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Tensile Strength Prediction of Fiberglass Polymer Composites Using Artificial Neural Network Model

PAULINA SPANU*, BOGDAN FELICIAN ABAZA
University Politehnica of Bucharest, 313 Splaiul Independentei, 060042, Bucharest, Romania

Abstract: *Highlighting the properties of polymer composites is a complex process given their great diversity and the wide range in which their characteristics could vary. An Artificial Neural Network model for predicting tensile strength was designed using LabVIEW software. The proposed model was developed for randomly reinforced polymeric composite materials with 30, 40 and 50% fiber-glass. Volume fraction of glass fibre has represented the independent variable for this study. The dependence of the tensile strength on the volume fraction was investigated and highlighted by modelling using neural networks. The designed Artificial Neural Network behaves as a computational system that process data input into a desired output using a network of functions composed of layers. The training process was developed with different Artificial Neural Network architectures with two hidden layers to produce the best prediction results. For each hidden layer the number of neurons was varied be-tween 3 to 50.*

Keywords*: artificial neural network, composite, LabVIEW, tensile strength*

1. Introduction

Polymeric composites are artificial materials made of two or more different, immiscible materials, to which can be added various constituent elements, which have the role of improving the properties of the composite [1, 2]. The properties of composites with polymeric matrix vary widely for the same composite material from one point to another, being dependent on many factors. The main factors that influence the properties of polymer composites are: the type of the constituents, their volume or mass percentages, the shape and dimensions of the reinforcing element, the arrangement of the reinforcing elements in the matrix, the interface between fibers and matrix and the technological conditions for obtaining constituent materials and composite material resulting from the combination of constituents (Figure 1). The shape and orientation of the fibers in the matrix determine the degree of anisotropy of the composite properties while the distribution of the reinforcing elements influences its homogeneity.

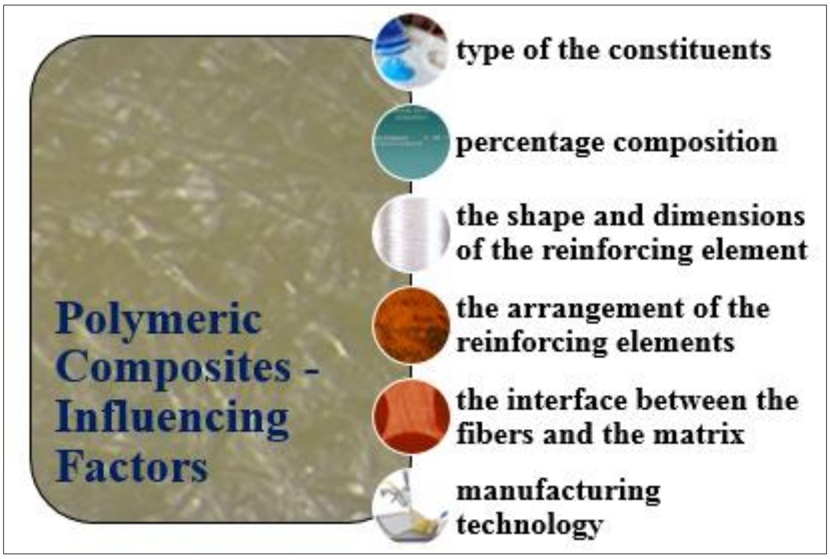

Figure 1. Influencing factors of the properties of polymeric composites

**email: pauspa16@yahoo.com*

The mechanical properties of polymeric composites can be optimized by judiciously combining the polymeric matrix and reinforcing materials, by properly choosing the shape and dimensions of the fibers, and by controlling the dispersion of the fibers in the matrix. The process of optimizing the properties according to the field of use of the final product proved to be quite difficult considering the possibilities of combining them from a quantitative and structural point of view.

Experimentally determined polymer composite property values can be used in preliminary design calculations of composite products, but require time and resources to determine them. Their determination using the theoretical models based on Artificial Neural Network proved to be extremely efficient in the design stage of composite materials.

Artificial Neural Network (ANN)

Artificial Neural Network (ANN) was inspired by the biological nervous system and it behaves as a computational system that process data input into a desired output using a network of functions. The network is composed from interconnected elements (nodes) called artificial neurons [3]. The common architecture of an ANN consists of three layers: input layer with neurons represented by input data, hidden layer which contains a specific number of hidden neurons, and output layer with neurons, represented by the output data (number of neurons are equal with the number of desired outputs) [4,5].

The mathematic representation of an individual neuron within an ANN is represented in Figure 2. The input vector (x1,x2,…xi) is transferred using a connection that multiples its strength by a weights (wi). The output is obtained to summation function with a specific bias (b) and an activation function. In this research it was used a feedforward neural network with sigmoidal unipolar activation function [5].

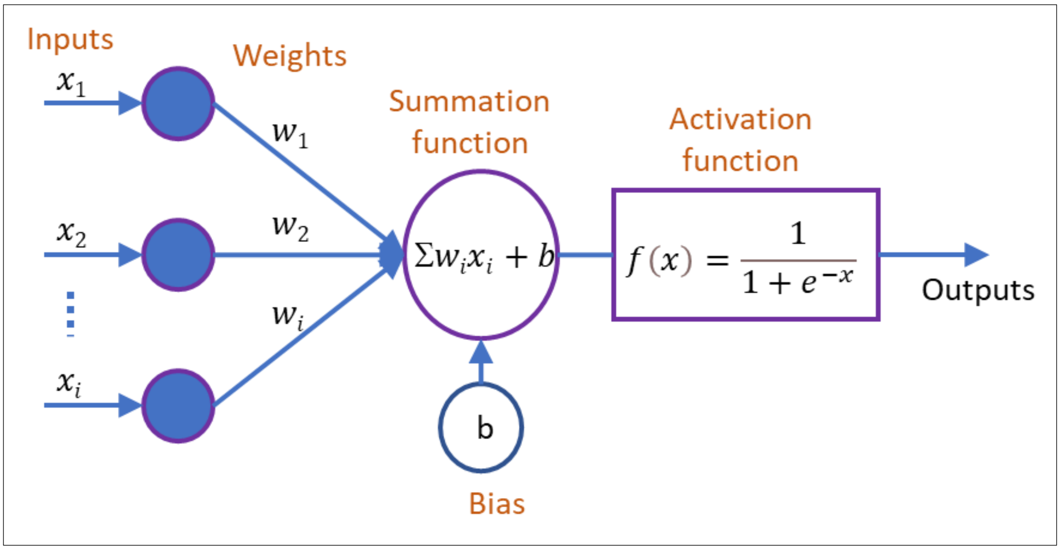

Figure 2. Mathematic representation of Artificial Neuron [5]

The chosen teaching algorithm for the ANN was Resilient Propagation (RProp) for actual study due its generality, and because it adjusts the step size dynamically for each weight independently [6].

2. Materials and methods

The materials used in this study were polymeric composites made of an AROPOL S 599 polyester resin matrix, and EC 12-2400 fiberglass. The fibers used were short with a filament diameter d = 12 [µm] and thread fineness = 2400 [tex]. The arrangement of the fibers was random, with a percentage of 30, 40 and 50% respectively, and was controlled by the technological equipment used to manufacture the composite. The technology used to combine the constituents of the composite was spray forming.

The determination of the tensile characteristics of polymeric materials, randomly reinforced with fiberglass, has performed using a standardized method, according to SR EN ISO 527: 2000. The equipment used to perform the tensile test was the universal machine LFV 25 HH WALTER-BAI.

For this study, ANN application software for tensile strength prediction (TS [MPa]) was designed for composite materials based on fiber volume fraction (Fiber_VF [%]). The volume fraction of the fibers was the independent variable for this research.

3. Results and discussions

The ANN Application Software was developed in a system engineering software, LabVIEW, using a graphical programming approach for developing data analysis algorithms, and which allows designing custom engineering user interfaces. For the ANN component it was used an addon toolkit: NI Super Simple Neural Network with these relevant specifications [7]:

- It uses a feedforward neural network with sigmoidal unipolar activation function, and it uses RProp teaching algorithm.
- Automatic linear scaling of inputs and outputs to the linear range of the neurons for optimum performance.
- Option to add BIAS inputs to every layer of the network.
- One hidden or two hidden layers.
- Teaching in chunks from a binary file.
- Option to evaluate error function over validation set.
- Saving and loading the network from file.

A key step in developing the ANN model is preparing the data sets for training, validation, and testing. In present research, the data sets that were prepared based on experimental research trials are presented in Table 1.

Table 1. Tensile strength results [MPa]

Sample	Tensile Strenght [MPa]		
	Fiber volume fraction 30 %	**Fiber volume fraction 40 %**	**Fiber volume fraction 50 %**
T1	90.39	115.39	132.12
T2	101.27	121.88	143.45
T3	87.68	116.65	140.11
T4	90.44	126.23	136.57
T5	92.44	118.44	145.67

For preventing the retraining of the ANN, the data sets were processed taking in account that, for value of fiber volume fraction there were developed five trials for measuring the tensile strength. In this sense, after normalizing the data, different data sets were generated using specific virtual instruments (sub-VIs) for preparing the datafiles used for teaching and validation of ANN (Figure 3).

The training process was developed with different ANN architectures with two hidden layers. One important key step in this process it was to investigate and discover the right architecture which produced the best prediction results. In this paper different architectures with different number of neurons for each hidden layer were tested. For each hidden layer the number of neurons was varied between 3 to 50. When the sub-VI RProp teaching algorithm found a solution (the ANN Error Trend out became less than the Error Goal) then the resulted ANN was saved, and its prediction was tested with another experimental data set. After that the Max Error [%] and coefficient of determination R^2 were calculated, and ANN Architecture was automatically saved [5]. A partial diagram with the algorithm for training process is presented in Figure 4.

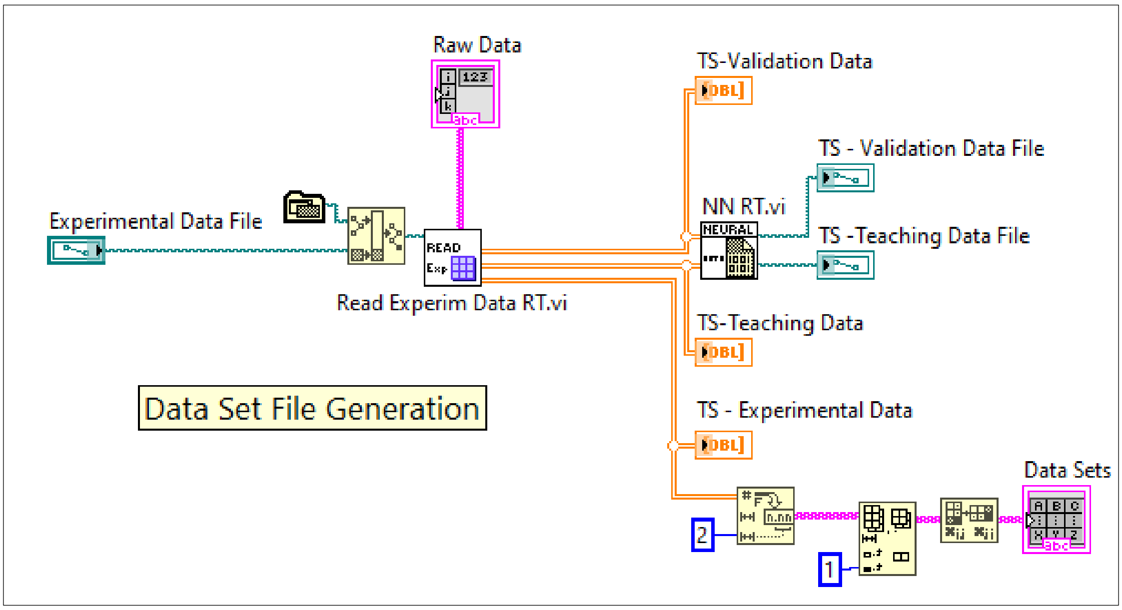

Figure 3. Partial diagram of Application Software for generation of data set files for teaching and validation the ANN

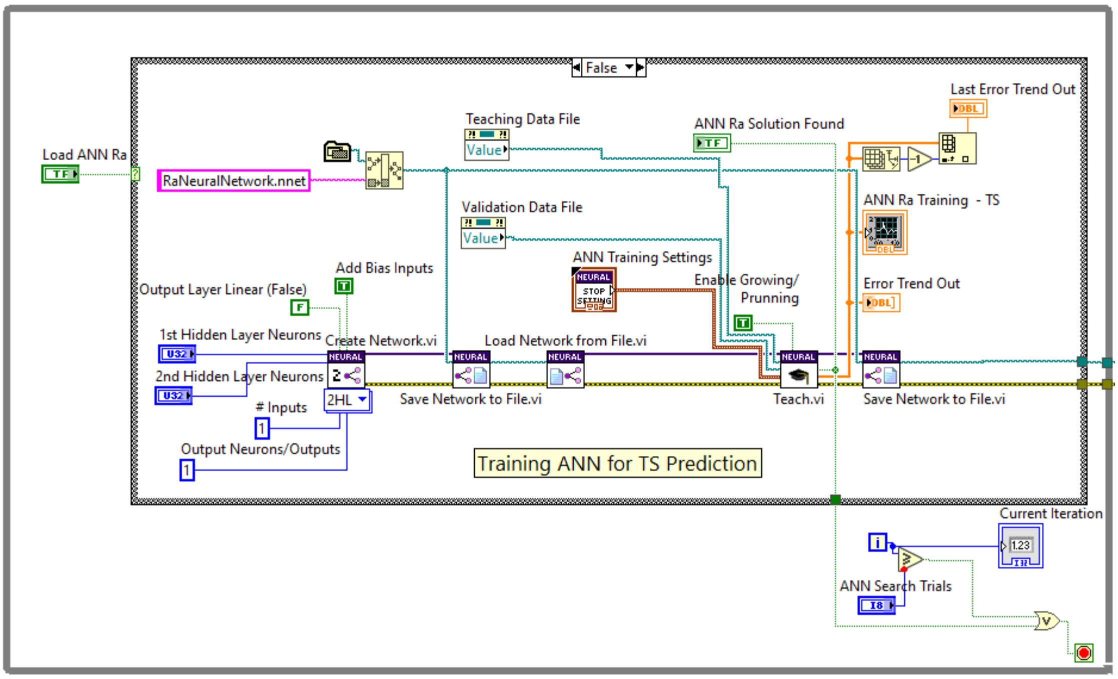

Figure 4. Partial diagram of Spplication Software for algorithm for training process of ANN model

In Figure 5 is presented the plot of Error Trend Out for the training ANN process. There are also indicated the associated training parameters: Error Goal, Max Time, Training Error Evaluation, Vectors per iteration. The algorithm of training indicates if solution was found and calculates the last Error Trend Out of the teaching process. When the process ends out with Solution Found then specific ANN data files for the model found are saved.

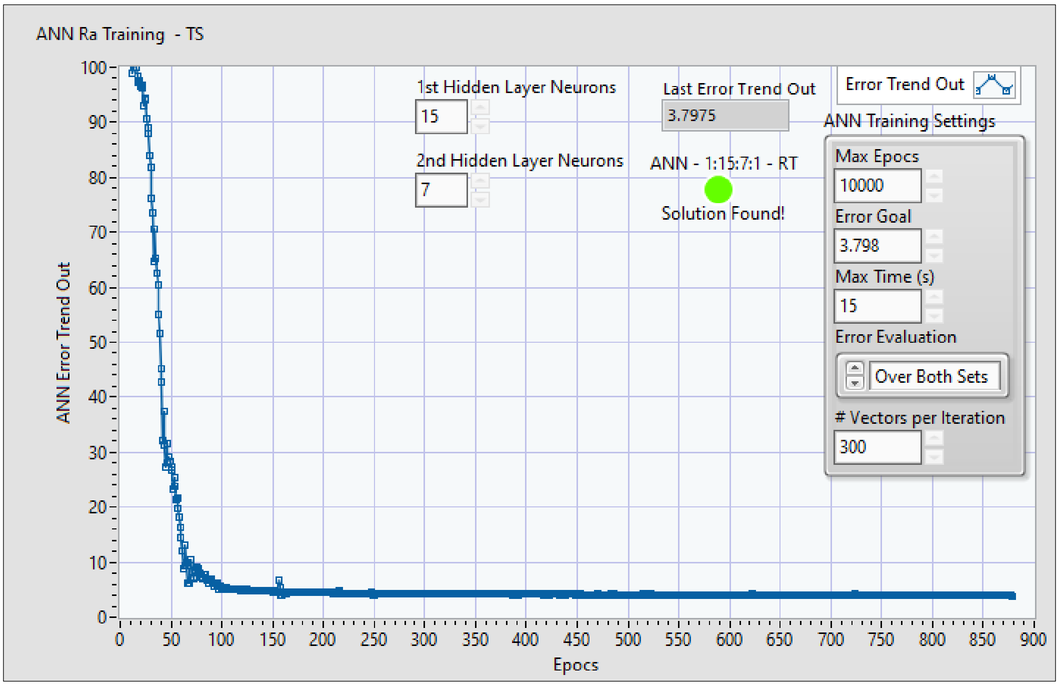

Figure 5. Plot of error trend out during ANN training

Prediction of tensile strength analysis

Prediction performance was analysed based on coefficient of determination (R^2) which is a statistical measure on how the prediction model matches with the real data points. For an ideal match fit of prediction data model should have a coefficient of determination of 1.0. In our study the analysis was made between the output (predicted TS) values and the target (experimental TS) values [8].

Figure 6 displays one of the ANN 1-15-7-1 model architectures found for our research with one input neuron (Fiber Volume Fraction - Fiber_VF), 15 neurons on first hidden layer, 7 neurons and second hidden layer and one output neuron (predicted Tensile Strength - TS). Using a specific sub-VI RProp teaching algorithm an architecture with a set of neurons for each hidden layer was generated and trained. In this ANN configuration in training process an ANN solution was found because the ANN Error Trend Out became less than the Error Goal. The current configuration of the ANN was saved, and its prediction was tested with another experimental data set. The Max Error [%] and coefficient of determination R^2 were calculated.

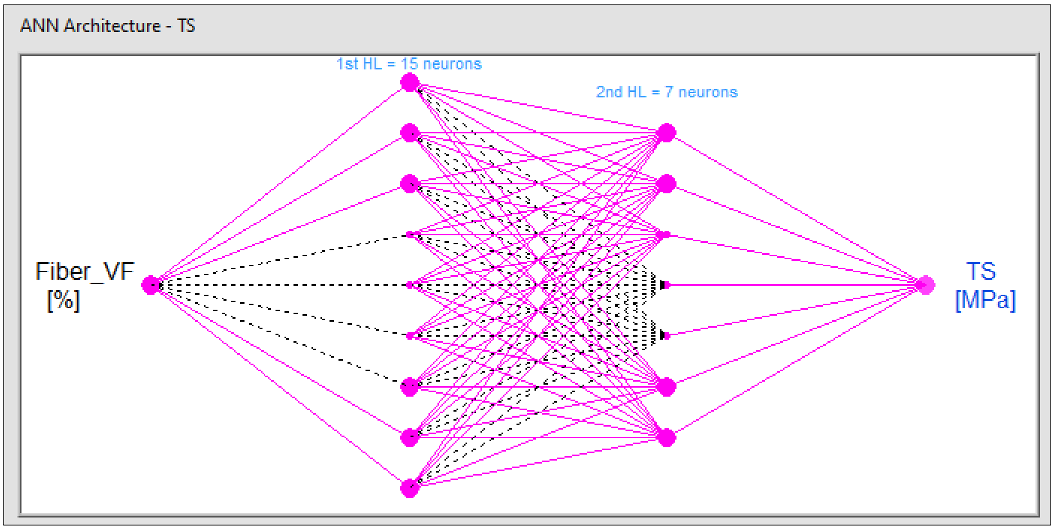

Figure 6. ANN architecture 1-15-7-1 for Tensile Strength prediction

The performance of prediction for this ANN 1-15-7-1 architecture was indicated in the Figure 7 with two plots of the tensile strength: one is for the experimental data set (TS Experimental), and the other is the data set with the prediction which resulted from the ANN model (TS ANN). This shows that the plot of predicted tensile strength is very close to the experimental one. The calculated R^2 and Max Error are also displayed. In this plot the current ANN 1-15-7-1 model has a prediction with a maximum error of 2.88075%.

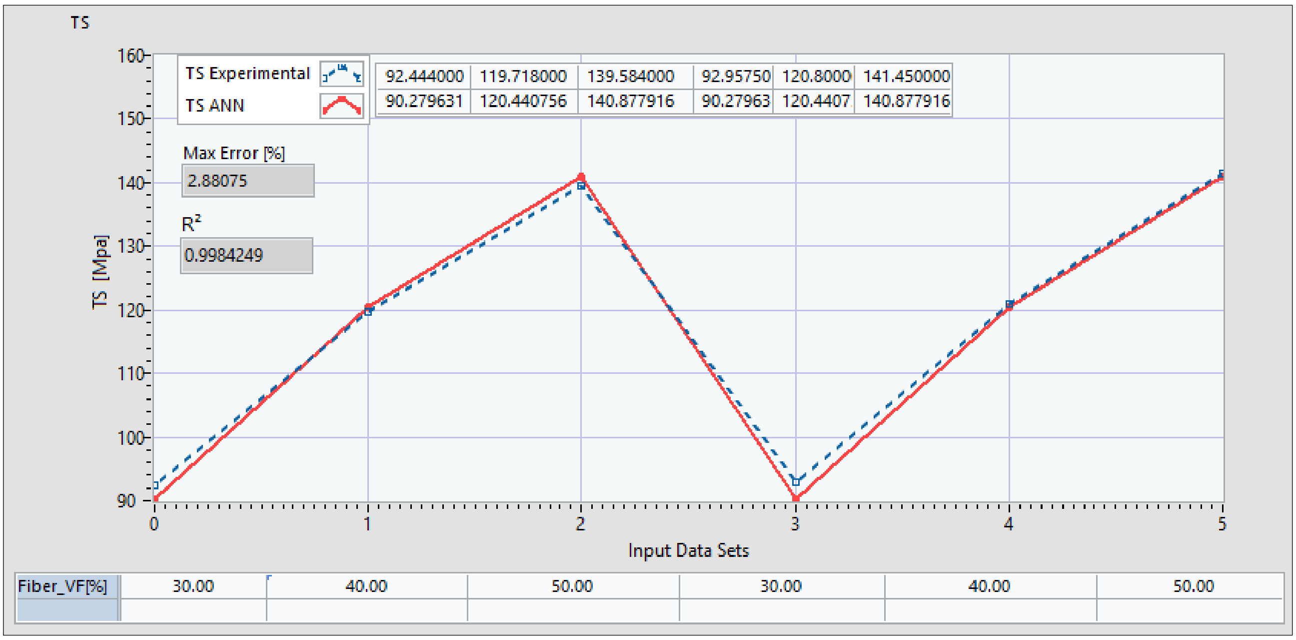

Figure 7. Tensile Strength comparation between experimental data and prediction with ANN 1-15-7-1

Figure 8 shows the tensile strength prediction performance of ANN 1:15:7:1 with error distribution per data set. This shows a deeper view of prediction error variance per each data set for the current ANN model.

In Figure 9 was calculated the coefficient of determination R^2 and correlation between the predicted values and experimental data. The resulted value of R^2 is very close to 1 which indicate a very close to the ideal match.

This research succeeds to investigate and discover an ANN model of a 1-15-7-1 architecture which predicts with an error less than 5% and to have a coefficient of determination R^2 greater than 0.9984249. One of the key steps was related to the discovering the ANN architecture model. In present work it was confirmed that there are no general rules for defining the number of hidden layers for all ANN architectures and this can be determined only by employing a trial-and-error method [3]. As a solution, in this paper it was also investigated a custom algorithm for generating different architectures with different number of neurons for each hidden layer. It was set to generate combinations of architectures with neurons which varied between 3 to 50 for each hidden layer. Based on error prediction it was selected and presented an architecture with ANN 1-15-7-1 model. The prediction result obtained proves that the current ANN 1-15-7-1 model has a very good prediction performance.

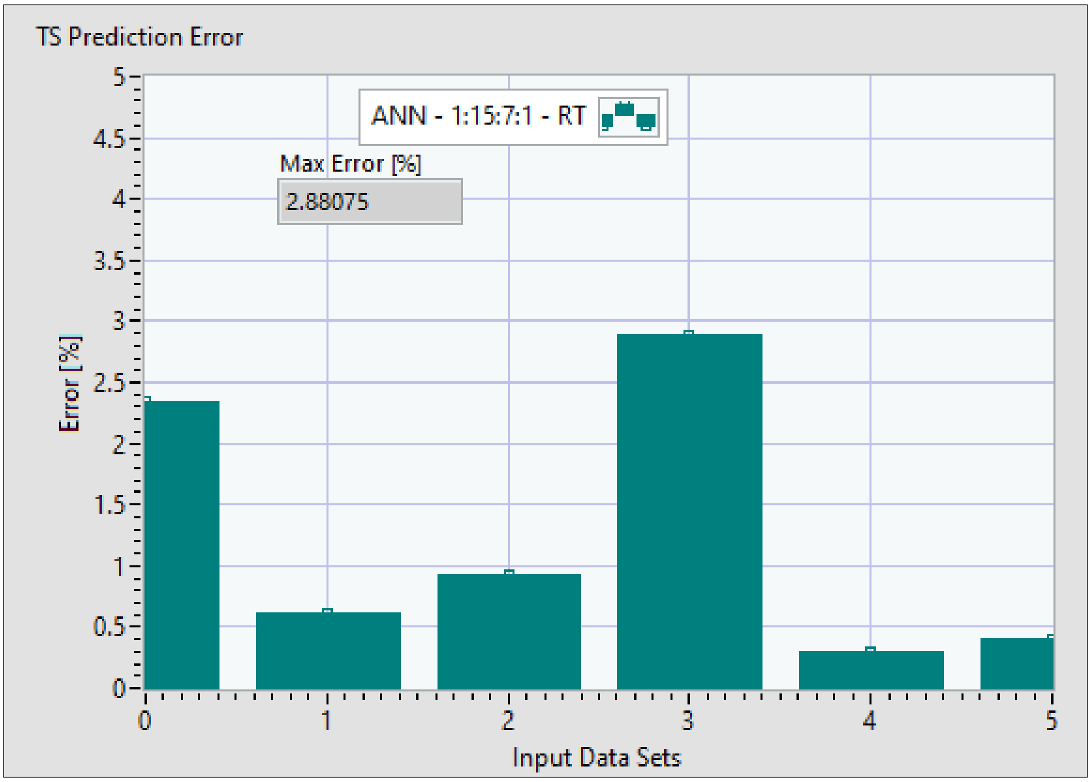

Figure 8. Tensile Strength prediction performance of ANN 1-15-7-1 - error distribution per data set

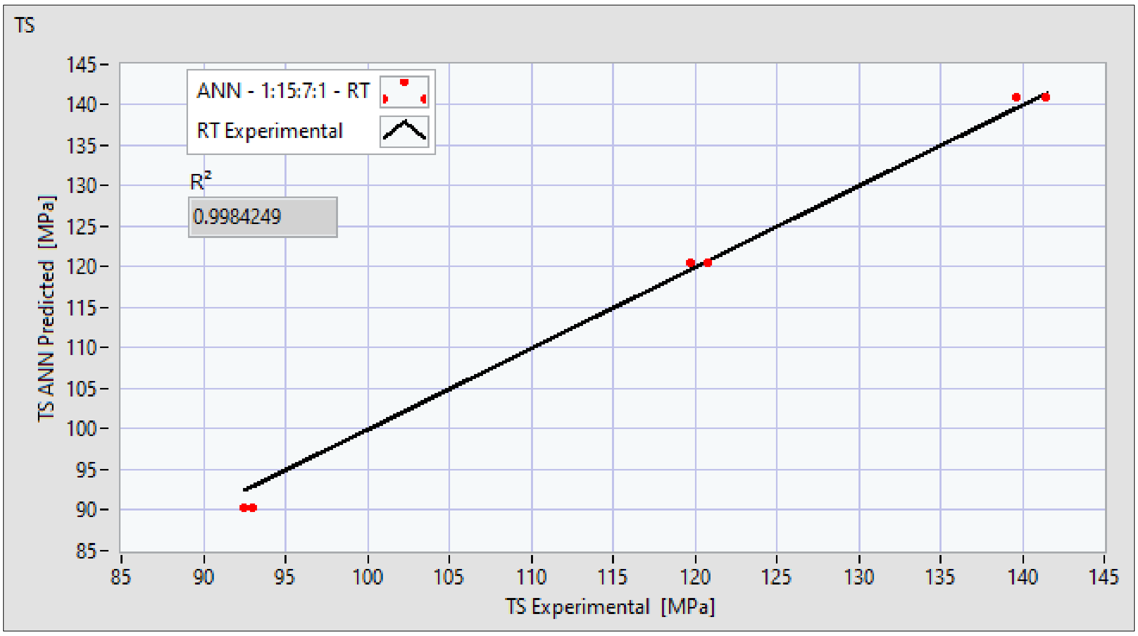

Figure 9. Coefficient of determination R^2 and correlation between the predicted values and experimental data

4. Conclusions

In this article, the highlighting was considered the influence of the volume fraction of glass fiber on the tensile strength of polymeric composites randomly reinforced with glass fiber. Therefore, an experimental research program was designed and implemented which involved tensile testing of 5 samples of each type of composite material. The experimental results were used as data entry for developing a prediction model where the volume fraction of glass fibre was selected as an independent variable in the Artificial Neural Network system. The proposed ANN model was trained using two hidden layers, for each hidden layer the number of neurons was varied be-tween 3 to 50.

The analysis of the results obtained with the ANN software application made in LabVIEW revealed a high prediction accuracy of the tensile strength. The prediction errors obtained with the proposed ANN 1-15-7-1 model were less than 5% and the coefficient of determination R^2 was greater than 0.99.

The results from this research encourage for further developments on theoretical and experimental research on compressive and bending strength using ANN's models implemented in custom developed software for assisting composite material designing process.

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