



Research Article

Experimental Exploration into Al 7075-T651 Machinability, Surface Quality, and MRR Using Avocado Cutting Fluid via Grey Optimization

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Abstract

This research aims to identify the optimal machining parameters for turning Aluminium Alloy 7075-T651 using a tungsten carbide insert cutting tool and a flood coolant system, applying the Grey-based Taguchi method. Aluminium Alloy 7075-T651 is commonly utilized in the automotive, marine, machine tools, and aerospace industries due to its excellent weight-to-strength ratio. A key focus of the study are the surface roughness and material removal rate, which is critical in machining. The research explores how various turning parameters affect surface roughness and material removal rate with investigates the role of coolant in these operations. Heat generated during machining can adversely affect tool life, workpiece dimensions, and surface quality. To address these challenges, an environmentally friendly, biodegradable, and non-toxic avocado oil-based cutting fluid was employed. An orthogonal array from the Taguchi method guided the experiments, with surface roughness and material removal rate measured as a response. Minitab software facilitated the statistical analysis of process parameters. Key performance metrics included material removal rate, and surface roughness, influenced by cutting speed, feed rate, depth of cut, and avocado oil proportion. So, an avocado oil (9%), depth of cut (1.0 mm), cutting speed (1000 rpm), and feed rate (85 mm/min) are an optimized parameter.

Keywords

ANOVA, Taguchi Method, Turning Operation, Spindle Speed, Surface Roughness

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1. Introduction

Aluminium alloys are among the most commonly used lightweight metallic materials, known for their attractive mechanical and thermal properties. Aluminium alloy 7075-T651 is widely used in the aviation, marine, and automobile sectors. Its extensive applications highlight the importance of researching this material in the manufacturing field. Surface roughness has received significant attention for many years. It is an important design feature in various situations, such as parts subjected to fatigue loads, precision fits, fastener holes, and aesthetic requirements. In addition to tolerances, surface roughness imposes one of the most critical constraints on the selection of machines and cutting parameters in process planning. A considerable number of studies have investigated the general effects of speed, feed, depth of cut, and cutting fluid on surface roughness. To improve the efficiency of these turning processes, it is essential to have a comprehensive understanding and model of the process. To simplify the problem, it is necessary to eliminate or select specific variables that correspond to practical applications. The productivity and efficiency of metal removal processes depend on machining parameters such as cutting conditions, cutting tool geometry, and the materials of both the workpiece and the tool. Optimizing these parameters during the turning process is crucial, as it directly influences surface roughness and the power consumed by the machine. In this experimental work, Aluminium Alloy 7075-T651, which is commonly used in the aeronautical and manufacturing industries, has been selected as the material for investigation. The effects of cutting speed, feed rate, depth of cut and avocado oil cutting fluid on surface roughness were analyzed using Taguchi methods. Experiments were conducted on Aluminium Alloy 7075-T651 using a CNC lathe machine, and the impact of speed, feed, and depth of cut on surface roughness was measured.

2. Literature Review

Machining is a fabrication process that removes chips from a workpiece to achieve the desired form, dimensions, and finish. It is one of the oldest and most widely used industrial processes in engineering part manufacturing. Machining encompasses various actions like turning, milling, and cutting. These processes involve the use of a sharp cutting tool to remove excess material from the workpiece surface, resulting in the formation of chips that shape the final product. The primary cutting action in machining is shear deformation, which forms the chips. When the cutting tool encounters the workpiece material, it removes a chip and creates a newly machined surface. Machining requires relative motion between the cutting tool and the work material. Speed and feed rate are key factors in this relative motion, often referred to as cutting conditions or parameters [6].

The shape, geometry, and contact of the cutting tool with the workpiece surface, combined with the motion, determine

the final shape of the product. The cutting tool tip has two faces: the rake face and the flank face. The rake face is angled with respect to the plane perpendicular to the workpiece surface and controls the chip flow direction. The rake angle can be positive for finishing or negative for roughing. Additionally, the rake face can influence chip flow more than the flank face. The flank face, aligned with a clearance angle, protects the newly machined surface from abrasion by maintaining a gap between the tool and the surface [7].

This paper study to determine the effect of cutting fluids on surface roughness and tool wear turning AISI 304 austenitic stainless steel with a carbide tool, inserts CNMG120408 as the cutting tool. The Taguchi $L_{27}(3^4)$ orthogonal matrix was implemented in the test plan. Factors and levels considered (low, medium and high) were depth of cut (1.2, 1.0 and 0.5 mm); cutting speed (97.38, 61.35 and 38.95 m/min); feeds (0.28, 0.25 and 0.20 mm/revolution); and type of cutting fluids (coconut oil, straight cutting oil and soluble oil). Numerical models of cutting parameters and cutting fluids (so each cutting fluid has a viscosity of 40°C) were obtained from regression analysis to estimate tool wear and surface roughness. ANOVA and signal-to-noise ratio (S/N) were performed to determine the significant parameter affecting tool wear and surface roughness. The observation showed that feed rate had a greater effect on surface roughness by 61.54%, while cutting speed had a greater effect on tool wear by 46.49%. Cutting fluids have been found to significantly affect both tool wear and surface roughness. The viscosity of coconut oil fell between soluble oil and straight cutting oil, which increases the effective movement of cutting fluids in a relatively low oil state [4].

This paper determined the effect of cutting fluids on tool wear rate and surface roughness in turning austenitic AISI 304 stainless steel. They performed turning using AISI 304 workpiece material. They used three different vegetable oil based cutting fluids: 1. Coconut oil 2. Soluble oil 3. Straight cutting oil. They concluded that feed rate affects surface roughness and cutting speed affects tool wear. Coconut oil is a better cutting fluid than conventional mineral oils for reducing tool wear and surface roughness [9].

This paper study evaluates the performance of MQL using castor oil as the cutting fluid and compares the results with dry cutting. They found that using a small amount of 50ml/h of lubricant during a given turning process gives better results compared to dry cutting in terms of longer tool life. They learned that MQL machining appears to be limited by cutting temperature as the oil mist effect dissipates at high speeds [3].

This paper conducted an experimental study on the performance of coconut oil-based nano fluids as lubricants in the turning of AISI 304 austenitic stainless steel. Nano fluid lubricants were prepared with suspensions of nano boric acid in coconut oil, so that the thermal conductivity and heat transfer

coefficient increased, and the specific heat decreased with increasing percentage of nano boric acid. Cutting temperatures, tool side wear and surface roughness were therefore significantly reduced with Nano lubricants compared to the base oil due to its superior lubricating properties. In all cases, coconut oil with 0.5% nano boric acid suspensions showed better results regarding cutting temperatures, tool flank wear and surface roughness compared to other nano fluids turning AISI 1018 steel with TiAlN coated inserts [2].

This paper investigates the effect of hybrid biodegradable nano fluids (CuO-ZnO) on surface roughness; Different classes of biodegradable liquids, especially palm oil and coconut oil, were investigated as base liquids and mixed with a mixture of CuO-ZnO (50:50) nano particles. The effects of cutting parameters and fluid volume concentration were investigated in dry cutting with MQL/coconut oil and MQL/palm oil CuO-ZnO mixture in hybrid nano-fluid mixed media. Taguchi's orthogonal matrix L_9 and L_{18} were selected exclusively for dry and palm oil MQL and coconut oil MQL mixture contrast separately. They reported that the addition of CuO-ZnO hybrid nano particles to the base cutting fluids significantly reduced the surface roughness compared to conventional dry machining. ZnO nano particles act as lubricating oils that reduce the

friction between the workpiece and the tool. Analysis of variance (ANOVA) showed that surface roughness is most affected by feed rate, followed by depth of cut and speed [8].

This paper studs the performed evaluations of turning Ti-6Al-4V alloy with uncoated tungsten carbide, CVD-coated and PVD-coated carbide tools under three different conditions, i.e., dry, palm oil, palm oil mixture, and boric acid lubricant. Surface roughness. Taguchi's $L_{27}(3^5)$ strategy was then used to reveal the ideal cutting parameters for surface roughness. Five control variables were selected in the study, namely, type of machining environment, depth of cut, feed rate, cutting speed and type of carbide tool material. The results showed that palm oil was stronger when used with boric acid cutting fluids compared to dry and palm oil. Palm oil, cutting speed 79 m/min, feed speed 0.206 mm/rev, depth of cut 1.0 mm and CVD coated tool are optimal and safer combination values to reduce surface roughness. The Taguchi model $L_9(3^4)$ was used to compare the experimental soybean-based coolant E52100 with dry and oil-based coolants in chrome steel turning operations. Analysis of the test results showed that the soybean-based cutting fluid performed better against tool wear than the alternative oil product, and both cutting fluids reduced surface roughness equally well [5].

3. Materials and Methodology

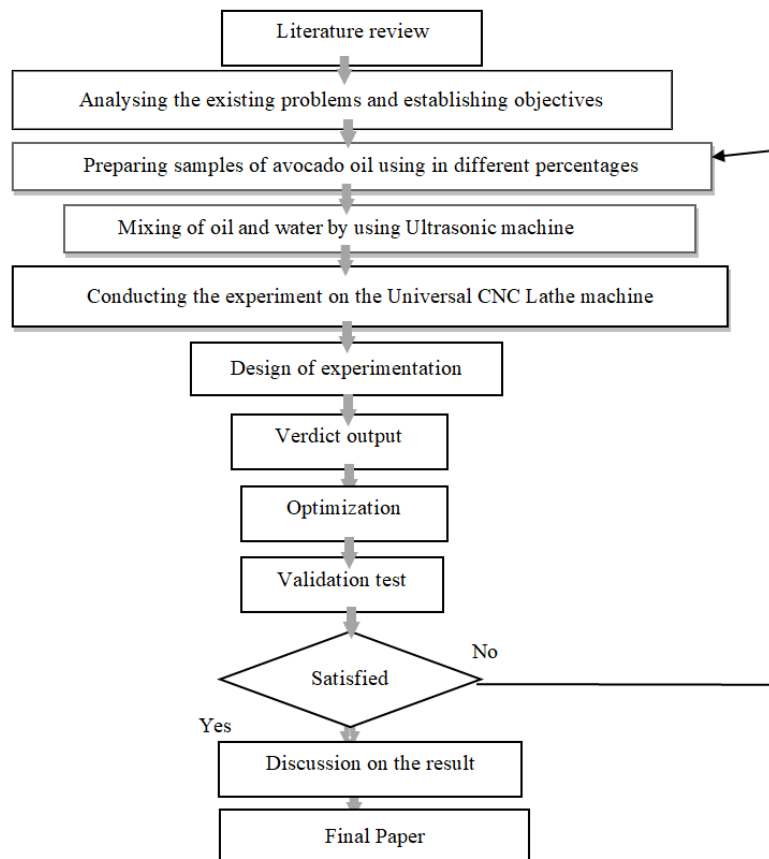


Figure 1. Research Flow chart.

These studies on avocado oil-based cutting fluids were specifically developed to achieve the previously mentioned objectives. To formulate an avocado oil-based cutting fluid for turning operations, a suitable flooding system was identified to improve the machining process's performance. The study

Materials

examined various parameters of the avocado oil-based cutting fluid, including different proportions. This research utilized a turning process to evaluate the effectiveness of the avocado oil-based cutting fluid in machining operations.

Table 1. Machines and equipment used in the experiments.

S.No	Device Name	Purpose of usage
1	CNC Lathe	Used to execute precision rotational machining (turning operations)
2	Sono-Bright Ultrasonic Homogenizer	Utilized to emulsify avocado oil with water
3	Round-Bottom Reaction Flask	Employed to hold the oil-water and distilled water solution
4	Handheld Angle Grinder	Used for surface grinding
5	Surface roughness tester	Employed to quantify surface texture and roughness parameters

3.1. Workpiece Material

The workpiece selected for the study was Aluminium Alloy 7075-T651, presented as a cylindrical bar with a length of 500mm and a diameter of 60 mm. This alloy provides medium strength, high corrosion resistance, and excellent formability. The most commonly available form of this alloy is in the T651 tempering condition. It is typically utilized in architectural applications, shop fittings, irrigation tubing, balustrades, window frames, extrusions, doors, marine equipment, and in both road and rail transport. It is also useful in all applications where high strength, fatigue and creep resistance are required, even at high temperatures.

3.2. Cutting Tool Material

However, when choosing a cutting tool, it is decided to choose an uncoated tungsten carbide insert. Tungsten carbide insert are used in small industries, they are cheaper and more readily available. There is no need to change the insert before and after machining operation. Therefore, tungsten carbide insert cutting tool was used in this study.

3.3. The Measurements of Output Parameters

The output parameters, such as surface roughness and material removal rate, were measured to evaluate the performance of the avocado oil-based cutting fluid. This section describes the equipment used to measure these output parameters and provides a detailed description of each.

3.3.1. Surface Roughness, (Ra) Measurement

In the manufacturing industry, particularly in machining, special attention is given to dimensional accuracy and surface finish. The surface roughness of the machined surface is crucial for determining quality, as it impacts tolerances, reduces assembly time, and minimizes the need for secondary operations. A good surface finish enhances the performance, fatigue strength, corrosion resistance, and aesthetics of the machined part. Surface roughness serves as the primary indicator of the mechanical part's effectiveness. If irregularities are present, cracks or corrosion can develop on the surface. Each machined part of the workpiece was measured three times at different points along the 100 mm length of the machined section of the square bar workpiece during each test, and the average of the three readings was used for analysis. Vogel surface roughness tester device is shown in below [Figure 2](#).



Figure 2. Photographic view of vogel surface roughness tester.

3.3.2. Material Removal Rate (MRR)

The material removal rate can be defined as the ratio of the volume of material removed to the machining time. The measurement is expressed in grams per second (g/sec). The weight of the work piece was measured with a digital weighing balance (Model: MP-6000g/1g, Citizon), which can measure up to 6000g accurately and thus eliminates a large possibility of error when calculating the material removal rate during milling operation. The difference in weight before and after the study is calculated. The machining time of each operation is well known during the machining. The measurement of material removal rate was performed at Wolaita Sodo University mechanical engineering machine shops using a digital weighing balance. The material removal rate is calculated using the following Equation (1) [13]:

$$MRR = \frac{L_{i\text{work piece}} - L_{f\text{work piece}}}{M_t} \quad (1)$$

Where: $L_{i\text{work piece}}$ - is the initial load of work piece (gm),

$L_{f\text{work piece}}$ - is the final load of work piece (gm),

M_t - is the machining time in second (sec.)

Material removal rate is determined by the support of digital weighing balance (Model: MP-6000g/1g, Citizon), as shown in Figure 3.



Figure 3. Digital weighing balance.

3.4. Design of Experiments (DOE)

3.4.1. Design of Experiment Techniques

The Taguchi Design is chosen to assess the relative importance of various parameters. This experimental design technique effectively reduces the number of required experiments by utilizing orthogonal arrays. Its primary goal is to minimize the influence of uncontrollable factors and their effects. The fundamental philosophy of the Taguchi method is to ensure quality during the design stage. The key advantages of this approach include shortened test duration, lower costs, and quicker identification of significant factors [4].

The most reliable aspect of Taguchi's techniques is the use

of parametric design, an engineering approach for product or process design. The primary goal of the Taguchi method is to identify the optimal parameter settings that achieve the highest quality characteristics while minimizing variation. A crucial step in planning an experiment is the selection of control factors. Including as many factors as possible allows for the rapid identification of irrelevant variables [17].

Taguchi utilized the signal-to-noise ratio (S/N) as his preferred quality characteristic. The signal-to-noise ratio is employed instead of the standard deviation as the measured value because when the mean value decreases, the standard deviation also tends to decrease, and vice versa [15].

A total of 16 experiments were conducted based on the orthogonal matrix $L_{16}(4^4)$ of the Taguchi method with different combinations of input parameter levels. In this study, the experimental setup was based on the design of experiments (DoE) using the Taguchi method, focusing on four variables: cutting speed, feed rate, depth of cut, and cutting fluids. These variables were treated as experimental factors. Consequently, there were four input parameters, each with four levels, as shown in Table 2. In a four-factor, four-level experiment, Taguchi defined an orthogonal matrix $L_{16}(4^4)$ for the experiment. The confidence level assigned to the analysis is 95%.

3.4.2. Orthogonal Arrays

To minimize the total number of tests, Sir Ronald Fisher developed the concept of "Orthogonal Arrays." Taguchi employs these specially designed arrays in experimental design to ensure that quality is integrated into the product at the design stage. In this study, the columns are orthogonal to each other, facilitating a comprehensive analysis of the factors involved [1].

This means that each pair of columns contains all combinations of factors and they occur the same number of times and parameters. If the model was $L_{16}(4^4)$ it represents the sixteen row, configurations or prototypes being tested. The specific test characteristics of each test evaluation are given in the corresponding row of the table [6].

Thus, ' $L_{16}(4^4)$ ' means that sixteen experiments must be conducted to examine four variables at four levels. At least four levels of process parameters are desirable to achieve sufficient accuracy.

3.4.3. Analysis of Variance (ANOVA)

Analysis of variance (ANOVA) is utilized to determine the percentage contribution of input process parameters to the response variables. To assess the significant effects and the individual impact of various machining conditions, the experimental results were evaluated using ANOVA [7].

This study was conducted using a 95% confidence level and a 5% significance level. The test results were analyzed using the signal-to-noise ratio (S/N) and analysis of variance (ANOVA) to identify the optimal and significant factors affecting surface roughness. The surface roughness of the machined part is influenced by cutting speed, feed rate, depth of

cut, and cutting fluid. Since a lower surface roughness value is desirable, the performance of the cutting fluids was analyzed using the Taguchi optimization process, which is based on the "smaller is better" principle for the characteristic ratio of surface roughness (S/N) in static tasks. Therefore, a method for calculating the Signal-to-Noise ratio has been employed to assess the quality characteristic. The two types of quality characteristics considered are as follows:

- (i) Smaller-the-better, and
- (ii) Larger-the-better

The performance of the avocado oil-based cutting fluid was analyzed using Taguchi's "lower-the-better" quality characteristic, specifically the signal-to-noise (S/N) ratio for surface roughness. The S/N ratios for surface roughness were calculated using the following Equation (2) [12]:

$$S/N = -10 \log_{10} \left(\frac{\sum y^2}{N} \right) \quad (2)$$

The performance of the avocado oil-based cutting fluid was analyzed using Taguchi's "higher-the-better quality" characteristic (S/N ratio) for the metal removal rate. The Signal-to-Noise ratio for the metal removal rate was calculated using the following Equation (3) [11]:

$$S/N = -10 \log_{10} \left(\frac{1}{n} \sum \frac{1}{y^2} \right) \quad (3)$$

The steps of grey relational analysis are as follows:

Step 1: Involves generating experimental data tables through the Design of Experiment.

Step 2: Generate Grey Relational Analysis. This process involves normalizing the values using a formula that scales the data to a range of 0 to 1. The surface roughness values are normalized, and the function is minimized according to the following Equation (4) [10].

Lower the better

$$Z_{ijk} = \frac{\max(y_{ij}) - y_{ij}}{\max(y_{ij}) - \min(y_{ij})} \quad (4)$$

Where: Z_{2jk} - an experimental run of Ra

y_{ij} - is an experimental run of Ra pre-processing.

Max (y_{ij}) - Maximum value of original data.

Min. (y_{ij}) - minimum value of original data, $i=1, 2, 3 \dots m$

The material removal rate values are normalized, and the function is maximized according to the following Equation (5) [14].

Higher the better

$$Z_{ijk} = \frac{y_{ij} - \min(y_{ij})}{\max(y_{ij}) - \min(y_{ij})} \quad (5)$$

Where: Z_{2jk} - an experimental run of MRR

y_{ij} - is an experimental run of MRR pre-processing.

Max (y_{ij}) - Maximum value of original data.

Min. (y_{ij}) - minimum value of original data, $i=1, 2, 3 \dots m$

Step 3: Calculation of the grey relational coefficient. To compute the GRC use below Equation (6) [8].

$$\lambda(Y_{oj}, Y_{ij}) = \left[\frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{ij} + \zeta \Delta_{\max}} \right] \quad (6)$$

ζ - Coefficient of distinguishing and its range 0 to 1.

Step 4: Involves calculating the Grey Relational grade, which is obtained by finding the mean of the grey coefficients for each variable at the i^{th} run. The Grey Relational Grade serves as a measure of the overall performance of the multiple response technique. The level with the highest Grey relational grade represents the optimum level of the process parameters. To achieve this, a multiple response optimization problem with a grey relational objective function is transformed into an overall grey relational grade using Equation (7) [16].

$$\gamma_i = \frac{1}{n} \sum_{k=1}^n \zeta_i(k) \quad (7)$$

Where: γ_i - grey relational grade

n - replication number for response

Step 5: The optimal factor setting for maximum overall grey relational grade can be performed by Taguchi's method.

The selection of factor

The parameters investigated in this study was surface roughness was influenced by several factors, including cutting speed, depth of cut, feed rate, and types of cutting fluid. The selection of parameters for this experiment was informed by previous research in machining, literature reviews, tool manufacturing recommendations, workpiece material properties, available machine settings, and various research articles and manuals. Consequently, these factors were considered in the experimental design.

3.4.4. The Selection of Input Parameter Value

When selecting parameter values, recommendations from the literature review, technical and technological limitations of the machine and tools, properties of the workpiece material, and findings from previous experimental studies were taken into account. However, considering all these factors proved to be costly and time-consuming. A review of the literature indicates that the most significant input factors influencing the values of the aforementioned output parameters, particularly surface roughness, are crucial for effective machining.

Table 2. Machining parameters and their levels.

Machining parameters		Levels			
Input parameter	Unit	Level 1	Level 2	Level 3	Level 4
Cutting speed	rpm	900	1000	1100	1200
Feed rate	mm/min	85	90	95	100
Depth of cut	mm	0.5	1	1.5	2
Avocado oil fluids	%	0	3	6	9

4. Result and Discussion

4.1. Design Summary

Taguchi Array L16 (4⁴)

Factors: 4

Runs: 16

Columns of L16 (4⁵) array: 1 2 3 4

Table 3. Experimental result for Ra and MRR.

S/N	Fluid: AO	Exp.No	Input parameters			Output parameters	
			Cutting speed	Feed rate	Depth of cut	Ra (μm)	MRR (g/sec)
1	0% AO with 100% DW	Exp.1	900	85	0.1	2.10	0.1325
		Exp.2	900	90	1	2.40	0.1250
		Exp.3	900	95	1.5	0.30	0.3125
		Exp.4	900	100	2	2.20	0.3000
2	3% AO with 97% DW	Exp.5	1000	85	1	2.20	0.3280
		Exp.6	1000	90	0.1	2.90	0.2550
		Exp.7	1000	95	2	2.30	0.2120
		Exp.8	1000	100	1.5	2.70	0.2040
3	6% AO with 94% DW	Exp.9	1100	85	1.5	1.30	0.3800
		Exp.10	1100	90	2	0.70	0.3600
		Exp.11	1100	95	0.1	0.10	0.2430
		Exp.12	1100	100	1	2.40	0.1730
4	9% AO with 91% DW	Exp.13	1200	85	2	0.20	0.3750
		Exp.14	1200	90	1.5	2.20	0.2040
		Exp.15	1200	95	1	1.14	0.3830
		Exp.16	1200	100	0.1	0.30	0.3760

4.2. Surface Roughness

4.2.1. Signal-to-Noise (S/N) Ratio Analysis

(i). Main Effect Plot for Surface Roughness, Ra (μm)

The main effect plots for the surface roughness obtained from S/N ratio values of the machining parameters at different levels are shown in below (Figure 4). The plot of the main effect of S/N ratio as shown in Figure 4 was used for optimum value determination for each input parameters during milling operation for the surface roughness. For surface roughness response, the smaller the better characteristics was chosen as shown Figure 4. The objective of this study was to minimize

surface roughness. These identified factor levels were considered as the optimum factors. Based on the analysis of Figure 4, it is evident that the minimum surface roughness, indicating optimal conditions, was achieved with specific factor levels. Specifically, a 3% proportion of avocado oil-based cutting fluid at level 1, a cutting speed of 1200 rpm at level 4, a feed rate of 95mm/min at level 3, and a depth of cut of 0.5mm at level 1 were found to yield the best results. The findings from the analysis suggest that the 9% proportion of avocado oil-based cutting fluid has a more significant impact on surface roughness compared to other proportions of the same cutting fluid. In other words, this particular factor level has a greater influence on achieving the desired outcome of minimizing surface roughness. Overall, this study highlights the importance of carefully selecting the appropriate factor levels to optimize surface roughness and achieve the desired results.

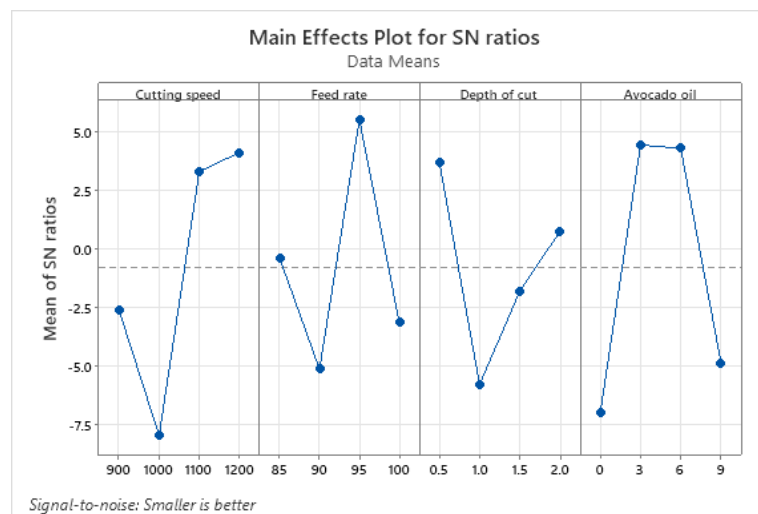


Figure 4. Main effect plot for Surface roughness.

(ii). ANOVA Analysis

The ANOVA result was used to study the significance of the input parameters on the surface roughness. It is another way of understanding the importance of avocado oil based cutting fluid on surface roughness in this study. The ANOVA for surface roughness shown in Table 4, a percentage error of 0.86% while 29.69% of avocado oil based cutting fluid, 8.56% of the depth of cut, 41.16% of cutting speed and 19.7% of feed rate. The ANOVA table generated using Minitab software version 19 reveals that all input parameters with P-values less than

0.05 have validated a significant impact on the variability of surface roughness.

Therefore, ANOVA table shows that 41.16% of cutting speed has highest significance and have most important factor affecting surface roughness during the turning operation compared to other input parameters on the surface roughness. Hence, the results indicated that the cutting speed based cutting fluids has the highest significance on the surface roughness, followed by the depth of cut. This is in agreement with the study carried out by (Hasan et al., 2022), in which their finding showed that the surface roughness is dependent on the cutting speed based cutting fluids.

Table 4. ANOVA for Ra versus Oil, Speed, Feed and Doc.

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%C	Hypothesis
Cutting speed	3	6.0518	2.01727	47.35	0.005	41.16	Significant

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%C	Hypothesis
Feed rate	3	2.8968	0.96560	22.67	0.015	19.7	Significant
Depth of cut	3	1.2578	0.41927	9.84	0.046	8.56	Significant
Avocado oil	3	4.3658	1.45527	34.16	0.008	29.69	Significant
Error	3	0.1278	0.04260			0.86	
Total	15	14.7000					

(iii). Regression Analysis: Ra versus Oil, Speed, Feed, Doc

Regression Equation

$$Ra = 5.41 - 0.00377 \text{ CS} - 0.00624 \text{ FR} - 0.082 \text{ DC} - 0.0523 \text{ AO} \quad (8)$$

4.3. Material Removal Rate

Signal-to-Noise (S/N) Ratio Analysis

4.3.1. Main Effect Plot for Material Removal Rate, MRR (g/sec)

The main effect plots for the material removal rate obtained from S/N ratio values of the machining parameters at different levels are shown in below Figure 5. The plot of the main effect of S/N ratio as shown in Figure 5 was used for optimum value determination for each input parameters during milling operation for the material removal rate. For material removal rate response, the larger the better characteristics was chosen as shown Figure 5. The objective of this study was to minimize

material removal rate. These identified factor levels were considered as the optimum factors. Based on the analysis of Figure 5, it is evident that the maximum material removal rate, indicating optimal conditions, was achieved with specific factor levels. Specifically, a 6% proportion of avocado oil-based cutting fluid at level 3, a cutting speed of 1200 rpm at level 4, a feed rate of 85mm/min at level 1, and a depth of cut of 2mm at level 4 were found to yield the best results. The findings from the analysis suggest that the 9% proportion of avocado oil-based cutting fluid has a more significant impact on material removal rate compared to other proportions of the same cutting fluid. In other words, this particular factor level has a greater influence on achieving the desired outcome of maximizing material removal rate. Overall, this study highlights the importance of carefully selecting the appropriate factor levels to optimize material removal rate and achieve the desired results.

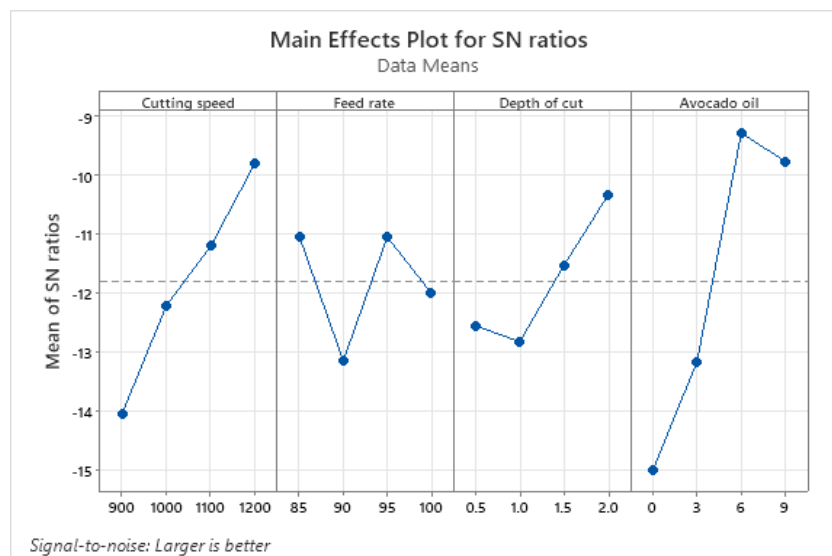


Figure 5. Main effect plot for material removal rate.

4.3.2. ANOVA Analysis

The ANOVA result was used to study the significance of the input parameters on the material removal rate. It is another way of understanding the importance of avocado oil based cutting fluid on material removal rate in this study. The ANOVA for material removal rate shown in Table 5, a percentage error of 0.2% while 58.73% of avocado oil based cutting fluid, 7.74% of the depth of cut, 24.79% of cutting speed and 8.51% of feed rate. The ANOVA table generated using Minitab software version 19 reveals that all input parameters

with P-values less than 0.05 have validated a significant impact on the variability of material removal rate. Therefore, ANOVA table shows that 58.73% of avocado oil has highest significance and have most important factor affecting material removal rate during the turning operation compared to other input parameters on the material removal rate. Hence, the results indicated that the avocado oil based cutting fluids has the highest significance on the material removal rate, followed by the depth of cut. This is in agreement with the study carried out in which their finding showed that the material removal rate is dependent on the avocado oil based cutting fluids.

Table 5. ANOVA for MRR versus Oil, Speed, Feed and Doc.

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%C	Hypothesis
Cutting speed	3	0.030635	0.010212	123.50	0.001	24.79	Significant
Feed rate	3	0.010523	0.003508	42.42	0.006	8.51	Significant
Depth of cut	3	0.009573	0.003191	38.59	0.007	7.74	Significant
Avocado oil	3	0.072576	0.024192	292.57	0.000	58.73	Significant
Error	3	0.000248	0.000083			0.2	
Total	15	0.123555					

4.3.3. Regression Analysis: Ra Versus Oil, Speed, Feed, Doc

$$\text{MRR} = -0.141 + 0.000390 \text{ CS} - 0.00141 \text{ FR} + 0.023455 \text{ DC} + 0.01849 \text{ AO} \quad (9)$$

4.4. Simultaneous Response Optimization

4.4.1. Grey Relational Analysis (GRA)

This analysis was performed on the response values to consolidate multiple performance characteristics into a unified

metric. By integrating the Taguchi method with Grey Relational Analysis (GRA), multi-response optimization was conducted to determine the ideal process parameters. GRA simplifies complex, multi-objective problems into an equivalent single-response framework by computing a grey relational grade, thereby merging various performance measures into a single representative value for optimization.

Table 6. Response with replication.

Factors	A	B	C	D	Response	
Exp.No	Column					
	Cutting speed	Feed rate	Depth of cut	Avocado oil	Ra (μm)	MRR (g/sec)
1	900	85	0.5	0	2.1	0.1325
2	900	90	1	3	2.4	0.125
3	900	95	1.5	6	0.3	0.3125
4	900	100	2	9	2.2	0.3
5	1000	85	1	6	2.2	0.328
6	1000	90	0.5	9	2.9	0.255

Factors	A	B	C	D	Response	
Exp.No	Column					
	Cutting speed	Feed rate	Depth of cut	Avocado oil	Ra (μm)	MRR (g/sec)
7	1000	95	2	0	2.3	0.212
8	1000	100	1.5	3	2.7	0.204
9	1100	85	1.5	9	1.3	0.38
10	1100	90	2	6	0.7	0.36
11	1100	95	0.5	3	0.1	0.243
12	1100	100	1	0	2.4	0.173
13	1200	85	2	3	0.2	0.375
14	1200	90	1.5	0	2.2	0.204
15	1200	95	1	9	1.14	0.383
16	1200	100	0.5	6	0.3	0.376
Maximum					2.9	0.383
Minimum					0.1	0.125
Maximum-Minimum					2.8	0.258

4.4.2. Normalization

During this stage, the available response data is normalized onto a consistent scale ranging from 0 to 1.

Higher the better

$$x_{1jk} = \left[\frac{y_{ij} - \min(y_{ij})}{\max(y_{ij}) - \min(y_{ij})} \right]$$

Where: x_{1jk} - an experimental run of Ra and MRR
 y_{ij} - is an experimental run of Ra and MRR before pre-processing

Max (y_{ij}) - Maximum value of original data.

Min. (y_{ij}) - Minimum value of original data, $i=1, 2, 3 \dots m$

Table 7. Normalized table for the response of Ra and MRR.

Factors	Response	
Exp. No	Ra (μm)	MRR(g/sec)
1	0.714285714	0.029069767
2	0.821428571	0
3	0.071428571	0.726744186
4	0.75	0.678294574
5	0.75	0.786821705
6	1	0.503875969
7	0.785714286	0.337209302
8	0.928571429	0.30620155
9	0.428571429	0.988372093

Factors	Response	
10	0.214285714	0.910852713
11	0	0.457364341
12	0.821428571	0.186046512
13	0.035714286	0.968992248
14	0.75	0.30620155
15	0.371428571	1
16	0.071428571	0.972868217

4.4.3. Absolute Difference

After, normalizing the responses, the next step is to calculate the deviations from the reference sequence.

$$Y_{oj} = \text{Max}_{ijk} = 1$$

$$\Delta_{ij} = |Y_{oj} - x_{ijk}| \quad (10)$$

Table 8. Absolute value of Δ_{ij} .

Factors	Response	
Exp.No	Ra (μm)	MRR(g/sec)
1	0.285714286	0.970930233
2	0.178571429	1
3	0.928571429	0.273255814
4	0.25	0.321705426
5	0.25	0.213178295
6	0	0.496124031
7	0.214285714	0.662790698
8	0.071428571	0.69379845
9	0.571428571	0.011627907
10	0.785714286	0.089147287
11	1	0.542635659
12	0.178571429	0.813953488
13	0.964285714	0.031007752
14	0.25	0.69379845
15	0.628571429	0
16	0.928571429	0.027131783
$\Delta_{\min}$	0	0
$\Delta_{\max}$	1	1

4.4.4. Grey's Relational Coefficient

After pre-processing and normalization of the original data, grey relational coefficients (GRC) are calculated for each run of experiment. The Grey relational coefficient is calculated by normalizing all responses between 0 and 1. The Grey grade is obtained by calculating the average of the Grey relational coefficients of the selected response. Initially, the responses are normalized using Equation (4) based on the smaller -better and the larger -better criterion are called Grey relational generations. Standard test values are compared to normalized values to determine GRC. Table 9 displays the Grey relational coefficients and Grey relational grade, which were calculated using Equations (11). The highest Grey relational grade was assigned a rank of 1. Consequently, experiment number 6 is identified as the optimal combination of composite parameters for achieving the best results in terms of surface roughness and material removal rate among all 6 experiments conducted. By

utilizing Grey relational analysis, the multi-objective optimization problem is transformed into a single equivalent objective function optimization problem. The Taguchi technique is then employed to identify the best combination of process parameters based on the highest Grey relational grade (0.750973). The Grey relational grade (GRG) was computed as the average Grey relational coefficient (GRC) of all output responses within a single experimental trial, as described in Equation (11). This calculation allows for the comparative ranking of all 16 experimental input parameters on a unified scale, with a grade output response of experiment number 16 was rank 1 with the result of GRG was 0.750973 indicating the best performance. Calculation of the grey relational coefficient. To compute the GRC use below Equation (11) [8].

$$\gamma (x_{0j}, x_{ij}) = \left[\frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{ij} + \zeta \Delta_{\max}} \right] \quad (11)$$

ζ – Coefficient of distinguishing and its range 0 to 1 but acceptable value was 0.5.

Table 9. Grey relational coefficient and grey relational grade.

Factors	Response		Total of GRC	Grey relational grade	Grey relational rank
Exp.No	Ra (μm)	MRR(g/sec)			
1	0.636363636	0.339920949	0.976285	0.488142	15
2	0.736842105	0.333333333	1.070175	0.535088	13
3	0.35	0.646616541	0.996617	0.498308	14
4	0.666666667	0.608490566	1.275157	0.637579	8
5	0.666666667	0.701086956	1.367754	0.683877	4
6	1	0.501945525	1.501946	0.750973	1
7	0.7	0.43	1.13	0.565	10
8	0.875000001	0.418831169	1.293831	0.646916	6
9	0.466666667	0.977272727	1.443939	0.72197	2
10	0.388888889	0.84868421	1.237573	0.618787	9
11	0.333333333	0.479553903	0.812887	0.406444	16
12	0.736842105	0.380530974	1.117373	0.558687	11
13	0.341463415	0.941605839	1.283069	0.641535	7
14	0.666666667	0.418831169	1.085498	0.542749	12
15	0.443037975	1	1.443038	0.721519	3
16	0.35	0.948529412	1.298529	0.649265	5

4.4.5. Grey Relational Grade

The GRG evaluation involves analyzing the relationship

between the reference sequence and the comparability sequences to select the optimal experimental outcome based on maximum similarity. When multiple responses are considered

simultaneously, a composite grey relational grade is derived by multiplying each output by its respective weight and aggregating the results.

Table 10. Grey Relational Grade.

Factors	A	B	C	D	
Exp.No	Column				Grey relational grade
	1	2	3	4	
1	1	1	1	1	0.488142
2	1	2	2	2	0.535088
3	1	3	3	3	0.498308
4	1	4	4	4	0.637579
5	2	1	2	3	0.683877
6	2	2	1	4	0.750973
7	2	3	4	1	0.565
8	2	4	3	2	0.646916
9	3	1	3	4	0.72197
10	3	2	4	3	0.618787
11	3	3	1	2	0.406444
12	3	4	2	1	0.558687
13	4	1	4	2	0.641535
14	4	2	3	1	0.542749
15	4	3	2	4	0.721519
16	4	4	1	3	0.649265

4.4.6. Analysis of S/N ratio of Grey Rational Grade (GRG)

The means of the Grey relational grade were calculated for each level of composite parameters using data from Table 10 and then it's summarized in the Table 11.

Table 11. Response table for mean Grey relational grade (GRG).

Level	Input parameters			
	Cutting speed	Feed rate	Depth of cut	Avocado oil
Level 1	0.53977925	0.633881	0.573706	0.5386445
Level 2	0.6616915	0.61189925	0.62479275	0.55749575
Level 3	0.576472	0.54781775	0.60248575	0.61255925
Level 4	0.638767	0.62311175	0.61572525	0.70801025
Max-Min	0.12191225	0.08606325	0.05108675	0.16936575
Rank	2	3	4	1

In Table 11, it was observed that the difference between the maximum and minimum values of GRG (Grey Relational Grade) for the parameter of avocado oil-based cutting fluid is higher compared to cutting speed, feed rate, and depth of cut. The equation in the above states that the larger the Grey relational grade, the better the multiple quality characteristics. The values in the Table 11 are highlighted in the bold to indicate the optimal values of the machining parameters. It can be concluded that avocado oil-based cutting fluid has a stronger effect on the performance characteristics compared to the other parameters. The optimized parameters are as follows: avocado oil (9%), depth of cut (1.0 mm), cutting speed (1000 rpm), and feed rate (85 mm/min).

4.5. Regression Analysis

The obtained data was analyzed using multiple regression

$$Ra = 5.41 - 0.00377 CS - 0.00624 FR - 0.082 DC - 0.0523 AO$$

$$Ra = 0.095$$

4.5.2. Regression Analysis: Material Removal Rate Versus Oil, Speed, Feed, Doc

Optimum parameters obtained from main effect plots of material removal rate are: Oil (6%), cutting speed (1200 rpm), feed rate (85 mm/min) and depth of cut (2 mm). Hence, the regression equation of material removal rate, MRR:

$$MRR = -0.141 + 0.000390 CS - 0.00141 FR + 0.023455 DC + 0.01849 AO$$

$$MRR = 0.365$$

4.6. Validation Tests

The confirmation test is conducted to determine whether the predicted results, based on the optimized process parameters, fall within an acceptable range when compared to the experimental results. Thus, analyzing the confirmation test results can be concluded that the predicted values surface roughness appear to be in good agreement with the experimental values. Confirmation tests were carried out by utilizing the optimal levels of the provided parameters for two cases. Specifically, for Surface roughness with avocado oil based cutting fluid, the optimal levels of cutting parameters were avocado oil based

analysis with Minitab software version 19. The independent variables in the analysis included avocado oil fluid, cutting speed, feed rate, and depth of cut, while the dependent variable of interest was surface roughness. Separate regression models were developed to predict surface roughness based on these cutting variables. The regression equations for the cutting parameters avocado oil, cutting speed, feed rate, and depth of cut were derived from the regression analysis conducted in Minitab.

4.5.1. Regression Analysis: Surface Roughness Versus Oil, Speed, Feed, Doc

Optimum parameters obtained from main effect plots of surface roughness are: Oil (3%), cutting speed (1200 rpm), feed rate (95 mm/min) and depth of cut (0.5 mm). Hence, the regression equation of surface roughness, Ra:

cutting fluid at level 2, cutting speed at level 4, feed rate at level 3 and depth of cut at level 1. The experimental value of Ra was found to be $0.1\mu\text{m}$ which is very close to $0.095\mu\text{m}$ as predicted by equation.

Also, for material removal rate with avocado oil based cutting fluid, the optimal levels of cutting parameters were avocado oil based cutting fluid at level 3, cutting speed at level 4, feed rate at level 1 and depth of cut at level 4. The experimental value of Ra was found to be 0.3830 g/sec which is very close to 0.365 g/sec as predicted by equation.

The results obtained from the generated equations, as well as the corresponding experimental values and percentage errors, have been calculated and are now presented in Table 12 below.

$$\text{Percentage error (\%)} = \frac{\text{Experimental value} - \text{Calculated value}}{\text{Experimental value}} \times 100 \quad (12)$$

Table 12. Validation test for Surface roughness and Material removal rate.

S/N	Response	Calculated value	Experimental value	Percentage Error (%)
1	Surface roughness (μm)	0.095	0.1	5
2	Material removal rate(g/sec)	0.365	0.3830	4.699

The confirmation test results presented in Table 12, showed that the use of avocado oil based cutting fluid in the milling of Alloy 075-T651 work piece produced percentage errors was 5% of surface roughness and 4.699% of material removal rate. In general, these percentage errors are considered statistically acceptable due to their values being below 10%. These results validate that a low percentage error was achieved, thereby indicating a strong correlation between the experimental results and the predicted regression models. In addition, the turning operation conducted using the formulated avocado oil based cutting fluid produced better surface roughness and material removal rate, compared to the other machining operation done using the different types of vegetable oil based cutting fluid. These findings revealed that the formulated avocado oil based cutting fluid can serve as a possible substitute for another vegetable oil based cutting fluid in the turning of machining operation of Alloy 075-T651.

5. Conclusion and Recommendation

5.1. Conclusion

This study explores the experimental evaluation and optimization of material removal rate, and surface roughness as responses in turning Alloy 075-T651 with tungsten carbide cutting tool using the Taguchi method. The findings from experimentation of these responses conclusions are drawn in the following:

The surface roughness by using surface roughness tester and material removal rate by using digital weighing balance involving Taguchi design of experiment using Minitab software version 19 to make simpler and minimized the needed machining runs in order to succeed the needed optimum result from the responses. The performance of the individual responses on the input parameters were accessed using Taguchi method through the evaluation and optimization of the turning parameters. Conclusions are drawn from the findings obtained through experimentation of these responses, as follows: An evaluation from the orthogonal optimal turning parameters for the surface roughness are 3% of avocado oil based cutting fluid (level 2), cutting speed 1200 rpm (level 4), feed rate 95mm/min (level 3) and depth of cut 0.5mm (level 1). Also, for the material removal rate are 6% of avocado oil based cutting fluid (level 3), cutting speed 1200 rpm (level 4), feed rate 85mm/min (level 1) and depth of cut 2mm (level 4).

The ANOVA show that the contribution of input parameters of avocado oil fluid, depth of cut, speed and feed rate has significant effect on the surface roughness with avocado oil fluid (29.69%), depth of cut (8.56%), cutting speed (41.16%) and feed rate (19.7%). So, cutting speed (76.78%) are the greatest significant parameters in decreasing of surface roughness. The confirmation tests carried out using regression equations show reliable results as the percentage error was 0.86%, for surface roughness respectively.

Additionally, an ANOVA show that the contribution of input parameters of avocado oil fluid, depth of cut, speed and feed rate has significant effect on the material removal rate with avocado oil fluid (58.73%), depth of cut (7.74%), cutting speed (24.79%) and feed rate (8.51%). So, an avocado oil fluid (58.73%) are the greatest significant parameters in decreasing of material removal rate. The confirmation tests carried out using regression equations show reliable results as the percentage error was 0.2%, for material removal rate respectively.

These percentage errors are generally believed statically acceptable (<10%).

This experimental study shows that avocado oil based cutting fluid could be used in machining process with potential ability to reduce the occupational health risks, lower costs towards waste treatment due to their higher biodegradability and better performance rate. From Taguchi analysis an optimized multi-response turning parameters was achieved by using the parameters are avocado oil (9%), cutting speed (1000 rpm), feed rate (85 mm/min) and depth of cut (1mm).

5.2. Recommendation

Extended studies are needed to evaluate and optimize the formulated avocado oil-based cutting fluid and address different machining process applications such as grinding, drilling and milling of different types of metals with different cutting tool and other machining variables such as cutting force, friction coefficient, cutting temperature, chip formation, which helps the machine industry access an environmentally friendly cutting fluid that produces suitable machined products. Thus, for future work, it is recommended to increase the range of cutting parameters such as cutting speed, feed rate, and depth of cut, with different mixing ratios of water with oil, which can later be used in different machining operation with fluid apply method to compare their effectiveness.

Abbreviations

ANOVA	Analysis of Variance
Adj MS	Adjusted Mean Square
Adj SS	Adjusted Sum of Square
Al	Aluminium
AO	Avocado Oil
CS	Cutting speed
DoE	Design of Experiments
DC	Depth of cut
DW	Distilled water
FR	Feed Rate
GRA	Grey Relational Analysis
GRG	Grey Relational Grade
MRR	Metal Removal Rate
OA	Orthogonal Array
Ra	Surface Roughness
R-sq	R Square

R-sq(Adj)	Adjusted R Square
R-sq(Pred)	Predicted R Square
S/N	Signal-to-Noise Ratio
R^2	Coefficient of Determination

Author Contributions

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Conflicts of Interest

The authors declare no conflicts of interest.

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