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MULTI-OBJECTIVE OPTIMIZATION FOR BALANCING SURFACE ROUGHNESS AND MATERIAL REMOVAL RATE IN MILLING HARDENED SKD11 ALLOY STEEL WITH SiO_2 NANOFLUID MQL

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Abstract

In manufacturing practice, manufacturers always strive to achieve both quality and productivity targets simultaneously. In the first part, this study examines the relationship between input factors, including cutting speed, depth of cut, and feed rate, and the output response, which is surface roughness, when milling hardened SKD11 alloy steel under minimum coolant lubrication conditions using SiO_2 nanofluid. The input parameters are divided into four levels to determine their influence on surface roughness and to find the optimal conditions for achieving the minimum surface roughness. The experimental design was conducted using an L16 array. A second-order regression model was developed to describe the relationship between the input variables and the output response. In the second part, multi-objective optimization was performed to simultaneously achieve the minimum surface roughness and the maximum material removal rate (MRR). The Response Surface Methodology (RSM) was employed in this study. The results indicated that to achieve the minimum surface roughness, machining should be performed at a cutting speed of 100 m/min, a cutting depth of 0.2 mm, and a feed rate of 0.01 mm/tooth. With these settings, the predicted surface roughness could reach 0.0451 µm. On the other hand, for the multi-objective optimization, to achieve the minimum surface roughness and the maximum MRR simultaneously, machining should be carried out at a cutting speed of 100 m/min, a cutting depth of 0.36 mm, and a feed rate of 0.0168 mm/tooth. With this cutting condition, the predicted surface roughness could reach 0.1069 µm, and the predicted MRR could reach 775.06 mm^3/min.

Keywords: SiO_2 nanofluid, MQL, hard milling, surface roughness, multi-objective optimization, ANOVA, response surface methodology.

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1. Introduction

SKD11 steel, also known as cold work tool steel, is one of the widely used steel types in the field of mechanical mold making. It exhibits excellent wear resistance, high hardness, and low toughness due to its high carbon and chromium content (12 % chrome), making it commonly employed in the production of various types of punching molds and cold work dies [1]. It can be heat treated to achieve a hardness of approximately 60 HRC.

With the traditional cutting process, the heat treatment to achieve the desired hardness is carried out after the cutting stages are completed. Once the cutting stages are finished, the workpiece undergoes a series of heat treatment steps, such as annealing, quenching, and tempering, depending on the specific material and hardness requirements. Annealing involves heating the workpiece to a specific temperature and then slowly cooling it to reduce internal stresses and increase its ductility. After the heat treatment process, the workpiece is now ready for the final machining step: grinding. This process helps achieve the required dimensional accuracy, surface finish, and tight tolerances. However, it's important to note that this traditional method of machining incurs costs and time due to the separate heat treatment and grinding processes [2].

In recent years, advancements in material science have paved the way for the development of cutting tools capable of machining workpieces with high hardness directly, eliminating the need for post-machining heat treatment. This approach, known as hard machining, offers several advantages, including reduced production time, cost savings, and improved process efficiency [3–6]. Two common forms of hard cutting are hard milling and hard turning. Hard milling involves using specialized milling tools with high-speed capabilities and wear-resistant coatings to remove material from workpieces with a hardness of around 50HRC or higher. Both methods require robust machine tools, cutting tool technologies, and machining strategies to effectively handle the challenges posed by the high hardness of the workpiece materials.

The biggest drawback of the hard machining method is the generation of significant heat during the cutting process. Cutting tools used in hard machining require maintaining high hardness and good resistance to wear under high cutting temperatures. The materials commonly used for cutting tools in hard machining, such as ceramics [7], coated carbide [8, 9], CBN (cubic boron nitride) [10], and diamond inserts [11], have high costs, which increases production expenses. The negative effects of high cutting temperatures need to be addressed through rapid heat dissipation and reduced friction in the cutting zone. The conventional solution is to flood the cutting zone with cutting fluid. In milling processes, which are non-continuous machining processes, thermal shock can occur, reducing the tool life and diminishing the surface quality of the workpiece [8, 9]. In addition, the traditional flood coolant process has a major drawback of increased costs associated with coolant purchase and disposal, as well as its negative environmental and occupational impacts [3, 12–14].

Minimum Quantity Lubrication (MQL) is an innovative approach to lubrication that addresses the limitations of traditional flood coolant systems. It involves the precise application of a small amount of lubricant directly to the cutting zone, providing targeted lubrication and cooling. The benefits of MQL are numerous. Firstly, it significantly reduces lubricant consumption, resulting in cost savings and environmental advantages. Secondly, MQL enhances workplace conditions and promotes operator safety. Additionally, MQL improves machining performance by reducing friction and heat generation, thus extending tool life and enhancing surface finish quality. The controlled lubricant application also aids in efficient chip evacuation, preventing chip buildup and facilitating optimal machining processes [12, 14–19]. The effectiveness of MQL is further enhanced by the addition of nanoparticles with sizes ranging from 10–100 nm into the cutting fluid. This is known as nanofluid-based MQL, an advanced lubrication technique. This innovative solution, initiated by Choi, has revolutionized the field of machining [20]. First and foremost, the addition of nanoparticles enhances the lubricating properties of the cutting fluid, resulting in reduced friction and wear between the cutting tool and workpiece. This, in turn, leads to prolonged tool lifespan and improved machining performance. Additionally, nanofluids demonstrate superior heat transfer characteristics compared to conventional cutting fluids. The presence of nanoparticles in the lubricant facilitates efficient heat dissipation during the cutting process, thus preventing thermal damage to both the tool and workpiece. Consequently, this contributes to enhanced dimensional accuracy, reduced distortion, and improved surface finish quality of the machined components. Moreover, apart from their lubricating and heat transfer properties, the nanoparticles employed in the MQL process can also function as solid lubricants, minimizing the occurrence of adhesive wear between the cutting tool and workpiece. As a result, cutting operations become smoother, and chip evacuation is improved [21–28].

Single-objective optimization problems focus on finding the best solution for a specific criterion, disregarding other criteria. However, manufacturers aim to achieve multiple criteria simultaneously, even when they may conflict with each other. The objective of multi-objective optimization is to identify a solution that addresses these conflicting criteria and achieves a «win-win» outcome. In this context, researchers commonly utilize the Response Surface Methodology, a statistical technique widely applied in engineering, manufacturing, and quality improvement. RSM is specifically designed to optimize the relationship between input variables, also known as independent variables, and the corresponding output responses. It involves fitting a mathematical model, typically a polynomial equation, to experimental data generated through a series of well-designed experiments. By analyzing the response surface derived from the model, RSM allows for the identification of optimal input settings that yield desired output responses [12, 29–32].

Some notable studies have focused on utilizing the RSM method for multi-objective optimization. For instance, in a study conducted by [33], RSM was applied to optimize cutting parameters such as cutting speed, feed, nose radius, axial depth of cut, and radial depth of cut in milling P20 steel. The aim was to achieve both the minimum surface roughness and the maximum material removal rate. Through this approach, an optimized set of parameters was successfully determined. Furthermore, the authors concluded that there was good agreement between the results obtained using the Taguchi method and RSM. The multi-objective optimization aiming to achieve the best surface roughness and maximum material removal rate was conducted by [34]. RSM provided a predictive model for surface roughness and MRR with an error margin of 6 %. In another study utilizing RSM [35], Carmita Camposeco-Negrete performed turning of AISI 6061 T6 aluminum to find the lowest energy consumption and the best machining quality. The relationship between machining parameters and three output factors, including energy consumption, surface roughness, and MRR, was established. The author concluded that the cutting feed rate was the most influential factor affecting the outcomes, which included reducing energy consumption, improving surface roughness, and increasing MRR. In another study conducted by [27], the minimum surface roughness and the maximum MRR were successfully determined. A mutually beneficial solution was also identified by using RSM and variance analysis.

In this study, sixteen SKD11 steel milling experiments were conducted, achieving a hardness of 50HRC under nanofluid based Minimum Quantity Lubrication conditions. The experimental design was carried out using the Taguchi Method. Three cutting parameters were considered as input factors, including cutting speed, cutting depth, and feed rate, each at four levels from low to high.

The Response Surface Methodology was employed to establish the relationship between the cutting parameters and the output responses, which were surface roughness and material removal rate. A second-order mathematical regression model was developed to describe the relationship between the three cutting parameters and the surface roughness. A multi-objective optimization was then performed to identify the optimal cutting parameters that yield the minimum surface roughness and the maximum MRR simultaneously.

2. Materials and methods

All the experiments were carried out on a state-of-the-art 5-axis CNC milling machine, DMU50, known for its high spindle speed and advanced capabilities. The cutting tool utilized was a TiAlN-coated ϕ10 end mill, specialized for machining hard steel with a hardness capacity of up to 55HRC. The SKD11 alloy steel workpiece underwent heat treatment to achieve a hardness of 50HRC (measured using Mitutoyo's Rockwell hardness tester) and had dimensions of 150×150×200 mm. Throughout the milling process, the workpiece was firmly clamped in place using a universal vise, which was securely mounted on the machine table.

The study involves the mixing of 100 nm-sized SiO_2 nano particles with a base solution at a concentration of 4 %wt. To ensure the uniformity and stability of the solution, a magnetic stirrer is used for the mixing process. During the machining process, the cutting fluid flow rate and compressed air pressure are fixed at 100 ml/h and 3 kg/cm^2, respectively. The MQL nozzle is positioned at a specific distance from the cutting tool, and groove milling is used as the milling type.

For each experiment, a new cutting tool was employed, and its setup remained consistent across all experiments. Immediately after each machining operation, the surface roughness is measured using the SJ-401 roughness measurement device from Mitutoyo. The results of the surface roughness were obtained for each experiment as the average value of three measurements taken at three different positions on the machined groove surface. During the measurement process, the probing direction of the measuring head was aligned along the machined groove, as depicted in **Fig. 1**. Details about the experimental setup, materials, equipment, and software used in the study can be found in **Fig. 1** and **Table 1**.

The cutting parameters, which include cutting speed, depth of cut, and feed rate, play a crucial role as input factors. To select their levels, the authors considered the recommendations from cutting tool manufacturers, drew on our own expertise, and referred to previous research studies. **Table 2** presents these parameters along with their corresponding four levels.

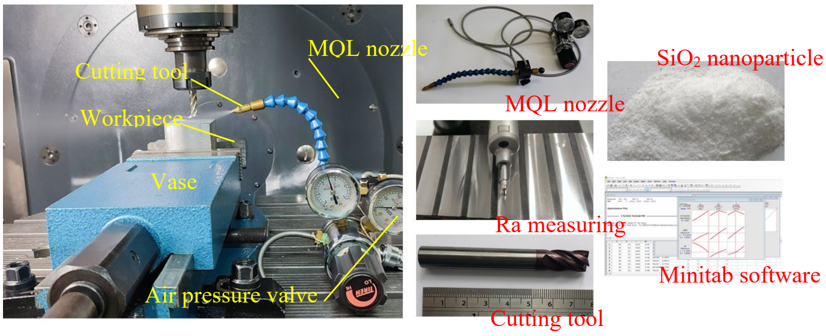


Fig. 1. Experiment setup

Table 1
Materials, equipment, and software used in the research

Items	Description
Machine	5-axis milling machine DMU50
Cutting tool	TiAlN ϕ10 end mill
Fixture	Universal vise
Roughness measuring device	Mitutoyo SJ-401
Solution spray nozzle	Noga MC1700 nozzle
Workpiece material	SKD11
Workpiece hardness	50HRC
Workpiece dimension	150x150x200 mm
Base fluid	Cutting oil CT232
Nanoparticle	SiO_2 100 nm
Nanoparticle concentration	4 %
Stirring device	Magnetic stirring device
CNC programming software	Mastercam X
Statistical software	Minitab v17

Table 2
Cutting parameters with their four levels

Parameters	unit	symbol	levels			
			1	2	3	4
Cutting speed	m/min	v	40	60	80	100
Depth of cut	mm	d	0.2	0.3	0.4	0.5
Feed rate	mm/min	f	0.01	0.015	0.02	0.025

3. Results and discussions

In this study, the surface roughness is measured using a measuring device from Mitutoyo. Meanwhile, the material removal rate is determined by the following formula:

$$MRR = \frac{d \times a_e \times v \times f \times z \times 1000}{3.14 \times D}. \quad (1)$$

Let (v) represent the cutting speed (m/min), (f) denote the feed rate (mm/tooth), (z) indicate the flute count of the cutter, and (D) symbolize the diameter of the cutting tool (mm).

This research involved the development of an experimental model for predicting the surface roughness using RSM. The relationship between the output response (in this case, the surface roughness) and the independent input variables (here, the cutting parameters) is described by a second-degree mathematical function as follows:

$$Ra = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i,j}^{k} \beta_{ij} x_i x_j + \varepsilon. \quad (2)$$

In which, k represents the input factors. The equation comprises coded variables (x_i), first-order term coefficients (β_i), second-order term coefficients (β_{ii}), and interactive term coefficients (β_{ij}).

Table 3 shows the results of sixteen experiments with values of roughness and MRR. It can be observed that the roughness ranges from 0.109 µm (experiment number 14) to 0.212 µm (experiment number 4). Meanwhile, the MRR will have values ranging from 101.9108 mm^3/min (corresponding to experiment 1) to 764.3312 mm^3/min (corresponding to experiments 7, 8, 10, 12, 14, and 15).

Table 3

The result of *Ra* and *MRR*

No.	*v* (m/min)	*d* (mm)	*f* (mm/tooth)	*Ra* (µm)	*MRR* (mm^3/min)
1	40	0.2	0.01	0.152	101.9108
2	40	0.3	0.015	0.167	229.2994
3	40	0.4	0.02	0.198	407.6433
4	40	0.5	0.025	0.212	636.9427
5	60	0.2	0.015	0.146	229.2994
6	60	0.3	0.01	0.136	229.2994
7	60	0.4	0.025	0.21	764.3312
8	60	0.5	0.02	0.169	764.3312
9	80	0.2	0.02	0.133	407.6433
10	80	0.3	0.025	0.188	764.3312
11	80	0.4	0.01	0.131	407.6433
12	80	0.5	0.015	0.153	764.3312
13	100	0.2	0.025	0.131	636.9427
14	100	0.3	0.02	0.109	764.3312
15	100	0.4	0.015	0.11	764.3312
16	100	0.5	0.01	0.115	636.9427

A second-degree mathematical regression equation was derived using the roughness data from the sixteen experiments through Minitab V17 software. The equation represents the relationship between roughness and the given cutting parameters as follows:

$$Ra = 0.1518 - 0.000847v + 0.124d + 0.29f - 0.000011v^2 - \\ - 0.238d^2 + 225.0f^2 + 0.00374v \cdot d - 0.0080v \cdot f - 8.55d \cdot f, \quad (3)$$

To evaluate experimental data, scientists commonly use Analysis of Variance (ANOVA) in empirical research. Specifically, in this study, ANOVA is applied to assess the direct effects and interactive influences of input parameters, including (v), (d), and (f), on the output response, which is the surface roughness of the machining process. The P-value in the ANOVA table is utilized to evaluate the statistical significance of the model and input factors. A P-value smaller than 0.05 indicates that the model or specific factor has statistical significance. Additionally, the percentage contribution (PC) of terms in the estimated model to the total variation is taken into account to assess the degree of influence of the controllable factors on the model. The analysis of variance for the model is presented in **Table 4**.

Table 4
ANOVA for *Ra*

Source	DF	Adj-SS	Adj-MS	F-Value	P-Value	PC
Model	9	0.017115	0.001902	46.81	0.000	98.6
Linear	3	0.008514	0.002838	69.85	0.000	49.0
v	1	0.004416	0.004416	108.69	0.000	25.4
d	1	0.000348	0.000348	8.57	0.026	2.0
f	1	0.003750	0.003750	92.30	0.000	21.6
Square	3	0.000920	0.000307	7.55	0.018	5.29
v^2	1	0.000324	0.000324	7.97	0.030	1.86
d^2	1	0.000090	0.000090	2.22	0.187	0.5
f^2	1	0.000506	0.000506	12.46	0.012	2.9
2-Way interaction	3	0.000658	0.000219	5.40	0.039	3.79
$v{\cdot}d$	1	0.000492	0.000492	12.11	0.013	2.8
$v{\cdot}f$	1	0.000006	0.000006	0.14	0.724	0.03
$d{\cdot}f$	1	0.000161	0.000161	3.95	0.094	0.92
Error	6	0.000244	0.000041	–	–	1.4
Total	15	0.017359	–	–	–	–
			$R\text{–}sq = 98.60$ %			

From the data presented in **Table 4**, the following observations can be drawn: Firstly, the developed model aligns well with the experimental design using the Taguchi method (*L*16 array) and holds statistical significance as evidenced by a regression coefficient (*P*-value) of 0 (less than 0.05). Furthermore, this is also evident in the determined coefficient *R-sq* of 98.6 %. It demonstrates that 98.6 % of the variations in the selected input variables within the model significantly influence the output response. The model terms, including (v), (d), (f), (v^2), (f^2), and ($v{\cdot}d$), exhibit statistically significant effects on the response, all with P-values less than 0.05 [2, 34].

Among these terms, the (v) term exerts the most significant impact on the response, contributing 25.4 % to its variation, followed by the (f) term with a contribution of 21.6 %. While the (d) term has a relatively smaller effect (2 % contribution), it still holds statistical significance. Among the squared terms, (f^2) shows the most notable influence with a contribution of 2.9 %, followed by (v^2) with a contribution of 1.86 %. Regarding the interaction terms, the ($v{\cdot}d$) term exhibits the most substantial influence, contributing 2.8 % to the response variation. The other interaction terms have negligible effects on the output response.

Fig. 2 illustrates the discrepancies between the measured roughness values and the roughness values predicted by the regression model. It can be observed that there is a relatively small deviation between the experimental results and the predicted values. In other words, the regression model exhibits a good correlation with the actual experimental values and can be effectively used to predict roughness values based on the cutting parameters.

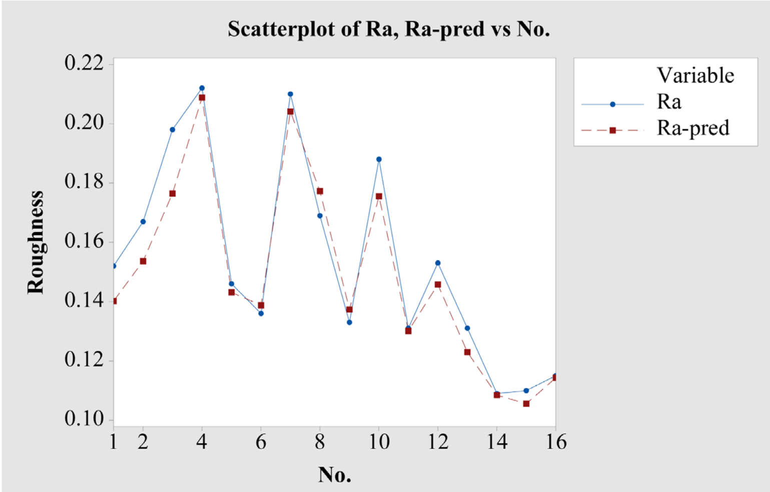


Fig. 2. The difference between measured and predicted surface roughness

Based on the desirability function, the optimal conditions of the cutting parameters to achieve the minimum roughness are determined and presented in **Fig. 3**. Accordingly, it can be observed that the optimal cutting conditions involve machining with a cutting speed of 100 m/min, a depth of cut of 0.2 mm, and a feed rate of 0.01 mm/tooth. By applying these cutting parameters, the predicted roughness can reach 0.0451 µm. A verification experiment was conducted with the given optimal cutting conditions, resulting in an achieved roughness of 0.054 µm. Once again, the experimental results confirm the reliability of the research findings.

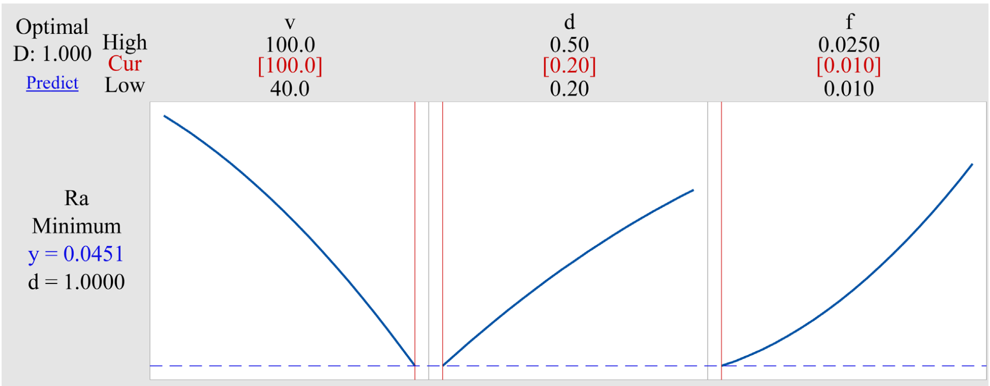
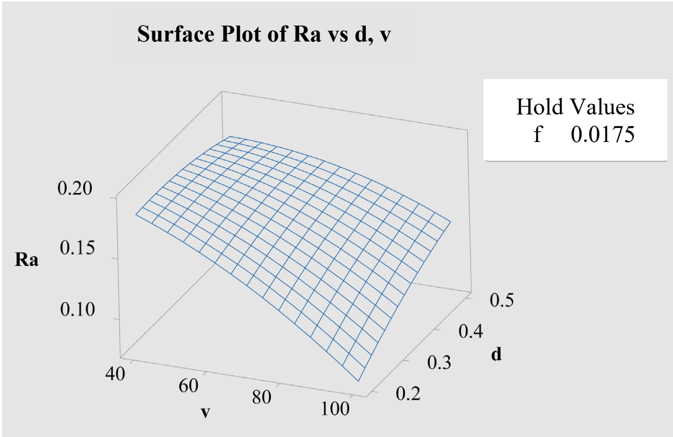


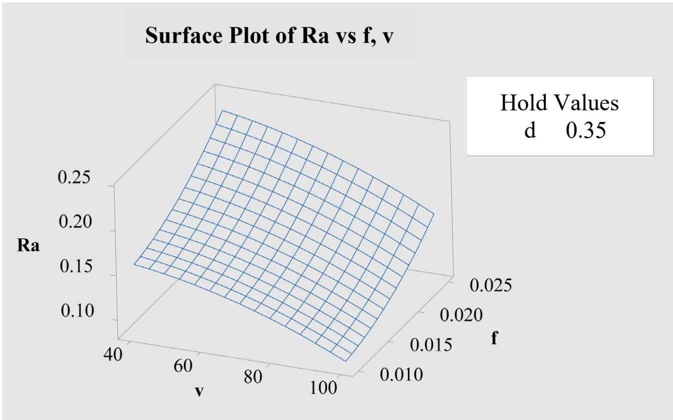
Fig. 3. Optimization plot for *Ra*

For a better understanding of the interactive influence of independent variables on the response, the 3D surface plots for Ra are constructed using Equation (3), as depicted in **Fig. 4**. Each graph represents the variation of two factors while keeping the remaining factor constant at its midpoint level.

The influence of the cutting speed and cutting depth on the surface roughness is depicted in **Fig. 4, *a*** with a constant feed rate of 0.0175 mm/tooth. Observing the surface representation of the relationship between the two input parameters and the output parameter, it can be observed that as the cutting speed increases (ranging from 40 m/min to 100 m/min), the surface roughness decreases. The minimum surface roughness occurs at the position with the highest cutting speed (the deepest area of the surface). An increase in cutting speed leading to a decrease in roughness is also shown in **Fig. 4, *b***. This result is also consistent with the research findings of two groups of authors, [35, 36]. This phenomenon can be explained as discussed in the study by [37]. When machining at higher cutting speeds, it generates significant cutting heat in the cutting zone, which softens the workpiece surface. As a result, the chips are more easily formed, leading to improved surface roughness. Another explanation related to the formation of Built-Up Edge (BUE) can be found in the explanation by [38]. When machining at low cutting speeds, BUE forms on the cutting edge of the cutting tool and negatively affects the surface roughness of the workpiece. However, as the cutting speed is increased, BUE disappears, leading to an improvement in surface roughness.



a



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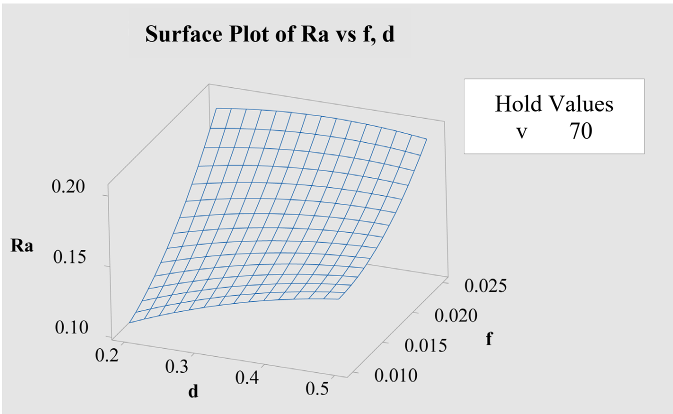

c

Fig. 4. The response surface plot for the roughness: *a* – *Ra* vs *d*, *v*; *b* – *Ra* vs *f*, *v*; *c* – *Ra* vs *f*, *d*

Observing **Fig. 4, *b, c*,** it can be seen that increasing the feed rate will lead to an increase in roughness. The helical motion of the cutting tool creates furrows on the machined surface. According to [39], as the feed rate increases, the furrows formed on the machined surface will become deeper and wider, resulting in an increase in roughness. In a study by [40], the authors concluded that an increase in the feed rate results in more heat generated in the cutting zone, giving less time for dissipation. As a result, chip accumulates within the cutting zone, negatively affecting surface roughness. Indeed, this is also consistent with the findings of Hughes and colleagues [41].

Fig. 4, *a, c* also demonstrate that increasing the depth of cut leads to an increase in surface roughness. This indicates that an increase in the depth of cut leads to a larger chip load, which in turn results in a noticeable rise in the applied cutting force. There is a strong correlation between cutting force and the quality of the machined surface, which has been found in many previous studies. When machining with high cutting forces, it will result in higher surface roughness compared to machining with lower cutting forces, as observed in the study conducted by [42]. Additionally, chatter vibrations are a contributing factor that affects surface roughness. When large cutting forces lead to significant chatter vibrations, it further increases surface roughness during machining [43, 44].

In this study, a multi-objective optimization approach was utilized to achieve two objectives: minimizing surface roughness and maximizing material removal rate. The optimal values for this multi-objective problem were determined using Minitab statistical software, employing the desirability function as illustrated in **Fig. 5**.

By considering a composite desirability value of 1.0, a compromise solution was obtained, resulting in a minimum surface roughness of 0.1069 µm and a maximum material removal rate of 775.0634 mm^3/min. These optimal values were achieved by employing specific machining parameters, including a cutting speed of 100 m/min, a depth of cut of 0.3611 mm, and a feed rate of 0.0168 mm/tooth.

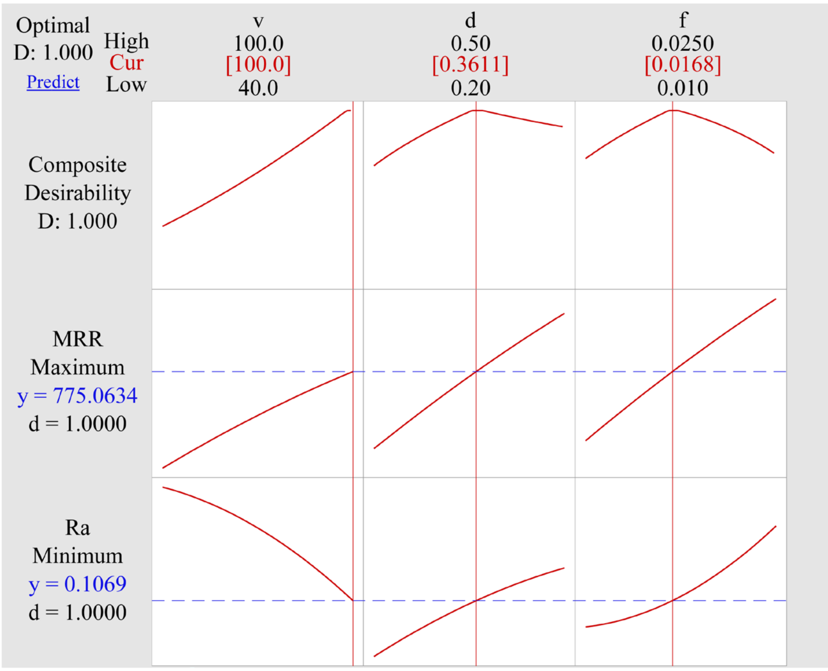

Fig. 5. Multi-objective optimization

Table 5 illustrates three different machining modes to achieve different objectives: minimum surface roughness, maximum MRR, and simultaneously achieving both minimum surface roughness and maximum MRR. In the first two objectives (single-objective optimizations), each outcome is achieved independently without considering other output factors. A compromise solution is presented in the third cutting mode.

The first cutting mode aims to achieve the minimum surface roughness (Ra = 0.054 µm). The result of this mode shows that the achieved MRR is relatively low (MRR = 254.7771 mm^3/min). On the other hand, the second cutting mode targets the maximum material removal rate (MRR = 1592.357 mm^3/min), but the surface roughness is not well-optimized (Ra = 0.190 µm). Meanwhile, the third cutting mode represents a compromise solution, where the surface roughness is good (Ra = 0.125 µm) and the material removal rate is relatively high (MRR = 772.8 mm^3/min). This compromise solution is more acceptable in practical manufacturing situations.

Table 5
Results of *Ra* and *MRR* with different cutting modes

Goal	Cutting parameters			Predicted *Ra* (µm)	Measured *Ra* (µm)	Predicted *MRR* (mm^3/min)	Measured *MRR* (mm^3/min)
	v (m/min)	*d* (mm)	*f* (mm/tooth)				
Min *Ra*	100	0.2	0.01	0.0451	0.054	167.8314	254.7771
Max *MRR*	100	0.5	0.025	0.1676	0.190	1506.3694	1592.357
Multi-goal optimization	100	0.3611	0.0168	0.1069	0.125	775.0634	772.8

In **Table 5**, there are two columns displaying surface roughness results and two columns displaying Material Removal Rate (*MRR*) results. One column represents the predicted results, while the other column represents the measured results. It can be observed that the results for both surface roughness and *MRR* are quite close. This indicates that the mathematical model provided is reliable.

Furthermore, if not overly concerned with productivity, machining can be carried out with the optimal conditions to achieve the minimum surface roughness. As shown in **Table 5**, the predicted minimum surface roughness is 0.0451 µm. As seen in **Table 3**, the surface roughness achieved in all experiments is above 0.1 µm. Therefore, a validation experiment was conducted to assess the reliability of the results obtained. The surface roughness achieved in the validation experiment is 0.054 µm (which is the average value of three roughness measurements taken at three different locations). Once again, this reaffirms the effectiveness of the hard-milling process combined with the nanofluid *MQL* cooling conditions.

Overall, the results and analysis of the study provide valuable reference for researchers and practitioners in the field. This research has provided good insights for optimizing the machining process to achieve the best surface finish. Furthermore, a compromise solution to achieve both the best quality (represented by surface finish) and high productivity (represented by *MRR*) has also been proposed using multi-objective optimization.

This study represents a typical case study. Therefore, the results presented are only completely accurate when applying the input conditions of this study, such as the levels of cutting parameters, equipment used for the study, cutting tools, workpieces and workpiece materials, fixtures, and cooling conditions (cutting fluid, size, and concentration of nanoparticles). When these conditions are correctly applied, the results obtained will accurately reflect those in the study.

To further guide future research, cooling condition parameters such as nano particle size, nano particle concentration in the coolant solution... need to be included to assess their impact on the output variables. Additionally, the combination of multiple types of nano particles should also be considered.

4. Conclusions

In this research, the hard-milling process of alloy steel SKD 11 was studied under the cooling condition of nanofluid based *MQL*. The primary objective was to investigate the relationship between three typical cutting parameters: cutting speed, depth of cut, and feed rate, and their influence on two output responses: surface roughness and material removal rate. Each cutting parameter was varied at four different levels. The experimental design was carried out using the *L*16 orthogonal array of the Taguchi method. Response Surface Methodology was employed to develop mathematical regression models for both single and multi-objective optimization. Several significant conclusions were derived from the study, which are presented as follows: a second-order regression model describes the relationship between machining parameters (cutting speed, depth of cut, and feed rate) and surface roughness. The difference between the predicted values given by the model and the experimental values is very small. This indicates a strong correlation between the model and the experimental values, making it suitable for predicting surface roughness.

In terms of the influence on surface roughness, the most significant factor is the cutting speed, accounting for 25.4 % of the effect, followed by the feed rate with 21.6 % influence. The depth of cut has a relatively minor impact on surface roughness. The effects of the cutting parameters on the output response are all statistically significant with a P-value less than 0.05.

The optimal machining conditions for achieving the minimum surface roughness are a cutting speed of 100 m/min, a cutting depth of 0.2 mm, and a feed rate of 0.01 mm/tooth, resulting in a surface roughness of 0.0451 µm.

A multi-objective optimization has been conducted to achieve simultaneous objectives of the minimum surface roughness and the minimum material removal rate. To attain these goals, a cutting mode with a cutting speed of 100 m/min, a cutting depth of 0.3611 mm, and a feed rate of 0.0168 mm/tooth should be applied under the condition of Nanofluid-based *MQL* cooling lubrication. With this cutting condition, the predicted surface roughness could reach 0.1069 µm, and the predicted *MRR* could reach 775.06 mm^3/min.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

Manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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