ISSN impresa 0717-3644
ISSN online 0718-221X

Maderas. Ciencia y tecnología 21(4): 493 - 510, 2019

DOI: 10.4067/S0718-221X2019005000406

OPTIMIZATION OF WOOD MACHINING PARAMETERS IN CNC ROUTERS: TAGUCHI ORTHOGONAL ARRAY BASED SIMULATED ANGLING ALGORITHM

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ABSTRACT

In the present study, two mathematical models were developed to optimize the surface roughness for machining condition of Cedar of Lebanon pine (*Cedrus libani*). Taguchi approach was applied to examine the effect of CNC processing variables. Quality characteristics parameters were selected as arithmetic average roughness (R_a) and average maximum height of the profile (R_z) for wood material. Analysis of variance (ANOVA) was used to determine effective machining parameters. Developed mathematical models using response surface methodology (RSM) were optimized by a combined approach of the Taguchi's L_{27} orthogonal array based simulated angling algorithm (SA). Optimum machining levels for determining the minimum surface roughness values were carried out three stages. Firstly, the desirability function was used to optimize the mathematical models. Secondly, the results obtained from the desirability function were selected as the initial point for the simulated angling algorithm. Finally, the optimum parameter values were obtained by using simulated angling algorithm. Minimum R_a value was obtained spindle speed of 17377 rpm, feed rate of 2,012 m/min, tool radius of 8 mm and depth of cut of 2,009 mm by using desirability function based simulated angling algorithm. For R_z these results were found as 16980 rpm, 2,004 m/min, 8,001 mm and 2,003 mm. The *R*-square values of the R_a and R_z were 95,91 % and 96,12 %, respectively. The proposed models obtained the minimum surface roughness values and provided better results than the observed values.

Keywords: *Cedrus libani*, response surface method, softwood, surface roughness, wood material.

INTRODUCTION

Wood surface roughness is a crucial indicator of the quality of CNC processing parameters. However, wood material has very complex structure parameters such as machining procedure, physical properties of panel, processing conditions and anatomical structure (Magoss 2008, Philbin and Gordon 2006, Hiziroglu and Kosonkorn 2006, Ozdemir and Hiziroglu 2007, Ratnasingman and Scholz 2006, Hazir and Ozcan 2019). For this reason, it is difficult and complex to investigate the optimum parameter levels. A systematic approach could be applying to provide the optimum process conditions. Therefore, a novel experimental design is required to reduce the number of experiment. Traditional experimental design was required have a long time and it increased the cost. Design of experiment (DOE) and the Taguchi methodology are powerful techniques to reduce the number of experiments. Moreover, these methods have been commonly applied in different engineering applications (Yang and Tarng 1998, Taguchi *et al.* 2005, Sarikaya and Güllü 2016, Rao and Murthy 2018, Selaimia *et al.* 2017, Azhiri *et al.* 2014, Majumder *et al.* 2017, Kant and Sangwan 2014, Deepanraj *et al.* 2017). In the recent years, metaheuristic algorithms have been applied to various engineering problems. Especially, experimental design based metaheuristic algorithms have become popular method for optimizing the param-

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Received: 11.08.2018 Accepted: 12.06.2019

eters (Rao and Kalyankar 2013, Mahes *et al.* 2015, Samanta 2009). Coelho *et al.* (2008) applied the Taguchi technique to evaluate the effective parameters for wood cutting conditions. Gaitonde *et al.* (2008) studied the Taguchi design to optimize drilling parameters such as cutting speed and feed rate to reduce delamination of medium density fiberboard (MDF). The delamination was reduced higher cutting speed and lower feed rate. Davim *et al.* (2009) studied the determination of cutting factors such as cutting speed and feed rate on surface roughness in MDF milling. According to the results, the wood surface roughness decreased with an increase of spindle speed and increased with the feed rate. Prakash and Palanikumar (2010) applied the Taguchi approach to find the effective ratio on R_a for drilling MDF. The drilling parameters were spindle speed, feed rate and drill diameter. According to the Taguchi analysis, the feed rate was found to be the most important factor affecting surface roughness. Sofuoglu (2017) investigated that the optimization of CNC machining parameters were examined using the Taguchi method on the surface quality of massive wooden panels made of Scots pine (*Pinus slyvestris*). Optimal cutting results of R_a and R_z were resulted with cutter 1, at a tool clearance strategy of a raster spindle speed of 16000 rpm, feed rate of 1000 mm/min and depth of cut of 4 mm. Hazir *et al.* (2018) used 2^k full factorial design to determine the significant variables and optimum processing levels to determine the lower the wood surface roughness. As a result of this study, two equations were created for radial and tangential cutting directions. Moreover, each models were solved by applying desirability function. Koç *et al.* (2017) applied full factorial design to find the significant variables on wood surface roughness. Surface roughness values were determined by using laser integrated measurement system and stylus type equipment. According to this study, the roughness values for these measurement methods were found similar. Wilkowski *et al.* (2011) used the Taguchi technique to determine CNC processing factors for wood surface roughness. The parameters such as feed rate and spindle speed were investigated. Asiltürk *et al.* (2016) used the Taguchi orthogonal array and RSM to determine the effective factor. Moreover, the effective parameters were optimized for CNC lathe machining. Zhou *et al.* (2017) applied multi objective optimization technique by using grey relation analysis (GRA), radial basis function (RBF) neural network and particle swarm algorithm. In this study, workpiece material was selected as Ni-based superalloy Inconel 718. According to results, presented method was determined as successfully for multi-axis ball-end milling process. Zhou *et al.* (2016) used response surface methodology and genetic algorithm to optimize the surface roughness of nickel-based single crystal superalloy using micro-grinding process. According to verification results, optimum parameter levels were found as reliable. Bharathi and Baskar (2011) proposed the particle swarm optimization (PSO) algorithm to analyze the optimal processing factors for minimizing the surface roughness and processing time using aluminum material. Parameters of cutting speed, feed, and depth of cut were optimized by using PSO. They indicated that presented method was efficient for machining process. Bao *et al.* (2018) predicted wood surface roughness conducting the neural network for wood sanding process. They reported that presented model was usefully predicting the roughness value. According to previous studies, the effective parameters on the wood surface roughness are defined in cause and effect diagram given in (Figure 1).

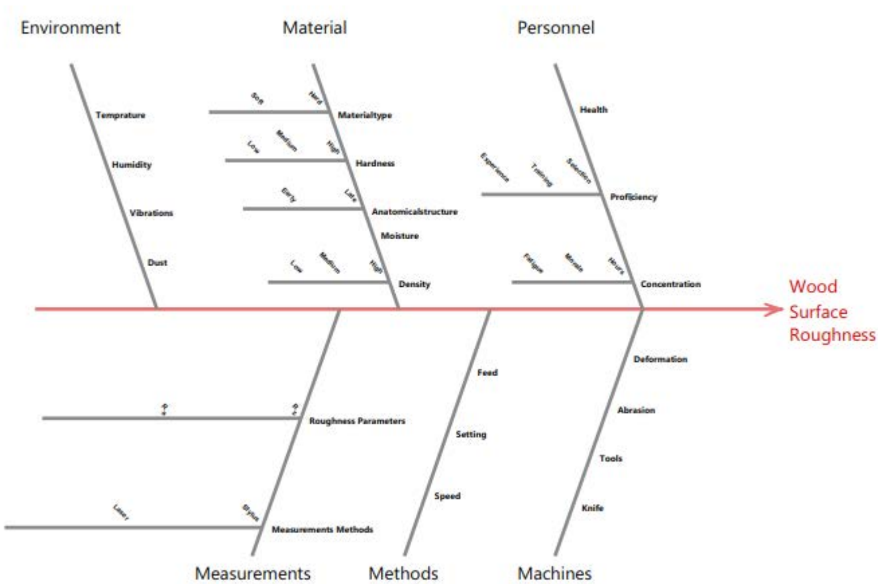

Figure 1: Cause and effect diagram of wood surface roughness parameters.

CNC processing parameters and their effects on wood surface roughness were determined in various past studies. However, there is little as no information evaluating the optimum cutting parameters for woodworking industries. Most of these studies presented various engineering problems not inherited to wood based products. Therefore, this study aims to present an approach for determining minimum surface roughness by integrating RSM, DF and SA in CNC processing.

MATERIALS AND METHODS

Cedar of Lebanon pine (*Cedrus libani A. Rich*) species with intensive use in the furniture industry was selected for the study. The samples were prepared with the dimension of 140 mm x 50 mm x 18 mm for each procedure. Density level of Cedar of Lebanon pine was measured randomly through 27 samples. Samples were conditioned in a climate room having a temperature of 20°C and relative humidity of 65% until they reach a moisture content of 9±1%. The value of wood density was 510 kg/m³. These samples were processed with 3-axis CNC. Alpha-CAM program was used for determination of the tool path for the sample. Roughness measurement device is a stylus-based portable profilometer that is Sutronic-25 type equipment. Parameters of R_a and R_z were used to evaluate the wood surface quality (ISO 4287-1997).

Statistical design of experiment

The statistical analysis was performed using Minitab software package 17. The Taguchi L_{27} orthogonal statistical designs were followed to optimize the experimental procedure. The processing variables were screened by ANOVA analysis. These factors were modeled by using response surface methodology (RSM). The results were analyzed by multiple regression analysis through least square method. All the terms of model were tested and verified statistically by *F*-test at probability levels (p<0,05). *R*-square and *Adj-R*-square were used to perform the developed the models. After the fitting models, 3D surface plots were applied to evaluate the process parameters. Finally, desirability function based simulated angling algorithm was used to screen the optimum parameter levels. The experimental produce is shown in (Figure 2).

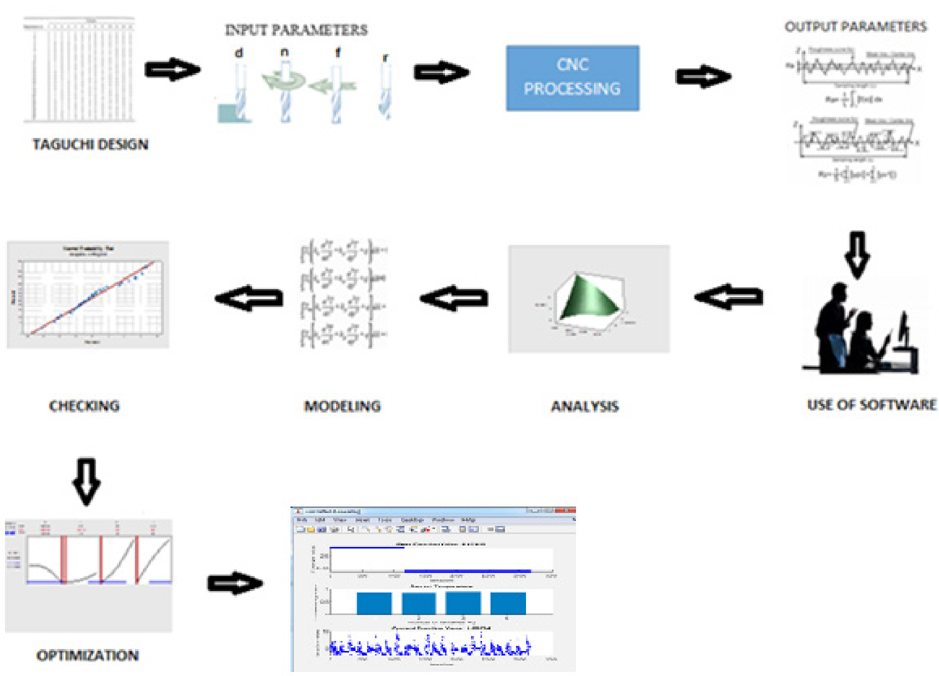

Figure 2: Experimental procedure.

Response surface method (RSM)

Response surface method (RSM) is a statistical based technique. RSM method involves three stages. The first stage is the selection of independent variables of major effects on the process through screening studies and the delimitation of the experimental region. The second stage is the mathematic-statistical apply of the obtained experimental data through the fit of a polynomial function and evaluation of the model's fitness. The third stage is the verification of the necessity and possibility of performing a displacement in direction to the optimal region and selection of optimum values of parameters. The general form second order polynomial equation is given Equation 1:

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_{i} \sum_{j}^{k} \beta_{ij} X_i X_j + \epsilon \qquad (1)$$

According to Equation 1 Y is the predicted reaction or reactions (R_a and R_z), X_i and X_j are variables, β_0 a constant, $\beta_{i,}$ β_{ii} and β_{ij} of linear, quadratic and the second-order terms, respectively and k is the number of independent parameters (k=4 in this study) and ϵ is the error term.

Experimental design

The traditional experimental design is time consuming and costly. L_{27} orthogonal design was used to overcome this issue. Especially, this method is used by manufacturing process and engineering analysis. These arrays of different combination for variables were applied by the Taguchi approach to analyze the experimental study. While 81 experiments are required to investigate all the effects of the parameters, 27 experiments are sufficient thanks to Taguchi orthogonal array. According to the Taguchi orthogonal array, the minimum number of experiment and coded variables were computed by using Equation 2 and Equation 3.

The Taguchi experiments trial number:

$$\left[(L-1)\, x\, P \right] + 1 \qquad (2)$$

The terms of L and P are displayed number of levels and number of parameters.

$$X_i = \frac{x_i - x_o}{\Delta_x} \qquad (3)$$

In terms of $X_{i,}$ X_o and Δ_x are coded variable, actual variable, center palace, and altered variable. (Table 1) shows the number of parameters and their levels.

Table 1: CNC experimental design procedure.

Symbol	Variables	Unit	(-1)	(0)	(+1)
n	Spindle speed	rpm	12000	15000	18000
f	Feed rate	m/min	2	5	8
d	Depth of cut	mm	2	4	6
r	Tool tip radius	mm	8	10	12

In this study, four parameters namely spindle speed, feed rate, depth of cut and tool radius were selected as input parameters while R_a and R_z were selected as output variables. (Table 2) shows the experimental parameters and their results.

Table 2: L_{27} experimental design results.

Run Order	Spindle Speed (*n*,rpm)	Feed Rate (*f*,m/min)	Depth of Cut (*d*,mm)	Tool Radius (*r*,mm)	Roughness(µm) R_a	R_z
1	12000	2	2	8	3,06	14,24
2	12000	2	4	10	4,29	17,16
3	12000	2	6	12	5,33	21,32
4	12000	5	2	10	7,25	29,30
5	12000	5	4	12	4,89	21,56
6	12000	5	6	8	6,37	27,48
7	12000	8	2	12	8,74	36,96
8	12000	8	4	8	9,18	35,72
9	12000	8	6	10	8,53	33,12
10	15000	2	2	10	4,59	18,36
11	15000	2	6	12	8,89	36,56
12	15000	2	6	8	6,59	23,36
13	15000	5	2	12	6,37	26,32
14	15000	5	4	8	5,03	21,18
15	15000	5	6	10	6,98	28,72
16	15000	8	2	8	7,11	29,32
17	15000	8	4	10	6,96	28,62
18	15000	8	6	12	6,81	28,12
19	18000	2	2	12	6,07	25,18
20	18000	2	4	8	3,96	16,42
21	18000	2	6	10	8,59	35,36
22	18000	5	2	8	3,72	12,16
23	18000	5	4	10	4,29	18,14
24	18000	5	6	12	8,29	34,12
25	18000	8	2	10	3,40	14,54
26	18000	8	4	12	4,89	20,34
27	18000	8	6	8	4,01	17,14

RESULTS AND DISCUSSION

In this section, two mathematical models used for optimization of the surface roughness were explained. The Taguchi orthogonal array integrated with response surface methodology and simulated angling algorithm for solving these models were detailed. In addition to these, the suggested models were tested by using verification test. Interactions between the variables were analyzed by using 3D surface plot. Finally, the results were compared and the suggested models were discussed.

Developing the mathematical models

The results were analyzed by conducting Minitab 17 software. Correlation of the experimental roughness value and the estimated values from the regression equation were shown in (Table 3). The experimental data were analyzed by the polynomial models such as linear, 2-way interaction and full quadratic models. The adequacy of models performed indicated that linear, interaction and quadratic models had lower *p*-value (<0,05). (Table 3) displays the R^2 and Adjusted-R^2 values were found low in linear and interaction models. *R*-square and Adj-*R*-square values were described with Multiple Linear Regression Analysis (MLR). Quadratic models were calculated to have maximum R^2 and Adj- R^2 values. Hence the quadratic models were chosen for R_a and R_z in this study.

Table 3: Regression models, R^2 and Adj-R^2.

Regression model	R^2	**Adj-R^2**	
Linear			
Ra (µm) = 3,73 - 0,000193 *n* + 0,167 *f* + 0,367 *d* + 0,292 *r*	29,83	17,07	
Rz (µm) = 13,5 - 0,000805 *n* + 0,717 *f* + 1,408 *d* + 1,407 *r*	10,04	4,32	
Linear + square			
Ra (µm) = -10,3 + 0,00180 *n* - 0,011 *f* - 1,26 *d* + 0,81 *r* - 0,000000 n^2 + 0,0192 f^2 + 0,201 d^2 - 0,027 r^2	37,17	9,24	
Rz (µm) = -68,3 + 0,00869 *n* + 1,13 *f* - 6,94 *d* + 6,8 *r* - 0,000000 n^2 - 0,026 f^2 + 0,960 d^2 - 0,302 r^2	30,64	0,00	
Linear + interaction			
Ra (µm) = 10,81 - 0,001040 *n* + 4,553 *f* - 1.127 *d* - 1.425 *r* – 0,000191 *nf* + 0,000115 *nd* + 0.000134 *nr* – 0,1357 *fd* – 0,0968 *fr* + 0,0413 *dr*	90,50	84,55	
Rz (µm) = 78,5 – 0,00630 *n* + 13,87 *f* – 4,52 *d* – 7,48 *r* – 0,000649 *nf* + 0,000607 *nd* + 0,000667 *nr* – 0,382 *fd* – 0,179 *fr* – 0,194 *dr*	82,58	71,69	
Full quadratic			
Ra (µm) = -2,69 + 0,000699 *n* + 4,294 *f* – 2,443 *d* – 0,69 *r* – 0,000000 n^2 + 0,0146 f^2 + 0,1740 d^2 - 0,0376 r^2 – 0,000190 *nf* + 0,000112 *nd* + 0,000133 *nr* – 0,1306 *fd* – 0,0876 *fr* + 0,0337 *dr*	95,91	91,15	suggested
Rz (µm) = 5,7 + 0,00128 *n* + 17,32 *f* – 10,61 *d* – 3,58 *r* – 0,000000 n^2 + 0,0337 f^2 + 0,637 d^2 - 0,105 r^2 – 0,000733 *nf* + 0,000558 *nd* + 0,000565 *nr* – 0,5088 *fd* – 0,3810 *fr* + 0,091 *dr*	96,12	95,93	suggested

Analysis of variance (ANOVA)

Table 4 and Table 5 indicated variance analysis for R_a and R_z. In this case *f, n, d, r,* n^2, d^2, *fd, fn, nd, nr, fr* are significant factors. Contribution (PC %) of each factor on the total variation is computed as percentage. The most effective parameters for R_a and R_z were interaction between feed rate and spindle speed, their contribution to the model values were 37,16 % and 34,47 %, respectively, on the surface roughness. The coefficient of determination R^2 for the R_a and R_z of were 95,91 % and 96,12 % respectively. The Adjusted R^2 values for R_a and R_z were computed as 91,15 % and 95,93 % respectively.

Table 4: ANOVA results for R_a.

Source	DF	PC (%)	SS	*F*	*P*
Model	14	95,91	86,82	20,12	0,000[a]
Linear	4	29,83	24,21	19,64	0,000[a]
n	1	6,66	6,03	19,57	0,001[a]
f	1	4,19	6,01	19,50	0,001[a]
d	1	12,21	7,60	24,67	0,000[a]
r	1	6,77	4,40	14,28	0,003[a]
Square	4	7,33	4,90	3,98	0,028[a]
n^2	1	3,12	1,55	5,04	0,044[a]
f^2	1	0,31	0,10	0,33	0,574
d^2	1	3,82	2,57	8,36	0,014[a]
r^2	1	0,08	0,13	0,44	0,521
2-Way Interaction	6	58,75	53,18	28,76	0,000[a]
$f * d$	1	37,16	31,92	106,81	0,000[a]
$n * d$	1	3,91	5,11	16,59	0,002[a]
$f * n$	1	4,79	7,16	23,25	0,000[a]
$n*r$	1	9,17	7,27	23,60	0,000[a]
$f*r$	1	3,48	3,00	9,76	0,009[a]
$d*r$	1	0,24	0,21	0,70	0,420
Error	12	4,09	3,69		
Total	26	100			

The terms of ([a]) indicates significant parameter.

Table 5: ANOVA results for R_z.

Source	DF	PC (%)	SS	*F*	*P*
Model	14	98,12%	1443,97	44,83	0,000[a]
Linear	4	32,95	439,20	47,72	0,000[a]
n	1	7,13	104,93	45,61	0,000[a]
f	1	4,87	106,88	46,45	0,000[a]
d	1	11,30	111,66	48,53	0,000[a]
r	1	9,65	110,32	47,95	0,000[a]
Square	4	6,08	64,06	6,96	0,004[a]
n^2	1	2,58	20,84	9,06	0,011[a]
f^2	1	0,16	0,55	0,24	0,634
d^2	1	3,31	34,49	14,99	0,002[a]
r^2	1	0,03	1,05	0,46	0,512
2-Way Interaction	6	59,09	869,54	62,99	0,000[a]
$f * d$	1	34,47	490,54	213,21	0,000[a]
$n * d$	1	6,29	125,84	54,69	0,000[a]
$f * n$	1	5,63	129,68	56,36	0,000[a]
$n*r$	1	8,61	110,38	47,98	0,000[a]
$f*r$	1	3,99	56,80	24,69	0,000 [a]
$d*r$	1	0,11	1,58	0,69	0,424

The terms of ([a]) indicates significant parameter.

Evaluation of the models

Normal Probability Plot (NPP) was applied to evaluate the data for normality. Residual is the mean difference between the observed value and the predicted or fitted value. If the residuals fall approximately along straight line, they are then normally distributed. In contrast, if the residuals do not fall fairly close to a straight line, they are then not normally distributed (Antony 2014). If the model is correct and if the assumptions are satisfied, the residuals should be structures; in particular, they should be unrelated to any other variable including the predicted response. Figure 3a, Figure 3b, Figure 4a and Figure 4b show that the residuals generally fall on a straight line implying that the errors were disturbed normally, meaning was the experimental data come from a normal population. As a result of the residuals, no unusual structures were apparent.

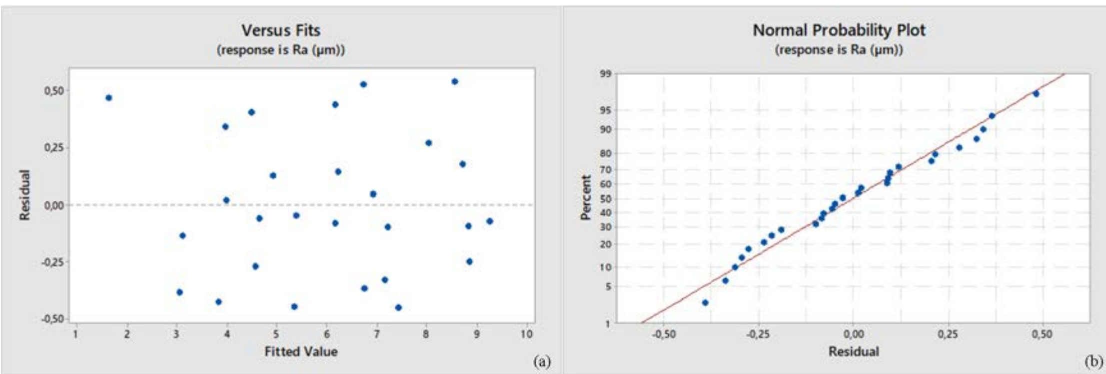

Figure 3: (a) Fitted value for R_a and (b) NPP of residuals for R_a.

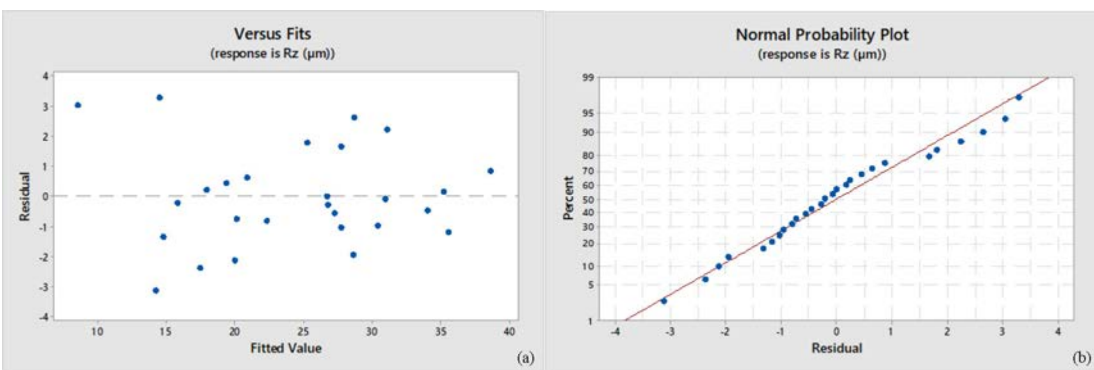

Figure 4: (a) Fitted value for R_z and (b) NPP of residuals for R_z.

Surface graphs and analysis

Response surface provides the relationship between the factors with each other and the response variable. (Figure 5a) shows the surface plot for R_a in CNC machining of wood material with three levels of feed rate and three levels of spindle speed for mid-level hold value of depth of cut with 4 mm and tool radius of 10 mm. The surface roughness increased with decreases the spindle speed and increases the feed rate. (Figure 5b) shows the surface plot for R_a in CNC machining of wood material with three levels of depth of cut and three levels of tool radius for mid-level hold value with feed rate of 5 m/min and spindle speed of 15000 rpm. The surface roughness decreased with a decrease of tool radius and depth of cut. (Figure 5c) shows the surface plot for R_a in CNC machining of wood material with three levels of feed rate and three levels of tool radius for mid-level hold value with spindle speed of 15000 rpm and 4 mm depth of cut. The surface roughness increased with the increase in tool radius and feed rate. (Figure 5d) shows the surface plot for R_a in CNC machining of wood material with three levels of feed rate and three levels of depth of cut for mid-level hold value with spindle speed of 15000 rpm and tool radius of 10 mm. The surface roughness increased with the increase in feed rate and depth of cut. (Figure 5e) shows the surface plot for R_a in CNC machining of wood material with three levels of spindle speed and three levels of tool radius for mid-level hold value with 5 m/min of feed rate and depth of cut of 4 mm. The surface roughness increased with the increase in tool radius and decreases with spindle speed. (Figure 5f) shows the surface plot for R_a in CNC machining of wood material with three levels of depth of cut and three levels of spindle speed for mid-level hold value with 5 m/min of feed rate and tool radius of 10 mm. The surface roughness increased with the increase in depth of cut and decrease with spindle speed.

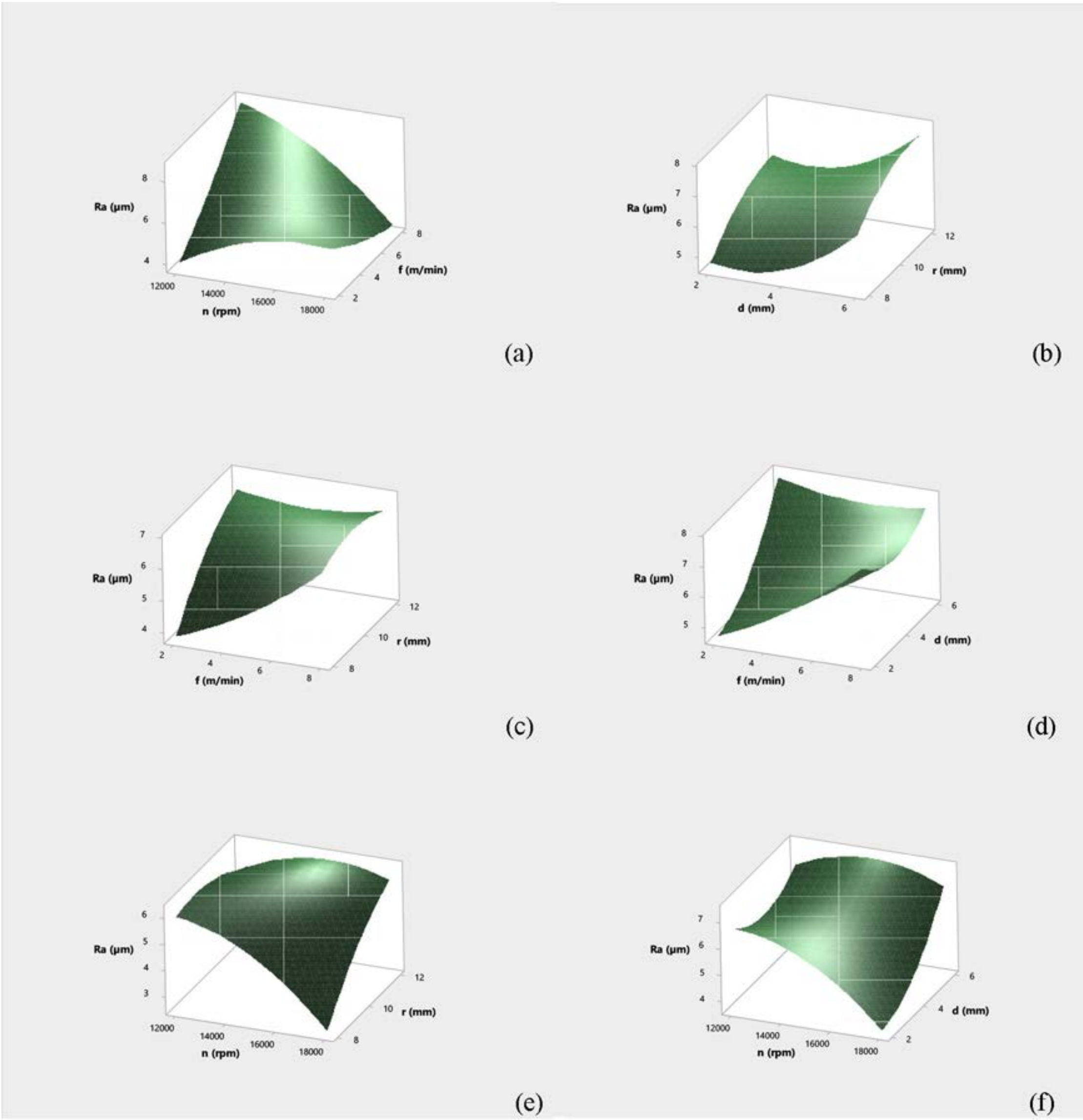

Figure 5: According to 3D surface plots (a, b, c, d, e, f) of different values processing parameters for R_a.

(Figure 6a) shows the surface plot for R_z in CNC machining of wood material with three levels of feed rate and three levels of spindle speed for mid-level hold value of depth of cut with 4 mm and tool radius of 10 mm. The surface roughness increased with decreases the spindle speed and increases the feed rate. (Figure 6b) shows the surface plot for R_a in CNC machining of wood material with three levels of depth of cut and three levels of tool radius mid-level hold value with feed rate of 5 m/min and spindle speed of 15000 rpm. The surface roughness decreased with a decrease of tool radius and depth of cut. (Figure 6c) shows the surface plot for R_a CNC machining of wood material with three levels of feed rate and three levels of tool radius for mid-level hold value with 15000 rpm of spindle speed and depth of cut of 4 mm. The surface roughness increased with the increase in tool radius and feed rate. (Figure 6d) shows the surface plot for R_a in CNC machining of wood material with three levels of feed rate and three levels of depth of cut for mid-level hold value with 15000 rpm of spindle speed and tool radius of 10 mm. The surface roughness increased with the increase in feed rate and depth of cut. (Figure 6e) shows the surface plot for R_a in CNC machining of wood material with three levels of spindle speed and three levels of tool radius for mid-level hold value with 5 m/min of feed rate and depth of cut of 4 mm. The surface roughness increased with the increase in tool radius and decreases with spindle speed. (Figure 6f) shows the surface plot for R_a in CNC machining of wood material with three levels of depth of cut and three levels of spindle speed for mid-level hold value with 5 m/min of feed rate and tool radius of 10 mm. The surface roughness increased with the increase in depth of cut and decrease with spindle speed.

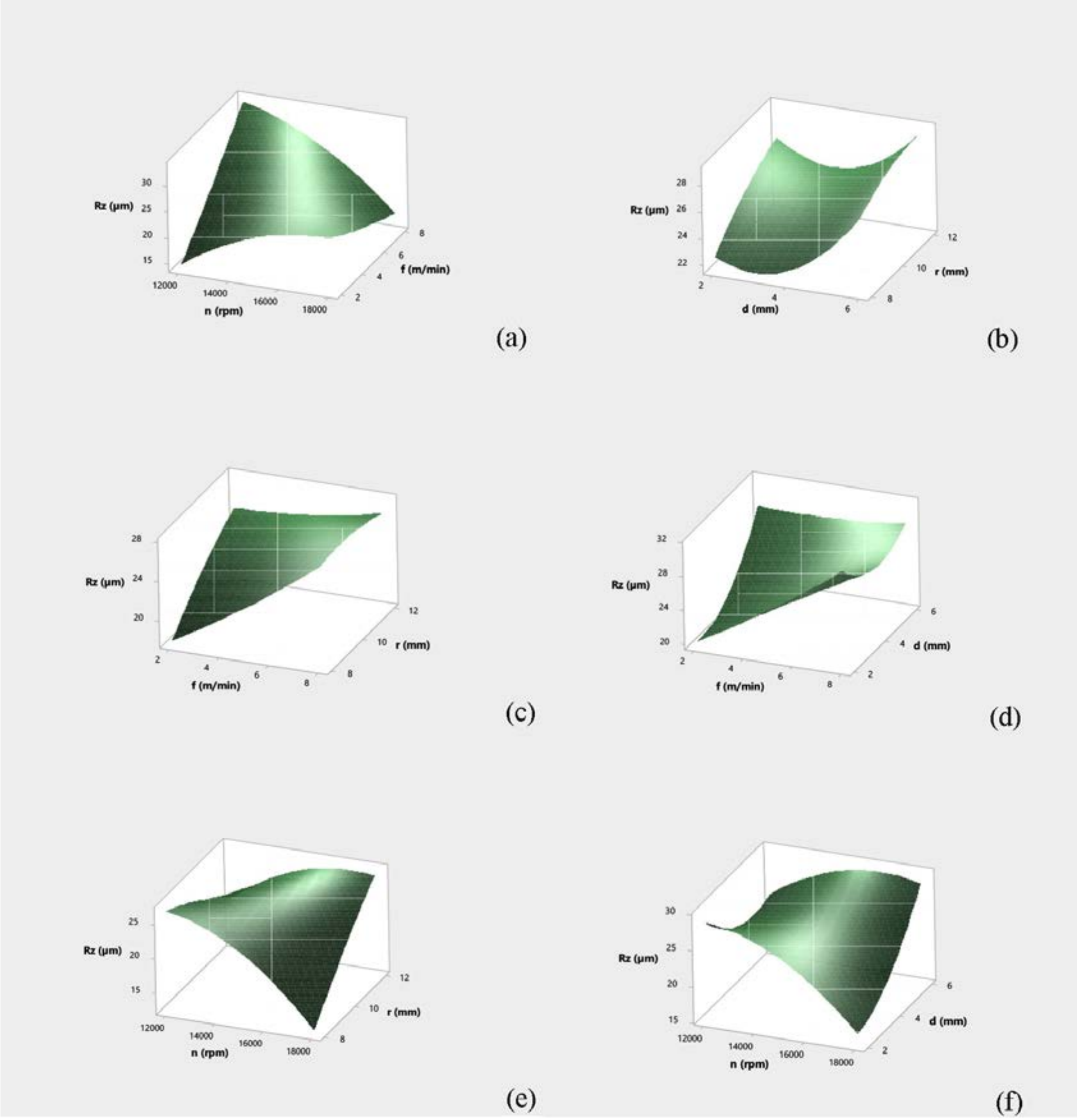

Figure 6: According to 3D surface plots (a, b, c, d, e, f) of different values processing parameters for R_z.

Parameter optimization

The aim of present work was to find the optimal processing levels leading to minimum values of R_a. and R_z. Two second order mathematical models were created by using RSM. Moreover, backward elimination method was carried out for determining the non-significant terms in mathematical models. To formulate the optimization problem, proposed models were presented in Equation 4 and Equation 5:

$$\begin{aligned} &Minimize\ Ra = 9,42 - 0,001069n + 4,510f - 0,710d - 1,251r - 0,000186nf \\ &+ 0,000115nd + 0,000134nr - 0,1374fd - 0,0990fr \end{aligned} \tag{4}$$

$$\begin{aligned} &Minimize\ \ Rz = 11,2 + 0,00134n + 17,56f - 9,68d - 5,29r - 0,000000n^2 \\ &+ 0,635d^2 - 0,000722nf + 0,000559nd + 0,000566nr - 0,5116fd - 0,3860fr \end{aligned} \tag{5}$$

These models were solved with two different methods namely, desirability function and simulated angling algorithm. Firstly, the desirability function was applied to determine the initial optimum parameter levels. Then, the results were used the initial point for the simulated angling algorithm. The functions terms were optimized within the specified range. The range of machining conditions was selected and given as follows Equation 6a, Equation 6b, Equation 6c, Equation 6d:

Within ranges of processing parameters,

$$2 \le f \le 8 \qquad 6(a)$$

$$12000 \le n \le 18000 \qquad 6(b)$$

$$2 \le d \le 6 \qquad 6(c)$$

$$8 \le r \le 12 \qquad 6(d)$$

The limitations of cutting variables value of spindle speed, feed rate, depth of cut and tool radius were 12000 rpm, 2 m /min, 2 mm and 8 mm as lower limits while 18000 rpm, 8 m/min, 6 mm and 12 mm were selected as upper limits, respectively.

Parameter optimization by using desirability function (DF)

This is commonly applied engineering problems for the optimization process. The function value is range 0 from 1. In the present work, selected quality characteristic was smaller-the-better for minimizing the surface roughness value. This equation was presented in Equation 7:

$$d_i = \begin{cases} 1 & y_i < T \\ \left(\dfrac{U - y_i}{U - T}\right)^{\omega} & T \le y_i \le U \\ 0 & y_i > U \end{cases} \quad (7)$$

Where T symbolizes the target value of the i th response, y_i, L symbolizes the acceptable lower limit value, U symbolizes the acceptable upper limit, for this response and W represents the weight. In (Table 6), optimal machining parameters for minimizing R_a was found with spindle speed of 17450 rpm, feed rate of 2,9 m/min, tool radius of 8,0 mm and depth of cut of 2,0 mm. optimal machining parameters for minimizing R_z was spindle speed of 16990 rpm, feed rate of 2,0 m/min, tool radius of 8,0 mm and depth of cut of 2,0 mm.

Table 6: Taguchi- DF results for R_a and R_z.

Response	Target	Optimal conditions				Predicted (µm)	Desirability
		f **(mm/min)**	***n*** **(rpm)**	***d*** **(mm)**	***r*** **(mm)**		
Ra (µm)	Min.	2,9	17450	2,0	8,0	3,1287	0,988
Rz(µm)	Min,	2,0	16990	2,0	8,0	11,254	1,000

From the Figure 7 and Figure 8, the optimum values for R_a and R_z were 3,1287 µm and 11,254 µm, respectively.

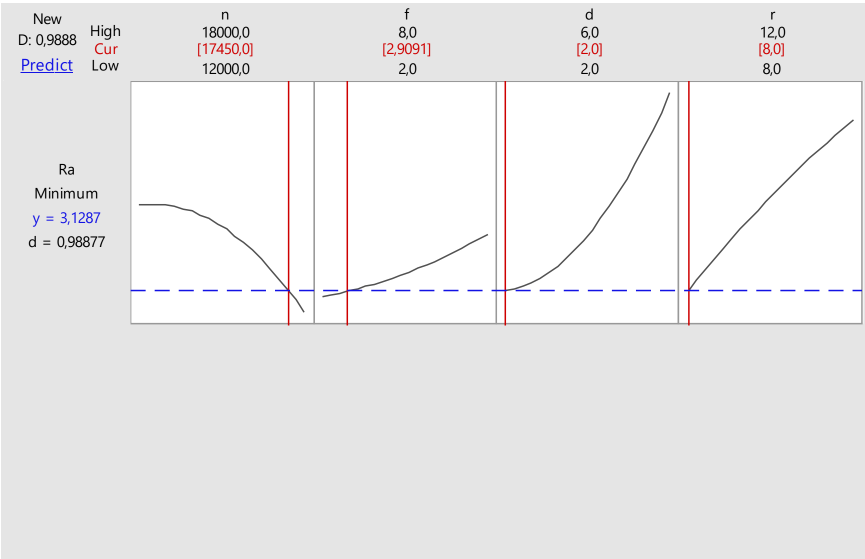

Figure 7: Response optimization plot for R_a.

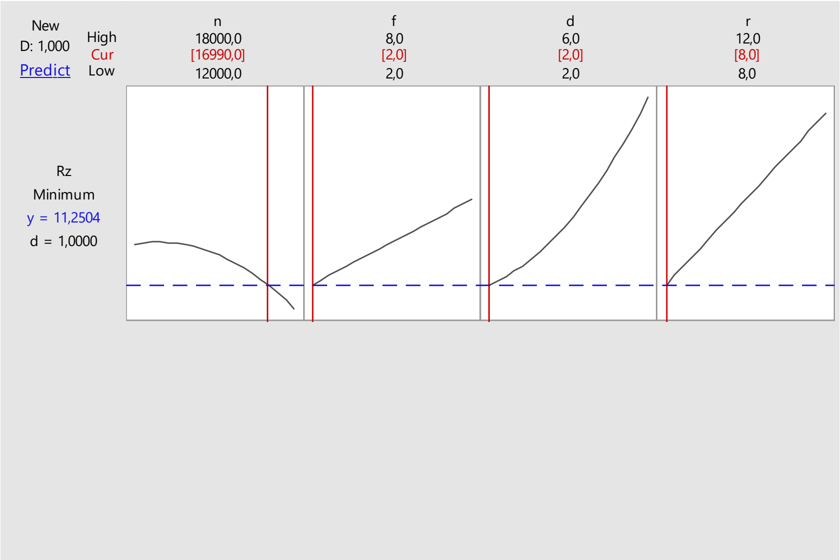

Figure 8: Response optimization plot for R_z.

Parameter optimization by simulated angling algorithm (SA)

In this study, simulated angling algorithm was applied to optimize the machining parameters. It is the one of the most useful metaheuristics method for solving the engineering problems due to easy application. It is a widely used method in solving optimization problems. SA is a probabilistic and single solving method based on the annealing process of metallurgy. The algorithm starts with an initial point using random solution, *S*, then a simple random change is produced to actual solution (*S'*). Obtained solution was compared with new solution by creating the objective function. The new solution is accepted when the objective *f(S')* is smaller than other objective. This solution is recognized with a probability of $\exp^{-(f(S')-f(S))/T}$. The term of *T* is a control variable and it is reduced from a relatively to near zero. SA was applied by solving the fitness function formulated in Equation 4 and Equation 5. In (Table 1), the range of processing variables was defined to solve the surface roughness problem. Initial points of SA are given in (Table 7).

Table 7: Initial points of SA for R_a and R_z.

Variables	R_a	R_z
Spindle speed	17450	16990
Feed rate	2,90	2,0
Depth of cut	2,0	2,0
Tool radius	8,0	8,0

Matlab optimization toolbox was used to solve the surface roughness problem. The values of the SA parameters such as annealing function, reannealing interval, temperature function, initial point of temperature, and probability function. Matlab software was used to determine the best optimal results using different simulated angling parameters. The best solution of these parameters was given in (Table 8).

Table 8: Selection of SA parameters to determine the optimal solution.

SA Parameters	Selected function and values	
	R_a	R_z
Annealing function	Boltzmann annealing	Fast annealing
Reannealing interval	100	100
Temperature function	Exponential	Exponential
Initial temperature	100	100
Probability function	SA	SA
Data type	Double	Double

Minimum R_a value was resulted with spindle speed of 17377 rpm, feed rate of 2,012 m/min, tool radius of 8,00 mm and depth of cut of 2,009 mm using simulated angling algorithm. Minimum R_z value was obtained spindle speed of 16980 rpm, feed rate of 2,004 m/min, tool radius of 8,001 mm and depth of cut of 2,003 mm using simulated angling algorithm. The results of Matlab SA toolbox were given in Figure 9a, Figure 9b, Figure 10a, Figure 10b. According to Figure 9a, Figure 10a, the best fitness values for R_a and R_z were 2,474 µm and 10,674 µm, respectively. In the Figure 10a, Figure 10b, the optimal solutions of R_a and R_z were performed at the 3106 and 4712 iteration, respectively.

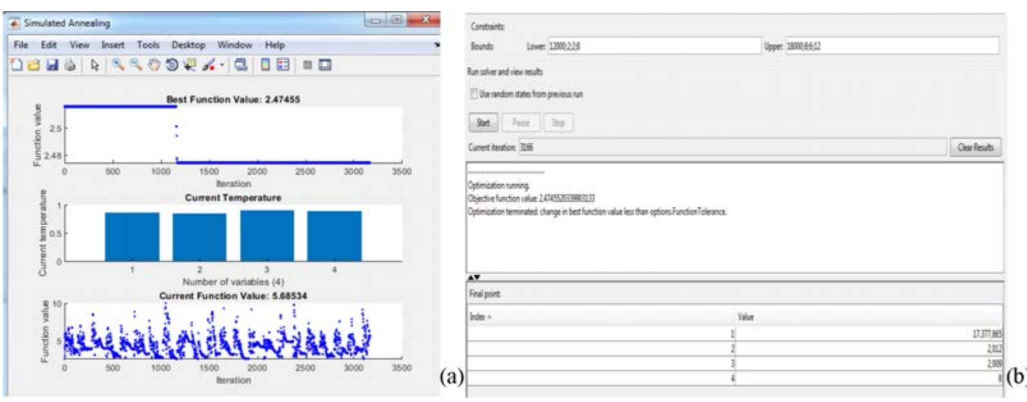

Figure 9: (a) Variation of fitness function and best individuals (b) Converged values of parameters.

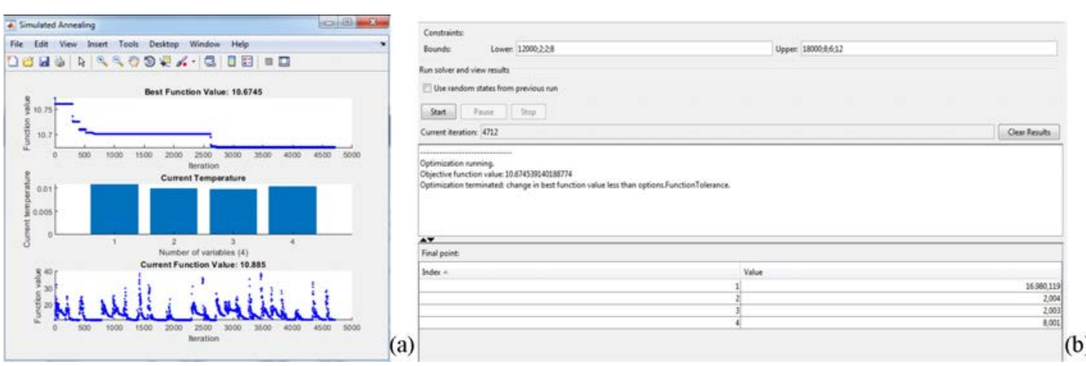

Figure 10: (a) Variation of fitness function and best individuals (b) Converged values of parameters.

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Comparison of results

The Taguchi orthogonal design based desirability function and desirability function integrated simulated angling algorithm results were given in (Table 9). From the (Table 9), the minimum R_a and R_z values were 2,474 µm and 10,674 µm. For this reason, the RSM-DF-GA approach should present an efficient methodology in order to minimize the surface roughness.

Table 9: Results of experiments and optimum values by Taguchi-RSM-DF and Taguchi-RSM-DF-SA models for R_a and R_z.

Proposed models	Optimal conditions				Response (µm)	
	f **(mm/min)**	***n*** **(rpm)**	***d*** **(mm)**	***r*** **(mm)**	R_a	R_z
Taguchi-RSM-DF	2,900	17450	2,000	8,000	3,128	-
Taguchi-RSM-DF-SA	2,012	17377	2,009	8,000	2,474	-
Taguchi-RSM-DF	2,000	16990	2,000	8,000	-	11,254
Taguchi-RSM-DF-SA	2,004	16980	2,003	8,001	-	10,674

CONCLUSIONS

In this work, effect of machining of Cedar of Lebanon pine (*Cedrus libani*), the surface roughness characteristics were investigated. The optimization process was adopted by a combined approach of L_{27} orthogonal array based simulated angling algorithm. A three-levels and four factors experimental design were applied to identify the most significant factors, desirability function and simulated angling algorithm were used to optimize the machining procedure. The results can be summarized as follows:

Different from other studies in the literature, two mathematical models were developed based on L_{27} orthogonal design and RSM method that the method has not been used to determine optimum CNC parameters for wood material.

The R_a and R_z were influenced by interaction between feed rate and spindle speed with PCR (%) of 37,16 % and 34,47 %, respectively.

Two different mathematical models were applied by using quadratic models. Moreover, backforward elimination method was applied to determine the non-significant variables. The non-significant terms were removed in these models.

Minimum R_a value was obtained spindle speed of 17377 rpm, feed rate of 2,012 m/min, tool radius of 8 mm and depth of cut of 2,009 mm by using desirability function based simulated angling algorithm. For R_z these results were found as 16980 rpm 2,004 m/min, 8,001 mm and 2,003 mm.

In this study, these models can be regarded as a method experimentally and statistically for the analysis, modeling optimization of CNC machining operations and can applied wood cutting process.

ACKNOWLEDGMENTS

The authors thank to TUBITAK (The Scientific and Technological Research Council of TURKEY) for support and contributions during the doctoral thesis.

REFERENCES

Antony, J. 2014. *Design of experiments for engineers and scientists.* 2th edn. Elsevier: London.

Asiltürk, I.; Neseli, S.; Ince, A.M. 2016. Optimization of parameters affecting surface roughness of Co-28Cr6Mo medical material during CNC lathe machining by using the Taguchi and RSM methods. *Measurement* 78:120-128.

Azhiri, R.B; Teimouri, R.; Baboly, M.G.; Leseman, Z. 2014. Application of Taguchi, ANFIS and grey relation analysis for studying, modeling and optimization of wire EDM process while using gaseous media. *Int J Adv Manuf Technol* 71(1-4):279-295.

Bao, X.; Ying, J.; Cheng, F.; Zhang, J.; Luo, B.; Li, L.; Liu, H. 2017. Research on neural network model of surface roughness in belt sanding process for *Pinus koraiensis. Measurement* 115:11-18.

Bharathi, S.R; Baskar, N. 2011. Particle swarm optimization technique for determining optimal machining parameters of different work piece materials in turning operation. *The International Journal of Advanced Manufacturing Technology* 54 (5-8):445-463.

Coelho, C.L.; Carvalho, L.M.H.; Martins, J.M.; Costa, V.A.V.; Masson, D.; Meausooner, P.J. 2008. Method for evaluating the influence of wood machining conditions on the objective characterization and subjective perception of a finished surface. *Wood Sci Technol* 42(3):181-195.

Davim, J.P.; Clemente, V.C.; Silva, S. 2009. Surface roughness aspects in milling MDF (medium density fiberboard). *Int J Adv Manuf Technol* 40(1-2):49-55.

Deepanraj, B.; Sivasubramanian, V.; Jayaraj, S. 2017. Multi-response optimization of process parameters in biogas production from food waste using Taguchi-Grey relational analysis. *Energy Conversion and Management* 141:429-438.

Gaitonde, V.N.; Karnik, S.R.; Davim, J.P. 2008. Taguchi multi-performance characteristics optimization in drilling of medium density fibreboard (MDF) to minimize delamination using utility concept. *J Mater Process Tech* 196(1-3):73-78.

Hazir, E.; Erdinler, E.S.; Koç, K.H. 2018. Optimization of CNC cutting parameters using design of experiment (DOE) and desirability function. *Journal of Forestry Research* 29(5):1423-1434.

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.

Hiziroglu, S.; Kosonkorn, P. 2006. Evaluation of surface roughness of Thai medium density fiberboard (MDF). *Building and Environment* 41(4):527-533.

International Organization for Standardization. ISO. 1997. Geometrical product specifications (GPS) surface texture: profile method-terms, definitions, and surface texture profile method terms, definitions and surface texture parameters. ISO 4287. 1997. International Organization for Standardization: Geneva.

Kant, G.; Sangwan, K.S. 2014. Prediction and optimization of machining parameters for minimizing power consumption and surface roughness in machining. *Journal of Cleaner Production* 83:151-164.

Koç, K.H.; Erdinler, E.S.; Hazir, E.; Öztürk, E. 2017. Effect of CNC application parameters on wooden surface quality. *Measurement* 107:12-18.

Magoss, E. 2008. General regularities of wood surface roughness. *Acta Silv Lign Hung* 4:81-93.

Mahes, G.; Muthu, S.; Devadasan, S.R. 2015. Prediction of surface roughness of end milling operation using genetic algorithm. *Int J Adv Manuf Technol* 77(1-4):369-381.

Majumder, H.; Paul, T.R.; Dey, V.; Dutta, P.; Saha, A. 2017. Use of PCA-grey analysis and RSM to model cutting time and surface finish of Inconel 800 during wire electro discharge cutting. *Measurement* 107:19-30.

Ozdemir, T.; Hiziroglu, S. 2007. Evaluation of some sanding factors on the surface roughness of particle-board. *Silva Fennica* 41(2):373-378.

Philbin, P.; Gordon, S. 2006. Recent research on the machining of wood-based composite materials. *International Journal of Machining and Machinability of Materials* 1(2):186-201.

Prakash, S.; Palanikumar, K. 2010. Modeling for prediction of surface roughness in drilling MDF panels using response surface methodology. *J Compos Mater* 45(16):1639-1646.

Rao, R.V.; Kalyankar, V.D. 2013. Parameter optimization of modern machining process using teaching-learning-based optimization algorithm. *Engineering Application of Artificial Intelligence* 26(1): 524-531.

Rao, V.K.; Murthy, N.S.G.B.P. 2018. Modeling and optimization of tool vibration and surface roughness in boring of steel using RSM, ANN and SVM. *J Intell Manuf* 29(7):1533-1543.

Ratnasingman, J.; Scholz, F. 2006. Optimal surface roughness for high-quality on Rubberwood. *Holz-als Roh-und Werkstoff* 64(4): 343-345.

Samanta, B. 2009. Surface roughness prediction in machining using soft computing. *International Journal of Computer Integrated Manufacturing* 22(3):257-266.

Sarikaya, M.; Güllü, A. 2016. Taguchi design and response surface methodology based analysis of machining parameters in CNC turning under MQL. *Journal of Cleaner Production* 65:604-616.

Selaimia, A.A.; Yallese, M.A.; Bensouilah, H.; Meddour, I.; Khattabi, R.; Mabrouki, T. 2017. Modeling and optimization in dry face milling of X2CrNi18-9 austenitic stainless steel using RSM and desirability approach. *Measurement* 107:53-67.

Sofuoglu, D.S. 2017. Determination of optimal machining parameters of massive wooden edge glued panels which is made of Scots pine (*Pinus sylvestris L.*) using Taguchi design method. *Eur J Wood Prod* 75(1):33-42.

Taguchi, G.; Chowdhury, S.; Wu, Y. 2005. *Taguchi's quality engineering handbook*. Wiley: Hoboken.

Wilkowski, J.; Czarniak, P.; Grześkiewicz, M. 2011. Machinability evaluation of thermally modified wood using the Taguchi technique. In: COST Action FP0904 Workshop Mechano-chemical transformations of wood during Thermo-Hydro-Mechanical processing: 109-111.

Yang, W.H.; Tarng, Y.S. 1998. Design optimization of cutting parameters for turning operations based on the Taguchi Method. *J Mater Process Technol* 84(1-3):122-129.

Zhou, Y.; Gong, Y.; Zhu, Z.; Gao, Q.; Wen, X. 2016. Modeling and optimization of surface roughness from micro grinding of nickel-based single crystal super alloy using the response surface methodology and genetic algorithm. *Int Adv Manuf Technol* 85(9-12):2607-2622.

Zhou, Y.; Ren J.;Yao, C. 2017. Multi-objective optimization of multi-axis ball-end milling Inconel 718 via grey relational analysis coupled with RBF neural network and PSO algorithm. *Measurement* 102:271-285.