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ZAMBERI JAMALUDIN

zamberi@utem.edu.my

UTeM: Universiti Teknikal Malaysia Melaka <https://orcid.org/0000-0002-5006-0226>

Agus Sudianto

ITPLN: Institut Teknologi PLN

Lokman Abdullah

UTeM: Universiti Teknikal Malaysia Melaka

Luping Luo

Zhejiang University of Technology

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Experimental Investigation on Machining of Aluminium Alloy (AA6041) using Response Surface Method for Optimal Surface Roughness, Cutting Temperature and Cutting Force

ZAMBERI JAMALUDIN^{1*}, AGUS SUDIANTO², LOKMAN ABDULLAH¹, LUPING LUO³,

¹*Faculty of Industrial and Manufacturing Technology and Engineering,
Universiti Teknikal Malaysia Melaka,
Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia.*

²*Institut Teknologi Perusahaan Listrik Negara, Menara PLN, Jl. Lingkar Luar Barat,
Duri Kosambi, Cengkareng, Jakarta Barat 11750, Indonesia*

³*College of Mechanical Engineering, Zhejiang University of Technology, Hangzhou 310023, China*

**Corresponding author: zamberi@utem.edu.my*

ABSTRACT: This paper presents a novel study on modelling and optimization of dry end-milling machining of aluminium alloy AA6041 for an engine connecting rod with impact on surface roughness, cutting temperature, and axial cutting forces. Machining parameters such as the cutting speed, feed rate, and depth of cut were first screened from a preliminary analysis using the Taguchi method. A Design Expert software with Response Surface Method (RSM) was applied to identify the best-fit model. Results of the three optimal response values were analysed in ANOVA using analysis of variance based on the quadratic model with randomized Box-Behnken method generating three regression equations. Feed rate was identified as the significant factor for surface roughness while for cutting temperature, the depth of cut and feed rate were significant factors affecting cutting temperature and the cutting force. The ANOVA analyses identified cutting speed, feed rate, and depth of cut of 155 m/min, 708.256 mm/min, 0.306 mm respectively as optimal cutting parameters. Validation experiments for the predicted responses were performed on the AA6041 material using a commercial HAAS three-axis computer numerical control (CNC) vertical machining centre with uncoated carbide end-mill tool under dry condition. The optimized cutting parameters produced predictive errors of 1.16%, 0.11%, and 3.21% while the validation experiments produced averaged error values of 5.10%, 0.82% and 8.01% for surface roughness, cutting temperature, and cutting force respectively. Further analysis on impacts of other process parameters such as the cutting tool geometry and the number and angle of the cutting edges are desired.

KEYWORDS: *Aluminium alloy; response surface method; surface roughness; end-milling, cutting temperature; cutting force*

1.0 Introduction

The current state of manufacturing process put great emphasize on accuracy, surface quality, production rate, cost, and efficiency in order to remain competitive while meeting the current market requirements. Manufacturing industry must produce products with concept that follows the development of technology; utilizing best product design with materials and standard components that are appropriate for their functions. Material removal process is a part of manufacturing process that is common in many industries. Milling process is often the most commonly use method for material

removal in manufacturing process activities. Machine tools which have been proven in processing complex geometric shapes have great impacts on the quality of the finished part or product. The capabilities of the machine tools to enhance the quality of the manufacturing process are often realised by the ability to minimize errors and wastages. In order to meet the stringent requirements for precision, process robustness, process efficiency, and cost savings, optimal milling process technology must be incorporated.

The objective of any machining process is to fulfil the optimal finishing quality as required [1]. Over the years, great efforts have been made by many researchers and practitioners in the field of machining on topics related to selection of Computer Numerical Control (CNC) machinery with optimal cutting parameters, advanced cutting tools technology, cutting conditions, manpower with motivation, discipline and high performance [2] for the purpose of establishing best quality parts and products. The ability to fulfil these requirements would result in manufacturing process that is efficient, of high quality and effective. Being able to identify factors that significantly affect machining quality is essential for efficient manufacturing process. In other words, the machine tools must perform to its optimal capabilities. Various factors have direct and indirect influences on the quality of the finished part of any machining process. These factors include cutting tools geometric parameters such as angle and cutting edge of the tool, the suitability between work piece and cutting tool, cutting parameters, rigidity of the machinery, surrounding environment, as well as knowledge and abilities of machine operators.

Surface quality is an important characteristic of any machined parts [3]. It is a good predictor of mechanical component performance during machining as irregularities on the surface form nucleation sites that are prerequisites for cracking or corrosion [4]. Rough surfaces are more quickly to reach the surface, thus wear out faster and have a higher coefficient of friction than smooth surfaces. Roughness is undesirable and is difficult to process and ultimately a contributor to cost variable in manufacturing products but can be avoided with efficient manufacturing process. Although roughness is often undesirable, controlling the machining process is difficult and can be expensive. Therefore, limiting it can be a challenge as efforts to decrease surface roughness would increase exponentially the cost of production [5]. Surface roughness plays an important role in deciding the final quality of the product. Roughness is classified from N1-N12 classes [6] whereby the roughness classification for machining processes lies between N3-N10 while the roughness classification for milling processes lies between N6-N9 [7].

Numerous scholars have examined various factors and their subsequent impacts on surface roughness in performance of milling process through experimental and modelling studies. Even the environment, for example the room temperature can affect the comfort standards for workers who then impacted the quality of the products produced [8]. Also, relative humidity is a factor that can influence the mechanical properties of metals. For example, when calculating the hydrogen embrittlement susceptibility of aluminium alloys in aircraft, the humidity factor must be changed by adjusting the aircraft movement area [9]. Process parameters measure the status of the process where their values indicate whether the process meets the process requirements and these parameters must be controlled to obtain effective execution of the process. These include main parameters such as spindle revolution, feed rate, length of cut, depth of cut and cutting speed while studies have also shown that tool grade selection, nose radius, cutting angle, cooling method, humidity and temperature of the room, machine rigidity, and the workpiece's type of material; all have some degree of influence on the machining quality and process performances. However, correct selection of cutting tool, machining parameters, and material are among factors that strongly determine the final quality of the surface finishing. Most often however, machine operators in industrial manufacturing areas commonly use the trial-and-error method to find suitable cutting conditions [10]. Optimal process parameters would ensure good surface finish quality [11,12].

Process modelling is a technique most often applied to ensure high surface finish quality. Several factors were commonly considered in modelling of milling process for optimal results. Previous results have shown that increased in cutting speed and feeding speed reduced the fatigue life of the

product [13] while [14-16] all have reported that improved surface roughness values were reported by increased in the feeding speed and the width of cut that also reduced the cutting time. Also, [17] have investigated cutting parameters such as cutting speed, feeding speed, depth of cut, width of cut and tool geometry for machining of aluminium alloy. The effect of machining conditions, feed rate, cutting speed and the various output responses like cutting temperature, cutting force and surface roughness were studied by [18]. Through the combination of process parameters selections, much lower estimated roughness value was realised by [19]. Process parameters optimization improves the overall machining process, especially production operation costs, as well as improving the overall sustainable manufacturing process. Meanwhile, product design considerations included cutting tool orientation, as well as process parameters that optimized the ongoing machining process [20]. [21] had elucidated that selecting optimal end milling parameters not only increased the economical cutting function but also reduced the temperature rise in the product during the process.

Aside from surface roughness, cutting parameters also impacted the cutting temperature during the milling process thus affecting the quality of the cutting surface. This was observed by [22, 23] that cutting temperature and even cutting force were influenced by the selection of the machining process parameters. Increased in temperature of the material during machining caused changes in the microstructure that then impacted the surface roughness value. Also, the ductility of the material is increased due to higher temperature operation [24]. For example, during drilling process, the constant running of the drill machine produces heat affected zones around the holes where the surface properties were altered from the parent material due to the presence of heat. For such reason, machining operations are mostly done in step rather than in one stroke to avoid overheating [25] that could affect the material property and changes the product behavior. It was commonly observed that higher cutting temperatures were generated from increased feed rate and resulted in increased tool wear levels [26].

Cutting forces are outcomes of a machining process and act in the direction of cutting speed and supplies the energy required to cut the workpiece [27]. Monitoring the cutting forces during machining processes is important to determine and control the conditions under which the machine, the tool, and the workpiece are performing [28]. Cutting forces data is important in ensuring process optimization in machining. Analyzing cutting forces prior to the start of production increases process capability and boosts productivity. Tool geometry and tool trajectories impacted the milling force. It can affect the roughness of machine parts and cause tool deformation. Cutting force decreased with increased in the cutting speed. The decrease in cutting forces with an increase in the cutting speed was due to thermal softening of the workpiece [29]. Due to the complex geometry of the ball part of the milling cutter, increase in depth of cut increases the axial engagement of the cutting edge with the workpiece material and results in an increase in chip thickness, which leads to an increase in cutting forces on the cutter. In addition, increase in cutting forces resulted in tool deflection that affected the surface finish as reported by [30,31] and in their investigation on relation between surface roughness and cutting force from machining of a magnesium alloy under dry cutting [32].

Automotive parts are commonly produced using both ferrous and non-ferrous materials. Weight reduction is particularly important as the average vehicle weight is expected to increase with the emergence of advanced new models with increased luxury, convenience, performance, and safety as demanded by the customers [33,34]. The materials must also be able to meet the surface finish quality requirement. To achieve good product finish quality, the machining process must operate efficiently at optimal machining conditions. Surface roughness is a good predictor of the mechanical component quality since irregularities on the surface form nucleation sites that are prerequisites for cracking or corrosion [35]. For this reason, research was performed on identifying optimal end milling process cutting parameters for a specific aluminium alloy that is AA6041. AA6041 is a suitable material for a connecting rod in the engine block. AA6041 has a nominal density of 2.73×10^3 (kg/m³) based on the data from the International Alloy Designations and Chemical Composition Limits for Wrought Aluminium and Wrought Aluminium Alloys. 95% alumina vitreous body has physical properties of density of 3.75 g/cc, mechanical properties including ultimate tensile strength of 240 MPa and elastic modulus of 275 GPa, electrical resistivity properties of 15.7 kV/mm at AC

voltage, thermal conductivity properties 38°C in 35 W/m ° K (Mat Web, 2024). One common concern in machining of aluminium based material is the surface integrity of the finished part or components [36].

The objective of this research is to precisely model an optimal milling cutting process of AA6041 material for an engine block part component for best surface roughness while ensuring good impact on cutting temperature and cutting forces. From the literature reviews and best knowledge of the authors', very limited works have been reported on machining optimization of AA6041 material in regard as an automotive engine part component. Three optimal models were realized by ANOVA software based on the Response Surface Method via Design Expert incorporating it into each other in predicting response values of surface roughness, cutting temperature and cutting force. Response Surface Method (RSM) is widely applied as process optimization tool involving multiple parameters. It yields mathematical model that establishes relationship between independent factors that are inputs to the machining process and dependent factors as the required output data.

Cutting speed, feeding speed, depth of cut, width of cut, and number of flutes of the cutting tool were initial machining parameters considered for process optimization of AA6041 material with the goal of achieving optimal responses in surface roughness, cutting temperature and cutting force. The method applied a Design Expert 13.0.5.0 employing the quadratic randomized Box-Behnken RSM method that optimized the end milling machining parameters assisted by a Python program to validate the three responses.

This article consists of four sections. Section 2 focusses on materials and design of experiment. Section 3 elaborates on the optimization process and validation experiments performed to analyse the responses of the factors. Section 4 focusses on analyses of the dependent factors. The paper ends with conclusions and suggestions for further studies.

2. Preliminary Analysis

This study examined modelling for optimal machining process parameters of a specific aluminium alloy - AA6041. The chemical composition of the material was first confirmed using an optical emission spectroscopy with American Standard Testing Material (ASTM) E1251. The result is shown in Table 1. Figure 1 illustrates the overall flow chart of the work processes consisting of two separate phases.

Table 1. Chemical composition of aluminium

Element	Al	Cr	Cu	Fe	Mg	Mn	Si	Ti	Ni	Pb	Zn
Wt (%)	96.3	0.103	0.24	0.138	2.31	0.109	0.639	0.014	<0.005	0.004	0.005

Firstly, screenings were performed on the AA6041 aluminium alloy blocks on a HAAS Computer Numerical Control (CNC) vertical machining centre using an uncoated carbide cutting tool of HPMT S42 1000072. Five machining parameters were first selected; namely (i) cutting speed (V_c), (ii) feed rate (V_f), (iii) depth of cut (D_{oc}), (iv) width of cut (W_{oc}), and (v) number of flute (Z). The Taguchi Parametric Design was selected as the DOE tool to predict the interactions among the cutting parameters. Minitab 19.1 software was applied based on Taguchi L8 with design level 2 and 5 number of factors. The input parameters consisted of cutting speed (V_c) at 100 m/min and 220 m/min, feed rate (V_f) at 150 mm/min and 1861 mm/min, depth of cut (D_{oc}) at 0.1 mm and 0.5 mm, width of cut (W_{oc}) at 4 mm and 6 mm, and sum of flute (Z) at 3 and 4. Table 2 lists the results whereby the best R_a value of 0.11 μ m was obtained with V_c at 220 m/min, V_f at 150 mm/min, D_{oc} at 0.5 mm, W_{oc} at 6 mm and Z of 3.

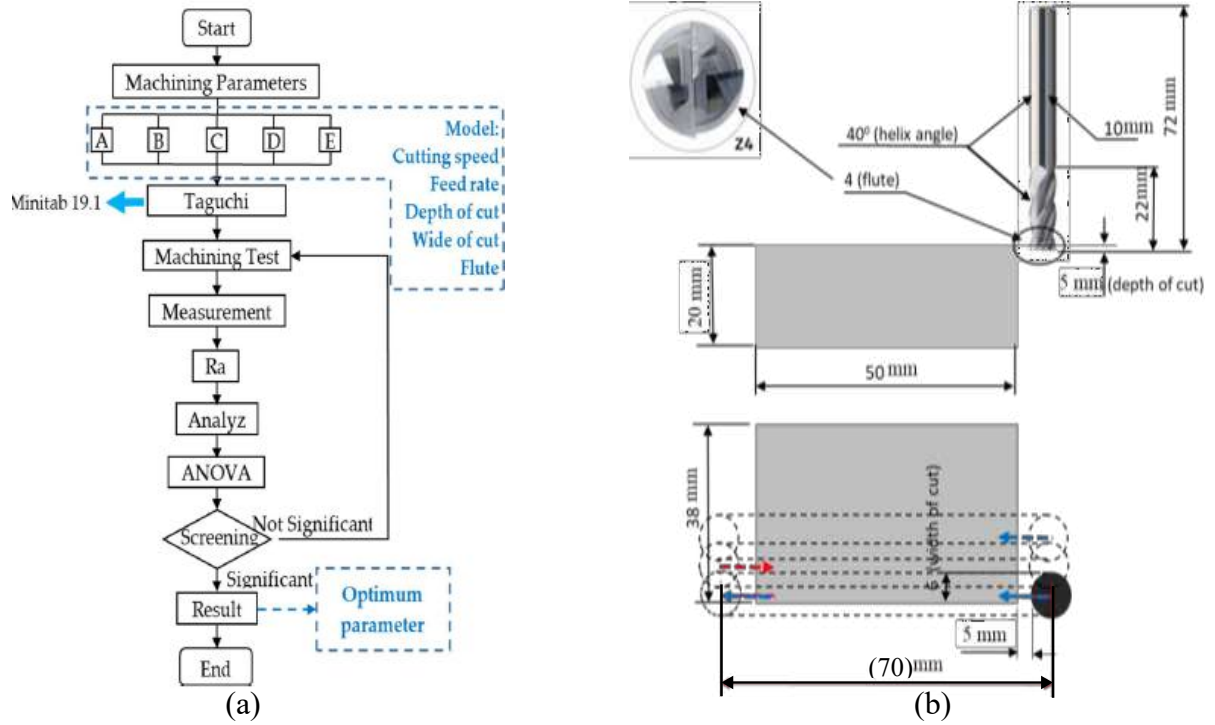


Fig. 1. (a) Overall process flowchart of study, (b) tool path trajectory

Table 2. Taguchi design and surface roughness experimental results

Run	V_c (m/min)	V_f (mm/min)	D_{oc} (mm)	W_{oc} (mm)	Z	R_a (μ m)
1	100	150	0.1	4	3	0.12
2	100	150	0.1	6	4	0.12
3	100	1681	0.5	4	3	0.75
4	100	1681	0.5	6	4	0.92
5	220	150	0.5	4	4	0.13
6	220	150	0.5	6	3	0.11
7	220	1681	0.1	4	4	0.27
8	220	1681	0.1	6	3	0.29

Regression analysis was performed based on the surface roughness (R_a) values screened from the five machining parameters against a p-value of less than 0.05. Table 3 shows results of the regression analysis that identified three significant parameters; (i) cutting speed (V_c), (ii) feed rate (V_f) and (iii) depth of cut (D_{oc}). These independent factors formed the basis for optimization of the dependent factors; surface roughness, cutting temperature and the cutting force.

Table 3. Coefficients of regression analysis with regression equation of R_a

Source	DF	Adj. Sum of Square	Adj. Mean of Square	F-value	p-value
Regression	5	0.707505	0.141501	37.45	0.026
V_c	1	0.153615	0.153615	40.66	0.024
V_f	1	0.392412	0.392412	103.86	0.009
D_{oc}	1	0.154355	0.154355	40.85	0.024
W_{oc}	1	0.003682	0.003682	0.97	0.428
Z	1	0.003441	0.003441	0.91	0.441

3. Modelling, Optimization, and Validation of Process Parameters

3.1 Analysis of Machining Parameters

Figure 2 shows the research methodology flow chart for the second part of the research which consisted of the machining tests and measurements, models realisation, evaluation, optimization, and validation. A set of 17 machining experiments were performed in dry condition using HAAS VF-1D 3-axes CNC milling machine, whereby the surface roughness, cutting temperature, and cutting forces were measured.

Optimization was performed based on the Response Surface Method (RSM) using Design Experts 13.0.5 statistical software with Box-Behnken design with numeric factors of 4, centre point per block of 5, and categorical factors of 0 for the 17 number of experiments. Table 4 summarizes the design expert specification and details of the machining parameters. Table 5 lists the measurement data of the independent and the dependent factors. Table 6 summarizes results of the dependent factors. Experimental variability and the accompanying degrees of freedom (DOF) were analysed using ANOVA approach. Finally, experimental validations were then performed using test workpieces. Surface roughness was measured using a Mitutoyo surface roughness tester with an accuracy of at least 0.01 micrometre with a numerical rating in R_a value, while a MLX90614 infrared sensor built using an Arduino-based program measured the cutting temperature. A Kistler 5233A dynamometer unit with Dynoware type 2825D-02 software was utilized for measurement of the cutting force.

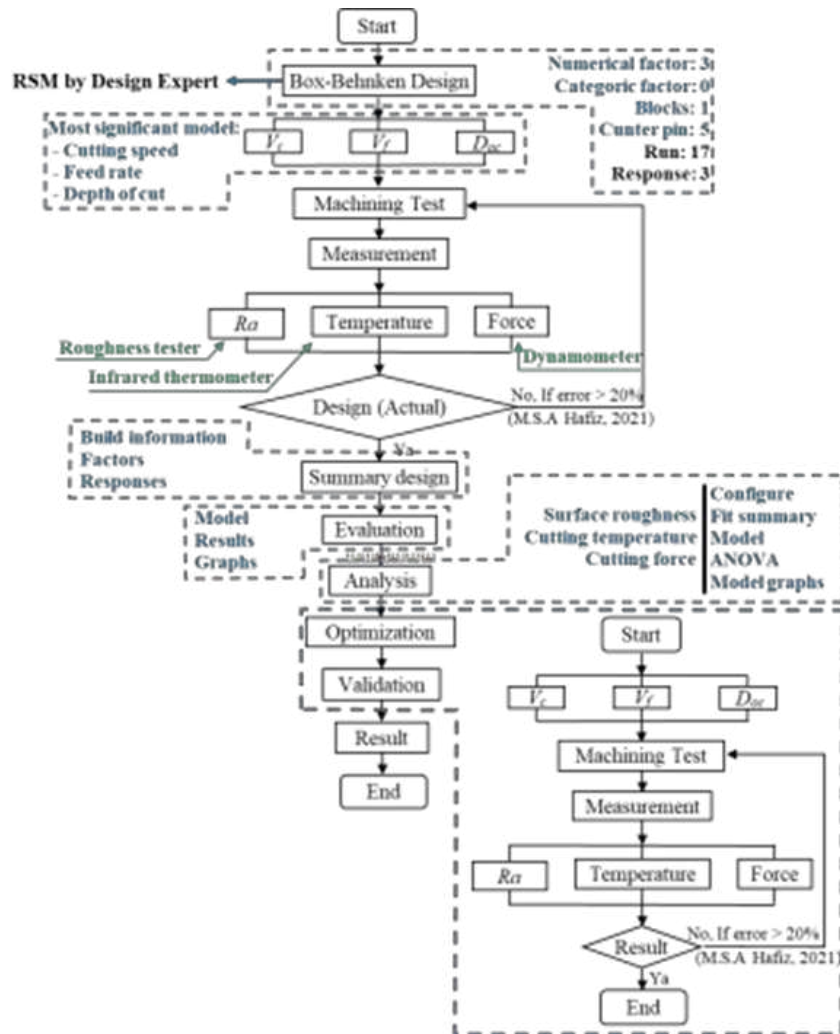


Fig. 2. Flow chart including the Response Surface Method (RSM), optimization and validation steps.

Table 4. Design expert specification and parameters

DOE	Software	Design - Expert Version 13.0.5.0	
	Design of Experiment	Response Surface Methodology (RSM)	
	Type of design	Box-Behnken Design	
	Numeric Factors	3	
	Category Factors	0	
	Responses	3	
	Runs	17	
Geometry tool	Tool diameter	10 mm - HPMT S42 1000 072	
	Flute of tool	4	
	Helix angle of tool	40 degrees	
Parameters	Cutting speed	V_c - High	220 m/min, (7006 rpm)
		V_c - Low	100 m/min, (3184 rpm)
	Feed rate	V_f - High	1681 mm/min
		V_f - Low	150 mm/min
	Depth of cut	D_{oc} - High	0.5 mm
		D_{oc} - Low	0.1 mm

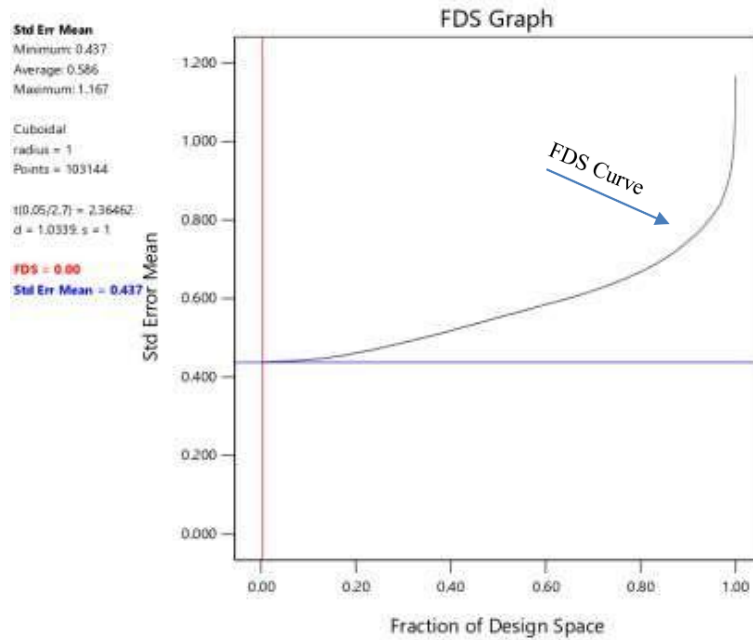
Table 5. Measurement results of milling cutting optimization experiments

Run	Controller factors as independent			Measured factors as response		
	V_c [m/min]	V_f [mm/min]	D_{oc} [mm]	Surface Roughness [μm]	Cutting Temp. [$^{\circ}\text{C}$]	Cutting Force [N]
1	160	915.5	0.3	0.18	30.88	21.97
2	100	1681	0.3	0.34	29.82	37.89
3	160	915.5	0.3	0.2	30.42	21.76
4	160	150	0.5	0.12	30.28	17.88
5	160	1681	0.5	0.37	31	62.37
6	100	915.5	0.1	0.24	29.6	19.57
7	100	150	0.3	0.14	29.44	8.68
8	220	915.5	0.1	0.13	29.6	14
9	220	150	0.3	0.11	30.66	9.72
10	160	915.5	0.3	0.25	29.98	22.14
11	160	150	0.1	0.12	29.44	7.03
12	100	915.5	0.5	0.26	29.66	41.87
13	220	1681	0.3	0.23	30.4	23.86
14	160	1681	0.1	0.25	28.9	30.32
15	220	915.5	0.5	0.15	30.4	35.68
16	160	915.5	0.3	0.24	29.82	21.88
17	160	915.5	0.3	0.16	30.14	34.78

Table 6. Response summary of end-milling dependent parameters

Responses	Name	Units	Observations	Min.	Max.	Mean	Std. Dev.	Ratio
R1	Surface Roughness	μm	17	0.11	0.37	0.2053	0.0769	3.36
R2	Cutting Temperature	$^{\circ}\text{C}$	17	28.9	31	30.03	0.5663	1.07
R3	Cutting Force	N	17	7.03	62.37	25.38	14.02	8.87

A Fraction of Design Space (FDS) – Design Expert calculated the volume of the design space having a prediction variance of less than or equal to a specified value. The ratio of this volume to the total volume of the design space is the fraction of design space (FDS). FDS sized the response surface (RSM) and mixture designs for which normal power calculations lose relevance. For optimization, an FDS score of at least 80% and 100% are desired for stability and robustness respectively. Statistical analysis of variance was used to determine factors that had significant impact on the analysis of variance (ANOVA). Figure 3 shows the FDS representation on the standard error mean with a minimum of 0.437, an average of 0.585 and a maximum of 1.167.

**Fig. 3.** Graph of fraction of design space

3.2 Response Surface Method Analysis – Surface Roughness

Predictive mathematical models of the dependent variables of the machining process ensure efficient and less costly processes. A linear inverse square model of the surface roughness was obtained using a linear regression method of ANOVA. This model maximizes the adjusted R^2 and the predicted R^2 values with leverage of 1.0000 as shown in Table 7. The inverse transform of the cutting parameters with zero constant in ANOVA for the linear model is listed in Table 8. Here, the model F-value of 33.90 implies that the model is significant. A p -value of less than 0.0500 indicates model terms were significant. In this case, A and B factors were significant model terms. Values greater than 0.1000 indicate the model terms were not significant. Also, an F -value of 0.3874 corresponds to the *Lack of Fit* that implies that it was not significant relative to the pure error.

Table 7. Statistics of model analysis

Source	Std. Dev.	R ²	Adjusted R ²	Predicted, R ²	Press
Linear*	0.1599	0.8867	0.8605	0.8347	0.4848
2fi	0.1724	0.8986	0.8377	0.7779	0.6512
Quadratic	0.1840	0.9192	0.8152	0.5808	1.23
Cubic	0.2107	0.9394	0.7578		

Table 8. Results of ANOVA for linear model using RSM

Source	Sum of Squares	Degree Of Freedom (DOF)	Mean Square	F-VALUE	p-value
Model	2.60	3	0.8666	33.90	< 0.0001
A-V _C	0.5334	1	0.5334	20.87	0.0005
B-V _F	2.02	1	2.02	78.91	< 0.0001
C-D _{OC}	0.0492	1	0.0492	1.93	0.1885
Residual	0.3323	13	0.0256		
Lack of Fit	0.1548	9	0.0172	0.3874	0.8907
Pure Error	0.1776	4	0.0444		
Corr. Total	2.93	16			

The model equation of the surface roughness, R_a was established as follow:

$$\frac{1}{R_a} = 2.34713 + 0.004304 V_c - 0.000656 V_f - 0.392251 D_{oc} \quad (1)$$

Figure 4 shows the normal plot residual values based on the data tabulated in Table 8. The x-axis plots the actual residual values while the y-axis shows the normal values in order of rank. Initially, the distribution of residual values was examined. These values were calculated as the difference between the predicted value and the observed value. The figure shows a normal graph of the plot of residuals, where the smallest value of $1/\sqrt{R_a}$ (surface roughness) was the residual value of $x = -2.389$ and the normal value was at $y = 2.9$. The largest value of $1/\sqrt{R_a}$ (surface roughness) was the residual value of $x = 1.208$ and the normal value of $y = 97.1$. If the values were on a straight line, residuals followed a normal distribution.

Figure 5 shows a 2-D and 3-D graphs of the surface roughness value at a depth of cut of 0.1 mm as function of the cutting speed and feed rate. The lowest predicted value was 0.135 micrometre while the highest predicted value was 0.35 micrometre. Point A is identified as run-6 with a cutting speed of 100 m/min, feed rate of 915.5 mm/min, and a surface roughness value of 0.24 micrometres. Point B describes run-14 for cutting speed of 160 m/min, feed rate of 1681 mm/min, and surface roughness value of 0.25 micrometre. Point C refers to run-8 for a cutting speed of 220 m/min, feed rate of 915.5 mm/min, and a surface roughness value of 0.13 micrometre. Finally, point D described run-11 at a cutting speed of 160 m/min, feed rate of 150 mm/min, and a surface roughness value of 0.12 micrometres. In statistical modelling of R_a , ANOVA results show that the significance factors of the cutting speed (V_c) at 100 m/min was 45%, feed rate (V_f) at 915.5 mm/min was at 54.5% and

finally the depth of cut (D_{oc}) at 0.1 mm was 10%. Also, surface roughness value increases with increases in cutting temperature irrespective of the depth of cut as consistent with the work of [8].

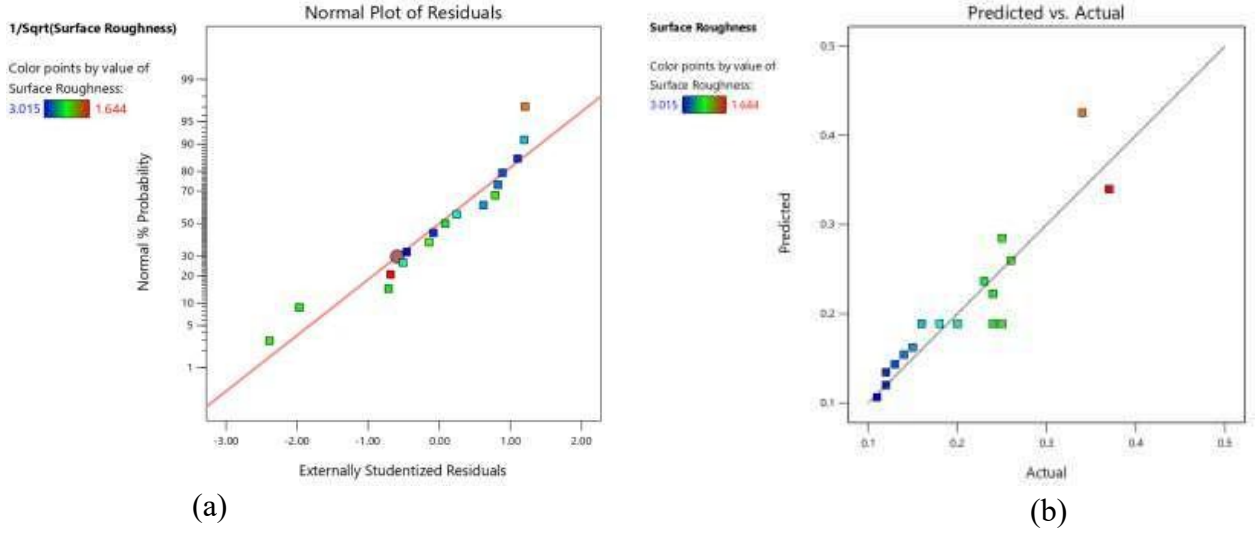


Fig. 4. (a) linear normal plot of residuals and probability (b) predicted against actual surface roughness of the measurement results

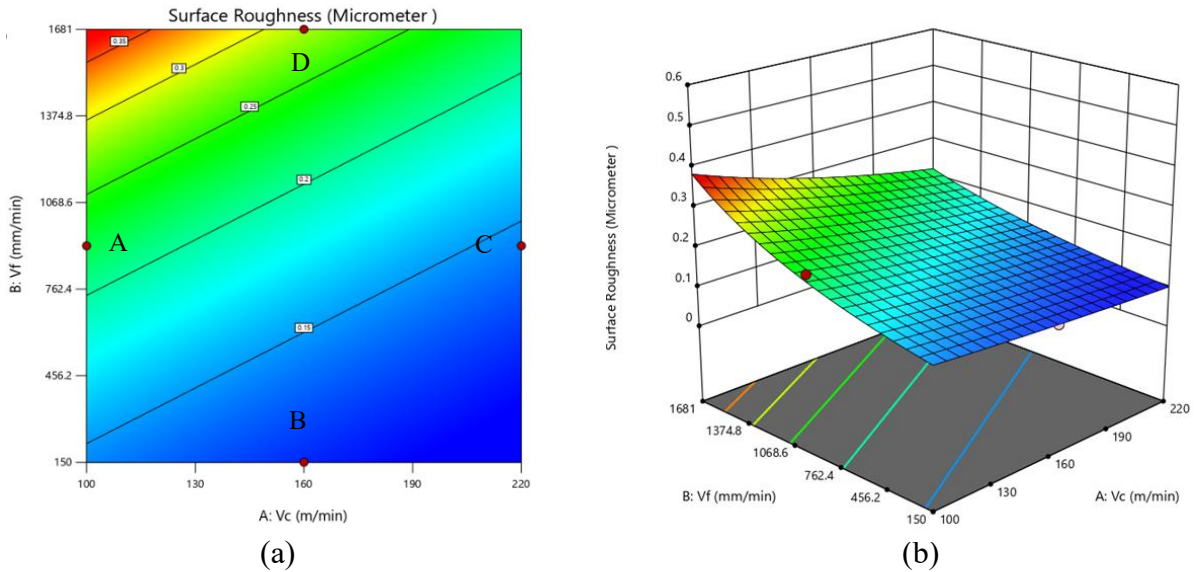


Fig. 5. (a) 2-D and (b) 3-D plots of surface roughness plots for a depth of cut of 0.1 mm

3.3 Response Surface Method Analysis - Cutting Temperature

Next, the cutting temperature model of the AA6041 material was established. Similar processes as that of surface roughness model derivation were repeated for cutting temperature, T_c . A model with a F -value of 4.53 was obtained implying that the model was significant. There was only a 2.20% chance that an F -value this large could occur due to noise. Also, a p -value of less than 0.0500 indicated that the model terms were significant. In this case, C (D_{oc}) was a significant model term. Values that were greater than 0.1000 implied that the model terms were not significant. If there were many insignificant model terms (not counting those required to support hierarchy), model reduction may improve the model. The *Lack of Fit* F -value of 1.16 implied that the *Lack of Fit* was not significant relative to the pure error. There was a 47.88% chance that a *Lack of Fit* F -value this large could occurred due to noise. Non-significant lack of fit was good as it indicated that the model was fitted.

Equation 2 states the linear cutting temperature model obtained using ANOVA via linear regression method without transformation.

$$T_C = 28.42187 + 0.005292 V_c + 0.000049 V_f + 2.37500 D_{oc} \quad (2)$$

Figure 6 shows the predicted cutting temperature against actual cutting temperature for each value in the test run sequence. For example, result for run-1 had a predicted value of 30.026° Celsius while the actual value was 30.88° Celsius. For run-17, the prediction value was 30.026° Celsius while the actual value was 30.14° Celsius. Increasing the feed rate increases the chip volume gain and thus requires more power. With an increase in cutting speed, the friction between the cutting tool and the workpiece increases resulting in a change in heat gain in the cutting zone area of the material. Heat flux during the machining process then induced the material cutting temperature to increase further.

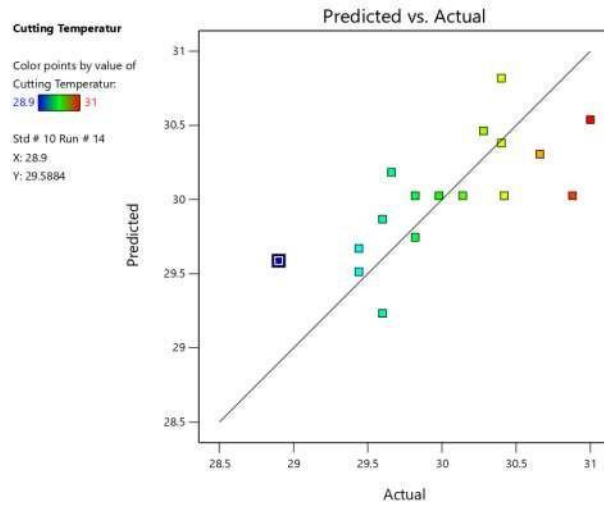
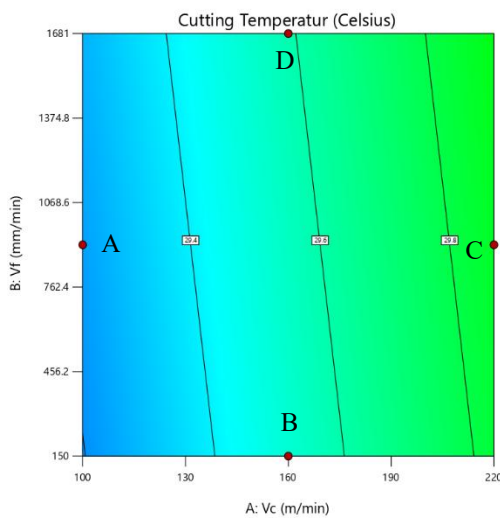
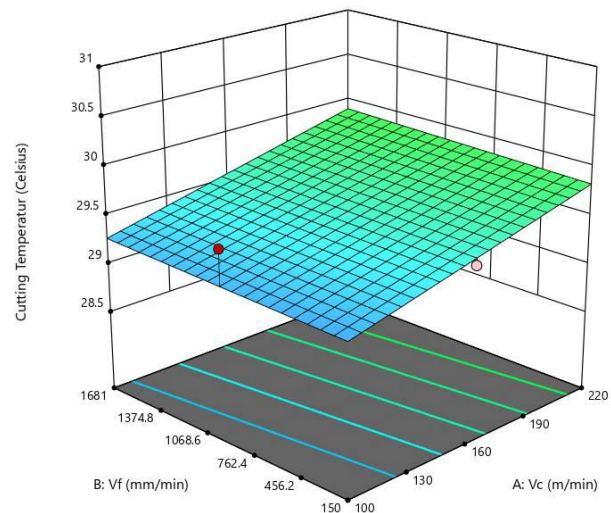


Fig. 6. Predicted against actual cutting temperature of measurement results

Figure 7 shows the 2-D and 3-D representation of cutting temperature in relation to cutting speed and feed rates. Results in (a) identify point A, B, C, and D correspond to run-6, run-14, run-8, and run-11 of the measurements. The lowest predicted value was 29.302° C while the highest predicted value was 29.8° C.



(a)



(b)

Fig. 7. (a) 2-D and (b) 3-D plots of cutting temperature plots for a depth of cut of 0.1 mm

3.4 Response Surface Method Analysis –Cutting Force

Table 9 list results of ANOVA for quadratic model of the cutting forces. The model *F-value* obtained was 21.82 that implies significance of the model. Data showed that there was only a 0.03% chance that an *F-value* this large could occur due to noise. The *p-value* of less than 0.0500 indicated that the model terms were significant. In this case; B, C, B² were significant model terms. Values greater than 0.1000 indicated that the model terms were not significant.

Table 9. ANOVA for quadratic model of cutting forces

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	5.26	9	0.5840	21.82	0.0003	significant
A- V_c	0.0891	1	0.0891	3.33	0.1108	
B- V_f	3.23	1	3.23	120.67	< 0.0001	
C- D_{oc}	1.40	1	1.40	52.45	0.0002	
AB	0.0828	1	0.0828	3.10	0.1219	
AC	0.0077	1	0.0077	0.2860	0.6094	
BC	0.0113	1	0.0113	0.4207	0.5373	
A ²	0.0576	1	0.0576	2.15	0.1857	
B ²	0.2692	1	0.2692	10.06	0.0157	
C ²	0.1177	1	0.1177	4.40	0.0742	
Residual	0.1873	7	0.0268			
Lack of Fit	0.0173	3	0.0058	0.1353	0.9340	not significant
Pure Error	0.1701	4	0.0425			
Corr. Total	5.44	16				

The *F-value* of 0.1353 implied that the *Lack of Fit* was not significant relative to the pure error. Also, there was a 93.40% chance that a *Lack of Fit F-value* this large could occur due to noise. The non-significant lack of fit was a good indicator. Figure 8 shows the ANOVA analysis of each value in the test run sequence of the specimen consisting of the normal plot of residual values and their probabilities and the relation between prediction and actual values of the cutting force. The cutting force model equation as in equation (3) enables predictions of the responses for given levels of each factor.

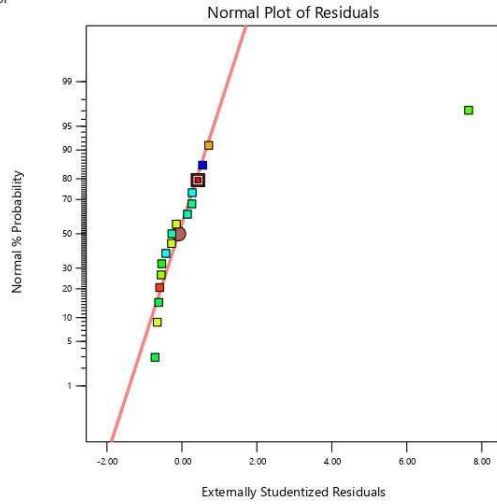
$$\begin{aligned}
 \ln(F_c) = & 0.877116 + 0.010415 V_c + 0.002225 V_f - 0.679419 D_{oc} - 0.00000313329 V_c V_f \\
 & + 0.003645 V_c D_{oc} - 0.000347 V_f D_{oc} - 0.000032 V_c^2 - 0.000000431483 V_f^2 \\
 & + 4.17961 D_{oc}^2
 \end{aligned} \quad (3)$$

In term of prediction, results show that for example in run-1, the predicted cutting force was 24.379 Newton while the actual value was 21.97 Newton. In case of run-17, the predicted value was 24.379 Newton with the actual value measured at 34.78 Newton. The highest cutting force value was 60.89 and 62.37 Newton for predicted and actual measurement respectively. This equation should not be used to determine the relative impact of each factor because the coefficients were scaled to accommodate the units of each factor and the intercept was not at the centre of the design space. Figure 9 shows a 2D representative of the cutting force graph against cutting speed and the feed rate indicating run-12, 5, 15 and 4 of the measurements as identified by label A, B, C, and D respectively. Results show that cutting forces were significantly influenced by changes in cutting speed, feed rate and the depth of cut. The predicted cutting force coefficient incorporates osteon orientation (parallel, cross section and transverse), tool geometry and edge effects using an integrated cutting approach.

In(Cutting Force)

Color points by value of
Cutting Temperature:
3.364 3.434

Std # 12 Run # 5
X: 0.428
Y: 79.4

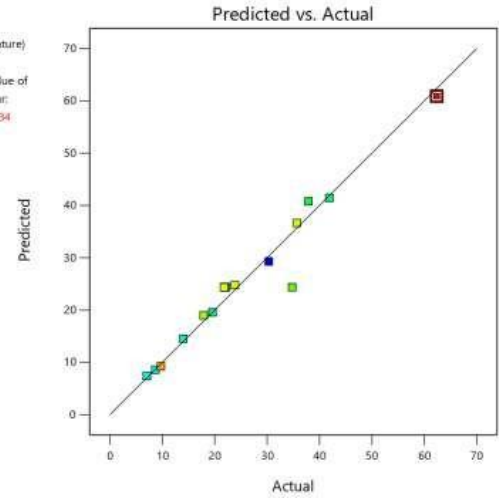


(a)

Cutting Force
(adjusted for curvature)

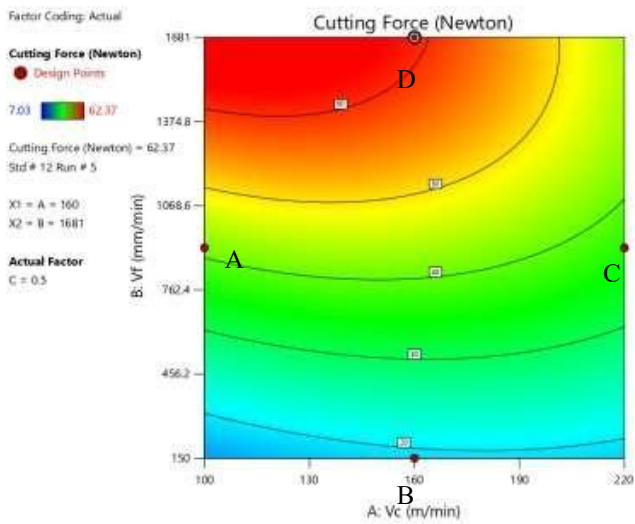
Color points by value of
Cutting Temperature:
3.364 3.434

Std # 12 Run # 5
X: 62.37
Y: 60.8989



(b)

Fig. 8. (a) linear normal plot of residuals and probability (b) predicted against actual surface roughness of the measurement results



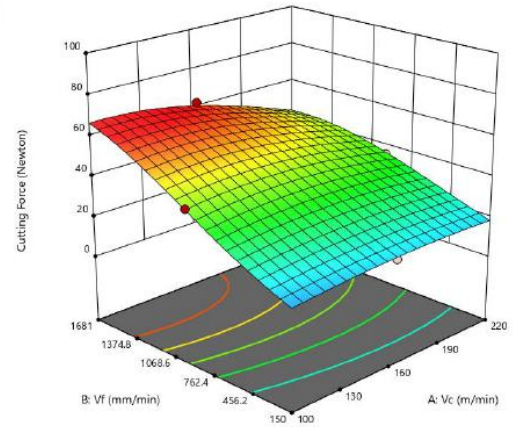
(a)

Cutting Force (Newton)

Design Points:
● Above Surface
○ Below Surface

7.03 62.37

X1 = A
X2 = B
Actual Factor
C = 0.5



(b)

Fig. 9. (a) 2-D and (b) 3-D of plots of cutting forces for a depth of cut at 0.5 mm

Table 10 lists the predicted and measured responses of the dependent factors. The predictive errors recorded were 1.16%, 0.11%, and 3.21% for surface roughness, cutting temperature, and cutting force respectively. The predicted results were well below the 5% threshold value indicating accurate and reliable prediction of the dependent variables.

Table 10. Results of optimization, measured and predicted values by ANOVA

Run	V_c m/min	V_f (mm/min)	D_{oc} (mm)	R_a (μ m)		T_c ($^{\circ}$ C)		F_c (N)	
				Predicted	Measured	Predicted	Measured	Predicted	Measured
Optimized parameters	155	708.256	0.306	0.172	0.17	30.004	29.971	20.511	19.852

3.5 Validations of Predictive Response Models

At the depth of cut of 0.1 mm, the surface roughness, cutting speed, and cutting force in machining of the AA6041 aluminium alloy ranged from a minimum of 0.135 micrometre to a maximum of 0.35 micrometre, a minimum of 29.2°C to a maximum of 29.8 °C and a minimum of 7 N with a maximum of 30N respectively. Results of the responses analysis is shown in figure 10 below.

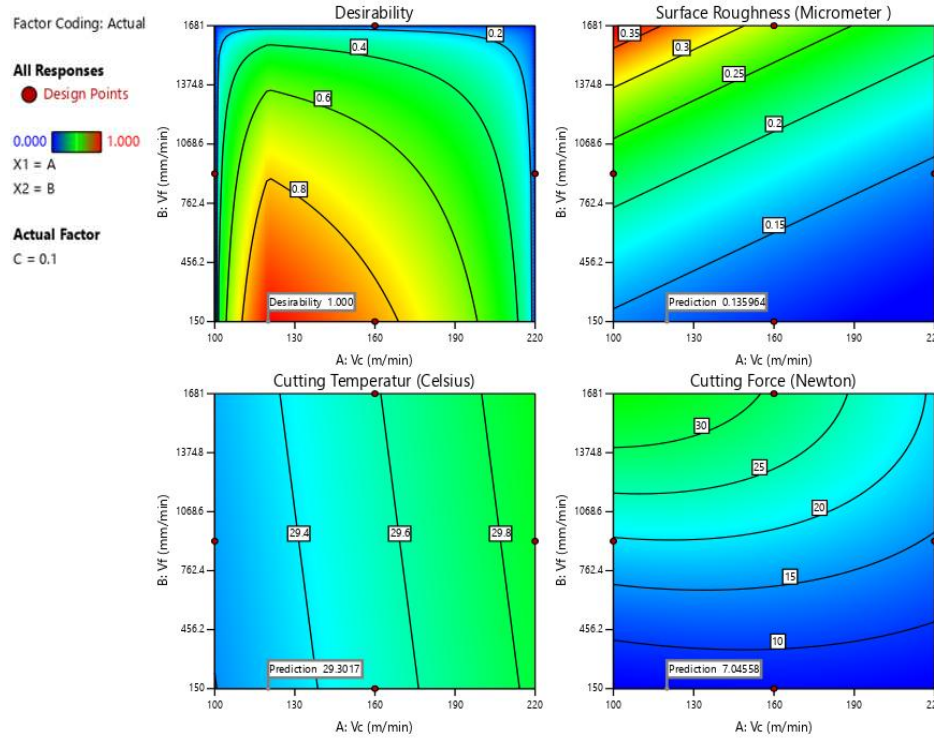


Fig. 10. Results of numerical analyses of the depended responses

Next, the three models (equation 1, 2, 3) were validated on similar experimental setup assisted with a Python program. Three validation runs were performed for the three dependent responses. The first validation involved target input of cutting speed, feed rate and depth of cut of 120 m/min, 150 mm/min and 0.1 mm respectively. The second validation had target inputs of 220 m/min, 1500 mm/min and 0.3 mm, respectively. Finally, the third validation comprised of target inputs of 150 m/min, 1681 mm/min and 0.5 mm, respectively. Table 11 summarizes the validation results. The validation errors ranged from 2.9% to 9 %, 0.2% to 1.5%, and 4% to 12% for surface roughness, cutting temperature, and cutting forces respectively.

In practice, minimum values of the surface roughness, cutting temperature, and cutting force are desired for efficient, productive, and safe milling cutting process. These results should serve as an excellent reference for practitioners during machining design stage so as to avoid wastage in time and materials. Table 12 lists the suggested ranges of the independent variables at the depth of cut of 0.1 mm.

Table 11. Summary of validation results

Run	V_c (m/min)	V_f (mm/min)	D_{oc} (mm)	Roughness, (μ)			Cutting Temp. ($^{\circ}$ C)			Cutting Force (N)		
				Pre-dicted	Meas'd	% Err.	Predicted	Meas'd	% Err.	Predicted	Meas'd	% Err.
1	120	1500	0.1	0.136	0.140	2.94	29.30	29.37	0.24	7.05	7.89	12.02
2	220	1500	0.3	0.211	0.230	9.00	30.37	30.16	0.70	24.51	23.44	4.37
3	150	1681	0.5	0.358	0.370	3.35	30.48	30.03	1.49	62.82	58.02	7.63

Table 12. Range of independent variable for minimum dependent responses

Dependent Responses	Cutting Speed m/min		Feed Rate mm/min	
	min	max	min	max
Surface Roughness,	100	220	150	760
Cutting Temperature	100	140	150	1681
Cutting Force	100	220	150	4500

4. Analysis of dependent parameters - Surface Roughness, Cutting Temperature, Cutting Force

4.1 Effect on cutting tools

Cutting parameters such as cutting speed, depth of cut, feed rate, and tool geometry have direct effect on surface roughness. Figure 11 shows the tool condition of the fifth machining run showing chips attached to the cutting-edge generating friction between the cutting surface and the sticking chip. This produced negative effect on the surface roughness of the product. In this study, the machining process was very decisive in determining the quality according to the functionality of the product. Results have shown that lowest roughness value was found at high cutting speeds, low feed rates and low depth of cut.

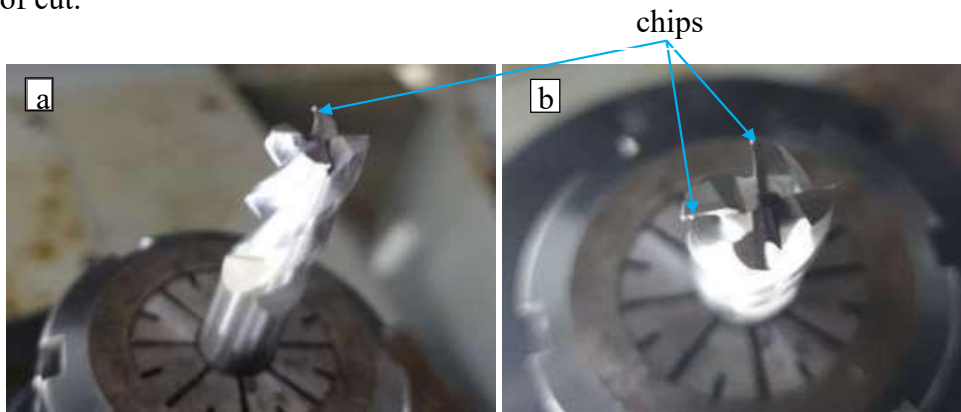


Fig. 11. Sticking chip on cutting tool

4.2 Materials microstructure analysis

The work material was exposed to thermal, mechanical and chemical energy as outcomes of the machining process resulting in static deformation and recrystallization of the materials. The effect of friction due to the ingestion of the workpiece on the cutting tool impacted the cutting temperature thus affecting the surface quality of the final product [37].

This impact can be visually inspected on the surface of the product. Non-optimal cutting parameters caused unfavourable colour on the surface of the product. Certain parameters such as cutting speed that was above 300 m/min generated heat which did not have significant direct effect but could affect the cutting tool because the time available to dissipate the heat on the tool is too short thus producing a rougher surface [23].

The two types of motions performed during the end milling process; rotation of the end mill and the straight movement of the workpiece produced spiral shape on the surface consistent with results presented by both [38,39]. The roughness pattern on the machined surface was in the form of cut-back where the effect of the edge of the side-back of the dominant tool formed the former cut. Roughness measurements were taken on the feed side, coupled with a feed rate that was generally lower than or

equal to the radial depth of cut. Figure 12 shows the microstructure results from the scanning electron microscope (SEM) machine of run-9 at a 0.5 mm magnification scale.

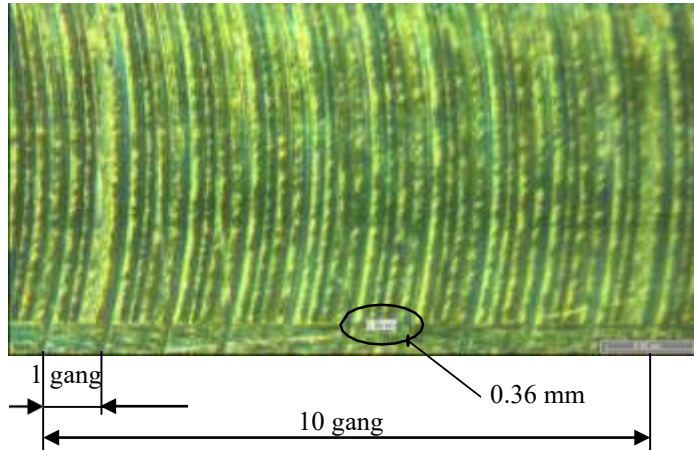
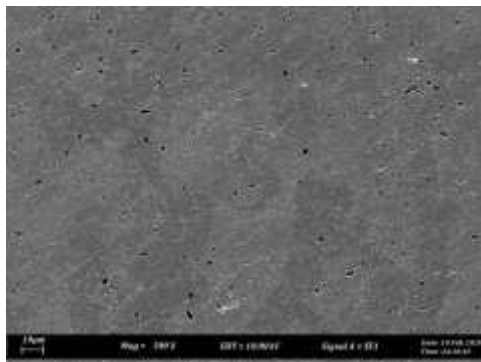


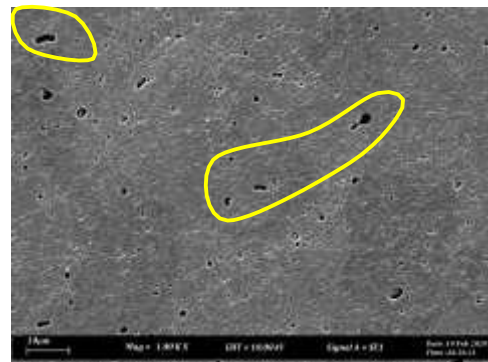
Fig. 12. Microstructure results of run-9 at 0.5mm magnification scale

The microstructure for 10 microns and 2 microns at magnification of 500, 1000, and 3000 respectively are shown in Figure 13. The presence of ferrous was visible in the structure as identified in figure 13 (b) and (c). The interaction between feed rate and depth of cut was the most significant factor on the surface roughness. Surface roughness was related to the kinematic effect caused by the shape of the end mill and the feed rate.

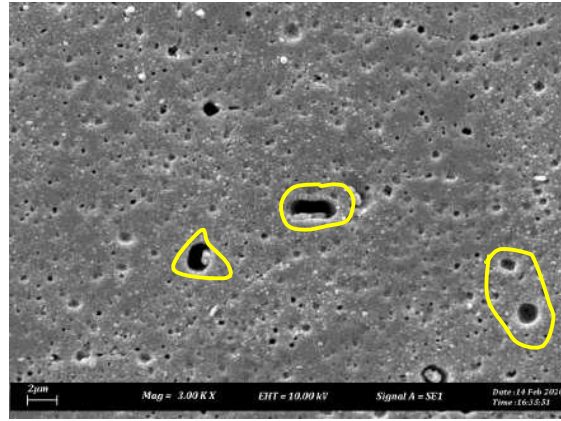
During machining, some areas were not completely removed producing feed marks as highlighted in Figure 14. The higher the feed rate and the deeper into the cut, the larger the feed marks. This observation was supported by [40] who stated that micro milling operations cinematically affected surface roughness. This was due to the effect of high cutting speed and increased axial depth. The roughness of the surface close to the centre line of the tool path was higher than at the edge of the path. Figure 15 (a) shows the feed mark distance at several locations along the rotation of the tool. It was found that the value was higher at the middle area of the cutting path (Q2). This affects the surface quality as observed in Figure 15 (b). The maximum feed mark distance was equal to the feed rate. It was smaller at the boundary of the cutting path (Q3 and Q2). However, the non-cut areas at Q1 and Q2 were discarded by the new cutting path as shown in Figure 15 (b) where the previous cuts were stacked with the new cuts.



(a)



(b)



(c)

Fig. 13. Microstructure of 10 μm (a) magnification of 500x, (b) magnification of 1000x, (c) Microstructure of 2 μm at magnification of 3000x

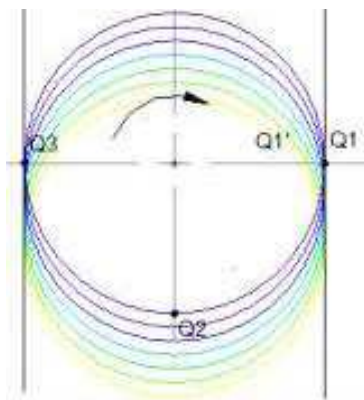


(a)

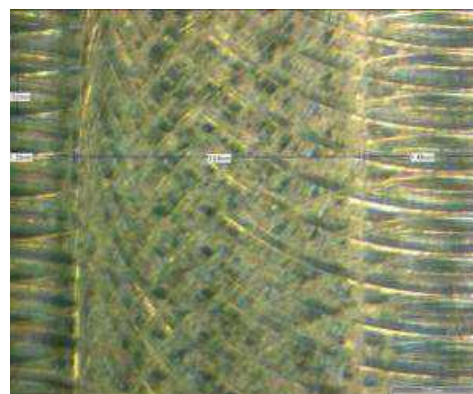


(b)

Fig. 14. SEM image showing the effect of feed (a) smearing, (b) back cut on the surface of test no.7 which yields an average R_a of 0.14 μm



(a)



(b)

Fig. 15. (a) Tool rotation geometry, (b) feed mark effect on tool path

The feed rate not only affected the surface finish but indirectly the cutting speed. This matter was discussed from the effect of each end milling operation parameter on the surface roughness, looking at the effect of width of cut and depth of cut during grooves and contour operations where the depth of cut had stronger effect than the width of cut. Experimental results presented have shown that cutting speed and feed rate had the greatest influence on the surface roughness.

4. Conclusions

The main contribution of this work relates to the optimization of a dry end-milling machining of aluminium alloy AA6041 for a connecting rod of an automotive engine component to ensure minimal impact on productivity and part quality. Three independent machining process parameters, namely the cutting speed, the feed rate, and the depth of cut were initially identified to have most influence on process outcomes in the forms of surface roughness, cutting temperature, and the cutting force. The ANOVA analysis has identified feed rate as the most significant factor contributing to surface roughness, the depth of cut for cutting temperature, and feed rate as the most significant parameter affecting the cutting force. The response surface method (Box-Behnken) based on Design Expert software has established a linear inverse square model for the surface roughness, a linear model for the cutting temperature, and a quadratic model with a natural log for the cutting force generating optimal parameters of 155 m/min, 708.256 mm/min and 0.306 mm for surface roughness, cutting temperature, and cutting force respectively. Detailed analysis on the microstructure level have revealed issues such as chips on the cutting tool, feed marks, and burnt ferrous marks for inefficient machining process. Indeed, various other factors could have some degree of impact on the surface quality of the part and deserved further investigations such as the cutting tool geometry and the number and angle of the cutting edges.

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Declarations

All authors declare that they have no conflicts of interest

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Statement and Declaration

This manuscript has not been published and is not under consideration by another journal. We have read and understood your journal’s policies, and we believed that neither the manuscript nor the study violates any of these. There are no conflicts of interest to declare.

