PREDICTION AND OPTIMIZATION OF SURFACE ROUGHNESS IN GRINDING OF S50C CARBON STEEL USING MINIMUM QUANTITY LUBRICATION OF VIETNAMESE PEANUT OIL

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This experimental research aimed to build the regression model of grinding S50C carbon steel based on a Regression Optimizer. The workpiece specimens were JIS S50C carbon steel that was hardened at 52HRC. Taguchi L27 orthogonal array was performed with 5 3-levels-factors. The studied factors were combining cutting parameters, such as cutting speed, feed rate, depth of cut, and lubricant parameters, including air coolant flow rate Q and air pressure P. The results show that cutting parameters includes workpiece velocity $V_w$, feed rate $f$, and depth of cut $a$, influence the most on surface roughness $R_a$, Root Mean Square Roughness $R_q$, and Mean Roughness Depth $R_z$. By contrast, the influence of lubrication parameters is fuzzy. Therefore, this present work focused on predicting and optimizing $R_a$, $R_q$, $R_z$ in surface grinding of JIS S50C carbon steel using MQL of peanut oil. In this work, combining of grinding parameters and lubrication parameters were considered as input factors. The regression models of $R_a$, $R_q$, and $R_z$ were obtained using Minitab 19 by Regression Optimizer tool, and then the multi-objective optimization problem was solved. The present findings have shown that Vietnamese vegetable peanut oil could be considered as the lubricant in the grinding process. The optimum grinding and lubricant parameters as following: the workpiece velocity $V_w$ of 5 m/min, feed rate $f$ of 3mm/stroke, depth of cut of 0.005mm and oil flow rate, air pressure of 91.94 ml/h, 1 MPa, respectively. Corresponding to the surface roughness $R_a$, Root Mean Square Roughness $R_q$, and Mean Roughness Depth $R_z$ of 0.6512μm, 4.592μm, 0.8570μm, respectively.

Key words: grinding, minimum quantity lubricant, optimization, regression optimizer, multi-response optimization

INTRODUCTION

JIS S50C carbon steel is popular in the manufacturing industry due to its suitable characteristics. The S50C steel could be manufactured under metal forming processes such as hot forging, cold forging...or under metal cutting processes like grinding, turning, milling...the essential criteria that have to consider in the cutting of S50C is surface roughness. In traditional machining processes, metal cutting fluid (WMF) is often used to reduce the cutting zone's temperature, tool wear...and improve surface quality by reducing the friction between the cutting tool and workpiece [1]. Due to the increase of competition in the global market and forward to sustainable manufacturing, reducing cutting fluid was new wattage that was considered research. Many published research studies have shown that MQL is applied in grinding carbon steel and improves the surface quality contemporaneously [1]-[4]. Akashi Subhash Awale et al. [5] carried out a multi-objective optimization in the grinding process assisted minimum quantity lubricant. The author claimed that controlling the cutting parameters and using optimal lubricant settings improves surface quality and reduces the tool wear.

In the recent few decades, many different optimization methods were presented to optimize surface roughness in the machining process, including milling, turning, grinding. However, the manufacturers have to consider improving the product's quality while reducing the cost due to the highly competitive market. Hence, multiple objective optimizations were more popular recently. Many researchers performed Taguchi and Taguchi-based optimization techniques because of their advantages [6]-[8], minimizing the number of experiments. Hung-Chang Liao et al. [6] successfully applied the DEAR-based Taguchi method in multiple optimization issues and compared it to the PCA method. The work-study has shown that Taguchi and other Taguchi based techniques are a powerful tool to solve multi-criteria optimization, where the DEAR approach performed better than Taguchi and PCA techniques. Mia et al. [7] carried out research applying Taguchi S/N (signal/Noise) ratio in multiple optimizations in the hard assisted MQL turning of AISI 1060 steel process, concentrate on increasing material removal rate and minimizing surface roughness and tool wear at the same time. The research's results revealed that selecting a grinding parameter set: $V_c$ of 90m/min, feed rate $f$ of 0.2mm/rev, and $a_p$ at 1.5mm provides the best quality surface and maximum production rate. Many other study results have shown that Taguchi based techniques are robust and easy to use to solve multi-objective optimization. But the disadvantage of these methods can be used to rank and find the best alternative instead of predicting the exact parameter set. Due to the lack of these methods, some new techniques, formulas...were announced.
to solve multiple criteria problems, such as coupling method of response surface (CMRS) [9], Artificial Neural Network (ANN) [10]–[13]… or computer software to build the regression model then predict the parameter sets corresponding to the optimum desired manufacturing responses. In this present work, computing software namely regression optimizer was selected to build the regression models then solve the multi-objective optimization problems. The Vietnamese peanut oil was used as the MQL lubricant.

**RESEARCH METHODOLOGY**

**Experimental material**

Experimental workpiece is S50C carbon steel with 52 HRC hardness after heat treatment. The chemical composition of S50C steel is present in Table 1.

| C(%) | Si(%) | Mn(%) | P(%) | S(%) | Cr(%) | Ni(%) | Cu(%) |
|------|-------|-------|------|------|-------|-------|-------|
| 0.47-0.55 | 0.17-0.37 | 0.50-0.80 | 0.035 | 0.035 | 0.25 | 0.25 | 0.25 |

Table 1: S50C steel Chemical Composition

The experimental machine and measurement equipment

The machine grinding APSG-820/2A was used for this experiment procedure. The surface roughness Ra, Root Mean Square Roughness R\(_q\) and Mean Roughness Depth R\(_z\) were measured by Surftest JS-201 of Mitutoyo (Japan).

Each experimental was measured 3 times at 3 separate positions, the measured results were filled in Table 3.

**MQL lubrication**

Vegetable peanut oil was used for MQL Lubrication in this experimental procedure according to the results of previous publication.

**The experimental design**

In this study work, Taguchi Orthogonal Array was applied to design the experimental matrix. The five three-level input factors and their values were listed in Table 2.

According to the number of input factors and the level of each factor, the Taguchi's orthogonal array L27(3\(^13\)) was used. The experimental matrix designed by Minitab 19, and has shown as Table 2.

The grinding parameters were selected according to the specification of grinding machine, where the level 1 and level 3 are the lower and upper limitation of parameter, respectively. And, level 2 are the average value of level 1 and level 3 values.

R\(_a\) is surface roughness; the values were determined by the formula (1), according to EN ISO 4287:1997 [14]

\[
R_a = \frac{1}{T} \int_0^T |Z(x)| dx
\]

Where: Z(x) is the arithmetic mean of the absolute ordinate within the sampling length.

R\(_z\) is Mean Roughness Depth. The values were calculated as [14]:

\[
R_z = R_q + R_a
\]

R\(_q\) is Root Mean Square (RMS) Roughness. The RMS Values were determined as [14]:

\[
R_q = \sqrt{\frac{1}{T} \int_0^T Z^2(x) dx}
\]

**Table 2: MQL parameters, Grinding parameters and their level**

| Parameters       | Symbol | Dimension | Level 1 | Level 2 | Level 3 |
|------------------|--------|-----------|---------|---------|---------|
| Flow rate        | Q      | ml/h      | 50      | 100     | 150     |
| Air pressure     | P      | MPa       | 2       | 4       | 6       |
| Workpiece Velocity | Vw  | m/min     | 5       | 10      | 15      |
| Feed rate        | f      | m/stroke  | 3       | 5       | 7       |
| Depth of cut     | ap     | mm        | 0.005   | 0.010   | 0.015   |
Experimental procedure

Each workpiece specimen was ground following the run of the experimental matrix. The surface roughness was measured by JS-210 surf test and the results were listed in Table 3.

RESULTS AND DISCUSSION

Taguchi Analysis

Influence of input factors on surface roughness \( R_a \)

Table 4: Response table for signal to noise ratios for \( R_a \)

Table 3: Experimental and prediction results

| Runs | \( V_w \) | f | \( a_1 \) | \( R_p \) | \( R_q \) | \( R_v \) | \( R_a \) | \( R_z \) | \( R_q \) |
|------|-----------|---|---------|--------|--------|--------|--------|--------|--------|
| 1    | 5         | 3 | 0.005   | 0.857  | 4.555  | 0.502  | 0.79092| 4.56008| 0.61358|
| 2    | 5         | 3 | 0.010   | 0.897  | 5.672  | 0.540  | 0.94996| 5.30668| 0.7008 |
| 3    | 5         | 3 | 0.015   | 0.988  | 5.266  | 0.864  | 1.08595| 5.9605 | 0.78803|
| 4    | 10        | 5 | 0.005   | 1.331  | 6.341  | 0.939  | 1.18578| 6.30368| 0.89735|
| 5    | 10        | 5 | 0.010   | 1.323  | 6.767  | 1.020  | 1.29728| 6.86332| 0.98458|
| 6    | 10        | 5 | 0.015   | 1.368  | 7.144  | 1.215  | 1.39993| 7.3805 | 1.07181|
| 7    | 15        | 7 | 0.005   | 1.559  | 7.543  | 1.036  | 1.47871| 7.66048| 1.18113|
| 8    | 15        | 7 | 0.010   | 1.644  | 8.460  | 1.343  | 1.56954| 8.12709| 1.26836|
| 9    | 15        | 7 | 0.015   | 1.684  | 8.342  | 1.231  | 1.65539| 8.56832| 1.35558|
| 10   | 10        | 7 | 0.010   | 1.425  | 7.094  | 0.929  | 1.37392| 7.31399| 1.05746|
| 11   | 10        | 7 | 0.010   | 1.366  | 8.085  | 1.136  | 1.47123| 7.80135| 1.14469|
| 12   | 10        | 7 | 0.015   | 1.454  | 7.837  | 1.220  | 1.56249| 8.26   | 1.23191|
| 13   | 15        | 3 | 0.005   | 1.266  | 5.399  | 0.928  | 0.9308 | 5.17306| 0.73713|
| 14   | 15        | 3 | 0.010   | 1.325  | 5.733  | 0.888  | 1.06923| 5.84184| 0.82435|
| 15   | 15        | 3 | 0.015   | 1.245  | 6.634  | 0.814  | 1.19169| 6.44156| 0.91158|
| 16   | 5         | 5 | 0.005   | 1.195  | 6.324  | 0.943  | 1.16348| 6.35368| 0.89274|
| 17   | 5         | 5 | 0.010   | 1.286  | 7.214  | 0.938  | 1.27693| 6.90912| 0.97997|
| 18   | 5         | 5 | 0.015   | 1.278  | 7.770  | 1.395  | 1.38109| 7.42311| 1.06719|
| 19   | 15        | 5 | 0.005   | 1.252  | 6.030  | 0.985  | 1.16101| 6.36525| 0.89724|
| 20   | 15        | 5 | 0.010   | 1.295  | 7.103  | 1.083  | 1.27468| 6.91975| 0.98446|
| 21   | 15        | 5 | 0.015   | 1.337  | 7.263  | 1.049  | 1.37902| 7.43301| 1.07169|
| 22   | 5         | 7 | 0.005   | 1.348  | 7.509  | 1.071  | 1.35471| 7.35698| 1.05285|
| 23   | 5         | 7 | 0.010   | 1.398  | 7.807  | 1.095  | 1.45331| 7.84167| 1.14007|
| 24   | 5         | 7 | 0.015   | 1.362  | 8.512  | 1.239  | 1.54563| 8.29809| 1.2273 |
| 25   | 10        | 3 | 0.005   | 1.125  | 5.434  | 0.791  | 0.90221| 5.23366| 0.73251|
| 26   | 10        | 3 | 0.010   | 1.139  | 5.335  | 0.683  | 1.04444| 5.89558| 0.81974|
| 27   | 10        | 3 | 0.015   | 1.149  | 6.153  | 0.665  | 1.1695 | 6.49033| 0.90697|
Table 5: Response table for means for Ra

| Level | Q   | P   | \(V_w\) | F   | t   |
|-------|-----|-----|---------|-----|-----|
| 1     | 0.9999 | 0.9544 | 0.9630  | 0.8005 | 0.9058 |
| 2     | 0.9924 | 1.0053 | 0.9787  | 1.0297 | 1.0040 |
| 3     | 0.9967 | 1.0293 | 1.0473  | 1.1588 | 1.0792 |
| Delta | 0.0075 | 0.0749 | 0.0843  | 0.3583 | 0.1733 |
| Rank  | 5    | 4    | 3       | 1    | 2    |

Figure 6: Main effects plot for means of \(R_a\)

Figure 7: Main effects plot for SN ratios of \(R_a\)

The data in table 4, table 5 depict the influence of cutting and lubrication parameters on the surface roughness \(R_a\). The cutting parameters, namely \(V_w\), \(F\), and \(t\) affect surface roughness \(R_a\) significantly. The influence of \(F\) is the most, followed by \(t\) and \(V_w\). The lubricant parameters include \(P\) and \(Q\) influence on surface roughness insignificantly.

Influence of input factors on mean roughness depth \(R_z\)

Table 6: Response table for signal to noise ratios for \(R_z\)

| Level | Q   | P   | \(V_w\) | F   | t   |
|-------|-----|-----|---------|-----|-----|
| 1     | -16.33 | -16.18 | -16.40  | -14.88 | -15.81 |
| 2     | -16.70 | -16.66 | -16.42  | -16.73 | -16.68 |
| 3     | -16.54 | -16.73 | -16.74  | -17.95 | -17.07 |
| Delta | 0.37  | 0.55  | 0.33    | 3.07   | 1.27  |
| Rank  | 4     | 3     | 5       | 1      | 2     |

Table 7: Response table for means for \(R_z\)

| Level | Q   | P   | \(V_w\) | F   | t   |
|-------|-----|-----|---------|-----|-----|
| 1     | 6.677 | 6.545 | 6.737   | 5.576 | 6.248 |
| 2     | 6.899 | 6.872 | 6.688   | 6.884 | 6.908 |
| 3     | 6.794 | 6.953 | 6.945   | 7.910 | 7.213 |
| Delta | 0.222 | 0.408 | 0.257   | 2.334 | 0.966 |
| Rank  | 5     | 3     | 4       | 1      | 2     |

Figure 8: Main effects plot for means of \(R_z\)

Figure 9: Main effects plot for SN Ratios of \(R_z\)

The data in tables 6,7 illustrate the influence of cutting and lubrication parameters on the mean roughness depth \(R_z\). Where, the cutting parameters influence surface roughness more significantly than the lubrication parameters. The cutting parameters include \(V_w\), \(F\), and \(t\) affect surface roughness significantly. The influence of \(F\) is the most, followed by \(t\) and \(V_w\). The lubricant parameters include \(P\) and \(Q\) influence on surface roughness insignificantly.
Besides, figures 8, 9 outline the interaction between cutting parameters with surface roughness value. The value of feed rate \( f \) increase from level 1 to level 3 causes quickly increasing from 5.5\( \mu \)m to around 8.0\( \mu \)m of mean roughness depth \( R_z \), an increase of around 40%. Similarly, the surface roughness rising significantly from 6.2\( \mu \)m to 7.2\( \mu \)m when the depth of cut \( ap \) rising from level 1 to level 3. By contrast, the maximum height \( R_h \) increases slightly from 6.9\( \mu \)m when \( V_w \) rising from Level 1 to level 2, then went down significantly when the \( V_w \) rising to the level 3 value.

**Influence of input factors on root mean square roughness \( R_q \)**

The data in tables 8 and 9 present the influence of cutting parameters, namely \( V_w, f, t \), and lubrication parameters includes \( P, Q \) on the Root Mean Square Roughness (RMS Roughness) \( R_q \). Where, the cutting parameters influence surface roughness more significantly than the lubrication parameters. By contrast, the lubricant parameters influence surface roughness insignificantly.

Figures 9 and 10 show that the values of \( P, V_w, F, \) and \( t \) are proportional to RMS Roughness. That means, increasing \( P, V_w, F, \) and \( t \) causes the rising value of RSM Roughness. When the values of \( F \) and \( V_w \) increase from level 1 to level 3, the RMS roughness goes up quickly from 1.1\( \mu \)m to 1.5\( \mu \)m and 1.2\( \mu \)m to 1.4\( \mu \)m, respectively. Similarly, when the depth of cut \( t \) rising from level 1 to level 3, the RMS roughness goes slightly from 1.28\( \mu \)m to 1.32\( \mu \)m.

![Figure 10: Main effects plot for means of \( R_q \)](image1)

**Regression model**

The regression model for Surface roughness \( R_s \), mean roughness depth \( R_z \), Root Mean Square (RMS) Roughness \( R_q \) were generated with the regression optimizer tool in Minitab 19, with the Box-Cox transformation selection. The regression models are shown as (4), (5), and (6). The regression models were applied to calculate the predicted value of \( R_s, R_z, R_q \). The summarize of prediction and measurement of \( R_s, R_z, R_q \) were shown in Table 3.

The R-squared for Regression Model of \( R_s, R_z, R_q \) are 89.08%, 92.42%, and 95.36%, respectively. That means the regression models could be applied to predict the value of surface roughness \( R_s \), mean roughness depth \( R_z \), and Root Mean Square Roughness \( R_q \). The regression models were used to solve multiple optimization problems.

**Regression model for surface roughness average \( R_s \)**

\[
R_s = -0.2190 - 0.00032Q + 0.0375P + 0.00843V_w + 0.0895f + 17.33t
\]  
(4)

**Regression model for mean roughness depth \( R_z \)**

\[
R_z^2 = -13.83 + 0.0105Q + 2.270P + 0.231V_w + 7.846f + 1307t
\]  
(5)

**Regression model for root mean square roughness \( R_q \)**

\[
R_q^2 = -0.345 - 0.0147Q + 0.1679P + 0.05625V_w + 0.2310f + 14.11t
\]  
(6)

By contrast, the influence of flow rate \( Q \) is not stable. When \( Q \) rising from level 1 to level 2, meaning from 50ml/h to 100ml/h, the RMS roughness rose slightly from 1.3\( \mu \)m to 1.31. However, with the continued increase of flow rate to 150ml/h (level 3), the RSM roughness reduces to 1.28\( \mu \)m.

Fig. 8, 10 and 12 also shown that each individual responses \( R_s, R_z, R_q \) reach to optimal point at the same combination of input factors.

![Figure 11: Main effects plot for SN Ratios of \( R_q \)](image2)
Multiple response optimization

In this work, the regression optimizer tool of Minitab was used to solve the multiple optimization problems, with the minimizing of $R_a$, $R_z$, $R_q$ approach. The results are shown in Tables 10, 11, 12 and Figure 15.

The data from Table 10, 11, 12 and Figure 15 shown that optimum cutting parameters as: workpiece velocity $V$, feed rate $f$, depth of cut $a_p$ are 5m/min, 3mm/stroke, 0.005mm, respectively, corresponding to the optimum lu-
lubrication parameters as oil flow rate of 91.94ml/h and air pressure of 1 MPa. Corresponding to the surface roughness $R_a$, root mean square roughness $R_q$, and mean roughness depth $R_z$ of 0.6512μm.

CONCLUSION

In summary, this paper argued that:

- The feed rate $f$ effect the most on the whole surface roughness $R_a$, Root Mean Square Roughness $R_q$, and Mean Roughness Depth $R_z$, followed by workpiece velocity $V_w$. The depth of cut $ap$ effect on the roughness values insignificant.

- The lubricant variants had an insignificant influence on $R_a$, $R_z$, $R_q$.

- In this experimental study, grinding of hardened S50C carbon steel was the first performed with assisted Vietnamese peanut oil as minimum quantity lubricant.

- The present findings confirm vegetable oil's ability based as the lubricant in the cutting process, including grinding. The combining grinding and lubricant parameters as following: The workpiece velocity $V_w$ of 3 m/min, feed rate $f$ of 3mm/stroke, depth of cut $ap$ of 0.005mm and oil flow rate, air pressure of 91.94 ml/h, 1 MPa, respectively. Corresponding to the surface roughness $R_a$, Root Mean Square Roughness $R_q$, and Mean Roughness Depth $R_z$ of 0.6512μm, 4.592μm, 0.8570μm.

- Computing software Minitab could be applied to generate the regression models and solve the multiple objective optimization problems.

- The effects of the combinations of input variables on $Ra$, $Rz$, $Rq$ are quite similar. Hence, it's sufficient to research only one of response $R_a$, $R_z$ or $R_q$.

- The disadvantage of

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