

## Modeling of Wood Bonding Strength Based on Soaking Temperature and Soaking Time by means of Artificial Neural Networks

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Accepted 3rd September 2016

**Abstract:** Adhesive bonding of wood enables sufficient strength and durability to hold wood pieces together and thus produce high quality wood products. However, it is well known that many variables have an important influence on the strength of an adhesive bonding. The objective of the present paper is to predict the bonding strength of spruce (*Picea orientalis* (L.) Link.) and beech (*Fagus orientalis* Lipsky.) wood joints subjected to soaking by using artificial neural networks. To obtain the data for modeling, beech and spruce samples were subjected to the soaking at different temperatures for different periods of time. In the ANN analysis, 70% of the total experimental data were used to train the network, 15% was used to test the validation of the network, and remaining 15% was used to test the performance of the trained and validated network. A three-layer feedforward back propagation artificial neural network trained by Levenberg–Marquardt learning algorithm was found as the optimum network architecture for the prediction of the bonding strength of soaked wood samples. This architecture could predict wood bonding strength with an acceptable level of the error. Consequently, modeling results demonstrated that artificial neural networks are an efficient and useful modeling tool to predict the bonding strength of wood samples subjected to the soaking for different temperatures and durations.

**Keywords:** Neural network, Bonding strength, Prediction, Wood, Soaking.

### 1. Introduction

Adhesives allow wood industry to use small dimension wood pieces to produce bigger dimension products, and therefore the strength of the adhesive bonding is of great importance for the wood products [1]. The main role of an adhesive in a product is to transfer the stress from one substrate to another. This means that an adhesive bond needs sufficient durability to hold together the joints produced under different conditions [2]. On the other hand, understanding and controlling the adhesive bonding of wood is a challenging task due to the heterogeneous nature of wood [3].

ANNs are a powerful data modeling method capable of defining complex and nonlinear relationships between input and output parameters related to any processes or systems without the need of any assumptions [4]. In recent years, ANNs have been one of the most attractive fields of the artificial intelligence and has been widely employed in solving the problems such as optimization, classification, prediction and pattern recognition in engineering applications [5] [6]. Unlike traditional modelling approaches, ANNs are capable of learning from examples or training patterns, storing the knowledge in their weights and bias values and using them to predict future values [7]. Due to these advantages, ANNs have been increasingly considered to model the bonding strength of various materials in engineering applications. Taşkın et al. [8] tried the ANN approach to model the bonding characteristics of SiCp reinforced aluminium alloy metal matrix composites. Sancak [9] used the ANN technique for modeling the bonding strength of

lightweight concretes. Golafshani et al. [10] modeled the bond strength of spliced steel bars in concrete by means of a ANN. Wang et al. [11] predicted heavy aluminum wire wedge bonding strength by means of the ANN modeling. On the other hand, the use of ANN technique to solve computational problems in wood science has increased rapidly in last two decades. Details of studies carried out to predict wood characteristics with ANN modeling approach are as follows. Ceylan [12] modeled drying characteristics of wood by developing a neural network model. Tiryaki et al. [13] employed the ANNs for minimizing the wood surface roughness in machining process. Yang et al. [14] modeled the mechanical properties of heat treated wood using a neural network. In another study, Esteban et al. [15] predicted the modulus of elasticity of wood by an ANN. In another study regarding the strength properties, Tiryaki and Aydın [16] trained a feed-forward ANN to model the compression strength of heat treated wood. Moreover, due to the importance of adhesive bonding of wood and wood products, substantial modeling activities have performed during the last decades with ANN models established with different variables. Ozsahin and Aydın [17] developed an intelligent model which is capable of predicting the optimum veneer drying temperature to ensure a quality bond formation in plywood manufacturing. In another study, Demirkir et al. [18] optimized manufacturing variables for the optimum bonding strength in plywood manufacturing by the ANN modelling. With regard to solid wood, Tiryaki et al. [19] used the ANNs to model the optimum bonding strength of wood joints subjected to different temperatures and machining conditions. In another study, Tiryaki et al. [20] designed a neural network structure for modeling the influences of amount of adhesive, pressing pressure and its duration on the joining strength. Finally, in the study of Bardak et al. [21], the influences of pressing conditions on the bonding quality of different wood

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Note: This paper has been presented at the 3<sup>rd</sup> International Conference on Advanced Technology & Sciences (ICAT'16) held in Konya (Turkey), September 01-03, 2016.

species were predicted by means of a multilayered neural network. These intensive efforts on estimating the bonding strength characteristics revealed that ANNs were quite useful in modeling the bonding characteristics of various engineering materials.

Our purpose in the present modeling study was to predict the bonding performances of wood samples exposed to different soaking temperatures and durations by means of artificial neural network approach, which is one of the soft computing techniques.

## 2. Artificial Neural Networks

ANN is a computational intelligence method that can cope with complex problems with a capacity to learn by examples. As a robust and versatile modeling tool, ANN has proved to be successful in the solution of various problems in a number of engineering fields [22]. There are different types of ANNs based on the parameters such as neuron configurations and their connection types, and training procedure. Based on a general acceptance, it is possible to say that multilayered perceptron (MLP) trained with the back propagation algorithm is the most popular network structure for engineering applications [23].

The MLP usually comprises an input layer, a few hidden layers and an output layer [24]. The neurons of a MLP network are connected from a layer to the next one by weights ( $w_{ij}$ ). A neuron in any layers of the network gets information ( $x_i$ ) from all the neurons of the previous layer. It gathers information ( $net_j$ ) weighted by factors corresponding to the connection and the bias ( $\theta_j$ ), and transmits output values ( $y_j$ ) computed by applying an activation function to  $net_j$  [4]. Figure 1 defines the general function of a neuron.

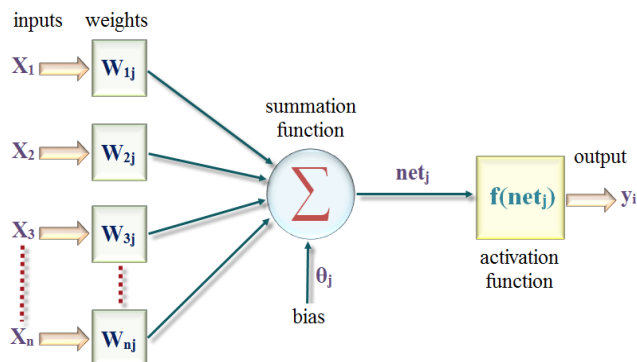


Figure 1. General functioning of an artificial neuron

An ANN needs a training process to perform a desired task. Training is a process of adjusting the connection weights by a learning procedure. After the training process, the network can be employed to make decisions or define associations in new input data sets. It is important to state that the weights gain meaningful information after training whereas they have no meaning before training. For training, the backpropagation is known as one of the most robust algorithms [24]. The details of ANNs are given in Tiryaki and Aydin [16].

## 3. Model Development Stages

### 3.1. Data Collection

The first stage in developing a neural network model is to collect the required data for modeling [25]. In this modeling study, the required data for the intended ANN model were experimentally obtained through soaking experiments carried out under different temperatures and durations. For this purpose, the experimental

samples of bonding strength with dimensions of  $150 \times 20 \times 10$  mm were thus prepared flawlessly. Figure 2 represents the dimension of experimental samples of the bonding strength.

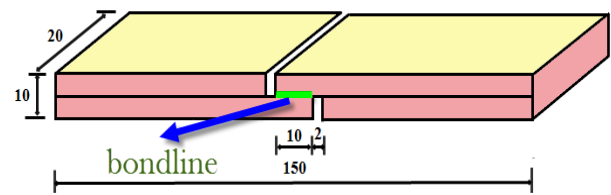


Figure 2. Experimental samples of bonding strength

Ten experimental samples were prepared for each variation in order to ensure the reliability of the measurements. Thus, a total of 320 samples were prepared for four different soaking temperatures, four different soaking durations and two wood species ( $4 \times 4 \times 2 \times 10$ ). The prepared wood samples were subjected to soaking for different temperatures (20, 40, 60 and  $80^\circ\text{C}$ ) and durations (10, 20, 30 and 40 min). After soaking process, the wood samples were acclimatized at  $20 \pm 2^\circ\text{C}$  and  $65 \pm 5\%$  relative humidity to achieve a moisture content of 12%. The experiments were performed according to BS EN 205 [26] standards. Eq. (1) was used to calculate the strength values of the experimental samples.

$$\sigma_y = \frac{F_{\max}}{a \times b} \text{ (N/mm}^2\text{)} \quad (1)$$

Where;  $\sigma_y$  gives the value of the bonding strength,  $F_{\max}$  refers maximum load at the break point,  $a$  and  $b$  constants represent the width and length of glued face, respectively.

Following the completion of the experimental procedure, the bonding strength data obtained were grouped into three sub-sets to start the modeling process; training, validation and testing. 70% of all experimental data (twenty-two data) were used for training the intended model. The remaining 30% of the data (ten data) were equally divided for validation (five data) and testing (five data) of the network.

### 3.2. Network Structure

The detection of the appropriate size of the network in designing a neural network is extremely important. As seen in Figure 3, a three-layer ANN structure was determined as the optimum architecture for this study.

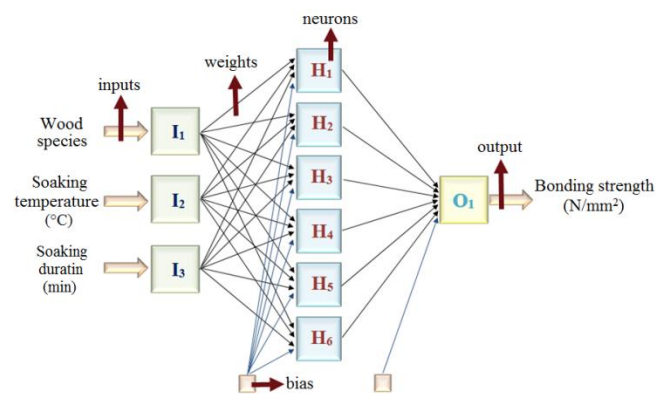


Figure 3. The optimum architecture of MLP used in predicting bonding strength

A three-layer feedforward ANN model with one hidden layer was constructed and a backpropagation algorithm was used to train

network. Levenberg–Marquardt algorithm was selected as learning algorithm in the present study. Each layer of the network is linked to the next layer, but no connections exist among the neurons located within the same layer. The first (input) and third (output) layers of the network include the input variables (wood species, soaking temperature and soaking duration) and output variable (bonding strength), respectively. Since there is no certain rule to decide the number of hidden layer neurons, various combinations was tried in terms of hidden layer numbers and their neurons. After trial and error procedure, best results with minimum errors were obtained with 3-6-1 neuron configuration for input, hidden and output layer, respectively. Here, the important point was to detect the optimal number of hidden layer and its neurons, since the number of input and output layers and their neurons is evident, as discussed above. As shown, the network architecture of the bonding strength prediction model has one hidden layer and six hidden neurons. Already, in the literature, it was reported that one hidden layer is mostly sufficient to solve engineering problems [23], as found sufficient for the present study.

### 3.3. Evaluation of model performance

In order to assess the prediction ability of the established neural network model, the differences between the actual and predicted outputs were analysed based on the statistical criteria of determination coefficient ( $R^2$ ), the mean absolute percentage error (MAPE) and the root mean square error (RMSE). A neural network model is accepted good when its  $R^2$  is close to 1 and error values such as the MAPE and RMSE is close to 0 [27]. These evaluation criteria can be calculated by Eqs. (2) - (4).

$$MAPE = \frac{1}{N} \left( \sum_{i=1}^N \left| \frac{t_i - td_i}{t_i} \right| \right) \times 100 \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (t_i - td_i)^2} \quad (3)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (t_i - td_i)^2}{\sum_{i=1}^N (t_i - \bar{t})^2} \quad (4)$$

Where,  $t_i$  is the actual output,  $td_i$  is the network output,  $N$  is the number of samples and  $\bar{t}$  is the mean of network outputs.

## 4. Results and Discussion

Table 1 gives the actual values, network output and % errors of the prediction as a result of neural network analysis. As seen from Table 1, in most cases, the ANN predictions are very close to the actual values. In other words, the developed ANN model is capable of giving very near prediction values to actual data of the bonding strength.

**Table 1.** The actual and predicted values of bonding strength

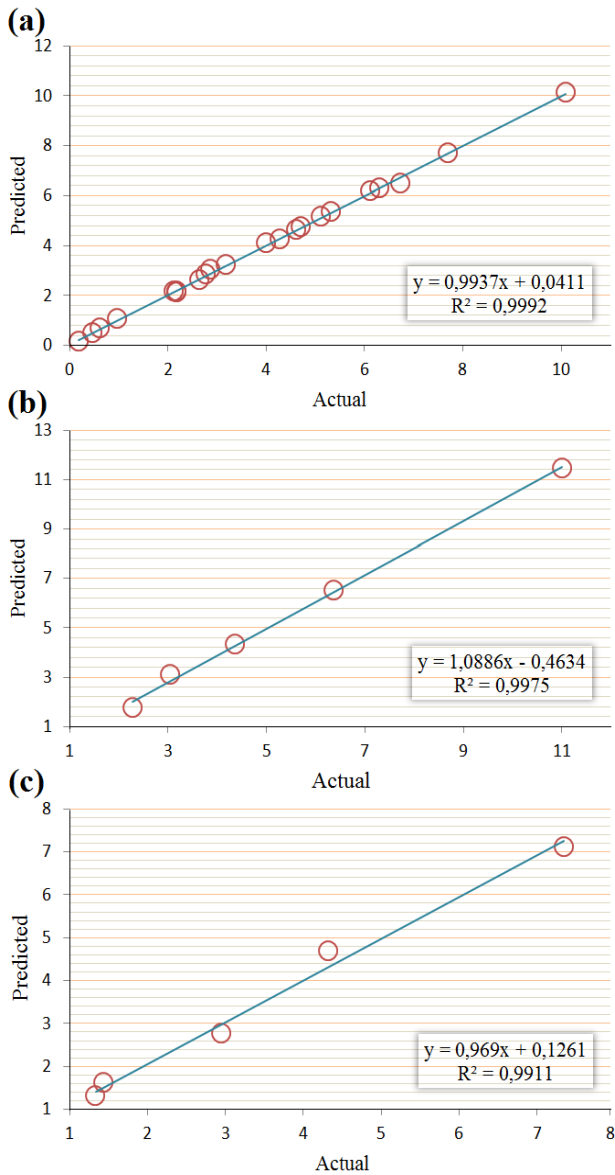
Soaking temperature (°C)	Soaking duration (min)	Bonding strength (N/mm <sup>2</sup> )					
		Beech			Spruce		
		a	p	e	a	p	e
20	10	<b>11.008</b>	<b>11.468</b>	<b>-4.179</b>	10.098	10.138	-0.396
20	20	7.704	7.718	-0.182	<b>7.348</b>	<b>7.122</b>	<b>3.076</b>
20	30	6.312	6.288	0.380	6.126	6.174	-0.784
20	40	6.736	6.507	3.400	<b>6.372</b>	<b>6.524</b>	<b>-2.385</b>
40	10	5.322	5.356	-0.639	5.122	5.15	-0.547
40	20	<b>4.328</b>	<b>4.679</b>	<b>-8.110</b>	<b>4.372</b>	<b>4.321</b>	<b>1.167</b>
40	30	4.708	4.738	-0.637	4.626	4.619	0.151
40	40	4.004	4.083	-1.973	4.284	4.262	0.514
60	10	2.876	3.051	-6.085	2.784	2.845	-2.191
60	20	3.194	3.237	-1.346	<b>3.056</b>	<b>3.117</b>	<b>-1.996</b>
60	30	<b>2.948</b>	<b>2.774</b>	<b>5.902</b>	2.642	2.617	0.946
60	40	2.178	2.145	1.515	2.122	2.157	-1.649
80	10	2.186	2.162	1.098	<b>2.286</b>	<b>1.748</b>	<b>23.535</b>
80	20	<b>1.442</b>	<b>1.613</b>	<b>-11.859</b>	<b>1.336</b>	<b>1.305</b>	<b>2.320</b>
80	30	0.982	1.057	-7.637	0.624	0.692	-10.897
80	40	0.466	0.495	-6.223	0.188	0.162	13.830

*Note:* bold italic data: testing, bold data: validation, the other data: training

a, p and e denote actual, predicted and error %, respectively

The performance of the model developed for bonding strength prediction was evaluated. This evaluation was mainly done for both confirming the goodness-of-fit of the model and the prediction accuracy of the bonding strength. As mentioned before, RMSE, MAPE, and  $R^2$  performance measures were considered to assess the performance in making the prediction of the established neural network. In the evaluation process, the smaller values of the RMSE and MAPE mean the better prediction. On the other hand, with respect to the  $R^2$  criterion, better prediction requires higher values.

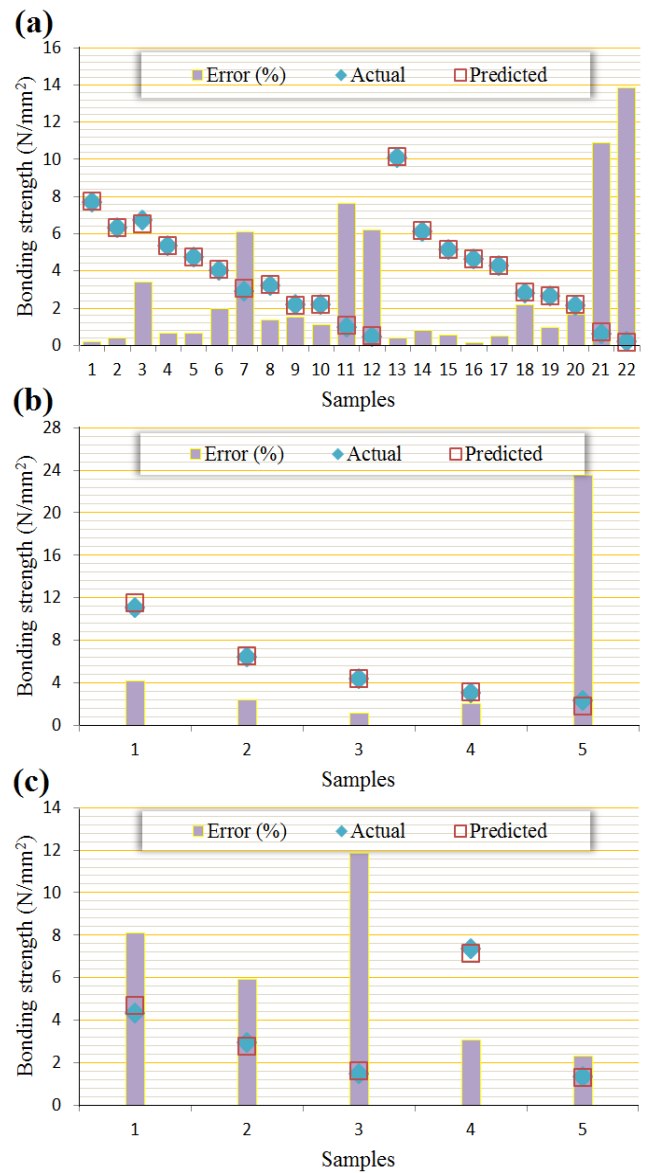
The criterion of the  $R^2$  is widely employed in order to demonstrate the level of the relationship between actual and network outputs. Figure 4 indicates graphical presentation of the fit between the actual and network outputs of the bonding strength of soaked wood, for training, validation and testing.



**Figure 4.** The graph of relationship between actual and network outputs of bonding strength: (a) training, (b) validation and (c) testing.

As seen in Figure 4, the  $R^2$  values were found to be 99.92% for training phase, 99.75% for validation phase, and 99.11% for the testing phase in neural network model. These values of the  $R^2$  are considered adequate for the bonding strength of soaked wood and thus the developed ANN structure can be employed effectively to make predictions.

The RMSE values were found to be 0.073 for training, 0.325 for validation, and 0.217 for testing. Among evaluation criteria, the MAPE criterion is very critical, and in the literature, many researchers have judged the performance of the model by computing the MAPE [20] [21] [28]. Thus, it was considered to be the primary criterion in terms of prediction accuracy. For the current study, the MAPEs were found to be 2.864% for training, 6.652% for validation, and 6.253% for test. In other words, the MAPEs of the designed model range from 2.864% to 6.652%. These results of the MAPE have demonstrated that the performance of the developed neural network in modeling the bonding strength of soaked wood is adequate. A comparison of the actual and predicted strength values for training, validation and testing stages is provided in Figure 5.



**Figure 5.** Comparison of actual and ANN prediction, and error values of bonding strength: (a) training, (b) validation and (c) testing.

From Figure 5, it is possible to see that the predicted values were found to be close to the actual values. In addition, the model outputs generally overlapped with the actual outputs. As expected, the matching of the predicted values and actual values especially in the training data set is excellent. With respect to the comparative graphs of the bonding strength prediction and actual results, it can be said that the established network was successfully trained and exhibited a reasonable accuracy in the prediction of the bonding strength behavior of the soaked wood. These results confirmed that a well-trained ANN is capable of predicting the strength of joints designed under different conditions. Furthermore, as mentioned before, ANNs can describe nonlinear characteristics of the existing variables in the process without any assumptions. It is possible to claim that this flexibility of ANNs makes it more suitable for predicting the bonding characteristics of soaked wood.

## 5. Conclusion

In this study, a feed forward backpropagation network was proposed in order to model the bonding strength of soaked wood. In training period of the network, Levenberg-Marquard learning

algorithm was employed. The best prediction results of the ANN were found in the network configuration of 3-6-1. In the proposed model, the values of  $R^2$  were over 99% for all data sets. In addition to the  $R^2$ , the performance criteria such as the RMSE and MAPE regarding the prediction errors for all data sets were within acceptable ranges. All these show that the learning ability of ANN for estimation is very good and the use of this method may strongly be suggested to eliminate laborious and time consuming experimental investigations. It is possible to say that ANNs are more economical to detect the bonding behavior of the wood soaked under different temperature and durations.

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