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jmr&t
Journal of Materials Research and Technology
journal homepage: www.elsevier.com/locate/jmrt



Original Article

Key initiatives to improve the machining characteristics of Inconel-718 alloy: Experimental analysis and optimization



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ARTICLE INFO

Article history:

Received 24 December 2021

Accepted 13 October 2022

Available online 20 October 2022

Keywords:

Inconel 718

Cooling/lubrication strategies

End milling

Advanced optimization approaches

NSGA-II and TLBO

ABSTRACT

Inconel 718 is a heat-resistant Ni-based superalloy widely used, particularly, in aircraft and aero-engineering applications. It has poor machinability due to its unique thermal and mechanical properties. For this reason, studies have been carried out from past to present to improve the machinability of Nickel-based (Ni) alloys. Further improvement can be achieved by applying hybrid multi-objective optimization strategies to ensure that cutting parameters and cooling/lubrication strategies are also adjusted effectively. That is why, in this research, the machinability of Inconel 718 is optimized under various sustainable lubricating environments i.e., dry medium, minimum quantity lubrication (MQL), nano-MQL, and cryogenic conditions at different machining parameters during end-milling process. Subsequently, the analysis of variance (ANOVA) approach was implanted to apprehend the impact of each machining parameter. Finally, to optimize machining environments, two advanced optimization algorithms (non-dominated sorting genetic algorithm II (NSGA-II) and the Teaching-learning-based optimization (TLBO) approach) were introduced. As a result, both methods have demonstrated remarkable efficiency in machine response prediction. Both methodologies demonstrate that a cutting speed of 90 m/min, feed rate of 0.05 mm/rev, and CO₂ snow are the optimal circumstances for minimizing machining responses during milling of Inconel 718.

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<https://doi.org/10.1016/j.jmrt.2022.10.060>

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1. Introduction

Ni-based superalloys with enhanced performance such as elevated mechanical strength at high temperatures and strong corrosion-resistance have been utilized in many different applications [1]. However, significant challenges arise during the machining of these superalloys due to poor heat transfer coefficient, high toughness, and also very inadequate work hardening conditions hindering efficiency by manufacturing pragmatic surface quality. The machinability of Ni-based superalloys can be improved depending on various input parameters, including lubrication medium (refer to Fig. 1), cutting parameter combination, and cutting tool properties [2]. In addition, adequate lubrication allows to control the integrity of the surface and prolong the life of the tool [3–5]. However, lubricants are usually not environment friendly. That is why, the research focus is shifted more on environment, human health and safety concerns during machining operations [6,7]. Therefore, to eliminate the usage of excessive and harmful lubricants, various cooling/lubrication conditions such as minimum quantity lubrication (MQL) and cryogenic cooling have been proposed.

For example, Zhang et al. [9] examined tool wear and cutting force during end-milling of Inconel 718 under dry and Minimum quantity cooling lubrication (MQCL) conditions using biodegradable vegetable oil. The authors' findings suggested that MQCL assisted milling can successfully enhance Inconel 718 machinability in term of tool life extension and cutting force reduction. Okafor and Nwoguh [10] compared the performance of mineral oil-based emulsion coolant with high oleic soybean oil based MQL at various flow rates in the face milling process of Inconel 718. The researchers' findings demonstrate that a 70 ml/h fluid flow rate of MQL provided the greatest tool life, which was equivalent to mineral oil-based emulsion flood cooling, while a 10 ml/h fluid flow rate of MQL provided the poorest tool life. Oliveria et al. [11] analysed the residual stress and cutting forces during end-milling operation of Inconel 718 under traditional wet cooling and MQL conditions. Anand and Mathew [12] intended to analyze the size effect and improvement in surface attributes of Inconel 718 micro-end-milling using sunflower oil-based MQL compared to dry cutting. They reported that when sunflower oil-based MQL-assisted micro-end milling of Inconel 718 was compared to dry condition, there was about 32% decrease in surface roughness, 36% decrease in top burr width, and 37% decrease in top burr height.

To summarize the studies conducted under cryogenic cooling, for example, Shokrani et al. [13] employed TiAlN coated carbide tools for cryogenic assisted end mill of Inconel 718. According to their findings, cryogenic cooling offered a great potential to reduce surface roughness of machined items when compared to dry machining without significantly

increasing machine tool power consumption. Aramcharoen and Chuan [14] conducted experiments to see how cryogenic cooling affects milling of Inconel 718 when compared to dry and traditional oil-based coolants. As a result, in terms of tool wear reduction, reduced friction in the secondary deformation zone, lower energy consumption, and contamination-free on the machined component, cryogenic cooling have the potential to improve machinability and sustainability when compared to traditional oil-based coolants and dry cutting. Musfirah et al. [15] carried out experiments to compare the effectiveness of cryogenic cooling for milling Inconel 718 to the dry cutting procedure. Their finding showed that cryogenic cooling reduces tool wear, lowers needed cutting force, improves surface roughness, reduces deformation of microstructure, and eliminates contamination of the machined surfaces better than dry cutting.

From the literature review summarized above, it can be deduced that in milling Inconel 718 superalloy, both the MQL and the cryogenic cooling environment conditions improved the machinability outputs compared to dry and flood cooling environments. However, in order to further improve performance indicators, both the cooling/lubricating environments and the cutting parameters need to be optimized together for multiple purposes. In this context, different tools have been used in the literature for multiple optimization.

To achieve the best process parameters, several classical optimization methods such as dynamic programming, nonlinear programming, geometric programming, goal programming and sequential programming have been proposed. These methods only create a local optimal combination with inadequate accuracy and resilience risk and cannot handle difficult and nonlinear situations. To optimize machining parameters, metaheuristic algorithms, such as Grey Relational Analysis (GRA) [16], Genetic Algorithm (GA) [17], ABC [18], TLBO and NSGA-II [19] have been proposed. While the meta-heuristic algorithms are better than conventional optimization techniques, but some downsides have also arisen. The main drawback of these algorithms is to obtain a good quality solution in a reasonable amount of time. Indeed, they cannot guarantee a global optimal solution, and cannot achieve the optimum simulation values. A genetic algorithm, for example, is an evolutionary optimization approach that may find a near-optimal solution to a tough issue with many variables and constraints [20]. However, algorithms such as GA and ABC have some limitations. Moreover, architectural modifications and hybridization can further increase complexity [21]. In order to achieve effective management of the manufacturing process parameters, an intelligent optimization strategy that employs fewer parameters in algorithms can be more advanced.

NSGA-II is a new optimization approach that is frequently employed in engineering applications nowadays [22]. For example, in a milling process, Chen [23] used NSGA-II for

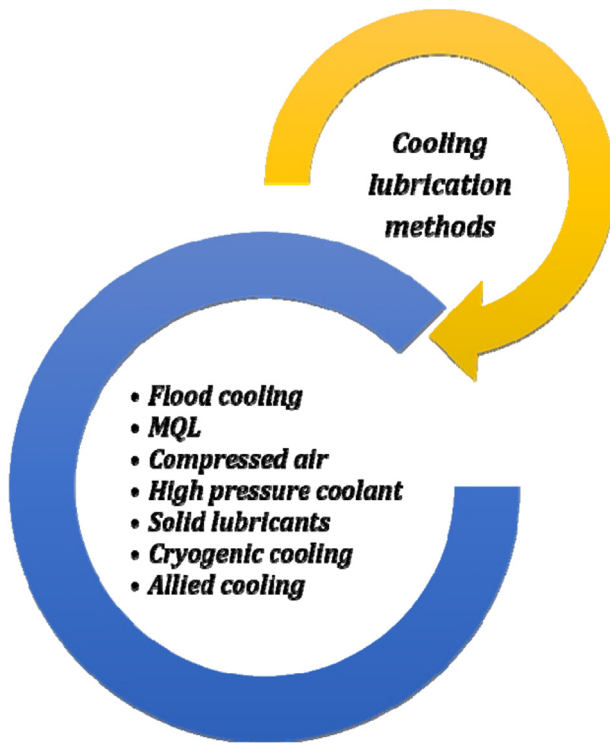


Fig. 1 – A diagram depicting the various cooling and lubrication options (Adopted from Ref. [8]).

optimization. As a consequence, the author discovered that NSGA-II is a cost-effective computational technique for successfully optimizing the milling process' various constraints. In another study, NSGA-II was used in the machining process by Qu et al. [24] According to findings, the authors reported that the NSGA-II approach was extremely efficient in providing a wide variety of optimal solutions, which aided in improving the study's process efficiency. Sen et al. [19] employed NSGA-II–coupled TOPSIS algorithm to improve machining responses of Ni-based alloy. The authors' findings revealed less than 1% error in comparison between experimental and simulated results. Therefore, they emphasized that more efforts should be made to develop hybrid Pareto-based optimization techniques, taking into account methods' industrial benefits.

On the other hand, in recent years, a novel approach i.e., teaching learning-based optimization (TLBO) has proposed by Rao and Savsani [25] and reported by Ref. [26] that it is computationally easier than GA, PSO, and other optimization techniques. Rao et al. [27] used the TLBO method to optimize operating variables in machining processes and found that it outperformed PSO and GA. It was reported by Ref. [28] the TLBO algorithm outperformed GA in terms of obtaining optimal outputs. Chaudhari et al. [29] utilized TLBO approach in order to obtain the best combination of multiple outputs. Moreover, TLBO finds a place in many applications because of its simple principle, rapid convergence, and ease of implementation [30].

Considering the studies outlined above, it is important to use cooling/lubrication conditions that apply less cutting fluid for efficient and environmentally friendly machining of

Inconel 718. In addition, optimizing cutting parameters with advanced algorithms is a key way to achieve the best results. Taking all this into account, the objectives of the current study are two-fold. First, to demonstrate that sustainable lubrication methods are beneficial to improving machining characteristics. Secondly, to employ modern techniques to optimize the cutting parameters for enhanced machining characteristics. In this paper, the optimization of end milling parameters and lubrication media utilizing two techniques namely NSGA-II and TLBO is proposed. The analysis of variance (ANOVA) and main effects plots were employed to analyze the effect of the processing parameters and the lubricating conditions on machining characteristics. In addition, this work achieves the optimal balance of process parameters that concurrently optimizes the machining responses to achieve a suitable machining environment.

2. Evolutionary optimization techniques

2.1. Overview of NSGA-II

NSGA-II is a multi-objective evolutionary algorithm developed by Srinivas and Deb [31] that can improve elite preservation and phenotype crowd comparison to maintain variety and reduce computational complexity [32]. Moreover, it constructs a Pareto ranking built on a non-Dominated Sorting method for each participant and employ the crowding distance technique of estimating density [33]. The key limitations of this technique are its reliance, its high computational intricacy, and its lack of elitism on the parameters of sharing. The following are the major steps of the NSGA-II [34–36]:

Step 1: The population size determines how many chromosomes (N_p) should be kept in each iteration. Multiple objectives are subsequently evaluated by an assessment function for various populations. For multiple subsequent generations, the same procedure is followed.

Step 2: Population is classified as a non-domination sorting form, which allows presenting diverse solutions at multiple Pareto fronts. Populations achieved a separate rank based on the level of non-domination. The individuals with the lowest rank conquered the highest level.

Step 3: A linear distance criteria approach is used to determine the crowding distance of every individual.

Step 4: To select individuals from the population, a binary tournament selection (BTS) operator is applied. Generally, when the members having the same rank are chosen as parents with the highest crowding distance. On the contrary, lower-ranking members are chosen from various fronts solutions.

Step 5: A population with the size of ($N_p + n$) is established via crossover, selection, and mutation operators. Afterward, following a sorting procedure a new population (N_p) is picked. Normally, the sorting process consists of two main ways: solutions are sorted downward in terms of the crowding distance, subsequently in upward order, with regard to the ranks of solutions.

Step 6: The method is continued till the stopping conditions are met. Finally, the decision-maker obtains a series of non-dominated Pareto solutions that best work towards

multi-objective optimization for any solution. Fig. 2 demonstrates the flow diagram of the NSGA-II algorithm.

2.1. Overview of TLBO

TLBO is a technique influenced by the teaching-learning procedure [25] that is focused on the importance of a teacher's involvement in the performance of students in the classroom. TLBO is employed to optimize mechanical parts, structural design, and production concerns [38–40]. In TLBO, a teacher is often an extremely trained individual who instructs learners to improve their scores or grades. In addition, learners learn from the interactions that also contribute to the improvement of their achievements.

The results of the learner are equivalent to the "fitness" of the optimization. The finest solution is regarded as the "teacher" in the whole population. TLBO's working principle is divided into the "teacher" and "learner" phases of two components. The operation of both phases are described below [41]:

(a) Teacher phase

This is the principal step in the process where students learn from their teachers. Throughout this stage, a teacher

attempts to raise the classroom's average result from the M1. However, this is not achievable in practice, and a teacher can change the mean of M2. Here, M2 is better than M1 relying on his or her skill. At any iteration, I assume M_j and T_i are considered a teacher. Now, T_i is aiming to advance the mean value of M_j . So the new average value will be denoted as M_{new} as shown by Ref. [41].

$$\text{Difference Mean}_i = r_i (M_{new} - T_i M_j) \quad (1)$$

where TF is the teaching factor that determines the quantity of the mean, and r_i is a number randomly taken between 0 and 1. The TF value will either be 1 or 2, that would be a heuristic step. It is determined randomly with equivalent probability as follows:

$$T_F = \text{round} [1 + \text{rand}(0, 2) \{2 - 1\}] \quad (2)$$

During the algorithm, TF is formed in the domain of 1–2. The range of values in between shows the quantity of knowledge that can be transferred. Depending on the learner's capacities, the transfer level of understanding can vary. The current study attempted to improve the results by examining values within 1 and 2, however, no improvement was noticed. As a result, according to the rounding up criteria, it is recommended that the teaching factor be set to either 1 or 2.

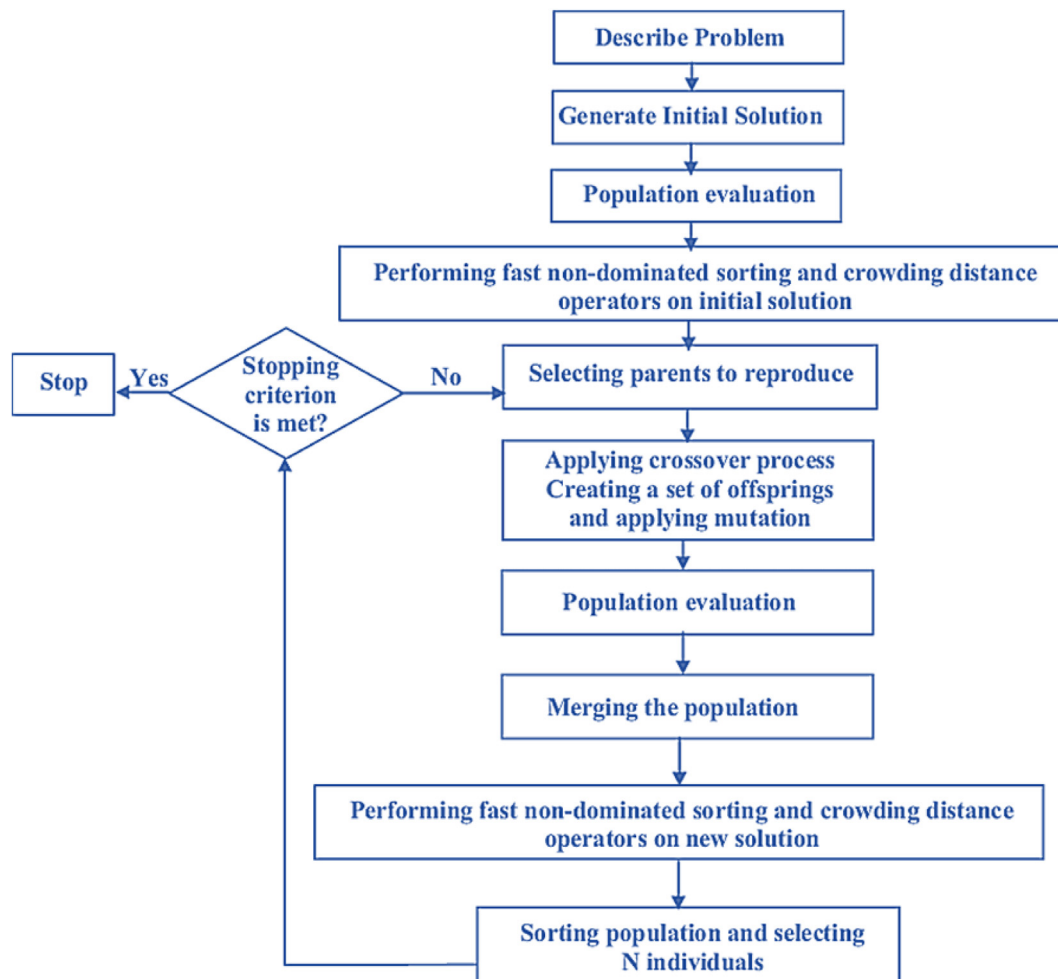


Fig. 2 – The flowchart of NSGA-II algorithm [37].

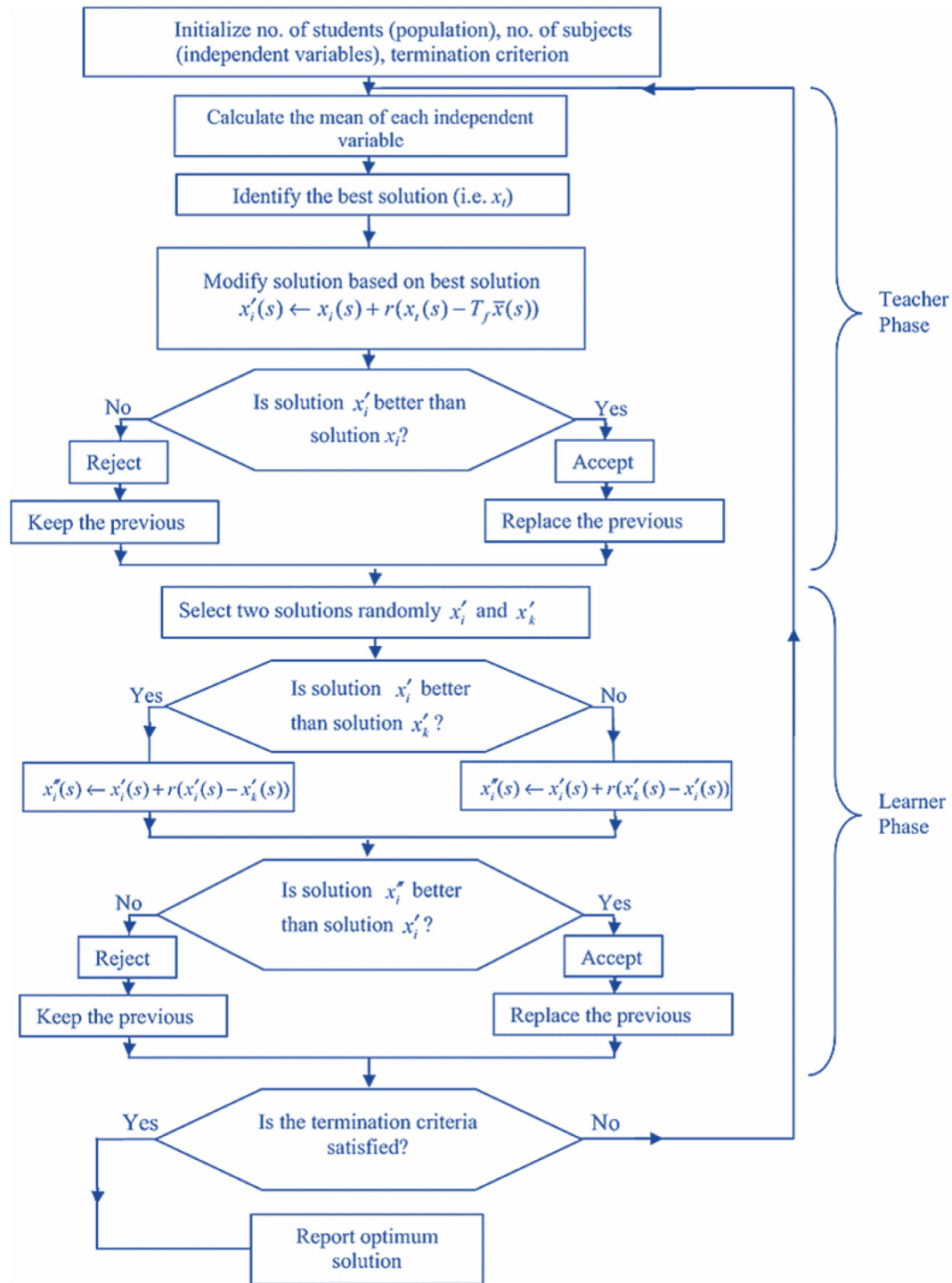


Fig. 3 – The outline of the TLBO algorithm [43].

However, any value of TF between 1 and 2 can be used. The present solution is revised as per the following formula depending on this difference mean.

$$X_{new,i} = X_{old,i} + DifferenceMean_i \quad (3)$$

(b) Learner phase

This is the step of the algorithm in which learners expand their understanding by co-operating with one another. A learner connects with others at random to improve his or her skills. When another learner has greater knowledge than the other, then the learner acquires new things. The knowledge acquiring process of this phase can be described mathematically as follows. Considering distinct learners, X_i and X_j , at any iteration i , where i and j are the number of iterations ($i \neq j$).

Table 1 – Mechanical features for Inconel 718 [44].

Feature	Value
Density (g/cm ³)	8.25
Poisson's ratio	0.25–0.35
Elastic modulus (GPa)	200
Tensile strength (MPa)	965
Yield strength (MPa)	550
Specific heat capacity (J/Kg·K)	440
Thermal conductivity (W/mK)	14–15

$$X_{new,i} = X_{old,i} + r_i(X_i - X_j) \text{ if } f(X_i) < f(X_j) \quad (4)$$

$$X_{new,i} = X_{old,i} + r_i(X_i - X_j) \text{ if } f(X_i) < f(X_j) \quad (5)$$

Consider X_{new} if the function value is better. Following are summarized the implementation stages of the TLBO [42]:

Step 1: Initialize randomly generated population (namely, the learners) with problem design variables (indicates the subjects assigned to the learner).

Step 2: Choose the preminent learner for every subject and calculate the average learner's result for the individual subject.

Step 3: Analyze the variance between the present average result and optimal average result with Eq. (1).

Step 4: Using teacher knowledge as per Eq. (3), update learners' skills.

Step 5: Update the knowledge of the learner using the knowledge as per Eqs. (4) and (5) of another learner.

Step 6: Repeat the step 2–5 procedure until the ending requirement is reached. Fig. 3 shows the outline of the TLBO algorithm.

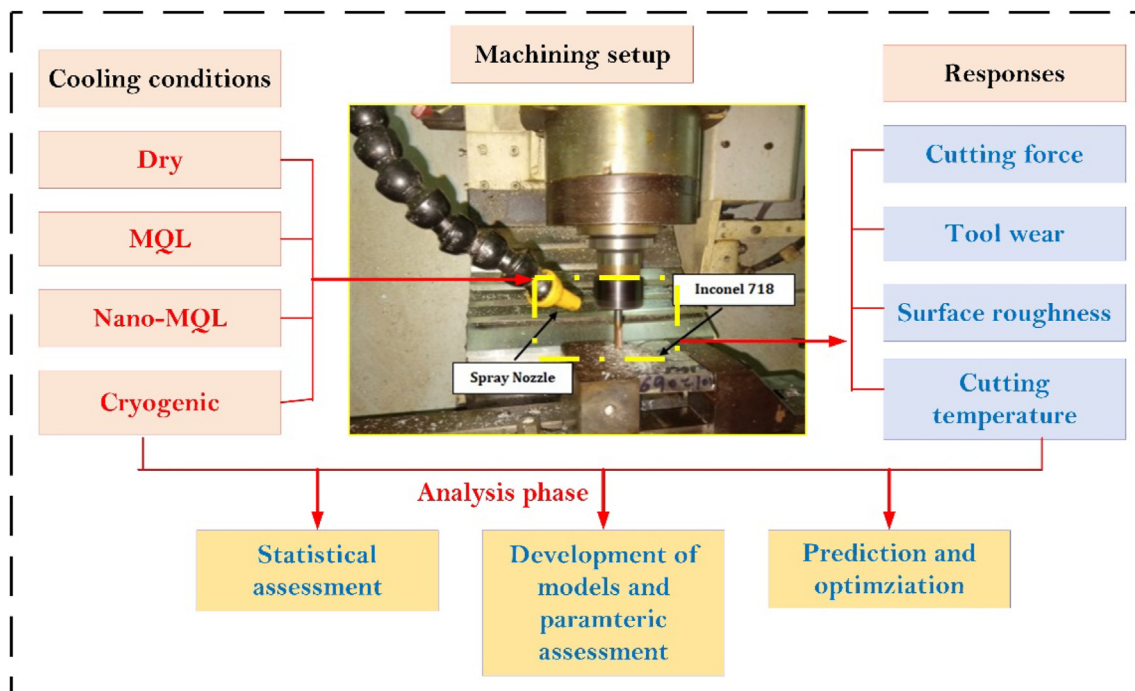
3. Materials and methods

3.1. Experimental procedure

A three-axis computer numerical control (CNC) milling machine was employed for the machining tests. On a block of Inconel 718 (100 × 100 × 50 mm), experiments were conducted. In the cutting process, TiAlN coated carbide end-mill (10 mm diameter, 25 mm blade-length, 75 mm complete length, and 70 °C flute angle) was used. The mechanical properties of Inconel 718 are shown in Table 1. A combination of sixteen experimental investigations was performed using four sets of machining parameters (cutting speed and feed rate) and four different lubrication media (Dry, MQL, nano-MQL, and Cryogenic). Throughout the experiment, the parameters viz., radial and axial depth of cut were kept constant. Finally, performance measures i.e., cutting force (F_r), tool wear

Table 2 – Cutting parameters.

Parameter	Unit	Level 1	Level 2	Level 3	Level 4
Cutting speed (V_c)	m/min	60	80	100	120
Feed rate (f)	mm/rev	0.05	0.10	0.15	0.20
Lubricating medium (LM)	–	Dry (1)	MQL (2)	Nano-MQL (3)	Cryogenic (4)

**Fig. 4 – The outline of experimental study.**

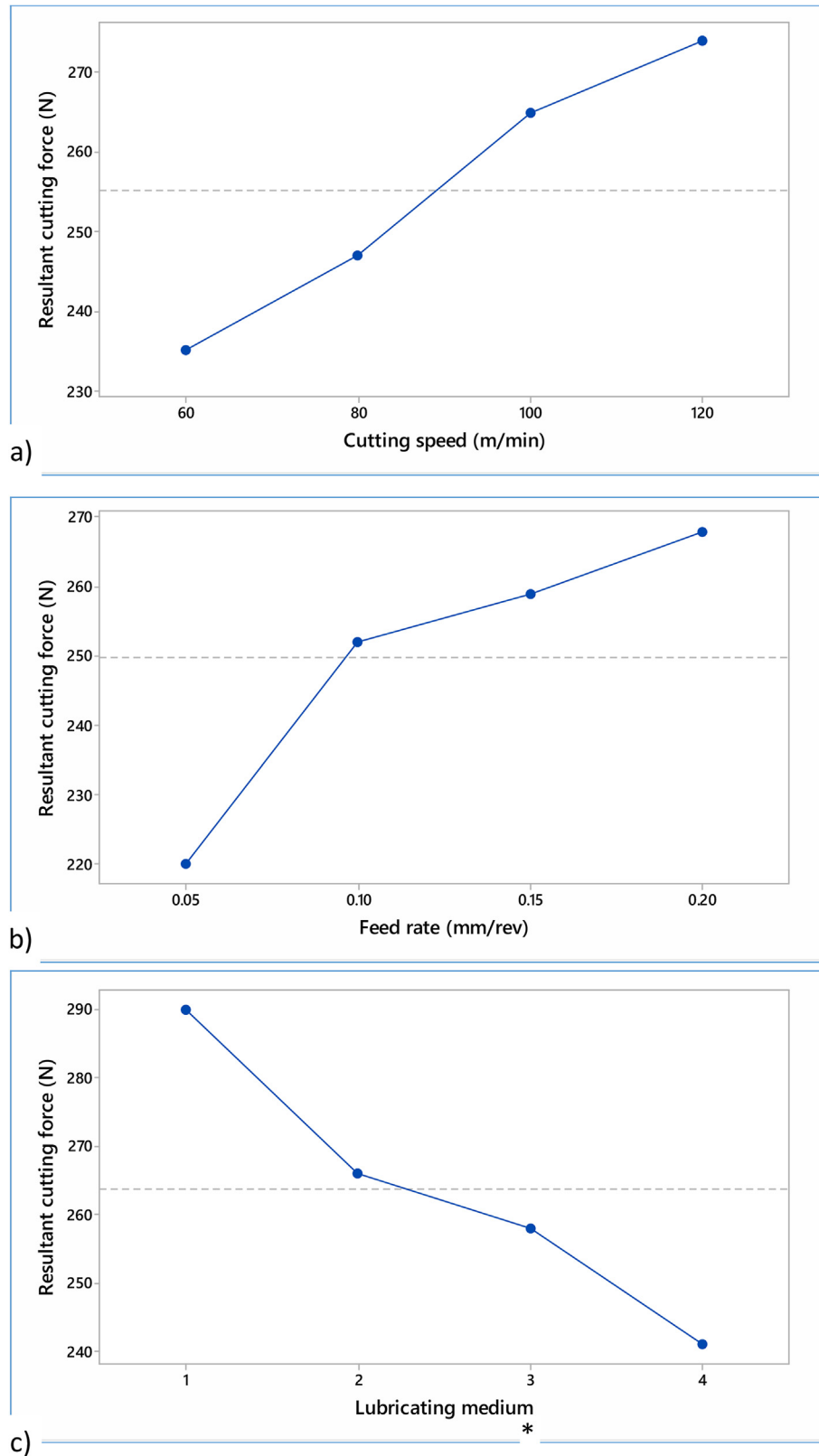


Fig. 5 – Main effect plot for resultant cutting force a) Effect of cutting speed b) feed rate c) lubrication medium (* (1): Dry, (2) MQL, (3) Nano-MQL, (4) Cryogenic).

(V_B), surface roughness (R_a), and cutting temperature (T) were assessed individually. The level of input parameters included for the present work is shown in Table 2. The vegetable oil

with flow rate and air pressure were set at 3.5 ml/min and 5 bar respectively. MQL nozzles (dia. 2 mm) were attached at a position of 35 mm from the machining zone. In addition, the

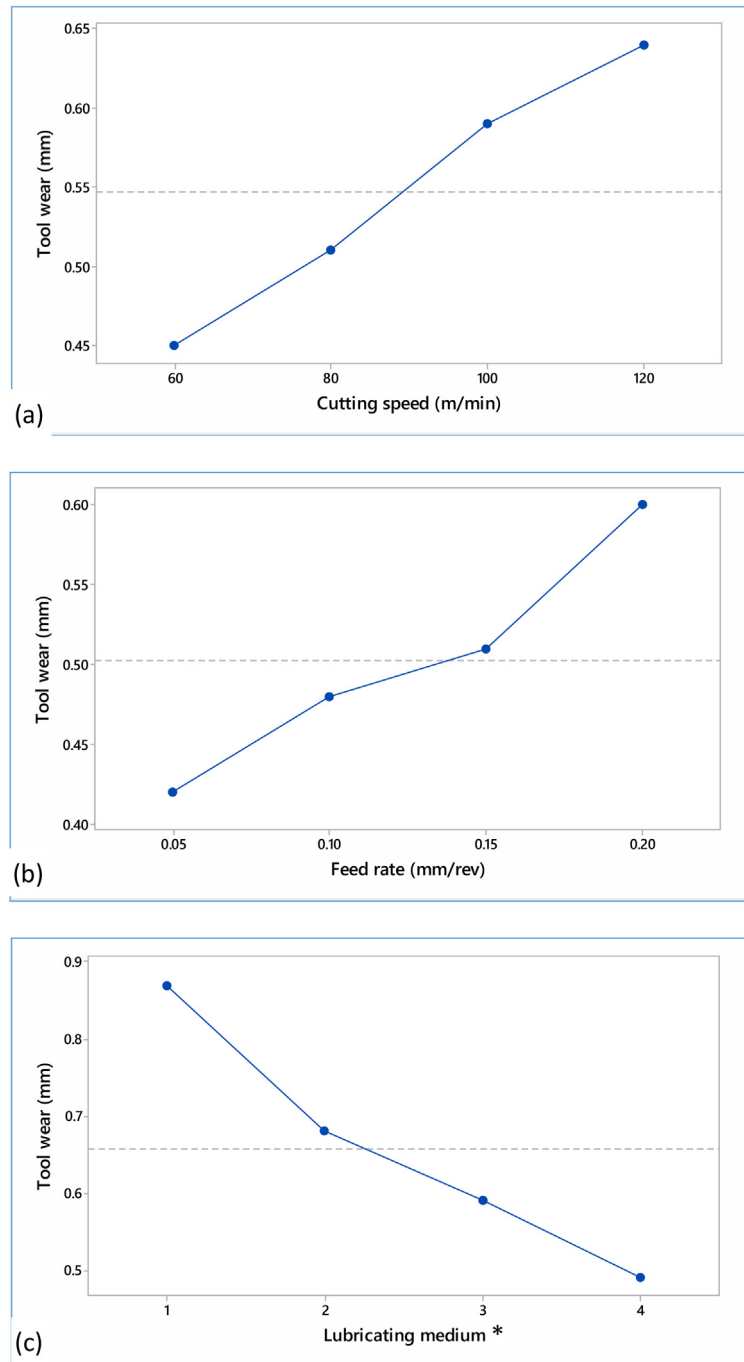


Fig. 6 – Main effect plot for tool wear a) Effect of cutting speed b) feed rate c) lubrication medium (*1): Dry, (2) MQL, (3) Nano-MQL, (4) Cryogenic).

graphene nano particles were supplied with MQL conditions. Finally, the compressed CO₂ snow was delivered to the tool-chip boundary with a 0.5 mm nozzle.

3.2. Response measurements

The cutting forces were determined with a Kistler piezoelectric dynamometer, using the analytical software DynoWare. A signal amplifier was utilized to intensify the signals and the readings were documented on a computer graphically. An

optical microscope was used to assess the flank of the wear of the end-mill after 60 s of machining tests. A portable perthometer with a measuring distance of 5.6 mm measured the average roughness of the milled surface. A thermal infrared camera measured the temperature-induced at the cutting zone. The temperature ranges of -20 to 600 °C with a precision of ± 2 °C using the thermal camera was used. In addition, the image analyzer SmartView® 4.0 was employed for the preparation of reports. Experiments were conducted 3 times and the mean value was taken into consideration to minimize the

probability of error. Fig. 4 provides the outline of the experimental investigation.

4. Results and discussion

4.1. Effect of process parameters on responses

4.1.1. Effect on resultant cutting force

Fig. 5(a) and (b) demonstrate that both speed and feed increase the magnitudes of resultant cutting force. This is due to the rise in cutting speed accompanied by the feed rate surges the tool-chip contact length, resulting in higher cutting forces [45,46]. Furthermore, Fig. 5(c) shows the change in lubricating medium is considerably different, which suggests that the resultant cutting force reduces when lubricating media changes. The dominance of ‘material hardening’ and ‘thermal softening’ can be explained by the higher cutting forces during dry and MQL circumstances compared to CO₂ snow. The material of the cutting region is softened due to localized high temperature [47]. MQL promotes quenching action that leads to plastic deformation of the material. The hardening dominates the softening effect; hence, the cutting force was raised in the first three lubricating conditions.

4.1.2. Effect on tool wear

Fig. 6 (a) and 6 (b) illustrate how tool wear increase substantially due to the growth in the cutting speed along with feed rate. High-speed-feed combinations produce higher cutting temperatures and stresses at the cutting edge [48], which is the basic cause behind this phenomenon. The elevated cutting temperature on the edge is related to the fragility of the tool material [49], which can result in the fracturing, cracking, and wear of the end-mill [50]. In contrast, the change in lubricating media diminishes tool wear significantly (Fig. 6(c)). Furthermore, the wear value under dry and MQL-assisted machining is higher than that of the CO₂ medium. It is observed that the lubricant flow offered by MQL was inadequate to offer efficient cooling as well as lubrication. However, across the tool-chip contact interface, the CO₂-snow produces a low-temperature area, which drastically reduces the wear profile of the tool. The carbon dioxide snow collects the surrounding water vapours and offers lubrication with the natural heat convection phenomenon. From the experimental findings, it is established that the correct cooling of the tool-work is very crucial for the protection of the tools for end-mill.

Fig. 7 Shows the micrographs for the end-mill. As a result, adhesion is a dominant wear process during all lubri-cooling media. The adhesive wear is also justified by BUE formation.

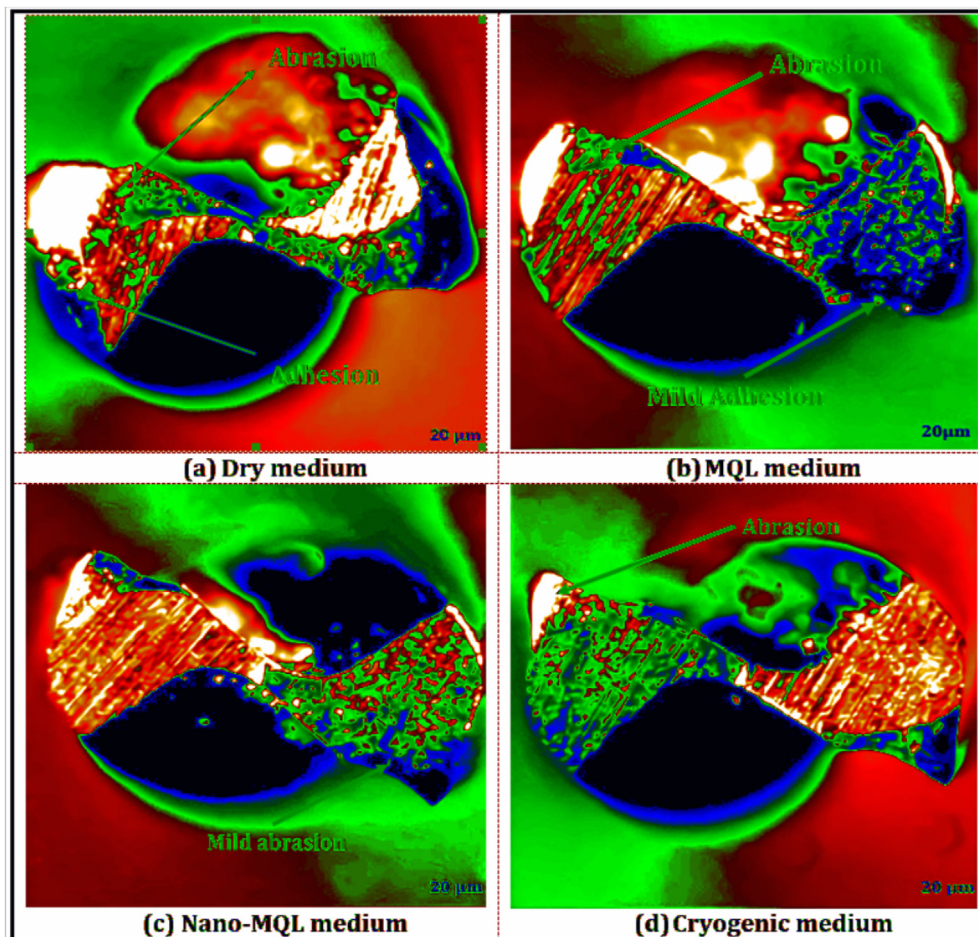


Fig. 7 – Optical pictures of the cutting tool in case of different lubri-cooling mediums (Scale: 20 μm).

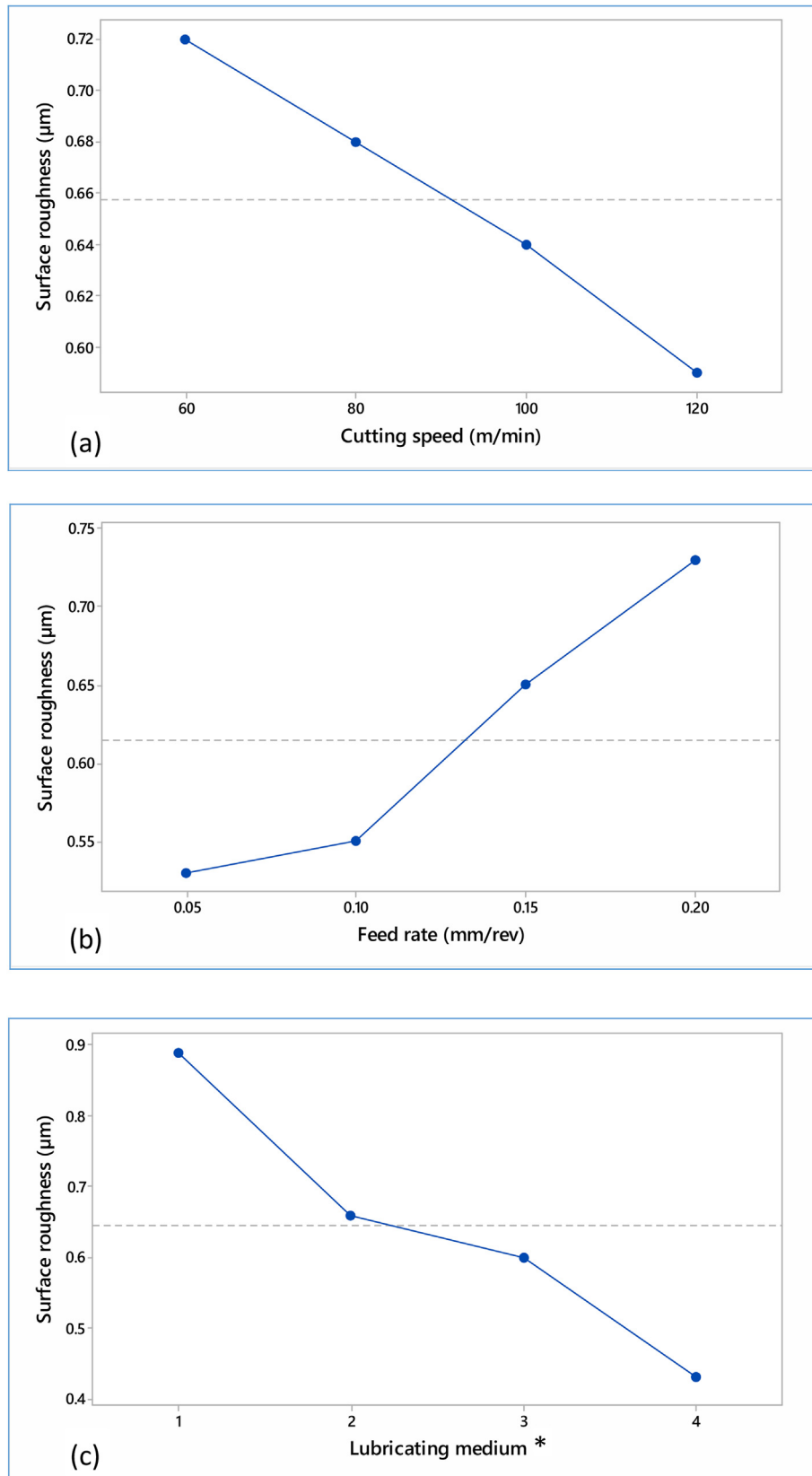


Fig. 8 – Main effect plot for surface roughness a) Effect of cutting speed b) feed rate c) lubrication medium (* (1): Dry, (2) MQL, (3) Nano-MQL, (4) Cryogenic).

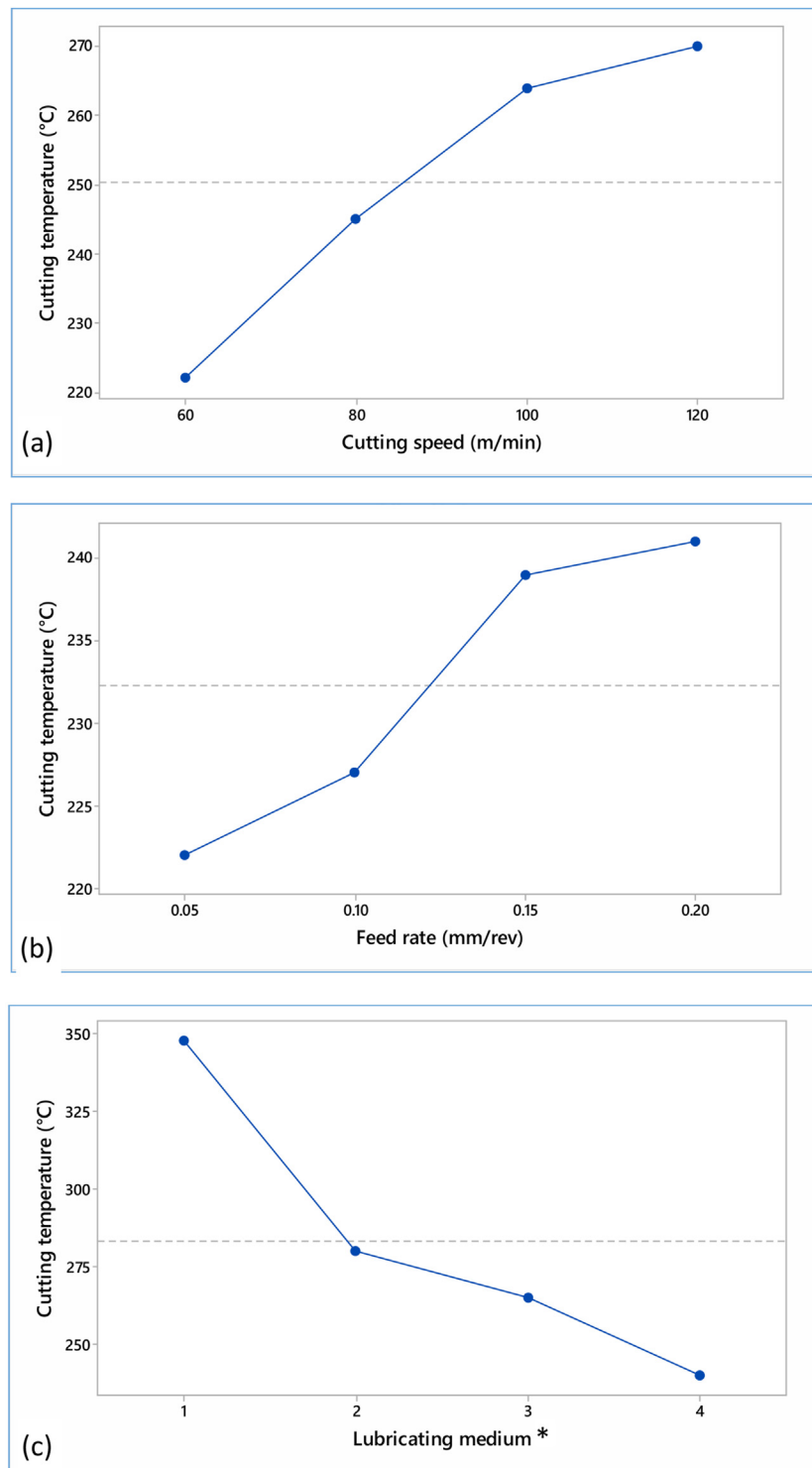


Fig. 9 – Main effect plot for cutting temperature a) Effect of cutting speed b) feed rate c) lubrication medium (* (1): Dry, (2) MQL, (3) Nano-MQL, (4) Cryogenic).

Further examination of the tool's edges reveals sticky components. During the machining of superalloys, it was observed that BUE & BUL production was a compulsive event [51]. On the other hand, Ezugwu et al. [52], discovered that tiny material chips were fused to the tool material eventually causing tool's destruction. When the cutting temperature rises above a certain point, smaller chips get increasingly glued to the tool.

As a result, BUE develops on the rake faces and finally transforms into BUL. Abrasive wear is another form of wear that occurs while machining a nickel-based alloy. This form of wear is indicated by grooves that run parallel to the chip flow direction. Nickel alloy has abrasive particles that infiltrate the tool-chip contact and cause a grinding action. Higher cutting speed exacerbates the problem. Olsson et al. [53], found out

Table 3 – ANOVA for combined objective.

Source	DOF	Adj SS	Adj MS	F-Value	P-Value	Contribution (%)
Model	5	0.013535	0.001692	105.99	0.000	
Linear	4	0.008573	0.002858	179.01	0.000	
v_c	1	0.025940	0.005940	372.14	0.000	21.273
F	1	0.012209	0.002209	138.38	0.000	10.012
LM	2	0.030067	0.000067	4.18	0.056	24.658
Square	1	0.000240	0.000080	5.01	0.011	
$f \times f$	1	0.000118	0.000118	7.36	0.014	
Error	10	0.000287	0.000016			
Total	15	0.121938				

$S = 0.0039954$, $R^2 = 96.8\%$, $R^2(\text{adj}) = 95.00\%$, $R^2(\text{pred}) = 95.32\%$

that cryogenic media are not particularly effective in reducing abrasive wear because of their low lubricating capacity. To put it another way, various lubricating media can lower tool wear values but not the kind of wear.

4.1.3. Effect on surface roughness

From the main effect plots provided in Fig. 8(a) and (b), it can be observed that the surface roughness value is substantially impacted by the machining parameters and lubricating media. The surface roughness value is moderately enhanced by the growth in cutting speed then upsurges drastically as feed rates rise [54]. The primary cause is that high speeds of cutting, and feed rate generate high friction, resulting in high roughness when huge amounts of the chip flow upon the cutting edge [55]. Moreover, friction creates heat, which alters the nickel alloy's thermo-physical state and results in a poor surface. Also, the machined surface pitch affects the feed rate significantly. Furthermore, the combination of high speed-feed combination increases chatter and vibration in machines, resulting in significant surface roughness [56,57]. Fig. 8(c) illustrates that, with a change in lubricating media, surface roughness levels also drop significantly.

The minute spray of MQL droplets cannot enter between the tool and workpiece. Hence, an even lubrication coating did not form in the machining area, resulting in a high coefficient of friction. In contrast, the cryogenic CO₂ vaporizes and gathers the water molecules to make the machining zone snowy, and wet. Furthermore, high-pressure snow prohibited chips from encountering the freshly created surface. Thus, the quality of the machined surface with CO₂-snow is improved. CO₂-snow generation had been an endothermic process and H₂O molecules were collected from surroundings. That has rendered the cutting surface moist and oily due to the amalgamation of CO₂ snow and water molecules. When CO₂ touched a new surface, it gets cold and oily and feels reduced friction and a smooth surface. Furthermore, a regulated and consistent chip removal system that reduces surface

resistance was introduced using 50–55 bar pressured snow. Thus, the heat was discharged and evaporated with cryogenic CO₂ near the cutting edge and was quickly discharged from the shearing zone.

4.1.4. Effect on cutting temperature

Fig. 9 (a) and 9(b) show that the cutting temperature increases when the speed and feed increases. The biggest reason is that the friction between tool and workpiece grows at faster cutting speeds, which can lead to high interface temperatures [58]. In addition, heat dissipation is lower owing to the lower thermal conductivity of nickel during the milling operation. Besides, the change in the cutting conditions reduces the cutting temperature, as shown in Fig. 9 (c). Owing to the severe friction between the tool-workpiece, high heat is generated in the cutting region [59,60]. The MQL mitigates the heat generation [61], but not as much as cryogenic coolant: The Joules-Thomson effect is prominent and turns compressed CO₂ into chilly snow as highly compressed CO₂ seeps out of a mini-nozzle hole. This pressurized CO₂-snow turns to dry-ice and penetrates well because of inertia. The main feature of CO₂-snow is the shift in phases which depends on cryogenic circumstances. The latent sublimation heat (591 kJ/kg), which exits from the nozzle as cryogenic CO₂ and specific heat allows the snow to remain upon this surface of the workpiece. When the cooling efficiency of cryogenic CO₂ is compared to MQL, a considerable quantity is disintegrated due to its extraordinary thermo-physical features at the cutting zone. Nonetheless, during machining of poor conductive materials, a little flow of cutting oil wasn't sufficient to efficiently remove the heat. Thus, CO₂-snow is considered as the best lubri-cooling medium when machining temperature is the primary concern.

4.2. Development of the combined objective function

After comprehensive experimental analysis, NSGA-II and TLBO were used to optimize the input parameters. To do so, we have developed a normalized combined objective function (COF) as described by Eq. (6):

$$\text{Minimum COF} = W_1 \times \frac{Fr}{Fr_{\min}} + W_2 \times \frac{VB}{VB_{\min}} + W_3 \times \frac{Ra}{Ra_{\min}} + W_4 \times \frac{T}{T_{\min}} \quad (6)$$

W_1 , W_2 , W_3 , and W_4 denotes the weights given to the various cutting force, tool wear, surface roughness, and cutting temperature, respectively. The weights were chosen in

Table 4 – The algorithm-specific parameters of NSGA-II.

Item	Response
Population	100
Generation	100
Objective function	03
Selection way	Binary tournament selection
Crossover	0.7
Mutation	0.4

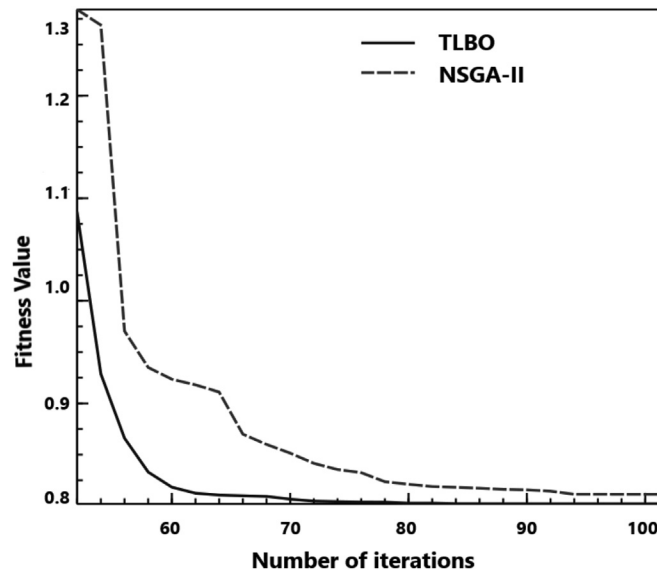


Fig. 10 – Convergence characteristics of NSGA-II and TLBO.

such a way that they added up to unity. For determining the weights to be used, a variety of random combinations can be tried. Individual weights can range from 0.1 to 0.5, with the sum remaining the same. In this paper equal weights of 0.25 was assigned to each objective. The cumulative objective approach yields a muddled result that may differ significantly from the individual value. This is the primary benefit of employing the aforesaid method.

4.3. Statistical assessment

In this section, the ANOVA test [45] was performed for the COF. Table 3 shows the outcome of ANOVA for the combined target. As this test shows, the model is relevant if the 'Probe > F' value is less than 0.0500. The value "Prob > F-value" is less than 0.0500 in this investigation for the proposed COF model. Furthermore, the value of the R-square for a model constructed, and the values of Adj R² and Pred R² show that the model explains the variance very well. The F-value for the cutting speed may be shown to be higher than other parameters, i.e., the lubri-cooling has the most effect. Furthermore, there is a statistically substantial effect of the machining parameters on the combined goal (P-value < 0.05). The lubricating media, cutting speed, and feed rate subsidized 21.273%, 10.012%, and 24.658% respectively.

4.4. Establishment of optimal process parameters using NSGA-II and TLBO

A regression analysis establishes the fitness function model of the combined goal. To minimize the combined objective, this fitness function is then used in NSGA-II and TLBO algorithms.

The machining performance acquired by the experimental research fully satisfied the computational optimization study requirement. To check the constancy of the Pareto results, NSGA-II is carried out with 100 populations and 100 generations. The confirmatory test was also conducted in various parametric configurations including all solutions. The identical study was done several times and average data was documented. For the optimization, the population size of such 100 individuals with a mutation and a crossover of 0.4 and 0.7 was examined. Table 4 shows the parametric setup of the NSGA-II technique. In TLBO, population sizes and iteration numbers were simulated until convergence has been established. The solution identified was premised on the approach to teaching/learning. Multiple potential solutions have been arbitrarily deleted and modified. Functions as expressed as $\{(2 * \text{population size} * \text{number of iterations}) + (\text{function aiming to activate duplication removal})\}$ are evaluated as whole numbers. The experiments have been carried out with varied population sizes to achieve optimal convergence, and the 1000 function evaluation has been conducted. The convergence characteristics of the NSGA-II and TLBO models are presented in Fig. 10. Table 5 provides a summary of the best, worst, and average values derived from researched methodologies, combined with important COF values. After 100 runs, the high percentage of precision and ideal simulation duration were discovered. The NSGA-II has shown a higher success rate (79.8%) than the TLBO, which has reached 76.7%. Nevertheless, the NSGA-II takes a maximum of 6.7 s, whilst the TLBO only requires 4.4 s. The flexibility of specific parameters implies less time and hence allows for faster TLBO convergence. The solutions acquired in the optimization process were experimentally validated. It should be noted that the values

Table 5 – NSGA-II vs. TLBO comparison.

Method	Best response	Worst response	Mean value	Time	Achievement (%)
NSGA-II	0.945	0.975	0.960	6.7	79.8%
TLBO	0.951	0.973	0.962	4.4	76.7%

Table 6 – Optimal parametric settings.

Parameters	Vc (m/min)	f (mm/rev)	LM	CO
NSGA-II	90	0.05	4	0.960
TLBO	90	0.05	4	0.962
Experimental	90	0.05	4	0.97

produced by optimization models are quite precise (Table 6), which shows the robustness of both optimization models.

4.5. Performance assessment of different lubricating medium

In this section, the milling performance of cryogenic CO₂ has been contrasted to that of other lubricating mediums under optimal machining conditions (Cutting speed = 90 m/min, Feed rate = 0.05 mm/rev). The comparison illustrates that milling Inconel 718 with a cryogenic medium exhibited superior machining behaviour to other lubricating media (Fig. 11). Cryogenic CO₂ resulted in 21.739%, 9.091%, and 6.250% lowering of resultant cutting force, 38.710%, 24%, and 9.524% decrement of tool wear, 48%, 27.778%, and 18.750% drop in surface roughness compared to that of dry, MQL, and nano-MQL environment, respectively. The cutting temperature produced in milling with cryogenic CO₂ was 30.325%, 13.063%, and 8.095% lower than that found in dry, MQL, and nano-MQL medium. Previously, Jamil et al. [62], also found almost similar results. Particularly, during material cutting,

heat is produced in three crucial zones: (a) primary shear zone, where heat is generated because of severe shearing and plastic deformation, (b) secondary friction zone, where tool-chip friction increases the cutting heat, and (c) Tertiary zone, where the friction of flank face and new surface enhances the cutting temperature. The metal chip removes the maximal quantity of heat from the cutting zone. Nonetheless, heat is conducted into the work material via the aforesaid sharing zones, impairing the tool's performance. A coolant/lubricant with a high heat transfer coefficient is typically used to alleviate thermal impacts on the secondary/tertiary sides of a cutting tool. As demonstrated in a recent study, evaporation of vegetable oil or nanofluids eliminated heat from the machining zone. Yet, a cryogenic coolant dissipated heat more effectively than MQL fluids. This lower cutting zone temperature strengthened the bond between the cutting tool and substrate and precluded their separation, which would be more vulnerable to heat. This could happen as a result of the correlation between the spindle's kinetic energy, its transformation to heat energy, and increasing the temperature. Consequently, during the experiments, it is seen that the cutting temperature is minimum when CO₂-snow aided cooling is used. Because of the higher heat transfer coefficient, CO₂-snow surpassed MQL in heat evacuation. It is because the initial temperature of the cryogenic CO₂ was the lowest, and the machining zone provided some of the latent heat essential for CO₂ evaporation [63]. Thus, the cutting zone's temperature was decreased.

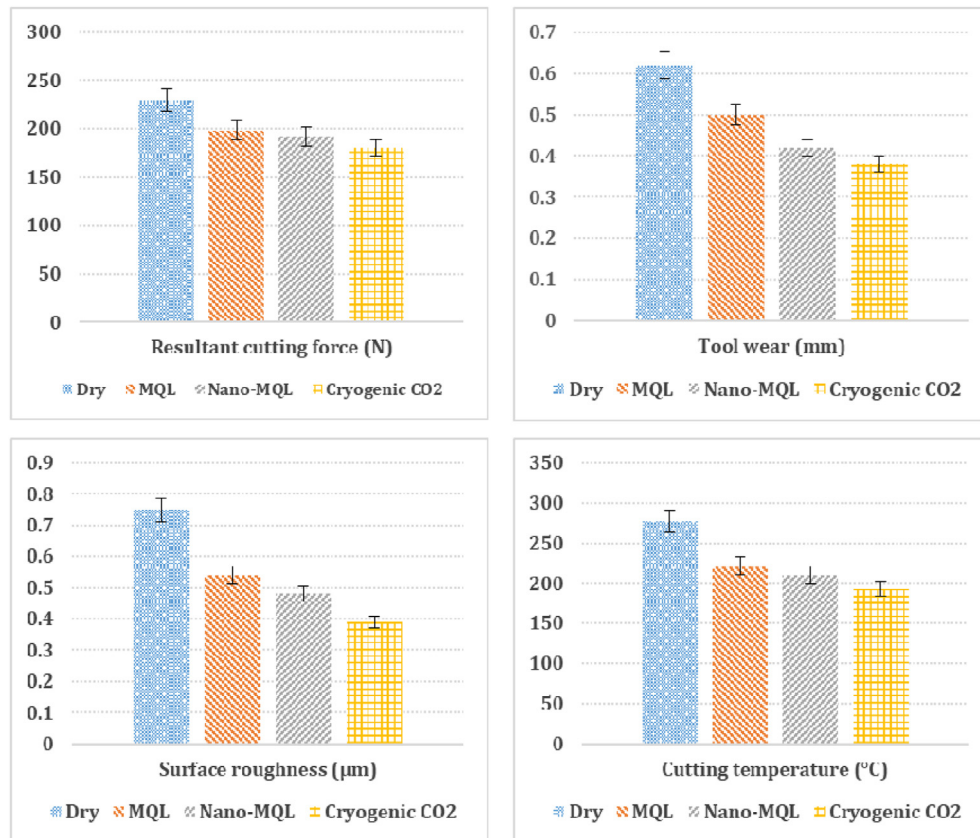


Fig. 11 – Performance assessment of different lubricating mediums under optimal machining conditions.

5. Conclusions

In present investigation, the machining performance of the Inconel 718 alloy under varied lubricating conditions was evaluated. First of all, the main effect diagrams were utilized to evaluate the effect of cutting parameters on certain responses. In order to ascertain the highly important characteristics, a combined goal was defined, and the ANOVA was executed. Additionally, two evolutionary approaches, NSGA-II and TLBO, were used to optimize the experimental results. Finally, an experiment was undertaken to determine the effectiveness of the algorithms being used. The following findings have been taken from these investigations:

- The evolutionary approaches like NSGA-II and TLBO are very similar in performance. Both methodologies demonstrate that a cutting speed of 90 m/min, feed rate of 0.05 mm/rev, and CO₂ snow are the optimal circumstances for minimizing machining responses during milling of Inconel 718.
- According to the ANOVA results, the effect of all machining parameters is statistically significant. The lubricating medium, cutting speed, and feed rate attributed 21.27%, 10.01%, and 24.65% respectively to COF.
- The main effect plot evaluation demonstrates that cutting forces, tool wear, and cutting temperature rise as cutting speed and feed rate increase, but the change in lubricating conditions significantly reduces the machining responses.
- In all lubri-cooling strategies, according to the microscopic pictures adhesion with abrasion appears to be the biggest cause of wear. On the end-mills, chipping and notching may also be observed. This demonstrates that while a suitable lubrication strategy can lower the tool wear values, but it cannot modify the type of wear during Inconel 718 milling.

The tactic of sustainable lubrication appears as the appropriate alternative in the category of hard machining. Hence, modern evolutionary optimization methods can therefore be employed as a future scope to select the sustainable machining environment.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

The work presented in this paper is, to the best of my knowledge and belief, original, except as acknowledged in the text, and the material has not been submitted, either in whole or in part, for a degree at this or any other university. There is no conflict of interest to declare.

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