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Advancing Sustainable Machining of Inconel 718 through Nanoparticle-Enhanced Coconut Oil and RSM–GA Optimization

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Abstract

Motivated by the growing imperative for greener and more sustainable machining practices, this investigation evaluates the potential of eco-benign lubricants to mitigate frictional interactions at the tool–workpiece interface. Particular attention is directed toward nanofluids derived from vegetable oils, which are examined as viable and environmentally responsible substitutes for conventional metalworking fluids. In the present study, coconut oil was systematically enhanced by dispersing alumina and silica nanoparticles in the range of 0–1.4%, after which the prepared nanofluid samples were thoroughly examined using spectroscopic techniques to determine the formulation with the highest dispersion stability. Hard milling trials on Inconel 718 were then carried out under four distinct lubrication environments: dry cutting, pure coconut oil, coconut oil enriched with 0.8% alumina nanoparticles, and coconut oil containing 0.8% silica nanoparticles. Among these conditions, the alumina-based nanofluid delivered the most pronounced improvements, achieving decreases of 43.089% in surface roughness, 27.397% in cutting force, 23.437% in cutting temperature, and 45.833% in tool wear relative to dry machining. Capitalizing on the superior capability of this nanofluid, a Taguchi L27 experimental framework was subsequently executed under the optimal lubrication condition, and the resulting data were further optimized using a Genetic Algorithm to determine the best combination of machining parameters. Experimental confirmation of the optimized parameters showed strong alignment with model predictions, with the average deviation limited to just 2.6%. Overall, the findings clearly demonstrate that nanoparticle-infused bio-lubricants substantially enhance machining performance, extend tool longevity, and offer a promising pathway toward more sustainable manufacturing practices.

Keywords: Nickel alloy; Nanoparticles; Coconut oil; Machining responses; Genetic algorithm

1. Introduction

Nickel-based superalloys containing elevated chromium concentrations are widely recognized for sustaining remarkable mechanical integrity and thermal stability even under extreme thermal loads. Owing to this robust performance, they have become critical materials in highly demanding applications, including aerospace hardware, marine propulsion units, and gas turbine systems. Paradoxically, the very attributes that enable their outstanding high-temperature performance also contribute to their inherently poor machinability, creating substantial obstacles during manufacturing. To address these limitations, numerous strategies have been investigated, with synthetic lubricants emerging as one of the most practical and widely explored solutions [1]–[3]. At the same time, the global shift toward environmentally conscious and sustainable manufacturing has prompted industries to align their machining practices with ISO 14000 guidelines, which emphasize reducing operational costs, maximizing resource utilization, and minimizing ecological impacts [4], [5]. Aligned with these emerging demands, Minimum Quantity Lubrication (MQL) has increasingly been recognized as a powerful substitute for traditional lubrication practices. Its ability to enhance machining performance while simultaneously supporting broader sustainability goals has drawn substantial attention from both academic researchers and industry professionals [6]–[10].

Vegetable oils have gained substantial attention in MQL applications owing to the superior lubricity imparted by their intrinsic polar functional groups. Despite these advantages, their performance often diminishes at elevated temperatures, where auto-oxidation accelerates molecular breakdown and restricts their effectiveness as cutting fluids [11], [12]. To overcome these thermal limitations, extensive research has focused on incorporating nanoparticles into vegetable-oil bases, resulting in marked enhancements in lubrication, thermal regulation, and overall machining stability [13]–[15]. Pioneering research by Zhang et al. [16] first established the viability of this approach by incorporating MoS_2 nanoparticles into rapeseed, palm, and soybean oils, which yielded marked reductions in friction and substantial enhancements in surface integrity. Subsequent investigations by Jia et al. [17], utilizing soybean and castor oils enhanced with MoS_2 nanoparticles, substantiated the earlier findings by showcasing notable enhancements in key machining parameters.

Building upon this trajectory, Singh et al. [18] introduced bio-lubricants infused with graphene for grinding operations on titanium alloys, revealing that a robust and persistent lubricating layer significantly boosted grinding efficiency. Simultaneously, Gajrani et al. [19] optimized eco-friendly lubricant formulations incorporating CaF_2 and MoS_2, identifying 0.3% MoS_2 as the most effective concentration for performance improvement. In a related study, Singh et al. [20] evaluated the dispersion of graphene, graphite, and MoS_2 in canola-oil-based nanofluids for grinding aluminum–titanium alloys, with results indicating that graphene achieved the greatest reduction in both cutting forces and surface roughness. Pal et al. [21] reinforced these observations, showing that graphene-modified vegetable oils markedly lowered thrust force, torque, and friction during drilling of AISI 321 steel. Additional studies have consistently affirmed the advantages of nano-MQL systems. Sirin et al. [22] reported enhanced machining efficiency and reduced tool wear when turning nickel alloys, while Öndin et al. [23] demonstrated that MWCNT-based nanofluids delivered superior surface finish and minimized thermal loads during machining of martensitic steel. Collectively, this body of evidence positions nano-reinforced vegetable oils as a promising and sustainable alternative to conventional lubricants, offering improved machinability while promoting environmentally responsible manufacturing. To support this understanding, Table 1 provides a concise overview of commonly used nanofluids, their roles, benefits, and associated limitations.

Table 1: Comparison of different types of nanofluids used in machining applications

Type of Nanofluid	**Common Examples**	**Significance in Machining**	**Key Benefits**	**Limitations**
Metal-oxide-based	Al_2O_3, SiO_2, TiO_2, ZnO	Improve heat dissipation and tool cooling at the cutting interface	• High thermal conductivity • Better wear resistance • Reduced	• Agglomeration at high concentration • Increased viscosity can

			cutting temperatures	clog MQL nozzles
Carbon-based	Graphene, CNTs, Graphite	Provide superior lubrication through protective tribo-film formation	• Reduced friction & cutting forces • Better surface finish • Enhanced tool life	• Higher cost • Poor dispersion stability • Requires surfactants for homogeneous mixing
Hybrid nanofluids	Al_2O_3 + MoS_2, CNT + Graphene, TiO_2 + Graphite	Combine cooling and lubricating properties of multiple nanoparticles	• Synergistic improvement in lubrication & heat transfer • Optimized surface quality • Improved machinability of hard alloys	• Complex preparation process • Optimizing ratios is challenging • Stability issues if improperly mixed
Bio-based	Coconut oil + Al_2O_3, Sunflower oil + MoS_2, Castor oil + Graphene	Eco-friendly alternative to synthetic lubricants; supports green manufacturing	• Biodegradable & non-toxic • Excellent natural lubricity due to polar compounds • Supports ISO 14000 sustainability standards	• Oxidative degradation at high temperatures • Lower thermal stability without nanoparticle reinforcement

Recent developments in manufacturing science increasingly emphasize the use of computational optimization frameworks to enhance machining efficiency and overall productivity [24]. The progression toward more sophisticated optimization methodologies is exemplified in the work of Shi et al. [25], who formulated a combined Taguchi–grey relational analysis framework to identify the most effective dry milling parameters for magnesium alloys. In their methodology, Taguchi signal-to-noise ratios were initially used to screen the most favourable parameter settings for achieving desirable surface roughness and microhardness. This preliminary selection was subsequently refined through grey relational analysis, enabling a more nuanced multi-response optimization. ANOVA results revealed that feed rate exerted the greatest influence on surface integrity, a conclusion further supported by confirmation trials that closely aligned with the model's projected enhancements. Complementing this line of research, Coppel et al. [26] introduced an adaptive control optimization (ACO) strategy capable of simultaneously monitoring tool wear and reducing overall machining costs in micro-machining operations involving hardened steel. By incorporating a suite of evolutionary algorithms—including particle swarm optimization (PSO), genetic algorithms (GA), and simulated annealing (SA)—their framework significantly strengthened process accuracy as well as system reliability. Among the tested algorithms, PSO displayed superior computational efficiency. Implementation of the ACO strategy reduced machining costs by 12.3% compared with conventional machining and by 29% relative to high-volume production scenarios. Malghan et al. [27] extended the scope of hybrid optimization by coupling particle swarm optimization (PSO) with response surface methodology (RSM) to fine-tune milling parameters for metal matrix composites. Using a central composite face-centered design, they rigorously evaluated how spindle speed, feed rate, and depth of cut shaped key machining outputs, including surface roughness, cutting force, and power consumption. The regression results identified spindle speed as the dominant parameter, and the PSO-optimized conditions closely matched those generated through desirability-based optimization. This alignment demonstrated the effectiveness of the integrated approach in significantly enhancing machining performance. In a related advancement, Cica et al. [28] carried out an extensive study on high-pressure jet-assisted turning of Inconel 718 using coated carbide inserts. The investigation utilized a Taguchi L27 experimental layout to systematically vary and optimize the principal process parameters, namely nozzle diameter, jet pressure, jet impingement distance, feed rate, and cutting speed. By integrating grey relational analysis with a genetic algorithm, the authors established an effective multi-objective optimization strategy that simultaneously improved six machining performance indicators, such as material removal rate and surface roughness. The incorporation of the analytic hierarchy process to establish response weights added further rigor to the optimization methodology, which was subsequently verified through confirmation experiments. Building on these advancements, Sen et al. [29] introduced an innovative three-tier computational framework that seamlessly combines gene expression programming (GEP), NSGA-II, and the TOPSIS decision-analysis approach to identify the most advantageous machining parameter configuration. In this scheme, GEP-derived predictive models form the analytical basis for NSGA-II to generate the Pareto-optimal set, after which TOPSIS is employed to extract the most balanced solution from the resulting trade-off surface. Achieving a mean prediction deviation of just 3.13%, the integrated framework exhibits strong predictive fidelity and robust methodological performance.

Escalating disposal costs and the environmental risks associated with synthetic lubricants have intensified global efforts to adopt more sustainable alternatives, aligning with the vision of “go green, think green, and act green.” In machining research, recent studies have demonstrated the effectiveness of artificial intelligence (AI)-driven predictive modeling in identifying optimal cutting conditions, thereby enhancing efficiency while reducing operational costs. Nature-inspired optimization techniques such as GA, SA, and PSO have been widely applied, with the genetic algorithm (GA) being particularly favoured due to its robustness in solving complex optimization problems. However, most existing studies address nanofluid development and optimization strategies independently, with limited emphasis on establishing a direct linkage between lubricant characteristics and machining performance. To address this gap, the present investigation proposes an integrated and application-specific framework by combining detailed characterization of coconut oil-based nanofluids enriched with alumina and silica nanoparticles with a coupled RSM–GA optimization approach. The empirical models developed using

Response Surface Methodology (RSM) are consolidated into a unified objective function and subsequently optimized through GA to identify globally optimal machining conditions. Furthermore, the study uniquely correlates the thermophysical and tribological properties of the developed nano-enhanced bio-lubricant with key machining responses such as surface quality, tool wear, and cutting performance under sustainable conditions. A confirmation experiment is conducted to validate the reliability and practical applicability of the proposed framework. This integrated approach not only distinguishes the present work from existing literature but also contributes to advancing sustainable manufacturing by bridging the gap between nanofluid design and machining optimization.

2. Materials and Methods

2.1. Formulation and Stabilization of Nanoparticle-Enhanced Green Lubricants

Coconut oil was chosen as the primary medium for formulating the nano-green lubricants due to its intrinsic biodegradability, excellent lubricity, strong oxidative stability, and relatively high thermal conductivity compared with many conventional cutting fluids. These attributes collectively establish coconut oil as an environmentally conscious and technically advantageous option for sustainable machining applications. To formulate the nano-green lubricants, high-grade coconut oil served as the carrier medium into which nano-alumina and nano-silica particles (average size: 40 nm) were incorporated. The nanoparticle volume fraction was adjusted in a controlled manner across the 0–1.4% range. A refined two-stage dispersion methodology [30] was adopted to achieve a stable and uniformly dispersed nanofluid. Initially, the mixture of oil and nanoparticles was homogenized through magnetic stirring using an Abdos® MS-H280-Pro setup. The pre-stirred suspension then underwent probe ultrasonication with a Johnson Plastosonic ITB-32D4A76D unit, ensuring effective de-agglomeration and improved particle uniformity within the medium. To reinforce the colloidal stability of the formulation, polysorbate 80 was added at 0.3% as a surfactant, while vitamin E (tocopherol) was incorporated to mitigate oxidative degradation of the base oil. After preparation, the nanofluids were subjected to dispersion and stability assessment using a SHIMADZU UV-1800 UV-Vis spectrophotometer. Samples held in cuvettes were irradiated with electromagnetic waves, and the resulting absorbance values—direct indicators of nanoparticle concentration and suspension uniformity—were analysed to assess agglomeration tendencies and overall dispersion stability. Comparable assessment techniques have been documented in the characterization of nanofluids for hard-turning operations [31]. The thermo-physical properties of the prepared lubricants—namely thermal conductivity and viscosity—were measured using a UVSAR SYSTRONICS-304 digital thermal conductivity meter and a Brookfield DV2T Extra viscometer, respectively. The noted rise in thermal conductivity and overall heat-dissipation capability is consistent with earlier findings reported for TiO_2-based nanofluid mist cooling during machining of hardened AISI D2 steel [32]. In parallel, recent investigations have also documented superior lubricity and enhanced machining responses when SiO_2-dispersed coconut-oil nanofluids are utilized [33].

2.2. Machining Setup, Cutting Conditions, and Process Parameters

Milling experiments were performed on an Inconel 718 specimen with dimensions of 60 × 15 × 10 mm using a CNC milling platform. The alloy's chemical composition, relevant to this investigation, is summarized in Table 2. Cemented carbide end mills—selected for their robustness and consistent performance under severe cutting conditions—were used, and their specifications are provided in Table 3. A carefully optimized nano-green lubricant formulation was employed for the MQL strategy, chosen only after evaluating its thermo-physical characteristics to ensure enhanced lubrication capability. The MQL unit incorporated in the setup consists of a dual-pump configuration connected to a 5 L reservoir and operates with compressed air assistance. Lubricant delivery occurs through a mist-spray system engineered to function effectively across a temperature span of −25 °C to 75 °C. The equipment offers fine control over operating air pressure within the 5–15 bar range, and the lubricant flow rate can be modulated between 0 and 300 mL/h. Compatible lubricants for this arrangement typically exhibit kinematic viscosities in the range of 25–150 cSt. Following the guidelines reported in earlier investigations [34], the primary MQL parameters were kept constant for all machining trials.

The experimental framework was established using the Taguchi design strategy, wherein an L_{27} orthogonal array was implemented to methodically investigate the influence of three principal machining variables: cutting speed (Vc: 60, 80, 100 m/min), feed rate (fz: 0.05, 0.15, 0.25 mm/tooth), and depth of cut (ap: 0.2, 0.6, 1.0 mm). The selection of these parameter levels was guided by a combination of tool manufacturer recommendations, evidence from prior scholarly investigations, and insights obtained from preliminary machining trials. This approach ensured the adoption of stable cutting conditions, optimal machining performance, and improved tool longevity. Moreover, the chosen ranges reflect realistic industrial practices typically applied in the machining of Inconel 718. To strengthen the robustness of the experimental outcomes, each run within the L_{27} array was replicated three times under identical conditions. The mean values of the measured responses were subsequently computed for analysis, while the corresponding standard deviations were used to evaluate measurement variability. These repeatability results, along with the relevant error metrics, have been incorporated into the revised manuscript to enhance clarity, transparency, and completeness.

Table 2: Constituent Elements of Inconel 718

Element	**Weight %**
Nickel (Ni)	52.5
Chromium (Cr)	19.0
Iron (Fe)	17.0
Niobium (Nb)	5.1
Molybdenum (Mo)	3.0

Titanium (Ti)	1.0
Aluminum (Al)	0.5
Cobalt (Co)	0.2
Carbon (C)	0.04
Manganese (Mn)	0.2
Silicon (Si)	0.2
Sulfur (S)	0.005
Phosphorus (P)	0.01
Copper (Cu)	0.245

Table 3: Technical details of the end-mill

Category	Parameter	Specification
Material	Base Material	Cemented Carbide
Geometry	Diameter	6 mm
	Overall Length	83 mm
	Number of Flutes	4
	Rake Angle	60°
	Helix Angle	30°
	Clearance Angle	15°
Microstructure	Grain Size	1 µm

2.3. Techniques for Monitoring Machining Responses

Surface roughness (Ra) was evaluated using a high-resolution, non-contact 3D optical profilometer (Taylor Hobson CCI MP). The instrument operated at 20× magnification and was calibrated with a 4.7 mm cut-off length. Measurements were taken at five evenly spaced points on each machined surface, and all scans were performed perpendicular to the cutting direction to ensure consistent, repeatable, and accurate characterization of the surface topography. Cutting force data were obtained using a Kistler 9272 piezoelectric dynamometer securely mounted on the machine table to maintain measurement stability. Signals from the dynamometer were routed through a multi-channel charge amplifier equipped with a low-pass filter to eliminate high-frequency noise generated during machining. The forces were recorded at a sampling rate of 10,000 Hz, enabling detailed capture of dynamic variations throughout the cutting operation. Simultaneously, the temperature at the tool–chip interface (T) was monitored using a Thermo Pro TP8 infrared thermal imaging system. The camera was operated at an emissivity of 0.5 and was capable of measuring temperatures within the 0–900 °C range. With a spatial resolution of 382 × 288 pixels and an acquisition rate of 80 Hz, it provided high-quality thermal data suitable for accurate mapping of the temperature field. Tool wear (VB) was assessed through microscopic examination using an optical microscope. A complete representation of the experimental procedure is provided in Figure 1.

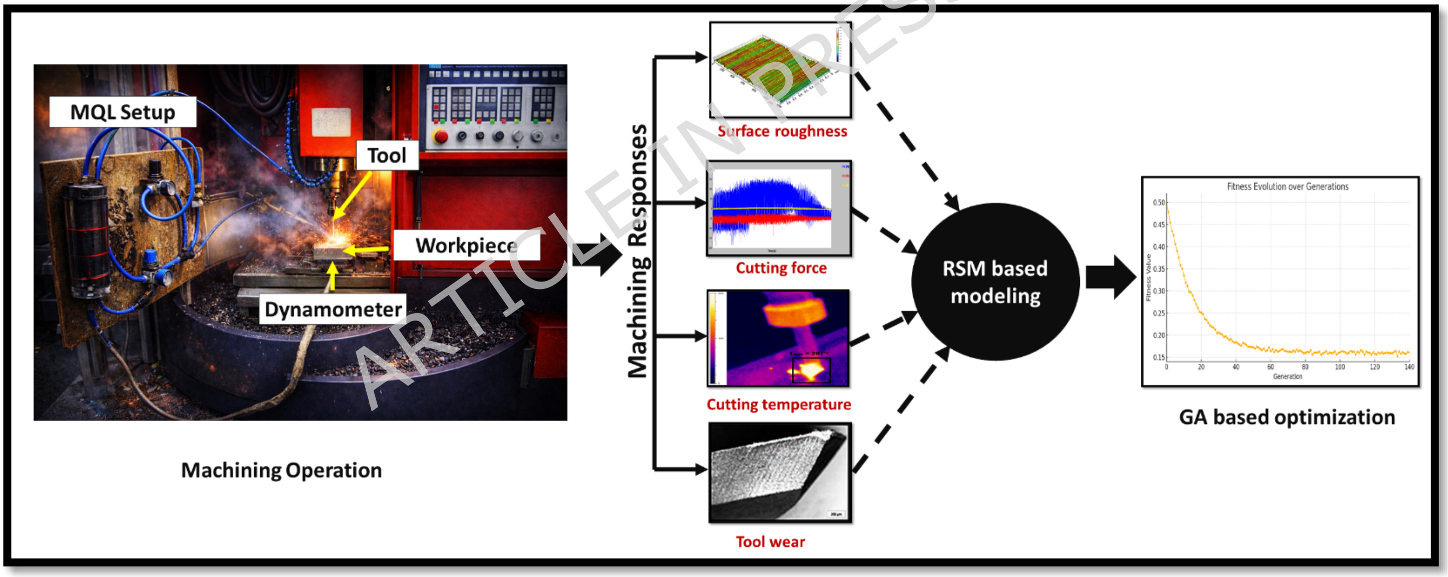


Figure 1: Schematic Representation of the Overall Research Workflow

2.4. Development of Predictive Models and Optimization Strategy

In this investigation, RSM [35] was utilized to construct predictive models capable of explaining how the selected machining parameters govern the associated output responses. As a combined statistical and mathematical framework, RSM integrates systematic experimental planning with regression-driven modeling and optimization tools to examine both the independent and combined influences of multiple process variables on machining performance indicators. By systematically varying cutting speed, feed rate, and depth of cut, the method facilitates the formulation of reliable empirical relationships that describe the collective impact of these parameters on critical responses such as surface roughness, cutting force, cutting temperature, and tool wear. This approach not only distinguishes the individual effects of each parameter but also captures their synergistic interactions, enabling accurate forecasting of process tendencies across the studied range. The generated models serve as valuable instruments for refining process parameters and enhancing overall machining efficiency, all while reducing the extent of experimental trials without compromising precision or robustness.

A GA technique was utilized to further strengthen the optimization potential of the responses obtained through RSM. As an evolutionary optimization method rooted in the mechanisms of inheritance and natural selection, GA is highly effective in locating global optima within nonlinear and high-dimensional design spaces. Within this approach, a population of candidate solutions—each representing a specific combination of machining parameters encoded in binary format—is systematically evolved across multiple generations. The performance of each solution is assessed using a fitness function that reflects its ability to satisfy the defined objective criteria. Through continuous application of evolutionary operators and iterative refinement of the population, GA gradually converges toward superior parameter configurations, ultimately enabling the identification of optimal machining conditions.

Within the GA framework, the optimization procedure is orchestrated through three core genetic operators—selection, crossover, and mutation—that collectively guide the evolutionary search process. The selection stage increases the probability that superior individuals will pass their genetic characteristics to subsequent generations. During crossover, the genetic material of two chosen parents is combined to generate offspring that encapsulate traits from both lineages. Mutation introduces small, random perturbations into individuals, thereby maintaining population diversity and mitigating the risk of premature convergence toward non-optimal regions. By repeatedly applying these operators across successive generations, the GA progressively investigates and refines the search domain, ultimately guiding the population toward an optimal configuration of machining parameters. The operational sequence of the GA utilized in this study is presented in Figure 2, while an extensive exposition of its theoretical principles, operator functionality, and computational trajectory is available in reference [36].

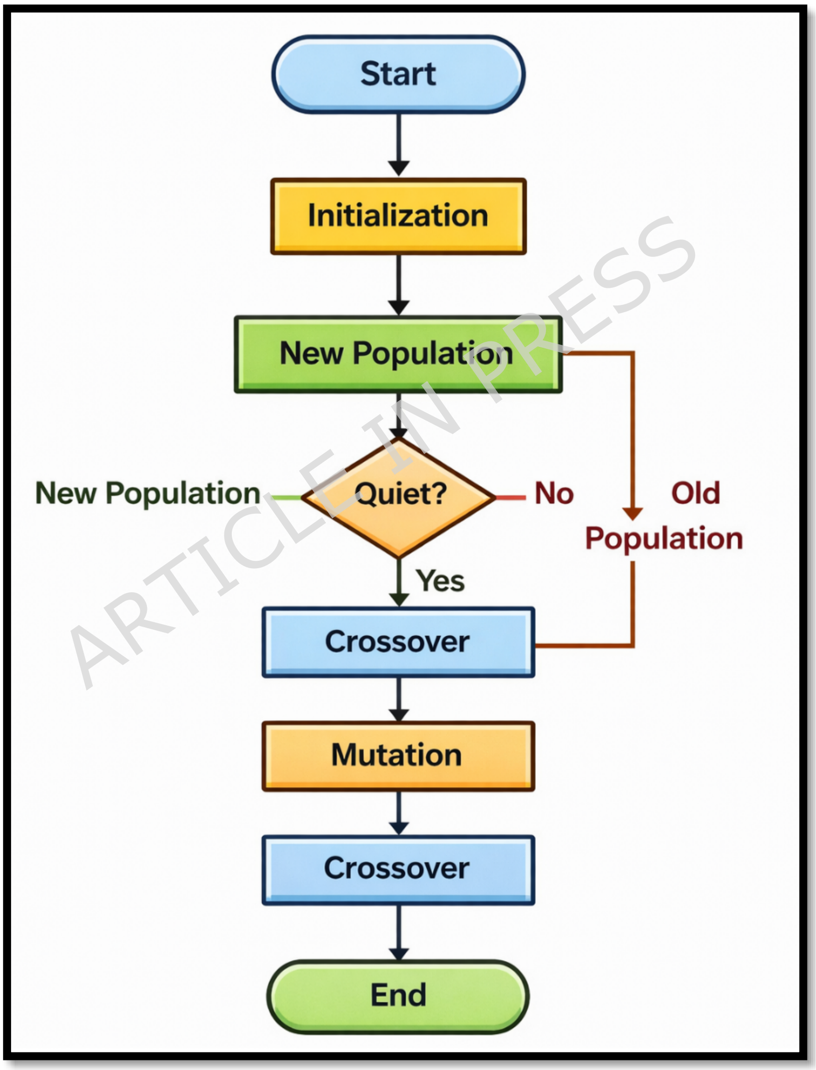


Figure 2: Process Flow of the Genetic Algorithm Optimization Procedure

3. Results and Discussion

3.1. Characterization of Nano-green Lubricants

Achieving a stable and homogeneous distribution of nanoparticles is crucial for maintaining the functional performance of nanofluids. Nevertheless, nanoparticles inherently exhibit a tendency to agglomerate under the influence of Van der Waals forces, which gradually compromises their uniformity within the base fluid. To mitigate the inherent tendency of nanoparticles to agglomerate, surfactants are routinely incorporated to enhance particle–particle separation, with sonication commonly applied as an auxiliary step to further suppress interparticle forces. Polysorbate 80 was added to coconut oil at a fixed concentration of 0.3% to facilitate the homogeneous and long-term dispersion of alumina and silica nanoparticles. As depicted in Figure 3, the absorbance profiles of the prepared nanofluids revealed a distinct peak at 270 nm for both nanoparticle formulations. This specific wavelength was therefore selected as the benchmark for evaluating the stability of nanoparticle dispersion in the developed samples. Absorbance values increased progressively with nanoparticle loading up to 0.8%, signifying enhanced dispersion within this interval. Beyond 0.8%, however, a reduction in absorbance was observed, indicating the onset of sedimentation or limited surfactant availability—both of which can negatively influence long-term dispersion stability.

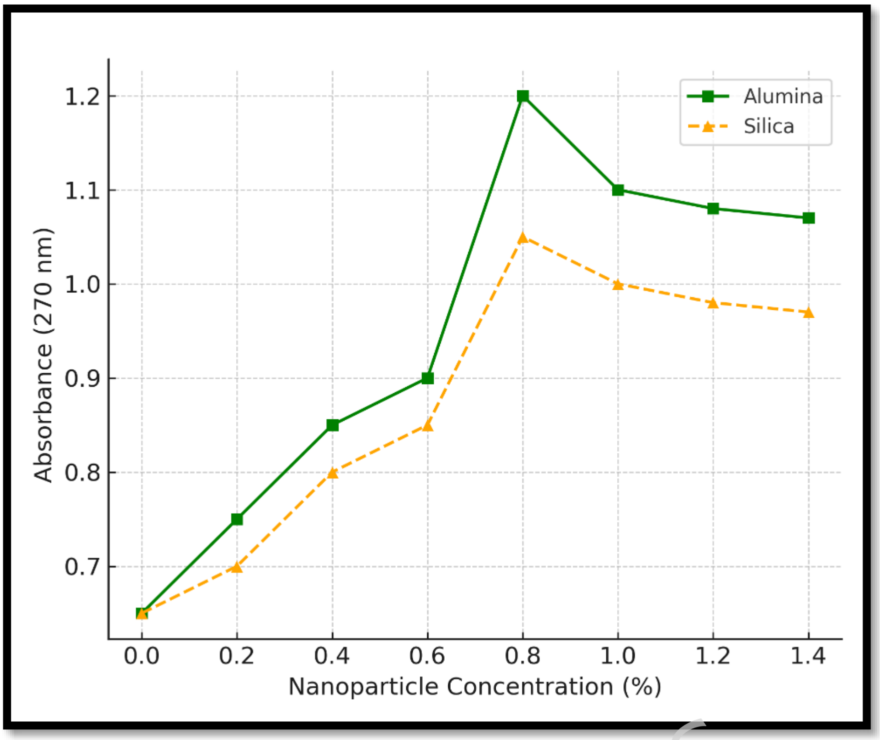
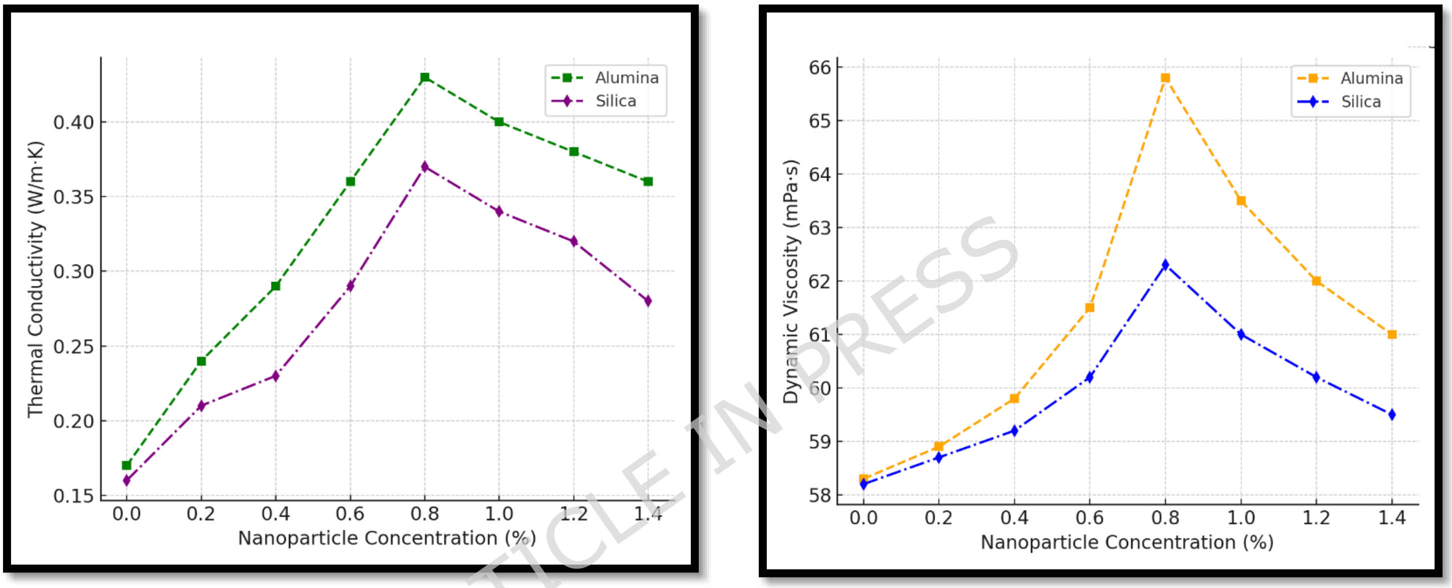


Figure 3: Absorbance Characteristics of Nanofluids at Varying Nanoparticle Concentrations

Because nanoparticles significantly modify the behaviour of the host fluid, their impact on the thermal and rheological properties of the base oil was examined more comprehensively. Figure 4(a) illustrates that the nanofluid's thermal conductivity increases consistently as the concentration of alumina nanoparticles rises, reaching its highest level at the 0.8% volume fraction. Beyond this concentration, the conductivity remains essentially unchanged, indicating a pronounced saturation phenomenon. According to Sen et al. [37], this plateauing trend arises from nanoparticle agglomeration, which suppresses Brownian motion, diminishes effective heat transport pathways, and consequently limits the expected thermal enhancement of the nanofluid under machining conditions. Figure 4(b) presents the variation in dynamic viscosity with changes in alumina concentration. Despite the natural tendency of vegetable oils to exhibit lower viscosity at elevated temperatures—primarily due to the expansion of intermolecular gaps—the introduction of nanoparticles counteracts this effect. Their addition results in a discernible rise in viscosity, with the 0.8% concentration once more producing the most pronounced enhancement. However, as highlighted by Gajrani et al. [19], excessively elevated nanoparticle levels may compromise dispersion stability, thereby inhibiting consistent and long-term viscosity enhancement. Collectively, these observations indicate that exceeding the optimal nanoparticle concentration can diminish overall performance, potentially yielding negligible—or even detrimental—effects on both thermal characteristics and flow behaviour.



(a) Thermal conductivity (b) Dynamic viscosity

Figure 4: Variation of Thermal Conductivity and Viscosity with Nanoparticle Concentration

3.2. Surface Roughness

Surface finish represents a key indicator of the interaction occurring between the cutting tool and the workpiece, providing meaningful clues about the mechanics governing the machining process. The quality of the finished surface not only influences overall machining effectiveness but also has a substantial impact on the durability, reliability, and operational performance of the final component. Previous studies have repeatedly demonstrated that surface roughness is shaped by multiple variables, such as tool geometry, coating properties, and the chosen lubrication method.

In the present study, the effect of various lubricating conditions on surface roughness was examined in a controlled manner, with all remaining machining parameters kept constant to isolate the contribution of each lubrication environment. The average roughness of the machined surfaces was quantified using a 3D profilometer for all tested conditions, as illustrated in Figure 5. The findings clearly indicate that nano-green lubricants, especially those formulated from environmentally benign oils, lead to a pronounced reduction in Ra values. This improvement is largely governed by the ability of ultra-fine lubricant droplets to infiltrate the tool–chip interface more efficiently, thereby mitigating the initiation and propagation of surface irregularities. Minimum quantity coconut oil lubrication not only enabled superior surface finish but also contributed to noticeable reductions in cutting force and temperature. These observations corroborate earlier findings asserting that nanofluids enhance surface characteristics [34], and that vegetable oil-based nano-lubricants typically outperform their conventional counterparts in improving finishing quality. Among the various lubrication strategies examined, the alumina-enhanced coconut oil exhibited the lowest surface roughness, with silica-infused coconut oil yielding the next best finish. These were followed by unmodified coconut oil, while dry machining resulted in the comparatively highest roughness. The outstanding performance of the alumina-based nanofluid can be linked to its relatively higher viscosity, which helps the lubricant remain in the cutting zone for a longer duration. An optimized nanoparticle loading of 0.8% was identified as the most efficacious concentration. At levels lower than this threshold, the particles are inadequate to establish a pronounced rolling mechanism, while concentrations exceeding 0.8% tend to induce agglomeration, undermine the stability of the lubricating film, and ultimately cause the fluid to function in a manner comparable to a conventional lubricant. The improvement in surface integrity achieved with nano-lubricated machining aligns with the observations of Gajrani et al. [19], who demonstrated that the presence of dispersed nanoparticles promotes the development of a thin, protective tribo-film at the tool–

workpiece interface. This film acts as a shielding barrier that limits direct contact between the tool and the workpiece, thereby lowering friction, reducing tool degradation, and suppressing the emergence of surface defects. Moreover, the tribo-film aids in smoothing the machined surface by occupying micro-level asperities. As a result, machining with alumina-enhanced coconut oil produced substantial gains in surface quality, outperforming dry cutting, base coconut oil, and silica-based lubrication by nearly 43.089%, 17.647%, and 6.667%, respectively.

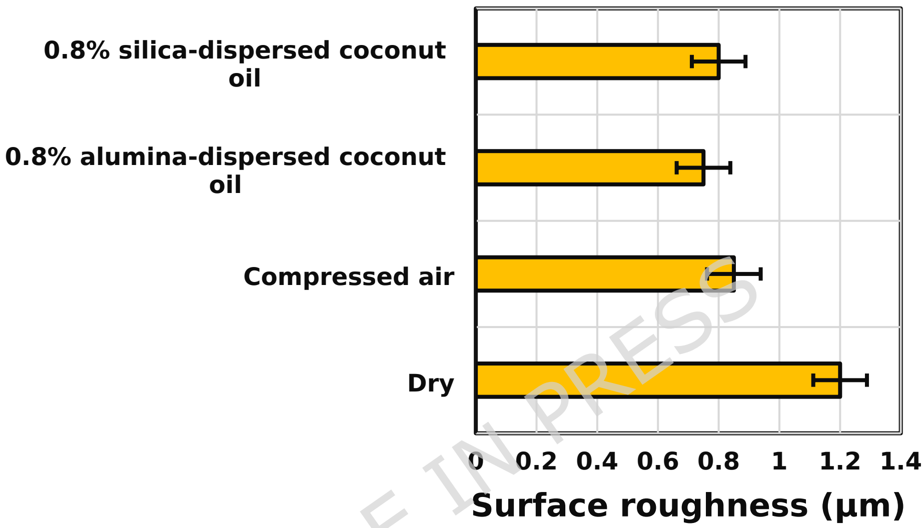


Figure 5: Comparative Surface Roughness Analysis Under Different Lubrication Methods

3.3. Resultant cutting force

Cutting force is a critical metric for evaluating machining performance, as it directly affects power consumption, accelerates tool degradation, and plays a decisive role in determining the final surface quality of a workpiece. When cutting forces increase, the thermal load at the tool–workpiece interface rises accordingly, often leading to deterioration in surface integrity. In the present investigation, the force components acting during machining were measured using a three-axis dynamometer capable of capturing forces along all principal directions. These components were subsequently combined to compute the resultant cutting force, enabling a clear assessment of the various lubrication conditions depicted in Figure 6. Among the tested environments, dry machining produced the highest cutting force owing to the absence of a protective lubricating film, which heightened friction at the tool–workpiece interface. Conversely, machining under MQL conditions with coconut oil markedly reduced the cutting force, as the oil efficiently reached the cutting zone and minimized interfacial friction. Even greater force reductions were observed with nanofluid-based lubrication. The formulation containing 0.8% alumina nanoparticles in coconut oil produced the minimum cutting force, achieving reductions of 27.397%, 11.074%, and 3.985% when compared with the other lubrication environments. The performance of nanofluids is strongly influenced by nanoparticle concentration. Insufficient particle loading can reduce viscosity and diminish lubrication efficacy, whereas excessively high concentrations may hinder the development of a stable tribo-film. In the present study, the incorporation of spherical alumina and silica nanoparticles induced a transition in the tool–chip tribological regime, promoting a predominantly rolling-type contact in place of conventional sliding friction. This modification in interfacial mechanics contributed to a substantial reduction in the overall cutting resistance.

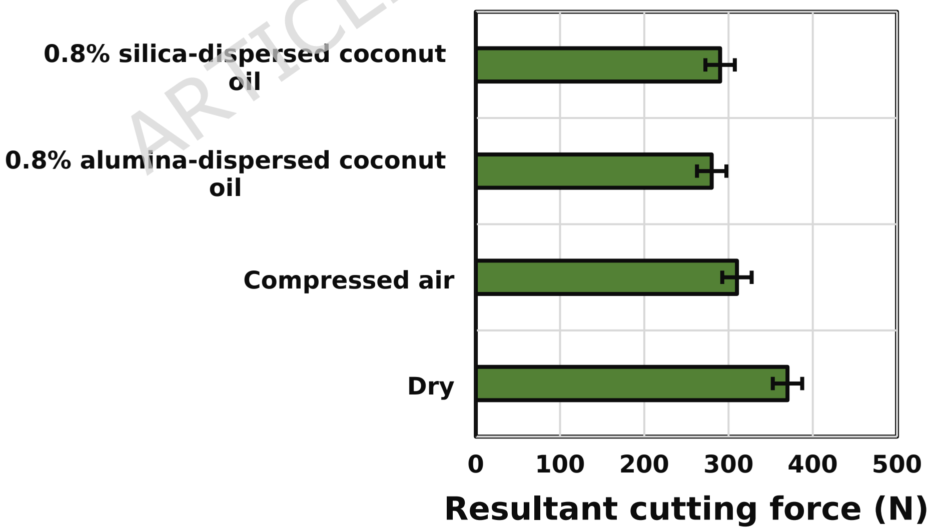


Figure 6: Resultant Cutting Force Response for Various Lubrication Conditions

3.4. Cutting temperature

During metal cutting, intense friction simultaneously arises at both the tool–chip and tool–workpiece interfaces. This localized sliding action generates substantial heat within the contact zone, which often accelerates surface degradation and expedites tool wear. Consequently, cutting temperature serves as a critical parameter for evaluating machinability and identifying pathways for improving overall process performance. In the present investigation, cutting temperatures were recorded under different lubrication conditions using a thermal infrared camera (Figure 7). Among all tested environments, dry cutting produced the highest thermal load, reaching 320 °C. Introducing coconut oil as a lubricant reduced the temperature to 260 °C, corresponding to an 18.75% decline. The observed enhancement can be ascribed to the capacity of coconut-oil microdroplets to penetrate the tool–workpiece interface, where they establish a persistent lubricating film that mitigates interfacial friction and facilitates smoother, more effective chip removal. The greatest attenuation in cutting-zone temperature was achieved when the coconut oil was enriched with 0.8% alumina. The enhanced cooling performance is primarily due to the increased thermal conductivity imparted by the alumina particles. A comparative evaluation of the alumina- and silica-enriched nanofluids revealed that the formulation exhibiting superior thermal conductivity invariably facilitated a more pronounced reduction in cutting temperature. Thermal profiling also directed that the benefit of improved heat conduction rises with nanoparticle addition only up to an optimal concentration (0.8%), beyond which further increments provide negligible additional advantage. Thus, maintaining an appropriate nanoparticle loading is essential for effective thermal regulation during machining. Overall, the alumina-enriched coconut oil achieved temperature reductions of 23.44% compared with dry machining, 4.67% relative to pure coconut oil, and 2.39% in comparison with silica-based nanofluid.

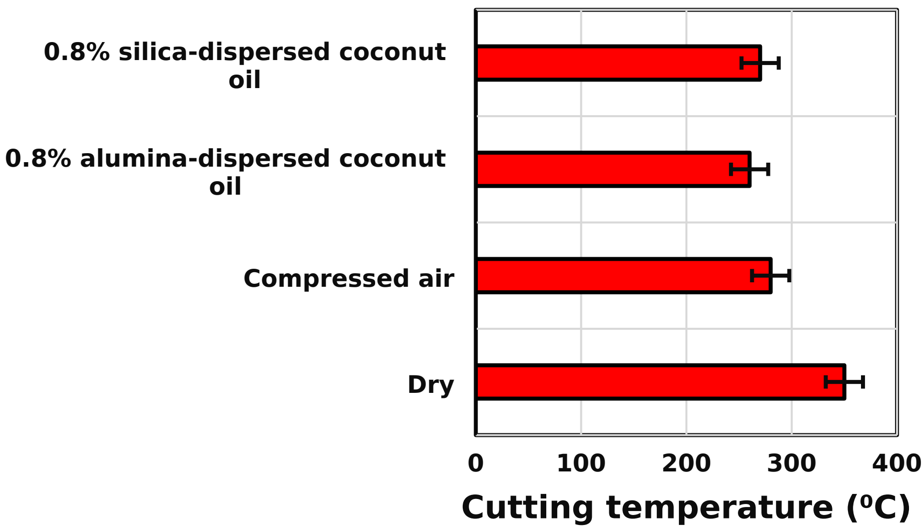


Figure 7: Influence of lubrication strategies on cutting temperature

3.5. Tool wear

Tool wear is a critical factor governing machining productivity and the associated operational costs. In this study, the wear characteristics of the end-mill were systematically evaluated under distinct lubrication regimes, with all machining parameters held constant. For each 30-minute milling trial, only the lubrication condition was varied, enabling an isolated assessment of its influence on tool degradation. Flank wear was quantitatively assessed through high-resolution imaging conducted with an optical microscopy system. The results demonstrate that the coconut-oil medium enriched with alumina nanoparticles delivered the most substantial improvement in wear suppression. Specifically, this formulation reduced tool deterioration by 45.83% compared with dry machining, by 16.13% relative to unmodified coconut oil, and by 3.70% in comparison with the silica-based nanofluid, underscoring its superior tribological performance. The progression of wear over time under the various lubrication strategies, as illustrated in Figure 8, unequivocally highlights the markedly enhanced performance delivered by the alumina-based nanofluid. These observations align well with the report of Şirin et al. [38-40], which emphasized that nanoparticle concentration in MQL formulations plays a pivotal role in governing tool wear characteristics. While an optimal nanoparticle dosage enhances lubrication by minimizing friction, excessively high concentrations elevate fluid viscosity and hinder effective flow. Such conditions promote particle agglomeration and adhesive interactions, thereby diminishing lubrication efficiency and accelerating tool wear. Hence, establishing the appropriate nanoparticle concentration is essential for achieving maximum lubrication performance.

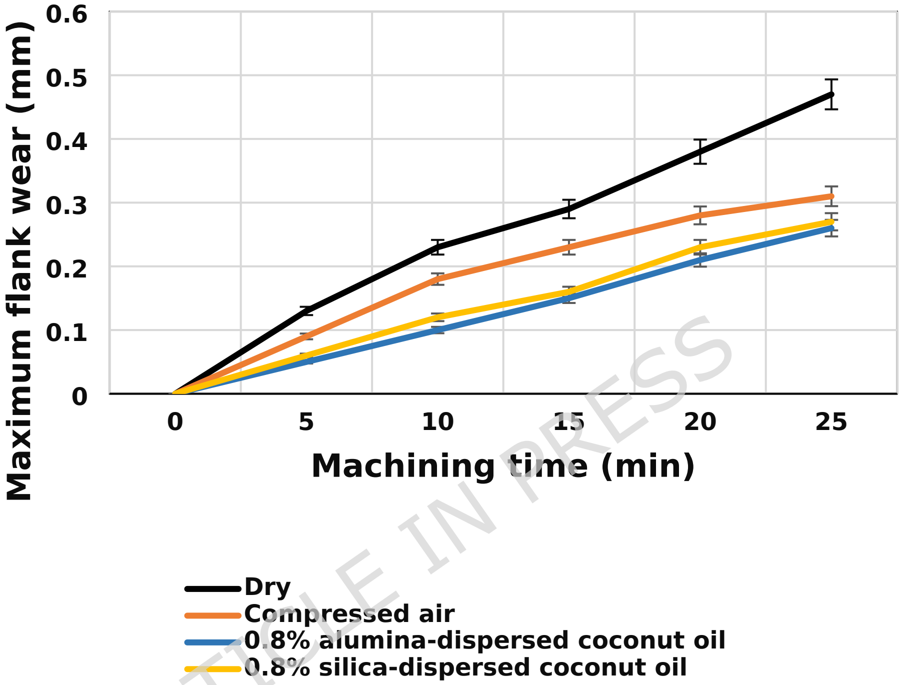


Figure 8: Flank Wear Progression Under Different Lubricating Strategies

A detailed microscopic investigation of the degraded carbide end-mills was undertaken to rigorously delineate how distinct lubricant environments governed the progression and underlying mechanisms of tool wear. As illustrated in Figure 9, adhesive and abrasive wear remained the prevailing wear modes under every lubricating condition. In machining the nickel-based superalloy, the cutting tool's carbide surface underwent steady degradation, with successive layers becoming exposed as material was progressively stripped away. The intense thermal loads and mechanical pressures generated at the tool–chip interface facilitated localized adhesion between the moving chip and the tool surface, leading to the formation of persistent built-up material layers. Although the flowing chip intermittently detached portions of these adhered layers, complete detachment did not occur, enabling a persistent built-up layer (BUL) to develop. Additionally, the substantial cutting forces generated throughout machining produced considerable wear debris accumulation near the cutting edge. Due to the strong chemical interaction between the tool material and the workpiece, the adhered debris served as an active promoter, accelerating both the initiation and enlargement of the built-up layer. The repeated sequence of adhesion, partial detachment, and subsequent redeposition progressively altered the geometry of the cutting edge, intensified frictional contact, elevated interface temperatures, and ultimately hastened the overall rate of tool wear progression.

Abrasive wear emerged as the dominant wear mechanism on the flank face, where microscopic examination revealed a sequence of shallow to deep groove formations. This behaviour is predominantly attributed to the distribution of hard carbide phases embedded throughout the nickel-based superalloy matrix. Owing to their high hardness, exceptional thermal stability, and resistance to plastic deformation, these particles function as micro-abrasive agents that continuously scratch and plough the tool surface. Their repeated interaction promotes the initiation of micro-cracks and accelerates cyclic surface fatigue, thereby expediting the progressive degradation of the cutting tool. Simultaneously, the rise in frictional forces and thermal stresses intensifies the surface damage, ultimately culminating in tool failure. Comparable observations were noted by Sen et al. [37], who attributed abrasive wear to the influence of hard carbide particles throughout the machining of superalloys. Although the use of nanoparticle-enriched vegetable oil lubrication markedly decreased the overall wear severity by enhancing both cooling and lubricating effects, it did not modify the fundamental wear mechanisms responsible for the deterioration of the carbide end-mill.

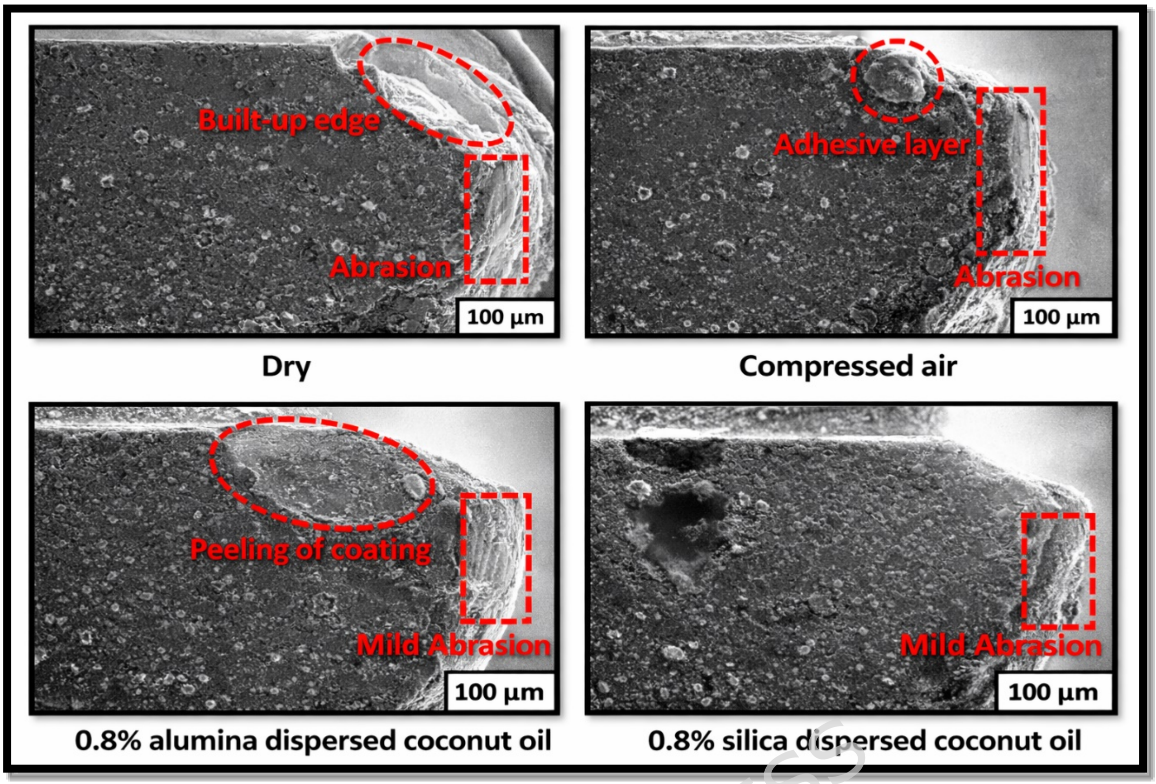


Figure 9: Microscopic images of Tool Wear Mechanisms Across Lubrication Conditions

3.6. Outcomes of Predictive Modeling and GA-Based Optimization

A detailed assessment of the thermo-physical properties revealed that, among all the evaluated lubricants, alumina-dispersed coconut oil delivered the most efficient lubrication for sustainable machining operations. To substantiate this observation, a comparative investigation was carried out under four machining conditions—dry, coconut oil, alumina-dispersed coconut oil, and silica-dispersed coconut oil. The results consistently demonstrated the superior performance of the alumina-based green lubricant. Guided by this outcome, twenty-seven machining experiments were subsequently executed using the identified optimal lubrication environment. To evaluate the machining responses with greater statistical rigour, the behaviour of the residuals was assessed using four diagnostic indicators: the normal probability plot, the residuals versus fitted values plot, the histogram of residuals, and the residuals versus observation-order plot, as illustrated in Figure 10. The normal probability plot confirmed that the residuals adhered closely to a normal distribution, while the residuals–fitted values plot displayed an unstructured, random dispersion, thereby demonstrating the presence of homoscedasticity. Although the histogram displayed minor skewness, the residuals versus order plot revealed visible fluctuations between consecutive observations. Conducting these diagnostic evaluations prior to optimization is crucial for validating the fundamental model assumptions, thereby enhancing the credibility, robustness, and precision of the subsequent optimization process.

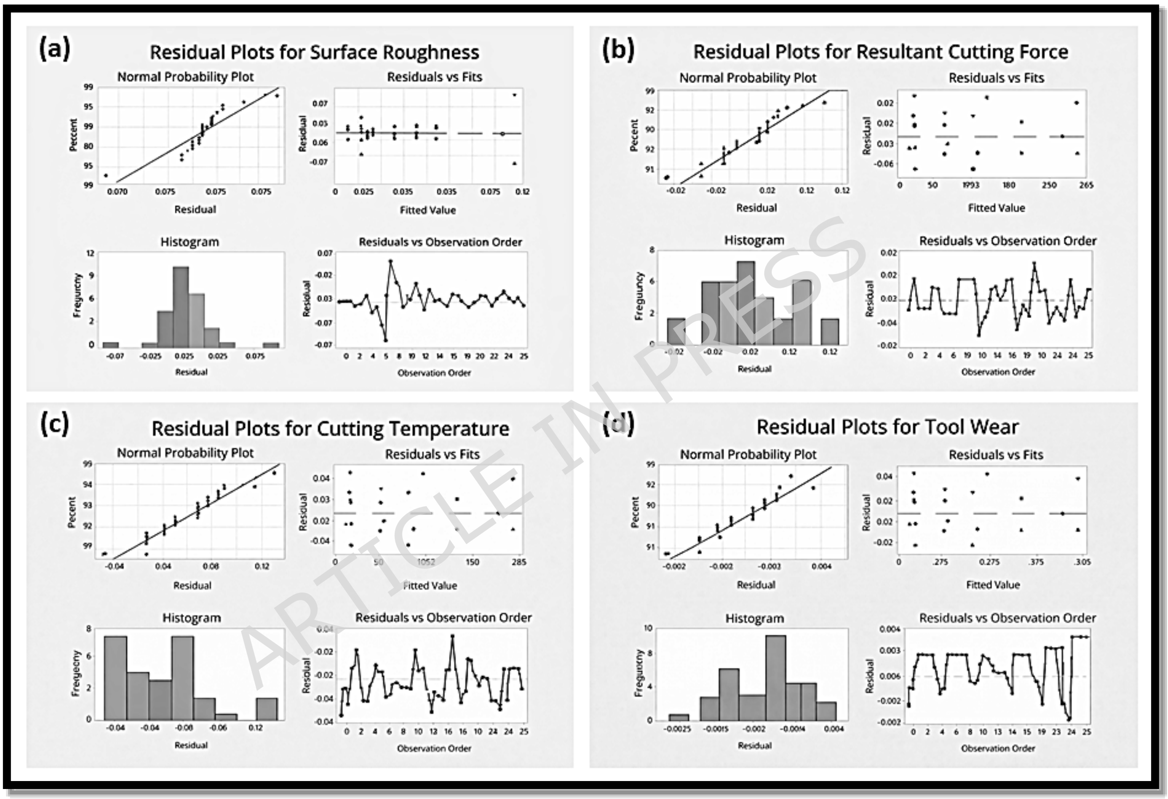


Figure 10: Residual plots corresponding to machining responses

In this investigation, RSM was employed as the central analytical framework owing to its proven effectiveness in developing reliable surrogate models for complex engineering processes. The adoption of RSM facilitated a structured and comprehensive investigation into the complex nonlinear interactions governing the selected machining parameters and their associated performance responses. Through the construction of empirical models, the methodology offered a dependable means for forecasting process behaviour under diverse operating conditions. Moreover, this modeling strategy supported the identification of dominant factors and significant interaction effects, thereby yielding a deeper understanding of how variations in machining parameters influence the overall performance of the system. A unified Combined Objective Function (COF) was formulated to streamline multi-response optimization, allowing multiple performance indicators to be merged into one consolidated assessment metric. Each response was initially transformed into a satisfaction index using a desirability-based mapping that quantified its closeness to the target specification. These individual desirability values were subsequently integrated using a multiplicative aggregation approach, designed to strengthen the collective performance of the machining process. To preserve an equitable and unbiased influence of every performance characteristic on the overall optimization process, each response variable was allotted an identical weight of 0.25, thereby guaranteeing a uniformly distributed contribution to the final optimized solution.

The COF optimization was performed in MATLAB applying a GA framework that leverages population-based evolution and a probabilistic search strategy. Given that the efficiency of a GA is highly dependent on its exploratory behaviour and inherent stochasticity, meticulous calibration of the control parameters was necessary to achieve reliable convergence and to avoid premature stagnation at suboptimal solutions. To establish an appropriate configuration, multiple preliminary runs were conducted, during which key factors—including population size, number of generations, crossover probability, and convergence tolerance—were systematically adjusted. Following several iterative refinement cycles, the Genetic Algorithm was finalized with a population size of 50, a maximum allowance of 300 generations, a function tolerance of 10^{-6}, and a crossover rate of 0.8. The optimization process was designed to conclude automatically once the improvement in fitness between successive generations dropped below the specified tolerance level. This stopping condition ensured a judicious compromise between computational economy and the precision of the obtained solution. The convergence trend depicted in Figure 11 demonstrates a consistent enhancement of the objective function, confirming the robustness and reliability of the optimization procedure under the optimized parameter scheme.

To verify the effectiveness of the optimized machining conditions derived from the integrated RSM-GA methodology, confirmation experiments were carried out using the predicted optimal parameter set. The resulting experimental responses demonstrated excellent agreement with the corresponding model predictions, with an average deviation of only 2.6%, as presented in Table 4. This close alignment reinforces the robustness, reliability, and high predictive capability of the RSM-GA framework for real-world machining applications. By utilizing RSM for process modelling and GA for parameter optimization, the proposed methodology efficiently captured the behaviour of the response variables while simultaneously addressing multi-objective requirements. As a result, the approach enhances overall process performance, ensures consistent product quality, and contributes to improved operational stability. Taken together, these outcomes highlight the adaptability and practical significance of the proposed strategy for tackling complex machining problems involving multiple interacting parameters.

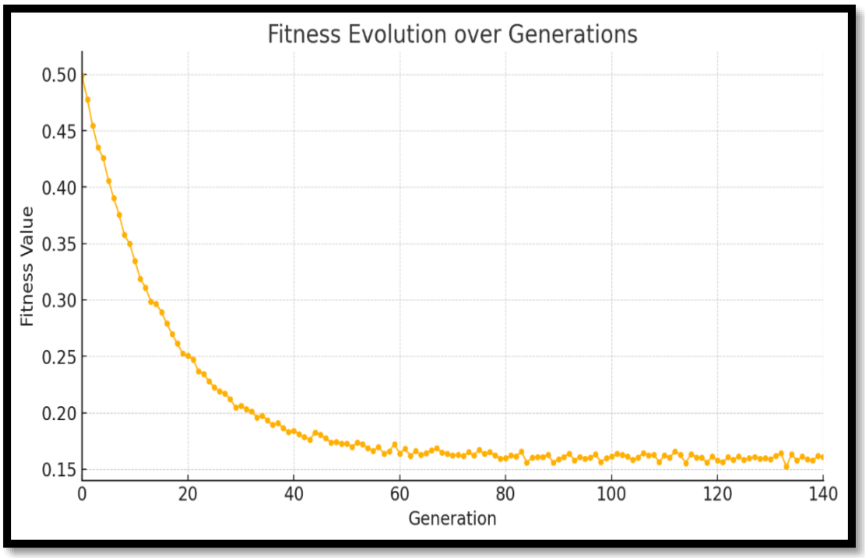


Figure 11: Evolution of the GA Fitness Function Across Generations

Table 4: Comparison Between Experimental Outcomes and Genetic Algorithm Predictions

Response parameter	Optimal parameters	Experimental Result	Model Output	% Deviation
Surface roughness (µm)	v_c = 70 m/min, f = 0.04 mm/tooth, and a_p = 0.25 mm	0.7	0.72	2.78
Cutting force (N)		265	264.05	0.36
Cutting temperature (˚C)		255	253.5	0.59
Tool wear (mm)		0.28	0.3	6.67
Overall Mean Error = 2.6 %				

4. Conclusions

In this study, both experimental trials and computational analyses were integrated to assess the machining behaviour of Inconel 718 when processed with alumina- and silica-enriched coconut oil nanofluids under

MQL conditions. To achieve optimal machining performance and promote sustainability, the machining parameters were refined through a combined application of RSM and GA. The primary outcomes of the work are outlined as follows:

- The alumina-dispersed coconut oil nanofluid (0.8%) significantly improved machining performance, diminishing surface roughness, cutting force, cutting temperature, and tool wear compared to dry and conventional lubrication, demonstrating its superior effectiveness in hard-to-cut Inconel 718 machining.
- The optimized nanofluid lowered surface roughness by 43.09% over dry machining by forming a stable lubricating film and reducing friction, thereby enhancing product quality and prolonging tool life under sustainable machining conditions.
- The application of the nanofluid resulted in a 27.40% reduction in cutting force, a performance enhancement primarily ascribed to its superior lubricating capability and the synergistic rolling action of the dispersed nanoparticles at the tool–chip interface, which lowered frictional resistance and enhanced material removal efficiency.
- The alumina-based nanofluid reduced cutting temperatures by 23.44% due to enhanced thermal conductivity and better heat dissipation, improving machining stability and protecting tools from premature wear during high-speed operations.
- Flank wear decreased by 45.83% with the optimized nanofluid, minimizing tool replacement frequency and reducing machining costs, which is crucial for industries dealing with superalloys requiring precise and cost-effective manufacturing solutions.
- The integrated RSM-GA approach effectively optimized machining parameters, with experimental results deviating by only 2.6% from predictions, validating the framework’s robustness and applicability in sustainable machining and modern industrial manufacturing environments.

Future investigations may direct attention toward the development of hybrid nanofluids formulated through the combination of multiple nanoparticles, enabling synergistic gains in both cooling and lubrication behaviour. Moreover, conducting systematic studies on the influence of different nanoparticle concentrations will be crucial for determining the most effective ranges suited to various machining conditions and material systems. The current approach also holds promise for application to other difficult-to-machine alloys—including titanium alloys, Hastelloy, and tool steels—to assess its wider relevance across advanced manufacturing domains. In addition, extended evaluations focusing on durability, tool life, and machine stability under nano-lubricated environments are necessary to support successful transition to industrial implementation. Lastly, integrating optimization strategies with machine learning and artificial intelligence-driven prediction tools can facilitate real-time control and monitoring, thereby further improving machining efficiency and sustainability.

Authors contributions: Omar Almomani contributed to the conceptualization, methodology formulation, investigation, data curation, and initial drafting of the manuscript. Vipulsinh Rajput supported the experimental design, formal analysis, and validation of results. A. C. Umamaheshwer Rao provided supervision, essential resources, and critical manuscript revisions. Sikata Samantaray assisted in data acquisition, characterization studies, and interpretation of findings. Nagaraj Patil contributed to software development, modeling, and statistical analysis. Ripendeep Singh handled visualization, figure preparation, and proofreading. B. Vishnu Vardhana Naidu supported materials preparation, laboratory activities, and technical review. Mohit Sahani conducted an extensive literature review, editing, and improvement of the scientific content. Abhijit Bhowmik contributed to project administration, quality assurance, and refinement of the manuscript. Lema Abate, as the corresponding author, oversaw the overall supervision of the study, managed funding acquisition, coordinated revisions, and approved the final version of the manuscript.

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