

PREDICTIVE PERFORMANCE OF ARTIFICIAL NEURAL NETWORK AND MULTIPLE LINEAR REGRESSION MODELS IN PREDICTING ADHESIVE BONDING STRENGTH OF WOOD

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The purpose of this study was to develop artificial neural network (ANN) and multiple linear regression (MLR) models that are capable of predicting the bonding strength of wood based on moisture content, open assembly time and closed assembly time of the joints prior to pressing process. For this purpose, the experimental studies were conducted and the models based on the experimental results were set up. As a result of the experiments conducted, it was observed that bonding strength first increased and then decreased with increasing the wood moisture content and adhesive open assembly time. In addition, the increased closed assembly time caused a decrease in bonding strength of wood. The ANN results were compared with the results obtained from the MLR model to evaluate the models' predictive performance. It was found that the ANN model with the R^2 value of 97.7% and the mean absolute percentage error of 3.587% in test phase exhibits higher prediction accuracy than the MLR model. The comparison results confirm the feasibility of ANN model in terms of predictive performance. Consequently, it can be said that ANN is an effective tool in predicting wood bonding strength, and quite useful instead of costly and time-consuming experimental investigations.

Keywords: artificial neural network, prediction, bonding strength, multiple linear regression, model comparison.

Introduction. The adhesive bond of wood is one of the main connection methods used in modern load-bearing structures [1]. The quality and durability of a wooden product primarily depends on the quality of its adhesive bonding [2]. The moisture content is among the most important factors affecting the final strength and durability of adhesive bonding [3]. The prolonged exposure to high moisture content severely reduces the load-bearing ability of a wood joint bonded with any adhesive. It is a fact that the penetration and cure of wood adhesives are greatly affected when the amount of moisture in wood is combined with water in adhesive [4]. The moisture content of wood at the time of bonding is also important since it influences the quality of the bond and thus the performance of the bonded product in service. A change in moisture content generally develops stresses in the adhesive joints. The magnitude of the stresses is roughly proportional to the magnitude of the change. Satisfactory adhesion between wood and adhesive is achieved with most adhesives when the wood has the moisture content ranging from 6 to 17%. The lower and upper limits of the moisture content vary depending on the adhesive type and

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composition [5]. In addition to the moisture content, other important factors affecting the adhesive bond strength of wood are the open assembly time and closed assembly time during jointing process of wood. The strength of adhesive bond of wood deteriorates if these time periods exceed the duration foreseen for adhesives [6].

The delay in obtaining the experimental results on material properties is an important problem that affects manufacturing industries [7]. Predictive model scan provides an opportunity to better evaluate the behavior of materials by carrying out a small number of complex experimental processes so that satisfactory results concerning the desired properties of materials can be obtained in a short period of time [8]. For this purpose, the two common methods are the multiple linear regression (MLR) and artificial neural network (ANN) techniques [9]. Especially, the ANN is of interest to engineers and researchers as a successful tool in modeling the behavior of materials due to its ability of describing complex and nonlinear relationships among variables by means of a small amount of data without any prior assumptions [10–12]. In addition to the ANN, the MLR has been used for modeling purposes since it is an appropriate technique for modeling when the research problem includes one dependent variable and two or more independent variables [13]. These techniques have been widely used to solve a wide variety of problems regarding the strength of materials in many engineering fields. The following literature lists some of ANN and MLR applications in predicting strength properties of various materials [9, 11, 14–18]. These modeling approaches have been also employed for predicting strength properties of wood and wood products. The applications regarding strength prediction in wood science can be listed as follows: Esteban et al. [19]; Esteban et al. [10]; Fernandez et al. [8]; Eslah et al. [20]; Tiryaki and Aydin [21]; Tiryaki et al. [22]; and Watanabe et al. [23].

As mentioned above, ANN and MLR methods have been widely employed in modeling strength of materials in many engineering fields, including wood science. However, no attempt has yet been made for predicting wood bonding strength under the conditions formulated in the present study. Therefore, one of the main goals of the present study was to predict the effect of wood moisture content, open assembly time and closed assembly time on bonding strength by ANN and MLR techniques. Another goal was to compare the predictive capabilities of these modeling techniques.

1. Materials and Methods. For this study, beech (*Fagus orientalis* L.) wood was chosen randomly from Artvin, Turkey. Special emphasis was made on the selection of non-deficient, knotless and defect-free beech specimens. Then the experimental specimens, which were obtained from beech wood with dimensions of 150×20×10 mm, were conditioned to different amount (8, 12, 16, and 20%) of moisture content.

Polyvinylacetate (PVA) was applied to the surface of the specimens having different moisture content with an amount of adhesive of 200 g/m² by brushing at room temperature. The PVAc had density of 1.1 g/cm³, pH = 5...6, and viscosity value 16.0±3.0 MPa·s. The surfaces treated with the adhesive were kept for different open assembly time (0, 5, 10, and 15 min) and closed assembly time (0, 30, and 60 min) prior to the pressing process. The pressing pressure of 15 kg/cm² and the pressing duration of 40 min were used in bonding the specimens. After the bonding operation, the specimens were conditioned at a temperature of 20±2°C and a relative humidity of 65±5%. Thus, a total of 480 specimens using four different values of moisture content, four different values of open assembly time and three different values of closed assembly time with ten replicates were prepared for bonding strength tests (4×4×3×10=480).

To determine the adhesive bond strength of the specimens, a universal testing machine with a capacity of 5000 kg and a loading speed of 2 mm/min was used. Figure 1 shows the experimental design for conducting the bonding strength tests of beech specimens.

The loading was terminated when a break or separation of the specimen surface occurred. The tests were performed according to the BS EN 205 [24]. The bonding strength of specimens was derived via Eq. (1):

$$\sigma_y = \frac{F_{\max}}{ab}, \quad (1)$$

where σ_y is the bonding strength (in N/mm²), F_{\max} is the maximum load at the break point, and a and b are the width and length of glued face, respectively.



Fig. 1. Experimental design for bonding strength tests.

2. Predictive Tools and Their Applications for the Bonding Strength Prediction.

2.1. Multiple Linear Regressions. Describing the functional relationship between a dependent variable and a set of independent variables is one of the classical problems in the statistical analysis. The MLR analysis is a statistical technique that is very useful for these types of problems. By using this method, the linear relationship between dependent and independent variables can be successfully modeled [25]. The MLR is based on the least squares. In such a model, the best fit is achieved when the sum of squares of differences between the measured and predicted outputs is minimized. In the MLR, the linear function can be formulated as Eq. (2):

$$Y = \beta_0 + \beta_1 X_1 + \dots + \beta_n X_n + \varepsilon, \quad (2)$$

where β_0 is a constant value, Y is the dependent variable, X_i is a set of independent variables, β_i is a set of predicted parameters, and ε is the error term [26].

2.2. Artificial Neural Networks. ANNs are known as a massively parallel distributed processor that is able to simulate the behavior of the biological neural network [27]. They have a good capability of nonlinear mapping, which allows the network to capture the complex relationship in data structure accurately [28]. The function of ANNs resembles the human brain in two respects: (1) the network acquires the knowledge by a learning procedure, and (2) connection strengths are used to store the acquired knowledge [27].

Among many different types of ANNs, the back-propagation neural network is the most popular ANN structure for engineering problems. It is classified as a multilayer feed-forward neural network or multilayer perceptron. This means that every neuron in any layer of the ANN is connected to all neurons of the previous layer by a connection weight [29]. Figure 2 shows a typical multilayered ANN structure. Equation (3) gives the output of the MLR shown in Fig. 2 [30],

$$Y = g \left(\theta + \sum_{j=1}^m v_j \left[\sum_{i=1}^n f(w_{ij} X_i + \beta_j) \right] \right), \quad (3)$$

where Y is the predicted value of dependent variable, X_i is the input value of i th independent variable, w_{ij} is the connection or synaptic weight between the i th input neuron and j th hidden neuron, β_j is the bias value of the j th hidden neuron, v_j is the connection weight between the j th hidden neuron and output neuron, θ is the bias value for output neuron, while $g(\cdot)$ and $f(\cdot)$ are the activation functions.

In Fig. 2, the input layer receives the incoming data for the ANN and delivers the data to the intermediate layer. The intermediate layer is known as the hidden layer, which transmits the information coming from the input

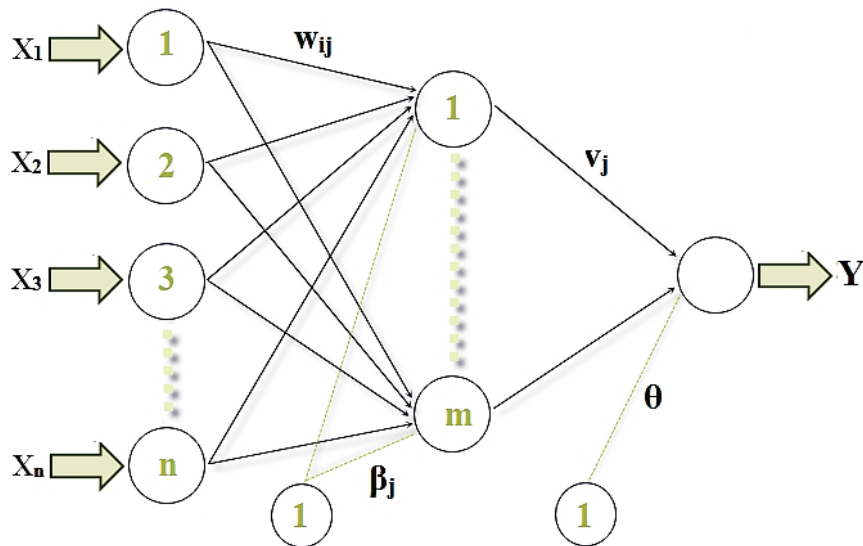


Fig. 2. A typical multi-layered ANN structure.

layer to the output layer. The output layer processes the information coming from the hidden layer and thus produces the output data [31]. The number of neurons in these layers is very important in terms of the performance of the network. The number of input and output neurons is equivalent to the number of input and output variables in the MLP structure [30]. Especially, the determination of the number of hidden layers and hidden neurons is highly important factor controlling the ANN efficiency. Hidden layers and their neurons help to uncover complex relationship between inputs and outputs. Several researchers reported that ANN structure with a single hidden layer is generally sufficient and gives satisfactory results in solving various engineering problems [32–34]. The excessive number of hidden neurons allows one to improve the memorization capability rather than generalization capability of the network. On the other hand, a too small number of hidden neurons is insufficient for the network to learn the hidden relationship between variables. Thus, the optimal number of hidden layers and hidden neurons is generally found by a procedure of trial and error [34, 35].

2.3. Data Preparation for Models. In the ANN analysis for the present work, moisture content, open assembly time and closed assembly time were considered as the prime processing variables. The analysis was performed by the MATLAB Neural Network Toolbox. The experimental data were grouped into training, validation and testing data sets to model the effects of the considered variables on the bonding strength. Thirty four data were used for training process of the ANN, while the remaining 14 data were subdivided equally for validation and testing processes of ANN. Each data point is an average of 10 measurements of the bonding strength. The training, validation and testing data sets used in the ANN are presented in Table 1. On the other hand, all of the 48 experimental data were used in developing the MLR model. The MLR analysis was performed using the SPSS 11.5 statistical software.

2.4. Training of Neural Network. The training is an important step of the model construction process. It is aimed at determining the optimal values of connection weights. In other words, it implies minimization of the error between the network output and the actual one [36]. To achieve this goal, the network is trained using the training data. The training algorithm chosen for the present study was the Levenberg–Marquardt algorithm. In addition, the applied learning rule was the back-propagation algorithm. To assess the generalization ability of the network, the trained models were then tested using the testing data. The models providing the best prediction values were selected for predicting the adhesive bond strength of wood.

2.5. Neural Network Structure. Figure 3 depicts the proposed optimal network structure for predicting the bonding strength.

The proposed model contains one input layer, one hidden layer and one output layer. Determining the number of neurons in the input and output layers is quite easy. In a prediction problem based on the cause and effect

TABLE 1. Measured and Predicted Bonding Strength Values and Their Percentage Errors

Moisture content (%)	Open assembly time (min)	Closed assembly time (min)	Bonding strength (N/mm ²)				
			Measured	ANN		MLR	
				Predicted	Error (%)	Predicted	Error (%)
1	2	3	4	5	6	7	8
8	0	0	10.11 (0.239)	10.05	0.59	12.29	-21.56
8	0	30	9.73 (0.295)	9.80	-0.72	11.28	-15.93
8	0	60	9.07 (0.241)	8.98	0.99	10.27	-13.23
8	5	0	10.25 (0.193)	10.24	0.10	11.93	-16.39
8	5	30	9.84 (0.272)	10.09	-2.54	10.92	-10.98
8	5	60	9.32 (0.189)	9.22	1.07	9.91	-6.33
8	10	0	9.66 (0.280)	9.43	2.38	11.58	-19.88
8	10	30	9.41 (0.185)	9.23	1.91	10.56	-12.22
8	10	60	8.06 (0.175)	8.25	-2.36	9.55	-18.49
8	15	0	9.58 (0.243)	9.01	5.95	11.22	-17.12
8	15	30	8.99 (0.387)	8.94	0.56	10.21	-13.57
8	15	60	7.78 (0.249)	8.04	-3.34	9.19	-18.12
12	0	0	13.49 (0.551)	12.59	6.67	11.25	16.60
12	0	30	11.27 (0.167)	11.42	-1.33	10.24	9.14
12	0	60	10.52 (0.244)	10.54	-0.19	9.23	12.26
12	5	0	14.90 (0.376)	13.86	6.98	10.90	26.85
12	5	30	11.85 (0.371)	11.76	0.76	9.88	16.62
12	5	60	10.80 (0.216)	10.76	0.37	8.87	17.87
12	10	0	12.18 (0.329)	12.14	0.33	10.54	13.46
12	10	30	11.13 (0.162)	10.99	1.26	9.53	14.38
12	10	60	9.73 (0.384)	9.78	-0.51	8.51	12.54
12	15	0	11.65 (0.160)	11.69	-0.34	10.18	12.62
12	15	30	10.64 (0.161)	10.72	-0.75	9.17	13.82
12	15	60	9.49 (0.376)	9.46	0.32	8.16	14.01
16	0	0	10.07 (0.207)	9.89	1.79	10.22	-1.49
16	0	30	9.72 (0.112)	9.51	2.16	9.20	5.35
16	0	60	9.00 (0.124)	8.90	1.11	8.19	9.00
16	5	0	10.19 (0.170)	10.43	-2.36	9.86	3.24
16	5	30	9.79 (0.275)	9.98	-1.94	8.85	9.60
16	5	60	9.23 (0.214)	9.27	-0.43	7.84	15.06
16	10	0	10.01 (0.148)	9.96	0.50	9.50	5.09
16	10	30	9.53 (0.120)	9.35	1.89	8.49	10.91
16	10	60	8.43 (0.361)	8.47	-0.47	7.48	11.27
16	15	0	9.71 (0.262)	9.64	0.72	9.14	5.87
16	15	30	9.13 (0.376)	9.08	0.55	8.13	10.95
16	15	60	8.21 (0.249)	8.22	-0.12	7.12	13.28
20	0	0	8.02 (0.209)	8.12	-1.25	9.18	-14.46
20	0	30	6.80 (0.196)	7.05	-3.68	8.17	-20.15
20	0	60	5.43 (0.348)	5.59	-2.95	7.15	-31.68
20	5	0	8.66 (0.325)	8.38	3.23	8.82	-1.85

1	2	3	4	5	6	7	8
20	5	30	7.21 (0.106)	7.23	-0.28	7.81	-8.32
20	5	60	6.03 (0.300)	6.07	-0.66	6.80	-12.77
20	10	0	7.49 (0.192)	7.68	-2.54	8.46	-12.95
20	10	30	6.36 (0.213)	6.36	0	7.45	-17.14
20	10	60	5.10 (0.169)	5.02	1.57	6.44	-26.27
20	15	0	7.03 (0.207)	7.01	0.28	8.11	-15.36
20	15	30	5.96 (0.156)	5.73	3.86	7.09	-18.96
20	15	60	4.42 (0.384)	4.44	-0.45	6.08	-37.56

Notes. Values in bold italic are testing data, values in bold are validation data, other values are training data. Values in parenthesis are standard deviations.

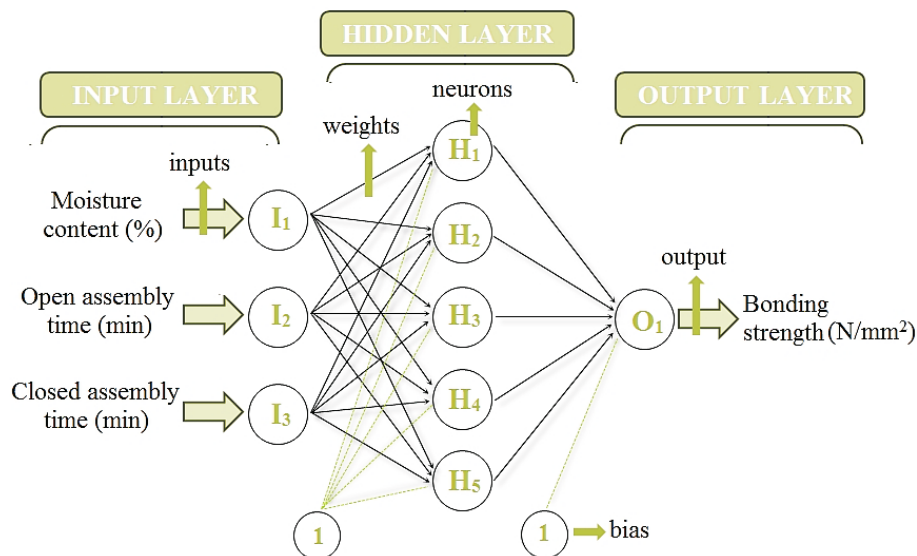


Fig. 3. The proposed optimal network structure for predicting bonding strength.

relationship, their number is equal to the number of input variables (moisture content, open assembly time and closed assembly time) and output variable (bonding strength), respectively. On the other hand, as it was mentioned previously, determining the number of hidden neurons is relatively complicated [34]. Hence, a heuristic approach was applied for deriving the optimum number of hidden neurons. This approach involves designing of different network structures using various network configurations and training parameters until the optimal model for the problem under consideration is obtained [37]. Consequently, the 3–5–1 neuron configuration was found to be the best for the network, as is shown in Fig. 3, since it provides an excellent prediction performance.

2.6. Evaluation of Predictive Performance of Models. In evaluating the performance of the established models, the mean absolute percentage error (MAPE), the root mean square error (RMSE) and correlation coefficient (R^2) are used, which are calculated via Eqs. (4)–(6):

$$\text{MAPE} = \frac{1}{N} \left(\sum_{i=1}^N \left[\left| \frac{t_i - td_i}{t_i} \right| \right] \right) \cdot 100, \quad (4)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (t_i - td_i)^2}, \quad (5)$$

TABLE 2. Results of Analysis of Variance Indicating the Effects of the Moisture Content (A), Open Assembly Time (B) and Closed Assembly Time (C) on the Bonding Strength

Source	Sum of squares	Degrees of freedom	Mean square	F value	Probability
Moisture content (A)	736.929	3	245.643	3519.765	***
Open assembly time (B)	57.870	3	19.290	276.402	***
Closed assembly time (C)	164.000	2	82.000	1174.960	***
A*B	7.767	9	0.863	12.366	***
A*C	24.145	6	4.024	57.662	***
B*C	2.665	6	0.444	6.363	***
A*B*C	9.191	18	0.511	7.316	***
Error	13.400	192	0.070		
Total	21,269.076	240			

*** Significant at $P \leq 0.001$ level.

$$R^2 = 1 - \frac{\sum_{i=1}^N (t_i - td_i)^2}{\sum_{i=1}^N (t_i - \bar{t})^2}, \quad (6)$$

where t_i are the measured values, td_i are the predicted values, N is the total number of specimens, and \bar{t} is the average of predicted values.

3. Results and Discussion.

3.1. Experimental Results. Table 1 includes the experimental (measured) data and the results predicted by the ANN for the bonding strength for training, validation and testing data sets.

To investigate the effects of moisture content, adhesive open assembly time and closed assembly time on the bonding strength of specimens, an analysis of variance was performed, which results are presented in Table 2 and clearly indicate that the effects of these variables on the bonding strength are statistically highly significant ($P \leq 0.01$).

Furthermore, the Duncan mean comparison test was employed to compare the average values of bonding strength based on the process variables. Thus, one can determine which level of related variable is different from the other levels. According to the above test results, the average values of the bonding strength depending on moisture content and open assembly time fall into four different homogeneity groups, while the closed assembly time corresponds to three different homogeneity groups. Table 3 presents the results of the Duncan grouping test.

It is shown that the wood moisture content strongly affects the strength of the bond between wood and adhesive. According to the average values of the process variables, an increase in moisture content from 8 to 12% yields a higher bonding strength. The increased moisture content above 12% leads to reduced bonding strength. This may be due to a decrease in the penetration of adhesive to wood with increasing moisture content. Several researchers reported that most of the strength properties of wood vary inversely with the moisture content of the wood below the fiber saturation point [38–40]. It was also claimed that some strength properties may exhibit a repeated decrease at low moisture content after reaching the maximum value [39].

In terms of the open assembly time, it was determined that the bonding strength increased first and then dropped for open assembly time of 10 to 15 min. In other words, the optimal bonding strength was obtained for open assembly time of 5 min. The reason behind the bonding strength reduction with the increased open assembly time may be due to the curing of the adhesive applied to the surface of the adherents before the bonding process is completed. Moreover, the adhesive bond strength is possibly reduced due to insufficient penetration of the adhesive into wood for a very low duration of open assembly time (0 min). In an earlier study, Minelga and Norvydas [6] reported that the increased open assembly time generally resulted in the wood bonding strength reduction.

TABLE 3. Homogeneity Groups of Bonding Strength Depending on the Process Variables

Variables	Value	Bonding strength (N/mm ²)	
		Average	Homogeneity group
Moisture content (%)	8	9.32	A
	12	11.47	B
	16	9.42	C
	20	6.54	D
Open assembly time (min)	0	9.43	A
	5	9.84	B
	10	8.92	C
	15	8.55	D
Closed assembly time (min)	0	10.19	A
	30	9.21	B
	60	8.16	C

TABLE 4. Performance Evaluation Criteria for the Bonding Strength Prediction

Model	Data sets	Performance evaluation criteria		
		MAPE	RMSE	R^2
ANN	Training	0.972	0.113	0.996
	Validation	2.707	0.427	0.995
	Testing	3.587	0.439	0.977
MLR	All data	14.220	1.410	0.524

As for the effects of the closed assembly time on the bonding strength, it was observed in this study that the bonding strength decreased with the closed assembly time. The highest value of bonding strength was obtained for wood specimens with 0 min of the closed assembly time as compared to those of 30 and 60 min. It was reported that the quality of the bond significantly deteriorates when the closed assembly time exceeds the one recommended for the adhesive [6]. This leads to the wood bonding strength reduction. Thus, it can be reported that the results of the present study are generally compatible with those of earlier studies.

3.2. Predictive Ability of the ANN and MLR Methods. In the present study, the ANN and MLR models were applied to predict the effects of moisture content, open assembly time and closed assembly time on the bonding strength. The ANN model produced highly satisfactory results as compared to the MLR model. As seen from Table 1, in the most cases, the neural network outputs are very close to the measured ones, while the MLR outputs are less satisfactory. In other words, the prediction of bonding strength by means of the ANN in the present study was achieved with a quite high accuracy.

As mentioned before, such criteria as MAPE, RMSE, and R^2 were used for assessing the model fit and prediction accuracy. The results obtained are given in Table 4.

As shown in Table 4, the RMSE value drawn from the ANN was 0.439 for testing data set in predicting the bonding strength under the given conditions. The corresponding value of MLR model was 1.410. On the other hand, the MAPE criterion is considered to be the decisive factor, since it is expressed in an easy generic percentage term [13]. According to this, the MAPE was found as 3.587% for the testing phase of the ANN, while the MAPE value produced by the MLR was 14.220%. According to Lewis [41], typical MAPE values for performance evaluation are categorized as follows: $MAPE \leq 10\%$ corresponds to a high accuracy prediction, $10 \leq MAPE \leq 20\%$ – a good prediction, $20 \leq MAPE \leq 50\%$ – a reasonable prediction, while $MAPE \geq 50\%$ means inaccurate prediction. In this regard, the ANN exhibited a high accuracy, while the MLR had a good accuracy in predicting the bonding strength. In other words, the ANN yielded more satisfactory results as compared to the MLR.

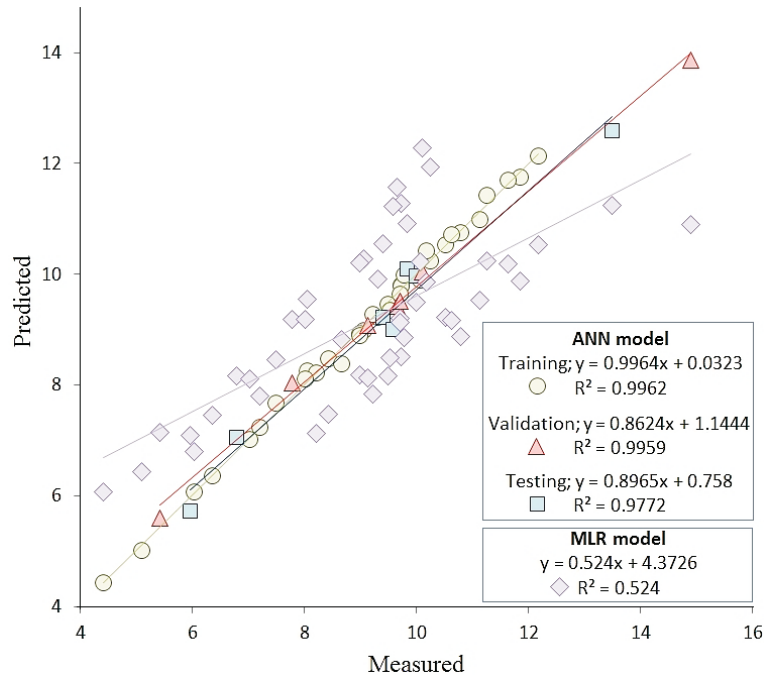
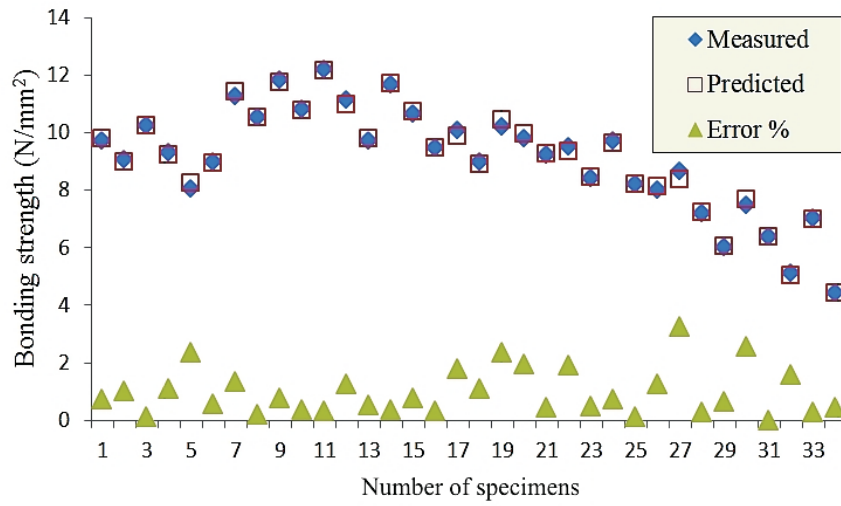


Fig. 4. Relationship between the measured and predicted bonding strength results of the ANN and MLR models.

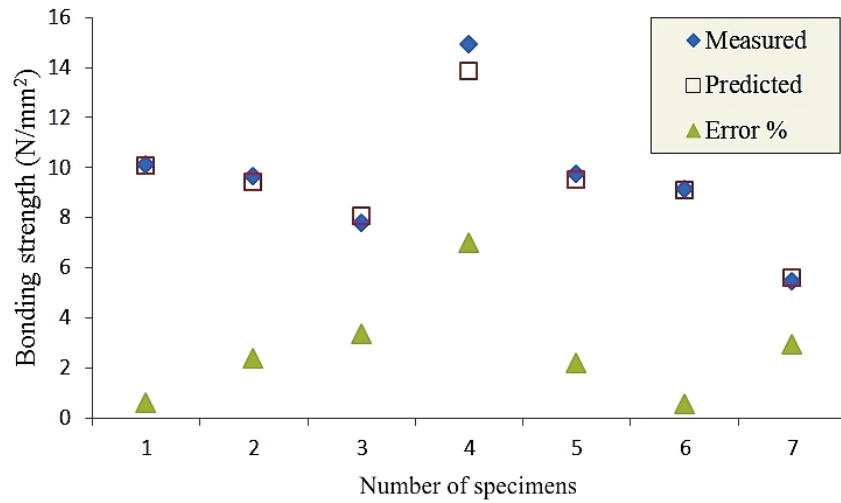
The goodness-of-fit of the ANN and MLR models was evaluated by means of the regression coefficient R^2 . Figure 4 gives a graphical presentation of the fit between the predicted and measured outputs of bonding strength for these models.

It can be seen from Fig. 4 that R^2 values are: 0.996, 0.995, and 0.977 for training, validation and testing data sets in predicting the bonding strength of the specimens, respectively. The R^2 results of the ANN indicate that the established model coincides with at least 97% of the measured data of bonding strength. It is also possible to observe from Fig. 4 that the MLR has yielded a low R^2 value of 0.524, which indicates that 52.4% of the variations for the bonding strength can be described by the MLR model. As a result, the analysis of data depicted in Fig. 4 demonstrates that the bonding strength prediction by the ANN ensures a better accuracy, in comparison to the MLR. It was reported that if a model gives R^2 over 0.90, there is an excellent correlation between the measured and predicted outputs. In other words, such a model exhibits an excellent performance. On the other hand, the value of R^2 in the range of 0.82 to 0.90 generally indicates a good performance, whereas the value of R^2 below 0.82 means a relatively poor performance [42, 43]. In this regard, quite high values of R^2 for the ANN in the current study imply an excellent agreement between the measured and predicted outputs of bonding strength, as well as the enhanced reliability of the ANN. Regarding the MLR, it can be reported that this model exhibited a relatively poor prediction performance. Figure 4 clearly demonstrates that the performance of the ANN is better than that of the MLR, judging by the values of R^2 .

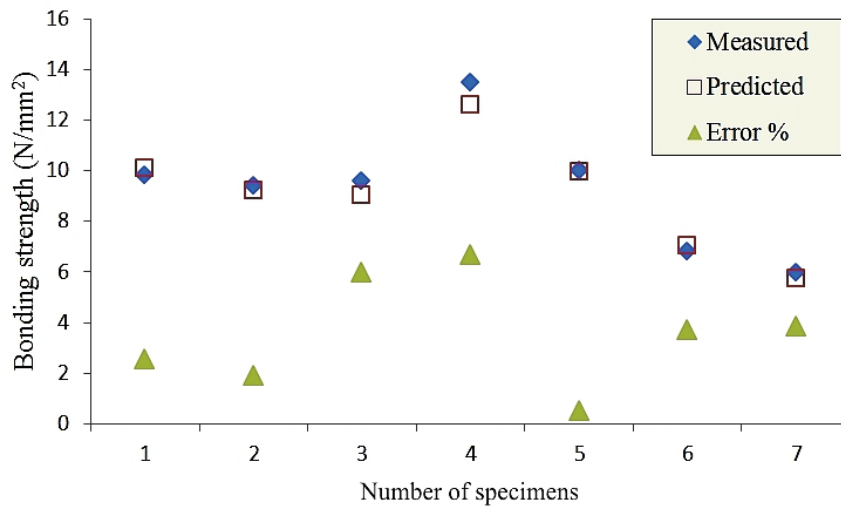
The results of performance evaluation of such criteria as MAPE, RMSE, and R^2 have proven that ANNs have a better predictive performance than the conventional statistical methods such as the MLR. These results support the superiority of ANN over the MLR. Previous investigations have reported similar results [8, 21–23]. Indeed, the main reason behind the ANN superiority is its ability for capturing complex, hidden and nonlinear relationships among variables by means of a small amount of data without any prior assumptions [44]. Moreover, the MLR technique, in contrast to the ANN, generally requires some assumptions such as normality, linearity, etc. [45]. For the present study, it is possible to conclude that the relationship between the bonding strength and process variables may be complex, and thus it may not be captured by MLR. As stated before, ANNs are capable of accurate



a



b



c

Fig. 5. Comparison of experimental and predicted results on the bonding strength for training data (a), validation data (b), and testing data (c).

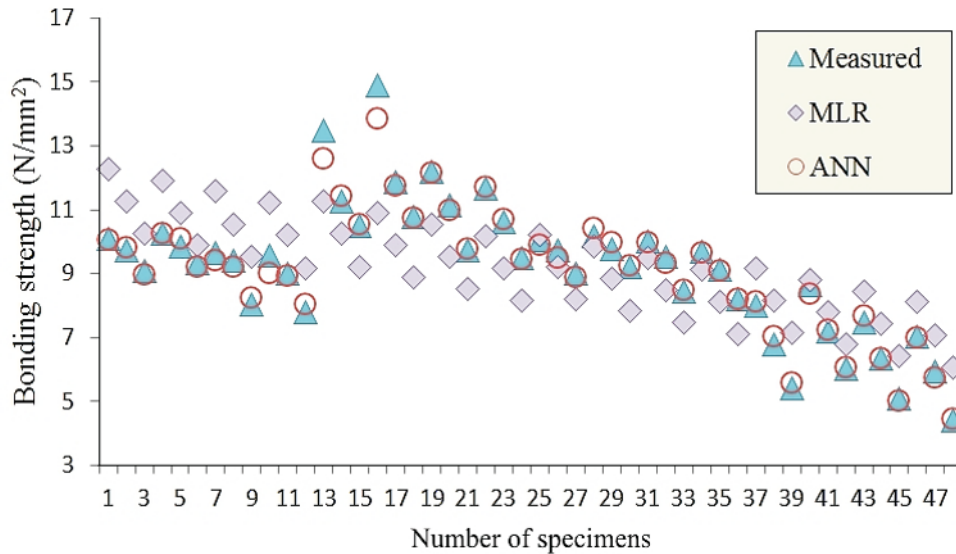


Fig. 6. Comparison of the measured data with the ANN- and MLR-predicted results.

mapping of complex or nonlinear relationship between the variables [28]. Therefore, findings of the present study are reasonable and compatible with those of earlier investigations.

The following MLR equation [Eq. (7)] was also derived by applying the MLR analysis to the measured data on the bonding strength:

$$Y = 14.366 - 0.259X_1 - 0.072X_2 - 0.034X_3. \quad (7)$$

In Eq. (7), Y is a dependent variable (bonding strength) and X_i are independent variables (moisture content, open assembly time, and closed assembly time, respectively).

Comparison of measured and predicted values of the bonding strength by the ANN model for training, validation and testing data sets is illustrated by Fig. 5. Figure 6 also gives a comparison of the ANN, MLR, and measured results for all data on the bonding strength.

Figure 5 indicates that the ANN results for training, validation and testing data sets have a high similarity with the measured bonding strength values. Meanwhile, it can be observed from Fig. 6 that the ANN prediction results exhibit very low deviations from the measured values, as compared to the MLR results. These results strongly suggest that the ANN modeling can be successfully employed for predicting bonding strength of the specimens under given conditions when its training is properly performed. In view of these findings, it is possible to conclude that the ANN exhibits a better predictive performance, as compared to the MLR, and the ANN model can be effectively applied to the bonding strength prediction.

Conclusions. In this study, the capability of ANN and MLP models for predicting the bonding strength of wood have been investigated. In order to evaluate the predictive performance of the models, the R^2 , MAPE, and RMSE criteria have been used.

The experimental results show that moisture content strongly affects the bonding strength. Bonding strength generally increases with reduced moisture content of wood, except for 8% of moisture content. The optimal value of bonding strength was obtained at 12% of moisture content. For open assembly time, the bonding strength first increases and then decreases with the increased open assembly time. Also, the increased closed assembly time leads to the bonding strength reduction. By considering these observations, a considerable improvement in the strength of the bond between wood and adhesive can be achieved.

The results of the ANN model were compared with those of the MLR and revealed the superiority of the former in predicting the bonding strength. In other words, the proposed ANN model has exhibited a higher prediction performance than the MLR model based on the performance criteria such as MAPE and R^2 . In the testing phase of

the ANN, the MAPE and R^2 equaled to 3.587% and 97.7%, respectively. The corresponding values of MLR were 14.22 and 52.4%, respectively. Therefore, it can be concluded that the ANN successfully models the effects of different process variables on wood bonding strength, in contrast to the MLR. Based on the present study findings, it can be also concluded that ANN approach offers a novel and alternative method for predicting the bonding strength with a smaller number of experimental tests.

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