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ARTIFICIAL NEURAL NETWORK MODELING TO PREDICT OPTIMUM POWER CONSUMPTION IN WOOD MACHINING

This paper investigates and models the effects of wood species, feed rate, number of cutters and cutting depth on power consumption during the wood planing process. For this purpose, the samples were planed at a feed rate of 7 and 14 m/min, a cutting depth of 0.5, 1.5, 2.5 and 3.5 mm, and using 1, 2 and 4 cutters, with measurements taken during this process. According to the results, power consumption increased with increasing feed rate, cutting depth and number of cutters. In artificial neural network model, the mean absolute percentage error values between the actual and predicted values were 0.32% for the training data set and 1.15% for the testing data set. In addition, the values of R^2 were found to be 0.99 and 0.97 in the training and testing data sets, respectively. It is evident from the results that the designed model may be used to optimize the effects of process parameters on power consumption during the planing process of different wood species. Thus, the findings of the current study can be effectively applied in the wood machining industry in order to reduce the time for further experimental investigations, to lower energy consumption and avoid high machining costs.

Keywords: neural network modeling, optimization, planing, power consumption, wood machining

Introduction

The manufacture of wood products mostly requires a series of transformation processes. Each of these processes enables the reduction of the wood size by machining [Aguilera and Martin 2001]. Planing is possibly one of the main processes in wood machining [Gurleyen and Budakci 2015]. The machines and cutters used during the planing process should be properly designed and operated in order to achieve a wood machining process with high productivity and lower costs [Korkut et al. 1999]. To do this, it is essential to have a basic knowledge of factors related to the machining process, such as wood density,

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chip formation, cutting tool geometry, feed rate, and cutting depth [Ilhan et al. 1990; Gurleyen 2010]. An optimum level of these parameters is also necessary for a reduction in production costs without reducing the quality of the product [Gunay 2003]. However, non-uniform characteristics of wood play a significiant role in its effective machining during the planing process. In particular, the behaviour of different wood species in contact with the cutter tools significantly affects power consumption during the machining process [Gurleyen and Subası 2009]. Therefore, an evaluation of the parameters relating to machining and wood properties is very important in order to achieve an economical machining process.

There have been several attempts to examine the influences of various parameters on power consumption during the machining of different wood species. Steawert [1974] compared the factors affecting machine force during hardwood planing. The results showed that increasing the feed rate, cutting depth and wood density led to higher power consumption within the planing process. Mendoza [1988] determined that an increase in cutting depth led to an increase in power consumption. Aguilera and Martin [2001] investigated power consumption during the planing of spruce and beech wood. They reported that power consumption increased with increasing cutting depth. In a study carried out to determine the cutting forces in wood species from tropical regions (*Pseudolachnostylis prunifolia* and *Swartzia madagascariensis*), Cristovao [2012] observed that chip thickness had a significant effect on the main cutting force.

The experimental studies conducted have revealed that a large number of process parameters significantly influence power consumption during wood machining. However, investigating the effect of each parameter on power consumption through experiments is both costly and wearisome. It is clear that such a laborious procedure would consume a lot of time. Therefore, it is absolutely crucial to predict the output values according to different levels of variables using a sufficient number of experimental results. Moreover, determining the optimal values of process parameters by modeling can provide information to help improve the economics of the machining process. Otherwise, numerous experiments have to be carried out to detect the desired optimum value of each parameter considered within the machining process. As already mentioned, this results in a loss of time and energy, as well as high costs, which is not desirable industrially. In the last few decades, an artificial neural network (ANN) modeling approach has drawn the attention of many researchers because of its capability in simulating the relationship between the variables of a process or system [Joo et al. 2014]. This approach has been successfully employed in the field of wood science, for example in research on the optimization of process parameters in the production of wood-based composites [Cook et al. 2000; Ozsahin 2013], calculating thermal conductivity [Avramidis and Iliadis 2005], moisture analysis [Zhang et al. 2006; Avramidis and Wu 2007], the drying process [Wu and Avramidis 2006; Ceylan 2008], classifing wood and veneer defects [Kurdthongmee 2008; Yuce et al. 2014], wood recognition [Khalid et al. 2008], the prediction of mechanical properties [Yang et al. 2015; Tiryaki et al. 2015], predicting wood surface roughness in the machining process [Tiryaki et al. 2014; Sofuoglu 2015], and predicting various properties in the bleaching process [Okan et al. 2015].

Although many applications of the ANN approach in wood science are available, information on modeling the power consumption in wood planing is very limited. In a study conducted to detect the strain of wood against machining tools during the planing process, Gurleyen [2010] observed a very high correlation (R^2=0.92) between the experiment results and regression model results. The goal of the current study was to develop a neural network model capable of simulating the influences of process parameters on power consumption during the planing process by using experimental results.

Materials and methods

Sample preparation

In this study, the aim was to study a low-density wood species as well as a higher-density species. The species selected were spruce (*Picea orientalis* (L.) Link.) and beech (*Fagus orientalis* Lipsky.) for low and high density, respectively. The samples for the experiments were harvested from the Black Sea Region of Turkey. Special care was taken to select the samples without any defects. The sample sizes were trimmed to a length of 910 mm, width of 102 mm and 20 mm thickness. Thirty samples were taken for each species. Thus, a total of sixty samples were used for the power consumption experiments. The samples were conditioned at a temperature of 20 ±2°C and a relative humidity of 65 ±5% to reach a moisture content of approx. 12%. The average density of the wood species was also determined: 0.704 g/cm^3 for the beech wood and 0.417 g/cm^3 for the spruce wood.

Power consumption tests

The wood machining process was conducted using a planer machine. The samples were planed at feed rates of 7 and 14 m/min, cutting depths of 0.5, 1.5, 2.5 and 3.5 mm and using 1, 2 and 4 cutters. The current intensity drawn by the machine motor during the planing process was measured using an ammeter. As the current which reached the engine was the same in 3 phases, an analogue ammeter was connected to one phase and an experimental setup was prepared. When the planer machine was operated for the first time, an ammeter capable of measuring high voltages was used due to the high current amount drawn from the engine. Moreover, it is important to mention that the power consumption was not linear during the planing process. At the beginning of planing, the power consumption was generally higher. However, it was seen that the power consumption reached a steady value after some time. To ensure the reliability of the measurement values, when the engine acceleration and the values shown by the ammeter and voltmeter were stable, the current and voltage values were recorded. Furthermore, to ensure the values recorded were reliable, five samples were used for each experimental variation. Special attention was paid to prevent the vibration of the ammeter and voltmeter used during measurement. Following this, the electrical power consumed was calculated using equation (1).

$$P=\sqrt{3}\ \times\ U\ \times\ I\ \times\ \cos\varphi\ \times\ 10^{-3} \tag{1}$$

where: P is electrical power consumed (kW), U is voltage drawn by the device, I is electrical current drawn by the device, φ is power coefficent (0.85).

Data analysis

The analysis of variance (ANOVA) was performed to evaluate the influence of the considered parameters on the power consumption during the planing of the wood. A total of 240 measurements obtained from 60 samples of beech and spruce were used for the analysis. As a relationship at the $P \leq 0.05$ level was available between the factors, Duncan's multiple mean comparison test was applied and homogenous groups were detected. The analysis was performed using SPSS 11.5 (Statistical Package for the Social Sciences).

Artificial neural network analysis

Artificial Neural Network (ANN)

ANN is an intelligent modeling method that consists of many nonlinear and densely interconnected processing elements called neurons [Ozsahin 2013]. The popularity of ANN has grown recently because of its ability to deal with nonlinear relationships between variables of any process [Khayet and Cojocaru 2013]. It can be said that ANN is a more effective tool when compared with conventional statistical techniques [Ceylan 2008]. Among different architectures of ANNs, the multilayer perceptron (MLP) is the most widely used network architecture to make predictions. The MLP architecture consists of an input layer, an output layer and one or more hidden layer(s) depending on the degree of complexity of the problem under consideration [Scott and Ray 1993; Panda and Tripathy 2014; Tiryaki and Hamzacebi 2014]. A typical example of the MLP is shown in figure 1. In addition, equation (2) calculates the output of the MLP in figure 1.

$$Y=g\left(\theta+\sum_{j=1}^{m} v_j\left[\sum_{i=1}^{n} f\left(w_{ij}X_i+\beta_j\right)\right]\right) \tag{2}$$

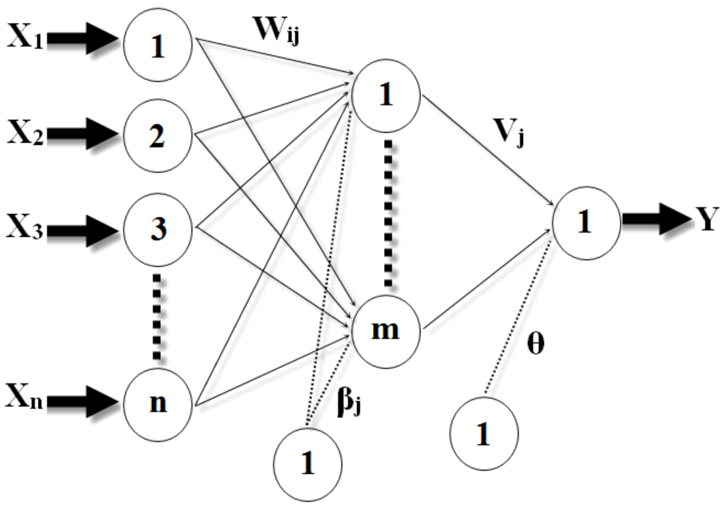


Fig. 1. Typical multi-layered ANN architecture

In equation (2), Y is the predicted value of the dependent variable; X_i is the input value of i^{th} independent variable; w_{ij} is the weight factor between the i^{th} input neuron and j^{th} hidden neuron; β_j is the bias value of the j^{th} hidden neuron; v_j is the weight factor between the j^{th} hidden neuron and output neuron; θ is the bias of the output neuron; g (.) and f (.) are the activation functions.

The first layer of the ANN is the input layer, which gathers the incoming information for the ANN. This layer then transmits the information to the intermediate (hidden) layer. The hidden layer processes this information and then sends the processed information to the output layer. The output layer takes the information and finally produces output data [Canakci et al. 2012]. This flow of information from one neuron to the other is provided by the connection weights between the neurons. On the other hand, all the layers in the ANN architecture include different numbers of neurons. The number of neurons in the input and output layers is equal to the number of the input and output variables, respectively [Tiryaki and Hamzacebi 2014]. Unlike the input and output layers, detecting the number of hidden layer neurons is an important task. They can perform nonlinear mapping between input and output and allow neural networks to capture unknown information regarding the modeled property. However, too many hidden neurons can lead to an overfitting of the model. Such a stuation leads to a gain in memorization capability rather than the generalization capability of the network. Obviously, this is not a desirable situation. On the other hand, too few hidden neurons are not enough for the network to uncover complex relationships between the input and output. Hence, the most popular way to find the optimum number of hidden neurons is to adopt a trial and error procedure [Zhang et al. 1998].

As mentioned above, each neuron in the ANN layers is connected to the neurons of the next layer with a weight factor. These weights have no meaning initially. However, they gain meaningful information after undergoing a training process [Qazi et al. 2015]. The training can be defined as the calibration of the connection weights of the network employing a training algorithm to reach the desired solution [Tiryaki and Hamzacebi 2014]. The back-propagation algorithm is highly popular in training neural networks [Zhang et al. 1998]. By employing this algorithm to produce a desired output, the weights are calibrated until the degree of error between the model output and the actual output is as close as possible to the targeted error [Srisaeng et al. 2015].

Data collection and preparation

The initial step in designing a neural network is to collect data of parameters that may affect the modelled property [Kalogirou 2001]. Therefore, the database of the present study derived from the experiments investigating the effects of machining parameters on power consumption. The data obtained as a result of the experiments were randomly divided into two data sets (training and testing data sets). Among this data, 32 pieces of data were considered to train the network, while the remaining 16 were used to test the model. The data sets are shown in table 1. Table 2 shows the predicted values of the experimental samples of power consumption and their percentage errors. In tables 1 and 2, the data in bold represent the testing data while the other data represent the training data.

Performance evaluation

The mean square error (MSE) was employed as the performance function. Training of the network terminated as the MSE reached an acceptable value. The value of the MSE is calculated with equation (3).

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

where: t_i is the measured values, td_i is the predicted values, and N is the total number of training patterns.

A normalization procedure for the data is often applied before training of the ANN starts [Zhang et al. 1998]. The existing data were therefore normalized to equalize the importance of the parameters prior to the training process within a range of -1 to 1 due to the use of hyperbolic tangent sigmoid function in the model.

The predictive ability of the designed network was assessed by the mean absolute percentage error (MAPE), the root mean square error (RMSE) and coefficient of determination (R^2), defined by equations (4), (5) and (6). The network configuration giving the best output was selected to predict the power consumption.

$$\mathrm{MAPE}=\frac{1}{N}\left(\sum_{i=1}^{N}\left[\left|\frac{t_i-td_i}{t_i}\right|\right]\right)\times 100 \tag{4}$$

$$\mathrm{RMSE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(t_i-td_i\right)^2} \tag{5}$$

$$R^2=1-\frac{\sum_{i=1}^{N}\left(t_i-td_i\right)^2}{\sum_{i=1}^{N}\left(t_i-\bar{t}\right)^2} \tag{6}$$

where: t_i is the measured values, td_i is the predicted values, is the average of the predicted values, and N is the total number of training patterns.

Neural network architecture

Designing a neural network is a crucial stage that can considerably affect the output of the model [Ritchie et al. 2003]. In the present study, a trial and error procedure was adopted to decide the network parameters, such as the number of hidden layers and their neurons, activation functions, the learning rule, the weights and the biases, etc. In this regard, different network architectures were tried until the level of the error between the experimental output and the model response became acceptable. Figure 2 depicts the optimal architecture of the network developed to predict the power consumption. It is possible to see from figure 2 that the optimal architecture of the network involved one input layer, two hidden layers and one output layer.

As can be obviously seen from figure 2, the optimum model had 4, 3, 3 and 1 neurons for the input layer, a first hidden layer, a second hidden layer and an output layer, respectively. In the ANN model, the wood species, cutting depth, number of cutters and feed rate consisted of model input, while power consumption (kW) was the output of the model. As stated previously, the optimum neuron configuration of the ANN was obtained by trying many different networks in terms of hidden layers and their neurons. Moreover, it is worth mentioning that the number of connections in the model was lower than the amount of data available for training. Therefore, it is possible to describe the model mathematically.

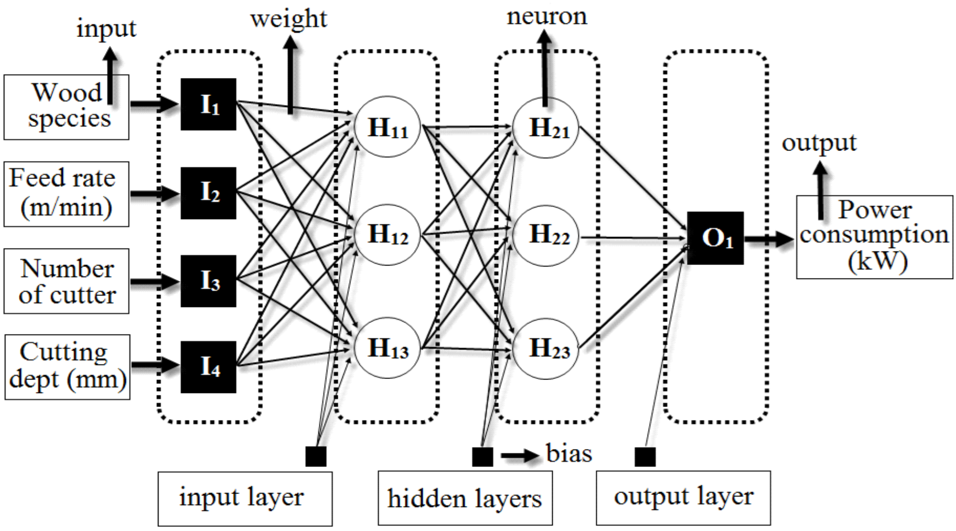


Fig. 2. The architecture of the ANN prediction model

Network training

A neural network is trained by adjusting the values of the connection weights between the neurons [Tiryaki and Hamzacebi 2014]. As a result of this process, the network learns complex relationships in the data structure. In the current study, a multilayer ANN was used to learn the relationship between the input and output data of the wood machining process. The Levenberg-Marquardt algorithm (trainlm) was considered in training the network. During the training process, the weights of the connections among the neurons were iteratively adjusted, and thus the error between the model output and the experimental output was minimized. The learning rule was a gradient descent with a momentum back propagation algorithm (traingdm). Figure 3 shows graphically the variation of the error during the training of the neural network model proposed to predict the power consumption.

As seen in figure 3, the training of the network was stopped after 22 epochs because the targeted error was reached.

Results and discussion

Effects of process parameters on power consumption

Table 1 shows the average values of power consumption acquired as a result of the experimental study and the results of the variance analysis.

The cutters and machines used in wood machining are exposed to different forces by different wood species during the planing process. In this study, it was determined that a lower wood density and feed rate, as well as a lower number

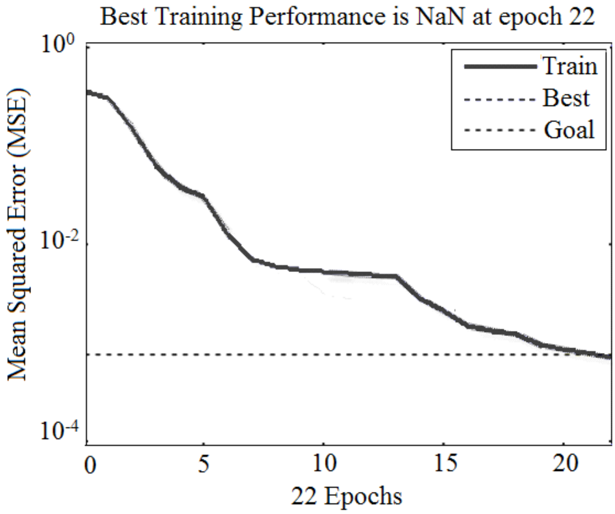


Fig. 3. Graph showing error variation depending on iteration of the ANN

of cutters and cutting depth applied in the planing process, generally reduced the current consumption and resistance of the wood to the machine and cutters.

Examining table 1 in terms of the wood species, it can be seen that the power consumption of the high density beech samples was generally higher than that of the low density spruce. Several researchers have reported similar results [Stewart 1974; Bozkurt 1985; Aguilera and Martin 2001]. The reason for the higher power consumption in the beech wood may have been due to higher resistance in planing a wood with increased density. For the effects of the process parameters on the power consumption, it was determined from the present study that power consumption was generally lower when the feed speed, cutting depth and number of cutters decreased. Bozkurt [1985] stated that, in general, power consumption increases as a result of increasing feed rate, cutting depth and number of cutters in the planing process. Mendoza [1988] and Aguilera and Martin [2001] found that power consumption was greater when cutting depth increases. Similarly, Stewart [1974] determined that increased feed rate and cutting depth led to higher power consumption during the planing process. According to Gurleyen [2010], this situation as regards the feed rate might be due to an increase in the amount of work corresponding to each cutter per unit of time in the planing process. The formation of thicker chips due to increasing cutting depth may be a reason for an increase in power consumption originating from cutting depth. In such cases, the planer machine encounters more resistance in machining. In a related study, Cristovao [2012] reported that the increased chip thickness during the planing process had a great effect on the power consumed.

Table 1. The average power consumption values (kW) obtained by experiments and the results of variance analysis

WS*	FR*	NC*	N	Cutting depth (mm)											
				0.5			1.5			2.5			3.5		
				Avg.	HG	SD	Avg.	HG	SD	Avg.	HG	SD	Avg.	HG	SD
Spruce	7	1	20	3.086	A	0.032	**3.252**	BC	0.068	3.561	GHIJ	0.045	3.703	KLM	0.129
		2	20	3.082	A	0.054	3.253	BC	0.058	**3.721**	LM	0.107	3.844	NO	0.073
		4	20	**3.302**	CD	0.035	3.353	CD	0.031	3.799	MN	0.067	**3.916**	NOPRS	0.117
	14	1	20	**3.417**	DEF	0.047	3.549	GHIJ	0.030	3.859	NOP	0.053	3.907	NOPRS	0.101
		2	20	3.486	FGHI	0.049	**3.499**	FGHI	0.035	3.933	OPRST	0.111	**3.941**	OPRST	0.081
		4	20	3.517	FGHI	0.099	3.567	HIJ	0.041	**3.946**	OPRSTU	0.066	4.002	RSTUVY	0.060
Beech	7	1	20	3.146	AB	0.032	3.470	EFGH	0.108	**3.885**	NOPR	0.105	3.963	OPRSTUV	0.122
		2	20	**3.180**	AB	0.027	3.487	FGHI	0.081	3.986	PRSTUVY	0.126	4.057	TUVY	0.098
		4	20	3.455	EFGH	0.149	**3.576**	HIJ	0.091	4.085	VYZ	0.231	**4.191**	Z	0.160
	14	1	20	3.431	EFG	0.033	**3.555**	GHIJ	0.044	3.998	RSTUVY	0.087	**4.030**	STUVY	0.074
		2	20	3.515	FGHI	0.042	3.606	IJKL	0.078	**4.105**	YZ	0.090	4.079	VYZ	0.097
		4	20	**3.585**	HIJK	0.087	3.655	JKL	0.054	4.071	UVYZ	0.096	4.110	YZ	0.058

*WS, FR and NC denote wood species, feed rate and number of cutters, respectively; N – number of measurements
Data in **bold** were used for ANN testing, whereas the other data were used for ANN training
Avg. – average, SD – standard deviation, HG – homogeneity groups
The same letters in columns indicate that there is no statistical difference between the samples, according to Duncan's multiple range test at $P < 0.05$

Optimizing power consumption by ANN

Table 2 presents the ANN output for the training and test data sets, percentage error ratios and the values of the performance indicators such as the RMSE and MAPE.

A regression analysis between the experimental output and neural network output is often useful to evaluate the validity and accuracy of the networks. For the present study, the graph of the relationship between the experimental and predicted output is shown in figure 4. The *R* (correlation coefficient) values were 0.99885 for training and 0.98671 for testing. Thus, the R^2 (determination coefficient) values obtained were 0.99 and 0.97 for the training and testing data, respectively. It is well known that if R^2 values approach 1, the accuracy of the prediction increases. This means that there is a perfect fit between the experimental (measured) output and network output. These results indicated that the designed network was capable of explaining at least 0.97% of the measured data. A high correlation between the model prediction and measured results confirmed the use of the ANN in predicting power consumption.

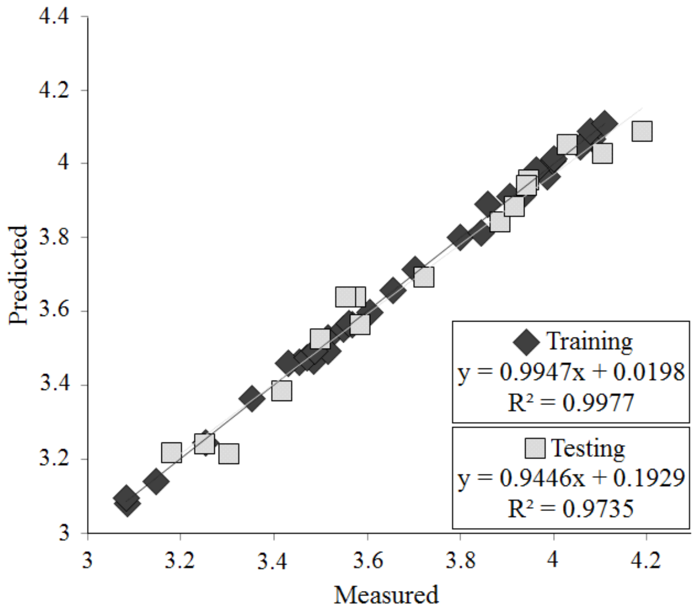


Fig. 4. Relationship between the measured and predicted values of power consumption

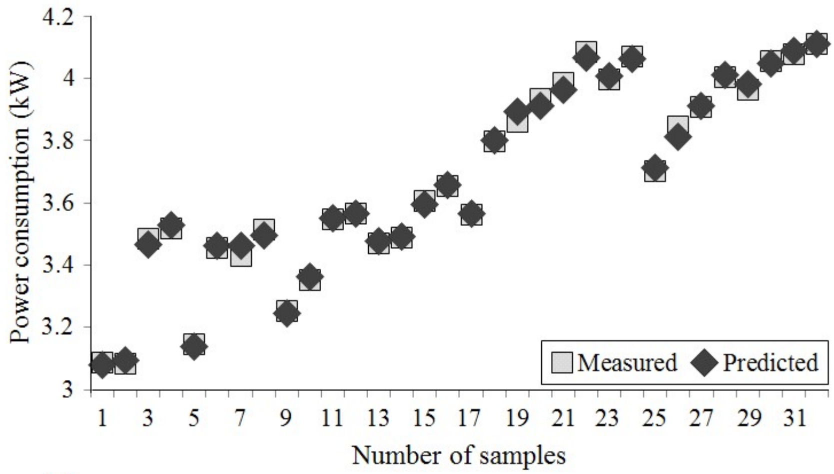
Figure 5 indicates the comparative plots of the measured and predicted power consumption values.

Table 2. Predicted values of power consumption and their percentage errors

Wood species	Feed rate (m/min)	Number of cutters	Cutting depth (mm)							
			0.5		1.5		2.5		3.5	
			p[a]	e[a]	p	e	p	e	p	e
Spruce	7	1	3.080	0.19	**3.243**	**0.26**	3.567	-0.18	3.713	-0.27
		2	3.096	-0.47	3.244	0.28	**3.692**	**0.78**	3.812	0.83
		4	**3.215**	**2.63**	3.365	-0.35	3.802	-0.08	**3.886**	**0.75**
	14	1	**3.384**	**0.96**	3.552	-0.08	3.892	-0.85	3.913	-0.15
		2	3.466	0.58	**3.526**	**-0.79**	3.911	0.56	**3.941**	**-0.01**
		4	3.528	-0.32	3.565	0.05	**3.957**	**-0.28**	4.013	-0.27
Beech	7	1	3.140	0.18	3.476	-0.16	**3.843**	**1.08**	3.982	-0.47
		2	**3.219**	**-1.23**	3.492	-0.14	3.964	0.56	4.047	0.26
		4	3.464	-0.26	**3.639**	**-1.76**	4.068	0.42	**4.087**	**2.48**
	14	1	3.461	-0.86	**3.639**	**-2.35**	4.007	-0.22	**4.053**	**-0.57**
		2	3.494	0.59	3.597	0.24	**4.027**	**1.91**	4.089	-0.25
		4	**3.565**	**0.56**	3.656	-0.03	4.064	0.16	4.109	0.01
MAPE training			0.322		MAPE testing				1.150	
RMSE training			0.015		RMSE testing				0.052	

[a]p and e denote predicted values and errors in %, respectively

a



b

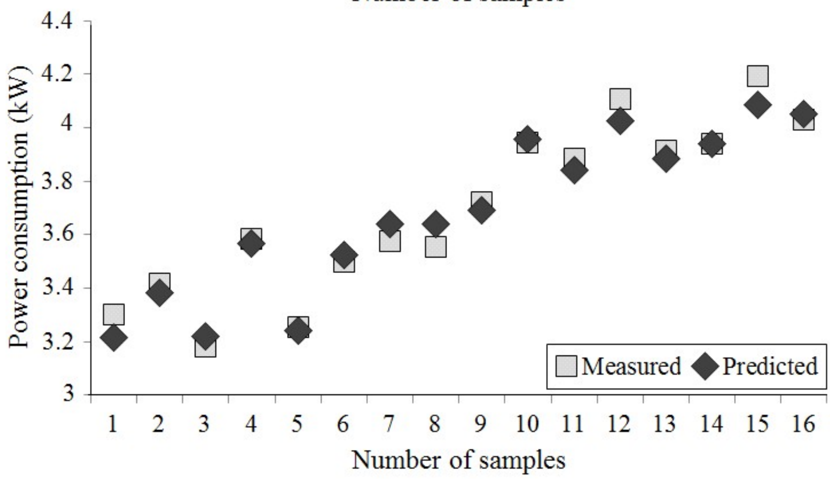


Fig. 5. Comparison of the measured and ANN predicted values: a – training, b – testing

From the plots presented in figure 5, it can be seen that the predicted output were very close to the measured output. The high similarity between the outputs supports the usability of the developed model in predicting power consumption.

The maximum absolute percentage errors obtained as a result of prediction by ANN were 0.86% and 2.63% for the training and the testing stages of the proposed model, respectively. The MAPE values were 0.32% for the training data and 1.15% for the testing data. Furthermore, the RMSE values were 0.015 for the training data and 0.052 for the testing data. Prediction becomes more accurate when the MAPE and RMSE are low because it implies there is a small difference between the network response and the experimental data. In this respect, for the present study, low values of MAPE and RMSE demonstrated that the network was sufficiently accurate and reliable to model power consumption within planing process.

Neural network models gain the ability to yield the desired intermediate values for optimization studies when they are properly trained [Ozsahin 2013]. This is one of the most distinct characteristics of ANNs. In the optimization of power consumption for the current study, the wood species (spruce) and number of cutters (two) were fixed, and the feed rate and cutting depth were changed. The intermediate power consumption values not provided from the tests were determined by means of the proposed model for different feed rates and cutting depths, and are shown graphically in figure 6.

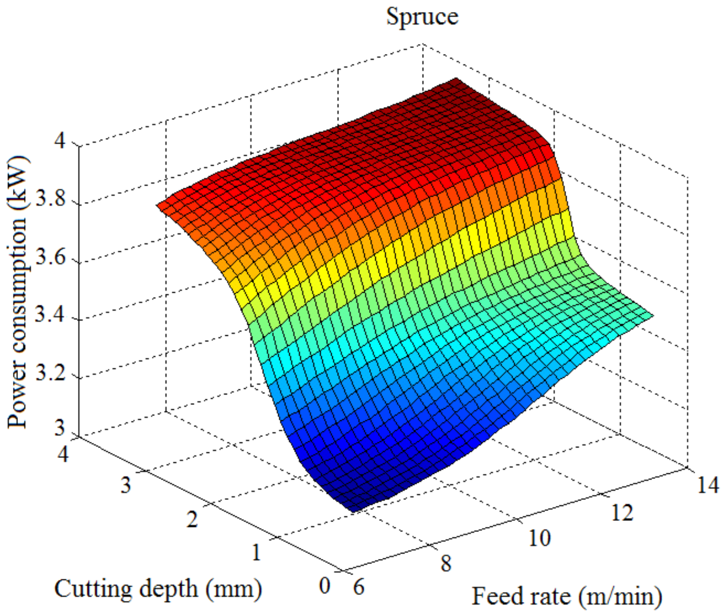


Fig. 6. The effect of cutting depth and feed rate on power consumption

The effect of the other parameters on the power consumption can be predicted by analysing the responses of the model. This model enabled us to better understand how different machining conditions affect power consumption.

Conclusion

This study investigated and modelled the influence of some machining parameters on power consumption during the planing of wood. According to the results of the study, power consumption increased with an increase in feed rate, cutting depth, and number of cutters. Likewise, high density beech showed greater power consumption values compared to low density spruce. Therefore, it is possible to say that wood materials should not be processed at high feed rates and cutting depth in order to avoid high electricity expenditure caused by excessive power consumption. In the ANN analysis, the MAPE and R^2 values were found to be 1.15% and 0.97 for the testing phase, respectively. The high values of the MAPE and R^2 were extremely effective in predicting power consumption. Based on these results, it can be said that the designed model may be employed to efficiently describe the relationship between machining parameters and power consumption. Further, it can be concluded that the approach presented is an applicable tool to predict with a high degree of accuracy power consumption in the wood planing process.

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