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The Use of an Artificial Neural Network for Predicting the Machining Characterizing of Wood Materials Densified by Compressing

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Abstract: In this study, an approach for artificial neural network (ANN) was presented to predict and control arithmetical mean surface roughness value (R_a), machining properties of wood materials densified by compressing in a computer numerical control (CNC) machine. Black poplar (*Populus nigra* L.) tree species were used as the experimental material. After specimens were densified by Thermo-Mechanical (TM) method at 0%, 20%, and 40% ratios, machining process of specimens were performed at 1000, 1500, and 2000 mm/min feed speeds and in 12000, 15000, 18000 rpm rotation speed on a CNC vertical wood machining center by using two different cutters. Data used for the training and testing of an ANN. Cutter type, compression ratio, feed rate, and spindle speed were selected as Four parameters. While hidden layer of the Ra model has ten neurons, one hidden layer was used, Compression ratio is the most significant parameter, followed by feed speed for R_a values. surface roughness increases with increased feed rate. R_a values in training, validation, and testing the data set for R_a were 0.97122, 0.8538, and 0.76685, respectively. The Mean Square Error (MSE) value was determined as 0.0019914 test of the network. The proposed ANN model came to agreement with the measured values in predicting surface roughness Ra values of MAPE. The MAPE value was calculated as 6.61, which can be considered a very good prediction (MAPE< 10 % = very good prediction). The study showed that obtained ANN prediction model is a practical and efficient tool to model the Ra of wood. For reducing energy, time and cost in the wood industry (densification and CNC wood machining), current research results can be implemented.

Keywords: Artificial neural networks, Thermo-Mechanics, densification, black poplar, machining, roughness

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1. INTRODUCTION

From the past to the present, development of different "Wood Modification Methods" have been performed because of all scientific studies carried out to rule out some of the unfavourableness of wood material. Wood modification applications were carried out to change or improve wood material properties (Şenol and Budakci, 2016; Senol, 2018).

The solid wood is mainly considered too soft or too weak for use in construction, which requires high strength, hardness, and durability. However, using wood material by increasing density can be an option in comparison to other materials (Blomberg and Persson, 2004; Pelit et al., 2014). The density of solid wood is mechanical (Rautkari, 2012) and machining (Lin et al., 2006; Malkocoglu and Ozdemir, 2006; Malkocoglu, 2007; Zhong et al., 2013; Pinkowski et al., 2018; Sofuoglu et al., 2022) significantly affect its properties. There is a relation between the surface quality of machined solid wood and its density, denser wood presents the best quality of the machined surface (Lopes et al., 2014; Sofuoglu et al., 2022). When examined in general, hardness, mechanical and physical properties increase, surface roughness and wettability decrease, and occurrence of spring back as a negative situation may be seen, contingent on the increase in density in compressed densified wood species.

Before the compressed wood materials are converted into the final product, they must be machined with the machines used in the machining of classical solid wood, as well as with modern computer-aided machining centers. The results obtained in this study will determine the parameters to obtain the highest surface quality. Efficiency will increase, and the next step, such as sanding, will need to be omitted or minimally applied.

For this purpose, in this study, the poplar tree species that is frequently produced and used worldwide were machined by using Computer Numerical Control with today's technology, after intensification. Wood machining parameters with different values affecting the surface quality were used; determination of densification effect for the processing properties and determination of optimum parameters for obtaining the smoothest surface were aimed.

Neural networks are frequently applied in many industrial applications. They are suitable for modeling various manufacturing functions due to their ability to learn complex non-linear and multivariable relationships between process parameters (Karayel, 2009). Using artificial neural networks (ANNs) have been applied in wood and wood-based materials science and the wood machining industry, such as in recognition of wood species (Esteban et al., 2009), the drying of solid wood (Wu and Avramidis, 2007) the mechanical properties (Fernández et al., 2012; Tiryaki and Aydin, 2014), machining parameters optimization (Sofuoglu, 2015; Gurgen et al., 2021), wood surface roughness (Ayanleye et al., 2021; Gurgen et al., 2021) the classification of wood and wood-based materials defects (Avramidis and Iliadis, 2005; Pan et al., 2021), the analysis of moisture (Zhang et al., 2016), noise emission in the machining of wood (Ozşahin and Singer, 2022) and fracture toughness of wood (Samarasinghe and Jamieson, 2007).

Investigation and evaluation of *Ra* CNC machining experiments for black poplar wood species were carried out in this study. Modeling the effects of some machining parameters on the R_a in CNC machining densified by compressing is the main objective of the present study.

2. MATERIAL AND METHOD

Sample preparation

Black poplar (*Populus nigra L.*) with low density and widely grown was selected for the experimental material in the study. Specimens were all randomly chosen from Afyonkarahisar, Turkey. Conditioning of samples were carried out at 20 ± 2 °C and 65 ± 5 °C, with relative humidity to moisture content (MC) of about 12%. The density of poplar solid wood material at 12% humidity was specified as 0.85 g / cm^3 (ISO 13061 2014; ISO 13061-2 2014). Figure 1 shows the experimental process of the study.

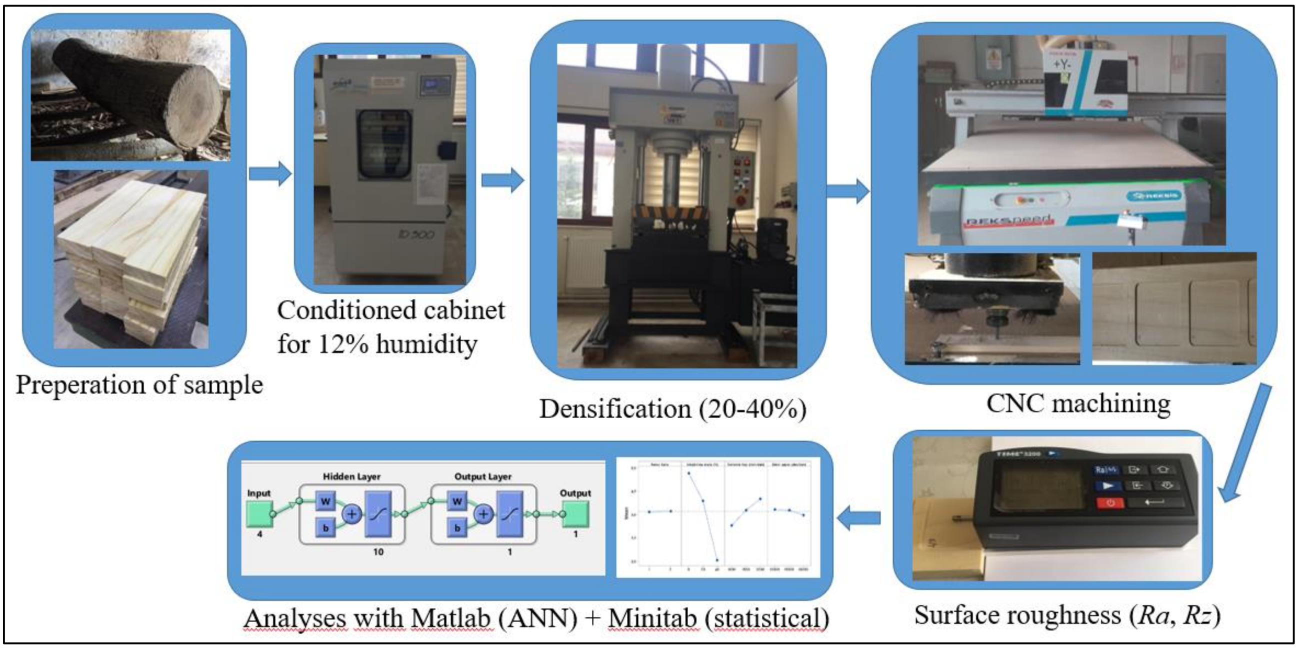


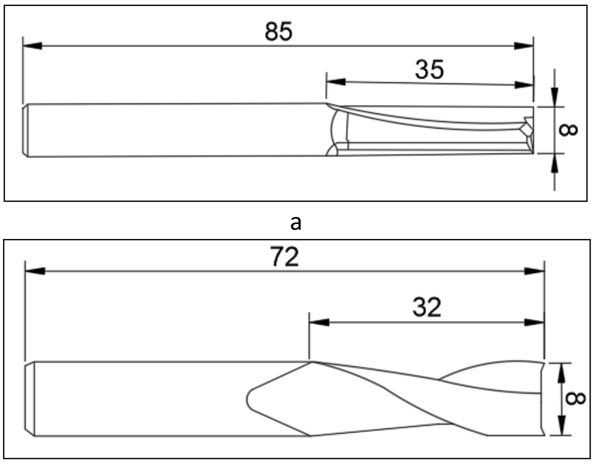
Figure 1. Schematic representation for experimental design

The densification process by compressing with the thermo-mechanical method (Total time = Heating time + 15 min, 0%, 20 %, and 40% ratios) for samples in the dimensions given in Table 1 were performed by a designed hydraulic press (Gazi University, Ankara / Turkey).

Table 1. Pre-compression dimensions of test samples (Tosun, 2021)

Compression ratio	Length (mm)	Width (mm)	Thickness (mm)
Control	430	85	20
20%	430	85	25
40%	430	85	33.3

After the densification process, a Reksis Rekspeed 2137 3-axis CNC milling machine (Çözüm Ahsap¸ Afyonkarahisar, Turkey) was used to carry out experiments. Experiments were carried out with different two router cutters (Figure 2). Using new cutters for each machining test was provided. Four machining parameters were used in the experiment (Table 2)



b

Figure 2. High-speed stell end mills (mm) a) Two-flutes straight end mill (Netmak), b) Two-flutes helisel end mill (Knob)

Table 2. Assignment of levels to factors (parameters used in the face milling of black poplar) (Tosun, 2021)

Machining parameter	Coded levels		
	Level 1	Level 2	Level 3
Cutter type	1	2	
Compression ratio (%)	0	20	40
Feed (mm/min)	1000	1500	2000
Spindle speed (rpm)	12000	15000	18000

Cutter 1: Two-flutes straight end mill, Cutter 2: Two-flutes helisel end mill

A total of 54 pieces with dimensions of 55x55 mm^2 were grooved on wood materials by a CNC router (Figure 3).

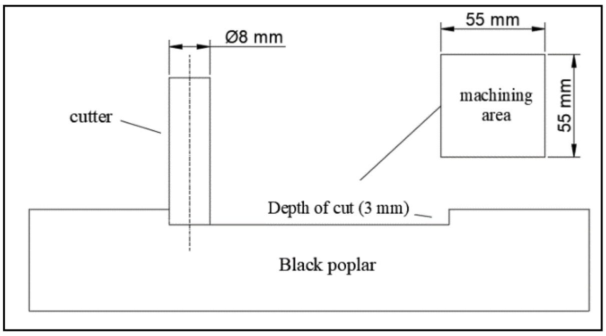


Figure 3. CNC process parameters

The optimal network structure for surface roughness CNC machining experiments is in Figure 4.

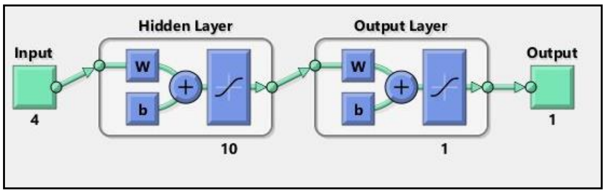


Figure 4. Optimal network structure for surface roughness CNC machining experiments.

Mean absolute percentage error (MAPE), root mean square error (RMSE), and correlation coefficient (R^2) was used to measure performance of the network.

3. RESULTS AND DISCUSSION

Comparison of the measured values and predicted values by the neural network model of the R_a is presented in Figure 5. Measured and predicted values of surface roughness (R_a) and their errors are given in Table 3.

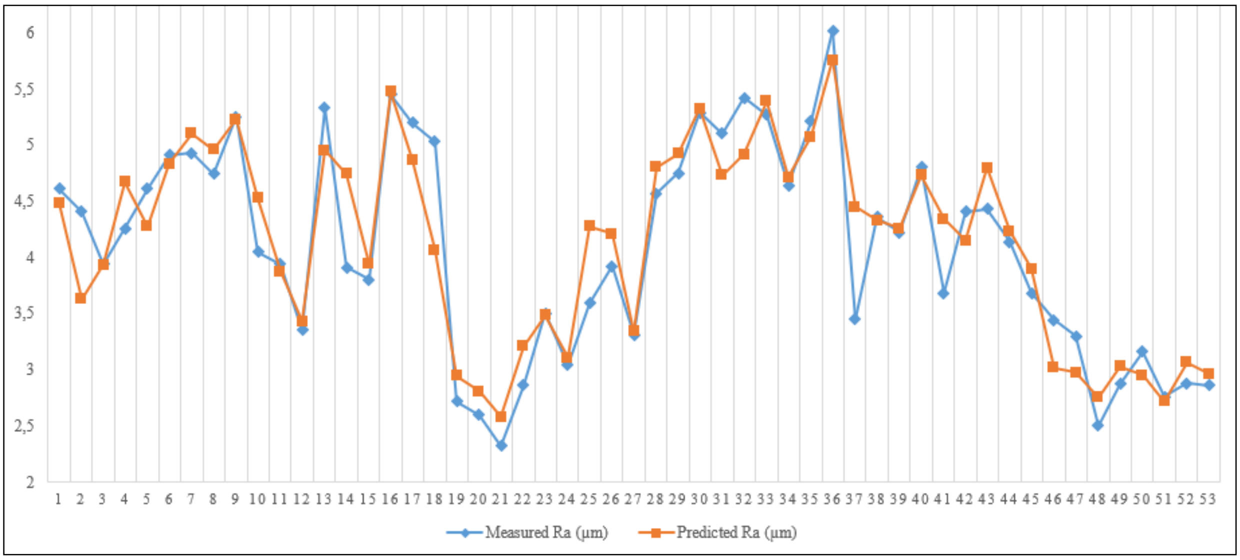


Figure 5. Comparison of measured and predicted results of R_a

Table 3. Measured and predicted values of R_a and their errors

Process No	Cutter type	Compression ratio (%)	Feed (mm/min)	Spindle speed (rpm)	Measured R_a (µm)	Predicted R_a (µm)	Error %
1	1	0	1000	12000	4.61	4.48	2,82
2	1	0	1000	15000	4.41	3.63	17,69
3	1	0	1000	18000	3.94	3.94	0,00
4	1	0	1500	12000	4.26	4.67	-9,62
5	1	0	1500	15000	4.61	4.27	7,38
6	1	0	1500	18000	4.91	4.83	1,63
7	1	0	2000	12000	4.93	5.10	-3,45
8	1	0	2000	15000	4.74	4.96	-4,64
9	1	0	2000	18000	5.25	5.23	0,38
10	1	20	1000	12000	4.05	4.53	-11,85
11	1	20	1000	15000	3.94	3.88	1,52
12	1	20	1000	18000	3.35	3.43	-2,39
13	1	20	1500	12000	5.33	4.95	7,13
14	1	20	1500	15000	3.91	4.74	-21,23
15	1	20	1500	18000	3.80	3.94	-3,68
16	1	20	2000	12000	5.45	5.47	-0,37
17	1	20	2000	15000	5.20	4.87	6,35
18	1	20	2000	18000	5.03	4.07	19,09
19	1	40	1000	12000	2.72	2.94	-8,09
20	1	40	1000	15000	2.60	2.81	-8,08
21	1	40	1000	18000	2.32	2.58	-11,21
22	1	40	1500	12000	2.86	3.21	-12,24
23	1	40	1500	15000	3.50	3.49	0,29
24	1	40	1500	18000	3.04	3.11	-2,30
25	1	40	2000	12000	3.59	4.27	-18,94
26	1	40	2000	15000	3.92	4.21	-7,40
27	1	40	2000	18000	3.31	3.34	-0,91
28	2	0	1000	12000	4.57	4.80	-5,03
29	2	0	1000	15000	4.75	4.92	-3,58
30	2	0	1000	18000	5.29	5.33	-0,76
31	2	0	1500	12000	5.10	4.73	7,25
32	2	0	1500	15000	5.42	4.92	9,23
33	2	0	1500	18000	5.27	5.39	-2,28
34	2	0	2000	12000	4.64	4.71	-1,51
35	2	0	2000	15000	5.21	5.07	2,69

36	2	0	2000	18000	6.02	5.76	4,32
37	2	20	1000	12000	3.45	4.45	-28,99
38	2	20	1000	15000	4.36	4.33	0,69
39	2	20	1000	18000	4.22	4.26	-0,95
40	2	20	1500	12000	4.80	4.73	1,46
41	2	20	1500	15000	3.68	4.34	-17,93
42	2	20	1500	18000	4.41	4.15	5,90
43	2	20	2000	12000	4.43	4.80	-8,35
44	2	20	2000	15000	4.14	4.23	-2,17
45	2	20	2000	18000	3.68	3.90	-5,98
46	2	40	1000	12000	3.44	3.02	12,21
47	2	40	1000	15000	3.30	2.97	10,00
48	2	40	1000	18000	2.50	2.75	-10,00
49	2	40	1500	12000	2.87	3.03	-5,57
50	2	40	1500	15000	3.16	2.95	6,65
51	2	40	1500	18000	2.76	2.71	1,81
52	2	40	2000	12000	2.88	3.06	-6,25
53	2	40	2000	15000	2.86	2.96	-3,50
54	2	40	2000	18000	2.78	2.75	1,08

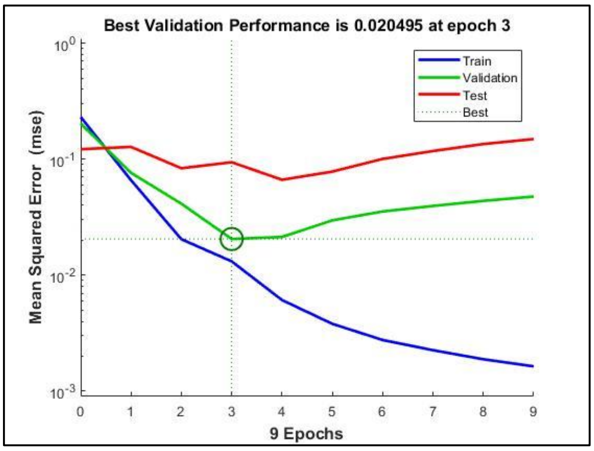


Figure 6. Performance of ANN model

In the literature, The MSE values were calculated as 1.05 and 3.70 surface roughness for solid wooden edge-glued panels (Sofuoglu, 2015) and 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 (Ozsahin and Singer, 2021). In this study, The Mean Square Error value was determined as 0.0019914 test of the network. MSE value is satisfactory for the accuracy of models. The performance of the ANN model for black poplar was shown in Figure 6.

One of the values to measure network ability to predict correctly is mean absolute percentage error (MAPE). MAPE values of artificial networks estimating the surface roughness of different materials under different machining conditions were reported as 3,866 for solid wood material (*Pinus sylvestris*) Gurgen et al. (2022) and 20,18 for massive wooden edge-glued panels (Sofuoglu, 2015). If the (MAPE) values are less than 10%, it is considered acceptable for a prediction with high accuracy (Nazerian et al., 2020). In this study, MAPE value was calculated as 6.61, which can be considered a good prediction. Figure 7 presents the relationship between the experimental results and theANN-predicted results. The measured Ra values of the samples show similarity with the values predicted by the ANN model. While the R-value is high in training (R=0.97122), it is lower in validation (R=0.8538) and Test (R=0.76685). Wood material has a heterogeneous structure. The roughness data obtained from a heterogeneous structure may cause this.

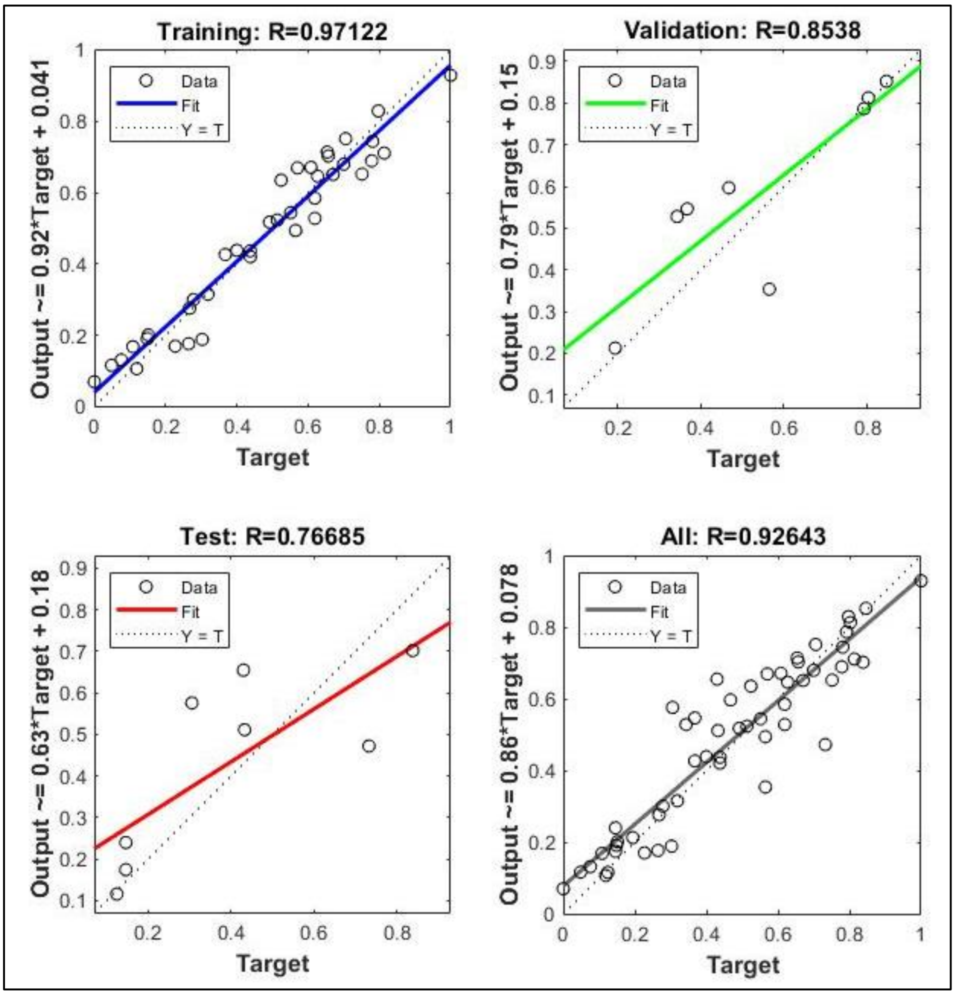


Figure 7. Relationship between experimental results and ANN-predicted results

4. CONCLUSIONS

In this study, the effects of cutter type, compression ratio, feed, and spindle speed on the R_a of wood were investigated and modeled using the ANN. The predicted R_a from the model is close to the values measured experimentally. The conclusions were summarized as follows:

1. Compression ratio is the most significant parameter, followed by feed speed for R_a values.
2. Feed rate is an important parameter, and surface roughness increases with increased feed rate.
3. The ANN modeling approach can be applied in predicting the R_a of wood samples under given conditions when the training of the model is properly completed.
4. R^2 values in training, validation, and testing the data set for R_a are 0.97122, 0.8538, and 0.76685, respectively.
5. The Mean Square Error (MSE) value was determined as 0.0019914 test of the network. MSE value is satisfactory for the accuracy of models.
6. The proposed ANN model came agreement with the measured values in predicting surface roughness R_a values of MAPE. The MAPE value was calculated as 6.61, which can be considered a very good prediction (MAPE < 10% = very good prediction).
7. In further research, the ANN approach can be used to predict the surface roughness of different wooden materials.

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In the calculations in this study, the data in the master's thesis titled "Effect of thermo-mechanical densification on machining properties of massive wooden material" were used.

Ethics Committee Approval

N/A

Peer-review

Externally peer-reviewed.

Author Contributions

M.T.: Construction of experiments, analysis of results. SDS: Experiment design, article writing and analysis of results. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest
The authors have no conflicts of interest to declare.

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