Fatih Yapıcı[1], Raşit Esen[2], Okan Erkaymaz[2], Hasan Baş[3]

Modeling of Compressive Strength Parallel to Grain of Heat Treated Scotch Pine (*Pinus sylvestris* L.) Wood by Using Artificial Neural Network

Modeliranje tlačne čvrstoće paralelno s vlakancima toplinski obrađenog drva škotskog bora (*Pinus sylvestris* L.) s pomoću umjetne neuronske mreže

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*In this study, the compressive strength of heat treated Scotch Pine was modeled using artificial neural network. The compressive strength (CS) value parallel to grain was determined after exposing the wood to heat treatment at temperature of 130, 145, 160, 175, 190 and 205ºC for 3, 6, 9, 12 hours. The experimental data was evaluated by using multiple variance analysis. Secondly, the effect of heat treatment on the CS of samples was modeled by using artificial neural network (ANN)***.**

Key words: *wood, heat treatment, Artificial Neural Network, compressive strength*

Rad prikazuje numeričku proceduru za analizu struktura izrađenih od kompleksnih laminata. PostuU radu se obrađuje modeliranje tlačne čvrstoće toplinski obrađenog drva škotskog bora uz pomoć umjetne neuronske mreže. Vrijednost tlačne čvrstoće (CS) paralelno s vlakancima određena je nakon toplinske obrade pri temperaturi 130, 145, 160, 175, 190 i 205 ºC tijekom 3, 6, 9 i 12 sati. Eksperimentalni podaci analizirani su primjenom višestruke analize varijance. Osim toga, učinak toplinske obrade na tlačnu čvrstoću uzoraka modeliran je uz pomoć umjetne neuronske mreže (ANN).

Ključne riječi: *drvo, toplinska obrada, umjetna neuronska mreža, tlačna čvrstoća*

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[1] Author is professor at Ondokuz Mayıs University, Engineering Faculty, Department of Industrial Engineering, Samsun, Turkey. [2]Authors are professors at Karabük University, Technical Education Faculty, Department of Furniture and Decoration Education, Karabük, Turkey. [c]Author is professor at Bülent Ecevit University, Engineering Faculty, Department of Computer Engineering, Zonguldak, Turkey.

[1] Autor je profesor Sveučilišta Ondokuz Mayıs, Fakultet inženjerstva, Odjel za industrijsko inženjerstvo, Samsun, Turska. [2]Autori su profesori Sveučilišta Karabük, Fakultet tehničkog obrazovanja, Odjel za namještaj i uređenje interijera, Karabük, Turska. [3]Autor je profesor Sveučilišta Bülent Ecevit, Fakultet inženjerstva, Odjel za računalno inženjerstvo, Zonguldak, Turska.

1 INTRODUCTION
1. UVOD

Heat treatment is a wood modification method used to improve some properties of the wood. Heat treatment also helps to diminish equilibrium moisture content of wood samples (Mazela *et al*., 2004). The temperature level and duration of heat treatment mostly change from 180 to 280 °C and from 15 min to 24 h depending on the heat treatment process, sample size, wood species, moisture content of the sample and the properties of the final product (Kandem *et al*., 2002; Militz *et al*., 2002).

The values of hardness and strength of wood decrease with the increase of heat treatment parameters (temperature and duration). These effects are achieved especially when heat treatment is carried out for a long time. The strength values of wood most affected by heat treatment are impact and static bending strengths, while the least affected property is the modulus of elasticity (Korkut *et al*., 2008).

Artificial neural network (ANN) is a computational model based on the information processing system of the human brain. ANN model is composed of three layers, which are called input layer, hidden layer and output layer. This network structure is also called MLP (Işeri and Karlık, 2009).

While the input layer receives the initial values of the variables, the output layer shows the results from the network for the input. The hidden layer carries out the operation design to achieve the output. The number of neurons in the input layer must correspond to the number of entry variables, and the output layer must have as many neurons as the number of outputs manufactured by the network. However, there is no rule to allow prior decisions to indicate the number of neurons contained in the hidden layer or sublayer. The only way to obtain the hidden layer is by a process of trial and error (Sha, 2007).

Artificial neural network has been widely used in many wood industries, such as in the wood identification system (Tou *et al*., 2007; Khalid *et al*., 2008; Estaben *et al*., 2009a; Junior *et al*., 2006) in the suggestion on the application of geodesy (Arslan *et al*., 2007), in the prediction of wood dielectric loss factor (Avramidis *et al*., 2006), in the calculation of wood thermal conductivity (Xu *et al*., 2007), in predicting fracture toughness of wood (Samarasinghe *et al*., 2007), in the evaluation of strength of wood timbers (Tanaka *et al*., 1996), in the prediction of bending strength and stiffness in western hemlock (Shawn *et al*., 2007), in the prediction of particleboard mechanical properties (Fernández *et al*., 2008), in the optimization of process parameter in a particleboard manufacturing process (Cook *et al*., 2000), in the detection of structural damage in medium density fiberboard panels (Long *et al*., 2008), in the prediction of modulus of rupture and modulus of elasticity of flake board (Yapıcı *et al*., 2009). It has also been applied to obtain the hygroscopic equilibrium points (Avramidis and Iliadis, 2005), to classify wood defects (Drake and Packianather, 1998), to determine the internal bond values of particleboard (Cook and Chiu, 1997; Fernandez *et al*., 2008), and in statistical process control in the manufacture of particleboard (Estaben *et al*., 2009b).

In this study, compression strength parallel to grain of heat treated Scotch pine wood samples was examined experimentally, and then artificial neural network (ANN) system was designed for predicting this value.

2 MATERIALS AND METHODS
2. MATERIJALI I METODE

Scotch pine wood (*Pinus sylvestris* L.) was chosen randomly from timber merchants of Karabuk, Turkey. In the selection of wood material, special emphasis was on the properties of non-deficient, proper, knotless, normally grown wood (without zone line, reaction wood, decay, insect and mushroom damages). The selected specimens were cut to sizes of 20×20×300 mm and they were exposed to heat treatment at 130, 145, 160, 175, 190 and 205 ºC for 3, 6, 9, and 12 hours. Then, they were resized to 20×20×30 mm. The compressive strength values were determined from test samples according to TS 2595 standard (TS 2595).

2.1 Statistical analyses
2.1. Statističke analize

Data for each test were statistically analyzed. Analysis of variance was used to test the significance between factors and levels. When the analysis of variance pointed a significant difference among the factors and levels, a comparison of the means was conducted employing a Tukey test.

2.2 Design of artificial neural network for CS value
2.2. Dizajn umjetne neuronske mreže za tlačnu čvrstoću

In this study, the effects of heat treatment conditions on compressive strength parallel to grain of scotch pine wood were determined experimentally. Secondly, artificial neural network model was applied

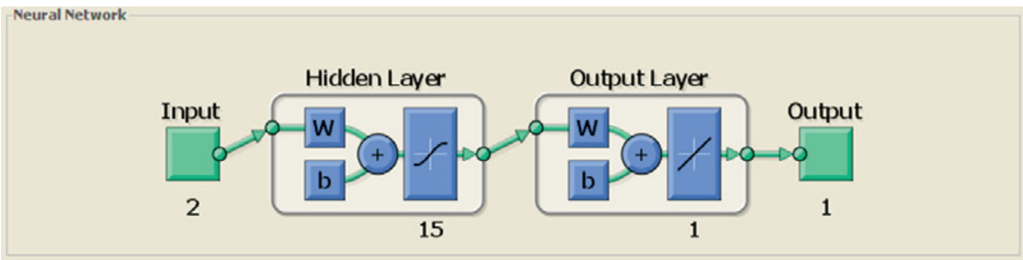

Figure 1 Design of ANN model
Slika 1. Dizajn modela umjetne neuronske mreže (ANN)

Table 1 The average values of CS
Tablica 1. Prosječne vrijednosti tlačne čvrstoće (CS)

Heat temperature conditions *Uvjeti toplinske obrade*		**Experimental value of CS** *Eksperimentalne vrijednosti tlačne čvrstoće* N/mm^2	**Prediction value of CS by using ANN** *Predviđene vrijednosti tlačne čvrstoće primjenom ANN* N/mm^2	
Time, hour *Vrijeme, sati*	Temperature, °C *Temperatura, °C*	Mean *Prosječno*	Mean *Prosječno*	Correct level, % *Razina točnosti, %*
0	0	45.46	44.80	98.54
3	130	50.40	48.40	96.03
	145	47.95	50.00	95.63
	160	49.20	50.80	96.75
	175	50.17	50.80	98.75
	190	50.80	51.20	99.21
	205	50.00	51.21	98.00
6	130	52.79	48.00	90.92
	145	51.14	50.00	97.77
	160	49.39	51.20	99.23
	175	50.96	51.20	99.52
	190	54.01	49.20	91.11
	205	51.08	51.21	99.98
9	130	54.53	51.60	95.97
	145	53.55	51.60	96.35
	160	51.14	52.00	98.42
	175	49.99	52.81	94.38
	190	50.70	52.60	97.26
	205	52.40	52.00	99.23
12	130	52.82	51.60	98.89
	145	49.77	52.40	97.66
	160	52.71	52.80	96.91
	175	53.52	50.80	98.45
	190	52.32	48.40	92.50
	205	49.60	48.40	97.58
Current level of the average value of CS, % *Trenutačna razina prosječne vrijednosti tlačne čvrstoće, %*				97.02

by using input values of heat treatment conditions and output values determined from the experimental results. Designed model is shown in Figure 1.

The aim of the network is to predict CS of test samples. The network is trained by using MATLAB neural network module (nftool). A total of 70 % of these data is used for training, 15 % is used for validation, 15 % is used for testing. The data for each class are chosen randomlly from the total data set.

In this study, the number of neurons in the hidden layer is 25. This number is obtained by trial and error. In the nftool nature hyperbolic tansig function $f(x)=1/(1+\exp(-x))$ is applied. Input data is applied after normalization process between -1 and +1.

3 RESULTS AND DISCUSSION
3. REZULTATI I RASPRAVA

The air dry density of Scots pine is 0.62 g/cm^3. The CS values of Scotch pine woods, obtained from experimental results, were compared with ANN model to determine the accuracy of the developed model. Our network was trained with designed data set to obtain the predicted result. Regression analysis of the training phase is given in Figure 2.

It is seen that regression coefficients obtained from training, validation and test phase of network are calculated close to 1. This result showed that the designed model is reliable.

Based on this comparison, the developed model agreed with average test results at the accuracy level of 97.02 % of CS value. Both experimental values and prediction values are given in Table 1.

The variance analysis of CS based on heat treatment circumstances was done by using variance analysis (Table 2.). The difference between the groups regarding the effect of variance sources on CS was significant (α =5 %).

It can be seen that the conditions of heat treatment has no effects on the CS values of Scotch pine wood according to variance analysis. So, the results of the Tukey test conducted to determine the importance of the differences between the groups are given in Table 3.

It can be seen that the CS values ranged between 45.46 N/mm^2 and 52.29 N/mm^2 according to Tukey's test (Table 3). It can be stated that when the temperature and time of the heat treatment increase, the value of CS increases. However, the ratio of increase is not statically significant. Thus, they are put into the same homogeneous group. The change of CS values, both experimental and prediction values, are given in Figure 3.

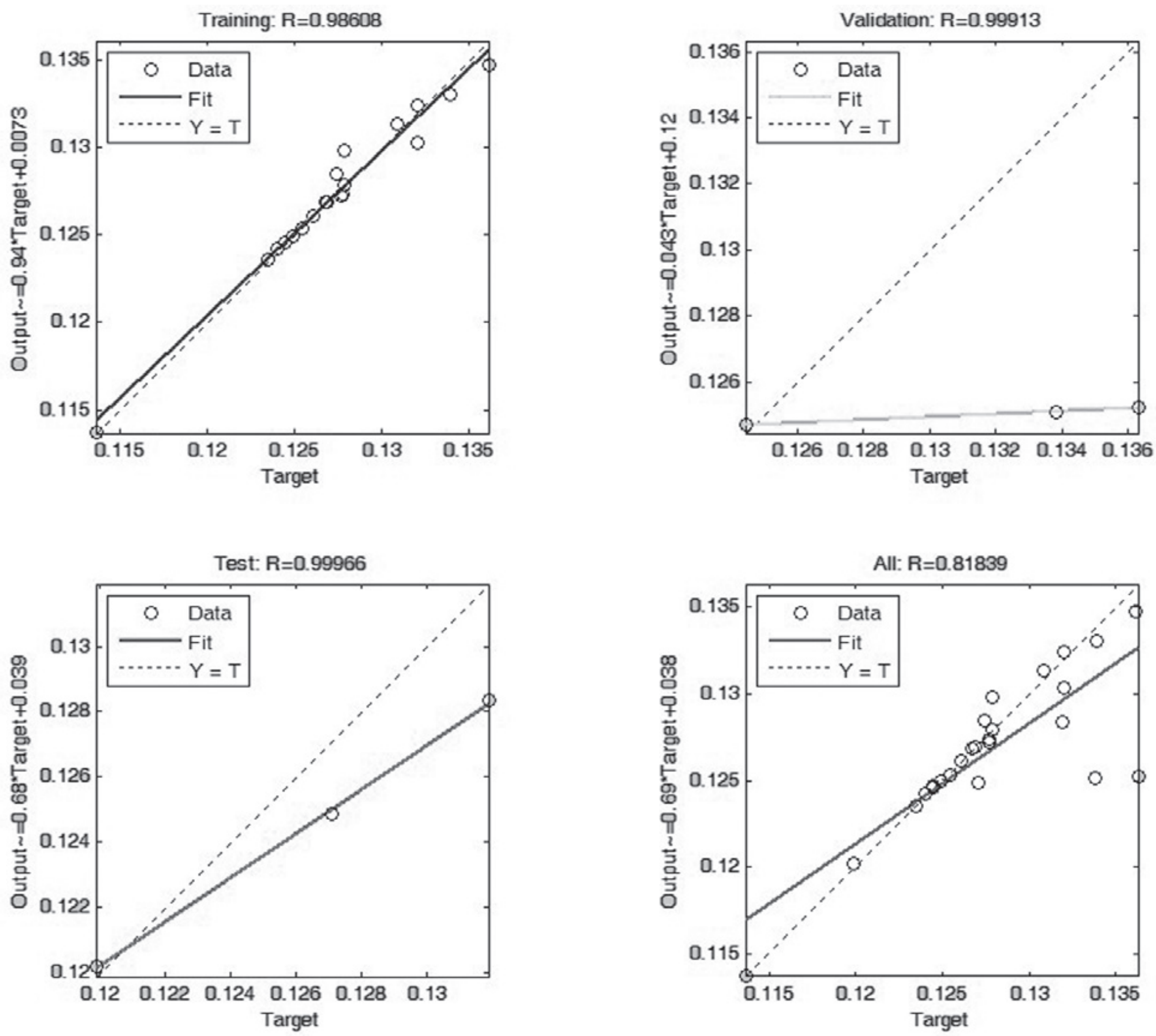

Figure 2 Network regression analyses of training
Slika 2. Regresijska analiza treniranja mreže

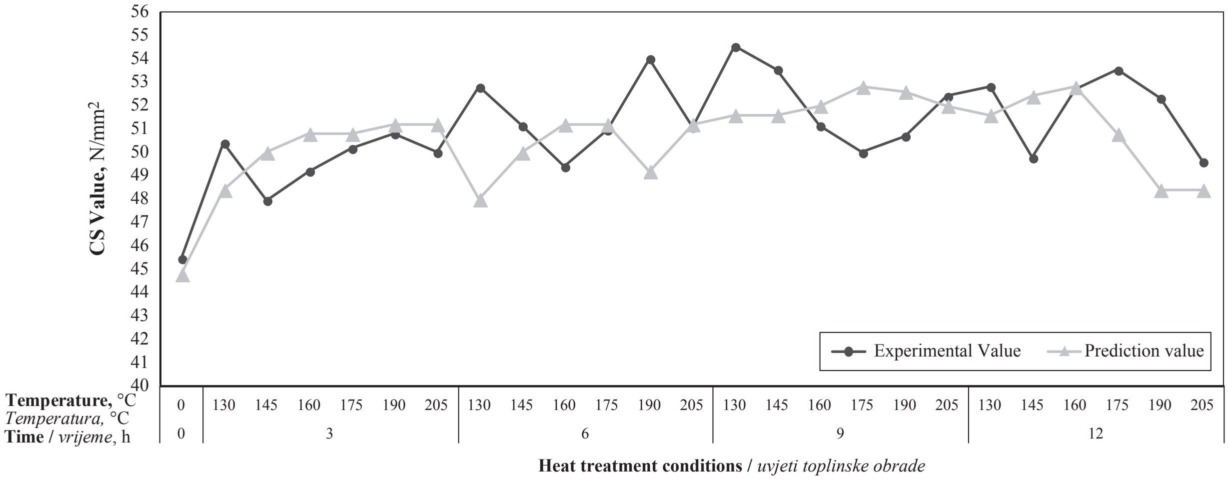

Figure 3 The change of experimental and prediction values of compressive strength
Slika 3. Promjena eksperimentalnih i predviđenih vrijednosti tlačne čvrstoće

Table 2 Result of the variance test
Tablica 2. Rezultati testa varijance

Source / *Izvor*	**Type III Sum of Squares** *Tip III zbroj kvadrata*	***Df***	**Mean Square** *Kvadrat srednje vrijednosti*	***F*-value** *F-vrijednost*	**Sig.level** *Razina signifikantnosti*
Corrected Model / *Ispravljeni model*	1474.17	24	61.42	1.87	0.09
A: Time, h / *vrijeme, h*	159.72	3	53.24	1.62	0.18
B: Temperature, °C / *temperature, °C*	292.87	5	58.57	1.78	0.11
A * B	529.79	15	35.31	1.07	0.37
Error / *Pogreška*	11482.28	350	32.80		
Total / *Ukupno*	991349.46	375			

Table3 Results of Tukey's Test
Tablica 3. Rezultati Tukeyeva testa

Conditions of heat treatment *Uvjeti toplinske obrade*		**Mean** / *Prosječno*	**HG***
Time, h *Vrijeme, sati*	0	45.46	A
	12	50.31	B
	6	51.29	B
	3	51.44	B
	9	52.18	B
Temperature, °C *Temperatura, °C*	0	45.46	A
	130	49.53	B
	190	51.01	B
	145	51.45	B
	160	51.47	B
	205	52.09	B
	175	52.29	B

HG: Homogenous Group / *homogena skupina*

4 CONCLUSIONS
4. ZAKLJUČAK

Based on the results of tests, it can be said that the properties of compression strength parallel to grain were slightly affected by applying the heat treatment. It can be seen that the CS values decrease with the increase of the time and temperature of heat treatment. The values obtained from experimental work are used for artificial neural network system. CS values of test samples have been predicted by the designed model at 97.33 % accuracy level. So, ANN model can be used to predict many mechanical and physical properties of wood and wood composite materials.

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Corresponding address:

Prof. FATIH YAPICI, Ph.D.

Ondokuz Mayıs University
Engineering Faculty
Department of Industrial Engineering
Samsun 55139, TURKEY
e-mail: fatih.yapici@omu.edu.tr