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Prediction of the color change of heat-treated wood during artificial weathering by artificial neural network

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Abstract

The purpose of this study was to predict the color change of heat-treated wood during artificial weathering by an artificial neural network (ANN) model. Chemical component analysis was used to analyze the origin of color change of the heat-treated wood. The network included an input layer consisting of three input nodes, namely, the weathering exposure time, heat treatment temperature, and heat-treated wood species, a hidden layer using six neurons and an output layer consisting of one output node, namely heat-treated wood color. A hyperbolic tangent sigmoid transfer function was used in the hidden layer, and the training algorithm was the Levenberg–Marquardt backpropagation. According to the results, the mean absolute percentage errors (MAPE) were 8.17, 9.70, and 9.85% for the prediction of color change (ΔE) for training, validation and testing data sets, respectively. Determination coefficients (R^2) above 0.92 were obtained with the proposed ANN model for all data sets. These results showed that the ANN model can be successfully used for predicting the color change of heat-treated wood during artificial weathering. FTIR results showed that the color change of heat-treated wood during artificial weathering is due to the change in the chemical composition, especially the photodegradation of lignin and wood extractives.

1 Introduction

The use of wood and heat-treated wood (HTW) as industrial product for outdoor applications is increasing. It is well known that the natural untreated wood is susceptible to environmental degradation induced by weathering factors, such as solar radiation (ultraviolet, visible, and infrared light), moisture (dew, rain, snow, and humidity), temperature, and oxygen (Feist et al. 1990). The colors of untreated wood vary rapidly when exposed to weathering. It is well acknowledged that wood changes the color due to the photodegradation of lignin and wood extractives (Feist et al. 1990). The advantages of HTW are related to the dimensional stability, durability, and attractive dark color (Nuopponen et al. 2003; Icel et al. 2015; Nguyen et al. 2018a). In addition, the HTW shows better color stability when exposed to UV radiation and moisture than the untreated wood, which is probably attributed to the thermally induced changes of lignin-cellulose and structural modification of chromophoric groups on lignin (Ayadi et al. 2003; Peng et al. 2015). Although the chemical composition of wood varies depending on the species, the main compounds are cellulose, hemicellulose, lignin, and extractives. As a result of weathering treatment, the color of wood changes appearing darker, which is usually explained by the formation of colored degradation products from hemicelluloses (Sehlstedt-Persson 2003; Sundqvist 2004) and extractives, the latter being likely also the origin of the color of the hydrothermally treated wood (Armondo 1997; Sundqvist and Morén 2002). The formation of oxidation products, such as quinones, is also referred to as a color change factor (Mitsui et al. 2001; Bekhta and Niemz 2003). During the artificial weathering, different wood species undergo different color changes due to the different chemical composition, i.e., cellulose, hemicellulose, lignin, and extractives (Bekhta and Niemz 2003; Tuong and Li 2010).

Knowing the color change of HTW during weathering helps to better apply environmentally-friendly HTW products. However, many experiments are needed to identify the optimum values, which is time-consuming, expensive, and difficult to do. Thus, a model that predicts the relationship between the process parameters of weathering time and

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color properties of HTW is necessary. The artificial neural network (ANN) has been applied in the field of wood science to aim for better use of wood materials, reduce the number of experiments, and optimize the process.

Artificial neural networks are an information processing system built on the generalization of a mathematical model of biological neurons adapted from the human brain. An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal from one artificial neuron to another. ANN learns the relationship between input and output variables through previously recorded data (Kalogirou 2001). To achieve this, the network is trained with the data related to the problem under consideration using a training algorithm. The training consists of a process of adjusting the connection weights that allow the ANN to produce outputs that are equal or close to desired targets (Hamed et al. 2004). ANN has been successfully used in several studies for predictions in the field of wood science. Fernandez et al. (2008) used the ANN approach for modeling the internal bond strength of particleboards. Tiryaki and Coşkun (2014) employed the ANN for predicting the modulus of rupture (MOR) and modulus of elasticity (MOE) of heat-treated wood. Demirkir et al. (2013) employed the same approach for modelling the plywood bonding strength. In a previous study, Nguyen et al. (2018b) employed the ANN for predicting color change in wood during heat treatment.

The aim of this study was to investigate the color change of heat-treated larch (HTL) and heat-treated poplar (HTP) during exposure to artificial weathering for 0, 240, 480, 720, 960, 1200, 1440, 1680, 1920, 2160, 2400, 2700, and 3000 h, and to identify the relationship between wood discolorations and degradation of wood components. Then, based on these results, an ANN model was used to predict the color change of HTW during artificial weathering with different time variables without the need of conducting expensive and time-consuming experiments.

2 Materials and methods

2.1 Materials

In this study, heat-treated larch (*Larix gmelinii*), a softwood species, and heat-treated poplar (*Populus alba*), a hardwood species, were used. Heat-treated larch (HTL) and heat-treated poplar (HTP) were provided by the Material Science and Engineering College of the Northeast Forestry University. Both types of wood were heat-treated at temperatures of 180, 190, 200, 210, and 220 °C, with a processing time of 4 h. 105 HTL and 105 HTP wood blocks measuring $80 \times 30 \times 3$ mm^3 ($l \times t \times r$) were randomly divided into 10 treatment groups, each of them having 21 samples. The samples were conditioned at a room temperature of 20 ± 2 °C and $65 \pm 5\%$ relative humidity to a moisture content of about 12%.

2.2 Experimental procedure

2.2.1 Color measurement

The color of the samples was measured at 0, 240, 480, 720, 960, 1200, 1440, 1680, 1920, 2160, 2400, 2700, and 3000 h. For each period of exposure to weathering, three samples were used for color measurement. Four measurements were taken for each sample, two of which were taken on early wood, and the other two on late wood.

The measurements of the HTW surface color were taken with a CM- 2300d spectrophotometer (D5003908, Konica Minolta Sensing, Inc., Japan) in a holder with a diameter of 8 mm. The overall color change, ΔE*, was measured using the CIE 1976 L*a*b* color measuring system. Accordingly, there are three important color parameters, L*, a*, and b*, to be calculated. The overall color change, ΔE*, was calculated using the following formulas:

$$\Delta L^* = L^{*1} - L^{*0} \tag{1}$$

$$\Delta a^* = a^{*1} - a^{*0} \tag{2}$$

$$\Delta b^* = b^{*1} - b^{*0} \tag{3}$$

$$\Delta E = \sqrt{\Delta L^{*2} + \Delta a^{*2} + \Delta b^{*2}} \tag{4}$$

where ΔL*, Δa*, and Δb* represent the color change before and after exposure to artificial weathering.

2.2.2 Weathering tests

Artificial weathering tests were conducted at the Key Laboratory of Bio-Based Material Science and Technology, Northeast Forestry University, Harbin, Heilong Jiang, China. Accelerated weathering test was conducted in a Q-panel QUV weathering tester (Q-Lab Corporation USA) equipped with UVA-340 lamps. The tester can reproduce the damage that may occur to wood over months or years of outdoor exposure. Each 12-hour weathering cycle consisted of 8 h of UV exposure at 60 °C followed by 4 h water spraying at 50 °C. The UV irradiance was 0.89 W/m^2 at 340 nm. The changes in the surface color of the samples were evaluated after weathering exposure for 0, 240, 480, 720, 960, 1200, 1440, 1680, 1920, 2160, 2400, 2700, and 3000 h.

2.2.3 Chemical analysis

The effect of the artificial weathering on the transformation induced to chemical compositions in heat-treated woods was studied by Fourier transform infrared (FTIR) spectroscopy. The FTIR spectra were recorded by a Magna-IR 560 FTIR instrument provided by Nicolet Co. Ltd (32 scans between 650 and 4000 cm^{-1} were collected with a resolution of 4 cm^{-1}).

2.2.4 Artificial neural network

In this study, a proposed ANN model was designed using the MATLAB Neural Network Toolbox and a multi-layer perception (MLP) model for prediction. The MLP architecture consists of an input layer, one or more hidden layers, and an output layer, the last one being the result of the network, as shown in Fig. 1 (Hamzaçebi et al. 2009). The training was carried out by trying to establish different ANN models with different network architecture and learning parameters. The models were tested using a test data set, which was not utilized for the training processes in order to test the performance of networks. Thus, the ANN models producing the closest values to the actual values were chosen as the prediction models (Tiryaki and Coşkun 2014).

The ANN structure selected as a prediction model included an input layer consisting of three input nodes, namely, the weathering exposure time, heat treatment temperature, and heat-treated wood species, a hidden layer using six neurons and an output layer consisting of one output node, namely heat-treated wood color (Fig. 2). A hyperbolic tangent sigmoid transfer function was used in the hidden layer, and the training algorithm was the Levenberg–Marquardt backpropagation.

In Fig. 1, X_i is the input value of *i*th independent variable; W_{ij} is the weight of connection between the *i*th input neuron and *j*th hidden neuron; β_j is the bias value of the *j*th hidden neuron; θ is the bias value of output neuron; Y is the prediction value of dependent variable.

To examine the effects of the exposure time to artificial weathering on the color change of heat-treated woods, the data were divided into training, validation, and testing sets (Zhang et al. 1998). The average values obtained for the color of the heat-treated wood were used in the ANN model with a total of data points. The data generated by these experiments were randomly divided into three groups, i.e., 84 data points (70% of total data) were used for the ANN training process group, 18 data points (15% of total data) for the validation group, and 18 data points (15% of all data) for the testing process group (Table 1).

The performance of each prediction model was evaluated and compared using statistical and graphical comparisons. The parameters considered to assess the prediction performance of the ANN models are the mean absolute percentage error (MAPE), root mean square error (RMSE), and coefficients of determination (R^2). The MAPE, RMSE, and R^2 values were calculated using Eqs. (5) (6), and (7), respectively. If RMSE and MAPE approach 0 and R^2 approaches 1, then the ANN predictions are optimum (Haghbakhsh et al. 2013).

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

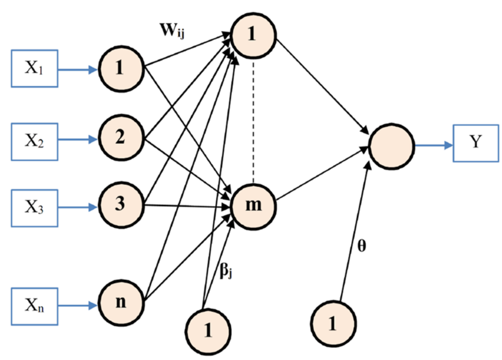

Fig. 1 A typical MLP structure

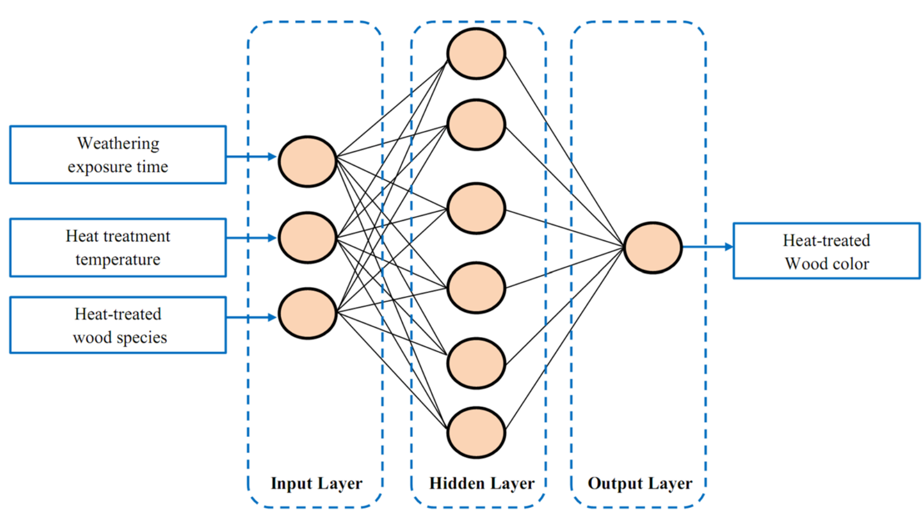

Fig. 2 ANN architecture used as a prediction model for color change of wood under artificial weathering

Table 1 Values of color change experimentally measured for heat-treated wood during artificial weathering

Heat-treated wood	Artificial weathering time (h)	Average of sample data							
		Heat-treated larch				Heat-treated poplar			
		ΔL	Δa	Δb	ΔE	ΔL	Δa	Δb	ΔE
180 °C	240	− 1.01	0.55	− 0.03	1.15	8.15	− 2.97	− 0.94	8.72
	480	− 0.86	0.25	− 0.28	0.94	6.52	− 2.13	− 0.53	6.88
	720	− 0.56	− 0.19	− 0.54	0.79	8.02	− 2.23	− 0.27	8.33
	960	− 3.22	0.70	− 0.41	3.32	6.19	− 0.92	2.33	6.68
	1200	− 3.88	1.08	− 0.40	4.05	5.92	− 0.52	2.05	6.29
	1440	− 3.19	1.20	− 0.53	3.44	4.15	0.19	2.89	5.06
	1680	− 3.85	1.22	− 0.38	4.06	4.34	− 0.07	2.88	5.20
	1920	− 5.09	1.88	0.41	5.44	5.48	− 0.60	2.86	6.21
	2160	− 5.19	2.51	− 0.25	5.77	5.57	− 0.74	2.46	6.13
	2400	− 5.00	2.47	− 0.45	5.59	5.90	− 1.14	0.98	6.09
	2700	− 4.68	1.73	− 0.57	5.02	5.47	− 2.55	− 0.48	6.05
	3000	− 3.76	1.45	− 1.28	4.23	5.24	− 2.75	− 0.78	5.97
190 °C	240	− 2.73	1.02	0.71	3.00	7.73	− 2.21	0.15	8.04
	480	− 2.12	0.73	0.80	2.38	14.30	− 1.69	2.10	6.58
	720	− 2.03	0.38	0.80	2.22	14.63	− 1.37	3.05	7.89
	960	− 3.33	1.04	0.83	3.58	5.00	0.01	6.06	7.85
	1200	− 3.81	1.21	0.71	4.05	4.70	0.57	6.34	7.91
	1440	− 3.24	1.26	0.85	3.57	5.72	0.57	6.93	9.01
	1680	− 3.63	1.74	0.87	4.12	5.77	0.58	7.67	9.62
	1920	− 4.28	1.78	1.27	4.81	5.81	0.64	9.17	10.88
	2160	− 4.44	2.03	1.43	5.09	6.05	1.61	9.39	11.28
	2400	− 3.94	1.90	1.37	4.58	6.57	1.27	8.60	10.90
	2700	− 3.66	1.77	1.05	4.20	6.86	0.61	8.09	10.62
	3000	− 3.09	1.35	0.82	3.47	6.33	0.17	6.96	9.41
200 °C	240	0.54	1.12	0.17	1.26	13.40	− 3.67	0.10	8.36
	480	1.00	1.05	0.35	1.49	5.09	− 0.07	4.10	6.53
	720	1.95	0.38	0.31	2.01	7.52	− 1.07	3.69	8.44
	960	0.30	1.09	0.79	1.38	8.60	− 0.92	5.06	10.02
	1200	0.50	1.46	1.53	2.17	6.45	0.27	5.57	8.52
	1440	0.14	1.29	1.02	1.65	7.50	0.31	5.81	9.49
	1680	0.07	2.02	1.87	2.75	8.44	− 0.02	6.24	10.50
	1920	− 0.04	2.17	2.96	3.67	9.79	− 0.35	6.78	11.91
	2160	0.11	2.22	3.63	4.26	9.90	− 0.42	6.82	12.03
	2400	0.27	2.20	3.31	3.98	10.12	− 0.65	6.03	11.80
	2700	0.29	1.75	2.62	3.17	10.35	− 0.86	5.34	11.68
	3000	0.85	1.28	1.52	2.16	9.91	− 0.97	4.68	11.00
210 °C	240	0.72	2.04	6.07	6.44	7.74	− 0.62	2.19	8.07
	480	4.04	2.04	7.89	9.10	3.85	1.33	3.17	5.16
	720	2.98	2.69	8.66	9.54	5.44	0.95	3.79	6.70
	960	− 1.09	3.16	7.04	7.80	3.48	2.19	6.00	7.28
	1200	− 0.05	3.23	6.74	7.48	2.92	2.83	6.52	7.68
	1440	0.55	3.16	7.20	7.88	4.77	2.88	7.17	9.08
	1680	0.27	3.47	7.20	8.00	4.08	2.92	7.65	9.15
	1920	− 0.59	3.73	7.62	8.51	3.96	3.39	8.64	10.09
	2160	− 0.57	3.77	7.90	8.77	3.18	3.48	9.09	10.23
	2400	− 0.35	3.66	7.77	8.60	3.69	3.01	8.41	9.66
	2700	− 0.25	3.56	7.65	8.44	4.00	2.86	8.22	9.58
	3000	0.27	3.23	7.07	7.78	3.36	2.83	7.97	9.10

Table 1 (continued)

Heat-treated wood	Artificial weathering time (h)	Average of sample data							
		Heat-treated larch				Heat-treated poplar			
		ΔL	Δa	Δb	ΔE	ΔL	Δa	Δb	ΔE
220 °C	240	− 3.42	2.19	4.31	5.92	6.13	− 0.39	3.33	6.99
	480	− 2.52	2.64	5.38	6.50	− 0.22	2.04	3.87	4.38
	720	− 1.43	2.93	5.85	6.69	2.65	1.82	4.92	5.88
	960	− 3.45	2.73	5.00	6.66	− 0.13	2.71	5.82	6.42
	1200	− 2.37	2.59	4.55	5.75	1.19	2.74	5.54	6.29
	1440	− 2.26	2.64	4.32	5.55	2.47	2.86	5.77	6.90
	1680	− 2.17	2.90	4.70	5.94	2.43	2.92	5.84	6.96
	1920	− 2.02	3.39	5.30	6.60	1.99	3.38	7.87	8.79
	2160	− 1.71	3.53	5.64	6.87	1.71	3.66	11.38	12.08
	2400	− 1.64	3.41	5.41	6.60	1.93	3.54	10.94	11.66
	2700	− 1.47	3.23	5.30	6.38	3.07	3.38	10.50	11.45
	3000	− 0.93	3.00	4.96	5.87	2.71	3.22	9.98	10.83

$$MAPE = \frac{1}{N}\left\{\sum_{i=1}^{N}\left[\left|\frac{t_i - td_i}{t_i}\right|\right]\right\} \times 100 \tag{6}$$

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

where t_i represents the experimental output, td_i represents the predicted output, N represents the total number of samples and $\bar{t}$ represents the mean of predicted outputs.

3 Results and discussion

3.1 Effects of artificial weathering on overall color change of heat-treated wood (ΔE)

Figure 3 shows that the ΔE of the untreated larch and poplar wood was more sensitive at an earlier stage in comparison with the heat-treated specimens. In Fig. 3a, it can be seen that the ΔE of the untreated larch increased from the beginning of the exposure to weathering for up to 1680 h, whereas from 1680 to 3000 h, the ΔE decreased. For the untreated poplar (Fig. 3b), the ΔE increased from the time 0 of the weathering exposure to 1200 h of exposure, then it decreases as the time further increases to 3000 h, which is in accordance with previous research (Xing et al. 2015). Regarding the heat-treated wood, the ΔE values for the HTL and HTP slowly increased with the exposure time, then slightly decreased and continued to increase up to 2160 h of exposure. From 2160 to 3000 h, the color of the

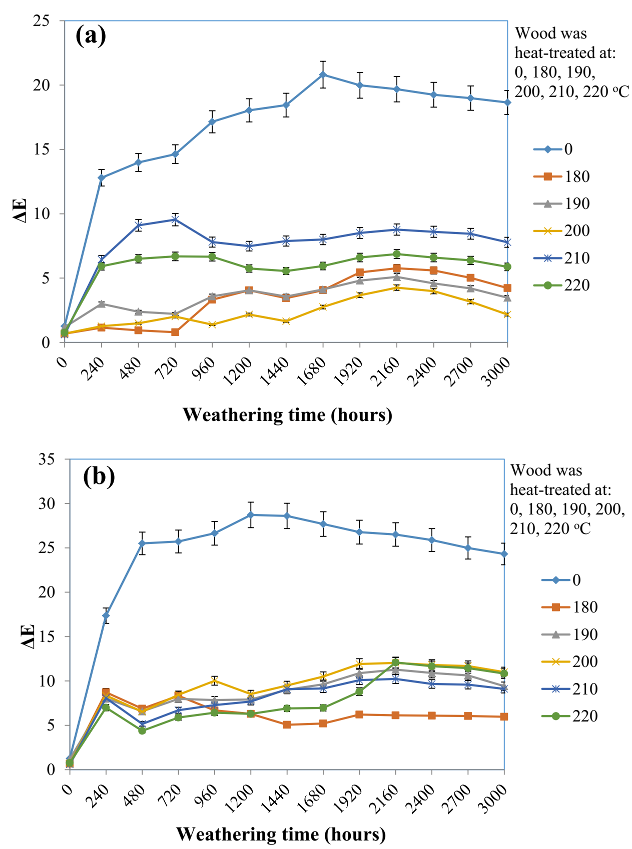

Fig. 3 Color change of untreated and heat-treated wood during artificial weathering obtained using the CIE-L*a*b* system. **a** Total color difference (ΔE) of HTL and **b** total color difference (ΔE) of HTP

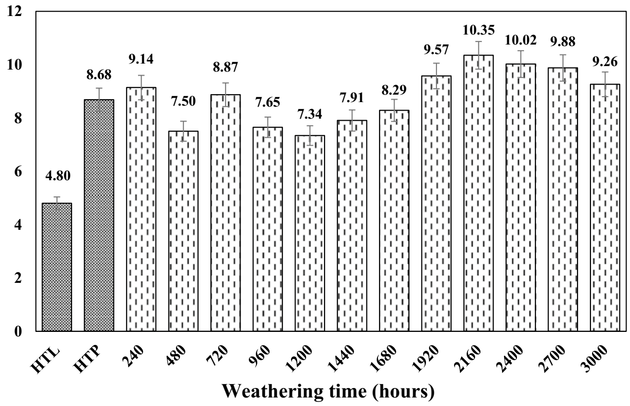

Fig. 4 Mean values of ΔE of experimentally measured samples and the results of Duncan's multiple mean comparison test

wood reduced. This result indicates a better color stability of heat-treated wood exposed to UV radiation and moisture spray, which is in line with previously reported data (Yildiz et al. 2013; Xing et al. 2015).

The effects of the exposure time to weathering on the change in HTW color was studied by variance analysis. With the aim to establish homogenous groups, the Duncan test (Duncan's Multiple Range Test) was applied to the results displayed in Fig. 4. As can be noticed, the change in ΔE value of HTP is higher than that of HTL. It was shown that the wood species has a considerable effect on the color change. At 240 h, the average value of color change of the two species of heat-treated wood was 9.14. This value dropped to 7.5 after 480 h of weathering exposure time and increased to 8.87 at 720 h, then decreased again for 960 and 1200 h. However, a constant increase was noticed as the time increased from 1440 to 2160 h. From 2160 to 3000 h, the color of the HTW decreased slightly. Therefore, the results clearly show that the weathering exposure time has a considerable effect on the color change of the heat-treated wood.

According to these results, the effect of weathering exposure time on the heat-treated wood color was statistically significant with 5% error margin. In addition, the average values for all parameters generally increased with increasing weathering exposure time.

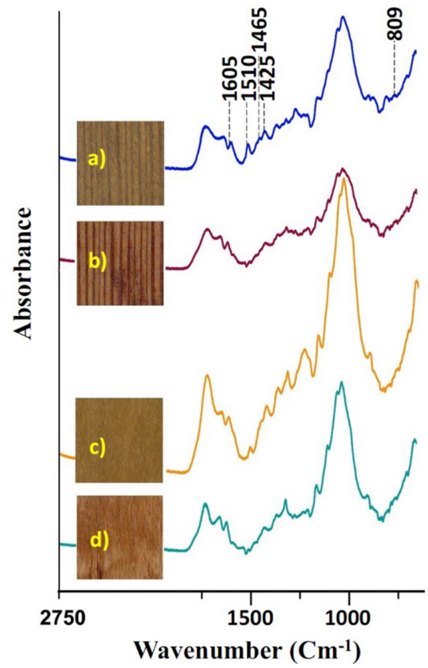

Fig. 5 FTIR spectra of heat-treated wood before and after 3000 h of exposure to artificial weathering. **a** HTL before exposure, **b** HTL after exposure, **c** HTP before exposure, **d** HTP after exposure

3.2 Chemical analysis of heat-treated wood

FTIR spectroscopy is a very useful technique for analyzing the chemical components of wood. In this study, the FTIR analysis of wood heat-treated at 200 °C (without artificial weathering) and wood, which was first heat-treated at 200 °C and then suffered artificial weathering was performed to investigate the changes in the chemical composition of the specimens.

The specimens before and after 3000 h of weathering exposure were considered for analysis. The characteristic bands identified in the corresponding FTIR spectra (Fig. 5) recorded from 650 to 2750 cm^{-1} are listed in Table 2. On the basis of the obtained results, the color change of HTW was related to the changes in the chemical composition of wood.

The absorption bands at around 1605, 1510, 1465, 1425 and 809 cm^{-1} (Colom et al. 2003; Temiz et al. 2007; Yildiz et al. 2013; Xing et al. 2015), assigned to lignin in

Table 2 FTIR absorption bands for heat-treated wood after exposure to artificial weathering

Wavenumber (cm^{-1})	Assignments	References
1605	Aromatic ring (syringyl lignin)	Temiz et al. (2007)
1510	Aromatic skeletal	Colom et al. (2003) and Temiz et al. (2007)
1465	Asymmetric bending in CH_3 (lignin)	Colom et al. (2003)
1425	Aromatic skeletal vibrations (lignin) and C-H deformation in plane (cellulose)	Kotilainen et al. (2000)
809	C-H (softwood guaiacyl) (lignin)	Nuopponen et al. (2004)

Table 3 Predicted outputs from the ANN and their percentage errors

Heat-treated wood	Artificial weathering time (h)	ΔE, Average of sample data			
		Heat-treated larch		Heat-treated poplar	
		Predicted	Error (%)	Predicted	Error (%)
180	240	1.82	− 0.67	***8.13***	***0.60***
	480	1.15	− 0.21	7.71	− 0.83
	720	**0.74**	**0.05**	8.62	− 0.29
	960	2.34	0.98	**6.25**	**0.43**
	1200	***3.31***	***0.73***	5.13	1.16
	1440	3.29	0.15	6.15	− 1.09
	1680	3.60	0.47	***5.85***	***− 0.64***
	1920	4.98	0.46	6.00	0.21
	2160	***5.73***	***0.05***	6.01	0.12
	2400	5.73	− 0.14	**6.73**	**− 0.64**
	2700	**4.65**	**0.37**	6.32	− 0.27
	3000	3.83	0.40	6.26	− 0.29
190	240	3.00	0.00	8.36	− 0.32
	480	***2.22***	***0.16***	15.17	− 0.62
	720	1.66	0.56	13.17	1.84
	960	3.28	0.30	**8.89**	**− 1.04**
	1200	***3.75***	***0.31***	8.35	− 0.44
	1440	3.70	− 0.13	8.65	0.36
	1680	4.85	− 0.73	***9.53***	***0.09***
	1920	5.07	− 0.27	11.08	− 0.21
	2160	**5.53**	**− 0.44**	11.68	− 0.40
	2400	5.24	− 0.65	10.63	0.27
	2700	4.93	− 0.73	**9.52**	**1.10**
	3000	3.85	− 0.38	8.80	0.60
200	240	0.69	0.56	13.83	0.06
	480	0.76	0.73	***7.45***	***− 0.92***
	720	***3.13***	***− 1.12***	8.79	− 0.35
	960	1.82	− 0.44	10.61	− 0.59
	1200	2.11	0.07	8.39	0.13
	1440	1.90	− 0.25	8.88	0.61
	1680	**3.09**	**− 0.33**	**11.02**	**− 0.52**
	1920	3.96	− 0.29	11.66	0.25
	2160	4.09	0.17	***11.65***	***0.37***
	2400	3.98	0.01	10.86	0.94
	2700	***3.24***	***− 0.07***	10.15	1.53
	3000	1.96	0.20	9.78	1.22
210	240	7.85	− 1.40	7.12	0.95
	480	**7.62**	**1.47**	***6.70***	***− 1.54***
	720	7.66	1.88	6.66	0.04
	960	8.53	− 0.73	**7.02**	**0.26**
	1200	7.85	− 0.37	8.24	− 0.55
	1440	**7.84**	**0.04**	7.45	1.62
	1680	7.67	0.33	***8.70***	***0.45***
	1920	8.06	0.45	9.58	0.51
	2160	***8.20***	***0.57***	**10.10**	**0.14**
	2400	8.08	0.51	9.88	− 0.22
	2700	**8.05**	**0.39**	9.44	0.15
	3000	7.84	− 0.06	9.70	− 0.59

Table 3 (continued)

Heat-treated wood	Artificial weathering time (h)	ΔE, Average of sample data			
		Heat-treated larch		Heat-treated poplar	
		Predicted	Error (%)	Predicted	Error (%)
220	240	***5.90***	***0.02***	***7.09***	***− 0.10***
	480	6.42	0.09	8.08	− 3.70
	720	6.55	0.14	**7.44**	**− 1.56**
	960	**6.30**	**0.36**	8.48	− 2.06
	1200	5.93	− 0.19	7.39	− 1.09
	1440	5.81	− 0.26	6.69	0.21
	1680	***5.98***	***− 0.04***	**6.69**	**0.27**
	1920	6.29	0.32	9.05	− 0.26
	2160	6.46	0.41	11.91	0.16
	2400	**6.30**	**0.29**	***11.93***	***− 0.28***
	2700	6.23	0.14	11.11	0.34
	3000	6.02	− 0.15	10.92	− 0.09

Bold values: testing data, bold italics underlined values: validation data, other values: training data

heat-treated specimens, significantly decreased compared with that of the untreated specimens, indicating that lignin is the component of heat-treated wood which was degraded during weathering. This result is in accordance with the results of the chemical component analysis of heat-treated wood after weathering reported in previous studies (Huang et al. 2012; Vartanian et al. 2015).

Besides the changes of lignin reflected in the FTIR spectra, according to other researches, the color change of the heat-treated wood during artificial weathering was also due to the movement of the extractives from inside to the wood surface (Huang et al. 2012) and the photodegradation of wood extractives (Hon and Minemura 2000; Kishino and Nakano 2004a, b), with the formation of chromophoric groups as carbonyl and carboxyl groups, which resulted from the degradation of α-carbonyl, biphenyl, and ring-conjugated double bond structures in lignin. The above phenomena regarding the extractives were not reflected in the FTIR spectra in this paper and will be further explored in future studies.

3.3 Predicting color change (ΔE) of heat-treated wood during artificial weathering by ANN

To predict the color change of HTL and HTP during artificial weathering, the experimental data were grouped into training, validation, and testing sets, which are shown in Table 3. The training was carried out by making attempts to establish different ANN models with different network architecture and learning parameters. The models were tested using a test data set, which was not utilized for the training processes in order to test the performance of networks. Thus, the ANN

Table 4 Statistical performance of ANN model used to predict color change of HTL and HTP during artificial weathering

Performance criteria	Data sets		
	Training	Validation	Testing
MAPE	8.177	9.705	9.858
RMSE	0.697	0.609	0.776
R^2	0.925	0.964	0.977

models producing the closest values to the actual values were chosen as the prediction models (Tiryaki and Coşkun 2014). Table 3 shows that the prediction values obtained by ANN model were determined with very low percentage errors (1.84 - 0.01%) for color change in HTL and HTP. As seen from Table 3, in most cases, the neural network prediction is very close to the measured values. This indicates that predicting the color change of heat-treated wood during weathering via the ANN model is feasible.

The predictability of the established models was evaluated by performance indicators, such as MAPE, RMSE, and R^2, the first two being the most important performance criteria (Sagıroglu et al. 2003; Canakci et al. 2012). It was reported that if RMSE and MAPE approach 0 and R^2 approaches 1, then the ANN predictions are optimum (Haghbakhsh et al. 2013). Table 4 summarizes the values of the criteria used in predicting the color change values of HTL and HTP. As can be seen, the values for MAPE are 8.17, 9.70, and 9.85% for training, validation, and testing, respectively. These values of MAPE are considered as satisfactory if the heterogeneity of the wood material is taken into account. In previous studies, 10% < MAPE ≤ 20% was considered as a good prediction (Aydin et al. 2014; Sofuoglu 2015). Thus, it can be affirmed that the values of MAPE obtained in this study are suitable. The values for RMSE are 0.69, 0.61 and 0.77% for training, validation, and testing, respectively. In addition, the R^2 values are 0.925, 0.964, and 0.977 for training, validation, and testing data sets, respectively, which indicates that the obtained network explains at least 0.92% of the observed data. The values of R^2 obtained by ANN in this study are higher compared to those obtained by other ANN applications for modeling in the field of research on wood materials. Some studies on R^2 value are summarized as follows:

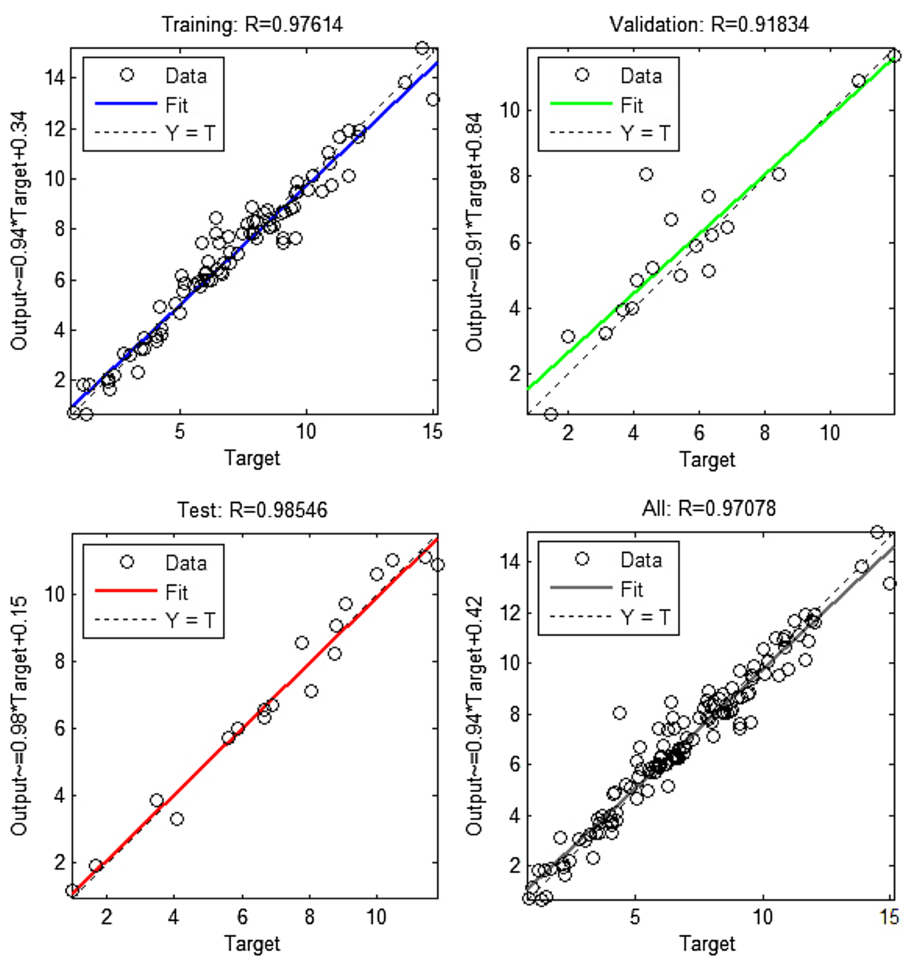

Fig. 6 Relationship between real and predicted values for color change of heat-treated wood during artificial weathering

Samarasinghe et al. (2007) obtained R^2 value of 0.62 in the determination of fracture toughness of solid wood; Fernandez et al. (2012) found R^2 values of 0.73 and 0.66 for MOR and MOE in prediction of MOR and MOE of structural plywood board, respectively; Luis et al. (2009) predicted a value for R^2 of 0.75 in modeling the MOE of solid wood. Therefore, this ANN model obtained reliable values to predict the color change of heat-treated wood during artificial weathering.

Figure 6 shows the relationship between real and predicted values for HTW color in training, validation, and testing. The R values were found as 0.976, 0.918, and 0.985 for training validation, and testing, respectively. The obtained values of R^2 listed in Table 4 confirm the excellent fit between measured results and model prediction. These results indicate that the ANN approach is quite accurate to predict the color change of heat-treated wood during artificial weathering.

Figure 7 illustrates a comparison between the real and predicted values for color change of HTW, and it is obvious that the real values match well the predicted ones. Thus, the proposed model was properly trained and showed an acceptable accuracy in predicting the color change of HTW during artificial weathering. Therefore, well-trained ANN models can predict the color change of HTW using different inputs.

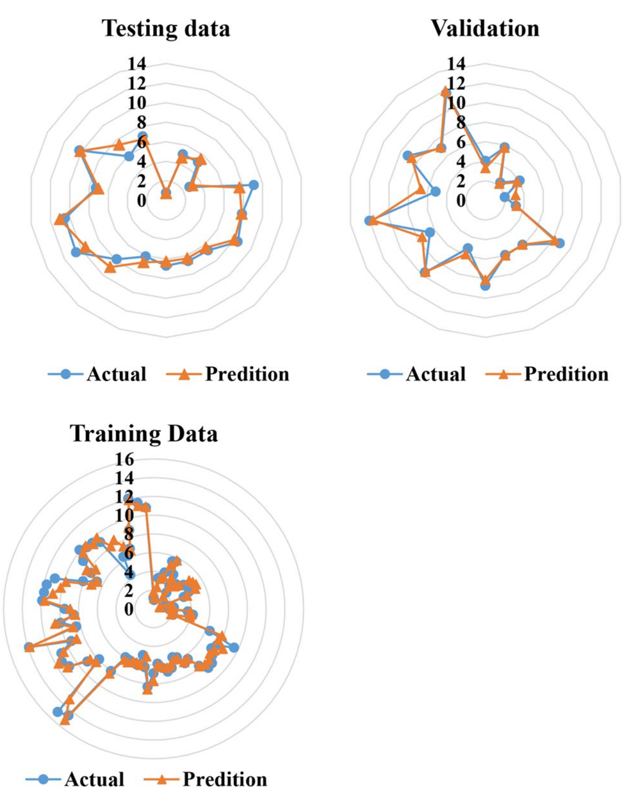

Fig. 7 Comparison between actual and predicted values for color change of HTW during artificial weathering

4 Conclusion

In this study, the effects of artificial weathering on color change in heat-treated wood were modeled by an artificial neural network. The data used for the modeling were those obtained experimentally for the color values of the heat-treated wood. The RMSE values for all data sets were less than 0.776%. Because the MAPE values were less than 10%, the prediction can be regarded as good. The value of the determination coefficients (R^2) in all data sets was higher than 0.92. The predicted color change of the heat-treated wood from the model and expressed as ΔE is close to the values measured experimentally. Therefore, the ANN model has proven to be an effective and successful tool to accurately predict the color change in HTW during artificial weathering. Chemical component analysis showed that the color change of heat-treated wood during artificial weathering is due to the photodegradation of lignin and wood extractives and the formation of the chromophoric groups, such as carbonyl and carboxyl groups, mainly resulting from the degradation of α-carbonyl, biphenyl, and ring-conjugated double bond structures in lignin. The results provided by the modeling studies using an artificial neural network model demonstrated the color change of heat-treated wood during artificial weathering can be successfully predicted without the need of conducting expensive and time-consuming experimental studies.

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