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Multi-objective Optimization of CNC Milling Parameters of 7075 Aluminium Alloy Using Response Surface Methodology

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Abstract

Optimizing the impact of technological parameters during CNC milling remains a highly practical research direction, hence there have been numerous published research works in this area. This article introduces the results of a multi-parameter optimization study when milling aluminum alloy 7075 on a CNC machine using the Response Surface Methodology (RSM). The experiments were conducted based on the Taguchi L18 orthogonal array with machining parameters including coolant condition, spindle speed, feed rate, and depth of cut. The response parameters in these experiments were surface roughness (Ra) and Material Removal Rate (MRR) measurements.The research results showed that regression models developed for Ra and MRR using the RSM method have high coefficient of determination (R^2) values of 97.67% and 99.36%, respectively, indicating that the developed models, coefficient models are significant. The ANOVA analysis results indicate that machining parameters have a direct impact on both Ra and MRR. Ra is affected by various factors including spindle speed, feed rate, coolant, and depth of cut. Among these factors, spindle speed has the highest impact with a percentage of 37.12%, followed by feed rate at 12.56%, coolant at 12.07%, and depth of cut at 10.13%. On the other hand, the material removal rate (MRR) is mostly influenced by feed rate and depth of cut, with percentages of 41.68% and 47.29%, respectively. Multi-objective optimization using RSM showed that under the conditions of coolant on, spindle speed of 5500 rpm, feed rate of 450 mm/min and depth of cut of 0.369 mm, the optimum values of Ra and MRR obtained are 0.159 µm and 32.019 g/min, respectively.According to the results of the confirmation experiment conducted to determine the optimal values for Ra and MRR, it was found that the deviation did not exceed 5%. This result is completely acceptable in practical production, thereby affirming the accuracy of the RSM method in solving multi-objective optimization problems in the aluminum alloy CNC miling.

Keywords: Multi-optimization; CNC Milling; Aluminium Alloy; Response Surface Methodology; Taguchi Orthogonal Array.

1. Introduction

Traditional machining methods often have low quality and low productivity. While CNC technology has brought significant advancements in machining processes, the quality of machining still depends on various factors such as cutting modes, tools, materials, cutting conditions, processing machines and others[1]. Therefore, it is essential and significant to investigate the forecasting and enhancement of machining processes to identify the suitable processing parameters for particular materials. Recently, several studies have used various methods related to machine learning to develop predictive models of surface quality and other factors and have obtained remarkable results. For instance, Lin, Wu [2]developed a surface roughness prediction model for CNC milling based on various technological parameters such as spindle speed, depth of cut, feed rate, and vibration. Their findings demonstrated that the spindle speed and depth of cut had a substantial impact on the surface roughness. Moreover, the artificial neural network (ANN) models used in the study had high accuracy in predicting the surface roughness. Similar findings have been reported in other publications that utilized ANN in various processing conditions [3-6]. Other machine learning methods have also been used in developing predict model such as random forest[7], decision trees [8], support vector machine [9, 10], and others.

Optimization is a critical factor in the machining industry, especially multi-objective optimization. Many previous studies have shown that cutting conditions should be selected to optimize economic efficiency and are often evaluated by productivity, total production costs per component, or other appropriate criteria[11-14].Selecting the optimal cutting parameters will enhance production efficiency and provide important data for automating the technology preparation process, reducing time and labor costs.

The Taguchi method is a useful and efficient approach for optimizing experimental design.Ghani, Choudhury [15]

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introduced the Taguchi method used to optimize the machining parameters when face milling AISI H13 hardened steel with TiN coating tools in semi-finished and finished machining conditions. The milling parameters to be considered were cutting speed, feedrate and depth of cut. The results illustrated that the optimal combination for low cutting force and good surface quality was high cutting speed, low feedrate and depth of cut.Dutta and Narala [16] utilized L9 array of Taguchi method to investigate the impact of turning parameters (i.e., feed, speed, and depth of cut) on cutting force and machined surface roughness. Analysis of variance and signal-to-noise ratio revealed that depth of cut had the most significant effect on cutting force, while feed had the greatest impact on surface roughness. George and Selvaraj [17] also employed the Taguchi method to optimize the parameters for dry milling of martensitic stainless steel (MSS) with AISI 410 and AISI 420 codes on CNC machines. They assessed the impact of machining parameters on surface roughness and observed that spindle speed had a more significant effect on surface roughness than feedrate, for both steels. The researchers identified the optimal cutting parameters at the spindle speed and compared the experimental values at the optimal cutting condition with the predicted values, showing a good agreement with low error rates. Several other studies have also applied the Taguchi method to optimize cutting parameters for machining operations [18-23].

Among the multi-objective optimization methods, many algorithms such as the Genetic Algorithm (GA), Grey Relational Analysis (GRA), Nondominated Sorting Genetic Algorithm (NSGA-II), Simulated Annealing (SA), Gene Expression Programming (GEP), Adaptive Neuro-Fuzzy Inference System (ANFIS), etc., are often used to find the optimal cutting parameters [24-26].Ganesan and Mohankumar [27] investigated the optimization of turning EN8 steel with a carbide cutting tool. To address the optimization problem, they utilized the non-dominated sorting genetic algorithm (NSGA-II) with three objectives: production cost, operation time, and tool wear, and three cutting parameters: depth of cut, feed, and spindle speed. Sahali, Belaidi [28] conducted research on the optimization of turning mild steel using a carbide cutting tool using the probabilistic non-dominated sorting genetic algorithm (P-NSGA-II) with two objectives: production cost and production rate, and three variables: depth of cut, feed, and cutting speed. Abbas, Pimenov [29] employed an ANN algorithm with the Edgeworth-Pareto method to optimize the technological parameters used for milling on a CNC machine. The ANN algorithm was developed using Matlab, and the 3-10-1 Multi-Layer Perceptron (MLP) model was used to predict the surface roughness (Ra) with an accuracy of ±5.78% under experimental conditions.Unune, Nirala [30] integrated NSGA-II with ANN to model and optimize the material removal rate (MRR) and Ra in grinding. While machine learning has numerous benefits and is widely utilized, it also has limitations. For instance, storing information across the entire network of an ANN can use up significant memory resources, particularly when working with vast datasets. Moreover, it may take a considerable number of samples to enhance control over the network's behavior.

The Response Surface Method (RSM) is a powerful optimization technique that is widely used in various fields, including engineering, science, and business. One of the main advantages of RSM is its ability to efficiently search for the optimal solution in a large design space with a relatively small number of experiments. Moreover, RSM can help to reduce the cost and time required for experimentation, making it a valuable tool for optimization in complex systems. This method has been used by many authors to study the optimization of machining process and has achieved certain results[31-34]

Aluminum alloys contain zinc as their primary alloying element and are known for their excellent mechanical properties. These alloys are highly ductile, exhibit good strength and toughness, and are resistant to fatigue. They are widely used in various engineering fields such as wheel parts, plates, structures, pistons, brake drums, and piston bushings in the automotive industry, as well as gears and shafts in aircraft parts. In aluminum alloys machining, surface roughness and MRR of aluminum alloys during milling are complex non-linear problems affected by many cutting parameters, making prediction difficult. Therefore, optimizing the machining process for these materials is also highly important[35]. Recently, Daniyan, Tlhabadira [36]conducted a study on the process design and optimization of milling aluminum alloy (AA6063 T6) using RSM. The research involved both physical and numerical experiments to obtain results that could be used to develop an optimization model for predicting the material removal rate. The findings of the study demonstrated a correlation between the physical and numerical experiments, which was used to develop the optimization model.Nguyen, Nguyen [37] utilized a combination of machine learning (ML) and Nondominated Sorting Genetic Algorithm (NSGA-II) to develop a model that could optimize both surface roughness (Ra) and maximum flank wear (Vbmax) during high-speed milling of 6061 aluminum alloy. Additionally, NSGA-II was used in combination with a fuzzy model to determine the optimal drilling conditions for minimizing thrust force and torque during drilling of reinforced AA6061 aluminum alloy [38]. Despite numerous studies on milling aluminum alloy, the literature lacks sufficient focus on developing a predictive model for process parameter optimization, surface roughness, and material removal rate estimation during cutting operations.

This paper introduces the research results on the effects of machining parameters (coolant condition, spindle speed, feed rate, and depth of cut) and finds optimal solutions to simultaneously minimize Ra and maximize MRR in the machining process of 7075 aluminum alloy. The orthogonal Taguchi L18 design is used to create a matrix table of experiments and the response surface methodology (RSM) is used to develop a model, investigate the influencing factors, and analyze the multi-objective optimization of Ra and MRR.

2. Materials and Methods

2.1. Experimentation

2.1.1. Equipment

In this study, 7075 aluminum alloy with size (80×75×40 ±1) mm was used for the experiment. The main chemical composition of the alloy includes 87.1-91.4% Al, 0.18-0.28% Cr, and 1.2-2.0% Cu, along with trace amounts of other elements. The density of the alloy is 2.81 g/cm³. The processing equipment is a CNC milling machine with code DMC 835V with Siemens control system at the workshop of Hanoi College for Electro - Mechanics. The cutting tool is a face mill, tool diameter ϕ63mm, 4 cutting edges of hard alloy RPMT1204- DURACARD as shown in Figure 1.

The TR200 Handheld Roughness Tester (USA) is utilized for surface roughness measurement. The Ra parameter is determined by running the measuring head parallel to the tool feed direction during machining according to the ISO 1997 standard (the measurement range was 4 mm). To ensure accuracy, each sample is measured three times in duplicate, and the final Ra value is calculated as the average of these measurements.

The MRR was determined by finding the difference in mass of the part before and after machining. The weight of the part was measured using the GS-303 electronic balance (Shinko, Japan) with an accuracy of 0.001g.

$$MRR=\frac{1}{t}(m_1-m_2)\ (g/min) \quad (1)$$

where m_1 is the initial mass of the workpiece [g]; m_2 is the mass of the part after machining [g], t is machining time [min].

All measurements were performed in triplicate. In which, the average Ra value of each test sample is measured at three different locations on the machined surface.

2.1.2. Experimental Design

Experiments were conducted on a CNC milling machine using a design of experiment such as an L18 orthogonal array. Four milling parameters, namely coolant condition (c), spindle speed (s), feed rate (f) and depth of cut (d)were determined along with their respective levels during the machining process. The L18 orthogonal array is detailed in Table 1, and the specific values of these parameters are described in Table 2.

Table 1. L18 orthogonal array

Sample	Coolant condition (on/off)	Feed rate (mm/min)	Depth of cut (mm)	Spindle speed (rpm)
1	1	3	1	1
2	1	1	2	2
3	1	1	3	3
4	1	2	1	1
5	1	2	2	2
6	1	2	3	3
7	1	3	1	2
8	1	3	2	3
9	1	3	3	1
10	2	1	1	3
11	2	1	2	1
12	2	1	3	2
13	2	2	1	2
14	2	2	2	3
15	2	2	3	1
16	2	3	1	3
17	2	3	2	1
18	2	3	3	2

Machining parameters were selected based on actual production, technological capabilities of machine tools and cutting tools. The coolant was Esterlube Cutting P25, the injection pressure and flow is 1.2÷1.3Mpa and 10 liters/min.

Table 2. Cutting parameters and their levels

Parameter	Level		
	1	2	3
Coolant condition	On	Off	-
Spindle speed (rpm)	3500	4500	5500
Feed rate (mm/min)	150	250	450
Depth of cut (mm)	0.1	0.25	0.4

2.2. Methodology

Response Surface Methodology (RSM) is a statistical method used to model and analyze the relationship between multiple independent variables and their effects on a dependent variable. It is a powerful tool used in engineering, science, and other fields to optimize processes, design experiments, and develop models that can predict the outcome of various scenarios.

RSM involves the use of mathematical and statistical models to approximate the response surface of a system. This surface is a representation of the relationship between the independent variables and the dependent variable. The aim of RSM is to identify the optimal combination of independent variables that results in the maximum or minimum value of the dependent variable. This optimization process helps in reducing costs, improving performance, and increasing efficiency. RSM has a wide range of applications in various fields, including engineering, chemistry, biology, and agriculture. It is used in the development of new products, the optimization of manufacturing processes, the design of experiments, and the analysis of complex systems.

The relationship between input and output can be represented by the equation:

$$y = \varphi(x_1, x_2, \dots x_n) + \varepsilon \quad (2)$$

With k input variables, the relationship between input and output can be rewritten as a quadratic equation.

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i \sum_{i=1}^{k} \beta_{ii} {x_i}^2 + \sum_{ij}^{k} \beta_{ij} x_i x_j + \varepsilon \quad (3)$$

Where x_i are the coding variables, β_i are the first order coefficients, β_{ii} are the quadratic coefficients, β_{ij} are the interaction coefficients of the equation, and is the statistical error of the mean.

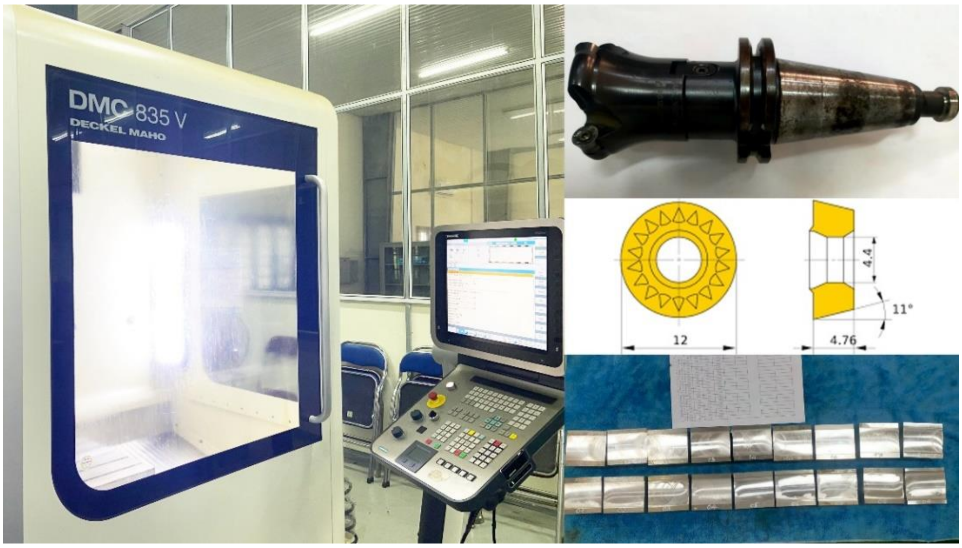

Figure 1. DMC 835V CNC milling machine, workpiece and cutting tool

2.3. . Data analysis

Analysis of variance (ANOVA) of the results of the RSM test and the correlations of four milling parameters and Ra and MRR were analyzed using Design-Expert 12.

3. Results and discussion

3.1. Prediction Model

ANOVA was used to examine the statistical significance of the terms, and the results are presented in Tables 3 and 4. Based on the findings of Ra analysis, the F-value of 29.38 indicates that the model is highly significant, as there is only a 0.01% chance that such a large F-value could occur due to noise. P-values less than 0.05 indicate that the model terms are significant. Specifically, Ra was significantly affected by spindle speed, followed by feed rate, coolant condition, and depth of cut, with respective percentage contributions of 37.12%, 12.56%, 12.07%, and 10.13%. On the other hand, the material removal rate (MRR) was primarily influenced by feed rate and depth of cut, with percentage contributions of 61.60% and 21.54%, respectively. The F-value of 108.40 implies that the model for MRR is significant, and there is only a 0.01% chance that such a large F-value could occur due to noise. P-values less than 0.05 indicate that the model terms are significant. Additionally, both the Ra and MRR models showed no significant lack of fit ($p > 0.05$), indicating that the models were suitable for predicting the responses.

Contour plots examine the relation between cutting parameters and two performance characteristics. Figure 2 shows the contour plots explaining the relation between the cutting parameters and Ra value. The results show that Ra decreases as the cutting speed increases because the increase in spindle speed tends to eliminate the built-up edge (BUE). In addition, the increase in spindle speed combined with the increase in temperature in the cutting zone creates a locally softened zone, making the chip easier to separate from the machined surface, reducing the scratches on the surface of the component and thus reducing the surface roughness. It is common for aluminum alloys to exhibit high surface roughness caused by tool marks when machined at low cutting speeds. This is largely attributed to the presence of multiple phases in their microstructure.

In machining processes, an increase in feed rate or depth of cut can lead to an increase in surface roughness. This is because increasing the depth of cut results in a larger contact area between the workpiece and the cutting tool, which in turn increases the amount of material that is removed. As a result, the cutting force increases, leading to higher surface roughness during the machining process.. In addition, the increased feedrate will also cause deeper and wider surface scratches and also increase the cutting force due to the increased chip thickness. These research results have similarities with the theory and results in previous published works.

Table 3. ANOVA for Ra

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Model	10	1.528	97.67%	1.528	0.153	29.38	0.000
Linear	4	1.124	71.87%	0.553	0.138	26.60	0.000
c	1	0.189	12.07%	0.209	0.209	40.25	0.000
s	1	0.581	37.12%	0.306	0.306	58.91	0.000
f	1	0.196	12.56%	0.198	0.198	38.10	0.000
d	1	0.158	10.13%	0.006	0.006	1.21	0.307
2-Way Interaction	6	0.404	25.80%	0.404	0.067	12.93	0.002
c*s	1	0.018	1.17%	0.046	0.046	8.88	0.021
c*f	1	0.141	8.99%	0.078	0.078	15.06	0.006
c*d	1	0.010	0.62%	0.005	0.005	1.03	0.344
s*f	1	0.198	12.65%	0.177	0.177	34.00	0.001
s*d	1	0.016	1.04%	0.013	0.013	2.46	0.161
f*d	1	0.021	1.33%	0.021	0.021	4.01	0.085
Error	7	0.036	2.33%	0.036	0.005		
Total	17	1.564	100.00%				

Table 4. ANOVA for MRR

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Model	10	1353.33	99.36%	1353.33	135.333	108.40	0.000
Linear	4	1216.53	89.32%	922.20	230.549	184.66	0.000
c	1	0.78	0.06%	0.35	0.348	0.28	0.614
s	1	4.01	0.29%	0.64	0.643	0.51	0.496
f	1	567.65	41.68%	491.11	491.112	393.37	0.000
d	1	644.09	47.29%	441.74	441.745	353.83	0.000
2-Way Interaction	6	136.79	10.04%	136.79	22.799	18.26	0.001
c*s	1	18.81	1.38%	0.26	0.264	0.21	0.660
c*f	1	0.00	0.00%	1.15	1.154	0.92	0.368
c*d	1	9.19	0.67%	1.85	1.846	1.48	0.263
s*f	1	0.62	0.05%	0.01	0.014	0.01	0.919
s*d	1	10.36	0.76%	5.13	5.133	4.11	0.082
f*d	1	97.82	7.18%	97.82	97.823	78.35	0.000
Error	7	8.74	0.64%	8.74	1.248		
Total	17	1362.07	100.00%				

The coolant used in machining 7075 aluminum alloy has a significant impact on the surface roughness. When the temperature in the cut zone area is too high, it can soften and deform the aluminum alloy, leading to increased surface roughness. Debris created during cutting can also contribute to surface roughness. If this debris is not effectively removed from the cutting area, it can become trapped between the tool and workpiece, resulting in scratches and other imperfections on the finished surface. Therefore, selecting the appropriate coolant for cutting 7075 aluminum alloy is crucial to achieving the desired surface roughness and overall quality of the finished product.

Figure 3 show that the MRR increases as the feed rate increases. This is because, in reality, a higher feed rate leads to an increase in the thickness of the chip, resulting in an increase in MRR. The influence of the depth of cut on MRR is also demonstrated in similar data. MRR also increases with increasing cutting speed, but in this study, the cutting speed and the coolant condition have a negligible effect on MRR.

The predictive mathematical models for the dependent variables of Ra and MRR were developed using RSM regression models in the Design-Expert 12 software. The independent variables included cooling condition (c), spindle speed (s), feed rate (f) and depth of cut (d). The predictive equations obtained from the regression analysis are shown in Eqs. (4) and (5) for Ra and MRR, respectively.

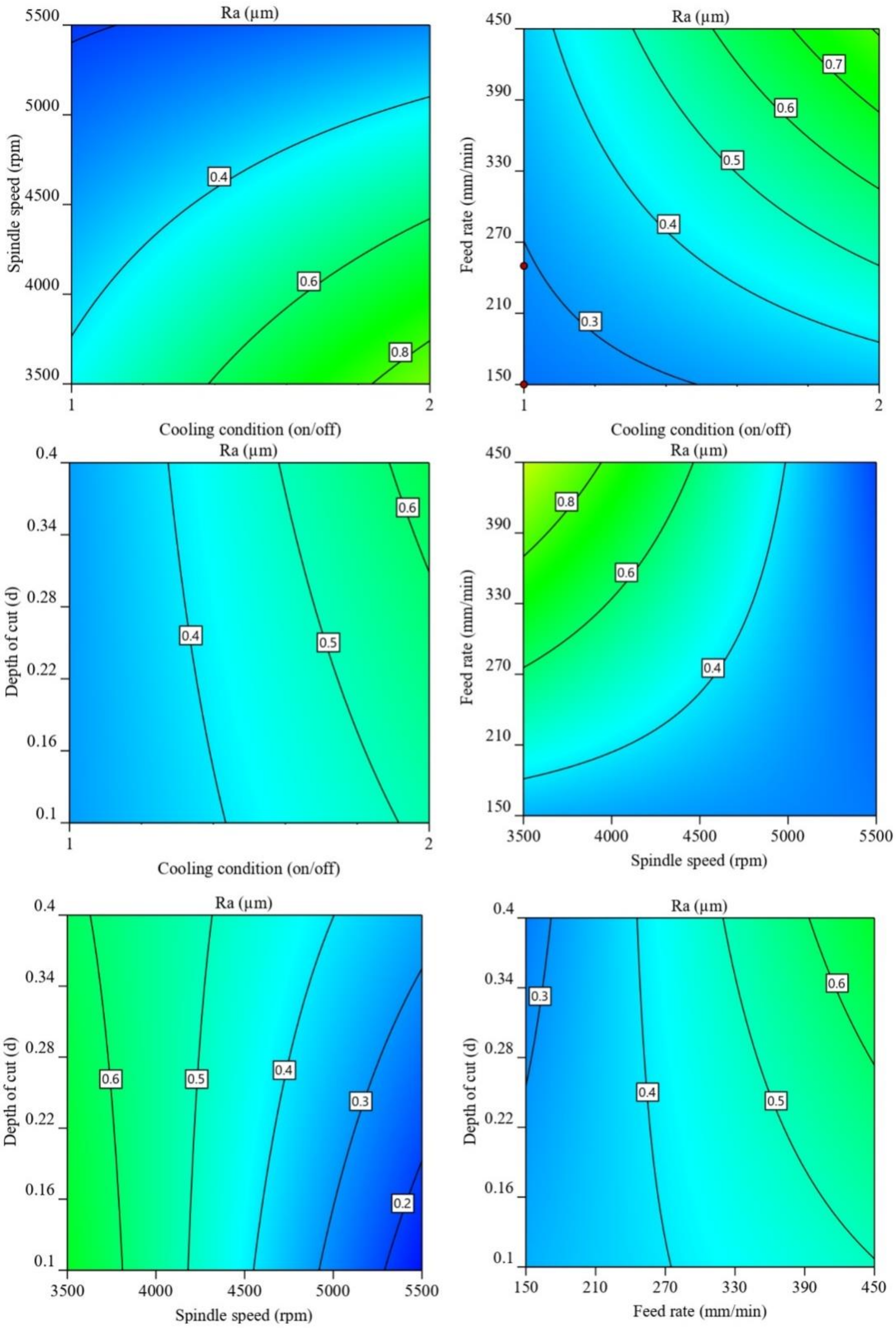

Figure 2. Contour plot for influence of cutting on Ra

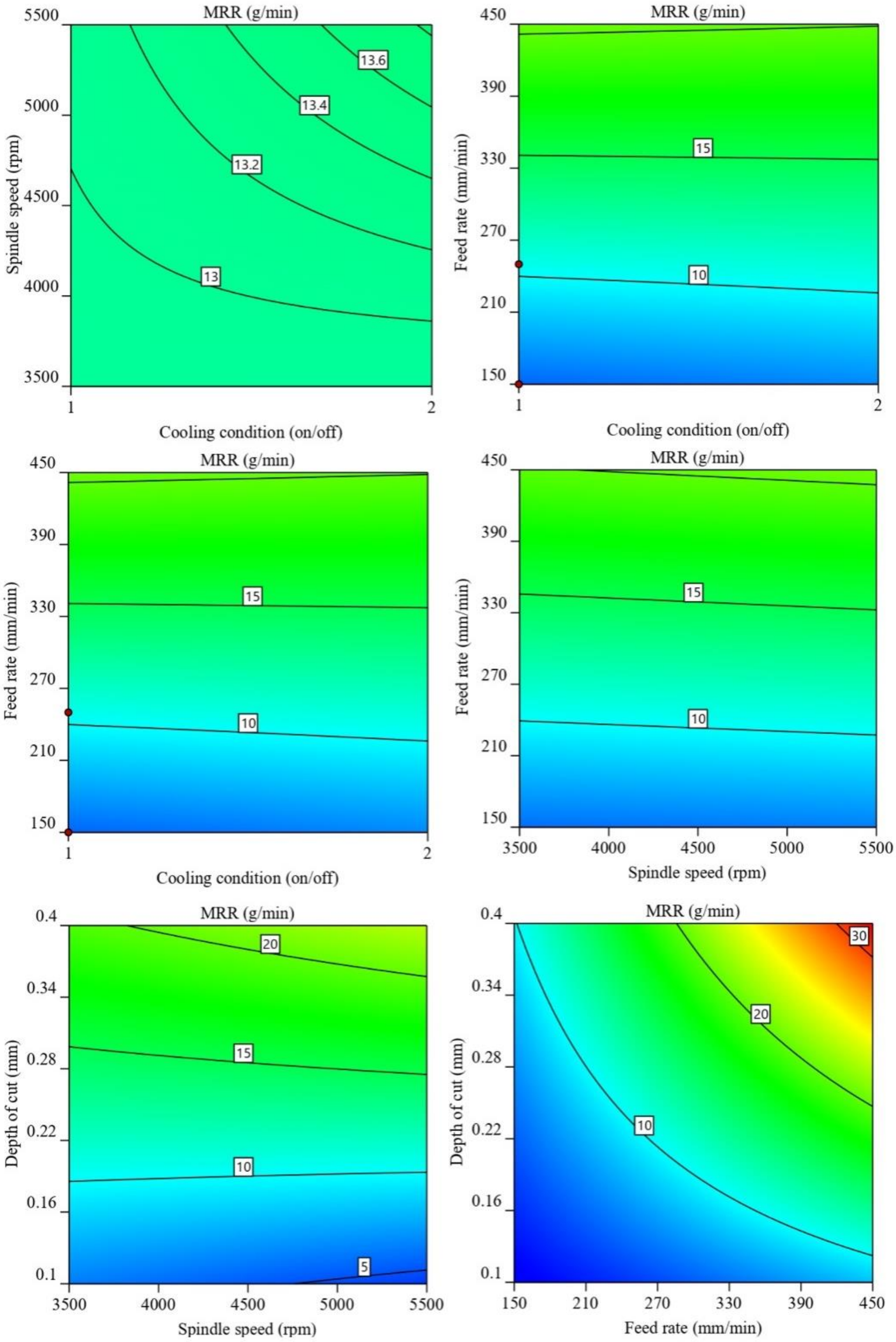

Figure 3. Contour plot for influence of cutting on MRR

$$Ra = -0.739821 + 0.584704\times c + 0.000296354 \times s + 0.00375128 \times f - 3.06919 \times d - 0.000172005 \times c \times s + 0.00119363 \times c \times f + 0.390832 \times c \times d + 0.00041746 \times s \times d + 0.00267838 \times f \times d \quad (4)$$

$$MRR = 5.53218 + 1.67983 \times c - 0.002505 \times s + 0.00681934 \times f - 29.0917 \times d + 0.000411147 \times c \times s - 0.00458168 \times c \times f - 7.24774 \times c \times d + 0.00836307 \times s \times d + 0.183346 \times f \times d \quad (5)$$

The performance of the developed models was assessed using the coefficient of determination R^2 [42], which ranges from zero to one. A value closer to one indicates a better fit between the dependent and independent variables. In this study, the regression models developed for Ra and MRR have high R^2 values of 97.67% and 99.36%, respectively. From Figure 4, it was observed that the residuals fall close to the straight line for both Ra and MRR, indicating that the developed model coefficient models are significant. The relationship between the experimental and predicted results for Ra and MRR is shown in Figure 5.

3.2. Multi-objective Optimization

After developing predictive models to predict Ra and MRR, the next logical step is optimization with respect to cutting conditions. Selection of optimum cutting conditions has always been a challenge in machining. Low Ra and high MRR values can be achieved by adjusting cutting conditions with the help of appropriate optimization methods.

To achieve high productivity and good surface quality, a multi-objective optimization process using the RSM method is conducted with input parameters, constraints, and objectives presented in Table 5.

Figure 6 presents the optimal results after analysis by RSM method with the confidence level for all intervals is 95. The optimal value obtained is that the minimum Ra value is 0.167 µm and the maximum MRR is 31.92 g/min, corresponding to the objective function expected value of 0.959. This value is very close to 1, so the multi-objective optimization process for surface roughness and material removal ensures reliability. This value is obtained in coolant condition, feed rate 450mm/min, dept of cut 0.373mm and spindle speed 5500rpm.

To verify the results of optimization, after preparing the machine and the workpiece, the study conducted the processing of three detail samples with the optimal cutting conditions that were calculated. The processing results are presented in Table 6.

Table 5. Constraint conditions and goals for optimization

Parameter	Target	Lower	Uper
Coolant condition	On/Off	1 (On)	2 (Off)
Spindle speed (rpm)	Range	3500	5500
Feed rate (mm/min)	Range	150	450
Depth of cut (mm)	Range	0.1	0.4
Ra (µm)	Minimum	0.122	1.332
MRR (g/min)	Maximum	2.608	31.918

Table 6. Actual Ra and MRR results in milling compared to optimized values

No.	c	s (rpm)	f (mm/min)	d (mm)	Ra		MRR	
					Result	Deviation (%)	Result	Deviation (%)
1	On	5500	450	0.369	0.155	2.6	33.121	3.3
2					0.162	1.9	32.919	2.7
3					0.167	4.8	33.204	3.6

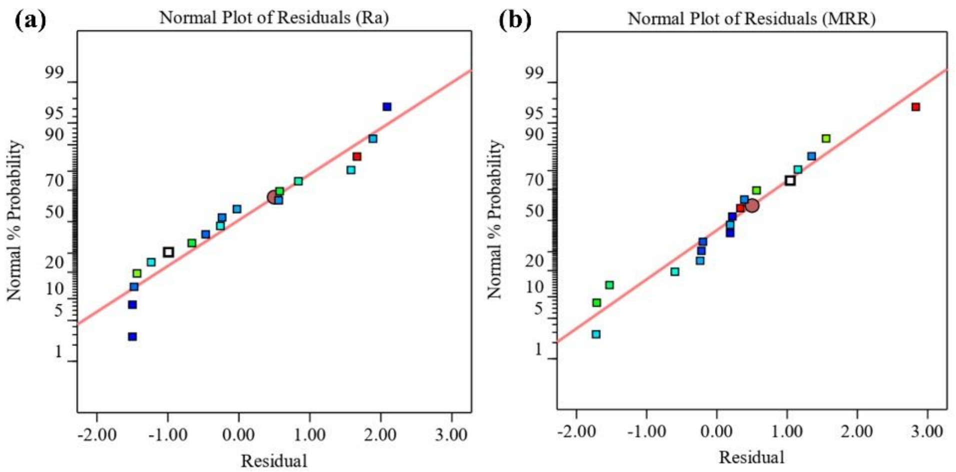

Figure 4. Normal probability plot of the residuals for Ra (a) and MRR (b)

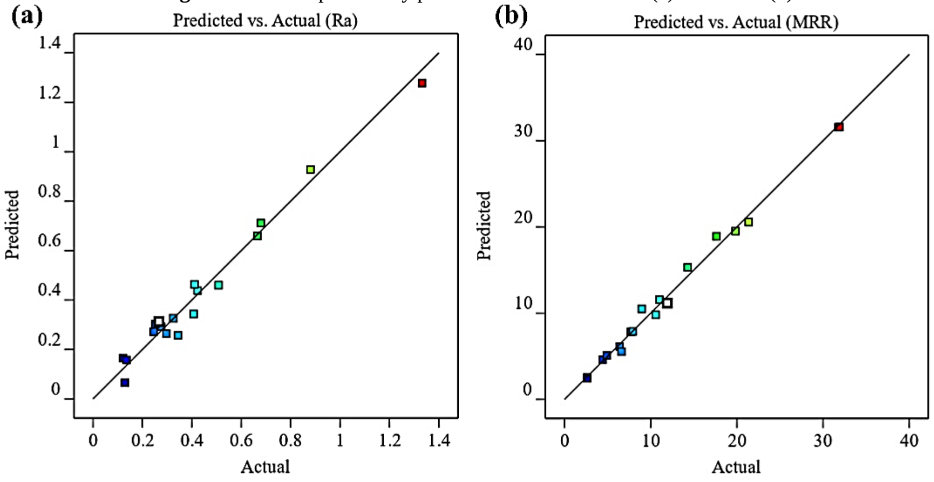

Figure 5. Comparison of experimental and prediction of Ra (a) and MRR (b)

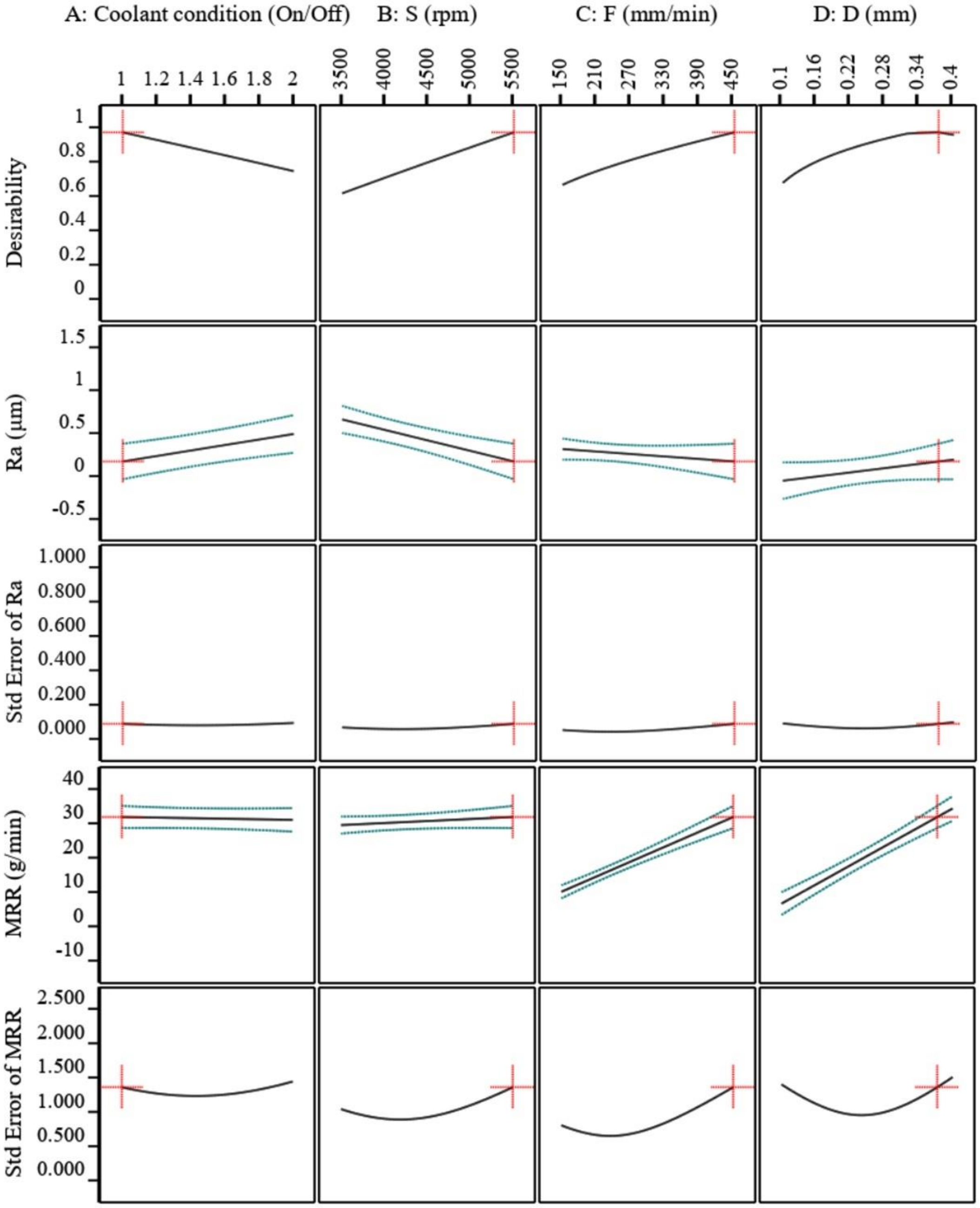

Figure 6. Graph of multi-objective optimization using RSM

Comparing the optimal results with the actual processing, it was found that the deviation between the optimal value and the actual value did not exceed 5%. This result is completely acceptable in practical production and confirms the accuracy of the RSM method when solving multi-objective optimization problems in the process of processing aluminum alloy.

4. Conclusion

In this article, the optimization of the influence of machining parameters on Ra and MRR when milling 7075 aluminum alloy on a CNC machine has been studied based on experimental data. The regression models constructed for Ra and MRR using the response surface methodology (RSM) shows that the model is suitable for correlative and predictive purposes. The ANOVA further indicates that Ra decreases as the cutting speed increases, and as the feed rate or depth of cut increases, the Ra increases. Additionally, the use of a coolant also plays an important role in affecting Ra during the machining process of aluminum alloys. The results also show that MRR increases as the feed rate and depth of cut increase, but the cutting speed and coolant conditions have a minimal effect on MRR. Among the machining parameters, Ra is most affected by the spindle speed, while MRR is primarily influenced by the feed rate. Multi-objective optimization using the RSM method has obtained optimal values for Ra and MRR simultaneously, and the testing results for this optimal parameter are within 5% deviation from reality. Therefore, the results of this study are highly effective for practical production, and manufacturers can use them to make informed decisions about their aluminum alloy processing methods. In addition, the optimization methodology used in this study not only provided an estimate of the optimal solution, but also offered a framework for selecting the most suitable cutting conditions based on desired criteria. In future research, the effect of machining parameters on flank wear, power consumption, environmental impact, etc., will be included and optimized, while using other optimization algorithms to select a method with high reliability.

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