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Comparison of artificial neural network and multiple linear regression models to predict optimum bonding strength of heat treated woods

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ABSTRACT

In this study, an artificial neural network (ANN) model was developed for predicting an optimum bonding strength of heat treated woods. The MATLAB Neural Network Toolbox was used for the training and optimization of the ANN model. The ANN model having the best prediction performance was detected by trying various networks. Then, the ANN results were compared with the results of multiple linear regression (MLR) model. It was shown that the ANN model produced more successful results compared to MLR model in all cases. The mean absolute percentage errors (MAPE) were found as 1.49% and 3.06% in the prediction of bonding strength values for training and testing data sets, respectively. Determination coefficient (R^2) values for training and testing data sets in the prediction of bonding strength by ANN were 0.997 and 0.986, respectively. The results also indicated that the designed model is a useful, reliable and quite effective tool for optimizing the effects of heat treatment conditions on bonding strength of wood. Thanks to using optimum bonding strength values obtained by the model, the increase of the bonding quality of wood products can be provided and the costs for experimental material and energy can be reduced.

1. Introduction

Wood products have been used for numerous applications where their adhesive bond strength is essential. Bonding strength is a frequently used reference parameter in the determination of adhesive bond strength of wood because it is the most common interfacial stress under service conditions. However, the various parameters such as heat treatment, wood density, grain orientation, amount of adhesive, adhesive type and pressure considerably influence bonding quality of wood. Hence, it is important to evaluate the parameters that affect bonding strength of wood so that different wood species can be used efficiently during their service life without having any possible failure [1–4].

Heat treatment applications in wood originally were developed in Europe during 1990s [5]. The main aim of heat treatment is to improve certain wood properties. For example, heat treatment enables desirable changes in the physical properties of wood, such as reduced shrinkage and swelling, enhanced weather resistance, a decorative dark color, and better decay resistance [6]. However, it was reported that heat treatment adversely influences most of mechanical properties of wood because it degrades wood polymers [7–9]. The use of heat treated wood in structural applications is restricted due to a reduction of mechanical properties of wood ranging from 10% to 30% [10]. Therefore, determining the effects of heat treatment on bonding strength is extremely necessary.

Some studies were carried out to detect the effects of heat treatment on bonding strength of wood. Kasemsiri et al. [8] reported that bonding strength of wood exposed to heat treatment showed a reduction, ranging from 25.12% to 52.67%, as compared to those of untreated samples. Dilik and Hiziroglu [5] performed a study on bonding strength of heat treated wood. Wood samples showed a 23.6% reduction in their shear strength when they were exposed to a temperature of 120 °C. Strength losses for the samples exposed to temperature levels of 160 °C and 190 °C were found as 44.4% and 64.1%, respectively. Bakar et al. [10] observed a reduction in bonding strength values ranging from 52.7% to 69.4% depending on wood species and treatment conditions in heat treatment applied to different wood species.

Results obtained from experimental studies illustrated that heat treatment applied to wood significantly affects bonding strength. However, the measuring of the effect of each parameter on bonding strength is too expensive, and carrying out tests is also time-consuming. Determining optimum bonding strength without strength loss is also very desirable from industrial viewpoint. However, a lot of temperature and time values need to be tested to determine the optimum values that cause the loss of much time

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and high costs. Therefore, it is quite important to try more economic methods providing the required results in a short period of time with very low error rates. To achieve this, ANNs have been widely used in the field of wood science, such as optimizing process parameter in manufacturing process of wood [11], drying process of wood [12,13], predicting mechanical properties in wood and wood composites [14,15], classifying of wood veneer defects [16,17], calculating wood thermal conductivity [18], moisture analysis in wood [19,20], the recognition of the wood species [21], and classifying wood defects [22].

ANNs have been also used for the applications such as prediction, modeling and optimization of bonding strength of the various wood based materials. Cook and Chui [23] predicted the internal bond strength of particleboard using a radial basis neural network at the accuracy levels of 87.5%. Esteban et al. [24] predicted bonding quality of plywood using an ANN model with 93% accuracy. Demirkir et al. [25] studied on optimization of some panel manufacturing parameters for predicting the best bonding strength of plywood. They predicted the bonding strength of plywood using an ANN at the accuracy levels of 98.0%.

The studies on determining effects of heat treatment on bonding strength, and predicting bonding strength of the various wood based materials by ANN were stated above. However, there is very limited information on modeling bonding strength of heat treated woods. Therefore, the main aim of this study is to model bonding strength of heat treated woods so that usability of such wood species for different purposes can be better understood.

2. Methods

2.1. Data preparation

Data used in this study were provided from a previous experimental study by Ozcan et al. [9]. Some experimental details about their study, which aims to measure shear strength values of wood samples subjected to heat treatment, can be stated briefly as follows:

Wood samples were conditioned at a temperature of 20 °C ± 2 °C and a humidity of 65% ± 5 until they reach to equilibrium moisture content of 12%. Then, samples were planned in radial and tangential orientations using 8 and 16 m/min feed speed. Polyvinyl acetate (PVAc) and melamine-urea formaldehyde (MUF) were used as adhesives. These adhesives were applied to the surface of bonding strength samples by brushing at a rate of 200 g/m^2. Samples were compressed by using a pressure of 2 kgf/cm^{2}for 6 h for PVAc and 5 min for MUF before they were tested on a Universal Test Machine. Then, samples were kept in a laboratory type heating oven at temperature levels of 120 °C, 150 °C and 180 °C for 2 h and 6 h. After heat treatment, samples were conditioned until they reach an average equilibrium moisture content of 10%. Then, the bonding strength values of samples were calculated [9].

In the present study, the bonding strength values were predicted with the ANN and MLR models using the experimental data. The MATLAB Neural Network Toolbox was used for the configuration, training and optimization of ANN model. Experimental data was randomly divided into two groups for training and testing of the model. Among this data, 72 data were selected for ANN training process, while the remaining 24 data were used for ANN testing process. On the other hand, all bonding strength values (namely 96 data) were used in the MLR prediction model. Table 1 shows the predicted values obtained by utilizing the ANN model for the training and testing data, the measured values and percentage error ratio.

2.2. Prediction models

2.2.1. Artificial neural networks (ANNs)

ANNs have been recently developed as a powerful modeling tool in comparison to the statistical or numerical methods [13]. Thus, ANNs have been used for many engineering applications such as prediction, optimization, classification and pattern recognition [26]. They have a highly interconnected structure similar to brain cells of human neural networks and consist of a great number of processing elements called neurons, which are arranged in different layers of the network. Each network comprises an input layer, an output layer and one or more hidden layers [27]. The neurons in the networks are interconnected using weight factors (w_{ij}). A neuron (j) in a given layer receives information (x_i) from all the neurons in the preceding layer (Fig. 1). It sums up information (net_j) weighted by factors corresponding to the connection and the bias of the layer (θ_j), and transmits output values (y_j) computed through applying a mathematical function ($f(.)$) to net_j, to all neurons of the next layer. This process is formulated in Eqs. (1) and (2), and illustrated in Fig. 1 [28].

$$\mathrm{net}_j = \sum_{i=1}^{n} X_i W_{ij} - \theta_j \tag{1}$$

$$y_j = f(\mathrm{net}_j) = \frac{1}{1+e^{-\mathrm{net}_j}} \tag{2}$$

The number of neurons in the ANN layers has an important effect on the network performance. The number of neurons in the input layer corresponds to the number of input (independent) variables, and the number of output neurons is equal to the number of output (dependent) variables in a prediction problem based on cause and effect relationship [29]. However, there is currently no explicit rule to detect the number of hidden neurons in the hidden layer(s). The number of hidden layer(s) and neurons in the hidden layers are generally detected by a process of trial and error. The influence of the number of neurons in the hidden layer on the performance of the network is quite complicated. If the architecture of ANN model is too simple, the trained network does not have sufficient ability to learn the relationship of inputs and outputs. Whereas, if the architecture is too complex, the training of the network will be over fitted or the model will not converge to the goal error [28–31].

2.2.1.1. Neural network training

In the present study, feed forward and back propagation multilayer ANN was chosen for solution of the problem. The hyperbolic tangent sigmoid transfer function (tansig) in the hidden layers and linear transfer function (purelin) in the output layer as the activation function were preferred. The Levenberg–Marquardt algorithm (trainlm) was used as the training algorithm. The gradient descent with a momentum back propagation algorithm (traingdm) was used as the learning rule.

It was decided that the 0.00075 targeted error values would be sufficient for the training of ANN. Fig. 2 shows the graphic of error variation depending on iteration of the ANN model chosen for the bonding strength. The training of the ANN was stopped after 22 epochs because the targeted MSE value (0.00075) was reached.

2.2.1.2. Neural network architecture

In order to determine the optimum network architecture and parameters such as the number of hidden layers, number of neurons in hidden layer, transfer functions, number of learning cycles, initialization of the weights and the biases etc., the trial and