Prediction of Optimum CNC Cutting Conditions Using Artificial Neural Network Models for the Best Wood Surface Quality, Low Energy Consumption, and Time Savings

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This study aimed to predict the CNC cutting conditions for the best wood surface quality, energy, and time savings using artificial neural network (ANN) models. In the CNC process, walnut, and ash wood were used as materials, while three different cutting tool diameters (3 mm, 6 mm, and 8 mm), spindle speed (12000 rpm, 15000 rpm, and 18000 rpm), and feed rate (3 m/min, 6 m/min, and 9 m/min) were determined as cutting conditions. After the cutting processes were completed with the CNC machine, energy consumption and processing time were determined for all groups. Surface roughness and wettability tests were performed on the processed wood samples, and their surface qualities were determined. The experimentally obtained data were analysed in ANN, and the models with the best performance were obtained. By using these prediction models, optimum cutting conditions were determined. Using the findings of the study, the optimum cutting condition values can be determined for walnut and ash wood with the smoothest and best wettable surface. Furthermore, in CNC processes using such materials, minimum energy consumption and shorter processing time can be obtained with optimum cutting conditions.

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INTRODUCTION

The furniture industry is a sector in which solid wood and wood-based panels are consumed in very high quantities to supply a fast-growing market worldwide. In particular, with the use of computer numerical control (CNC) router machines in the furniture industry, production quantities have increased rapidly, while the production costs and labour have decreased (Pelit *et al*. 2021). These machines are highly preferred in processes such as patterning, milling, drilling, and grooving, and their integration with other automation systems is very flexible. These machines, which increase productivity and reduce time loss, also improve the surface quality of the processed materials (Sutcu 2013; Koc *et al*. 2017; Sofuoglu 2017).

The most accurate determination of the parameters describing the surface quality of materials such as surface roughness and wettability is extremely significant for the successful application of wood finishing processes such as painting, coating and varnishing (Qin *et al*. 2015; Sofuoglu 2017; Martha *et al*. 2020). The most important factors affecting the surface roughness are classified as the factors originating from the material, such as wood species, density, hardness, moisture, and factors originating from the process applied to the material such as cutting tool diameter, tool shape, radius of the tool nose, spindle speed, step-over, depth of cut, and feed rate (Bajić *et al*. 2008). Wettability, which is sensitive to the interactions between the wood surface and liquid substances such as water, adhesive, paint, varnish, and coating, is traditionally determined by the contact angle, and the small angles indicate more wettable surfaces (Gindl and Tschegg 2002; Gindl *et al*. 2004; Rathke and Sinn 2013; Fang *et al*. 2016). The most important factors affecting the wettability of wood surface are wood species, moisture, fibre direction, polarity, pH, surface roughness, wood aging, and processing (Mohammed-Ziegler *et al*. 2004; Cao *et al*. 2005; Unsal *et al*. 2011; Qin *et al*. 2015).

Table 1. The Comparison of Some Optimization Studies with this Study

Previous studies	Studied wood species	Investigated properties	Determined CNC cutting conditions	Optimization method
Gürgen *et al*. (2022)	Pine wood	Surface roughness	Spindle speed, feed rate, depth of cut, and axial depth of cut	Artificial Neural Network (ANN) and genetic Algorithm (GA)
Demir *et al*. (2021a)	Beech wood Spruce wood	Surface roughness	Spindle speed, feed rate, and tool diameter	ANN
Hazir and Ozcan (2019)	Beech wood	Surface roughness	Spindle speed, feed rate, tool radius and depth of cut	Response surface method (RSM), desirability function (DF) and GA
Hazir and Koc (2019	Cedar wood	Surface roughness	Spindle speed, feed rate, tool radius and depth of cut	RSM and Taguchi's L27 orthogonal array based simulated angling algorithm (SA)
Stanojevic *et al*. (2017)	Oak wood	Surface roughness,	Feed rate, cutting depth, and rake angle	Neuro-fuzzy method
This study	Walnut wood Ash wood	Surface roughness, wettability, energy consumption, processing time	Spindle speed, feed rate, and tool diameter	ANN

Before performing the operations on CNC machines, cutting conditions such as step-over, spindle speed, cutter plunge speed, feed rate, tool diameter, depth of cut, and tool strategy must be set correctly. Otherwise, problems may occur in the surface quality of the processed wood and wood-based panels (Koc *et al*. 2017; Bal and Akcakaya 2018).

The necessity of determining the optimum CNC cutting condition values that give the best surface quality for wood materials used in the furniture industry has recently been an important research issue in the literature. Therefore, many researchers have focused on this issue in their studies. The comparison of some of these studies which investigated on solid wood with this study is presented in Table 1.

Table 1 shows that only surface roughness values are used as output variables in the parameter optimization studies related to CNC-processed solid wood in the literature. Furthermore, it has been determined that factors such as energy consumption and processing time, which are very important in terms of environment and cost, are not used in the optimization studies. Therefore, this study aimed to predict optimum cutting conditions depending on the surface roughness, wettability, energy consumption, and processing time of the solid wood processed with CNC machine.

EXPERIMENTAL

Materials

In this study, walnut (*Juglans regia* L.) and ash (*Fraxinus excelsior* L.) wood, which are widely used in the furniture industry, were used unlike the studies in the literature (Table 1). The wood samples were conditioned in an air-conditioning chamber until they reached a moisture content of 12% ± 1% before the cutting process with a CNC machine. A four-axis CNC milling machine (Megatron 2128, Bursa, Turkey) with a spindle power of 9 kW and a maximum spindle speed of 24000 was used for cutting operations. The toolpath strategy was chosen as offset and double flute straight milling cutters in three different diameters (3 mm, 6 mm, and 8 mm) were preferred. The offset strategy was applied constantly in tangential directions of wood samples. The CNC processing of wood samples and the used cutting tools are shown in Fig. 1.

Fig. 1. CNC processing of wood samples and the used cutting tools

Spindle speed and feed rate were determined not only by the most frequently used values in the literature, but also by choosing homogeneous parameter ranges for a successful ANN modelling. Consequently, three spindle speed (12000, 15000, and 18000 rpm) and feed rate (3, 6, and 9 m/min) were used for CNC processing. The depth of cut was 3 mm. The energy consumption of each sample was determined using a wattmeter immediately after processing with the CNC machine, and the total processing times were recorded using a stopwatch. In the energy consumption measurements, a value was taken from the wattmeter just before the CNC process starts, and another value was taken right after the CNC process was finished, and the difference between these two values (last wattmeter value - first wattmeter value) gave the energy consumption of that group. Similarly, the processing time of the groups was determined by using a stopwatch. Afterwards, the samples were sized to 50 mm x 50 mm and test specimens were obtained for surface roughness and wettability measurements. Five test specimens were prepared to represent each group and the test phase was started.

Methods

Surface roughness measurements

The surface roughness measurements were performed according to DIN 4768 (1990) standard to determine the surface quality of wood materials. The R_a (arithmetic mean) values of the measurement parameters were determined perpendicular to the fibres of the wood specimens in the Mitutoyo Surftest SJ-301 test device (Kawasaki, Japan) according to the DIN 4798 (1990) standard. The device with detector nose radius of 5 µm was set as evaluating length of 12.5 mm, cut-off length of 2.5 mm, resolution of 350 µm. Ten measurements were made for each group.

Contact angle measurements

The wettability of the wood surfaces was determined by measuring the contact angles between the surface of the wood specimens and the droplets of distilled water. Using the DSA100 Drop Shape Analysis System (KRUSS GmbH, Hamburg, Germany) equipped with image analysis software, a total of ten drops of 5 µL volume were randomly dropped onto the specimen surfaces. The contact angle values of the specimens were calculated five seconds after the droplets were deposited on the surface.

Artificial neural network analysis

Artificial neural network (ANN) analyses were carried out using the energy consumption and processing time values measured immediately after the CNC process, and the surface roughness and contact angle values obtained from the tests. As a result of the ANN analysis, the prediction models with the best performance were used both to predict the surface roughness, wettability, energy consumption and processing time values of the cutting conditions that were not used in the experimental studies, and to determine the optimum cutting condition values that give the best surface quality and energy-time savings for walnut and ash wood. The CNC cutting conditions such as spindle speed, feed rate, and cutting tool diameter were main variables in ANN modelling of this study. The data obtained from experimental studies were modelled using the MATLAB Neural Network Toolbox. The experimental data were randomly grouped as training data, validation data, and testing data for each test. Training data were presented to the network during training, and the network is adjusted according to its error. Validation data is used to measure network generalization and to halt training when generalization stops improving. Testing data has no effect on training and so provide an independent measure of network performance during and after training. Each network was trained with 38 data (about 70% of total data) and was subsequently validated with 8 experimental data (about 15% of total data) and tested with 8 experimental data (about 15% of total data).

The data sets used in the prediction models are given in Tables 3 and 4. The Levenberg Marquardt algorithm (trainlm) was chosen as the training algorithm. This algorithm typically requires more memory but less time. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error (MSE) of the validation samples. The MSE calculated by Eq. 1 was preferred as the performance function,

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

where ti is the actual output (targeted values), *tdi* is the neural network output (predicted values), and N is the total number of training patterns.

The feed forward and backpropagation multilayer ANN were used to determine prediction models. In ANN analysis trials, the transfer (activation) function was used the hyperbolic tangent sigmoid function (tansig) in the hidden layer whilst it was used the linear transfer function (purelin) in the output layer. The layers in which these activation functions are used are shown in Fig. 2.

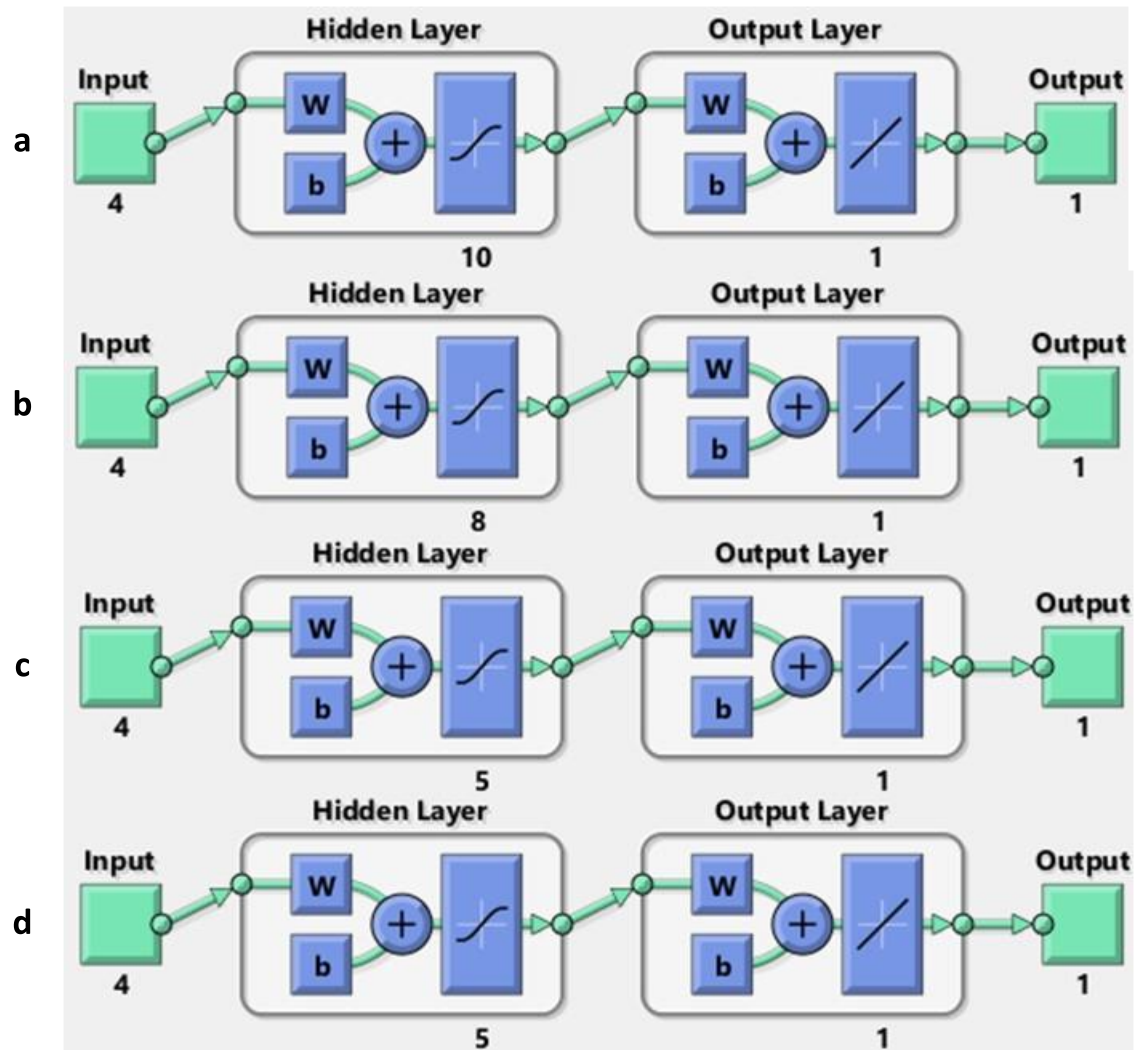


Fig. 2. The network structures of the surface roughness (a), wettability (b), energy consumption (c) and processing time (d) prediction models

Table 2. Connection Weights and Bias Values of the Prediction Models

Surface Roughness	Hidden Layer											Output Layer	
	n1	n2	n3	n4	n5	n6	n7	n8	n9	n10	b1	n1	b2
	-1.417	-0.501	-0.414	1.990	0.838	0.393	1.135	-0.500	-2.157	2.048	2.676	0.374	0.465
	0.465	0.317	1.731	-1.490	-0.902	2.596	-1.933	1.780	0.338	1.714	-1.789	0.216	
	0.184	-0.996	1.864	1.496	1.160	-0.807	-0.851	-2.166	0.720	0.128	2.114	-0.308	
	1.771	-2.613	-0.699	0.767	-0.107	-1.907	1.186	1.270	1.145	-0.753	-2.160	0.664	
											-0.916	-0.714	
											0.871	0.318	
											1.471	-0.038	
											1.776	-0.392	
											-2.154	0.380	
											1.952	-0.412	

Wettability	Hidden Layer									Output Layer	
	n1	n2	n3	n4	n5	n6	n7	n8	b1	n1	b2
	1.712	-1.359	0.801	0.521	0.613	-0.545	2.113	-1.040	-2.958	-1.326	0.487
	2.514	-0.623	1.231	0.848	0.265	2.507	-0.561	-2.581	1.100	-0.822	
	0.511	-0.265	-2.564	1.937	-1.800	0.673	0.970	0.628	-0.801	-0.496	
	-0.035	0.222	1.257	2.168	1.035	-0.067	0.196	0.131	-0.048	0.005	
									-0.167	0.771	
									-0.842	1.090	
									1.765	0.048	
									-3.479	1.357	

Energy Consumption	Hidden Layer						Output Layer	
	n1	n2	n3	n4	n5	b1	n1	b2
	-0.971	-0.025	0.798	-1.063	0.034	3.928	-0.193	2.593
	-1.533	-0.690	-3.411	0.471	-0.376	-0.474	0.436	
	0.560	0.012	2.741	0.091	0.006	0.314	-0.007	
	1.320	0.018	-2.648	-1.174	-0.603	-2.062	0.099	
						-1.517	2.980	

Processing Time	Hidden Layer						Output Layer	
	n1	n2	n3	n4	n5	b1	n1	b2
	0.453	-0.028	0.015	-0.005	0.097	1.752	-0.023	1.681
	-1.684	-2.100	1.936	0.387	-1.298	-2.135	0.252	
	1.027	-0.039	0.307	-0.018	0.821	0.322	-0.140	
	-0.145	-0.079	-0.478	0.747	-1.646	1.533	-2.273	
						1.964	0.062	

n: neuron, b: bias

The actual (measured) values were compared with the prediction values obtained from ANN analyses after the testing process. The performances of the prediction models were determined by using the root mean square error (RMSE) calculated by Eq. 2 and the mean absolute percent error (MAPE) calculated by Eq. 3,

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

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

where t_i is the actual output values, td_i is the neural network predicted values, and N is the number of objects.

The connection weights (w) and biases (b) of the surface roughness and wettability, energy consumption, and processing time prediction models were given in Table 2. Moreover, the neurons and biases were denoted by n and b in Table 2.

RESULTS AND DISCUSSION

Experimental and ANN Analysis Results

The experimentally obtained data and the prediction values obtained from ANN models of these data are given in Tables 3 and 4 according to wood species. In addition, training, validation and testing data sets used in ANN analysis are indicated.

The performance values of the surface roughness, wettability, energy consumption and processing time prediction models are given in Table 5.

The MAPE values for the surface roughness were 4.71% for training, 6.88% for validation, and 9.60% for testing, whilst the values for the wettability were 1.64% for training, 2.02% for validation, and 3.86% for testing. The values for the energy consumption were 1.11% in training phase, 1.62% in validation phase, and 2.33% in testing phase, while the values for the processing time were 1.14% in training phase, 1.97% in validation phase, and 1.53% in testing phase (Table 5). The MAPE value, which is frequently used by researchers to evaluate ANN model performances, is expected to be below 10% (Antanasijević *et al*. 2013; Tiryaki *et al*. 2016). It has been demonstrated that the prediction performance of ANN models is high with these values lower than 10% (Yadav and Nath 2017). It is stated in the literature that it is extremely important to calculate RMSE values as well as MAPE values in order to determine the performance of prediction models (Kucukonder *et al*. 2016). In this study, the RMSE values of the surface roughness prediction model for training, validation, and testing phase were 0.32, 0.42, and 0.45 whilst the values of the wettability were 1.98, 2.23, and 3.98, respectively. The RMSE values of the energy consumption prediction model for training, validation, and testing phase were 1.07, 2.77, and 2.22 while the values of the processing time were 0.37, 1.07, and 0.51, respectively (Table 5). Taspınar and Bozkurt (2014) stated that the low RMSE values obtained from the ANN analyses are an indicator of the successful performance of the prediction models. The MAPE and RMSE values obtained from the study proved that the ANN models used for prediction and optimization are reliable and can give satisfactory accurate results.

The MSE changes of the ANN prediction models depending on iteration are shown in Fig. 3. The best validation performances of the surface roughness, wettability, energy consumption and processing time prediction models were realized in the 6th, 7th, 37th, and 14th iterations, respectively. After these iterations, the training phases of the networks were stopped. The MSE values after this stage are given in Table 5.

Table 3. Experimental and ANN Analysis Results for Walnut Wood

Wood species	Tool diameter (mm)	Spindle speed (rpm)	Feed rate (m/min)	Surface roughness (µm)			Wettability (º)			Energy consumption (W)			Processing time (sec)		
				a	p	e (%)	a	p	e (%)	a	p	e (%)	a	p	e (%)
Walnut	3	12000	3	6.80	6.93	-1.88	78.68	79.42	-0.94	***230***	***224***	***2.4***	***109***	***109***	***0.3***
			6	5.22	5.69	-9.03	87.48	86.80	0.78	132	131	0.4	63	63	-0.1
			9	7.15	6.30	11.91	85.84	85.20	0.75	99	98	0.8	47	47	-0.1
		15000	3	6.22	6.29	-1.08	82.22	83.89	-2.03	229	227	0.8	110	109	0.7
			6	4.62	4.81	-4.30	***87.76***	***88.53***	***-0.87***	130	132	-1.6	**63**	**63**	**0.0**
			9	**6.20**	**5.79**	**6.67**	98.75	99.07	-0.33	99	98	1.0	**48**	**48**	**1.0**
		18000	3	4.16	4.31	-3.44	97.34	95.18	2.22	229	230	-0.3	109	110	-0.5
			6	***4.81***	***5.02***	***-4.29***	95.92	96.89	-1.01	133	133	-0.3	***62***	***63***	***-1.3***
			9	5.93	5.92	0.25	***96.68***	***98.73***	***-2.12***	100	98	1.8	**47**	**47**	**-0.6**
	6	12000	3	4.46	5.00	-12.24	75.00	77.68	-3.57	125	126	-0.6	53	53	-0.7
			6	5.50	5.30	3.59	78.48	78.78	-0.38	***73***	***73***	***0.3***	32	32	0.8
			9	5.88	6.02	-2.37	75.96	78.94	-3.92	55	56	-2.7	25	25	0.0
		15000	3	**4.29**	**5.07**	**-18.09**	**86.98**	**84.00**	**3.43**	126	126	-0.3	53	53	0.4
			6	**5.17**	**5.15**	**0.36**	91.50	85.79	6.24	***74***	***74***	***0.4***	**31**	**30**	**1.9**
			9	***5.29***	***5.28***	***0.17***	**92.70**	**89.55**	**3.39**	58	57	1.8	24	24	-0.1
		18000	3	***6.02***	***5.98***	***0.70***	90.18	91.84	-1.84	128	128	-0.2	53	53	-0.1
			6	4.87	5.12	-5.09	**96.68**	**91.56**	**5.29**	73	74	-0.8	***32***	***30***	***7.6***
			9	4.40	4.80	-9.32	89.60	91.95	-2.62	57	57	-0.6	***24***	***24***	***-0.2***
	8	12000	3	5.19	4.79	7.62	94.76	94.74	0.02	91	91	-0.3	***39***	***39***	***-0.1***
			6	4.58	4.85	-6.04	**101.4**	**99.42**	**1.97**	54	54	0.9	22	23	-2.3
			9	4.24	5.42	-27.97	102.7	100.4	2.27	**42**	**42**	**1.2**	18	18	2.2
		15000	3	***4.08***	***4.97***	***-21.65***	***92.04***	***94.75***	***-2.94***	***88***	***91***	***-3.6***	39	39	-0.5
			6	***5.01***	***5.06***	***-0.99***	96.82	95.37	1.49	***55***	***54***	***1.1***	25	24	3.3
			9	5.93	5.49	7.34	96.06	98.21	-2.24	42	42	0.4	17	17	-2.1
		18000	3	5.45	5.54	-1.65	95.70	94.79	0.95	92	91	1.3	39	39	0.3
			6	5.27	5.23	0.63	***91.74***	***94.72***	***-3.25***	**55**	**55**	**-0.5**	24	24	-1.4
			9	4.56	5.07	-11.08	**96.68**	**95.52**	**1.20**	42	42	-0.4	**17**	**18**	**-4.6**

Note: Bold values: Testing data; Bold italics values: Validation data; The other values: training data. a: actual value; p: predicted value; e: error

Table 4. Experimental and ANN Analysis Results for Ash Wood

Wood species	Tool diameter (mm)	Spindle speed (rpm)	Feed rate (m/min)	Surface roughness (µm)			Wettability (º)			Energy consumption (W)			Processing time (sec)		
				a	p	e (%)	a	p	e (%)	a	p	e (%)	a	p	e (%)
Ash	3	12000	3	***4.35***	***3.73***	***14.29***	***87.46***	***83.33***	***4.72***	**231**	**232**	**-0.3**	109	109	0.2
			6	3.69	3.69	-0.18	77.78	78.24	-0.59	**134**	**135**	**-0.6**	**63**	**63**	**0.5**
			9	4.94	4.98	-0.68	77.70	76.32	1.78	99	98	0.8	47	47	0.5
		15000	3	**4.26**	**3.65**	**14.19**	77.70	78.41	-0.91	***233***	***234***	***-0.2***	109	109	-0.4
			6	**3.61**	**4.03**	**-11.56**	85.38	84.76	0.72	***132***	***136***	***-3.0***	62	63	-1.1
			9	4.04	3.96	1.98	82.86	84.11	-1.51	96	98	-1.9	47	47	0.0
		18000	3	2.76	2.86	-3.91	79.34	79.81	-0.60	235	235	-0.2	110	110	0.3
			6	3.43	3.51	-2.49	78.28	78.62	-0.44	138	137	0.7	63	62	0.9
			9	**3.81**	**3.79**	**0.48**	80.22	81.16	-1.18	98	98	-0.5	***46***	***47***	***-1.6***
	6	12000	3	***3.18***	***3.12***	***1.95***	89.22	85.31	4.38	**126**	**127**	**-1.2**	53	53	-0.2
			6	3.84	3.89	-1.40	77.66	83.73	-7.81	73	73	0.5	31	31	-0.6
			9	***3.95***	***4.38***	***-11.01***	82.54	81.43	1.35	57	56	2.2	**25**	**24**	**2.9**
		15000	3	2.41	2.41	-0.05	83.08	84.18	-1.33	124	124	-0.1	53	53	-0.1
			6	3.23	3.08	4.58	85.06	85.43	-0.44	72	72	0.0	31	30	2.3
			9	3.66	3.69	-0.66	85.86	83.20	3.10	57	56	1.5	24	24	-0.6
		18000	3	3.49	3.51	-0.50	83.14	82.81	0.40	123	124	-0.6	**54**	**54**	**0.9**
			6	4.68	4.52	3.51	**81.62**	**82.12**	**-0.62**	75	72	3.9	***31***	***30***	***4.5***
			9	2.73	2.81	-2.95	84.18	85.02	-1.00	54	56	-2.9	24	24	-0.7
	8	12000	3	3.43	3.43	0.04	***83.90***	***82.59***	***1.56***	***105***	***107***	***-1.9***	39	39	0.2
			6	**3.05**	**3.58**	**-17.42**	81.28	81.44	-0.20	**55**	**56**	**-1.5**	23	23	1.4
			9	3.61	3.71	-2.69	***78.80***	***79.16***	***-0.46***	40	41	-3.3	17	17	-1.6
		15000	3	3.19	3.08	3.41	**74.30**	**79.53**	**-7.03**	97	97	0.0	39	39	0.8
			6	**2.96**	**3.20**	**-8.05**	***82.54***	***82.37***	***0.20***	**55**	**53**	**4.5**	23	24	-3.1
			9	3.78	3.59	4.98	82.98	83.28	-0.36	40	41	-3.0	17	17	1.8
		18000	3	2.62	2.77	-5.90	80.68	80.38	0.37	88	88	-0.4	***39***	***39***	***0.2***
			6	2.88	3.16	-10.04	**87.72**	**80.72**	**7.97**	**56**	**51**	**9.6**	24	24	-0.6
			9	3.96	4.04	-2.01	82.32	82.19	0.16	42	41	1.7	18	18	0.7

Note: Bold values: Testing data; Bold italics values: Validation data; The other values: Training data. a: actual value; p: predicted value; e: error

Table 5. The Performance Values of the Prediction Models

		Surface roughness	Wettability	Energy consumption	Processing time
Training	**MSE**	0.10	3.91	1.14	0.14
	RMSE	0.32	1.98	1.07	0.37
	MAPE	4.71	1.64	1.11	0.89
Validation	**MSE**	0.18	4.99	7.65	1.14
	RMSE	0.42	2.23	2.77	1.07
	MAPE	6.88	2.02	1.62	1.97
Testing	**MSE**	0.21	15.85	4.92	0.26
	RMSE	0.45	3.98	2.22	0.51
	MAPE	9.60	3.86	2.33	1.53

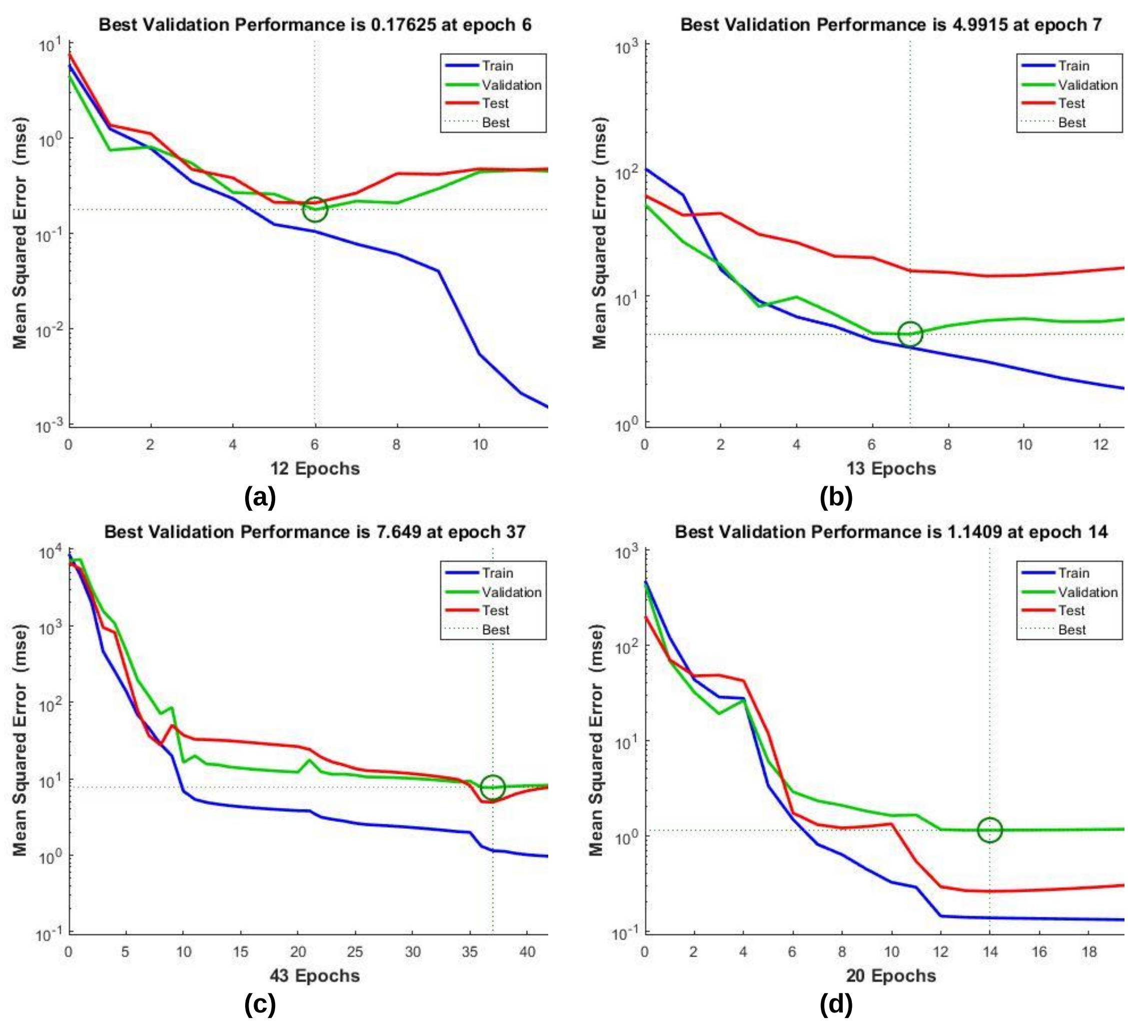


Fig. 3. MSE changes at each iteration for the surface roughness (a), wettability (b), energy consumption (c) and processing time (d) prediction models

The error histograms of the prediction models are shown in Fig. 4. The blue, green, and red bars denote the training data, validation data and testing data respectively. The error values were calculated as the difference between the experimental and the predicted values. The orange line marks the zero-error line. The largest portion of data in the prediction models coincided with the zero-error line.

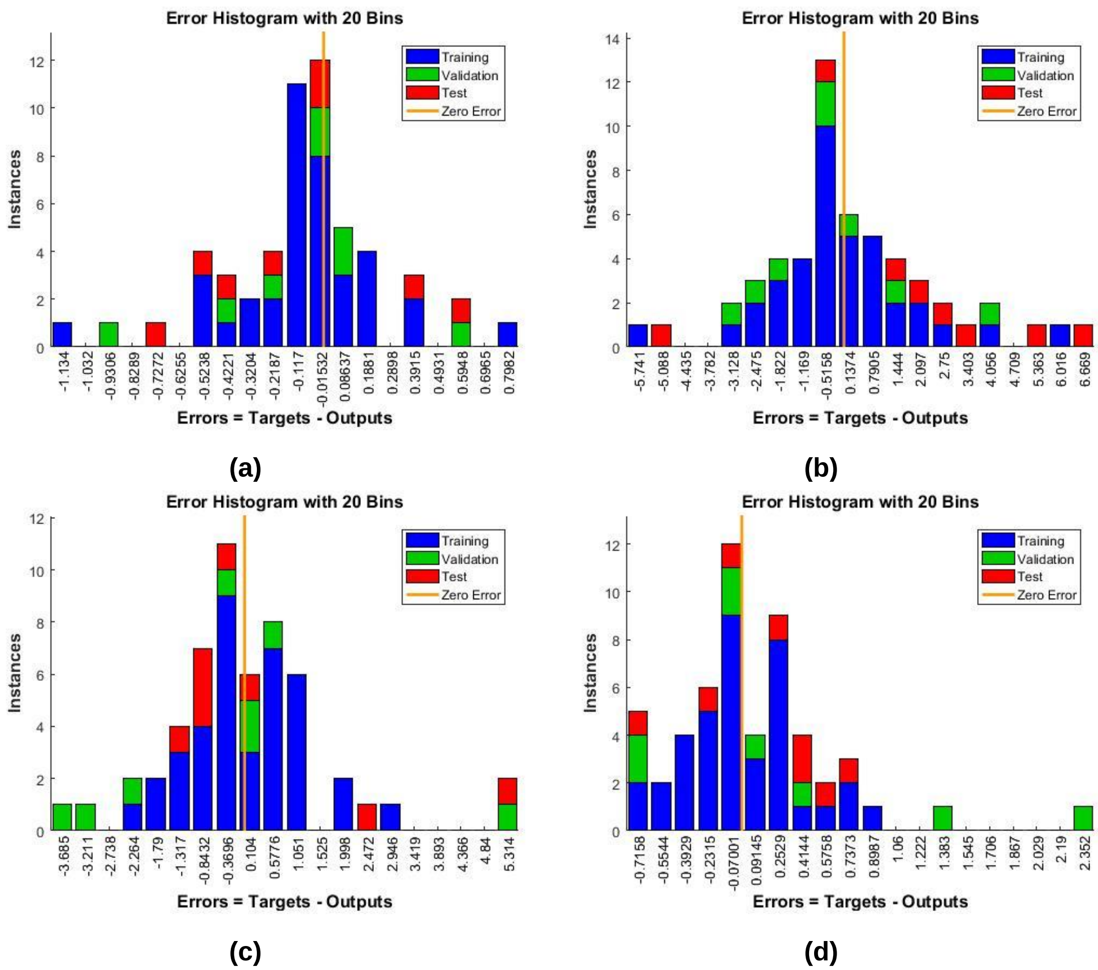
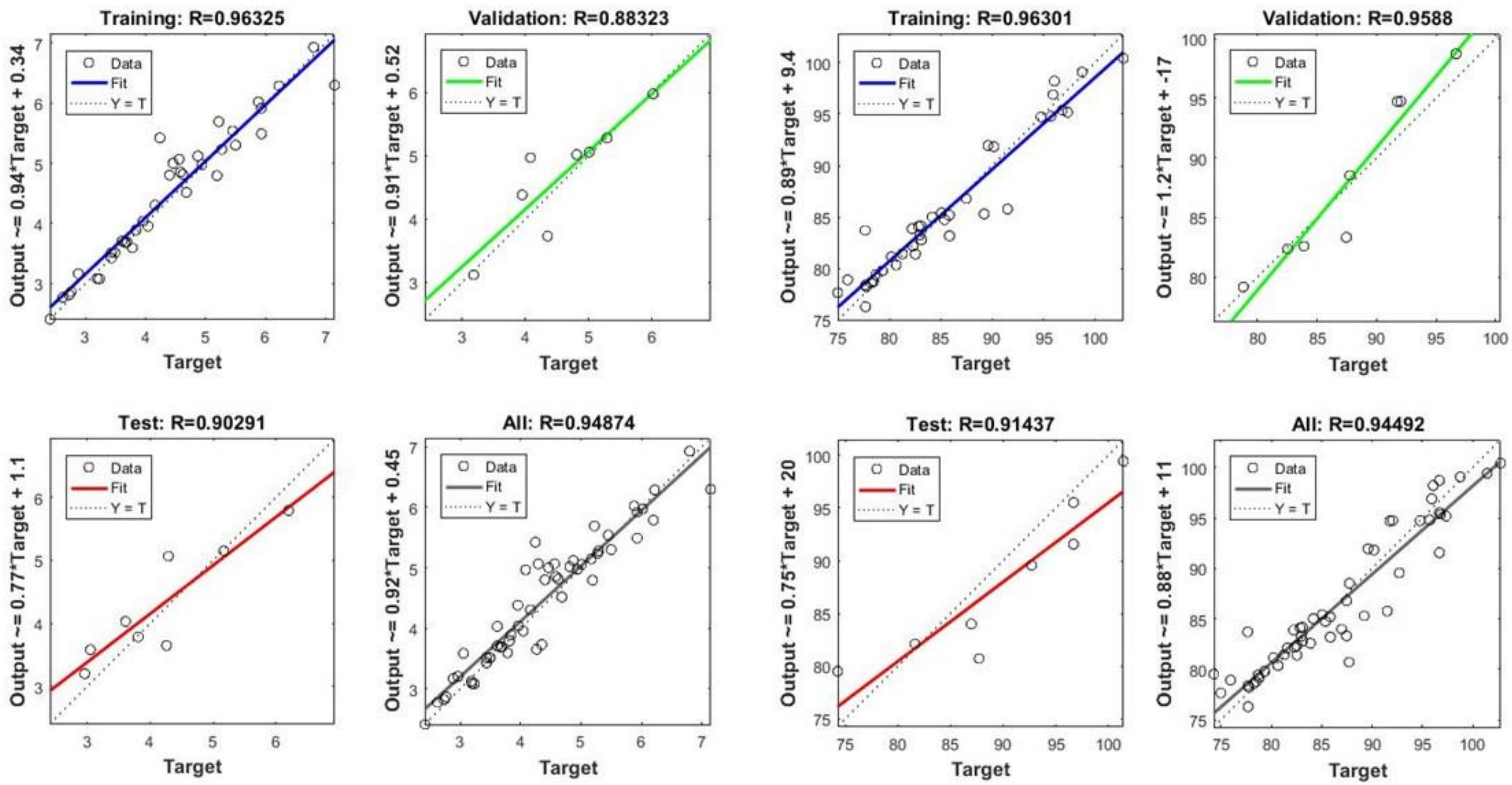


Fig. 4. Error histograms of the surface roughness (a), wettability (b), energy consumption (c) and processing time (d) prediction models

Regression analysis between predicted values and measured values is often used to evaluate the validity and accuracy of networks. The estimation accuracy of models increases when the Pearson correlation coefficients approach to 1 (Ozsahin 2012). This indicates that there is a perfect fit between the real values and the predicted values. The diagrams showing the relationships between calculated values and real values are presented in Figs. 5 and 6. The Pearson correlation coefficients of the surface roughness prediction model were 0.96325, 0.88323, 0.90291, and 0.94874 respectively for the training, validation and testing data sets and for all data sets. These values for the wettability prediction model were 0.96301, 0.95880, 0.91437, and 0.94492, respectively. These values for the energy consumption prediction model were 0.99977, 0.99925, 0.99950, and 0.99956, respectively. These values for the energy consumption prediction model were 0.99992, 0.99926, 0.99958 and 0.99979, respectively. These values showed that the developed models have a good performance and supported the predictive use of ANNs.



(a) (b)

Fig. 5. Regression plots of the surface roughness (a) and wettability (b) prediction models

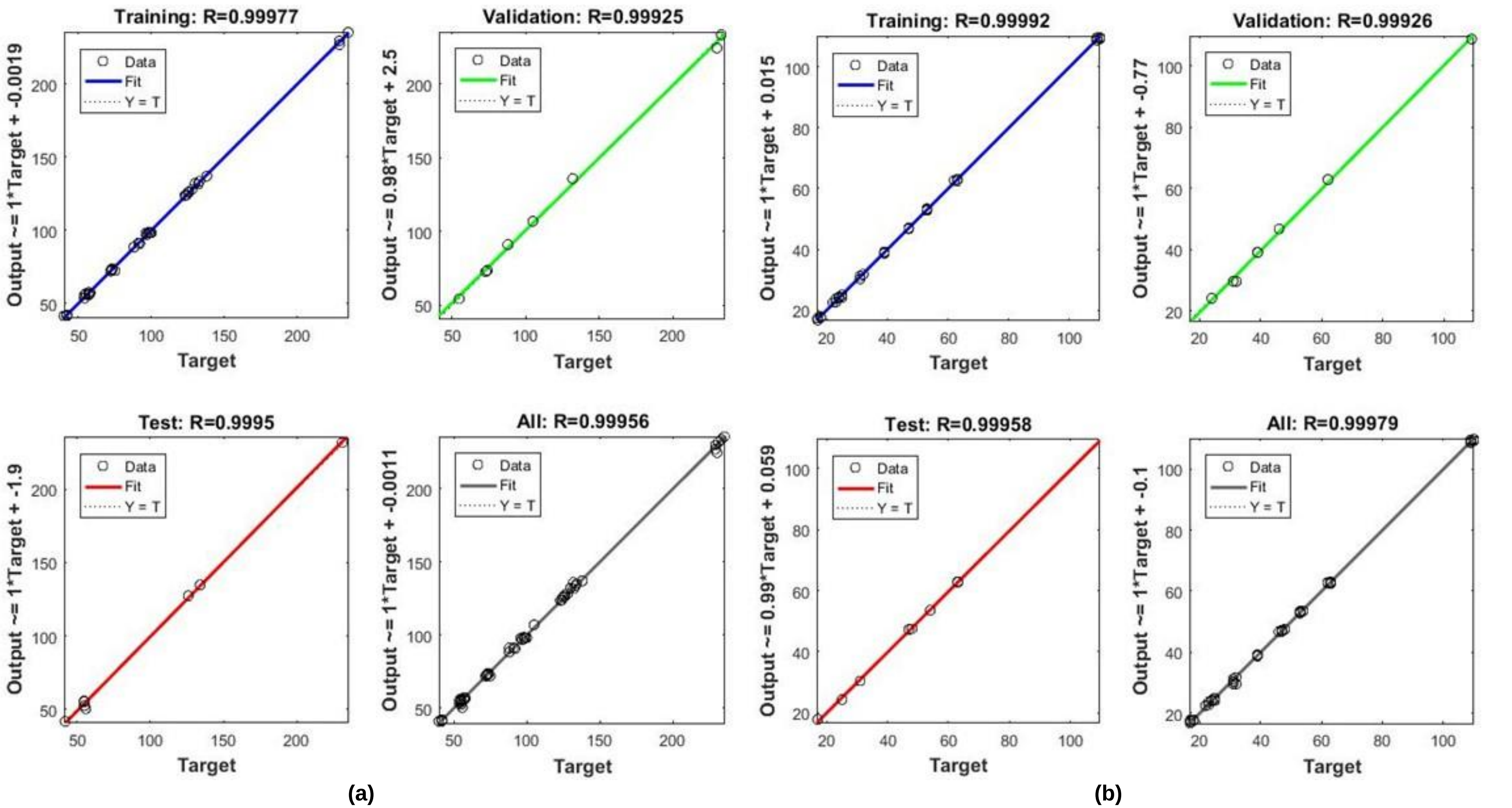


Fig. 6. Regression plots of the energy consumption (a) and processing time (b) prediction models

Optimization Results

Thanks to ANN models with low error values (MAPE and RMSE) and high performance, output values can be predicted with high accuracy for intermediate input values that are not used in experiments (Varol *et al*. 2018). In this study, the surface roughness, wettability, energy consumption, and processing time values were determined by the ANN prediction models for different spindle speed and feed rate values and were shown in Figs. 7 through 10 according to the wood species and tool diameter.

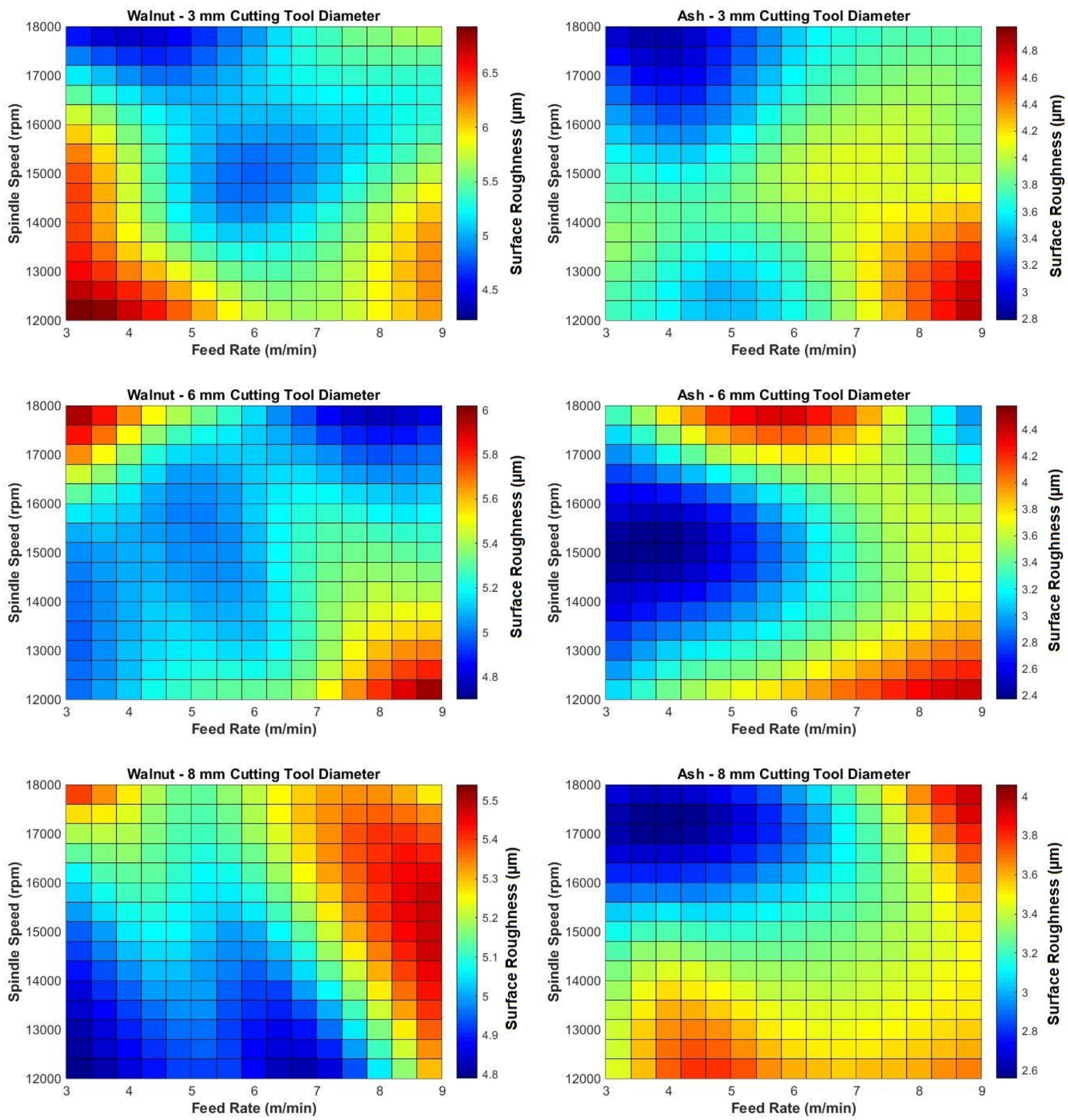


Fig. 7. Effects of CNC cutting conditions on the wood surface roughness

Figure 7 shows that the surface roughness prediction values vary considerably according to the wood species and cutting tool diameter. The smoothest surfaces were obtained from high spindle speed values in both wood species of wood samples processed with 3 mm cutting tool. Furthermore, similar changes were observed in the walnut wood processed with 6 mm cutting tool and the ash wood processed with 8 mm cutting tool.

Suresh *et al*. (2012) stated that with increasing spindle speed, the temperature in the cutting zone increases, causing the material surface to soften, and therefore the surface roughness of the material decreases. In addition, high spindle speed causes less vibration by removing less material from the cutting tooth, and therefore, the surface roughness is reduced (De Deus *et al*. 2015).

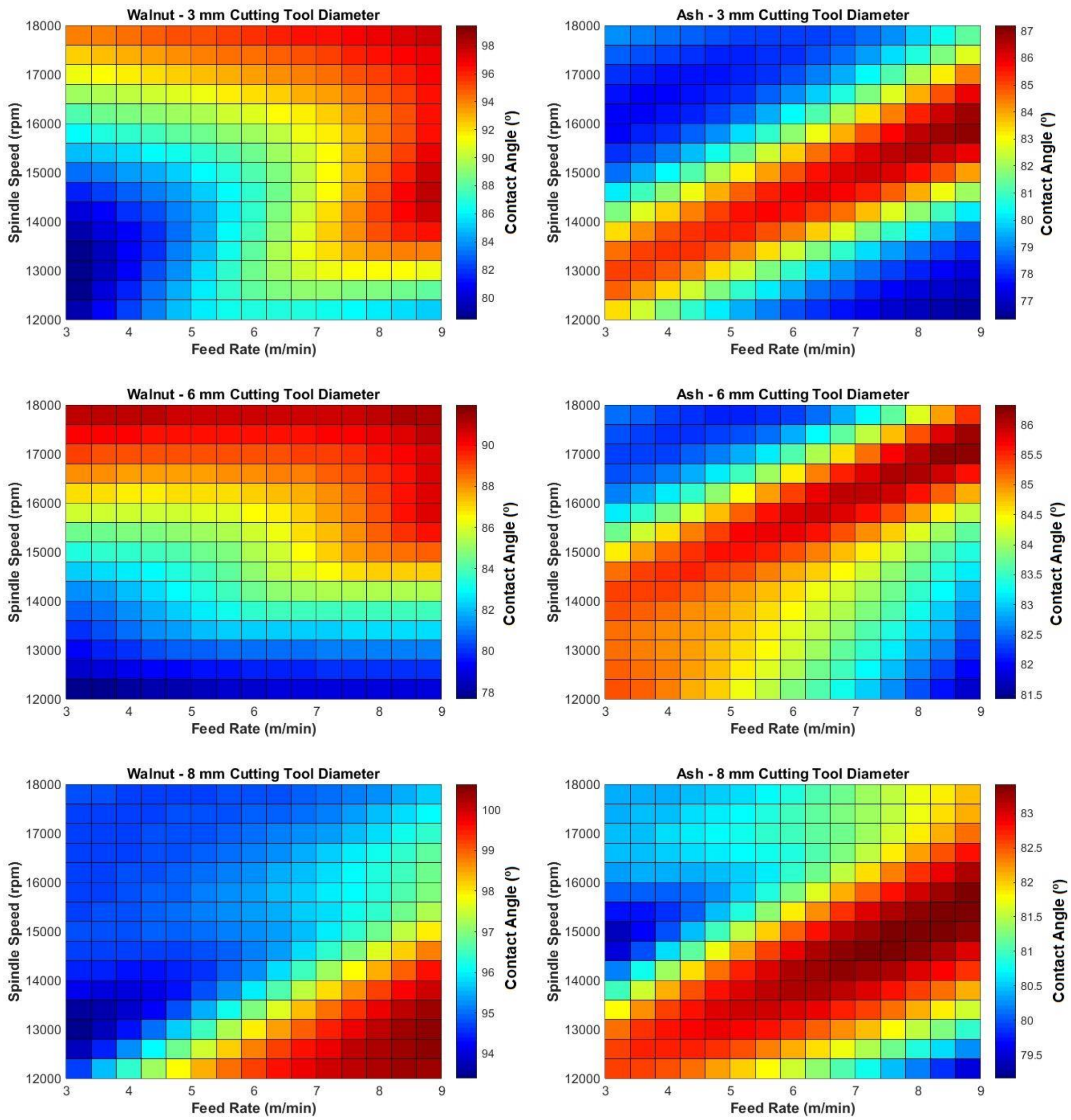


Fig. 8. Effects of CNC cutting conditions on the wettability of wood surface

Higher spindle speed causes higher tooth passing frequencies, shortening the plane area, reducing the chip thickness, and as a result smoother surfaces are obtained (Sarikaya and Gullu 2014). The same relationship between spindle speed and surface roughness was found in many studies (Prakash and Palanikumar 2011; Sofuoglu 2017; Sedlecký *et al.* 2018; Hazir and Koc 2019). The lowest surface roughness prediction values were obtained from low feed rate values, especially for ash wood. Both the vibration and temperature between the workpiece and the cutting tool increase, depending on the increase in the feed rate, and therefore the surface roughness increases (Suresh *et al*. 2012).

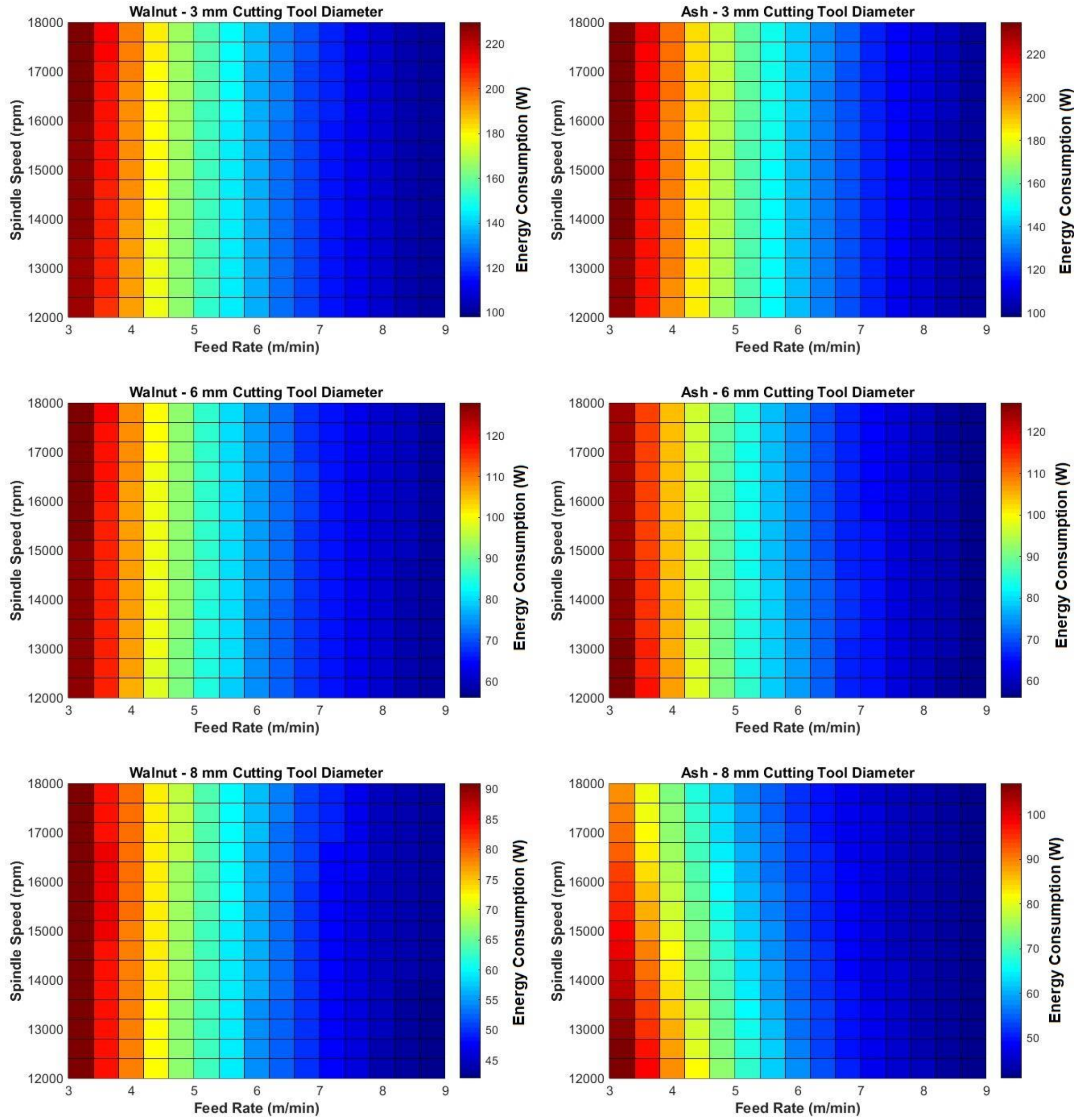


Fig. 9. Effects of cutting conditions on the energy consumption of CNC process

The smoothest surfaces are obtained from low feed rate values (De Deus *et al*. 2015; Koc *et al*. 2017; Isleyen and Karamanoglu 2019). Moreover, the highest surface roughness values were predicted at 3 mm cutting tool diameter in both wood species. The smoothest surface of the samples also differed according to wood species and tool diameter. Although the most effective cutting conditions on the surface roughness of CNC machines are spindle speed and feed rate, tool geometry and tool diameter are some of the other effective conditions (Prakash and Palanikumar 2011). In this study, the surface roughness values of ash wood were generally found to be lower than walnut wood. Zhong *et al.* (2013) compared the surface roughness values of many wood species, including ash and walnut wood, and found that ash wood had smoother surfaces than walnut wood.

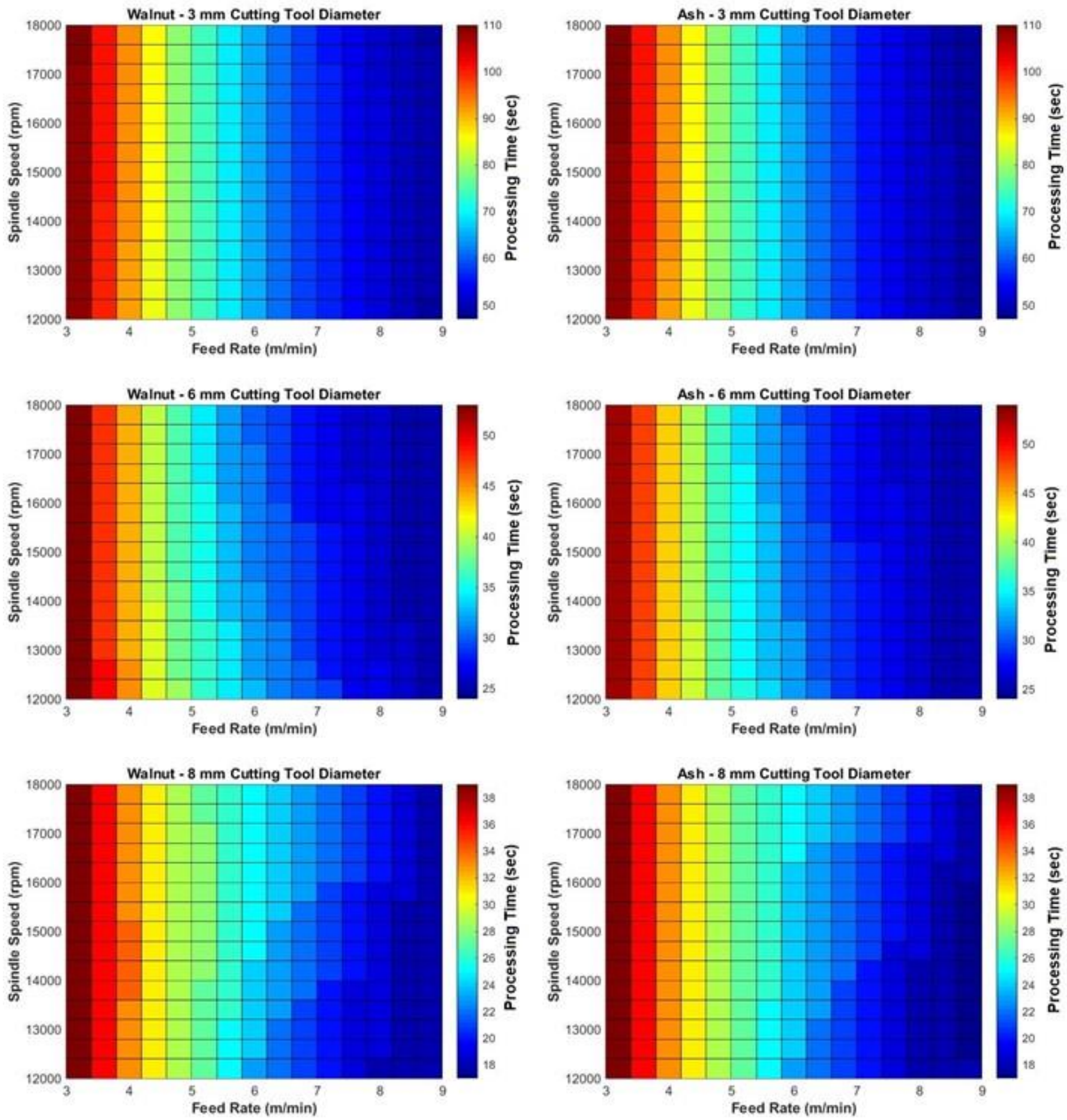


Fig. 10. Effects of cutting conditions on the processing time of CNC process

Figure 8 shows the prediction of the contact angle values indicating the wettability of the CNC machined wood sample surfaces and their differences according to the wood species and cutting tool diameter. Chemical residues and dust particles cause contamination of the surfaces of the materials due to their different wetting and adsorption properties, and therefore different contact angles can be obtained from these heterogeneous surfaces (Chau *et al*. 2009). In this study, the lowest contact angles with the best wettability were generally obtained from low spindle speed values. The lowest contact angle values were obtained from the lowest feed rate value for walnut wood whilst they were obtained from the highest feed rate value for ash wood. In the literature, Demir *et al*. (2021b) found that the contact angles of CNC-machined medium density fibreboard (MDF) samples increased with the increase in feed rate while Hosseinabadi *et al*. (2018) found that the contact angles of CNC-machined metal samples decreased with the increase in feed rate. These show that the type of material processed with CNC is an important factor in the effect of the feed rate. In this study, 3 mm cutting tool diameter gave the highest contact angle values for ash wood, while 8 mm cutting tool diameter gave the highest contact angle values for walnut wood. In general, it was determined that the contact angle values of ash wood were higher than walnut wood. The similar relationship was also seen in the surface roughness values. A close relationship was observed in the literature between the surface roughness and wettability of wood material surfaces (Ayrilmis 2011; Unsal *et al*. 2011). Moreover, wettability is known as one of the functions of surface roughness and the contact angles increased as the surface roughness of wood and wood-based panels increased (Mittal 2008; Akgul *et al*. 2012; Candan *et al*. 2012).

Figures 9 and 10 show that there was a similar relationship between energy consumption and processing time, spindle speed and feed rate in both wood species and all cutting tool diameters. As a result of the experiments and predictions, it has been determined that the feed rate is a very effective parameter in both energy consumption and processing time. Similarly, Camposeco-Negrete (2013) found that feed rate is the most significant factor for minimizing energy consumption and surface roughness. In this study, the energy consumption and processing time values decreased as the feed rate values increased. However, an accurate relationship with the change of spindle speed has not been determined. Bal and Dumankaya (2019) investigated the effects of spindle speed and feed rate on the energy consumption and total processing time of MDF processed in CNC machine and determined that these two properties decrease depending on the increase in the feed rate. However, no statistical difference was found in the processing time while an increase in energy consumption was observed due to the increase in spindle speed (Bal and Dumankaya 2019). Li *et al*. (2019) stated that the production time decreases with the increase in the feed rate, but the spindle speed is one of the main factors and it can increase or decrease the production time. It was observed that energy consumption and processing times decreased for both wood species with the increase in cutting tool diameter.

The values of optimum spindle speed and feed rate based on the surface roughness, wettability, energy consumption, and processing time values could be obtained thanks to prediction models. The optimum spindle speed and feed rate values which gave the smoothest surfaces, the lowest contact angle, minimum energy consumption and processing time are given in Table 6. In addition, the optimum values were predicted among the intermediate tool diameter values that were not used in the study.

Table 6 shows that the optimum spindle speed and feed rate values, which give the lowest values of both surface roughness and contact angle, differ according to wood species and tool diameter.

Table 6. Optimum CNC Parameter Results

	Wood Species	Cutting Tool Diameters (mm)	Spindle Speed (rpm)	Feed Rate (m/min)	Optimum values
Surface Roughness (µm)	Walnut	**3**	**18000**	**3.8**	**4.22**
		4	14800	5.8	4.65
		5	16000	6.2	4.88
		6	18000	7.8	4.70
		7	18000	9	4.66
		8	12000	3	4.79
	Ash	3	18000	3.4	2.79
		4	13600	3.4	2.95
		5	14000	3.4	2.43
		6	**14800**	**3.4**	**2.37**
		7	16000	3.8	2.45
		8	17200	3.8	2.56
Wettability (Contact Angle, º)	Walnut	3	12800	3	78.44
		4	**14000**	**3**	**68.49**
		5	14000	3	69.41
		6	12000	3	77.68
		7	12000	3	89.87
		8	12800	3	93.39
	Ash	**3**	**12000**	**9**	**76.32**
		4	12000	9	77.82
		5	12000	9	79.94
		6	12000	9	81.43
		7	12000	9	79.12
		8	12000	9	79.16
Energy Consumption (W)	Walnut	3	16000	9	98
		4	12000	9	83
		5	12000	9	68
		6	12000	9	56
		7	12000	9	48
		8	**12000**	**9**	**42**
	Ash	3	14000	9	98
		4	15600	9	82
		5	17200	9	67
		6	18000	9	56
		7	12000	9	47
		8	**14400**	**9**	**41**
Processing Time (sec)	Walnut	3	12000	9	47
		4	12000	9	37
		5	18000	9	31
		6	15200	9	24
		7	15200	9	19
		8	**15600**	**9**	**17**
	Ash	3	18000	9	47
		4	12000	9	37
		5	18000	9	30
		6	13600	9	24
		7	14000	9	19
		8	**14400**	**9**	**17**

Among all variables, the smoothest samples for walnut wood were obtained from 3 mm cutting tool diameter, 18000 rpm spindle speed and feed rate 3.8 m/min. In the ash wood, these values were 6 mm cutting tool diameter, 14800 rpm spindle speed and 3.4 m/min feed rate. In the parameter optimization studies on the surface roughness of solid wood samples processed with CNC machines in the literature, different values were found according to the specified parameter ranges, wood species, and prediction methods used. In our previous study, the optimum CNC machining parameter results were 2 mm cutting tool diameter, 10000 rpm spindle speed and 5 m/min feed rate for spruce wood, 4 mm cutting tool diameter, 12500 rpm spindle speed, and 5 m/min feed rate for beech wood (Demir *et al*. 2021a). While Hazir and Ozcan (2019) found these values as 8 mm cutting tool diameter, 17377 rpm spindle speed, and 2.012 m/min feed rate for cedar wood, Hazir and Koc (2019) in another study determined as 9.88 mm cutting tool diameter, 21000 rpm spindle speed, and 2.21 m/min feed rate for beech wood. Furthermore, Gürgen *et al*. (2022) found the optimum parameter results for pine wood as 17900 rpm spindle speed and 3 m/min feed rate. In this study, the samples with the highest wettability were obtained in walnut wood with a 4 mm cutting tool diameter, 14000 rpm spindle speed and 3 m/min feed rate while these values were determined as 3 mm cutting tool diameter, 12000 rpm spindle speed and 9 m/min feed rate in the ash wood.

Table 6 shows that the feed rate in the energy consumption and processing time was the same among all groups, and the spindle speed differed according to the wood species and tool diameter. The most energy-saving cutting conditions were 12000 rpm spindle speed for walnut wood, 14400 rpm spindle speed for ash wood, and 8 mm cutting tool diameter and 9 m/min feed rate for both wood species. The most time-saving cutting conditions were 15600 rpm spindle speed for walnut wood and 14400 rpm spindle speed for ash wood and 8 mm cutting tool diameter and 9 m/min feed rate for both wood species.

Apart from the CNC cutting conditions used in this study, there are many parameters such as tool geometry, tool strategy, step-over, and depth of cut. Therefore, based on this study, it is recommended to make optimization estimates for other parameters in future studies. Furthermore, in studies where similar wood species will be used, tool diameter, spindle speed and feed rate can be determined by utilizing the findings of this study.

CONCLUSIONS

1. The MAPE values of surface roughness, wettability, energy consumption and processing time prediction models were calculated as 9.60%, 3.86%, 2.33%, and 1.53%, whilst the RMSE values of these were 0.45, 3.98, 2.22, and 0.51 in the testing data sets, respectively. The Pearson correlation coefficient (R) values of these were 0.94874, 0.94492, 0.99956, and 0.99979 in all data sets, respectively. Although there was a complex and non-linear relationship between the input and output variables in the study, the performances of the models were validated with diagnostic tools and accurate, encouraging, and satisfactory results were obtained.
2. The output values corresponding to the intermediate cutting conditions not used in the study were also successfully predicted. Among all predicted groups, optimum cutting tool diameter, spindle speed and feed rate values, which gave the smoothest surface samples, were 3 mm, 18000 rpm and 3.8 m/min in walnut wood, while these values

were 6 mm, 14800 rpm and 3.4 m/min in ash wood, respectively. The values, which gave the highest wettability samples, were 4 mm, 14000 rpm and 3 m/min in walnut wood, while these values were 3 mm, 12000 rpm and 9 m/min in ash wood, respectively.

3. The optimum cutting tool diameter and feed rate values, which minimized energy consumption and processing time, were 8 mm and 9 m/min for both wood species, respectively. The spindle speed values for energy consumption were 12000 rpm in the walnut wood and 14400 rpm in the ash wood. The values for processing time were 15600 rpm in the walnut wood and 14400 rpm in the ash wood.
4. In the case of using another cutting between 3 mm and 8 mm tool diameters, the cutting conditions for walnut and ash wood that gave the smoothest surface, lowest contact angle, minimum energy consumption and processing time can be determined from Table 6. Moreover, Figs. 7 to 10 can be used to determine surface roughness, contact angle values, energy consumption and processing time of walnut and ash wood processed with CNC at any spindle speed (between 12000 and 18000 rpm) and feed rate (between 3 m/min and 9 m/min) without conducting experimental research.
5. It is thought that the findings obtained from the study will make a significant contribution to both science and industry. The surface quality properties of wood species that are frequently used in the furniture industry such as walnut and ash can be predicted according to any cutting conditions, and energy and time losses can be minimized. Optimization studies using methods such as ANN that will minimize material losses and save time and energy in CNC cutting processes are extremely important. The accuracy of the prediction models decreases in the case of using other values outside the cutting conditions ranges used in the study and using different tree species. These are the main shortcomings of this study and similar optimization studies. Therefore, further optimization studies of CNC cutting conditions are needed in the literature in the future.

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