# Using Artificial Neural Networks to Model the Surface Roughness of Massive Wooden Edge-Glued Panels Made of Scotch Pine (*Pinus sylvestris* L.) in a Machining Process with Computer Numerical Control

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An artificial neural network (ANN) approach was employed for the prediction and control of surface roughness ($R_a$ and $R_z$) in a computer numerical control (CNC) machine. Experiments were performed on a CNC machine to obtain data used for the training and testing of an ANN. Experimental studies were conducted, and a model based on the experimental results was set up. Five machining parameters (cutter type, tool clearance strategy, spindle speed, feed rate, and depth of cut) were used. One hidden layer was used for all models, while there were five neurons in the hidden layer of the $R_a$ and $R_z$ models. The RMSE values were calculated as 1.05 and 3.70. The mean absolute percentage error (MAPE) values were calculated as 20.18 and 15.14, which can be considered as a good prediction. The results of the ANN approach were compared with the measured values. It was shown that the ANN prediction model obtained is a useful and effective tool for modeling the $R_a$ and $R_z$ of wood. The results of the present research can be applied in the wood machining industry to reduce energy, time, and cost.

*Keywords: Artificial neural networks; Machining parameters; Surface roughness*

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## INTRODUCTION

The surface quality of solid wood is one of the most important properties influencing further manufacturing processes such as joining application, bonding quality, and strength characteristics (Tiryaki *et al.* 2014). In wood finishing, roughness reflects faults on a wood surface as a result of the operations carried out in production, which are repeated periodically with a low probability. Control and monitoring of surface roughness are required to maintain product quality at the same level throughout production, as this property affects wood adhesion and changes can increase losses. After solid wood undergoes machining through sawing, planing, sanding, *etc.*, it becomes a final product. Wood finishing is an important factor in determining the economic value of the final product. Accordingly, surface roughness is a definitive property for measuring the success of the wood finish. Surface roughness can be evaluated both quantitatively and qualitatively. Each approach has advantages and disadvantages, such as the speed of testing, the sensitivity, and the accuracy of results (Malkocoglu and Ozdemir 1999).

There have been many studies on the effects of various machining parameters on the surface roughness of wood. Also, there are various surface roughness measuring methods in the area of woodworking. Lumber surface roughness can be measured with an airflow method (Porter *et al.* 1971). An imaged light and needle-scan can be also used to measure surface roughness (Peters and Cumming 1970). It is thought that surface roughness in industrial applications can be easily determined with the light-sectioning shadow scanner method (Sandak and Tanaka 2005). However, the stylus trace method, a type of profilometry, has emerged as the most suitable and applicable method for measuring surface roughness (Peters and Mergen 1971; Faust 1987).

Stumbo (1960) mentioned that a decrease in surface roughness will occur with an increase in cutter speed and number of teeth in the cutting saw. An increase in surface roughness occurs with increased feeding speed. For planing and milling, roughness is greater when cutting perpendicular to the grain than when cutting along the grain, and greater in soft tree types compared with hard tree types. In general, worn cutters increase surface roughness. With respect to average roughness values, approximately the same values are obtained in directions perpendicular to the grain and along the grain (Steward 1970).

Roughness has been investigated for various tree types. Ors and Baykan (1999) studied the planing and sanding operations of planed and sanded massive wooden material using oriental beech and Scotch pine. Unsal and Kantay (2002) studied the surface roughness of massive parquets from oak and oriental beech in Turkey using the stylus trace method. Ilter *et al.* (2002) studied surface roughness in the planing and sanding of Uludag fir. Efe and Gurleyen (2003) carried out surface roughness measurements in planing experiments on black locust and walnut conducted under various conditions. Aslandoğan (2005) determined the surface roughness after planing and sanding experiments on artificially grown European black pine. Sonmez and Sogutlu (2005) determined surface roughness in the planing of wood from black locust, European pear, chestnut, oak, and cedar of Lebanon. Aras *et al.* (2007) evaluated surface roughness in the turning of walnut, oriental beech, largeleaf linden, and aspen with the stylus trace method. Malkocoglu (2007) looked at the planing properties and surface roughness of oriental beech grown in the Eastern Black sea region, Anatolian chestnut, black alder, Scots pine, and oriental spruce. It was observed that using veneer with tough surfaces in plywood production reduced adhesion quality (Faust and Rice 1986). Hiziroglu *et al.* (2013) determined surface roughness in the sanding of pine, borneo camphor, and meranti. Zhang *et al.* (2007) evaluated surface roughness in various commercially-produced composite panels including particleboard, medium-density fibreboard (MDF), and plywood in addition to ten different solid wood species commonly used in furniture production. Tiryaki *et al.* (2014) studied the effects of wood species, feed rate, number of cutter, cutting depth, and wood zone, and the grain size of abrasives on surface roughness were investigated and were modeled by artificial neural networks.

Artificial neural networks (ANNs) have been widely used in wood science, such as in the recognition of wood species (Esteban *et al.* 2009; Khalid *et al.* 2008), the drying process of wood (Wu and Avramidis 2006; Ceylan 2008), the prediction of some mechanical properties in wood and wood products (Mansfield *et al.* 2007; Fernández *et al.* 2012; Tiryaki and Aydin 2014), the optimization of process parameters in the manufacturing process of wood products (Cook and Whittaker 1993; Cook *et al.* 2000), the classification of wood and wood veneer defects (Drake and Packianather 1998; Nordmark 2002; Packianather and Drake 2005; Castellani and Rowlands 2008; Kurdthongmee 2008), the calculation of wood thermal conductivity (Avramidis and Iliadis 2005), the analysis of moisture in wood (Zhang *et al.* 2006; Avramidis and Wu 2007), and the prediction of fracture toughness of wood (Samarasinghe *et al.* 2007).

Although there are have been numerous studies on the effects of machining parameters on the surface roughness of wood, there has been a lack of studies on modeling the effects of these parameters.

This study investigates and evaluates surface roughness CNC machining experiments for Scotch pine wood species commonly used in Turkey. The main objective of this study was to model the effects of some process parameters on the surface roughness in CNC machining massive wooden edge glued panels made of Scotch pine (*Pinus sylvestris* L.).

## EXPERIMENTAL

In this study, a massive wooden edge-glued panel (EGP) from Scots pine (*Pinus sylvestris* L.) trees with 18 mm in thickness was used as a study material. The density of the EGP was 0.39 g/cm$^3$, at an 8% moisture content (ISO 3130 (1975); ISO 3131 (1975)). The experiments were carried out on a Skilled CNC milling machine (Beysantaş A.Ş., Turkey) with a maximum spindle speed of 18,000 rpm and a maximum feed rate of 2000 mm/min. The experiments were carried out with two router cutters (a solid carbide straight bit and a changeable router turnblade that was 8 mm in diameter).

The experiments evaluated five machining parameters (cutter type, tool clearance strategy, spindle speed, feed rate, and depth of cut). A total of 36 pieces with dimensions of 50 x 50 mm were grooved on EGP panels by a CNC router (Fig. 1). Surface roughness was measured five times as parallel to the grain for every piece. The measuring parameters ($R_a$ and $R_z$) are described in ISO 468 (2009).

The measurement of surface roughness was conducted according to the protocols in ISO 4287 (1997) and ISO 3274 (2005).


**Fig. 1.** (a) CNC milling machine during wood machining; (b) surface roughness tester TR200

The measurement of surface roughness was conducted according to the protocols in DIN 4768 (1989). The time surface roughness tester (TR200, TIME, China) was used for the determination of the surface roughness values *via* the contact stylus trace method (Fig. 2).

Measurements were taken along the grain. The sampling length was taken as 2.5 mm, and the evaluation length was chosen as Lt = 12.5 mm. Surface roughness values were measured with a sensitivity of ± 0.01 µm. The tool measurement speed was chosen as 10 mm/min, the diameter of the measurement needle was 4 µm, and the needle tip was 90°. Care was taken to have a measurement environment of approximately 18 to 22 °C, away from noise sources, and without vibrations. The tool was calibrated before the measurement, and the calibration was checked at established intervals. Average surface roughness ($R_a$) and mean peak-to-valley height ($R_z$) were used for roughness measurements of all the samples.

Neural networks are popular, and there are many industrial applications which they can be usefully applied. They are suitable for modeling various manufacturing functions because of their ability to learn complex non-linear and multivariable relationships between process parameters (Karayel 2009).

In the ANN modeling of this manuscript, cutter type, spindle speed, feed rate, depth of cut, and tool clearance strategy were considered as the prime machining variables (Table 1). The neural networks were used as an alternative way to estimate surface quality in machining. The proposed ANN model was designed by software developed using the MATLAB Neural Network Toolbox to examine the effects of machining parameters on surface roughness values, the experimental data were grouped into training and testing data. Among this data, 78 (72% of total data) samples were selected for ANN training process, while the remaining 30 (28% of total data) samples were used to verify the generalization capability of ANN. As mentioned before, each data for training and predicting contains an average of five surface roughness measurements.

**Table 1.** Machining Parameters for CNC

| Machining variables | Levels | | |
|---|---|---|---|
| | 1 | 2 | 3 |
| Cutter type | Cutter 1 | Cutter 2 | |
| Direction | Raster | Offset | |
| Spindle speed (rpm) | 8000 | 12000 | 16000 |
| Feed rate (mm/min) | 1000 | 1500 | 2000 |
| Depth of cut (DoC) (mm) | 2 | 4 | 6 |

In this study, the ANN structure chosen as the prediction model included the input layer consisting of five input nodes: namely, cutter type, direction, spindle speed (rpm), feed rate (mm/min), and depth of cut (DoC) (mm). The output layer consisted of one output node: namely, surface roughness ($R_a$ and $R_z$).

A heuristic approach was used in determining the number of hidden neurons. Such an approach involves training different ANN models using different combination of network configurations until the optimal model is identified (Baratti *et al*. 2003). By following this procedure, the 5-5-1 neurons configuration in terms of the prediction performance of the network was found as the best configuration for the present study. One hidden layer was in the structure as well with 5 neurons. The ANN structure is shown in Fig. 2.

In measuring the performance of the network, the mean absolute percentage error (MAPE), root mean square error (RMSE), and coefficient of determination ($R^2$) were used.

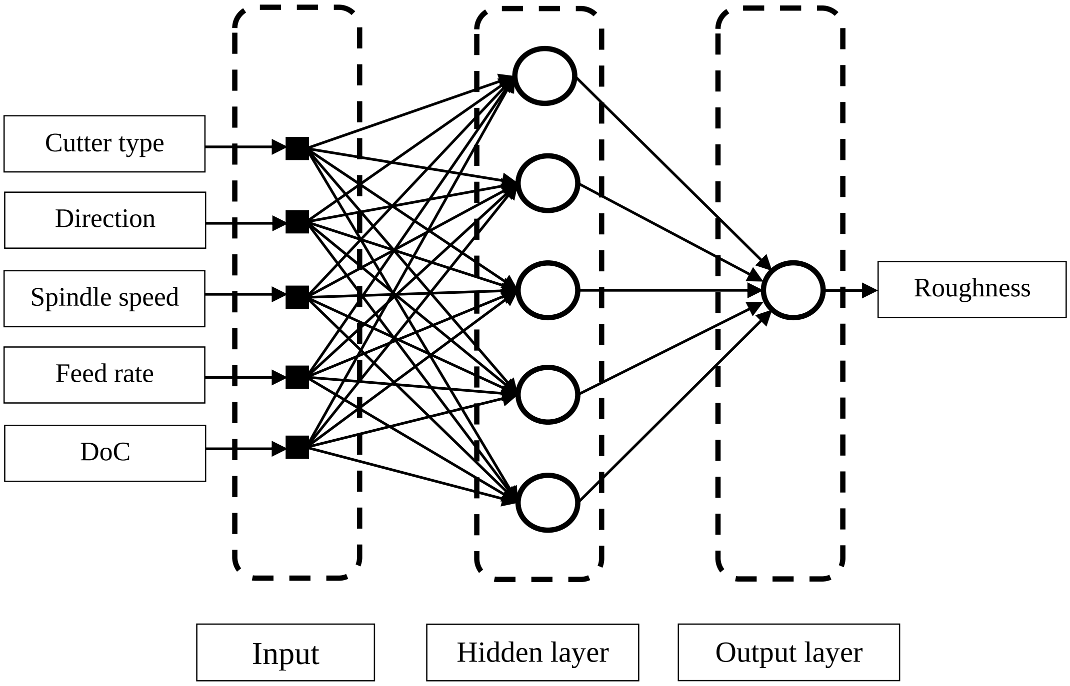


**Fig. 2.** Optimal network structure for surface roughness CNC machining experiments

## RESULTS AND DISCUSSION

Table 2 gives the measured and predicted values of surface roughness ($R_a$ and $R_z$) and their percentage errors.

Figure 3 presents the relationship between the experimental results and the ANN-predicted results. The measured $R_a$ and $R_z$ values of the samples show similarity with the values predicted by the ANN model.

Comparison of the measured values and predicted values by the neural network model of the $R_a$ and $R_z$ are presented in Figs. 4 and 5.

In measuring the model fit and prediction accuracy of the ANN model, the mean absolute percentage error (MAPE) and the root mean square error (RMSE) were used. The RMSE values were calculated as 1.05 and 3.70 and MAPE values were calculated 20.18 and 15.14 (Table 1).

These values of RMSE and MAPE can be judged as satisfactory because of the heterogeneity of the wood material. In some previous studies, it was stated the 10% < MAPE ≤ 20% of the MAPE is considered as good prediction (Aydin *et al.* 2014) (Levis 1982).

From the results, the ANN modeling approach can be employed in predicting the surface roughness (for $R_a$ and $R_z$) of wood samples (especially Scotch pine) under given conditions when the training of the model is properly completed.

**Table 2.** Measured and the Predicted Values of Surface Roughness ($R_a$ and $R_z$) and their Percentage Errors

| Cutter | Direction | Spindle speed (rpm) | Feed rate (mm/ dak) | DoC | Measured $R_a$ (µm) | Predicted $R_a$ (µm) | Error $R_a$ | Measured $R_z$ (µm) | Predicted $R_z$ (µm) | Error Rz |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 8000 | 1000 | 2 | 1.84 | 1.83 | 0 .01 | 10.12 | 11.73 | −1.62 |
| 1 | 1 | 8000 | 1000 | 4 | 2.86 | 1.97 | 0.89 | 15.08 | 19.09 | −4.01 |
| 1 | 2 | 8000 | 1000 | 6 | 3.64 | 3.03 | 0.61 | 18.47 | 20.21 | −1.74 |
| 1 | 2 | 8000 | 1500 | 6 | 4.33 | 3.69 | 0.63 | 22.60 | 20.79 | 1.81 |
| 1 | 2 | 12000 | 1500 | 2 | 2.88 | 3.50 | −0.63 | 14.13 | 14.88 | −0.75 |
| 1 | 1 | 12000 | 1500 | 4 | 3.37 | 2.24 | 1.13 | 18.16 | 14.44 | 3.72 |
| 1 | 1 | 12000 | 1500 | 6 | 2.81 | 2.80 | 0.02 | 15.42 | 22.51 | −7.10 |
| 1 | 2 | 12000 | 2000 | 2 | 4.75 | 4.08 | 0.67 | 24.94 | 14.88 | 10.06 |
| 1 | 2 | 16000 | 1000 | 4 | 2.01 | 2.69 | −0.67 | 11.42 | 14.87 | −3.45 |
| 1 | 1 | 16000 | 2000 | 2 | 2.35 | 2.26 | 0.09 | 13.18 | 13.68 | −0.50 |
| 1 | 2 | 16000 | 2000 | 4 | 3.30 | 3.22 | 0.08 | 16.77 | 14.88 | 1.89 |
| 1 | 1 | 16000 | 2000 | 6 | 2.97 | 2.10 | 0.87 | 16.70 | 20.10 | −3.40 |
| 2 | 1 | 8000 | 1500 | 2 | 7.00 | 4.82 | 2.19 | 32.20 | 26.19 | 6.01 |
| 2 | 1 | 8000 | 1500 | 4 | 3.26 | 4.62 | −1.36 | 18.17 | 21.27 | −3.09 |
| 2 | 2 | 8000 | 2000 | 2 | 5.85 | 7.67 | −1.81 | 29.15 | 34.24 | −5.09 |
| 2 | 1 | 8000 | 2000 | 4 | 5.34 | 5.99 | −0.65 | 26.69 | 22.38 | 4.31 |
| 2 | 2 | 8000 | 2000 | 4 | 6.22 | 8.19 | −1.97 | 33.40 | 30.54 | 2.86 |
| 2 | 2 | 8000 | 2000 | 6 | 6.66 | 8.45 | −1.79 | 26.10 | 29.46 | −3.36 |
| 2 | 2 | 12000 | 1000 | 2 | 3.11 | 4.35 | −1.24 | 16.42 | 17.97 | −1.55 |
| 2 | 2 | 12000 | 1000 | 4 | 3.95 | 4.54 | −0.59 | 20.20 | 22.06 | −1.86 |
| 2 | 1 | 12000 | 1000 | 6 | 3.97 | 4.09 | −0.12 | 19.26 | 22.48 | −3.23 |
| 2 | 2 | 12000 | 1000 | 6 | 5.97 | 5.00 | 0.97 | 28.21 | 28.79 | −0.58 |
| 2 | 1 | 12000 | 2000 | 4 | 4.70 | 5.23 | −0.53 | 22.63 | 21.55 | 1.08 |
| 2 | 1 | 12000 | 2000 | 6 | 4.73 | 5.52 | −0.79 | 22.87 | 21.23 | 1.64 |
| 2 | 1 | 16000 | 1000 | 2 | 4.11 | 3.78 | 0.33 | 22.60 | 21.98 | 0.63 |
| 2 | 1 | 16000 | 1000 | 6 | 5.78 | 4.61 | 1.18 | 29.94 | 27.87 | 2.06 |
| 2 | 1 | 16000 | 1500 | 2 | 5.46 | 3.93 | 1.53 | 26.47 | 22.79 | 3.68 |
| 2 | 2 | 16000 | 1500 | 2 | 4.29 | 4.33 | −0.04 | 22.39 | 19.66 | 2.72 |
| 2 | 2 | 16000 | 1500 | 4 | 2.93 | 4.74 | −1.81 | 15.38 | 21.46 | −6.08 |
| 2 | 2 | 16000 | 1500 | 6 | 5.58 | 5.15 | 0.42 | 28.36 | 28.61 | −0.25 |
| | | | | | RMS error | 1.05 | | RMS error | 3.70 | |
| | | | | | MAPE error | 20.18 | | MAPE error | 15.14 | |

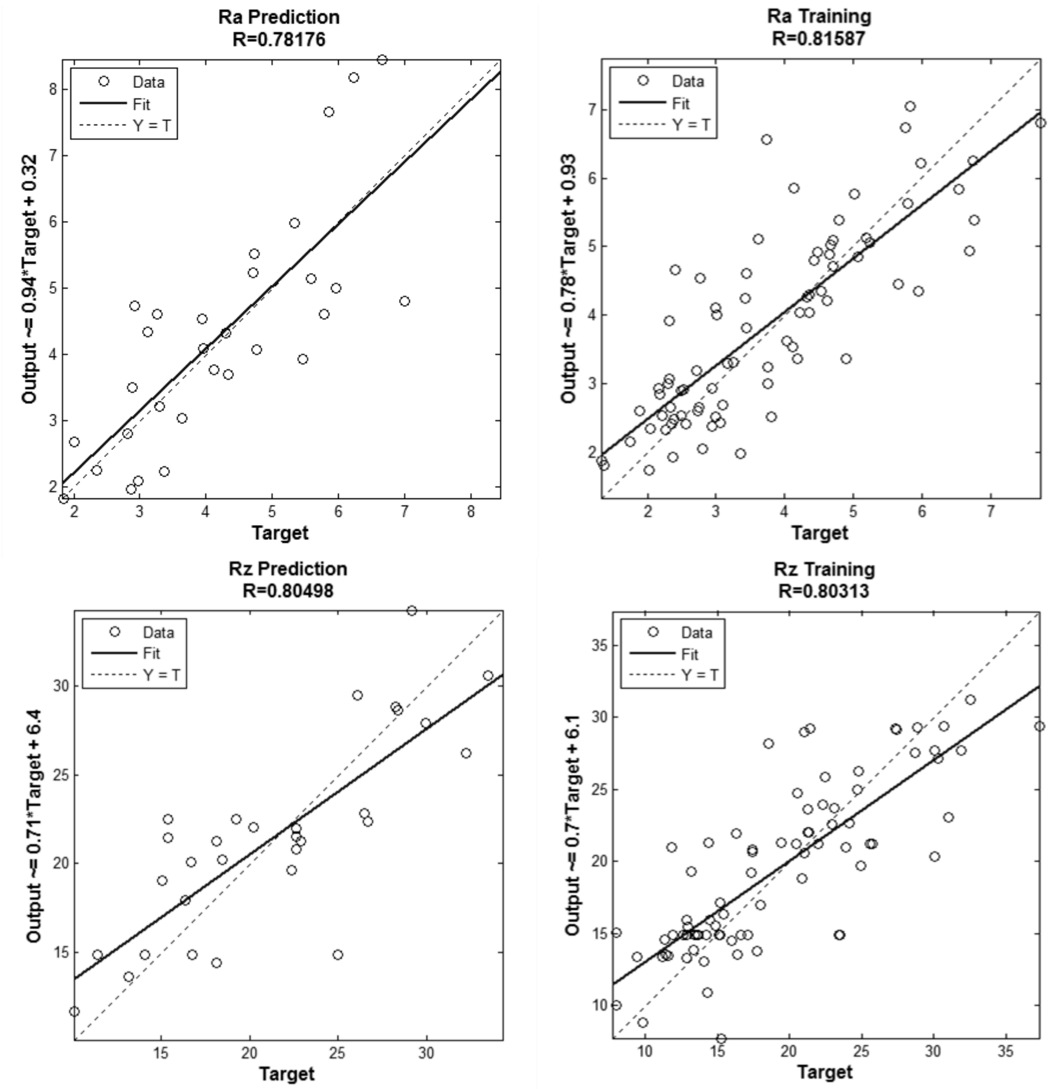


**Fig. 3.** Relationship between experimental results and ANN-predicted results

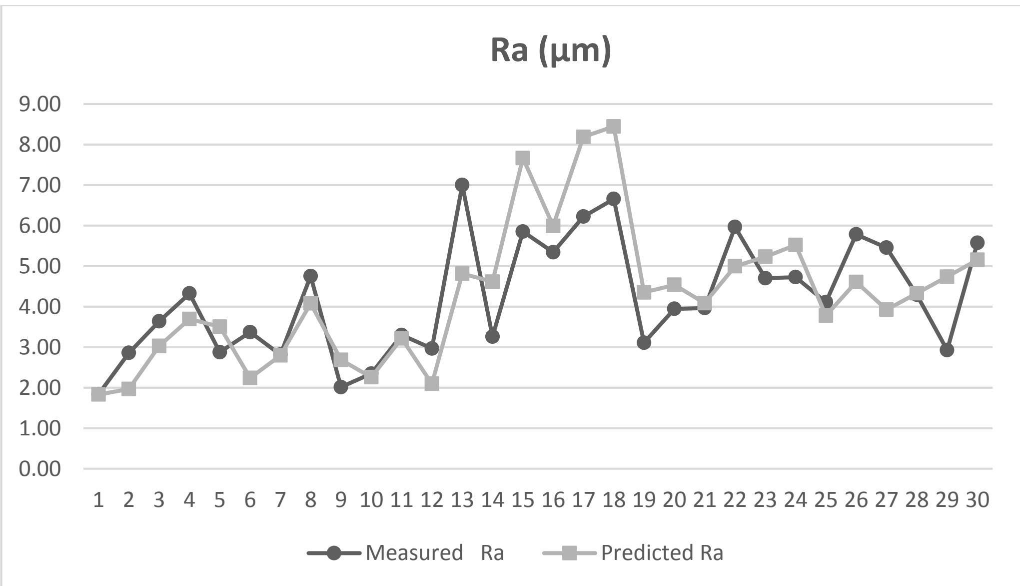


**Fig. 4.** Comparison of measured and predicted results of $R_a$

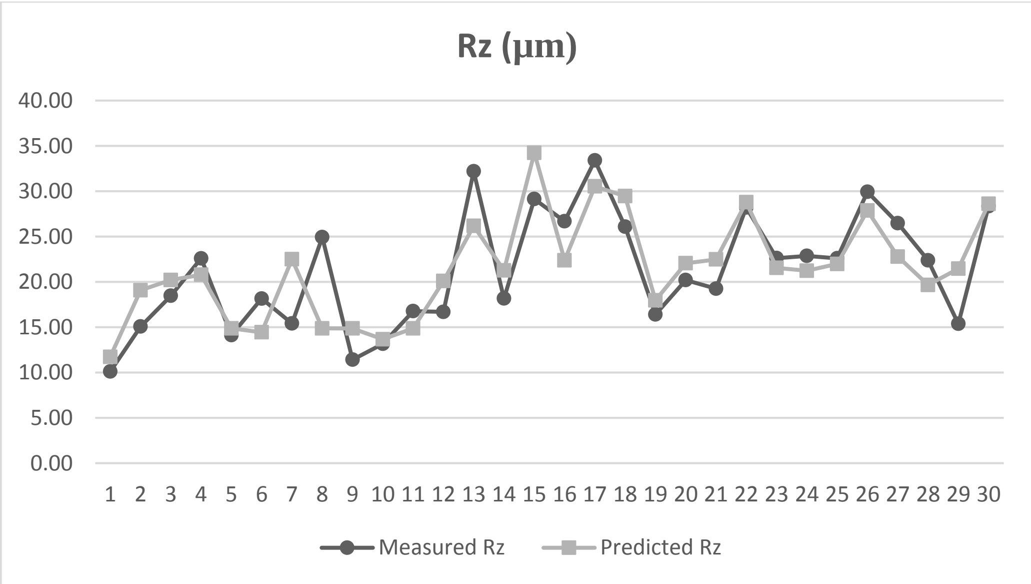


**Fig. 5.** Comparison of measured and predicted results of $R_z$

## CONCLUSIONS

In this study, the effects of cutter type, tool clearance strategy, spindle speed, feed rate, and depth of cut on the surface roughness of wood were investigated and were modeled using the ANN approach. A modeling approach using an ANN for the prediction and measured (control) of surface roughness in wood machining was developed. Generally, the predicted surface roughness from the model is close to the values measured experimentally. The conclusions can summarized as follows:

1. The measured mean roughness ($R_a$) and peak-to-valley distance ($R_z$) values of the samples showed similarity with the values predicted by the artificial neural network (ANN) model.
2. The ANN modeling approach can be employed in predicting the surface roughness (for $R_a$ and $R_z$) of wood samples (especially Scotch pine) under given conditions when the training of the model is properly completed.
3. The proposed ANN model was in agreement with the measured values in predicting surface roughness $R_a$ and $R_z$ values of MAPE. In the test phase, MAPE $R_a$ and $R_z$ values were found to be 20.18 and 15.14, respectively.
4. As the MAPE values were within the range 10% < MAPE ≤ 20%, the prediction can be regarded as a good one.
5. If this research is repeated with similar wood species and different parameters for other machine tools, it can be generalized and be applied to other machining types and different wood species.

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## REFERENCES CITED

Aras, R., Budakcı, M., and Ozisik, O. (2007). "The effect of wood turning techniques on surface roughness of wood material," *Journal of Polytechnic* 10(3), 325-330.

Aslandoğan, C. (2005). *Research on Determination of Surface Roughness of Crimean Pine (Pinus nigra Arnold) Wood*, M.S. thesis, Hacettepe University, Ankara, Turkey.

Avramidis, S., and Iliadis, L. (2005). "Predicting wood thermal conductivity using artificial neural networks," *Wood and Fiber Science* 37(4), 682-690.

Avramidis, S., and Wu, H. (2007). "Artificial neural network and mathematical modeling comparative analysis of nonisothermal diffusion of moisture in wood," *Holz Als Roh-Und Werkstoff* 65(2), 89-93. DOI: 10.1007/s00107-006-0113-0

Aydin, G., Karakurt, I., and Hamzacebi, C. (2014). "Artificial neural network and regression models for performance prediction of abrasive waterjet in rock cutting," *Int. J. Adv. Manuf. Technol.* 75, 1321-1330. DOI: 10.1007/s00170-014-6211-y

Baratti, R., Cannas, B., Fanni, A., Pintus, M., Sechi, G. M., and Toreno, N. (2003). "River flow forecast for reservoir management through neural networks," *Neurocomputing* 55, 421-437. DOI: 10.1016/S0925-2312(03)00387-4

Castellani, M., and Rowlands, H. (2008). "Evolutionary feature selection applied to artificial neural networks for wood-veneer classification," *International Journal of Production Research* 46(11), 3085-3105. DOI: 10.1080/00207540601139955

Ceylan, I. (2008). "Determination of drying characteristics of timber by using artificial neural networks and mathematical models," *Drying Technology* 26(12), 1469-1476. DOI: 10.1080/07373930802412132

Cook, D. F., and Whittaker, A. D. (1993). "Neural-network process modeling of a continuous manufacturing operation," *Engineering Applications of Artificial Intelligence* 6(6), 559-564. DOI: 10.1016/0952-1976(93)90052-Y

Cook, D. F., Ragsdale, C. T., and Major, R. L. (2000). "Combining a neural network with a genetic algorithm for process parameter optimization," *Engineering Applications of Artificial Intelligence* 13(4), 391-396. DOI: 10.1016/S0952-1976(00)00021-X

DIN 4768 (1989). "Determination of surface roughness values of the parameters Ra, Rz, Rmax by means of electrical contact (stylus) instruments; Terminology, measuring conditions," German Institute for Standardization, Berlin, Germany.

Drake, P. R., and Packianather, M. S. (1998). "A decision tree of neural network for classifying images of wood veneer," *International Journal of Advanced Manufacturing Technology* 14(4), 280-285. DOI: 10.1007/BF01199883

Efe, H., and Gurleyen, L. (2003). "Effects of the cutting direction the number of cutter and the rotation value on surface smoothness for some wood species," *The Journal of the Industrial Arts Education Faculty of Gazi University* 11(12), 34-44.

Esteban, L. G., Garcia Fernandez, F., de Palacios, P., and Conde, M. (2009). "Artificial neural networks in variable process control: Application in particleboard manufacture," *Investigacion Agraria-Sistemas Y Recursos Forestales* 18(1), 92-100. DOI: 10.5424/fs/2009181-01053
Faust, D.T. (1987). "Real time measurement of veneer surface roughness by image analysis," *Forest Products Journal* 37(6), 34-40.
Faust, D. T., and Rice, J. T. (1986). "Effect of veneer surface roughness on the bond quality of southern pine plywood," *Forest Products Journal* 36(4), 57-62.
Fernández, F. G., de Palacios, P., Esteban, L. G., Garcia-Iruela, A., Rodrigo, B. G., and Menasalvas, E. (2012). "Prediction of MOR and MOE of structural plywood board using an artificial neural network and comparison with a multivariate regression model," *Composites Part B: Engineering* 43(8), 3528-3533. DOI: 10.1016/j.compositesb.2011.11.054
Hiziroglu, S., Zhong, Z. W., and Tan, H. L. (2013). "Measurement of bonding strength of pine, kapur and meranti wood species as function of their surface quality," *Measurement* 46(9), 3189-32010. DOI: 10.1016/j.measurement.2013.05.005
Ilter, E., Camliyurt, C., and Balkiz, O. D. (2002). *Researches of the Determination of the Surface Roughness Values of Bornmullerian Fir (Abies bornmülleriana Mattf.)*, Central Anatolia Forestry Research Institute.
ISO 468 (2009). "Surface roughness-parameters, their values and general rules for specifying requirements," International Organization for Standardization, Geneva, Switzerland.
ISO 3130 (1975). "Wood -- Determination of moisture content for physical and mechanical tests," International Organization for Standardization, Geneva, Switzerland.
ISO 3131 (1975). "Wood -- Determination of density for physical and mechanical tests," International Organization for Standardization, Geneva, Switzerland.
ISO 3274 (2005). "Geometrical Product Specifications (GPS) - Surface texture: Profile method - Nominal characteristics of contact (stylus) instruments," International Organization for Standardization, Geneva, Switzerland.
ISO 4287 (1997). "Geometrical product specifications surface texture profile method terms, definitions and surface texture parameters," International Organization for Standardization, Geneva, Switzerland.
Karayel, D. (2009). "Prediction and control of surface roughness in CNC lathe using artificial neural network," *Journal of Materials Processing Technology* 209(7), 3125-3137. DOI: 10.1016/j.jmatprotec.2008.07.023
Khalid, M., Lee, E., Yusof, R., and Nadaraj, M. (2008). "Design of an intelligent wood species recognition system," *International Journal of Simulation System, Science and Technology,"* 9(3), 9-19.
Kurdthongmee, W. (2008). "Colour classification of rubberwood boards for fingerjoint manufacturing using a SOM neural network and image processing," *Computers and Electronics in Agriculture* 64(2), 85-92. DOI: 10.1016/j.compag.2008.04.002

Levis, C. D. (1982). *Industrial & Business Forecasting Methods*, Butterworth-Heinemann Press, United Kingdom.

Malkocoglu, A. (2007). "Machining properties and surface roughness of various wood species planed in different conditions," *Building and Environment* 42(7), 2562-2567. DOI: 10.1016/j.buildenv.2006.08.028

Malkocoglu, A., and Ozdemir, T. (1999). "Surface roughness of the historical development," *Furniture Decoration* 32(1), 60-68.

Mansfield, S. D., Iliadis, L., and Avramidis, S. (2007). "Neural network prediction of bending strength and stiffness in western hemlock (*Tsuga heterophylla* Raf.)," *Holzforschung* 61(6), 707-716. DOI: 10.1515/hf.2007.115

Nordmark, U. (2002). "Knot identification from CT images of young *Pinus sylvestris* sawlogs using artificial neural networks," *Scandinavian Journal of Forest Research* 17(1), 72-78. DOI: 10.1080/028275802317221109

Ors, Y., and Baykan, İ. (1999). "The effect of planing and sanding on surface roughness of massive wood," *Turkish Journal of Agriculture and Forestry* 23(3), 577-582.

Packianather, M. S., and Drake, P. R. (2005). "Comparison of neural and minimum distance classifiers in wood veneer defect identification," *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture* 219(11), 831-841. DOI: 10.1243/095440505X32823

Peters, C., and Mergen, A. (1971). "Measuring wood surface smoothness: A proposed method," *Forest Products Journal* 21(6), 28-30.

Peters, C. C., and Cumming, J. D. (1970). "Measuring wood surface smoothness: A review," *Forest Products Journal* 20(12), 40-43.

Porter, A. W., Kusec, D. J., and Sonders, J. L. (1971). *Air-Flow Method Measures Lumber Surface Roughness*, Canadian Forest Industries.

Samarasinghe, S., Kulasiri, D., and Jamieson, T. (2007). "Neural networks for predicting fracture toughness of individual wood samples," *Silva Fennica* 41(1), 105-122. DOI: 10.14214/sf.309

Sandak, J., and Tanaka, C. (2005). "Evaluation of surface smoothness using a light-sectioning shadow scanner," *Journal of Wood Science* 51(3), 270-273. DOI: 10.1007/s10086-004-0637-z

Sonmez, A., and Sogutlu, C. (2005). "The effect of planning on the surface roughness in wood material," *Teknoloji* 8(3), 287-293.

Steward, H. A. (1970). "Cross grain knife planing, hard maple produces high quality surfaces and flakes," *Forest Products Journal* 20(10), 39-42.

Stumbo, D. A. (1960). "Surface texture measurement for quality and production control," *Forest Products Journal* 10(12), 122-124.

Tiryaki, S., and Aydin, A. (2014). "An artificial neural network model for predicting compression strength of heat treated woods and comparison with a multiple linear regression model," *Construction and Building Materials* 62, 102-108. DOI: 10.1016/j.conbuildmat.2014.03.041

Tiryaki, S., Malkocoglu, A., and Ozsahin, S. (2014). "Using artificial neural networks for modeling surface roughness of wood in machining process," *Construction and Building Materials* 66, 329-335. DOI: 10.1016/j.conbuildmat.2014.05.098

Unsal, O., and Kantay, R. (2002). "Investigation of surface roughness of oak and beech wood parquets produced in Turkey," *Review of the Faculty of Forestry, University of İstanbul* 52(1), 81-94.
Wu, H., and Avramidis, S. (2006). "Prediction of timber kiln drying rates by neural networks," *Drying Technology* 24(12), 1541-1545. DOI: 10.1080/07373930601047584
Zhang, J. W., Cao, J., and Zhang, D. Y. (2006). "ANN-based data fusion for lumber moisture content sensors," *Transactions of the Institute of Measurement and Control* 28(1), 69-79. DOI: 10.1191/0142331206tm163oa
Zhang, J., Cao, J., and Sun, L. (2007). "A novel fusion technique based functional link artificial neural network for LMC measuring," Second IEEE Conference on Industrial Electronics and Applications, 471-475. DOI: 10.1109/ICIEA.2007.4318453

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