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Using artificial neural networks for modeling surface roughness of wood in machining process

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HIGHLIGHTS

- Effects of machining parameters on surface roughness of wood were studied.
- Surface roughness decreased with increasing grit number and number of cutter.
- Surface roughness increased with increasing cutting depth and feed rate.
- Experimental results obtained were modeled by artificial neural network (ANN).
- It was shown that ANN can be used successfully for modeling surface roughness.

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ABSTRACT

Surface quality of solid wood is very important for its effective utilization in further manufacturing processes. In this study, the effects of wood species, feed rate, number of cutter, cutting depth, wood zone (earlywood–latewood) and grain size of abrasives on surface roughness were investigated and modeled by artificial neural networks. It was shown that the artificial neural network prediction model obtained is a useful, reliable and quite effective tool for modeling surface roughness of wood. Thus, the results of the present research can be successfully applied in the wood industry to reduce the time, energy and high experimental costs.

1. 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 its strength characteristics [1]. Adhesives used in such applications are absorbed by the wood depending on surface roughness, thereby increase the strength of the mechanical bond between the wood and adhesive. The roughness level of the wood surface also affects the wettability of its surface thus the bond quality. Good wettability means good bonding quality. In other words, as a result of the decrease in the surface roughness, contact angle values decrease and consequently, the bonding strength of the wood product increase. However, ultra-smooth surfaces can reduce the bonding strength of wood [2]. Therefore, it is important to determine surface roughness of the final product in the wood machining. On the other hand, determination of the surface roughness is a complex process due to the anatomical structure of wood, the cutting processes and machining conditions [3,4].

Although there are several methods including laser, pneumatic technique and stylus type equipment, there is no accepted standard method to determine surface roughness of wood and wood products. Stylus type equipment has been used successfully in many experimental studies to quantify surface roughness of wood and wood based products [5,6]. It provides objective and quantitative numerical values about the surface profile of wood [7].

There are many studies about the effects of various machining parameters on the surface roughness of wood. Usta et al. [8] investigated the effects of cutting depth, feed rate, and number of cutter on the surface roughness in the planing process. In conclusion, they stated that the smoother surfaces were obtained with decreasing cutting depth and feed rate. The surface roughness also decreased with the increase in the number of cutter. Aslan et al. [9] studied the effects of cutting direction, grit size of abrasive, and number

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of cutter on surface roughness in the planing process. They observed a better surface quality with the increasing grit number of abrasive in the sanding operation. Kilic et al. [10] investigated the effects of the various processing parameters on surface roughness. They claimed that cutting direction, grit number of abrasive and wood species affected surface roughness. Skaljic et al. [11] determined that feed rate, number of cutter, and rake angle influenced the surface roughness in the planing process. Efe et al. [12] studied the effects of feed rate, cutting direction, cutting depth and number of cutter on surface roughness in the planing of beech (*Fagus orientalis* Lipsky) wood. They reported that the smoother surfaces ran tangential to the annual rings with the increasing number of cutter, the decreasing of feed rate and cutting depth. Sonmez and Sogutlu [13] investigated the effects of the various machining factors on surface roughness. They observed that the smoother surfaces were obtained in the tangential section with the increasing of number of cutter in the planing. Efe and Gurleyen [14] evaluated the effects of number of cutter on surface roughness in the planing operation. They reported that the best results were obtained with the increasing of number of cutter. Ors and Baykan [15] studied the effects of cutting direction and the number of cutter on the surface roughness of beech (*F. orientalis* Lipsky) and pine (*Pinus sylvestris* L.) woods in planing. In conclusion, they determined that the smoother surfaces were obtained with the increasing number of cutter, and in both wood species tangential to the annual rings, compared to a radial direction. Also, they observed that the surface roughness of beech (*F. orientalis* Lipsky) was greater than pine (*P. sylvestris* L.). Burdurlu et al. [16] investigated the effects of feed rate, number of cutter, grit size of abrasive and cutting direction on the surface roughness of Black poplar (*Populus nigra* L.) and Black pine (*Pinus nigra* A.) in the planing process. They obtained the higher surface quality on the sanded surfaces in a tangential direction for both wood species. Sulaiman et al. [17] studied the effects of sanding on the surface roughness of Rubber wood (*Hevea brasiliansis*). They reported that smoother surfaces were obtained by increasing the grit number of abrasive. Malkocoglu [1] investigated machining properties and surface roughness of various wood species planed in different conditions. In conclusion, it was reported that machining performance increased with the reduction of rake angle and feed rate, and the smoother surfaces were obtained in latewood compared to earlywood. Ulusoy [18] studied the effects of anatomical structures and machining conditions on the surface roughness of spruce and beech woods. In conclusion, it was found that the surface roughness of spruce is lower than that of beech.

A lot of samples and exhaustive tests are needed to optimize surface roughness in the planing process. Also, the measuring of the effect of each parameter influencing surface roughness is too expensive, and carrying out experiments is also time-consuming. Hence, it is important to find more economic methods providing desirable results concerning surface quality of wood. For this aim, ANNs have been widely used in the field of wood science, such as the recognition of the wood species [19,20], drying process of wood [21,22], the prediction of some mechanical properties in particleboard, plywood and wood [23–25], the optimization of process parameter in manufacturing process of wood products [26,27], the classification of wood veneer defects [28–30], the calculation of wood thermal conductivity [31], analysis of moisture in wood [32,33], the prediction of fracture toughness of wood [34], the classification of wood defects [35,36].

Although there are many studies about the effects of machining parameters on surface roughness of wood, studies on modeling the effects of these parameters is very limited. Therefore, the main objective of this study is to model the effects of some process parameters on the surface roughness in processing of beech and spruce woods.

2. Materials and methods

2.1. Sample preparation

In this study, beech wood as hardwood (*F. orientalis* Lipsky.) and spruce wood as softwood (*Picea orientalis* (L.) Link.), which are commonly utilized in the forest industry sector, were chosen for the materials of the experiment. The samples used in the experiment were all randomly selected from naturally grown woods in the Black Sea region of Turkey. Sample logs were obtained from the trunk of each wood species at a height of 2.5–5.5 m with a minimum length of 1.30 m. Special attention was paid to choose samples without any defects. The preparation of the test samples was carried out according to principles of ASTM-D 1666 87 [37]. The dimensions of the samples were trimmed to 910 mm long, 102 mm wide and 20 mm thick with flatsawn. Thus, the dimensions were obtained as $20 \times 102 \times 910$ mm. Thirty samples were taken for each wood species, thereby using a total of sixty samples. The samples were planed at 7 and 14 m/min feed rate, 0.5 and 1.5 mm cutting depth and using 1, 2 and 4 cutters with a thickness planer machine, and then sanded with 80 and 100 grit numbers using a belt sanding machine. Also, the average densities of wood species have been determined as 0.704 g/cm^3 and 0.417 g/cm^3 for beech and spruce woods, respectively. They were conditioned at a temperature of 20 ± 2 °C and relative humidity of 65 ± 5% to the moisture content of about 12%.

2.2. Determination of wood surface roughness

The surface roughness tests were conducted using a Mitutoyo Sj-301. During the measurements, operations were tracing speed of 0.5 mm/s, pick-up length (λ_c) of 2.5 mm, stylus tip radius of 5 μm and the stylus tip angle of 90°. The surface roughness values were determined by a sensitivity of ±0.01 μm. Mean peak-to-valley height (R_z) was used for roughness measurements of the samples. All these measurements also complied with the principles of DIN 4768 [38].

2.3. Artificial neural network (ANN) method

In the ANN modeling for the present work, wood species, feed rate, number of cutter, cutting depth, sanding condition and wood zone were considered as the prime processing variables. The proposed ANN model was designed by software developed using the MATLAB Neural Network Toolbox. The data was obtained from the experimental study. To examine the effects of the various machining parameters on the surface roughness, the experimental data were grouped into training data and testing data. Among this data, 96 samples were selected for ANN training process, while the remaining 48 samples were used to verify the generalization capability of ANN. The data (training and testing data) used in the prediction model is shown in Table 1.

2.4. Artificial neural network analysis

A change in the process conditions of anisotropic wood material alters the roughness values. Also, the relationship between process and roughness parameter is difficult to express mathematically. In the study, the change in values of the roughness parameter depending on wood species, feed rate, number of cutter, cutting depth, sanding condition, and wood zone was modeled with the ANN approach, producing consistent results with experimental data without mathematical modeling. The determination of weight and bias values, the minimization of the mean square error (MSE) for the ANN models, and ANN training processes were performed with MATLAB package software. The models were tested using a set of data (test data) including input–output pairs which were not utilized for the training process to determine the performance of networks. Thus, the aim was to obtain the most appropriate ANN results.

The real (measured) values were compared with the prediction values obtained as a result of the testing process. The model providing the best prediction values with respect to the root mean square error (RMSE) ratio, calculated using Eq. (1), and the mean absolute percentage error (MAPE) ratio, calculated with Eq. (2), was chosen as the prediction model.

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

$$\mathrm{MAPE} = \frac{1}{N}\left(\sum_{i=1}^{N}\left[\left|\frac{t_i - td_i}{t_i}\right|\right]\right) \times 100 \tag{2}$$

where t_i is the actual output (targeted values), td_i is the neural network output (predicted values), and N is the total number of measurements.

The values predicted with the using of the ANN model for the training and test data, measured values, percentage errors, and RMSE and MAPE values are presented in Table 1.

The ANN model containing one input layer, two hidden layers and one output layer is shown in Fig. 1.