Prediction of noise emission in the machining of wood materials by means of an artificial neural network

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Abstract

Background: Noise produced during machining of wood materials can be a source of harm to workers and an environmental hazard. Understanding the factors that contribute to this noise will aid the development of mitigation strategies. In this study, an artificial neural network (ANN) model was developed to model the effects of wood species, cutting width, number of blades, and cutting depth on noise emission in the machining process.

Methods: A custom application created with MATLAB codes was used for the development of the multilayer feed-forward ANN model. Model performance was evaluated by numerical indicators such as MAPE, RMSE, and $R^2$.

Results: The ANN model performed well with acceptable deviations. The MAPE, RMSE, and $R^2$ values were 0.553%, 0.600, and 0.9824, respectively, in the testing phase. Furthermore, this study predicted the intermediate values not provided from the experimental study. The model predicted that lower noise emissions would occur with decreased cutting width and cutting depth.

Conclusions: ANNs are quite effective in predicting the noise emission. Practitioners relying on the ANN approach for investigating the effects of various factors on noise emission can save time and costs by reducing the number of experimental combinations studied to generate predictive models.

Keywords: artificial neural network, noise emission, machining, wood, prediction

Introduction

Wood is a naturally occurring material consisting of cellulose, hemicelluloses, lignin, extractives, and inorganic components (Uysal & Yorur 2013). It can be used in both a solid form or further processed into wood-based composites (Sedlecký & Gašparík 2017). One of the most important wood-based composites is medium-density fiberboard (MDF). MDF is made from wood fibers that are glued together with heat and pressure. The physical and mechanical properties and surface qualities of MDF panels are relatively standardised and uniform. These characteristics make the panels a suitable alternative to solid wood for industrial manufacturing of furniture (Fathollahzadeh et al. 2013).

The production of furniture and decoration elements requires a series of transformation processes. The machines used in these processes must be properly designed and operated, otherwise, noise problems may arise. Noise is generally defined as an unwanted sound (Engin et al. 2019) and is a major occupational and environmental hazard. The continuous exposure of workers to high noise levels can cause detrimental health effects such as hearing loss, sleep disturbance, fatigue, and hypertension (Hong et al. 2013). According to the National Institute of Occupational Safety and Health, an estimated 14% of workers are exposed to noise higher than the permissible limit (85 dB(A)) (Lee et al. 2009; Ismaila & Odusote 2014).

Occupational exposure to noise is unavoidable in the wood processing industry; however, this exposure could be minimised by better understanding the factors affecting noise. The most important main factors influencing the noise level are wood properties and machining parameters. Therefore, it is important to...
evaluate subfactors related to both wood properties and machining parameters for the reduction of noise emission in the machining process (Owoyemi et al. 2017; Çota et al. 2019).

In recent years, several attempts have been made to examine the influences of various factors on noise emission in wood machining. Ratnasingam and Scholz (2008) stated that the use of smaller engines and breaking of fewer chips led to lower noise emission. Sovrě et al. (2010) reported that the circular saw blade with sigmoid compensating slots had the lowest noise levels in the range of (2-5) dB(A). Pinheiro et al. (2015) determined that an increase in the moisture content of wood led to a decrease in noise emission. Krilek et al. (2016) observed that the number of saw blade teeth had a significant effect on noise emission. This observation was also confirmed by Kvietková et al. (2015). Durcan and Burdurlu (2018) noted that decreasing the blade number led to higher noise emission, while Çota et al. (2019) reported that noise emission increased with increasing feed speed.

It is clear that plenty of values for factors have to be investigated to detect a change in noise emission. However, the measuring of the effect of each factor on noise emission is expensive, and conducting tests is also time-consuming. Therefore, it is important to find reliable and economic methods providing the desired results (McKenzie et al. 2003). Owing to the heterogeneous nature of wood, wood-related factors possess nonlinear changes. Hence, traditional linear models are inadequate in describing the characteristics of these factors. Ignoring the presence of nonlinearities leads to misleading results. Machine learning techniques are more appropriate for modeling and optimization purposes. Artificial neural networks (ANNs), one of the most attractive branches in artificial intelligence, are able to deal with linear and nonlinear problems and learn complex cause-and-effect relationships among inputs and outputs. ANNs are good for tasks involving fuzzy or incomplete information. They can be faster, cheaper, and more adaptable than conventional methods (Ozsahin & Murat 2018).

The ANN approach has brought a new insight into the solution of many problems in wood science. This approach has been employed for analyzing moisture in wood (Avramidis & Wu 2007), prediction of fracture toughness (Samarasinghe et al. 2007), classification of veneer defects (Castellani & Rowlands 2008), wood recognition (Khalid et al. 2008), modeling of some properties of oriented strand board (Ozsahin 2012; Ozşahin 2013), determination of optimum power consumption in wood machining (Tiryaki et al. 2016), prediction of formaldehyde emission (Akyüz et al. 2017), and modeling of physical properties of heat-treated wood (Ozsahin & Murat 2018). These studies have shown that the ANN approach produces highly successful results.

Consequently, the existing literature has a gap in the prediction of noise emission by the ANN approach. Therefore, the objectives of this study are to: 1) develop an ANN model for modeling the effects of wood species, cutting width, number of blades, and cutting depth on noise emission in the machining process; 2) to present a road map for the wood processing industry seeking to enhance worker health and safety; and 3) to fill the gap in the literature.

**Methods**

**Dataset**

The data used in this study were taken from Durcan and Burdurlu (2018). The experimental process conducted by the authors can be briefly explained as follows. Lombardy poplar (*Populus nigra* L.), Oriental beech (*Fagus orientalis* L.), and MDF were selected as materials for the experiments. In the planing of the samples, five different levels of cutting width (6, 12, 18, 25, and 30 mm), three different levels of cutting depth (1, 2, and 3 mm), and two different levels of number of blades (1 blade and 4 blades) were tested. The cutting speed was chosen as 26.7 m/s, and the feed rate was 5 m/min. The Extech HD 600 device (Extech Instruments, NH, USA) was used for the measurement of noise emission. A total of 1800 measurements were recorded with 20 measurements (replications) for each combination of factors. More information about the experimental procedure can be found in Durcan and Burdurlu (2018).

**Artificial neural network approach**

The ANN is a computational model that is inspired by the human brain (Mia & Dhar 2016). The ANN approach offers many advantages over traditional statistical methods because it is capable of describing the relationship between input and output variables without any prior knowledge (Venkata Ramana et al. 2013; Shebani & Iwnicki 2018). ANNs can be used for data sorting, pattern recognition, optimisation, clustering, and simulation (Yadav & Chandel 2014).

The most widely used network is the multilayer perceptron (MLP). It consists of one input layer, one hidden layer(s), and one output layer (Drouillet et al. 2016). The input layer receives the data and transmits them to the hidden layer(s). The hidden layer(s) processes the information and sends the result to the output layer. The output layer provides the outputs of the network (Kara et al. 2016).

The MLP network comprises a number of neurons (nodes) organized in layers (Ghorbani et al. 2016). Each node is connected to other nodes by communication links (connections). Each connection has a weight (Ozsahin 2012). In order to obtain the net input, inputs are multiplied by weights and combined with the relevant bias. Outputs are calculated by applying a mathematical function to the net input. This process is summarised in Equations (1) and (2) (Ozsahin 2013).

\[
\text{net}_j = \sum_{i=1}^{n} x_i w_{ij} + \theta_j
\]  

\[
y_j = f(\text{net}_j)
\]
where: $x_i$ is the input signal, $w_{ij}$ is the weight between the $i$th node and the $j$th node, $\theta_j$ is the bias, net, is the net input of the $j$th node, $f(.)$ is one of the activation functions, and $y_j$ is the output of the $j$th node.

Input nodes and output nodes represent inputs and outputs, respectively. However, hidden nodes vary depending on the complexity level of the handled problem (Beltramo et al. 2016). If too few hidden nodes are used, the network does not have enough ability to model complex relationships between inputs and outputs. On the other hand, if too many hidden nodes are used, overfitting problems may arise (Quintana et al. 2011).

Neural networks must be trained with known input-output data. During the training process, the values of weights and biases are changed to obtain the best prediction results (Haghdadi et al. 2013). When the error reaches a determined value or the specified number of iterations is reached, the training of ANNs is finished (Ertunc et al. 2013). If the model responds correctly to input values that are not employed in training, the weights and biases of the trained network are saved. These weights and biases can be used to predict outputs for new input vectors (Yildirim et al. 2011).

Artificial neural network analysis
In this study, the noise emission values were predicted with the ANN approach. The wood species, cutting width, number of blades, and cutting depth were considered as inputs, while the noise emission was the output of the ANN model. We ran the ANN model with a range of values for the given parameters. The other process parameters, environmental conditions, and wood-related parameters were held constant. The ANN modeling steps were performed using MATLAB (MathWorks, MA, USA). Figure 1 shows the steps of this study.

The data were grouped randomly and homogeneously in the form of training and testing data. 60 data points (66.67% of total data) were used for the training process and 30 data points (33.33% of total data) were used to test the validity of the ANN model. Different data groups were constituted from the data. Each data group was tested to detect suitable data sets. The subsets used in the ANN analysis are shown in Table 1.

In modeling, a feed-forward backpropagation neural network was used. The activation functions were the hyperbolic tangent sigmoid function (tansig) and the linear transfer function (purelin). The Levenberg-Marquardt algorithm (trainlm) was employed for training, and the gradient descent with a momentum backpropagation algorithm (traingdm) was considered as the learning rule. The training progress was monitored through the mean square error (MSE) [Equation (3)]:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (t_i - td_i)^2$$

(3)

where, $t_i$ refers to the actual value, $td_i$ refers to the model output, and $N$ refers to the number of measurements.

Normalising the data before the training and testing of ANNs is recommended to equalise the significance of variables (Canakci et al. 2015). As the tansig function was used as the activation function, the experimental data were normalised between −1 and 1. The mapping of each variable to a value between −1 and 1 was carried out using Equation (4). The outputs of the ANN model were converted into the real values by using a reverse normalising process.

$$X_{\text{norm}} = 2 \times \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} - 1$$

(4)

FIGURE 1: The steps of this study based on the ANN approach.
| Sample ID | Measured | Predicted | Error (%) |
|-----------|----------|-----------|-----------|
| B1        | 83.06    | 83.10     | -0.05     |
| A2        | 82.00    | 82.00     | 0.00      |
| C3        | 81.98    | 81.98     | 0.00      |
| D4        | 81.94    | 81.94     | 0.00      |

**TABLE 1:** The measured and predicted values of noise emission and their percentage errors.

Bold values: testing data, the other values: training data

A and B denote sample IDs in training and testing, respectively.
where, \(X_{\text{norm}}\) is the normalised value, \(X\) is the real value, and \(X_{\text{min}}\) and \(X_{\text{max}}\) are the minimum and maximum values of \(X\), respectively.

The performance of ANN-based models is affected by many factors such as activation functions, learning rule, momentum, and the number of nodes in the hidden layer(s) (Mohanraj et al. 2012). Therefore, different network parameters and configurations were tried until the difference between the measured and predicted values was minimised. The established models were checked by employing the testing data. As a result, the ANN model yielding the nearest values to the experimental results was run for predictions. The optimum values of weights and biases of the ANN model are shown in Table 2.

Figure 2 shows the developed model. The input layer of the ANN model consists of four nodes representing wood species, cutting width, number of blades, and cutting depth. The output node represents the output parameter called noise emission. ANNs should be not too large to prevent the loss of generalisation. The attention should be paid to the number of nodes in each hidden layer (Muralitharan et al. 2018). In this study, the ANN model was designed on the trial-and-error basis. The best performance was obtained with 3-3 hidden nodes. The proposed model is mathematically logical and defined because the number of the connections is lower than the number of data points available for training.

The performance of prediction models can be evaluated by using various statistical measures. In this study, the mean absolute percentage error (MAPE), the root mean square error (RMSE), and the coefficient of determination (\(R^2\)) were used to compare the established models. The MAPE, RMSE, and \(R^2\) values were calculated by using the following equations:

\[
\text{MAPE} = \frac{1}{N} \left( \sum_{i=1}^{N} \left| \frac{t_i - \hat{t}_i}{t_i} \right| \right) \times 100
\]

\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (t_i - \hat{t}_i)^2}
\]

\[
R^2 = 1 - \frac{\sum_{i=1}^{N} (t_i - \hat{t}_i)^2}{\sum_{i=1}^{N} (t_i - \bar{t})^2}
\]

where \(\bar{t}\) is the average of predicted values.

\[
\text{MAPE} = \frac{1}{N} \left( \sum_{i=1}^{N} \left| \frac{t_i - \hat{t}_i}{t_i} \right| \right) \times 100
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R^2 = 1 - \frac{\sum_{i=1}^{N} (t_i - \hat{t}_i)^2}{\sum_{i=1}^{N} (t_i - \bar{t})^2}
\]

where \(\bar{t}\) is the average of predicted values.

| Hidden layer 1 | Hidden layer 2 | Output layer |
|----------------|----------------|--------------|
| Neuron 1 | Neuron 2 | Neuron 3 | Bias 1 | Neuron 1 | Neuron 2 | Neuron 3 | Bias 2 | Neuron 1 | Bias 3 |
| 0.01109 | -3.27308 | -0.04546 | -0.51600 | 2.13712 | 3.20086 | -8.24474 | -6.65524 | 0.26429 | -2.53834 |
| -0.01309 | -1.92293 | -0.01902 | 0.03776 | -12.69931 | -11.60765 | 0.00014 | 12.65040 | 0.48143 | - |
| 0.00226 | 0.08328 | 0.03226 | 5.17537 | -14.63688 | 0.50336 | 0.11658 | -3.50894 | 5.29178 | - |
| -0.00803 | -3.63630 | -4.84149 | - | - | - | - | - | - | - |

**TABLE 2:** The optimum values of weights and biases.

**Figure 2:** The proposed network architecture.
Results and Discussion

In this study, a feed-forward backpropagation neural network was designed for the prediction of noise emission. The network was trained and tested using 90 data points. As a result of the modeling process, the 4:3:3:1 architecture was selected to make predictions. The actual and predicted values and their percentage errors are given in Table 1. The MAPE, RMSE, and $R^2$ values were employed as the main criteria to evaluate the performance of the ANN model. Table 3 shows the MAPE, RMSE, and $R^2$ statistics calculated for the ANN model.

According to Lewis (1982), typical MAPE values for performance evaluation are categorised as follows: MAPE ≤ 10% – high, 10% ≤ MAPE ≤ 20% – good, 20% ≤ MAPE ≤ 50% – reasonable, and MAPE ≥ 50% – inaccurate. In this study, the MAPE values were calculated as 0.46% for the training phase and 0.55% for the testing phase. As seen from the results, the ANN model has an excellent performance in the prediction of noise emission.

RMSE measures the deviation between actual and predicted values. The lower value of RMSE suggests better model performance (Chen & Chau 2016). In this study, the RMSE values were calculated as 0.521 dB(A) and 0.600 dB(A) for the training and testing phases, respectively. It can be thus said that the prediction of noise emission is successful in terms of the RMSE criterion.

$R^2$ is an indicator of the strength of the relationship between measured and predicted values. If the $R^2$ value of a model is above 0.90, the model has a high performance (Özşahin 2012). In this study, the regression analysis was carried out to calculate the $R^2$ values of the proposed model. The $R^2$ values were calculated as 0.98 and 0.98 for the training and testing phases, respectively. The values of the $R^2$ criterion show that the established network has the ability to explain at least 98% of the observed variation in noise emission.

The comparisons between the measured and predicted values are presented in Figure 3. The predicted values showed a close match with the measured values. Therefore, it is concluded that the ANN model can be used as an appropriate tool to predict noise emission.

The investigation of the influence of each factor on noise emission requires a large number of experimental studies. However, extra experiments are time-consuming and give rise to an increase in costs. The combinations obtained by ANNs may be used to improve experimental processes. In this respect, the use of the ANN approach is important because it is capable of predicting the

| Phase  | Performance criterion |
|--------|-----------------------|
|        | MAPE | RMSE  | $R^2$                  |
| Training| 0.461 | 0.521 | 0.9811 ($y = 0.9811x + 1.6467$) |
| Testing| 0.553 | 0.600 | 0.9824 ($y = 0.9792x + 1.7365$) |

FIGURE 3: The comparison of the measured and predicted values: (a) training; and (b) testing.
untested experimental results (Akyüz et al. 2017). In this study, wood species and number of blades were fixed, and cutting width and cutting depth were changed. The intermediate values not obtained from the experimental study were determined by the ANN model for different cutting widths and cutting depths. The surface plots showing the changes in noise emission are given in Figure 4. As seen in this figure, noise emission decreases with decreased cutting width and cutting depth. The optimisation can be performed via an analysis of responses of the model.

Each wood type possesses a different structure. This differentiates the changes in noise emissions. As can be seen in Figure 4, the structural heterogeneities of the poplar and beech woods give rise to nonuniform changes in noise emissions. The MDF material has a more homogeneous structure than the others. Hence, the changes in the noise levels emitted during the cutting of the MDF boards show homogeneous-like behaviour. The modeling results provided a better understanding of the effect of wood structure on machining noise. The improper setting of machining parameters leads to high noise levels. Revealing the mutual relations of different factors is very important for obtaining the best results. Because the developed model operates with an average error of 0.55%, the results are acceptable and guiding. By taking into account interval values, the ANN model can allow earlier detection of noise levels and help to control the noise.

It has been reported that approximately 16% of adult-onset hearing loss is caused by workplace noise (Thepaksorn et al. 2019) and the wood processing industry is one of the noisiest industries. In order to reduce noise emissions, processing conditions and workplace-specific factors must be properly set via scientific approaches. It is clear that each change in noise emission will affect workers. Loud noise can cause workplace accidents and injuries. Hence, preventive measures must be applied to reduce the severity of high noise. Some important control strategies are as follows: changing the loudest technological processes and machines, performing routine maintenance on machinery and equipment, preserving the sharpness of blades, ensuring the balance of rotating parts, installing isolation dampers, utilising helicoidal gears, clamping of parts or panels, using flexible connections, ensuring pressure tightness and homogeneity, and using acoustic silencers and sound insulating control cabins. Furthermore, effective hearing loss prevention programs that comprise exposure assessments, noise controls, regular audiometric monitoring, usage of hearing protectors for exposure >85 dB(A), worker training, and good record keeping are required to reduce adverse results.

The modeling results show that there is a good agreement between the actual and predicted values. Based on the results of this study, it can be said that the effects of various factors on noise emission can be predicted by ANNs without the need for experimental studies that require much time and high costs. In further research, different variables can be used to predict noise emission.

**Conclusions**

The use of the ANN approach for modeling the effects of wood species, cutting width, number of blades, and cutting depth on noise emission in the machining process has been studied. The main results obtained
from this study are summarised below.

1. The values obtained with the ANN model are very close to the measured values.
2. The ANN model provides very satisfactory results with acceptable deviations. The MAPE, RMSE, and $R^2$ values are 0.55%, 0.60 dB(A), and 0.98, respectively, in the testing phase. These values demonstrate that the developed model can provide accurate, fast, and acceptable results.
3. In the predictive examples, it is seen that noise emission increases with increased cutting width and cutting depth. The usage of the ANN approach would be useful for the wood processing industry in obtaining the emission values of the noise which creates a potential threat for worker health.
4. ANNs are quite effective in predicting the noise emission. This capability to prediction and faster decision-making help the wood processing industry to get precautions and achieve better results. Hence, the ANN model can reduce the experimental time and costs.

**Competing interests**
The authors declare that they have no competing interests.

**Authors’ contributions**
The first author planned the study and carried out the ANN analysis. The second author wrote the manuscript.

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**References**
Akyüz, İ., Özşahin, Ş., Tiryaki, S., & Aydın, A. (2017). An application of artificial neural networks for modelling formaldehyde emission based on process parameters in particleboard manufacturing process. *Clean Technologies and Environmental Policy*, 19(5), 1449–1458. https://doi.org/10.1007/s10098-017-1342-0

Avramidis, S., & 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. https://doi.org/10.1007/s00107-006-0113-0

Beltramo, T., Ranzan, C., Hinrichs, J., & Hitzmann, B. (2016) Artificial neural network prediction of the biogas flow rate optimised with an ant colony algorithm. *Biosystems Engineering*, 143, 68–78. https://doi.org/10.1016/j.biosystemseng.2016.01.006

Canakci, A., Varol, T., & Özşahin, S. (2015). Artificial neural network to predict the effect of heat treatment, reinforcement size, and volume fraction on AlCuMg alloy matrix composite properties fabricated by stir casting method. *International Journal of Advanced Manufacturing Technology*, 78(1-4), 305–317. https://doi.org/10.1007/s00170-014-6646-1

Castellani, M., & Rowlands, H. (2008). Evolutionary feature selection applied to artificial neural networks for wood-veneer classification. *International Journal of Production Research*, 46(11), 3085–3105. https://doi.org/10.1080/0020754060139955

Chen, X.Y., & Chau, K.W. (2016). A hybrid double feedforward neural network for suspended sediment load estimation. *Water Resources Management*, 30(7), 2179–2194. https://doi.org/10.1007/s11269-016-1281-2

Çoğa, H., Lato, E., & Quku, D. (2019). Analysis of noise level at MDF and particleboard processing with different feeding speed. *Pro Ligno*, 15(2), 10–17.

Drouillet, C., Karandikar, J., Cath, N., Journeaux, A.C., El Mansori, M., & Kurfess, T. (2016). Tool life predictions in milling using spindle power with the neural network technique. *Journal of Manufacturing Processes*, 22, 161–168. https://doi.org/10.1016/j.jmapro.2016.03.010

Durcan, F.M., & Burdurlu, E. (2018). Effects of some machining parameters on noise level in planing of some wood materials. *Bioresources*, 13(2), 2702–2714. https://doi.org/10.1016/j.jmapro.2016.03.010

Engin, I.C., Ozkan, E., & Çetin, S. (2019). Determination of risky areas at the marble workshops in terms of noise. *Acoustics Australia*, 47(1), 79–90. https://doi.org/10.1007/s40857-018-0146-7

Ertunc, H.M., Ocak, H., & Aliustaoglu, C. (2013). ANN and ANFIS-based multi-staged decision algorithm for the detection and diagnosis of bearing faults. *Neural Computing and Applications*, 22, 435–446. https://doi.org/10.1007/s00521-012-0912-7

Fathollahzadeh, A., Enayati, A.A., & Erdil, Y.Z. (2013). Effect of laboratory-accelerated aging treatment on the ultimate strength of a 4-sided MDF kitchen cabinet. *Turkish Journal of Agriculture and Forestry*, 37(5), 649–656. https://doi.org/10.3906/tar-1208-43

Ghorbani, M.A., Zadeh, H.A., Isazadeh, M., & Terzi, O. (2016). A comparative study of artificial neural network (MLP, RBF) and support vector machine models for river flow prediction. *Environmental Earth Sciences*, 75(6), 476. https://doi.org/10.1007/s12665-015-5096-x

Haghdadi, N., Zarei-Hanzaki, A., Khalesian, A.R., & Abedi, H.R. (2013). Artificial neural network modeling to...
predict the hot deformation behavior of an A356 aluminum alloy. *Materials and Design*, 49, 386-391. https://doi.org/10.1016/j.matdes.2012.12.082

Hong, O.S., Kerr, M.J., Poling, G.L., & Dhar, S. (2013). Understanding and preventing noise-induced hearing loss. *Disease-a-Month*, 59(4), 110–118. https://doi.org/10.1016/j.disamonth.2013.01.002

Ismaila, S.O., & Odusote, A. (2014). Noise exposure as a factor in the increase of blood pressure of workers in a sack manufacturing industry. *Beni-Suef University Journal of Basic and Applied Sciences*, 3(2), 116–121. https://doi.org/10.1016/j.bibjas.2014.05.004

Kara, F., Aslantaş, K., & Çiçek, A. (2016). Prediction of cutting temperature in orthogonal machining of AISI 316L using artificial neural network. *Applied Soft Computing*, 38, 64–74. https://doi.org/10.1016/j.asoc.2015.09.034

Khalid, M., Lee, E.L.Y., Yusof, R., & Nadaraj, M. (2008). Design of an intelligent wood species recognition system. *International Journal of Simulation: Systems, Science and Technology*, 9(3), 9–19.

Krilek, J., Kováč, J., Barcik, Š., Svořeš, J., Štefánek, M., & Kuvík, T. (2016). The influence of chosen factors of a circular saw blade on the noise level in the process of cross cutting wood. *Wood Research*, 61(3), 475–486.

Kvietková, M., Gaff, M., Gašparík, M., Kminíak, R., & Kriš A. (2015). Effect of number of saw blade teeth on noise level and wear of blade edges during cutting of wood. *BioResources*, 10(1), 1657–1666. https://doi.org/10.15376/biores.10.1.1657-1666

Lee, J.H., Kang, W., Yaang, S.R., Choy, N., & Lee, C.R. (2009). Cohort study for the effect of chronic noise exposure on blood pressure among male workers in Busan, Korea. *American Journal of Industrial Medicine*, 52(6), 509–517. https://doi.org/10.1002/ajim.20692

Lewis, C.D. (1982). *International and business forecasting methods*. Butterworths: London.

McKenzie, H.M., Shelbourne, C.J.A., Kimberley, M.O., McKinley, R.B., & Britton, R.A.J. (2003). Processing young plantation-grown *Eucalyptus nitens* for solid-wood products. 2: predicting product quality from tree, increment core, disc, and 1-m billet properties. *New Zealand Journal of Forestry Science*, 33(1), 79–113.

Mia, M., & Dhar, N.R. (2016). Prediction of surface roughness in hard turning under high pressure coolant using Artificial Neural Network. *Measurement*, 92, 464–474. https://doi.org/10.1016/j.measurement.2016.06.048

Mohanraj, M., Jayaraj, S., & Muraldeeharan, C. (2012). Applications of artificial neural networks for refrigeration, air-conditioning and heat pump systems - a review. *Renewable and Sustainable Energy Reviews*, 16(2), 1340–1358. https://doi.org/10.1016/j.rser.2011.10.015

Muralitharan, K., Sakhthivel, R., & Vishnuvarthan, R. (2018). Neural network based optimization approach for energy demand prediction in smart grid. *Neurocomputing*, 273, 199–208. https://doi.org/10.1016/j.neucom.2017.08.017

Owoyemi, M.J., Falemara, B.C., & Owoyemi, A.J. (2017). Noise pollution and control in mechanical processing wood industries. *Biomedical Statistics and Informatics*, 2(2), 54–60. https://doi.org/10.20944/preprints201608.0236.v1

Özşahin, S. (2013). Optimization of process parameters in oriented strand board manufacturing with artificial neural network analysis. *European Journal of Wood and Wood Products*, 71(6), 769–777. https://doi.org/10.1007/s00107-013-0737-9

Özşahin, S., & Murat, M. (2018). Prediction of equilibrium moisture content and specific gravity of heat treated wood by artificial neural networks. *European Journal of Wood and Wood Products*, 76(2), 563–572. https://doi.org/10.1007/s00107-017-1219-2

Özşahin, S. (2012). The use of an artificial neural network for modeling the moisture absorption and thickness swelling of oriented strand board. *BioResources*, 7(1), 1053–1067.

Pinheiro, C., de Sampaio Alves, M.C., & Simões Amaral, S. (2015). Moisture content and its influence on the roughness and noise emission during wood machining. *Advanced Materials Research*, 1088, 680–685. https://doi.org/10.4028/www.scientific.net/AMR.1088.680

Ratnasingam, J., & Scholz, F. (2008). Noise level evaluation in the Malaysian wood working industry (Report No:10/08). International Furniture Research Group: USA.

Quintana, G., Garcia-Romeu, M.L., & Ciurana, J. (2011) Surface roughness monitoring application based on artificial neural networks for ball-end milling operations. *Journal of Intelligent Manufacturing*, 22(4), 607-617. https://doi.org/10.1007/s10845-009-9323-5

Samarasinghe, S., Kulasiri, D., & Jamieson, T. (2007). Neural networks for predicting fracture toughness of individual wood samples. *Silva Fennica*, 41(1), 105–122. https://doi.org/10.14214/sf.309

Sedlecký, M., & Gašparík, M. (2017). Power consumption during edge milling of medium-density fiberboard and edge-glued panel. *BioResources*, 12(4), 7413–7426.

Shebani, A., & Iwnicki, S. (2018). Prediction of wheel and rail wear under different contact conditions using artificial neural networks. *Wear*, 406-407, 173–
Svoreň, J., Javorek, L., & Murin, L. (2010). Effect of the shape of compensating slots in the body of a circular saw blade on noise level in the cutting process. *Pro Ligno, 6*(4), 5–12.

Thepaksorn, P., Koizumi, A., Harada, K., Siriwong, W., & Neitzel, R.L. (2019). Occupational noise exposure and hearing defects among sawmill workers in the south of Thailand. *International Journal of Occupational Safety and Ergonomics, 25*(3), 458–466. https://doi.org/10.1080/10803548.2017.1394710

Tiryaki, S., Malkoçoğlu, A., & Özşahin, Ş. (2016). Artificial neural network modeling to predict optimum power consumption in wood machining. *Drewno, 59*(196), 109-125. https://doi.org/10.12841/wood.1644-3985.140.08

Uysal, B., & Yorur, H. (2013). The effect of steam treatment on bonding strength of impregnated wood materials. *Journal of Adhesion Science and Technology, 27*(8), 896–904. https://doi.org/10.1080/01694243.2012.727161

Venkata Ramana, R., Krishna, B., Kumar, S.R., & Pandey, N.G. (2013). Monthly rainfall prediction using wavelet neural network analysis. *Water Resources Management, 27*(10), 3697–3711. https://doi.org/10.1007/s11269-013-0374-4

Yadav, A.K., & Chandel, S.S. (2014). Solar radiation prediction using Artificial Neural Network techniques: a review. *Renewable and Sustainable Energy Reviews, 33*, 772–781. https://doi.org/10.1016/j.rser.2013.08.055

Yıldırım, I., Özsahin, S., & Akyüz, K.C. (2011). Prediction of the financial return of the paper sector with artificial neural networks. *BioResources, 6*(4), 4076–4091.