# Predicting Color Change in Wood During Heat Treatment Using an Artificial Neural Network Model

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Understanding and mastering the color change of wood during heat treatment is essential in the wood working industry because it saves time and reduces energy costs. An artificial neural network (ANN) was employed in this study to establish the relationship between the process parameters of heat treatment and the color change of wood. Three important parameters: temperature (180 °C, 190 °C, 200 °C, 210 °C, and 220 °C), treatment time (2 h, 4 h, 6 h, and 8 h), and wood species (larch and poplar) were considered as inputs to the neural network. There were four neurons in the hidden layer that were used, and an output layer as wood color. According to the results, the mean absolute percentage errors were determined as 0.53%, 0.65%, and 0.31% in the prediction of color change color ($\Delta E$) values for training, validation, and testing data sets, respectively. Determination coefficients ($R^2$) greater than 0.99 were obtained for all data sets with the proposed ANN models. These results showed that ANN models can be used successfully for predicting the color changes in wood during heat treatment.

*Keywords: Larch wood; Poplar wood; Color change in wood; Heat treatment; Artificial neural network*

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## INTRODUCTION

For many years, wood has been a favorite material for human use. There is a natural abundance, and it is sustainable, environmentally friendly, lightweight, and strong (Nguyen *et al.* 2017). Moreover, wood exhibits beauty in color and grain and provides a higher aesthetic value over other materials. In recent years, there has been a growing need for timber due to the depletion of global forest resources (Gulpen 2014). Therefore, application of wood resources from plantation forests has been intensively studied. Larch and poplar are fast-growing tree species that are dominant in the planted forests of northeast China (Zhang *et al.* 2000; Mao *et al.* 2010). Every year a large quantity of larch and poplar wood is harvested, but the light color ranges from nearly white to grayish-white. This limits its application in luxury markets. Moreover, special applications can require higher biological durability and better dimensional stability.

In recent years, due to an increased demand for solutions to the problems common in fast-growing wood, several novel wood treatments such as acetylation, furfurylation, and heat treatment have been commercialized. In comparison with previously reported methods, heat treatment of wood is an environmentally friendly wood protection method that results in value-added wood products. Though heat treatment research began in the 1920s, it has established itself, in recent years, within a growing number of industrial treatment centers in various countries in Europe, America, and Asia. One of the most improved properties *via* heat treatment is the attainment of a dark color that resembles more precious wood, making it attractive to consumers (Brischke *et al.* 2007; Esteves *et al.* 2008;

Shi *et al.* 2011; Nguyen *et al.* 2017).

Among all heat treatment conditions, heat treatment temperature and time are the two most important factors that influence wood color. Generally, heat treatment involves temperatures between 150 °C and 260 °C and treatment time for 2 to 10 h. Thus, choosing the right temperature and time assists in the acquisition of the desired color values and is the basis for industrial production. However, many experiments need to be performed to determine optimum values, which are time consuming, expensive, and labor intensive. Thus, building a model that predicts the relationship between the process parameters of thermal treatment and the color properties of wood is necessary. An artificial neural network (ANN) has been used in the field of wood science to better utilize 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. The concept of artificial neural networks was inspired by biological neural networks that consist of many nerve cells called neurons that process information in the 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. An artificial neuron that receives a signal can process it and then signal additional artificial neurons connected to it. Its architecture essentially mimics the biological system, thinking and working abilities of the human brain. Artificial neural networks have successfully been used to build predictive models using historical data sets to predict future data (Nikam *et al.* 2010; Pilevar *et al.* 2011; Taormina *et al.* 2015; Prasad *et al.* 2017). ANNs learn 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).

Some studies have utilized an ANN to predict wood properties such as modulus of rupture (MOR) and modulus of elasticity (MOE) of heat-treated wood (Tiryaki and Hamzaçebi 2014), compression strength of heat-treated wood (Tiryaki and Aydın 2014; Yapici *et al.* 2016), volumetric swelling and shrinkage of heat-treated wood (Tiryaki *et al.* 2016), wood classification (Khalid *et al.* 2008; Nisgoski *et al.* 2017), classification of knots in wooden floorboards (Çetiner 2016), wood veneer classification (Castellani and Rowlands 2008; Castellani and Rowlands 2009), wood defects classification (Marcano-Cedeño *et al.* 2009; Ramírez and Chacón 2005), fracture toughness (Samarasinghe *et al.* 2007), bonding quality of plywood (Esteban *et al.* 2011 ), bonding quality based on pressing conditions (Bardak *et al.* 2016), wood modification at high temperature and pressurized steam (Yang *et al.* 2015), the impacts of various factors on failure load of screw joints for particleboard (Bardak 2018), surface roughness of wood in machining processes (Tiryaki *et al.* 2014), and elastic strain of white birch disks during drying (Fu *et al.* 2017). However, there are no published studies on the prediction of heat-treated wood color changes by ANN. This study used an ANN model to predict the color change of larch and poplar wood during heat treatment with different temperature and time variables.

## EXPERIMENTAL

### Materials

Larch (*Larix gmelinii*), a softwood species with a density of 0.55 g/cm³, and poplar (*Populus alba*), a hardwood species with a density of 0.35 g/cm³, were used. Wood was provided by the Material Science and Engineering College of the Northeast Forestry University (Harbin, China). For color experiments, 120 larch and 120 poplar wood blocks measuring 200 × 100 × 20 $mm^3$ ($l \times t \times r$) were cut and oven-dried at 103 °C for 48 h prior to heat treatment.

### Experimental Procedures

*Heat treatment*

In the early stage of heat treatment, the temperature rose gradually from room temperature to 100 °C at a ramp rate of 18 °C/h and from 100 °C to 120 °C at a ramp rate of 10 °C/h. At 120 °C the temperature was held for 5 h and nitrogen was introduced into the tank at 120 °C as the protective gas to ensure that the mass fraction of oxygen in the heat treatment equipment was lower than 2%. From 120 °C to 150 °C a ramp rate of 2 °C/h was used, and at 150 °C the temperature was held for 5 h. The temperature was ramped at 2 °C/h set values of 180 °C, 190 °C, 200 °C, 210 °C, and 220 °C and held at the respective temperatures for 2 h, 4 h, 6 h, and 8 h. The heat-treated wood was cooled to room temperature under ambient conditions.

*Color measurement*

The color of the samples was measured at 180 °C, 190 °C, 200 °C, 210 °C, and 220 °C, and for every time at 2 h, 4 h, 6 h, and 8 h (Fig. 1). Each temperature and each hold time utilized 6 samples for color measurement before and after heat treatment with 6 points measured in each sample, of which 3 were measured on early wood and 3 on late wood (Fig. 2).

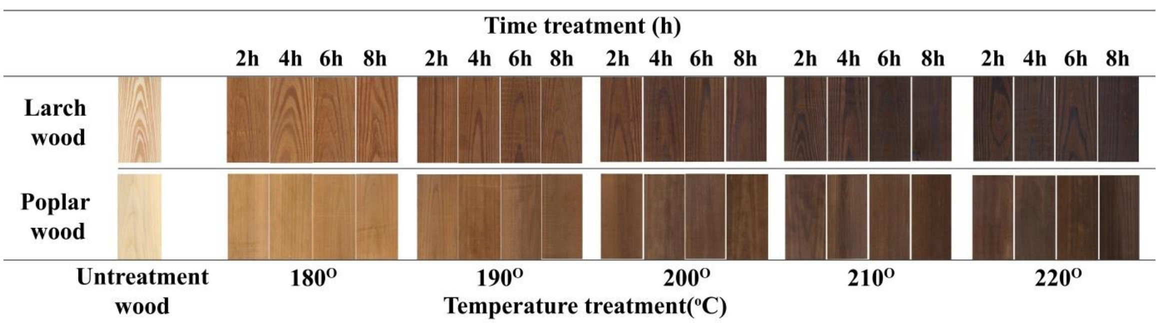


**Fig. 1.** Color of wood changes during heat treatment due to temperature and time

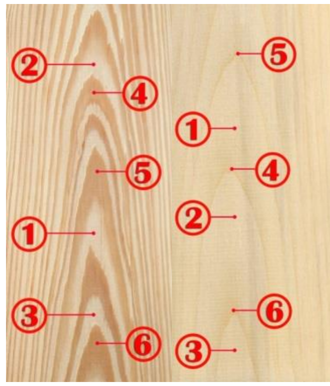


**Fig. 2.** Color measurement method on the sample

The measurements of the surface color were performed with a CM-2300d spectrophotometer (D5003908, Konica Minolta Sensing, Inc., Osaka, Japan). Measurements were made within an 8 mm diameter spot. According to the CIE $L^*$ $a^*$ $b^*$ color system there are three important parameters: $L^*$, $a^*$, and $b^*$ (Fig. 3). The overall color change $\Delta E^*$ was measured using the CIE $L^*$ $a^*$ $b^*$ color measuring system according to CIE 1976 $L^*$ $a^*$ $b^*$ color space. The overall color change $\Delta \underline{E}^*$ was calculated using the following formulae,

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

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

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

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

where $\Delta L^*$, $\Delta a^*$, and $\Delta b^*$ are the changes in value between before and after heat treatment.

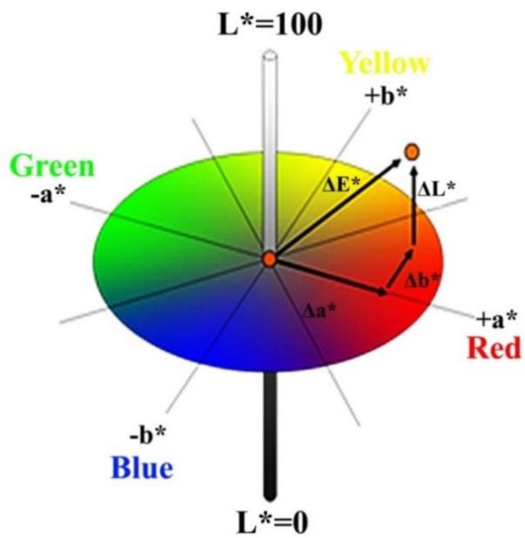


**Fig. 3.** The three-dimensional CIE $L^*a^*b^*$ color space

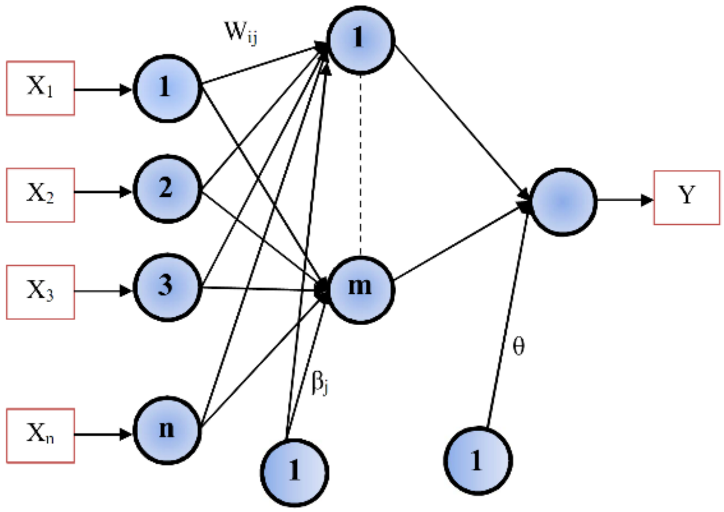


**Fig. 4.** A typical MLP structure

*Artificial neural network*

A proposed ANN model was designed with software developed using the MATLAB Neural Network Toolbox (MathWorks, Natick, MA, USA) and using a multi-layer perception (MLP) model for prediction (Tiryaki and Hamzaçebi 2014). The MLP architecture consisted of an input layer, one or more hidden layers, and an output layer as a result of the network (Hamzaçebi *et al.* 2009) (Fig. 4). The ANN structure chosen as the prediction model included the input layer that consisted of three input nodes: wood species, treatment temperature, and treatment time. The hidden layer utilized four neurons, and the output layer consisted of one output node: wood color (Fig. 5). The hidden layer used a hyperbolic tangent sigmoid transfer function and the training algorithm was the Levenberg-Marquardt backpropagation.

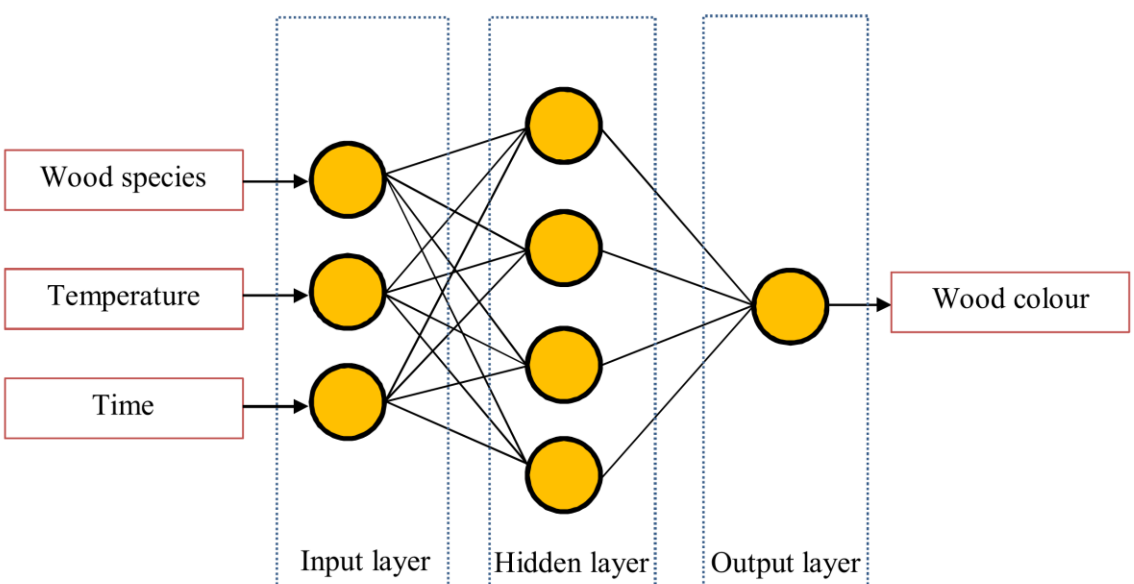


**Fig. 5.** ANN architectures selected as the prediction models for color change of wood

To examine the effects of treatment temperature and treatment time on the color change of wood, the existing data are generally divided into training, validation, and testing sets (Zhang *et al.* 1998). The average values of the wood color were used in the ANN model with the total of data points. The data generated by these experiments were randomly divided into three groups without repetition, including the 28 data points (70% of the total data) used for the ANN training process group, 6 data points (15% of the total data) for validation group, and 6 data points (15% of all data) for the testing processes group (Table 1).

The mean absolute percentage error (MAPE), the root mean square error (RMSE), and determination coefficient ($R^2$) were utilized to evaluate the performance of the ANN. The values were mathematically calculated with Eqs. 1, 2, and 3.

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

$$MAPE = \frac{1}{N}\left\{\sum_{i=1}^{N}\left[\left|\frac{t_i - td_i}{t_i}\right|\right]\right\}x100 \quad (6)$$

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

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

**Table 1.** Experimental Measured Change of Wood Color

| Treatment Temperature (°C) | Treatment Time (h) | *N* | Average of Sample Data | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Larch | | | | Poplar | | | |
| | | | Δ*L* | Δ*a* | Δ*b* | Δ*E* | Δ*L* | Δ*a* | Δ*b* | Δ*E* |
| 180 | 2 | 6 | -19.59 | 2.07 | -1.88 | 19.79 | -19.47 | 6.57 | 9.37 | 22.58 |
| | 4 | 6 | -21.83 | 1.96 | -2.80 | 22.09 | -20.92 | 6.51 | 9.11 | 23.73 |
| | 6 | 6 | -23.29 | 1.79 | -3.70 | 23.65 | -22.51 | 7.15 | 10.07 | 25.67 |
| | 8 | 6 | -23.52 | 1.65 | -4.06 | 23.93 | -24.04 | 7.52 | 9.81 | 27.03 |
| 190 | 2 | 6 | -22.23 | 1.90 | -3.60 | 22.60 | -21.39 | 6.89 | 9.41 | 24.36 |
| | 4 | 6 | -24.78 | 1.87 | -4.67 | 25.29 | -24.54 | 6.70 | 9.29 | 27.08 |
| | 6 | 6 | -25.76 | 1.02 | -4.82 | 26.22 | -25.39 | 6.61 | 8.95 | 27.72 |
| | 8 | 6 | -26.15 | 0.99 | -5.14 | 26.67 | -26.23 | 6.35 | 8.10 | 28.18 |
| 200 | 2 | 6 | -25.91 | 0.12 | -4.85 | 26.35 | -28.02 | 6.47 | 3.47 | 28.96 |
| | 4 | 6 | -26.16 | -0.99 | -6.44 | 26.96 | -30.38 | 5.94 | 3.26 | 31.12 |
| | 6 | 6 | -28.10 | -2.16 | -6.93 | 29.03 | -32.97 | 5.71 | 2.26 | 33.53 |
| | 8 | 6 | -30.22 | -3.50 | -8.41 | 31.56 | -34.56 | 5.86 | 2.11 | 35.12 |
| 210 | 2 | 6 | -29.99 | -2.23 | -7.71 | 31.04 | -33.94 | 5.32 | 1.09 | 34.37 |
| | 4 | 6 | -30.20 | -4.99 | -8.99 | 31.90 | -36.93 | 4.14 | 0.73 | 37.16 |
| | 6 | 6 | -32.12 | -5.47 | -11.11 | 34.42 | -37.52 | 4.91 | 0.56 | 37.84 |
| | 8 | 6 | -34.28 | -6.90 | -13.91 | 37.63 | -37.97 | 4.92 | 0.62 | 38.29 |
| 220 | 2 | 6 | -32.09 | -4.52 | -10.02 | 33.92 | -36.11 | 3.81 | -1.04 | 36.33 |
| | 4 | 6 | -33.68 | -6.10 | -12.93 | 36.59 | -38.74 | 3.86 | -2.22 | 39.00 |
| | 6 | 6 | -34.03 | -8.10 | -13.93 | 37.66 | -39.98 | 3.47 | -2.25 | 40.19 |
| | 8 | 6 | -34.93 | -8.93 | -15.77 | 39.35 | -41.42 | 3.67 | -3.81 | 41.76 |

## RESULTS AND DISCUSSION

### Effects of Heat Treatment on Change Overall Wood Color (Δ*E*)

The results of the Δ*E* for larch and poplar are shown in Table 1. The spectrophotometrical color measurements in Table 1 show that the Δ*a*, Δ*b*, and Δ*L* values decreased and Δ*E* increased. The Δ*E* variable increased from 180 °C to 220 °C and exhibited the highest at 220 °C when the treatment time was 8 h. Analysis of total color change *via* Δ*E* showed a decrease in the lightness (Δ*L*) was the dominant contributor, Δ*L* reduction in lightness due heat treatment was also found in previous studies (Brischke *et al.* 2007; Tuong and Li 2010; Chen *et al.* 2012; Cirule and Kuka 2015).

The wood color became darker with increasing treatment time and temperature of heat treatment, which agreed with earlier findings (Bekhta and Niemz 2003; Mitsui *et al.* 2003). The wood color change due to thermal treatment can be explained *via* the change in formation of colored degradation products from extractives, hemicelluloses, and lignin (Sehlstedt-Persson 2003; Sundqvist 2004; Brischke *et al.* 2007; Esteves *et al.* 2008; Yao *et al.* 2012).

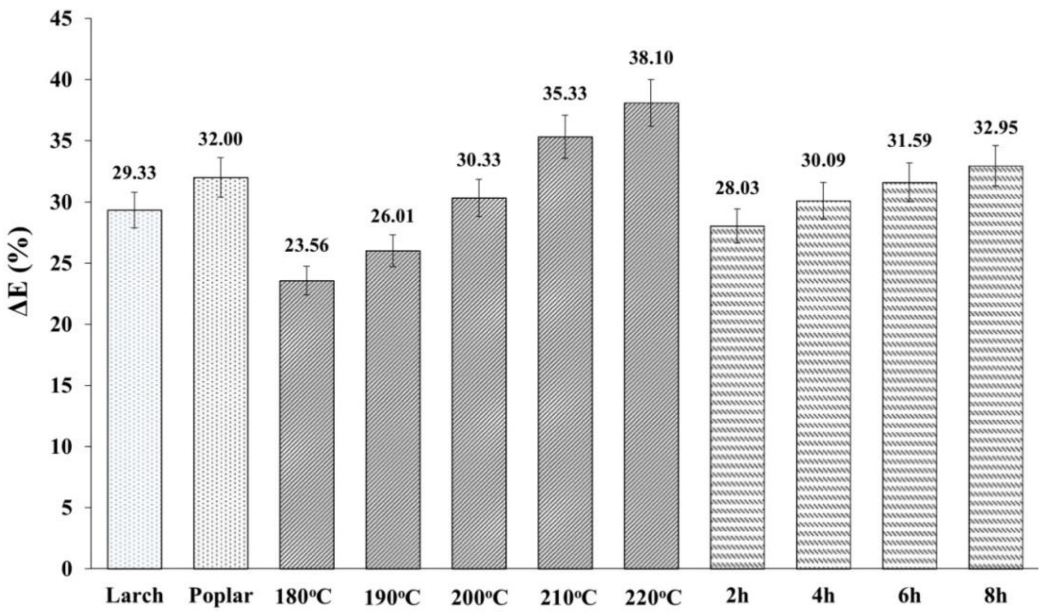


**Fig. 6.** Mean values of Δ*E* of experimental samples and the results of Duncan's multiple mean comparison test

The evaluation effects of treatment temperature, treatment time, and wood species on the change in wood color was carried by means of variance analysis. To establish homogenous groups the Duncan test (Duncan's Multiple Range Test) was applied with the results shown in Fig. 6. The averages for all parameters generally increased with increasing treatment temperature and treatment time. According to the test results, the effects of the parameters on wood color were statistically significant with a 1% error margin.

### Predicting Change Wood Color (Δ*E*) by ANN

To predict the color change of larch and poplar wood, the experimental data were grouped into training, validation, and testing sets, which are shown in Table 2.

The prediction values obtained by ANN were determined with very low percentage errors with the maximum absolute percentage error of 0.47% and the minimum absolute percentage error was 0.01% for color change in larch and poplar wood. This indicated that predicting the color change of wood with heat treatment *via* the ANN model is excellent.

Predictive ability of the established models was evaluated by performance indicators such as MAPE, RMSE, and $R^2$. Table 3 shows evaluation results of the criteria used in predicting color change values of larch and poplar wood.

The MAPE and RMSE values are the most important performance criteria (Sagiroglu *et al.* 2003; Canakci *et al.* 2012). Haghbakhsh *et al.* (2013) reported that if RMSE and MAPE approach 0, and $R^2$ approaches 1, then the ANN predictions are optimum. Table 3 shows that MAPEs were determined as 0.53%, 0.65%, and 0.31% in the prediction of percentage $\Delta E$ values for training, validation, and testing data sets. RMSEs were found as 0.19% for training, 0.25% for validation, and 0.09% for testing. From these results the prediction of color change for wood after heat treatment was successful in terms of the MAPE and RMSE criterion.

**Table 2.** Predicted Outputs from the ANN and their Percentage Errors

| Treatment Temperature (°C) | Treatment Time (h) | *N* | $\Delta E$ Average of Sample Data | | | |
|---|---|---|---|---|---|---|
| | | | Larch | | Poplar | |
| | | | Predicted | Error (%) | Predicted | Error (%) |
| 180 | 2 | 6 | **19.94** | **-0.154** | 22.76 | -0.181 |
| | 4 | 6 | 21.89 | 0.198 | 23.81 | -0.082 |
| | 6 | 6 | 23.51 | 0.140 | **25.71** | **-0.042** |
| | 8 | 6 | ***23.92*** | ***0.007*** | 27.08 | -0.047 |
| 190 | 2 | 6 | 22.61 | -0.010 | 24.57 | -0.207 |
| | 4 | 6 | **25.22** | **0.071** | 26.90 | 0.184 |
| | 6 | 6 | 26.12 | 0.103 | ***27.49*** | ***0.227*** |
| | 8 | 6 | 26.59 | 0.084 | 27.96 | 0.223 |
| 200 | 2 | 6 | 26.37 | -0.023 | 29.17 | -0.209 |
| | 4 | 6 | 27.13 | -0.173 | 31.03 | 0.086 |
| | 6 | 6 | **29.14** | **-0.110** | ***33.32*** | ***0.215*** |
| | 8 | 6 | 31.59 | -0.032 | 34.79 | 0.326 |
| 210 | 2 | 6 | 30.90 | 0.139 | 34.13 | 0.238 |
| | 4 | 6 | ***32.37*** | ***-0.472*** | **37.07** | **0.092** |
| | 6 | 6 | 34.38 | 0.036 | 37.65 | 0.194 |
| | 8 | 6 | 37.23 | 0.396 | 38.09 | 0.198 |
| 220 | 2 | 6 | 33.81 | 0.112 | ***36.09*** | ***0.239*** |
| | 4 | 6 | 36.18 | 0.410 | **38.98** | **0.015** |
| | 6 | 6 | 37.85 | -0.193 | 40.35 | -0.160 |
| | 8 | 6 | ***39.22*** | ***0.126*** | 42.03 | -0.267 |

Note: Bold values: testing data; bold italics values: validation data; Other values: training data; *N*: number of samples

**Table 3.** Evaluation Results of the Criteria Used in Predicting Color Change of Larch and Poplar Wood

| Performance Criteria | Data Sets | | |
|---|---|---|---|
| | Training | Validation | Testing |
| MAPE | 0.5347 | 0.6584 | 0.3108 |
| RMSE | 0.1944 | 0.2564 | 0.0921 |
| $R^2$ | 0.9989 | 0.9975 | 0.9998 |

Figure 7 shows the relationship between actual values and predicted values of wood color in training, validation, and testing. The R values were found as 0.99947 for training, 0.99966 for validation, and 0.99975 for testing. According to Table 3 the $R^2$ values were 0.9989, 0.9975, and 0.9998 for training, validation, and testing data sets, respectively. The obtained values of $R^2$ for the present study confirm the excellent fit between the measured results and the model predication. These results indicate that the ANN approach is quite accurate for the prediction of wood color change.

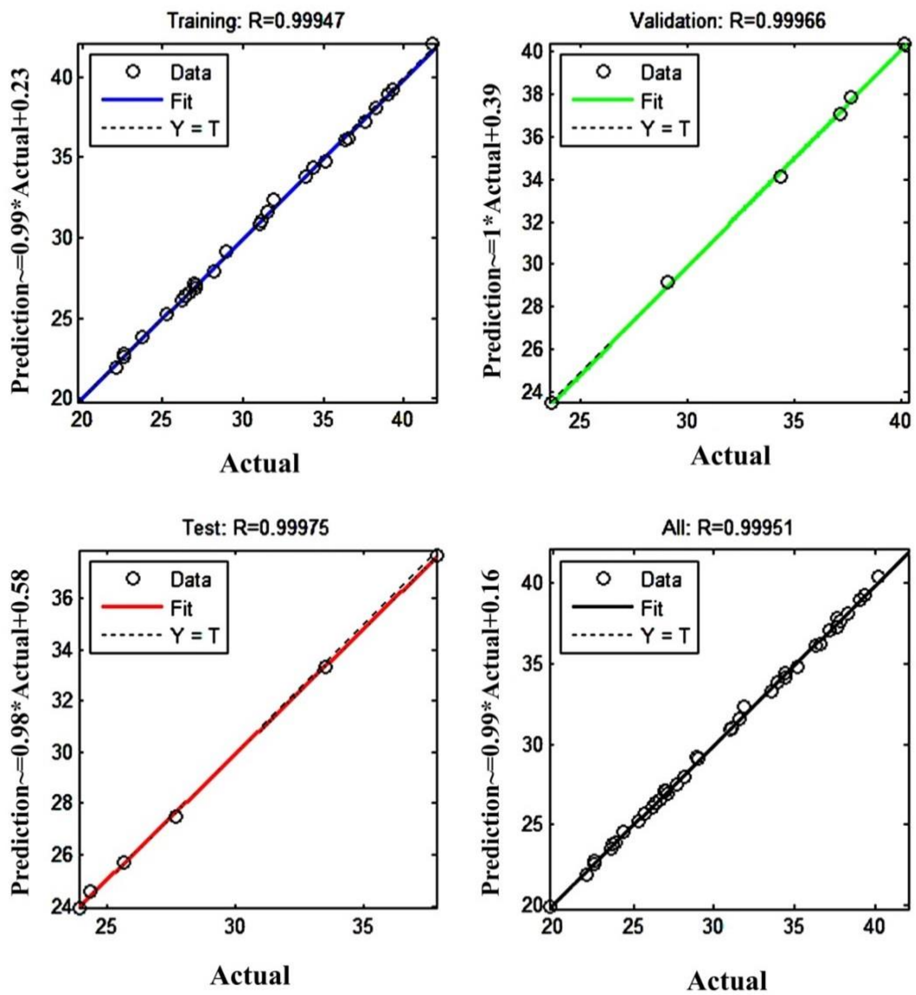


**Fig. 7.** Relationship between actual values and predicted values of wood color

Based on data in Tables 1 and 2, comparison of predicted values for the outputs of the ANN model and the experimental $\Delta E$ values for the color change of wood are shown in Fig. 8. The predicted outputs overlapped with the actual measured outputs and indicated that the predicted values are very close to the actual values. Thus, the proposed model was properly trained and showed an acceptable accuracy in predicting the color change of wood after heat-treatment. Therefore, well-trained ANN models can predict the color change of wood using different inputs.

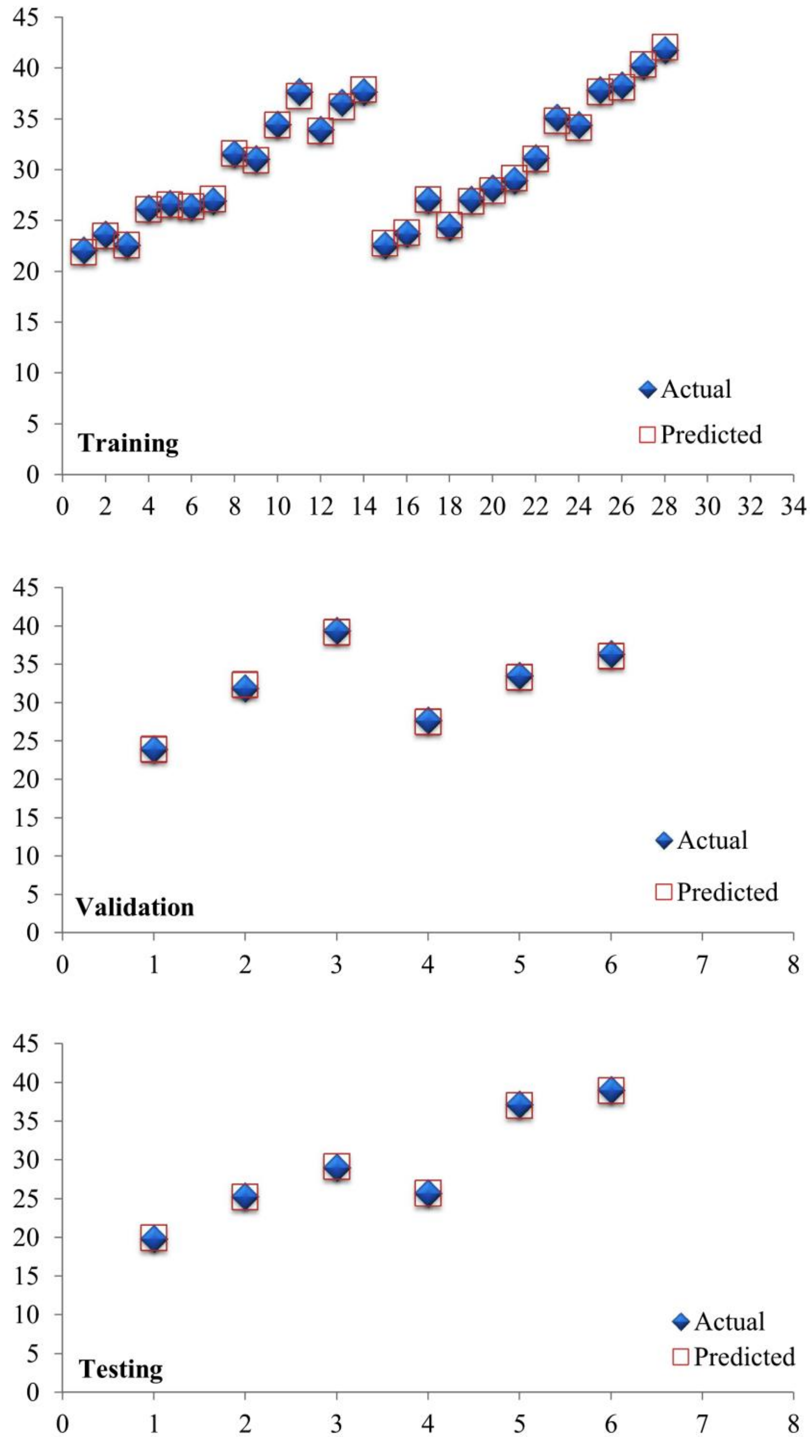


**Fig. 8.** Comparison of actual and predicted values of Δ*E*

## CONCLUSIONS

1. The effects of treatment temperature and time on color change in larch and poplar wood samples were modeled by an artificial neural network. The data for the modeling application were obtained from wood color values that were measured experimentally.
2. The MAPE and RMSE values in all of the sets were less 1%. The value of the determination coefficients ($R^2$) in all of the sets were higher than 0.99. The predicted color change in the wood represented by $\Delta E$ from the model is close to the values measured experimentally. Therefore, the ANN model has proven to be a sufficient and successful tool for accurately modeling predicted color change in wood during heat treatment.
3. This study also points to a new application for predicting color change in wood during heat treatment using the artificial neural network model. From there, it is possible to create a suitable heat treatment program that corresponds to a desired color without the need of conducting experimental studies that are expensive and time consuming. However, only two wood species were adopted in this study, and thus, there is a lot of work related to other wood species to be done in the future.

## ACKNOWLEDGEMENTS

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