Modeling of Mechanical Properties of Wood-Polymer Composites with Artificial Neural Networks

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Mechanical properties (tensile strength (TS), modulus of elasticity in tensile (MET), flexural strength (FS), modulus of elasticity (MOE)) of the material to be obtained depending on the production parameters in the production of high-density polyethylene (HDPE) wood-polymer composites with Scots pine wood flour additive were predicted using Artificial Neural Networks (ANN) model and without destructive testing. In the first stage of the study, an ANN model was developed using data from 56 different studies in the literature on the mechanical properties of wood polymer composites. In the second stage, in order to determine the reliability of the model, output values were estimated using input parameters that had not been used in training and testing of the model. Based on the same input parameters, test specimens were produced and mechanical tests were performed. The results obtained from the experiments and ANN model were compared by considering the mean absolute percentage error (MAPE) value. The coefficient of determination (R^2) values obtained in the training and testing phase of the ANN models were all higher than 0.90. In this way, the mechanical properties of the wood polymer composite were successfully predicted by the ANN model. Because most of the MAPE values obtained from the mechanical tests were below 10%, the model was considered a reliable model.

DOI: 10.15376/biores.19.3.4468-4485

Keywords: Tensile strength; Flexural strength; Modulus of elasticity; HDPE; MAPE

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INTRODUCTION

New material that is formed by the combination of at least two different materials in macro dimensions is called a composite material. In the production of composite materials, materials that are not suitable on their own and cannot dissolve in each other are given new properties such as lightness, cost, flexibility, and strength to make them suitable for their areas of application. Wood polymer composites are also used to replace wood materials. The variety of materials and production parameters used in the manufacture of wood polymer composites results in a wide range of mechanical properties of the resulting material. Determining the mechanical properties of composites of different compositions using destructive testing methods is both laborious and costly. For example, for the validation experiments carried out in the later stages of this study, approximately 40 working hours were spent with two people in the laboratory environment. From a manufacturer's perspective, extra time spent on production, labor costs, electricity costs, machine depreciation, *etc.*, will arise. Additionally, the manufacturer may not have the necessary equipment and skills to perform mechanical testing, resulting in the need to hire outside services, which can be time-consuming and costly. Using the ANN method, it is possible to reach the same result within minutes by trying different parameters. In this way, predicting the properties of the material to be produced in advance will save time and money.

To effectively use ANN, the usual procedure is to collect information about samples, make generalizations, and then make decisions about those samples using the learned information to make predictions about samples not yet considered in the analysis. Due to these learning and generalization properties of ANN, it finds wide application in many fields of science today and demonstrates its ability to solve complex problems (Ergezer *et al.* 2003). Therefore, ANN modeling can be successfully applied to the prediction of mechanical properties of composite materials.

One important class of composite materials is wood polymer composites. Only one study on predicting the mechanical properties of these composites with ANN using low-density polyethylene (LDPE) was found (Atuanya *et al*. 2014). When looking at the studies on determining the mechanical properties of wood polymer composites, it is apparent that HDPE, LDPE, and polypropylene (PP) polymers are often used due to their low cost and ease of processing.

The studies using HDPE as the polymer used pine, poplar, fir, acacia, oak, maple, beech, rubber, and cedar wood flour as fillers, maleic anhydride grafted polypropylene (MAPP), maleic anhydride grafted polyethylene (PE-g-MA) as coupling agent, and various minerals as additives. The tensile and flexural properties of composites made from recycled HDPE are similar to those of composites made from virgin HDPE (Adhikary *et al.* 2008). Significant increases in mechanical properties have been reported with the addition of coupling agents and additives such as MAPP, PE-g-MA, and silane (Adhikary *et al.* 2008; Nourbakhsh and Ashori 2009; Mbarek *et al.* 2011; Koohestani *et al.* 2017). In general, mechanical properties improve with increasing wood filler content (Bouafif *et al.* 2009; Nourbakhsh and Ashori 2009; Mbarek *et al.* 2011; Koohestani *et al.* 2017; Martins *et al.* 2017). Modulus of elasticity, flexural values, and tensile strength values increase with increasing wood flour particle size (Bouafif *et al.* 2009; Rafighi *et al.* 2014; Chaudemanche *et al.* 2018). However, some studies reported a decrease in mechanical properties with increasing particle size (Homkhiew *et al.* 2018), and an increase in wood flour content decreased flexural, tensile, and impact strength (Balasuriya *et al.* 2001). Rafighi *et al.* (2014) reported that there was no significant difference in the mechanical properties of wood polymer composites concerning wood species.

In the studies with PP, Scots pine, poplar, maple, oak, Weymouth pine, beech, cypress, spruce, fir, red pine, and eucalyptus, MAPP as coupling agent and various minerals as additives were preferred as fillers. Different results on the mechanical properties of wood-PP composites have been reported in the literature. In some studies, the mechanical properties of the composites were found to decrease with increasing wood flour content (Bledzki *et al.* 2002; Kaymakçı 2015). The mechanical properties increase when coupling agents are used (Oksman and Clemons 1997; Bledzki *et al.* 2002; Stark and Rowlands 2002; Bledzki and Faruk 2003; Ndiaye *et al.* 2010; Nourbakhsh and Ashori 2010; Kaymakçı 2015) and when wood flour particle size is reduced (Nourbakhsh and Ashori 2010; Haque *et al*. 2019; Leu *et al.* 2012; Delviawan *et al.* 2019; Murayama *et al.* 2019).

It was found that polymer-wood flour blend samples had lower impact resistance values compared to pure polymer (Nourbakhsh and Ashori 2010; Haque *et al.* 2019). In another study, the notched impact strength increased with increasing wood flour size (Stark and Rowlands 2002). Increasing wood flour content increases flexural strength and modulus of elasticity, decreased impact strength and tensile strength, and adding 5% clay to the samples significantly decreased modulus of elasticity (Ndiaye *et al.* 2010). Increasing wood flour content increases modulus of elasticity and modulus of elasticity in tensile, decreases flexural and tensile strength, and increases notched impact strength but decreases unnotched impact strength (Stark and Berger 1997; Leu *et al.* 2012). Minerals increase the impact strength of composites (Oksman and Clemons 1997). Karmarkar *et al.* (2007) reported that an increase in wood flour content increased tensile strength and modulus of elasticity in tensile and decreased notched impact strength.

In the studies using LDPE, spruce, radiata pine, eucalyptus, acacia, oak, and rubber were preferred as fillers, PE-g-MA as coupling agent, and various minerals as additives. While there are studies indicating that increasing the amount of wood flour positively affects the mechanical properties of the samples (Turku *et al.* 2017; Moreno and Saron 2017), Effah *et al.* (2018) stated that increasing the wood flour content caused a decrease in the mechanical properties of the samples and pure LDPE had higher impact resistance than all composites. Prachayawarakorn *et al.* (2006) reported that as the amount of wood flour increased, the modulus of elasticity in tensile and modulus of elasticity increased, and the tensile, flexural, and impact resistance decreased significantly. The use of coupling agents (Turku *et al.* 2017) and minerals (Prachayawarakorn *et al.* 2006) has been reported to improve the mechanical properties of composites.

In the studies available in the literature on predicting the mechanical properties of wood polymer composites using ANN, a back-propagation multilayer perceptron ANN model was used to predict the mechanical properties of samples made from palm wood fiber and recycled LDPE. Increasing filler content decreased tensile strength, increased flexural and notched impact strength, and achieved a coefficient of determination over 0.95 between ANN predictions and experimental results in all tests (Atuanya *et al.* 2014).

This study aimed to predict the mechanical properties of the material to be obtained as a function of the production parameters in the production of wood polymer composites using the ANN model, without destructive testing, much faster and at a low cost.

Because the test specimens produced in small numbers and under the same conditions are mostly used in the studies modeling with ANN, it is assumed that the models tend to be memorized rather than learned, and therefore R^2 values are high. However, due to the different machinery, equipment, and working environment conditions used in the production of wood polymer composites, and the variations in the structure of the polymers used depending on the manufacturer, the variation in the results obtained is greater. It is predicted that the use of a larger database obtained from different sources in the training of the model will provide more realistic results. For this reason, this study aims to make more realistic predictions by using studies in the literature on the mechanical properties of wood polymer composites in the creation of the ANN model. It is aimed to determine the reliability of the model by comparing the mechanical test results of the samples produced with the input parameters not included in the training of the model with the values predicted with the same input parameters.

EXPERIMENTAL

Materials

To determine the reliability of the ANN model, the wastage parts were evaluated in species with high market value that are frequently used as filler in composites. Scots pine (*Pinus sylvestris*) wood chips were obtained from Bağdatlı Kereste in Safranbolu Industrial Zone. Polymer HDPE (density: 0.964 g/cm^3, melting index: 190 °C, 8 to 22 g/10 min, pellet form, white and odorless) and coupling agent PE-g-MA (density: 0.97 to 0.99 g/cm^3, pour point: 120 to 126 °C, viscosity 80 to 200 mPa-s, white, fine-grained powder) were used.

Methods

The study consisted of two stages. In the first stage, a literature search was conducted on the mechanical properties of wood polymer composites, and an ANN model was developed using data obtained from 56 different studies directly related to the mechanical properties of wood polymer composites. In the second stage, to determine the reliability of the model, output values were estimated using input parameters that were not previously used in the training and testing of the model. Based on the same input parameters, test specimens were produced, and mechanical tests were performed. The results obtained from the experiments and the ANN model were compared by considering the MAPE value.

Creating the ANN Model

The literature showed that the values of tensile strength, flexural strength, modulus of elasticity in tensile and modulus of elasticity of wood-polymer composites were the most commonly investigated, as well as the effect of filler content, particle size, and coupling agent use on these mechanical properties was also investigated. The data used to create ANN models are given in Table 1, and accordingly, the input parameters and output values of the ANN model were determined. Because the mechanical properties determined in the studies in the literature were not the same, a separate model was created for each of the above mechanical properties. Polymer type, filler type, filler blend ratio, filler particle size, and coupling agent use were determined as input parameters, and the corresponding mechanical property was determined as an output parameter.

When modeling the ANN, the "feed-forward backpropagation" ANN algorithm was used because it can reduce errors backward and from output to input (Gönül *et al.* 2015). Eighty percent of the data obtained from the literature were used to train the model, and 20% were used to test the model. ANN models were created using MATLAB® R2017b software. The ANN architecture proposed in this study consists of an input layer, two hidden layers, and an output layer (5-n1-n2-1) (Fig. 1). The input layer represents the input parameters, and the output layer represents the mechanical property, which is the dependent parameter of the model. Although the structure of an ANN and the number of neural cells vary, there is no accepted rule for the formation of an ANN. Neural networks with fewer than the required number of hidden layers are inadequate for solving complex functions, while neural networks with too many hidden layers encounter undesirable instabilities. There is no mathematical test for how many neurons should be placed in the hidden layer in the most efficient way. These questions should be decided by trial and error (Ataseven 2013). Because of the complexity of the problem, two hidden layers were used instead of a single layer in this study. In the hidden layers, different numbers of neurons ranging from 5 to 20 were used experimentally to select the number of neurons with the highest accuracy of the model.

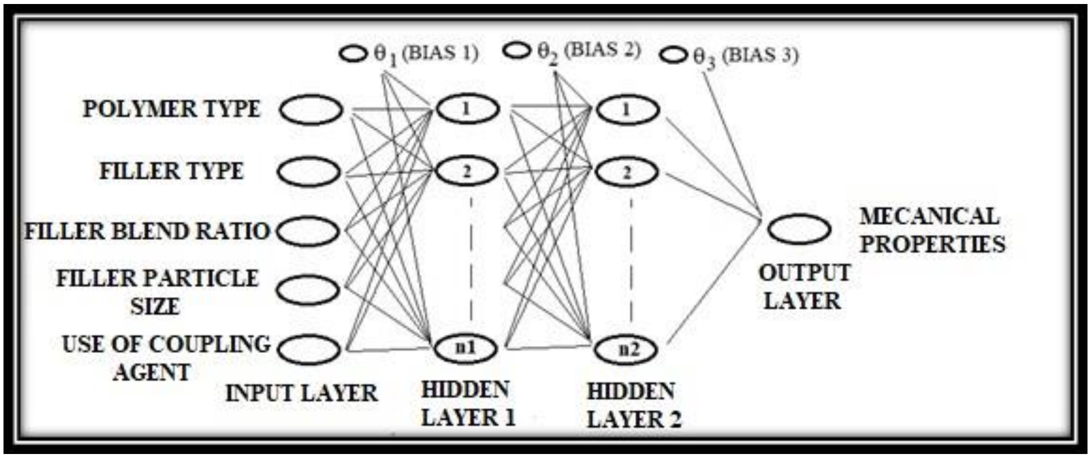

Fig. 1. ANN architecture developed to predict mechanical properties of wood polymer composites

In ANN, the activation function decides whether to activate a node or not. If each layer's activation functions were linear, they would be equivalent to a single layer, called linear transformations. Therefore, nonlinear activation functions are needed for the neural network to have multiple layers in a meaningful way. Among the nonlinear activation functions, sigmoid and tangent hyperbolic activation functions are widely preferred in the literature. The sigmoid function tends to vanish gradients when inputs are large or small (with gradients approaching zero). This can cause the gradients to "jam" and disappear during back-propagation. The tanh function preserves the gradients even when the inputs are large, resulting in a more stable training process. Since the tangent hyperbolic activation function derivative is steeper than the sigmoid function derivative, it can take more values, and this means that when using the tangent hyperbolic activation function, the ANN will be more efficient, as it will have a broader range for faster learning and classification (Szandała 2021). This property also helps to accelerate convergence during training.

In this study, ANN was used to predict the effects of production inputs on mechanical properties, which are considered material quality criteria in the wood polymer composite production process. Due to the diversity of inputs in ANN training and the variability in the predicted mechanical properties due to this input diversity, it was deemed appropriate to use the tangent hyperbolic activation function (Eq.1), which promises more stable training due to the advantages mentioned above.

$$f(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \tag{1}$$

Calculation of the change in bias and weight values used in the ANN model-learning algorithm (Duman *et al.* 2018) is given in Eq. 2 and 3.

$$\Delta w_{st}(k) = \alpha_{st}\Delta w_{st}(k\text{-}1) + \eta_{st}\left(-\frac{\partial E}{\partial e}\frac{\partial e}{\partial y_t}\frac{\partial y_t}{\partial \chi_t}\frac{\partial \chi_t}{\partial w_{st}}\right) \tag{2}$$

$$\Delta\theta_t(k) = \alpha_{st}\Delta\theta_t(k\text{-}1) + \eta_{st}\left(-\frac{\partial E}{\partial e}\frac{\partial e}{\partial y_t}\frac{\partial y_t}{\partial \chi_t}\frac{\partial \chi_t}{\partial w_{st}}\right) \tag{3}$$

The momentum and learning coefficients used in the ANN model were chosen in the range of 0 to 1 (Duman *et al.* 2018). As a result of the experiments conducted to obtain the highest R^2 value in the ANN model, the momentum and learning coefficients were applied as 0.0001.

Table 1. Studies Used in the ANN Model

No	Studies Using Data	TS	MET	FS	MOE	No	Studies Using Data	TS	MET	FS	MOE
1	Ratanawilai and Taneerat 2018	+	+	+	+	29	Ghahri *et al.* 2014			+	+
2	Turku *et al.* 2017	+	+	+	+	30	Gozdecki *et al.* 2012	+	+	+	+
3	Adhikary *et al.* 2008	+	+	+	+	31	Khonsari *et al.* 2015			+	+
4	Fabiyi and McDonald 2010			+	+	32	Bledzkı and Faruk 2003	+	+	+	+
5	Kaymakcı 2015	+	+	+	+	33	Turku *et al.* 2018	+	+	+	+
6	Nourbakhsh and Ashorı 2010	+	+			34	Gosselın *et al.* 2006		+		+
7	Koohestani *et al.* 2017	+	+	+	+	35	Homkhiew *et al.* 2018	+	+	+	+
8	Stark and Rowlands 2002	+	+	+	+	36	Najafi *et al.* 2006	+	+	+	+
9	Rafighi *et al.* 2014	+		+	+	37	Nourbakhsh and Ashorı 2009	+		+	
10	Stark and Berger 1997	+	+	+	+	38	Bouafif *et al.* 2009	+	+	+	+
11	Ndiaye *et al.* 2010	+		+	+	39	Bledzki *et al.* 2002	+			
12	Stark and Berger 1997	+	+	+	+	40	Prachayawarakorn *et al.* 2006	+	+	+	+
13	Moreno and Saron 2017	+	+			41	Atuanya *et al.* 2014	+	+	+	+
14	Mbarek 2011	+	+			42	Balasuriya *et al.* 2001	+	+	+	+
15	Oksman and Clemons 1997	+	+			43	Murayama *et al.* 2019	+		+	+
16	Arwinfar *et al.* 2016	+	+	+	+	44	Rasat *et al.* 2013		+	+	+
17	Effah *et al.* 2018	+	+			45	Ayrilmis *et al.* 2015	+	+	+	+
18	Haque *et al.* 2019	+	+			46	Ge *et al.* 2018	+		+	+
19	Martins *et al.* 2017	+				47	Gezer *et al.* 2016	+	+	+	+
20	Leu *et al.* 2012	+	+	+	+	48	Soccalingame *et al*. 2015			+	+
21	Chaudemanche *et al.* 2018	+	+	+	+	49	Hyvärinen *et al.* 2019	+	+	+	+
22	Delviawan *et al.*2019	+			+	50	Keskisaari *et al.* 2016			+	+
23	Kamdem *et al.* 2004			+	+	51	Keskisaari and Kärki 2018			+	+
24	Bengtsson *et al.* 2006			+	+	52	Badji *et al.* 2017	+	+		
25	Zhang *et al.* 2018	+	+	+	+	53	Homkhiew *et al*. 2014			+	+
26	Karmarkar *et al.* 2007	+	+	+		54	Tajvidi *et al.* 2006			+	+
27	Najafi and Englund 2013	+	+	+	+	55	Nitz *et al.* 2000	+	+		
28	Ghahri *et al.* 2011			+	+	56	Raj *et al.* 1990	+	+		

TS: Tensile Strength, MET: Modulus of elasticity in tensile, FS: Flexural Strength, MOE: Modulus Of Elasticity

The scaling of input parameters and output values in the back-propagation model significantly affects the performance of the ANN (Çay *et al.* 2012). For this reason, the input and output data sets used in the ANN model were normalized prior to the training and testing process (Eq. 4), and the data were ensured to take values between 0 and 1.

$$V_N = \frac{V_i - V_{min}}{V_{max} - V_{min}} \tag{4}$$

where V_N is the normalized data (input or output), V_i is the input value, V_{min} is the smallest value in the input set, and V_{max} is the largest value in the input set.

Root mean square error (RMSE) given in Eq. 5 and R^2 given in Eq. 6 (Duman *et al.* 2018) were used to evaluate the performances in trial and test data of the ANN model.

$$\text{RMSE}\ (X_p, X_i) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_p - X_i)^2} \tag{5}$$

$$R^2 = 1 - \left(\frac{\sum (X_i - X_p)^2}{\sum (X_p)^2}\right) \tag{6}$$

where X_i is the observed value, X_p is the predicted value and N is the total number of samples.

To determine the reliability of the ANN model, the MAPE value (Eq. 8) was taken into account when comparing the test results of the samples produced using input parameters not included in the training and testing of the model and the prediction values of the model. Before calculating the MAPE the ANN output data were converted back to real values using Eq. 7 and the prediction values were obtained in this way.

$$X_{po} = X_p(X_{imax} - X_{imin}) + X_{imin} \tag{7}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|X_{ie} - X_{po}|}{X_{ie}}\right)x100 \tag{8}$$

where X_{po} is the predicted value, X_{imax} is the largest observed value in the training data set, X_{imin} is the smallest observed value in the training data set, X_{ie} is the set of experimental values, and n is the number of samples used.

Preparation of Mechanical Test Specimens

The composition of the wood polymer composite samples prepared to determine the reliability of the ANN model is shown in Table 2. For this purpose, the Scots pine chips used as filler were sieved on a shaker sieve (LOYKA ESM-200) at 30-35-100-120 mesh. The wood flour remaining between 30-35 and wood flour remaining between 100-120 was collected and dried in the drying oven (NÜVE KD 400) at 103±2°C until it reached a constant weight. The HDPE supplied in granular form was pulverized by grinding in a grinding machine (Elmas Makine, Turkey) and sieved to obtain the same dimensions as sawdust. The obtained polymer and powdered coupling agent were dried in drying ovens (NÜVE FN 055) at 60 °C until constant weight.

The filler, polymer, and coupling agent, which were obtained in the same particle size and dried, were homogeneously mixed using a multidirectional mechanical mixer. The mixture was then mixed in a twin screw extruder (screw diameter: 18 mm; L/D: 44; speed: 20 rpm) (Polartek Polymer Research Technologies Ind. Trade Co. Ltd., Istanbul, Turkey) according to the melting temperature of the polymer (190 °C) and crushed into granules in the crushing machine. Mechanical test specimens were obtained by injection molding method according to the relevant standard, with ten specimens for each group.

Table 2. Composition Ratios of HDPE Samples Produced with Scots Pine Filler

Composite Material Code	HDPE Polymer Ratio (%)	Scots Pine Filling Material Ratio (%)	Coupling Agent Ratio (%)	Filling Material Particle Size (Mesh)
67H30S3M-30	67	30	3	30
70H30S-30	70	30	0	30
67H30S3M-120	67	30	3	120
70H30S-120	70	30	0	120
52H45S3M-30	52	45	3	30
55H45S-30	55	45	0	30
52H45S3M-120	52	45	3	120
55H45S-120	55	45	0	120

Mechanical Tests Applied

Type 1 specimens were used for tensile testing in accordance with ASTM D638-14 (2014). The tensile test was performed on a Shimadzu AG-IS testing machine at a tensile speed of 5 mm/min, at room temperature (23 °C) and constant relative humidity (50%). Modulus of elasticity in tensile values were calculated during the tensile test. Three-point flexure test was performed in accordance with ASTM D790-03 (2003) using a Zwick/Roell Z50 testing machine with a support spacing of 54 mm, a testing speed of 2 mm/min, room temperature (23 °C), and constant relative humidity (50%). Modulus of elasticity values were calculated during the flexural test.

RESULTS AND DISCUSSION

ANN Model

During the training and testing of the model in ANN, an R^2 value over 0.90 was achieved. Considering the heterogeneous nature of the wood material, the fact that the studies were conducted in different physical environments, and the expectation that the materials used have different properties, these values are considered reasonable. Table 3 shows the number of data used, the number of neurons in the hidden layers where the model achieved the highest R^2 value, and the R^2 values in the training and testing phases.

Table 3. Number of Data Used During Modeling and R^2 Value Obtained

Mechanical Properties	Number of Data Used	First Hidden Layer Neurons (n_1)	Second Hidden Layer Neurons (n_2)	R^2 Training	R^2 Test
Tensile Strength	190	6	6	0.9478	0.9107
Flexural Strength	155	13	13	0.9695	0.9515
Modulus of Elasticity in Tensile Mode	165	13	13	0.9415	0.9028
Modulus of Elasticity	143	8	8	0.9257	0.9185

Results showed that the number of hidden layer neurons used in the ANN and the R^2 value do not always have a linear relationship, and the highest R^2 value can be obtained with different numbers of hidden layer neurons. The R^2 value obtained by the model were higher than 0.90, and thus it is seen that the model can successfully predict the mechanical properties of wood polymer composites.

Atuanya *et al.* (2014) modeled the mechanical properties of a composite material made of palm wood and recycled LDPE with ANN; similarly, Nasri and Toubal (2024) used ANN to model the mechanical properties of composites made of pine and PP, and R^2 values of 0.99 were reported for both these studies. Also, Tosun and Sofuoğlu (2023) reported that they obtained mean R^2 values of 0.92 for training, validation, and testing in modeling the surface roughness of densified wood material with ANN.

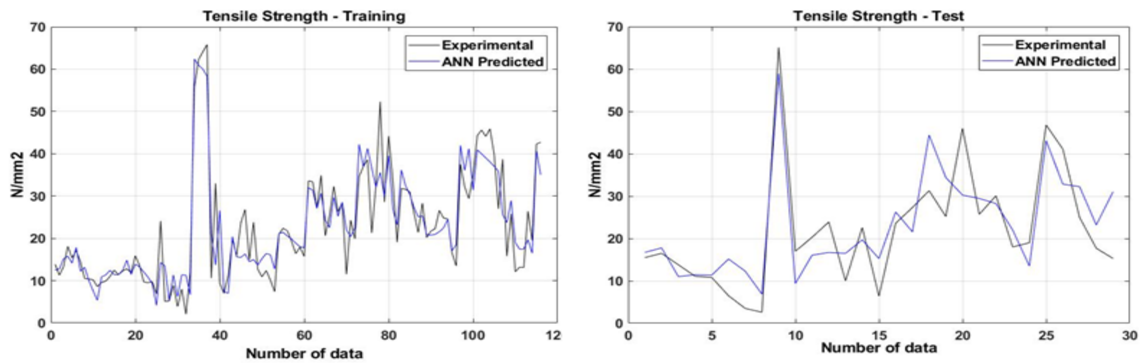

Fig. 2. Training and test values for tensile strength

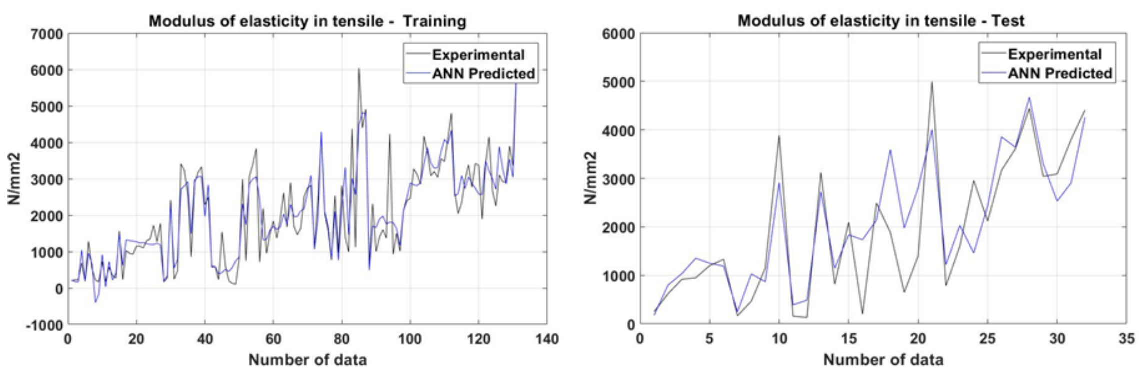

Fig. 3. Training and test values for modulus of elasticity in tensile mode

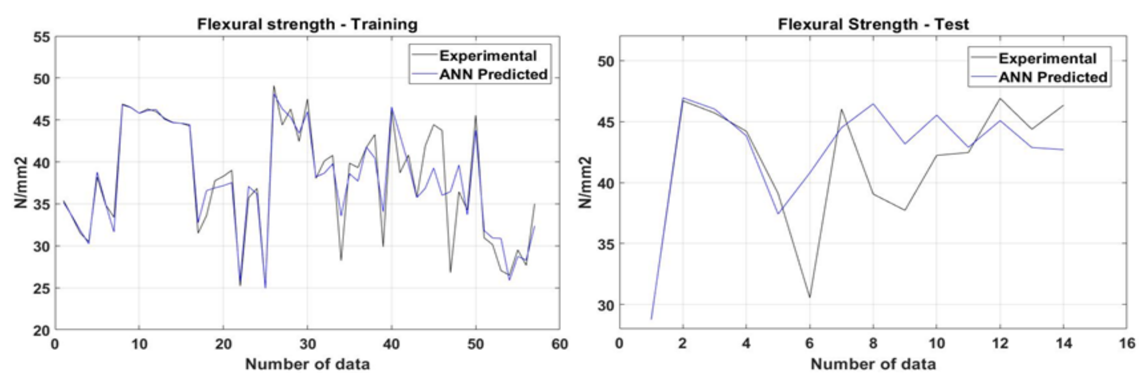

Fig. 4. Training and test values for flexural strength

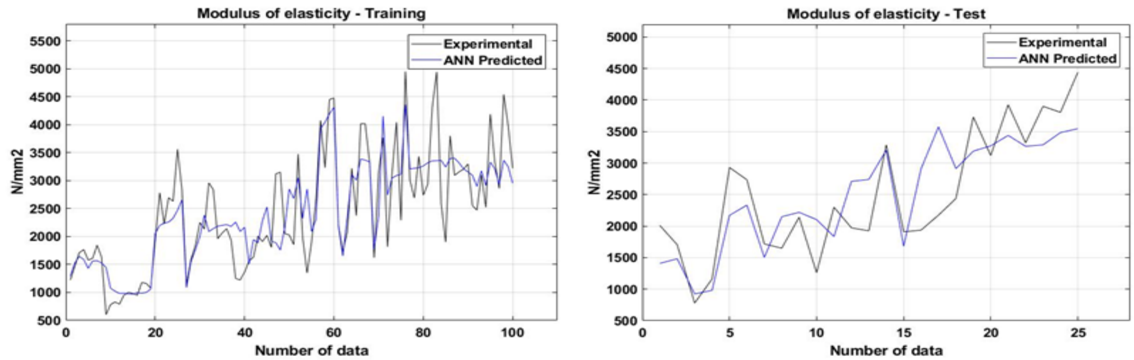

Fig. 5. Training and test values for modulus of elasticity

The high R^2 values in these studies could be achieved due to the use of a small number of samples and constant sample production and test conditions. In this study, although relatively lower R^2 values were obtained since the production conditions, which are the input parameters, were taken from the literature and varied, it can be said that this value is within acceptable limits. The experimental and ANN-predicted values for training and test of the model are given in Figs. 2 to 5.

It can be inferred from the learning curves presented in Figs. 6 and 7 that the RMSE values had reached a plateau, indicating that learning had occurred adequately.

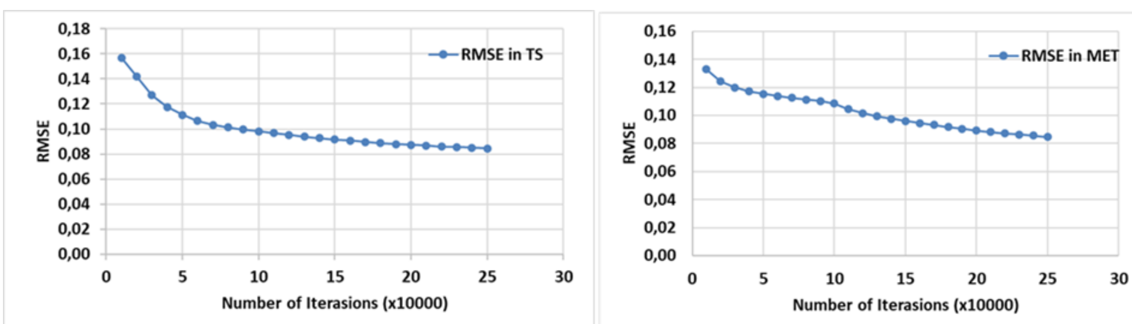

Fig. 6. Learning curve analysis for tensile strength and modulus of elasticity in tensile mode

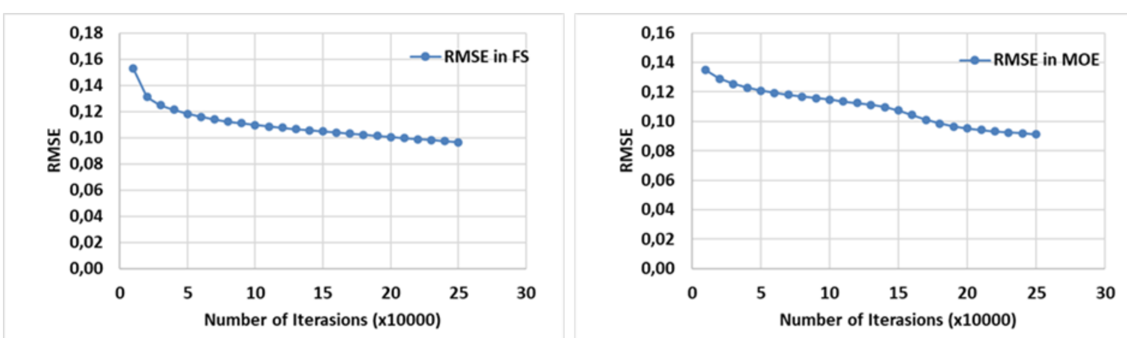

Fig. 7. Learning curve analysis for flexural strength and modulus of elasticity

Values Obtained from the Mechanical Test

The results of the mechanical tests performed to determine the reliability of the ANN model are shown in Table 4. The tensile strength and flexural strength values decreased as the filler mixture ratio increased, while the modulus of elasticity in tensile and modulus of elasticity values increased. Balasuriya *et al.* (2001) found that the flexural and tensile strengths decreased with the increase in the wood flour ratio. Gosselin *et al.* (2006) reported that increased use of wood flour increased the modulus of elasticity values in composites made with HDPE. The use of a coupling agent had a positive effect on the final values in all cases and, as expected, had an increasing effect on the values. Similar results were found in other studies, and significant increases in mechanical values were observed with the addition of coupling agents and additives such as PE-g-MA (Adhikary *et al.* 2008; Nourbakhsh and Ashori 2009; Mbarek *et al.* 2011; Koohestani *et al.* 2017). Considering the effect of the particle size of the samples on the results, larger particle size had a positive effect on all mechanical properties. Rafighi *et al.* (2014), Chaudemanche *et al.* (2018), and Bouafif *et al.* (2009) found that the values of modulus of elasticity, flexural strength, and tensile strength increased with increasing particle size of wood flour. The mechanical tests showed results in agreement with the literature.

Table 4. Mechanical Test Results

Composite Material Code	Values Obtained as Test Result (N/mm^2)			
	TS	MET	FS	MOE
67H30S3M-30	24.6 ± 1.1	2031 ± 187.6	46.2 ± 1.2	2426 ± 134.9
70H30S-30	19.1 ± 2.2	1835 ± 214.1	41.7 ± 0.5	2181 ± 69.1
67H30S3M-120	22.2 ± 0.3	1696 ± 111.5	36.3 ± 0.9	1538 ± 103.6
70H30S-120	19.0 ± 0.7	1660 ± 118.1	31.3 ± 1.6	1285 ± 74.6
52H45S3M-30	23.6 ± 0.9	2547 ± 210.0	40.8 ± 2.3	2713 ± 136.1
55H45S-30	18.6 ± 0.8	2050 ± 225.4	37.6 ± 2.0	2392 ± 305.3
52H45S3M-120	21.0 ± 0.3	2181 ± 171.1	33.5 ± 1.0	2041 ± 134.2
55H45S-120	17.1 ± 1.1	1994 ± 186.9	30.2 ± 0.5	1855 ± 158.6

TS: Tensile Strength, MET: Modulus of elasticity in tensile, FS: Flexural Strength,
MOE: Modulus Of Elasticity

Reliability of the ANN Model

The comparison of mechanical test results with the output values of the ANN model with the same input parameters is shown separately for each mechanical property in Figs. 8 and 9. The MAPE and R^2 values calculated to determine the reliability of the ANN model are given in Table 5. It is an expected result that the difference between the prediction and the test value was relatively high in some groups due to the diversity of production conditions from which the data used to train the ANN model were obtained. According to similar studies in the literature (Atuanya *et al.* 2014; İlçe and Singer 2019; Özşahin and Singer 2019; Özbay and Kökten 2020), these values are considered more realistic.

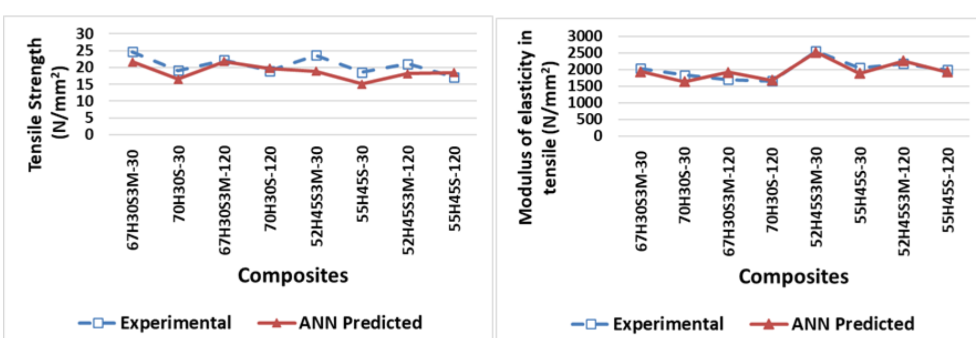

Fig. 8. Comparison of test results and ANN prediction values for TS and MET

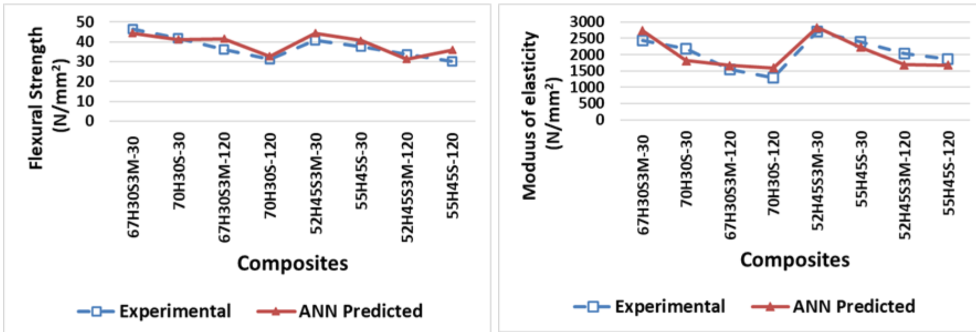

Fig. 9. Comparison of test results and ANN prediction values for FS and MOE

After conducting mechanical tests, the R^2 values for tensile strength were found to be 0.97 or higher, except for the 55H45S-30 and 52H45S3M-30 groups (R^2=0.94). The MAPE values varied between 2% and 18.8%. R^2 values for modulus of elasticity in tensile were 0.97 or higher in all groups. The MAPE values were found to be between 6.2% and 13.3% in all composite groups. For flexural strength, R^2 values between test results and ANN model predictions were 0.97 or higher in all groups; MAPE values were less than 10% except for two composite groups (67H30S3M-120 and 55H45S-120). For modulus of elasticity, R^2 values were 0.96 or higher, and MAPE values were 12.9% or below, except for the 70H30S-120 (17.1%) group. R^2 values close to 1 indicate a strong correlation between predicted and actual values (Bewick *et al.* 2003). Models with MAPE values higher than 50% are considered faulty, 20 to 50% acceptable, 10 to 20% good, and below 10% very good (Lewis 1983). Based on the R^2 and MAPE values obtained in this study, it was determined that the ANN model generated good predictions and can be efficiently used to anticipate the mechanical properties of wood polymer composites. Similar results were reported in studies on the prediction of surface roughness and adhesion resistance of wood using ANN (İlçe and Singer 2019; Özşahin and Singer 2019).

Table 5. R^2 and MAPE Values for Mechanical Properties

Composite Material Code	TS		MET		FS		MOE	
	R^2	MAPE	R^2	MAPE	R^2	MAPE	R^2	MAPE
67H30S3M-30	0.984	10.73	0.990	7.92	0.994	4.08	0.991	10.11
70H30S-30	0.978	9.20	0.972	12.87	0.999	1.26	0.969	12.56
67H30S3M-120	0.999	2.09	0.984	13.29	0.984	14.37	0.994	6.57
70H30S-120	0.997	3.56	0.996	6.25	0.996	4.58	0.979	17.14
52H45S3M-30	0.943	18.87	0.994	6.38	0.991	9.05	0.996	4.96
55H45S-30	0.943	18.81	0.981	10.85	0.993	8.80	0.993	7.09
52H45S3M-120	0.975	13.42	0.994	6.79	0.994	6.74	0.971	12.94
55H45S-120	0.996	5.69	0.991	8.37	0.976	18.29	0.982	11.41
TS: Tensile Strength, MET: Modulus of elasticity in tensile, FS: Flexural Strength, MOE: Modulus of Elasticity								

CONCLUSIONS

1. With increasing filler content in wood polymer composites, a decrease in tensile and flexural strength and an increase in modulus of elasticity in tensile and modulus of elasticity were observed.

2. When coupling agents were added to the mixture forming wood polymer composites, an increase in all mechanical properties was observed.
3. As the particle size of the filler used in wood polymer composites increased, an increase in all mechanical properties was observed.
4. Considering the values obtained in the training and testing phases of the model, the established ANN model can successfully predict the TS, TEM, FS, and FEM values of the wood polymer composites.
5. Because most of the R^2 values obtained as a result of the mechanical tests were 0.99 or higher and the MAPE values were below 10%, it can be said that the reliability of the model was relatively high.

ACKNOWLEDGMENTS

The authors are grateful to Professor Dr. Uğur Güvenç and Associate Professor Dr. Serhat Duman for help in development of the ANN model. The authors are grateful for the support of the Karabuk University Scientific Research Project Coordination Office Under Grant No: KBUBAP-22-DS-133.

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Article submitted: December 28, 2023; Peer review completed: April 30, 2024; Revised version received: April 30, 2024; Accepted: May 3, 2024; Published: May 17, 2024.
DOI: 10.15376/biores.19.3.4468-4485