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INTEGRATING TAGUCHI DESIGN WITH MCDM FRAMEWORKS FOR MULTI-OBJECTIVE OPTIMIZATION OF TI6AL4V GRINDING VIA ESTER-BASED MINIMUM QUANTITY LUBRICATION (MQL)

Ti6Al4V is characterized by its superior strength and exceptional corrosion resistance. Due to its high strength-to-weight ratio, this alloy is extensively utilized in fabricating high-precision components within the aerospace industry, such as turbine blades and engine casings as well as in the medical sector for artificial joints and dental implants. This study explores the multi-objective optimization of the grinding process for this specific alloy using SiC abrasive wheels under Ester-based MQL conditions. The Taguchi method was implemented to develop the experimental matrix, focusing on four primary input parameters: fluid pressure, workpiece velocity, feed rate, and depth of cut. To evaluate the process performance, surface roughness and three cutting force components were analysed. Five distinct ranking methodologies (SAW, RAM, PIV, ROV, and FUCA) were integrated with four weighting techniques (Equal, Entropy, MEREC, and SD) to determine the optimal processing conditions. Experimental analysis reveals that Ester oil in the MQL system effectively penetrates the cutting zone to mitigate friction, maintaining a minimum surface roughness of 0.828 μm and suppressing the material plowing effect associated with SiC wheels. The findings further confirm the process stability, as surface quality remained consistently controlled even at low normal forces ($F_z = 7.39 \text{ N}$), allowing for greater flexibility in selecting cutting regimes. All weighting methods and ranking methods used consistently found the optimal values for the process parameters. These values include a fluid pressure of 6 (bar), a workpiece velocity of 10 (m/min), a feed rate of 8 (mm/stroke), and a cutting depth of 0.03 mm. Corresponding to these parameter values, the surface roughness and the three cutting force components in the x , y , and z directions are 1.305 (μm), 83.036 N, 35.502 N, and 61.019 N, respectively. The results of the sensitivity analysis also confirm the reliability and objectivity of the determined optimal values.

NOMENCLATURE

MCDM: Multi-Criteria Decision-Making

MQL: Minimum Quantity Lubrication

MEREC: MEthod based on the Removal Effects of Criteria

SD: Standard Deviation

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RAM: Root Assessment Method
PIV: Proximity Indexed Value
ROV: Range OF Value
FUCA: Faire Un Choix Adéquat
AHP: Analytic Hierarchy Process
TOPSIS: Preference by similarity to the ideal solution
S/N: Signal-to-Noise
P: Lubricant pressure
V: Workpiece velocity
S: Feed rate
t: Depth of cut
Ra: The arithmetical mean deviation of the assessed profile
F_x: The x-axis force component
F_y: The y-axis force component
F_z: The z-axis force component

1. INTRODUCTION

The demand for Ti6Al4V alloys continues to rise, driven by their superior attributes such as exceptional corrosion resistance and high structural strength. This alloy is a staple in the aerospace and medical sectors; reports indicate that Ti6Al4V constitutes approximately 11% of the components in the Boeing 777, rising to 15% in the Boeing 787 and various fighter jets [1]. Furthermore, it is extensively utilized in nuclear reactor components, chemical processing equipment [2], horology, and high-precision electronic devices [3]. Despite its utility, it is classified as a difficult-to-machine material due to its high elasticity [4]. Its machinability index is only about 20%; coupled with poor thermal conductivity, this leads to extreme temperatures in the cutting zone, causing rapid tool wear when using traditional edged-tool methods like milling or turning [5, 6]. Consequently, because this material is often destined for high-precision components yet remains resistant to conventional cutting, grinding is frequently considered an essential manufacturing process [7]. In any machining process—and specifically during grinding—mitigating cutting heat is critical, particularly for small-scale components sensitive to fatigue stress, precision assemblies, threaded holes, and parts with high aesthetic requirements [8, 9].

A primary drawback of conventional flood cooling when machining Ti6Al4V involves significant environmental and occupational health risks due to the massive volume of cutting fluids containing hazardous chemicals. Moreover, flood cooling often fails to penetrate the high-speed cutting zone effectively, resulting in elevated contact temperatures that promote material adhesion to the tool, thereby compromising tool life and surface integrity [9, 10]. Implementing Minimum Quantity Lubrication (MQL) is necessary for Ti6Al4V processing to counteract the alloy's low thermal conductivity and high chemical reactivity. The MQL system delivers fluid to the cutting zone in the form of aerosolized droplets (nanoparticles), minimizing the adhesion zone between tool and workpiece while creating rolling and plowing mechanisms that reduce friction and shorten the tool-chip contact length. Consequently, this method not only extends tool life and enhances surface quality but also serves as a sustainable alternative that protects the environment and operator health compared to traditional methods [11, 12]. Research suggests that MQL reduces cutting zone temperatures through the heat

dissipation caused by the oil-air flow [13]. The misting effect of MQL generates a lubricating film between the grinding wheel and the workpiece, reducing the contact area and friction [14]. Additionally, MQL does not require a secondary power source for fluid delivery, providing a distinct advantage over flood irrigation [7].

Given these advantages, numerous studies have explored Ti6Al4V grinding under MQL conditions using various approaches. Three predominant methodologies in recent literature are summarized below:

The first approach involves auxiliary technologies and nano-lubricants. Study [15] utilized ultrasonic vibration-assisted MQL to deliver fluid more effectively, outperforming conventional MQL. Other researchers developed specialized CBN wheels by incorporating 2% to 7% carbon nanotubes (CNTs), finding that even small CNT concentrations significantly enhanced grinding performance [16]. Furthermore, adding 2% CNTs to the MQL system reduced power consumption by 11.5% and surface roughness by 45% compared to standard MQL [17], while a 4% concentration yielded a 38% reduction in roughness [18].

The second approach utilizes univariate experimentation to identify the influence of technological parameters. Grinding Ti6Al4V with SiC wheels (39C46 KVK) under MQL confirmed that smaller depths of cut lead to lower surface roughness [19]. Study [20] varied parameters—oil pressure, flow rate, cutting speed, depth of cut, and feed rate—individually to assess their independent impact on roughness and tangential force using Al₂O₃ wheels (91A46I8AV), concluding that a pressure of 4 bar and a flow rate of 60 ml/h were optimal for force reduction.

The third approach focuses on process optimization, frequently employing the Taguchi method for experimental design. Taguchi was used to optimize Ti6Al4V grinding with CBN wheels by varying nanoparticle concentration (SiO₂), air pressure, and nozzle orientation. By analysing Signal-to-Noise (S/N) ratios, researchers optimized surface roughness and cutting force individually, finding that nanoparticle concentration had the most significant impact [21]. Similarly, Al₂O₃ wheels (WA80M5V) were tested using Taguchi designs across various fluids and lubrication techniques, identifying sunflower oil as the optimal medium for surface hardness [22, 23]. In [24], Taguchi and S/N analysis determined optimal speeds and feed rates for SiC wheels (CGC60-K5-VG) to achieve minimum roughness. Another study highlighted that increasing MQL concentration, pressure, and flow rate consistently reduced both force and roughness [25].

It is observed that, firstly, CBN and Al₂O₃ grinding wheels have been used in the grinding process of Ti6Al4V alloy. However, the lack of studies on grinding this alloy using SiC wheels needs to be addressed. This will enrich the understanding of grinding technology for this alloy when using MQL cooling. Furthermore, production practice has shown that using SiC grinding wheels for Ti6Al4V alloy plays an important role due to their good chemical compatibility. This helps minimize material adhesion and chemical wear at high temperatures. This is a common and highly economical solution in industrial production. The reason is that SiC wheels have a much lower cost than diamond or CBN wheels while still ensuring the surface quality and cutting performance required for aerospace and medical components.

Secondly, although all three approaches have certain values, the first approach (nano and ultrasonic) faces barriers of high investment costs and complex fabrication processes, making it difficult to apply widely. Meanwhile, the second approach (univariate

experimentation) is simple but time-consuming. Additionally, it fails to demonstrate the interaction between technological variables. Conversely, the third approach is superior due to its use of mathematical tools like Taguchi to survey multiple factors with minimal experiments. However, relying solely on Taguchi for single-objective S/N analysis often fails to achieve harmony between conflicting objectives. To bridge this gap, this research integrates Taguchi experimental design with Multi-Criteria Decision-Making (MCDM) methods to solve the multi-objective optimization problem. Recent literature has used TOPSIS for ranking and AHP for weighting in Ti6Al4V grinding [26], yet relying on a single MCDM method (like TOPSIS) is a known gap, as different algorithms can yield varying rankings [27, 28].

This indicates that to obtain an optimal grinding solution objectively, it is necessary to conduct the process using multiple different methods simultaneously. In this study, five different MCDM methods were employed, including SAW, RAM, PIV, ROV, and FUCA. The simultaneous use of these five methods to solve the multi-objective optimization problem in Ti6Al4V alloy grinding is a novelty compared to published literature. The reasons for selecting these five methods, as well as their algorithms, will be clarified in the following section. Furthermore, published studies (such as reference [26]) have used the AHP method, which is a subjective method for calculating criteria weights. Clearly, this leads to the weights being heavily influenced by subjective thinking or depending significantly on the experience of the problem solver. This affects the objectivity of the identified optimal grinding solution [29, 30]. To achieve objectivity in the optimal solution, this study simultaneously used four objective weighting methods: Equal, Entropy, MEREC, and SD. The reasons for using these four methods will also be clarified in the following section. The simultaneous application of four objective weighting methods to calculate criteria weights in Ti6Al4V alloy grinding is also noted as a novelty of this study compared to previously published works.

Section 2 of this article presents the Ti6Al4V alloy grinding experiment process. It also explains the reasons for and the algorithms of the used MCDM methods. The grinding experimental results and the ranking of experiments to find the optimal values of the technological parameters are presented in Section 3. Section 4 contains the sensitivity analysis to evaluate the stability of the experimental rankings when using different MCDM methods. The conclusions of the study and the tasks to be implemented in future research are the final contents of this article.

2. MATERIALS AND METHODS

2.1. EXPERIMENTAL DESIGN

The experimental trials were conducted on a precision surface grinding machine. The tool utilized for this study was a Silicon Carbide (SiC) grinding wheel, designated as Sx100.MV1.G.V1x300.40.127. Ti6Al4V alloy workpieces have length, width, and height dimensions of 80 mm, 40 mm, and 10 mm, respectively. The weight percentage of the main elements in this material is presented in Table 1.

Table 1. Elemental composition of Ti6Al4V

Ti	Al	V	Fe	C	N	H	O
Balance	5.6÷6.8	3.6÷4.6	0.30	0.10	0.05	0.015	0.20

For the lubrication and cooling system, a synthetic ester oil, specifically SHL SAMSTER T2600 was applied via the Minimum Quantity Lubrication (MQL) method. This lubricant is characterized by its high viscosity index, superior lubricity, elevated flash point, low volatility loss, excellent biodegradability, and minimal toxicity [31, 32]. Notably, synthetic ester has been demonstrated to outperform vegetable-based esters in the grinding of Ti6Al4V alloys regarding surface roughness, tangential force components, surface burn prevention, and microstructural integrity [20]. The MQL parameters were strictly controlled throughout the experimental process to ensure consistency. The lubricant (Ester) was supplied at a flow rate of 50 ml/h using an air pressure of 0.5 MPa. A single nozzle with a diameter of 3.25 mm was positioned at an angle of 20° and placed 20 mm away from the grinding zone [33, 34]. Four operational factors were selected as input parameters for each experiment: MQL fluid pressure, workpiece velocity, feed rate, and depth of cut. These parameters were chosen due to their ease of adjustment by machine operators, thereby enhancing the practical industrial relevance of this research. Each factor was assigned three discrete levels, coded as 1, 2, and 3, as summarized in Table 2. Since the novelty of this study involves using SiC wheels to grind Ti6Al4V alloy with MQL cooling using ester solution, the basis for selecting the parameter values in this table was carefully filtered from documents using SiC grinding wheels for Ti6Al4V alloy. Additionally, the selection was based on the technological capabilities of the machine used for the experiments in this study [35–39]. Based on these levels, the Taguchi method was employed to develop an L9 orthogonal array, resulting in nine experimental runs as detailed in Table 3. Compared to methods such as Box-Behnken or CCD, the Taguchi method demonstrates superior advantages through several key characteristics. It minimizes the number of experiments while still fully reflecting the influence of input parameters on the output responses. Particularly, this method is suitable for practical experimental systems where input parameters cannot be adjusted infinitely, or when input parameters are qualitative (such as colour or style). Due to its high flexibility and applicability, the Taguchi matrix helps researchers easily implement experimental results into production. This avoids obstacles related to adjusting fractional values or overcomplicating the modelling process [40].

To evaluate the grinding performance, surface roughness and the three orthogonal cutting force components were selected as response variables. Surface roughness (Ra) was chosen due to its critical influence on the functional performance of components, including wear resistance, corrosion protection, and fatigue life [41]. Furthermore, it significantly dictates the aesthetic quality of the finished product. The three cutting force components were also designated as objectives because of their profound impact on the grinding process. The x-axis force component (along the longitudinal movement of the table) significantly influences power consumption, grinding zone temperature, and wheel wear. The y-axis force component (transverse feed direction) is closely linked to surface finish and geometric deviations, such as straightness and flatness. The z-axis force component (normal to the ground surface) affects the elastic deformation of the machine-tool-workpiece system, vibrations, and dimensional accuracy [42–44].

In each trial, surface roughness was measured using a Mitutoyo SJ-201 tester, while the three force components (F_x , F_y , F_z) were captured using a Kistler 9139AA piezoelectric dynamometer. The fundamental configuration of the experimental setup is illustrated in Fig. 1. The measurement of cutting force components was performed during the grinding process. Meanwhile, surface roughness was measured on the ground surface of the workpiece after it had been cleaned and dried with alcohol. To reduce noise during the experimental process, parameters including surface roughness and the three cutting force components were each measured at least three times for every experiment. The value of these parameters for each experiment was then calculated as the average value of the consecutive measurements.

Table 2. Input Parameters and their levels

Parameter	Symbol	Unit	Value at levels		
			1	2	3
Lubricant pressure	p	atm	4	5	6
Workpiece velocity	V	m/min	8	10	12
Feed rate	S	mm/stroke	8	13	18
Depth of cut	t	mm	0.01	0.02	0.03

Table 3. Experimental Design Matrix

Exp.	Code value				Real value			
	p	V	S	t	p (bar)	V (m/min)	S (mm/sroke)	t (mm)
1	1	1	1	1	4	8	8	0.01
2	1	2	2	2	4	10	13	0.02
3	1	3	3	3	4	12	18	0.03
4	2	1	2	3	5	8	13	0.03
5	2	2	3	1	5	10	18	0.01
6	2	3	1	2	5	12	8	0.02
7	3	1	3	2	6	8	18	0.02
8	3	2	1	3	6	10	8	0.03
9	3	3	2	1	6	12	13	0.01



Fig 1. Schematic of the experimental setup: a) Overview of the surface grinding system, b) Surface roughness measurement; c) Workpiece samples, d) MQL supply system, e) Kistler dynamometer setup

In addition to the aforementioned technological parameters and experimental setup, specific measures were taken to mitigate the impact of wheel wear on the output data. After each experimental run, the grinding wheel was dressed at a depth of 0.01 mm with a dressing feed rate of 120 mm/min to ensure a consistent abrasive topography.

2.2. MATHEMATICAL METHODOLOGIES

Five distinct Multi-Criteria Decision-Making (MCDM) methodologies were implemented in this research: SAW, RAM, PIV, ROV, and FUCA. These techniques were selected specifically for the structural differences in their underlying algorithms, ensuring that the optimization results achieve maximum objectivity. Specifically, the SAW method ranks alternatives based on the principle of linear combination. After normalizing the criteria to a common scale, each alternative's score is derived from the weighted sum of its performance values [45]. The RAM utilizes a radical summation function, where the ranking index is calculated as the root of the ratio between total cost criteria and total benefit criteria [46]. The PIV approach ranks alternatives by quantifying the distance (proximity index) from each candidate to the ideal best value within each criterion. These weighted distances are then accumulated to provide a global proximity value for each alternative [47]. The ROV method evaluates alternatives by calculating the best and worst utility values for each candidate based on criteria weights. The final hierarchy is determined by the midpoint (mean) of these two utility extremes [48]. Finally, the FUCA transforms the quantitative performance of each criterion into discrete ranks (from 1 for the optimal value to m for the least desirable). The final index is the weighted sum of these rank positions [49].

Furthermore, the diversity of these five methods is reflected in their respective normalization techniques. SAW employs linear normalization [45], RAM uses sum-linear normalization [46], PIV relies on vector normalization [47], and ROV implements Weitendorf normalization [48]. In contrast, FUCA bypasses the normalization stage entirely [49–51]. It must be emphasized that the specific normalization technique utilized within an MCDM framework exerts a profound influence on the resulting rankings [52, 53]. By integrating five MCDM methods with disparate approaches—four of which use unique normalization types and one that does not—the objectivity of the optimization outcome is significantly bolstered.

To rank the alternatives (which in this study represent the titanium alloy grinding trials), a decision matrix must be constructed. This matrix consists of m rows and n columns, where m denotes the number of alternatives and n represents the evaluation criteria. Let x_{ij} represent the performance value of criterion j for alternative i , where $i = 1 \div m$ and $j = 1 \div n$. The notations B and C refer to “Benefit” (higher-is-better) and “Cost” (lower-is-better) criteria, respectively. Let w_j be the weight assigned to criterion j . The execution of these MCDM methods is summarized as follows: SAW Procedure [45]:

$$n_{ij} = \frac{x_{ij}}{\max x_{ij}} \quad \text{if } j \in B \quad (1)$$

$$n_{ij} = \frac{\min x_{ij}}{x_{ij}} \quad \text{if } j \in C \quad (2)$$

- Calculate the preference value (V_i) for each alternative via Eq. (3). The optimal alternative is that with the maximum V_i .

$$V_i = \sum_{j=1}^n w_j \cdot n_{ij} \quad (3)$$

RAM Procedure [46]:

- Normalize criteria according to Eq. (4).

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}} \quad (4)$$

Calculate weighted normalized values via Eq. (5).

$$y_{ij} = w_j \cdot r_{ij} \quad (5)$$

- Compute weighted sum scores using Eq. (6) and (7).

$$S_{+i} = \sum_{j=1}^n y_{+ij} \quad \text{if } j \in B \quad (6)$$

$$S_{-i} = \sum_{j=1}^n y_{-ij} \quad \text{if } j \in C \quad (7)$$

- Determine final scores per Eq. (8). Alternatives are ranked in descending order of their scores.

$$RI_i = \frac{2 + S_{-i}}{\sqrt{2 + S_{+i}}} \quad (8)$$

PIV Procedure [47]:

- Compute normalized values per Eq. (9).

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (9)$$

- Calculate weighted normalized values per Eq. (10).

$$V_{ij} = w_j \times n_{ij} \quad (10)$$

- Evaluate the weighted proximity index via Eq. (11) and (12);

$$u_i = v_{\max} - v_i \quad \text{if } j \in B \quad (11)$$

$$u_i = v_i - v_{\min} \quad \text{if } j \in C \quad (12)$$

- Identify the global proximity region (d_i) using Eq. (13). The best alternative is that with the minimum d_i .

$$d_i = \sum_{j=1}^n u_i \quad (13)$$

ROV Procedure [48]:

- Normalize data using Eq. (14) and (15).

$$n_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \quad \text{if } j \in B \quad (14)$$

$$n_{ij} = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} \quad \text{if } j \in C \quad (15)$$

- Calculate utility magnitudes (u_i) via Eq. (16). The alternative with the highest u_i is ranked first.

$$u_i = \sum_{j=1}^n n_{ij} \cdot w_j \quad (16)$$

FUCA Procedure [49]:

- Rank alternatives for each criterion (r_{ij}), assigning 1 to the best value and m to the worst. This ranking is performed n times.
- Calculate the final score via Eq. (17). The optimal alternative is the one with the minimum S_i .

$$S_i = \sum_{j=1}^n r_{ij} \cdot w_j \quad (17)$$

Determining the criteria weights is a pivotal step in ranking the experimental trials. This study utilizes four distinct objective weighting techniques: Equal, Entropy, MEREC, and Standard Deviation (SD). The Equal weighting method is the most straightforward, assigning identical importance to all parameters. The Entropy and MEREC were chosen due to their widespread adoption and reliability in previous literature [54, 55]. The SD method was selected because it calculates weights based on the standard deviation of the dataset for each parameter, reflecting the inherent variability of the machining process data [56]. The simultaneous application of these four objective weighting methods ensures that the conclusions drawn are unbiased and mathematically robust.

The procedure for ranking the alternatives (the experiments) using the methods mentioned above is illustrated in Fig. 2.

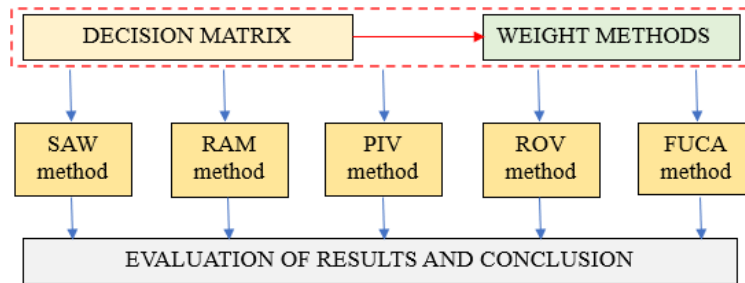


Fig. 2. Procedure for ranking the experiments

According to the diagram in Fig. 2, the decision matrix is created after obtaining the experimental results. The next stage involves calculating the weights for the criteria using the Equal, Entropy, MEREC, and SD methods. Subsequently, the SAW, RAM, PIV, ROV, and FUCA methods are applied to rank the experiments. Finally, the results are evaluated to provide conclusions regarding the ranking of the experiments.

3. RESULTS AND DISCUSSION

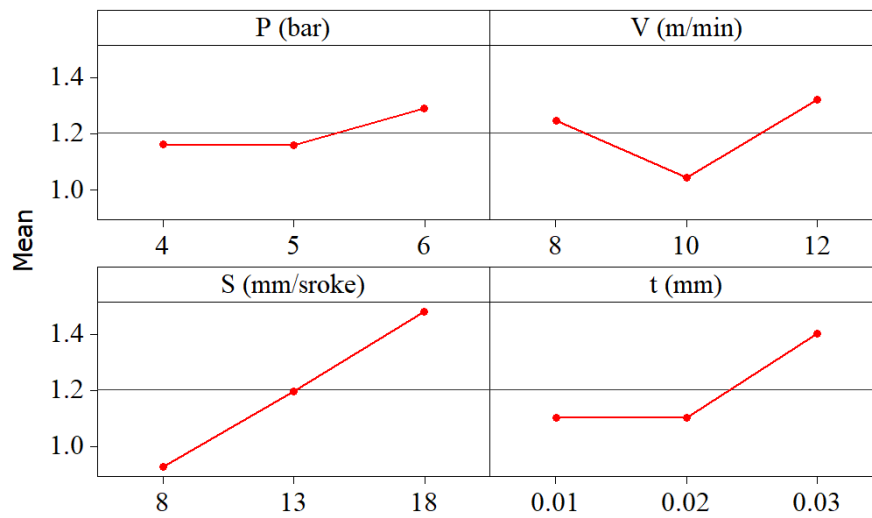
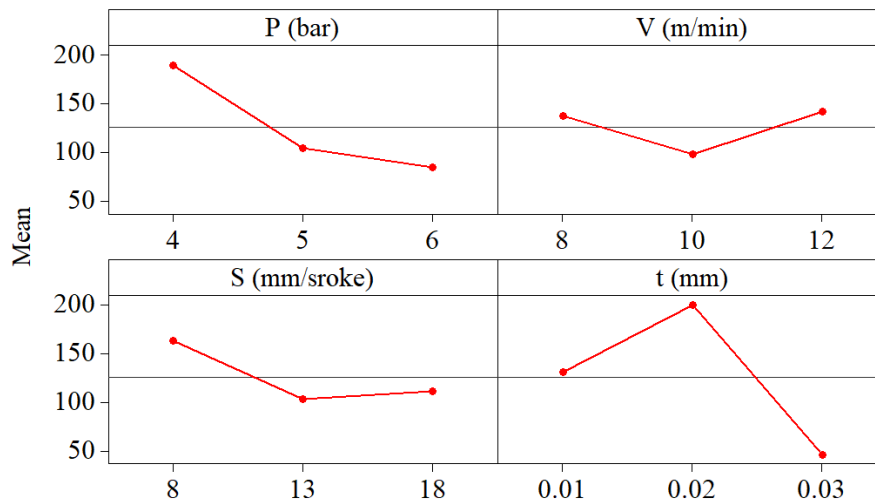
The experimental trials were conducted according to the design matrix presented in Table 3. Surface roughness and the three cutting force components were measured at least three times per experiment, and the mean values are compiled in Table 4.

Table 4. Experimental outcomes for surface quality and cutting forces

Exp.	Ra (μm)	F_x (N)	F_y (N)	F_z (N)
1	0.828	244.184	58.624	281.011
2	0.894	212.825	38.870	135.120
3	1.758	110.960	32.219	19.911
4	1.396	13.038	94.410	28.897
5	1.173	66.954	21.380	25.067
6	0.901	233.080	46.393	7.390
7	1.513	156.288	101.603	19.617
8	1.053	14.113	22.929	17.991
9	1.305	83.036	35.502	61.019

According to the data in Table 3, the lubrication efficiency during surface grinding using SiC abrasives paired with synthetic ester oil via MQL is vividly demonstrated through its ability to control surface quality under demanding machining conditions. Given that SiC wheels typically exhibit aggressive material removal tendencies, achieving a minimum surface roughness (Ra) of 0.828 μm (Exp. 1) and maintaining stability generally below 1.5 μm is a significant result. This suggests that the polar molecules of the ester oil formed a resilient lubricating film, effectively coating asperities and mitigating the material plowing effect, a common challenge when grinding high-ductility or difficult-to-machine alloys with SiC wheels. Even amidst substantial fluctuations in cutting forces, the surface finish remained stable, reinforcing the critical role of ester oil in stabilizing the cutting interface.

From a dynamic perspective, the relationship between force components indicates that the ester oil significantly intervened in the wheel-workpiece contact zone. Although the normal force (F_z) reached high levels in certain conditions, the ester oil maintained its friction-reduction capacity, ensuring consistent surface integrity throughout the tests. Conversely, in regimes with exceptionally low normal forces (only 7.39 N in Exp. 6), roughness remained well-controlled, suggesting that the synergy between SiC abrasives and ester-based MQL enhances process adaptability. This provides operators with a broader range of cutting parameters while maintaining an equilibrium between productivity and surface quality. Figures 3 to 6 respectively illustrate the influence of input parameters on surface roughness and the cutting force components in the x , y , and z directions. Observing these figures, it is evident that the degree and patterns of the influence of technological parameters on the responses are very complex. The following comments will further clarify this observation. Regarding surface roughness (Fig. 3), when the MQL fluid pressure increases from 4 bar to 5 bar, the surface roughness remains almost unchanged. However, if the fluid pressure continues to increase, the surface roughness also increases. When the workpiece velocity increases from 8 m/min to 10 m/min, the surface roughness decreases. Conversely, the surface roughness increases if the workpiece velocity is further increased. An increase in the feed rate always leads to a very rapid increase in surface roughness. As for the cutting depth, the surface roughness value remains almost constant when the cutting depth increases from 0.01 mm to 0.02 mm. However, increasing the cutting depth from 0.02 mm to 0.03 mm causes the surface roughness to increase rapidly.

Fig 3. Main effects plot for R_a Fig 4. Main effects plot for F_x

Regarding the cutting force component in the x-direction (Fig. 4), increasing the MQL fluid pressure consistently leads to a decrease in this force component. However, the rate of decrease varies across different pressure stages. Increasing the workpiece velocity from 8 m/min to 10 m/min causes this force component to decrease. Conversely, further increasing the workpiece velocity leads to an increase in this force component. Increasing the feed rate from 8 mm/stroke to 13 mm/stroke results in a decrease in this force component. However, if the feed rate continues to increase, this force component increases again, though very slowly. Increasing the cutting depth from 0.01 mm to 0.02 mm causes this force to increase rapidly. In contrast, the force decreases rapidly if the cutting depth is further increased.

Regarding the cutting force component in the y-direction (Fig. 5), increasing the MQL fluid pressure and the feed rate causes almost no significant change in this parameter. This force component decreases very rapidly as the workpiece velocity increases from 8 m/min to 10 m/min. However, if the workpiece velocity continues to increase, this force component increases again. When the cutting depth increases from 0.01 mm to 0.02 mm, it causes this

force component to increase. In contrast, the force decreases if the cutting depth is further increased.

Regarding the cutting force component in the z-direction (Fig. 6): Increasing the MQL fluid pressure from 4 bar to 5 bar causes this force component to decrease rapidly. However, further increasing the pressure leads to a slow increase in this force component. Increasing all three parameters, workpiece velocity, feed rate, and cutting depth results in a decrease in this force.

The above comments show that it is very difficult to determine the values of technological parameters that ensure small values for all four responses. Another observation clarifies this issue further. For example, to achieve low surface roughness, the MQL fluid pressure must be low, as illustrated in Fig. 3. However, when the MQL fluid pressure is low, the force components in the x and z directions reach their maximum values, as shown in Fig. 4 and Fig. 6. Consider another example: when the feed rate is at its minimum value of 8 mm/stroke, the surface roughness and the cutting force component in the y-direction are also small. Yet, at this same feed rate value, the cutting force components in the x and z directions both reach their maximum values.

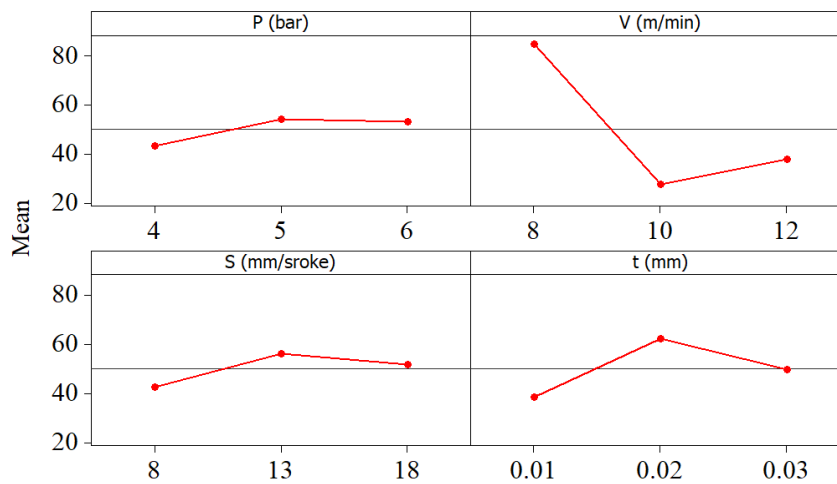


Fig 5. Main effects plot for F_y

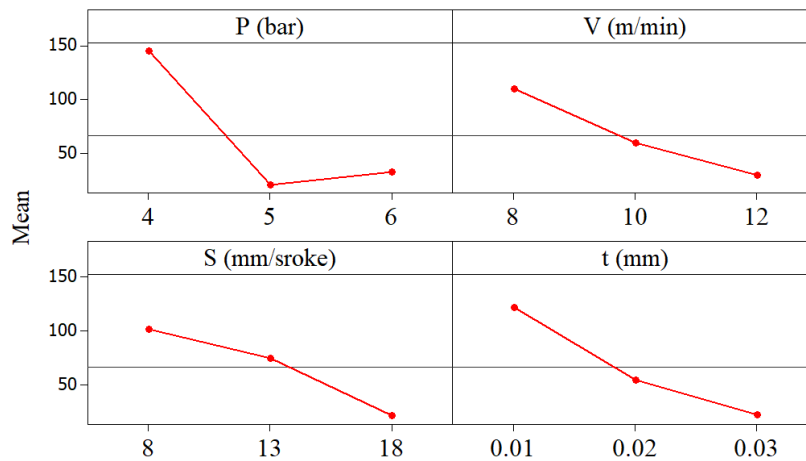


Fig 6. Main effects plot for F_z

These comments further demonstrate that to determine the technological parameter values that simultaneously ensure small values for all four responses, solving a multi-objective optimization problem is essential.

Two forms are commonly used to solve multi-objective optimization problems: the first is based on regression equations, and the second uses MCDM methods. According to the first form, it is first necessary to build mathematical models representing the relationship between the responses and the technological parameters. To apply this approach, this study would need to construct four regression equations for surface roughness and the three cutting force components. However, since this study used the Taguchi method to design the experimental matrix, the number of experiments is minimal. This would affect the accuracy of the regression models. In other words, this form is not suitable for solving the multi-objective optimization problem in this research. Therefore, this study applies the second form to solve the multi-objective optimization problem by using multi-criteria decision-making methods.

An analysis of Table 3 further reveals that among the nine trials, the minimum values for surface roughness and the cutting forces along the X, Y, and Z axes occurred in different Exp. 1, Exp. 4, Exp. 5, and Exp. 6, respectively. It is evident that no single experiment simultaneously minimizes all four responses (Ra , F_x , F_y , F_z). Consequently, determining an “optimal” trial requires a comprehensive ranking approach to balance these conflicting objectives.

To facilitate this, weights for Ra , F_x , F_y , and F_z were calculated using four distinct methods, with the results summarized in Table 5.

Table 5. Distribution of criteria weights

Weight method	Ra	F_x	F_y	F_z
Equal	0.2500	0.2500	0.2500	0.2500
Entropy	0.3937	0.1991	0.2081	0.1990
MEREC	0.3475	0.2421	0.2411	0.1692
SD	0.0015	0.4300	0.1406	0.4279
max/min	260.06	2.16	1.78	2.53

The data in Table 5 show that weights vary significantly depending on the calculation method. For instance, the weight for Ra shifted by over 260 times when using the SD method compared to the Entropy method. This divergence is attributed to the unique mathematical foundations of each weighting technique [57, 58]. Specifically, the Equal method is the simplest approach, which considers all criteria to be of equal importance, regardless of data characteristics. The Entropy method calculates criteria weights based on the measure of data uncertainty. A criterion with more distinct values across alternatives (high dispersion) will have a lower Entropy value, resulting in a higher weight being assigned to that criterion because it provides more information for classification [59]. The MEREC method determines weights based on the impact of removing a criterion. This method measures the change in overall performance when a criterion is excluded; the criterion that causes the greatest change is considered the most important and receives the highest weight [60]. Meanwhile, the SD method calculates criteria weights based on the standard deviation of the criteria [56]. However, this variance actually enhances the objectivity of the final optimization. According

to the data in this table, there is also a significant difference in the ratio between the maximum and minimum weight values when using each method. When using the Equal, Entropy, and MEREC methods, these ratios are relatively small, at 1, 1.978, and 2.054, respectively. However, when using the SD method, this ratio reaches 286.667. This can be explained by the fact that the SD method calculates criteria weights based on the standard deviation, while the ratios between the maximum and minimum values of the criteria themselves differ greatly. Specifically, the ratio between the maximum and minimum values for surface roughness is 2.123; for the cutting force in the x-direction, it is 18.728; for the cutting force in the y-direction, it is 4.752; and for the cutting force in the z-direction, it is 38.025. Consequently, when using the SD method, the weight for surface roughness is very small, while the weights for the other criteria are significantly larger.

After the criteria weights were calculated as summarized above, the ranking of the experiments was performed by applying the steps of the SAW, RAM, PIV, ROV, and FUCA methods. First, the set of criteria weights calculated by the Equal method was used, and the resulting rankings of the experiments are summarized in Table 6.

Table 6. Experimental rankings under Equal Weighting

No.	SAW	RAM	PIV	ROV	FUCA
1	8	9	9	9	8
2	6	8	7	7	6
3	5	3	4	6	4
4	4	5	5	5	6
5	3	2	2	2	2
6	2	6	6	4	3
7	9	7	8	8	8
8	1	1	1	1	1
9	7	4	3	3	4

As shown in Table 6, the rankings across the five MCDM methods are not perfectly uniform. Such discrepancies are common in decision science and have been documented in various studies, given that each MCDM algorithm employs a distinct logic for prioritizing alternatives [61–63]. Nevertheless, all five methods consistently identified Exp. 8 as the top-ranked alternative. This identifies it as the superior processing window within the experimental scope, where the parameters—fluid pressure at 6 bar, workpiece velocity at 12 m/min, feed rate at 13 mm/stroke, and depth of cut at 0.03 mm—represent the optimal grinding configuration.

Rankings were also generated using weights derived from Entropy, MEREC, and SD methods (Tables 7–9). Despite the inconsistencies in intermediate rankings across different methods again attributed to the varying algorithmic approaches [61, 62], trial 8 was consistently identified as the optimal solution in every single scenario. Regardless of whether Entropy, MEREC, or SD was used for weighting, or SAW, RAM, PIV, ROV, or FUCA for ranking, Exp. 8 emerged as the absolute winner. However, applying MCDM methods does not stop at selecting the best option among the available alternatives. Another task of applying these methods is to evaluate the ranking stability of the alternatives under different scenarios [64]. This is also the content of the sensitivity analysis presented in Section 4 of this article.

Table 7. Rankings using Entropy weights

No.	SAW	RAM	PIV	ROV	FUCA
1	6	9	9	7	6
2	5	7	7	5	4
3	8	5	6	8	8
4	4	6	5	6	7
5	3	2	2	2	2
6	2	3	4	3	3
7	9	8	8	9	9
8	1	1	1	1	1
9	7	4	3	4	5

Table 8. Rankings using MEREC weights

No.	SAW	RAM	PIV	ROV	FUCA
1	6	9	9	8	7
2	5	7	7	5	4
3	8	4	5	7	8
4	4	6	6	6	6
5	3	2	2	2	2
6	2	5	4	4	3
7	9	8	8	9	9
8	1	1	1	1	1
9	7	3	3	3	5

Table 9. Rankings using SD weights

No.	SAW	RAM	PIV	ROV	FUCA
1	9	9	9	9	9
2	8	8	8	8	8
3	5	4	4	4	4
4	2	3	3	3	3
5	4	2	2	2	2
6	3	7	7	7	5
7	6	6	6	6	6
8	1	1	1	1	1
9	7	5	5	5	7

4. SENSITIVITY ANALYSIS

Sensitivity analysis is the process of evaluating the stability of the rankings of alternatives across different scenarios. Creating different scenarios can be achieved by changing the ranking methods, the methods for calculating criteria weights, the number of alternatives to be ranked, or the nature of the criteria [65]. Since Section 3 already provided

the results for ranking the experiments using five MCDM methods with criteria weights calculated by four different methods, the sensitivity analysis in this study is conducted to evaluate the stability of the rankings when different ranking methods are applied. This task is performed sequentially for four cases, corresponding to the four different weight calculation methods.

To evaluate the stability of the rankings of alternatives when using different ranking methods, this study employs the Spearman's rank correlation coefficient, calculated according to formula (19) [65]. In this formula, D_i represents the difference in the rank of the i^{th} alternative when ranked by different methods.

$$S = 1 - \frac{6 \sum_{i=1}^m D_i^2}{m(m^2-1)} \quad (19)$$

Table 10 summarizes the Spearman correlation coefficients between the methods when using the set of criteria weights calculated by the Equal method.

Table 10. Spearman coefficients between ranking methods when criteria weights are calculated by the Equal method

Method	RAM	PIV	ROV	FUCA	Average
SAW	0.6667	0.6833	0.7833	0.8583	0.8433
RAM		0.9667	0.8667	0.8583	
PIV			0.9333	0.8917	
ROV				0.9250	

It can be observed that the Spearman coefficients between the SAW and RAM methods, and between the SAW and PIV methods, are relatively small, at only 0.6667 and 0.6833, respectively. However, in compensation, the Spearman coefficients between all other pairs of methods are quite high. Notably, the Spearman coefficient between the RAM and PIV methods is very large, at 0.9667, and it is also very high between the PIV and ROV methods, at 0.9333. The average value of the Spearman coefficient among the ranking methods in this case is 0.8433. This result indicates that when using the Equal method to calculate criteria weights, the experiments exhibit relatively high ranking stability across the five different methods [66]. Similarly, when criteria weights were calculated using the Entropy, MEREC, and SD methods, the average Spearman coefficients among the five ranking methods (SAW, RAM, PIV, ROV, FUCA) were determined to be 0.8217, 0.7900, and 0.9067, respectively. These values also demonstrate that when using these three weighting methods, the rankings of the experiments maintain high stability across different ranking approaches [66]. The fact that the average Spearman coefficient reaches its highest value when criteria weights are calculated by the SD method can be explained by the method's ability to clearly distinguish the importance of the criteria. Specifically, the weights for the cutting force components are very large, particularly for the force component in the x-direction, while the weight for surface roughness is the smallest. This heavy prioritization of cutting force components combined with the significant reduction in priority for surface roughness may be the reason for the high similarity in rankings, as they are heavily influenced by the criteria with the largest weights.

The use of four distinct weighting methods and five separate MCDM ranking algorithms created significant fluctuations in individual values. However, the convergence of all these

techniques on Trial 8 provides a robust and indisputable conclusion. The optimal grinding parameters are: fluid pressure as 6 bar, workpiece velocity as 12 m/min, feed rate as 13 mm/stroke, and depth of cut as 0.03 mm. Under these conditions, the performance metrics were: $Ra = 1.053 \mu\text{m}$, $F_x = 14.113 \text{ N}$, $F_y = 22.929 \text{ N}$, and $F_z = 17.991 \text{ N}$. Notably, in this optimal trial, Ra ranked 4th while all three force components ranked 2nd among the trials, demonstrating that this configuration successfully harmonizes all competing grinding objectives. The results of the sensitivity analysis also demonstrate that the different weighting methods significantly affect the degree of ranking similarity for the experiments across various ranking methods. Among these, the SD weighting method was determined to ensure the highest stability in the ranking of the experiments. The use of the SD method to calculate criteria weights in this case clearly demonstrates a superior ability to prioritize criteria compared to the other methods.

5. CONCLUSION

This study conducted a multi-objective optimization of the grinding process for Ti6Al4V alloy using SiC grinding wheels under MQL with an ester-based solution. Four parameters were varied in each experiment: MQL fluid pressure, workpiece velocity, feed rate, and cutting depth. The MQL fluid pressure was set at three values: 4 bar, 5 bar, and 6 bar; the workpiece velocity varied across three values: 8 m/min, 10 m/min, and 12 m/min; the three values used for the feed rate were 8 mm/stroke, 13 mm/stroke, and 18 mm/stroke; and the cutting depth also varied across three values: 0.01 mm, 0.02 mm, and 0.03 mm. Four responses were measured to evaluate the grinding process, including surface roughness and the three cutting force components. Four objective weighting methods: Equal, Entropy, MEREC, and SD were employed to calculate the weights for these responses. Five methods: SAW, RAM, PIV, ROV, and FUCA were used to determine the optimal values of the technological parameters to ensure that all four responses achieve their minimum values. Several conclusions can be drawn as follows:

- Utilizing Ester as the MQL medium consistently maintained low and stable surface roughness, even amidst significant fluctuations in cutting forces. The polar molecules in the ester oil established a resilient lubricating film that effectively mitigated friction and suppressed the material plowing effect inherent to SiC grinding wheels. Experimental data showed a minimum roughness of $0.828 \mu\text{m}$, with the majority of trials successfully controlled below $1.5 \mu\text{m}$.

- Using five ranking methods across four different weighting methods consistently identified the optimal values for the parameters—MQL fluid pressure, workpiece velocity, feed rate, and cutting depth—as 6 bar, 12 m/min, 13 mm/stroke, and 0.03 mm, respectively.

- Despite the different approaches to calculating criteria weights using four methods and the variations in ranking the experiments using five different methods, the sensitivity analysis results showed that the experiments achieved relatively high consistency across the different techniques. The minimum average Spearman coefficient among the five ranking methods was 0.7900 when response weights were calculated by the MEREC method, while the maximum

was 0.9067 when weights were calculated by the SD method. Within the scope of this study, the use of the SD method demonstrated a much clearer distinction in the importance of the criteria compared to the other three weighting methods.

- The exclusive use of objective weighting methods, as in this study, may have overlooked the users' perspectives regarding the actual importance of criteria according to their specific requirements. Integrating user opinions by combining subjective weighting methods with objective ones is expected to provide a set of optimal technological parameter values that both ensure objectivity and satisfy user expectations. This represents a promising direction for future research.

- While Ester-based MQL demonstrated significant efficacy in this study, integrating sub-zero cold air (cryogenic MQL) holds great promise for further enhancing process efficiency due to superior heat dissipation. Future research should prioritize investigating this hybrid cooling approach to verify its potential benefits.

- To further refine the multi-objective optimization of this process, subsequent studies should incorporate additional output responses such as vibration components, surface microstructures, and material removal rates. Furthermore, integrating expert consensus regarding the relative importance of specific criteria would enhance the practical and industrial relevance of the optimization model.

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