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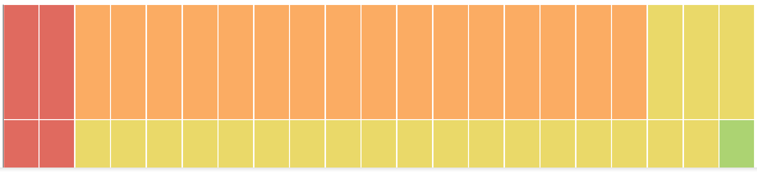

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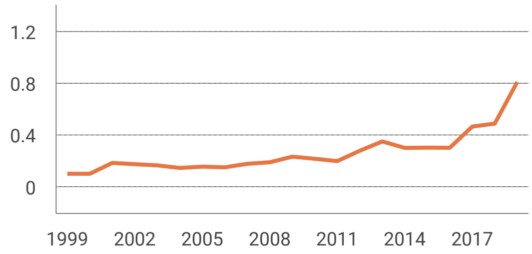

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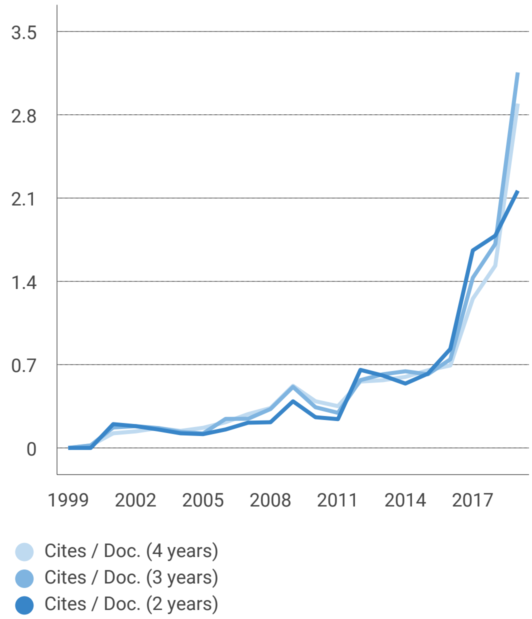

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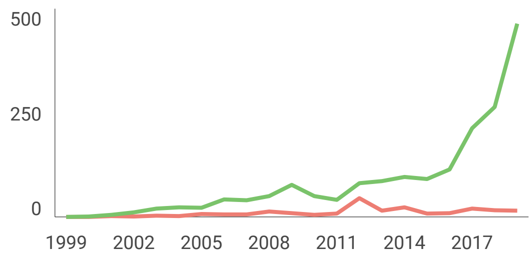

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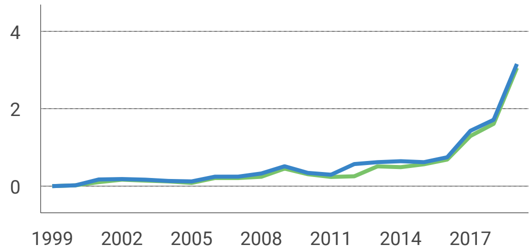

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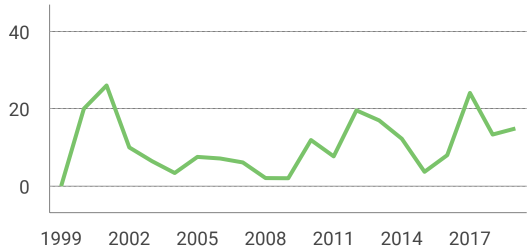

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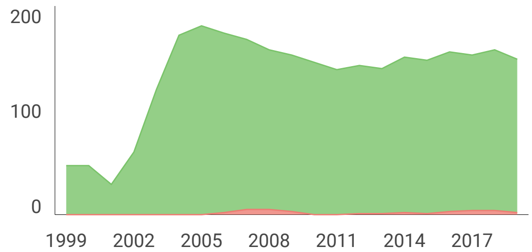

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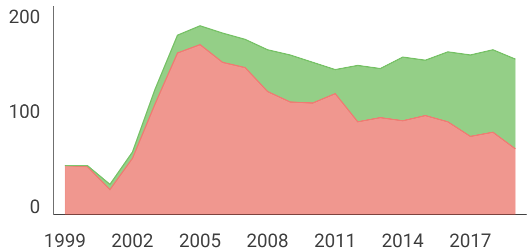

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Milling strategy optimized for orthotics insole to enhance surface roughness and machining time by Taguchi and response surface methodology

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ARTICLE

Milling strategy optimized for orthotics insole to enhance surface roughness and machining time by Taguchi and response surface methodology

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ABSTRACT

The machining strategy of EVA rubber foam for insole shoe orthotics of diabetic patient (ISO-diabetes) by CNC milling is presented in the work. Five parameters such as type of ISO-diabetes (A), toolpath strategy (B), spindle speed (C), step over (D) and feed rate (E) were optimized with Taguchi. Five factors that influence the surface roughness value (Ra) and machining time (Ta) were examined using the response surface methodology (RSM). Regression analysis of RSM as a function of machining parameters resulted in the optimum yields of both Ra and Ta. The optimal ISO-diabetes type with a tolerance of 0–2 mm corresponding with the toolpath strategy raster of 45^{O}, spindle speed of 14000rpm, feeding rate of 800 mm/rotation, and step over of about 0.2 mm, were reached for Ra of 5.0 µm and Ta of 154.05 s. These optimal conditions could be a promising machining strategy aimed at providing a low-cost manufacturing operation of ISO-diabetes.

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EVA rubber foam; ISO-diabetes; surface roughness; Taguchi; RSM

1. Introduction

The human feet play an important role in supporting the body when performing daily activities such as standing, running and walking. In the course of these activities, the feet could suffer a lot of plantar pressure. The weight of the human body could be the main source of pressure on the feet when walking or standing. Having a comfortable footwear is very essential for everyone, whether having normal feet or foot deformities caused by diabetes. The foot disorders experienced by diabetic patients are commonly associated with abnormal plantar pressure distribution [1,2]. This condition causes foot sickness or illness syndrome due to poor biomechanics. The use of personalized insoles provides patients with a well-improved gait, thus increasing efficiency when carrying out everyday activities. Conversely, the human foot has a complex anatomy comprising twenty-six bones, thirty-three joints, ligaments, and seven hundred and nineteen muscles. This complex surface structure of the foot requires the design of customized footwear with a good fitting and the most comfortable standard [3]. In order to fabricate an appropriate insole for patients, a reasonable amount of focus must be put into their biomechanical requirements and likewise the physical demands of their usual activities.

The orthotic insoles are frequently manufactured making use of a footprint process in a foam box and then formed by cast molding. This traditional method is being employed by so many podiatrists today, but it requires a long processing time and a relatively high production cost. Also, the product fails to meet customers' required specification. Accordingly, the fabrication of orthotic insoles can be classified as a method with low manufacturing efficiency which generates products with poor surface finish. Also, the product might be a poor fit for feet having unnatural shapes [4,5]. The alternative approach for solving these problems is to employ a reverse innovative design (RID) methodology, which is reliant on scanning device for digitizing the plantar surface of the foot. In this method, a direct machining of a CAD model for various insole materials such as polypropylene and polyoxymethylene (POM C) can be conducted [5,6]. Accordingly, bespoke ISO-diabetes can be designed and manufactured resulting in more comfortable and better functional insoles, which can accommodate excessive motions when walking.

Currently, RID offers an interesting design methodology to reprocess of data base for 3D digital design applications. The primary aspect of RID methodology is associated with the construction of feature-based parametric solid models from the scanned data. The solid model can therefore be created from the feature data to facilitate design modification and iteration. Such construction simplifies both downstream analysis and rapid prototyping. The application of RID on designing six types of ISO-diabetes provided products fitted to the foot's contour surface of diabetic patients [7,8]. These types of design for ISO-diabetes, having a wide tolerance of 0–2 mm between insole and

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outsole sizes could be made. In addition, a direct CNC machining of input data from 3D surface scans of a patient's foot allows rapid manufacturing of the personalized footwear. Hence, the lengthy processes of cast manipulation and injection molding can be abolished.

Currently, ISO-diabetes is made with a semirigid of soft materials. A variety of materials for this insole orthotics have the required rigidity and geometry. Polymers are widely employed in shoe and sandal industries due to their excellent properties such as low density, excellent corrosion resistance, possibility of mass production, friction, low coefficient, and the ability to be processed quietly and without external lubrication [9]. Among the various types of insole materials, EVA (Ethylene Vinyl Acetate) rubber foam is not easily machined as a consequence of its low elastic modulus, high rate of moisture absorption, high coefficient of thermal expansion, and internal stresses [10,11]. The machining of EVA rubber foam is very challenging, especially with the integrity of its finished surface. For that, the surface roughness is a key parameter characterizing the technological quality of a product, and also a factor that has a highly significant effect on the manufacturing cost [12–14].

In addition to surface roughness, cutting force, time machining and material removal rate (MRR) have become topics of outstanding concern for the machining of various polymers. The machinability of typical thermoplastic and thermosetting polymers as well as their viscous properties will have certain influence on the surface integrity, chip formation, and cutting forces during machining [15]. An increase in the cutting speed gives rise to an improvement in the surface roughness [16]. Conversely at a high cutting speed, the rise in temperature of the tool/workpiece interaction is more significant than that of the strain rate generated in the material.

Recently, the use of statistical methods for the prediction of surface roughness and cutting forces during the machining of polymers is very common [17,18]. An artificial neural net (ANN) methodology has been presented for modeling and optimizing cutting parameters and for minimizing surface roughness during the milling of polyoxymethylene (POM C) and polyamide PA6 polymer [4,19]. For example, machining of polyamide PA6 polymer requires the lowest specific cutting force at a lower cutting speed and higher feed rate. In contrast, the smallest specific cutting force was achieved at a high cutting speed and feed rate during the cutting of PA66 GF30.

Furthermore, in respect to that are many literatures available as regards the machining of metallic materials and alloys. However, literatures on machining of polymer are very limited, particularly the machining of EVA rubber foam for ISO-diabetes [20–22]. In this paper, the technological parameters {toolpath strategy (B), spindle speed (C), step over (D) and feed rate (E)} were firstly examined by Taguchi in the course of milling the typical ISO-diabetes (A). The selection of the five factors are based on the results of the research on the optimization of manufacturing insole shoe orthotics using CNC machines and was successfully conducted by [7,8,23,24]. These became the basis of determining the parameters of independent research that are really significant effect against the response data (surface roughness and time machining).

Secondly, mathematical modeling of the surface roughness and time machining through the response surface methodology was presented. Finally, optimizations of the cutting conditions were performed using the desirability function (DF) according to three objectives (surface roughness, time machining, and surface roughness and time machining, simultaneously).

2. Methodology

2.1. Work-piece material

In this work, EVA Rubber foam with dimensions of 250 × 95 and 23 mm thick was selected as the workpiece material. This material is widely used in healthcare applications such as orthopedic shoes, insoles, exercise mats, and orthotic support [10]. The important properties of material mainly include: density of 55–65 kg/m^3, nominal size of 2000 mm x 1000 mm, nominal thickness (split) of 3–36 mm, hardness of 25–30 grade, tensile strength of 800 kPa, and tear strength of 4.5 kN/m^2. Machining experiments were conducted in CNC milling (Rolland Modela MDX40R), equipped with a maximum spindle speed of 16000 rpm. The cutting tool materials selected were carbide end mill (SECO-93060F) and ballnose cutter milling (JS533060D1B0Z3-NXT). The surface roughness was measured instantly by means of MarkSurf PS1 with a tolerance of nearly 0.001 mm at three different locations to minimize the deviation. Cutoff length of 5 mm and three of the samplings were selected for the surface roughness measurements.

2.2. Process parameters and experimental design

The machining parameters used in milling type of ISO-diabetes (A) were considered in the experiments corresponding to toolpath strategy (B), spindle speed (C), step over (D) and feed rate (E). The values of cutting parameters were chosen from the manufacturer's handbook. The cutting parameters along with their levels are given in Table 1. The experimental design for five milling parameters with two levels are presented by Taguchi's $L_{12}2^5$ orthogonal arrays as shown in Table 2. In the Taguchi method, the orthogonal array (OA) can provide an efficient procedure of the experiments with the least number of trials. This method can be characterized by the signal-to-noise (SN) ratio for the linear interaction of the responses. There are three SN ratio's characteristics

Table 1. The machining parameters and their levels.

Factor	Levels Low(−1)	High (+1)
Type of ISO-diabetes	1	2
Toolpath Strategy	*raster 90*	*raster 45*
Spindle Speed (rpm)	14,000	15,000
Feed rate (mm/rot.)	800	900
Step over (mm)	0.2	0.3

Table 2. $L_{12}2^5$ orthogonal array and experimental data.

No.	Type ISO-diabetes (A)	Toolpath (B)	Spindle speed (C)	Feeding rate (D)	Step over (E)
1	1	1	1	1	1
2	1	1	1	1	1
3	1	1	2	2	2
4	1	2	1	2	2
5	1	2	2	2	1
6	1	2	2	1	2
7	2	1	2	1	2
8	2	1	2	2	1
9	2	1	1	2	2
10	2	2	2	1	1
11	2	2	1	1	2
12	2	2	1	2	1

in the optimization of process parameters, and they include “the lower-the better”, “the higher-the better” and “the nominal-the better” [21]. In this study, the arithmetic average roughness (Ra), average maximum height of the profile (Rz) and the machining time (Ta) in the optimal conditions can be estimated using Equation (1) [21]:

$$^{S}/_{N}\,ratio = -10\log\frac{1}{n}\left(y_1^2 + y_2^2 + y_3^2 + \ldots + y_n^2\right) \quad (1)$$

where y_1, y_2, y_3,..., y_n represent the responses of the machining characteristic, for a trial condition at n repeated times. The SN ratios were calculated using Equation (2) for each of the 12 trials and the values are presented in Table 3. The experimental process design of $L_{12}2^5$ is illustrated in Figure 1. The experiment illustrated in Figure 1 underwent three stages. In the first stage, based on the results of variation design, ISO-diabetes already retrieved [Anggoro, et al. 2017] two different designs of insole (0.75 mm and 1.50 mm) as the independent factors in this research, while the other parameters (Toolpath, spindle speed, step over and feed rate) were produced based on previously conducted researches [7,23,24]. This analysis was carried out using the software minitab v17, orthogonal matrix generation process done array (OA) accordingly. The obtained result was a matrix of OA $\mathbf{L_{12}2^5}$. In the second stage, during the experimentation process, the researchers made use of CNC machine Roland Modela MDX 40R with EVA rubber foam material. Treatments were conducted as many as 12 times with the response data measurements performed on the foot that often suffered deformity [8]. The measured response data were surface roughness value (Ra) and machining time insole shoe orthotics (Ta). In the final stage, the optimum cutting condition parameter is derived from the value of the obtained response data using the taguchi method and response surface methodology (RSM) on software minitab v17.

2.3. Response surface methodology (RSM)

Design of experiments (DOE) was adopted in the course of this study as it can reduce the number of experimental runs, which is required for a larger and more realistic design problem. The response surface models of DOE work efficiently in the optimization of real designs [20]. RSM is being now widely used as a design methodology due to its accuracy towards modeling and experimental validation. This technique can provide a clear prediction as regards the significance of interactions and square terms of parameters. 2D and 3D surfaces produced by RSM can bring about visualization of the effect of parameters in response to the entire range specified [25]. Here, the effects of machining parameters on the response of surface roughness and time machining were predicted by RSM, which has been known to be a better tool for the optimization of these parameters in the milling process [25]. Accordingly, the surface roughness and machining time analyses were performed by means of RSM, using the results of numerical experiments presented in the orthogonal experimental design [25]. Generally, a functional relationship between the response and the independent variables can be explicated using a second-order polynomial model given in Equation (2) by [12,26,27]:

Table 3. The experimental results and the calculated S/N ratios.

	Coded values					Actual values					Experimental results and S/N ratios			
No	A	B	C	D	E	Type ISO (mm)	toolpath	spindle speed (rpm)	Feeding (mm/rot)	step over (mm)	Ra (μm)	SN Ra (dB)	Ta machining (second)	SN Ta (dB)
1	1	1	1	1	1	0.75	raster 90	14,000	800	0.2	5.033	23.098	186.30	−13.636
2	1	1	1	1	1	0.75	raster 90	14,000	800	0.2	4.767	23.218	146.33	−13.658
3	1	1	2	2	2	0.75	raster 90	15,000	900	0.3	6.067	22.170	145.00	−13.458
4	1	2	1	2	2	0.75	raster 45	14,000	900	0.3	5.300	22.757	188.52	−13.571
5	1	2	2	2	1	0.75	raster 45	15,000	900	0.2	5.733	22.416	175.00	−13.506
6	1	2	2	1	2	0.75	raster 45	15,000	800	0.3	5.067	22.953	154.05	−13.608
7	2	1	2	1	2	1.5	raster 90	15,000	800	0.3	7.200	22.366	152.55	−13.496
8	2	1	2	2	1	1.5	raster 90	15,000	900	0.2	6.500	21.871	176.97	−13.399
9	2	1	1	2	2	1.5	raster 90	14,000	900	0.3	6.967	21.739	148.63	−13.372
10	2	2	2	1	1	1.5	raster 45	15,000	800	0.2	6.067	22.170	166.30	−13.458
11	2	2	1	1	2	1.5	raster 45	14,000	800	0.3	5.667	22.518	146.08	−13.525
12	2	2	1	2	1	1.5	raster 45	14,000	900	0.2	7.167	21.487	166.97	−13.322

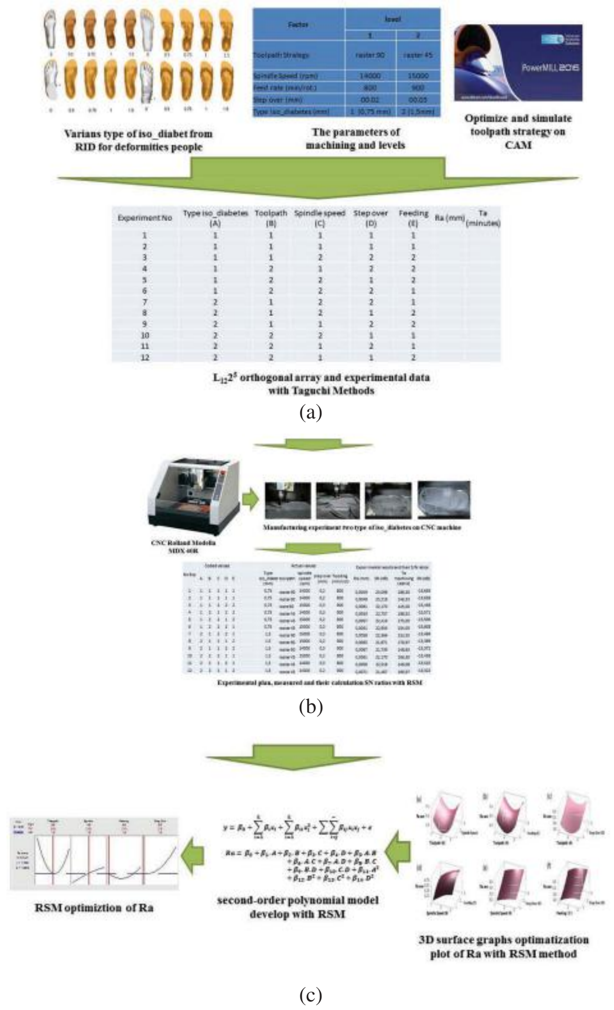

Figure 1. Schematic diagram of the experimental setup: (a) making orthogonal array matrix based on five orthotic shoe insole design parameters, (b) research experiment using CNC Rolland Modela MDX 40R machine, (c) Processing response of experimental data using Minitab v17 software.

$$y = \beta_0 + \sum_{i=1}^{\infty} \beta_i X_i + \sum_{i=1}^{\infty} \beta_{ii} X_{ii}^2 + \sum_{i} \sum_{j}^{\infty} \beta_{ij} X_i X_j + \varepsilon \quad (2)$$

where y represents the estimated response (surface roughness and time machining of ISO-diabetes), β_0 is constant, β_i, β_{ii} and β_{ij} represent the coefficients of linear, quadratic, and cross-product terms, respectively. X stands for the coded variables. The common approach in the RSM is using regression methods based on the least square method.

3. Results and discussion

3.1. Analysis of the signal-to-noise and surface plots

The effects of each factor level on the surface roughness (Ra) and time machining (Ta) were analyzed using the signal-to-noise (S/N) ratio. The average S/N ratio for every level of experiment and result of ANOVA (Analysis of Varians) for Ra and Ta is shown in Tables 3 and 4. Table 3 shows the distinction of variation value of Ra and Ta at each treatment. This comes about due to the dissimilarities in food consumption (feed rate) which is owing to the process of simulation and real time on CNC machines (usually because the randomly generated numbers simulate the machining process speed using CAM PowerMILL 2016). This has therefore led to the variations in surface roughness value and time of machining. Simulation of the machining time brings about the difference in machining speed and resolution time (Tm).

The different values of S/N ratio between maximum and minimum (main effect) are also presented in Table 5. An illustration of S/N ratio of these levels can be seen in Figure 2. From the S/N ratio analysis, the optimal cutting parameters for the yield of Ra and Ta could be identified corresponding to combined factors of $\mathbf{A_1\text{-}B_2\text{-}C_1\text{-}D_1\text{-}E_1}$. Obtained during the experiments were: type of ISO-diabetes of 0.75 mm at level 1, toolpath strategy of raster 45° at level 2, spindle speed of 14000 rpm at level 1, feeding of 800 mm/rot at level 1 and the step over factor of 0.2 mm at level 1. The levels of the significant factors of which the best result and the optimal design were obtained are presented in bold values in Table 5 (Means).

3.2. ANOVA of Ra and Ta as a function of machining parameters

The response of surface roughness and machining time were analyzed using a column effect of machining parameters. The column effect was presented by Taguchi as a simplified ANOVA. The experimental design was evaluated at a confidence level of 95% (the level significance was 5%). Table 4 is a presentation of ANOVA analysis of the experimental results for both the surface roughness (Ra) and machining time (Ta). *F*-ratios and their Rho **%** (% contribution) were taken into consideration in identifying the significance level of variables. Upon the analyses, the most effective parameter influencing the Ra value was feeding rate (D) with 37.72% of the contribution, while step over (E) with 31.6% of Rho, typical ISO-diabetes (A) by 14.682%, toolpath strategy (B) by 8.002% and spindle speed (C) by 8.002% were the subsequent key terms influencing the Ra value. Accordingly, the feed rate has a higher contribution in the machining process of EVA rubber, and the result is in accordance with previous findings on the machining of polymer [9].

Likewise, the most significant effects of feeding rate and step over are confirmed for the contribution of the optimum Ta (Rho of 43.29% and 30.55%, respectively). However, the next largest parameter affecting Ta is toolpath strategy, followed by type of ISO-diabetes, and spindle speed. Their contributions were 10.86%, 7.65% and 7.65% of the model, respectively. Similar results for the significant contribution of feed rate in the machining time of polymer have also been previously reported [9,28].

Table 4. ANOVA analysis of Ra and Ta.

Source	Sum of squares	Degrees of freedom	Mean square	F-ratio	Mean square	Rho %
			Anova for Ra			
A	148.448	1	148.448	8.899	131.766	14.682
B	88.495	1	88.495	5.305	71.813	8.002
C	88.495	1	88.495	5.305	71.813	8.002
D	355.150	1	355.150	21.290	338.468	37.715
E	300.267	1	300.267	5.391	283.585	31.599
e	300.267	18	16.681	1.000		
SD	1281.120	23	55.701		**897.446**	**100**
mean	1677.630	1				
Source	Sum of squares	Degrees of freedom	Mean square	F-ratio	Mean square	Rho %
			Anova for Ta			
A	3179.90	1	3179.90	18.57	3008.70	7.65
B	4.439.08	1	4439.08	25.93	4267.88	10.86
C	3177.81	1	3177.81	18.56	3006.61	7.65
D	17,189.02	1	17,189.02	100.40	17,017.82	43.29
E	12,181.61	1	12,181.61	6.48	12,010.41	30.55
e	3081.61	18	171.20	1.00		
SD	43,249.04	23	1880.39		**39,311.43**	**100.00**
mean	3179.90	1				

Table 5. Response table for S/N ratio (dB), means Ra (µm) and Ta (sec).

	Surface roughness Ra			
Control factor	Level 1	Level 2	Delta	Rank
SN ratio for Ra (dB)				
(A) Type of ISO-diabetes	**31.9667**	37.8333	5.8667	5
(B) Toolpath strategy	36.5333	**35.0000**	1.5333	2
(C) Spindle Speed	**34.9000**	36.6333	1.7333	3
(D) Feeding	**35.5667**	36.4000	0.8333	1
(E) Step over	**33.8000**	36.6333	2.8333	4
Means (µm)				
(A) Type of ISO-diabetes	**5.3278**	6.3056	0.9778	5
(B) Toolpath strategy	6.0889	**5.8333**	0.2556	2
(C) Spindle Speed	**5.8167**	6.1056	0.2889	3
(D) Feeding	**5.9278**	6.0667	0.1389	1
(E) Step over	5.6333	**6.1056**	0.4722	4
	Machining time Ta (second)			
Control factor	Level 1	Level 2	Delta	Rank
SN ratio for Ta (dB)				
(A) Type of ISO-diabetes	165.867	**159.583**	6.2833	4
(B) Toolpath strategy	**163.805**	168.245	4.4444	2
(C) Spindle Speed	163.805	**161.645**	2.1667	1
(D) Feeding	169.645	**155.805**	13.8444	5
(E) Step over	**158.602**	166.848	8.24667	3
Means (s)				
(A) Type of ISO-diabetes	13.573	13.429	0.14417	4
(B) Toolpath strategy	13.514	13.486	0.02833	2
(C) Spindle Speed	13.515	13.487	0.02650	1
(D) Feeding	13.496	13.505	0.0085	5
(E) Step over	13.563	13.438	0.1255	3

3.3. *Taguchi-based selection of optimum machining condition*

In the final step of Taguchi method, optimization results of a response were verified using confirmation experiments after determining the variable levels that gave rise to the optimal results. The confirmation of experimental results was performed at the optimum variable levels for surface roughness and machining time. Figure 2 indicates that combined factors of $\mathbf{A_1\text{-}B_2\text{-}C_1\text{-}D_1\text{-}E_1}$ and their levels were used in calculating the predicted optimal Ra and Ta. The equation for the predicted optimal Ra can be expressed as shown in Equation (3a) by [21]:

$$Ra_{pred} = T_{Raexp} + \left(A_1 - T_{Raexp}\right) + \left(B_2 - T_{Raexp}\right) + \left(C_1 - T_{Raexp}\right) + \left(D_1 - T_{Raexp}\right) + \left(E_1 - T_{Raexp}\right) \tag{3a}$$

where $T_{Ra\ exp}$ = 5.8; A_1 = 5.33; B_2 = 5.83; C_1 = 5.82; D_1 = 5.93 and E_1 = 5.63. Hence, the value of Ra predictive is 0.00534 mm (5.34 µm). Furthermore, the machining time, Ta can be estimated making use of Equation (3b):

$$Ta_{pred} = T_{Taexp} + \left(A_1 - T_{Taexp}\right) + \left(B_2 - T_{Taexp}\right) + \left(C_1 - T_{Taexp}\right) + \left(D_1 - T_{Taexp}\right) + \left(E_1 - T_{Taexp}\right) \tag{3b}$$

where $T_{Ta\,\mathrm{exp}}$= 159.53, A_1 = 153.583, B_2 = 163.81, C_1 = 161.65, D_1 = 155.81 and E_1 = 158.61. Hence, the predicted value of Ta is 154.05sec.

The confidence interval (CI) was determined to verify the quality characteristics of the confirmation experiment. Hence, the confidence interval for the predicted optimal values was calculated using the following Equation (4) by [21]:

$$CI = \sqrt{F_{\alpha;1;dofVe} x V_{ep} x \frac{1}{n_{eff}}} \tag{4}$$

The confidence interval for the surface roughness Ra is as follows: $F_{0.05,1,12}$ = 2.23 (tabulated), V_{ep}= 0.0167 from Table 4, n_{eff}= 1.8, the calculated CI_{Ra} is ± 0.14 µm. The predicted mean of Ra is: $\left|Ra_{pred}\right|$= 5.34 µm.;

$$\left|Ra_{pred} - CI\right| < Ra_{pred} < \left|Ra_{pred} + CI\right|$$

$$\text{i.e. } 5{,}20 < Ra_{pred}(\mu m) < 5.48$$

The confidence interval for the machining time (Ta) is as follows:$F_{0.05,1,12}$ = 2.23 (tabulated), V_{ep} = 0.048 from Table 4, n_{eff} = 1.8, the calculated CI_{Ta} is ± 41.7s. The predicted mean of Ta is: $\left|Ta_{pred}\right|$ = 159.53 s;

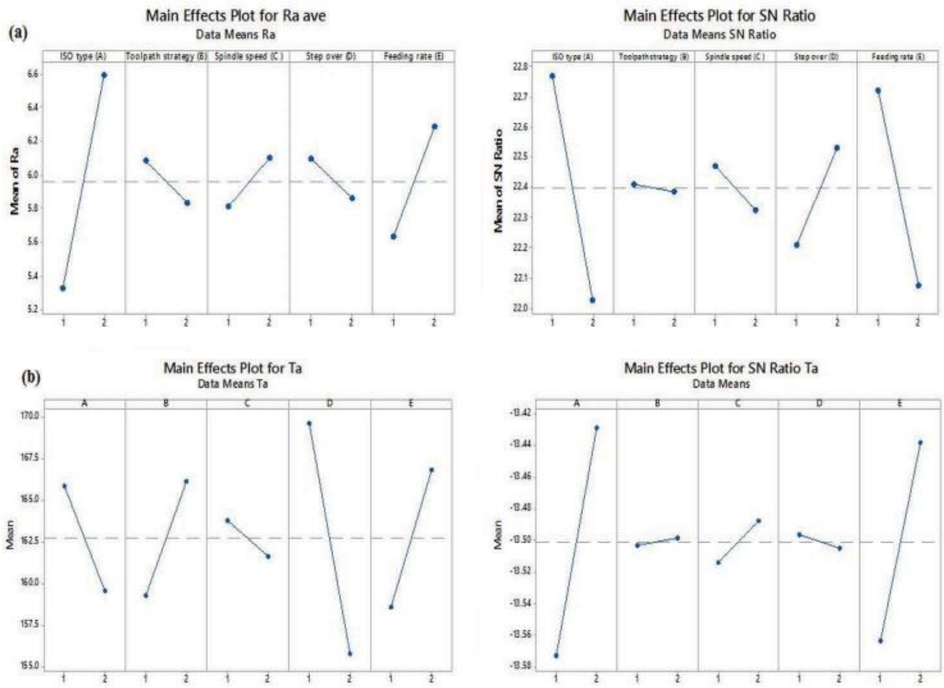

Figure 2. Main effect plot for SN ratios and means (a) surface roughness (Ra); (b) Time machining (Ta).

$$\left|Ta_{pred} - CI\right| < Ta_{pred} < \left|Ta_{pred} + CI\right|$$

$$\text{i.e. } 154.05\ \text{s} < Ta_{pred}(s) < 188.52s$$

Table 5 provides a comparative data of factors and levels influencing the various roughness and machining time responses. In this case, three different levels of five significant factors provided a lower roughness response. Moreover, level 1 of factors **D** and **E** provided the lowest roughness values. Similarly, factor **A** at level 1 provided lower roughness values Ra. However, factors **B** and **C** had no significant effect on roughness values of Ra. Likewise, the lowest machining time was mostly contributed by factor D (feeding rate) and E (step over), both at level 1. However, the type of ISO-diabetes, toolpath strategy, and spindle speed are less important factors in the machining of EVA rubber foam.

Table 6 shows a comparison of results derived from confirmation experiments which were conducted in line with the optimum levels of the variables, and the values calculated using Equation (4). The CI was calculated to yield Ra of 0.14 µm and Ta of 41.7s. Table 6 shows that the values of the confirmation test conducted for the responses were obtained at a 95% confidence level. Thus, an optimization of Ra and Ta was achieved using the Taguchi method at a significance level of 0.05.

Furthermore, the measured and predicted responses were fitted to the quadratic model illustrated in Figure 3. This graphical method was employed to examine the content of residuals within the models. The normal probability plot of the residuals for Ra indicates that they are more or less on a straight line, of which the errors are usually dispersed (Figure 3(a)). Moreover, each observed value is compared with its fitted value calculated from the model. Upon analyses, the regression model of Ra was well fitted with the observed values.

Correspondingly, the residuals for predicted Ta were calculated from the model and the results can be seen plotted in Figure 3(b). The normal probability plots of the residuals and plots of predicted vs actual values of Ta establish that the errors can be judged as normally distributed, while the regression model of Ta is in accordance with observed values.

3.4. RSM-based modeling for surface roughness and machining time

The experimental machining data of EVA rubber foam in CNC milling were used in developing the mathematical models of surface roughness and machining time by RSM. The response of surface quadratic model

Table 6. Results of experiments and predicted values by Taguchi method.

Response	Confirmatory experiment result	Calculated value	Confidence Interval (CI)	Difference	Optimization
Ra (µm)	$Ra_{exp} = 5.8$	$Ra_{cal} = 5.34$	$CI_{Ra} = 0.14$	$Ra_{cal} - Ra_{exp} = -0.46$	$-0.46 < 0.17$ Successful
Ta (s)	$Ta_{exp} = 159.53$	$Ta_{cal} = 154.05$	$CI_{Ta} = 41.7$	Ta_{exp} -Ta = 5.48	$4.08 < 41.7$ Successful

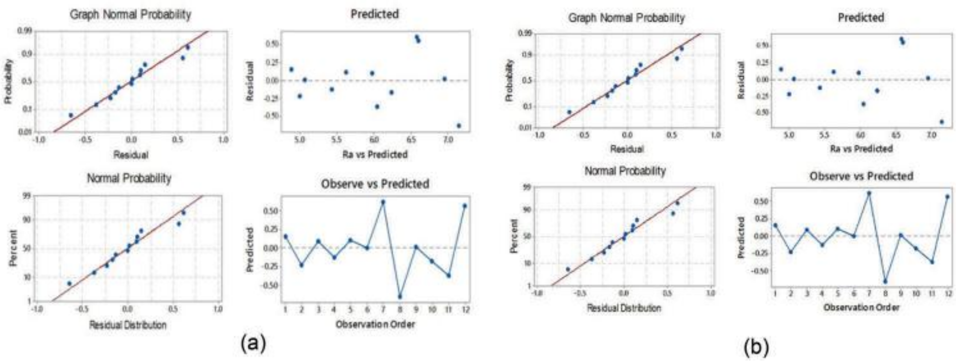

Figure 3. Relationship between the observed and predicted response values: (a) Normal probability surface roughness (Ra); (b) Normal probability time machining (Ta).

was further justified through ANOVA and the results can be seen presented in Table 7. Here, the adjusted mean squares represent the significant factors contributed to the surface response. From the ANOVA in Tables 4 and 7(a), it was understood that the toolpath strategy (B), feeding rate (D) and spindle speed (C) significantly influenced the model of Ra. The interaction factors of B*D, A*B, and A*C have appeared to be the most influencing parameters of Ra, while the adjusted mean square values greater than 0.05 indicate that the model terms are considered to be insignificant factors. On the contrary, model terms of feeding rate (D) and step over E on machining time (Ta) can be considered to be relatively significant (Tables 4 and 7(b)). The interactions (A*B, A*C, A*E, B*C, B*E, and C*E) are less important, due to the fact that the adjusted mean square values are greater than 0.05.

The quadratic model of Ra and Ta can be expressed as a function of the cutting parameters (toolpath strategy, spindle speed, feed rate and step over). From Equation (2), the relationship between Ra and Ta with the milling parameters are given below (Equations 5a and 5b):

Table 7. ANOVA of quadratic response for Ra and Ta.

Source		Degree of freedom	Adjusted sums of squares	Adjusted mean squares	R^2
(a)					
Model		11	7.97519	0.72502	100
Linear		5	2.9810	0.59619	
	ISO Type (A)	1	.98097	1.60444	
	Toolpath Strategy (B)	1	0.00250	0.00250	
	Spindle Speed (C)	1	0.01000	0.01000	
	Feeding (D)	1	0.00681	0.00681	
	Step Over (E)	1	0.15125	0.15125	
Square		6	1.39522	0.23254	
	ISO type (A)*Toolpath strategy (B)	1	0.01779	0.01779	
	ISO type (A)*Spindle speed (C)	1	0.02118	0.02118	
	ISO type (A)*Step over (E)	1	0.05281	0.05281	
	Toolpath strategy (B)*Spindle speed (C)	1	0.00059	0.05281	
	Toolpath strategy (B)*Step over (E)	1	0.00059	0.00059	
	Spindle speed (C)*Step over (E)	1	0.45125	0.45125	
Error		11	0	0	
Total		11	7.97519	0	
(b)					
Model		10	7.94060	0.79406	100
Linear		5	2.10217	0.42043	
	ISO Type (A)	1	0.68953	0.68953	
	Toolpath Strategy (B)	1	0.43578	0.43578	
	Spindle Speed (C)	1	0.20496	0.20496	
	Feeding (D)	1	0.19096	0.19096	
	Step Over (E)	1	0.11036	0.11036	
Square		6	1.30735	0.26147	
	ISO type (A)*Toolpath strategy (B)	1	0.44445	0.44445	
	ISO type (A)*Spindle speed (C)	1	0.18792	0.18792	
	ISO type (A)*Step over (E)	1	0.17389	0.17389	
	Toolpath strategy (B)*Spindle speed (C)	1	0.44422	0.44422	
	Toolpath strategy (B)*Step over (E)	1	1.21000	1.21000	
	Spindle speed (C)*Step over (E)	1	0.45125	0.45125	
Error		11	0	0	
Total		11	7.97519	0	

$$Ra = 4.23 + 0.57A + 2.1B - 2.3C - 1.03D + 0.73E + 0.075^{*}A^2 - 0.015^{*}B^2 - 0.009^{*}C^2 + 0.063^{*}D^2 + 0.003^{*}E^2 + 0.004A^{*}C + 0.015A^{*}D + 0.042B^{*}C + 0.002B^{*}E + 1.267C^{*}D \quad (5a)$$

$$Ra = 4.23 + 0.57A + 2.1B - 2.3C - 1.03D + 0.73E + 0.075^{*}A^2 - 0.015^{*}B^2 - 0.009^{*}C^2 + 0.063^{*}D^2 + 0.003^{*}E^2 + 0.004A^{*}C + 0.015A^{*}D + 0.042B^{*}C + 0.002B^{*}E + 1.267C^{*}D \quad (5b)$$

The mathematical models of Ra and Ta as a function of the milling parameters were subsequently established, using the experimental data as the input values in Equations (5a and 5b). Accordingly, the models of Ra and Ta can be expressed as (Equations 6a and 6b):

$$Ra = 4.23 + 0.57A + 2.1B - 2.3C - 1.03D + 0.73E + 0.075^{*}A^2 - 0.015^{*}B^2 - 0.009^{*}C^2 + 0.063^{*}D^2 + 0.003^{*}E^2 + 0.004A^{*}C + 0.015A^{*}D + 0.042B^{*}C + 0.002B^{*}E + 1.267C^{*}D \quad (6a)$$

$$Ta = 198 - 33A + 38B - 271C - 17D + 11E + 1.5^{*}A^2 - 2.5B^2 - 3C^2 + 2D^2 + 1^{*}E^2 - 16.2A^{*}C + 3.8A^{*}C + 0.1A^{*}D - 4.6B^{*}C + 3.5B^{*}D + 13C^{*}D \quad (6b)$$

With correlation square ($R^2 = 100\%$)

The establishment of regression model of order 2 (Equation 6a and 6b) was conducted after being unable to have the order regression models to significantly respond to the data taken. This led to the difficulty of determining the optimal value of the response measured. Once the formation of the regression model of order 2 and ANOVA has been generated from the response data, the prediction of the optimum parameter values can then be derived using the surface plots curve and desirability function. It can be observed in Figure 4 that the estimated value of the quadratic model represents the roughness value in relation to the design machining parameters. Variable interaction effects on the surface roughness are illustrated using three-dimensional (3D) plots corresponding to the second-order model (Equation (6)). This is an indication that for any level of toolpath strategy (B), spindle speed (C), feeding (D) and step over (E), the surface roughness value increases in line with an increasing level type of ISO-diabetes (A). Minimum Ra is therefore obtained from the low values of B, C, D, and E. It is found to be minimal at middle tool path strategy (level 1) with low spindle speed (level 1), feeding and step over (level 1) (Figure 4(b)-top). This descending order could be due to an increasing spindle speed and feed rate, resulting in vibration, generating more heat and hence, contributing to a higher surface roughness [9].

Figure 4(a) demonstrates the interaction effect between toolpath strategy (B), spindle speed (C), feeding (D) and step over (E) on the surface roughness. It can be observed that the surface roughness decreases with an increase in the spindle speed and step over, whereas the best surface roughness is obtained at a low level of the spindle speed, feeding and step over (Figure 4(b)). Moreover, a lower step over brought about a reduction in the surface roughness accordingly.

Furthermore, the interactive factor of toolpath strategy (B), spindle speed (C), feeding (D) and step over (E) on the machining time (Ta) are illustrated in Figure 4(c). The 3D response surface plots indicate that the lower Ta is obtained when high levels of machining parameters (B, C, and D) are applied. Accordingly, the minimum value of Ta can be achieved through the selection of high-level machining parameters (Figure 4(d)). Higher cutting speeds imply higher strain rates and lower machining times [9].

The models were fitted using a numerical method, employing the coefficient of determination R^2, which shows how a lot of the variability observed in the data accounted for the model and were then calculated as given in Equation (7):

$$R^2 = 1 - \frac{SS_{\text{residual}}}{SS_{model} + SS_{\text{residual}}} = 1 - \frac{0}{0+0} = 100\% \quad (7)$$

The SS_{model} represents the sum of the squares of the model, while SS_{residual} is the sum of the squares of the residual. The response surface models were acquired in this subject field with R^2 values higher than 80%, say 100% for surface roughness Ra. The R^2 values, in this case, fit on 1, which are desirable. Consequently, outcomes from the coefficients of determination (R^2) indicate that mathematical models on Equation (6) can be effectively applied in predicting the surface roughness and machining time. The models in question can be used in making this prediction at particular design points.

3.5. Optimization using desirability function analysis

In the desirability function (DE) approach, the measured properties of each predicted response are transformed into a dimensionless desirability value [29]. The scale of the desirability function ranges from 0 to 1. In this study, the DE was selected to be the smaller the better, and this was due to the minimum surface roughness being achieved with the optimization of milling parameters. The DE of "the-smaller-the better" is demonstrated in Figure 5.

The goal set, the lower limits, the upper limits, the weights used, and the importance of the factors are all given in Figure 5. The optimization was performed by a combination of goals applied to control factors and responses. The goal used for the surface roughness was "to minimize", while that used for the factors was "within range". From

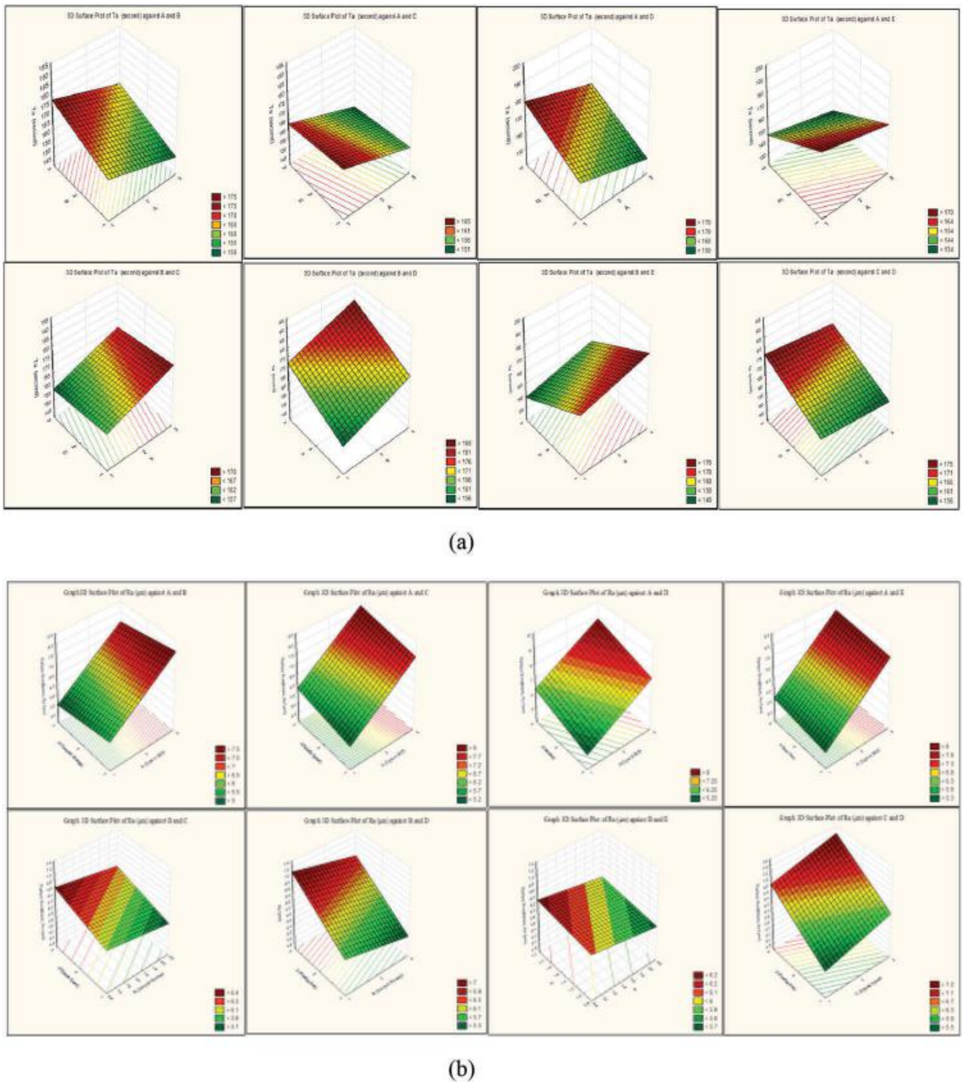

Figure 4. 3D plot surface: (a) 3D RSM plots showing the effects of setting parameters on surface roughness; (b) 3D RSM plots showing the effects of setting parameters on machining time.

the analysis results, the optimization values were obtained for the Ra model of 5 μm (0.005 mm) (Figure 5(a)). Moreover, the desirability value for Ra was 1.0000, of which it can be closer to 1 and then having the response to be perfect of the target value. The goal used for the machining time was "to minimize", while that used for the factors was "within range". From the analysis results, 154.05 s was obtained as the optimization value for Ta (the Ta model given in Figure 5(b)).

4. Conclusion

This study employed a combination of Taguchi method and RSM in order to optimize the appropriate machining parameters in CNC milling of EVA rubber foam. The optimum results at the different combinations of milling parameters provided a surface roughness of 5.34 μm by Taguchi method. Based on the SRM and the composite desirability method, the optimal milling parameters of ISO-diabetes with EVA rubber foam were obtained for optimum Ra in accordance with the toolpath strategy of raster 45°, spindle speed of 14000 rpm, feed rate of 800 mm/rotation and step over of about 0.2 mm. The mean Ra of 5.0 μm could be achieved at a desirability (dF) of 1.000. Also, the toolpath strategy of raster 45°, spindle speed of 14000 rpm, feed rate of 800 mm/rotation and step over of 0.3 mm were set-up to yield a Ta of 154.05 s with desirability (dF) of 0.79. Accordingly, the main factors influencing both Ra and Ta provided 100% and 79.2% contribution of the model, respectively. The significance of the quadratic interaction of parameters can be predicted using a design of machining process in RSM. These methods can be regarded as important experimental methods and statistically modeling for optimization of CNC milling operations for EVA rubber foam, resulting in the reduction of manufacturing time and cost [30].

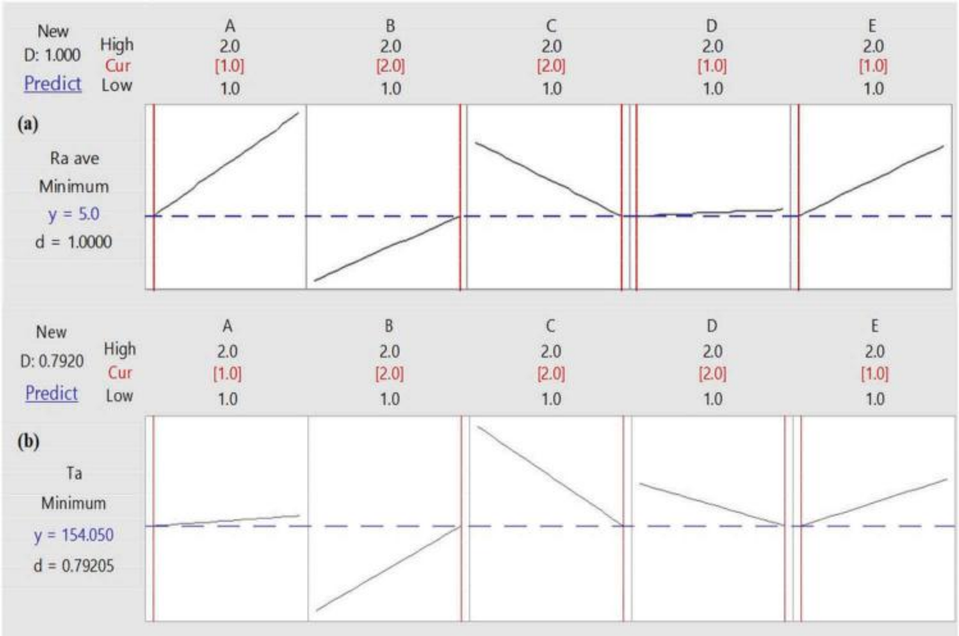

Figure 5. Plots of response optimization of a) surface roughness (Ra) and b) machining time (Ta) as a function of machining parameters.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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