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Original article

Artificial Neural Network–based Prediction Model to Minimize Dust Emission in the Machining Process

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ABSTRACT

Background: Dust generated during various wood-related activities, such as cutting, sanding, or processing wood materials, can pose significant health and environmental risks due to its potential to cause respiratory problems and contribute to air pollution. Understanding the factors influencing dust emission is important for devising effective mitigation strategies, ensuring a safer working environment, and minimizing environmental impact. This study focuses on developing an artificial neural network (ANN) model to predict dust emission values in the machining of black poplar (*Populus nigra* L.), oriental beech (*Fagus orientalis* L.), and medium-density fiberboards.
Methods: The multilayer feed-forward ANN model is developed using a customized application built with MATLAB code. The inputs to the ANN model include material type, cutting width, number of blades, and cutting depth, whereas the output is the dust emission. Model performance is assessed through graphical and statistical comparisons.
Results: The results reveal that the developed ANN model can provide adequate predictions for dust emission with an acceptable level of accuracy. Through the implementation of the ANN model, the study predicts intermediate dust emission values for different cutting widths and cutting depths, which are not considered in the experimental work. It is observed that dust emission tends to decrease with reductions in cutting width and cutting depth.
Conclusion: This study introduces an alternative approach to optimize machining-process conditions for minimizing dust emissions. The findings of this research will assist industries in obtaining dust emission values without the need for additional experimental activities, thereby reducing experimental time and costs.
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1. Introduction

In the forest industry, the utilization of cutting and processing technologies for wood and wood-based materials is a critical component of production. However, these activities inherently give rise to various detrimental factors that significantly impact the work environment and the well-being of workers. Among these, the generation of dust stands out as a particularly concerning issue. When workers cut, grind, and manipulate wood, substantial quantities of dust are released into the air [1]. Continuous inhalation of wood dust by workers can lead to serious health issues, including asthma, emphysema, and chronic bronchitis. This can significantly diminish both their quality of life and work productivity [2]. Furthermore, there is a correlation between exposure to wood dust and an elevated risk of upper respiratory tract cancers [3]. The accumulation of wood dust on surfaces and in the air not only poses a threat to respiratory health but also elevates the potential for fire hazards within industrial settings. This risk

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substantially increases the likelihood of workplace explosions [4]. Proactive strategies, such as regular equipment maintenance, the incorporation of dust collection systems, and the adoption of advanced technologies, are crucial. These measures not only create a safer and healthier work environment but also enhance operational efficiency and overall safety standards [5].

In an effort to mitigate the adverse impacts of harmful factors on human health, various institutions and organizations have established exposure limits. In 1999, the European Union (EU) took a significant step by implementing regulations to address the dangers associated with breathable wood dust. The specified limit was set at 5 mg/m^3, and this standard was based on an 8-hour workday. Several European countries have chosen to adopt exposure limits that are more stringent than the recommendations outlined in EU legislation. For instance, Germany and Slovenia have established a limit of 3 mg/m^3, Sweden maintains a threshold of 2 mg/m^3, and France has implemented a stringent standard at 1 mg/m^3 [6].

Machining processes encompass a range of activities such as cutting, sanding, and shaping, all of which contribute to the generation of wood dust. To ensure optimal performance and minimize environmental impact, it is important to analyze various variables during machining procedures [7]. Several researchers have examined the effect of grit size, wood species, feed speed, depth of cut, temperature modification, step over, cutting speed, feed per tooth rate, and drying mode on dust generation and distribution [8–11]. The majority of previous studies have concentrated on comparing the rate of dust emission among various wood species and products derived from wood [12]. Some research studies have focused on confirming the issues linked to exposure to wood dust [13–15]. The complete elimination of wood dust is unfeasible. Nonetheless, efforts can be directed toward minimizing its quantity by identifying and optimizing factors influencing dust emission [16]. Experimentation aimed at understanding the impact of these factors is a common approach, but it often entails significant costs and time requirements. An alternative and more efficient solution lies in using artificial neural networks (ANNs). These networks provide a cost-effective, time-efficient, and data-driven approach to understanding and optimizing processes [17].

ANNs are computational models inspired by the functioning of biological neural networks in the human brain. The ability of ANNs to capture nonlinear relationships makes them particularly useful in situations where interactions between process variables are intricate [18]. ANNs learn from data, and by exposing them to a diverse set of data, they can identify patterns and trends that might be challenging for traditional methods. ANNs can be continuously updated and improved as more data become available. Instead of relying solely on physical experiments, researchers can leverage the computational power of ANNs to explore various scenarios and predict outcomes. This accelerates the decision-making process and minimizes the need for resource-intensive experiments [19,20].

In recent years, there has been a notable surge in research focusing on the application of ANNs to address various challenges within the field of wood science. Noteworthy studies have delved into diverse aspects such as wood density prediction [21], modeling formaldehyde emission [22], estimating wood resistance [23], minimizing power consumption [24], optimizing surface roughness and adhesion strength of wood [20], classifying wood species [25], improving wood surface quality [26], predicting the modulus of elasticity of bamboo-wood composites [27], quantifying the wood volume [28], wood classification [29], predicting the modulus of rupture of laminated wood products [30], analyzing the color change of thermally treated wood surfaces [31], and optimizing the drilling process of medium-density fiberboards (MDFs) [32]. On the other hand, ANNs have been successfully utilized to predict dust in various contexts: material sawing [12], atmospheric investigations [33], open-pit mine blasting [34], wind erosion [35], limestone storage piles [36], and almond harvesting [37]. The previous studies have highlighted that ANNs are reliable tools for predicting the amount of inhalable dust. The current body of literature lacks comprehensive insights into the mathematical modeling of dust generation during the machining of wood and wood-based materials.

The objective of the current study is to create a neural network model for predicting the influence of material type, cutting width, number of blades, and cutting depth on dust emission levels. This study provides valuable insights into the complex relationships between the specified variables and dust emission. The research can inform the creation of optimized procedures to minimize environmental impact and improve efficiency. Furthermore, the findings of this study offer practical guidance for industry practitioners. Understanding the factors contributing to dust emission enables the implementation of preventive measures, resulting in a safer working environment and reduced potential health risks associated with prolonged exposure to wood dust.

2. Materials and methods

2.1. Data collection

In this study, black poplar (*Populus nigra* L.), oriental beech (*Fagus orientalis* L.), and MDF are used as experimental materials. A conditioning chamber is utilized to adjust the samples to the air-dry moisture content (12%). Large-sized MDFs are transformed into narrow pieces measuring 105 × 30 cm for each cutting-width group. Poplar and beech woods are initially transformed into 1-meter short lumbers through length cutting. From these lumbers, draft sample pieces are produced with a net cutting width and width tolerance of +8 mm. The sample pieces are subjected to waiting in a closed and heated environment. At the end of this period, 15 sample pieces, each measuring 1 meter in length and 9 cm in width, are produced from each cutting-width group. The samples are planned using two different blade numbers (1 and 4), five different cutting widths (6, 12, 18, 25, and 30 mm), and three different cutting depths (1, 2, and 3 mm). The TSI SIDEPAK AM 510 device is utilized for measuring dust emission. Operation for 20 minutes on the machining machine is carried out for each situation.

2.2. Artificial neural network

ANNs draw inspiration from the structural and functional aspects of biological nervous systems. The ANN approach stands out from traditional statistical methods due to its capacity to learn intricate and nonlinear relationships between variables. Among the diverse types of networks, the multilayer perceptron (MLP) is widely utilized. The MLP's architecture comprises an input layer for receiving data, one output layer for presenting outputs, and *t* intermediate (hidden) layers for processing information. In Fig. 1, a representative illustration of the MLP structure is presented [38].

The layers of the MLP network are composed of processing units, commonly referred to as neurons. Each neuron within a layer establishes connections with neurons in adjacent layers through specific weights (w_{ij}). An artificial neuron (j) combines the bias (θ_j) and weighted inputs ($x_i w_{ij}$), applies an activation function to the sum (net_j), and then conveys the outcome (y_j) to the subsequent layer. This process is visually presented in Fig. 2 [24].

ANNs undergo training and testing processes to enhance their ability to make accurate predictions. In the training phase, the network learns from a dataset by adjusting its weights and biases. This process continues until a stopping criterion is met. A separate

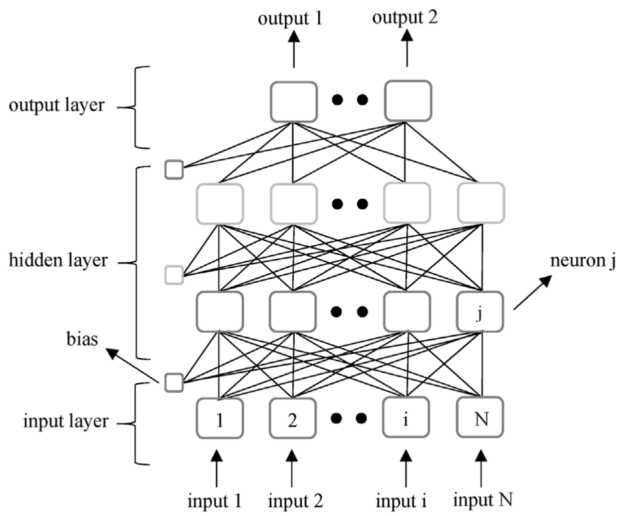

Fig. 1. Multi-layered ANN architecture. Abbreviation: ANN, artificial neural network.

dataset, not used during training, is used to assess model performance. After successful testing, the ANN model can be ready for deployment in real-world scenarios [39].

2.3. Artificial neural network analysis

This study focuses on developing an ANN model to predict dust emission values during the machining of various wood and wood-based materials. The choice to use the ANN approach is driven by several factors. Machining processes involve complex interactions between multiple variables. These interactions are inherently nonlinear. Unlike traditional statistical models, ANNs are designed to effectively handle nonlinear patterns [39]. ANNs can be adjusted in terms of architecture and parameters to improve model performance. Considering the variety of materials and the diversity in machining settings, this flexibility is important for achieving optimal prediction accuracy. Machining processes can introduce variability and noise into the data. ANNs are effective at handling noisy data due to their ability to learn underlying patterns [40]. In this study, a substantial amount of data is collected across various materials and machining parameters. ANN models thrive in data-rich environments [20]. This allows for more accurate predictions based on our extensive data collection.

The input variables considered for the ANN model are the material type, cutting width, number of blades, and cutting depth. The output variable of the ANN model is the dust emission. The development and execution of the ANN model are carried out using MATLAB. The methodological steps of the ANN modeling process are visually elucidated in Fig. 3.

The experimental data are organized in a random and homogeneous manner to form distinct training and testing datasets. A total of 90 data points are utilized. The training phase involves the utilization of 60 data points, constituting 66.67% of the total dataset, to teach the network and enhance its learning capabilities. Subsequently, the model's performance is assessed using a separate set of 30 data points, equivalent to 33.33% of the overall dataset. The training and testing datasets are presented in Tables 1 and 2.

The modeling process utilizes a feed-forward backpropagation neural network. The activation functions are the hyperbolic tangent sigmoid function and the linear transfer function. Training is performed using the Levenberg–Marquardt algorithm, whereas the gradient descent with a momentum backpropagation algorithm serves as the learning rule. The monitoring of training progress is carried out using the mean square error (MSE).

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

Here, t_i represents the actual value, td_i denotes the model output, and N stands for the number of measurements.

The normalization process involves mapping all the variables to the $[-1, 1]$ interval. This data standardization is preferred because the model uses the hyperbolic tangent sigmoid function. A reverse normalizing process is applied to convert the model outputs back to their original values. The normalization is accomplished using Equation (2).

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

Here, X_{norm} represents the normalized value, X is the actual value, and X_{min} and X_{max} correspond to the minimum and maximum values of X, respectively.

To optimize the performance of ANN-based models, thorough experimentation is important. This process entails systematically testing different combinations of network parameters and configurations to narrow the divide between actual and model outputs. In this study, it is observed that optimal performance is attained with a configuration comprising 4-4 neurons in the hidden layers (Fig. 4). The chosen ANN model, which yields values closest to the experimental results, is used for predictions.

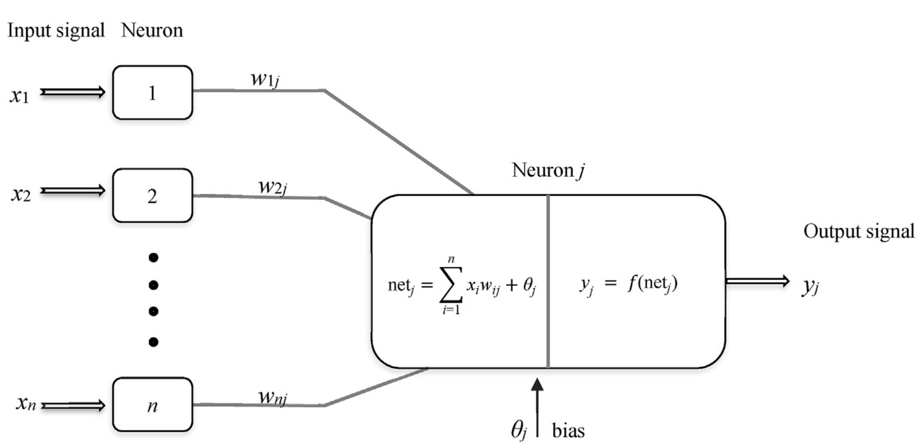

Fig. 2. General operation of a neuron.

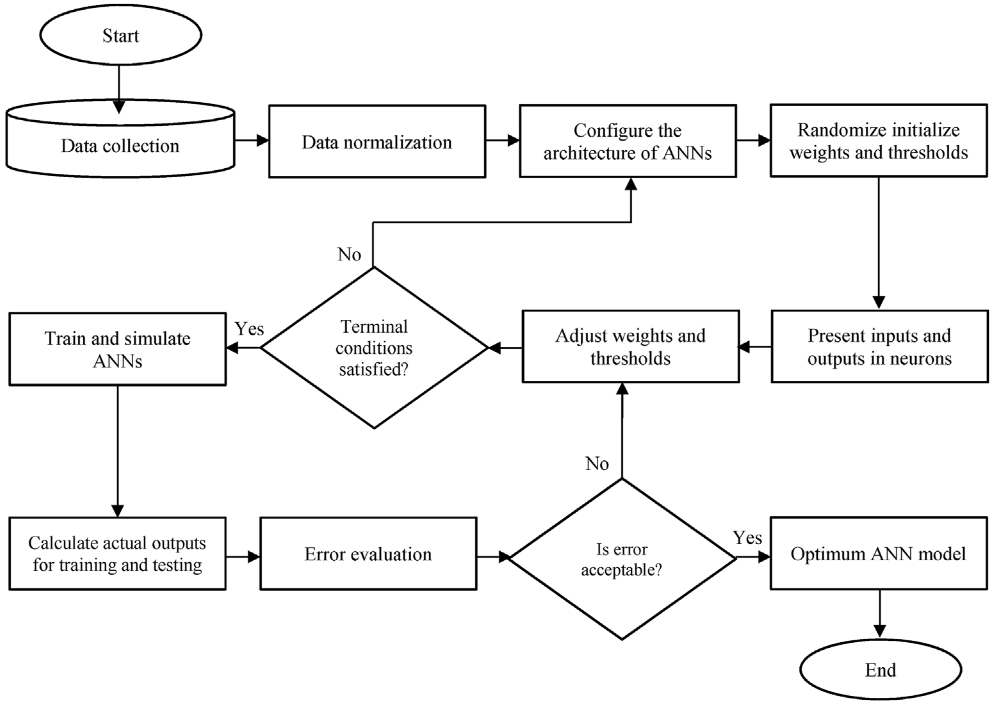

Fig. 3. Model-design steps.

To assess the performance of the established models, three widely used metrics are considered: the mean absolute percentage error (MAPE), represented by Equation (3); the root mean square error (RMSE), denoted by Equation (4); and the coefficient of determination (R^2), expressed through Equation (5).

$$MAPE = \frac{1}{N}\left(\sum_{i=1}^{N}\left[\left|\frac{t_i - td_i}{t_i}\right|\right]\right) \times 100 \tag{3}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i - td_i)^2} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(t_i - td_i)^2}{\sum_{i=1}^{N}(t_i - \bar{t})^2} \tag{5}$$

where $\bar{t}$ is the average of model outputs.

3. Results

A neural network model for dust emission is developed based on material type, cutting width, number of blades, and cutting depth. Tables 1 and 2 present the model results for the training and testing datasets, respectively. The MAPE, RMSE, and R^2 metrics are used to evaluate the accuracy and reliability of the tried models. Table 3 displays the performance statistics derived from assessing the selected model.

MAPE is a widely used metric for assessing the reliability of prediction models. It measures the average percentage difference between predicted and actual values. In this study, the MAPE values for the training and testing datasets are calculated to be 4.86% and 5.01%, respectively. A MAPE of ≤10% is considered indicative of a highly accurate prediction model [41], and the results presented in this study meet that criterion. The low MAPE values indicate that the predicted values closely align with the actual observations.

RMSE is a valuable metric for assessing the performance of prediction models by measuring the average magnitude of errors between observed and calculated values. A lower RMSE suggests better agreement between predicted and actual values. The calculated RMSE values for the training and testing datasets are 0.01 and 0.02, respectively. The slight discrepancies between the predicted dust emission values and the actual observations specify the model's success in modeling dust emission.

R^2 serves as a measure of the degree of association between observed and calculated values. Its values range from 0 to 1. A prediction model with an R^2 value exceeding 90% is considered to demonstrate high performance [22]. Regression analysis is used to compute R^2 values for the proposed model. As seen in Fig. 5, the R^2 values calculated for the training and testing datasets are 0.995 and 0.987, respectively. This result indicates that the developed network possesses the capability to elucidate a minimum of 98.7% of the actual data pertaining to dust emission.

The comparative plots illustrating the actual values versus the predicted values are presented in Fig. 6. The proximity of these values is clearly evident from the visualization. This close alignment enhances the applicability and reliability of the ANN model.

Neural network models play an important role in optimization studies by enabling the computation of intermediate values. Well-trained ANNs can not only efficiently process existing data but also extrapolate to provide untested experimental results [38]. In this research, the material type and the number of blades remain constant, whereas the cutting width and cutting depth are varied. The ANN model predicts intermediate dust emission values across numerous combinations of cutting widths and cutting depths, as depicted in Fig. 7. The study's findings reveal that dust emission tends to decrease with the reduction of cutting width and cutting depth.

Table 1
Training dataset and prediction model results

Material type	Cutting width (mm)	Blade no.	Cutting depth (mm)	Dust emission level (mg/m^3)		
				Actual	Predicted	%Error
Populus nigra L.	6	1	2	0.05	0.06	−12.50
Populus nigra L.	6	1	3	0.12	0.09	22.32
Populus nigra L.	6	4	1	0.06	0.07	−15.44
Populus nigra L.	6	4	3	0.16	0.16	−2.36
Populus nigra L.	12	1	1	0.11	0.11	−1.20
Populus nigra L.	12	1	2	0.11	0.11	−1.01
Populus nigra L.	12	4	2	0.13	0.15	−12.30
Populus nigra L.	12	4	3	0.16	0.17	−8.72
Populus nigra L.	18	1	1	0.16	0.17	−5.89
Populus nigra L.	18	1	3	0.19	0.20	−5.77
Populus nigra L.	18	4	1	0.18	0.18	2.46
Populus nigra L.	18	4	2	0.20	0.20	1.41
Populus nigra L.	25	1	1	0.20	0.20	1.08
Populus nigra L.	25	1	3	0.31	0.29	5.77
Populus nigra L.	25	4	2	0.27	0.27	−0.96
Populus nigra L.	25	4	3	0.33	0.33	−0.45
Populus nigra L.	30	1	1	0.27	0.27	1.23
Populus nigra L.	30	1	2	0.29	0.31	−7.49
Populus nigra L.	30	4	1	0.30	0.29	3.14
Populus nigra L.	30	4	3	0.40	0.40	−0.12
Fagus orientalis L.	6	1	1	0.05	0.06	−14.10
Fagus orientalis L.	6	1	3	0.06	0.09	−47.59
Fagus orientalis L.	6	4	2	0.15	0.14	8.90
Fagus orientalis L.	6	4	3	0.18	0.16	8.43
Fagus orientalis L.	12	1	2	0.14	0.12	11.44
Fagus orientalis L.	12	1	3	0.14	0.13	6.37
Fagus orientalis L.	12	4	1	0.13	0.12	7.63
Fagus orientalis L.	12	4	2	0.15	0.15	0.06
Fagus orientalis L.	18	1	1	0.18	0.18	1.25
Fagus orientalis L.	18	1	2	0.20	0.20	1.41
Fagus orientalis L.	18	4	1	0.19	0.19	1.40
Fagus orientalis L.	18	4	3	0.25	0.25	1.46
Fagus orientalis L.	25	1	2	0.27	0.28	−4.23
Fagus orientalis L.	25	1	3	0.33	0.32	3.08
Fagus orientalis L.	25	4	1	0.25	0.26	−2.75
Fagus orientalis L.	25	4	3	0.37	0.37	−0.37
Fagus orientalis L.	30	1	1	0.31	0.30	3.09
Fagus orientalis L.	30	1	3	0.36	0.36	−0.10
Fagus orientalis L.	30	4	1	0.32	0.32	−0.13
Fagus orientalis L.	30	4	2	0.35	0.35	−0.38
MDF	6	1	1	0.10	0.08	16.75
MDF	6	1	3	0.11	0.12	−5.06
MDF	6	4	2	0.17	0.16	3.10
MDF	6	4	3	0.20	0.20	−2.09
MDF	12	1	1	0.17	0.18	−4.57
MDF	12	1	2	0.18	0.19	−2.87
MDF	12	4	1	0.17	0.18	−5.48
MDF	12	4	3	0.26	0.25	3.64
MDF	18	1	2	0.32	0.32	−0.94
MDF	18	1	3	0.37	0.37	−0.72
MDF	18	4	1	0.32	0.31	3.17
MDF	18	4	3	0.43	0.43	−0.64
MDF	25	1	1	0.38	0.38	−0.79
MDF	25	1	2	0.45	0.45	−0.25
MDF	25	4	2	0.51	0.50	1.14
MDF	25	4	3	0.69	0.69	−0.14
MDF	30	1	1	0.46	0.45	1.43

(continued on next page)

Table 1 (*continued*)

Material type	Cutting width (mm)	Blade no.	Cutting depth (mm)	Dust emission level (mg/m^3)		
				Actual	Predicted	%Error
MDF	30	1	3	0.58	0.58	0.68
MDF	30	4	1	0.50	0.50	−0.39
MDF	30	4	2	0.56	0.57	−1.83

Abbreviation: MDF, medium-density fiberboard.

Table 2
Testing dataset and prediction model results

Material type	Cutting width (mm)	Blade no.	Cutting depth (mm)	Dust emission level (mg/m^3)		
				Actual	Predicted	%Error
Populus nigra L.	6	1	1	0.05	0.05	−6.61
Populus nigra L.	6	4	2	0.13	0.14	−8.25
Populus nigra L.	12	1	3	0.12	0.12	−1.80
Populus nigra L.	12	4	1	0.11	0.11	0.99
Populus nigra L.	18	1	2	0.18	0.18	−1.00
Populus nigra L.	18	4	3	0.22	0.22	−2.07
Populus nigra L.	25	1	2	0.25	0.25	1.22
Populus nigra L.	25	4	1	0.22	0.22	−0.89
Populus nigra L.	30	1	3	0.32	0.34	−6.60
Populus nigra L.	30	4	2	0.32	0.33	−2.79
Fagus orientalis L.	6	1	2	0.06	0.06	2.42
Fagus orientalis L.	6	4	1	0.06	0.07	−14.72
Fagus orientalis L.	12	1	1	0.11	0.12	−13.20
Fagus orientalis L.	12	4	3	0.18	0.18	0.41
Fagus orientalis L.	18	1	3	0.21	0.22	−5.76
Fagus orientalis L.	18	4	2	0.22	0.21	2.97
Fagus orientalis L.	25	1	1	0.23	0.23	−0.49
Fagus orientalis L.	25	4	2	0.31	0.30	2.09
Fagus orientalis L.	30	1	2	0.33	0.34	−1.92
Fagus orientalis L.	30	4	3	0.42	0.44	−4.50
MDF	6	1	2	0.10	0.09	12.56
MDF	6	4	1	0.09	0.10	−7.47
MDF	12	1	3	0.22	0.20	9.59
MDF	12	4	2	0.20	0.21	−5.53
MDF	18	1	1	0.29	0.28	3.64
MDF	18	4	2	0.37	0.36	2.94
MDF	25	1	3	0.51	0.51	−0.55
MDF	25	4	1	0.39	0.44	−11.57
MDF	30	1	2	0.51	0.51	−0.19
MDF	30	4	3	0.69	0.80	−15.51

Abbreviation: MDF, medium-density fiberboard.

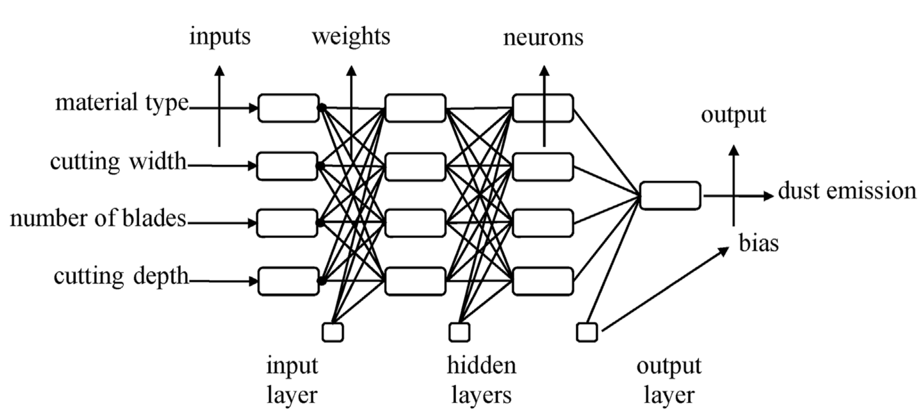

Fig. 4. Proposed network architecture.

Table 3
Results of the performance criteria for the ANN model

Dataset	Performance criterion		
	MAPE	RMSE	R^2
Training	4.86	0.01	0.995
Testing	5.01	0.02	0.987

Abbreviations: MAPE, mean absolute percentage error; RMSE, root mean square error.

4. Discussion

The reduction in dust emission as cutting width and cutting depth decrease can be explained by considering the physics of material cutting and the mechanics of dust generation. Dong et al. [42] reported that the width and depth of the cut significantly affect the production of dust and chips. Cutting width and depth are directly related to the volume of material removed during the machining process. When these parameters are reduced, the total volume of material removed also decreases [11]. In previous works [43,44], the average chip thickness emerged as the most important factor influencing the amount of dust emissions. Kos et al. [45] stated that the machining process affects the range of chip thickness produced. The researcher also noted that the average chip thickness impacts machine efficiency, specific cutting energy, dust emissions, and the quality of the machined surface. Therefore, chip thickness is important for managing dust levels. Ugulino and Hernández [46] reported the importance of controlling cutting depth to manage dust emissions and surface roughness. The study found a significant relationship between cutting depth and the amount of dust emitted during the machining process. Additionally, it was observed that dust emissions increased with greater cutting depths. This was attributed to the larger volume of wood being removed with each cut. Rautio et al. [47] indicated that the average chip thickness was the most crucial factor influencing the amount of dust generated during the machining process. The researchers suggested that to minimize dust production, milling parameters should be adjusted to ensure that the average chip thickness exceeds 0.05 mm. Similar results were also reported by Palmqvist and Gustafsson [48]. Rabiei and Souri [11] carried out a Pareto analysis to analyze the effect of cutting depth, step-over, cutting speed, and feed rate on wood dust. According to the results, cutting depth had the greatest effect. Furthermore, it was reported that by increasing cutting depth, wood dust increases up to a maximum value. Smaller cutting widths and depths require less force and energy to achieve

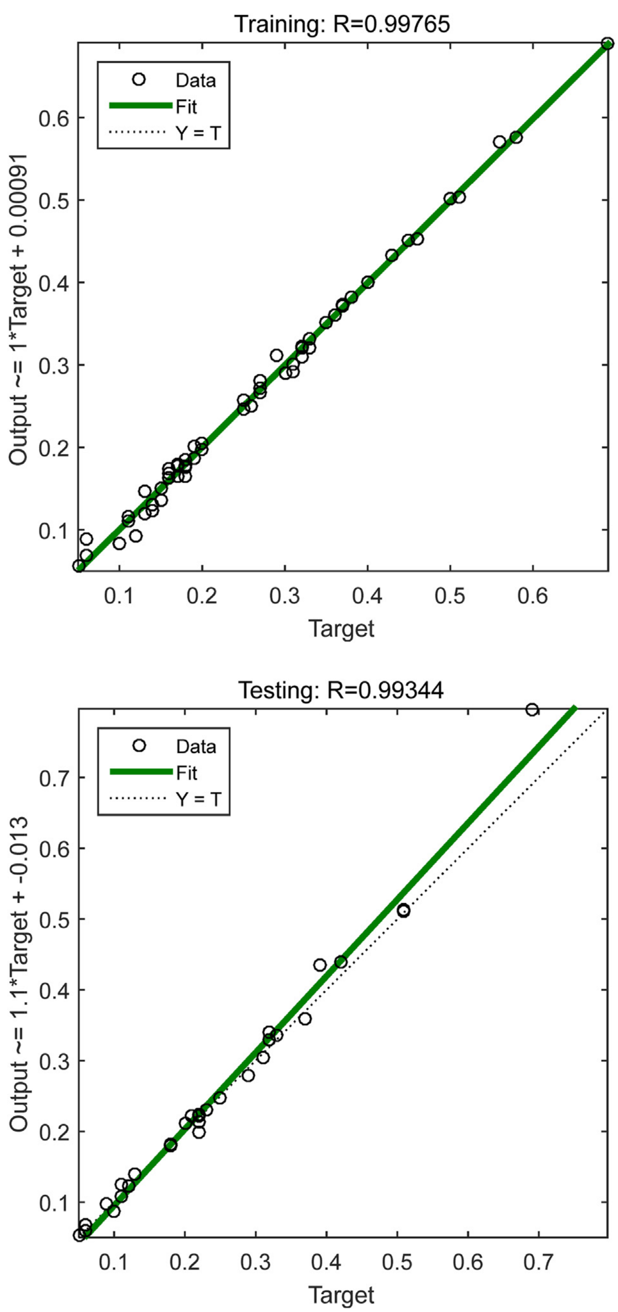

Fig. 5. Relationship between the measured and predicted values.

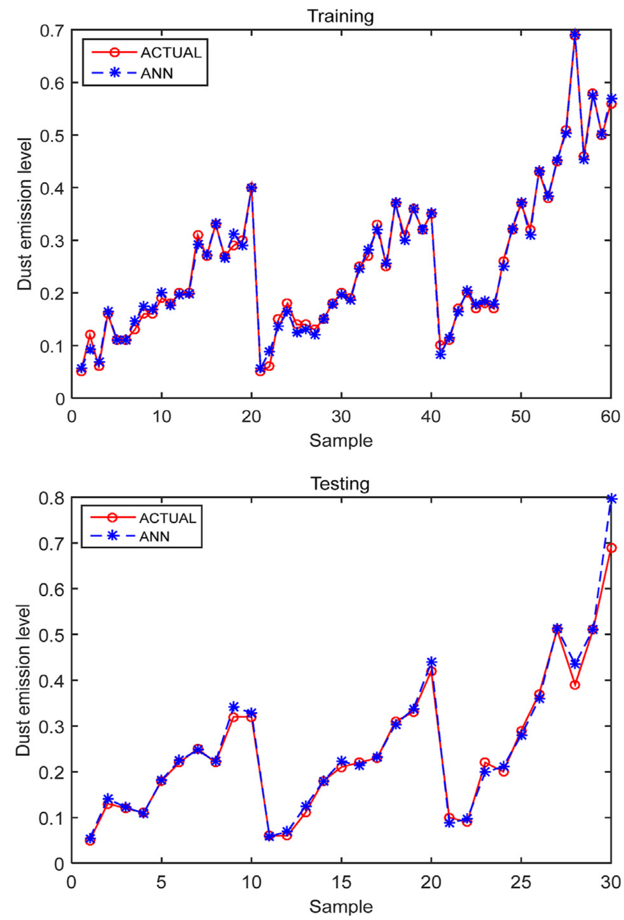

Fig. 6. Comparison between the measured and predicted values.

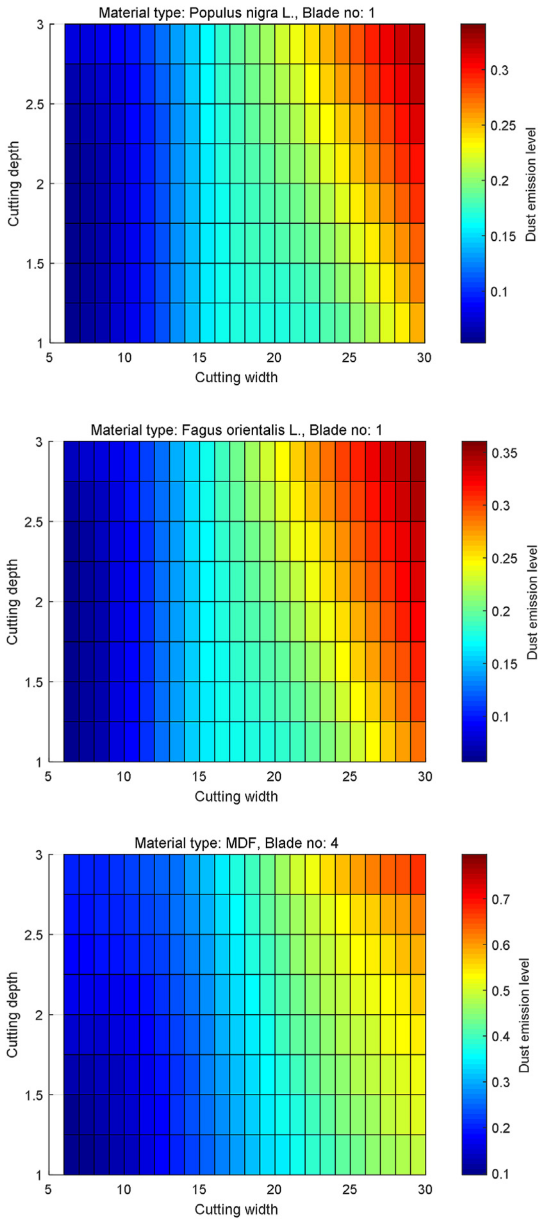

Fig. 7. Variations in dust emission across various cutting widths and cutting depths.

the cut. This reduction in force can lead to fewer particles being dislodged during the cutting process. High-energy cutting can cause more violent material breakage, leading to increased dust production [9]. Friction between the cutting tool and the material is another crucial factor. High friction and heat can cause materials to break apart more violently [7]. In an experimental study conducted by Očkajová et al. [10], it was observed that the highest percentage of particles occurred at the highest heat. Undesirable effects can be reduced by adjusting machining parameters [7].

Wood dust emission is a common concern in industries involved in woodworking activities such as cutting, sanding, and shaping wood. The fine particles generated during these processes can pose significant health risks to workers, including respiratory issues and allergic reactions. Different wood types produce dust with varying compositions, and certain species may contain substances that contribute to specific health concerns [8]. One key strategy for controlling dust emission levels is the use of local exhaust ventilation systems. These systems capture dust at the source, typically near machinery or tools, preventing its dispersion into the air. Dust collection systems, which centralize the capture and containment of wood dust, play a crucial role in maintaining air quality [49]. Additionally, personal protective equipment, such as respirators, can be used to reduce inhalation exposure, especially in situations where other control measures may not be fully effective [50]. Workplace design also contributes to dust control. Optimizing the layout of machinery and workstations helps minimize the spread of wood dust, and the use of enclosures and barriers can contain dust within specific areas. Regular cleaning is essential to prevent the accumulation of dust, and proper disposal methods help avoid resuspension of particles into the air [51]. Employee training on the risks associated with wood-dust exposure and the proper use of control measures are critical for creating awareness and ensuring compliance. Monitoring air quality, conducting regular equipment maintenance, and exploring alternative materials or processes that generate less dust are additional components of a comprehensive wood dust control strategy [5]. By combining these measures, industries can effectively reduce wood dust emission levels and safeguard the health of their workforce. This study not only demonstrates the reliability of ANNs in this domain but also highlights their capacity to generate intermediate dust emission values. The significance of this lies in eliminating the need for resource-intensive and time-consuming experimental endeavors.

The predictions generated by the chosen ANN model exhibit a remarkable correspondence with the actual values. In the predictive examples derived from the ANN model, it is observed that dust emission tends to decrease with reductions in cutting width and cutting depth. The adoption of the ANN approach offers a strategic advantage for decision-makers investigating the influence of various decision variables on dust levels. By relying on the ANN model, substantial savings in terms of both time and costs associated with experimental studies can be realized. The study affirms the efficacy of the ANN approach in providing reliable predictions and facilitating informed decision-making in the context of dust emission management during wood machining.

The significance of the current study can be elucidated as follows: (1) the study provides important insights into how material type, cutting width, number of blades, and cutting depth influence dust emissions in wood machining; (2) the current model considers different machining variables and predicts intermediate values that are not directly derived from the experimental process; (3) the study's findings enable decision-makers to optimize their processes without extensive trial and error, leading to significant time and cost savings; (4) the study serves as a valuable resource for decision-makers seeking to create safer, more sustainable, and more efficient machining environments; (5) the study contributes to the existing body of knowledge on the relationship between machining parameters and dust emissions; and (6) the study serves as a valuable reference for future modeling efforts aimed at predicting dust emissions during the machining of different wood and wood-based materials. Future research endeavors can consider different influential factors to expand our knowledge on dust generation and distribution. An examination of different wood species and their characteristics could enhance the generalizability of findings. Future studies could also extend their focus to the environmental impact of dust emission from wood machining.

CRediT authorship contribution statement

Hilal Singer: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Abdullah Cemil İlçe:** Writing – review & editing, Writing –

original draft, Methodology, Conceptualization. **Yunus Emre Şenel:** Validation, Investigation, Conceptualization. **Erol Burdurlu:** Supervision, Investigation, Conceptualization.

Conflict of interest

The authors have no conflicts of interest to declare.

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