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ORIGINAL ARTICLE

# Comparison of metal removal rate and surface roughness optimization for AISI 316L using sunflower oil minimum quantity lubrication and dry turning processes

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**ABSTRACT** – The turning process is one of the significant machining processes widely applied in manufacturing industries. The study compared the minimum quantity lubrication turning process using sunflower oil lubrication and the dry turning process for AISI 316L material. In this study, a genetic algorithm was used to optimize material removal rate and surface roughness. Tool nose radius, cutting speeds, feed rates, and depth of cut was chosen as process parameters. The result of the process was a fitness function, which reflects the correlation between process parameters and material removal rate or surface roughness. The genetic algorithm uses the fitness function to yield optimum process parameters with the highest material removal rate and lowest surface roughness in a separate optimization process. The optimization method developed in the study can be applied to predict optimum material removal rate and surface roughness values for minimum quantity lubrication or dry turning process. The study concluded that the minimum quantity lubrication technique could yield favorable machining results with a higher material removal rate and lower surface roughness.

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## INTRODUCTION

Material removal rate (MRR) and surface roughness ($R_a$) are significant factors in machining quality evaluation [1, 2]. Turning is a dominant machining process widely found in manufacturing industries. In turning, speeds and feeds, tool condition, work material, and cutting fluid are machining parameters that affect the overall machining process efficiency and performance. Selecting the most appropriate machining parameters to improve cutting productivity and product quality is essential [3].

Today, clean production has become a prime goal in manufacturing industries. A key method to reduce environmental pollution in manufacturing involves reducing pollution caused by cutting fluid. Clean production is a concept that aims to improve environmental quality. Krolczyk et al. [4] reported a series of experiments involving dry and lubricated turning and measurement of surface roughness, cutting force, tool life, cutting energy, and tool-chip friction coefficient. Their study focused on the effect of dry cutting on duplex stainless steel machining using coated carbide cutting tool.

Heightened global awareness of environmental and health issues has caused industries to exert efforts to reduce or stop the use of cutting fluid. The minimum quantity lubrication machining technique helps reduce the use of cutting fluid. The minimum quantity lubrication technique involves the use of a small amount of cutting fluid applied to the cutting tool-workpiece interface. Compared to dry turning and cutting with cooling fluid, the minimum quantity lubrication technique can reduce the friction coefficient and cutting temperature. Some experimental studies have investigated the potential of the minimum quantity lubrication technique in the high-speed drilling process [5]. According to Karabulut et al. [6], minimum quantity lubrication has been proven as an effective method to replace the application of cooling fluid in the metal cutting process. Minimum quantity lubrication eliminates cutting fluid purchase and management from cost components and thus reduces overall machining costs [7]. In the study of Panday et al. [8], the performance of different oils in turning aluminum 6061 with minimum quantity lubrication is compared to machining under dry circumstances. The minimum quantity lubrication condition was studied using vegetable oil and hydraulic oil. The results show that the minimum quantity of lubrication utilizing vegetable and hydraulic oils produces a higher surface finish. In addition, requirements for green manufacturing are being studied, with technically and economically favorable results. Using vegetable oils as cutting fluids is a path to a cleaner, more sustainable production. The performance of corn oil was investigated in terms of surface roughness and tool wear of AISI D2 hardened steel with ceramic wiper inserts. They concluded that the surface roughness observed with minimum quantity lubrication turning was lower than dry turning [9]. Touggui et al. [10] conducted a study to improve the machining performance in turning on AISI 304 austenitic stainless steel (ASS) under dry, minimum quantity lubrication, nanofluids, and hybrid nanofluid-assisted minimum quantity lubrication conditions. The main purpose of this experimental study is to evaluate and compare the effect of dispersed nano-additives in the vegetable cutting fluid on the responses under consideration. Multi-walled carbon nanotube, nano


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molybdenum disulfide, and nanographene particles have been used as nano-additives. It is worth mentioning that the nanographene can perform as a lubricant/coolant, thus contributing positively to the turning process.

There has been a significant increase in the use of stainless steel in various fields of engineering. Austenitic stainless steel (ASS) is high-quality material with high chromium content but low molybdenum content. A type of chromium-nickel-molybdenum ASS, AISI 316L is designed to provide corrosion resistance in environments with medium corrosivity and can be used in biomedical equipment and human body implants [11, 12]. Asiltürk and Akkus [13] performed a series of dry-cutting experiments on hardened AISI 4140 steel using a coated carbide tool. Their study concluded that feed rate significantly affected surface hardness.

Vegetable oils show similar or even better lubrication performance than petroleum [14]. The type of vegetable oil selected for this study was reviewed based on its thermal and lubricating properties. The thermal properties reviewed include heat capacity, thermal conductivity, and dynamic viscosity. In general, the coolant is expected to have a low viscosity so that the coolant can reach the cutting area properly. In addition, the coolant should also have a high value of heat capacity and thermal conductivity. One that affects the lubricating properties of an oil is the composition of unsaturated fatty acids. The greater the chain composition of unsaturated fatty acids, the better the lubrication layer that will be produced [14]. Estearic is a fatty acid chain with 18 unsaturated carbons. Rojas et al. [15] show the composition of fatty acid chains of various types of vegetable oils and compare the thermal properties of those vegetable oils. Sunflower oil was then chosen because it is better than canola oil, corn oil, cotton oil, and soybean oil, based on an assessment of the Estearic fraction, heat capacity, thermal conductivity, and dynamic viscosity. The assessment is carried out by giving a load for each criterion of thermal properties and also its lubricating properties.

The development of manufacturing processes has resulted in the increasing need to optimize the process for better time, cost, and result efficiencies. Mathematically, optimization is a way to obtain extreme maximum or minimum values from a certain function under certain limiting factors [16]. As a random seeking method, the genetic algorithm (GA) is widely used due to its ability to obtain optimum global values. Several studies have claimed the genetic algorithm is a method that could yield satisfactory results in various manufacturing processes [17–19].

This study compared the material removal rate and surface roughness values resulting from AISI 316L turning process using the minimum quantity lubrication technique with sunflower oil and the dry-cutting technique. The study used the genetic algorithm optimization method to obtain the optimum material removal rate and surface roughness. Optimization was achieved by using the data obtained from a limited number of experiments. The data were then processed using the genetic algorithm optimization method chosen to obtain the optimum results desired.

## EXPERIMENTAL DETAIL

### Mathematical Models

The model generated by this method is affected by various parameters, and the goal is to optimize the model. The response is expressed as a function of process parameters and is called a variable called a multiple regression model. Generally, Eq. (1) gives a multiple regression second-order cross-product model with k independent variables [20].

$$y_i = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + \sum_{j=1}^{k} \beta_{jj} x_{ij}^2 + \sum_{j<i}^{k} \beta_{ij} x_i x_j \tag{1}$$

$$i = 1, 2, \ldots, n; j = 1, 2, \ldots, k$$

where $\beta_0$ is a constant term, $\beta_j$ is the coefficient of the linear terms, $\beta_{jj}$ is the coefficient of the quadratic terms, $\beta_{ij}$ is the coefficient of the cross-product term, and $x_i$, $x_j$ are variables.

### Genetic Algorithms

Inspired by the biological evolution process, the genetic algorithm, which was first introduced by Holland in the 1970s, is a seeking and optimizing algorithm whose application involves computational techniques [21]. With its easy operability, minimum requirements, and global perspective, the genetic algorithm has proven to successfully solve various problems [21]. The genetic algorithm simulates such biological system characteristics as self-repair and reproduction. The evolution process is random but is guided by a selection mechanism based on the individual structural match. The genetic algorithm optimization process starts with establishing an initial population from possible solutions and proceeds toward better a better solution. A group of individuals represents a population and a group of populations will form another population until a certain number of generations or a satisfactory fitness level is achieved for that population. Generally, the genetic algorithm optimization process follows the following procedure: determination of initial population, evaluation, selection, crossover, and mutation. The first generation is created randomly based on a set of predetermined chromosomes. To produce the desired solution and a certain number of chromosomes in a population, a set of requirements must be fulfilled in the process [22, 23]. A chromosome consists of several genes. As in biological evolution, each gene in a chromosome shows certain process parameters. For example, gene 1 represents cutting tool nose radius, gene 2 represents cutting speed, gene 3 represents feed rate, and gene 4 represents cutting depth. Too small several chromosomes pose a limitation on the number of individuals that can be used in crossover and mutation processes, causing the whole process to be futile. Conversely, too many chromosomes would slow down the genetic algorithm process. Therefore, it is recommended that the number of chromosomes is higher than that of the genes in one chromosome. However, another fundamental factor to be considered is that too many genes are not recommended [22].

### Materials and Equipment

The work material used was AISI 316L, with the following chemical composition: 0.03% C, 17% Cr, 0.1% N, 2% Mn, 2.5% Mo, 12% Ni, 0.045% P, 0.03% S, 0.75% Si (% of weight). With a tensile strength of 485 MPa and a hardness of 195 BHN, the material comes in a cylindrical shape of 63 mm in diameter and 100 mm in length. All tests were performed on an LA-530 lathe as shown in Figure 1. The machine has 12 levels of rotation speed and 16 levels of feed speed. In the experiments, tungsten carbide inserts with VBMT-160404 and VCMT-160408 were used. The resulting surface roughness was measured using Mitutoyo (SJ-410) testing instrument with a cut-off value of 0.8 mm (Figure 2).

**Figure 1.** A machine tool was used for the experiments [3]

**Figure 2.** Portable surface roughness tester [3]

Selected sunflower oil for cutting fluids is based on the evaluation of the Estearic fraction, heat capacity, thermal conductivity, and dynamic viscosity. Experiments with minimum quantity lubrication conditions were achieved when the cutting fluid rate was between 5 – 500 ml/h [24]. Cutting fluid is dripped onto the tooltip every 1 second. Each drop has a volume of 0.04 ml, so the cutting fluid rate is 144 ml/h.

### Research Methodology

Research methodology is the representation of the procedures performed in a study. As Figure 3 illustrates, the study followed the following algorithm: identification of process parameters and responses, finding limits and levels, construction of design experiment, data collection, model development, and optimization. The material removal rate was directly affected by cutting speed, feed rate, and depth of cut, while surface roughness was by cutting speed, feed rate, and tool nose radius. Machining work began with determining the number of independent process parameters and their levels. The process parameters consisted of tool nose radius, cutting speed, feed rate, and depth of cut. Levels were decided based on the range suggested in the reference of each of the parameters. The study referred to the material and tool specifications from Mitsubishi Materials Technical Data [25] and the process parameters and levels listed in Table 1.

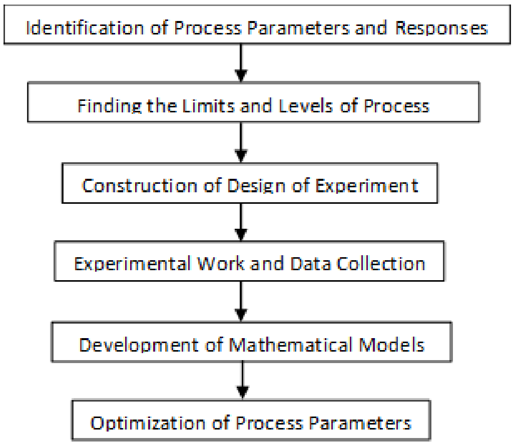


**Figure 3.** Optimization procedure flow diagram

**Table 1.** Process parameters and their levels

| Symbol | Process parameters | Levels | | |
|---|---|---|---|---|
| | | 1 | 2 | 3 |
| $r_\varepsilon$ | Tool nose radius (mm) | 0.4 | 0.8 | - |
| $v_c$ | Cutting speed (m/min) | 95 | 127 | 185 |
| $f$ | Feed rate (mm/rev) | 0.053 | 0.11 | 0.21 |
| $d$ | Depth of cut (mm) | 0.3 | 0.6 | 0.9 |

## Design of Experiments

An orthogonal structure design matrix was used in planning the experiment. Based on the design, the purpose of the experiment was to obtain the material removal rate and surface roughness. The correlation between the response and process parameter variables was determined using a second-order cross-product model multiple regression. The minimum number of experiments that can represent the entire data is indicated by the $L_{18}$ orthogonal array. The resulting combination and level of process parameters can be regarded as an experimental design, as shown in Table 2. The cutting process model was based on the cutting conditions, namely cutting tool nose radius, cutting speed, feed rate, and depth of cut.

**Table 2.** Design of experiments

| No. | Tool nose radius $r_\varepsilon$ (mm) | Cutting speed $v_c$ (m/min) | Feed rate $f$ (mm/rev) | Depth of cut $d$ (mm) |
|---|---|---|---|---|
| | $x_1$ | $x_2$ | $x_3$ | $x_4$ |
| 1 | 0.4 | 95 | 0.053 | 0.3 |
| 2 | 0.4 | 95 | 0.11 | 0.6 |
| 3 | 0.4 | 95 | 0.21 | 0.9 |
| 4 | 0.4 | 127 | 0.053 | 0.3 |
| 5 | 0.4 | 127 | 0.11 | 0.6 |
| 6 | 0.4 | 127 | 0.21 | 0.9 |
| 7 | 0.4 | 185 | 0.053 | 0.6 |
| 8 | 0.4 | 185 | 0.11 | 0.9 |
| 9 | 0.4 | 185 | 0.21 | 0.3 |
| 10 | 0.8 | 95 | 0.053 | 0.9 |
| 11 | 0.8 | 95 | 0.11 | 0.3 |
| 12 | 0.8 | 95 | 0.21 | 0.6 |
| 13 | 0.8 | 127 | 0.053 | 0.6 |
| 14 | 0.8 | 127 | 0.11 | 0.9 |
| 15 | 0.8 | 127 | 0.21 | 0.3 |
| 16 | 0.8 | 185 | 0.053 | 0.9 |
| 17 | 0.8 | 185 | 0.11 | 0.3 |
| 18 | 0.8 | 185 | 0.21 | 0.6 |

# RESULTS AND DISCUSSION

## Experiment and Modeling

Schematically, experimental modeling is shown in Figure 4.

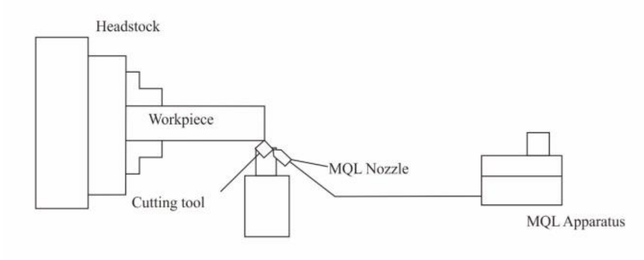


**Figure 4.** Experimental set-up

The responses produced by this experiment are material removal rate and surface roughness. Use the following equation to obtain the material removal rate (MRR) value:

$$MRR = \frac{V}{t_c} \tag{2}$$

The volume ($V$) of the cut material is obtained by subtracting the final weight after machining from the initial weight of the material. This value is divided by the material density of AISI 316L steel of 7.98 g/cm$^3$. The processing time of $t_c$ is measured with a stopwatch. The surface roughness value is obtained using a surface roughness measuring instrument.

Table 3 lists the material removal rate and surface roughness values obtained through experiments under dry turning [3] and minimum quantity lubrication turning.

**Table 3.** Material removal rate and surface roughness resulting from experiments

| No. | MRR | | | $R_a$ | | |
|---|---|---|---|---|---|---|
| | $y_{1dry}$ (cm$^3$/min) | $y_{1MQL}$ (cm$^3$/min) | *Difference* (cm$^3$/min) | $y_{2dry}$ (µm) | $y_{2MQL}$ (µm) | *Difference* (µm) |
| 1 | 0.83 | 0.50 | -0.33 | 0.75 | 1.01 | 0.26 |
| 2 | 2.75 | 1.00 | -1.75 | 1.54 | 0.95 | -0.59 |
| 3 | 6.89 | 7.52 | 0.63 | 2.91 | 1.38 | -1.53 |
| 4 | 0.47 | 0.50 | 0.03 | 1.01 | 1.10 | 0.09 |
| 5 | 1.73 | 2.01 | 0.28 | 1.32 | 1.41 | 0.09 |
| 6 | 8.37 | 10.53 | 2.16 | 2.84 | 1.60 | -1.24 |
| 7 | 1.74 | 2.01 | 0.27 | 1.39 | 1.43 | 0.04 |
| 8 | 8.51 | 9.02 | 0.51 | 1.63 | 0.88 | -0.75 |
| 9 | 4.22 | 6.02 | 1.80 | 3.55 | 1.94 | -1.61 |
| 10 | 1.84 | 2.01 | 0.17 | 2.72 | 0.77 | -1.95 |
| 11 | 0.70 | 0.75 | 0.05 | 1.54 | 2.07 | 0.53 |
| 12 | 5.52 | 4.51 | -1.01 | 2.41 | 3.77 | 1.36 |
| 13 | 1.68 | 2.01 | 0.33 | 1.33 | 1.03 | -0.30 |
| 14 | 5.83 | 3.76 | -2.07 | 1.99 | 0.74 | -1.25 |
| 15 | 5.49 | 4.51 | -0.98 | 2.37 | 2.65 | 0.28 |
| 16 | 3.25 | 3.51 | 0.26 | 1.35 | 1.96 | 0.61 |
| 17 | 2.96 | 3.01 | 0.05 | 1.02 | 1.81 | 0.79 |
| 18 | 10.23 | 9.02 | -1.21 | 2.22 | 2.81 | 0.59 |

Experimental data were standardized and put into Eq. (1). The second-order cross-product was chosen because the $R^2$ (coefficient of determination) has the highest value compared to the second-order cross-product with squared variables. Equations (3) to (4) give a development model of predicted material removal rate and surface roughness.

Material removal rate:

$$y_{1MQL} = 4.05 + 0.33\,x_1 + 1.43\,x_2 + 2.25\,x_3 + 1.65\,x_4 + 0.28\,x_1x_2 + 0.20\,x_1x_3 - 0.39\,x_1x_4 + 0.78\,x_2x_3 + 0.48\,x_2x_4 + 0.86\,x_3x_4 \tag{3}$$

Surface roughness:

$$y_{2MQL} = 1.63 + 0.36\,x_1 + 0.10\,x_2 + 0.65\,x_3 - 0.28\,x_4 - 0.05\,x_1x_2 + 0.11\,x_1x_3 + 0.22\,x_1x_4 - 0.31\,x_2x_3 + 0.15\,x_2x_4 + 0.04\,x_3x_4 \tag{4}$$

Figures 5 and 6 show the comparison of the experiment performance graphic of material removal rate and surface roughness using minimum quantity lubrication and dry turning.

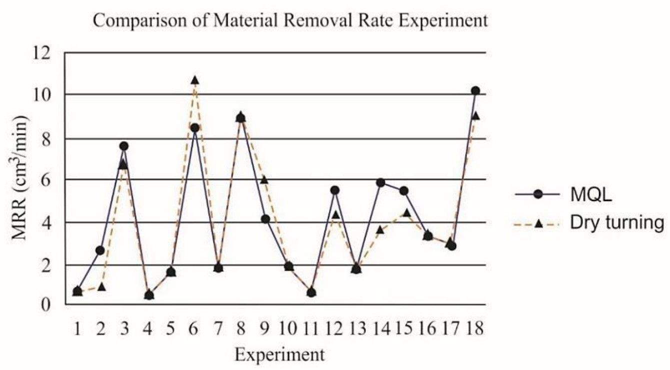


**Figure 5.** Comparison of the material removal rate experiment performance

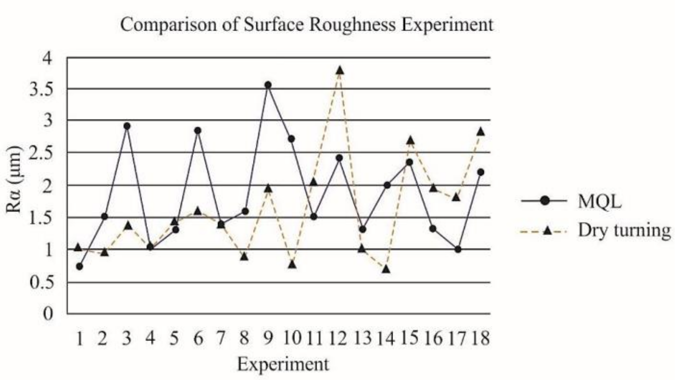


**Figure 6.** Comparison of the surface roughness experiment performance

It is seen from Figure 5 that the largest difference in the MRR value from the minimum quantity lubrication turning to dry turning occurred in experiment number 6 with 2.16 cm$^3$/min, and the smallest difference in experiment number 4 with a value of 0.03 cm$^3$/min. The largest MRR experimental value in minimum quantity lubrication turning is 10.53 cm$^3$/min and in dry turning is 10.23 cm$^3$/min. Figure 6 shows that the largest difference in the $R_a$ value from the minimum quantity lubrication turning to dry turning occurred in experiment number 10 with 1.95 µm, and the smallest difference in experiment number 7 with a value of 0.04 µm. The smallest $R_a$ experimental value in minimum quantity lubrication turning is 0.74 µm and in dry turning is 0.75 µm.

### Statistical Test

Before data processing, the modeling formulas of material removal rate and surface roughness must be tested. There are two statistical tests, *F*-test and the *t*-test. Based on Eqs. (5) and (6), *F* values and *t* values are obtained in Tables 4 and 5.

$$F = \frac{SSR/q}{SSE/n-q-1} \tag{5}$$

$$t = \frac{\hat{\beta}_j}{s\sqrt{g_{jj}}} \tag{6}$$

$$s^2 = \frac{SSE}{n-q-1} \tag{7}$$

$$\hat{\beta} = (X'X)^{-1}X'y \tag{8}$$

where *SSR* is the sum of squared residuals, *SSE* is the sum of squared errors, $s^2$ is the variance, and the value of $g_{jj}$ is the diagonal value of the matrix $(X'X)^{-1}$.

**Table 4.** *F*-test results

| | $F_{dry}$ value | $F_{MQL}$ value | $F_{0.05;4,13}$ |
|---|---|---|---|
| $y_1$ | 82.8 | 72.12 | 3.18 |
| $y_2$ | 54.9 | 17.78 | 3.18 |

**Table 5.** *t*-test results

| Variable | $t(y_{1dry})$ | $t(y_{1MQL})$ | $t(y_{2dry})$ | $t(y_{2MQL})$ | $t_{0.025;13}$ |
|---|---|---|---|---|---|
| $t_1 = x_1$ | 1.72 | 0.16 | -0.82 | 3.32 | 2.16 |
| $t_2 = x_2$ | 5.74 | 6.94 | -1.38 | 0.99 | 2.16 |
| $t_3 = x_3$ | 10.30 | 9.62 | 9.16 | 5.77 | 2.16 |
| $t_4 = x_4$ | 9.77 | 7.13 | 2.52 | -2.50 | 2.16 |

Based on various previous studies, the value of the confidence level that is often used is 95%, so an $\alpha$ value of 0.05 is obtained [26]. The values of $n$ and $q$ to determine *F*-statistics and *t*-statistics were 18 and 4.

Compared with the *F*-statistic, the *F*-test value in dry turning and the minimum quantity lubrication turning equation has a larger value. This shows that there is a difference between the material removal rate value and the surface roughness value between the modeled and experimental variances, so the null hypothesis can be rejected. Each variance between the two populations is not obtained randomly with 95% confidence. These results prove that the characteristic equations obtained in material removal rate and surface roughness modeling can predict statistically significant responses.

From the results of Martowibowo and Damanik's study [3], the *t*-test value for dry turning shows that when $y_{1dry}$ (material removal rate) is modeled, the variables that have a significant impact are $x_2$ (cutting speed), $x_3$ (feed rate), and $x_4$ (depth of cut), and the two variables have a positive effect on $y_{2dry}$ (surface roughness), namely $x_3$ (feed rate) and $x_4$ (depth of cut). The *t*-test value of minimum quantity lubrication turning shows that when $y_{1MQL}$ (material removal rate) is modeled, the variables that have a significant impact are $x_2$ (cutting speed), $x_3$ (feed rate), and $x_4$ (depth of cut), and the two variables have larger influences on the model $y_{2MQL}$ (surface roughness), namely $x_1$ (tool nose radius) and $x_3$ (feed rate).

## Genetic Algorithm Implementation

In the optimization process using the genetic algorithm method, there are three important factors, namely selection, crossover, and mutation. However, the first step before determining the value and nature of each operator is to determine a set of solutions in the initial population form. Equation (9) must be used to set this set of solutions to dimensionless values so that the lower and upper limits of the initial population in the genetic algorithm optimization process can be seen in Table 6.

$$x_j' = \frac{x_j - \bar{x}_j}{s} \tag{9}$$

**Table 6.** Lower and upper limits of the set of solutions

| Limit | $x_1$ | $x_2$ | $x_3$ | $x_4$ |
|---|---|---|---|---|
| Lower | -0.95 | -1.48 | -1.12 | -1.48 |
| Upper | 0.95 | 1.48 | 1.72 | 1.48 |

The conditions in Table 6 are used in the optimization process of material removal rate and surface roughness. Table 7 lists the values and characteristics of each genetic algorithm parameter. The number of variables depends on the independent variables used, namely the nose radius ($x_1$), cutting speed ($x_2$), feed rate ($x_3$), and depth of cut ($x_4$). The double vector fill type is chosen because the optimization process is performed on integers. The overall size is determined based on the value determined by MATLAB to optimize less than five variables (that is, 50). Compared with the hierarchical feature, the highest is used as the target value scale feature to create a new population that is more viable and has less diversity. Using selections with roulette characters to increase the possibility of selecting individuals with higher adaptability values can speed up the optimization process. An elite value of 2 can ensure the number of individuals surviving as a population in the next generation. This value was chosen because the larger the value used, the more likely it is trapped in the local optimum. A smaller value provides a more accurate value and is close to the global optimal value [27]. The high probability of crossover with multipoint features will reduce the quality of new populations with higher fitness values, resulting in poor offspring. Usually, the range of probability cross value is 0.4~1. Uniform characters are chosen because these characters are used in the integer optimization process. The smaller the probability mutation value is, the faster the optimization process can obtain the convergence value. The selected termination criterion is a stalled generation with a value of 70, which is to avoid an optimization process that lasts too long.

**Table 7.** Genetic algorithm parameters

| Parameters | Description | Value |
|---|---|---|
| # of independent variables | - | 4 |
| Population | Double vector | 50 |
| Scale of fitness | Top | 0.4 |
| Selection | Roulette wheel | - |
| Elitism | - | 2 |
| Crossover | Single point | 0.7 |
| Mutation | Uniform | 0.001 |
| # of iteration | Stall generations | 70 |

## Optimization Results

In this study, optimization of material removal rate and surface roughness was conducted using the genetic algorithm method. The larger the material removal rate value, the better the consideration. However, to adapt to the current needs of the medical industry, certain restrictions have been applied. In this case, the acceptable surface roughness of bones and metal nails is $0.0 < R_a < 0.6$ μm [28]. Also, the smaller the surface roughness value, the better the consideration. The formula limitation of material removal rate optimization may be one of the termination conditions. If it is not met, the optimization process must be stopped. The boundary equation used in this optimization is nonlinear inequality constraints, as shown below.

Minimum quantity lubrication turning:

$$1.63 + 0.36\,x_1 + 0.10\,x_2 + 0.65\,x_3 - 0.28\,x_4 - 0.05\,x_1x_2 + 0.11\,x_1x_3 + 0.22\,x_1x_4 - 0.31\,x_2x_3 + 0.15\,x_2x_4 + 0.04\,x_3x_4 > 0 \tag{10}$$

When optimizing surface roughness, the limitation of optimization is only the lower and upper limits of the solution set, without any other boundary equations. This is done to obtain the lowest possible surface roughness value so that it can be considered the optimum.

The optimization process was performed using MATLAB software. The Global Optimization Toolbox is a MATLAB feature that can be used to find global solutions for maxima and minima. The parameters of the optimization process can be entered into this toolbox as required. The results obtained are fed directly into the answer value and each parameter used. Taking Eqs. (3) and (4) as characteristic equations, the upper and lower limits of the solution set are shown in Table 6, the properties of each operator correspond to Table 7, and the limit equation adopts Eq. (10).

Tables 8 and 9 show the optimum results of material removal rate and surface roughness. From the experimental results (Table 3), it can be seen that $R_a > 0.6$ μm. So, the optimization results prove that using the genetic algorithm method, a combination of tool nose radius, cutting speed, feed speed, and depth of cut can be obtained, all of which can produce $R_a < 0.6$ μm.

**Table 8.** Optimization results of material removal rate

| | | Unit | Results | |
|---|---|---|---|---|
| | | | Dry | MQL |
| Process parameters | Tool nose radius, $r_\varepsilon$ | mm | 0.4 | 0.431 |
| | Cutting speed, $v_c$ | m/min | 96.9 | 139.8 |
| | Feed rate, $f$ | mm/rev | 0.035 | 0.054 |
| | Depth of cut, $d$ | mm | 0.217 | 0.955 |
| Responses | Material removal rate, $MRR$ | cm$^3$/min | 0.64 | 3.11 |
| | Surface roughness, $R_a$ | μm | 0.59 | 0.11 |

**Table 9.** Optimization results of surface roughness

| | | Unit | Results | |
|---|---|---|---|---|
| | | | Dry | MQL |
| Process parameters | Tool nose radius, $r_\varepsilon$ | mm | 0.4 | 0.442 |
| | Cutting speed, $v_c$ | m/min | 95.0 | 87.2 |
| | Feed rate, $f$ | mm/rev | 0.035 | 0.112 |
| | Depth of cut, $d$ | mm | 0.1 | 0.955 |
| Responses | Surface roughness, $R_a$ | µm | 0.46 | 0.07 |
| | Material removal rate, $MRR$ | cm$^3$/min | 0.178 | 3.38 |

The optimum material removal rate of 0.64 cm$^3$/min, and surface roughness of 0.59 µm for dry turning were obtained with 0.4 mm tool nose radius; 96.9 m/min cutting speed; feed rate 0.035 mm/rev; and 0.217 mm depth of cut. To simultaneously achieve an optimum surface roughness of 0.46 µm and a material removal rate of 0.178 cm$^3$/min, the following conditions were required; process parameters with a tool nose radius of 0.4 mm; a cutting speed of 95 m/min; a feed rate of 0.035 mm/rev; and 0.1 mm depth of cut.

The optimum material removal rate of 3.11 cm$^3$/min, and surface roughness of 0.11 µm for minimum quantity lubrication turning were obtained with 0.4 mm tool nose radius; 139.8 m/min cutting speed; feed rate 0.054 mm/rev; and 0.955 mm depth of cut. To simultaneously achieve an optimum surface roughness of 0.07 µm and material removal rate of 3.38 cm$^3$/min, the following conditions were required; process parameters with a tool nose radius of 0.4 mm; a cutting speed of 87.2 m/min; a feed rate of 0.112 mm/rev; and 0.955 mm depth of cut.

Minimum quantity lubrication has improved machining output over time in comparison with dry-cutting techniques. Machining parameters such as material removal rate, and surface roughness have improved in addition to reducing the burden on the environment and enhancing the safety of the personnel. The material removal rate increased, and the surface roughness decreased significantly with the use of the minimum quantity lubrication technique when compared to dry turning. From Tables 8 and 9, the comparison of minimum quantity lubrication and dry turning indicated the superior performance of the minimum quantity lubrication. They show an increase in material removal rate and a decrease in surface roughness. Surface roughness of machined components is enhanced with minimum quantity lubrication than dry turning as efficient lubrication reduces cutting force, friction between workpiece-tool interface, and conduction of heat away from the cutting zone, as confirmed by Masoudi et al. and Abbas et al. [29, 30].

The results showed that using minimum quantity lubrication, the optimum material removal rate increased at higher cutting speed, feed rate, and depth of cut, and then the optimum surface roughness increased at higher feed rate and depth of cut compared to dry turning. Therefore higher productivity can be achieved without deteriorating the final surface quality. Figures 7 and 8 show the best optimization results of the genetic algorithm using dry turning and minimum quantity lubrication. It is seen that the optimal result obtained using minimum quantity lubrication is better than obtained using dry turning.

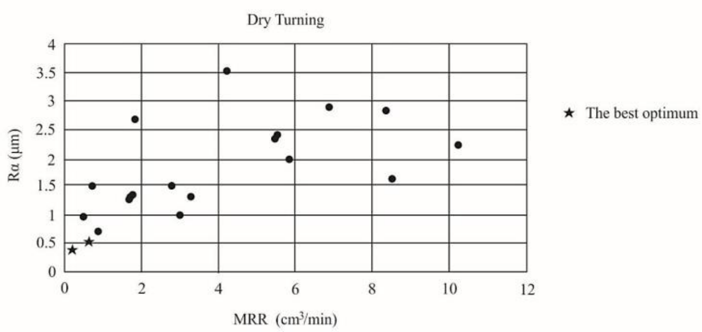


**Figure 7.** The best optimal point of the dry turning

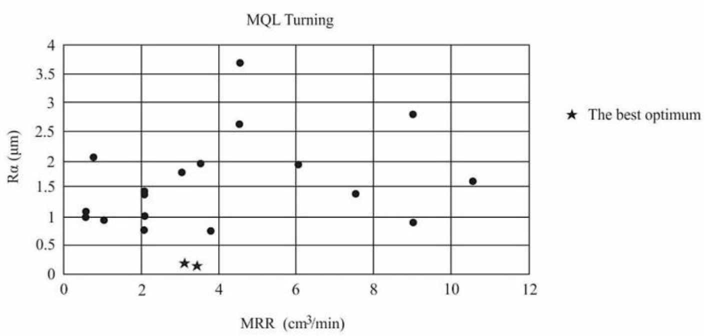


**Figure 8.** The best optimal point of the minimum quantity lubrication turning

## CONCLUSION

Based on the results of the modeling and using the genetic algorithm method to optimize the material removal rate (MRR) and surface roughness ($R_a$) of the minimum quantity lubrication using sunflower oil and compared to the dry turning process for AISI 316L, it can draw the following conclusions:

- The genetic algorithm method can play a good role in the optimization of the minimum quantity lubrication turning and dry turning process.
- The optimum material removal rate of 3.38 cm3/min, and surface roughness of 0.07 μm for minimum quantity lubrication turning, then the following conditions were required; process parameters with a tool nose radius of 0.4 mm; a cutting speed of 87.2 m/min; a feed rate of 0.112 mm/rev; and 0.955 mm depth of cut.
- The material removal rate obtained by optimizing the minimum quantity lubrication turning process is 528% (5.3 times) larger than the dry turning result. The optimized surface roughness of the minimum quantity lubrication turning process is 657% (6.6 times) smaller than that of dry turning.
- Minimum quantity lubrication turning using sunflower oil can increase material removal rate and reduce surface roughness, and it will also result in environmental safety and personnel health.

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