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INVESTIGATION AND OPTIMIZATION OF PARAMETERS IN FACE MILLING OF S50C STEEL UNDER MQL SYSTEM

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This paper aims to investigate cutting and lubrication parameters on surface roughness, cutting force, and material removal rate in face milling of JIS S50C carbon steel under a peanut oil-assisted Minimum Quantity Lubricant system. The five 3-level cutting process parameters were considered variants, including cutting speed, feed rate, depth of cut, air pressure, and lubrication flow. The experimental design was based on Taguchi's orthogonal array L27. The Analysis of variance is used to analyze the effect of cutting parameters and lubrication conditions on the surface roughness and cutting force. In addition, both regression optimizer procedures based on regression models and the Multi-Criteria Decision Making method were successfully applied to find the optimum conditions of the cutting parameter. The results showed the advantage and disadvantages of each technique. The Multi-Objective Optimization by Ratio Analysis was used in finding the best alternative. However, these values may not be an optimum condition. Mathematically, a regression optimizer may better determine the optimal value.

Keywords: minimum quantity lubricant, multi-criteria decision making, multi-objective optimization

1 INTRODUCTION

S50C (JIS G4051, ASTM 1050) carbon steel is the standard carbon steel grade with a wide range of applications. Therefore, much research on S50C cutting ability with different machining processes such as turning [1], grinding [2] and other machining conditions [3], [4]… and optimization of technological parameters have been published. By contrast, the figure for milling of S50C in the Minimum Quantity Lubricant (MQL) condition is insignificant. Hence, this study research focused on multi-objective optimization of the S50C milling process using peanut oil-assisted MQL system [6], where all responses, including surface quality, cutting force and cutting productivity, are calculated to find the optimal point together. In the metal cutting process, surface roughness R_a is often considered the most important criterion. Depending on the range of roughness R_a, suitable cutting techniques such as milling and grinding are applied [5]. The experimental research about the influence of cutting parameters on surface quality and the relationship between them is established as the regression models that have been published to improve product quality, especially surface roughness [7], [8]. Many authors have also claimed that applying MQL in a suitable machining process reduces the amount of fluid coolant while increasing tool life and improving product quality [9], [10]. Several studies have demonstrated that vegetable oils such as peanut oil [11], [12], and palm oil [9] are appropriate for MQL. These single objective optimization methods are quite simple and can be easily applied in manufacturing. In recent decades, manufacturers have to find a solution to keep product quality while reducing production costs due to increasing pressure in the global industrial market. The cost of fluid coolant accounts for up to 16% of the machining cost [6-9], and the figures for energy and employee are about 7% and 10%, respectively [13], [14]. Hence, improving product quality while reducing power consumption and manufacturing costs in cutting tools, processing time, metalwork fluid (MWF) consumption, etc., is the multi-objective optimization problem that researchers have to solve.

Many multi-purpose optimization methods based on Taguchi orthogonal array [10], such as MOORA [11], TOPSIS [15], WPCA [13] are applied, due to its simplicity. Recently, the development of computers and computer application [14], mathematical algorithms [15], machine learning [16] or Genetic Algorithm [17], the combing of computer application and the algorithms to solve complicated multiple objective optimization problems has become popular. However, many have not been published comparing each method's effectiveness, advantages, and disadvantages.

In this research, both MCDM and computing software was used to solve the multi-objective optimization problem. The results were compared and presented the advantages and disadvantages of each method.

2 MATERIALS AND METHODOLOGY

2.1 Materials

In this study work, JIS S50C Carbon Steel was chosen as a workpiece specimen for the experimental research. The chemical composition of S50C carbon steel workpiece is shown in Table 1 [16].

Table 1. S50C Steel Chemical Composition

C (%)	Mn (%)	P (%)	S (%)	Si (%)	Cr (%)	Ni (%)
0.47-0.53	0.60-0.90	0.030	0.035	0.15-0.35	0.25	0.25

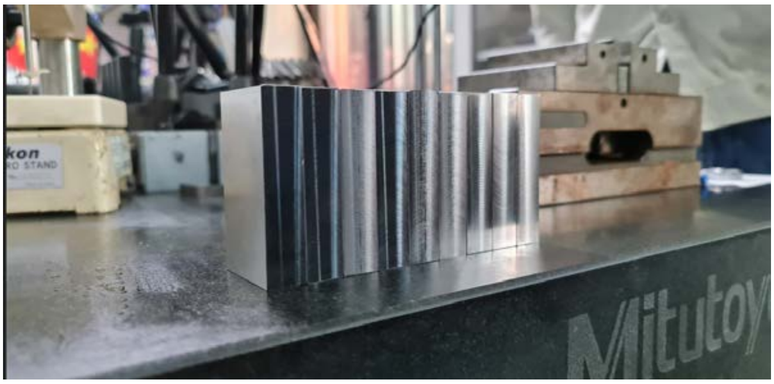

Fig. 1. JIS S50C Steel Experimental Workpieces

All S50C workpiece specimens were prepared in the dimensions of 50 mm x 35 mm x 15 mm (Fig.1). All sides of each workpiece were face-ground to guarantee the positioning process. The experimental workpiece was implemented on the CNC machine (Fig 2) under MQL conditions.

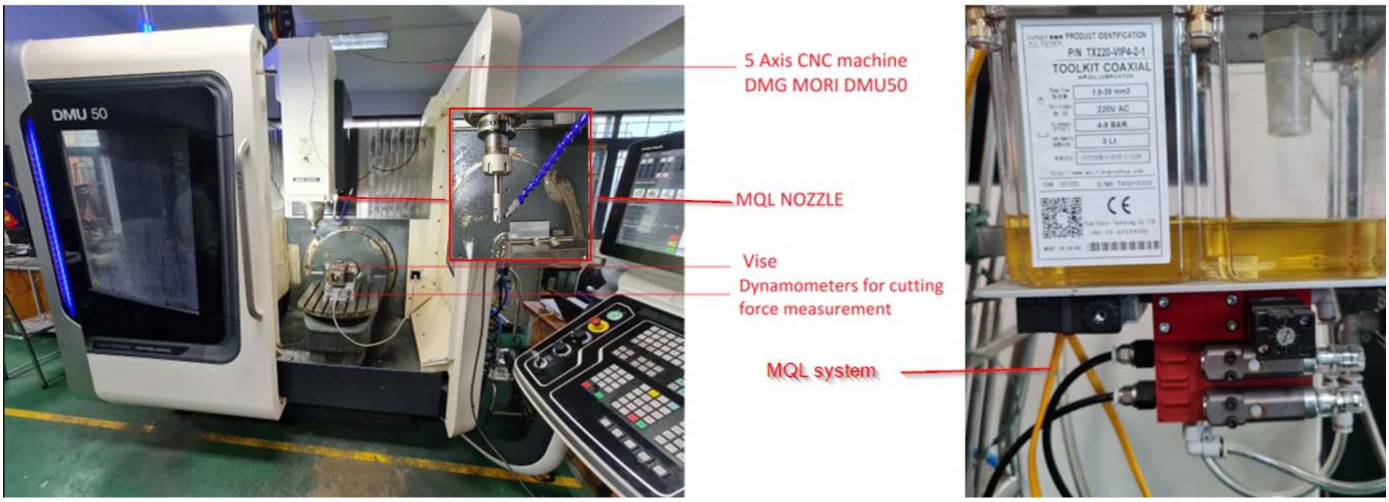

Fig. 2. The 5-Axis CNC Milling DMG Mori Seiki DMU 50

The experimental workpiece specimens were machined using a 20mm of diameter cutting tool and the cutting-edge angle is 90 deg.

2.2 Experimental Design

Taguchi AO was used to reduce the number of experiments. In this research, five 3-level input factors include cutting parameters: cutting speed V_c, feed rate f_z, depth of cut ap, and lubrication parameters: air pressure P, the flow rate of lubricant Q considered research. Level 1, level 3, and level 2 are each parameter's minimum, maximum, and median values. The parameter's value was chosen based on the CNC machine's specification, the handbook from the cutting tool manufacturer, and references to the results in previous publications. The value of the input factors is described in Table 2. According to 5 of the 3-level variants and 3 responses, Taguchi OA L_{27} is used.

The viscosity of peanut oil is 0.0574 Pa·s.at 26°C [18], and it's suitable for MQL lubrication. In this experiment, peanut oil is used to assist the MQL system because the viscosity of peanut oil is lower than other vegetable oils such as sunflower oil, Soybean oil, and Walnut.

Table 2. Experimental factors definition

No	Variant	Parameter	Dimension	Level		
				1	2	3
1	V_c	Cutting Speed	m/min	120	210	300
2	f_z	Feed per tooth	mm/tooth	0.02	0.06	0.10
3	a_p	Depth of cut	mm	0.1	0.5	0.9

No	Variant	Parameter	Dimension	Level		
				1	2	3
4	P	MQL Pressure	MP_a	1	2	3
5	Q	MQL Flow Rate	ml/h	50	100	150

2.3 Experimental data acquisition

Measurement Equipment

The average surface roughness R_a was defined as Eq. (1):

$$R_a = \frac{R_{a1} + R_{a2} + R_{a3}}{3} \tag{1}$$

The finishing roughness of each workpiece was measured three times at a different position by Mitutoyo Surftest JS-210 (Fig.3; Fig 4). The average surface roughness value of each experimental workpiece was calculated, and then filled in Table 3.

Fig. 3. Profilometer tester Mitutoyo Surftest JS-210

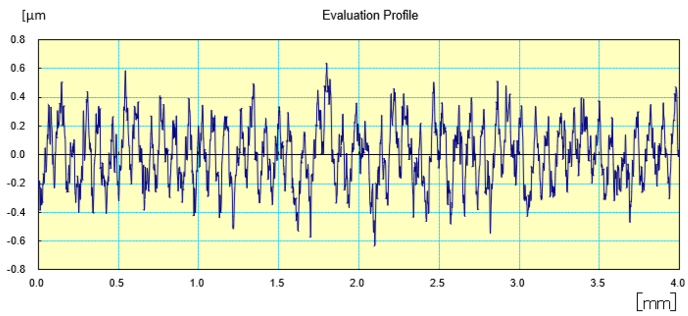

Fig. 4. Result of Surface Roughness in Measurement

The cutting force in the three-dimensions F_x, F_y, and F_z was collected by the Kistler cutting force dynamometer (Fig.5, Fig 6). The measured cutting force result for each experiment was calculated by Eq (2):

$$F_c = \sqrt{F_X^2 + F_Y^2 + F_Z^2} \tag{2}$$

And the summarized results corresponding to the experimental runs are presented as Table 3.

Table 3 The experimental data

Run	P	Q	V_c	f_z	a_p	R_a	F_c	MRR
	MPa	ml/h	m/min	mm/tooth	mm	µm	N	cm^3/min
1	1	50	120	0.02	0.1	0.8460	5.852	229.3
2	1	50	120	0.02	0.5	0.7900	27.951	1146.6
3	1	50	120	0.02	0.9	0.6200	49.166	2063.9
4	1	100	210	0.06	0.1	0.5040	13.905	1203.8
5	1	100	210	0.06	0.5	0.4320	58.731	6019.2
6	1	100	210	0.06	0.9	0.4020	93.748	10834.6
7	1	150	300	0.1	0.1	0.3760	19.526	2866.2
8	1	150	300	0.1	0.5	0.3770	81.496	14331.0
9	1	150	300	0.1	0.9	0.2930	148.384	25795.8
10	2	50	210	0.1	0.1	0.6070	17.698	2006.4
11	2	50	210	0.1	0.5	0.5310	80.864	10032.0
12	2	50	210	0.1	0.9	0.5640	125.816	18057.6
13	2	100	300	0.02	0.1	0.1510	9.395	573.2

Run	P	Q	V_c	f_z	a_p	R_a	F_c	MRR
	MPa	ml/h	m/min	mm/tooth	mm	µm	N	cm^3/min
14	2	100	300	0.02	0.5	0.1760	34.485	2866.2
15	2	100	300	0.02	0.9	0.1690	52.062	5159.2
16	2	150	120	0.06	0.1	1.0160	15.134	688.0
17	2	150	120	0.06	0.5	0.9280	57.217	3439.8
18	2	150	120	0.06	0.9	0.8020	94.384	6191.6
19	3	50	300	0.06	0.1	0.2290	13.942	1719.7
20	3	50	300	0.06	0.5	0.2120	55.234	8598.6
21	3	50	300	0.06	0.9	0.1910	87.976	15477.5
22	3	100	120	0.1	0.1	1.2790	16.730	1146.6
23	3	100	120	0.1	0.5	1.1530	78.769	5733.0
24	3	100	120	0.1	0.9	0.9190	132.958	10319.4
25	3	150	210	0.02	0.1	0.2840	7.159	401.3
26	3	150	210	0.02	0.5	0.2520	26.539	2006.4
27	3	150	210	0.02	0.9	0.2430	46.783	3611.5

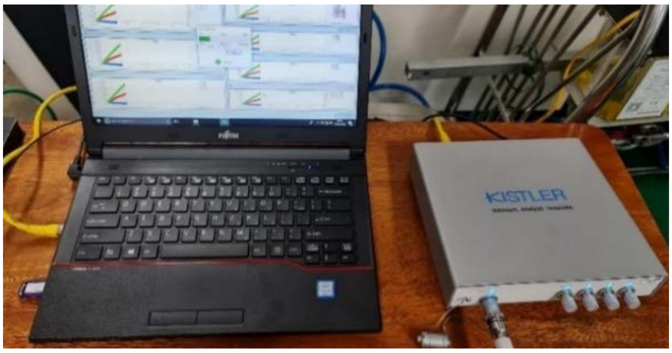

Fig. 5. Kistler cutting force dynamometer

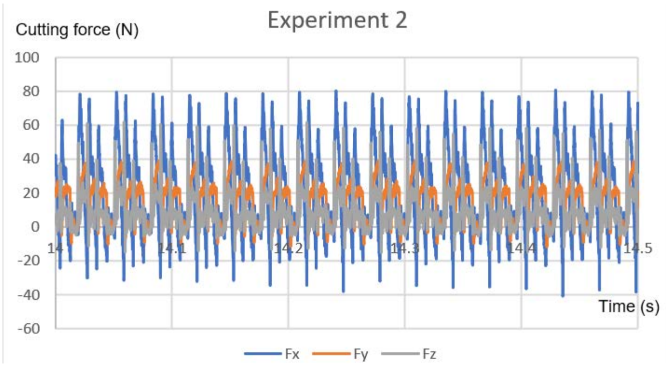

Fig. 6. Measured Cutting Force Result

2.3.1 Material Removal Rate MRR

Material removal rate (MRR) is defined as the volume of material removed per unit of time. MRR is a fundamental criterion of the machining process and depends on the values of cutting speed (V_c), feed rate (V_f), and depth of cut (a_p). The MRR could be determined using the Eq. (3)

$$MRR = \frac{w.a_p.v_f}{1000} \tag{3}$$

Where: v_f is feed rate in m/min and w (mm), a_p is the width of cut and depth of cut, respectively.

The MRR value for each experiment is calculated by equation (3) and the results are shown in table 3.

2.4 Multiple criteria optimization framework

In this experimental research, Multi-Objective Optimization by Ratio Analysis (MOORA) is applied to solve the optimization problem. MOORA is a multiple objective decision-making method; it was presented by Willem Brauers in the year 2004 [19] which is considered an objective approach. Moreover, desirable and undesirable criteria are used simultaneously for ranking to find the best alternative among various experiments. The MOORA method could be conducted with eight following steps:

Step 1: Calculating the value of each p_{ij} by Eq. (4)

$$P_{ij} = \frac{dij}{m + \sum_{i=1}^{m} d_{ij}^2}, i = 1, 2, ..m; j = 1, 2, ..n \tag{4}$$

Step 2: Calculating the degree of entropy e_j of each C_j by Eq. (5)

$$e_j = -\sum_{i=1}^{m}\left[p_{ij}\ln\left(p_{ij}\right)\right] - \left(1 - \sum_{i=1}^{m} p_{ij}\right) \times \ln\left(1 - \sum_{i=1}^{m} p_{ij}\right) \tag{5}$$

Step 3: Calculating entropy weight w_j of each criterion C_j by Eq. (6)

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{n}\left(1 - e_j\right)}, i = 1, 2..m; j = 1, 2..n \tag{6}$$

Step 4: Determination of the normalized decision matrix $[X_{ij}]_{m\times n}$ using Eq. (7)

$$X = \left[X_{ij}\right]_{mxn}$$

where

$$X_{ij} = \frac{d_{ij}}{\sqrt{\sum_{i=1}^{m} d_{ij}^2}}, i = 1, 2..m; j = 1, 2..n \tag{7}$$

Step 5: Calculating the values of the decision matrix $W = [W_{ij}]_{m\times n}$ by Eq. (8):

$$W_{ij} = w_j \times x_{ij}, i = 1, 2..m; j = 1, 2..n \tag{8}$$

Step 6: Calculating P_i và R_i using Eqs. (9), (10):

$$P_i = \frac{1}{|B|}\sum_{J \in B} W_{ij} \tag{9}$$

$$R_i = \frac{1}{|NB|}\sum_{J \in NB} W_{ij} \tag{10}$$

Where B and NB are the set of benefit and non-benefit criteria of i. i = 1, 2,.., m.
Step 7: Calculating the MOORA ranking scores using Eq. (11):

$$Q_i = P_i - R_i \tag{11}$$

Step 8: Arranging the ranking of Alternatives
$A_k > A_i$ if $Q_k < Q_i$, $i, k = 1, 2...m$

3 RESULTS AND DISCUSSION

3.1 Predictive and fitness models

The equations (12) and (13) show the full developed models of surface roughness Ra, and cutting force Fc, respectively. They were generated by using the Minitab version 19 application.

3.1.1 Regression Equation for Ra

$$R_a = -0.272 + 1.557P + 0.00111Q + 0.00202V_c - 4.12f_z - 0.064a_p - 0.0270P \times P + 0.000042Q \times Q - 0.00642P \times Q - 0.003811P \times V_c - 0.000129Q \times a_p - 1.23f_z \times a_p \tag{12}$$

3.1.2 Regression Equation for Fc

$$F_c = -12.5 + 13.7P + 0.143Q + 0.0390V_c - 57.4f_z + 18.48a_p - 0.051P \times P - 0.00003Q \times Q - 0.0848P \times Q - 0.0238P \times V_c + 0.0928Q \times a_p + 1184.4f_z \times a_p \tag{13}$$

In order to assess the adequacy of these models, the ANOVA was adopted and conducted with 95% confidence and 5% significance. The analyse results for the predictive models of surface roughness R_a and cutting force F_c are presented in Tables 4 and 5, respectively.

Table 4. ANOVA for the predictive model of Ra

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	11	2.74570	0.249609	60.41	0.000
P	1	0.12849	0.128487	31.10	0.000
Q	1	0.00043	0.000426	0.10	0.753
Vc	1	0.00786	0.007864	1.90	0.188
fz	1	0.02660	0.026600	6.44	0.023
ap	1	0.00115	0.001147	0.28	0.606
P*P	1	0.00437	0.004374	1.06	0.320
Q*Q	1	0.02177	0.021771	5.27	0.037
P*Q	1	0.15456	0.154561	37.41	0.000
P*Vc	1	0.08824	0.088237	21.36	0.000
Q*ap	1	0.00008	0.000080	0.02	0.891
fz*ap	1	0.00468	0.004681	1.13	0.304
Error	15	0.06198	0.004132		
Total	26	2.80768			
"R2" = 94.54%, "Adjusted R2" = 93.24%, and "Predicted R2" = 91.20%					

SS: Sum of squares; MS: Mean square; Cont.: Contribution

Table 5. ANOVA for the predictive model of Fc

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	11	43604.3	3964.03	300.45	0.000
P	1	10.0	9.98	0.76	0.398
Q	1	7.1	7.09	0.54	0.475
Vc	1	2.9	2.92	0.22	0.645
fz	1	5.2	5.18	0.39	0.541
ap	1	94.8	94.78	7.18	0.017
P*P	1	1.6	1.59	0.12	0.733
Q*Q	1	0.0	0.01	0.00	0.980
P*Q	1	27.0	26.99	2.05	0.173
P*Vc	1	3.4	3.44	0.26	0.617
Q*ap	1	41.3	41.31	3.13	0.097
fz*ap	1	4316.8	4316.78	327.18	0.000
Error	15	197.9	13.19		
Total	26	43802.2			

“R^2” = 99.55%, “Adjusted R^2” = 99.22%, and “Predicted R^2” = 98.29%

SS: Sum of squares; MS: Mean square; Cont.: Contribution

The terms of the regressional models corresponding to a p-value small than 0.05 are statistically significant. Accordingly, the terms air pressure P and cutting feed f_z are significant in the surface roughness R_a model, and the terms depth of cut a_p is significant in the cutting force F_c model. The coefficients, including R-square (R^2), "Adjusted R^2" and "Predicted R^2", reveal the accuracy of the developed models. In this study research, the values of "R^2" for the models of surface roughness R_a is 95.54% and cutting force is 99.55%, present an appropriate fitting between the predictive and experimental values. The "Predicted R^2" of these models for R_a and F_c are 91.2% and 98.29%, respectively. These values are also reasonable agreement with the "Adjusted R^2" for R_a at 93.24% and for F_c at 98.29%.

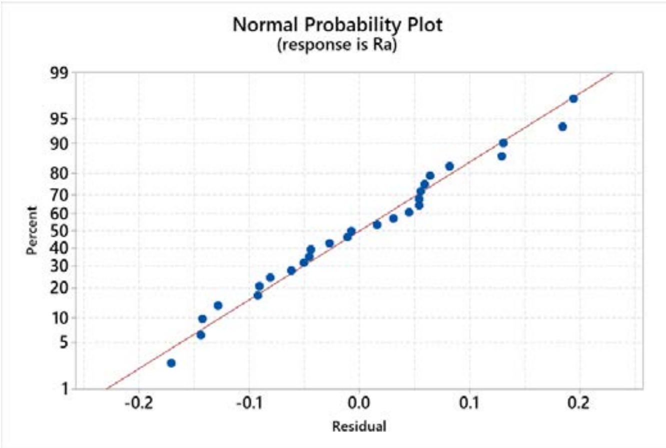

Fig. 7. Normal probability plot for R_a

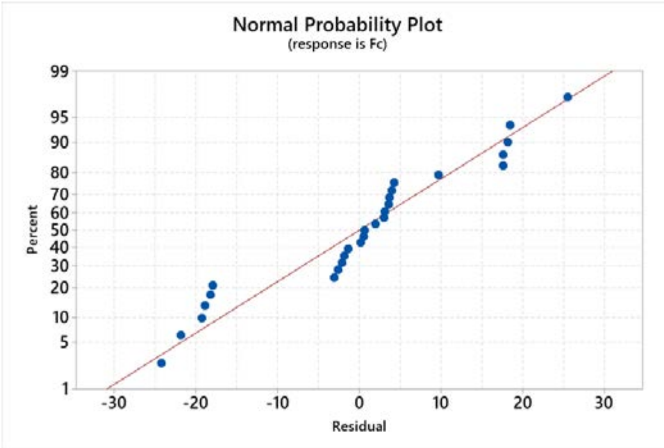

Fig. 8. Normal probability plot for F_c

Moreover, in the normal probability plots of the standardized residual for surface roughness Ra (Fig.7) and cutting force Fc (Fig. 8), the standardized residuals distribute along a straight line with insignificant deviations. Thus, the mathematical modeled results are appropriate in terms of statistics [19]. Based on these observations, it is concluded that the developed models of Ra and Fc are validated in the entire designing space, and they can be used for predicting the appropriate milling parameters

3.2 Effects of variables on the responses

3.2.1 Influence of cutting parameters on Surface roughness Ra

The data in Table 6 and Fig.9 present the relationship between cutting parameters (V_c, f_z, a_p) and lubrication parameters (P, Q) and surface roughness R_a. Where the influence of cutting speed on roughness is most significant, following by feed of tooth f_z and depth of cut a_p. The average value of surface roughness R_a is inversely related to cutting speed Vc and depth of cut ap. However, R_a is proportional to the f_z. When V_c increases from 120 m/min to 210 m/min, the surface roughness drops quickly from around 1.2 µm to about 0.22 µm, then continues to decline a bit when V_c rises up to 300 m/min. Similarly, when the depth of cut ap increase from 0.1 mm to 0.5 mm, the surface roughness reduces a bit around 0.62 µm before a drop to 0.4 µm when ap reach to 0.9 mm.

Table 6. Response for means of Surface Roughness Ra

Level	P	Q	V_c	f_z	a_p
	MPa	l/min	m/min	mm/tooth	mm
1	0.5811	0.5356	1.1648	0.4323	0.6447
2	0.5993	0.5917	0.2932	0.6451	0.6423
3	0.5613	0.6146	0.2838	0.6643	0.4548
Delta	0.0380	0.0790	0.8810	0.2320	0.1899
Rank	5	4	1	2	3

The influence of lubrication parameters such as air pressure P and flow rate of lubricant Q are insignificant. Hence, V_c, f_z, and a_p were considered to analyze to find the surface roughness of R_a's optimum value.

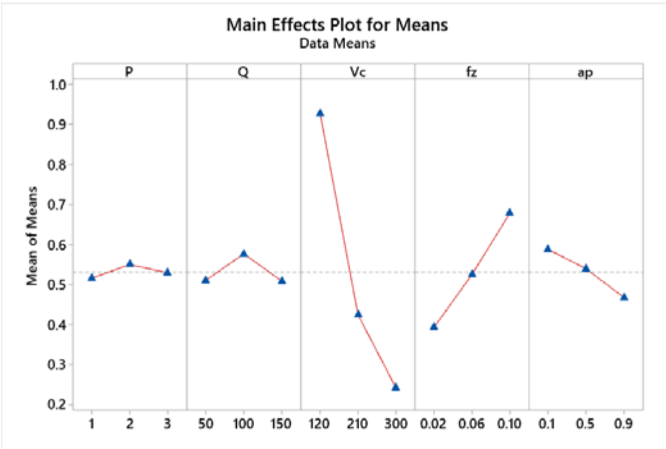

Fig. 9. Main effects plot for Mean of R_a

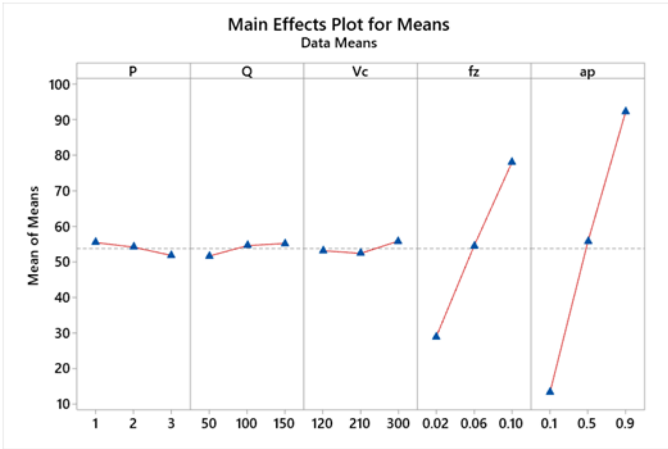

Fig. 10. Main effects plot for Mean of F_c

3.2.2 Influence of cutting parameters on cutting force Fc

The data in Table 7 and Fig.10 illustrate the relationship between cutting parameters (V_c, f_z, a_p) and lubrication parameters (P, Q) and the cutting force F_c. Where the influence of cutting speed V_c, flow rate of lubricant Q are insignificant. By contrast, feed of tooth f_z and depth of cut a_p are affected on cutting force the most. Hence, the cutting force could be reduced quickly by decreasing the feed of tooth f_z or/and depth of cut a_p.

Table 7. Response Table for means of cutting force Fc

Level	P	Q	V_c	f_z	a_p
	MPa	l/min	m/min	mm/tooth	mm
1	55.42	51.61	53.13	28.82	13.26
2	54.12	54.53	52.36	54.47	55.70
3	51.79	55.18	55.83	78.03	92.36
Delta	3.63	3.57	3.47	49.21	79.10
Rank	3	4	5	2	1

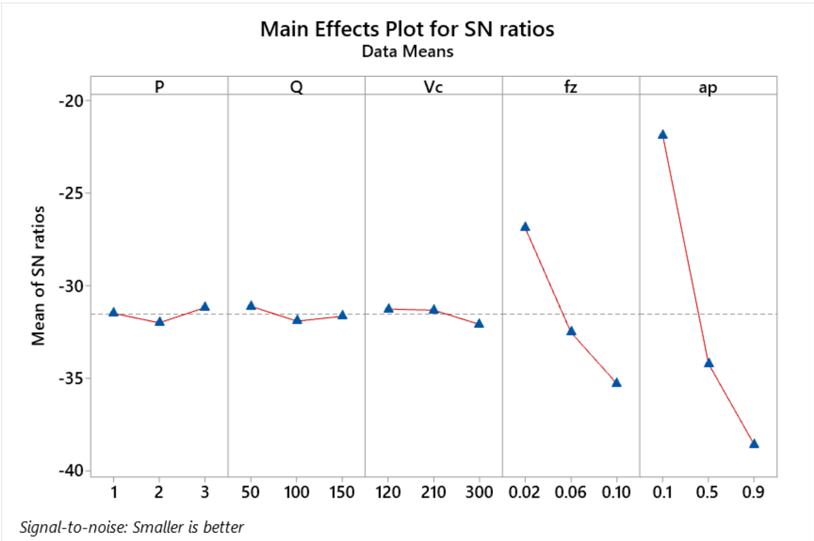

Fig. 11. SN ratios of Cutting Force Fc

3.2.3 The influence of cutting parameters on material removal rate MRR

As shown in Table 8, the material removal rate MRR is proportional to cutting speed V_c, feed of tooth f_z, and depth of cut a_p. The value of MRR increases quickly with the rising of V_c, f_z, and a_p. It could be explained by Eq. (3). This Eq. is also confirmed that MRR is independent of the air pressure P and lubrication flow rate Q, as Figs 12 and 13.

Table 8. Response Table for means of material removal rate MRR

Level	P MPa	Q l/min	V_c m/min	f_z mm/tooth	a_p mm
1	7166	6592	3440	2006	1204
2	5446	4873	6019	6019	6019
3	5446	6592	8599	10032	10835
Delta	1720	1720	5159	8026	9631
Rank	4	5	3	2	1

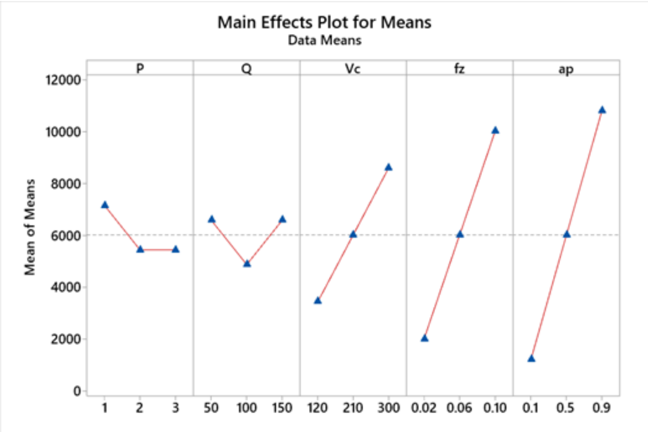

Fig. 12. Main effects plot for Mean of Material Removal Rate

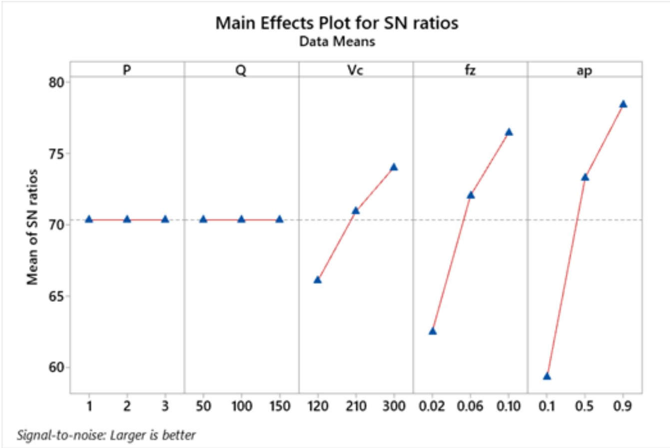

Fig. 2. Main effects plot for SN Ratio of Material Removal Rate

3.3 Optimization results

As aforementioned, MOORA method and computer-based application were used concurrently to solve the multiple objective optimization problem. The experimental results were optimized using the MOORA technique. Moreover, the mathematical regression models of R_a and F_c were generated to predict the find the optimal point of cutting parameters. The results were compared with the MOORA technique to choose the most suitable method which could be applied in multiple objective optimizations of cutting parameters in milling of S50C carbon steel. The experimental data were arranged to the multi-objective optimization form, the result shown as a Table 10

3.3.1 MOORA Method

The sequence to find the optimal alternative with MOORA method is performed by the following steps:

Step 1: Present the matrix of the 27 alternatives, which is shown in Table 9

Table 9. The matrix of alternatives

Alternative	Ra µm C1	FC N C2	MRR cm3/min C3	Alternative	Ra µm C1	FC N C2	MRR cm3/min C3
1	0.8460	5.852	229.3	15	0.1690	52.062	5159.2
2	0.7900	27.951	1146.6	16	1.0160	15.134	688.0
3	0.6200	49.166	2063.9	17	0.9280	57.217	3439.8
4	0.5040	13.905	1203.8	18	0.8020	94.384	6191.6
5	0.4320	58.731	6019.2	19	0.2290	13.942	1719.7
6	0.4020	93.748	10834.6	20	0.2120	55.234	8598.6
7	0.3760	19.526	2866.2	21	0.1910	87.976	15477.5
8	0.3770	81.496	14331.0	22	1.2790	16.730	1146.6
9	0.2930	148.384	25795.8	23	1.1530	78.769	5733.0
10	0.6070	17.698	2006.4	24	0.9190	132.958	10319.4
11	0.5310	80.864	10032.0	25	0.2840	7.159	401.3
12	0.5640	125.816	18057.6	26	0.2520	26.539	2006.4
13	0.1510	9.395	573.2	27	0.2430	46.783	3611.5

Alternative	Ra µm	FC N	MRR cm3/min	Alternative	Ra µm	FC N	MRR cm3/min
	C1	C2	C3		C1	C2	C3
14	0.1760	34.485	2866.2				

Step 2: Transform the responses data to non-dimension form using Eq. (3)

Table 10. Normalized Data for the Milling Process

Alt	P1j	P2j	P3j	Alt	P1j	P2j	P3j
1	0.034283924	2.84561E-05	1.12932E-07	15	0.000565575	3.96555E-05	1.77936E-07
2	0.003674652	2.02283E-05	4.03125E-08	16	0.00474748	4.55175E-06	2.37491E-08
3	0.001399793	3.5771E-05	6.77302E-08	17	0.004822368	3.76803E-05	1.18747E-07
4	0.001680961	2.94111E-06	3.95119E-08	18	0.003405303	6.63661E-05	2.13833E-07
5	0.001008763	3.79571E-05	1.97569E-07	19	0.000780044	3.03676E-06	5.94705E-08
6	0.001010184	6.47114E-05	3.56047E-07	20	0.001065644	3.67856E-05	2.97383E-07
7	0.000787672	3.37514E-06	9.45543E-08	21	0.001061448	6.27405E-05	5.36662E-07
8	0.001260286	5.05983E-05	4.729E-07	22	0.004367829	3.99762E-06	4.00899E-08
9	0.001982188	0.000102073	8.57027E-07	23	0.005674149	4.93861E-05	2.00459E-07
10	0.001195399	3.8618E-06	6.81667E-08	24	0.00273454	9.00476E-05	3.61241E-07
11	0.001109929	5.03751E-05	3.4088E-07	25	0.000640249	2.29923E-06	1.40998E-08
12	0.00121869	8.46555E-05	6.1569E-07	26	0.00052685	1.84779E-05	7.04992E-08
13	0.000507361	1.62279E-06	1.97649E-08	27	0.000495626	3.61238E-05	1.26916E-07
14	0.000588986	2.30112E-05	9.88254E-08				

Alt: alternatives; j: 1-27 is the numerical order of experiment.

Step 3: Determining entropy eij using Eq. (6)

Step 4: Determining entropy weight by Eq. (7)

Table 4. Entropy values set

e_{1j}	e_{2j}	e_{3j}
-0.891477988	-0.999703069	-0.999998194

Table 5. Entropy weight set

w_{1j}	w_{2j}	w_{3j}
0.321069502	0.339440201	0.339490297

Step 5: Determining the decision matrix by Eq. (7), the results illustrated in Table 13.

Step 6: According to the weight set in Table 14, calculating the weighted normalized decision matrix using Eq. (8)

Step 7: Determining the worst and the best solution by Eqs. (11), (12):

Step 8: Ranking to alternatives using Eq. (13), the results presented as shown in Table 14

Table 13. The decision matrix

Alternative	X_{1j}	X_{2j}	X_{3j}	Alternative	X_{1j}	X_{2j}	X_{3j}
1	0.3712	0.0070	0.0051	15	0.0108	0.0423	0.0317
2	0.0670	0.0210	0.0071	16	0.0903	0.0048	0.0042
3	0.0268	0.0394	0.0127	17	0.0911	0.0401	0.0212
4	0.0321	0.0032	0.0074	18	0.0639	0.0705	0.0381
5	0.0193	0.0417	0.0370	19	0.0146	0.0032	0.0106
6	0.0193	0.0710	0.0667	20	0.0199	0.0389	0.0529
7	0.0150	0.0037	0.0176	21	0.0198	0.0663	0.0952
8	0.0241	0.0553	0.0882	22	0.0816	0.0042	0.0071
9	0.0378	0.1112	0.1587	23	0.1054	0.0520	0.0353
10	0.0228	0.0042	0.0123	24	0.0503	0.0945	0.0635
11	0.0211	0.0543	0.0617	25	0.0118	0.0024	0.0025
12	0.0232	0.0910	0.1111	26	0.0097	0.0192	0.0123
13	0.0097	0.0017	0.0035	27	0.0091	0.0376	0.0222

Alternative	X_{1j}	X_{2j}	X_{3j}	Alternative	X_{1j}	X_{2j}	X_{3j}
14	0.0112	0.0245	0.0176				

Table 14. The weighted normalized decision matrix

Alternative	w_{1j}	w_{2j}	w_{3j}	Alternative	w_{1j}	w_{2j}	w_{3j}
1	0.1192	0.0024	0.0017	15	0.0035	0.0143	0.0108
2	0.0215	0.0071	0.0024	16	0.0290	0.0016	0.0014
3	0.0086	0.0134	0.0043	17	0.0293	0.0136	0.0072
4	0.0103	0.0011	0.0025	18	0.0205	0.0239	0.0129
5	0.0062	0.0142	0.0126	19	0.0047	0.0011	0.0036
6	0.0062	0.0241	0.0226	20	0.0064	0.0132	0.0180
7	0.0048	0.0013	0.0060	21	0.0064	0.0225	0.0323
8	0.0077	0.0188	0.0299	22	0.0262	0.0014	0.0024
9	0.0121	0.0378	0.0539	23	0.0339	0.0176	0.0120
10	0.0073	0.0014	0.0042	24	0.0162	0.0321	0.0216
11	0.0068	0.0184	0.0210	25	0.0038	0.0008	0.0008
12	0.0074	0.0309	0.0377	26	0.0031	0.0065	0.0042
13	0.0031	0.0006	0.0012	27	0.0029	0.0128	0.0075
14	0.0036	0.0083	0.0060				

Table 15. The MOORA index and the ranking of alternatives

Alternative	P_i	R_i	Q_i	Ranking	Alternative	P_i	R_i	Q_i	Ranking
1	0.002	0.122	-0.120	27	15	0.011	0.018	-0.007	14
2	0.002	0.029	-0.026	21	16	0.001	0.031	-0.029	23
3	0.004	0.022	-0.018	19	17	0.007	0.043	-0.036	25
4	0.003	0.011	-0.009	18	18	0.013	0.044	-0.032	24
5	0.013	0.020	-0.008	16	19	0.004	0.006	-0.002	7
6	0.023	0.030	-0.008	15	20	0.018	0.020	-0.002	6
7	0.006	0.006	0.000	4	21	0.032	0.029	0.003	2
8	0.030	0.026	0.003	3	22	0.002	0.028	-0.025	20
9	*0.054*	*0.050*	*0.004*	*1*	23	0.012	0.051	-0.040	26
10	0.004	0.009	-0.005	11	24	0.022	0.048	-0.027	22
11	0.021	0.025	-0.004	10	25	0.001	0.005	-0.004	9
12	0.038	0.038	-0.001	5	26	0.004	0.010	-0.005	12
13	0.001	0.004	-0.002	8	27	0.008	0.016	-0.008	17

Step 9: The higher alternative among 27 different alternatives was 9^{th}, with the cutting parameters set (V_c=300 m/min; f_z=0.1 mm/tooth and a_p=0.9 mm) and lubrication set (air pressure P=1 MPa; flow rate of lubrication Q=150 ml/h), corresponding to value of surface roughness Ra, cutting force F_c and material removal rate are 0.593 µm, 148.384 N and 25795.8 cm^3/min, respectively.

3.3.2 Minitab Response Optimizer function

Response Optimizer is a function of Minitab application; it is often used to solve the multiple optimization problems.

In this research, the experimental results were calculated then predicted the optimum conditions by response optimizer function. The result is shown in Table 16 and Fig.14.

Table 16. The response optimizer results

Variable	Setting
P	1
Q	50
Vc	300
fz	0.1
ap	0.414668

Response	Fit	SE Fit	95% CI	95% PI
MRR	12619	2721	(6819, 18419)	(5291, 19947)
Fc	61.14	4.70	(51.11, 71.16)	(48.47, 73.80)
Ra	0.1683	0.0832	(-0.1091, 0.2458)	(-0.1558, 0.2925)

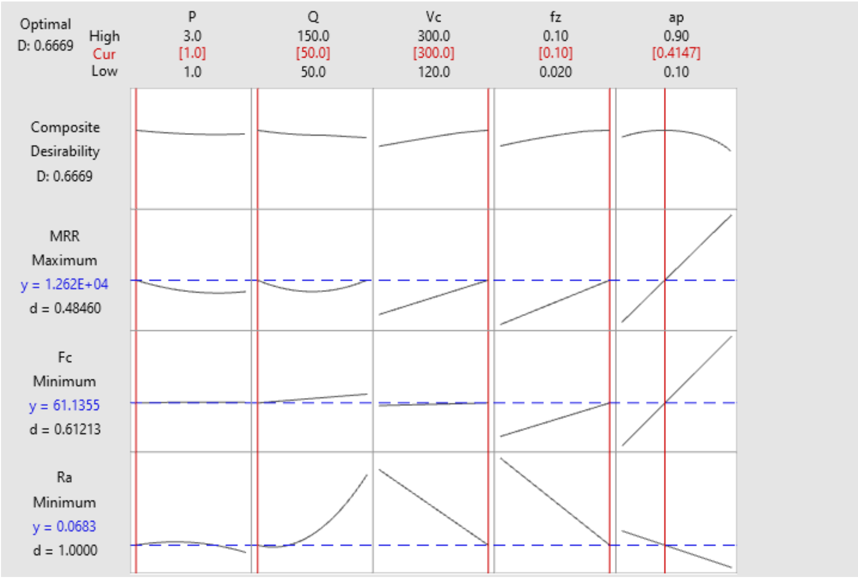

Fig. 14. Response optimization of Ra, Fc, MRR

3.3.3 Comparing the results of MOORA and Response Optimizer

The determined optimum results by MOORA and Response Optimizer were summarized in Table 17. The results have shown the difference between the two methods. MOORA method provided the real value of MRR, F_c, and R_a, corresponding to the cutting parameters and lubricant parameters. However, the disadvantage of MOORA is that this method can help to rank and selects the best values of all experiments only. This value set usually is not the optimal conditions. Therefore, MOORA is also known as the Multi-Criteria Decision Making (MCDM) method.

Table 17. Results of MOORA method in comparison to Regression Optimizer

Method	P	Q	V_c	f_z	a_p	MRR	F_c	R_a
MOORA	1	150	300	0.10	0.9	25795.8	148.384	0.2930
Response Optimizer	1	50	300	0.074	0.536	12619	61.14	0.1683
Comparison between MOORA vs. RSM-DA						↓ 56.13%	↓ 54.45%	↓ 42.56%

By contrast, the regression optimizer is multiple optimization methods based on regression models. That means this method can predict the optimum value of responses like MRR, F_c, R_a corresponding to the predicted parameters set. In this case, the optimal conditions may not coincide with 1 out of 27 experimental points. However, this is also the disadvantage of this method because the parameter value selected may not match the experimental machine, and the MRR, F_c, R_a's values are predicted mathematical values only.

4 CONCLUSION

This study aimed at predicting the effect of the cutting parameters and also the lubrication parameters in the flat finish milling process of JIS S50C carbon steel under minimum quantity lubrication condition, including cutting speed V_c, feed of tooth f_z, cutting depth a_p, flow rate of cooling air Q and air pressure P. The Taguchi technique with L_{27} OA were performed to design the experimental array. The ANOVA was used to identify the significant input factors on each response such as surface roughness R_a, cutting force F_c and cutting productivity MRR. The optimal point of milling and MQL parameters were also solved by Minitab Response Optimizer function and MOORA methods. The main conclusions can be illustrated as follows:

- The regressional models for among surface roughness R_a, cutting force F_c have a high R-squre values, at 99.54% and 99.55%, respectively, indicating a appropriate relation- ship between experimental data and the predicted data. Hence, the gressional mathematical models could be performed in the actual manufacturing process to calculate the cutting parameters to reach to desirable response, like as surface roughness R_a.
- The "Predicted R-squre" of these regressional models for both of R_a and F_c are 91.2% and 98.29%, respectively. These value is also reasonable agreement with the "Adjusted R^2" for R_a at 93.24% and for F_c at 98.29%.
- The machining parameters significant influences on the surface quality Ra in flat finishing milling of S50C under MQL condition. The ANOVA results show that feed of tooth f_z shows the most significant influence on the surface roughness R_a, follow by depth of cut a_p and cutting speed V_c. By contrast, the effect of flow rate Q is insignificant.
- In this multiple objective optimization problem, both MOORA method and computer based software tool, minitab response optimizer could be performed. However, interm of declining the surface roughness R_a and cutting force F_c, response optimizer provides the best optimal point with a declining of 54.45% for cutting force F_c and 42.56% for surface roughness R_a. By contrast, in term of cutting productivity MRR, MOORA give the best solution with the reduction of 56%, in comparison with response optimizer function.
- The findings of this experimental study give manufacturers and researchers more knowledge about the ability in finishing milling of S50C carbon steel under minimal lubrication conditions.
- In future works, other lubrication parameters of MQL system (e.g. type of lubrication, number of lubrication nozzles, cooling MQL…) and other responses including cutting thermal, tool life will be taken into research.

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