WOOD RESEARCH doi.org/10.37763/wr.1336-4561/70.2.286298
e-ISSN 2729-8906
70(2): 2025 286-298 pp.

MODELLING OF BIRCH WOOD (BETULA SPP.) SURFACE ROUGHNESS DEPENDING ON LASER PROCESSING PARAMETERS WITH RESPONSE SURFACE METHODOLOGY

ÇAĞATAY ERSİN
ÇANKIRI KARATEKİN UNIVERSITY
TÜRKİYE

MEHMET GÜNEŞ
ÇANKIRI KARATEKİN UNIVERSITY
TÜRKİYE

(RECEIVED MARCH 2025)

ABSTRACT

In this study, the effect of laser engraving parameters on birch wood surface roughness was investigated with response surface methodology (RSM) and a mathematical model was developed. Laser power (W%), speed (mm/min) and space (mm) were selected as independent variables. Ra, Rq and Rz surface roughness indices were measured as response variables. In the study, 20 experimental conditions were conducted with 3-factor and 3-level experimental designs using central composite design (CCD). Laser engraving power and space were determined as the most effective factors on surface roughness. Regression models were developed for each surface roughness index and the measurements were estimated. In the model created for Ra surface roughness, $R^2 = 97.0\%$ and the average error was found to be 4.9%, for Rq, $R^2 = 96.8\%$ and the average error was found to be 4.5%, for Rz, $R^2 = 96.6\%$ and the average error was found to be 4.0%. It is understood that the surface roughness values will be predicted with high accuracy with the created model.

KEYWORDS: Laser engraving, birch, surface roughness, optimization, response surface methodology.

INTRODUCTION

Wood is very important in industrial uses as it is a renewable and environmentally friendly material (Demir et al. 2022). However, high surface quality during wood processing affects the aesthetic, functional, and mechanical properties of the final product (Bal 2018; Kang et al. 2023). Smooth surfaces increase the quality of processes such as coating, painting, and varnishing and extend the service life of the product (Poletto 2017). While traditional wood processing methods include cutting, sanding, and milling with the development of technology.

CNC and woodworking machines have gained an important place in these processes (Hazir & Ozcan 2019). Woodworking machines offer a more consistent quality on machined surfaces by increasing precision in production (Miccoli et al. 2014). The most important factors determining the surface quality in wood processing include cutting speed, feed rate, depth of cut, and tool geometry (Kaba & Bal 2024). While roughness increases with increasing cutting speed, surface quality can be positively affected at low feed rates (Ay & Madenci 2024). In addition, parameters such as cutting angle and tool diameter significantly affect surface roughness (Yaghoubi & Rabiei 2024). The moisture content of the material used and the type of tool can be decisive on surface quality (Dumanoglu & Bal 2022). In recent years, artificial intelligence (AI) and machine learning techniques have taken an important place in woodworking research to improve surface quality (Demirdöğen et al. 2022). Artificial neural networks (ANNs) and genetic algorithms have been applied to optimize wood processing parameters to predict optimal roughness (Loc & Hung 2021). These methods require less time and cost than traditional experimental processes and increase production efficiency (Bostan & Bal. 2023). With modeling and prediction tools such as RSM, it is possible to determine and optimize the effects of parameters such as cutting time, focal length, and laser power on surface quality (Corleto et al. 2024). It shows that CO_2 laser cutting significantly changes the roughness of the wood surface and that the surface quality can be improved by optimizing certain parameters (Vosniakos et al. 2024; Henke et al. 2022). Especially in fine fibrous material such as birch, the variation of laser power and feed rate can cause micro-roughness on the surface (Žigon et al. 2025). Laser-processed surfaces of different wood species were found to have different surface morphologies compared to conventional processing methods (Islam et al. 2023). Therefore, industry and academic research need to study the effects of the CO_2 laser cutting process in detail and determine the optimal processing parameters (Reinprecht & Vidholdová 2021; Nugraha et al. 2024). It was determined that moderate laser power and slow feed rate provided the best surface quality when processing larix wood with CO_2 laser (Gurău et al. 2021). The relationship between laser parameters, grain, and material type was investigated in hardwoods, and it was found that lower laser power provided better surface quality (Agus 2023). It was determined that the surface roughness increases with increasing CO_2 laser cutting speed, but it negatively affects the surface quality at extremely low speeds (Brenci & Gurău 2023). It has been observed that the use of oxygen gas in laser cutting causes excessive carbonization, while nitrogen gas provides better surface quality by reducing roughness (Stutzman et al. 2021). The effect of different cutting angles, the width of the heat-affected zone, and the carbonization effect on surface quality in laser engraving of wood has been studied in detail (Dogan et al. 2024). Existing research has evaluated specific wood species or limited process parameters, and most studies are based on experimental approaches. However, some research has focused on surface roughness prediction using modern optimization methods (Rezaei et al. 2022). In particular, there is an increasing use of AI-assisted prediction models for determining the optimal parameters in CO_2 laser cutting (Adamčík et al. 2024). Compared to conventional cutting methods, laser cutting has been found to provide smoother edges and lower material loss (Gurau et al. 2024; Sobri et al. 2025). In this study, the factors affecting surface quality in CO_2 laser cutting processes were comprehensively discussed and comparisons were made with studies in the literature.

MATERIAL AND METHODS

Wood material

Birch (*Betula Spp.*) samples were selected by random selection method and were cleaned from surface roughness such as knots, cracks, grain curl and elements that would negatively affect the laser engraving process. In order to ensure that the tangential cross-section surface taken from the birch tree was smooth, it was sanded with 240 numbered sandpaper and made ready for the tests. Sample dimensions were determined as 5×100×150 mm. Before the laser process, all samples were kept in an air conditioning cabinet set at 20ºC ± 1□ and 65 ± 2% relative humidity levels in order to reach 10 ± 1% moisture content under the determined experimental conditions until they reached a constant weight.

Surface roughness tests

Surface roughness measurements were carried out using the Mitutoyo SJ-410 device. The image of the samples engraved with the CO_2 laser cutting device is shown in Fig. 1.

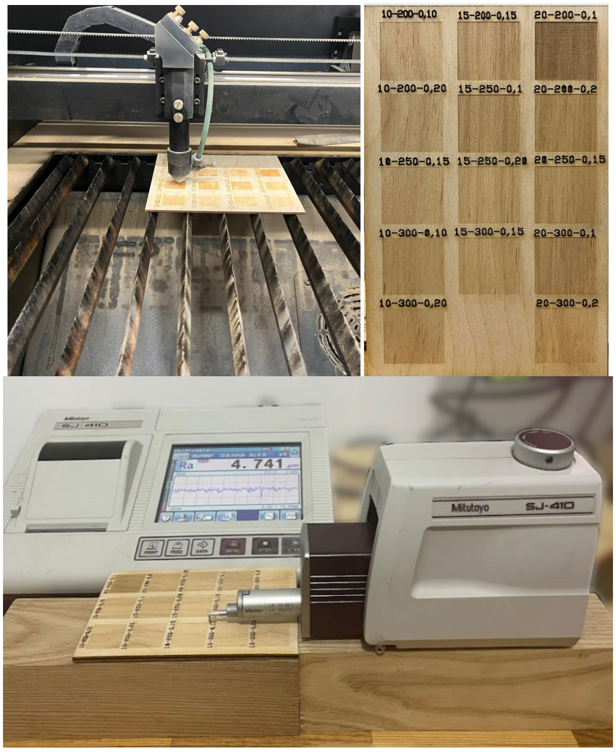

Fig. 1: Surface roughness measurement setup and test samples.

Roughness measurements were made in two different directions parallel and perpendicular to the wood grain direction. Ra, Rz and Rq indices were used to evaluate surface roughness. Measurements were determined as 20 mm measuring length, 5.5 mm/s measuring speed, λc (cut-off wavelength) = 2.5, λs (Short-wavelength cut-off) = 8 in the ISO 21920-2:2021 (Geometrical Product Specifications (GPS) - Surface texture: Profile) and repeated ten times in both directions perpendicular and parallel to the grain and the average was taken. Roughness values measured parallel and perpendicular to the grain direction were obtained as Ra, Rz, and Rq parallel and perpendicular, respectively.

Experimental design

In this study, Response Surface Methodology (RSM) was used to optimize the factors affecting the determined dependent variable. RSM is a statistical and mathematical technique used to model and optimize the effects and possible interactions of factors in multivariate systems. Central Composite Design (CCD) approach was preferred for experimental design. CCD consists of three basic components: 2^3=8 diagonal points, 2x3=6 axes, 6 center points (recommended number of repetitions). In this study, 3 factors (power, speed and space) were selected and each was evaluated at 3 levels. In this direction, a total of 20 experimental conditions were carried out. The dependent variables targeted for optimization in the study were determined as Ra, Rq and Rz surface roughness values. Independent variables are indicated in Table 1 as A: Power (W%), B: Speed (mm/min), C: Space (mm). The minimum, medium and maximum levels of these factors were determined based on preliminary trials and literature review.

Tab. 1: Laser engraving parameters.

Independent variables	Symbol	Level		
Power W (%)	A	10	15	20
Speed (mm/min)	B	200	250	300
Space (mm)	C	0.10	0.15	0.20

Modelling and statistical analysis

The collected experimental data were analyzed using a quadratic model with the following Eq. 1:

$$Y = b_0 + \sum_{i=1}^{k} b_i X_i + \sum_{i,j}^{k} b_{ij} X_i X_j + \sum_{i=1}^{k} b_{ii} X_i^2 + \qquad (1)$$

where: Y is the dependent variable, b_0 is the constant term, bi is the linear coefficients, b_i is the quadratic coefficients and b_{ij} is the interaction coefficients. ε is the error term.

Model fit was evaluated with R^2 (determination coefficient), adj-R^2 and p-values. In addition, ANOVA (Analysis of variance) was performed in the Minitab 21.4 program for the validity of the model. Using the model obtained for optimization, the optimum levels of the independent variables were determined in such a way that the highest value of the dependent variable would be obtained.

RESULTS AND DISCUSSION

The surface roughness values of Ra (roughness average), Rq (root mean square) and Rz (mean peak-to-valley height) for birch were measured with a needle probe tip measuring device at a measurement distance of 20 mm with a linearity deviation of 0.3 µm with high accuracy. The measurement results are shown in Tab. 2. The estimated values of the values measured from 20 test samples with CCD are also given in the table. According to the data obtained from all tests, the average estimation error rate of the model for Ra roughness values was determined as 4.6%, the average error for Rq was 4.3%, and the average error for Rq was 3.9%. These average error rates were found to be approximately 5% in a similar RSM study on beechwood by Corleto et al. Demir et al. also reported an average absolute error rate of approximately 4.8% in the ANN model they developed for birch wood surface quality. When the percentages are examined, it is seen that the estimation percentage of the model is high.

Tab. 2: Cutting parameters and surface roughness.

No	Power (W%)	Speed (mm/min)	Space (mm)	Ra (µm)	Rq (µm)	Rz (µm)
1	10	200	0.10	9.29	12.25	75.54
2	20	200	0.10	22.77	28.20	139.47
3	10	300	0.10	7.76	10.74	71.96
4	20	300	0.10	21.42	27.01	139.89
5	10	200	0.20	7.54	9.72	57.82
6	20	200	0.20	12.71	16.38	92.41
7	10	300	0.20	6.02	8.00	51.67
8	20	300	0.20	14.49	19.15	107.06
9	10	250	0.15	7.67	10.33	65.52
10	20	250	0.15	15.55	20.10	108.54
11	15	200	0.15	17.37	22.23	115.32
12	15	300	0.15	12.60	17.05	98.59
13	15	250	0.10	17.51	22.26	114.89
14	15	250	0.20	11.40	15.41	90.46
15	15	250	0.15	13.50	17.32	96.87
16	15	250	0.15	14.12	18.33	103.33
17	15	250	0.15	14.50	18.74	106.19
18	15	250	0.15	13.83	17.67	96.48
19	15	250	0.15	14.25	18.48	105.00
20	15	250	0.15	13.98	18.44	106.52

Tab. 3 shows the results of the variance analysis of Ra surface roughness. It is seen that the model explains 96.98% of the total variance; this is a very high explanatory power. The most effective factor is the A parameter with a contribution rate of 64.16% and a significance level of $p < 0.001$.

Tab. 3: Variance analysis of Ra.

Source	DF	Adj SS	Contribution	Adj MS	F-value	P-value
Model	9	358.022	96.98%	39.780	35.66	0.000
Linear	3	313.074	84.80%	104.358	93.56	0.000
A	1	236.879	64.16%	236.879	212.37	0.000
B	1	5.469	1.48%	5.469	4.90	0.049
C	1	70.726	19.16%	70.726	63.41	0.000
A x B	1	1.524	0.41%	1.524	1.37	0.270
A x C	1	22.775	6.17%	22.775	20.42	0.001
B x C	1	1.225	0.33%	1.225	1.10	0.319
Error	10	11.154	3.02%	1.115		
Total	19	369.176	100.00%			

DF: Degrees of freedom Adj SS: Adjusted sum of squares. Contribution: Contribution (to Total Variation). Adj MS: Adjusted mean squares. F-value: F-statistic. P-value: Probability value.

Brenci & Gurău’s study on beech wood with a CCD design found that laser power was the most effective parameter explaining approximately 66% of the variance in surface roughness. The C factor is also statistically significant with a contribution of 19.16% (p = 0.000). In the RSM study conducted by Nugraha et al. with plywood, dot spacing (space) accounted for 18–20% of the variance. The contribution of the B factor is limited (p = 0.049) and is at the limit of statistical significance. Only the AxC combination was found to be significant (p = 0.001) among the binary interactions, and the contribution of the other interaction factors is negligible. The low error percentage of the model (3%) shows a strong fit.

The results of the variance analysis performed for the surface roughness Rq in Tab. 4 show that the model is highly significant and successfully explains 97.01% of the total variance. Among the variables, the A factor alone played a decisive role by explaining 65.68% of the change in the model. This confirms that this parameter is a dominant factor in the system. Similarly, in the ANN model applied to birch wood processed with CNC by Demir et al. (2022), it was shown that the power parameter was more effective than speed and space. The C factor also made a significant contribution (18.55%) and showed a strong statistical significance (p = 0.000). On the other hand, the B factor was not found to be statistically significant in terms of its effect on Rq (p = 0.121) and its effect within the model was limited. When the binary interactions are examined. It is seen that only the AxC factor is significant (p = 0.003), and the other interactions showed a statistically weak effect. The error margin of the model was found to be at the level of 2.99% which supports the reliability of the results.

Tab. 4: Variance analysis of Rq.

Source	DF	Adj SS	Contribution	Adj MS	F-value	P-value
Model	9	528.272	97.01%	58.697	36.04	0.000
Linear	3	463.361	85.09%	154.454	94.83	0.000
A	1	357.645	65.68%	357.645	219.59	0.000
B	1	4.675	0.86%	4.675	2.87	0.121
C	1	101.040	18.55%	101.040	62.04	0.000
A x B	1	2.898	0.53%	2.898	1.78	0.212
A x C	1	25.974	4.77%	25.974	15.95	0.003
B x C	1	1.753	0.32%	1.753	1.08	0.324
Error	10	16.287	2.99%	1.629		
Total	19	544.559	100.00%			

The variance analysis performed for the surface roughness Rz in Tab. 5. shows that the model created has a very strong explanatory power. The variable with the highest effect was by far the A factor; this factor stood out as a determining parameter on Rz with a contribution rate of 66.51% and a very high F-value (204.87).

Tab. 5: Variance analysis of Rz.

Source	DF	Adj SS	Contribution	Adj MS	F-value	P-value
Model	9	10205.0	96.75%	1133.88	33.11	0.000
Linear	3	9054.2	85.84%	3018.08	88.14	0.000
A	1	7015.2	66.51%	7015.17	204.87	0.000
B	1	12.9	0.12%	12.94	0.38	0.552
C	1	2026.1	19.21%	2026.13	59.17	0.000

A x B	1	76.9	0.73%	76.86	2.24	0.165
A x C	1	219.3	2.08%	219.28	6.40	0.030
B x C	1	17.0	0.16%	17.00	0.50	0.497
Error	10	342.4	3.25%	34.24		
Total	19	10547.4	100.00%			

Corleto et al. (2024) stated that laser power is the highest determining parameter in the Rz models, which supports this result. Following this, factor C was the second most effective variable with a contribution of 19.21% and showed strong statistical significance ($p < 0.001$). In contrast, the B factor did not have a significant effect on the system ($p = 0.552$) and its contribution to the variance remained negligible. When the interactions were examined, only the AxC binary interaction was found to be statistically significant ($p = 0.030$), and the effect of other interactions on the model was found to be low and insignificant. The low mean square error supports the reliability and predictive ability of the model.

It was understood that the most effective parameters in the laser engraving process for the surface roughness values Ra, Rq and Rz were power and space. When the bilateral interaction of these parameters was examined, it was determined that AxC factors were the most effective.

Surface roughness regression equations

Minitab 21.4 software was used to create models for surface roughness. Due to the higher values of the correlation coefficient (R^2). Quadratic models were chosen to establish the relationship between the input laser parameters and surface roughness. The correlation graph between the predicted value and the actual value also confirms this result (Fig. 2). Detailed models for Ra, Rq, and Rz are shown in Eqs. 2. 3. and 4.

$$Ra = 10.6 + 4.560\,A - 0.238\,B - 31.5\,C - 0.1004\,A^2 + 0.000348\,B^2 + 135\,C^2 + 0.00175\,A \times B - 6.75\,A \times C + 0.157\,B \times C \tag{2}$$

$$Rq = 15.0 + 5.62\,A - 0.305\,B - 42\,C - 0.1314\,A^2 + 0.000455\,B^2 + 133\,C^2 + 0.00241\,A \times B - 7.21\,A \times C + 0.187\,B \times C \tag{3}$$

$$Rz = 72.5 + 23.73\,A - 1.216\,B - 155\,C - 0.613\,A^2 + 0.00184\,B^2 + 127\,C^2 + 0.01240\,A \times B - 20.94\,A \times C + 0.583\,B \times C \tag{4}$$

Ra, Rz and Rq surface roughness values were estimated using the regression equation in Eqs 1. 2 and 3. The estimated values obtained are given in Tab. 6.

Tab. 6: Surface roughness prediction

No	Power (W%)	Speed (mm/min)	Space (mm)	Ra(μm)	Rq(μm)	Rz(μm)	Ra(μm) Predict	Ra(%) Predict Error	Rq(μm) Predict	Rq(%) Predict Error	Rz(μm) Predict	Rz(%) Predict Error
1	10	200	0.10	9.29	12.25	75.54	10.57	13.72	13.74	12.14	80.19	6.15
2	20	200	0.10	22.77	28.20	139.47	22.80	0.13	28.13	0.25	137.45	1.45
3	10	300	0.10	7.76	10.74	71.96	7.49	3.49	10.27	4.39	68.82	4.38
4	20	300	0.10	21.42	27.01	139.89	21.47	0.20	27.07	0.20	138.48	1.01
5	10	200	0.20	7.54	9.72	57.82	7.86	4.19	10.06	3.40	59.22	2.41
6	20	200	0.20	12.71	16.38	92.41	13.34	4.91	17.24	5.20	95.54	3.39
7	10	300	0.20	6.02	8.00	51.67	6.35	5.46	8.46	5.66	53.68	3.88

8	20	300	0.20	14.49	19.15	107.06	13.58	6.30	18.05	5.77	102.40	4.36
9	10	250	0.15	7.67	10.33	65.52	6.86	10.56	9.16	11.35	60.56	7.57
10	20	250	0.15	15.55	20.10	108.54	16.59	6.65	21.15	5.19	113.55	4.61
11	15	200	0.15	17.37	22.23	115.32	15.82	9.00	20.25	8.95	108.10	6.27
12	15	300	0.15	12.60	17.05	98.59	14.40	14.20	18.92	10.93	105.85	7.35
13	15	250	0.10	17.51	22.26	114.89	17.22	1.68	21.95	1.42	116.96	1.79
14	15	250	0.20	11.40	15.41	90.46	11.92	4.57	15.60	1.23	88.44	2.24
15	15	250	0.15	13.50	17.32	96.87	14.24	5.41	18.44	6.45	102.38	5.69
16	15	250	0.15	14.12	18.33	103.33	14.24	0.79	18.44	0.57	102.38	0.93
17	15	250	0.15	14.50	18.74	106.19	14.24	1.85	18.44	1.60	102.38	3.60
18	15	250	0.15	13.83	17.67	96.48	14.24	2.91	18.44	4.34	102.38	6.11
19	15	250	0.15	14.25	18.48	105.00	14.24	0.17	18.44	0.21	102.38	2.50
20	15	250	0.15	13.98	18.44	106.52	14.24	1.79	18.44	0.03	102.38	3.89
							Average Error	4.9%		4.5%		4.0%

The regression graph showing the relationship between the actual Ra and the Ra predicted by the model (Fig. 2a). There is a high accuracy relationship between the predicted and actual values. The regression equation obtained is (Ra = 0.0000 + 1.000 × Ra $_{\text{Predict}}$). The R^2 value is 96.8%. This reveals that the predictions are quite reliable. The green line on the graph represents the confidence interval for the regression line at the 95% confidence level, and the purple dashed lines represent the 95% prediction interval. The fact that the blue data points are largely clustered around the regression line shows that the model accurately captures the general trends and that random errors are low. The standard error value (S = 0.7872) indicates that the mean deviation of the predictions is quite low. All these indicators reveal that the created model is extremely successful in predicting Ra values and provides a reliable basis for further analysis.

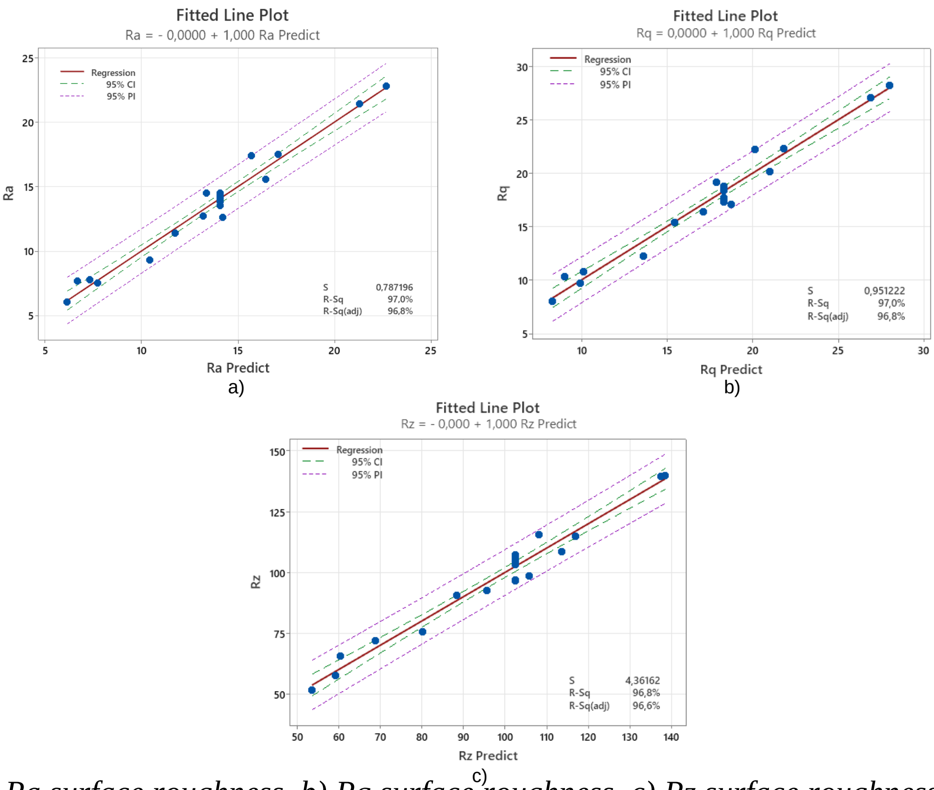

Fig. 2: a) Ra surface roughness. b) Rq surface roughness. c) Rz surface roughness actual and estimated values graph.

The regression line graph (Fig. 2b) showing the relationship between Rq values shows that the model works with high accuracy. The regression equation (Rq = 0.0000 + 1.000 × Rq Predict) reveals that there is no systematic deviation in the predictions. The R^2 value is 96.8%, indicating that the model has a strong explanatory power. The green and purple lines indicate the 95% confidence and prediction intervals, respectively, and the symmetric distribution of data points within these intervals supports the reliability of the model. The standard error value (S = 0.9512) is at a low level. Indicating that the prediction performance is successful. These findings prove that the model is an effective tool in Rq estimation. In Fig. 2c. the relationship between the predicted and observed Rz values is displayed on the graph with high accuracy. The regression line shows that the Rz estimates almost match the actual measurements. The R^2 value was calculated as 96.6%, indicating that the explanatory power of the model is quite strong and stable. The data points distributed around the predicted values show that the model produces reliable results even in a wide range. The standard deviation value showing the average prediction error is S = 4.3616, and this value is at an acceptable level when the general value range of the Rz variable is taken into account. The results show that the model provides a strong prediction performance in terms of both accuracy and reliability.

Surface roughness interaction plots

When the Ra surface graphics are examined, the Ra value increases significantly as the power increases in Fig. 4. but the increase in speed reduces this effect. It is observed that the roughness value reaches the highest levels with low speed and high space distance. It is seen that the Ra value increases rapidly when the power and space distance increase. In general low power, low space distance and high-speed combinations can be recommended to obtain low surface roughness.

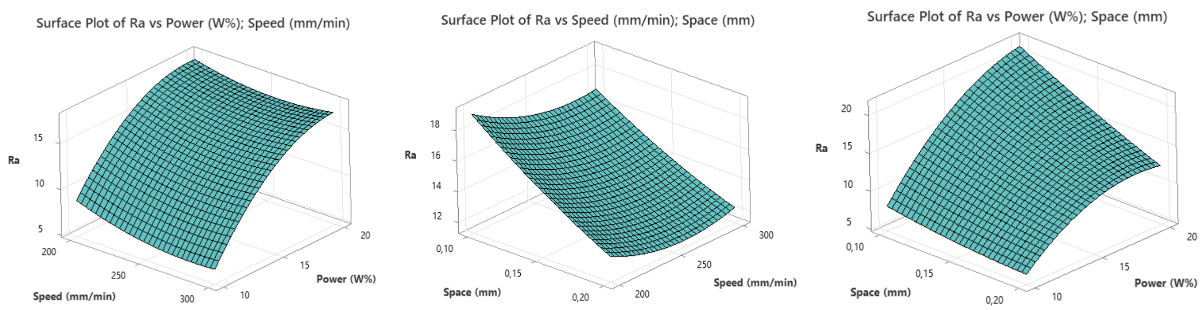

Fig. 4: Ra surface roughness power. speed and space interaction graphs.

When looking at the Rq surface graphs in Fig. 5. the effect of the power parameter is particularly striking. In the first graph, it is observed that while the lowest Rq values are reached with low power and low space values, the increase in these two parameters increases the roughness significantly. The second graph shows the relationship between power and speed; it is seen that the combination of low speed and high power increases the Rq values to higher levels. This indicates that the material surface is scraped more or irregularities are created. In the third graph, speed and space are evaluated together and it is observed that the roughness increases especially in low-speed and increasing space combinations. In general, it is understood that the process conditions have a strong bidirectional effect on Rq, and the lowest roughness can be achieved with low power, high speed and narrow space. Hazir & Ozcan (2019) showed that similarly high feed rate and low feed provide minimum roughness in CNC milling operations.

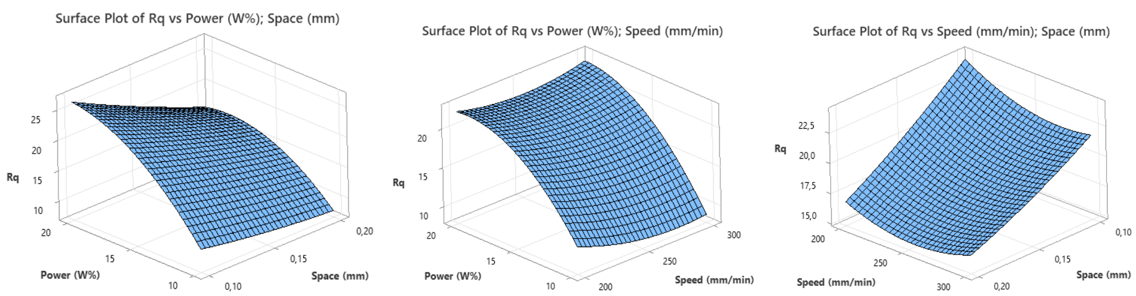

Fig. 5: Rq surface roughness power, speed and space interaction graphs.

The behavior of the Rz value under varying process parameters is shown in the surface graphs in Fig. 5. In the first graph, when the power and speed parameters are evaluated together, it is seen that Rz exhibits a rapid increase especially at increasing power levels. This situation can be explained by the increase in the heat transferred to the surface and the energy density. Although the increase in speed partially limits this effect, high power levels create a dominant effect. In the second graph, it is observed that the Rz values are high under low speed and wide space distance conditions, thus negatively affecting the surface quality. In the third graph, the power and space parameters are considered together; it is understood that the increase in both parameters creates a cumulative increasing effect on Rz.

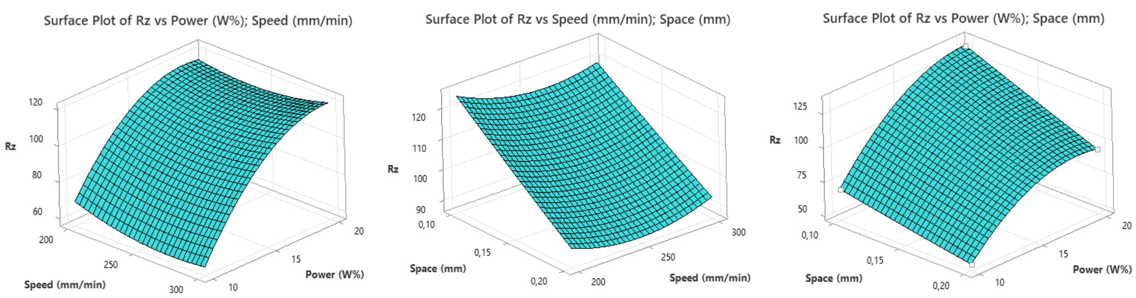

Fig. 6: Rz surface roughness power. speed and space interaction graphs.

These three graphs reveal that it is appropriate to choose low power, narrow space and high-speed combinations to optimize the Rz surface roughness.

CONCLUSIONS

This study focuses on the processing of birch wood surfaces with a CO_2 laser cutting machine and the optimization of surface roughness in this process. In this context, the effects of laser power, speed and space on surface roughness were investigated and modeled using RSM. Laser power was determined as the most effective factor in all three surface roughness parameters. With the increase in the power parameter, deteriorations occurred on the wood surface and surface roughness increased. The increase in space caused a significant increase in roughness values. It was understood that the selected scanning speeds were not a very effective factor in changing the roughness values. A more homogeneous surface was formed in the wood in direct proportion to the decrease in laser power and space. This provided lower surface roughness values. The high R^2 values and low error rates obtained as a result of variance analysis increased the reliability of the model. It was understood that the power and space interaction were the most effective parameters in all three surface roughnesses. When all parameters are taken into consideration, it is understood that the lowest surface roughness values will be obtained at low power, low space and high speeds. It is seen that the average correct prediction percentage of the model created for Ra, Rq and Rz roughness measurements is a high value of 96%.

These findings reveal the necessity of determining the optimal parameter combinations in the laser modification process and are an important guide for industrial applications. In this context, the predictability of laser processing parameters for a wide range of materials can be increased by using multiple optimization techniques.

REFERENCES

1. Adamčík, L., Kminiak, R., & Banski, A. (2024). Comparison of the roughness of the CNC milled surface of selected wood species. *Acta Facultatis Xylologiae Zvolen*. *66*(2). 61-74.
2. Agus, W.G.P. (2023). Effect of CO_2 laser power and speed on surface roughness and color of jabon wood (*Anthocephalus cadamba*). *8*.174-177.
3. Ay, E.B., & Madenci, B. (2024). Effect of cutting parameters on surface roughness in milling S355j2+N steel using carbide tool. *Journal of Engineering Sciences and Design*. *12*(4). 603-615.
4. Bal, B.C. (2018). The effects of some tool paths adjustments of CNC machines on surface roughness and processing time of fiberboards. *Furniture and Wooden Material Research Journal*. *1*(1). 21-30.
5. Bostan, T., & Bal, B.C. (2023). The importance of resolution and tolerance values in the shaping of wood surfaces with CNC machines. *Duzce University Journal of Forestry*. *19*(2). 129-142.
6. Brenci, L.M., & Gurău, L. (2023). A stratified characterization of surface quality of beech processed by profile milling. *Applied Sciences*. *14*(1). 129.
7. Corleto, R., Gaff, M., Sethy, A.K., Kelkar, B.U., Nemeth, R., Ditommaso, G., Kamboj, G., Todaro, L., & Rezaei, F. (2024). Effects of CO_2 laser parameters on quality of laser cut beech wood (*Fagus sylvatic*a L) surface and extent of heat affect zone. *Journal of the Indian Academy of Wood Science*. 1-11.
8. Demir, A., Cakiroglu, E.O., & Aydin, I. (2022). Determination of CNC processing parameters for the best wood surface quality via artificial neural network. *Wood Material Science & Engineering*. *17*(6). 685-692.

9. Demirdöğen, M.F., Kılıç, S., & Öztürk, F. (2022). Investigation of different methods for estimating surface roughness. *Cukurova University Journal of the Faculty of Engineering*. *37*(2). 531-542.
10. Dogan, G., Wascher, R., Avramidis, G., & Gerhard, C. (2024). Using taguchi optimization to increase machining quality and efficiency when CO_2 laser structuring thermally modified beech wood veneers. *Lasers in Engineering (Old City Publishing)*. *58*. 379–391
11. Dumanoğlu, F., & Bal, B.C. (2022). Effects of machining parameters on the processing time and Surface roughness of fiberboards formed by CNC machine. *Kahramanmaras Sutcu Imam University Journal of Engineering Sciences*. *25*(4). 615-621.
12. Gurau, L., Angelescu, A.M., & Timar, M.C. (2024). Surface morphology and chemical changes of maple and beech cut through by CO_2 laser under different angles relative to the wood grain. *Forests*. *15*(10). 1767.
13. Gurău, L., Coşereanu, C., & Paiu, I. (2021). Comparative surface quality of larch (*Larix decidua* Mill.) fretwork patterns cut through by CNC routing and by laser. *Applied Sciences*. *11*(15). 6875.
14. Hazir, E., & Ozcan, T. (2019). Response surface methodology integrated with desirability function and genetic algorithm approach for the optimization of CNC machining parameters. *Arabian Journal for Science and Engineering*. *44*(3). 2795-2809.
15. Henke, M., Lis, B., & Krystofiak, T. (2022). Evaluation of surface roughness parameters of HDF for finishing under industrial conditions. *Materials*. *15*(18). 6359.
16. Islam, M.N., Das, A.K., Billah, M.M., Rahman, K.S., Hiziroglu, S., Hattori, N., Agar, D. A., & Rudolfsson, M. (2023). Multifaceted laser applications for wood – a review from properties analysis to advanced products manufacturing. *Lasers in Manufacturing and Materials Processing*. *10*(2). 225-250.
17. Kaba, O., & Bal, B.C. (2024). Investigation of the effect of CNC machine cutting parameters on the surface roughness of walnut wood. *Kahramanmaras Sutcu Imam University Journal of Engineering Sciences*. *27*(1). 69-77.
18. Kang, C.W., Hashitsume, K., Jang, E., & Kolya, H. (2023). Relationship between wood anatomical features and surface roughness characteristics. *Wood Research*. *68*. 455-464.
19. Loc, N.H., & Hung, T.Q. (2021). Optimization of cutting parameters on surface roughness and productivity when milling wood materials. *Journal of Machine Engineering*. *21*(4).71-89.
20. Miccoli, L., Müller, U., & Fontana, P. (2014). Mechanical behaviour of earthen materials: a comparison between earth block masonry. rammed earth and cob. *Construction and building materials*. *61*. 327-339.
21. Nugraha, M.D., Iswandaru, D., & Hidayat, W. (2024). Optimization of CO_2 laser cutting variables of sengon plywood (*Paraserianthes falcataria*) using response surface methodology. *Journal of Sylva Indonesiana*. *7*(2). 97-109.
22. Poletto, M. (2017). Assessment of the thermal behaviour of lignins from softwood and hardwood species. *Maderas. Ciencia y Tecnología*. *19*(1). 63-74.
23. Reinprecht, L., & Vidholdová, Z. (2021). The impact of a CO_2 laser on the adhesion and mold resistance of a synthetic polymer layer on a wood surface. *Forests*. *12*(2). 242.

24. Rezaei, F., Wimmer, R., Gaff, M., Gusenbauer, C., Frömel-Frybort, S., Kumar Sethy, A., Corleto, R., Ditommaso, G., & Niemz, P. (2022). Anatomical and morphological characteristics of beech wood after CO_2-laser cutting. *Wood Material Science & Engineering*. *17*(6). 459-468.
25. Sobri, M.S., Sobri, A.S., Norizan. M.N., Hermawan, A., Amini. M.H., Mohamed, M., Wan Ismail, W.O.A.S., & Mohamed Sultan, A.A. (2025). The influence of laser cutting parameters on the heat-affected zone in fast-growing Malaysian wood species. *Journal of Manufacturing and Materials Processing*. *9*(2). 1-28.
26. Stutzman, C.B., Mitchell, W.F., & Nassar, A.R. (2021). Optical emission sensing for laser-based additive manufacturing- what are we actually measuring. *Journal of Laser Applications*. *33*(1).
27. Vosniakos, G.C., Kyriopoulou, I., Benardos, P., & Pantelis, D. (2024). Laser cutting of wood: Experimental study for machine learning. *International Journal of Mechatronics and Manufacturing Systems*. *17*(3). 319-347.
28. Yaghoubi, S., & Rabiei, F. (2024). A profound evaluation of different strategies to improve the surface roughness of manufactured parts in wood- CNC machining process. *Journal of Engineering Research*. *33*. 2-7.
29. Žigon, J., Pavlič, M., Kovač, J., & Straže, A. (2025). Recoating performance of fresh and weathered wood surfaces through atmospheric dielectric barrier discharge plasma activation. *Wood Material Science & Engineering*. 1-16.

ÇAĞATAY ERSİN*
ÇANKIRI KARATEKİN UNIVERSITY
DEPARTMENT OF ELECTRONIC AND AUTOMATION
CANKIRI
TÜRKİYE
*Corresponding author: cagatayersin@karatekin.edu.tr

MEHMET GÜNEŞ
ÇANKIRI KARATEKİN UNIVERSITY
DEPARTMENT OF DESIGN
CANKIRI
TÜRKİYE