Advances in Technology Innovation, vol.10, no.3, 2025, pp.254-268

Optimizing Nanofluid Minimum Quantity Lubrication Machining of Inconel-800 Using Kriging Non-Dominated Sorting Genetic Algorithm II

Ngoc-Chien Vu*, Huu-That Nguyen, Xuan- Phuong Dang

Department of Mechanical Engineering, Nha Trang University, Nha Trang City, Vietnam

Received 27 September 2024; received in revised form 15 December 2024; accepted 18 December 2024

DOI: https://doi.org/10.46604/aiti.2024.14339

Abstract

This study optimizes the machining process of Inconel-800 superalloy using nanofluid minimum quantity lubrication (MQL) with multi-wall carbon nanotubes (MWCNTs) and biodegradable coconut oil. A Taguchi design with 27 trials is used to examine the effects of varying nanoparticle concentrations and machining parameters on surface roughness and temperature. The optimized nanofluid MQL system improves surface roughness by 26.22%, reduces surface roughness peak-to-valley by 12.06%, and significantly lowers temperature, demonstrating improved quality and thermal management. A Kriging model predicts outcomes with high accuracy ($R^2 > 0.9$), and multi-objective optimization using Kriging and the non-dominated sorting genetic algorithm II identifies an optimal balance between surface roughness and temperature. Additionally, using coconut oil as the lubricant base in the nanofluid MQL system promotes sustainable machining by reducing reliance on conventional lubricants and environmental impact. These findings validate the effectiveness of advanced optimization techniques combined with nanofluid MQL for superior sustainable machining of superalloys.

Keywords: nanofluid, machining optimization, sustainable machining, super-alloy, minimum quantity lubrication (MQL)

1. Introduction

Machining is crucial for producing components with precise dimensions and superior surface quality. Technological advancements have led to the development of high-strength materials, which pose greater machining challenges. These materials include toughened steels, titanium alloys, superalloys, metal matrix composites, and ceramics. Superalloys are widely utilized for high-performance applications due to their exceptional mechanical strength, thermal resistance, and corrosion resistance, as shown in Fig. 1 [1-2]; for example, Inconel-800, a notable superalloy, is selected for its performance in extreme environments. However, its properties, such as high hardness, heat resistance, and work-hardening tendency pose significant machining challenges, including rapid tool wear, elevated cutting forces, and poor surface finish [3-4]. Therefore, the development of environmentally friendly and effective machining methods for these materials is essential [5-6].

Minimum quantity lubrication (MQL) has emerged as a potential alternative to conventional lubrication techniques in machining. Unlike flood cooling, which consumes a significant amount of coolant, MQL minimizes the fluid used while ensuring sufficient lubrication and cooling at the cutting area [7-8]. Nanofluids, which consist of suspensions of nanoparticles in a base fluid, have improved the effectiveness of MQL [9-12]. As previously mentioned, nanofluids exhibit offer boosted thermal conductivity, superior lubricating qualities, and lower friction compared to conventional lubricants [13-14]. Coconut oil, renowned for its biodegradability and excellent lubricating characteristics, has received interest as an environmentally acceptable base fluid for nanofluids. The use of coconut oil-based nanofluids in MQL not only increases machining performance but also aligns with acceptable standards for sustainable manufacturing [15-16].

* Corresponding author. E-mail address: chienvn@ntu.edu.vn

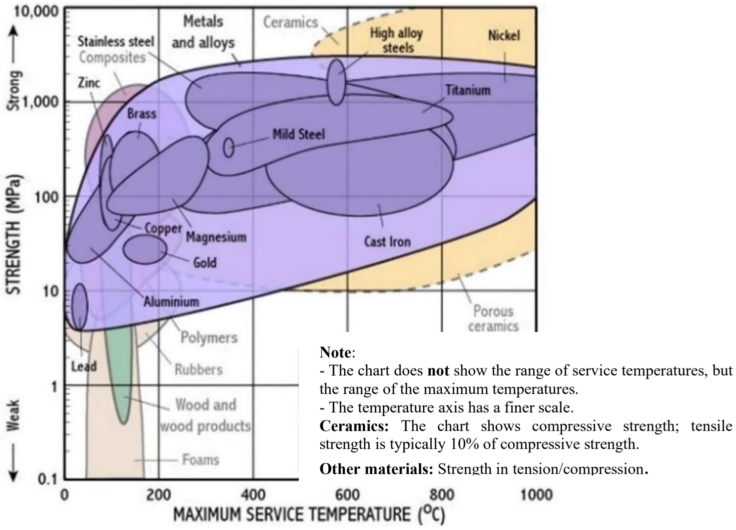


Fig. 1 The correlation between mechanical strength and operating temperature for difficult-to-cut alloys [17]

Despite the advantages of nanofluid MQL, optimal performance requires precise selection of nanoparticle concentration and machining parameters. This study employs multi-wall carbon nanotubes (MWCNTs) based nanofluids in the MQL system for machining Inconel-800, aiming to enhance thermal conductivity and lubrication [18-20]. A novel optimization framework integrating the Kriging model with non-dominated sorting genetic algorithm II (NSGA-II) balances surface quality and thermal management. Accurate parameter optimization is essential to prevent inadequate lubrication and minimize tool wear, underscoring the need for further research on nanoparticle concentration and cutting parameters in machining superalloys.

Superalloys, particularly Inconel-800, are prized for their high-temperature strength, oxidation resistance, and durability, making them vital for demanding engineering applications [3]. However, these properties also render them difficult to machine. Traditional superalloy machining methods often lead to excessive tool wear, high cutting forces, and poor surface quality [5]. Advanced machining solutions such as coated tools (physical vapor deposition (PVD), chemical vapor deposition (CVD), atomic layer deposition (ALD)), optimized cutting parameters, and innovative cooling systems (e.g., cryogenic and high-pressure cooling) have been explored [21-22]. Although effective, these technologies can be costly or environmentally challenging, emphasizing the need for more sustainable alternatives such as nanofluid MQL.

Nanofluid MQL has transformed machining by incorporating nanoparticles (10–100 nm) into the lubrication fluid, enhancing thermal and frictional performance compared to traditional methods. It improves parameters like surface roughness, cutting force, power, energy, temperature, and material removal rate (MRR) [23-24].

Nanofluid MQL systems utilize lubricants, including vegetable (e.g., coconut, canola), synthetic, and mineral oils, combined with metallic, metal oxide, carbon-based, or ceramic nanoparticles. Each component is selected to perform specific lubrication functions tailored to the operational requirements of the MQL system [17, 19, 25]. Particularly, coconut oil-based nanofluid MQL, known for eco-friendly and effective lubrication, provides superior cooling and promotes sustainable machining by reducing the environmental impact of conventional lubricants [15-16].

MWCNT-based nanofluids in MQL machining have gained importance for improving surface roughness, cutting temperature, and MRR. The integration of MWCNTs into base fluids, particularly coconut oil, has demonstrated substantial potential for enhancing machining efficiency and product quality. Numerous studies focusing on optimizing machining parameters using MWCNTs nanofluids and highlighting the benefits of incorporating coconut oil into MQL systems.

For instance, Okokpujie et al. reported a surface roughness of 1.16 µm and an MRR of 52.1 mm^3/min when machining AL8112 using MWCNT-doped nanofluid MQL [26]. Similarly, Ali et al. demonstrated significant improvements in tool life, cutting force, and surface finish when employing MWCNT-based nanofluids in turning Inconel 718 under dry, MQL, and nanofluid MQL conditions, showcasing the lubricant's effectiveness [27].

Optimizing machining configurations is crucial for improving performance, especially with difficult-to-machine materials like superalloys. The effective implementation of nanofluid MQL requires an organized framework that incorporates experimental design, mathematical modeling, and multi-objective optimization techniques. These methods balance lubrication, cooling, and cutting parameters, improving challenging machining performance in scenarios. For example, Te-Ching Hsiao et al. utilized a combination of the response surface methodology (RSM) model and NSGA-II optimization, achieving a reduction of up to 20.2% in specific cutting energy and 6.4% in overall energy consumption [28-29]. Other models, such as Kriging and radial basis function (RBF), have also proven effective in predicting optimal parameter combinations for machining.

This study confirms that nanofluids significantly enhance the machining performance of superalloys like Inconel-800, utilizing MWCNT-based nanofluids with coconut oil, providing superior thermal conductivity and lubrication over conventional nanoparticles. This eco-friendly approach improves machining efficiency and promotes sustainability. For example, Bui et al. demonstrated that optimizing cutting parameters improved surface roughness and MRR when machining SKD11 with SiO_2 nanofluid [30]. Vu et al. reported a 14% reduction in cutting energy during hard milling of AISI H13 steel using Al_2O_3 MQL nanofluids [28]. Similarly, Perera and Wegala demonstrated that coconut oil-based nanofluids reduced surface roughness by 9.8–73.7% in machining SS400 and AISI 304, with optimal results at 0.3% (w/w) Al_2O_3 and graphite concentrations [16]. These findings highlight the benefits of optimizing machining processes with nanofluids, particularly in enhancing surface quality, minimizing cutting zones, and increasing MRR through advanced optimization techniques.

Furthermore, while traditional optimization methods such as Taguchi and RSM primarily focus on single-objective optimization and often assume linear relationships, the Kriging-NSGA-II approach adopted in this study captures complex nonlinear interactions and enables multi-objective optimization. This method surpasses conventional techniques by providing a more precise and efficient mechanism of achieving Pareto-optimal trade-offs between conflicting objectives, such as surface roughness and cutting temperature.

Developing and optimizing MWCNT-based nanofluids in coconut oil for milling present significant industrial potential. This study systematically investigates the influence of cutting parameters and nanoparticle concentration on machining performance, seeking to promote sustainable machining processes. Integrating nanotechnology into traditional manufacturing enhances productivity, reduces environmental impact, and improves product quality. As the field of nanofluid-assisted machining continues to advance, the findings of this research may serve as an essential reference for future attempts to develop greener and more efficient manufacturing processes.

2. Materials and Methods

The material utilized in this study was Inconel-800, a superalloy known for its high strength, exceptional corrosion resistance, and tendency for work harden, thereby incurring the challenge to machine. The mechanical properties of Inconel-800 are detailed in Table 1, while its chemical composition is listed in Table 2. The workpiece dimensions were 210 mm in length, 100 mm in width, and 40 mm in height, with a cutting length of 100 mm.

Table 1 Mechanical specifications of Inconel-800

Temperature^{0}C	Tensile strength MPa	Yield Strength MPa	Elongation %	R.A. %
27	448- 549	172- 226	30- 48	76

Table 2 Chemical composition (weight percent) of Inconel-800

Element	Ni	Cr	Fe	C	Al	Ti	Ti+ Al	Mn
% weight	30.0-35.0	19.0-23.0	46.99	0.1 max	0.5	0.15-0.60	1.01	1.5 max

The slot milling operations were conducted using a computer numerical control (CNC) vertical milling machine (VCM-2216 XV). A Sandvik CoroMill R390 square shoulder milling cutter, with a diameter of 16 mm and equipped with two flutes, was employed as the cutting tool. The tool inserts were Sandvik R390-11 T3, featuring a nose radius of 0.8 mm, as shown in Fig. 2. The cutting parameters were selected based on both the recommendations provided by the cutting tool manufacturer and the operators' experience.

Dimensions of tool holder (mm)				
LF	DCON	DC	APMX	LU
100	16	16	10	25

Dimensions of inserts (mm)				
W1	LE	RE	BS	S
6.8	10	0.4 – 0.8 – 1.2	0.9	3.59

Fig. 2 Tool used in experimental cutting

Coconut oil was utilized as the base fluid in the nanofluid MQL system, and MWCNTs were incorporated as nanoparticle additives. MWCNTs were selected for their superior thermal conductivity (300 W/m·K), which enhances heat dissipation during the machining process. The MWCNTs, with an average particle size of less than 30 nm, were dispersed into coconut oil at varying concentrations (0.5%, 1.0%, and 1.5% by weight). The concentration ranges for MWCNTs were determined by integrating previous studies [25, 28], initial experimental trials, and the aim of enhancing machining performance while maintaining environmental sustainability.

The nanoparticle dispersion process begins with the exact weighing of MWCNTs using a Kern PLJ 2000-3A precision balance, after which the nanoparticles were combined with coconut oil. To ensure uniform dispersion, the mixture was continuously stirred for 48 hours using a magnetic stirrer (Ezdo MS-11C), thereby attaining homogeneity before its application in the experiments. The nanofluid MQL system was configured to maintain an oil flow rate of 120 mL/h and an air pressure of 3.5 kg/cm², with the nozzle positioned 20 mm from the cutting zone at a 60° angle. This arrangement was consistently followed throughout the evaluation to maintain optimal lubrication and cooling conditions during the experiments.

A systematic design of experiments (DOE) approach, including the orthogonal array method, was employed to investigate the influence of machining parameters and nanoparticle concentrations. A total of 27 experiments were undertaken, equating to an L9 orthogonal array, with each factor examined at three different levels. The factors considered included the cutting parameters such as cutting velocity (v_c) (95, 125, and 155 m/min), feed per tooth (f_z) (0.03, 0.06, and 0.09 mm/tooth), depth of cut (a_p) (0.3, 0.7, and 1.1 mm), and nanoparticle concentration (% nano) (0.5%, 1%, and 1.5%). These parameter levels were carefully selected based on previous studies, practical expertise, personal knowledge, and recommendations from cutting tool manufacturers. As shown in Fig. 3, the experimental setup comprises slot milling operations on superalloy Inconel-800 workpieces under these established machining parameters. The nanofluid, delivered through the MQL system, supplied constant lubrication and cooling during each test, enabling an accurate evaluation of the machining outputs under controlled conditions.

Surface roughness (Arithmetic mean deviation, R_a, Peak-to-valley, R_z, and Root mean square deviation, R_q) was measured using a Mitutoyo SJ-301 portable surface roughness tester. Three measurements were conducted for each machined surface, and the average surface roughness ((R_a, R_z, R_q) value was calculated. Cutting temperatures (T_c) were monitored using a thermal camera (UNI-T UTi260B), which was positioned near the cutting zone to record the maximum temperature during machining.

A Kriging model was developed to model the relationship between the cutting parameters v_c, f_z, a_p, and *% nano* and output responses (surface roughness and cutting temperature). This model was used to predict the responses based on the experimental data collected from the orthogonal array design, while the NSGA-II algorithm was employed to optimize cutting parameters.

The NSGA-II algorithm simultaneously minimizes surface roughness and cutting temperature, ensuring an optimal balance between these conflicting objectives.

Isight software was utilized to integrate the Kriging model with the NSGA-II algorithm facilitating the optimization process. Isight enabled the efficient coupling of the predictive model with the optimization algorithm, providing a robust framework for multi-objective optimization. This integration allowed for precise and reliable optimization of machining parameters, ensuring the best possible trade-off between surface quality and thermal control.

The complete methodology is visually summarized in Fig. 4, which comprehensively illustrates the process flow, including the implementation of the Kriging model for accurate response prediction, followed by the optimization process using the NSGA-II algorithm within the Isight framework.

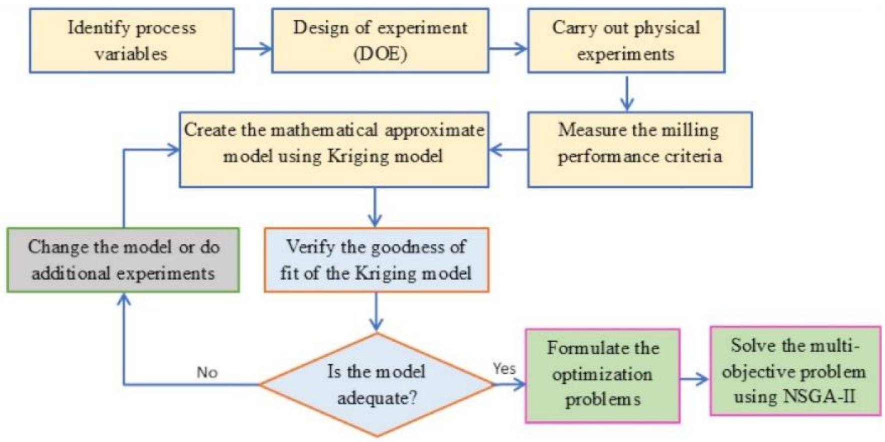


Fig. 3 The structured approach to modeling and optimizing machining parameters

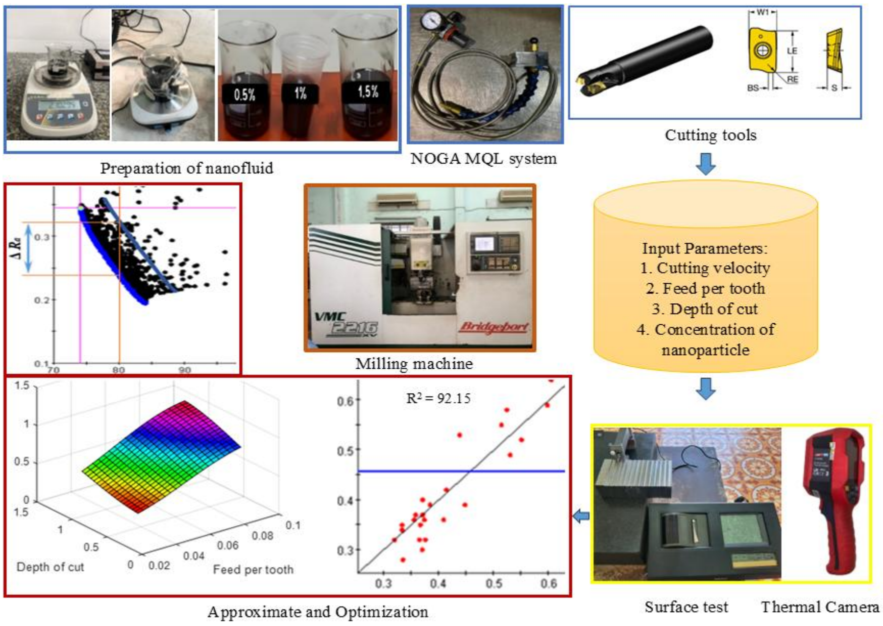


Fig. 4 The methodology employed in the current work

3. Results and Discussion

This study systematically collected and analyzed experimental data to comprehensively investigate the relationship between process parameters and surface roughness metrics—specifically, *Ra*, *Rz*, *Rq*, and cutting temperature. Table 3 presents the results of 27 experiments conducted using the Taguchi orthogonal array method. The Kriging model was employed to estimate the impact of input parameters on technical responses, as detailed in the Materials and Methods section, based on the previously provided data.

Table 3 Design of Experiment and outcome of investigation

No.	Input Parameters				Output parameters			
	a_p (mm)	f_z (mm/tooth)	v_c (m/min)	*% nano* (%)	R_a (μm)	R_z (μm)	R_q (μm)	T_c (0^0)
1	0.3	0.03	95	0.5	0.32	2.00	0.39	82.2
2	0.3	0.03	125	1.0	0.23	1.65	0.27	87.5
3	0.3	0.03	155	1.5	0.42	2.80	0.53	81.1
4	0.3	0.06	125	0.5	0.35	2.38	0.44	83.2
5	0.3	0.06	155	1.0	0.26	1.65	0.32	88.3
6	0.3	0.06	95	1.5	0.53	3.25	0.66	90.2
7	0.3	0.09	155	0.5	0.45	2.93	0.56	81.8
8	0.3	0.09	95	1.0	0.29	1.78	0.36	97.2
9	0.3	0.09	125	1.5	0.64	3.71	0.78	100.5
10	0.7	0.03	125	0.5	0.27	1.76	0.37	78.7
11	0.7	0.03	155	1.0	0.32	1.97	0.40	146.6
12	0.7	0.03	95	1.5	0.30	2.13	0.37	146.1
13	0.7	0.06	155	0.5	0.36	2.31	0.47	95.1
14	0.7	0.06	95	1.0	0.37	2.45	0.45	109.3
15	0.7	0.06	125	1.5	0.49	3.05	0.60	150.2
16	0.7	0.09	95	0.5	0.39	2.68	0.48	117.6
17	0.7	0.09	125	1.0	0.81	4.30	0.96	107.3
18	0.7	0.09	155	1.5	0.59	3.27	0.71	143.3
19	1.1	0.03	155	0.5	0.36	2.17	0.45	141.2
20	1.1	0.03	95	1.0	0.32	2.31	0.41	129.9
21	1.1	0.03	125	1.5	0.34	2.25	0.42	182
22	1.1	0.06	95	0.5	0.42	3.01	0.54	156.1
23	1.1	0.06	125	1.0	0.79	4.54	0.97	187.1
24	1.1	0.06	155	1.5	0.55	2.87	0.67	183.7
25	1.1	0.09	125	0.5	0.52	3.00	0.64	125.8
26	1.1	0.09	155	1.0	0.81	4.70	1.00	160.5
27	1.1	0.09	95	1.5	0.58	3.35	0.71	176.4

The reliability and accuracy of the Kriging model in representing the experimental data are substantiated by the coefficient of determination (R^2) derived from regression analysis. Specifically, the R^2 values for the surface roughness parameters R_a, R_z, and R_q, as well as the T_c, were determined to be 0.9215, 0.9638, 0.9379, and 0.9504, respectively. As shown in Fig. 5, these values are all above the criterion of 0.9,indicating a strong correlation between the predicted and observed data. The excellent R^2 values emphasize the precision and confidence of the Kriging model in precisely representing the experimental data. Therefore, based on these results, it can be inferred that the Kriging model is not only adequate but alsohelpful in capturing the complex relationship between the process variables and the related technical responses. This is further evidenced by previous studies that utilized the Kriging surrogate model to analyze the relationships between various cutting parameters and machining process outcomes [28].

Surface roughness plays a critical role in the performance of machined components, particularly in high-stress applications. As shown in Fig. 6(a)-(c) the direct correlation between the depth of cut and feed per tooth with surface roughness (R_a, R_z, R_q). An in-depth analysis indicates that a higher depth of cut increases chip load and tool-workpiece contact, leading to more significant material deformation and rougher surfaces. Similarly, higher feed rates induce more aggressive cutting forces and vibrations, which exacerbate surface irregularities.

On the other hand, cutting speed exhibited an inverse trend. As shown in Fig. 6(d), at optimal cutting speeds, the heat generated during machining slightly softens the material, reducing cutting forces and producing a finer surface finish. However, excessive cutting speeds may led to tool wear and thermal damage, as evidenced by the increased in surface roughness observed beyond the optimal speed range. The nanofluid MQL system, enhanced by nanoparticles, plays a crucial role by reducing friction and improving lubrication [3]. Specifically, the lubricant forms a thin and stable film at the tool-workpiece interface, effectively minimizing friction and mitigating material adhesion. Furthermore, the overall thermal management provided by the nanofluid MQL system helps maintain surface smoothness at higher cutting speeds, as shown in Fig. 6(e), by dissipating heat more efficiently and preventing excessive temperature rise.

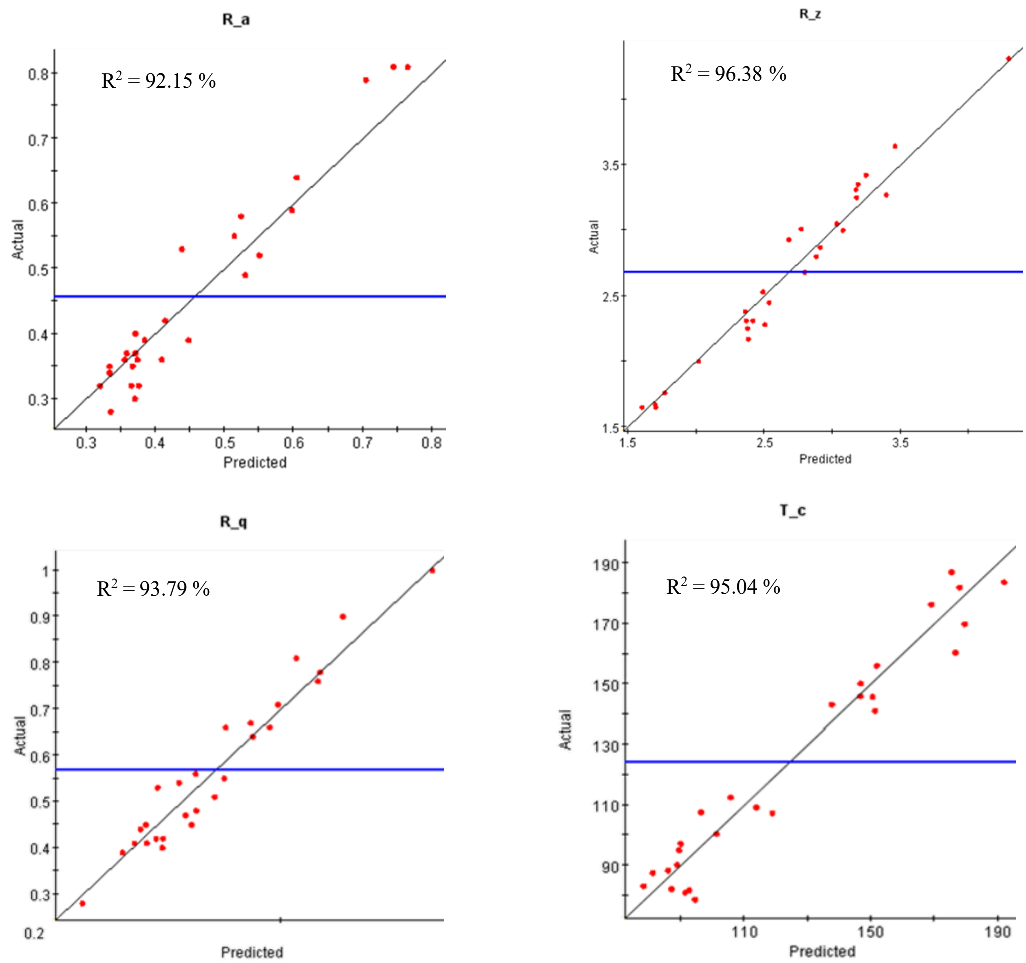


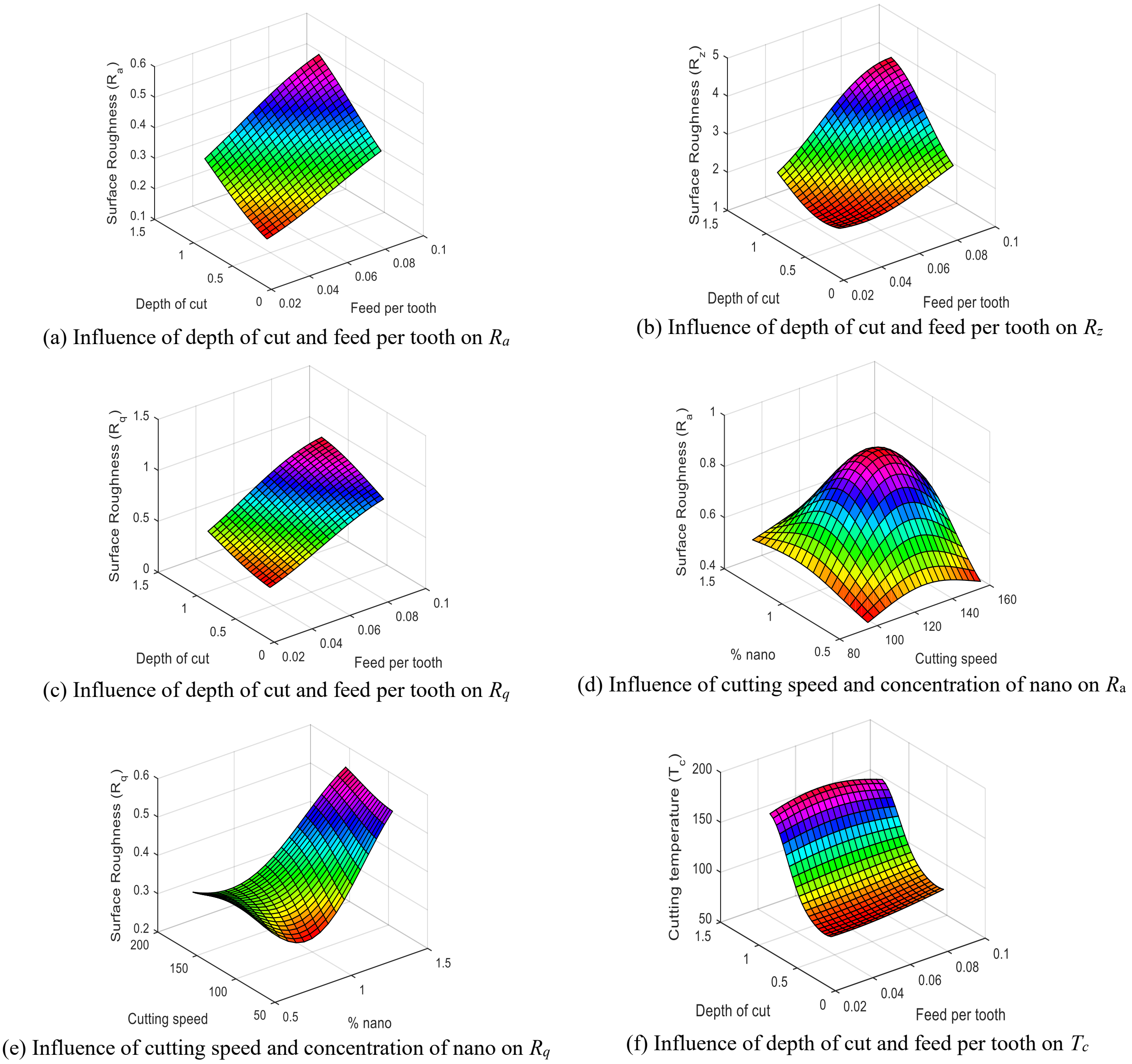
Fig. 5 R² values (>0.9) confirm the Kriging model's accuracy in representing experimental data for R_a, R_z, R_q, and T_c.

Previous studies have demonstrated significant improvements the enhancement of surface roughness attained via nanofluid MQL, which may be ascribed to four primary nanoparticle mechanisms: rolling, self-repairing, tribo-film formation, and polishing, as shown in Fig. 7. Rolling diminishes friction by functioning as miniature ball bearings, thereby facilitating tool movement smoothness. Self-repairing fills the surface with minute cavities and layers, creating a protective coating to reduce adhesion. Polishing further enhances the surface, yielding a significantly smoother finish and illustrating the beneficial effect of nanofluid MQL for boosting machining quality [19]. Therefore, the synergistic effect of these mechanisms contributes to the superior performance of nanofluid MQL systems compared to conventional lubrication methods. Thus, the Kriging model demonstrates that an optimized nanofluid MQL system significantly reduces R_a, R_z, and R_q, particularly at high cutting speeds, highlighting the advantages of nanofluid MQL in achieving superior surface finishes when milling Inconel-800 superalloy.

Cutting temperature significantly affects both tool wear and workpiece integrity during machining. As shown in Fig. 6(f), the relationship between cutting temperature and machining parameters, revealing that depth of cut and feed per tooth are critical factors contributing to elevated cutting temperatures. As these parameters increase, they contribute to higher material removal rates and greater friction at the tool-workpiece interface, resulting in amplified temperatures. This temperature rise can accelerate tool wear and deteriorate the microstructure of the workpiece, leading to diminished mechanical properties and potential failure in high-stress applications. This observation corresponds with fundamental cutting principles, wherein increased cutting forces result in a corresponding rise in temperature, as demonstrated in several previous studies [3, 28].

As shown in Fig. 8(a), the overall effect of input parameters on T_c, further validating these findings by presenting the global effects of the four input factors (a_p, f_z, v_c, *% nano*) on T_c. It reveals that f_z and a_p exhibit the most significant influence on T_c. In contrast, *% nan o*and v_c have a minor impact on temperature regulation. Although these factors contrinute to the machining process, their influence on T_c is relatively low compared to the primary cutting parameters (a_p, f_z).

The nanofluid MQL system serves a critical function in cutting temperature management, limiting excessive heat accumulation. By providing efficient cooling and lubrication, the nanofluid MQL system extends tool life and preserve workpiece quality, particularly during the milling operations of the Inconel-800 superalloy, which is a difficult-to-cut material. However, the optimization of a_p, f_z remains critical for controlling T_c under challenging machining conditions.



(a) Influence of depth of cut and feed per tooth on R_a

(b) Influence of depth of cut and feed per tooth on R_z

(c) Influence of depth of cut and feed per tooth on R_q

(d) Influence of cutting speed and concentration of nano on R_a

(e) Influence of cutting speed and concentration of nano on R_q

(f) Influence of depth of cut and feed per tooth on T_c

Fig. 6 The effect of variables on surface finish and cutting temperature

In summary, an increase in depth of cut and feed per tooth leads to higher surface roughness, whereas greater nanoparticle concentrations and cutting speeds enhance surface quality and reduce cutting temperature. The Kriging model highlights the importance of optimizing these parameters to enhance performance when machining Inconel-800. The application of nanofluids proves particularly effective in improving surface finish and controlling temperature during high-speed milling. This finding corroborates previous studies and aligns with established cutting principles in machining processes [28].

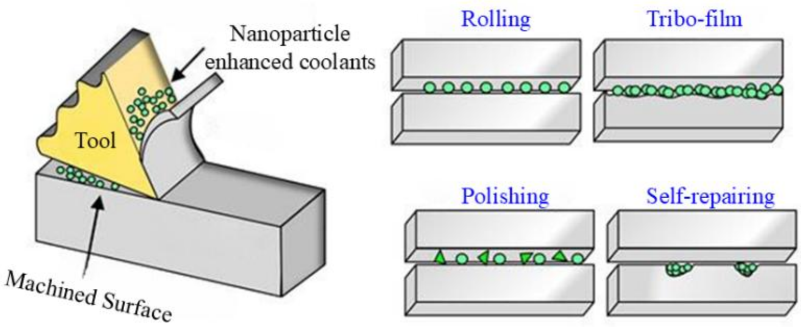
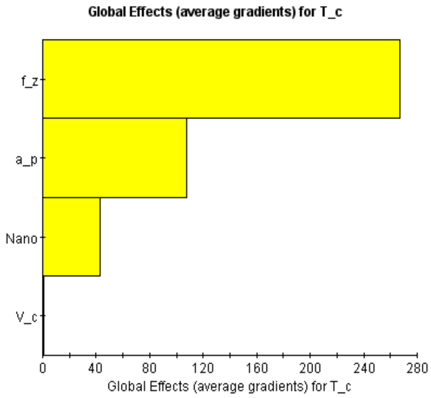
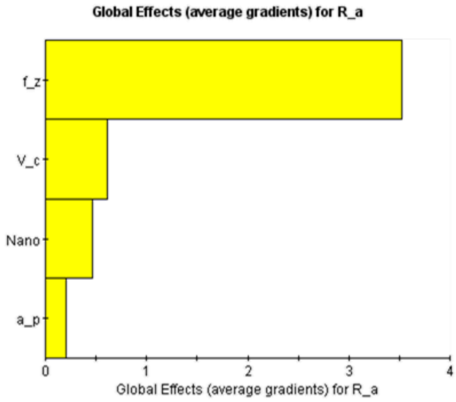


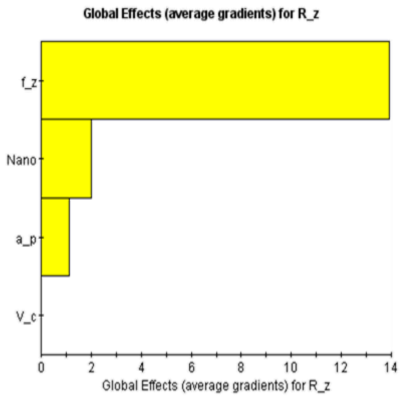
Fig. 7 Four fundamental nanoparticle mechanisms: Rolling, tribo-film, polishing, and self-repairing

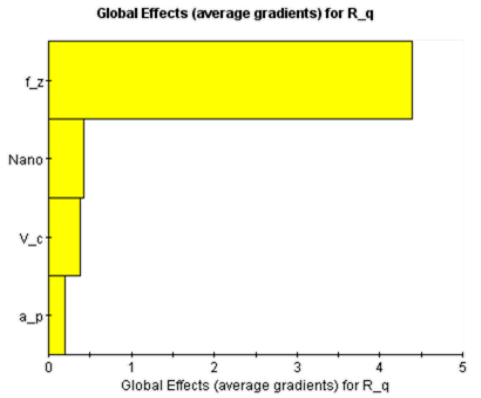
The analysis of Fig. 8(b)-(d) highlights the predominant effect of f_z on surface roughness parameters (R_a, R_z, R_q). Among all responses, f_z has the greatest inpact, aligning with established principles suggesting that elevated feed rates enhance material deformation and interaction at the tool-workpiece interface, leading to rougher surfaces.





(a) Global effects of input parameters on T_c (b) Global effects of input parameters on R_a





(c) Global effects of input parameters on R_z (d) Global effects of input parameters on R_q

Fig. 8 The global effect of input parameters on response parameters

In relationship with R_a, Fig. 8(b) indicates that f_z is the primary determinant, whereas v_c and nanoparticle *% nano* exert negligible influence. This signifies that feed rate optimization is essential for enhancing surface finish. In Fig. 8(c), R_z demonstrates that f_z is the primary factor, with a slight influence from nanoparticle concentration, whereas a_p exerts a negligible effect. This suggests that elevated feed rates result in heightened surface limitations.

Fig. 8(d) substantiates the dominant role of f_z in relation to R_q, with insignificant contributions from v_c. This finding emphasizes the vulnerability of surface texture, highlighting the necessity for meticulous feed control during machining to maintain surface quality. In conclusion, f_z is the most important criterion in reducing surface roughness, whereas *% nano* provides supplementary, though lesser, improvements.

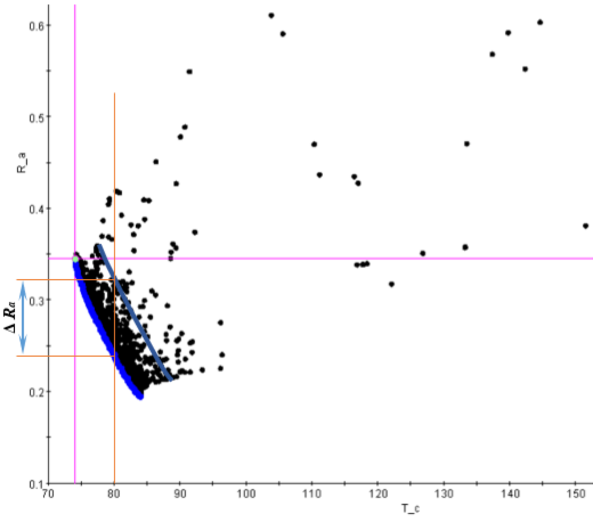


Fig. 9 Scatter plot of multi-objective optimization for R_a and T_c using Kriging and NSGA-II (scenario 1)

In machining, surface quality is typically assessed using R_a and R_z; however, these parameters are generally not used simultaneously in the same case. This study proposes two scenarios for multi-objective optimization in the machining of Inconel-800 using CMWNTs nanofluid MQL conditions, with the objective of enhancing the performance of machining difficult materials. In the first scenario, the objectives are to minimize both R_a and T_c, despite their conflicting nature. Higher cutting speeds tend to reduce R_a but increase T_c, while lower T_c may raise R_a due to decreased cutting efficiency. Therefore, balancing the simultaneous minimization of these two out parameters is crucial for optimal performance.

The Kriging model combined with the NSGA-II algorithm was applied as a multi-objective optimization method to achieve the optimal values for R_a and R_z. The parameters of the NSGA-II algorithm used are as follows: Crossover Distribution Index = 10.0, Crossover Probability = 0.9, Mutation Distribution Index = 20.0, Number of Generations = 100, and Population Size = 16. The starting design points are:

$$0.5 < \%Nano < 1.5 \tag{1}$$

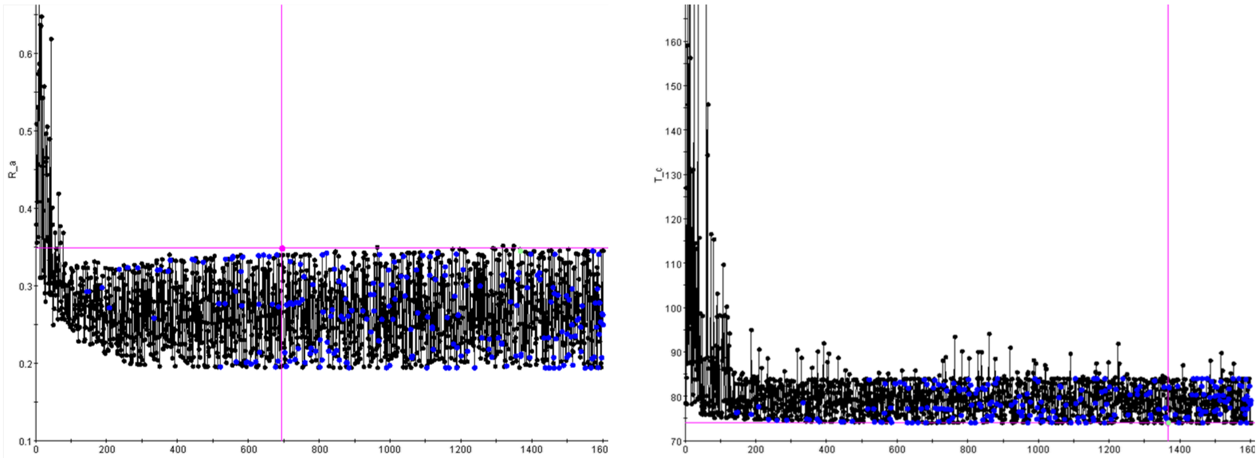
$$95.0 < v_c < 155.0 \tag{2}$$

$$0.3 < a_p < 1.1 \tag{3}$$

$$0.03 < f_z < 0.09 \tag{4}$$

Fig. 9 displays a scatter plot illustrating the multi-objective optimization for R_a and T_c using Kriging and NSGA-II. Feasible solutions are depicted as individual points. The Pareto front, represented by a distinct curve (also referred to as the Pareto line), shows the optimal trade-offs between R_a and T_c. Each point on the Pareto front signifies the best possible compromise between these two objectives.

For instance, if the operator or engineer aims to maintain T_c at 80°C, the Pareto front suggests a R_a value of approximately 0.284 μm. Without referencing the Pareto front, one might mistakenly choose a R_a value of 0.3231 μm (as indicated by a point in Fig. 9), which is suboptimal by around 26.22% (with the variation of ΔR_a = 0.3231 – 0.2384 = 0.0847). These optimal results demonstrate a notable improvement in surface quality compared to the study by Hsiao et al. (approximately 16.7% versus 26.22%) when machining the same steel grade and nanoparticle type. This study utilized commercially available CT232 mineral-based cutting oil [3]. Thus, the Pareto front derived from the Kriging and NSGA-II combination not only serves as a robust decision-making tool but also enables precise tailoring of the machining process to achieve optimal results, enhancing efficiency and reducing waste when milling Inconel-800 superalloy. Based on the specific machining requirements, the operator or engineer can select the point that best aligns with their objectives and adjust cutting parameters accordingly. The multi-objective optimization process history is depicted in Fig. 10.



(a) History of the optimization process refining R_a trade-offs (b) History of the optimization process refining T_c trade-offs

Fig. 10 History of the optimization process depicting the gradual refinement of trade-offs between R_a and T_c

In the second scenario, the optimization is employed the same methodology as before: integrating the Kriging model and the NSGA-II approach, while maintaining constant input parameters and a dual objective of minimizing both R_a and T_c aiming to construct a Pareto front that maps R_z against T_c.

Similar to the first scenario, Fig. 11 indicates an inverse relationship between R_z and T_c. When the operator maintains T_c at approximately 80°C, the Pareto front reveals two potential solutions: an optimized R_z of 1.4909 µm and a feasible but suboptimal R_z of 1.6955 µm, with a difference of $\Delta R_z = 0.2046$ µm. This improvement of approximately 12.06% highlights how NSGA-II optimization combined with the Kriging model significantly enhances surface texture without compromising T_c.

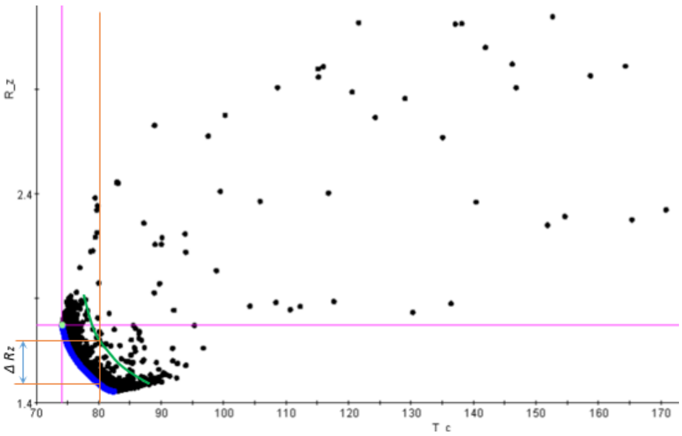
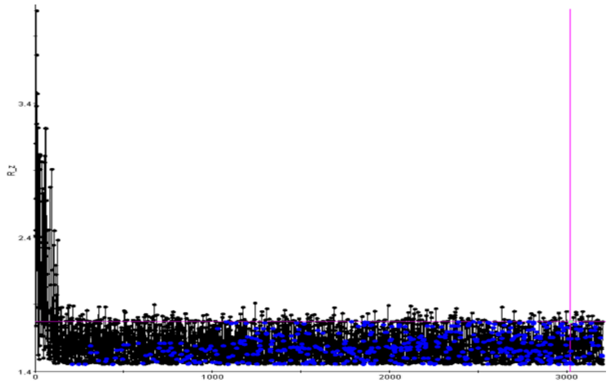


Fig. 11 Scatter plot of multi-objective optimization R_z and T_c using Kriging and NSGA-II (scenario 2)

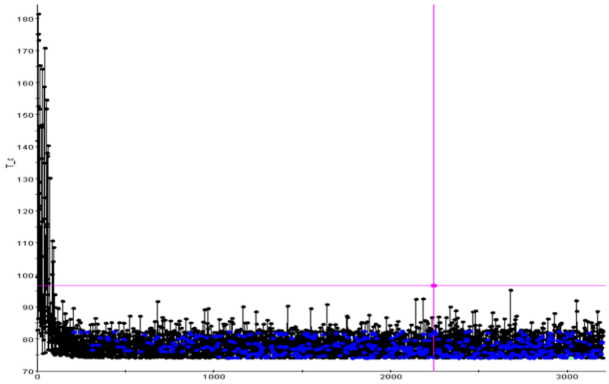
The trade-off between optimizing R_z and T_c presents a conflict, accentuating the Pareto front for selecting a balanced solution. If minimizing R_z is the primary objective, a higher T_c may need to be accommodated. Conversely, if T_c is prioritized to extend tool life or prevent thermal damage, careful control of T_c is crucial. This Pareto-based optimization enables decision-makers to choose the best compromise based on specific needs, whether for to achieve superior surface finish or to maintain a safe and controlled cutting temperature. Fig. 12 illustrates the optimization history, depicting the algorithm's convergence and the gradual refinement of trade-offs between R_z and T_c. This incremental improvement demonstrates the algorithm's efficiency in identifying the optimal balance, reducing both R_z and T_c over successive iterations to achieve improved machining performance.

The analysis of the experimental results reveals that machining Inconel-800 with MWCNT nanofluid MQL led to substantial improvements in surface finish and cutting temperature. Specifically, R_a values decreased by up to 26.22%, R_z showed a 12.06% improvement. These results strongly support the hypothesis that integrating MWCNT nanoparticles into the

MQL coolant system is crucial in reducing surface roughness. Moreover, the cutting temperature (T_c) increased with higher feed rates and depths of cut, which is consistent with fundamental machining principles. However, the nanofluid MQL system effectively moderated the temperature rise, facilitating a more stable and controlled machining environment. Lowering cutting temperature is particularly critical in high-performance machining, as it prolongs tool life and preserves material integrity, especially when machining challenging materials such as Inconel-800.



(a) Evolution of the optimization process fine-tuning R_z trade-offs



(b) Evolution of the optimization process fine-tuning T_c trade-offs

Fig. 12 History of the optimization process depicting the gradual refinement of trade-offs between R_z and T_c

The Kriging model analysis provided valuable insights into the influence of process parameters, underscoring the pivotal roles of f_z and a_p in regulating surface roughness and cutting temperature. The model's high predictive accuracy (with R^2 values exceeding 0.9) further reinforces the reliability of these findings. This highlights the potential of the Kriging model as an effective tool for optimizing machining processes, especially in complex operations such as milling Inconel-800 superalloy.

Although the nanoparticle concentration (MWCNT) was of secondary importance relative to cutting speed and feed per tooth, its contribution to improving surface finish and reducing cutting temperature remains significant. The results suggest that future research should focus on optimizing nanoparticle concentrations to identify the ideal balance between surface quality and thermal management.

4. Conclusions

The study aims to optimize the machining process of inconel-800 superalloy by utilizing nanofluid MQL, enhanced with biodegradable coconut oil and MWCNTs, to achieve improved surface texture and lower cutting temperature. A systematic design of experiments (DOE) was conducted to highlight the role of nanofluid MQL in sustainable machining, addressing the challenges of processing Inconel-800 superalloy and promoting sustainable practices in modern manufacturing. The key findings are summarized as follows:

(1) Utilizing nanofluid MQL with MWCNTs in coconut oil effectively improves surface texture, lowers cutting temperature, and enhances lubrication and cooling efficiency in machining Inconel-800 superalloy.

(2) The Kriging model is highly effective in capturing the complex relationship between cutting parameters (a_p, f_z, v_c, *% nano*) and response parameters (R_a, R_z, R_q, and T_c), achieving a high level of accuracy ($R^2 > 0.9$).

(3) The combination of the Kriging model with the NSGA-II algorithm efficiently balances conflicting multi-objective functions related to machining performance and efficiency. The Pareto front facilitates informed decision-making, allowing operators and engineers to identify optimal solutions tailored to their specific requirements.

(4) In the first scenario, a 26.22% improvement in R_a was achieved when minimizing R_a at a constant T_c. Similarly, in the second scenario, approximately a 12.06% improvement in R_z was observed, showcasing the effectiveness of nanofluid MQL in sustainable machining.

(5) The study emphasizes the potential of sustainable manufacturing when employing nanofluid MQL with environmentally friendly coconut oil, suggesting its applicability in industrial manufacturing. It provides deeper insights into the machining Inconel-800 and similar materials.

Future research should investigate the long-term effects of MWCNT-enhanced nanofluid MQL on tool life and explore its integration into manufacturing processes to minimize reliance on conventional lubricants while maintaining machining efficiency. Additionally, applying the optimized nanofluid MQL system to other challenging materials, such as titanium alloys and harder ceramics, and incorporating the Kriging-NSGA-II optimization method into real-time adaptive machining systems will enhance scalability and industrial applicability.

Acknowledgment

The paper is sponsored by Nha Trang University under project No. TR2023-13-12.

Nomenclature

Symbol	Description	Symbol	Description
MQL	Minimum quantity lubrication	a_p	Depth of cut
MWCNTs	Multi-Wall Carbon Nanotubes	*Tc*	Cutting temperature
RSM	Response Surface Methodology	*Ra*	Surface roughness (Arithmetic mean deviation)
DOE	Design of experiments	*Rz*	Surface roughness (Maximum height)
R^2	coefficient of determination	*Rq*	Surface roughness (Root mean square deviation)
RBF	Radial Basis Function	MRR	Material removal rate
f_z	Feed per tooth	% nano	Nanoparticle concentration
v_c	Cutting velocity	NSGA-II	Non-dominated Sorting Genetic Algorithm II

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] M. Ganesh, N. Arunkumar, N. E. Kumar, and R. Sathish, “Investigation of Surface Grinding on Inconel Under Distinct Cooling Conditions,” Materials and Manufacturing Processes, vol. 38, no. 14, pp. 1823-1836, 2023.

[2] A. Palanisamy, N. Jeyaprakash, V. Sivabharathi, and S. Sivasankaran, “Influence of Heat Treatment on the Mechanical and Tribological Properties of Incoloy 800H Superalloy,” Archives of Civil and Mechanical Engineering, vol. 21, article no. 10, 2021

[3] T. C. Hsiao, N. C. Vu, M. C. Tsai, X. P. Dang, and S. C. Huang, “Modeling and Optimization of Machining Parameters in Milling of Inconel-800 Super Alloy Considering Energy, Productivity, and Quality Using Nanoparticle Suspended Lubrication,” Measurement and Control, vol. 54, no. 5-6, pp. 880-894, 2021.

[4] N. C. Vu, H. T. Nguyen, V. H. Nguyen, Q. N. Phan, N. T. Huynh, and X. P. Dang, “Experimental and Metamodel Based Optimization of Cutting Parameters for Milling Inconel-800 Superalloy under Nanofluid MQL Condition,” Mathematical Modelling of Engineering Problems, vol. 10, no. 1, pp. 189-194, 2023.

[5] G. Gudivada and A. K. Pandey, “Recent Developments in Nickel-Based Superalloys for Gas Turbine Applications: Review,” Journal of Alloys and Compounds, vol. 963, article no. 171128, 2023

[6] M. K. Gupta, M. Mia, C. I. Pruncu, W. Kapłonek, K. Nadolny, K. Patra, et al., “Parametric Optimization and Process Capability Analysis for Machining of Nickel-Based Superalloy,” The International Journal of Advanced Manufacturing Technology, vol. 102, pp. 3995-4009, 2019

[7] B. Boswell, M. N. Islam, I. J. Davies, Y. R. Ginting, and A. K. Ong, “A Review Identifying the Effectiveness of Minimum Quantity Lubrication (MQL) during Conventional Machining,” The International Journal of Advanced Manufacturing Technology, vol. 92, pp. 321-340, 2017

[8] V. S. Sharma, G. Singh, and K. Sørby, “A Review on Minimum Quantity Lubrication for Machining Processes,” Materials and Manufacturing Processes, vol. 30, no. 8, pp. 935-953, 2015.

[9] R. Shah, K. A. Shirvani, A. Przyborowski, N. Pai, and M. Mosleh, “Role of Nanofluid Minimum Quantity Lubrication (NMQL) in Machining Application,” Lubricants, vol. 10, no. 10, article no. 266, 2022

[10] K. Kadirgama, “A Comprehensive Review on the Application of Nanofluids in the Machining Process,” The International Journal of Advanced Manufacturing Technology, vol. 115, pp. 2669-2681, 2021

[11] S. Chinchanikar, S. S. Kore, and P. Hujare, “A Review on Nanofluids in Minimum Quantity Lubrication Machining,” Journal of Manufacturing Processes, vol. 68, no. A, pp. 56-70, 2021.

[12] V. K. Pasam, P. Rapeti, and S. B. Battula, “Efficacy of Nanocutting Fluids in Machining-an Experimental Investigation,” Advances in Technology Innovation, vol. 3, no. 2, pp. 78-85, 2018.

[13] A. Hafeez, F. M. Aldosari, M. M. Helmi, H. A. Ghazwani, M. Hussien, and A. M. Hassan, “Heat Transfer Performance in a Hybrid Nanofluid (Cu-Al_2O_3 /Kerosene Oil) Flow Over a Shrinking Cylinder,” Case Studies in Thermal Engineering, vol. 52, article no. 103539, 2023.

[14] I. Nouzil, M. Drummond, A. Eltaggaz, I. Deiab, and S. Pervaiz, “Experimental and Numerical Investigation of Cooling Effectiveness of Nano Minimum Quantity Lubrication,” Journal of Manufacturing Processes, vol. 108, pp. 418-429, 2023.

[15] S. K. Yadav, S. Ghosh, and A. Sivanandam, “Surfactant Free Enhancement to Thermophysical and Tribological Performance of Bio-Degradable Lubricant with Nano-Friction Modifier for Sustainable End Milling of Incoloy 925,” Journal of Cleaner Production, vol. 428, article no. 139456, 2023.

[16] G. I. P. Perera and T. S. Wegala, “Improving the Novel White Coconut Oil-Based Metalworking Fluid Using Nano Particles for Minimum Surface Roughness and Tool Tip Temperature,” Cleaner Materials, vol. 11, article no. 100227, 2024.

[17] D. Y. Pimenov, L. R. R. da Silva, A. R. Machado, P. H. P. França, G. Pintaude, D. R. Unune, et al., “A Comprehensive Review of Machinability of Difficult-to-Machine Alloys with Advanced Lubricating and Cooling Techniques,” Tribology International, vol. 196, article no. 109677, 2024.

[18] A. Ç. Şencan, Ş. Şirin, E. N. S. Saraç, B. Erdoğan, and M. R. Koçak, “Evaluation of Machining Characteristics of SiO_2 Doped Vegetable Based Nanofluids with Taguchi Approach in Turning of AISI 304 Steel,” Tribology International, vol. 191, article no. 109122, 2024.

[19] S. Hu, C. Li, Z. Zhou, B. Liu, Y. Zhang, M. Yang, et al., “Nanoparticle-Enhanced Coolants in Machining: Mechanism, Application, and Prospects,” Frontiers of Mechanical Engineering, vol. 18, article no. 53, 2023.

[20] X. Du, J. Zheng, T. Chen, B. Guo, and X. Li, “Probing the Tribology and Drilling Performance of High Performance Cutting Fluid on Inconel 690 Superalloy by Minimum Quantity Lubrication Technology,” Alexandria Engineering Journal, vol. 88, pp. 58-67, 2024.

[21] F. Abedrabbo, D. Soriano, A. Madariaga, R. Fernández, S. Abolghasem, and P. J. Arrazola, “Experimental Evaluation and Surface Integrity Analysis of Cryogenic Coolants Approaches in the Cylindrical Plunge Grinding,” Scientific Reports, vol. 11, article no. 20952, 2021.

[22] N. Khanna, P. Shah, and Chetan, “Comparative Analysis of Dry, Flood, MQL and Cryogenic CO_2 Techniques during the Machining of 15-5-PH SS Alloy,” Tribology International, vol. 146, article no. 106196, 2020.

[23] M. Raja, R. Vijayan, P. Dineshkumar, and M. Venkatesan, “Review on Nanofluids Characterization, Heat Transfer Characteristics and Applications,” Renewable and Sustainable Energy Reviews, vol. 64, pp. 163-173, 2016.

[24] A. M. Khan, M. Jamil, K. Salonitis, S. Sarfraz, W. Zhao, N. He, et al., “Multi-Objective Optimization of Energy Consumption and Surface Quality in Nanofluid SQCL Assisted Face Milling,” Energies, vol. 12, no. 4, article no. 710, 2019.

[25] A. H. Abdelrazek, I. A. Choudhury, Y. Nukman, and S. N. Kazi, “Metal Cutting Lubricants and Cutting Tools: A Review on the Performance Improvement and Sustainability Assessment,” The International Journal of Advanced Manufacturing Technology, vol. 106, pp. 4221-4245, 2020.

[26] I. P. Okokpujie, O. S. Ohunakin, and C. A. Bolu, “Multi-Objective Optimization of Machining Factors on Surface Roughness, Material Removal Rate and Cutting Force On End-Milling Using MWCNTS Nano-Lubricant,” Progress in Additive Manufacturing, vol. 6, pp. 155-178, 2021.

[27] S. Sarkar and S. Datta, “Machining Performance of Inconel 718 under Dry, MQL, and Nanofluid MQL Conditions: Application of Coconut Oil (Base Fluid) and Multi-Walled Carbon Nanotubes as Additives,” Arabian Journal for Science and Engineering, vol. 46, pp. 2371-2395, 2021.

[28] N. C. Vu, X. P. Dang, and S. C. Huang, “Multi-Objective Optimization of Hard Milling Process of AISI H13 in Terms of Productivity, Quality, and Cutting Energy under Nanofluid Minimum Quantity Lubrication Condition,” Measurement and Control, vol. 54, no. 5-6, pp. 820-834, 2021.

[29] T. T. Nguyen, X. B. Le, “Optimization of Roller Burnishing Process using Kriging Model to Improve Surface Properties,” Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, vol. 233, no. 12, pp. 2264-2282, 2019.

[30] G. T. Bui, T. V. Do, Q. M. Nguyen, M. H. P. Thi, and M. H. Vu, “Multi-Objective Optimization For Balancing Surface Roughness and Material Removal Rate in Milling Hardened SKD11 Alloy Steel with SiO_2 Nanofluid MQL,” EUREKA: Physics and Engineering, no. 2, pp. 157-169, 2024.