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Milling of Inconel 718: an experimental and integrated modeling approach for surface roughness

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ORIGINAL ARTICLE

Milling of Inconel 718: an experimental and integrated modeling approach for surface roughness

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Abstract

Inconel 718, a hard-to-cut superalloy is reputed for having poor machining performance due to its low thermal conductivity. Consequently, the surface quality of the machined parts suffers. The surface roughness value must fall within the stringent limits to ensure the functional performance of the components used in aerospace and bioimplant applications. One doable way to enhance its machinability is the adequate dissipation of heat from the machining zone through efficient and ecofriendly cooling environment. With this perspective, an experimental and integrated green-response surface machining-based-evolutionary optimization (G-RSM-EO) approach is presented during this investigation. The results are compared with two base-line techniques: the traditional flooded approach with Hocut WS 8065 mineral oil, and the dry green approach. A Box-Behnken response surface methodology (RSM) is employed to design the milling tests considering three control parameters, i.e., cutting speed (v_s), feed/flute (f_z), and axial depth of cut (a_p). These control parameters are used in the various experiments conducted during this research work. The parametric analysis is then accomplished through surface plots, and the analysis of variance (ANOVA) is presented to assess the effects of these control parameters. Afterwards, a multiple regression model is developed to identify the parametric relevance of v_s, f_z, and a_p, with surface roughness (SR) as the response attribute. A residual analysis is performed to validate the statistical adequacy of the predicted model. Lastly, the surface roughness regression model is considered as the objective function of the particle swarm optimization (PSO) model to minimize the surface roughness of the machined parts. The optimized SR results are compared to the widely employed genetic algorithm (GA) and RSM-based desirability function approach (DF). The confirmatory machining tests proved that the integrated optimization approach with PSO being an evolutionary technique is more effective compared to GA and DF with respect to accuracy (0.05% error), adequacy, and processing time (3.19 min). Furthermore, the study reveals that the Mecagreen 450 biodegradable oil-enriched flooded strategy has significantly improved the milling of Inconel 718 in terms of eco-sustainability and productivity, i.e., 42.9% cost reduction in cutting fluid consumption and 73.5% improvement in surface quality compared to the traditional flooded approach and the dry green approach. Moreover, the G-RSM-EO approach presents a sustainable alternative by achieving a Ra of 0.3942 µm that is finer than a post-finishing operation used to produce close tolerance reliable components for aerospace industry.

Keywords Inconel 718 · Green-RSM-based-evolutionary optimization (G-RSM-EO) · Biodegradable-enriched flooded strategy · RSM · PSO · GA · DF

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1 Introduction

Due to their desirable properties such as having high corrosion and oxidation endurance limits and mechanical stability in extreme conditions, Ni-based superalloys-Inconel 718 have widespread applications in leading industries such as aerospace and marine [1, 2]. It is believed that half of the aerospace engine weight consists of these superalloys [3]. To ensure the functional performance of these mechanical components, the surface roughness of the machined parts must confine to the stringent limits [4, 5]. Despite its superior properties, Inconel 718 exhibits poor machinability due to its low thermal conductivity, work hardening, and high affinity towards tool materials [6, 7]. These particularities have detrimental imprints on the part's surface finish and tool life, thus impacting productivity and processing costs. Machinability can be enhanced through adequate heat dissipation at the tool-workpiece interface via efficient cooling approaches. In this regard, the conventional flooded strategy has been employed for years. However, with the growing interest regarding the environmentally conscious machining, attempts have been made to replace this strategy with more ecofriendly alternatives such as dry, minimum quantity lubrication (MQL), and cryogenic MQL. It is reasoned that the cutting fluids employed during the conventional wet approach consist of many harmful additives such as sulphates, chlorine, and phosphates, which adversely affect the worker's health, the environment, and the machine tool itself [8–10].

Extensive research has been dedicated to improving the machinability aspects of Inconel 718 via different cooling environments. For instance, Ucun et al. [11] perform micro-milling of Inconel 718 using dry and MQL cutting approaches taking three control parameters: 48 m/min cutting speed,1.25, 2.5, 3.75, and 5 mm/flute feed; and 0.1-, 0.15-, and 0.2-mm depth of cut. The study concludes that the MQL works better to improve the reduction of tool radius. Working on the similar alloy, Kaynak et al. [12] investigate the effects of different cooling conditions for its machinability in terms of cutting forces and tool wear during the milling at 90 m/min cutting speed and 0.5-mm depth of cut. The research reveals that the cryogenic approach presents improved results compared to dry and traditional oil-based methods. To upgrade the machinability of Inconel 718, Feyzi and Safavi [13] propose a hybrid cutting approach combining cryogenic, plasma heating, and ultrasonic vibrations method while performing milling process at much lower values of cutting speed such as 5, 7.5, and 10 m/min. The experimental findings suggest that the surface finish and the tool wear have been improved compared to conventional milling. Similarly, Hafiz et al. [14] evaluate the effects of ultrasonic machining for the surface quality of Inconel 718. Their research concludes that 27 kHz ultrasonic vibrations are not capable to reduce the surface roughness significantly.

In contrast to the above-cited literature, recent research suggests that these ecological sustainable methods are still inadequate to match the performance of traditional flooded techniques. For example, Fernandez et al. [15] present an experimental comparison for the turning of Inconel 718 under conventional wet and ecofriendly alternatives. Their results claim that the cold air MQL works more efficiently than a dry environment but no better than the traditional cooling. The work of Iturbe et al. [16] supports this claim through a surface integrity and tool wear analysis of Inconel 718. It suggests that the traditional wet method is worth considering for the enhanced machinability attributes. It further adds that the achieved tool life in case of cryoMQL is three times shorter when compared to conventional environment.

During the recent developments involving the application of plant-based biodegradable oils as green cutting fluids, the research trend inclines in favor of MQL strategy [8, 9, 17, 18]. Pereira et al. [17] employ various biodegradable oils integrated with MQL technique. A 15% improvement in surface finish is seen for high oleic sunflower oil with better ecological impacts. Studies are also available which tried to combine the advantages of biodegradable oil in a flooded environment [19, 20]. Zahoor et al. [19] weigh the outcomes of Mecagreen 450 biodegradable oil when applied in a flood form in the machining zone. The research reveals that the biodegradable oil integrated with flooded approach being a green alternative can work effectively compared to contemporary methods to improve the surface quality, tool life, and material removal rate for the slot milling of Inconel 718.

While there is a notable research on the machinability improvement aspects of Inconel 718 employing biodegradable oil in flooded conditions, there is no absolute machinability conditions to acquire an optimum output value. Consequently, the process optimization represents a current research need, particularly for a complex nonlinear system that depends on multiple input variables like the milling process. Considering that the production economy and part quality are the ultimate objectives for the manufacturers, the efficient and suitable utilization of input parameters is imperative for economic gains in the industry. This need extends the research domain in a new direction, i.e., optimization. In totality, the optimization techniques can adequately control the machining outcomes in favor of the manufacturer after identifying the significance between input and response variables. Among the dominant optimization approaches, the intelligent techniques are reputed more evolutionary, fast, highly accurate in approximation, and effective for nonlinear complex machining systems [21–23]. Similarly, this experimental investigation utilizes the optimization for surface roughness (SR) with respect to cutting speed (v_s), feed/flute (f_z), axial depth of cut (a_p), and eco-efficient cooling strategy, which is not reported before. The novelty of the present work includes effectively designing the input parameters for the required response attribute, i.e., surface roughness (SR), by a systematic comparison of results obtained from three different intelligent approaches.

In the field of optimization for the machining characteristics of Ni-based hard-to-cut materials, Gupta and Sood [24] improve turning operation for the aerospace alloys under MQL green approach. The authors apply particle swarm optimization (PSO) and bacteria forging optimization (BFO) evolutionary techniques and compare the results with desirability approach. The research concludes that PSO is the best among all with respect to processing time and percentage error. Ali et al. [25] optimize the turning process of the same superalloy under MQL mixed with Al_2O_3 nanoparticles. The study utilizes Taguchi-based signal-to-noise (S/N) ratio for the optimization and determines that 70 m/min cutting speed, 0.05-mm depth of cut, and 0.05 m/rev feed rate are optimal parameters for surface roughness. Similarly, Thirmalai et al. [26] use Taguchi-based optimization for the turning of Inconel 718 under wet (mineral oil-based) and dry conditions, considering surface roughness and flank wear as response attributes. The results reveal that the flood conditions produce better surface roughness and wear with 7% and 8% error, respectively.

The optimization of the milling process, which is widely used in various industries, becomes vital. Therefore, Jang et al. [27] optimize the process for dry and MQL-assisted milling using evolutionary techniques such as neural networks, and PSO with respect to energy optimization. The study determines that more specific energy reduction is possible under MQL and that the PSO is the preferred optimization tool with 1% error. Likewise, Pimenov et al. [28] apply artificial neural networks (ANN) and random forest for the optimization of face milling regarding wear and surface roughness. It is revealed that the random forest approach is more efficient with high accuracy. Zhou et al. [29] accomplish the multi-attribute optimization for Inconel 718 during the ball-end milling using grey relational analysis, ANN and PSO. Sing et al. [30] perform parametric optimization for tool wear while milling Inconel 718 under three different environments, i.e., dry, traditional wet (mineral oil-based) and MQL. The PSO and BFO methods are used to optimize the flank wear. The study reveals that the PSO and the MQL yield good results. More recently, Kar et al. [31] give multi-objective optimization for the CNC milling of Inconel 718 alloy through Fuzzy logic-based desirability approach. The optimum combination of 3500 rpm spindle speed, 100 mm/min feed rate, and 0.25-mm depth of cut are obtained for the required surface roughness and material removal rate.

Based on the literature, it is evident that the conducted research tackling the thermal ills during the machining of Inconel 718 with inclusion of ecofriendly cutting fluids is mostly dedicated to MQL, and intelligent optimization has been explored for either conventional flooded conditions embedded with traditional cutting fluids or MQL employing eco-efficient fluids. The addition of ecofriendly fluids in flooded strategy is critical, particularly in the machining of the high resistant super alloys Inconel 718 [15, 16, 19]. Moreover, the incorporation of intelligent optimization techniques is worth to consider as they can help determine the values of control parameters for desired machinability characteristics. Therefore, the proposed research presents a novel integrated green-RSM-based-evolutionary optimization (G-RSM-EO) approach that evaluates the advantages of synthetic vegetable ester-based biodegradable oil embedded with flooded method, and carefully determines the optimal values of the milling parameters (v_s, f_z, a_p) for a better surface quality, which is a fundamental requirement for aerospace and bioimplants applications. These surface quality or surface roughness (SR) values are then compared with the baseline values achieved under wet and dry machining environments. In addition, the optimization approach presents a systematic comparison of the results obtained from three different techniques, i.e., particle swarm optimization, genetic algorithm, and RSM-based desirability function approach. Lastly, the confirmatory milling (machining) tests are performed to validate the robustness of all the three intelligent methods. Figure 1 below provides a flowchart depicting all the steps of the G-RSM-EO approach employed in this research work.

2 Experimental conditions

This section addresses the experimental setup used for the milling of Inconel 718 under flooded conditions enriched with biodegradable oil. The extensive usage of Inconel 718 in aerospace and marine applications is the motivation for its selection as work piece material in this investigation. Table 1 indicates the spectroscopic results for the chemical composition of the alloy. The methodology adopted during this research is presented as a block diagram (see

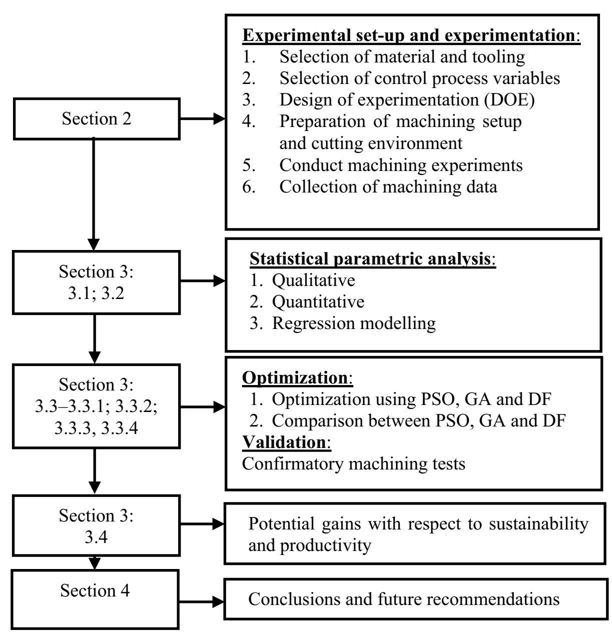

Fig. 1 Experimental methodology flowchart

Table 1 Spectroscopic results of elemental composition of Inconel 718

Element	C	Mn	S	Cu	Ni	Mo	Cr	Al	Ti	Nb	Si	Co	Fe
Weight (%)	0.03	0.08	0.00001	0.06	53.51	3.00	18.23	0.52	1.01	5.10	0.11	0.14	balanced

Fig. 1). The titanium aluminum nitride (TiAlN) coated micro-grained carbide inserts with wiper edge (0.4 mm tool nose radius, 90° flank angle, and 0.7 mm wiper edge length) were selected for the milling process on LG-800 Hartford CNC machining center. The manufacturer highly recommends these inserts for the interrupted cutting of high-strength alloys because they show low affinity towards work piece metal [32]. The inserts were securely fixed on a specially designed two-flute tool-holder to mill a 63 × 9.7 × 3 mm^3 slot. During the machining, new cutting inserts were used for each experiment to precisely evaluate the effects of process parameters on the machining response. The machining time (Tm) for each slot was noted using a stopwatch.

During this experimental work, ecofriendly cooling conditions using Mecagreen 450 synthetic vegetable ester-based biodegradable oil with a concentration ratio of 6% were applied. The 0.05 l/s flow rate was recorded using two nozzles, 2 mm in diameter each, at a 120° angle to target the machining zone at 20-bar pressure [19, 33]. The prominent machinability indicator or the surface roughness (SR) was calculated with the help of surface profilometer (WYKO NY 1100), and the established range of surface roughness for aerospace applications was set as a benchmark, i.e., 0.8 to 1.6 µm [34]. The arithmetic average (R_a) mode was selected for the SR measurements, and they were accomplished at three different positions on the milled slot (Fig. 2a–b), and the average of all three readings was calculated using Eq. (1) below and used in statistical analysis presented in the forthcoming section. The milling tests were carried out at three different levels of cutting speed (v_s), feed/flute (f_z), and axial depth of cut (a_p). Table 2 below presents the full description of the parameters with their levels. The selection of the parametric levels was purely based on the feedback from the pilot runs, the literature review, and the manufacturer recommendations [10, 30, 35].

$$\mathrm{Ra(slot)} = \frac{\mathrm{Ra(start)} + \mathrm{Ra(middle)} + \mathrm{Ra(end)}}{3} \tag{1}$$

The experiments were designed using the Box-Behnken response surface methodology (RSM), which recommends a set of 15 test runs. The Box-Behnken method was preferred over central composite design (CCD) due to its high-quality prediction capability for the fewer combinations of experimental runs with the focus to reduce the tooling cost [36, 37]. The milling tests were performed in three replicate sets (45 runs) to measure the dispersion in the data, which turned out to be insignificant. For baseline comparison purposes, additional experimental runs (Tests A and B) were carried-out under traditional wet approach using Hocut WS 8065 mineral oil at 6% concentration ratio and dry milling (as a green strategy) at v_s 60 m/min, f_z 0.10 mm/flute, and a_p 0.3 mm. A multiple regression model was developed to identify the parametric relevance (v_s, f_z, a_p) with the SR

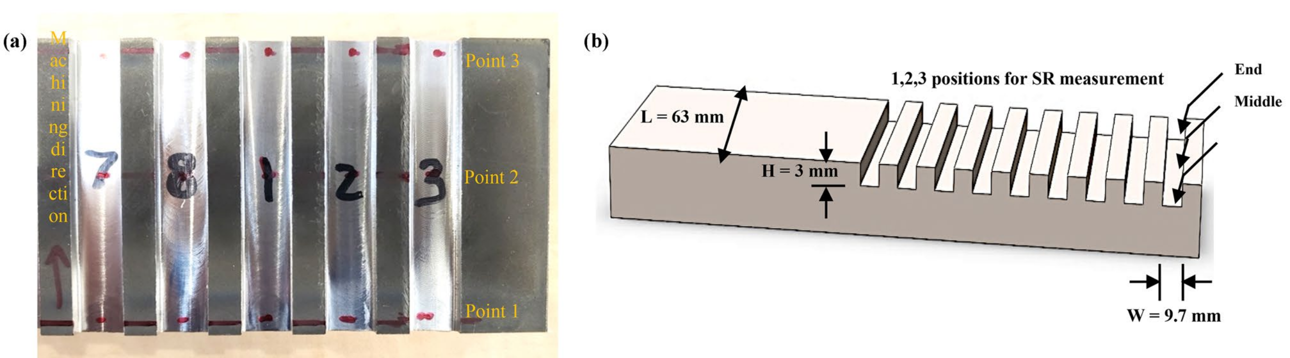

Fig. 2 Machining of Inconel 718 under biodegradable oil-enriched flooded environment: **a** Work piece after machining; **b** schematic of work piece

Table 2 Parametric details of experimentation during the current study

Parameters	Specifications
Cutting speed (v_s), m/min	60, 70, 80
Feed/flute (f_z), mm/flute	0.1, 0.15, 0.20
Axial depth of cut (a_p), mm	0.2, 0.3, 0.4
Tool hang, mm	32
Cutting environment	Biodegradable oil-assisted flooded approach
Flow rate for flooded conditions, l/s	0.05
Applied pressure, bar	20
Lubricant concentration, %	6
Cutting inserts	TiAlN coated micro-grained carbide inserts
Work piece alloy	Inconel 718

response attribute. The analysis of variance (ANOVA) and the residual analysis were performed to validate the statistical adequacy of the predicted model. Afterwards, an integrated G-RSM-EO approach was employed to optimize the SR with respect to three control parameters. Also, the obtained results were compared with Genetic algorithm (GA) and desirability function (DF) approach. The same range of parametric levels given in Table 2 was used for the PSO, GA, and the DF optimization. Lastly, the confirmatory machining tests were carried out at optimal parametric values obtained from the PSO, GA, and the DF. Moreover, the achieved work piece surface topography was analyzed using FEI Quanta 200F scanning electron microscope (SEM).

3 Experimental results and discussion

The experimental results for surface roughness and machining time of the Inconel 718 milling under green-flooded conditions, the statistical analysis, and the process optimization are all discussed systematically in the following subsections.

3.1 Parametric analysis of surface roughness

The response surface methodology (RSM) - an advanced design of experiments [38, 39] that helps to better understand and optimize the response - is employed during this study. The design matrix based on Box-Behnken's response surface methodology along with the average SR and Tm results is presented in Table 3. The surface roughness and machining time results for an additional experiment (Test A) are presented in Table 4.

For the sake of parametric analysis, the surface plots for the three control parameters are presented against SR (see Fig. 3a–c).

From Fig. 3a, the cutting speed (v_s) and the feed/flute (f_z) demonstrate a similar increasing behavior towards surface roughness, while the axial depth of cut (a_p) possesses a nonlinear trend (Fig. 3b). Figure 3a shows that there is an increment in Ra values with the increase in f_z and v_s values. The behavior in the case of f_z is expected. It can be explained based on a metal cutting phenomenon that f_z increases the pitch of the peaks and valleys generated on the machined surface (i.e., $R_a = f^2/32\ r$, where f is the feed rate and r is the tool nose radius). Moreover, the higher values of feed rate contribute to the tool vibration and excessive heat generation [40]. Consequently, tool wear

Table 3 RSM-based Box-Behnken layout with Ra and Tm values for Inconel 718 milled under green-flooded environment

Experimental run, #	Cutting speed v_s (m/min)	Feed/flute f_z (mm/flute)	Axial depth of cut a_p (mm)	Surface roughness Ra (µm)	Machining time Tm (s)
1	80	0.10	0.3	1.20	67
2	60	0.15	0.4	0.59	63
3	70	0.10	0.2	0.70	69
4	80	0.20	0.3	1.40	59
5	80	0.15	0.4	1.58	58
6	70	0.10	0.4	0.78	71
7	60	0.20	0.3	0.58	60
8	70	0.20	0.4	0.83	59
9	60	0.15	0.2	0.46	58
10	70	0.15	0.3	0.71	61
11	60	0.10	0.3	0.45	72
12	70	0.20	0.2	0.78	59
13	70	0.15	0.3	0.77	65
14	80	0.15	0.2	1.45	58
15	70	0.15	0.3	0.78	66

Table 4 Test A, Test B, Ra, and Tm values for Inconel 718 milled under mineral oil-flooded environment and dry environment

Experimental run	Cutting speed v_s (m/min)	Feed/flute f_z (mm/flute)	Axial depth of cut a_p (mm)	Surface roughness Ra (µm)	Machining time Tm (s)
Test A **Flooded + mineral**	60	0.10	0.3	1.7	71
Test B **Dry condition**	60	0.10	0.3	1.81	69

occurs due to the formation of built-up edges. In addition, considerable heat results in thermal softening of the work piece material. This ultimately yields work hardening due to sudden quenching, as machining was performed under the flooded conditions. The behavior of feed rate is consistent with other works [3, 40]. Zahoor et al. [40]reveal that the spindle vibrations and the feed rate are the most influencing variables for the surface roughness during the vertical milling of AISI P20 (a hard-to-cut material). Regarding the axial depth of cut (a_p), a nonlinear impact can be visualized (Fig. 3b). Firstly, Ra decreases, then increases. This initial decrease could be due to the chipping of tool nose [40].

In the case of cutting speed (v_s), a contradictory pattern has been observed. In general, smaller cutting speed values are associated with deteriorated surface finish [41]. Reportedly, at low v_s, high temperature production takes place, which traps heat in the machining zone due to the low thermal conductivity of Inconel 718 (11.2 W m^{-1} K^{-1} [42]). Further, the detrimental impacts of heat worsen due to ineffective dissipation of heat under the conventional cutting environments. Moreover, the work hardening property of

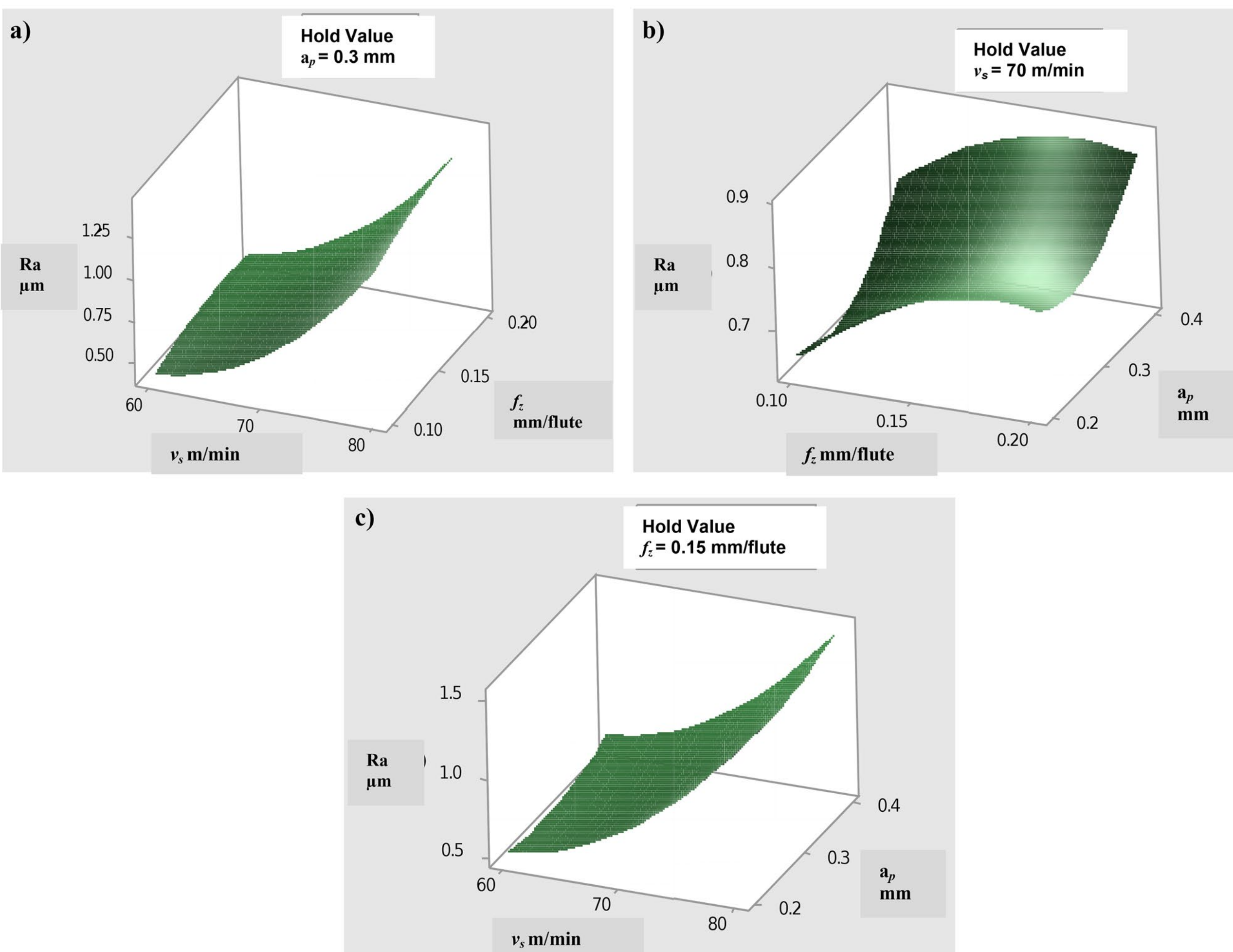

Fig. 3 Surafce plots for the Ra of Inconel 718: **a** cutting speed *vs* feed/flute; **b** feed/flute *vs* axial depth of cut; **c** cutting speed *vs* axial depth of cut

Inconel 718 reduces the machinability at high temperature, thus resulting in high Ra values. During the present study, the small Ra (0.45 µm) was achieved at low v_s (60 m/min). Although the surface roughness increases with v_s, lower Ra values (0.45–1.58 µm) are achieved as compared to studies reported on the milling of the same alloy under different cutting strategies, such as dry, conventional wet, MQL, and cryoMQL [3, 26]. For example, Qiang et al. [3] obtained Ra ranges from 2.5 to 3.5 µm under dry and 2.0 to 2.6 µm under MQL environments while milling the Inconel 718. This can be attributed to the biodegradable oil-enriched flooded approach that makes the milling process capable of producing a better surface finish, even at a low cutting speed of 60 m/min. This is due to the excellent lubricating and cooling characteristics of the biodegradable-assisted wet approach over other current methods. This green alternative enhances the heat dissipating ability of the cutting environment, thus flushing away most of the heat from the machining envelope. In addition, the Mecagreen 450 biodegradable cutting oil penetrates effectively into the tool-workpiece interface and develops a strong fatty acid adhesive cushion. The sliding effects of this adhesive film decrease the friction at the tool nose, eventually reducing the tool wear and improving the surface quality [10, 43]. These results are aligned with the previous work of Zahoor et al. [19].

To summarize, this biodegradable-assisted flooded approach shows an ability to improve the machining of Ni-based alloys in terms of sustainability and productivity (i.e., part surface quality and manufacturing cost reduction). With respect to eco-sustainability, the Mecagreen 450 is a responsive choice to the environment, machine tool, and machinist as it is fully made of renewable sources, completely boron free to anticipate health regulations, paraffin free thus providing stability from harmful bacteria, and it can be easily washed by alkaline solvent as compared to conventional methods utilizing mineral-based soluble fluids.

Regarding productivity, superior surface quality (0.45 µm) is obtained with the existing strategy compared to 1.7 µm when using Hocut WS 8065 mineral fluid and 1.81 µm under dry conditions (see Table 4 above), thus achieving a 73.5% surface quality improvement. The current approach offers a cost reduction associated with the cutting oil consumption. Only a 6% concentration ratio with water is recommended, which provides a 30–45% reduction in use as compared to mineral oils (10–20% concentration ratio). For instance, 180 l/h. flow rate is calculated according to the above-stated specifications (see Table 2). For an hour of machining, an approximate amount of \$54 for Mecagreen 450 (\$5 per liter) and \$94.5 for Hocut WS 8065 (\$3.5 per liter using an average of 15% concentration rate) were estimated yielding an average of 42.9% cost reduction in fluid consumption.

3.2 Statistical analysis and modeling

After analyzing the process parameters of the superalloy, the quantitative effects of these independent parameters, as well as the RSM model accuracy, have been determined using ANOVA. The analysis has been carried out at 95% confidence interval ($\alpha = 5\%$). To comprehend the impact of each parameter with respect to the response characteristics, the "*F*-value" was obtained using "higher-the-better" rule. Likewise, "R^2" suggests the significance of the model, i.e., the higher the "R^2", the better the model [24]. Table 5 presents the ANOVA results for the Ra of Inconel 718. It can be observed that the RSM model proves significant, because its "*p*-value" is less than 0.05. Additionally, the cutting speed (v_s) is identified as the most significant variable affecting Ra among all the three parameters with a higher "*F*-value." The

Table 5 ANOVA results for Ra of Inconel 718 milled under green-flooded approach using RSM-based Box-Behnken design matrix

Source	DF	Adjusted sum of squares	Adjusted mean squares	*F*-value	*P*-value	Remarks
RSM model	6	1.79525	0.299209	73.78	0.000	Significant
v_s	1	0.10538	0.105379	25.99	0.001	Significant
f_z	1	0.01153	0.011535	2.84	0.130	
a_p	1	0.01214	0.012141	2.99	0.122	
$v_s \times v_s$	1	0.14893	0.148926	36.72	0.000	
$f_z \times f_z$	1	0.00804	0.008041	1.98	0.197	
$a_p \times a_p$	1	0.01600	0.016003	3.95	0.082	
Error	8	0.03244	0.004055			
Lack-of-fit	6	0.02957	0.004929	3.44	0.242	Insignificant
Pure error	2	0.00287	0.001433			
Total	14	1.82769				
S		R^2	R^2 (adjusted)	R^2 (predicted)		
0.0636805		98.22%	96.89%	93.17%		

results from the other reported works are aligned with this research [24, 30]. It is also noted that the lack-of-fit is insignificant at a 95% confidence interval, depicting the robustness of the model, which is further validated by the "R^2" value that turned out to be an extremely high or 98.22%.

Afterwards, the statistical approach of regression analysis was employed to model a predictive equation based on the experimental data presented in Table 3 above using MINITAB 19.0. Equation (2) represents the developed regression model for Ra of the Inconel 718 milled under the Mecagreen 450 green fluid-enriched flooded condition.

$$\begin{aligned}\mathrm{Ra} = 7.34 &- (0.2368 \times v_s) + (6.75 \times f_z) - (3.46 \times a_p) \\ &+ (0.002008 \times v_s{}^2) - (18.7 \times f_z{}^2) + (6.58 \times a_p{}^2)\end{aligned} \tag{2}$$

Further, the validation of the developed regression model was performed to ensure its accuracy and adequacy. For the said purpose, different statistical tools are available but residual analysis is the most employed technique. Hence, the same approach is utilized in the present study to validate the predictive model for Ra. The basic working principle (Eq. (3)) of this technique is to calculate the difference between the achieved value of the response parameter and the predicted value of the same parameter through the regression Eq. (2) under the same cutting conditions.

$$e_i = R_{\mathrm{actual}} - R_{\mathrm{predicted}} \tag{3}$$

The residuals for the Ra of Inconel 718 difficult-to-cut-alloy considering a green wet approach were calculated and illustrated in Fig. 4. As it can be observed, the residuals appear in a straight-line pattern on the normal probability plot except a few points on both ends of the line, which are expected in the normal plot. While on the versus fit plot, the residuals scatter randomly suggesting that the predictive model fits the data well through approximating the error; thus, validating the regression equation. This Eq. (2) will serve as the objective function in the particle swarm optimization (PSO) algorithm.

3.3 Experimental optimization using RSM-based PSO, GA, and DF

This section will discuss the methodology and results of the proposed integrated G-RSM-EO approach and compare it with DF approach.

3.3.1 Particle swarm optimization

Various authors offered their contribution to optimize different machining processes using several traditional approaches

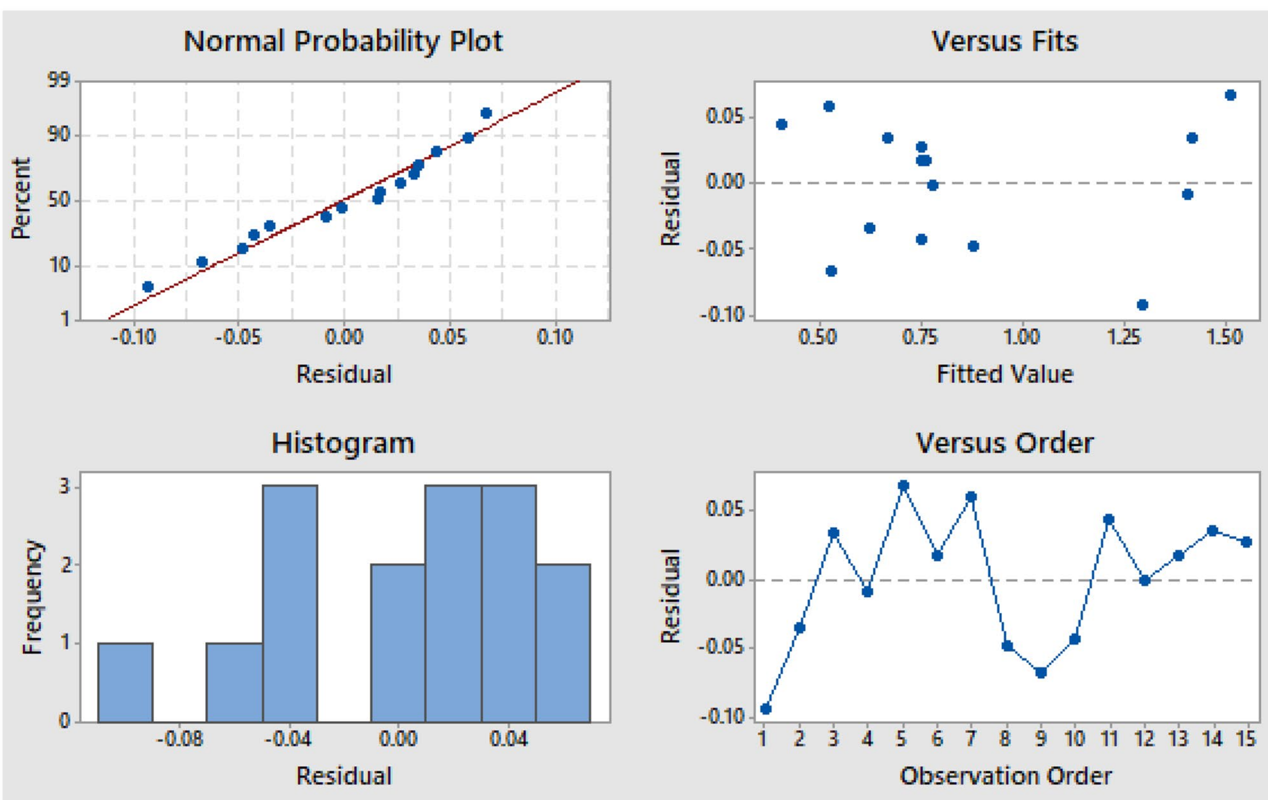

Fig. 4 Residual plots for Ra values of Inconel 718 superalloy

such as Taguchi signal-to-noise (S/N) ratios and grey relation analysis [25, 26, 29, 44]. However, drawbacks associated with the local optimal solution reduce their accuracy and robustness. To overcome these deficiencies, the adoption of evolutionary approaches is practical. The PSO is selected since it is an efficient and time saving evolutionary technique [45].

As mentioned earlier, PSO has been utilized successfully in certain research works using different cooling environments [27, 28, 31, 35]. However, no work is reported in which PSO has been employed for the milling of Inconel 718 under biodegradable-assisted flooded strategy. Hence, it gives an inspiration for the current experimental research to optimize the surface quality of Inconel 718. To obtain a global optimal, continuous type PSO classical variant technique was employed for the parametric optimization of surface roughness of Inconel 718. Further, the PSO results were compared with DF approach. The parameters v_s, f_z, and a_p were considered as the swarms/particles in PSO. The range of these control parameters was presented earlier in Table 2.

After a careful literature review [46–51], and multiple simulation runs, the PSO working parameters were selected and presented in Table 6.

The following are the PSO steps used to optimize the milling parameters during this study:

i. Creation and initialization of an array of 250 particles possessing random positions and velocities. The velocity vector has three components: cutting speed (v_s), feed per flute (f_z), and axial depth of cut (a_p). To avoid premature convergence of solution as well as long processing time [50, 51], a careful selection of 250 particle population size was made after performing multiple simulations. These simulation runs were tried with particle sizes 50, 100, 250, 500, 750, and 1000.

ii. PSO objective function (i.e., minimization of surface roughness with respect to each particle): the regression Eq. (2) presented in Sect. 3.2 above serves as the objective function and was inputted in the PSO program in MATLAB (R2020b) software.

Table 6 PSO working parameters

Input Parameter	Specification
Number of parameters	3
Population size/number of particles	250
Number of Iterations	100
Inertia weight, w	0.9 (max), 0.4 (min)
Acceleration factor, c1	1
Acceleration factor, c2	2

iii. New position of each particle was calculated using Eq. (4) [30]:

$$x_i^t = x_i^{t-1} + v_i^t \tag{4}$$

where v_i^t is the velocity of the "ith" particle at "t" iteration, x_i^t is the particle current position, and x_i^{t-1} is the particle previous position. The pbest value for each particle is replaced with the current value in case a better position is attained.

iv. Determination of gbest: if the particle finds a better *gbest* value (minimum surface roughness) than the previous one, it is updated and stored. If $f(x_i) < f(\text{gbest})$, then $f(\text{gbest}) = f(x_i)$ and $\text{gbest} = x_i$. The optimized value is a vector gbest having three components, i.e., v_s, f_z, and a_p.

v. Evaluation of particle's new velocity using Eq. (5) [30] and updating the new position towards achieving the objective function of minimum surface roughness.

$$v_i^t = wv_i^{t-1} + c_1 u1\left(\text{pbest}_i - x_i^t\right) + c_2 u2(\text{gbest} - x_i^t) \tag{5}$$

where w is the inertia weight, c_1 and c_2 are learning coefficients, $u1$ and $u2$ are random variables uniformly distributed (0, 1) to start the search, pbest_i stands for local best position of particle "i," and gbest presents the global best position. The inertia weight "w" was calculated using Eq. (6) [30].

$$w = w_{\max} - [(w_{\max} - w_{\min}) \times \text{itercurrent}] \tag{6}$$

where $w_{\max}$ and $w_{\min}$ are the maximum and minimum inertia weight, respectively, and $\text{iter}_{\text{current}}$ and $\text{iter}_{\text{total}}$ stand for current iteration and total number of iterations. All Eqs. (3)–(5) were inputted in the PSO program in MATLAB (R2020b) software.

vi. Repeating steps ii–v until the stopping criterion of a predefined iteration number was achieved, i.e., 100. To decide the stopping criterion, the established norms of the PSO technique were followed [24, 29, 30, 51, 52] and PSO for various stopping criteria ranging from iterations 5 to 120 was simulated.

Table 7 represents the optimized values of the objective function (fitness function = 0.3940 µm) up to 16 digits precision for stopping criteria of 5, 10, 30, 40, 50, 100, 110, and 120 iterations at 250 population size. From the fitness function precision, it is noted that the gbest value of fitness function (Ra = 0.3940 µm) is achieved at 100 iterations at v_s = 60 m/min, f_z = 0.10 mm/flute, a_p = 0.26 mm and no further improvements are observed at 110 and 120 iterations. The fitness function or evaluation function estimates

Table 7 PSO simulation results up to 16 digits precision for different stopping criteria

Simulation run	Particle size	Fitness function (μm)	Stopping criteria
1	250	0.393952056326780	5
2	250	0.393951976627593	10
3	250	0.393951975691943	30
4	250	0.393951975683928	40
5	250	0.393951975683892	50
6	250	0.393951975683889	100
7	250	0.393951975683889	110
8	250	0.393951975683889	120

that how close a given solution is to the optimum solution of the given problem. The fitness function value represents the specific type of objective function (i.e., minimization of surface roughness for the present research). The rounded-off optimized value of surface roughness (0.3940 μm) obtained from PSO is shown in Table 9 below.

3.3.2 Genetic algorithm

Genetic algorithm (GA) is considered as a novel method that provides a wide range of optimal settings of process control variables (parameters); hence, it offers flexibility to the machining operation. In this study, the GA optimization was accomplished to minimize the surface roughness of Inconel 718, which is one of the direct measures of process productivity. The main reason to select GA for the comparison with PSO is its discrete nature since it converts the process variables into binary ones; therefore, it can easily solve discrete problems such as machining [53], while PSO is continuous and needs to be modified for the discrete optimization problems.

The above-cited regression model (Eq. (2)) was used as an objective function, and the GA parameters (see Table 8) were set to run the optimization code. The range of the control parameters presented in Table 2 above was employed as the boundary limits. To observe the weighted average

Table 8 Setting parameters for GA used for the optimization of Ra

Setting parameter	Value
Selection function	Tournament of size 2
Crossover function	Uniform
Mutation function	Gaussian
Direction of migration	Forward with migration fraction of 0.2
Distance measure function	Distance-crowding
Population size	50
Stopping criteria	100 × number of input process variables

variation of fitness function, a stopping criterion of 500 generations was selected [54]. However, the optimal solution was achieved after eighteen iterations utilizing 3.56 min processing time and is presented in Table 9 below.

3.3.3 Desirability function approach

DF is an optimization technique introduced by Suich and Derringer in 1980. The approach finds the optimum parametric combinations targeting the desired values of response attributes. Here, in this approach, each response attribute is converted into an individual desirability function d_i which ranges from $0 < d_i < 1$. The desirability function has three categories: (i) smaller-the-better, (ii) greater-the-better, and (iii) target-the-better. In this present work, the objective function and surface roughness were optimized using smaller-the-better desirability function as per Eq. (7).

$$d_i(Y_i) = \begin{cases} 1.0 & if\ \mathrm{Y}_i(x) < \mathrm{T}_i \\ \left(\frac{Y_i(x)-U_i}{T_i-U_i}\right)^s & if\ \mathrm{T}_i \le \mathrm{Y}_i(x) \le \mathrm{U}_i \\ 0 & if\ \mathrm{Y}_i(x) > \mathrm{U}_i \end{cases} \quad (7)$$

where $d_i(Y_i)$ is the desirability function for "Y_i" response attribute; i.e., Ra, T_i, and U_i are the target and the upper values of control parameters (v_s, f_z, a_p), respectively; s is the function values; i.e., linear, convex, and concave.

During the DF approach, all the three control parameters (v_s, f_z, a_p), were permitted to vary to the full range of their variability and the combined goal was chosen to be minimized (using Eq. (7)), i.e., SR, in MINITAB 19.0. Figure 5 graphically demonstrates the optimization process performed under the desirability function approach with an ideal composite desirability function value of 1. In Fig. 5, the optimal level of each control process is indicated in red as the current value to achieve a minimum Ra of 0.4117 μm (see Table 9 below).

Table 9 compares the optimal values of the control and response parameters obtained from the three different optimization approaches, i.e., PSO, GA, and DF. It can be clearly noticed that all the three optimization methods yield different results for the SR of Inconel 718 using Mecagreen 450 wet cutting conditions. Further, it is important to note that optimal Ra = 0.3940 μm (PSO), Ra = 0.4110 μm (GA), and Ra = 0.4117 μm (DF), are obtained at v_s = 60 m/min, f_z = 0.10 mm/flute, and a_p = 0.26 mm.

3.3.4 Validation through confirmatory milling test

To validate the results produced by PSO, GA, and DF approach, Table 10 lists the experimental results of the confirmatory milling tests that are carried out on the CNC machining center (LG-800 Hartford) under three different

Table 9 Comparison of results obtained from PSO, GA and DF modeling approaches

Optimization approach	Cutting speed, v_s (m/min)	Feed/flute, f_z (mm/flute)	Axial depth of cut, a_p (mm)	Surface roughness, Ra (μm)	Processor time (min)	Improvement in response attribute (%)
PSO	60	0.10	0.26	0.3940	3.19	12.44
GA	60	0.10	0.26	0.4110	3.56	8.67
DF	60	0.10	0.26 (0.2566)	0.4117	6	8.51

environment, i.e., G-RSM-EO, flooded + Mineral oil, and dry. The confirmatory machining runs were performed in three replicate sets for each environment to measure the dispersion. From Table 10, it is obvious that the achieved experimental value of Ra (0.3942 μm) is very close to the PSO predicted value for all the three cutting conditions. Thus, confirming that the PSO provides a better accuracy over the GA and DF approaches with very small error (0.05%). It can also be noted from Table 10 that the PSO reading (0.3940 μm) is practically like the experimental Ra value (0.3942 μm). This very small percentage error can be attributed to the surface profilometer precision limitation.

It is important to note that the optimized (predicted) Ra obtained at $v_s = 60$ m/min, $f_z = 0.10$ mm/flute, and $a_p = 0.26$ mm is close or even better than the post-polishing processes that are employed to improve the surface quality of Inconel 718 parts [55–58]. Moreover, the G-RSM-EO approach improves the productivity through reducing the machining time. The average machining time before optimization was 63 s/slot (see Table 3 above). This time has reduced to 52 s/slot, thus achieving a saving of 17.5% of machining time.

$$\mathrm{Error}(\%) = \frac{\mathrm{Rapred} - \mathrm{Raexp}}{\mathrm{Rapred}} \times 100$$

Additionally, the SEM image of surface topography of confirmatory tests of the Inconel 718 workpiece milled under Mecagreen 450 biodegradable-enriched flooded environment (Fig. 6a) reveals that a fine surface is achieved at the optimized parametric values $v_s = 60$ m/min, $f_z = 0.10$ mm/flute, and $a_p = 0.26$ mm. A very few traces of built-up-layer (BUL) with clear feed marks can be easily observed compared to the surface obtained under flooded approach integrated with mineral oil and dry conditions, respectively. Figure 6b–c reveals that the tearing, microcrack, and BUL are the prominent topographical features of the machined surface. The excessive formation of BUL can be observed in case of dry machining, thus confirms the achieved surface roughness results. These results can be explained on the basis that tearing and BUL are attributed to the improper flushing of metal chips. The excessive heat generation during the machining of Inconel 718 causes the chip material to melt and stick with the machined surface [19]. Consequently, this leads to the formation of built-up-layer (BUL).

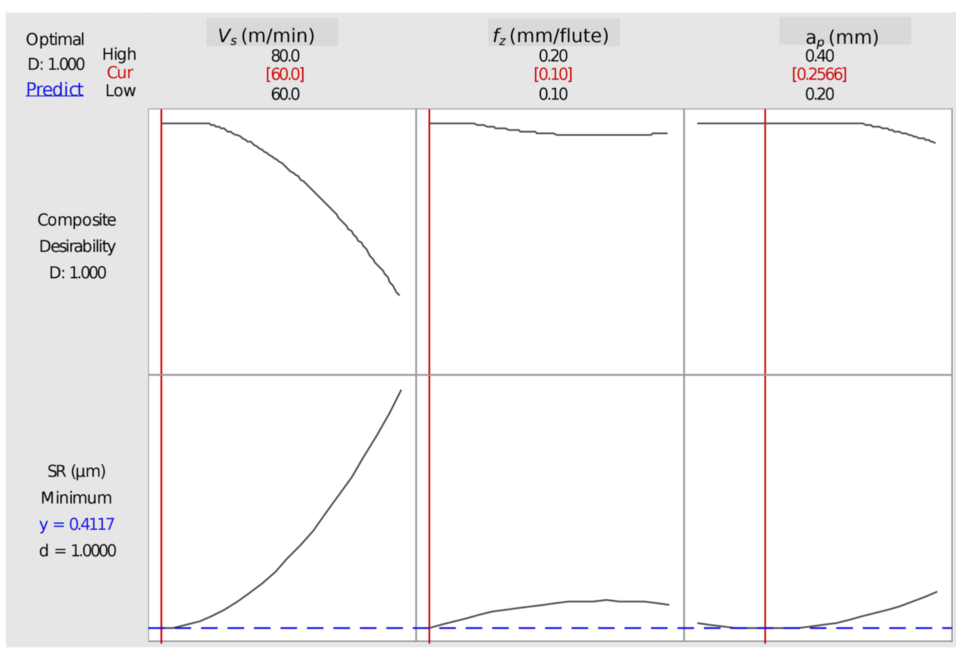

Fig. 5 Ra optimization using RSM-based desirability function approach

Table 10 Comparison of experimental results of confirmatory milling tests for Ra of Inconel 718 under three different cutting environments

Cutting environment	Cutting speed, v_s (m/min)	Feed/flute, f_z (mm/flute)	Axial depth of cut, a_p (mm)	Ra pred by PSO (µm)	Ra pred by GA (µm)	Ra pred by DF (µm)	Ra exp (µm)	Error PSO (%)	Error GA (%)	Error DF (%)
G-RSM-EO	60	0.10	0.26	0.3940	0.4110	0.4117	0.3942	0.05	−4.08	−4.25
Flooded + mineral	60	0.10	0.26	0.3940	0.4110	0.4117	0.3990	1.2	−2.91	−3.08
Dry	60	0.10	0.26	0.3940	0.4110	0.4117	0.4010	1.7	−2.43	−2.60

Ra pred Ra-predicted; *Ra-exp* Ra-experimental

The BUL is more aggressive in case of dry machining due to the absence of flushing mechanism, while the microcracks happened due to sudden quenching when machining is performed under the flooded conditions.

3.4 Potential gains with respect to sustainability and productivity

Inconel 718 is widely used in airfoils, pressure vessels of aircraft engine, critical rotating components, and bioimplants. Accordingly, improving machined surface quality and reducing manufacturing cost are a vital concern of the manufacturing community. Moreover, sustainable machining encourages the use of alternative strategies, which are ecofriendly as well as efficient to the machining gains. The experimental results of the current study show that G-RSM-EO approach produced better results in terms of surface roughness and machining time as compared to flooded approach integrated with mineral oil and dry approach. A comparison of the proposed G-RSM-EO approach to its counterparts is presented in Table 11 below.

Recently, additive manufacturing (AM) is considered as a gateway to the sustainable manufacturing of Inconel 718 for aerospace and bioimplant markets. One inherent disadvantage of AM is that it fosters a need to incorporate the post-finishing operations to meet the surface quality requirements for final products. The literature indicates that several methods are currently employed such as milling, grinding, electropolishing, and drag finishing. To further enlighten the significance of proposed G-RSM-EO strategy, a comparison of the G-RSM-EO approach is also made with several AM variants and is presented in Table 11, separately.

From Table 11, the one-to-one comparison G-RSM-EO approach with base-line techniques (flooded + mineral oil and dry approach) reveals that it enables the conventional milling operation to produce a better surface quality compared to its counterparts as well existing non-conventional manufacturing methods. Although there is not an available one-to-one cost comparison, the current approach presents substantial advantages over advanced manufacturing operations (i.e., AM and its variants) with respect to the following significant cost factors: (i) post-finishing operation cost, (ii) AM equipment cost itself, and (iii) raw material cost due to lack of economy of scale as the literature reveals that AM is limited to small batch production environment [59, 60]. Moreover, the G-RSM-EO approach can anticipate a promising post-finishing operation to machine the near-net shape complex profiles for the above-mentioned applications. Further, G-RSM-EO strategy reveals a 12.44% SR improvement (see Table 9) and 17.5% savings in machining time.

Additionally, the proposed cooling approach demonstrates several gains regarding sustainability and productivity. As indicated earlier, it provides a 42.5% cost reduction associated

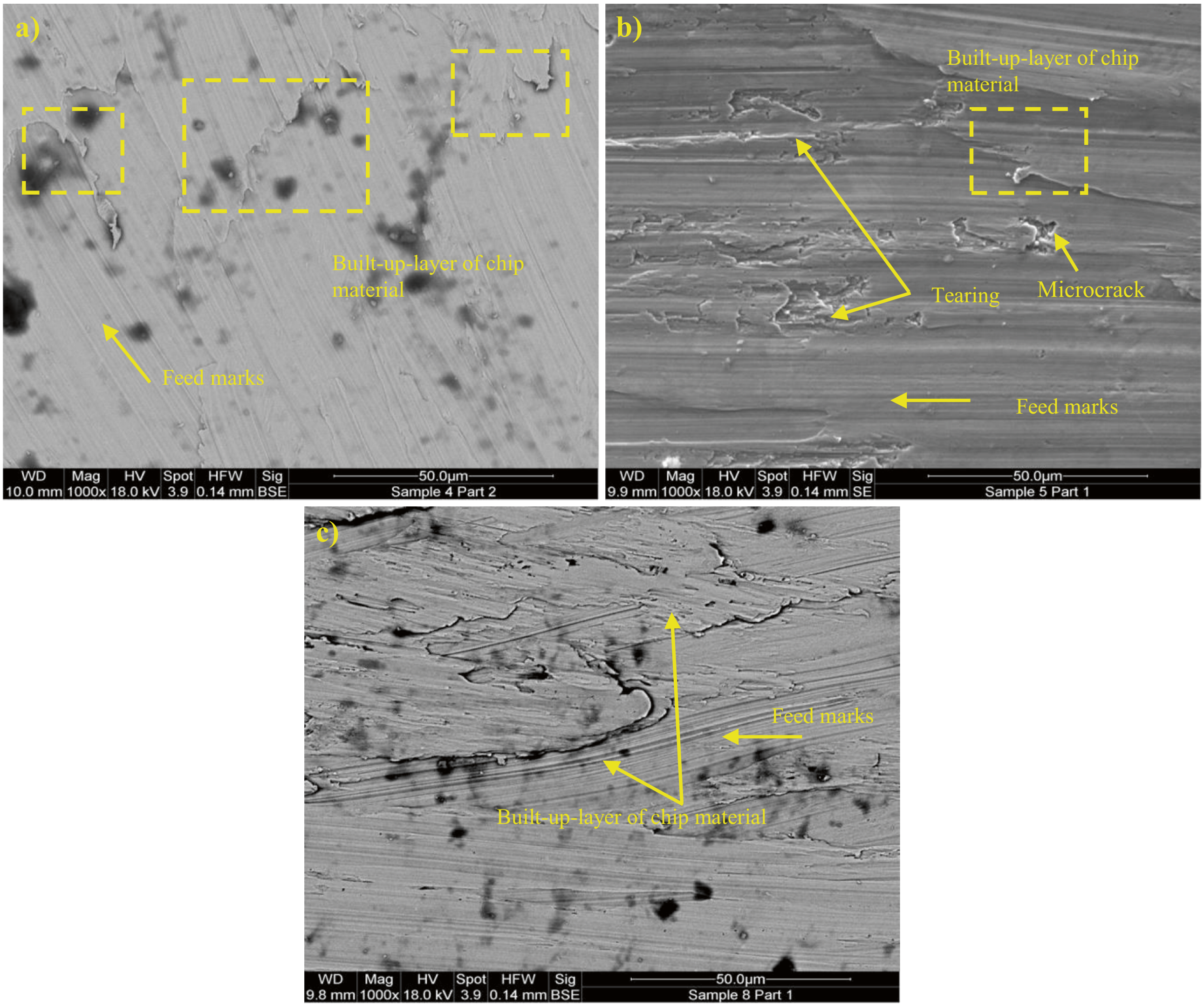

Fig. 6 SEM image for surface topography at 60 m/min v_s, 0.10 mm/flute f_z, and 0.26 mm a_p optimized parameters given by PSO, GA, and DF; **a** under G-RSM-EO**, b** under flooded approach integrated with mineral oil, and **c** under dry environment

Table 11 Surface roughness comparison of G-RSM-EO to its counterparts and additive manufacturing (AM) variants

Approach	Workpiece material	Achieved Ra (μm)
G-RSM-EO	Inconel 718	0.39
RSM-EO under flooded + mineral oil strategy	Inconel 718	0.41
RSM-EO under dry approach	Inconel 718	0.41
Comparison with AM variants		
Main manufacturing process: laser melting AM Post-finishing process: conventional flooded milling [54]	Inconel 625	1.28
Main manufacturing process: AM Post-finishing process: grinding [55]	Inconel 718	0.5
Main manufacturing process: laser powder bed fusion AM Post-finishing process: electropolishing [56]	Inconel 718	~3
Main manufacturing process: selective laser melting AM Post-finishing process: drag finishing operation [58]	Inconel 718	2.56

with the cutting oil consumption and 73.5% surface quality improvement compared to the traditional wet strategy.

4 Conclusions and suggested future research

This research work undertook various experiments and tests while milling Inconel 718 alloy by considering an integrated G-RSM-EO approach with Mecagreen 450 biodegradable cutting fluid. Based on the experimental outcomes, statistical analysis, and parametric optimization, the following can be noted:

1. The milling process of Inconel 718 in terms of surface roughness (SR) has been considerably improved under the proposed G-RSM-EO evolutionary cutting approach. This research work presented a green alternative offering the advantages of superior cooling attributes of flooded condition, ecofriendly traits of biodegradable oil as a cutting fluid, and process optimization by particle swarm optimization (PSO) technique.
2. The parametric analysis reveals that as cutting speed and feed/flute increase, the surface roughness increases. A contradiction lies in the cutting speed behavior, as high surface roughness values are traditionally associated with low cutting speeds when milling Inconel 718. Thus, it can be claimed that the presently employed cooling strategy enables the milling operation to produce better surface quality even at low cutting speeds.
3. Through ANOVA analysis, it has been demonstrated that the surface roughness was more sensitive to the cutting speed with higher "F-value" during the milling of Inconel 718.
4. The Mecagreen 450 assisted cooling approach proves itself as a sustainable alternative through yielding a 42.5% cost reduction in cutting oil consumption and 73.5% enhancement in surface quality of the machined part compared to the mineral oil (Hocut WS 8065)–assisted conventional wet approach, and dry green machining approach.
5. The optimization results show that 60 m/min cutting speed, 0.10 mm/flute feed, and 0.26 mm axial depth of cut were the best values of the control parameters suggested by particle swarm optimization (PSO) to achieve a 0.3940-μm Ra at 52 s/slot machining time (Tm). Based on these values, 12.44% and 17.5% reduction in surface roughness and Tm have been obtained, respectively. These results have been validated through confirmatory milling tests with 0.05% error. The achieved surface quality is better than the one produced through post-polishing operations, which are employed to achieve the desired surface quality of Inconel 718 components for aerospace and biomedical applications.
6. The PSO approach shows better performance for all the three environments in terms of accuracy (0.05%, 1.2%, and 1.7%, respectively), adequacy, and processing time (3.19 min) in determining the optimal solution compared to GA (accuracy 4.08%, 2.91%, and 2.4%, respectively; processing time 3.56 min) and DF approaches (accuracy 4.25%, 3.08%, and 2.60%, respectively; processing time 6 min).

To summarize, the findings are dedicated to Inconel 718 superalloy, a specific mill cutter and a cooling method though. The proposed approach can be utilized for other similar materials such as different grades of Ni-based alloys, and titanium and its alloys. Regarding optimization, aerospace and biomedical manufacturing industries will directly benefit from the proposed integrated G-RSM-EO approach by designing cost-effective machining of Inconel 718.

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Availability of data and material It will be provided on request.

Code availability It will be provided on request.

Declarations

Conflict of interest The authors declare no competing interests.

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