Taguchi-grey-fuzzy method for optimization of turning process parameters with environmentally friendly cooling

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Abstract. Surface roughness is an indicator of the quality of workpieces produced by machining processes. Whereas, the indicator of the productivity of the machining process is the metal removal rate. Surface roughness and metal removal rate have different characteristics. Setting the combination of turning parameters results is essential to get optimal responses. This research has been carried out of determining the parameters of the turning process to produce an optimal response with the use of environmentally friendly coolant. The turning process parameters that are varied are the cutting fluids, spindle rotation, feeding motion, and cutting depth while the tool used is the CNMG insert tool. The optimization method used is Taguchi, combined with grey and fuzzy logic. The results showed that to obtain the optimum arithmetic surface roughness, average total surface roughness and metal removal rate, the cutting fluids is set at level 1, which is soluble cold water + air pressure, level 3 spindle rotation with a value of 1200 rpm, level 3 feeding with an amount of 0.161 mm rev⁻¹, and cutting depth level 3 of 0.5 mm.

Keywords: grey-fuzzy, metal removal rate, surface finis, Taguchi, turning.

1. Introduction
The machining process plays a very important role in the manufacturing industry. One of the most common machining processes is the turning process. The turning process is a metal cutting process using a single-edged cutting tool with a workpiece rotating on its chuck [1]. One indicator of the quality of the turning process is the value of the workpiece surface roughness [2]. The lower the workpiece surface roughness value, the higher the quality of the workpiece resulting from the turning. Besides being demanded to have high quality, the turning process is also demanded to have high productivity. Indicator of productivity in the turning is the rate of metal removal rate (MRR). The higher of metal removal rate, the higher the productivity. Workpiece surface roughness and metal removal rate resulting from the turning process is determined by variables as cutting speed, feeding motion and cutting depth [3-5].

Besides being influenced by turning process variables, surface roughness and the metal removal rate are also influenced by the cutting fluid. The coolant in the turning process is essential because it can reduce the friction coefficient and reduce heat on the cutting tool caused by friction between the workpiece and the cutting tool so that the cutting tool does not wear out quickly. In addition, the use of coolant in the turning process can improve the surface quality of the workpiece [6]. In the turning process, one way of providing coolant is using the flooding method. It
is a method of administering coolant by flooding the surface of the workpiece. However, excessive use of coolant, such as flooding methods can induce health problems for the operator such as irritation of the skin and environmental problems [7]. Some environmentally friendly methods of cutting fluids as an alternative to the flooding method are the Minimum Quantity Lubrication (MQL) methods. In the MQL method, the coolant used is minimized [8]. In addition to the MQL method, an environmentally friendly cooling fluid method is the Minimum Quantity Cooling Lubrication (MQCL) method. In this method, in addition to minimizing the coolant, cold pressurized air is also added so that the cooling process is more optimal [9-11].

Determination of the proper setting of the turning process variables to get a low surface roughness of the workpiece with a high metal removal rate simultaneously is very necessary to be done. However, in the turning process, surface roughness has opposite characteristics to the metal removal rate (MRR). Surface roughness has the characteristics, the smaller the better while the MRR has the characteristics, the greater the better. Therefore, determining the combination of turning parameters or optimization process is very important to get optimal results. The optimization method that is often used in the machining process for single responses is Taguchi. As for multi-response, the Taguchi-Grey-Fuzzy method can be used [12-14].

2. Methods and material

2.1 Research material
This research uses ST 60 material with dimensions of Ø50 mm x 100 mm. An insert cutting tool with CNMG type used as the cutting tool in this study, which has a corner radius of 0.4 mm. Conventional turning with 2000 rpm spindle rotation is used in this research. Surface roughness is measured using Mahr Surftest. The cutting time is measured with a stopwatch which is then entered into equation (1) to get the metal removal rate (MRR).

\[
MRR = \frac{\text{Volume of workpiece removed}}{\text{Machining time}} \text{ (mm}^3\text{min)}
\]  

(1)

2.2 Cooling system installation
The cooling system installation diagram used in this study can be seen in Figure 1. The cooling liquid in the form of soluble oil is cooled to a cooler at 9-10°C then sprayed with a flow rate of 200 ml/hour with 8 bar of compressed air relief produced by the compressor. The volume of coolant that is sprayed is kept to a minimum through the screw regulating the discharge of the coolant.

![Cooling system installation diagram](image-url)
2.3 Process variables and orthogonal matrix
Table 1 shows the process variables used in the study. Response variables used in this study are arithmetic surface roughness (Ra), average total roughness (Rz) and metal removal rate (MRR). Whereas the orthogonal matrix used can be seen in Table 2.

| No. | Process Variable          | Level                  |
|-----|---------------------------|------------------------|
| 1   | Cutting fluids (CF)       | Cold Soluble oil+air   |
| 2   | Spindle Rotation (N)/rpm  | 550                    |
| 3   | Feeding Motion (F)/mm/rev.| 0.053                  |
| 4   | Cutting depth (A)/mm      | 0.125                  |

Table 2. Orthogonal matrix L_{18}

| No. | CF   | N   | F   | A   | No. | CF   | N   | F   | A   |
|-----|------|-----|-----|-----|-----|------|-----|-----|-----|
| 1   | 1    | 1   | 1   | 1   | 10  | 2    | 1   | 1   | 3   |
| 2   | 1    | 1   | 2   | 2   | 11  | 2    | 1   | 2   | 1   |
| 3   | 1    | 1   | 3   | 3   | 12  | 2    | 1   | 3   | 2   |
| 4   | 1    | 2   | 1   | 1   | 13  | 2    | 2   | 1   | 2   |
| 5   | 1    | 2   | 2   | 2   | 14  | 2    | 2   | 2   | 3   |
| 6   | 1    | 2   | 3   | 3   | 15  | 2    | 2   | 3   | 1   |
| 7   | 1    | 3   | 1   | 2   | 16  | 2    | 3   | 1   | 3   |
| 8   | 1    | 3   | 2   | 3   | 17  | 2    | 3   | 2   | 1   |
| 9   | 1    | 3   | 3   | 1   | 18  | 2    | 3   | 3   | 2   |

2.4 Taguchi-grey-fuzzy method
The Taguchi method is an optimization method that can only be used for one response. To optimize multiple responses simultaneously, it is used a combination of the Taguchi with grey and fuzzy logic method. Grey relational analysis is used to create relationship models and analyze the relationships between responses and parameters, and as a basis for predicting and making decisions. Basically, GRA is used in optimization to convert several responses into one response. Fuzzy logic is formulated to find a middle value between 0 and 1. Fuzzy logic has the ability to process response variables that are fuzzy or cannot be described exactly, for example, high, slow, and noisy. The ambiguity in describing a response variable can be naturally modelled using fuzzy logic. The steps of the optimization process with the Taguchi-Grey-Fuzzy method can be seen in Figure 2.

Figure 2. The steps of the grey-fuzzy method optimization process

3 Results and discussion
3.1 Research Results Data
The results of the study in the form of arithmetic surface roughness (Ra), average total roughness (Rz) and metal removal rate (MRR) can be seen in Table 3.


The first step in the Taguchi-Grey-Fuzzy optimization process is calculate of the S/N ratio of the research data results shown in Table 3. The S/N ratio is determined by the quality characteristics of the responses. For arithmetic surface roughness (Ra) and average total roughness (Rz), they have the characteristics the smaller the better following equation 2, while the characteristics of quality for metal removal rate (MRR) are the greater the better according to equation 3 [14-15]. Smaller the better

\[
S/N = -10 \log \left[ \frac{1}{n} \sum_{i=1}^{n} y_i^2 \right]
\]  

(2)
Greater the better

\[
S/N = -10 \log \left( \frac{1}{n} \sum_{i=1}^{n} \left( \frac{1}{y_i^2} \right) \right)
\]  

(3)

The results of S/N ratio calculation can be seen in Table 4.

### 3.3 Normalization of data for each response

The second step is the normalization of data for each response. Normalization is changing the S/N ratio value in Table 4 to a value that is among 0 and 1 [16-17]. Quality characteristics the smaller the better for surface roughness is using equation 4 and the greater the better for the rate of material work is using equation 5. The results of normalization can be seen in Table 5.

#### The smaller the better:

\[
X_{i}^+(k) = \frac{X_{i}(k) - \min X_{i}(k)}{\max X_{i}(k) - \min X_{i}(k)}
\]

(4)

#### The greater the better:

\[
X_{i}^-(k) = \frac{\max X_{i}(k) - X_{i}(k)}{\max X_{i}(k) - \min X_{i}(k)}
\]

(5)

### Table 5. Normalization of response data

| No | S/N Ra | S/N Rz | S/N MRR | Ra | Rz | MRR |
|----|--------|--------|---------|----|----|-----|
| 1  | 1.211  | -10.024| 61.256  | 0.000 | 0.042 | 0.000 |
| 2  | 1.255  | -15.226| 73.209  | 0.338 | 0.129 | 0.191 |
| 3  | 2.232  | -13.830| 83.082  | 0.451 | 0.283 | 0.734 |
| 4  | 0.454  | -15.001| 63.447  | 0.237 | 0.154 | 0.019 |
| 5  | 1.645  | -14.698| 75.652  | 0.385 | 0.187 | 0.275 |
| 6  | 5.628  | -12.495| 85.579  | 0.760 | 0.430 | 1.000 |
| 7  | 6.533  | -8.568 | 73.794  | 0.820 | 0.862 | 0.209 |
| 8  | 8.101  | -8.029 | 85.390  | 0.914 | 0.921 | 0.976 |
| 9  | 8.706  | -8.810 | 77.915  | 0.946 | 0.835 | 0.376 |
| 10 | -0.084 | -16.233| 73.443  | 0.163 | 0.019 | 0.199 |
| 11 | 0.542  | -16.296| 67.440  | 0.248 | 0.012 | 0.067 |
| 12 | 1.097  | -15.992| 76.970  | 0.320 | 0.045 | 0.331 |
| 13 | 0.425  | -16.402| 69.367  | 0.234 | 0.000 | 0.100 |
| 14 | 4.884  | -11.550| 81.664  | 0.701 | 0.534 | 0.614 |
| 15 | 1.663  | -14.344| 73.085  | 0.397 | 0.226 | 0.188 |
| 16 | 8.171  | -7.310 | 79.605  | 0.918 | 1.000 | 0.471 |
| 17 | 5.823  | -10.357| 74.157  | 0.770 | 0.665 | 0.221 |
| 18 | 9.813  | -8.688 | 83.380  | 1.000 | 0.848 | 0.762 |

### 3.4 Determining the deviation sequence \( \Delta_{0,x}(k) \)

The third step is to determine the value of the deviation sequence \( \Delta_{0,x}(k) \). The deviation sequence is the absolute difference between the maximum values of the result of normalization of one magnitude with the normalized data [18]. Calculation of the value of the deviation sequence uses equation 6 [18]. Deviation sequence values can be seen in Table 6.

\[
\Delta_{0x}(k) = |X_{0}(k) - X_{x}^{*}(k)|
\]

(6)
Table 6. Deviation sequence value

| No | Normalization \((x_1[k])\) | Deviation sequence | Normalization \((x_2[k])\) | Deviation sequence |
|----|------------------------|-------------------|------------------------|-------------------|
|    | Ra         | Rz      | MRR      | Ra       | Rz      | MRR      |
| 1  | 0.000      | 0.042   | 0.000    | 1.0000   | 0.9585  | 1.0000   |
| 2  | 0.338      | 0.129   | 0.191    | 0.7763   | 0.8707  | 0.5086   |
| 3  | 0.451      | 0.283   | 0.734    | 0.6877   | 0.7172  | 0.1026   |
| 4  | 0.237      | 0.154   | 0.019    | 0.8490   | 0.8459  | 0.9099   |
| 5  | 0.385      | 0.187   | 0.275    | 0.7410   | 0.8126  | 0.4081   |
| 6  | 0.760      | 0.430   | 1.000    | 0.3797   | 0.5703  | 0.0000   |
| 7  | 0.820      | 0.862   | 0.209    | 0.2975   | 0.1383  | 0.4845   |
| 8  | 0.914      | 0.921   | 0.976    | 0.1554   | 0.0791  | 0.0078   |
| 9  | 0.946      | 0.835   | 0.376    | 0.1005   | 0.1650  | 0.3151   |
| 10 | 0.163      | 0.019   | 0.199    | 0.8978   | 0.9815  | 0.4989   |
| 11 | 0.248      | 0.012   | 0.067    | 0.8410   | 0.9883  | 0.7458   |
| 12 | 0.320      | 0.045   | 0.331    | 0.7906   | 0.9549  | 0.3539   |
| 13 | 0.234      | 0.000   | 0.100    | 0.8516   | 1.0000  | 0.6665   |
| 14 | 0.701      | 0.534   | 0.614    | 0.4471   | 0.4664  | 0.1609   |
| 15 | 0.397      | 0.226   | 0.188    | 0.7393   | 0.7737  | 0.5137   |
| 16 | 0.918      | 1.000   | 0.471    | 0.1489   | 0.0000  | 0.2456   |
| 17 | 0.770      | 0.665   | 0.221    | 0.3620   | 0.3352  | 0.4696   |
| 18 | 1.000      | 0.848   | 0.762    | 0.0000   | 0.1516  | 0.0904   |

3.5 Calculating grey relational coefficient (GRC)

Table 7. Grey Relational Coefficient (GRC) value

| No | Deviation sequence \((\Delta_q(k))\) | Grey relational coefficient \((\xi(k))\) |
|----|------------------------|------------------------|
|    | Ra         | Rz      | MRR      | Ra       | Rz      | MRR      |
| 1  | 0.000      | 0.042   | 0.000    | 1.0000   | 0.9585  | 1.0000   |
| 2  | 0.338      | 0.129   | 0.191    | 0.7763   | 0.8707  | 0.5086   |
| 3  | 0.451      | 0.283   | 0.734    | 0.6877   | 0.7172  | 0.1026   |
| 4  | 0.237      | 0.154   | 0.019    | 0.8490   | 0.8459  | 0.9099   |
| 5  | 0.385      | 0.187   | 0.275    | 0.7410   | 0.8126  | 0.4081   |
| 6  | 0.760      | 0.430   | 1.000    | 0.3797   | 0.5703  | 0.0000   |
| 7  | 0.820      | 0.862   | 0.209    | 0.2975   | 0.1383  | 0.4845   |
| 8  | 0.914      | 0.921   | 0.976    | 0.1554   | 0.0791  | 0.0078   |
| 9  | 0.946      | 0.835   | 0.376    | 0.1005   | 0.1650  | 0.3151   |
| 10 | 0.163      | 0.019   | 0.199    | 0.8978   | 0.9815  | 0.4989   |
| 11 | 0.248      | 0.012   | 0.067    | 0.8410   | 0.9883  | 0.7458   |
| 12 | 0.320      | 0.045   | 0.331    | 0.7906   | 0.9549  | 0.3539   |
| 13 | 0.234      | 0.000   | 0.100    | 0.8516   | 1.0000  | 0.6665   |
| 14 | 0.701      | 0.534   | 0.614    | 0.4471   | 0.4664  | 0.1609   |
| 15 | 0.397      | 0.226   | 0.188    | 0.7393   | 0.7737  | 0.5137   |
| 16 | 0.918      | 1.000   | 0.471    | 0.1489   | 0.0000  | 0.2456   |
| 17 | 0.770      | 0.665   | 0.221    | 0.3620   | 0.3352  | 0.4696   |
| 18 | 1.000      | 0.848   | 0.762    | 0.0000   | 0.1516  | 0.0904   |

The fourth step is to calculate the value of the GRC. It shows the relationship between the ideal and the actual conditions of normalized responses that are worth one if the normalized responses match the ideal condition [18]. Calculation of the value of the deviation sequence uses equation 7.
\[ \xi_i (k) = \frac{\Delta \min + \zeta \Delta \max}{\Delta a_i (k) + \zeta \Delta \max} \]  
(7)

\( \zeta \) is the distinguish coefficient, the value used in general is 0.5 [19]. The results of the Grey Relational Coefficient (GRC) can be seen in Table 7.

3.6 Fuzzification stage
Fuzzification is the process of changing the initial value, namely the grey relation coefficient to fuzzy numbers using the membership function. The membership value interval used is between 0 to 1 [20]. The input variable in the fuzzification process is the GRC value of each response. The output variable of the fuzzy logic system in this study is the grey-fuzzy reasoning grade (GFRG) which is converted into fuzzy linguistic subsets, using triangular membership functions.

3.7 Fuzzy Rules
Fuzzy rules are rules that explain the relationship between input variables and output variables. This study uses 3 input variables, namely GRC from arithmetic surface roughness response (Ra), average total surface roughness (Rz) and metal removal rate (MRR) with each having 3 fuzzy subsets, so 27 fuzzy rules are needed to combine all inputs. The overall fuzzy rules used in this study are shown in Table 8.

| Table 8. Fuzzy rules |
|----------------------|
| No | Ra | Rz | MRR | GFRG | No | Ra | Rz | MRR | GFRG |
|-----|----|----|-----|------|-----|----|----|-----|------|
| 1   | S  | S  | S   | T    | 15  | M  | M  | L   | LM   |
| 2   | S  | S  | M   | VS   | 16  | M  | L  | S   | SM   |
| 3   | S  | S  | L   | S    | 17  | M  | M  | L   | LM   |
| 4   | S  | M  | S   | S    | 18  | M  | L  | L   | VL   |
| 5   | S  | M  | M   | SM   | 19  | L  | S  | S   | S    |
| 6   | S  | M  | L   | M    | 20  | L  | S  | M   | SM   |
| 7   | S  | L  | S   | S    | 21  | L  | S  | L   | M    |
| 8   | S  | L  | M   | SM   | 22  | L  | M  | S   | M    |
| 9   | S  | L  | L   | M    | 23  | L  | M  | M   | LM   |
| 10  | M  | S  | S   | VS   | 24  | L  | M  | L   | L    |
| 11  | M  | S  | M   | SM   | 25  | L  | L  | S   | M    |
| 12  | M  | S  | L   | M    | 26  | L  | L  | M   | L    |
| 13  | M  | M  | S   | SM   | 27  | L  | L  | L   | H    |
| 14  | M  | M  | M   | M    |      |     |     |     |       |

3.8 Defuzzification
Defuzzification is the conversion of fuzzy values to grey fuzzy reasoning grade (GFRG) by mapping fuzzy sets to firm sets. The input variable from the defuzzification process is the GRC value. The results of defuzzification in the form of GFRG values can be seen in Table 9.

| Table 9. Grey Fuzzy Reasoning Grade (GFRG) |
|-----------------|
| No. | CF | N | F | A | GFRG | No. | CF | N | F | A | GFRG |
|-----|----|---|---|---|------|-----|----|---|---|---|------|
| 1   | 1  | 1 | 1 | 1 | 0.3372 | 10  | 2  | 1 | 1 | 3 | 0.3615 |
| 2   | 1  | 1 | 2 | 2 | 0.3795 | 11  | 2  | 1 | 2 | 1 | 0.3587 |
| 3   | 1  | 1 | 3 | 3 | 0.4707 | 12  | 2  | 1 | 3 | 2 | 0.4012 |
| 4   | 1  | 2 | 1 | 1 | 0.3552 | 13  | 2  | 1 | 2 | 1 | 0.3608 |
| 5   | 1  | 2 | 2 | 2 | 0.4047 | 14  | 2  | 2 | 2 | 3 | 0.5842 |
| 6   | 1  | 2 | 3 | 3 | 0.6356 | 15  | 2  | 2 | 3 | 1 | 0.3891 |
| 7   | 1  | 3 | 1 | 2 | 0.6112 | 16  | 2  | 3 | 1 | 3 | 0.7507 |
| 8   | 1  | 3 | 2 | 3 | 0.7902 | 17  | 2  | 3 | 2 | 1 | 0.572 |
| 9   | 1  | 3 | 3 | 1 | 0.681 | 18  | 2  | 3 | 3 | 2 | 0.7732 |
3.9 Determining the combination of process variables for optimum responses

Determination of the best combination of variables begins with making an average table of GFRG as shown in Table 10. The greater the value of GFRG, the better the responses of the process to the combination of these variables. After the average table of GFRG is made, the next step is to create a graph for the average of GFRG at each level of the cutting fluid, spindle rotation, feed motion and cutting depth as shown in Figure 3.

Table 10. The average of GFRG

|       | Level 1 | Level 2 | Level 3 |
|-------|---------|---------|---------|
| CF    | 0.518   | 0.506   | -       |
| N     | 0.385   | 0.455   | 0.696   |
| F     | 0.463   | 0.515   | 0.558   |
| A     | 0.449   | 0.488   | 0.599   |
| Average | 0.512 |

Figure 3. Plot GRFG average value

Based on Figure 4, the combination of levels of process variables that produce arithmetic surface roughness (Ra), average total surface roughness (Rz) and optimum metal removal rate (MRR) are cutting fluids (CF) level 1 that is Cold soluble oil + air pressure, spindle rotation (N) level 3 with a value of 1200 rpm, feed motion (F) level 3 with a value of 0.161 mm/rev and cutting depth (A) level 3 with a value of 0.5 mm.

4. Conclusion

Combination settings for turning process parameters that can minimize arithmetic surface roughness (Ra) and average total surface roughness (Rz), as well as maximizing metal removal rate (MRR) simultaneously are as follow:

- Type of coolant is cold soluble oil + air pressure.
- Spindle rotation of 1200 rpm.
- Feeding of 0.161 mm/rev
- Cutting depth 0.5 mm
5. Acknowledgement
Thanks to the directorate of research and community service, directorate general of strengthening research and development (DRPM), the ministry of research, technology and higher education who has provided financial support through a research scheme for novice lecturers in 2019.

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