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CNC Milling of Medical-Grade PMMA:

Optimization of Material Removal Rate and Surface Roughness

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ABSTRACT

This study evaluates CNC milling parameters (spindle speed, depth of cut, and feed rate) on medical-grade PMMA. A single objective analysis conducted showed that the optimal material removal rate (MRR) occurs at a spindle speed of 1250 rpm, a depth of cut of 1.2 mm, and a feed rate of 350 mm/min. The ANOVA showed that feed rate is the most significant factor towards the MRR, and spindle speed (11.83%) is the least contributing. The optimal surface roughness (Ra) occurred at spindle speed of 500 rpm, depth of cut of 1.2 mm, and feed rate of 200 mm/min. The milling factors were insignificant. A regression analysis for prediction was also conducted. Further, a multi-objective optimization was conducted using the grey relational analysis. It showed that the best trade-off between the MRR and the Ra could be obtained from a combination of 1250 rpm (spindle speed), 1.2 mm (depth of cut), and 350 mm/min (feed rate). The depth of cut was the largest contributor towards the grey relational grade (54.48%), followed by the feed rate (10.36%), and finally, the spindle speed (4.28%).

KEYWORDS

ANOVA, Depth of Cut, Feed Rate, Grey Relational Analysis, Multi-Objective, Optimal, S/N Ratio, Spindle Speed

INTRODUCTION

Polymeric materials have attracted applications in various industries, especially the medical field, due to their desirable properties such as high strength and low weight and biocompatibility with human tissues. However, the manufacture of components from these materials has faced several challenges, including their poor machinability leading to the generation of poor surfaces and low production rates (Yan et al., 2021). These challenges necessitate the evaluation of the primary machining parameters

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(spindle speed, depth of cut, feed rate, nose radius, tool geometry, tool vibrations) and their impact on the quality of products to identify the optimal parameters for production (Aslaliya et al., 2014).

Various researchers have conducted studies on optimizing the material removal rates and surface quality of different materials. These optimization studies involve selecting the most common machining parameters and determining the most suitable combination for the highest material removal and the least surface roughness. For example, in most milling processes, the most common machining parameters are spindle speed, cutting speed, feed rate, and depth of cut (Ribeiro et al., 2017; Ratnam, 2017). In addition, the parameters tend to largely influence the surface roughness and material removal of milled components (Sakthivelu et al., 2017).

In a study conducted by Lazarević et al. (2012) on the optimization of cutting parameters for the least surface roughness of polyethylene, it was found out that the feed rate was the most significant factor. The authors concluded that the optimum parameters for the least surface roughness were approximately 213 m/min, 0.049 mm/rev, 2 mm, and 0.8 mm for the cutting speed, feed rate, depth of cut, and nose radius, respectively. Similar findings were presented by Hamlaoui et al. (2017) during the machining of polyethylene, where the feed rate was identified as the most significant parameter towards the surface roughness. Tamiloli & Venkatesan (2016) investigated the impact of milling parameters on surface quality and heat generation. They found that high spindle speed and low feed and depth of cut were most preferred for a better surface finish. Low speeds and feeds were also desired for low heat generation.

Further, Ali et al. (2012) found out that during the micro-milling of PMMA, the feed rate and depth of cut were the most significant parameters towards the generation of machining vibrations, while for the minimum surface roughness, the spindle speed was the most significant. In a PMMA facing operation conducted by Dhakad et al. (2017) to optimize the cutting parameters for the best surface finish, it was found out that the feed rate was the most significant parameter followed by the cutting speed and depth of cut. Therefore, the authors recommended the maximum cutting speed, minimum feed rate, and a moderate depth of cut. Similar results were also identified by Korkmaz et al. (2017) in the micro-milling of PMMA, where the feed rate and spindle speed were the most significant factors towards the surface finish. On the other hand, the depth of cut had a negligible influence on the surface roughness. Additionally, during the CNC milling process, Pant et al. (2017) found out that the material removal rate was affected mainly by the cutting speed and depth of cut.

Thermoplastic polymers, such as PMMA, have been considered hard-to-cut materials due to their mechanical and chemical properties, such as poor thermal conductivity and chip formation, among others (Yan et al., 2021). These properties affect machining processes such as heat dissipation which leads to high machining temperatures. High machining temperatures impact the tool wear, which affects the tool's cutting ability, affecting the surface quality and removal of chips. This also increases the machining forces, translating to workpiece fracture and delamination (Arhamnamazi et al., 2021). As a result, these materials have been machined using non-conventional methods such as laser-assisted machining and ultrasonic-assisted milling, among others. However, these machining methods involve complex procedures and requirements, limiting the polymers' application in high precision fields such as in medical and aerospace (Halim et al., 2017; Bharat & Bose, 2020).

In literature, the material removal rate of different machines has been presented as the product of cutting speed, the tool feed, and the depth of cut (Aslaliya et al., 2014). However, this method of computing MRR has been less efficient due to the presence of numerous factors affecting the rate of material removal and the interaction of other responses that affect it. This has warranted research and experimental studies to determine the optimal parameters for machining different materials to reduce the chance occurrences and minimize impacts of external factors. Such studies include that conducted by Shagwira et al. (2020), who concluded that the optimal parameters for the highest MRR were 600 rpm for cutting speed, 200 mm/min for feed rate, and 0.8 mm for depth of cut in the milling of polypropylene + 60 wt% quarry dust composite. The feed rate was the most significant factor towards the material removal rate.

Therefore, this study aims at expanding the existing knowledge on the machinability of medical-grade PMMA through a conventional machining method, i.e., CNC milling. To achieve this, optimization of the milling parameters: spindle speed, depth of cut, and feed rate is conducted using samples obtained from used lens samples. The interaction of the parameters is evaluated against the material removal rate (MRR) and surface roughness (Ra), which are primary determinants of the productivity of a production system and the surface quality of products. The experiments in the study are designed using the Taguchi methodology to reduce the number of experiments conducted. The results are analyzed using the Taguchi methodology (single-objective optimization), where the interaction of the machining parameters with single responses (MRR and Ra) is considered.

Further, a multi-objective analysis and optimization (MOO) study is conducted using the Grey Relational Analysis (GRA) to evaluate the impact of the milling parameters on the overall responses. Through the MOO, a trade-off between the two responses is assessed, which leads to the optimal machining parameters of medical-grade PMMA for the best overall responses (MRR and Ra). Regression analysis is then conducted on the results and regression equations formulated. A prediction model is then developed and compared with the experimental data for verification. The analysis of variance (ANOVA) is then conducted to determine the significance of each machining parameter towards the MRR and Ra and their percentage contributions. This study contributes to the broader knowledge of machinability of the medical-grade PMMA by providing prediction models for the optimal CNC milling parameters and can act as a reference to manufacturers and industrial researchers. Furthermore, the methodology and analyses provided in this study can also be used to guide researchers in the academic field.

METHODOLOGY

Design of Experiments (DoE)

Three factors were adopted in this study: spindle speed (V), depth of cut (Dc), and feed rate (Fr). From experimental trials conducted on the medical grade PMMA, four levels were adopted for each factor. The levels were 1250 rpm, 2500 rpm, 3750 rpm, and 5000 rpm for the spindle speed. For the depth of cut, the four levels were 0.3 mm, 0.6 mm, 0.9 mm, and 1.2 mm. Lastly, for the feed rate, the four levels were 50 mm/min, 100 mm/min, 200 mm/min, and 350 mm/min. The experiments were designed following the Taguchi methodology. An L16 orthogonal array was adopted, where 16 experiments were produced for the combination of factors, as shown in Table 1.

Characterization Techniques

Medical grade PMMA samples measuring approximately 45 mm by 30 mm by 6 mm were obtained from used optical lenses. First, they were cleaned and weighed with an electronic balance (WT2001K) with a sensitivity of 0.1 g. This gave the initial mass (Mi). The workpieces were then milled in a programmed Benchmill 6000 CNC machine with a 3 mm diameter multi-edged high-speed steel tool (four teeth). The experiments were carried out according to the orthogonal array produced from the design of experiments. Each experiment was replicated thrice. For each experiment, the machining time was recorded in minutes.

After the experiments, the milled surfaces were cleaned to remove chips. They were then weighed to obtain the final mass (Mf). A difference between the initial and final mass was obtained to get the change in mass. Using the average recorded milling time, the material removal rate was computed from Equation 1 and recorded in Table 1:

$$Material\,Removal\,Rate\left(g\,/\,min\right) = \frac{Mi - Mf}{Tavg} \tag{1}$$

Mi = Initial mass of workpiece in grams
Mf = Final mass of workpiece in grams
Tavg = Average milling time in minutes

The milled surfaces were then investigated for the arithmetic mean surface roughness. Three roughness values were obtained along the tool path for each workpiece, and a mean was obtained. This is presented in Table 1.

RESULTS AND DISCUSSION

Experimental Results

The experimental results for the material removal rate (MRR) and the average surface roughness (Ra) obtained for each experiment were recorded in Table 1.

Single Objective Analysis

Single objective analysis was conducted using the Taguchi methodology, where signal-to-noise (S/N) ratios were obtained for the two responses. The main objective for the material removal rate was to get the highest possible value to optimize the milling process. Therefore, the '*larger is better*' criterion (Equation 2) was adopted. On the other hand, the '*smaller is better*' criterion (Equation 3) was adopted since the goal was to obtain the least possible surface roughness for optimality (Equations obtained from Minitab 17 software):

Table 1. L16 orthogonal array and experimental results

Experiment No.	V (rpm)	Dc (mm)	Fr (mm/min)	MRR (g/min)	Ra (μm)
1	1250	0.3	50	0.081	0.489
2	1250	0.6	100	0.375	0.658
3	1250	0.9	200	0.688	0.764
4	1250	1.2	350	0.810	0.848
5	2500	0.3	100	0.178	0.749
6	2500	0.6	50	0.132	0.881
7	2500	0.9	350	0.667	0.690
8	2500	1.2	200	0.667	0.893
9	3750	0.3	200	0.169	0.714
10	3750	0.6	350	0.588	0.660
11	3750	0.9	50	0.108	0.477
12	3750	1.2	100	0.420	0.157
13	5000	0.3	350	0.418	0.746
14	5000	0.6	200	0.357	1.224
15	5000	0.9	100	0.210	0.919
16	5000	1.2	50	0.128	0.092

$$\frac{S}{N}ratio = -10\log[\frac{1}{n}\sum_{i=0}^{n}\frac{1}{yi^2} \qquad (2)$$

$$\frac{S}{N}ratio = -10\log[\frac{1}{n}\sum_{i=0}^{n}yi^2 \qquad (3)$$

The Taguchi analysis yielded the S/N ratios presented in Table 2.

From the S/N ratios, the largest values for each response were identified, which represented the most significant factor impact. For the MRR and Ra, the largest S/N ratios were -1.8303 and 20.7242, respectively. For the MRR, the largest S/N ratio corresponded to the largest MRR (0.810 g/min) obtained from a factor combination of 1250 rpm, 1.2 mm, and 350 mm/min for the spindle speed, depth of cut, and feed rate, respectively. This depicted that the lowest spindle speed and the highest levels of the depth of cut, and the feed rate led to the highest MRR. These results were similar to those obtained by Shinge & Dabade (2018) and Parashar & Purohit (2017). This could be attributed to the increase in tool contact area as the depth increased.

An increase in feed rate reduced the machining time, which is inversely related to the MRR (Equation 1). The feed rate is also linearly associated with the feed per tooth, which is the material cut by each tooth in the tool (Kiswanto et al., 2019). Therefore, an increase in feed rate led to an increase in MRR. Additionally, High spindle speed increases the tool-workpiece contact friction and milling forces, limiting the tool movement, and increasing machining time. On the other hand, a lower spindle speed allows a smooth flow of chips, which reduces friction between the tool and the workpiece (Sulaiman et al., 2014). The least MRR was obtained using a spindle speed of 1250 rpm, depth of cut of 0.3 mm, and feed rate of 50 mm/min. This could be associated with the low tool-workpiece contact area (due to shallow depth of cut) and a high machining time (due to low feed rate).

For the average surface roughness, the largest S/N ratio corresponded to a value of 0.092 µm obtained from a factor combination of spindle speed (5000 rpm), depth of cut (1.2 mm), and feed rate (200 mm/min). On the other hand, the largest surface roughness was obtained from spindle speed of 5000 rpm, depth of cut of 0.6 mm, and feed rate of 200 mm/min. Similar trends have been observed in the literature [5-6]. An increase in spindle speed with a low feed rate reduced the feed per tooth on the tool, reducing the load on every tooth. This reduced the friction force and hence a lower surface roughness (Kiswanto et al., 2019). In addition, the high depth of cut increased heat dissipation through the tool as a larger section was in contact with the workpiece. Further, increased spindle speed reduced

Table 2. S/N ratios for the material removal rate and surface roughness

Experiment No.	S/N Ratios		Experiment No.	S/N Ratios	
	MRR	Ra		MRR	Ra
1	-21.8303	6.2138	9	-15.4423	2.9260
2	-8.5194	3.6355	10	-4.6125	3.6091
3	-3.2482	2.3381	11	-19.3315	6.4296
4	**-1.8303**	1.4321	12	-7.5350	16.0820
5	-14.9916	2.5104	13	-7.5765	2.5452
6	-17.5885	1.1005	14	-8.9466	-1.7556
7	-3.5175	3.2230	15	-13.5556	0.7337
8	-3.5175	0.9830	16	-17.8558	**20.7242**

built-up edges (BUE), which reduced the surface roughness. On the other hand, an increase in feed rate increased the tool wear, leading to the deterioration of the surface integrity (Kumar et al., 2012).

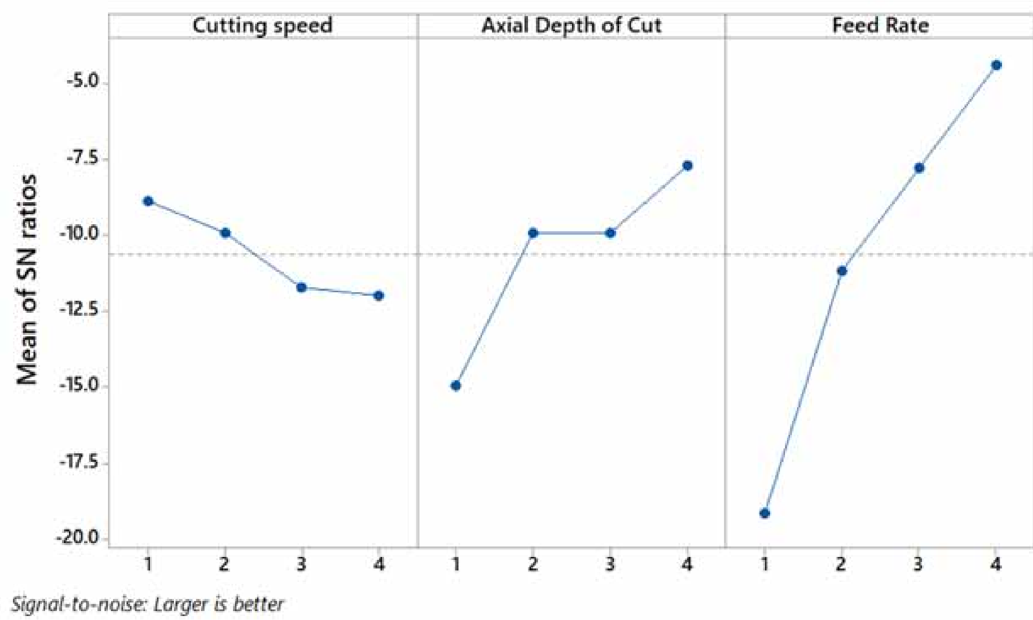
To obtain the optimal milling parameters for the MRR and Ra, the S/N ratios were ranked for the specific responses and parameters as presented in Table 3.

The S/N ratios were ranked according to the delta values. For the MRR, the feed rate was the most dominant, followed by the depth of cut, and lastly, the spindle speed. For the average surface roughness, the depth of cut was the most prevalent, followed by the feed rate and the spindle speed (Table 3). For the maximum MRR, the optimal parameters, presented by the bolded S/N ratios, were spindle speed of 1250 rpm, depth of cut of 1.2 mm, and feed rate of 350 mm/min. These dominant parameters are presented in Figure 1. From the Figure, it could be observed that an increase in the

Table 3. Response table for the MRR and Ra

Levels	Control factors					
	MRR			Ra		
	Spindle speed	Depth of cut	Feed rate	Spindle speed	Depth of cut	Feed rate
1	**-8.857**	-14.960	-19.152	3.405	3.549	**8.617**
2	-9.904	-9.917	-11.150	1.954	1.647	5.740
3	-11.730	-9.913	-7.789	**7.262**	3.181	1.123
4	-11.984	**-7.685**	**-4.384**	5.562	**9.805**	2.702
Delta	3.127	7.276	14.767	5.307	8.158	7.494
Rank	3	2	1	3	1	2

Figure 1. S/N ratios main effect plots for the MRR



depth of cut and the feed rate increased the MRR. However, an increase in the spindle speed, from 1250 rpm to 5000 rpm, led to a decrease in the material removal rate.

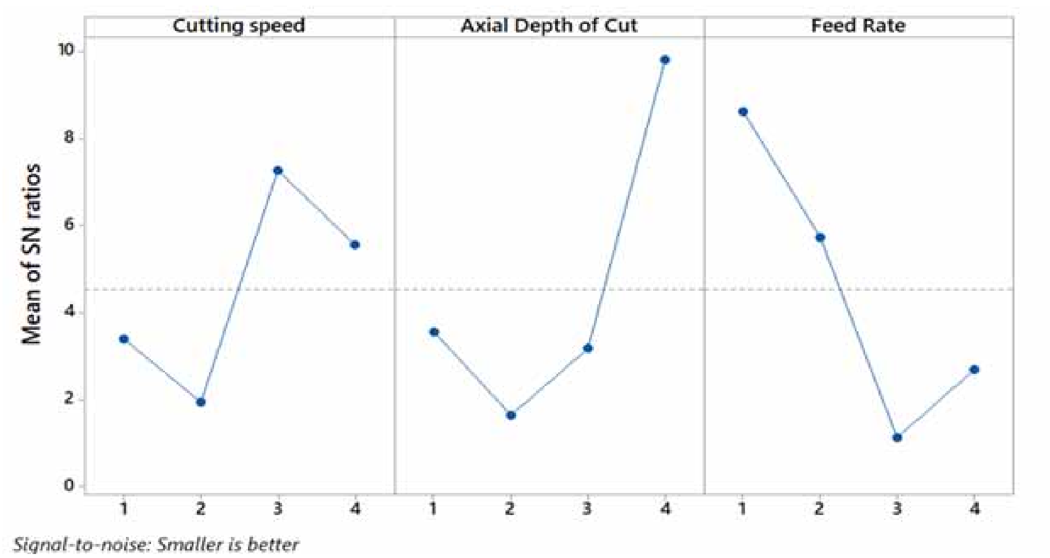
The least MRR was obtained from a parameter combination of 5000 rpm, 0.3 mm, and 50 mm/min for the spindle speed, depth of cut, and feed rate, respectively. An increase in spindle speed with a low feed rate reduces the feed per tooth, which reduces the amount of material milled, and hence a lower MRR (Kiswanto et al., 2019). These results agreed with the literature (Dhakad et al., 2017; Korkmaz et al., 2017; Pant et al., 2017). An increase in depth of cut and feed rate increases the tool-workpiece contact area and chip removal rate. As the tool goes deeper into the workpiece, the area in contact increases. As the tool advances towards the workpiece at a higher rate, contact increases. This contributes to a higher rate of material removal.

Consequently, from the S/N ratios presented in Table 3 for the average surface roughness, the depth of cut was the most significant parameter towards the surface roughness of the medical-grade PMMA. The feed rate followed this, and finally, the spindle speed. This variation is presented in Figure 2. From the analysis, the optimal milling parameters for PMMA to obtain the lowest surface roughness were spindle speed of 3750 rpm, a depth of cut of 1.2 mm, and a feed rate of 50 mm/min. For the highest roughness, the parameter combination was spindle speed of 2500 rpm, depth of cut of 0.6, and feed rate of 200mm/min.

From Figure 2, it could be observed that the impact of spindle speed decreases slightly as the speed increases from 1250 rpm to 2500 rpm, then increases as the speed increase to 3750 rpm, and finally slightly reduces as the speed increase to 5000 rpm. Likewise, the impact of the depth of cut reduces slightly as the depth increases from 0.3 mm to 0.6 mm, and then increases sharply with an increase in depth of cut to 1.2 mm. Lastly, the impact of the feed rate on the surface roughness reduces as the feed rate increases from 50 mm/min to 200 mm/min and then increases as the feed rate increases to 350 rpm (Figure 2).

An increase in spindle speed increases the feed per tooth, which increases the rate of clean-up of chips. This reduces surface roughness (Kiswanto et al., 2019). Similarly, a lower feed rate increases the tool-workpiece contact time, ensuring finer chip production, reducing the formation of tool contours on the workpiece, which translates to a better finish (Korkmaz et al., 2017). For difficult to machine materials such as the medical-grade PMMA, there are stress-induced transformations in front of the

Figure 2. S/N ratios main effect plots for the average surface roughness



tool surface as the tool moves on the workpiece. Therefore, a higher depth of cut ensures that the tool's cutting surface is lower than the strain-induced region (Parhad et al., 2015). As a result, the increased depth of cut in the milling of medical-grade PMMA ensured lower tool wear and a better surface finish. However, this high depth of cut is often associated with machining forces contributing to friction and high-temperature generation (Wang et al., 2016). If these temperatures exceed the glass transition temperature, the surface roughness is likely to increase.

ANOVA

The analysis of variance was then conducted on the S/N ratios to evaluate the significance and contribution of each factor towards the MRR and Ra using the p-values and percentage factor contributions. The ANOVA results for the two responses are presented in Table 4.

The *p-values* were less than the significance value for the material removal rate, that is, 0.014, 0.004, and 0.000 for the spindle speed, depth of cut, and feed rate (Table 4). This meant that all the parameters were significant towards the material removal rate. Further, considering the percentage contributions, the feed rate had the highest (64.81%), followed by the depth of cut (20.58%), and finally, the spindle speed (11.83%). Higher feed rates and depths of cut increased the feed per tooth, chip removal, and lower machining time, hence a higher MRR. These findings agreed with the literature (Korkmaz et al., 2017; Pant et al., 2017).

Considering the surface roughness, all the *p-values* were more than the significance value, that is, 0.393, 0.306, and 0.197 for the spindle speed, the depth of cut, and the feed rate, respectively (Table 4). This meant that all the milling parameters were insignificant towards the surface roughness. However, the percentage contributions depicted that the feed rate was the most significant contributor towards the surface roughness (31.31%), followed by the depth of cut (22.06%), and finally, the spindle speed (17.30%). These results agreed with the literature (Hamlaoui et al., 2017).

Regression Analysis

Regression analysis was then conducted to generate regression equations relating the responses (dependent) and the factors (independent). For the MRR, a linear regression analysis conducted yielded Equation 4:

Table 4. ANOVA for the S/N ratios for MRR and Ra

Factor	Degree of freedom	Sum of squares	Mean squares	%Contribution	F-Value	*P*-Value
Material Removal Rate						
Spindle speed	3	0.10571	0.035237	11.83	8.52	0.014
Depth of cut	3	0.18389	0.061298	20.58	14.83	0.004
Feed rate	3	0.57913	0.193045	64.81	46.70	0.000
Error	6	0.02480	0.004134			
Total	15	0.89354				
Surface Roughness						
Spindle speed	3	0.2045	0.06817	17.30	1.18	0.393
Depth of cut	3	0.2607	0.08690	22.06	1.50	0.306
Feed rate	3	0.3701	0.12336	31.31	2.14	0.197
Error	6	0.3466	0.05777			
Total	15	1.1819				

$$\text{MRR (g/min)} = 0.0394 - 0.000058\text{ V} + 0.3132\text{ Dc} + 0.001603\text{ Fr} \quad (4)$$

Equation 4 was used to predict the values of the MRR using the experimental factors. The experimental MRR values were then plotted against the predicted MRR values, as shown in Figure 3. The plot produced a regression coefficient (R^2) of 0.9179. This meant that the linear regression model in Equation 4 could be sufficiently employed to predict the MRR in the CNC milling of medical-grade PMMA (Obiko et al., 2020). Furthermore, the regression coefficient of 0.9179 meant that approximately 91% of the predicted MRR values fit the linear regression model. Therefore, the MRR could be predicted using the model at an accuracy level of about 91%.

Further, linear regression analysis for surface roughness was also conducted. This yielded equation 5:

$$\text{Ra } (\mu\text{m}) = 0.740 - 0.000011\text{ V} - 0.225\text{ Dc} + 0.000840\text{ Fr} \quad (5)$$

Equation 5 yielded an R^2 value of 0.2055. However, this value was deficient, indicating that the linear regression model could not predict the surface roughness. A quadratic regression analysis was then conducted, which yielded a regression Equation 6:

$$\text{Ra } (\mu\text{m}) = 0.608 - 0.57\text{ Dc}^2 - 0.000013\text{ Fr}^2 - 0.000124\text{ VDc} + 0.00649\text{ DcFr} \quad (6)$$

The R^2 value obtained from Equation 6 was 0.9101. This value showed that the quadratic model could predict the surface roughness during the CNC milling of PMMA. Further, a comparison was made between the experimental and predicted surface roughness values, as shown in Figure 4. This showed that the quadratic model was sufficient in predicting surface roughness.

Figure 3. A plot of the experimental MRR against the predicted MRR

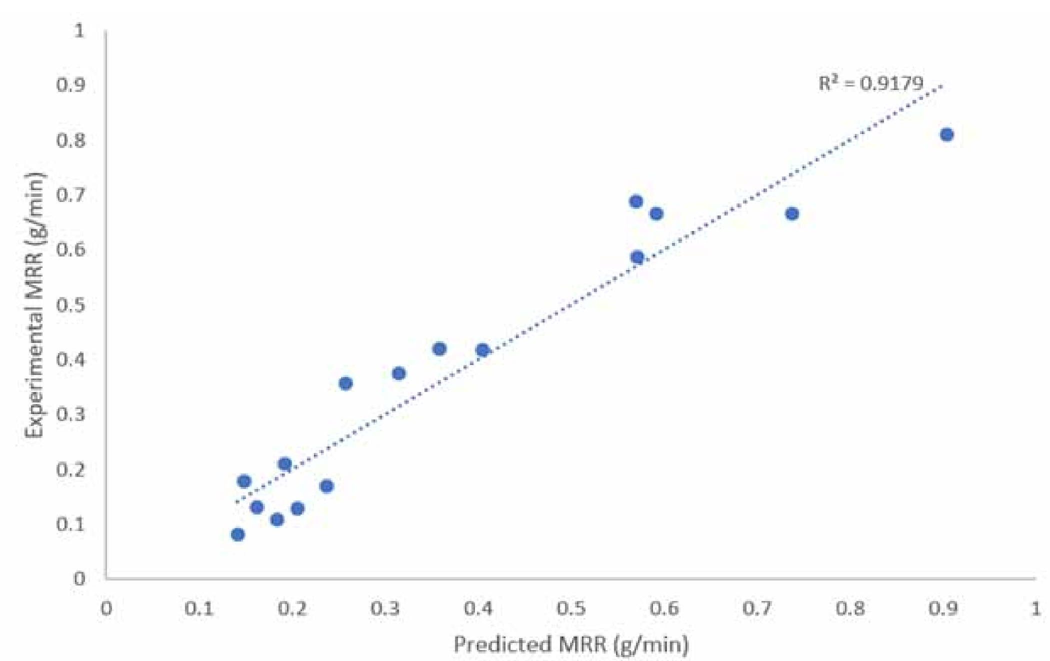
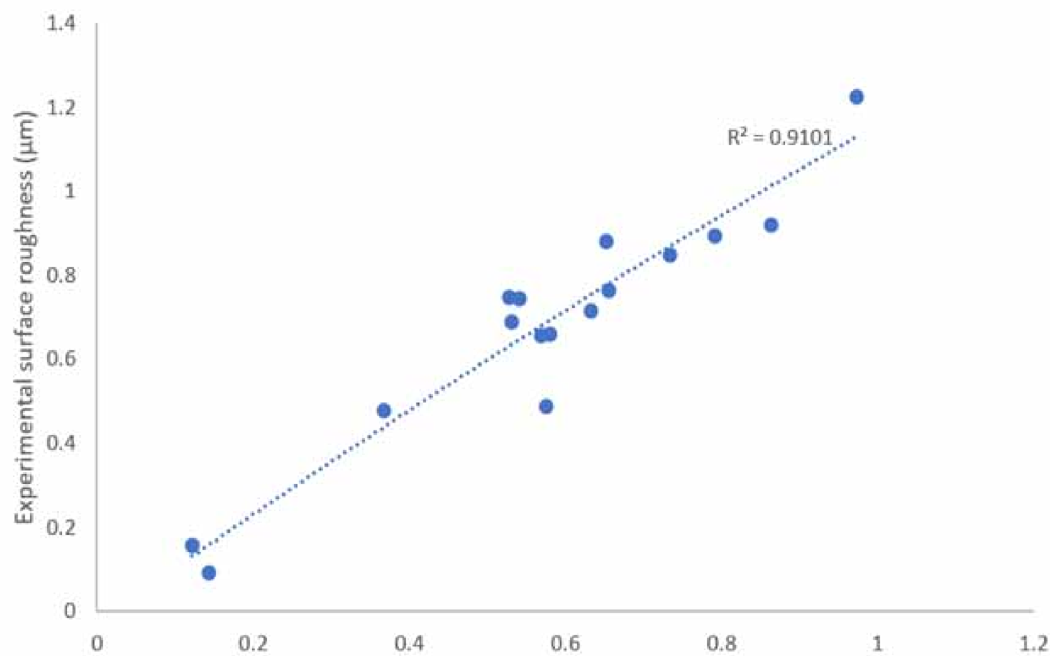


Figure 4. A plot of the experimental surface roughness against the predicted surface roughness



Multi-Objective Analysis - Grey Relational Analysis

The Taguchi methodology was only sufficient in obtaining the optimal PMMA milling parameters for every single response. However, these responses were different in quality characteristics. Moreover, the milling parameters affected all the responses in a particular mode which could not be identified using the Taguchi method (Sylajakumari et al., 2018). Therefore, to obtain the interaction and impacts of the milling parameters on all the responses, Grey Relational Analysis (GRA) was adopted. The analysis was conducted in three stages. First, the data obtained for the MRR and Ra were normalized to obtain a uniform data format. Second, for the MRR, the *'larger is better'* normalization model was adopted (Equation 7). On the other hand, the 'smaller is better' normalization model (Equation 8) was adopted for the average surface roughness. The equations are adopted from Kiswanto et al. (2019) and Sulaiman et al. (2014):

$$x_i^*\left(k\right) = \frac{x_i\left(k\right) - \min x_i\left(k\right)}{\max x_i\left(k\right) - \min x_i\left(k\right)} \tag{7}$$

$$x_i^*\left(k\right) = \frac{\max x_i\left(k\right) - x_i\left(k\right)}{\max x_i\left(k\right) - \min x_i\left(k\right)} \tag{8}$$

where:

i = 1…...n
K = 1……m

n = number of experimental trials
m = number of responses to be evaluated.
Min $x_i(k)$ = smallest value of $x_i(k)$ (for k^{th} response)
Max $x_i(k)$ = largest value of $x_i(k)$ (for k^{th} response)

Secondly, the grey relational coefficients (GRC) were computed from the normalized data using Equation 9 and recorded in Table 5:

$$\gamma_{o.i}\left(k\right) = \frac{\Delta min + \delta \cdot \Delta max}{\Delta_{o \cdot i}\left(k\right) + \delta \cdot \Delta max} \tag{9}$$

where:

$$\Delta_{o.i} = x_o^*\left(k\right) - x_i^*\left(k\right)$$
$$\Delta max = max_i max_k x_o^*\left(k\right) - x_i^*\left(k\right)$$
$$\Delta min = min_i min_k x_o^*\left(k\right) - x_i^*\left(k\right)$$
$$\delta \in \left[0,1\right]$$

The component δ (identification coefficient) was employed to adjust the variations of the relational coefficient. From the literature, this value was obtained as 0.5 (Meral et al., 2019). The Deviation Sequence ($\Delta_{o.i}$), was also computed. Lastly, the grey relational grades (GRG) for each experiment were computed using Equation 10 and 11 adopted from Kiswanto et al. (2019) and ranked as shown in Table 5:

$$\gamma\left(x_o^*, x_i^*\right) = \sum_{k=1}^{n} \beta_k \, \gamma[x_o^*\left(k\right), \; x_i^*\left(k\right)] \tag{10}$$

$$\sum_{k=1}^{n} \beta_k = 1 \tag{11}$$

Table 5 depicted that experiment 4 was optimal with a spindle speed of 1250 rpm, depth of cut of 1.2 mm, and feed rate of 350 mm/min. This was followed by experiments 12 and 16 for the second and third ranks, respectively. From experiment 4, the MRR was the highest (0.81 g/min) and moderate surface roughness (0.848 μm). The second rank presented by experiment 12 had the second-lowest surface roughness of 0.157 μm. The third rank (experiment 16) depicted the lowest surface roughness (0.092 μm) and a moderate MRR (0.128 g/min). Rank 1 displayed a possible trade-off between the MRR and the surface roughness, where the surface roughness could be traded for a high MRR. Rank 2 showed a trade-off between the MRR and the surface roughness where significant amounts could be sacrificed for a moderate machining rate (0.420 g/min) and average surface roughness (0.157 μm). This can be adopted as the best parameter combination. The third rank showed a possible trade-off between the two responses, where the MRR could be traded off for the best surface quality.

Table 5. Grey Relational Coefficients, Grey Relational Grades, and Ranking

Experiment	Spindle speed (rpm)	Depth of cut (mm)	Feed rate (mm/min)	Grey Relational Coefficient, $\gamma_{o.i}$		Grey Relational Grade	Rank
				MRR	Ra		
1	1250	0.3	50	0.3333	0.5877	0.4605	11
2	1250	0.6	100	0.4559	0.5000	0.4780	8
3	1250	0.9	200	0.7492	0.4572	0.6032	4
4	1250	1.2	350	1.0000	0.4281	0.7141	1
5	2500	0.3	100	0.3658	0.4628	0.4143	13
6	2500	0.6	50	0.3496	0.4177	0.3837	16
7	2500	0.9	350	0.7182	0.4863	0.6023	5
8	2500	1.2	200	0.7182	0.4140	0.5661	6
9	3750	0.3	200	0.3625	0.4764	0.4195	12
10	3750	0.6	350	0.6215	0.4991	0.5603	7
11	3750	0.9	50	0.3418	0.5952	0.4685	10
12	3750	1.2	100	0.4831	0.8970	0.6901	2
13	5000	0.3	350	0.4818	0.4639	0.4729	9
14	5000	0.6	200	0.4459	0.3333	0.3896	15
15	5000	0.9	100	0.3779	0.4063	0.3921	14
16	5000	1.2	50	0.3483	1.0000	0.6742	3

ANOVA for the GRG

An ANOVA was conducted to evaluate the percentage contributions of the factors to the GRG using a significance value of 0.05. The ANOVA values are presented in Table 6.

From Table 6, it was observed that the depth of cut *p-value* (0.045) was less than the significance value of 0.05. This means that the depth of cut influences the GRG significantly. For the spindle speed

Table 6. ANOVA for the GRG

Response	Degree of freedom	Sum of squares	Mean squares	%Contribution	F-Value	*P*-Value
Regression	3	0.131943	0.043981	-	8.91	0.002
Spindle speed	1	0.008181	0.008181	4.28	1.66	0.222
Depth of cut	1	0.104141	0.104141	54.48	21.10	0.001
Feed rate	1	0.019621	0.019621	10.26	3.98	0.069
Error	12	0.059218	0.004935			
Total	15	0.191161				

and feed rate, the *p-values* were more than the significance level (0.222 and 0.069, respectively), meaning that their influence was insignificant. Regarding the percentage contributions, the depth of cut was the most significant contributor towards the GRG with 54.48%. This was followed by the feed rate (10.36%) and, finally, the spindle speed (4.28%). This could be attributed to the increase in tool-workpiece contact. From the multi-objective analysis, the depth of cut was constant for the first three ranks (1.2 mm). A high depth of cut increased the MRR and moderate surface roughness, as depicted in experiments 12 and 16 (Prakash et al., 2020).

CONCLUSION

This study presented an investigation of the single objective and multi-objective analyses of the CNC milling of medical-grade PMMA with emphasis on the rate of production (material removal rate) and the surface quality (average surface roughness). From the study, the following conclusions were be drawn:

- The optimal CNC milling parameters for the maximum MRR are spindle speed of 1250 rpm, depth of cut of 1.2 mm, and feed rate of 350 mm/min. The MRR was observed to increase with the depth of cut and feed rate.
- The feed rate is the largest contributing factor towards the MRR with 64.81%, followed by the depth of cut (20.58%) and the spindle speed (11.83%). All the factors are significant towards the MRR.
- The optimal milling parameters for the lowest surface roughness are spindle speed of 5000 rpm, depth of cut of 1.2 mm, and feed rate of 200 mm/min. The surface roughness was observed to reduce with increasing spindle speed and depth of cut.
- The feed rate was the most significant contributor towards the surface roughness (31.31%), followed by the depth of cut (22.06%), and finally, the spindle speed (17.30%). However, the milling factors were insignificant towards the surface roughness.
- The maximum MRR and the minimum surface roughness can be predicted using linear and quadratic regression models.
- The best trade-off between the MRR and the surface roughness could be obtained from a factor combination of 1250 rpm (spindle speed), 1.2 mm (depth of cut), and 350 mm/min (feed rate). The second-best trade-off could be obtained from a factor combination of 3750 rpm (spindle speed), 1.2 mm (depth of cut), and 100 mm/min (feed rate). Finally, the third-best trade-off could be obtained from a factor combination of 5000 rpm (spindle speed), 1.2 mm (depth of cut), and 50 mm/min (feed rate).
- The depth of cut was the most significant contributor towards the GRG with 54.48%. This was followed by the feed rate (10.36%) and, finally, the spindle speed (4.28%).

This study provides a model for selecting parameters in the CNC milling of medical-grade PMMA and the impacts of milling parameters on productivity and surface integrity.

FUTURE STUDY

The authors recommend future studies on other machining parameters affecting the machinability of medical-grade PMMA. In addition, the machining levels can be adjusted and investigated individually to assess the impact of parameter variation on different responses in milling of medical-grade PMMA.

CONFLICT OF INTEREST

The authors declare no known competing interests in the materials, methods, and data presented in this study.

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