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Tool geometry and machining variables influence on the surface roughness of end-milling process: a comparative study with application of RSM and GA tools and techniques

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Abstract: This study investigates the effects of cutting speed, feed rate, depth of cut, and radial rake angle on the surface roughness of aluminium 5083 (Al5083), acrylic and polyethylene terephthalate (PET) in the computer numerical control end-milling operation. Taguchi L9 orthogonal array of experimental design was used to conduct the research. Response surface methodology was employed to generate prediction models. To achieve minimal surface roughness, optimal machining conditions were found using genetic algorithm approach. It was found that the optimal surface roughness for Al5083 was 0.143 µm, acrylic was 0.048 µm and PET was 0.612 µm. Further, it was deduced that the noise factors significantly affected the validation results for Al5083 but had little effect on acrylic and PET. Additionally, the study results confirm that the surface condition of different materials respond differently to identical process parameters and noise conditions.

Keywords: surface roughness; aluminium 5083; acrylic; polyethylene terephthalate; PET; Taguchi experiments; response surface methodology; genetic algorithm; end-milling.

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1 Introduction

In the manufacturing context, surface finish is defined as the outer texture, a.k.a. surface, of a piece, sheet, or block of material (Elder, 2021). Surface roughness of a component can be generally represented as the minute irregularities of a surface at the microscopic level by virtue of three major physical components of roughness, waviness, and form factor (Choudhury and Chinchanikar, 2017). Further, surface finish plays a critical role in evaluating the quality of machined components in the manufacturing industry which significantly affect various functional characteristics such as fatigue, friction, wear resistance, lubrication and coatings (Shahrom et al., 2013). Average surface roughness (R_a) is a commonly used index to ascertain the surface finish in machining processes (Zain et al., 2010a, 2010b). R_a is defined as the arithmetic average value of departure of the roughness profile from the mean line throughout the sampling length of the material (Oktem, 2009). Further, R_a is simply a common indicator of the level or degree of surface roughness in relation to the surface finish that has been facilitated by the respective machining processes (Ali and Hung, 2017).

Various workpiece materials include metals such as aluminium, mild steel, cast iron and brass (Todd et al., 1994), as well as thermoset plastics, thermoplastics and composites are commonly used in milling operations. When selecting materials for end-milling, typical parameters such as cost, strength, wear resistance and machinability of material should be considered. Additionally, surface finish is one measure of machinability (Boothroyd and Knight, 2005) and every material produces different surface finishes with changing process parameters (Dandge and Harne, 2013). However, on viewing the present literature, it was observed that studying and comparing the effects of machining parameters on the surface roughness of thermoplastic materials has drawn relatively little attention by the academia. Thus, a systematic methodology is proposed in this paper for investigating the influence of machining and a tool geometry parameter on the surface roughness of two commercially available thermoplastics as well as a comparison with a traditional workpiece material. Further, based on a comprehensive review of literature, the work reported in this paper differs from previous works in following manner:

- After reviewing the literature in the area of end-milling, very few studies combined the machining parameters with cutting-edge angle for assessment of part surface roughness. Further, this study is focussed on comparing the impact of process parameters on surface roughness of thermoplastics.
- Radial rake angle is included in the study as it has not been sufficiently investigated in the past.

The rest of the paper is organised as follows: a review of the literature on the end-milling process with a focus on modelling of the machining process in terms of various machining parameters, and process optimisation is presented in Section 2. Information about the experiments carried and measurement of surface roughness, generation of prediction models, optimisation of cutting parameters can be seen under research methodology in Section 3. The results and discussion on the optimised parameters is presented in Section 4. The research is concluded in Section 5 followed by the future work directions.

2 Related research on end-milling process modelling and optimisation

To meet the objective of the study, literature has been reviewed from the perspective of factors influencing surface roughness, approaches for optimisation of surface roughness, and issues in machinability of materials for end-milling operation. In this context, a comprehensive review of literature is presented in this section.

Numerous techniques were used in the past to model and optimise surface roughness in terms of the key cutting parameters. Sur et al. (2022) used single-objective and multi-objective techniques to optimise cutting speed, feed rate, and cutting tool helix angle for minimisation of cutting force and surface roughness in peripheral milling of Ti6Al4V. The experiments were performed using carbide end-milling tools with fixed and variable helix angles. The effects of control factors and interactions on cutting force and surface roughness were determined by analysis of variance. The study found that the helix angle of the cutting tool was the most effective parameter on the cutting force and the feed rate on the surface roughness. Further it was observed that the cutting force and surface roughness values decreased in peripheral milling at high cutting speed, whereas the cutting forces increased, and the surface finish of the workpiece decreased at high feed rates. Furthermore, the helix angle of the cutting tool has a significant impact on the cutting force and surface roughness when performing milling operation with fixed helix tools.

Zhang et al. (2022) conducted a milling parameter optimisation study for accomplishment of efficient rough machining process by combining the off-line optimisation and real-time monitoring. In this regard a mathematical model was developed with machining efficiency as the study objective and the spindle speed, radial and axial depth of cuts as the process variables along with the basic parameter feasible region, cutting force, stability, spindle torque and power as constraints of the study. Further, a series of experimental runs on the titanium alloy Ti5Al5Mo5VCrFe machining has been performed. The study results show that the developed parameter optimisation method can significantly enhance the machining effectiveness.

Daniyan et al. (2021), focussed on process design and optimisation of the milling operation of aluminium alloy (AA6063 T6) in order to enhance the overall sustainability of the machining process. The study includes the orientations of the cutting tool, process parameters and energy requirements for performing the milling operations. Further, the study developed RSM led correlation model while the physical experiments were conducted using a 5-axis CNC milling machine for the end-milling operation. At the end the paper stated that the study can be utilised in various manufacturing firms such as aerospace, rail and automobile industries.

Kuntoğlu et al. (2020) orchestrated a study to understand the ideal cutting conditions, vibration analysis and surface roughness under varying cutting speeds, feed rates and cutting-edge angles by deployment of response surface methodology (RSM). This methodology was used to obtain the optimal turning parameters for R_a and three components of vibration (axial, radial and tangential), governed by prediction models to a satisfactory degree of accuracy. The outcome of the study proved that the feed rate dominantly affected the increase of surface roughness (69.4%) and axial vibration (65.8%) while cutting-edge angle and cutting speed were the parameters which had the most critical effect on radial vibration (75.5%) and tangential vibration (64.7%), respectively. Additionally, this study concluded that the predicted and measured values of surface roughness and vibration during turning of AISI 5140 were very close and fell within a 10% error range.

Kumar and Hynes (2020) presented a study on predicting and optimising the surface roughness of a thermally drilled hole on galvanised steel by employing an integrated adaptive network-based fuzzy inference system (ANFIS) and genetic algorithm (GA) approach. In this study, important metrics including spindle speed, tool angle and workpiece thickness were varied while keeping feed rate as constant. The experimental results allowed for the creation of an ANFIS model to estimate surface roughness. This model was then used as the precursor to generate an objective function focused on minimising surface roughness. This model was then integrated into a GA toolbox in the MATLAB programme to produce the desired surface roughness of the thermally drilled hole. Conclusively, the predicted and experimental results were very close in margin, and it was observed that the spindle speed and tool angle were the most significant factors affecting surface roughness of drilled holes in galvanised steel workpieces.

Bhasha and Balamurugan (2020) investigated the machinability of a ceramic-reinforced aluminium hybrid composite (Al-MMC) by means of end-milling. The Taguchi L9 orthogonal array (OA) with low, medium, and high-level parameters was employed to assess the effect of the governing parameters on part's surface roughness and material removal rate (MRR). To perform end-milling operation, 8 mm diameter WC bit was employed. It was observed that the spindle speed and depth of cut were the most significant variables that influenced the part R_a.

Zeelanbasha et al. (2020) studied the effect of several geometrical parameters such as spindle speed, feed rate, axial depth of cut, radial depth of cut and radial rake angle on spindle and worktable vibration by assessment of acceleration amplitude and surface roughness. Central composite design (CCD) approach was used to conduct experiments on aluminium alloy 6061-T6 material with high-speed steel end-milling cutter. Further, RSM was employed to develop predictive models and the suitability of these models were tested using analysis of variance technique (ANOVA). Furthermore, non-dominated sorting of genetic algorithm (NSGA-II) was implemented to solve the multi-objective optimisation model for minimisation of vibration and surface roughness in the end-milling process. Additionally, the technique for order preference by similarity to ideal solution (TOPSIS) and analytical hierarchy process (AHP) were deployed to rank the Pareto optimal solutions.

Ghosh et al. (2019) examined the impact of spindle speed, feed, and depth of cut on surface roughness for keyway milling operation of C40 steel under wet condition. Artificial neural network (ANN) and RSM approaches were applied for modelling of surface roughness in terms of the selected process parameters. Further, ANN and RSM were linked with the GA as well as interfaced with the PSO to optimise the process parameters that lead to minimum surface roughness. The study concluded that the RSM coupled PSO gives better result in optimisation of the process parameters.

Tlhabadira et al. (2019), performed an experimental design using the Autodesk Fusion and L9 OA with depth of cut, cutting speed and cutting feed as process parameters to evaluate the surface roughness of M200 TS material. The experiments were conducted on a 3-axis, CNC vertical milling machine with carbide inserts. The surface roughness was measured using the Mitutoyo-201 machine. The study found that the selected mathematical modelling approach is a good decision making tool for choosing the values of the process parameters during the milling process.

Pillai et al. (2018) derived a set of optimal process parameters for end-milling of Al6005A alloy on a 6-axis robotic machining centre. Further this study focused on investigating the impact of several process parameters such as tool path strategy, spindle speed and feed rate on machining time and surface roughness by applying Taguchi-grey relational optimisation method. The study found that the tool path strategy has the most significant influence on surface roughness and machining time.

Das et al. (2018) analysed the effect of cutting speed, feed rate and depth of cut on the surface roughness of aluminium alloy under CNC face milling operation. Further, the optimum combination of the three selected parameters has also been assessed under single and multi-objective setting by means of GA and ABC optimisation methods. The study proved that the selected controlling parameters of the milling operation have a great impact on the surface roughness of the machined product.

Lmalghan et al. (2018) conducted a study to examine the influence of spindle speed, feed rate and depth on the cutting force, surface roughness and power consumption of face-milling operation. In this regard, experiments have been carried out on AA6061 aluminium samples. Further, the selected milling process parameters was optimised by means of RSM, PSO technique and desirability approach. It was concluded that the performance ability of PSO can be comparable with the values of the desirability approach.

Chowdary et al. (2017) conducted a study to optimise the machining of aluminium 5083 using RSM. The study included a combination of several process parameters such as spindle speed, feed rate, depth of cut and tool diameter. It was concluded that the selected combination of machining and tool parameters improved the performance of the end-milling process.

Shahrom et al. (2013) studied the effect of lubrication conditions on the surface roughness in milling operation of AISI 1060 aluminium as work material. Feed rate, depth of cut and cutting speed were also investigated and the Taguchi method was used to predict the surface roughness. It was found that, minimum quantity lubricant produced better surface finish result over the wet machining environment.

Wibowo and Mohammad (2012) performed a study for investigation of the optimal machining conditions for improvement of surface roughness using kernel-based regression and GA approaches. The study showed that the GA technique is superior to the traditional regression model. Lakshmi and Subbaiah (2012) examined the effect of cutting speed, feed rate and depth of cut on the surface roughness and MRR of hardened steel. RSM and ANOVA techniques were used for modelling and optimisation. It was found that feed rate and cutting speed are the dominant parameters for improvement of part surface roughness which decreases with decrease in feed rate and increase in cutting speed. Bozdemir and Aykut (2012) investigated the effect of process parameters on the surface roughness of castamide in wet and dry conditions. The investigated parameters were cutting speed, feed rate, tool diameter and depth of cut. ANN modelling technique was used to validate the experimental results and proved that the developed ANN can be used effectively for prediction of part surface roughness.

Pare et al. (2011) used the PSO approach in optimisation of cutting speed, feed rate, radial rake angle and depth of cut. The optimisation results were compared to those obtained using GA and it was found that PSO produces better results in a shorter time.

Zain et al. (2010a) applied GA technique to optimise the cutting conditions in an end-milling process to attain minimum surface roughness. Radial rake angle, feed rate and cutting speed were the investigated in this research. The GA technique was proven as superior in estimating the optimal parameters for minimum surface roughness.

Oktem (2009) optimised the surface roughness of an end-milling process when machining AISI 1040 steel with TiAlN solid carbide tool under wet condition. The effect of the four investigated parameters on surface roughness was modelled by means of ANOVA technique. GA approach was then used to find the best combination of parameters for minimum surface roughness. It was found that the GA technique improved the surface roughness by 12%.

In summary, modelling approaches based on RSM combined with GA led tools for optimisation of end-milling process improve the competitiveness of a company. Today, it has become more frequent and reasonably easy to machine various composite materials and thermoplastics. However, more empirical studies on comparison of machinability of traditional materials with thermoplastics will benefit the present-day machinists. This forms the basis to conduct the current research for development of predictive models for assessment of surface roughness of end-milling process in terms of the critical machining parameters. In conclusion, the present study investigates the impact of variations in cutting speed, feed rate, depth of cut, and radial rake angle on the surface roughness of Al5083, acrylic and polyethylene terephthalate (PET) materials. Taguchi OA approach will be used to plan the DOE. Then the RSM and ANOVA will be applied to analyse the experimental data and establish prediction models. Finally, GA technique will be employed for optimisation of the end-milling process for obtaining minimal surface roughness.

3 Research methodology

3.1 Taguchi experimental design

To perform the study, Taguchi design of experiments (DOEs) methodology was followed with the objective of obtaining data in a controlled way. The steps included in the Taguchi design are: selecting the proper OA according to the number of parameters, conducting experiments, analysing the experimental data, identifying the optimum parameter settings and performing validation runs.

Four parameters, radial rake angle (A), spindle speed (B), feed rate (C) and depth of cut (D) were selected from the review of literature and varied each at three levels. All other process parameters were kept as constant. The parameters and their respective levels are given in Table 1. Further, the parameter ranges were selected as per the previous studies (Raja and Baskar, 2012; Ojolo et al., 2014). Then the Taguchi OA approach was applied to determine the number of experimental runs required in which an L9 array was selected. Table 2 shows the selected parameter combinations of the study.

Table 1 Cutting parameters and their levels

Parameters	*Levels*		
	1	*2*	*3*
Radial rake angle (A) in 0	15	30	30
spindle speed (B) in rpm	2,000	3,000	4,000
Feed rate (C) in mm/rev	100	200	300
Depth of cut (D) in mm	0.2	0.4	0.6

Table 2 Parameters and the recorded average roughness values

Experiment number	*A*	*B*	*C*	*D*
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

Table 3 Settings of Mitutoyo surface roughness tester

Measurement condition	*Value*
Standard	JIS 2001
Profile	R_J01
Sample length	0.8 mm
Cut-off length	0.25 mm
Filter	Gaussian
Evaluation length	4.0 mm
Pre-travel	0.4 mm
Post-travel	0.4 mm
Smooth connection	Off
Range	80 µm
Speed	0.5 mm/s

3.2 Experimental details

Figure 1(a) shows the Boxford CNC milling machine employed to perform the experiments. The experimental samples were prepared with dimensions of 100 mm × 100 mm × 12.7 mm. The workpiece was clamped onto the vice of the Boxford CNC milling machine. The machining was performed by means of straight cuts made 15 mm from one end of the workpiece to the other end. A snapshot of the simulation of experimental runs can be seen in Figure 1(b). On completion of the experimental runs, the surface roughness of the machined cuts was measured with the Mitutoyo surface roughness tester as shown in Figure 1(c), whose settings are shown in Table 3. The tester was first calibrated with a standard sample. The surface roughness of each cut was then measured on either side of the run to observe the impact of the radial rake angle parameter. On each side, three readings were taken, and the mean of all readings can be seen in Tables 4a–4c. A sample set of Al5063 test specimens after performing the experiments can be seen in Figure 2.

3.3 Generation of prediction model using RSM

The RSM tool available in Minitab software was used to obtain prediction models in the form of regression equations for each of the three selected materials. The derived equation was fine-tuned using a stepwise regression design approach in which all irrelevant terms were removed and tested to ensure proper agreement with the experimental data.

Table 4a Surface roughness results for Al5083 material

Test #	*Material*	*Radial rake angle (°)*	*Spindle speed (rpm)*	*Feed rate (mm/rev)*	*Depth of cut (mm)*	*Surface roughness, R_a (µm)*
1	Aluminium alloy (5083)	15	2,000	100	0.2	0.155
2			3,000	200	0.6	0.529
3			4,000	300	0.4	0.174
4		30	2,000	200	0.4	0.346
5			3,000	300	0.2	0.231
6			4,000	100	0.6	0.179
7		30	2,000	300	0.6	0.487
8			3,000	100	0.4	0.369
9			4,000	200	0.2	0.160

Table 4b Surface roughness results for acrylic

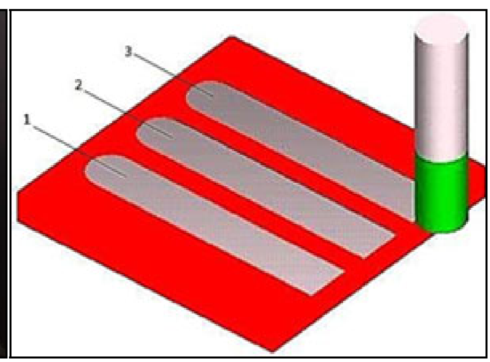
Test #	*Material*	*Radial rake angle (°)*	*Spindle speed (rpm)*	*Feed rate (mm/rev)*	*Depth of cut (mm)*	*Surface roughness, R_a (µm)*
1	Acrylic	15	2,000	100	0.2	0.073
2			3,000	200	0.6	0.086
3			4,000	300	0.4	0.053
4		30	2,000	200	0.4	0.185
5			3,000	300	0.2	0.106
6			4,000	100	0.6	0.064
7		30	2,000	300	0.6	0.401
8			3,000	100	0.4	0.069
9			4,000	200	0.2	0.113

Table 4c Surface roughness results for PET material

Test #	*Material*	*Radial rake angle (°)*	*Spindle speed (rpm)*	*Feed rate (mm/rev)*	*Depth of cut (mm)*	*Surface roughness, R_a (µm)*
1	Polyethylene terephthalate (PET)	15	2,000	100	0.2	1.807
2			3,000	200	0.6	1.276
3			4,000	300	0.4	1.053
4		30	2,000	200	0.4	2.337
5			3,000	300	0.2	1.783
6			4,000	100	0.6	1.329
7		30	2,000	300	0.6	1.012
8			3,000	100	0.4	1.916
9			4,000	200	0.2	1.267

Figure 1 (a) Boxford CNC milling machine (b) A snapshot of simulated experimental runs (c) Mitutoyo surface roughness tester (see online version for colours)

(a)



(b)

(c)

Figure 2 Sample of Al5083 workpieces showing after performing machining (see online version for colours)

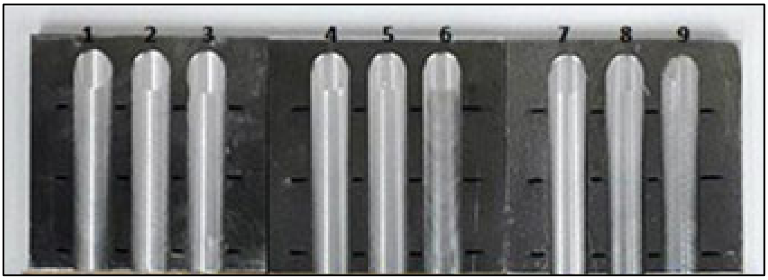


Table 5 Statistical analysis for Al5083 prediction model

Estimated coefficients for R_a (un-coded units)					
Predictor		*Coefficient*		*P-value*	
Constant		–0.458		0.056	
A		0.00062		0.937	
B		–0.000079		0.317	
C		0.00348		0.652	
D		3.47		0.441	
C * C		–0.000008		0.525	
D * D		–3.98		0.265	
Analysis of variance					
Source	*DF*	*Adjusted SS*	*Adjusted MS*	*F-value*	*P-value*
Model	6	0.126543	0.021090	0.98	0.585
Linear	4	0.063340	0.015835	0.73	0.646
Square	2	0.063203	0.031601	1.47	0.405
Error	2	0.043103	0.021551		
Total	8	0.169646			

Table 6 Statistical analysis for acrylic prediction model

Estimated coefficients for R_a (un-coded units)					
Predictor		*Coefficient*		*P-value*	
Constant		0.076		0.021	
A		0.00571		0.236	
B		–0.000072		0.114	
C		0.00059		0.172	
D		0.013		0.947	
Analysis of variance					
Source	*DF*	*Adjusted SS*	*Adjusted MS*	*F*	*P*
Model	4	0.066275	0.016569	2.19	0.233
Linear	4	0.066275	0.016569	2.19	0.233
Error	4	0.030203	0.007551		
Total	8	0.096478			

Table 7 Statistical analysis for PET prediction model

Estimated coefficients for R_a (un-coded units)		
Predictor	*Coefficient*	*P-value*
Constant	3.30	0.055
A	0.0152	0.512
B	–0.000251	0.272
C	0.0037	0.353
D	–9.39	0.698
C * C	–0.000014	0.669
D * D	12.20	0.234

Analysis of variance					
Source	*DF*	*Adjusted SS*	*Adjusted MS*	*F*	*P*
Model	6	1.27599	0.21267	1.27	0.503
Linear	4	0.75829	0.18957	1.13	0.519
Square	2	0.51770	0.25885	1.55	0.393
Error	2	0.33492	0.16746		
Total	8	1.61091			

Then the ANOVA analysis was performed on the selected samples to ascertain the effects of the process parameters on surface roughness. The sum of squares (SS) is used to approximate the square of deviation from the grand mean, mean squares (MS) are estimated by dividing the SS by the degrees of freedom (DF) and F and P values are used to check the adequacy of the developed model. Tables 5–7 give the statistical analyses of each of the prediction models. The regression equation correlating the process parameters to surface roughness in un-coded units are given below:

$$\begin{aligned} R_{a(Al5083)} = &-0.458 + 0.00062\ A - 0.000079\ B + 0.00348\ C \\ &+3.47\ D - 0.000008\ C * C - 3.98\ D * D \end{aligned} \tag{1}$$

$$R_{a(Acrylic)} = 0.076 + 0.00571\ A - 0.000072\ B + 0.000590\ C + 0.013\ D \tag{2}$$

$$\begin{aligned} R_{a(PET)} = &\ 3.30 + 0.0152\ A - 0.000251\ B + 0.0037\ C \\ &-9.39\ D - 0.000014\ C * C + 12.20\ D * D \end{aligned} \tag{3}$$

3.4 Optimisation of results using GA approach

The GA tool available in MATLAB software was used to obtain the optimum values of the parameters to achieve the minimum surface roughness using equations (1), (2) and (3) as the fitness functions. In this regard, the optimisation model was formulated as follows:

$$\text{Minimise Ra (A, B, C, D)} \tag{4}$$

Within parameter ranges:

$$15° \le A \le 30° \tag{5}$$

$$2,000 \text{ rpm} \leq B \leq 4,000 \text{ rpm} \tag{6}$$

$$100 \text{ mm/rev} \leq C \leq 300 \text{ mm/rev} \tag{7}$$

$$0.2 \text{ mm} \leq D \leq 0.6 \text{ mm} \tag{8}$$

The default settings of the GA solver were used to optimise equations (1), (2) and (3) and are shown in Table 8. The ranges of the parameters in the optimisation were chosen as the lowest and highest levels in the DOE, i.e., levels 1 and level 3 respectively.

Table 8 GA solver default settings

Option	*Setting*
Population type	Double vector
Creation function	Constraint dependent
Scaling function	Rank
Selection function	Stochastic uniform
Mutation function	Constraint dependent
Crossover function	Scattered
Direction	Forward
Hybrid function	None

4 Results and discussion

4.1 Comparison of R_a

Workpiece material properties can affect the surface finish of machined components and any small changes in these properties can have a significant influence on the produced surface (Dandge and Harne, 2013). The workpiece materials studied in the present investigation were Al5083, acrylic and PET. Al5083 alloy has high thermal conductivity, ductility, excellent corrosion resistance and its common applications include storage tanks, pressure vessels and armour plate. Acrylic is a transparent thermoplastic commonly used for light-duty mechanical and decorative applications and optical and transparent parts. PET is a low-cost thermoplastic with excellent chemical resistance and electrical properties and used to fabricate small housings and hollow shapes (Juvinall and Marshek, 2012). In comparing the mean R_a values from the results of the experimental runs, as shown in Figure 3, it can be observed that acrylic produced the lowest surface roughness, followed by Al5083 and then PET. This confirms that the same process parameter settings can have varying effects on the surface roughness of different types of materials and hence each material characteristics need to be modelled independently to optimise the parameters for minimum surface roughness.

4.2 Adequacy of prediction models

The adequacy of the prediction models was determined using a normal probability plot. The normal probability plots of the residuals are given in Figure 4. It can be perceived in all three plots that the residuals are close to the line of best fit and evenly dispersed, indicating that the errors are normally distributed.

Figure 3 Comparison of results (see online version for colours)

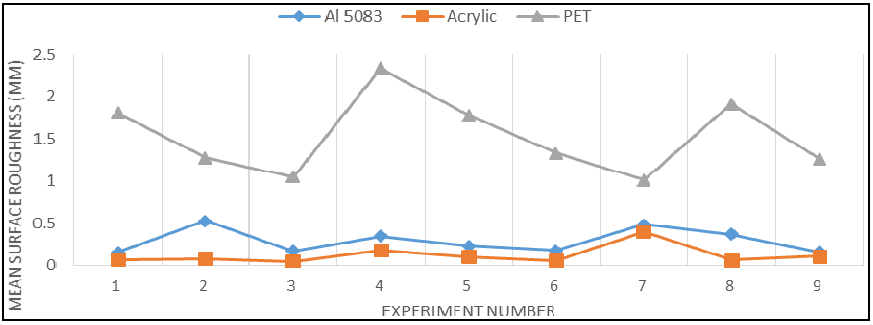
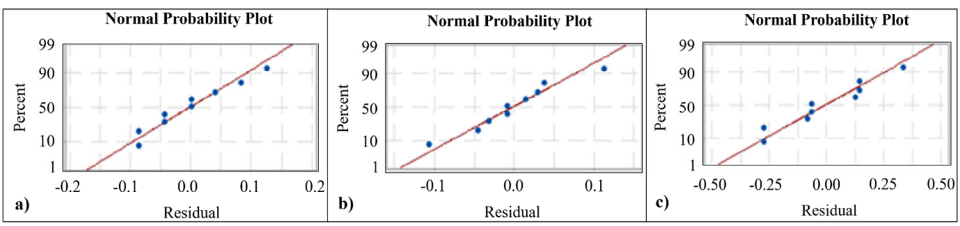


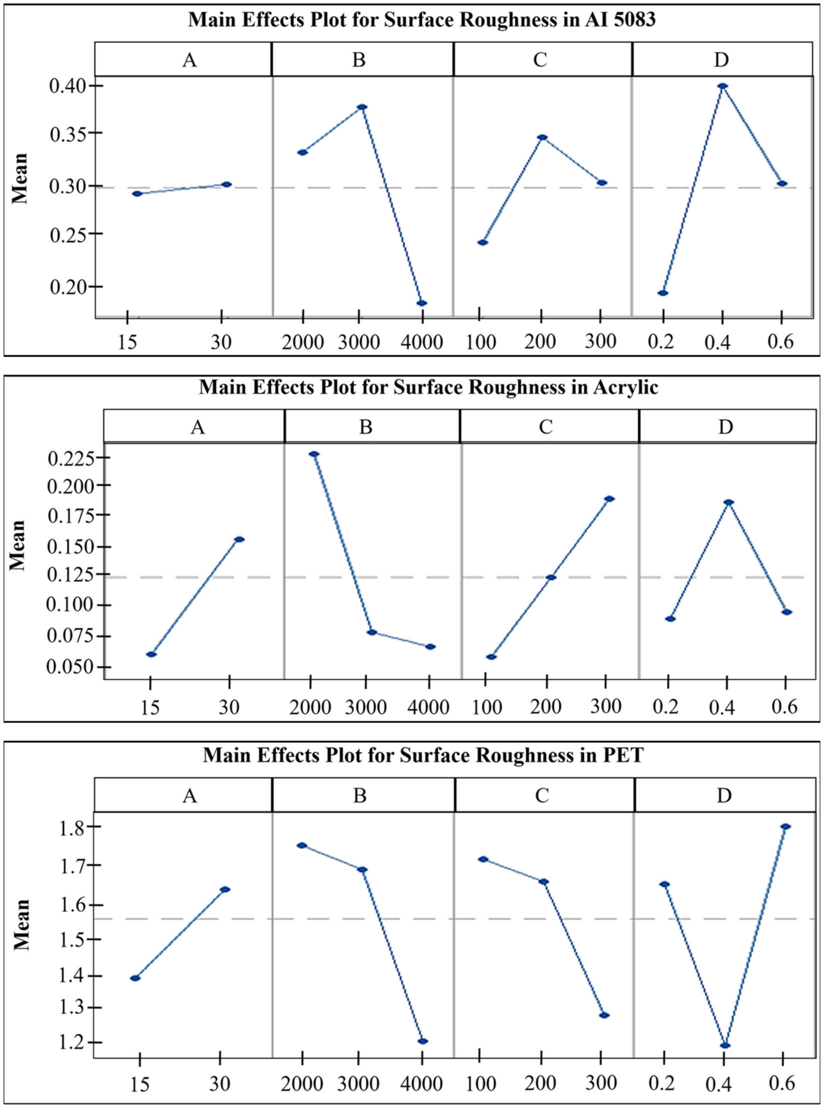
Figure 4 Normal probability plots for, (a) Al5083 (b) acrylic (c) PET (see online version for colours)



4.3 Effects of process parameters on R_a

The main effects plots were generated to establish the significance of each of the parameters and are shown in Figure 5. For Al5083, surface roughness increases with an increase in radial rake angle. Additionally, it was observed that there is no clear relationship between surface roughness and spindle speed, feed rate and depth of cut. Further, the surface roughness increases with a spindle speed increase up to 3,000 rpm, after which it decreases with an increase in spindle speed. The same trend can be observed for feed rate and depth of cut. The plot for acrylic shows that surface roughness increases with an increase in radial rake angle and feed rate and decreases with an increase in spindle speed. Furthermore, it can be seen that there is no clear relationship between surface roughness and depth of cut; the surface roughness increases with an increase in depth of cut until 0.4 mm and then it decreases. In the PET plot, it can be observed that surface roughness increases with increasing radial rake angle and decreases nonlinearly with increasing spindle speed and feed rate. Like for the previous two materials, there is no clear relationship between surface roughness and depth of cut for PET. It decreases with an increase in depth of cut until 0.4 mm, after which it increases with an increase in depth of cut. Surface roughness decreasing with an increase in spindle speed and increasing with an increase in feed rate. The indistinct relationships may have been due to parameter interactions such as the change in coolant type.

Figure 5 Main effects plots (see online version for colours)



4.4 Optimisation and validation

GA tool was employed for optimisation of the selected machining parameters to achieve minimum surface roughness. The optimal surface roughness for each material is presented in Table 9. The accuracy of the optimal results was verified using the Boxford CNC milling machine and the Mitutoyo surface roughness tester. Results in this regard are shown in Table 10. The average R_a obtained for Al5083 as 0.176 µm which had a deviation of 0.033 µm from the predicted value. For acrylic, R_a was found as 0.049 µm which had a deviation of 0.001 µm and for PET, R_a was measured as 0.623 µm which had a deviation of 0.011 µm. These slight deviations may have been due to temperature changes, uncontrolled noise, and airflow during use of the surface roughness tester. Also, when compared to the experimental results in Table 4, the average R_a values of the acrylic and PET validation runs were smaller than the experimental runs. Hence these results confirm that the optimal parameter values generated by the GA for the three selected materials produced a minimum surface roughness. Additionally, during the validation exercise, the actual to optimised surface roughness of Al5083 was found as 23.08%. This deviation in surface roughness results could be due to tool wear, machine vibration, built up edge (BUE) chips and variations in properties of the workpiece material. According to Yallese et al. (2009) an increase in tool wear leads to a degradation in surface quality of a machined component. Also as shown in Karim et al.'s (2013) study, tool wear increases with an increase in tool rake angle. Therefore, in performing the experimental runs with rake angles of 15° and 30°, as well as due to bluntness the cutting tool edge may have affected the surface roughness of the specimen. Machine tool vibration causes an increase in tool wear and a decrease in surface quality of machined components in the milling process. Workpiece material properties affect the formation of BUE chips while machining. BUEs occur when the friction between chip and tool causes a shear fracture in the locality of the tool face. It has been shown by Gokkaya and Taskesen (2008) that BUE cause poor surface finish in aluminium alloys. Hence these factors may have attributed to the large deviation in results for the Al5083 workpiece material as its metallic properties, especially hardness, are considerably different to those of the two selected thermoplastics.

Table 9 Optimum values predicted by GA solver

Parameter	*Optimised values*		
	Al5083	*Acrylic*	*PET*
A (°)	15	15	15
B (rpm)	2,677.64	2,430.71	3,854.15
C (mm/rev)	100	100	298.366
D (mm)	0.2	0.2	0.387
R_a (μm)	0.143	0.048	0.612

Table 10 Optimum and actual surface roughness values

Validation run	*Optimum surface roughness value from GA (μm)*	*Actual average surface roughness value from validation experiments (μm)*	*Error (%)*
Al5083	0.143	0.176	23.08
Acrylic	0.048	0.049	2.08
PET	0.612	0.623	1.8

5 Conclusions

In the present study, the influence of radial rake angle, spindle speed, feed rate and depth of cut on the surface roughness of the three selected workpiece materials produced in the CNC end-milling process was presented. The L9 OA was utilised to reduce the number of experimental runs. RSM and ANOVA techniques were employed to establish the prediction models. GA tool was used to optimise the selected parameters to achieve minimum surface roughness. A summary of the study findings is given below:

- The developed prediction model has the potential to predict the surface roughness when machining Al5083, acrylic and PET within the parameter ranges investigated.
- Acrylic produced the lowest surface roughness, followed by Al5083 and then PET.
- For Al5083, the minimum surface roughness was achieved at a radial rake angle of 15°, spindle speed of 2,677.64 rpm, feed rate of 100 mm/rev and depth of cut of 0.2 mm.
- For acrylic, the minimum surface roughness was achieved at a radial rake angle of 15°, spindle speed of 2,430.71rpm, feed rate of 100 mm/rev and depth of cut of 0.2 mm.
- For PET, the minimum surface roughness was achieved at a radial rake angle of 15°, spindle speed of 3,854 rpm, feed rate of 298 mm/rev and depth of cut of 0.387 mm.
- Validation experiments supported the GA results for Al5083, acrylic and PET with 23.08%, 2.08% and 1.80% error respectively.
- Noise factors such as tool wear, machine tool vibration and BUE chips significantly affected the results for Al5083 but had little effect on acrylic and PET.

5.1 Scope for future work

The scope of this work is very wide and leaves opportunity for improvements and changes. There are numerous variables at play, and each one can be further examined. In this regard, some future modifications that can be made to this study are:

- Investigation of new parameters, such as coolant flow rate and number of cutting edges, which were held during this study.
- Other angles of cutting tool can be optimised and compared to determine which one has the greater effect on surface roughness.

References

Ali, M.Y. and Hung, W.N.P. (2017) 'Finish machining and net shape forming', in *Comprehensive Materials Finishing*, Vol. 1, pp.322–343.

Bhasha, A.C. and Balamurugan, K. (2020) 'Multi-objective optimization of high-speed end milling on Al6061/3% RHA/6% TiC reinforced hybrid composite using Taguchi coupled GRA', in *2020 International Conference on Computational Intelligence for Smart Power System and Sustainable Energy (CISPSSE)*, pp.1–6, DOI: 10.1109/CISPSSE49931.2020.9212295.

Boothroyd, G. and Knight, W.A. (2005) *Fundamentals of Machining and Machine Tools*, CRC Mechanical Engineering, 3rd ed., Marcel Dekker Inc., New York.

Bozdemir, M. and Aykut, S. (2012) 'Optimization of surface roughness in end milling castamide', *International Journal of Advanced Manufacturing Technology*, Vol. 62, No. 5, pp.495–503.

Choudhury, S.K. and Chinchanikar, S. (2017) 'Finish machining of hardened steel', in *Comprehensive Materials Finishing*, Vol. 1, pp.47–92.

Chowdary, B.V., Kisraj, M., Ojha, K. and Ali, F. (2017) 'Mathematical modelling and numerical optimisation of machining parameters for the CNC end milling process using response surface methodology', *International Journal of Experimental Design and Process Optimisation*, Vol. 5, No. 3, pp.190–205.

Dandge, M.M. and Harne, M.S. (2013) 'Determining the effect of process parameters on surface finish in CNC turning', *International Journal of Engineering Research and Technology*, Vol. 2, No. 12, pp.3106–3114.

Daniyan, I.A., Tlhabadira, I., Mpofu, K. and Adeodu, A.O. (2021) 'Process design and optimization for the milling operation of aluminum alloy (AA6063 T6)', *Materials Today: Proceedings*, Vol. 38, No. Part 2, pp.536–543.

Das, J., Laya, D., Basu, S. and Roy, S. (2018) 'Modelling and analysis of roughness characteristics of aluminium alloy under CNC face milling operation', *International Journal of Machining and Machinability of Materials*, Vol. 20, No. 4, pp.299–319.

Elder, S. (2021) *The Basics of Surface Finish*, GD&T Basics [online] https://www.gdandtbasics.com/basics-of-surface-finish/ (accessed 10 June 2022).

Ghosh, G., Mandal, P. and Mondal, S.C. (2019) 'Modelling and optimization of surface roughness in keyway milling using ANN, genetic algorithm, and particle swarm optimization', *The International Journal of Advanced Manufacturing Technology*, Vol. 100, pp.1223–1242, https://doi.org/10.1007/s00170-017-1417-4.

Gokkaya, H. and Taskesen, A. (2008) 'The effects of cutting speed and feed rate on bue-bul formation, cutting forces and surface roughness when machining Aa6351 (T6) alloy', *Journal of Mechanical Engineering*, Vol. 54, pp.521–530.

Juvinall, R.C. and Marshek, K.M. (2012) *Fundamentals of Machine Component Design*, 5th ed., John Wiley & Sons Inc., NJ.

Karim, Z., Azuan, S.A.S. and Yasir, M.S.A. (2013) 'A study on tool wear and surface finish by applying positive and negative rake angle during machining', *Australian Journal of Basic and Applied Sciences*, Vol. 7, No. 10, pp.46–51.

Kumar, R. and Hynes, N.R.J. (2020) 'Prediction and optimization of surface roughness in thermal drilling using integrated ANFIS and GA approach', *Engineering Science and Technology, An International Journal*, Vol. 23, No. 1, pp.30–41.

Kuntoğlu, M., Aslan, A., Pimenov, D.Y., Giasin, K., Mikolajczyk, T. and Sharma, S. (2020) 'Modeling of cutting parameters and tool geometry for multi-criteria optimization of surface roughness and vibration via response surface methodology in turning of AISI 5140 steel', *Materials*, Vol. 13, No. 19, p.4242.

Lakshmi, V.V. and Subbaiah, K.V. (2012) 'Modelling and optimization of process parameters during end milling of hardened steel', *International Journal of Engineering Research and Applications*, Vol. 2, No. 2, pp.674–679.

Lmalghan, R., Rao, M.C.K., Kumar, S.A., Rao, S.S. and Herbert, M.A. (2018) 'Machining parameters optimization of AA6061 using response surface methodology and particle swarm optimization', *International Journal of Precision Engineering and Manufacturing*, Vol. 19, pp.695–704, https://doi.org/10.1007/s12541-018-0083-2.

Ojolo, S.J., Orisaleye, I.J. and Obiajulu, N. (2014) 'Machining variables influence on the fatigue life of end-milled aluminium alloy', *International Journal of Materials Science and Applications*, Vol. 3, No. 6, pp.391–398.

Oktem, H. (2009) 'An integrated study of surface roughness for modelling and optimization of cutting parameters during end milling operation', *The International Journal of Advanced Manufacturing Technology*, Vol. 43, No. 9, pp.852–861.

Oktem, H. (2009) 'An integrated study of surface roughness for modelling and optimization of cutting parameters during end milling operation', *Int. J. Adv. Manuf. Technol.*, Vol. 43, pp.852–861.

Pare, V., Agnihotri, G. and Krishna, C. (2011) 'Optimization of cutting conditions in end milling process with the approach of particle swarm optimization', *International Journal of Mechanical and Industrial Engineering*, Vol. 1, No. 2, pp.21–25.

Pillai, J.K.U., Sanghrajka, I., Shunmugavel, M., Muthuramalingam, T., Goldberg, M. and Littlefair, G. (2018) 'Optimisation of multiple response characteristics on end milling of aluminium alloy using Taguchi-grey relational approach', *Measurement*, Vol. 124, pp.291–298, https://doi.org/10.1016/j.measurement.2018.04.052.

Raja, S.B. and Baskar, N. (2012) 'Application of particle swarm optimization technique for achieving desired milled surface roughness in minimum machining time', *Expert Systems with Applications*, Vol. 39, No. 5, pp.5982–5989.

Shahrom, M.S., Yahya, N.M. and Yusoff, A.R. (2013) 'Taguchi method approach on effect of lubrication condition on surface roughness in milling operation', *Procedia Engineering*, Vol. 53, pp.594–599.

Sur, G., Motorcu, A.R. and Nohutçu, S. (2022) 'Single and multi-objective optimization for cutting force and surface roughness in peripheral milling of Ti6Al4V using fixed and variable helix angle tools', *Journal of Manufacturing Processes*, Vol. 80, pp.529–545, https://doi.org/10.1016/j.jmapro.2022.06.016.

Tlhabadira, I., Daniyan, I.A., Masu, L. and Van Staden, L.R. (2019) 'Process design and optimization of surface roughness during M200 TS milling process using the Taguchi method', *Procedia CIRP*, Vol. 84, pp.868–873.

Todd, R.H., Allen, D.K. and Alting, L. (1994) *Manufacturing Processes Reference Guide*, Industrial Press Inc, Connecticut, USA.

Wibowo, A. and Mohammad, I.D. (2012) 'Kernel based regression and genetic algorithms for estimating cutting conditions of surface roughness in end milling machining process', *Expert Systems with Applications*, Vol. 39, No. 14, pp.11634–11641.

Yallese, M.A., Chaoui, K., Zeghib, N., Boulanouar, L. and Rigal, J.F. (2009) 'Hard machining of hardened bearing steel using cubic boron nitride tool', *Journal of Materials Processing Technology*, Vol. 209, No. 2, pp.1092–1104.

Zain, A.M., Haron, H. and Sharif, S. (2010a) 'Application of GA to optimize cutting condition for minimizing surface roughness in end milling machining process', *Expert Systems with Applications*, Vol. 37, No. 6, pp.4650–4659.

Zain, A.M., Haron, H. and Sharif, S. (2010b) 'Prediction of surface roughness in the end milling machining using artificial neural network', *Expert Systems with Applications*, Vol. 37, No. 2, pp.1755–1768.

Zeelanbasha, N., Senthil, V. and Mahesh, G. (2020) 'A hybrid approach of NSGA-II and TOPSIS for minimising vibration and surface roughness in machining process', *International Journal of Operational Research*, Vol. 38, No. 2, pp.221–254.

Zhang, X., Pan, T., Ma, A. and Zhao, W. (2022) 'High efficiency orientated milling parameter optimization with tool wear monitoring in roughing operation', *Mechanical Systems and Signal Processing*, Vol. 165 [online] https://doi.org/10.1016/j.ymssp.2021.108394.