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MODELLING THE THERMAL CONDUCTIVITY OF VENEER SHEETS WITH DIFFERENT MOISTURE CONTENT USING ARTIFICIAL NEURAL NETWORK

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Abstract:
Moisture content in wood significantly affects the bonding process of veneer-based products such as plywood and also causes changes in some technological properties such as thermal and electrical conductivity. Therefore, it is necessary to determine the most appropriate moisture content of wood materials to be used in end-use areas according to the desired technological properties. The aim of this study was to model the experimentally obtained thermal conductivity coefficient values of veneer sheets with different moisture content levels by using artificial neural network (ANN). Beech (Fagus orientalis Lipsky), scots pine (Pinus sylvestris L.) and poplar (Populus deltoides) were used as wood species. The veneer sheets were dried or air-conditioned to reach 3%, 6%, 9%, 12% and 15% moisture content. To determine the insulation properties of veneer sheets, the thermal conductivity coefficients were determined according to ASTM C 518 standard. The prediction model with the best performance and acceptable deviations was determined by using statistical and graphical comparisons between the experimental data and the prediction values obtained as a result of ANN analysis. Then, using this prediction model, the thermal conductivity coefficient values were estimated for the intermediate veneer moisture content values that were not experimentally tested. According to the analysis findings, as the veneer moisture content increased, the thermal conductivity coefficient values increased. Poplar veneers gave the lowest thermal conductivity coefficient values among wood species. The findings of this study could be employed effectively into the furniture and building industry to reduce time, energy and cost for experimental investigations.

Key words: *ANN; beech; poplar; scots pine; veneer moisture content; thermal conductivity coefficient.*

INTRODUCTION

Plywood has been used extensively in the construction and furniture industry recently. Plywood is one of the best sheathing materials for shear walls of structures exposed to earthquake loads since it allows for the largest displacement before failure (Demirkir *et al.* 2013a). Moreover, plywood provides sufficient rigidity, stiffness, strength and joint durability for wooden constructions (Demir *et al.* 2019). The use of plywood in structures is restricted due to its negative properties such as being easily burned and quickly affected by humidity changes (Bryn *et al.* 2016, Aydin *et al.* 2006).

Wood is a hygroscopic material and exchanges its moisture content with air; the amount and direction of the exchange (gain or loss) depend on the relative humidity and temperature of the air and the current amount of water in the wood. This moisture relationship has an important influence on wood properties and performance (Aydin *et al.* 2006). In addition, the moisture of wood; affect various properties such as weight, rot susceptibility, permeability, strength, electrical properties, heat transfer properties, formaldehyde emission, adhesion and dimensional stability (Simpson and Tenwolde 1999, Green and Evans 2003, Mitchell 2004).

The process of gluing of veneer-based products, as plywood or laminated veneer lumber, is significantly affected by the moisture content in wood combined with water in an adhesive. This moisture directly influences the curing process and properties of the used adhesive, economic costs (consumption of glue, pressing time and costs for veneer drying) as well as physical and mechanical properties of veneer-based products (Bekhta *et al.* 2014). In addtion, it was stated in some studies in the literature that the moisture content affected the thermal conductivity, which is one of the thermal properties of wood materials (Troppova *et al.* 2015, Liu *et al.* 2013, Yu *et al.* 2011). Sonderegger and Niemz (2009) also found that plywood showed the highest change of thermal conductivity with increasing moisture content and OSB the lowest, while particle and fibre boards had medium values. The transfer of heat from the panel is provided by the ratio of the voids (Bekhta and Dobrowolska 2006). Filling these voids with a liquid such as water higher than the thermal conductivity of air also increases the thermal conductivity of the material (Kol *et al.* 2008).

Especially in the plywood sector, the moisture content of the veneer sheets to be used in production should be adjusted according to the desired technological properties. However, it is known that this will lead to many experiments. Therefore, it is very important to use economical methods that do not require more trial, labor, time, energy loss and high cost (Demirkir *et al.* 2013b). Artificial neural networks (ANN), which is more adaptable than traditional methods, were used by researchers for optimization of wood and wood-based materials due to faster and economical (Avramidis and Iliadis 2005, Esteban *et al.* 2011, Demirkir *et al.* 2013b, Ozsahin and Aydin 2014, Tiryaki *et al.* 2017, Ozsahin and Murat 2018). Even if the relationships between the experimentally obtained input and output data were complex and meaningless, ANN modelling could be successfully performed to obtain desiring optimum values (Fernandez *et al.* 2008).

OBJECTIVE

The aim of this study was to model the experimentally obtained thermal conductivity coefficient values of veneer sheets with different moisture content levels by using artificial neural network (ANN). For this aim, the thermal conductivity coefficient values of the intermediate moisture content values not used in experimental studies were also estimated and the effects of moisture content for each wood species were revealed.

MATERIALS AND METHODS

Data Collection

In this experimental study, 2mm - thick rotary cut veneers with the dimensions of 500mm by 500mm were obtained from beech (*Fagus orientalis* Lipsky), scots pine (*Pinus sylvestris* L.) and poplar (*Populus deltoides*) logs. While the poplar veneers were manufactured from freshly cut logs, beech and scots pine logs were steamed for 12h before veneer production. The horizontal opening between knife and nosebar was 85% of the veneer thickness, and the vertical opening was of about 0.5mm in the rotary cutting process. Some of the veneers were brought to the values of 3% and 6% moisture content by drying in the dryer at 110°C. Another part of the veneers reached the values of 9%, 12% and 15% moisture content by keeping them in the climazitation cabinet at a certain temperature and relative humidity. Five veneer sheets were subjected to thermal conductivity measurements for each wood species reaching the specified five moisture content levels. The thermal conductivity coefficients of the veneer sheets were determined by the Lasercomp Fox-314 thermal conductivity device (Fig. 1) according to the ASTM C 518 (2004) standard.

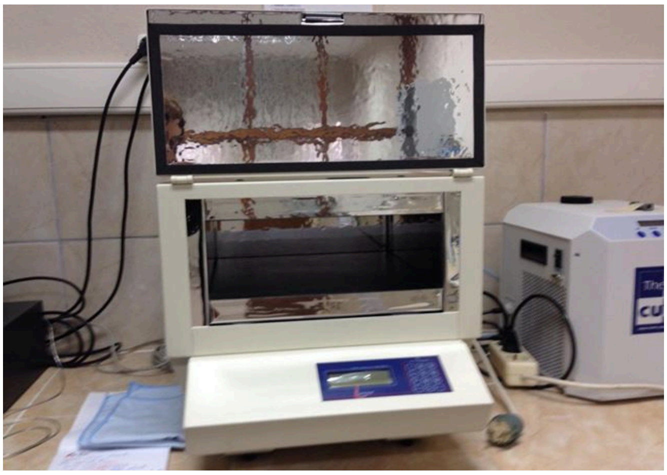


Fig. 1.
Lasercomp Fox-314 thermal conductivity device.

Artificial Neural Network (ANN) Analysis

Thermal conductivity coefficient values corresponding to other intermediate veneer moisture content that could not be obtained in experimental studies were estimated by modeling ANN. In this way, it was aimed to reveal the effect of the veneer moisture content for each wood species in order to determine the change of thermal conductivity coefficient values.

The wood species and veneer moisture content were main variables in ANN modelling of this study. The data obtained from experimental studies were modelled using the MATLAB Neural Network Toolbox. The experimental data were grouped as training data and testing data to determine the effects of veneer moisture content on the thermal conductivity of veneer sheets according to wood species. The training data set was used for the development of the network whilst the testing data set was used to evaluate the performance of the model. For modelling of the thermal conductivity coefficient, 10 data (66.67% of the total data) among the experimental data were allocated for the training set and the remaining 5 data (33.33% of the total data) were allocated for the testing set. The data sets used in the prediction models, the ANN analysis results and the experiment results were given in Table 1.

Table 1

Training and test data sets of thermal conductivity coefficient values

Training Data				
Wood Species	**Veneer Moisture Content (%)**	**Thermal Conductiviy Coefficient (W/mK)**		
		Actual	**Predicted**	**Error (%)**
Beech	3	0.02612	0.02612	0.00
	9	0.02998	0.02998	0.00
	15	0.03254	0.03254	0.00
Scots pine	6	0.02602	0.02607	-0.20
	9	0.02788	0.02772	0.58
	12	0.02915	0.02928	-0.45
Poplar	3	0.02368	0.02367	0.04
	6	0.02506	0.02507	-0.05
	12	0.02864	0.02869	-0.17
	15	0.03022	0.03015	0.23
MAPE Training			0.17126	
RMSE Training			0.00007	
Testing Data				
Wood Species	**Veneer Moisture Content (%)**	**Thermal Conductiviy Coefficient (W/mK)**		
		Actual	**Predicted**	**Error (%)**
Beech	6	0.02818	0.02812	0.20
	12	0.03105	0.03139	-1.11
Scots pine	3	0.02482	0.02482	-0.01
	15	0.03102	0.03057	1.43
Poplar	9	0.02688	0.02693	-0.17
MAPE Testing			0.58425	
RMSE Testing			0.00025	

After the testing process, the actual (measured) values were compared with the prediction values obtained from ANN analyses. The models giving the best predictive values were determined by taking into account the root mean square error (RMSE) calculated by Eq.1, the mean absolute percent error (MAPE) calculated by Eq.2 and coefficient of determination (R^2) calculated by Eq.3, which are well known and widely used performance functions.

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

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

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(t_i - td_i)^2}{\sum_{i=1}^{N}(t_i - \bar{t})^2} \tag{3}$$

where: *ti* is the actual output values, *tdi* is the neural network predicted values, and *N* is the number of objects.

The network structure of the prediction model consisting of an input layer, a hidden layer and an output layer is shown in Fig. 2. In the ANN structure, the wood species and veneer moisture content were selected as the input variables, while the thermal conductiviy coeficient was selected as the output variable.

The processing element numbers (neurons) of the hidden layer were 3 for the models. The connection weights and bias values of the prediction model of thermal conductivity coefficient values were given in Table 2, respectively.

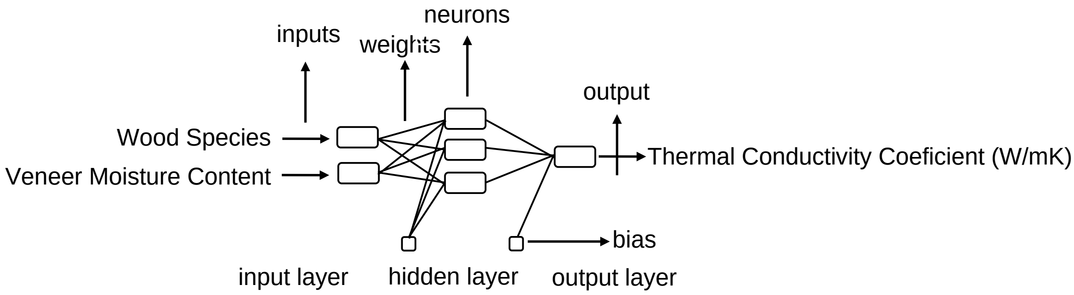


Fig. 2.
The ANN structure selected as the prediction model.

Table 2

Connection weights and biases of the thermal conductivity prediction model

Hidden Layer			Output Layer		
Neuron1	**Neuron 2**	**Neuron 3**	**Bias1**	**Neuron 1**	**Bias2**
-0.03647	-0.05062	12.09131	1.74485	-29.52680	11.49059
0.51713	0.43043	-2.72697	1.21499	19.54003	-
-	-	-	10.25784	-0.17856	-

In the determination of thermal conductivity models, feed forward and backpropagation multilayer ANNs were used. In the proposed models, the hyperbolic tangent sigmoid function (tansig) is preferred as the transfer (activation) function in the hidden layer (s) and the linear transfer function (purelin) in the output layer. The Levenberg marquardt algorithm (trainlm) was chosen as the training algorithm, the momentum gradient reduction backpropagation algorithm (traingdm) was used as the learning rule, and the mean square error (MSE) calculated by Eq. 4 was preferred as the performance function.

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(t_i - td_i)^2 \tag{4}$$

where: *ti* is the actual output (targeted values), *tdi* is the neural network output (predicted values), and *N* is the total number of training patterns.

In order to contribute equally to the models for each parameter, the data in the training and testing set were normalized (-1, 1 range) since the hyperbolic tangent sigmoid function was used in the models and then the data were converted to their original values by reverse normalization so that the results could be interpreted. The normalization (scaling) operations were carried out by using Eq. 5.

$$X_{\text{norm}} = 2 \times \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} - 1 \tag{5}$$

where: X_{norm} is the normalized value of a variable X (real value of the variable), and X_{max} and X_{min} are the maximum and minimum values of X, respectively.

RESULTS AND DISCUSSION

The MSE changes of the thermal conductivity prediction model of ANN depend on iteration were shown in Fig. 3 and the best training performance was realized as 0.00027299 in the 1000th iteration for the thermal conductivity coeficient.

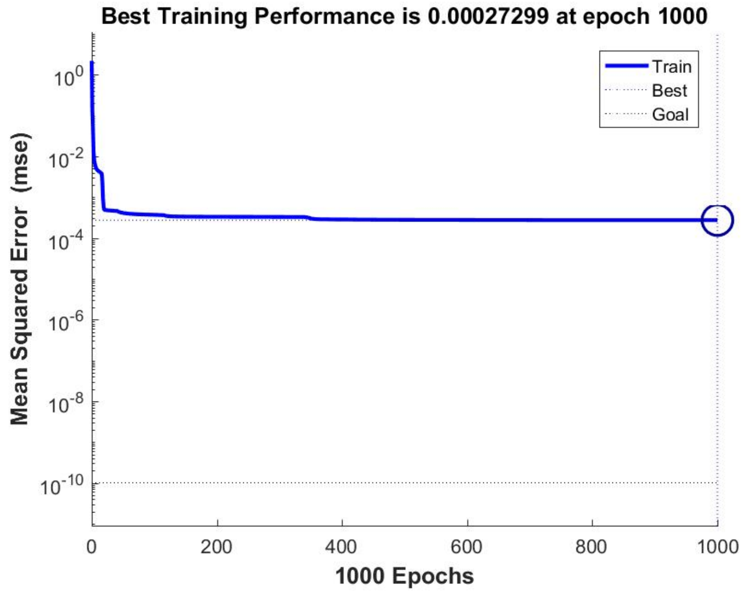
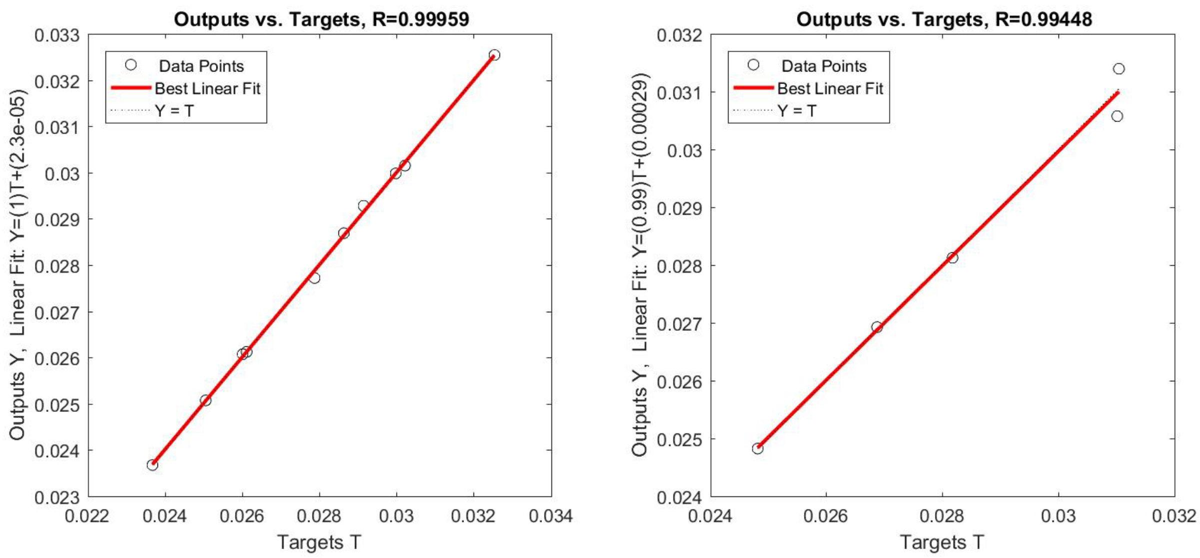


Fig. 3.

MSE changes at each iteration for thermal conductivity prediction model.

Regression analysis between predicted values and measured values is often used to evaluate the validity and accuracy of networks. The estimation accuracy of models increases when the correlation coefficients approach to 1 (Ozsahin 2012). This indicates that there is a perfect fit between the real values and the predicted values. The diagrams showing the relationships between calculated values and real values were presented in Fig. 4 (training R = 0.99918, testing R = 0.98899). These values proved that the developed models had a good performance and supported the predictive use of ANNs.



(a) **(b)**

Fig. 4.

Regression models of the training (a) and testing (b) set for the thermal conductivity.

Fig. 5 showed the comparison of the outputs of ANN prediction model with their experimental results. As can be seen from the figure, the values were very close to each other. High similarity between the experimental results and predicted values increased the reliability of proposed ANN models.

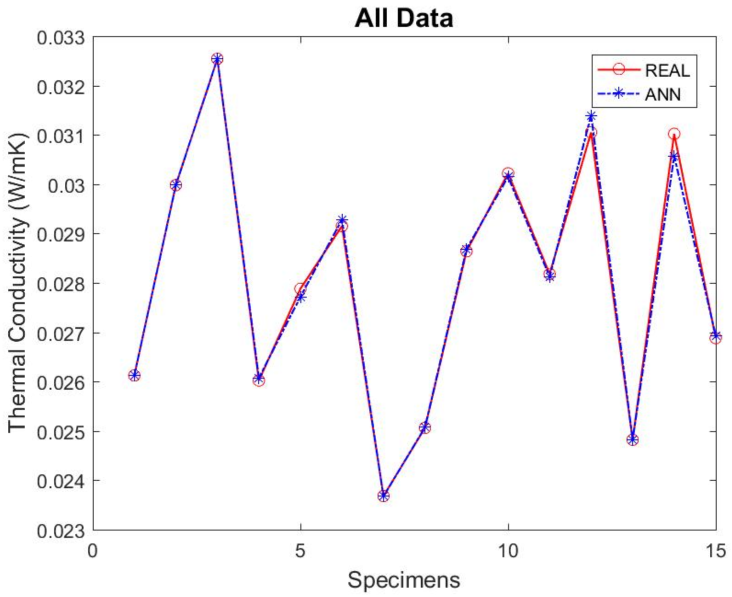


Fig. 5.
The comparison of the measured and predicted values for the thermal conductivity.

MAPE is one of the most significant evaluation criteria and many researchers have evaluated model performance using MAPE (Antanasijević *et al*. 2013, Tiryaki *et al.* 2016, Yadav and Nath 2017). In the literature, it has been stated that the model performance is high if the MAPE value is below 10% (Yadav and Nath 2017). In this study, the MAPE values for the thermal conductivity were 0.17126% for training and 0.58425% for testing (Table 1). These error levels show that ANN prediction models provide satisfactory results effectively and have adequate accuracy and reliability. In the determination of the best ANN model, RMSE values are also taken into consideration in addition to MAPE values (Küçükönder *et al.* 2016). Low RMSE values are one of the parameters showing good model performance (Taşpınar and Bozkurt 2014). The RMSE values for training and testing data were 0.00007 and 0.00025, respectively (Table 1). These levels of error are satisfactory for the thermal conductivity.

Using a high-performance prediction model obtained by ANN analysis, high accuracy rates can be achieved in the prediction of output data corresponding to intermediate data of input variables that are not used in experimental studies (Varol *et al.* 2018). The thermal conductivity coefficient values corresponding to the intermediate values of the veneer moisture content values determined as the input variable, which are not used in the experiments, were estimated according to the wood species and the changes of these values according to the moisture content were given in Fig. 6. In addition, the thermal conductivity coefficient values corresponding to the intermediate moisture content values not used in the experimental study from the prediction model were given in Table 3.

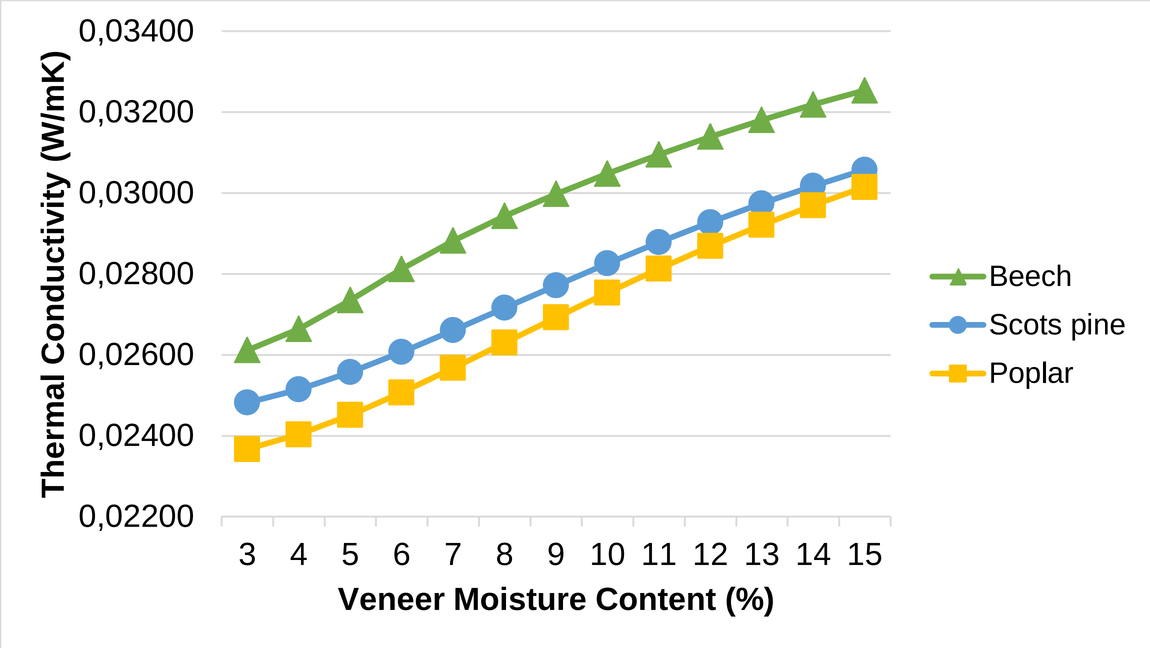


Fig. 6.
Effects of veneer moisture content on the thermal conductivity of veneer sheets.

Table 3

Thermal conductivity prediction for intermediate veneer moisture content

Wood Species	Veneer Moisture Content (%)	Thermal Conductivity (W/mK)
Beech	4	0.02664
	5	0.02735
	7	0.02883
	8	0.02944
	10	0.03048
	11	0.03095
	13	0.03181
	14	0.03219
Scots pine	4	0.02515
	5	0.02557
	7	0.02661
	8	0.02716
	10	0.02826
	11	0.02878
	13	0.02975
	14	0.03018
Poplar	4	0.02403
	5	0.02451
	7	0.02567
	8	0.02630
	10	0.02754
	11	0.02813
	13	0.02921
	14	0.02970

As can be seen in the Fig. 6. and Table 3, the predicted thermal conductivity coefficient values differed according to both the wood species and the veneer moisture content. It was expressed in many studies that the thermal conductivity coefficient value varied according to the wood species (Kol and Sefil 2011, Rice and Shepard 2004). In all three wood species, as the veneer moisture content increased, the thermal conductivity coefficient values also increased. Moreover, the thermal conductivity coefficient of beech veneers was found to be the highest, while the thermal conductivity coefficient values of poplar veneers were found to be the lowest. In the literature, it is known that the oven dry density of beech wood (0.63g/cm^3) is higher than both scots pine (0.50g/cm^3) and poplar (0.37g/cm^3) (Bozkurt 1992). This situation explained the variation of the results obtained from the study according to the wood species.

In the study, while the lowest thermal conductivity coefficients were obtained from 3% veneer moisture content among all three wood species, the highest values were obtained from 15% moisture content values. Liu *et al.* (2013) found that increase of moisture content in a range of 10-22%, the thermal conductivity and specific heat of the plywood assembly enhanced significantly. Density, moisture content, fiber direction, early and late wood ratios are important properties that affect the thermal conductivity of the wood material. It was stated that there was a relationship between thermal conductivity and the density of the wood material, moisture content, temperature and heat flow direction (Suleiman *et al.* 1999, Bader *et al.* 2007). It was also determined in another study that thermal conductivity increased with the increase of moisture content, ambient temperature and density, and panel thickness does not had a significant effect (Sonderegger and Niemz 2009). Yu *et al.* (2011) found similarly that the transverse thermal conductivity of wood increased with density, temperature, and moisture content and linear correlating equations were proposed in terms of these factors.

CONCLUSIONS

In this study, ANN models were developed to reveal the effects of wood species and veneer moisture content variables on the thermal conductivity coefficient values of veneer sheets and to determine some intermediate moisture content values that are not used in the experimental study. Depending on the results of the study, it was satisfactorily proven that the input and output variables consisting of complex and nonlinear relationships colud be predicted by ANN analysis. The MAPE value was calculated as 0.58425%, the RMSE value was 0.00025 and the R^2 value was 0.98899 during the testing phase of the prediction model of the thermal conductivity coefficients used to determine the insulation properties of veneer sheets, and the performance of this model was proven by diagnostic tools.

As a result of the ANN analysis, the thermal conductivity coefficient values of the veneers increased due to the increase in the moisture content. The lowest thermal conductivity coefficient values were obtained from 3% moisture content in all three wood species whilst the highest values were obtained from 15% moisture content. Among the wood species, poplar veneers gave lower thermal conductivity coefficient values than both beech and scots pine veneers. Using the findings obtained from the study, the thermal conductivity coefficient values of the veneers can be determined for the range of 3% -15% veneer moisture content, saving both time and costs required for testing.

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