

PREDICTION OF STRENGTH PROPERTIES OF NATURAL FIBER-POROUS COMPOSITES BY NEURAL NETWORKS

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Abstract. There is a real need to reduce the scope of determining the physical and mechanical properties of natural fiber-porous composites. The application of an artificial neural network for the prediction of the strength of natural chrome-tanned leather made of bovine and calfskin was investigated in this work. The results were obtained by applying a single-layer and a two-layer neural network. The results indicate a great potential of using an artificial neural network in determining the predicted values of natural leather properties.

Keywords: natural fiber-porous composites, prediction, neural networks, ultimate strain, stress

1. Introduction

State-of-the-art technologies make it possible to obtain a wide range of composite materials either by modification of matrix and filler structures [1,2,3,4,5], or by using matrix and filler materials of different nature [6,7,8]. Technological processes for the creation of artificial composites, in most cases, lend themselves well to modelling, which allows us to obtain materials with predetermined properties [9,10,11,12]. At the same time, the creation of natural fibrous-porous materials from natural biocomposites with predetermined properties is a difficult task due to the properties of the initial raw materials [13].

Methods designed to predict the qualitative and quantitative indicators of material properties can be divided into methods based on analytical mathematical models [14], methods based on expert evaluations [20], and methods based on experimental data [15].

Methods for predicting material properties based on analytical mathematical models are more universal and cost-effective, but have limited use, as when the development of mathematical models for their use it is not possible to take into account a large number of factors.

Expert methods of predicting the properties of materials are based on the use of experts as the main sources of information. The main disadvantages of these methods are the qualitative assessment of material properties and the principal impossibility of complete elimination of subjectivity in the assessments.

In practice, prediction methods based on experimental data are widely used.

Statistical methods combine various methods of processing quantitative information about an object to identify the mathematical patterns and mathematical relationships of

characteristics contained in it in order to obtain predictive models. Thus, statistical methods by type are divided into methods of extrapolation and interpolation; methods that use the instrument of regression and correlation analysis; methods that use factor analysis [16,17,18,19].

Regression analysis establishes the relationship between random and non-random variables. Regression analysis is closely related to correlation analysis. When the prerequisites of correlation analysis are met, the prerequisites of regression analysis are also met. At the same time, regression analysis has less stringent requirements for the initial information. For example, it is possible to perform it even when the distribution of a random variable differs from the normal distribution.

Predictive extrapolation uses mathematical extrapolation, in which the choice of approximating function is to be carried out taking into account the physical meaning and nature of the process under consideration. Predictive extrapolation and interpolation methods use simple standard functions, polynomials of various degrees, and extrapolation of functions with a flexible structure. To determine the values of the parameters of the extrapolating function, the least squares method is used.

Factor analysis in forecasting involves a statistical analysis of the structure of the material in order to exclude insignificant variables from consideration and minimize the dimension of the description.

Recently, one of the promising forecasting methods is the method based on the use of various neural networks [20,21,22,23]. Prediction or forecasting tasks are basically the tasks of constructing a regression dependence of the output data on the input data. Neural networks can efficiently construct highly nonlinear regression dependencies and allow for reducing significantly the number of physical tests. Despite the advances in neural network prediction, the possibilities of their application for natural fibrous-porous materials, and in particular for natural leathers, have not yet been fully explored.

2. Research methodology

One type of natural fibrous-porous material is natural leather. During manufacturing and use of products, loading and deformation occur in different directions, which can lead to the destruction of both the material and the structure as a whole [24,25,26].

Bovine and chrome-tanned leathers, which are widely used in shoe-making, furniture, and automotive production, were chosen as model materials to predict the strength properties of natural leathers using artificial neural networks. Figure 1 shows the structure of natural fiber-porous materials (leather) under stud.

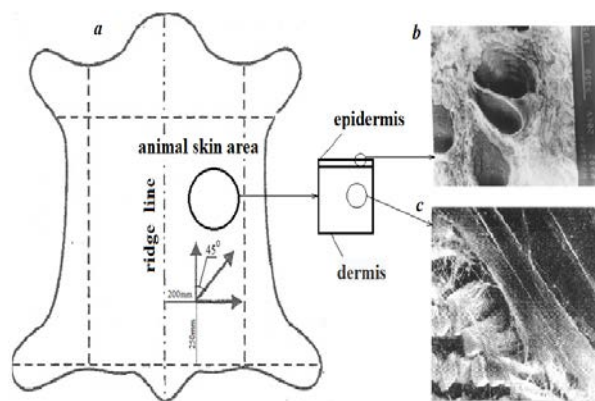


Fig. 1. The structure of leather: a) the plane of the leather; b) a photo of the leather surface at a magnification of 350 times; c) a network of collagen fibers

This material shows probabilistic anisotropic physical and mechanical properties [27]. At the same time, the value of the property indicators can vary both in magnitude and direction [28,29].

If we accept the hypothesis of orthotropic properties of leathers, then to assess the strength in the plane of the material, it is necessary to know the indices for two main mutually perpendicular axes and at an angle of 45° to them [30].

Thus, the number of physical tests for the strength of the material increases, which leads to an increase in the complexity of the measurement process and material consumption.

This study set the task of obtaining predictive values of strength indicators in two directions depending on the obtained experimental values in one direction of anisotropy.

Samples were taken from 20 calfskins; the ultimate strength of the leather fabric was determined by uniaxial tensile tests on specimens cut in the longitudinal (along the ridge-line) and transverse directions and at an angle of 45°. Uniaxial tensile testing of specimens up to the moment of rupture was performed according to the standard procedure [31] on a Tinius Olsen H25KS tensile-testing machine, with the registration of the results on a paper carrier.

Due to the limited number of samples, the entire data set was divided into a training, test, and control set in the percentage ratio of sample volumes 40-30-30.

The hypothesis of normal distribution of experimental data was put forward. Table 1 shows the values of testing the hypothesis by the Pearson criterion.

Orthographicity is a special case of anisotropy. This is a hypothesis, i.e. the assumption that the material exhibits orthotropic properties in the plane of the sheet, while the properties along the thickness of the material are not considered, since, in products, it is necessary to monitor the strength properties of the material only in the plane.

Table 1. Values of Pearson criterion quantities χ^2

Material	Direction	Calculated value χ^2	Critical value χ^2
Chrome-tanned bovine leather	along the ridge-line	5.944	5.991
	across the ridge-line	1.836	5.991
	at an angle of 45° to the ridge-line	1.570	5.991
Chrome-tanned calfskin	along the ridge-line	5.801	5.991
	across the ridge-line	4.52	5.991
	at an angle of 45° to the ridge-line	1.982	5.991

The critical value of the Pearson χ^2 test, at a significance level of $p = 0.05$ and a number of degrees of freedom of 1, is 5.991. Correlation analysis of data between properties in different directions was not considered in this work. It can be the goal of independent work.

In accordance with the obtained values of the Pearson criterion, the hypothesis about the selected distribution laws can be considered as plausible [32]. Data sets were obtained and probability models of the data were made taking into consideration the functional dependencies and generation of random variables according to the normal law.

After modeling the data for the training set, the data retrieval was obtained in the ratio 60-20-20, while the calculated data were included only in the training set. The test and control data sets were formed based on the results of physical experiments.

3. Artificial neural network

A single-layer neural network of back propagation with the number of neurons in the hidden layer of the network equal to 20 was used during the work (Fig. 2). As well as a two-layer neural network of direct propagation with four inputs and two outputs with the number of neurons in the hidden layers of the network is equal to 10 in one layer (Fig. 3). In both cases, the backpropagation network was used.

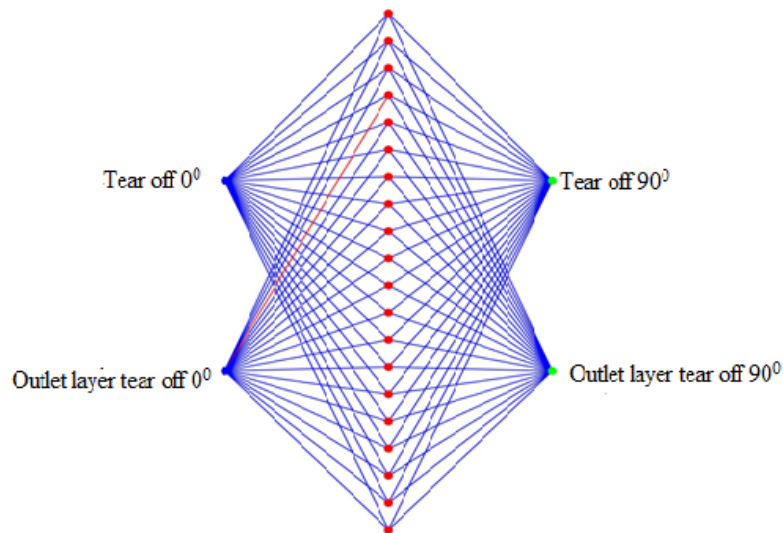


Fig. 2. Single-layer neural network

The values of the algorithm parameters: learning rate coefficient $\eta = 0.1$; learning moment coefficient $\mu = 0.9$; the weights are corrected after presenting each example of the training set.

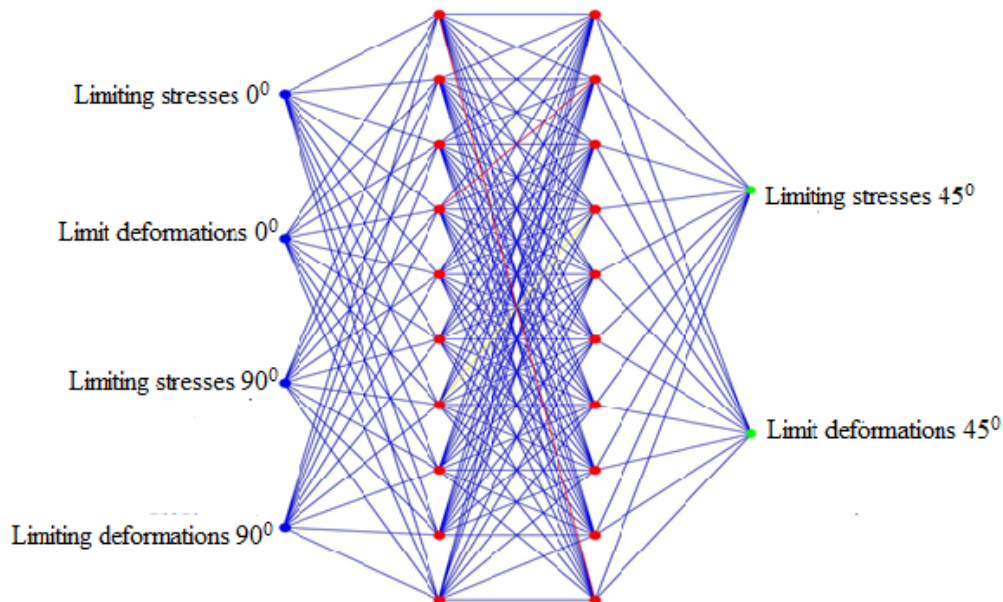


Fig. 3. Two-layer neural network

4. Results and discussion

A single-layer neural network was used to predict the values of ultimate tensile stress and ultimate tensile stress of the Outer layer in the direction perpendicular to the ridge-line, based

on the values of ultimate tensile stress and ultimate tensile stress of the Outer leather layer in the direction parallel to the ridge-line. Figures 4 and 5 show the scatter diagrams of the output parameters of the training and test network for common data of natural bovine and calfskin leathers. The diagrams show that the largest error of the neural network is 15% on the data of the Outer layer tearing (cracking).

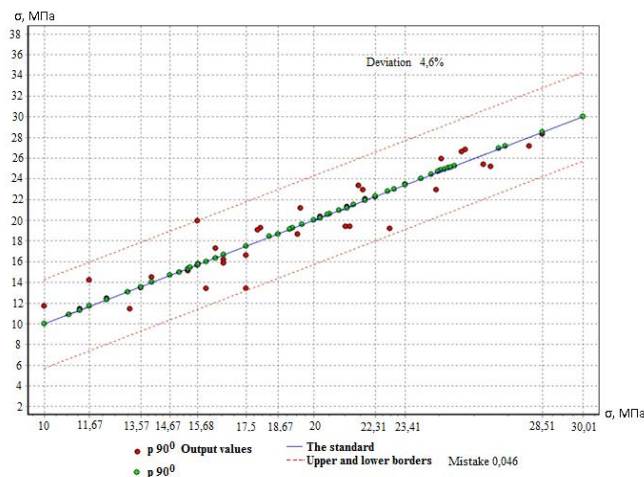


Fig. 4. Scatter diagram of the output parameters when tear-off a leather in the direction perpendicular to the ridge I

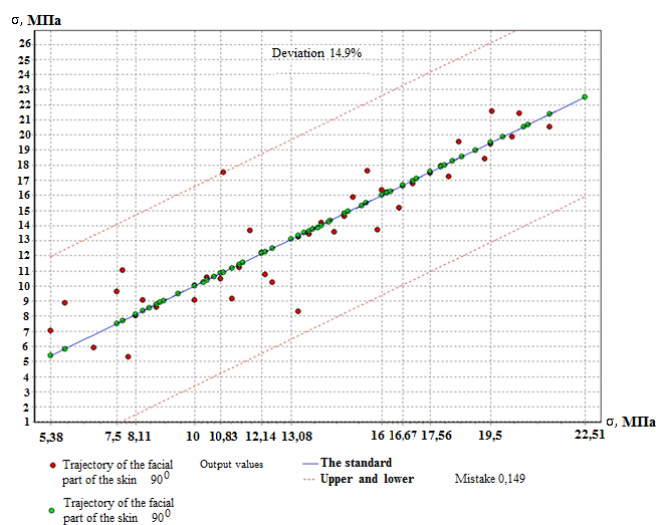


Fig. 5. Scatter diagram of the output parameters when tear-off of the leather outer layer in the direction perpendicular to the ridge-line

The largest discrepancy between the experimental and calculated values on the control set is 13.84% for the ultimate stresses at the tearing (cracking) of the Outer layer, a large scatter of errors at the tearing of the Outer layer occurs due to the difference in the structure and properties of this layer in different types of leather. Analysis of the data presented for training, testing, and control calculations shows that the accuracy of the calculations is greatly influenced by the order of grouping. In this case, the data were grouped randomly, without taking into account the types of leathers understudy, which led to a decrease in the accuracy of the network model. Prediction of the ultimate stress value in 45° direction to the ridge-line direction, based on the values of the limit states of stresses and strains for tearing in the direction parallel and perpendicular to the ridge-line of the calfskin was carried out using a two-layer neural network. This is a standard display of scatterplots that graphically show the

result of the neural network during training. The text indicates that the stresses were measured in MPa, the relative ultimate deformations are dimensionless and were determined by the Cauchy formula.

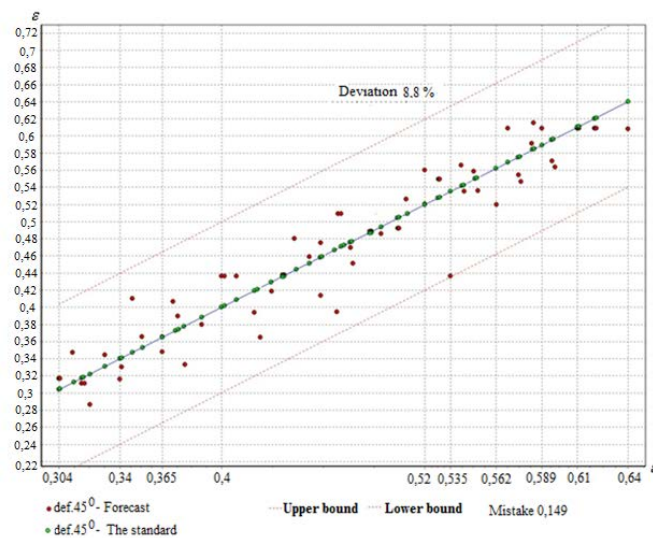


Fig. 6. Scatter diagram of the output parameters when the determination of the Ultimate strains of chrome-tanned calfskin in 45° direction to the ridge-line

As a result, the scatter diagrams (Fig. 6) of output parameters of the training and test sets network were obtained. The diagrams allow us to conclude that the largest neural network error when modeling the indicators of limiting states of chrome-tanned calfskin in the direction of 45° and the ridge-line is 8.8% for the Ultimate strains and 3.1% for the Ultimate stresses. This indicates that the predicted and experimental data were fairly well consistent.

5. Conclusion

Analysis of the results shows that the values of Limit states of leather fabric obtained using neural networks agree well enough with the experimental data, which allows us to recommend neural network technology for predicting the strength properties of chrome-tanned leather. The conducted studies have shown that in order to increase the accuracy of the forecast, it is necessary to build a neural network model for each type of leather separately. The usage of an artificial neural network for forecasting will reduce the time spent on testing and consumption of natural leather at enterprises that produce leather and use it for products manufacturing in the manufacture of products.

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