness (ShA)	Granite tile roughness (μm)	Speed (mm/s)	Surface condition	Normal load (N)	Measuring distance (mm)
1.	0,24	65	0.03	50	Dry	100	300
2.	0,35	65	4.70	300	Wet		
3.	0,39	65			Soap		
4.	0,46	60					

For measuring network generalization, a validation sample of 60 data was used. When generalization stopped improving, network training was halted. During the ANN training process, although a larger number of iterations were expected, it was observed that fewer iterations were sufficient to train ANN (Fig. 5).

To evaluate the network's performance, the coefficient correlation R was used, with the results presented in Fig. 6. This coefficient indicates how effectively the network was trained by comparing the predicted "outputs" to the actual "targets." A higher R value signifies a better network performance, with R=1 representing a perfect match between "targets" and "outputs." As shown in Fig. 6, the correlation coefficient during ANN training was R=0.99877, indicating excellent training. The trained network was then tested on a separate testing dataset, achieving R=0.99854. The overall performance of the trained ANN was R=0.99792, which is considered a highly satisfactory result.

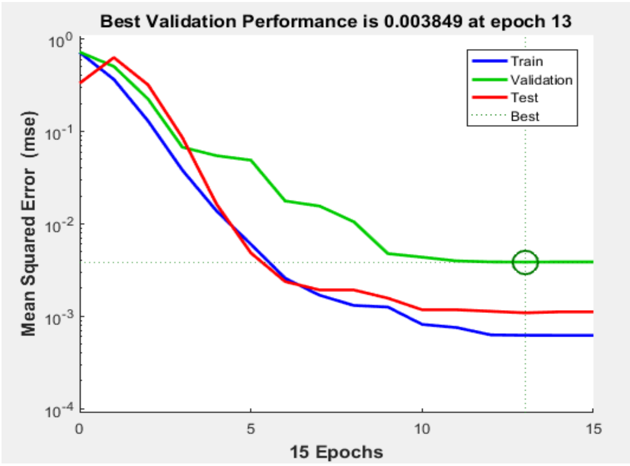


Fig. 5 Mean squared error during the ANN training process for kinetic friction coefficient prediction

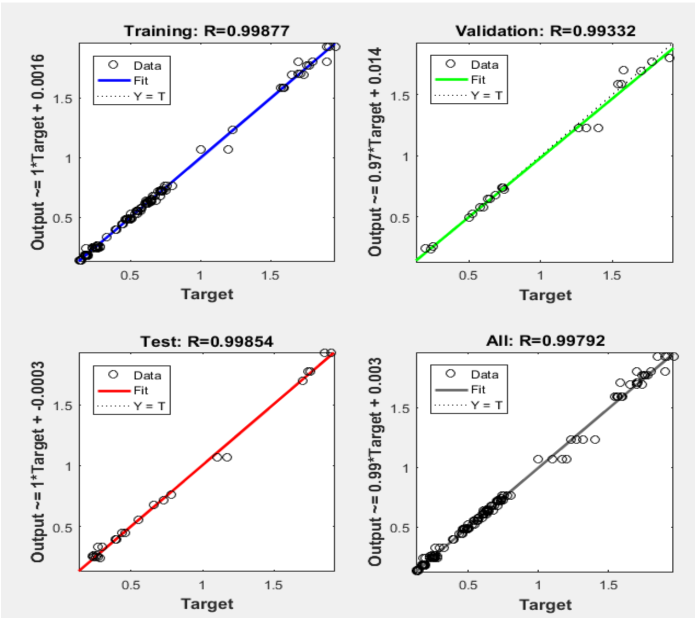


Fig. 6 The results of network performance for training, validation and test dataset (kinetic friction)

4. RESULTS AND DISCUSSION

It was determined by previous authors research [14] that the regression analysis cannot predict friction coefficient value well enough to agree with the experimental data. The difference between prediction of friction coefficient values and actual experimental results occurred because regression assumes a linear relationship, which obviously does not apply to rubber friction on ceramic tiles with different surface conditions. Additional methods, such as Taguchi method, yield better results [14], but again there is still discrepancy between the prediction values of friction coefficient and actual experimental data. As ANN have proven themselves as a valuable tool for prediction the friction coefficient values, this study focused on design and training of ANN to predict the friction coefficient value based on the following parameters: rubber hysteresis and hardness, surface roughness and condition (dry, wet, soapy) and sliding speed.

Table 2 shows the experimentally determined and predicted values of the kinetic coefficients of friction based on 5 input parameters and 3 sets of measurements used to train the network. The total number of measurements of kinetic friction coefficient used to train the network is 180 and 60 for confirmation.

Table 2 Predicted end measured kinetic friction coefficients

Hysteresis	Hardness (ShA)	Roughness (*Ra*-µm)	Speed (mm/s)	Surface condition		Measured *µkp*	Predicted *µk*	Deviation %
0.35	65	0.03	50	1	dry	1.72	1.73	0.75
0.35	65	0.03	300	1	dry	1.82	1.85	1.80
0.35	65	4.51	50	1	dry	0.57	0.84	47.96
0.35	65	4.51	300	1	dry	0.67	0.73	9.27
0.35	65	0.03	50	2	wet	0.33	0.33	0
0.35	65	0.03	300	2	wet	0.17	0.26	54.11
0.35	65	4.51	50	2	wet	0.66	0.82	23.94
0.35	65	4.51	300	2	wet	0.60	0.59	1.86
0.35	65	0.03	300	3	soap	0.16	0.23	43.83
0.35	65	4.51	50	3	soap	0.53	0.58	8.65
0.35	65	4.51	300	3	wet	0.46	0.60	31.82

Figure 7 shows a diagram with the predicted and measured kinetic COF. Some of the predicted values are almost identical with the measured ones, with a maximal error of 54%. The difference between prediction and actual experimental data is the largest for the higher sliding speed indicating that more experimental data are necessary at speeds between 50 and 300 mm/s to enable more accurate prediction at larger speeds.

Since the predicted results obtained by the neural network are satisfactory, it can be concluded that the neural network can be used to predict the friction coefficient. Comparing the values obtained by ANN and other statistic methods (regression and Taguchi) [14] it can be seen that ANN gives a better accuracy, as the correlation coefficient is much higher for ANN in comparison to regression and Taguchi method.

ANN should perform better with more experimental data used in a training set [15] and deviation from predicted and experimental results should be smaller. For further research and improvement of the neural network's prediction accuracy, a larger number of experiments should be conducted to increase the amount of input data for training the network.

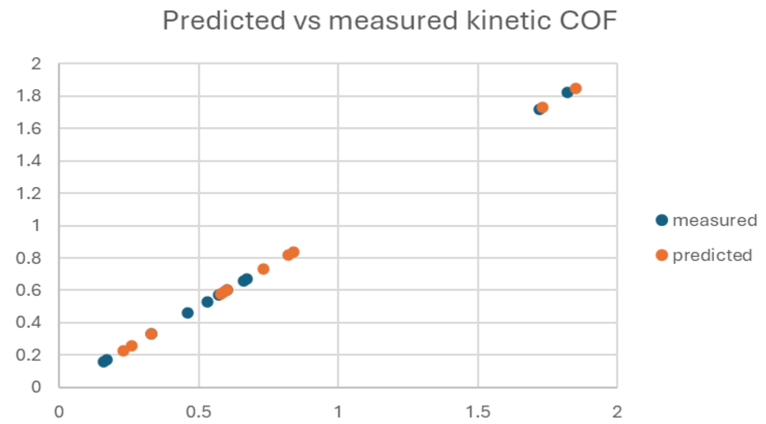


Fig. 7 Predicted vs measured friction coefficient diagram

Forecasting using neural networks essentially involves processing a specific dataset, training a model, and expecting the network to perform well in predicting the output. However, during the learning process, the network is typically trained on a limited dataset comprising both training and test data, which may not encompass the full diversity of inputs and scenarios encountered by the neural network in a real-world environment [9].

5. Conclusion

This paper describes an attempt to predict the friction coefficient using a neural network based on five input parameters, one of which is hysteresis, a factor not previously used for this purpose in the existing research. This research confirmed that rubber hysteresis is an important property of rubber (among other mechanical and physical properties) to consider when performing the tribological research of contact between rubber soles and a hard substrate (tiles, laminate, vinyl, concrete). Experimental research showed that different rubber mixtures with the same or similar hardness have different COF due to different hysteresis. The results obtained in this study show that the prediction of the friction coefficient can be accurate and with certain improvements and optimizations could be even better. It is necessary to collect more experimental data for better and precise ANN friction coefficient prediction. The created ANN showed a high correlation between the target data and the data gathered from the simulation of the artificial neural network. Further research should focus on increasing the training data through additional experimental measures and neural network optimizations.

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