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Prediction of the Effect of CO_2 Laser Cutting Conditions on Spruce Wood Cut Characteristics Using an Artificial Neural Network

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Abstract: In addition to traditional chip methods, performance lasers are often used in the field of wood processing. When cutting wood with CO_2 lasers, it is primarily the area of optimization of parameters that is important, which include mainly laser performance and cutting speed. They have a significant impact on the production efficiency and cut quality. The article deals with the use of an artificial neural network (ANN) to predict spruce wood cut characteristics using CO_2 lasers under several conditions. The mutual impact of the laser performance (P) and the number of annual circles (AR) for prediction of the characteristics of the cutting kerf and the heat affected zone (HAZ) were examined. For this purpose, the artificial neural network in Statistica 12 software was used. The predicted parameters can be used to qualitatively characterize the cutting kerf properties of the spruce wood cut by CO_2 lasers. All the predictions are in good agreement with the results from the available literary sources. The laser power P = 200 W provides a good cutting quality in terms of cutting kerf widths ratio defined as the ratio of cutting kerf width at the lower board to the cutting kerf width at upper board and, therefore, they are optimal for cutting spruce wood at $1.2 \cdot 10^{-2}$ m·s^{-1}.

Keywords: CO_2 laser; artificial neural networks; wood kerf; spruce wood; heat affected zone

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1. Introduction

Wood cutting by CO_2 lasers is one of the basic methods of wood cutting to relatively cut any dimensions and shapes. Among their advantages in comparison to other cutting techniques such as CNC processing and water jet processing, belong quickness, non-contact, good wood cutting, efficiency and therefore also the good surface properties of the wood. Another advantage also lies in fact that by changing the parameters of the laser ray such as power, cutting speed, cutting angle, protective atmosphere and its pressure, it is possible to reach any sample dimensions with a good quality of surface which is crucial for the next step of processing the sample. Another advantage of laser cutting lies in the fact that lasers affect only limited areas by thermal stress. [1–6].

In the world of science there are many articles which deal with the effect of CO_2 laser parameters and their effect on wood cut parameters. Factors which influence final the cut of wood can be divided into three groups which are properties of the radiation beam, properties of the laser device and the characteristics of the cutting process such as laser power P, cutting speed v, number of annual rings AR, moisture, focal point position and many more. The effect of P, v, and AR on the cut characteristics of spruce wood was studied in [7].

Nukman et al. [8] studied the same cut parameters for Malaysian-based woods and plywood and also presented the dependence of material removal rate MRR vs. P, v from which it is good to see that the MRR increases with the laser power in the exponential stabilizing form in the compressed air or nitrogen atmosphere. Other authors have studied the effect of CO_2 laser parameters on the width of the heat affected zone in wood-based materials and wood composites. [9].

Th effect of laser parameters on the cut properties of wood-based composite materials such as MDF were studied in [10]. The authors studied MDF cutting by a CO_2 laser for P = 520–530 W in the pulse and continuous mode. They found out that narrow kerf widths can be achieved for the pulse mode.

Eltawahni et al. [11] defined methodology for evaluation of radiation beam efficiency and quality based on the values of parameter WKR defined as the ratio of cutting kerf width at the lower board WKL vs. the cutting kerf width at the upper board WKU (WKR = WKL/WKU) which is mainly affected by P, v and position of the focal point. They also find out that roughness increases with cutting speed and air pressure and decreases with P and focal point position. In other work Eltawahni et al. [12] studied the effect of laser parameters on the final cut of plywood materials.

Many authors have also studied the effect of focal point position on the final cut properties. For wood-based materials the results are listed in [13] and for wood composites they are listed in [14,15]. The effect of moisture content on the cutting of pine wood by CO_2 lasers was studied in [16]. The effect of assistance gas on the laser cutting of wood-based materials was studied in [17] and the effect of processing parameters and the parameters of gas on the cutting of micro thin wood was studied in [18].

Values of cut parameters are often processed by K—means clustering algorithm from the measured picture of the surface by several types of microscopies which is described in [19].

CO_2 lasers together with UV lasers, VIS and NIR lasers offer similar results in cutting. All these lasers offer better results than other techniques. Several authors use UV, VIS and NIR lasers for wood cutting. The next part deals with the effect of such laser's parameters on the machining of wood and wood composites.

Authors in the work [20] have studied the effect of wavelength and pulse width on the cut of Japanese larch, cedar and beech wood using UV laser. In the work [21], the authors have analyzed the effect of UV, VIS and NIR laser wavelengths on the machining performance of wood.

The effect of laser properties on the surface characteristics of different types of woods was studied in the works [22–25]. The authors of the work [22] studied the surface properties of beech wood after CO_2 laser engraving. In the previous work [23] the authors studied impact of radiation forms on beech wood color changes. The effect of CO_2 laser parameters on color changes in hardwoods and in limewood was published in the works [24,25].

Artificial neural networks have found very broad usage in material science such as wood science, polymers science, metals science but also optimization of technologies for materials processing. Many authors have used this very useful method for predicting wood materials properties. Authors of the work [26] have predicted thermal conductivity of wood using artificial neural networks. Surface roughness of wood in machining process was modelled in [27] and ANN was applied for minimalizing surface roughness and power consumption in abrasive machining of wood in the work [28]. ANN was also applied for prediction of optimum power consumption in wood machining in the work [29].

Neural networks have also been widely used for optimization of materials technologies. The authors in the work [30] modelled formaldehyde emissions during a particleboard manufacturing process and published the effect of the manufacturing technology on the modulus of rupture (MOR) and the modulus of elasticity (MOE) vs. pressing conditions in the work [31].

Other authors have dealt with prediction of adhesive bonding strength and bonding quality vs. pressing conditions using ANN or multiple linear regression models [32–34].

Artificial neural networks have also been used for prediction of color changes in wood which are largely affected by radiation from CO_2 or other types of lasers. The authors in the work [35] predicted the color changes of heat-treated wood during artificial weathering and during heat treatment by natural atmospheric conditions in the work [36].

The authors of the work [37] used ANN for determination of CNC processing parameters for the best wood surface quality. In the article [38], they determined the surface properties of MDF and optimized CNC processing parameters for this type of wood composite.

In comparison to MLP and RBF networks, artificial neural networks offer other possibilities for prediction of manufacturing industry demands using a deep learning approach. This method was described in detail in [39].

The goal of the article was to the predict values of cutting parameters at non-measured values of laser power *P*. These results can be successfully used for complex characterization of *P*, the AR effect on cut parameters for all applicable values of laser power for Picea abies. The results of ANN can be used for prediction of cut parameters at any laser power values between 100 and 500 W for all possible values of AR.

2. Materials and Methods

The experiments were carried on spruce wood (*Picea abies* L.). Experimental equipment LCS 400 (VEB Feinmechanische Werke, Halle, Germany) was used for cutting. This system consists of a CO_2 laser (wavelength 10.6 µm and maximum power output 400 W), a positioning table system (laser head positioning in the plane formed by the *x* and *y* axes) and a special PC control system. The sample was placed in lens focus. The focused laser beam stroked perpendicularly on the surface of the sample and the laser head carriage moved along the width (axis *x*) at a certain scanning speed until the wood sample was cut off. Cutting kerf was obtained from the wood specimens with dimensions T × R × L (8 × 100 × 1000) mm (Figure 1) with average density $\rho = 428.4 \pm 27.9$ kg·m^{-3}. Samples were cut tangentially by continuous laser powers 100 and 150 W, with cutting speeds of (3, 6, 9)·10^{-3} m·s^{-1}. The focal length was 1.27·10^{-1} m, beam diameter was 10^{-2} m, and spot diameter was 3·10^{-4} m. The focal point position of laser beam was set up to 1/2 of the sample thickness (measured from the upper surface of the board). The process gas was supplied through a Laval contour nozzle with compressed air of 0.25 MPa. The parameters of the cut were determined using digital microscopy through *K*-cluster analysis. The total number of measurements was 108 in one block. The ratio of kerf width on the upper and lower surface was calculated subsequently.

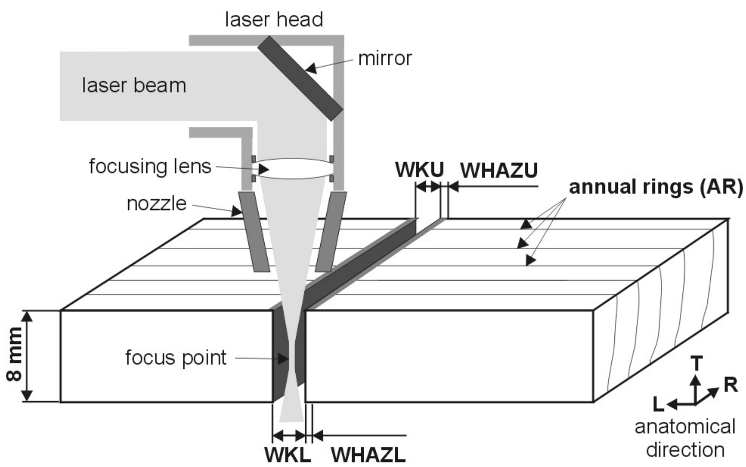


Figure 1. Cutting scheme.

Abbreviations are used in the text, the meaning of which is as follows: cutting kerf width on upper surface (WKU), cutting kerf width on lower surface (WKL), ratio of WKU and WKL (WKR), width of heat affected zone on upper surface (WHAZU), width of heat affected zone on lower surface (WHAZL), laser power (*P*) and number of annual rings (AR).

Definitions of investigated parameters are described in Figure 1.

In the research, we define 5 cut characteristics whose meaning are as follows: cutting kerf width on upper surface (WKU), cutting kerf width on lower surface (WKL), ratio of WKU and WKL (WKR), width of heat affected zone on upper surface (WHAZU), width of heat affected zone on lower surface (WHAZL), laser power (P) and number of annual rings (AR).

Basics of Artificial Neural Networks

Artificial neural networks are used for prediction of materials properties when analytical mathematical approximation cannot be found. From this very robust mathematical tool, material properties can be predicted.

The advantages of neural networks are as follows:

- The neural network can learn
- The neural network can generalize

The disadvantages are as follows:

- Neural networks need more values of one or more parameters that change in every dataset as input compared with standard fitting procedures such as the-least squares method and many others.

ANN usage is tested by statistical parameters root mean square error RMSE, coefficient of determination R^2 and the slope between the predicted and real measured values and the relative root mean square error defined as the ratio of RMSE and minimal measured value of predicted the parameter.

3. Results and Discussion

The results and discussion section will be divided into three parts namely measuring the parameters results, ANN prediction results and studying the AR and *P* effect on WKU, WKL, WKR, WHAZU, WHAZL. All the results were discussed with literature references.

3.1. Measured Values

Table 1 shows the average values with standard deviation for all input values of *P* equal to 100 and 150 W. The figures in Table 2 show the average values together with the standard deviations for all the input values of v equal to (3, 6, 9)$\cdot 10^{-3}$ m$\cdot$s^{-1}. In Table 3 the average values together with the standard deviations for all the input values of AR from 3 to 11 are shown.

Table 1. Descriptive statistics of all the measured parameters vs. *P*.

Value at *P*	WKU (10^{-3} m)	WKL (10^{-3} m)	WKR (-)	WHAZU (10^{-3} m)	WHAZL (10^{-3} m)
100	0.81 ± 0.17	0.50 ± 0.09	0.48 ± 0.04	0.16 ± 0.02	0.18 ± 0.02
150	0.91 ± 0.22	0.58 ± 0.14	0.77 ± 0.06	0.19 ± 0.02	0.26 ± 0.03

Table 2. Descriptive statistics of all the measured parameters vs. v.

Value at v	WKU (10^{-3} m)	WKL (10^{-3} m)	WKR (-)	WHAZU (10^{-3} m)	WHAZL (10^{-3} m)
3	1.04 ± 0.11	0.65 ± 0.08	0.64 ± 0.17	0.15 ± 0.02	0.20 ± 0.04
6	0.91 ± 0.13	0.56 ± 0.07	0.61 ± 0.16	0.18 ± 0.03	0.22 ± 0.06
9	0.62 ± 0.04	0.40 ± 0.02	0.63 ± 0.13	0.19 ± 0.02	0.23 ± 0.05

Table 3. Descriptive statistics of all the measured parameters vs. AR.

Value at *AR*	WKU (10^{-3} m)	WKL (10^{-3} m)	WKR (-)	WHAZU (10^{-3} m)	WHAZL (10^{-3} m)
3	0.90 ± 0.24	0.57 ± 0.15	0.67 ± 0.19	0.17 ± 0.03	0.21 ± 0.06
4	0.91 ± 0.23	0.57 ± 0.14	0.66 ± 0.19	0.17 ± 0.03	0.21 ± 0.06
5	0.90 ± 0.23	0.56 ± 0.15	0.64 ± 0.18	0.16 ± 0.03	0.21 ± 0.06
6	0.87 ± 0.23	0.54 ± 0.14	0.63 ± 0.16	0.17 ± 0.03	0.21 ± 0.06
7	0.85 ± 0.22	0.53 ± 0.13	0.62 ± 0.16	0.17 ± 0.03	0.22 ± 0.05
8	0.81 ± 0.19	0.51 ± 0.12	0.60 ± 0.15	0.17 ± 0.03	0.22 ± 0.05
9	0.83 ± 0.21	0.52 ± 0.13	0.61 ± 0.17	0.18 ± 0.03	0.22 ± 0.05
10	0.82 ± 0.18	0.51 ± 0.11	0.61 ± 0.14	0.18 ± 0.02	0.23 ± 0.06
11	0.82 ± 0.19	0.52 ± 0.11	0.61 ± 0.14	0.19 ± 0.02	0.23 ± 0.06

3.2. ANN Prediction

In this article, we have used values of laser power 100 and 150 W, the number of annual rings 3 to 11 and cutting speed $(3, 6, 9) \cdot 10^{-3}$ m$\cdot$s^{-1} as input values for teaching and measured values of WKL, WKU, WHAZL and WHAZU and WKR, thus the training groups have 54 lines. By routine, we obtained the five best artificial neural networks for prediction of WKU, WHAZU, WKL, WHAZL and WKR.

In the measured values teaching and generalization we have used all the basic neural networks used in the Statistica 12 software. According to a characteristic sum of squares, we obtained the five best neural networks which are shown in Table 4. All the studied multilayer perceptron networks used the Quasi–Newton training algorithm and the best neural network MLP 3-3-5 used the BFGS 73 training algorithm with error function sum of squares. The hidden layer was activated by logistic function and the output activation function was exponential. The number of the hidden neurons' possibilities were between 1 and 54 (length of dataset).

Table 4. Error propagation in the best neural networks.

Net	Training Error (-)	Testing Error (-)	Validation Error (-)
MLP 3-7-5	0.019	0.023	0.022
MLP 3-3-5	0.010	0.013	0.011
MLP 3-10-5	0.018	0.022	0.022
MLP 3-6-5	0.004	0.014	0.011
MLP 3-10-5	0.030	0.030	0.036

In this article we will present the results of the P and AR effect on the abovementioned parameters of wood cutting for all the possible parameters of CO_2 lasers from which it is possible to predict Picea abies wood cutting properties at any laser power between 100 and 500 W and the number of annual rings between 3 and 11 with a goal to optimize the cutting process. The results are given for Picea abies wood, therefore they can be successfully used for CO_2 laser cutting of Picea abies.

Artificial neural networks have been used for prediction of WKU, WKL, WKR, WHAZU, WHAZL parameters for input parameters P = 200, 300, 400, 500 W, cutting speed $v = 1.2 \cdot 10^{-2}$ m$\cdot$s^{-1} and the number of annual rings AR = 3, 4, 5, ... , 11. The error propagation of the networks are presented in Table 4. All the types of errors are decimal form of variance coefficient.

From Table 4, it is good to see that the lowest error (the standard is the mean square error) is obtained for network MLP 3-3-5 which was also found to be the best according to the slope of the predicted vs. measured values, coefficient of determination R^2, root mean square error RMSE and relative root mean square error Rel_RMSE, which are shown in Table 5.

Table 5. Statistical parameters of the ANN networks.

Statistical Parameter of	WKU (10^{-3} m)	WKL (10^{-3} m)	WKR (-)	WHAZU (10^{-3} m)	WHAZL (10^{-3} m)
Slope (-)	0.970	0.960	0.940	0.960	0.970
R^2 (-)	0.950	0.980	0.933	0.960	0.970
RMSE (parameter units)	0.010	0.004	0.012	0.001	0.002
Rel_RMSE (-)	0.018	0.012	0.035	0.009	0.013

From Table 5, we can conclude:

- The coefficient of determination R^2 for all the output parameters dependent on the input parameters is at least 0.933.
- The slope which should be close to 1 is for all the studied parameters higher than 0.94, which is a very good result.
- The maximum value of Rel_RMSE which in percentage is equal to 3.5% is highly under the measuring accuracy from which we can conclude that ANN can predict with accuracy all the studied cutting results' parameters.
- ANN can teach and predict with very high accuracy all the studied parameters.
- In the next three chapters we will deal with prediction of (WKU, WHAZU), (WKL, WHAZL) and WKR vs. *P* and AR and discuss the effects of *P* and AR on all the predicted parameters.

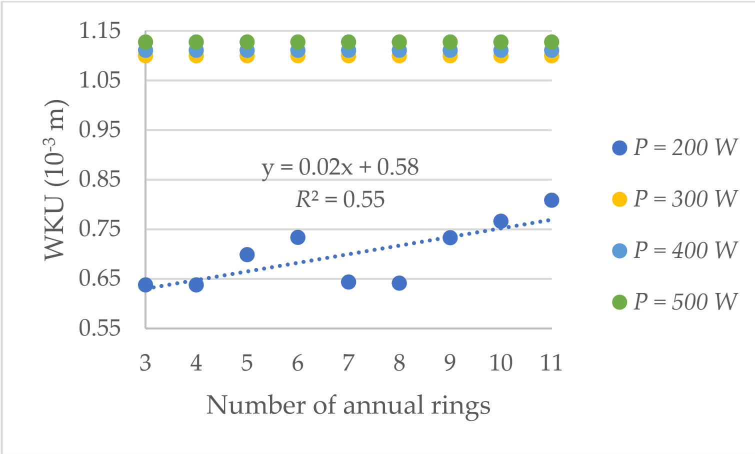
3.3. Prediction of WKU, WHAZU versus AR and P

In this chapter we will deal with prediction of WKU and WHAZU vs. AR, *P* at non-measured parameters which give information on the quality of Picea abies cut on the upper board. The results we will be presented as a graph of output property vs. AR, *P* in categories of laser power at a cutting speed of $1.2 \cdot 10^{-2}$ m$\cdot$s^{-1}.

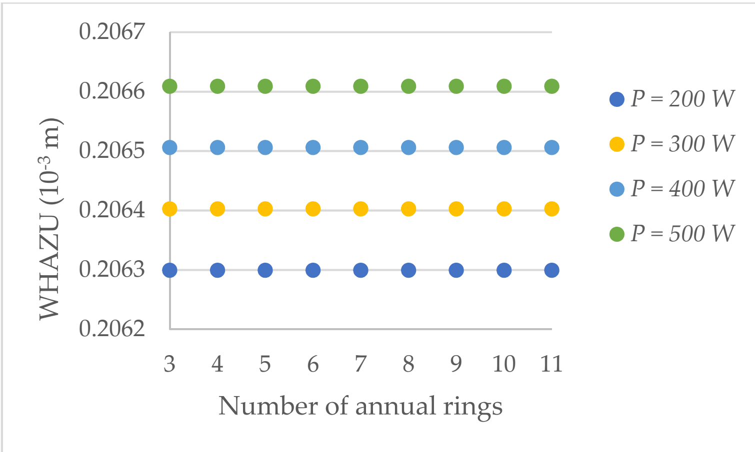
In Figure 2a,b we are show the dependence WKU and WHAZU vs. AR and *P* for cutting speed $1.2 \cdot 10^{-2}$ m$\cdot$s^{-1} in this order.

From Figure 2a,b we can see that AR have effect on WKU only for laser power 200 W and don't have effect on WHAZU. WKU is changing in average from 0.64 mm to 0.81 mm which correspond to 26.5% which is above the measuring error of this dimension. Therefore, we can conclude that AR does have statistically significant effect on WKU. Change of WKU vs. AR at low power 200 W lies in fact that at 200 W is material removal rate MRR low thus heat transfer through higher thermal conductivity by higher AR is significant which leads to accumulation of heat in kerf region thus higher cutting kerf width which is proportional to mass of wood which is burned.

At higher laser powers WKU don't change with AR and *P* which can be described by fact that at these values of *P* material removal rate MRR is at maximal value and therefore heat transfer in the cutting kerf region don't occur. This fact was also recorded by many authors in literature like as Hernandez (16) on pine wood and Barnekov (13) and Asibu (6). From the Figure 2 it is also good to see that laser power increases the cutting kerf width at upper board which was found out also by Nukman (8), Ready (5) and Liu (18).



(**a**)



(**b**)

Figure 2. (**a**) WKU vs. AR, P at $1.2{\cdot}10^{-2}$ m$\cdot$s^{-1}; (**b**) WHAZU vs. AR, P at $1.2{\cdot}10^{-2}$ m$\cdot$s^{-1}.

From Figure 2b is good to see that laser power don't have significant effect on WHAZU which is caused by fact that at higher cutting speed upper board thickness is cut quicker and therefore heat propagation in HAZ region don't occur which is in good agreement with Asibu (6), Barcikowsky (9) and Lum (15). All presented results in Figure 2 is in good agreement with Kubovský (7).

3.4. Prediction of WKL, WHAZL versus AR, P

In this chapter we will deal with prediction of WKL and WHAZL vs. AR, P at non-measured input parameters which give information about quality of Picea abies cut on lower board. The results we will present as graph of output property vs. AR, P in categories of laser power at cutting speed $1.2{\cdot}10^{-2}$ m$\cdot$s^{-1}.

In the Figure 3a,b we are showing dependence of WKL and WHAZL vs. AR and P for a cutting speed of $1.2{\cdot}10^{-2}$ m$\cdot$s^{-1} in this order.

From Figure 3a,b we can see that AR has an effect on WKL only for a laser power pf 200 W and does not have an effect on WHAZL. WKL however changes on average from 0.6 mm to 0.53 mm which corresponds to 11.7% decrease. During cutting of wood HAZ increases with depth of cut and this is mainly because of local heat sources above the lower board which lead to heat transfer from the "higher" parts of the wood to the lower surface. This also leads to enlargement of the width of HAZ together with fact that at a lower board, the heat transfer to the heat affected zone is more significant thus the heat generated in the cutting kerf region is transferred to the heat affected zone. This fact also is in good agreement with Figures 2b and 3b from which it is good to see that the width of heat affected zone at the lower board 0.29 mm is statistically significantly higher than for the upper board of 0.21 mm which correspond to a 39% increase. However, a decrease of WKL vs. AR is on the bounds of measurement error.

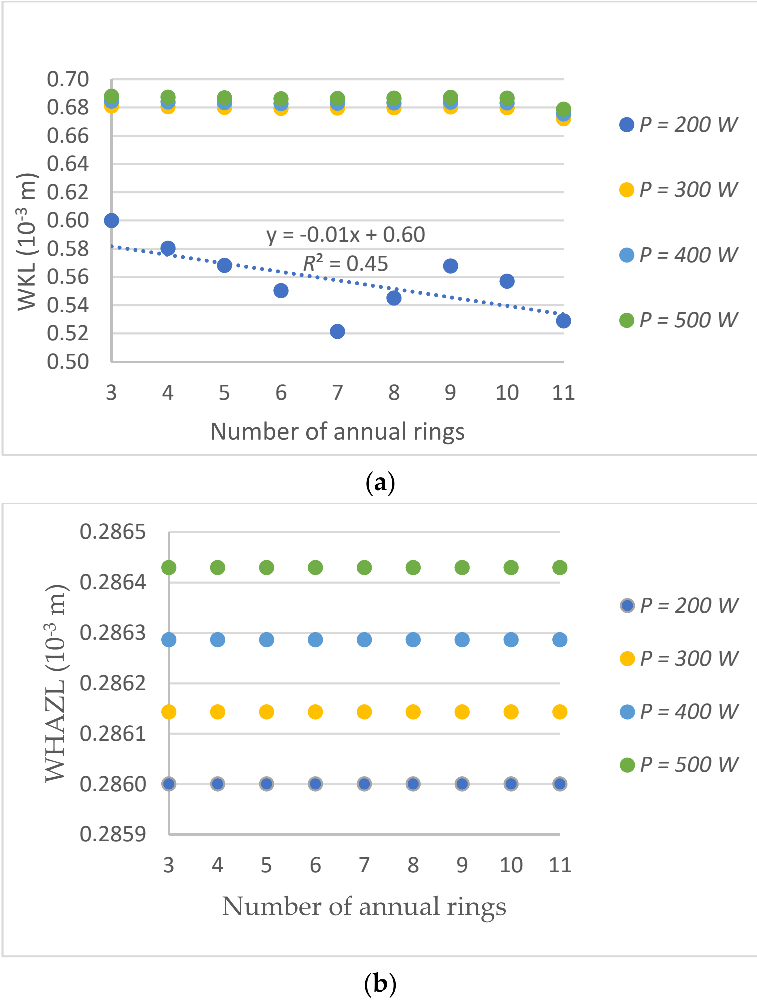


Figure 3. (**a**) WKL vs. AR, *P* at $1.2{\cdot}10^{-2}$ m$\cdot$s^{-1}; (**b**) WHAZL vs. AR, *P* at $1.2{\cdot}10^{-2}$ m$\cdot$s^{-1}.

On the other side, similar to the cutting kerf width at the upper board WKU, WKL increases with laser power only for laser powers lower than 300 W at which the cutting kerf width at the lower board reaches stabilization. This describes why the values of WKL have statistically equal values for all laser powers between 300 and 500 W. These results have been recorded in many scientific journal papers such as those by Ready (5), Lum (15), Lum (10), Eltawahni (11) and Kubovský (7).

From Figure 3b, it is good to see that P and AR do not have a significant effect on WHAZL. The reason for this lies in the fact that *P* and AR are not the main reasons for the width of heat affected zone increasing, which is caused by heat transfer from the upper parts of the wood to the lower parts of wood.

3.5. Comparison of P and AR Effect on Cutting Kerf Width and Width of the Heat Affected Zone for the Upper Board and Lower Board

From Figures 2 and 3, we can conclude:

- For all values of *P*, AR value of WKU is statistically significantly higher than for WKL which is caused by the fact that at lower board heat transfer, it plays a more significant role in the kerf region.

- For all values of P, AR value of WHAZU is statistically significantly lower than for WHAZL which is caused by the fact that at lower board heat transfer, it plays a more significant role in the heat affected zone region.
- The smallest difference between the values of WKU and WKL is at a minimal power of 200 W.
- AR and P do not play a significant role in both WHAZU and WHAZL.
- WHAZU is significantly lower than WHAZL because of heat transfer from the upper board to the lower board in the HAZ region.

3.6. Prediction of WKR versus Number of Annual Rings AR and Laser Power P

In this chapter we will deal with the prediction of WKR vs. AR, P at non-measured input parameters which give information on the quality of Picea abies cut at whole thickness. The results we will present as presented in a graph of output property vs. AR, P in categories of laser power at a cutting speed of $1.2 \cdot 10^{-2}$ m·s^{-1}.

In Figure 4, we show the dependence of WKR vs. the AR and P for a cutting speed of $1.2 \cdot 10^{-2}$ m·s^{-1}.

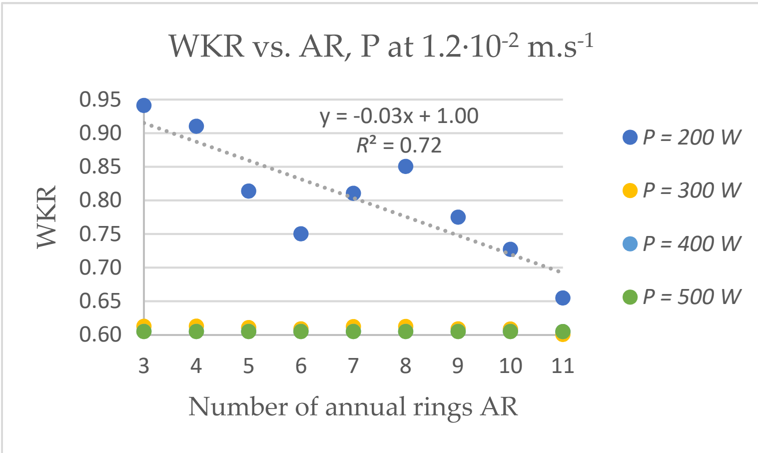


Figure 4. WKR vs. AR, P at $1.2 \cdot 10^{-2}$ m·s^{-1}.

From Figure 4, we can see that AR has an effect on WKR only for a laser power of 200 W. WKR decreases with AR cca. 3% by increased values of AR by 1 thus statistically significant changes occur only for values of AR = 8 and higher. From this graph, it is good to see that increasing P causes worse cutting therefore it is better to use lower laser values at a cutting velocity of $1.2 \cdot 10^{-2}$ m·s^{-1}. Changes of WKR at higher values of AR are caused by the fact that with increasing AR, heat transfer through thermal conductivity of wood plays a more significant role at the lower board vs. the upper board. The lower value of laser power is also good according to manufacturing costs. The presented results are in good agreement with Eltawahni (11) and Kubovský (7).

4. Conclusions

The results of this study suggest that the following conclusions:

- According to Tables 4 and 5, we can conclude that artificial neural networks are able to predict values of all the studied parameters of cutting, with MLP 3-3-5 which has low error backpropagation characteristics being the optimal neural network.
- The width of a kerf at the upper surface (WKU) and the width of a kerf at the lower surface (WKL) do not increase with a P higher than 300 W.
- Both AR and P do not have a significant effect on WHAZU and WHAZL.
- AR changes WKR only when P is lower than 300 W, thus AR has an effect on WKR only for low CO_2 laser powers.

- The values of WKU for all the studied parameters of P and AR are statistically significantly higher than for WKL which is in contrast with the increased value of WHAZL vs. WHAZU at cca. 40% level.
- The values of WKR at a P higher than 200 W are cca. equal to 0.7 which is a very low value therefore higher powers lead to worse cutting quality so we can conclude that they are not appropriate for a cutting speed of $1.2 \cdot 10^{-2}$ m·s^{-1}.
- Generally, the value of P = 200 W improves the cutting quality in the terms of WKR values and therefore they are optimal for wood cutting at $1.2 \cdot 10^{-2}$ m·s^{-1}. The values of WKR at P = 200 W are higher than the values of this parameter at 100 and 150 W even if the cutting speed at optimization (1.2.10^{-2} m·s^{-1}) is higher than at the measured dataset (max 0.9. 10^{-2} m·s^{-1}).
- Prediction of the cutting conditions of spruce wood machined by CO_2 laser effects on cut characteristics, obtained by artificial neural network MLP 3-3-5, can be used for qualitative characterization of the cutting conditions in wooden technological processes.
- In our article, we predicted the effect of P and AR by constant value of v on the cut characteristics and therefore we used regression modelling using ANN in Statistica software. According to abovementioned parameters this showed a very good correlation, and a low sum of squares error, which for characterization of wood materials cutting is highly under the error level at which these properties are measured, which is in good agreement with other authors' results.
- In the next stage of research, we will focus on studying the cutting speed v, the number of annual circles (AR) and the laser power P effect on all above-mentioned parameters, as it is very useful to compare the results with other approaches, which should be deep learning approaches, non-linear parametric fitting procedures and many others to optimize the accuracy of the prediction of cut characteristics.

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