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4 authors:

Ioanna Kyriopoulou
PPC SA

George-Christopher Vosniakos
National Technical University of Athens

Dimitrios I. Pantelis
National Technical University of Athens

Panorios Benardos
National Technical University of Athens

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I. Kyriopoulou[1], G.-C. Vosniakos[2*], D. I. Pantelis[1] and P. G. Benardos[3]

[1]School of Naval Architecture and Marine Engineering, NTUA Athens, 15780, Greece

[2]School of Mechanical Engineering NTUA Athens, 15780, Greece

[3]Faculty of Engineering University of Nottingham Nottingham, NG7 2RD, UK

Abstract

Criteria on which wood laser milling parameters are decided concern: milling depth, surface waviness and machined surface colour. These properties are measured through 3D laser scanning, optical microscopy and image analysis methods. Machine parameters affecting them are: laser power, laser feed, scanning resolution and number of milling passes. An experimental program reduced to the barely necessary through Taguchi designs is used in order to provide the data for training ANN models. Analysis of variance is employed to investigate significance of factors, thus ensuring completeness of the ANN metamodels. According to the latter, the most significant parameter of the system is scanning speed, followed by the number of passes and scanning resolution. ANN models offer adequate representation of the experiments, especially in the case of surface waviness and milling depth prediction. In the case of colour difference, errors are more pronounced, but they are still acceptable. The ANNs presented are a good "what-if" tool to determine surface quality results for a specific set of values of process parameters.

1. Introduction

Laser milling uses a laser beam to remove material to small depth forming a 2D motif. If the depth of milling is substantial, a 3D motif is formed and the process may be termed 'deep engraving' or 'milling' as adopted in this paper. Its advantages include high repeatability, scanning speed and flexibility. Production of clear, sophisticated motifs that cannot be easily realised with other mechanical manufacturing processes is possible. In the case of wood processing, the main problems are dimensional accuracy, surface carbonisation and the resulting colour change. Selecting combinations of process parameter values that result in high quality surfaces is the major issue. This is usually done by experiments and not by theoretical models. For instance, in [1] bamboo lamina was milled using various laser power and speed levels and empirical equations were fitted to experimental results. In [2] the influence of the process parameters and wood inhomogeneity on the wood removal rates and milling depth were investigated, using a Q-switched diode-pumped Nd:YAG green laser and creating an energy-based model.

According to most popular current practice, parametric design of experiments is carried out using Taguchi technique [3] instead of one-factor-at-a-time (OFAT). This enables determination of the effect of changing any one variable with the same accuracy, as if varying only one factor at a time, as well as effects of factor interactions. Taguchi methods may be complemented by Artificial Neural Networks (ANNs) as a prediction tool with a strong generalisation flavour. ANNs have been used as models connecting process conditions and manufacturing process results for a variety of both processes, especially for those employing lasers, and materials, yet not for laser milling of wood. To get an idea at a neighbouring application field, ANN modelling has been used intensively for laser welding [4]. Pertinent inputs to ANNs are common sense, e.g. laser power, welding speed, beam incident angle, focused beam spot size, focusing plane, but also not so trivial, e.g. welding gap, alignment of the laser beam with respect to it, workpiece thickness etc. [5], [6]. Outputs naturally vary according to the process and the target of the study [7]. The ANNs developed are mostly of the backpropagation type or, sometimes, of the learning vector quantization type. They often show better agreement with experiments compared to regression models [8]. In some cases a few tens of vectors were used for training the ANN, usually in conjunction with an experiment design technique, such as three level Box-Behnken design with replication [4]. In other cases hundreds of experiments were performed for this reason [7].

In this work process parameters resulting in controlled quality of laser milling of wood are determined, based on an experimental investigation reduced as much as necessary. This is due to the extensive time needed for performing

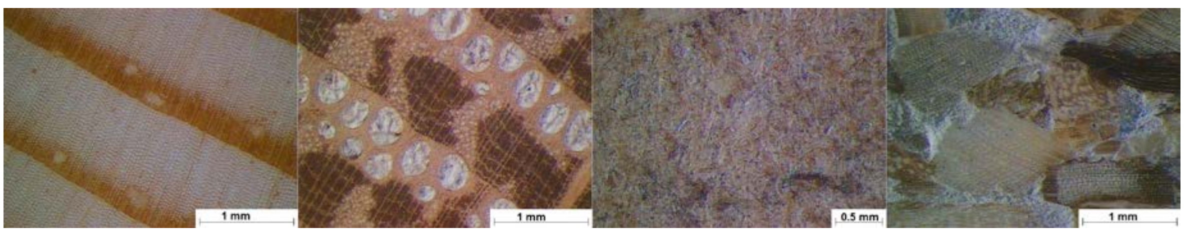
* Corresponding Author: Tel. +30 210 7721457 e-mail: vosniak@central.ntua.gr

measurements of the results of each experiment. Section 2 outlines experiment details concerning wood material, laser milling equipment, as well as measurement techniques and devices employed. The experimental program was designed and executed using Taguchi orthogonal arrays and analysis of variance (ANOVA) was employed to investigate significance of factors including their interactions. This part of the work is presented in Section 3. Ultimately, the experimental data were used to train ANN metamodels to enable them to predict process outcome achieved by any process parameter value combinations. This is the subject of Section 4. Conclusions are summarised in Section 5.

2. METHODS

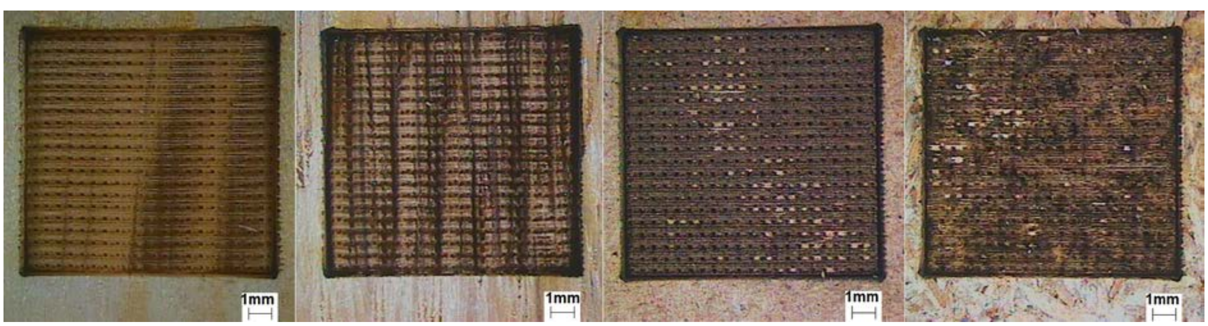
2.1. MATERIALS

Two types of wood and two types of wood products were used for the experiments: swedish pine (softwood), oak (hardwood), MDF (medium density fiberboard) and particleboard. These are commonly found materials differing in several properties, such as microstructure, density, hardness and color. Wood may be considered as a composite foam-type material of cellular structure. Hollow hexagonal capillary cells with a mean length of 2-5 mm and diameter 20-40 μm are characteristic of wood structure, see Fig. 1(a). In Figure 1(a) and (b) annual growing rings are obvious. Inside each ring two areas can be distinguished, namely the inner area (early or spring wood), which is lighter and of lower density and consists of cells with large diameter and thin wall, and the outer area (late or summer wood), which is darker, of higher density and consists of cells of smaller diameter and thicker wall. Oak contains whitish veins of large diameter that constitute a feeding network. By contrast, wood products such as MDF and particle board are much more isotropic and homogenous compared to pure wood, see Fig. 1(c) and (d).



a b c d

Figure 1: Microstructure of wood types investigated (a) swedish pine (b) oak (c) MDF (d) particle board



a b c d

Figure 2: Plan view of milled surfaces (P=20 W, S=320 mm/sec, R=200 dpi) (α) pine and (b) oak (c) MDF (d) particleboard

2.2. LASER MILLING

Experiments were performed using a commercial 25 Watt CO_2 laser machine (Mercury, Laser Pro). The beam has a wavelength of 10.6 μm and a diameter on the focal plane of about 65 μm. Geometric patterns to be worked were created as raster images. The laser power (P) and cutting speed (S) are variable within the ranges 0.25W - 25W and 1 - 1067 mm/sec, respectively. Scanning resolution (R) can be set at 200, 250, 300, 500, 600 and 1000 dpi. The work area of the machine is 640 mm x 460 mm. Note that the laser is continuous but pulses are produced through a mechanical diaphragm operating in combination to speed so as to achieve the particular scanning resolution setting. Scanning resolution determines in effect density of coverage of the surface by laser spots, i.e. the displacement step, d, which is equal to 1/R, hence degree of overlap of successive spots. For instance at the lowest scanning resolution, 200 dpi, d_{200}=122 μm, resulting at no overlap, whereas at the highest, d_{1000}=24.4 μm, resulting at an overlap of d/D=24.4/64≈38%. Note that displacement step is the same in both directions horizontally and vertically.

Laser milling tests were performed on samples obtained by 20mm-thick plates of the four different kinds of wood. Square cavities 10x10mm^2 in plane dimension, were obtained on the samples, by milling a sequence of linear paths, see Fig. 2. The distance between linear paths, indicated as step (st), was fixed at the value of 65 μm. Two cavities were realized for each testing condition. The cavities were obtained by varying the laser power (P), the scanning speed (S), the scanning resolution (R) and the number of scanning passes (N).

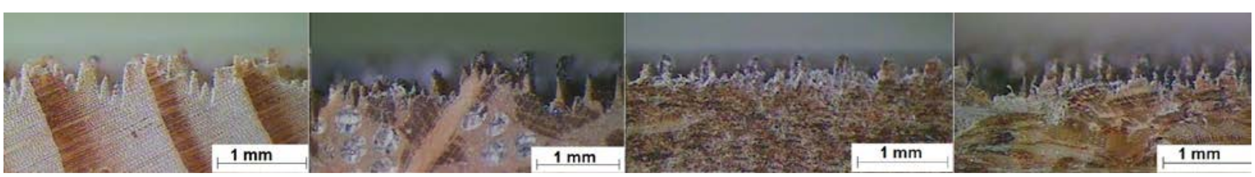
2.3 SAMPLES CHARACTERIZATION

The geometric profiles of the milled cavities were photographed using a Leica MZ6 modular stereo-microscope. The geometric profiles of the milled cavities were measured using Nextec Hawk 3D laser scanner. This system adopts a non-contact 3D measurement optical gauge of 10 μm resolution. For each of the cavities no less than 5 profiles were analyzed. Surface quality was estimated by measuring surface waviness/roughness (SW), milling depth (MD) and color difference (CD) of the milled profiles.

The waviness/roughness (SW) of the milled area was calculated from the geometric profiles obtained with the 3D laser scanning system, as the arithmetic mean of the absolute ordinate values z(x) within a sampling length of 9mm, inside the milled area. Average milling depth (MD) was calculated from 14mm scanning length profiles, obtained using the 3D laser scanning system, as the difference of the arithmetic means of the absolute ordinate values z(x), inside and outside the milled cavity. Color difference was estimated from stereomicroscope photos of the milled cavities, measuring average grayscale intensity inside and outside of the milled cavity (ranging from 0 [black] to 255 [white]), using commercial image analysis software (Image-Pro Plus). A black and white reference tape was used in all stereomicroscopic photos. In each photo brightness and contrast were adjusted so that grayscale intensity of black and white reference is always 0 and 255 respectively. Color difference of the milled cavity was calculated as the difference in grayscale intensity before and after milling relative to the former.

2.4 PROCESSED SURFACE CHARACTERISTICS

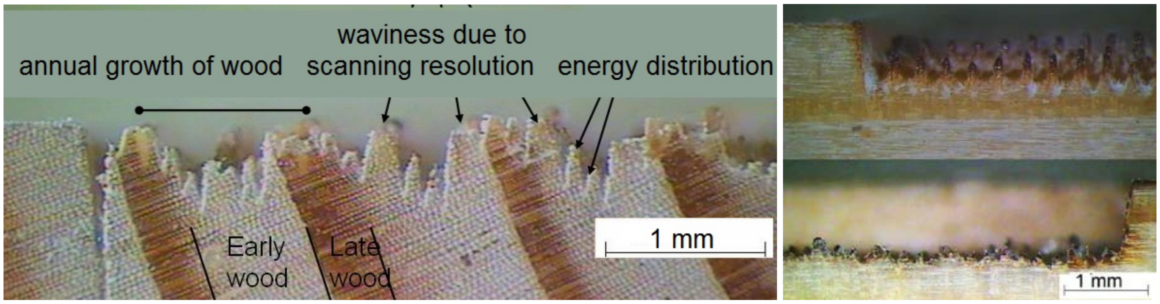
Examination of the processed surfaces on the stereomicroscope, revealed material removal and darkening of the wood surface due to wood carbonization, see Figure 3. In most cases, the milled surface possesses considerable waviness/roughness (of some hundreds μm) and periodicity. A transverse section of the milled surface of pine wood is shown in Figure 4, presenting three kinds of waviness/roughness, namely: low, medium and large.



a b c d

Figure 3: Transverse sections of milled surfaces (P=20 W, S=320 mm/sec, R=200 dpi) (α) pine (b) oak (c) MDF (d) particleboard.

Low scale waviness, i.e. roughness is due to the distribution of the laser beam energy in 2D cross sections. The machine used produces laser beams of multiple Transverse Electromagnetic Modes, provoking inhomogeneous wood removal inside the area of a dot [9]. Medium scale waviness, again deemed as roughness, is due to low scanning resolution causing the laser dots to not overlap leaving voids between them. The milled surface is characterized by periodical peaks of non-milled areas and valleys consisting of regions where dots overlap. Large scale waviness is due to the alternation of high and low density areas inside wood growth rings. During the spring, wood growth produces low density vessels that are wide, while during the summer the vessels are denser and narrower. As the laser beam works through a low density towards a high density wood area, material removal rate changes from higher to lower values [2]. For oak, in particular, it seems that the white areas are extremely sensitive to laser processing, see Figures 1(b) and 3(b). MDF, which consists of cellulose fibers, does not present large scale waviness. In particleboard, which consists of 0.2-5mm particles, large scale waviness is not periodical due to the particles randomness.



a b

Figure 4: Surface waviness (a) classification (b) variation for P=20W, S=320 mm/sec, R= 300(upper) and 500 dpi (lower)

3. DESIGN OF EXPERIMENTS

3.1 TAGUCHI ARRAYS AND RESULTS

The Taguchi technique was used [3] in order to quantify the influence of each studied parameter and was realized in two phases: for a single pass and for multiple passes. The experiments performed were based on two L9 orthogonal arrays, see Tables 1 and 2, consisting of 3 columns (input parameters) and 9 rows (experimental runs).

Table 1: L9 matrix and results for first Taguchi design. Inputs: P=laser power (W), S=scanning speed (mm/sec), R=Scanning resolution (dpi), N=number of passes. Outputs: Milling depth (MD (μm)), surface waviness (SW(μm)), Colour difference (CD(%))

Exp. no	P	S	R	MD				SW				CD			
				Pine	Oak	MDF	PB	Pine	Oak	MDF	PB	Pine	Oak	MDF	PB
1	15	213	600	1025	917	661	738	208	249	39	99	32,8	60,5	51	53
2	15	320	1000	1318	962	701	722	80	205	57	71	30,3	62,9	45	48,4
3	15	427	500	529	323	240	256	167	133	36	48	5,4	24,8	26,7	14,7
4	20	213	1000	1755	1595	1190	1173	310	217	71	129	51,4	71,8	62,4	67,8
5	20	320	500	702	689	449	533	200	162	36	72	29	48,4	34,5	33,3
6	20	427	600	673	536	463	516	113	144	39	60	11,3	30,1	29,4	31,8
7	25	213	500	1450	1197	707	799	106	191	46	125	36,5	60,5	49,3	51,7
8	25	320	600	1009	579	547	587	251	201	46	84	25,6	51,8	41,8	38,2
9	25	427	1000	1125	830	677	660	114	141	44	92	25,7	52,8	39,2	45,6

Table 2: L9 matrix and results for second Taguchi design. Inputs: S=scanning speed (mm/sec), R=Scanning resolution (dpi), N=number of passes. Outputs: Milling depth (MD (μm)), Surface waviness (SW(μm)), Colour difference (CD(%))

Exp. no	S	R	N	MD				SW				CD			
				Pine	Oak	MDF	PB	Pine	Oak	MDF	PB	Pine	Oak	MDF	PB
1	213	500	1	1175	858	95	634	49	219	155	102	47,5	74,7	55,6	58,8
2	213	600	2	2980	2165	1395	1407	80	278	76	166	65,2	79,3	71,5	70,8
3	213	300	3	1862	1373	855	1068	258	291	133	276	74,3	93,6	72	72,1
4	320	500	2	1657	1288	700	911	117	183	35	89	42,3	73,4	21,8	60,7
5	320	600	3	2906	1858	1358	1586	107	228	68	156	49,3	73,4	59,6	63,9
6	320	300	1	428	364	148	338	92	115	42	68	33,5	49	22,9	53,1
7	427	500	3	1794	1452	781	983	73	236	38	73	31,9	80,7	28,2	46,4
8	427	600	1	572	429	271	356	63	97	21	52	30,5	42,5	26	45,6
9	427	300	2	724	465	311	451	118	117	24	77	27	51,1	27,6	49,9

The total degree of freedom was calculated by assuming that there are no interactions among the different control factors, since there was no indication of the opposite. All experiments were repeated for each of the four kinds of wood.

In the first design, see Table 1, scanning resolution where all values were higher than 500dpi was used, in order to achieve full overlapping of laser spot ‘dots’. In the second design, see Table 2, laser power was constant and equal to 20W, since it was noticed that laser power was the least significant factor when single pass scanning was performed. Furthermore, low scanning resolution values were adopted to avoid wood burning after multiple passes.

In general, the denser the material, the smaller the milling depth. Density of pine and oak wood is 500 and 745 (kg/m^3), respectively, whereas for MDF and particleboard it is 720-875 and 720-850 (kg/m^3) [12]. As expected, pine is deeper milled, followed by oak, whilst particleboard and MDF exhibit smallest milling depthm see Tables 1 and 2.

In Tables 3 and 4 the results of SN calculations are presented according to Taguchi theory. The Signal to Noise (SN) ratio of the quadratic quality loss function is used to determine the deviation of the quality characteristic from the desired value in a different way, depending on the type of the desired performance response. In particular Surface Waviness and Colour Difference outputs are treated as ‘the-smaller-the-better’(STB), whereas Milling Depth is treated as ‘the larger the better’ (LTB). Thus for n experiments (commonly at the same level) with Q_i denoting the i-th value of the quality characteristic of STB type, SN is calculated as [3]: $SN=-10\log_{10}((1/n)sum_{i=1-n}(Q_i^2))$. In the case of LTB quality characteristics, the inverse of Q_i is entered in equation (1). The influence of each input factor on each quality characteristic can be estimated through the respective SN values, whereby larger values are favoured.

Table 3: S/N for first Taguchi design (legend as in Table 1). Optimum values are shown in bold.

		Pine			Oak			MDF			PB		
Input	Level	MD	SW	CD	MD	SW	CD	MD	SW	CD	MD	SW	CD
P (W)	15	57,7	**-44,1**	**-28,3**	54,0	-46,1	**-34,4**	51,4	**-33,1**	**-32,5**	52,0	**-37,6**	**-32,5**
	20	58,2	-47,0	-30,8	57,0	**-45,0**	-34,5	54,6	-34,2	-33,0	55,7	-39,3	-33,5
	25	**61,3**	-44,6	-29,5	**57,7**	-45,1	-34,8	**56,0**	-33,1	-32,8	**56,5**	-40,2	-33,2
S (mm/ sec)	213	**62,3**	-47,0	-32,3	**61,2**	-46,9	-36,2	**57,8**	-34,6	-34,7	**58,6**	-41,5	-35,3
	320	59,2	-45,6	-29,1	56,9	-45,6	-34,8	54,6	-33,5	-32,2	55,6	-37,6	-32,1
	427	56,6	**-42,5**	**-24,4**	53,2	**-42,9**	**-31,6**	50,9	**-32,0**	**-30,2**	51,5	**-36,8**	**-30,4**
R (dpi)	600	58,6	-46,0	-27,9	55,9	-46,1	-33,8	54,6	-32,4	-32,4	55,5	**-38,3**	-32,5
	1000	**62,5**	-45,9	-31,5	**60,1**	-45,6	-36,0	**57,8**	-35,3	-34,0	**57,8**	-40,0	-34,8
	500	56,9	**-44,2**	**-28,7**	53,8	**-44,3**	**-33,4**	50,9	**-32,0**	**-31,6**	51,7	-38,9	**-31,2**

Table 4: S/N for second Taguchi design (legend as in Table 2). Optimum values are shown in bold.

		Pine			Oak			MDF			PB		
Input	Level	MD	SW	CD	MD	SW	CD	MD	SW	CD	MD	SW	CD
S (mm/ sec)	213	**64,3**	-44,0	-36,0	**61,5**	-48,4	-38,4	44,3	-42,0	-36,5	**58,9**	-45,8	-36,6
	320	57,0	-40,5	-32,5	55,5	-45,2	-36,4	47,9	-34,0	-31,8	54,6	-40,9	-35,5
	427	57,5	**-38,9**	-29,5	56,2	**-44,2**	-35,6	**50,7**	**-29,1**	**-28,7**	53,4	**-36,7**	**-33,5**
R (dpi)	500	**63,3**	**-38,5**	-32,3	**60,9**	-46,6	-37,7	44,2	-39,5	**-31,6**	**58,0**	**-39,0**	**-34,9**
	600	59,6	-38,6	-34,0	57,0	-46,6	**-36,5**	**53,1**	**-35,6**	-34,9	55,3	-42,6	-35,7
	300	55,9	-44,7	-33,9	55,0	**-45,7**	-36,6	47,2	-38,2	-33,3	53,1	-44,6	-35,4
N	1	55,1	**-36,9**	**-31,6**	53,2	**-43,7**	**-35,1**	42,5	-39,4	**-31,6**	52,0	**-37,7**	**-34,4**
	2	61,0	-40,5	-33,5	61,4	-46,2	-36,8	53,7	**-34,0**	-33,3	56,6	-41,4	-35,7
	3	**66,2**	-44,4	-34,8	**63,7**	-48,1	-38,4	**59,3**	-39,0	-35,0	**61,1**	-45,5	-35,8

Thus, referring to Table 3, laser power increase seems to cause an increase in milling depth, small increase in waviness, though not for all types of wood, and a slight increase on color difference. Reduction of the scanning speed, i.e. input of greater amount of energy to the system, clearly increases the milling depth, decreases waviness and increases darkening of the surface, for all kinds of wood. In the case of the lowest laser speed all kinds of wood were inflamed. Pure woods present slightly higher waviness than wood products, especially at higher values of scanning speed, possibly due to wood inhomogeneity influencing large scale waviness. Scanning resolution values are related to the overlapping of laser dots on wood. Scanning resolution increase causes an increase in milling depth, as well as in milled surface darkening. Its effect on surface waviness seems to be noticeable only at the highest level. Note that scanning direction with respect to the direction of the wood growth rings did not seem to have any important influence.

Similarly, referring to Table 4, an increase in milling depth, surface waviness and color difference (milder, however) is observed as the number of scanning passes increases, with the exception of MDF in the case of surface waviness.

3.2 Analysis of Variance (ANOVA)

ANOVA was conducted for each quality parameter [3]. Tables 5 and 6 present the factors of significance for these parameters, in terms of contribution percentage. The contribution percentage of a factor refers to the overall variance of a quality parameter and reveals its significance in the system. When contribution percentage sum is far from 100%, other parameters, not taken into account in the study, are also important for the system; in that case the examined parameters alone cannot explain the total variance of a quality parameter.

Table 5: Contribution (%) of laser power (P), scanning speed (S) and scanning resolution (R) on colour difference (CD), surface waviness (SW) and milling depth (MD) corresponding to first Taguchi design, see Table 1.

	MD				SW				CD			
	Pine	Oak	MDF	PB	Pine	Oak	MDF	PB	Pine	Oak	MDF	PB
P	0	4,59	6,77	8,40	0	6,05	0	18,61	0	1,38	0	2,47
S	45,29	61,36	44,18	56,63	0	76,71	3,64	72,39	27,95	64,22	74,69	57,96
R	22,94	29,88	44,67	33,28	0	16,24	37,49	8,56	37,65	27,98	21,28	33,65
SUM	68,23	95,83	95,62	98,31	0,00	99,00	41,13	99,56	65,60	93,58	95,97	94,08

Table 6: Contributions (%) of scanning speed (S), scanning resolution (R) and number of passes (N) on colour difference (CD), surface waviness (SW) and milling depth (MD), corresponding to second Taguchi design, see Table 2.

	MD				SW				CD			
	Pine	Oak	MDF	PB	Pine	Oak	MDF	PB	Pine	Oak	MDF	PB
S	17,8	16,1	18,10	17,96	0,0	48,2	42,69	45,1	71,7	39,5	67,2	75,48
R	25,0	20,7	27,77	20,94	13,2	3,5	6,91	5,4	0,0	10,3	9,6	3,03
N	45,3	44,3	43,07	53,74	6,3	39,8	28,47	28,2	10,7	46,4	11,8	15,44
SUM	88,10	81,10	88,94	92,64	19,50	91,50	78,07	78,70	82,40	96,20	88,60	93,95

Results reported in Table 5 lead to the following conclusions: Color difference is affected primarily by scanning speed and then by scanning resolution. Waviness is affected primarily by scanning speed. Scanning resolution and laser power do not affect waviness significantly. In the case of MDF and especially of pine wood, the sum of contribution percentages is far from 100%, which probably means that there are missing factors, e.g. distance of growth rings or humidity, which affect waviness. Milling depth is mostly affected for all kinds of wood by scanning speed (primarily) and scanning resolution.

Results reported in Table 6 lead to the following conclusions: Number of passes is the most significant factor affecting milling depth and the second most significant, after scanning speed, affecting color difference and waviness. Color difference is influenced primarily by scanning speed followed by the number of passes. Scanning resolution does not seem to affect noticeably color change. Waviness is influenced by scanning speed, followed by the number of passes. Note that the sum of the contribution percentages for pine is only 19.50, hence other important factors are missing, e.g. growth ring density or the distance from the vertical axis of the log. The latter affect wood density as well as the growth ring process and consequently the way in which wood interacts with laser beam. The most significant factors affecting milling depth is the number of passes. In all cases the sum of contribution of the factors considered is large enough to justify that no other significant factors were left out.

4. Predictive models

4.1. Artificial Neural Networks (ANNs)

ANNs are information (signal) processors possessing many simple processing elements (neurons). Typically, a neuron sends its internal state (activation) as a signal to several other neurons. Each neuron applies a usually non-linear activation function to its net input to determine its output signal, e.g. identity, hyperbolic tangent function etc. The basic ANN architecture includes an input layer of neurons, a number of hidden (intermediate) layers and an output layer with one or more neurons, see Figure 5. In the most typical neural network type, training is accomplished by presenting a sequence of training vectors, or patterns, each with an associated target output vector. The weights are then adjusted according to a learning algorithm finding the set of weight values that minimizes the total error between predicted and known outputs by a lowering of gradient according to the weight vector (gradient back-propagation). After many repetitive presentations of the training set (epochs), the network output converges to desired values [10].

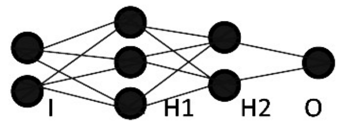


Figure 5: Typical feed forward-back propagation neural network architecture (I=input, H=hidden, O=output layers).

A neural network model can be developed on commercially available software platforms providing easy means to specify topology, selection of activation function and a variety of possible training algorithms. In this work the Matlab Neural Toolbox™ was employed. Optimum topology can certainly be found by brute-force exhaustive enumeration of alternatives when these alternatives are relatively few and/or network training time is low. However, when these conditions are not met, it is possible to use software that optimizes network topology using tools such as genetic algorithms. Such a solution is provided in [11], and was used in this work to determine the best topology in all ANN cases presented next.

Table 7: Details of the developed ANNs concerning Milling depth (MD), Surface waviness (SW), Colour difference (CD)

Wood	ANN output	Input neurons	Hidden neurons 1	Hidden neurons 2	Output neurons	% MRE training	% MRE generalization
Pin	MD	4	3	4	1	4,74	4,71
	SW	4	5	0	1	0,00	18,36
	CD	4	10	0	1	14,61	6,53
Oak	MD	4	7	12	1	2,71	8,60
	SW	4	4	1	1	1,19	4,99
	CD	4	9	0	1	10,48	8,27
MDF	MD	4	7	26	1	0,17	12,88
	SW	4	13	7	1	0,24	8,72
	CD	4	8	14	1	7,23	1,72
PB	MD	4	4	0	1	0,98	7,30
	SW	4	7	4	1	0,14	4,34
	CD	4	1	31	1	9,80	4,46

4.2 PREDICTIVE ANNS FOR LASER MILLING OF WOOD

For each of the four wood types examined three ANNs were constructed referring to milling depth, surface waviness and color difference respectively. All models had the same four inputs, i.e. laser power (expressed as % of the maximum power), scanning speed (% of the maximum velocity), resolution in dpi, and number of passes. Input data were normalized, e.g. power was divided by 10, dpi was divided by 100 etc. to yield the same order of magnitude.

For each type of wood three subsets of the available experimental data (Tables 1 and 2) were constructed, namely the training set consisting of 12 vectors, used in training the ANN, the validation set consisting of 3 vectors, used to implement the early stopping technique (to avoid data over-fitting in the training session) and the testing set consisting of 3 vectors, used to check the ability of the ANN to generalize on the data used in its training.

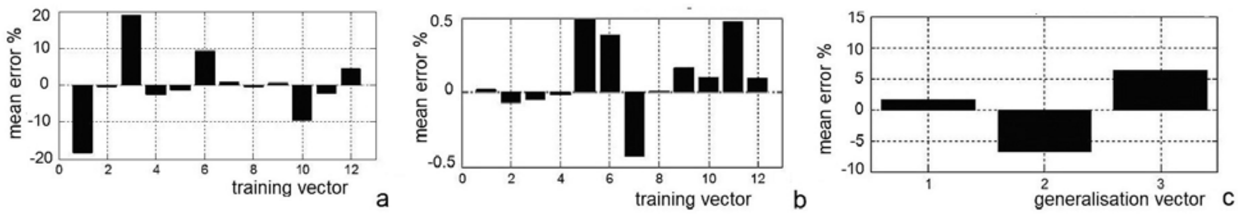


Figure 6: Typical examples of ANN response in terms of relative error on vertical axis for each data vector represented on the horizontal axis: (a) Training SW-oak, (b) Training MD-MDF (c) Generalization CD-PB.

The architecture, number of data vectors used and mean square relative error for training and generalization are shown in Table 7 for each type of wood and each targeted output. Response is deemed acceptable, except for few cases where training error exceeds 6% and generalization error exceed 10%. Figure 6 presents characteristic charts for relative error between ANN output and corresponding real data value for different target outputs types of wood. Response would certainly improve by increasing training vectors through new experiments. This is easily achieved by means of the software used [11] that determines the best ANN architecture, which is the hardest part. The easiest part is network training, which is achieved on any suitable commercially available software.

5. Conclusions

The examination of laser milled wood surfaces using stereoscopy and image analysis showed, in all cases, non-homogenous material removal and wood surface carbonization. Results indicate that milling depth and color difference increase as laser power increases, scanning speed reduces, scanning resolution increases and number of passes increases. Surface waviness increases as laser power and number of passes increase and as scanning speed and scanning resolution decrease. The highest value of milling depth is attained on pine wood, followed by oak wood. Taguchi-ANOVA results concerning color difference, waviness and milling depth show that the most significant parameter of the system is scanning speed, followed by the number of passes and scanning resolution. Laser power has relatively less influence on the system in the range examined. ANN models were proposed as a predictive model, relating milling depth, surface waviness and color difference, with process parameters. The models offer adequate representation of the experiments, especially in the case of surface waviness and milling depth prediction. In the case of color difference, errors are more pronounced, but they might be deemed to be acceptable. More training vectors would certainly improve ANN response, but experimental work to produce such examples is significant. To maximize ANN performance for a low number of training vectors, special ANN topology optimization software is important.

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References

[1] *C. J. Lin, Y. C. Wang, L. D. Lin, C. R. Chiou, Y. N. Wang, and M. J. Tsai: "Effects of feed speed ratio and laser power on milling depth and color difference of Moso bamboo lamina", J. Mater. Process. Technol., Vol. 198, pp.419–425. 2008.*

[2] *C. Leone, V. Lopresto, and I. De Iorio: "Wood milling by Q-switched diode-pumped frequency-doubled Nd:YAG green laser", Opt. Lasers Eng., Vol. 47, pp.161–168, 2009.*

[3] *P.J. Ross, Taguchi Techniques for Quality Engineering: Loss Function, Orthogonal Experiments, Parameter and Tolerance Design, McGraw-Hill, 1988.*

[4] *K.R. Balasubramanian, G. Buvanashekaran and K. Sankaranarayanasamy: "Modeling of laser beam welding of stainless steel sheet butt joint using neural networks", CIRP J. Manufacturing Science and Technology, Vol. 3, No 1, pp.80-84. 2010.*

[5] *J.-Y. Jeng, T.-F. Mau and S.-M. Leu: "Prediction of laser butt joint welding parameters using back propagation and learning vector quantization networks", J. Materials Processing Technology, Vol. 99, No 1-3, pp.207-218, 2000.*

[6] *M.-J. Tsai, C.-H. Li and C.-C. Chen: "Optimal laser-cutting parameters for QFN packages by utilizing artificial neural networks and genetic algorithm", J. Materials Processing Technology, Vol. 208, No 1-3, pp.270-283, 2008.*

[7] *D.-C. Lim and D.-G Gweon: "In-Process joint strength estimation in pulsed laser spot welding using artificial neural*

networks", J. Manufacturing Systems, Vol. 18, No 2 (Suppl.1), pp.31-42, 1999.

[8] *B. Acherjee, S. Mondal, B. Tudu and D. Misra: "Application of artificial neural network for predicting weld quality in laser transmission welding of thermoplastics", Applied Soft Computing, Vol. 11, No 2, pp. 2548-2555, 2011.*

[9] *V.G. Barnekov, C.W. Mc Millin and H.A. Huber: "Factors influencing laser cutting wood", Forest Products J., Vol. 36, No 1, pp.55-58. 1986.*

[10] *G. Dreyfus, Neural Networks: Methodology and Applications, Springer, 2010.*

[11] *P.G. Benardos and G.-C. Vosniakos: "Optimising feedforward artificial neural network architecture", Engineering Applications of Artificial Intelligence, Vol. 20, No 3, pp.365-382, 2007.*

[12] *USDA Forest Service, Forest Products Laboratory, Wood handbook: Wood as an Engineering Material, University of Wisconsin, 1999.*