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

Şükrü Özşahin[1] and Hilal Singer[2,*]

[1] *Department of Industrial Engineering, Karadeniz Technical University, Trabzon, Turkey*
[2] *Department of Industrial Engineering, Bolu Abant Izzet Baysal University, Bolu, Turkey*

*Corresponding author: hilal.singer@hotmail.com

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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 (Sedleckỳ & 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. Svoreň 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 optimisation 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 (Özşahin 2012; Ozsahin 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, *t* 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) organised in layers (Ghorbani et al. 2016). Each node is connected to other nodes by communication links (connections). Each connection has a weight (Özşahin 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).

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

$$y_j = f(\text{net}_j) \tag{2}$$

where: x_i is the input signal, w_{ij} is the weight between the ith node and the jth node, θ_j is the bias, net_j is the net input of the jth node, $f(.)$ is one of the activation functions, and y_j is the output of the jth 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)]:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(t_i - td_i)^2 \quad (3)$$

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

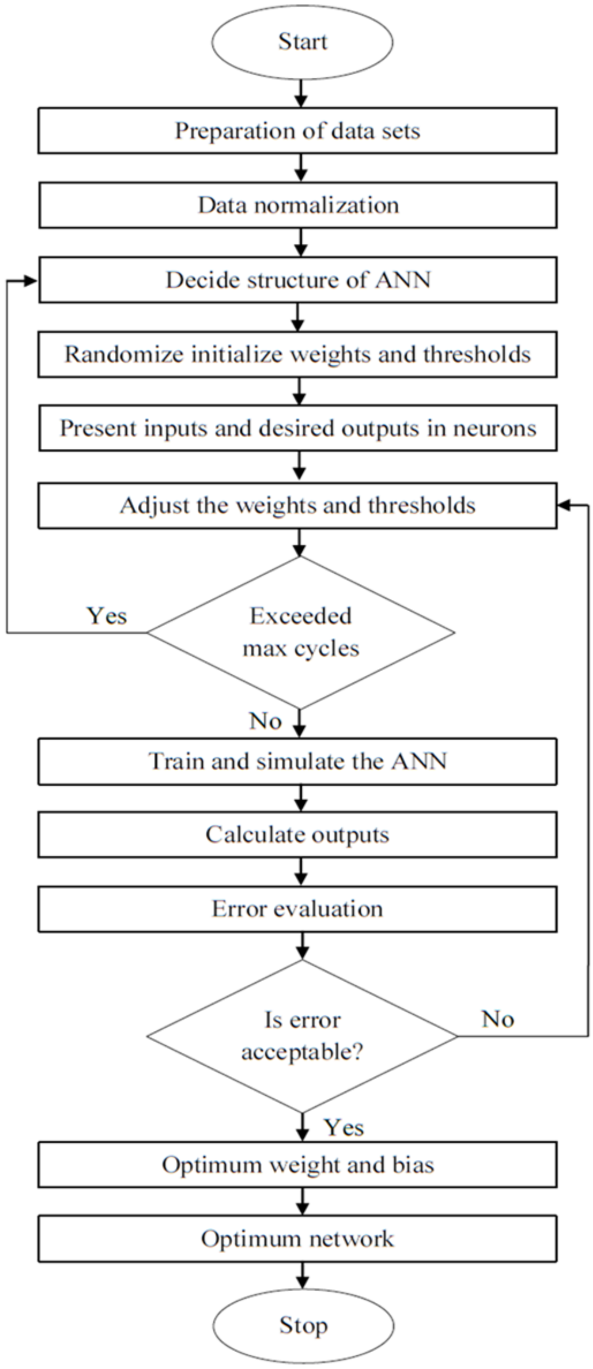


FIGURE 1: The steps of this study based on the ANN approach.

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.

$$X_{norm} = 2 \times \frac{X - X_{min}}{X_{max} - X_{min}} - 1 \quad (4)$$

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

Operation			Noise emission levels (dBA)											
Cutting width (mm)	Blade no	Cutting depth (mm)	Poplar				Beech				MDF			
			Sample ID	Measured	Predicted	Error (%)	Sample ID	Measured	Predicted	Error (%)	Sample ID	Measured	Predicted	Error (%)
6	1	1	**B1**	**83.06**	**83.10**	**-0.05**	A21	80.07	80.35	-0.35	A41	78.62	78.48	0.18
6	1	2	A1	85.26	84.97	0.34	**B11**	**84.23**	**84.42**	**-0.23**	**B21**	**83.75**	**83.54**	**0.25**
6	1	3	A2	86.87	86.70	0.20	A22	86.70	87.16	-0.53	A42	85.85	86.48	-0.74
6	4	1	A3	82.75	82.00	0.91	**B12**	**79.74**	**79.17**	**0.71**	**B22**	**78.14**	**76.93**	**1.54**
6	4	2	**B2**	**84.01**	**83.93**	**0.10**	A23	82.90	82.79	0.13	A43	82.24	82.29	-0.06
6	4	3	A4	84.94	85.08	-0.16	A24	84.59	84.71	-0.14	A44	84.39	84.20	0.22
12	1	1	A5	84.56	84.63	-0.08	**B13**	**81.43**	**82.01**	**-0.71**	A45	83.49	82.89	0.71
12	1	2	A6	87.81	86.43	1.57	A25	87.90	88.10	-0.22	A46	84.89	85.29	-0.47
12	1	3	**B3**	**90.86**	**89.78**	**1.19**	A26	91.12	90.46	0.73	**B23**	**88.05**	**88.31**	**-0.30**
12	4	1	**B4**	**82.98**	**83.58**	**-0.72**	A27	80.76	80.87	-0.14	A47	81.32	81.31	0.02
12	4	2	A7	85.83	85.43	0.46	A28	86.61	86.92	-0.36	**B24**	**83.15**	**84.09**	**-1.13**
12	4	3	A8	89.46	88.96	0.55	**B14**	**87.60**	**87.60**	**0.00**	A48	86.51	86.23	0.33
18	1	1	A9	86.20	86.09	0.13	A29	82.86	83.65	-0.96	**B25**	**84.20**	**84.91**	**-0.84**
18	1	2	**B5**	**88.29**	**87.94**	**0.40**	A30	89.16	89.67	-0.57	A49	86.94	86.97	-0.04
18	1	3	A10	91.19	91.21	-0.02	**B15**	**92.71**	**92.37**	**0.37**	A50	89.99	90.06	-0.08
18	4	1	A11	84.66	85.09	-0.50	A31	81.92	82.55	-0.76	A51	83.50	83.70	-0.23
18	4	2	A12	86.93	86.95	-0.03	**B16**	**89.05**	**88.60**	**0.51**	**B26**	**85.75**	**85.82**	**-0.08**
18	4	3	**B6**	**89.94**	**90.44**	**-0.55**	A32	89.52	89.74	-0.25	A52	88.48	88.17	0.35
25	1	1	A13	87.13	87.70	-0.66	**B17**	**86.63**	**86.04**	**0.68**	A53	86.23	86.88	-0.75
25	1	2	**B7**	**91.87**	**90.73**	**1.24**	A33	91.22	91.40	-0.20	A54	88.22	88.85	-0.71
25	1	3	A14	93.91	93.49	0.45	A34	94.56	94.31	0.27	**B27**	**92.86**	**92.01**	**0.92**
25	4	1	**B8**	**85.99**	**86.76**	**-0.89**	A35	85.46	84.82	0.75	**B28**	**85.54**	**85.72**	**-0.21**
25	4	2	A15	89.16	89.46	-0.33	**B18**	**90.52**	**90.38**	**0.15**	A55	87.46	87.75	-0.33
25	4	3	A16	91.35	92.14	-0.86	A36	91.22	91.88	-0.72	A56	90.27	90.33	-0.06
30	1	1	A17	89.50	88.80	0.79	A37	88.82	89.39	-0.65	A57	89.86	88.23	1.81
30	1	2	A18	94.59	94.46	0.14	**B19**	**92.19**	**92.58**	**-0.42**	**B29**	**91.31**	**90.13**	**1.29**
30	1	3	**B9**	**96.33**	**96.52**	**-0.20**	A38	95.11	95.60	-0.52	A58	93.71	93.33	0.41
30	4	1	A19	86.75	87.89	-1.32	A39	87.94	87.78	0.18	A59	87.57	87.11	0.52
30	4	2	**B10**	**92.60**	**93.13**	**-0.57**	A40	91.56	91.60	-0.05	A60	89.97	89.07	1.00
30	4	3	A20	94.54	93.97	0.61	**B20**	**93.54**	**93.32**	**0.23**	**B30**	**91.88**	**91.79**	**0.10**

Bold values: testing data, the other values: training data
A and B denote sample IDs in training and testing, respectively

where, X_{norm} is the normalised value, X is the real value, and X_{min} and X_{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:

$$\text{MAPE} = \frac{1}{N}\left(\sum_{i=1}^{N}\left[\left|\frac{t_i - td_i}{t_i}\right|\right]\right) \times 100 \quad (5)$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i - td_i)^2} \quad (6)$$

$$\text{R}^2 = 1 - \frac{\sum_{i=1}^{N}(t_i - td_i)^2}{\sum_{i=1}^{N}(t_i - \bar{t})^2} \quad (7)$$

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

TABLE 2: The optimum values of weights and biases.

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	12.65604	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	-	-	-	-	-	-	-

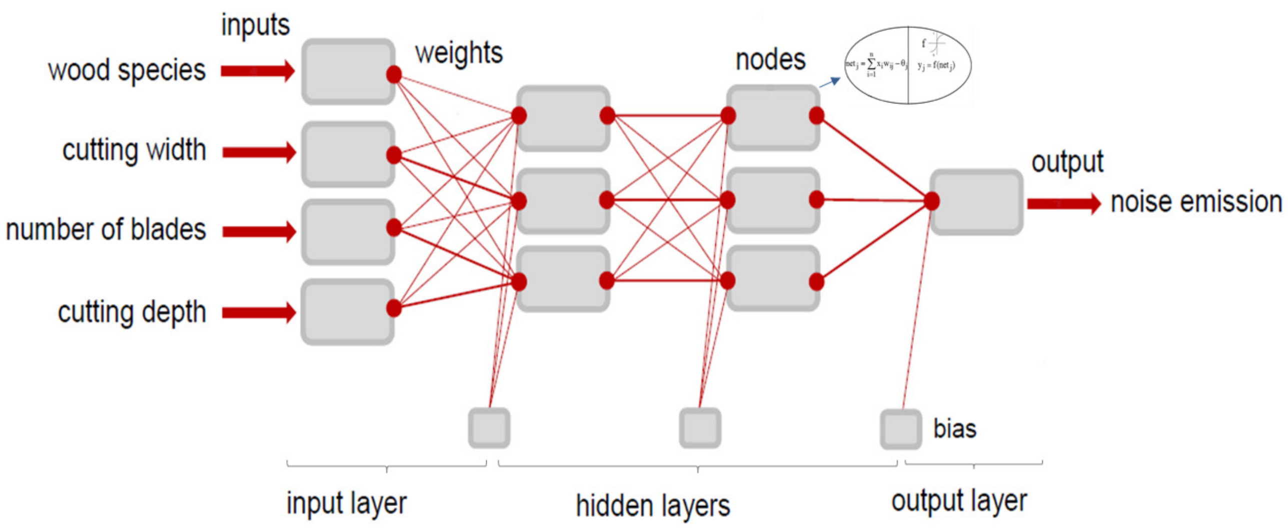


FIGURE 2: The proposed network architecture.

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.

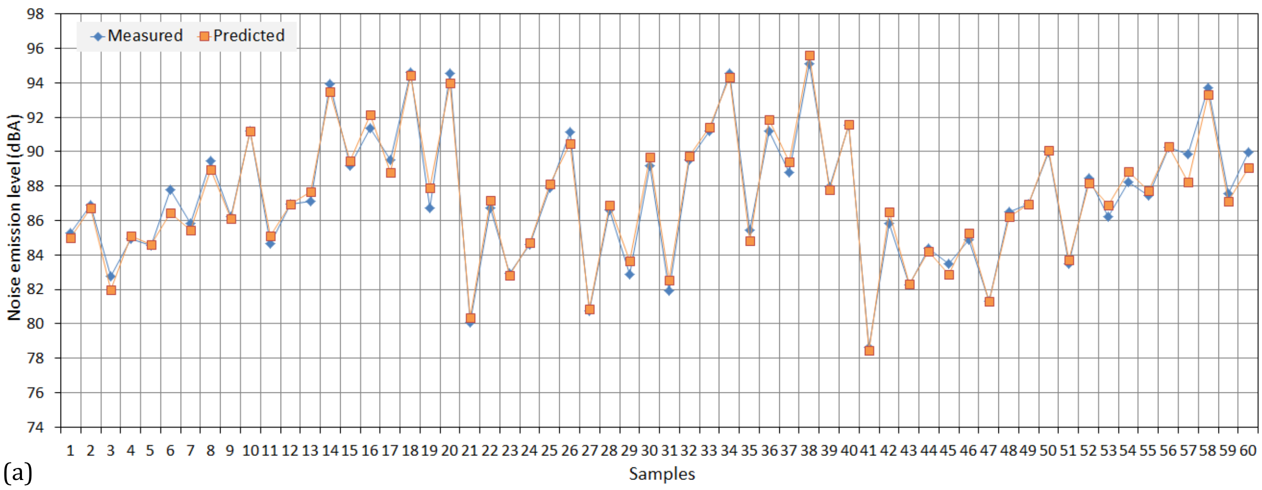
R^2 is an indicator of the strength of the relationship between measured and predicted values. If the R^2 value of a model is above 0.90, the model has a high performance (Özşahin 2012). In this study, the regression analysis was carried out to calculate the R^2 values of the proposed model. The R^2 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.

TABLE 3: Performance evaluation criteria for the noise emission prediction.

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)

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



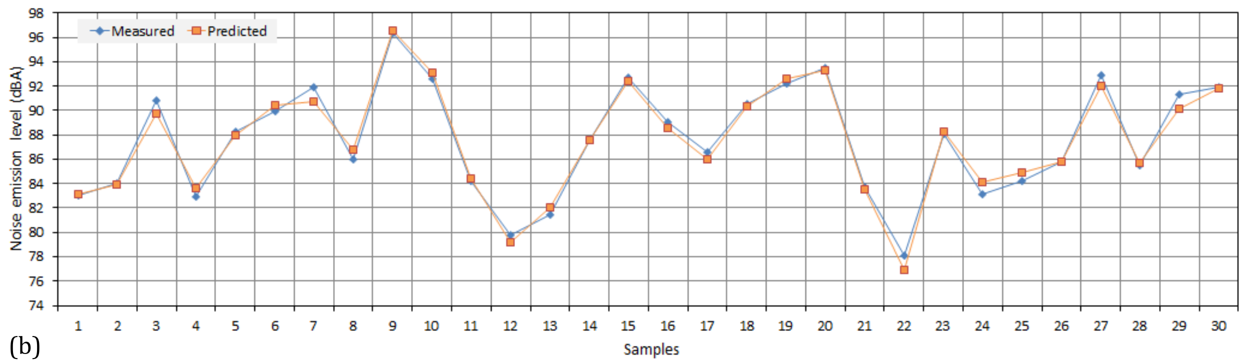


FIGURE 3: The comparison of the measured and predicted values: (a) training; and (b) testing.

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.

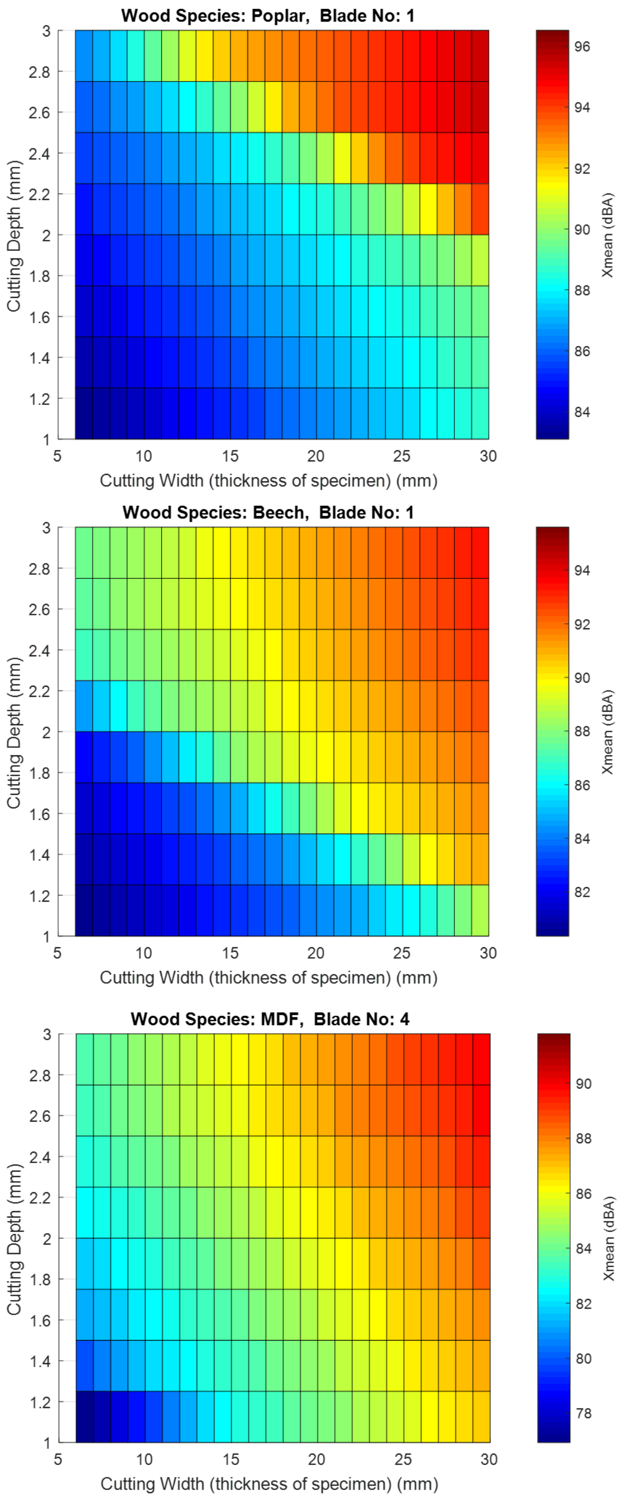


FIGURE 4: Predictive changes in noise emission for different cutting widths and cutting depths.

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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