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The use of an artificial neural network for predicting the gloss of thermally densified wood veneers

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Abstract

In this study, an artificial neural network (ANN) model was developed to predict the gloss of thermally densified wood veneers. A custom application created with MATLAB codes was employed for the development of the multilayer feed-forward ANN model. The wood species, temperature, pressure, measurement direction, and angle of incidence were considered as the model inputs, while the gloss was the output of the ANN model. Model performance was evaluated by using the mean absolute percentage error (MAPE), the root mean square error (RMSE), and the coefficient of determination (R^2). It was observed that the ANN model yielded very satisfactory results with acceptable deviations. The MAPE, RMSE, and R^2 values of the testing period of the ANN model were found as 8.556%, 1.245, and 0.9814, respectively. Consequently, this study could be useful for the wood industry to predict the gloss with a smaller number of labour consuming experimental activities.

Keywords: artificial neural network, gloss, prediction, veneer, wood

Introduction

Wood has been widely used for exterior and interior applications due to its availability, natural beauty, and strength (Aydin and Colakoglu 2005, Akbiyik et al. 2007, Scrinzi et al. 2011). However, wood is exposed to a number of detrimental factors such as humidity and ultraviolet radiation in exterior and interior environments (Temiz et al. 2005). Several modification methods have been developed to improve the various properties of wood and to extend the service life of wood and wood-based products. Thermal and thermo-mechanical treatments are some modification methods (Herrera et al. 2015, Pelit et al. 2015, Percin et al. 2015). Heating the wood at high temperatures reduces shrinking-swelling characteristics and equilibrium moisture content, and increases the weather resistance of the final product (Yildiz et al. 2006, Kocaefe et al. 2008). Such treatment also causes certain changes in the surface roughness, colour, and gloss of wood.

Gloss is one of the most important criteria in determining the quality of wood products (Slabejová et al. 2016). High gloss surfaces have gained importance in the furniture industry. Due to the increasing demand for high gloss surfaces, it is important to make reliable statements about the gloss of wood (Ettwein et al. 2017). There are many factors (such as temperature, grit size, pressure, and varnish type) influencing the gloss of wood, and these factors interact with each other (Aksoy et al. 2011, Bekhta et al. 2014, Pelit et al. 2015, Turkoglu et al. 2015, Gupta et al. 2016, Salca et al. 2016).

In recent years, some studies have focused on evaluating the influences of various factors on the gloss of wood. Aksoy et al. (2011) investigated the effect of heat treatment on gloss. They observed that heat treatment decreased the gloss values of wood. This observation was also confirmed by Gurleyen et al. (2017). Karamanoğlu and Akyıldız (2013) claimed that long-term weathering increased the gloss values of heat-treated wood. Baysal et al. (2014) investigated the effect of artificial weathering on the surface roughness, colour, and gloss of heat-treated wood. They reported that artificial weathering caused a decrease in gloss values. Budakçı and Karamanoğlu (2014) noted that hardness, gloss, and colour changes caused by weathering conditions can be reduced by the bleaching procedure. Turkoglu et al. (2015) studied the influence of natural weathering on the surface hardness and gloss of wood. The results of their study showed that natural weathering caused a decrease in the gloss values of wood specimens. Salca et al. (2016) found that finer grit sizes increased surface glossiness.

The investigation of the influence of each factor on gloss requires many experimental studies. However, extra experiments cause high costs and the loss of much time and energy. Various methods are available to predict the gloss of wood without spending much time, costs, and energy. The artificial neural networks (ANNs), the response surface methodology (RSM), the support vector machine (SVM), and the multiple linear regression (MLR) are some prediction methods. The ANN approach has become increasingly popular over the past decade. It deals with complex problems, which are difficult to solve by conventional statistical techniques. Furthermore, ANNs can define complicated and nonlinear relationships between inputs and outputs without any prior assumptions (Sun et al. 2010, Barelli et al. 2018). Therefore, we have used the ANN approach in our research.

The ANN approach has been widely employed in wood science to model input-output relationships. ANN applications to wood science include analyzing moisture in wood (Avramidis and Wu 2007), predicting fracture toughness (Samarasinghe et al. 2007), classifying wood veneer defects (Castellani and Rowlands 2008), wood recognition (Khalid et al. 2008), optimization of process parameters in oriented strand board manufacturing (Özşahin 2012, Ozsahin 2013), predicting the bonding strength of wood joints (Bardak et al. 2016), determination of optimum power consumption in wood machining (Tiryaki et al. 2016), prediction of formaldehyde emission (Akyüz et al. 2017), and prediction of surface roughness and adhesion strength of wood (Özşahin and Singer 2019). These studies have shown that the ANN approach produces highly successful results.

However, the current literature has a gap in predicting the gloss of wood by the ANN approach. Therefore, the objectives of our study are to develop an ANN model for modelling the effects of wood species, temperature, pressure, measurement direction, and angle of incidence on gloss and to present a road map for the wood industry seeking to enhance the quality of products.

Materials and methods

Data set

The data used in this study were taken from Bekhta et al. (2014). Some experimental details about their study can be briefly explained as follows. Alder (*Alnus glutinosa* Goertn.), beech (*Fagus sylvatica* L.), birch (*Betula verrucosa* Ehrh.), and pine (*Pinus sylvestris* L.) were selected as the materials of the experiments. Rotary cut veneer sheets were logged at the Sklejka-Multi S.A. plywood company in Bydgoszcz, Poland. Defect-free veneer sheets with dimensions of 300×300×1.5 mm^3 were then transported to the laboratory. Tangential sheets of veneer were cut into 140×100 mm^2 rectangular pieces. The whole test specimens were conditioned at 20°C and 65% relative humidity. Thermo-mechanical densification was applied to the wood specimens for nine combinations of three different temperatures (100, 150, and 200°C) and three different pressures (4, 8, and 12 MPa). The densification time was 4 min. The gloss of each veneer surface was measured at three different angles (20°, 60°, and 85°) and two different directions (across ($\perp$) the grain and along ($\parallel$) the grain). The gloss values were obtained using a PICO GLOSS 503 photoelectric apparatus. The measurements were carried out according to DIN 67530 (1982) and ISO 2813 (1994).

Artificial neural network approach

ANN is a data modelling tool that offers effective solutions to deal with complex problems. The ANN approach has been widely employed in many applications such as prediction, data sorting, pattern detection, optimization, clustering, and simulation due to its ability in learning complex and nonlinear relationships among variables (Yadav and Chandel 2014). The ANN approach learns these relationships from the previously recorded data (Bardak et al. 2016).

The most widely used ANN type for process modelling and prediction purposes is the multilayer perceptron (MLP). The MLP structure consists of three different layers: the input layer, where the data are introduced to the network, the hidden layer(s), where the information coming from the input layer is processed, and the output layer, where the results of the network are produced. Figure 1 depicts a typical example of the MLP structure (Ozsahin 2013).

Data processing is performed with neurons, which are placed in the layers of the MLP network. Input neurons and output neurons represent inputs and outputs, respectively. However, hidden neurons vary depending on the complexity level of the handled problem (Nastos et al. 2013). Too few hidden neurons may hinder the learning process. On the other hand, a large number of hidden neurons can lead to overfitting (Quintana et al. 2011). It is very difficult to detect the most suitable neural network, even for an experienced user (Ma et al. 2012).

Each neuron is connected to other neurons by communication links (connections) (Özşahin 2012). An artificial neuron sums the bias and weighted inputs, processes the sum with an activation function, and transmits the result

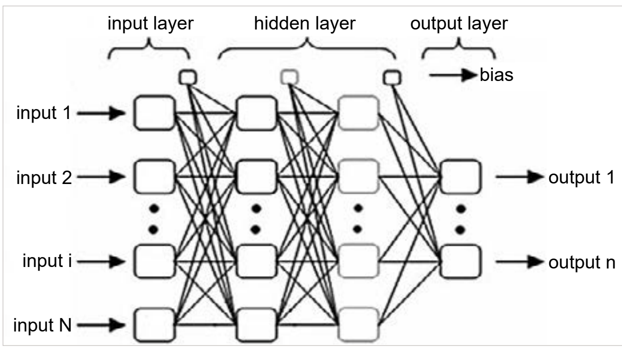

Figure 1. A typical multi-layered ANN structure

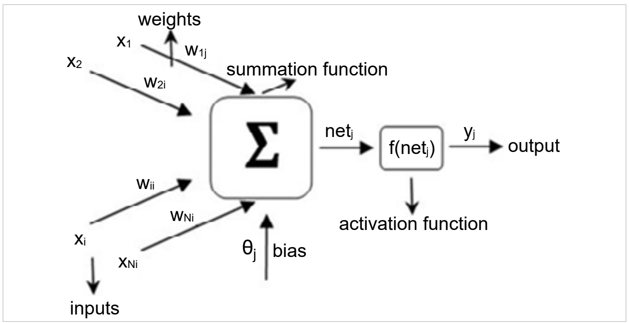

Figure 2. General functioning of an artificial neuron

to the next layer (Yalçin et al. 2015). Figure 2 illustrates the process described above. This process is summarized in Equations (1) and (2) (Ozsahin 2013).

$$\mathrm{net}_j = \sum_{i=1}^{n} x_i w_{ij} + \theta_j \ , \quad (1)$$

$$y_j \ = \ f(\mathrm{net}_j) \ , \quad (2)$$

where, x_i is the input signal, w_{ij} is the weight between the i^{th} neuron and the j^{th} neuron, θ_j is the bias (threshold), net_j is the net input of the j^{th} neuron, $f(.)$ is one of the activation functions, and y_j is the output of the j^{th} neuron.

Neural networks must be trained with known input-output data. During the training process, the values of weights and biases are changed to obtain the best prediction results (Haghdadi et al. 2013). When the error reached a determined value or the specified number of iterations is reached, the training of ANNs is finished (Ertunc et al. 2013). If the model responds correctly to input values that are not employed in training, the weights and biases of the trained network are saved. These weights and biases can be used to predict outputs for new input vectors (Yildirim et al. 2011).

Artificial neural network analysis

The gloss of thermally densified wood veneers was modelled using the ANN approach. For this, the wood species, temperature, pressure, measurement direction, and angle of incidence were considered as the model inputs, while the gloss was the output of the ANN model. The training and testing procedures were performed using MATLAB® (MathWorks 2015a). Figure 3 shows the steps of this study based on the ANN approach (Canakci et al. 2015).

The experimental data (216 samples) were classified into two different groups: training and testing. 162 data samples (75% of total data samples) were randomly selected for the training process and 54 data samples (25% of total data samples) were employed to evaluate the generalization ability of the ANN model. The data sets are presented in Table 1.

The network parameters such as activation functions, learning rule, momentum, and the number of hidden layers and neurons must be efficiently determined (Tiryaki et

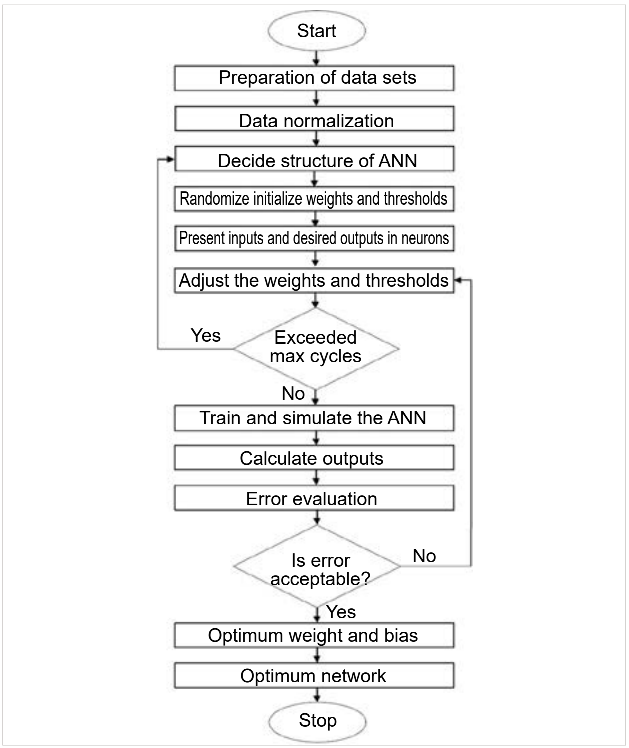

Figure 3. Steps of this study based on the ANN approach

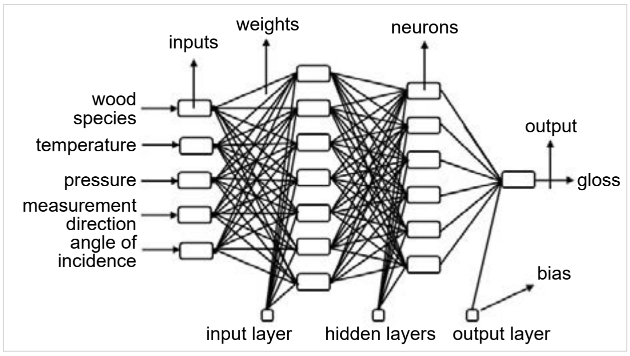

Figure 4. The proposed network structure for predicting gloss

al. 2017). Different ANN structures and parameters were tried to minimize the difference between the measured and predicted values. The ANN model providing the closest values to the experimental results was chosen to make predictions. The architecture of the selected ANN model is presented in Figure 4.

The number of input and output neurons corresponds to the number of input and output variables, respectively (Akyüz 2019). Therefore, 1 and 5 neurons were devoted to the output and input layers, respectively. The number of hidden neurons was determined by the trial-and-error approach. 7 and 6 neurons were devoted to the first and second hidden layers, respectively. The number of the connections in the ANN model was lower than the number of the data used for training. Hence, the proposed model can be mathematically described.

In modelling, a feed-forward backpropagation neural network was used. The activation functions were select-

Table 1. Measured and predicted gloss values and their percentage errors

Wood species	Densification parameters		Angle of incidence (°)																	
			Gloss measured across (⊥) the grain									Gloss measured along (∥) the grain								
	Temperature (°C)	Pressure (MPa)	20			60			85			20			60			85		
			a[a]	p[a]	e[a]	a	p	e	a	p	e	a	p	e	a	p	e	a	p	e
Alder	100	4	1.1	1.05	4.78	3.9	3.82	1.92	**5.2**	**5.82**	**–11.96**	1.2	1.05	12.73	5.4	5.61	–3.82	10.5	10.49	0.11
Alder	100	8	**1.2**	**1.11**	**7.58**	4.5	4.51	–0.25	5.7	5.76	–1.03	1.3	1.15	11.78	6.0	6.24	–3.96	12.6	12.60	–0.02
Alder	100	12	1.2	1.23	–2.65	**5.1**	**6.07**	**–19.06**	5.7	5.69	0.10	**1.3**	**1.34**	**–3.43**	6.6	6.57	0.46	**14.2**	**14.37**	**–1.17**
Alder	150	4	1.1	1.07	2.92	4.5	4.61	–2.40	7.3	7.33	–0.46	1.2	1.09	9.54	**6.4**	**6.93**	**–8.31**	16.9	16.92	–0.10
Alder	150	8	1.3	1.14	12.02	5.5	5.43	1.34	**10.8**	**8.87**	**17.82**	1.4	1.22	13.03	7.9	7.71	2.40	18.1	18.05	0.26
Alder	150	12	**1.3**	**1.30**	**0.23**	5.4	5.20	3.65	8.2	7.95	3.11	1.4	1.46	–4.07	7.5	7.62	–1.66	16.4	16.59	–1.15
Alder	200	4	1.1	1.07	2.59	**4.9**	**5.60**	**–14.32**	12.0	12.01	–0.12	1.2	1.12	6.61	7.5	7.44	0.73	21.2	21.18	0.08
Alder	200	8	1.2	1.17	2.10	7.0	7.14	–2.00	23.8	23.81	–0.04	**1.4**	**1.28**	**8.61**	**10.7**	**8.61**	**19.52**	**31.5**	**31.98**	**–1.53**
Alder	200	12	1.5	1.47	1.76	8.3	8.28	0.20	**24.3**	**25.26**	**–3.96**	1.7	1.62	4.54	12.3	12.29	0.07	32.2	32.16	0.14
Beech	100	4	**0.9**	**1.03**	**–14.79**	2.8	2.85	–1.76	3.3	3.32	–0.58	1.1	1.03	6.32	4.0	3.69	7.86	**5.5**	**6.61**	**–20.23**
Beech	100	8	1.0	1.07	–7.07	3.5	3.35	4.26	5.4	5.20	3.67	**1.1**	**1.10**	**0.35**	**4.5**	**4.50**	**–0.01**	8.9	8.90	–0.01
Beech	100	12	1.1	1.14	–3.77	4.0	4.04	–1.04	**5.5**	**5.23**	**4.85**	1.1	1.22	–10.78	4.7	4.60	2.19	12.0	11.84	1.29
Beech	150	4	**1.0**	**1.04**	**–4.27**	3.2	3.12	2.46	4.8	4.75	1.03	**1.0**	**1.05**	**–4.85**	4.2	4.43	–5.46	7.3	7.44	–1.90
Beech	150	8	1.1	1.09	1.13	**4.1**	**3.68**	**10.12**	8.1	8.12	–0.31	1.1	1.13	–2.81	5.5	5.45	0.93	12.7	12.70	0.00
Beech	150	12	1.1	1.17	–6.37	4.2	4.05	3.64	7.4	7.68	–3.78	1.1	1.28	–16.70	**5.5**	**5.69**	**–3.47**	**14.1**	**15.18**	**–7.69**
Beech	200	4	0.7	1.04	–48.60	3.3	3.37	–2.27	**7.9**	**6.53**	**17.39**	0.8	1.07	–33.34	4.7	4.65	1.15	13.9	13.79	0.76
Beech	200	8	**0.9**	**1.09**	**–21.07**	4.4	4.39	0.33	8.8	8.70	1.14	0.9	1.16	–29.04	6.0	5.97	0.45	17.3	17.28	0.11
Beech	200	12	1.0	1.21	–20.75	**5.3**	**5.38**	**–1.57**	12.8	12.85	–0.35	**1.0**	**1.36**	**–36.07**	6.8	6.96	–2.38	21.7	21.72	–0.09
Birch	100	4	1.4	1.23	11.97	4.3	4.32	–0.48	**4.2**	**3.90**	**7.04**	1.5	1.37	8.87	6.2	6.31	–1.78	7.7	7.68	0.24
Birch	100	8	1.5	1.33	11.36	**5.5**	**5.31**	**3.47**	5.8	5.77	0.55	**1.6**	**1.50**	**6.28**	7.3	7.62	–4.42	**14.7**	**11.08**	**24.62**
Birch	100	12	1.5	1.48	1.14	5.8	5.88	–1.30	6.7	6.97	–4.03	1.7	1.68	1.01	**8.3**	**8.10**	**2.41**	17.3	17.33	–0.20
Birch	150	4	1.3	1.25	4.06	4.5	4.87	–8.29	7.8	7.60	2.51	1.5	1.39	7.48	**7.0**	**7.15**	**–2.09**	**12.7**	**11.29**	**11.09**
Birch	150	8	**1.6**	**1.36**	**15.12**	6.3	5.97	5.25	13.9	14.03	–0.95	1.7	1.53	9.99	9.1	8.62	5.26	20.4	20.40	0.02
Birch	150	12	1.7	1.53	9.79	**6.8**	**6.79**	**0.19**	17.2	17.10	0.57	1.9	1.70	10.44	10.2	10.13	0.67	25.7	25.68	0.09
Birch	200	4	1.2	1.24	–3.40	5.1	5.01	1.78	12.1	12.04	0.46	**1.3**	**1.42**	**–8.91**	**8.0**	**7.60**	**5.04**	**19.4**	**18.39**	**5.22**
Birch	200	8	1.2	1.35	–12.82	6.5	6.77	–4.12	**15.8**	**17.15**	**–8.54**	1.4	1.59	–13.78	9.9	10.07	–1.71	24.7	24.77	–0.27
Birch	200	12	**1.7**	**1.61**	**5.06**	8.5	8.50	–0.01	23.1	23.09	0.04	1.9	1.92	–0.95	13.6	13.55	0.39	37.2	37.20	0.01
Pine	100	4	1.6	1.64	–2.71	**6.7**	**6.95**	**–3.68**	9.0	9.02	–0.25	**1.8**	**1.81**	**–0.53**	9.8	9.80	0.03	18.6	18.59	0.07
Pine	100	8	1.7	1.73	–1.94	7.4	7.59	–2.52	**7.6**	**9.03**	**–18.87**	1.9	1.86	1.88	10.5	10.06	4.21	17.9	17.90	0.01
Pine	100	12	**1.8**	**1.86**	**–3.08**	7.8	7.84	–0.54	9.6	9.58	0.16	1.8	1.94	–7.82	10.0	10.08	–0.78	18.3	18.26	0.21
Pine	150	4	1.6	1.67	–4.15	**6.6**	**7.57**	**–14.63**	10.3	10.30	0.01	1.8	1.82	–0.92	9.9	10.08	–1.86	19.3	19.32	–0.10
Pine	150	8	1.9	1.77	6.81	8.7	8.29	4.71	18.7	18.70	–0.02	**2.1**	**1.86**	**11.24**	**13.0**	**10.93**	**15.92**	**27.5**	**26.99**	**1.86**
Pine	150	12	1.7	1.91	–12.61	8.3	8.63	–3.96	**21.5**	**27.05**	**–25.80**	1.9	1.91	–0.73	11.9	11.94	–0.33	29.8	29.86	–0.22
Pine	200	4	**1.6**	**1.67**	**–4.42**	7.9	7.76	1.80	21.4	21.41	–0.04	1.7	1.84	–8.14	11.0	11.01	–0.07	27.1	27.13	–0.13
Pine	200	8	1.6	1.77	–10.47	**8.9**	**9.70**	**–8.93**	29.4	29.43	–0.12	1.8	1.92	–6.58	13.3	13.30	0.00	35.3	35.25	0.15
Pine	200	12	2.2	1.99	9.76	11.5	11.47	0.25	32.3	32.29	0.03	2.3	2.10	8.77	**16.3**	**16.59**	**–1.81**	**39.5**	**40.91**	**–3.57**

Note: bold values – testing data, the other values: training data;
[a] a, p, and e stand for actual values, predicted values, and percentage errors, respectively.

ed as the hyperbolic tangent sigmoid function (tansig) and the linear transfer function (purelin). The Levenberg-Marquardt algorithm (trainlm) was employed for training, the gradient descent with a momentum backpropagation algorithm (traingdm) was considered as the learning rule, and the mean square error (MSE) [Equation (3)] was used as the performance function.

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(t_i - td_i)^2 \ , \tag{3}$$

where, t_i refers to the actual value, td_i refers to the model output, and N refers to the number of measurements.

As the tansig function was used, the original data set was scaled to the range [–1, 1]. The output values of the ANN model were converted back to the real values by applying a reverse normalizing process. The normalization was performed using the following equation:

$$X_{norm} = 2 \times \frac{X - X_{min}}{X_{max} - X_{min}} - 1 \ , \tag{4}$$

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

To compare the established models, the mean absolute percentage error (MAPE), the root mean square error (RMSE), and the coefficient of determination (R^2) were used. The MAPE, RMSE, and R^2 values were calculated by using the following equations:

$$\mathrm{MAPE} = \frac{1}{N}\left(\sum_{i=1}^{N}\left[\left|\frac{t_i - td_i}{t_i}\right|\right]\right) \times 100 \ , \tag{5}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i - td_i)^2} \ , \tag{6}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(t_i - td_i)^2}{\sum_{i=1}^{N}(t_i - \bar{t})^2} \ , \tag{7}$$

where, $\bar{t}$ is the average of predicted values.

Results

The effects of wood species, temperature, pressure, measurement direction, and angle of incidence on gloss were modelled by employing the ANN approach. The ANN model was designed with 5 neurons in the input layer, 7 neurons in the first hidden layer, 6 neurons in the second hidden layer, and 1 neuron in the output layer.

As stated previously, the MAPE, RMSE, and R^2 criteria were used to compare the performance of the established models and to determine the best model. The values of MAPE, RMSE, and R^2 were calculated using Equations (5), (6), and (7), respectively. Table 2 shows the MAPE, RMSE, and R^2 statistics calculated for the ANN model.

MAPE is one of the most important performance criteria. In the literature, many researchers have determined the robustness of different models by using this performance criterion (Bardak et al. 2016, Tiryaki et al. 2016, Akyüz et al. 2017). The MAPE values were 2.856% for the training set and 8.556% for the testing set. Several researchers reported that model performance is accepted as excellent if MAPE ≤ 10% (Chang et al. 2007, Aydin et al. 2014, Yadav and Nath 2017). Accordingly, the prediction ability of the ANN model can be accepted as excellent since its MAPE value is lower from 10%.

From Table 2, it is possible to see that the RMSE values are 0.097 and 1.245 for the training and testing sets, respectively. Low RMSE values indicate a well-fitting model (Canakci et al. 2015, Bardak et al. 2016). Therefore, it can be said that the proposed model is successful in terms of the RMSE criterion.

R^2 is an indicator of the strength of the relationship between observed and predicted values. It must be close to 1 for an excellent fit (Sanusi et al. 2016). The regression analysis was carried out to calculate the R^2 values of the proposed model. The predicted outputs were graphically correlated with the experimental results as in Figure 5. According to this figure, the R^2 values are 0.9997 and 0.9814 for the training and testing sets, respectively. The R^2 value in the testing set shows that the established network can explain at least 98.14% of the actual data of gloss. This result encourages the applicability of neural networks in predicting the gloss of thermally densified wood veneers.

The comparative plots of the measured and predicted values are presented in Figure 6. In most cases, the predicted values are very close to the experimental results; however, some values are not as close as others. This is attributed to the errors caused by the materials, measurements, and process parameters. These errors can be neglected because the learning level of the ANN model is high (Özşahin 2012, Canakci et al. 2013).

Table 2. Results of the performance criteria used in predicting gloss

Data set	Performance criterion		
	MAPE	RMSE	R^2
Training	2.856	0.097	0.9997
Testing	8.556	1.245	0.9814

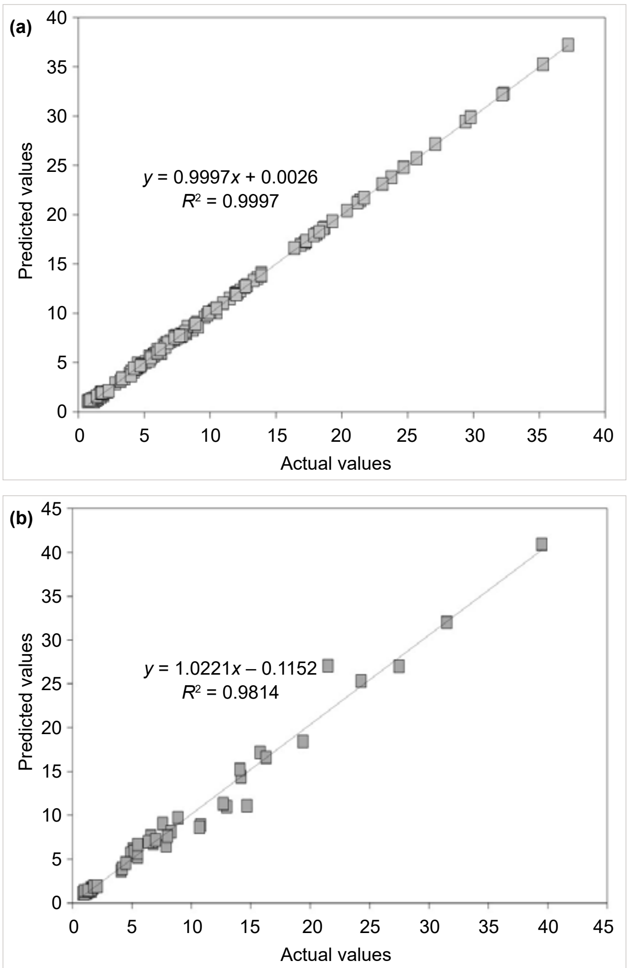

Figure 5. The relationship between the measured and predicted values: (a) the training data set and (b) the testing data set

Neural network models can compute intermediate values for optimization studies. Namely, the untested experimental results can be easily predicted by employing the ANN approach. All outputs of the impacts of process parameters on gloss can be predicted for numerous combinations. So, the intermediate gloss values not obtained from the experimental study were determined by the ANN model for different temperatures and pressures. The temperature and pressure values giving the highest gloss values according to wood species, measurement direction, and angle of incidence (85°) are given in Table 3. Based on the findings of this study, it can be said that the gloss of wooden materials increases with increasing of temperature and pressure.

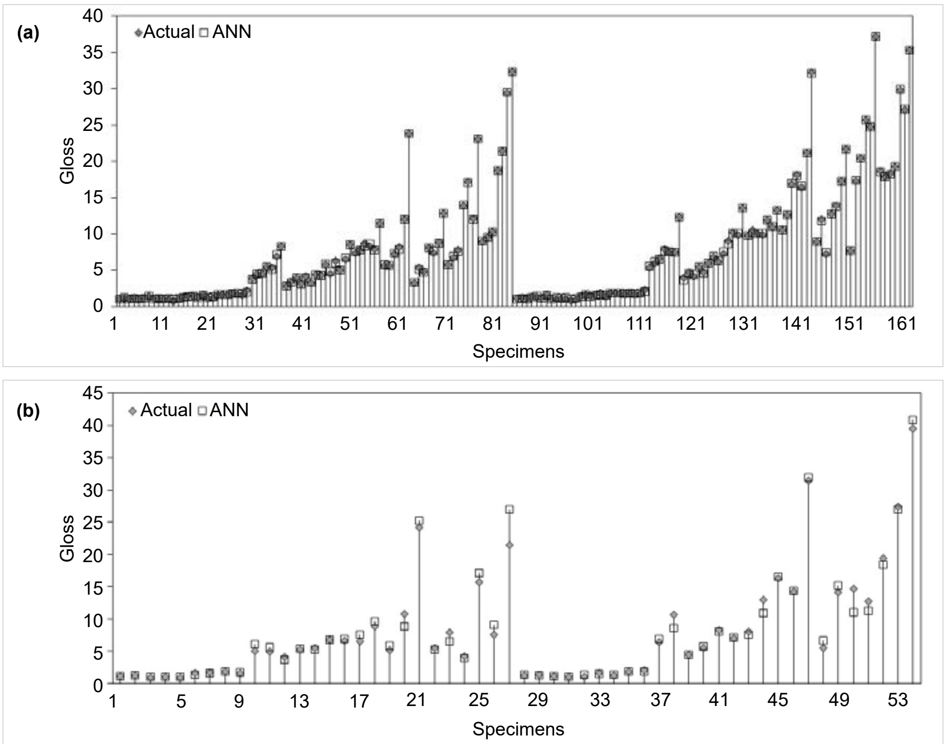

Figure 6. The comparison of the measured and predicted values: (a) the training data set and (b) the testing data set

Table 3. Optimization of gloss according to different densification conditions

Wood species	Measurement direction	Temperature (°C)	Pressure (MPa)	Gloss
Alder	across (┴) the grain	200	9-12	25.262-25.808
	along (ǁ) the grain	200	9-12	32.156-32.316
Beech	across (┴) the grain	190-200	11-12	11.102-12.845
	along (ǁ) the grain	195-200	12	19.824-21.718
Birch	across (┴) the grain	195-200	12	21.277-23.090
	along (ǁ) the grain	195-200	12	34.750-37.195
Pine	across (┴) the grain	175-180	11-12	34.193-34.504
	along (ǁ) the grain	200	11-12	39.983-40.910

Discussion and conclusions

The obtained result regarding the gloss change was also reported by several researchers (Lamason and Gong 2007, Pelit et al. 2015). After the densification process, wood may have high gloss surface. This can be caused by decreasing roughness values and increasing beam reflection of surfaces (Pelit et al. 2015, Bekhta et al. 2018).

The determination of suitable densification conditions is very significant to achieve value-added products and to remain more competitive in the market. In this perspective, the present optimization study provides useful information to improve the aesthetic appearance of the final product. The ANN approach has enabled the prediction of unknown data of gloss within acceptable error margins using known data of gloss. The findings obtained in this study may supply flexibility to producers to decide densification conditions.

The use of the ANN approach for modeling the effects of wood species, temperature, pressure, measurement direction, and angle of incidence on gloss has been studied. A multilayer neural network was developed based on the data obtained from the literature. The following conclusions could be drawn from the study:

1. The ANN model with the 5-7-6-1 structure successfully captured the relationship between the input and output variables. The predicted values showed a close match with the measured values.
2. The MAPE, RMSE, and R^2 values of the testing period of the ANN model were found as 8.556, 1.245, and 0.9814%, respectively. Based on the high correlation and low errors between the actual and predicted values, it can be said that the developed model could provide accurate and acceptable results.
3. The intermediate values not obtained from the experimental study were predicted by the designed ANN model. It was observed that the gloss of thermally densified wood veneers increased with increasing of temperature and pressure when the other variables were fixed.
4. The ANN approach was proved to be a useful tool in characterizing the effects of wood species, temperature, pressure, measurement direction, and angle of incidence on gloss. The proposed model is reliable and easily accessible for different densification conditions. The desired values of gloss can be predicted by the ANN approach instead of carrying out full experimental studies. Thus, it is possible to reduce the experimental time and costs.
5. In further research, the ANN approach can be used to predict the gloss of different wooden materials.

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