Combination of taguchi method and moora method for multi-objective optimization of SCM400 steel milling process

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Abstract. In this article, a study on multi-objective optimization of the milling process is presented. CNC milling machine, cutting tool as TiAIN, experimental material as SCM400 steel and coolant as Caltex Aquatex 3180 oil have been used in the experiment. The objective of this study is to simultaneously ensure the minimum surface roughness and the maximum material removal rate (MRR). Taguchi method has been applied to design an experimental matrix with five input parameters, including coolant flow, coolant pressure, cutting velocity, feed rate, and cutting depth. Analysis of experimental results by Pareto chart has determined the effect of input parameters on output parameters. Moora method has been applied to determine the values of input parameters to simultaneously ensure the two criteria as mentioned above. Finally, the direction for further research has also been recommended in this study.

1 Introduction

SCM400 steel (JSC standard) is a material with high chromium content, and is widely used in mechanical engineering. This steel is characterized by high hardness, high wear resistance, and high strength during use. Therefore, it is often used to manufacturing parts in the mold industry or parts such as gears, transmission shafts [1, 2]. When machining these types of parts, the milling method is used quite a lot, especially when machining planes on those parts. Surface roughness has a direct effect on the workability and durability of the product, and MRR is a characteristic parameter to evaluate the productivity of the machining process. Therefore, ensuring the surface of the workpiece with a small roughness and a large MRR is always the desire of most machining methods in general and milling methods in particular [3-5].

When milling, surface roughness and MRR depend on many parameters of the machining process, such as parameters of cutting parameters and parameters of lubricating and cooling [6, 7]. Therefore, it is necessary to determine the optimal values of these parameters to ensure the minimum value of surface roughness and the maximum value of MRR. This work is known as the optimization of the milling process.

When researching to determine the optimal values of parameters of the milling process, there have been many studies applying the Taguchi method in designing the experimental matrix. This is a matrix design method enabling to conduct few experiments with a large number of input parameters. In addition, qualitative input parameters can also be included in the matrix design, which is an outstanding advantage that only this method has [8-11].

A. A. Thakre conducted the experiment of 1040 MS steel milling with a Taguchi-type experimental matrix with the input parameters including spindle speed, feed rate, cutting rate, and coolant flow. He used the method of analysis of signal-to-noise ratio (S/N) to determine the optimal values of these parameters in order to ensure the minimum value of surface roughness [12]. This work has also been done by M. Pra-kash et al. when milling OHNS steel [13]. M. Kumar et al. [14] also used the Taguchi method to design experiments when milling D2 steel. The input parameters including cutting velocity, feed rate and cutting depth were chosen. Then, the S/N ratio analysis method was also selected to determine the optimal values of these parameters, one to ensure the minimum surface roughness and the other to ensure the maximum MRR. This work was also carried out by P. V. Krishna et al. when milling 6061 aluminum alloy [15], by S. S. Phanshet-ty et al. when milling 7076 aluminum alloy [16], by H. Shagwira et al. when milling Polypropylene + 5wt.% Quarry Dust Composites [17], by D. P. Vansh et al. when milling Titanium alloy [18], etc.

However, if only using the Taguchi method to design the experimental matrix and then using the S/N analysis method to analyze the experimental results, only a
certain criterion of the milling process can be achieved, in particular, it is only possible to ensure either the minimum surface roughness or the maximum MRR. In order to ensure these two criteria simultaneously, it is necessary to solve the problem of multi-objective optimization of the milling process. In this article, we will apply the Moora method to solve this problem. The Moora method has been successful in optimizing the division of students into each class at the beginning of admission in universities [19], optimizing the identification of raw materials for the mushroom growing process [20], multi-objective optimization of grinding process [21], etc. However, there have been no published studies on the application of this method to the multi-objective optimization of the milling process so far.

2 Multi-Objective Optimization by Moora Method

2.1 Multiple criteria decision-making model

Multiple criteria decisions making (MCDM) model helps us to choose the best option from the set of options \( A = \{ A_1, A_2, \ldots, A_m \} \) based on the set of criteria \( C = \{ C_1, C_2, \ldots, C_n \} \). Where each criterion \( C_j \) is assigned with a weight \( w_j \) \((j = 1, 2, \ldots, n)\) so that \( \sum_{j=1}^{n} w_j = 1 \). An MCDM problem can be represented by a matrix in the form of:

\[
\begin{bmatrix}
A_1 & A_2 & \cdots & A_m \\
\vdots & \vdots & \ddots & \vdots \\
A_3 & \vdots & \ddots & \vdots \\
\end{bmatrix}
\]

Where \( d_{ij} \in R^+ \) with all \( i = 1, 2, \ldots, m \) and \( j = 1, 2, \ldots, n \).

In this study, the weighting of criteria will be calculated using the Entropy measure because it provides high accuracy. The weight calculation steps are performed as follows [22, 23]:

Step 1: Calculate the values \( P_{ij} \) with all \( i = 1, 2, \ldots, m \) and \( j = 1, 2, \ldots, n \).

\[
P_{ij} = \frac{d_{ij}}{m + \sum_{j=1}^{n} C_{ij}^2}
\]  

Step 2: Calculate the entropy measures \( e_j \) of each criterion \( C_j \) with all \( j = 1, 2, \ldots, n \).

\[
e_j = \frac{\sum_{i=1}^{m} P_{ij} \ln[P_{ij}]}{- \left( \sum_{i=1}^{m} P_{ij} \right) \times \ln \left( \sum_{i=1}^{m} P_{ij} \right) + 1}
\]  

Step 3: Calculate the weights \( w_j \) of each criterion \( C_j \) with all \( j = 1, 2, \ldots, n \).

\[
w_j = \frac{1 - e_j}{\sum_{j=1}^{n} (1 - e_j)}
\]

2.2 MOORA method

The Moora method introduced for the first time by W. K. M. Brauers [24] in 2004 is a multi-objective optimization that can be successfully applied to solve complex decision-making problems in production environments, where the goals may conflict. The multi-objective optimization method based on the Moora method includes the following steps:

Step 1: Calculate the values \( P_{ij} \) with all \( i = 1, 2, \ldots, m \) and \( j = 1, 2, \ldots, n \) in accordance with the formula (1).

Step 2: Calculate the entropy measures \( e_j \) of each criterion \( C_j \) with all \( j = 1, 2, \ldots, n \) in accordance with the formula (2).

Step 3: Calculate the weights \( w_j \) of each criterion \( C_j \) with all \( j = 1, 2, \ldots, n \) in accordance with the formula (3).

Step 4: Calculate the normalized decision matrix \( X_{ij} \) with all \( i = 1, 2, \ldots, m \) and \( j = 1, 2, \ldots, n \) in accordance with the formula (4).

\[
X = \left[ X_{ij} \right]_{m \times n} \quad X_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} C_{ij}}
\]

Step 5: Calculate the decision matrices after the normalization of number \( W = [W_{ij}]_{m \times n} \) with all \( i = 1, 2, \ldots, m \) and \( j = 1, 2, \ldots, n \) in accordance with the formula (5).

\[
W_{ij} = w_j \times x_{ij}
\]

Step 6: Calculate \( P_i \) in accordance with the formula (6) and calculate \( R_i \) in accordance with the formula (7).

\[
P_i = \frac{1}{|B|} \sum_{j \in B} W_{ij}
\]

\[
R_i = \frac{1}{|NB|} \sum_{j \in NB} W_{ij}
\]

Where \( B \) and \( NB \) are the set of benefit criteria and the set of non-benefit criteria, respectively, with all \( i = 1, 2, \ldots, m \).

Step 7: Calculate the priority values with all \( i = 1, 2, \ldots, m \) in accordance with the formula (8).

\[
Q_i = P_i - R_i
\]

Step 8: Rank the options \( A_k < A_i \) if \( Q_k < Q_i \) with all \( i, k = 1, 2, \ldots, m \)

3 Experimental Process
3.1 Experimental system

An experimental process has been carried out to mill SCM440 steel samples with its length, width, and height of 80 mm, 50 mm, and 40 mm respectively. The experiments have been conducted on 3-axis CNC milling machine of HAAS brand (Figure 1). The used cutting tool has been TiAlIN chip with a tool nose radius of 0.3 mm, beck edge length of 0.8 mm, main cutting angle of 90° and edge with of 6.8 mm. This type of cutting tool has high thermal strength, good cutting performance, high wear resistance and it is very suitable for machining alloy steels [25,26]. During the experiment, each chip is used only once. The purpose of this is to eliminate the effect of tool wear on the output parameters. A 14 mm diameter tool body has been used to attach two chips for each experiment. The used coolant has been Caltex Aquatex 3180 type mixed with water at a concentration of 2%. This is the oil commonly used in CNC milling technology [27]. In order to reduce the effect of random factors on the output parameters of the experimental process, the surface roughness was measured on each experimental sample at least 3 times, then the surface roughness value at each experiment will be taken as the average value of measurements. The MRR is calculated in accordance with the formula (9), Where \( V_f \) is the feed rate (mm/min), \( a_p \) is the cutting depth (mm) and \( b_w \) is the milling width (mm). In this case, the symmetrical milling process has been performed, which means that the milling width is equal to the diameter of the milling cutter.

\[
MRR = V_f \cdot a_p \cdot b_w \text{ (mm}^3\text{/min)}
\]  

(9)

![Fig. 1. Experimental machine](image)

3.2 Experimental design

The selected parameters are the input parameters of the experimental process, including coolant flow, coolant pressure, cutting velocity, feed rate, and cutting depth. Taguchi method has been chosen to design the experimental matrix, in which each input parameter has 3 levels of values selected as shown in Table 1, the experimental matrix of 27 experiments has been set up as shown in Table 2.

### Table 1. Input parameters

| Parameter          | Symbol | Unit | Value at level |
|--------------------|--------|------|----------------|
| Coolant flow       | \( C_l \) | litre/min | 10 15 20 |
| Coolant pressure   | \( C_p \) | Mpa | 1 4 7 |
| Cutting velocity   | \( V_c \) | m/min | 85 125 165 |
| Feed rate          | \( V_f \) | mm/min | 140 200 240 |
| Depth of cut       | \( a_p \) | mm | 0.30 0.5 0.7 |

### Table 2. Experimental matrix

| No. | Code value | Actual value |
|-----|------------|--------------|
| \( C_l \) | \( C_p \) | \( V_c \) | \( V_f \) (m/min) | \( V_f \) (mm/min) | \( a_p \) (mm) |
| 1    | 1 1 1 1 1 1 | 10 1 85 140 0.3 |
| 2    | 1 1 1 1 1 2 | 10 1 85 140 0.5 |
| 3    | 1 1 1 1 1 3 | 10 1 85 140 0.7 |
| 4    | 1 2 2 2 1   | 10 4 125 200 0.3 |
| 5    | 1 2 2 2 2   | 10 4 125 200 0.5 |
| 6    | 1 2 2 2 3   | 10 4 125 200 0.7 |
| 7    | 1 3 3 3 1   | 10 7 165 240 0.3 |
| 8    | 1 3 3 3 2   | 10 7 165 240 0.5 |
| 9    | 1 3 3 3 3   | 10 7 165 240 0.7 |
| 10   | 2 1 2 3 1   | 15 1 125 240 0.3 |
| 11   | 2 1 2 3 2   | 15 1 125 240 0.5 |
| 12   | 2 1 2 3 3   | 15 1 125 240 0.7 |
| 13   | 2 2 3 1 1   | 15 4 165 140 0.3 |
| 14   | 2 2 3 1 2   | 15 4 165 140 0.5 |
| 15   | 2 2 3 1 3   | 15 4 165 140 0.7 |
| 16   | 2 3 1 2 1   | 15 7 85 200 0.3 |
| 17   | 2 3 1 2 2   | 15 7 85 200 0.5 |
| 18   | 2 3 1 2 3   | 15 7 85 200 0.7 |
| 19   | 3 1 3 2 1   | 20 1 165 200 0.3 |
| 20   | 3 1 3 2 2   | 20 1 165 200 0.5 |
| 21   | 3 1 3 2 3   | 20 1 165 200 0.7 |
| 22   | 3 2 1 3 1   | 20 4 85 240 0.3 |
| 23   | 3 2 1 3 2   | 20 4 85 240 0.5 |
| 24   | 3 2 1 3 3   | 20 4 85 240 0.7 |
| 25   | 3 3 2 1 1   | 20 7 125 140 0.3 |
| 26   | 3 3 2 1 2   | 20 7 125 140 0.5 |
| 27   | 3 3 2 1 3   | 20 7 125 140 0.7 |

4. Results and Discussion

The order of experiments as shown in Table 2 has been performed, the results are shown in Table 3. With the chosen significance level of 0.05 [28, 29], the Pareto chart represents the effect of input parameters on surface roughness as shown in Figure 2. We can see that the curves of four four parameters in cluding coolant flow (\( C_l \)), cutting velocity (\( V_c \)), feed rate (\( V_f \)) and cutting depth (\( a_p \)) are all over the dark blue limiting curve of Pareto chart. Therefore, it can be confirmed that all four parameters have a significant effect on the surface roughness [28, 29]. In which, the effect of these four parameters on surface roughness decreases in order of feed rate, cutting velocity, coolant flow, and cutting
depth. The curve of coolant pressure ($C_p$) does not exceed the limit of Pareto chart, so this parameter does not significantly affect the surface roughness.

For MRR, out of the five input parameters, only two of them, feed rate and cutting depth, are present in the formula (9). Therefore, only these two parameters have a significant effect on the MRR. And it is obvious that the MRR will increase when increasing the values of these two parameters. Thus, we can see that the effect of input parameters on surface roughness and MRR is not the same. For example, cutting velocity and coolant flow have a great effect on surface roughness but have no effect on MRR. On the other hand, the data in Table 3 show that, in experiment #13, the surface roughness has the smallest value, but in this experiment (and the experiments of #1 and #25), the MRR also has the smallest value. The MRR has the largest value in the experiments of #9, #12 and #24. However, also in these experiments, the surface roughness value is also quite large (for experiment #12, the surface roughness has the largest value among 27 conducted experiments). Since then, it is shown that if only based on the chart in Figure 2 and the experimental results in Table 3, it is very difficult to determine which experiment simultaneously ensures the “minimum” surface roughness value and the “maximum” MRR value. This problem can only be resolved by the method of solving the optimization problem.

### Table 3. Experimental results

| No | $C_1$ (litre/min) | $C_p$ (Mpa) | $V_c$ (m/min) | $V_f$ (mm/min) | $a_p$ (mm) | Ra (µm) | MRR (mm$^3$/min) |
|----|------------------|-------------|---------------|---------------|-----------|---------|-----------------|
| 1  | 10               | 1           | 85            | 140           | 0.3       | 1.212   | 588             |
| 2  | 10               | 1           | 85            | 140           | 0.5       | 1.302   | 980             |
| 3  | 10               | 1           | 85            | 140           | 0.7       | 1.372   | 1372            |
| 4  | 10               | 4           | 125           | 200           | 0.3       | 1.442   | 840             |
| 5  | 10               | 4           | 125           | 200           | 0.5       | 1.325   | 1400            |
| 6  | 10               | 4           | 125           | 200           | 0.7       | 1.411   | 1960            |
| 7  | 10               | 7           | 165           | 240           | 0.3       | 1.132   | 1008            |
| 8  | 10               | 7           | 165           | 240           | 0.5       | 1.226   | 1680            |
| 9  | 10               | 7           | 165           | 240           | 0.7       | 1.422   | 2352            |
| 10 | 15               | 1           | 125           | 240           | 0.3       | 1.322   | 1008            |
| 11 | 15               | 1           | 125           | 240           | 0.5       | 1.502   | 1680            |
| 12 | 15               | 1           | 125           | 240           | 0.7       | 1.888   | 2352            |
| 13 | 15               | 4           | 165           | 140           | 0.3       | 0.692   | 588             |
| 14 | 15               | 4           | 165           | 140           | 0.5       | 0.778   | 980             |
| 15 | 15               | 4           | 165           | 140           | 0.7       | 0.854   | 1372            |
| 16 | 15               | 7           | 85            | 200           | 0.3       | 1.252   | 840             |
| 17 | 15               | 7           | 85            | 200           | 0.5       | 1.406   | 1400            |
| 18 | 15               | 7           | 85            | 200           | 0.7       | 1.123   | 1960            |
| 19 | 20               | 1           | 165           | 200           | 0.3       | 0.942   | 840             |
| 20 | 20               | 1           | 165           | 200           | 0.5       | 1.022   | 1400            |
| 21 | 20               | 1           | 165           | 200           | 0.7       | 0.868   | 1960            |
| 22 | 20               | 4           | 85            | 240           | 0.3       | 1.034   | 1008            |
| 23 | 20               | 4           | 85            | 240           | 0.5       | 1.333   | 1680            |
| 24 | 20               | 4           | 85            | 240           | 0.7       | 1.542   | 2352            |
| 25 | 20               | 7           | 125           | 140           | 0.3       | 0.954   | 588             |
| 26 | 20               | 7           | 125           | 140           | 0.5       | 0.722   | 980             |
| 27 | 20               | 7           | 125           | 140           | 0.7       | 0.946   | 1372            |
5 Multi-Objective Optimization of Scm400 Steel Milling Process

In order to facilitate the use of mathematic symbols when performing the optimization by Moora method, we set the surface roughness criterion as $C_1$ (i.e. $Ra = C_1$), set the MRR criterion as $C_2$ (i.e. $MRR = C_2$) as shown in Table 4.

Table 4. Surface roughness and MRR for different values of input parameters

| No. | $C_1$  | $C_2$  |
|-----|--------|--------|
| A1  | 1.212  | 588    |
| A2  | 1.302  | 980    |
| A3  | 1.372  | 1372   |
| A4  | 1.442  | 840    |
| A5  | 1.325  | 1400   |
| A6  | 1.411  | 1960   |
| A7  | 1.132  | 1008   |
| A8  | 1.226  | 1680   |
| A9  | 1.422  | 2352   |
| A10 | 1.322  | 1008   |
| A11 | 1.502  | 1680   |
| A12 | 1.888  | 2352   |
| A13 | 0.692  | 588    |
| A14 | 0.772  | 980    |
| A15 | 0.854  | 1372   |
| A16 | 1.252  | 840    |
| A17 | 1.406  | 1400   |
| A18 | 1.123  | 1960   |
| A19 | 0.942  | 840    |
| A20 | 1.022  | 1400   |
| A21 | 0.868  | 1960   |
| A22 | 1.034  | 1008   |
| A23 | 1.333  | 1680   |
| A24 | 1.542  | 2352   |
| A25 | 0.954  | 588    |
| A26 | 0.722  | 980    |
| A27 | 0.946  | 1372   |

From the data in Table 4, the Moora method is used to calculate the following values:

Step 1: Calculate the values $p_{ij}$ in accordance with the formula (1). The results are shown in Table 5.

Table 5. Table of values of $p_{ij}$

| No. | $p_{ij}$ |
|-----|----------|
| C1  | C2       |
| A1  | 0.021894 | 0.006045 |
| A2  | 0.025267 | 0.016791 |
| A3  | 0.028057 | 0.03291  |
| A4  | 0.030993 | 0.012336 |
| A5  | 0.026167 | 0.034267 |
| A6  | 0.029674 | 0.067163 |
| A7  | 0.019099 | 0.017764 |
| A8  | 0.022403 | 0.049344 |
| A9  | 0.030139 | 0.096714 |
| A10 | 0.026049 | 0.017764 |
| A11 | 0.033625 | 0.049344 |
| A12 | 0.053129 | 0.096714 |
| A13 | 0.007137 | 0.006045 |
| A14 | 0.008883 | 0.016791 |
| A15 | 0.01087  | 0.03291  |
| A16 | 0.023363 | 0.012336 |
| A17 | 0.029464 | 0.034267 |
| A18 | 0.018797 | 0.067163 |
| A19 | 0.013221 | 0.012336 |
| A20 | 0.015568 | 0.034267 |
| A21 | 0.01123  | 0.067163 |
| A22 | 0.015936 | 0.017764 |
| A23 | 0.026464 | 0.049344 |
| A24 | 0.03544  | 0.096714 |
| A25 | 0.013565 | 0.006045 |
| A26 | 0.00777  | 0.016791 |
| A27 | 0.013339 | 0.03291  |
Step 2: Use the formula (2) to calculate the entropy measures $e_j$ of each criterion $C_j$. The results are shown in Table 6.

Step 3: Use the formula (3) to calculate the weights $w_j$ of each criterion $C_j$. The results are also shown in Table 6.

Table 6. Weight of criteria

| Parameters in Copras | C1 | C2 |
|----------------------|----|----|
| Entropy              | 0.44998 | 3.02717 |
| Weight               | -0.37236 | 1.37236 |

Table 7. Normalized matrix

| No. | X_{ij} |
|-----|--------|
|     | C1     | C2     |
| A1  | 0.19141 | 0.07775 |
| A2  | 0.20563 | 0.12958 |
| A3  | 0.21668 | 0.18141 |
| A4  | 0.22774 | 0.11107 |
| A5  | 0.20926 | 0.18511 |
| A6  | 0.22284 | 0.25916 |
| A7  | 0.17878 | 0.13328 |
| A8  | 0.19362 | 0.22214 |
| A9  | 0.22458 | 0.31099 |
| A10 | 0.10929 | 0.07775 |
| A11 | 0.12192 | 0.12958 |
| A12 | 0.13487 | 0.18141 |
| A13 | 0.19773 | 0.11107 |
| A14 | 0.22205 | 0.22214 |
| A15 | 0.14877 | 0.11107 |
| A16 | 0.18511 | 0.11107 |
| A17 | 0.16141 | 0.18141 |
| A18 | 0.13708 | 0.25916 |
| A19 | 0.16330 | 0.13328 |
| A20 | 0.21052 | 0.22214 |
| A21 | 0.24353 | 0.31099 |
| A22 | 0.15067 | 0.07775 |
| A23 | 0.11403 | 0.12958 |
| A24 | 0.14940 | 0.18141 |

Step 4: Use the formula (4) to calculate the normalized matrix $X = [X_{ij}]_{n \times k}$, the results are shown in Table 7.

Step 5. Use the formula (5) to calculate the decision matrices after the normalization of number $W$. The results are shown in Table 8.

Step 6. Use the formula (6) to calculate the value of $P_i$, use the formula (7) to calculate the value of $R_i$. The results are shown in Table 9.

Step 7. Use the formula (8) to calculate the value of $Q_i$. The results are also shown in Table 9.
6. Conclusion

The experimental process of milling SCM400 steel with TiAlN coated chip has been performed in this study. The Taguchi method has been used to design experiments with five input parameters, including coolant flow, coolant pressure, cutting speed, feed rate, and cutting depth. The coolant is Caltex Aquatek 3180. The Moora method has been applied to solve the multi-objective problem. A number of conclusions are drawn as follows:

- Parameters including coolant flow, cutting velocity, feed rate, and cutting depth all have a significant effect on surface roughness. In which the effect of these four parameters on surface roughness decreases in order of feed rate, cutting velocity, coolant flow, and cutting depth. Meanwhile, the coolant pressure does not significantly affect the surface roughness.

- In order to simultaneously ensure the two criteria, including the minimum surface roughness and the maximum MRR, the values of parameters of coolant flow, coolant pressure, cutting velocity, feed rate, and cutting depth are 20 (litre/min), 1 (Mpa), 165 (m/min), 200 (mm/min), and 0.7 (mm), respectively.

- Determination of the optimal parameters of the concentration of coolant type and cutting tool type to ensure the multi-objective of SCM400 steel milling process is the work that will be done by the authors of this study in the next time.

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