

DESIGN AND MANUFACTURING ORTHOTICS SHOE INSOLE WITH OPTIMUM SURFACE ROUGHNESS USING THE CNC MILLING

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Abstract

This experimental study shows the designing of orthotics shoe insole for diabetic patients (ISO-diabetes) and determines the optimal machining parameters in CNC milling of the insole made with EVA rubber foam. The CAD model of ISO-diabetes and mathematical modelling of the average surface roughness for the insole were explored. Firstly, 3D models of ISO-diabetes was brought from the digitized scanned data, then four cutting parameters such as: tool path strategy, spindle speed, feed rate and step over were optimized using the Taguchi method according to L934 orthogonal array. The optimum surface roughness as a function of cutting parameters was predicted using the response surface methods. Lastly, the mathematical model of surface roughness was validated using the ANOVA. Based on the S/N and ANOVA, the optimal cutting parameters yielded the optimum Ra, which corresponds to the tool path strategy with raster 45O, spindle speed of 1300 rpm, the feed rate of 800 mm/minutes and step over about 0.2 mm, of which, is the most influential parameter. And these optimized conditions provided important input data for application of the low-cost milling of ISO-diabetes.

Keywords: CAD, Cutting parameters, ISO-diabetes, RSM, Surface roughness.

1. Introduction

Various leg disorders such as pronation, metatarsalgia, flat feet, neuroma, plantar fasciitis, arch pain, and diabetes are mainly caused by abnormal distribution of plantar pressure along the feet. Pains as a result of these conditions or other syndrome can move to the feet when wearing inappropriate footwear. For example, diabetic patients with a history of never amputees are usually found with swollen bone in both legs and categorized as patients with a high-risk of having injured foot [1]. And for such people, they need the bespoke insole shoe orthotics in order to reduce the pains and also improve the way they walk.

Many podiatrists now recommend some ISO-diabetes products using the footprints method in a foam box and then by mold casting [2, 3]. This manual method involves expensive products with less accuracy and poor surface finish. Munro [4] explained that it can also result to insole products that could be uncomfortable for diabetic patients with foot wounds and those having ulcers. However, the computer aided design (CAD) technology helps to reduce both the design time and production cost of orthotic footwear [3, 5]. CAD provides designs that are fitted to the plantar surface of the foot. In this way, reverse innovative design (RID) methodology have been proposed in recent years due to the robust applications of CAD, which can take a data file from a 3D scanner for digitizing the plantar surface of the foot [3]. Also, the direct machining of the CAD model for some tough polymers like polypropylene, polyoxymethylene (POM C) and the HD1000 (UHMWPE) can be performed on CNC turning [2, 6]. Consequently, RID helps in producing ISO-diabetes products faster, more precise and exact. Consequently, the difficulty in modelling of foot abnormalities can be solved by using the 3D scanner, which gives an accurate and precise data of the 3D mesh leg.

The RID method has also provided a design model of ISO-diabetes with high precision dimensional results, which could be produced by two types of manufacturing technology, namely: adaptive manufacturing using a 3D printer and subtractive manufacturing technology using CNC machines [3, 5]. Here, various designs of ISO-diabetes can then be produced by controlling some parameters in order to improve the surface roughness in accordance to the shape and contour of the patient's foot [1].

Based on studies by Anggoro et al. [7], work has initially been done on the optimization of influential parametric manufacturing in the CNC milling of ethylene-vinyl acetate (EVA) rubber foam by Taguchi method for shoe insoles of a normal foot together with the Analysis of Variance (ANOVA). This work made use of the optimal tool path, which are: raster finishing strategy and step and shallow finishing strategy. The response to the surface roughness was seriously influenced by the model type of the insole and its cutting parameters; tool path strategies, spindle speed, step over, and feeding rate. The optimal cutting conditions of CNC milling and mathematic models for surface roughness (R_a) were obtained using Taguchi method and response surface methodology (RSM). The optimum value of R_a for the insole shoe products received during the study was $< 8 \mu\text{m}$. For this reason, this finding may be a desirable approach for determining the optimal parametric machining of ISO-diabetes based on the statistical Design of Experiments (DOE) for optimum surface roughness, which has been known as a good strategic plan for machining process resulting in the optimum yields of response [8, 9].

And in the recent years, various attempts have been made to combine and compare different statistical methods that can examine the importance and significance of influential machining parameters on the quality of surface roughness. For instance, the DOF approach for optimizing machining parameters with Taguchi and RSM have been widely adopted in CNC milling for metals and alloys. However, only a limited number of studies have been reported on machining of polymers in particular for EVA rubber foam in the manufacture of ISO-diabetes [7, 9-11]. In this, the mathematical modelling of surface roughness and optimization of influential cutting parameters are the two important issues in manufacturing ISO-diabetes, when it comes to machining the polymers [6, 9, 10, 12-14].

According to Jeng et al. [15], furthermore, the machinability of typical thermoplastic and thermosetting polymers is related to their viscous properties, which can control the surface integrity, chip formation, and cutting forces during machining. Normally, a higher cutting speed is set up for an improved surface roughness of polymer but this makes the temperature on the tool-work piece interface to rise, though the use of coolants may reduce the temperatures. Nevertheless, the impact of machining temperatures becomes critical, especially in the dry and high-speed machining of polymer. This could affect the surface integrity of the polymer due to the poor thermal conductivity when compared with the metal tool thereby making it more likely to be damaged by heat [6].

Apart from the cutting parameters, the work piece and tools' materials, dynamic performance of machining system, the coolant, and tool condition, all have a significant influence on the surface roughness. And recently, modelling, simulation and optimization of surface roughness have been intensively studied by different optimized cutting parameters using statistical methods. Mathematical modelling of surface roughness in terms of arithmetic average roughness (R_a) and average maximum height of the profile (R_z) has been reported in the optimum cutting parameter of CNC turning [12]. And it has been established that cutting speed, feed rate and depth of cut are significant factors that influence the quality of surface roughness during turning. Substantially, the machining parameters such as cooling system condition, cutting speed material, feed rate and depth of cut have significant influence on R_a and R_z during turning of AISI 1050 steel [10]. However, the machining experiments under dry cutting condition (DC), conventional wet cooling (CC) and minimum quantity lubrication (MQL) provided that the most influential parameter of the surface roughness is feed rate. In general, using coolants has a significant effect on the machining temperature and the quality of surface roughness. For example, MQL can be used to improve the machine surface quality during machining operations of composites [16-18]. Going through previous papers [6, 9, 10, 12-19], it would be discovered there were enough discussion about the cutting optimization of machining parameters and optimum surface roughness limited to metal and polymer materials alone fixed on one method such as Taguchi method [13, 16-19] or surface method response [6, 9, 10, 12].

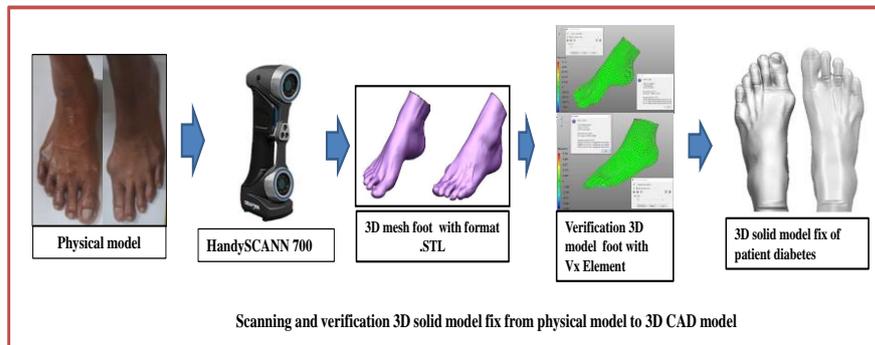
In a bid to extent the main frame of the previously published work, this study would like to fill the gap in terms of CAD design and manufacturing optimization of insole shoes orthotics products made from EVA foam. The main aim of this research is to design ISO-diabetes and then determine the optimum cutting parameters of the insole with EVA rubber foam in CNC milling. Also, to optimize or improve the surface roughness response in term of center line average roughness (R_a) by Taguchi method and RSM. The L_93^4 orthogonal array of Taguchi is selected

as the sequential experiments. Calculation of signal to noise (S/N) ratio for each response parameter and ANOVA analysis are conducted to optimize the milling parameters that influence the surface roughness and the optimum results are later analysed by RSM using the 3D-contour and 2D-surface graphs. Lastly, the validation of the optimized multiple-response surfaces was done using the desirability function approach.

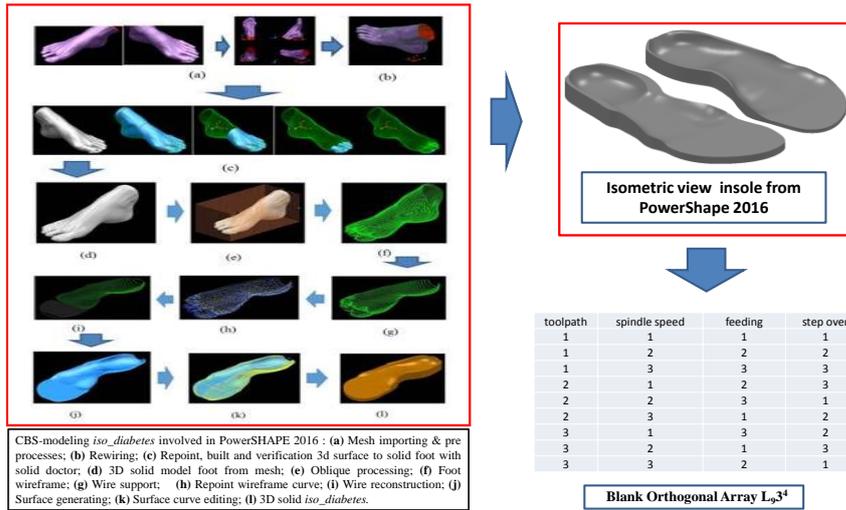
2. Experiment procedures and Test Results

This study was conducted in CNC milling machine (Roland Modella MDX 40R-Japan) where EVA rubber foam with a thickness of 250 x 95 x 23 mm and hardness of 35-40 HRC, was selected as a work piece. This material is suitable as healthcare solutions for orthopaedic shoes or insole or orthotic support. The physical and mechanical properties of the material are as follows: density of 55-65 kg/m³, nominal size of 2000 x 1000 mm, nominal thickness (split) of 3-36 mm, hardness of 30 HRC grade, tensile strength of 800 kPa, and tear strength of 4.5 kN/m². 3D models of ISO-diabetes with a wide tolerance of 0.75 mm was selected in this study (Fig. 1). The cutting tool used for all the experiments with the standard specification was SECO-93060F for end mill cutter (6 mm diameter) and JS533060D1B0Z3-NXT for ball nose cutter. Also, a surface roughness tester (Mark Surf PS1) was used to measure the average surface roughness (R_a). The cut off distance was specified as 2.5 millimetre. The measurements were repeated three times at three different spots on the end-milled surface, in which, the average value was taken as R_a . A schematic diagram of the experimental setup is shown in Fig. 1.

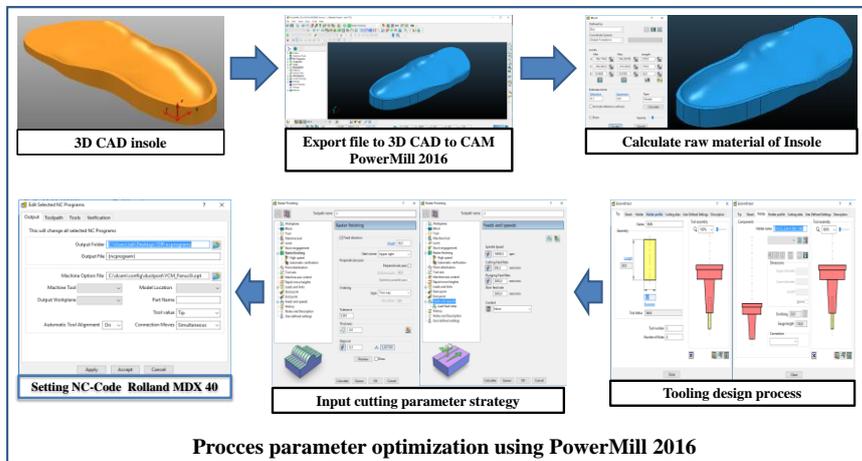
The 3D models of ISO-diabetes was from the digitized scanner as reported previously [11] using the method of Curve Base Surface (CBS) modelling and smart features in Power SHAPE 2016. The result of Reverse Engineering (RE) is a variation of a special insole shoe orthotic for diabetes and the RE stage of this process are presented in Fig. 1.



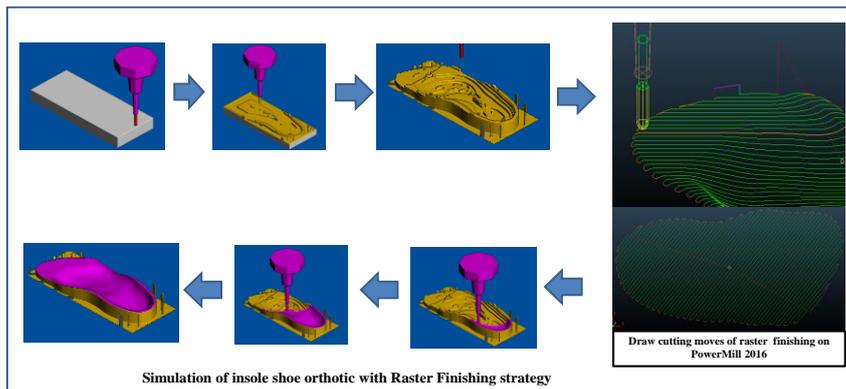
(a)



(b)



(c)



(d)

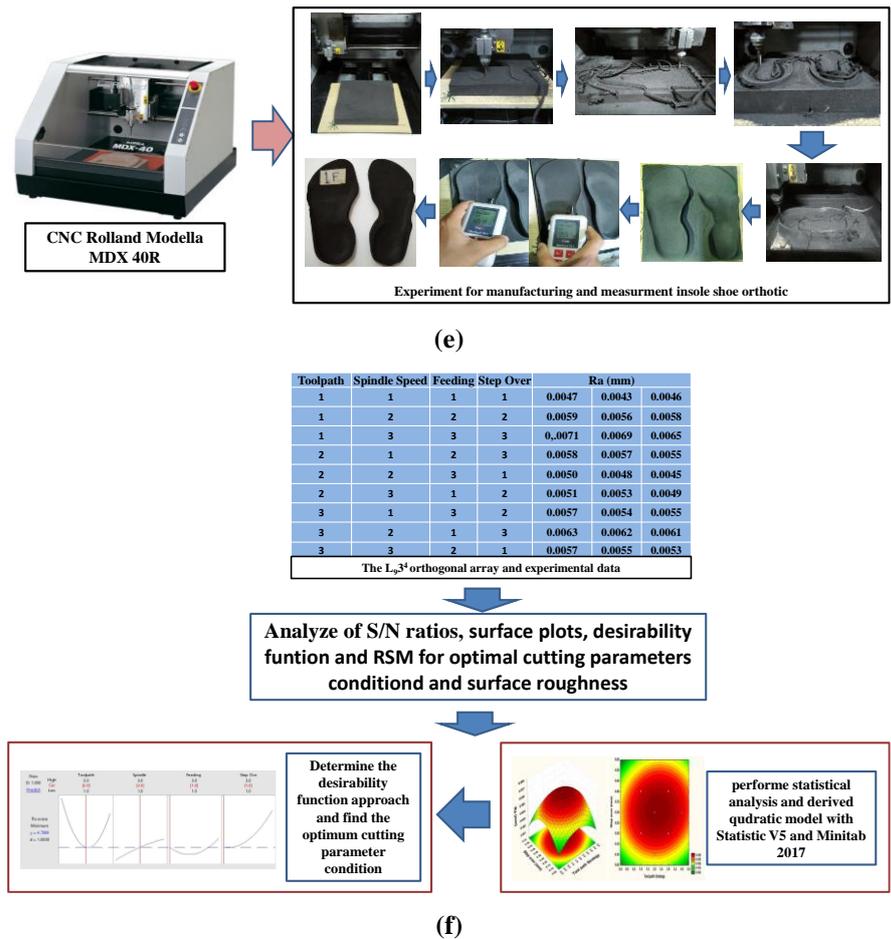


Fig. 1. Workflows of design and manufacturing experiments for ISO-diabetes, which include: (a) Scanning process and verification of 3D mesh of foot solid, (b) Design of 3D CAD insole and blank orthogonal array, (c) Tooling design in CAM software Power MILL 2016, (d) Simulation of tool path strategy product insole in CAM Power MILL 2016 before CNC process, (e) Manufacturing and measurement of CNC using Rolland Modella MDX 40R machine and Mark Surf PS 1, (f) Processing response for surface roughness data using Taguchi method – RMS with Minitab software and V Statistic 5.

3. Design of Experiment and S/N Ratio Analyses

The setting parameters were selected as follows: toolpath strategy (*A*), spindle speed (*B*), feed rate (*C*) and step over (*D*). The values of cutting parameters for the tested material were determined from the handbook recommended by the manufacturer. The cutting parameters and their levels are given in Table 1. The machining parameters are set at three levels. In the experimental run, the machining process was conducted under the dry cutting condition. As shown in Table 2, Taguchi’s $L_9 3^4$ orthogonal array design was taken into consideration for the experimentation of ISO-diabetes (Response table for the S/N ratios corresponding to R_a are presented in Table 3).

Table 1. Cutting parameters and setting levels.

Factor	Level		
	1	2	3
Tool path strategy	step shallow	raster 45	raster 90
Spindle speed (rpm)	13000	14000	15000
Feeding (mm/min)	800	900	1000
Step over (mm)	0.2	0.3	0.4

Table 2. L₉3⁴ orthogonal array and experimental data.

Toolpath	Spindle speed	Feed rate	Step over	<i>R_a</i> (mm)		
1	1	1	1	0.0047	0.0043	0.0046
1	2	2	2	0.0059	0.0056	0.0058
1	3	3	3	0.0071	0.0069	0.0065
2	1	2	3	0.0058	0.0057	0.0055
2	2	3	1	0.0050	0.0048	0.0045
2	3	1	2	0.0051	0.0053	0.0049
3	1	3	2	0.0057	0.0054	0.0055
3	2	1	3	0.0063	0.0062	0.0061
3	3	2	1	0.0057	0.0055	0.0053

Table 3. Analysis for S/N ratio.

Toolpath	Spindle speed	Feeding	Step over	<i>R_a</i> (mm)			<i>R_a</i> (average)	S/N ratio <i>R_a</i>
1	1	1	1	0.0071	0.0069	0.0065	0.0068	23.4358
1	2	2	2	0.0059	0.0056	0.0058	0.0058	22.3908
1	3	3	3	0.0047	0.0043	0.0046	0.0045	21.6537
2	1	2	3	0.0058	0.0057	0.0055	0.0057	22.4667
2	2	3	1	0.0050	0.0048	0.0045	0.0048	23.2179
2	3	1	2	0.0051	0.0053	0.0049	0.0051	22.9243
3	1	3	2	0.0057	0.0054	0.0055	0.0055	22.5701
3	2	1	3	0.0063	0.0062	0.0061	0.0062	22.0761
3	3	2	1	0.0057	0.0055	0.0053	0.0055	22.5964

The term ‘signal’ means the desirable value (means) and the term ‘noise’ is the undesirable value (SD) for the machining parameter. Therefore, the S/N ratio is the ratio of the mean to the standard deviation. Taguchi employs the S/N ratio to measure the surface quality deviating from the desired value. Usually three categories of the performance characteristic are used for the analysis of S/N ratios, which are: “Nominal the best”, “Larger-is-the-better (maximize)” and “Smaller-is-the-better (minimize)”: This study aims at minimizing the value of surface roughness (*R_a*) in the milling operation. Smaller *R_a* is equivalent to a better or improved surface roughness. Accordingly, “smaller-is-the-better” quality was applied and presented in this study.

Substantially, the design of experiments and the measured roughness parameters are presented in Table 2. It shows that the experimental results for surface roughness parameters (*R_a*, and their S/N ratios are based on the experimental parameter combinations (Table 1). These four different performance characteristics in the

Taguchi method and the S/N ratios corresponding to the surface roughness parameters were subsequently calculated by Minitab v17 and Statistical V.6 software.

4. Response Surface Methodology (RSM)

The RSM is a combination of statistic and mathematical techniques for modelling and experimental validation of a relationship between various input parameters and responses. The objective of the method is to explore the effect of these parameters on responses and to also optimize these responses [20, 21]. Accordingly, RSM can generate 2D and 3D surface plots in visualizing the effect of parameters on the response in the entire range specified. The functional relationship between response (y) and the set of independent variables (input parameters) is shown in the Eq. (1)

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k + \varepsilon \quad (1)$$

Also, Eq. (2) is RSM-based mathematical model of surface roughness

$$y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{i < j}^{\infty} \beta_{ij} x_i x_j + \varepsilon \quad (2)$$

where y is the surface roughness (R_a) and X_i (A, B, C, D) are the function of machining parameters. The RSM is a sequential process and its procedure can be summarized in Fig. 1. In this present research, MINITAB 17 and Statistics v.6 were used for the computation work.

5. Results and Discussion

5.1. Analysis of CAD and CAM insole shoe orthotic

Considering Fig. 1, the 3D image of ISO-diabetes was obtained from the foot scan of the patient using HandyScan700™. The results of the scan in the STL file format were verified into 3D images and converted into 3D CAD insole [3, 11]. The foot belongs to the category of organic products; therefore, it must be changed into the mesh of a 3D file STL format, while the IGES files in CAD were used for the CBS modelling to build 3D CAD model insole involved in Power SHAPE 2016 (Fig. 1).

As also shown in Fig. 1, the 3D CAD model of these insoles is exported to CAM Power Mill 2016 for the optimization process of cutting machine parameters. This was performed based on treatment on orthogonal array $L_9 3^4$ (Table 2). The results of CAM simulation from 3D CAD model involved in Power SHAPE 2016 were exported to CAM Power Mill 2016 until create NC Code Rolland Modella 40R.

Then the NC code file for each treatment, then performed to machining process on CNC milling machine to obtain the resulting orthotic shoe insole as shown on Fig. 1. The value of R_a is obtained by measuring the three point of surface insoles already made using Mark Surf PS 1 to get an accurate R_a value (Table 2). An optimal value of cutting parameters conditions and surface roughness of insoles (R_a) is obtaining using approach the Taguchi and RSM methods.

In the present paper, the toolpath strategy machining is seen as dependent factor affecting the surface roughness, because the machined product has shape of contour whose is non-fat consisting of wall and flat, which is more complex compared to previous publications [6, 9, 10, 12]. In CAM Power MILL 2016, there are some

toolpath strategies of machining chosen by workers to determine the optimal machining in insole manufacturing and as a result, the toolpath raster and step and shallow are chosen, which is able to give the response value of surface roughness expected as published in previous works [7, 12] toolpath strategy machining is considered as dependent factor affecting the measured respond, that is, surface roughness, because the machined product has shape of contour whose is non-fat consisting of wall and flat, which is more complex compared to previous published [6, 9, 10, 12]. In CAM PowerMILL 2016 there are some toolpath strategies of machining chosen by workers to determine the optimal machining in insole manufacturing. In this case, the toolpath raster and step & shallow are chosen as toolpath, which is able to obtain the respon value of surface roughness expected as published in previous works [7, 22]. These two reason are considered as independent factor for toolpath strategy.

5.2. Analysis of the S/N ratios and their surface plots

The surface roughness of ISO-diabetes ranging from 4.0 μm to 7.0 μm was set-up in order to examine the optimal cutting parameters condition, and DOF was represented as the orthogonal array of L_93^4 . Myers et al. [23] proposed that this layout design of experiments should be prepared to form 2^k or 3^k . Table 2 presents an orthogonal array of L_93^4 , of which, the machining experiments of the work piece were performed in CNC milling. The experimental results for machining ISO-diabetes was then analysed by Taguchi and RSM for optimum surface roughness.

Then the effects of each factor level on the surface quality were analysed using the S/N ratio. Table 3 presents experimental results of surface roughness and corresponding to S/N ratio using the input values and the effect of each cutting parameter at every level of the experiments. It also showed that the smaller the SN ratio value, the smaller the surface roughness value of the insole and the higher the insole quality. This is because the small value SN ratio will reduce the noise on the machining process such it makes a better quality of the insole surface.

Figure 2 shows the main effect plots for SN Ratios and Means. On analysing, it was found that the $A_2-B_1-C_1-D_1$ combination factors yielded the minimum surface roughness. In this experiment, tool path strategy (A) at the level 2, the spindle speed factor (B) at the level 1 (13000 rpm), the feeding factor (C) at the level 1 (800 mm/rot) and the step over control factor (D) at the level 1 (0.2 mm) are the optimal level combination of factors for milling operation in CNC milling of EVA rubber foam.

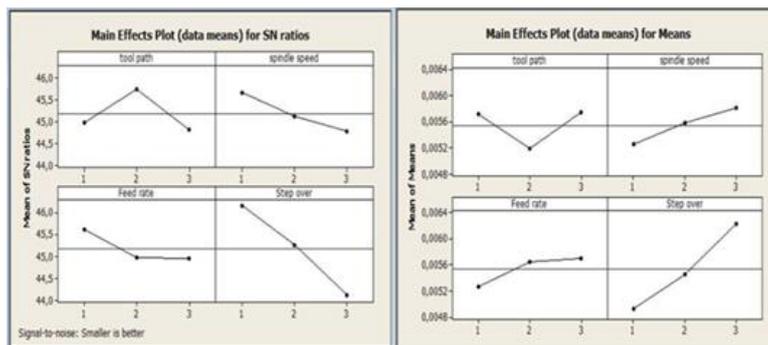


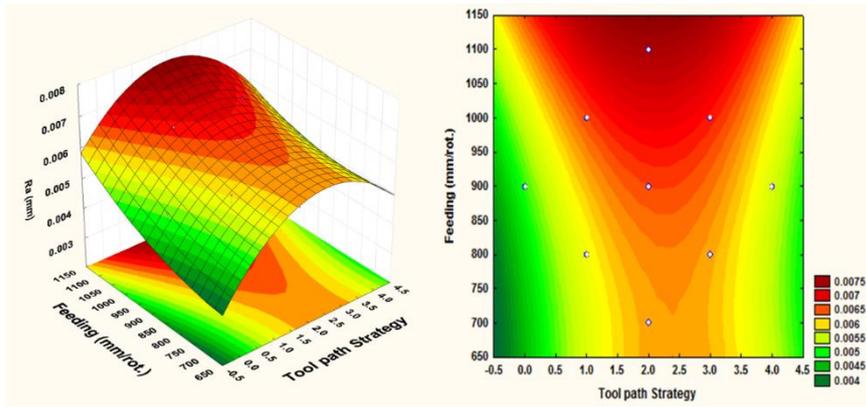
Fig. 2. Main effect plots for SN ratios and means.

The residuals can be judged as normally distributed; therefore, this meets the normality assumptions for all responses. These figures indicate that the quadratic models are capable of representing the system under the given experimental domain. In the milling operations, the surface roughness is mainly controlled by the cutting condition parameters. To better understand the interaction effect of variables on roughness parameters, 3D plots for the measured responses were created based on the model equations in Eq. (6). Since each model had four variables, one variable was kept constant at the centre level for each plot; therefore, a total of 6 response surface plots of 3D and 2D were produced for the responses and given in Figs. 3(a) to 3(f), which show the 3D and 2D surface graphs for the roughness parameter R_a . Apparently, R_a increases as the feed rate increases, but the toolpath strategy, spindle speed and step over stay on middle level. Hence, a minimum and maximum level of toolpath strategy, spindle speed, step over, and a minimum of feed rate factor equivalent to level 1 is required for minimum R_a .

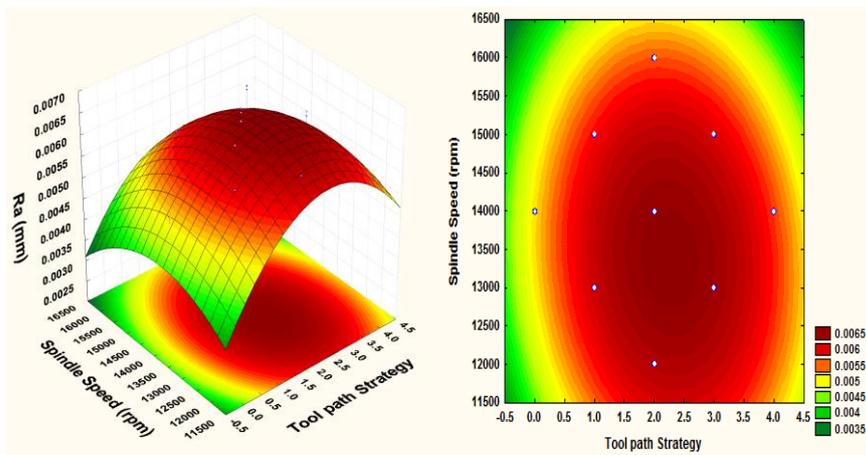
Then the surface plot contour is obtained by processing the response data using the Statistic 5 software, which is used to know significant effect on the measured response. It is also used to determine the value of respond based on model of 2nd order regression as shown in Eq. (6). The R_a measured is obtained from the foot part of patient that uses insole as discussed in [11]. And by using surface plot contour, the predicted optimum value of response and optimal cutting parameters produced by insole manufacturing of orthotic shoe in CNC machine as described in [10, 12].

Figure 3 shows the 2D and 3D plots of surface roughness, which were drawn using the developed RSM model by varying the two different parameters, and keeping the four parameters at the various level. The tool path has a significant effect on the surface roughness followed by spindle speed, feeding and step over in Figs. 3(a) to (f). It can be seen that level of surface roughness can be enhanced by an increase in the feeding rate, spindle speed and step over. However, the surface roughness is found to be minimal at the first tool path (level 1) with middle spindle speed and step over but feeding rate set at level 1 (Figs. 3(a), (b) and (e)). This can be explained that an increasing feed rate yields vibration and more heat, thereby contributing to the higher value of surface roughness [6]. However, the value of surface roughness decreases sharply, when step over and feed rate decreased for a given value of tool path (Figs. 3(a) and (c)).

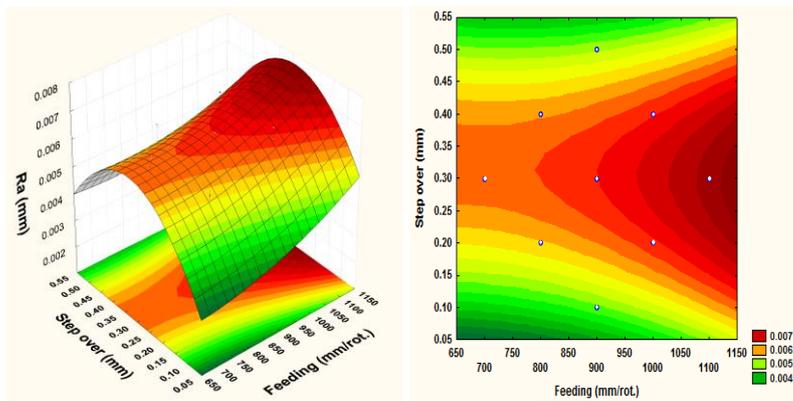
Figures 3(a), (c), (d) and (f) also show the interactive effect of spindle speed and the feeding rate, step over on the yields of surface roughness. It is demonstrated that the value of surface roughness decreases with an increase in the spindle speed and step over, while the best value of surface roughness was observed at a low level of the spindle speed, feeding and step over. It seems that at the lower step over, there is a reduction in the surface roughness values. Table 4 shows the “bold Means”, i.e., the value levels of the significant factors to obtain best result and the calculated optimal value. All level totals are compared and the combination giving the highest combined S/N ratio was selected for a minimum value of surface roughness. In this experiment, factors of $A_2-B_1-C_1-D_1$ combination yielded the minimum value of surface roughness. This is the optimal level combination of factors for CNC milling of the EVA rubber foam.



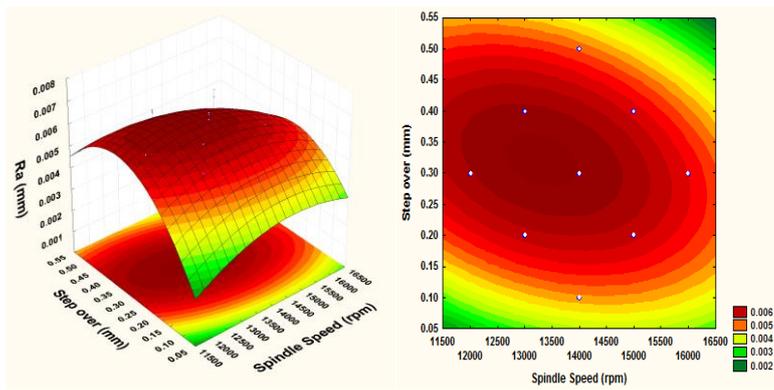
(a) Curve plot of R_a vs. feeding (mm/min) – toolpath strategy.



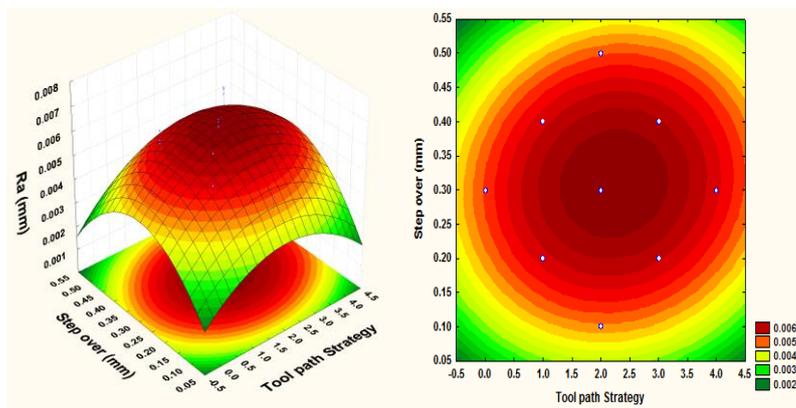
(b) Curve plot of R_a vs. spindle speed (rpm) – toolpath strategy.



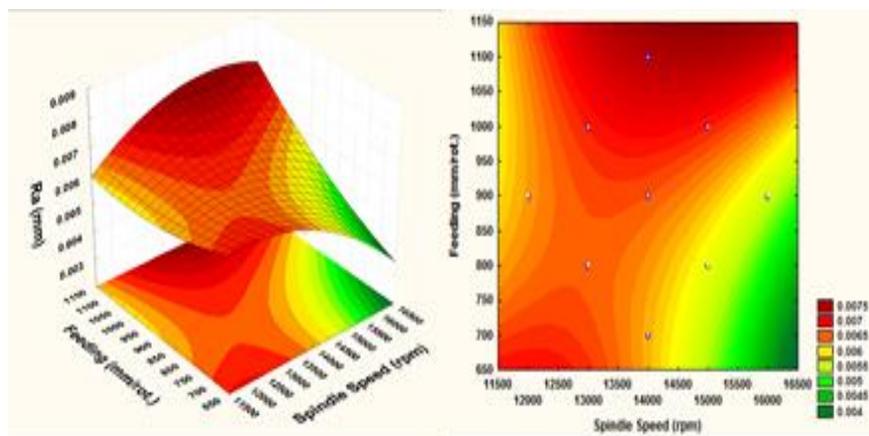
(c) Curve plot of R_a vs. step over (mm) – feeding rate (mm/rot).



(d) Curve plot of R_a vs. step over (mm) - spindle speed (rpm).



(e) Curve plot of R_a vs. step over (mm) - toolpath strategy.



(f) Curve plot of R_a vs. feeding (mm/min) - spindle speed (rpm).

Fig. 3. Plot 3D and 2D curve of data experiment.

Table 4. Response value for S/N ratio (dB) and means (mm).

Control factor	Surface roughness R_a				Rank
	Level 1	Level 2	Level 3	Delta	
S/N ratio (dB)					
(A) Toolpath strategy	44.98	45.73	44.83	0.91	2
(B) Spindle speed	45.64	45.12	44.78	0.87	3
(C) Feeding	45.62	44.97	44.96	0.66	4
(D) Step over	46.16	45.25	44.13	2.03	1
Means (mm)					
(A) Toolpath strategy	0.00571	0.00518	0.00574	0.00058	2
(B) Spindle speed	0.00524	0.00558	0.00558	0.00057	3
(C) Feeding	0.00528	0.00564	0.00571	0.00043	4
(D) Step over	0.00493	0.00547	0.00623	0.0013	1

5.3. Analysis of Variance (ANOVA) for surface roughness

The ANOVA and column effect were used to investigate the effects of setting parameter such as toolpath strategy (*A*), cutting speed (*B*), machining feed rate (*C*) and step over (*D*) on the value of surface roughness. The column effect was introduced by Taguchi as a simplified ANOVA to identify columns, which may have a large effect on the response [24]. Table 5 shows the results of ANOVA analysis for value of surface roughness. The experimental design was evaluated at a confidence level of 95 %, that is, the level significance of 5%. The % Rho in Table 5 is the percentage of the contribution of parameter settings that gives a significant effect on the level of the parameter. The values of F-ratio and the % Rho indicated the significance level of the variable. The F-value (97.72449) and % Rho (65.50 %) for step over is more, which indicates that step over significantly contributes towards the optimum value of surface roughness. Based on % Rho in Table 5, the next significant factor is toolpath strategy (18.03%) and spindle speed (10.32%), while the least significant factor is feeding rate (6.15%). In this case, it is seen that step over was the most significant factor to the surface roughness. This is because the smaller step over set in this case, the lower the surface roughness value such that the surface quality of the insole will be higher.

The variance values in this research are made up of three of the four significant factors yielding a lower roughness response. Table 5 shows that level 1 of factor *D* provides for the lowest roughness values. The same is true for factor *A*, where level 2 provides for lower roughness values R_a and for factor *B*, where level 1 provides for lower roughness values of R_a . Factor *C*, however, has no significant effect on the roughness values of R_a .

Table 5. Results of the ANOVA for squares and % Rho.

Source	Sq	DoF	Mq	F ratio	Sq'	Rho %
<i>A</i>	0.3033	2	0.1517	0.0728	0.2767	14.0837
<i>B</i>	0.2433	2	0.1217	0.0584	0.2167	11.0294
<i>C</i>	0.2433	2	0.1217	0.0584	0.2167	11.0294
<i>D</i>	1.2811	2	0.6406	0.3073	1.2544	63.8575
<i>E</i>	0.0133	1	0.0133	12.0000	0.0000	0.0000
<i>St</i>	2.0844	1				
mean	2.0844	9				
ST	0.0000	9	0	0	1.9644	100

5.4. Taguchi based selection of optimum cutting conditions

After selecting the optimum result of machining parameters by Taguchi, the final step was to predict and verify the improved performance characteristics using the optimum level cutting parameters. The optimum variable levels for surface roughness (R_a), as determined in Fig. 2, are A_2 - B_1 - C_1 - D_1 combination factors. These, together with their levels were used for calculating the predicted optimal surface roughness (R_a) of ISO-diabetes. The predicted optimal R_a can be calculated according to Eq. (3) [10, 12]:

$$Ra_{pred} = T_{Ra\ exp} + (A_2 - T_{Ra\ exp}) + (B_1 - T_{Ra\ exp}) + (C_1 - T_{Ra\ exp}) + (D_1 - T_{Ra\ exp}) \quad (3)$$

where, $T_{Ra\ exp} = 0.0051$, $A_2 = 0.00518$, $B_1 = 0.00524$, $C_1 = 0.00528$, and $D_1 = 0.00493$ are obtained from Table 5, providing that the estimated value of R_a is 0.00533 mm (5.33 μm).

Also, the confidence interval (CI) was used to verify the quality characteristics of the confirmation experiment. The CI for the predicted optimal values can be calculated with the use of Eq. (4) [10]:

$$CI = \sqrt{F_{\alpha;1; dofVE} \times V_{ep} \times \frac{1}{n_{eff}}} \quad (4)$$

The confidence interval (CI) for the surface roughness of R_a can be shown as follows: $F_{0.05, 1.26} = 4.23$ (tabulated), $V_{ep} = 0.0363$ from Table 4, $\eta_{eff} = 5.4$, the calculated CI_{Ra} is $\pm 0.17 \mu\text{m}$. The predicted mean of R_a is: $Ra_{pred} = 0.00533 \text{ mm} = 5.33 \mu\text{m}$

$$\left| Ra_{pred} - CI \right| < a_{pred} < \left| Ra_{pred} + CI \right|, \text{ where } 5.16 < Ra_{pred} (\mu\text{m}) < 5.50$$

The results of the confirmation experiments, which were conducted according to the optimum levels of the variables, are shown in Table 6. The CI for R_a was attained at 0.17 μm . Also from the table, the values of the confirmation test for the responses were at 95% confidence level, which makes the system optimization using the Taguchi method for surface roughness (R_a) to be achieved at a significance level of 0.05.

Table 6. Comparisons for the results of experiments and the predicted values by Taguchi method.

Response	R_a (μm)
Confirmatory experiment result	$R_{a\ exp} = 5.1$
Calculated value	$R_{a\ cal} = 5.33$
Confidence interval (CI)	$CI_{Ra} 0.17$
Difference ($R_{a\ exp} - R_{a\ cal}$)	-0.23
Optimization	$-0.23 < 0.17$ (successful)

Differences between the measured and the predicted responses are shown in Fig. 4. The graphical method was used to show the content of residuals of the models. The residual shows the normal probability plot between predicted and actual data, given in Fig. 4(a). This figure was established as the difference between an observed value and its fitted value. If the residuals plot approximately along a straight line, therefore, the normality assumption is satisfied. The residual versus predictive was used to check if there is any deviation in the process, which is shown

in Fig. 4(c). The normal probability plots of the residuals and plots of predicted versus actual values of the R_a values are shown in Figs. 4(b) and (d) and it can be seen that the error calculated was very small.

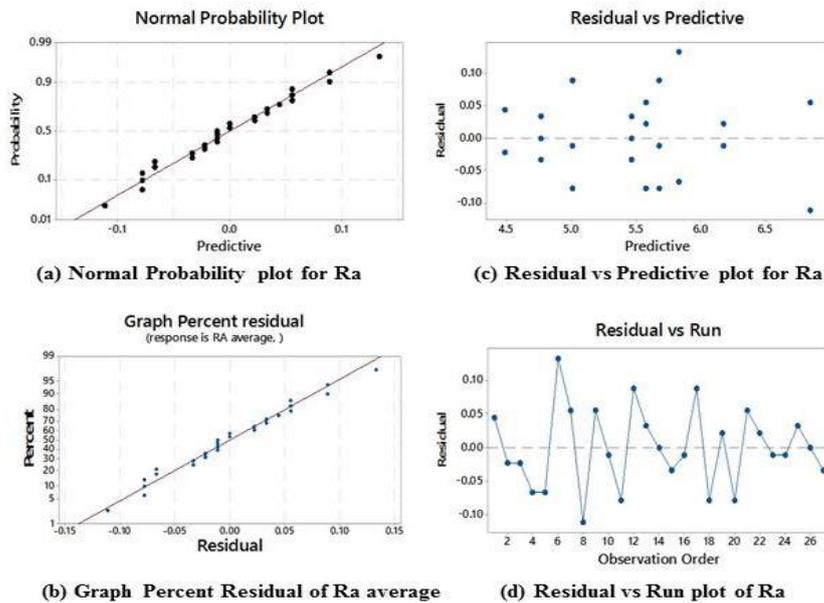


Fig. 4. Relationship between the observed and the predicted response values for Graph Normality test for R_a (μm).

Substantially, by applying Taguchi method in this research, we were able to achieve optimal cutting parameter condition (Fig. 2 and Table 6), where the optimal value of the experimental results is verified by Eqs. (3) and (4). The results of this verification shown that the suitability between the experimental results and the theoretical calculations. Then the RSM methods were used to get the optimal R_a value, based on the regression model in Eqs. (5) and (6) and Fig. 6.

5.5. RSM based modeling for surface roughness

The RSM was conducted for the purpose of modeling and analyzing several variables, which have the relationship between a dependent variable and one or more independent variables. Thereby, the experimental results in CNC milling of EVA rubber foam were used to develop the mathematical models of surface roughness. Also, the adequacy of the response surface quadratic model was verified by ANOVA and the results are shown in Table 7. In the present study, the values of F and P were obtained by performing the number of the experiment as illustrated in Table 2 and 5 to 3 times. It means that the total number of experiemnt is 27 time. The main reason is to generate the distribution of more stabil and important respond data, as shown in Table 7. It reveals that the first-order of step over (D) has more significant effects on the R_a corresponding to spindle speed (B) and feed rate (C), while the first-order of toolpath strategy (A), quadratic and pairwise interactions of A , B and C have no significant effects on the roughness parameters.

Table 7(a). ANOVA analyses of quadratic response surface design for R_a .

Source	DF	Adj SS	Adj MS	F-value	P-value	R^2
Model	8	12.6082	1.57603	311.36	0.000	96.2
Linear	4	10.2993	2.57483	508.69	0.000	
• Toolpath (A)	1	0.0015	0.00154	0.3	0.588	
• Spindle speed (B)	1	1.2447	1.24469	245.9	0.000	
• Feeding (C)	1	1.1417	1.14173	225.56	0.000	
• Step over (D)	1	7.9114	7.91136	1562.98	0.000	
Square	4	2.3089	0.57723	114.04	0.000	
• Toolpath (A)*Toolpath (A)	1	2.0158	2.01582	398.25	0.000	
• Spindle speed (B)*Spindle speed (B)	1	0.0398	0.03984	7.87	0.120	
• Feeding (C)*Feeding (C)	1	0.1976	0.19761	39.04	0.000	
• Step Over (D)*Step over (D)	1	0.0556	0.05564	10.99	0.004	
• Toolpath (A)*Spindle speed (B)	1	0.0004	0.00044	0.01	0.943	
• Toolpath (A)*Feeding (C)	1	0.0816	0.08155	0.97	0.337	
• Spindle speed (B)*Feeding (C)	1	0.5645	0.56445	6.71	0.018	
Error	18	0.0911	0.00506			
• Lack-of-Fi	17	0.0911	0.00536			
• Pure error	1	0.0000	0.0000			
Total	26	12.6993				

Table 7(b). ANOVA analyses for optimum variable of response R_a for second order model regression.

Source	SS	DoF	MS	F-value	F-table	R^2
S.S. Regression	0.000031032	15	0.00003103	62.016794	2.84	0.956
S.S. Error	0.000005504	11	0.00000050			
S.S. Total	0.000036536	26				

Furthermore, the second order model of surface roughness R_a can be generated as a function of the machining parameters (toolpath strategy, spindle speed, feed rate and step over). Therefore, the relationship between the surface roughness R_a and the milling parameters (factors A, B, C, and D) can be expressed as shown in Eq. (5):

$$\begin{aligned}
 Ra = & \beta_0 + \beta_1.A + \beta_2.B + \beta_3.C + \beta_4.D + \beta_5.A.B + \beta_6.A.C + \\
 & \beta_7.A.D + \beta_8.B.C + \beta_9.B.D + \beta_{10}.C.D + \beta_{11}.A.B.C + \beta_{12}.B.C.D + \\
 & \beta_{13}.A^2 + \beta_{14}.B^2 + \beta_{15}.C^2 + \beta_{16}.D^2
 \end{aligned} \quad (5)$$

Accordingly, the mathematical model of the surface roughness (Ra) can be generated using the results of optimized milling parameters (A, B, C, D) and Table 2 by substituting the values in Eq. (5). Surface roughness (R_a) model can be expressed using the RSM through Eq. (6):

$$\begin{aligned}
 Ra = & -0.010979 + 0.002142A - 0.0002958A^2 + 0.00000312B - \\
 & 1.583x10^{-10}B^2 - 0.0000326C + 6.667x10^{-9}C^2 + 0.05217D - \\
 & 0.04208D^2 - 3.75x10^{-8}A.B - 5x10^{-7}A.C + 0.0005A.D + \\
 & 1.875x10^{-9}B.C - 1.625x10^{-6}B.D - 5x10^{-6}C.D
 \end{aligned} \quad (6)$$

With correlation square ($R^2 = 96.20\%$).

The models were subsequently checked using a numerical method employing the coefficient of determination R^2 . The value R^2 shows how much of the observed variability in the data accounted for by the model and then calculated as shown in Eq. (7):

$$R^2 = 1 - \frac{SS_{residual}}{SS_{model} + SS_{residual}} = 1 - \frac{0.09911}{2.3089 + 0.0911} = 96.20\% \quad (7)$$

The SS model is the sum of the square value of the model and SSresidual is the sum of the squares of the residual. The response surface models for surface roughness R_a were developed in this study with R^2 values of 96.20 %, which is higher than 80 %. The R^2 values in this case are quite high and close to 100 %, which is desirable for this experiment. Therefore, results from the coefficients of determination (R^2) indicate that mathematical models of Eq. (6) could be applicable for predicting of the surface roughness. The above models can be used to predict surface roughness parameters at the particular design points. The same predictive can be shown with the Pareto chart in Fig. 5.

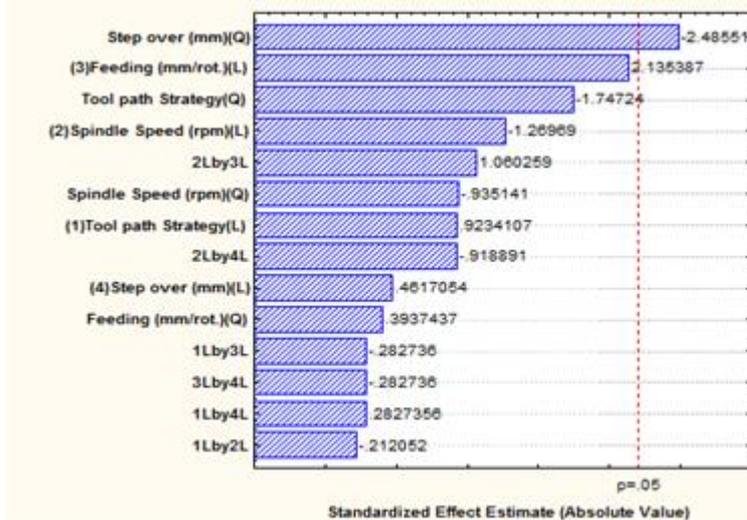


Fig. 5. Pareto chart optimization variables with response R_a (mm).

The p-value value greater than 0.05 shows the variable that has the most significant effect. The pareto chart shows the optimization variables in the R_a (mm) response, with the most influential effect being the quadratic of the step over factor (D_2).

The residual value in this study has a tendency to be normally distributed; therefore, normality assumptions for all responses are satisfied. Also it shows that the quadratic models are capable of representing the system under the given experimental domain. And to better understand the interaction effect of machining variables on surface roughness, 3D- plots for the measured responses can be developed based on the model equation in Eq. (6), which has four variables, one variable was kept constant at the center level for each plot; therefore, a total of 6 response surface plots was produced for the responses (Figs. 3(a) to (f)).

5.6. Optimization using desirability function analysis

The measured properties of each predicted response can be transformed into a dimensionless desirability value (dF) in this approach [19]. The scale of the desirability function ranges between 0 and 1. If the value $dF = 0$ or closes to 0, then the response is considered completely unacceptable. If dF equals to 1 or closes to 1, then the response value is of the target value. In this study, the desirability function was selected as “the smaller the better” because the minimum surface roughness was achieved at the optimum milling parameters. The desirability function of “the-smaller-the better” can be shown in Fig. 6. The optimal value of R_a in the model was achieved at 4.7889 μm , while the desirability value of R_a is close to 1.0000. Consequently, the response is considered perfect of the target value. It should be noted the orthotic shoe has been manufactured and implemented by the patient with satisfactory result. For detail, the reader can refer to the previously published work [22].

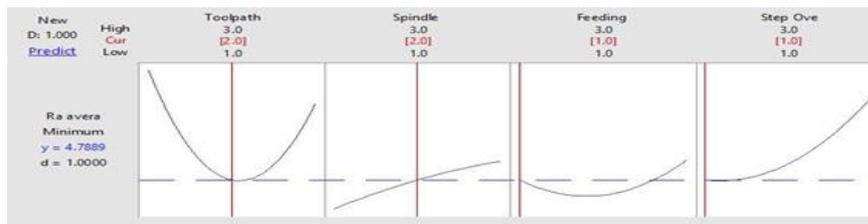


Fig. 6. Response optimization plot for R_a .

6. Conclusions

The present work demonstrated the CAD design of ISO-diabetes and the combination of Taguchi and RSM methods for determining the optimal setting parameters in CNC milling. Based on the discussion earlier, the conclusions can be drawn as follows:

- In this machining of EVA rubber foam, the minimum value of surface roughness (0.0053 mm) was obtained at the different combinations of cutting conditions. The confirmation tests for Taguchi's optimum value indicated that this experimental result is reliable.
- Considering the response surface optimization and the composite desirability of RSM, the optimal milling parameters of ISO-diabetes were found as: tool path strategy of raster 450, spindle speed of 14000 rpm, feed rate of 800 mm/rotation and step over about 0.2 mm. Also, the optimum R_a of 4.7889 μm with desirability of 1.00 was obtained.
- The combination of Taguchi and RSM confirmed that the step over is the most significant factor on the surface roughness (R_a) contributing 96.20 %. The Taguchi and RSM were found to be effective for the identification and development of significant factor relationships between setting parameter of each cutting parameter. The significance factor of interactions and the square model of the parameter is more clearly predicted in RSM and both methods may be beneficial for optimizing input data in milling operations of ISO-diabetes, leading to a reduction in the manufacturing time and cost.

Substantially, the number of patient as well as the type of patient should be widened in further studies in order to obtain shoe insole with better quality.

Nomenclatures

<i>A</i>	Toolpath strategy
<i>B</i>	Spindle speed, rpm
<i>C</i>	Feeding / Feed rate, mm/min
<i>CBS</i>	Curve base surface
<i>CI</i>	Confident Interval for surface roughness to verify the quality characteristic of the confirmation experiment
<i>D</i>	Step over, mm
<i>dF</i>	Desirability value
<i>HRC</i>	Hardness of rockwel C
<i>R_a</i>	Aritmetic average surface roughness
<i>R_{a,exp}</i>	Value of <i>R_a</i> from the experiment
<i>R_{a,pred}</i>	Predictive value of <i>R_a</i>
<i>S/N ratio</i>	Ratio of the mean to the standard deviation
<i>x_i</i>	Function of machining parameters
<i>% Rho</i>	Percentage of the contribution of parameter settings

Greek Symbols

β	Constant parameter of control factor
---------	--------------------------------------

Abbreviations

CAD	Computer Aided Design
CNC	Computer Numerical Control
ISO-diabetes	Insole Shoe Orthotic for diabetic patient
EVA	Ethylene-vinyl acetate
RSM	Response Surface Methods
ANOVA	Analysis of Variant
RID	Reverse Innovative Design
DoF	Design of Experiments

References

1. Uccioli, L. (2006). The role of footwear in the prevention of diabetic foot problems. *The Diabetic Foot*, 523-541.
2. Vicenzino, B. (2004). Foot orthotics in the treatment of lower limb conditions: A musculoskeletal physiotherapy perspective. *Manual Therapy*, 9(4), 185-196.
3. Ye, X.; Liu, H.; Chen, L.; Chen, Z.; Pan, X.; and Zhang, S. (2008). Reverse innovative design - an integrated product design methodology. *Computer Aided Design*, 40(7), 812-827.
4. Munro, W. (2005). Orthotic prescription process for the diabetic foot. *The Diabetic Foot*, 8(2), 72-82.
5. Xia, Z. (2014). Application of reverse engineering based on computer in product design. *International Journal of Multimedia and Ubiquitous Engineering*, 9(5), 343-353.
6. Chabbi, A.; Yallese, M.A.; Nouioua, M.; Meddour, I.; Mabrouki, T.; and Girardin, F. (2017). Modeling and optimization of turning process parameters during the cutting of polymer (POM C) based on RSM, ANN, and DF methods.

- The International Journal of Advanced Manufacturing Technology*, 91(5-8), 2267-2290.
7. Anggoro, P.W.; Bawono, B.; Andreyas, W.; Jamari, J.; and Bayuseno, A.P. (2016). Parameter optimization of strategies at CNC milling machines rolland modela MDX 40R CAM against surface roughness made insole shoe orthotic eva rubber foam. *International Journal of Mechanical and Mechatronics Engineering (IJMME-IJENS)*, 16(4), 96-102.
 8. Montgomery, D.C. (2013). *Design analysis of experiments* (8th ed.). Hoboken, New Jersey: John Wiley and Sons, Inc.
 9. Aggarwal, A.; Singh, H.; Kumar, P.; and Singh, M. (2008). Optimizing power consumption for CNC turned parts using response surface methodology and Taguchi's technique and a comparative analysis. *Journal of Materials Processing Technology*, 200(1-3), 373-384.
 10. Sarıkaya, M.; and Güllü, A. (2014). Taguchi design and response surface methodology based analysis of machining parameters in CNC turning under MQL. *Journal of Cleaner Production*, 65, 604-616.
 11. Anggoro, P.W.; Saputra, E.; Tauviqirrahman, M.; Jamari, J.; and Bayuseno, A.P. (2017). A 3D dimensional finite element analysis of the insole shoe orthotic for foot deformities. *International Journal of Applied Engineering Research*, 12(15), 5254-5260.
 12. Asiltürk, I.; and Neseli, S. (2012). Multi response optimization of CNC turning parameters via Taguchi method-based response surface analysis. *Measurement*, 45(4), 785-794.
 13. Mahapatra, S.S.; Patnaik, A.; and Patnaik, P.K. (2006). Parametric analysis and optimization of cutting parameters for turning operations based on taguchi method. *Proceedings of the International Conference on Global Manufacturing and Innovation*. 8 pages.
 14. Wang, Z.; Meng, H.; and Fu, J. (2010). Novel method for evaluating surface roughness by grey dynamic filtering. *Measurement*, 43(1), 78-82.
 15. Jeng, Y.R.; Liu, D.S.; and Yau, H.T. (2012). Designing experimental methods to predict the expansion ratio of EVA foam material and using finite element simulation to estimate the shoe expansion shape. *Material Transaction*, 53(9), 1685-1688.
 16. Fratila, D.; and Caizar, C. (2012). Investigation of the influence of process parameters and cooling method on surface quality of AISI-1045 during turning. *Materials and Manufacturing Processes*, 27(10), 1123-1128.
 17. Bhattacharya, A.; Das, S.; Majumder, P.; and Batish, A. (2009). Estimating the effect of cutting parameters on surface finish and power consumption during high speed machining of AISI 1045 steel using Taguchi design and ANOVA. *Production Engineering*, 3(1), 31-40.
 18. Xavier, M.A.; and Adithan, M. (2009). Determining the influence of cutting fluids on tool wear and surface roughness during turning of AISI 304 austenitic stainless steel. *Journal of Materials Processing Technology*, 209(2), 900-909.
 19. Sait, A.N.; Aravindan, S.; and Haq, A.N. (2009). Optimization of machining parameters of glass-fibre-reinforced plastic (GFRP) pipes by desirability function analysis using Taguchi technique. *The International Journal of Advanced Manufacturing Technology*, 43(5), 581-589.

20. Aloufi, M.; and Kazmierski, T.J. (2011). A response surface modelling approach to performance optimisation of kinetic energy harvesters. *International Journal of Research and Reviews in Computer Science (IJRRCS)*, 9 pages.
21. Carley, K.M; Kamneva, N.Y.; Reminga, J. (2004). Response surface methodology. *CASOS Technical Report, CMU-ISRI-04-136*. Carnegie Mellon University School of Computer Science, Pittsburgh, United States of America.
22. Anggoro, P.W., Tauviquirrahman, M., Jamari, J., Bayuseno, A.P., Bawono, B., and Avellina, M.M. (2018). Computer-aided reverse engineering system in the design and production of orthotic insole shoes for patients with diabetes. *Cogent Engineering*, 5(1), 20 pages.
23. Myers, R.; Montgomery, C.; Douglas, C.M.; and Anderson-Cook, C.M. (2009). *Process and product optimization using designed experiments*. (3rd ed.). New York, United States of America: John Wiley and Sons, Inc.
24. Ross, P.J. (1996). *Taguchi techniques for quality engineering* (2nd ed.). New York, United States of America: McGraw-Hill.