

**AN INVESTIGATION OF TURNING OPERATION
CHARACTERISTICS USING HYBRID NANOFLUID
MINIMUM QUANTITY LUBRICATION (MQL)**

A Thesis submitted to Gujarat Technological University

for the Award of

Doctor of Philosophy

in

Mechanical Engineering

by

Nalbandh Altaf Hanifbhai

[Enrolment No.: 199999919525]

under the supervision of

Dr. Neerajkumar K. Chavda



GUJARAT TECHNOLOGICAL UNIVERSITY

AHMEDABAD

September 2026

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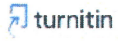
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ABSTRACT

Turning is simple and one of the most used fundamental machining operations, where a single-point cutting tool is used for material removal from a rotating part in order to shape cylindrical surfaces, shoulders, and grooves. Nanofluid-assisted minimum quantity lubrication (MQL) offers a promising route towards cleaner and more resource-efficient machining in line with UN SDG 9, by reducing coolant consumption while maintaining or improving cutting performance.

This study investigates the turning behaviour of AISI 1040 medium-carbon steel under thirteen cooling cases/conditions, including dry cutting, conventional wet cooling with water and SAE-40 oil, MQL with base oil, MQL with Al_2O_3 and ZnO mono nanofluids, and MQL with Al_2O_3 -ZnO hybrid nanofluids prepared in SAE-40 oil. In each case the CS: Cutting Speed ranges from 31.71-107.55 m/min, FR: feed rate from 0.11-0.25 mm/rev and the DC: depth of cut from 0.2-0.6 mm were adjusted to Box-Behnken Response Surface Methodology (RSM) design for each cooling condition in the total of 195 runs, after which CF: Cutting Force, CT: Cutting Temperature, and SR: Surface Roughness were measured. Separate regression models developed for all thirteen cases were statistically significant, with high coefficients of determination and reasonable residual diagnostics, as indicated by ANOVA. In all conditions, FR and DC were significant in influencing all three responses, and CS was significant, though to a lesser extent. Comparative analysis of nanofluid formulations shows that Al_2O_3 yields lower forces and better surface integrity, whereas ZnO provides greater temperature reduction; an intermediate nanoparticle concentration of 1 wt% offers the best overall balance.

A desirability-based multi-response optimization (equal weighting, smaller-is-better) identifies MQL with 1 wt% Al_2O_3 /ZnO (75/25, Case-H1) as the most suitable overall lubrication condition among the thirteen cases. It yields a global optimum at a CS of 107.55 m/min, a FR of 0.11 mm/rev, and a DC of 0.2 mm. Validation tests in this setting show prediction errors of only 8.23% (force), 6.83% (temperature), and 3.56% (roughness), and reductions of about 25.1%, 18.26%, and 16.33% in these responses, respectively, compared with dry cutting. In parallel, Artificial Neural Network modeling demonstrates that a feed-forward distributed time-delay network (N4P2T2) most accurately predicts the three responses across all cooling conditions, indicating that the combined RSM-desirability-ANN

framework provides a robust, data-driven basis for designing sustainable, high-performance turning processes using hybrid nanofluid MQL.

Keywords: Minimum Quantity Lubrication, Mono Nanofluids, Hybrid Nanofluids, Response Surface Methodology, ANOVA, Al_2O_3 , ZnO

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“Intelligence helps, but persistence is what gets most people to the finish line!!!”

- Nalbandh Altaf Hanifbhai

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List of Abbreviations

2FI	Two-factor interaction	MgO	Magnesium Oxide
Ag	Silver	MoS ₂	Molybdenum Disulfide
Al ₂ O ₃	Aluminium Oxide	MQLNF	Minimum quantity lubrication with Nanofluid
AlN	Aluminium Nitride	MWCNT	Multi-Wall Carbon Nanotube
ANOM	Analysis of Means	M. Sq.	Mean Squares
ANOVA	Analysis of Variance	NFsMQL	Nanofluid with minimum quantity lubrication
Au	Gold	NM	Not Mentioned
BFO	Bacterial Foraging Optimization	PSO	Particle Swarm Optimization
CCD	Central Composite Design	PVD	Physical Vapor Deposition
CFsMQL	Conventional Fluids with minimum quantity lubrication	PWD	Physical Vapor Deposition
CNT	Carbon Nanotube	RSM	Response Surface Methodology
CO ₂	Cryogenic Cooling	SAE	Society of Automotive Engineers
CRSM	Coupling Response Surface Methodology	SEM	Scanning Electron Microscopy
Cu	Copper	SiO ₂	Silicon Oxide
CuO	Copper Oxide	ST	Surface Topography
CVD	Chemical Vapor Deposition	S. Sq.	Sum of Squares
DFA	Desirability Function Approach	TiO ₂	Titanium Oxide
EDM	Electro Discharge Machining	WS ₂	Tungsten Disulfide
Fe	Iron	XRD	X-ray Diffraction
Fe ₂ O ₃ /Fe ₃ O ₄	Iron Oxide	ZnO	Zinc Oxide
GRA	Gray Rational Analysis		
hBN	Hexagon Boron Nitride		
LN2	Liquid Nitrogen		

List of Symbols

Symbol	Description	Unit
CF	Cutting Force	N
CP	Cutting Pressure	Bar
CS	Cutting Speed	m/min
CT	Cutting Temperature	°C
DC	Depth of Cut	mm
F	Force	N
FR	Feed Rate	mm/rev
SR	Surface Roughness	μm
TW	Tool Wear	-
v%	Volume Fraction	%
wt%	Weight Fraction	%

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CHAPTER 1. INTRODUCTION

1.1 Background and Motivation

Machining processes remain central to the manufacture of precision components in automotive, aerospace, power, and general engineering sectors. Manufacturing industries increasingly demand higher productivity, tighter dimensional tolerances, and improved surface quality, while simultaneously facing strong pressure to reduce cost and environmental impact. Among various manufacturing processes, machining remains indispensable for achieving the final shape, dimensional accuracy, and surface integrity of a wide variety of metallic components across sectors such as automotive, aerospace, energy, and general engineering.

Machining processes can mainly be classified into orthogonal cutting processes (turning, planing), multi-point processes (milling, drilling), and abrasion-dominated processes (grinding, honing). Among these processes, turning is one of the most fundamental and widely used operations for generating rotationally symmetric parts with a single-point cutting tool. Turning is employed for facing, straight turning, profiling, and grooving operations and is often the final or near-final step in achieving dimensional accuracy and surface finish. Consequently, even incremental improvements in turning performance can have a significant cumulative impact on productivity, tool consumption, and energy usage at the plant level.

During turning operations, considerable generation of heat by severe plastic deformation in the cutting shear zone and by intense sliding at the cutting tool-workpiece interface. This heat increases the cutting temperature and, if not controlled, accelerates tool wear, degrades surface integrity, and limits allowable cutting speed and material removal rate. In addition, high cutting forces and unstable chip formation can lead to chatter, dimensional inaccuracy, and poor surface roughness. It is therefore essential to manage both the thermal and tribological conditions at the cutting zone to achieve high productivity with acceptable tool wear and surface finish.

Fundamentals of Turning

Historically, these conditions were managed primarily by applying cutting fluids under flood-cooling conditions. However, increasing awareness of environmental, health, and economic constraints has driven a transition toward near to dry strategies, including minimum quantity lubrication (MQL), and toward advanced cutting fluids such as nanofluids & hybrid nanofluids that can provide superior heat-transfer and friction-reducing performance at much lower flow rates.

1.2 Fundamentals of Turning

Turning is conventionally carried out on lathes or CNC turning centers, where the workpiece rotates while the cutting tool advances along prescribed paths. The tool is fed parallel to, radially, or at an angle to the workpiece axis, enabling operations such as longitudinal turning, facing, taper turning, and grooving.

Three primary cutting parameters govern the process:

- o **Cutting speed (CS)**, determined by spindle speed and workpiece diameter, primarily influences heat generation, tool wear, and, in many cases, surface finish.
- o **Feed rate (FR)**, defined as tool advance per revolution, directly controls undeformed chip thickness and has a dominant effect on CF and surface finish.
- o **Depth of cut (DC)**, the radial arrangement of the cutting tool, largely dictates MRR and cutting force.

The cutting zone comprises three distinct zones: the primary zone involves bulk plastic deformation of the chip. The secondary zone occurs at the interface junction of the cutting tool and the chip. The tertiary zone is located at the flank of the tool and the newly machined surface. Severe plastic shear, sliding contact, and plowing in these regions generate substantial heat and complex stress and temperature fields. If not controlled, the elevated temperature and stresses accelerate tool wear, induce residual stresses in the upper surface layer & deteriorate surface integrity.

1.3 Heat Generation, Tribology, and the Purpose of Cutting Fluids

During turning, the key sources of heat include plastic deformation within the main shear

Cutting Fluids: Types, Functions and Environmental Issues

zone, sliding friction between the cutting tool and chip, and rubbing between the cutting tool and work material. The part's chips take away a substantial portion of this heat, but a significant fraction is conducted into the tool and workpiece, especially at low cutting speeds and when chip removal is constrained. Elevated temperatures in the cutting zone led to: (i) rapid tool wear through abrasion, adhesion, diffusion, and oxidation, (ii) softening of the cutting edge, (iii) dimensional inaccuracy due to thermal expansion, and (iv) degradation of surface integrity (roughness, subsurface plastic deformation, residual stress).

At the same time, the tribological conditions at the interface strongly influence machining forces, chip formation, and tool wear. High friction and adhesion increase cutting force and promote built-up edge, leading to fluctuating cutting forces, chatter, and poor surface finish. Effective control of both heat and friction is therefore essential for reliable and economical turning.

Cutting fluids perform three principal roles: cooling the cutting zone, lubricating the contact interfaces, and transporting chips away from the tool and workpiece. Traditional cooling strategies fall into two broad categories:

- o **Dry cutting**, where no fluid is used, results in minimal environmental burden but generally higher cutting temperatures and poorer surface finish due to high friction and unmitigated heat generation.
- o **Wet or flooded cooling**, where large volumes of mineral or water-based emulsions are directed at the tool–workpiece interface. Flood cooling effectively removes heat and reduces friction, but it entails high consumption and disposal costs, and raises concerns regarding operator health and environmental impact.

The limitations of both extremes—thermal and tribological issues in dry cutting and sustainability concerns in flood cooling—have prompted the development of alternative lubrication strategies that provide adequate thermal and tribological control while using much less fluid.

1.4 Cutting Fluids: Types, Functions and Environmental Issues

Cutting fluids for turning operations are commonly categorized into straight (neat) oils,

Evolution of Near-Dry Machining and MQL

water-miscible emulsions, synthetics and semi-synthetics, and more recent vegetable-oil-based fluids. Straight oils provide excellent lubrication but relatively poor cooling, whereas water-based emulsions and synthetics offer superior cooling but lower lubricity. Vegetable oils, with their high lubricity and biodegradability, have emerged as promising alternatives to mineral oils.

The principal functions of cutting fluids can be summarised as:

- o **Cooling:** diminishing temperature rise in the shear cutting zone to delay tool wear and maintain dimensional accuracy.
- o **Lubrication:** forming films that reduce friction and adhesion, thereby lowering cutting force and improving surface finish.
- o **Chip removal:** chips are being transported away from the cutting region. Chip recutting is avoided to provide a free space for cutting.
- o **Protection:** providing corrosion protection for the workpiece, machine, and tools.

Despite these benefits, conventional flood cooling suffers from several well-documented drawbacks:

- o high fluid consumption and associated procurement, storage, and disposal costs,
- o environmental and work-related health problems from mist, fumes, and biodegradation by-products,
- o regulatory pressures related to waste-fluid handling and effluent treatment.

These limitations have driven a gradual transition towards more sustainable lubrication strategies that drastically reduce fluid usage while maintaining or improving machining performance.

1.5 Evolution of Near-Dry Machining and MQL

Early attempts to reduce fluid consumption focused on optimizing flood delivery and, where possible, on dry machining. However, for many materials and operations—especially at higher speeds—dry-cutting conditions limit tool life and degrade surface finish. Mist

Evolution of Near-Dry Machining and MQL

lubrication emerged as an intermediate solution, in which an air–oil mixture was directed at the cutting zone.

MQL [1], [2], [3], [4] can be viewed as a refined form of mist lubrication, designed to combine the benefits of both dry and flood cooling: extremely low coolant consumption and targeted lubrication/cooling. In MQL, the measured quantity of oil is atomized with compressed air, delivered to the mixing unit to form an aerosol, and injected at high velocity toward the tool-chip zone via an internal or external nozzle. Typical fluid flow rates are only a few tens of milliliters per hour, compared with several liters per minute in flood cooling. A basic MQL system (Figure 1.1) consists of:

- fluid reservoir,
- metering pump,
- air + oil mixing unit,
- compressor,
- nozzle + connecting pipelines.

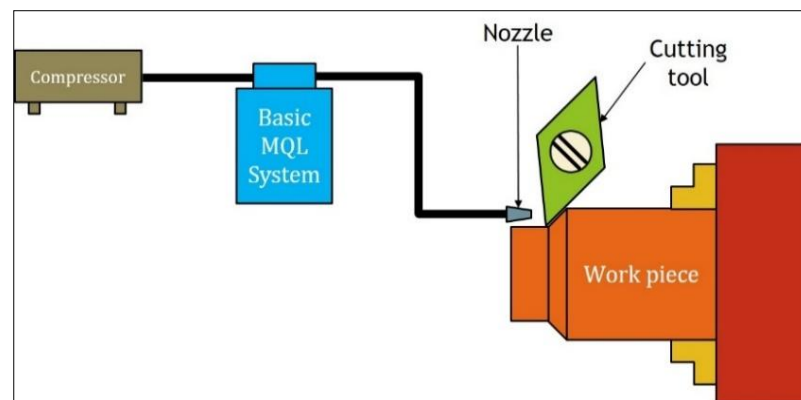


Figure 1.1 A particular arrangement of MQL in a lathe-based turning operation

The aerosol is generated by atomization and can be supplied in two configurations:

- o **External MQL**, where the aerosol is sprayed through an external nozzle towards the tool–chip interface.
- o **Internal MQL**, where the aerosol is formed in an internal atomizer and delivered

Nanofluids in MQL Turning

through channels in the spindle and cutting tool.

In both cases, as shown in Figure 1.2, the fine droplets and high-velocity air stream improve the lubricant's accessibility to the active cutting zone compared with bulk flood jets. This results in:

- o a dramatic reduction in total fluid consumption compared to flood cooling,
- o enhanced accessibility of lubricant to the cutting interface,
- o improved control over local temperature and friction conditions.

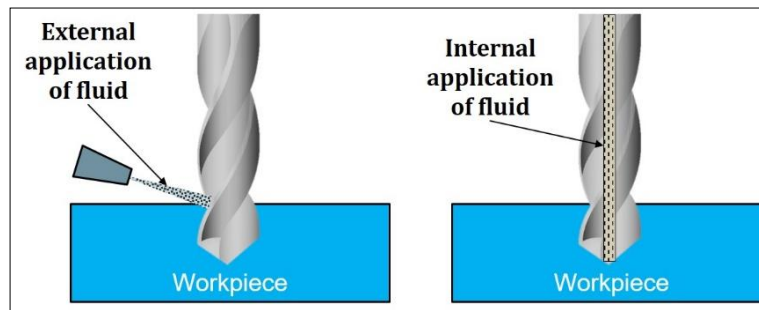


Figure 1.2 External and Internal MQL configurations [5]

1.6 Nanofluids in MQL Turning

The key benefit of using nanofluids is that a small amount of nanoparticles with high thermal conductivity can significantly increase the effective thermal conductivity of the base fluid and, in some cases, its specific heat capacity.

1.6.1 Definition

Nanofluids are colloidal suspensions of nanoparticles, typically less than 100 nanometres in size, dispersed in conventional base fluids including water, mineral oils, or vegetable oils [6]. The nanoparticles may be metallic, ceramic, or carbonaceous. In the context of MQL turning, “mono nanofluids” are those with a single nanoparticle type dispersed in the base fluid (e.g., Al_2O_3 in vegetable oil).

Hybrid Nanofluids in MQL Turning

1.6.2 Mechanisms and benefits

In machining, nanofluids have been investigated primarily as cutting fluids under MQL and related lubrication schemes. Several mechanisms contribute to their performance:

- o **Enhanced thermal conductivity:** NPs with high thermal conductivity create additional heat transfer pathways in the fluid, allowing more effective transport of heat from the cutting zone.
- o **Tribofilm formation:** oxides such as Al_2O_3 can form protective, load-bearing tribofilms at the interface junction of: tool & chip and tool & workpiece, lowering friction and mitigating adhesive wear.
- o **Nano-rolling and nano-bearing effects:** Roughly spherical particles can roll between surfaces at asperity contacts, reducing shear resistance and thus cutting force.
- o **Surface polishing and filling of micro-asperities:** fine particles may polish or fill micro-valleys, leading to smoother surfaces and reduced roughness.

Experimental studies summarised in the literature show that MQL with mono nanofluids typically yields lower CT, CF, SR, and TW than MQL with conventional oils. Among various nanoparticles, Al_2O_3 has emerged as one of the most widely used due to its strong tendency to form tribofilms and its relatively easy dispersion in oils.

1.7 Hybrid Nanofluids in MQL Turning

Hybrid nanofluids (HyNFs) are created by suspending two or more different types of NPs in a base fluid to combine complementary properties. [7]. For example, a hybrid Al_2O_3 – MoS_2 nanofluid can exploit the good load-bearing tribofilm formation of alumina with the solid-lubricant behavior of MoS_2 , while a hybrid Al_2O_3 – CuO nanofluid can simultaneously enhance thermal conductivity and tribological performance.

Reported hybrid combinations in turning include Al_2O_3 – MoS_2 , Al_2O_3 –graphene nanoplatelets, Al_2O_3 –MWCNT, hBN– Al_2O_3 , Al_2O_3 – CuO , CuO – ZnO , and MWCNT– MoS_2 , mostly in vegetable-oil or soluble-oil base fluids. Compared with mono nanofluids, hybrid

Preparation of Nanofluids

nanofluids under MQL have been shown to:

- further reduce cutting force and surface roughness,
- improve thermal conductivity and reduce cutting temperature,
- decrease tool wear and improve chip morphology.

Beyond machining, mono- and hybrid nanofluids have been explored for heat pipes, automotive radiators, solar water distillation, solar collectors, and thermal energy storage systems, reinforcing their relevance as advanced heat-transfer media. However, issues such as long-term stability, potential toxicity of certain nanoparticle types, nozzle clogging, and increased viscosity at higher concentrations remain active areas of research.

1.8 Preparation of Nanofluids

The performance of mono and hybrid nanofluids in MQL systems critically depends on achieving stable, homogeneous dispersions with reproducible properties. The preparation procedure typically includes:

1. **Nanoparticle selection and characterization:** Nanoparticles are chosen based on thermal conductivity, hardness, chemical compatibility, morphology, and cost. For example, Al_2O_3 and ZnO particles with 30–50 nm in size, high purity ($\approx 99.9\%$), and spherical morphology offer favorable thermal and tribological characteristics for cutting-fluid applications.
2. **Base fluid selection:** Base fluids may be mineral oils, synthetic oils, soluble oils, or vegetable oils (e.g., coconut, groundnut, palm oils), selected for lubricity, biodegradability, and compatibility with nanoparticles.
3. **Calculation and weighing of nanoparticle mass:** For a given target concentration (e.g., 1 wt% or 2 wt%), the required mass of nanoparticles is calculated based on the base fluid volume and true density of the particles, and accurately weighed using precision balances or ultrasonic weight gauges.
4. **Dispersion via mechanical stirring:** The NPs are added to the base fluid and stirred using magnetic stirrers to promote initial dispersion and avoid large agglomerates.

Artificial Neural Networks (ANNs) in Machining

Stirring times of 1–2 hours per batch are typical.

5. **Ultrasonication:** Ultrasonic homogenizers are then used to subject the suspensions to high-frequency acoustic energy, which breaks up agglomerates and enhances dispersion stability. Ultrasonication durations of around 2 hours per batch are common.

These preparation steps are similar for both mono and hybrid nanofluids, with the latter requiring precise proportioning of multiple nanoparticle types (e.g., 75/25, 50/50, and 25/75 ratios of $\text{Al}_2\text{O}_3/\text{ZnO}$ in SAE-40 oil in the present work).

1.9 Artificial Neural Networks (ANNs) in Machining

Artificial neural networks are data-driven models composed of interconnected processing units (“neurons”) arranged in layers. They can approximate complex nonlinear mappings between input and output variables without requiring an explicit functional form, provided there is sufficient training data.

In machining and cooling-strategy studies, ANNs are commonly used to:

- predict output machining responses for new combinations of cutting parameters and cooling conditions,
- investigate the impact of various inputs such as nanofluid composition, concentration, and MQL parameters,
- support multi-objective optimization by enabling rapid evaluation of candidate parameter sets.

Feed-forward networks with one or more hidden layers, trained using back-propagation algorithms and gradient-based optimization, are the most common architectures. Alternative architectures such as cascade-forward networks, Elman recurrent networks, distributed time-delay networks, and generalized regression networks have also been applied and compared.

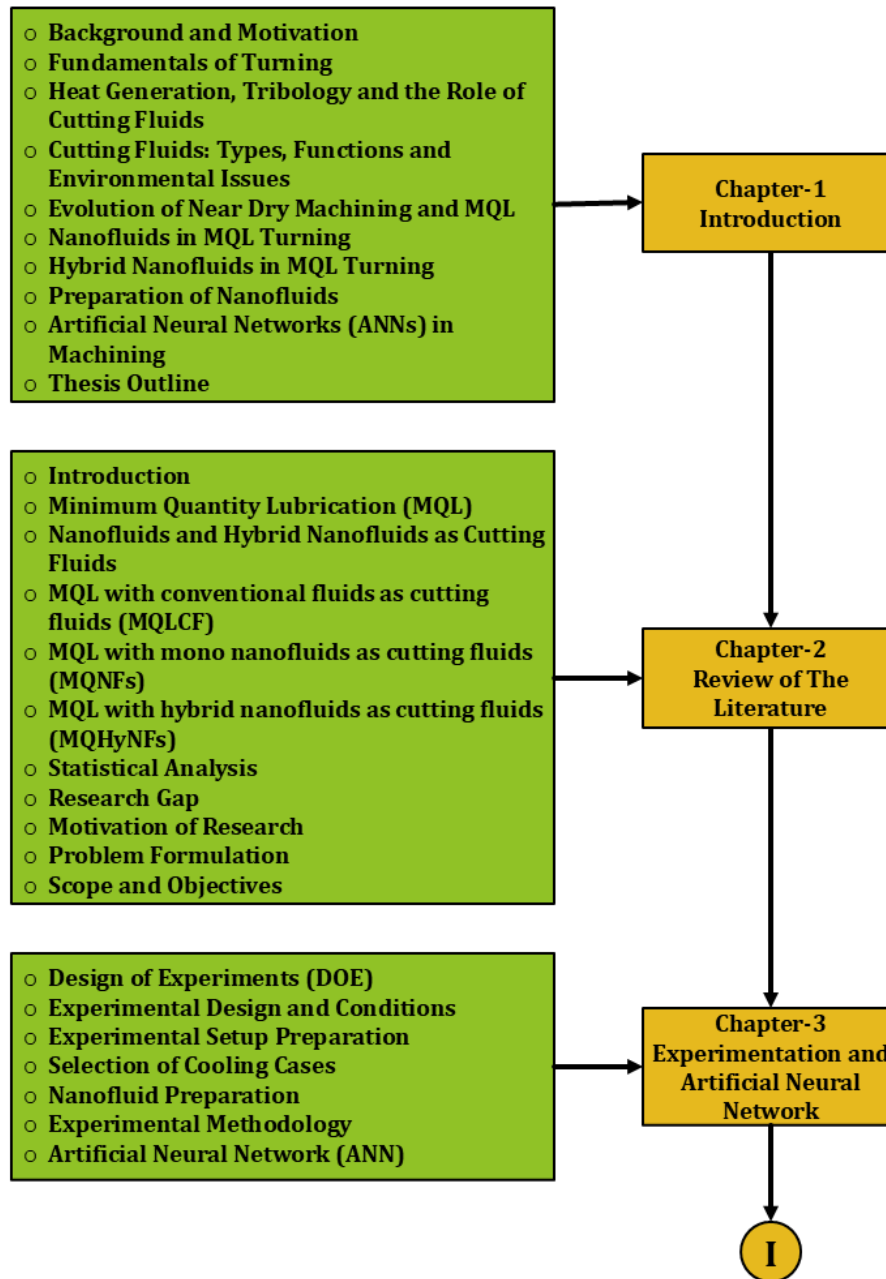
The objective is to obtain networks with low error and high R^2 for all output variables, thereby achieving reliable predictive capability. In the context of cooling-condition

Thesis Outline

performance, ANNs can incorporate both continuous parameters (speed, feed, depth of cut, nanoparticle fraction) and categorical inputs (cooling condition: dry, wet, MQL with conventional, mono, or hybrid nanofluid), making them particularly suitable for the present research.

1.10 Thesis Outline

This research consists of six chapters. Figure 1.3 depicts the thesis structure.



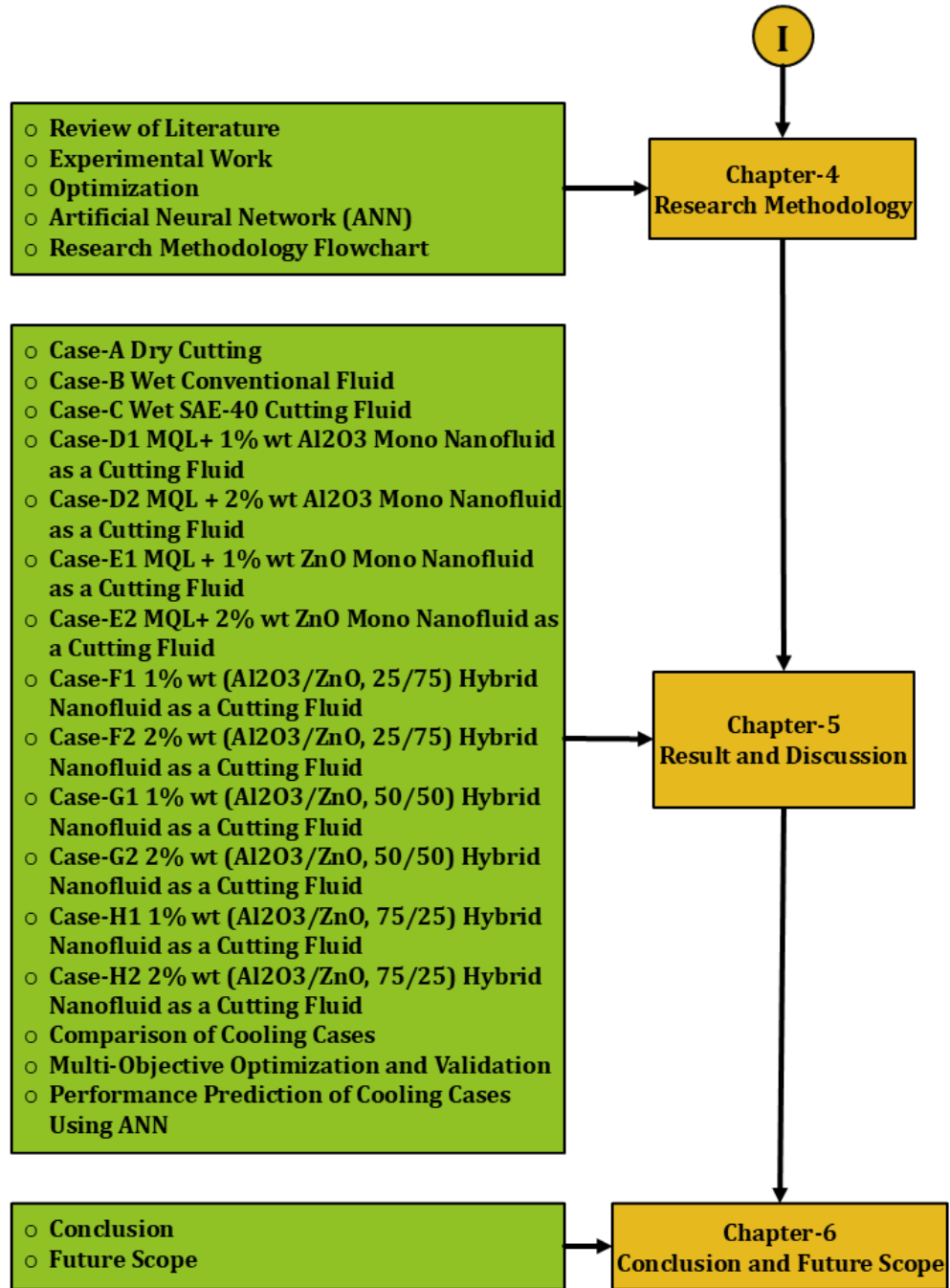


Figure 1.3 Diagram of Thesis Outline

CHAPTER 2. REVIEW OF THE LITERATURE

2.1 Introduction

Turning is the most commonly employed manufacturing process for producing rotational parts using a single-point cutting tool. Significant plastic deformation and sliding contact occur at the interface between the cutting tool and the chip-workpiece during this process, generating substantial heat; the high temperatures increase tool wear and reduce surface quality. Such an effect is not good for high-productivity production. For this purpose, cutting fluids are used to cool the cutting zone, lubricate, and remove chips.

Conventional cooling strategies are broadly classified into dry and wet (flooded) methods. Dry cutting eliminates fluid-related costs but generally results in higher cutting temperatures and poorer surface finish due to unmitigated friction at the cutting interface. Flood cooling delivers a large volume of emulsion or oil to the tool–workpiece interface, thereby improving heat removal. Still, it suffers from high consumption, waste-treatment costs, and environmental and health concerns. These limitations have motivated the development of more sustainable lubrication strategies, notably minimum quantity lubrication (MQL) and, more recently, MQL combined with mono and hybrid nanofluids.

2.2 Minimum Quantity Lubrication (MQL)

2.2.1 Principle of MQL

MQL is a nearly dry machining technique in which a small quantity of lubricant is mixed with pressurized air to form a fine aerosol, which is then directed onto the cutting zone. Typical oil flow rates are only a few tens of milliliters per hour, which is orders of magnitude lower than those of flood systems. A basic MQL system comprises the following: a fluid tank, a pump, an air & oil mixer, a compressor, a nozzle, and interconnecting pipework.

The aerosol is generated by atomization and is supplied either externally through nozzles or internally through passages within the tool or spindle. In external MQL, the spray is delivered from outside the tool toward the tool–chip region. In contrast, in internal MQL,

Nanofluids and Hybrid Nanofluids as Cutting Fluids

the aerosol forms within the system and is transported through internal channels to the cutting edge. The atomized droplets can penetrate more effectively into the contact region than a bulk jet, thereby improving access to the active cutting zone.

2.2.2 Advantages and limitations

By combining the cooling effect of compressed air with the lubricating action of micro-droplets, MQL has been shown to decrease CT, CF, SR, and wear rate, as estimated under dry machining conditions, in some turning, drilling, milling, and grinding studies. Since only a small amount of fluid is used, MQL significantly reduces coolant consumption, handling, and disposal requirements, and is regarded as more economical, safer, and more environmentally friendly than flood cooling.

However, the limited fluid volume makes thermal control sensitive to nozzle position, air pressure, spray angle, and flow rate, and performance strongly depends on the tribological behavior of the chosen base fluid. To further improve heat transfer and friction reduction under MQL, nanofluids and hybrid nanofluids have been introduced as advanced cutting-fluid formulations.

2.3 Nanofluids and Hybrid Nanofluids as Cutting Fluids

The primary rationale for nanofluids is that even low concentrations of high-conductivity nanoparticles can substantially increase the base fluid's effective thermal property and, in certain cases, its specific heat capacity. In addition, the presence of nanoparticles can modify viscosity, wetting behavior, and tribological response, thereby enabling improved lubrication and heat transfer in compact systems.

2.3.1 Nanofluids (NFs)

Nanofluids are colloidal suspensions containing nanoscale particles—typically smaller than 100 nm—made from metals, metal oxides, carbides, nitrides, or carbon-based materials, dispersed in traditional base fluids including water, mineral, and vegetable oils. Commonly reported nanoparticle types include pure metals, metal oxides, carbides, nitrides, and carbon-based materials.

MQL with conventional fluids as cutting fluids (MQLCF)

The motivation for using nanofluids in machining is to tailor thermal and mechanical properties beyond those of the base fluid. At suitable concentrations, nanoparticles enhance thermal properties, support the generation of protective tribofilms at the junction of the tool–workpiece interface, and may introduce nano-rolling or shear-reducing effects at asperity contacts. Hence, the CT, CF, SR, and TW could be reduced more effectively with nanofluid-assisted MQL compared to conventional fluid MQL.

2.3.2 Hybrid nanofluids (HyNFs)

Hybrid nanofluids contain two or more different nanoparticle types in the same base fluid. They are designed to combine complementary advantages, for example, pairing a high-conductivity particle with a solid-lubricant particle. In turning applications, reported hybrid combinations include Al_2O_3 – MoS_2 , Al_2O_3 –graphene nanoplatelets, Al_2O_3 –MWCNT, hBN– Al_2O_3 , Al_2O_3 –CuO, CuO–ZnO, and MWCNT– MoS_2 , dispersed in vegetable oils, soluble oils, or conventional cutting oils.

Recent work shows that hybrid nanofluids can offer higher effective thermal conductivity and improved tribological behavior compared with mono nanofluids, leading to further reductions in output parameters. At the same time, issues such as dispersion stability, increased viscosity at higher loadings, and safe handling of nanoparticles remain important considerations in design and implementation.

2.4 MQL with conventional fluids as cutting fluids (MQLCF)

The earliest MQL investigations were conducted with conventional cutting fluids (mineral oils, emulsions, and vegetable oils) without nanoparticles. These studies provide the baseline for evaluating the benefits of nanofluid and hybrid nanofluid formulations.

The potential of MQL with conventional cutting fluids has been extensively explored in turning operations, particularly for alloy and carbon steels. Dhar et al. [8] reported that for AISI 4340 steel, MQL markedly decreased CT, SR, and TW compared with both dry and wet cooling methods. SEM analysis of the inserts revealed reduced notch growth and less damage along the cutting edge. In a related study on AISI 1040 steel, Dhar et al. [9] found lower cutting temperatures, improved chip color and morphology, and better dimensional

MQL with conventional fluids as cutting fluids (MQLCF)

accuracy under MQL, demonstrating that MQL can provide both thermal and geometric benefits over conventional cooling strategies.

Subsequent work showed that the extent of MQL's advantage depends on the workpiece material, tool, and parameter range. Bruni et al. [10], studying AISI 420B stainless steel with conventional and wiper inserts, found that the choice of cooling environment (dry, wet, or MQL) did not markedly influence tool wear, suggesting that material and tooling can moderate the relative benefit of MQL—conversely, Dhar et al. [11], on AISI 1040 steel, reported that adopting MQL instead of dry machining reduced cutting force by about 5–15%, significantly lowered cutting temperature, and improved SR and dimensional correctness due to reduced flank wear. Davim et al. [12] compared MQL and wet machining in CNC turning of commercial brass and observed only small differences in cutting power between the two systems; nevertheless, lubricated conditions helped control surface roughness as feed increased. Khan et al. [13] examined alloy steel AISI 9310 under vegetable-oil MQL and found approximately 10% reduction in temperature of chip–tool interface relative to wet machining, smoother chip back surfaces, and markedly longer tool life, indicating that biodegradable oils under MQL can provide strong tribological advantages.

Several researchers have focused on medium-carbon and stainless steels to elucidate the parametric effects of MQL. Hwang and Lee [14] used a fractional factorial design and central composite RSM to compare cutting of AISI 1045 steel by MQL and wet turning; their RSM models satisfactorily predicted cutting forces in both environments, although surface-roughness behavior remained more difficult to capture. Leppert [15] compared dry, emulsion, and MQL-assisted machine turning of medium carbon steel AISI 1045 and found that, at low feeds, the absence or reduction of CF tends to raise cutting forces, but MQL still gives clear advantages in surface quality, surface topography, profile bearing ratio, and waviness; feed rate was identified as a dominant factor in these responses. Che Haron et al. [16] applied a Box–Behnken RSM design to study Inconel 718 under MQL and showed that surface roughness values were confined to a small range of approximately 0.4–2.9 μm , with ANOVA confirming that FR is the most influential input factor on surface finish. In complementary work on AISI 316L stainless steel, Leppert [17] found that maximum cutting force occurred with emulsion cooling and minimum force in dry cutting, while MQL had little effect on force but clearly reduced surface roughness and suppressed built-up edge

MQL with conventional fluids as cutting fluids (MQLCF)

formation; again, SEM analysis indicated improved surface quality under MQL at low feeds.

Other studies have emphasized the combined effects of lubrication mode, tool type, and nozzle design. Lohar and Nanavaty [18] investigated hardened AISI 4340 steel turned with a CBN tool under conditions like dry, wet, and MQL, using Taguchi methods for optimization, and reported that MQL meaningfully reduced both CF and CT by about 40% and 36%, respectively, and improved surface finish by roughly 30% compared with dry and wet cutting. Hadad and Sadeghi [19] examined AISI 4140 steel and demonstrated that both MQL nozzle position (rake, flank, or both) and cutting parameters significantly affect cutting forces, temperature, and surface roughness; a heat-source–heat-sink temperature model developed for MQL turning showed good agreement with measured data. Saini et al. [20] studied AISI 4340 steel using PVD- and CVD-coated carbides under dry and MQL conditions and observed that PVD-coated inserts yielded lower cutting forces and temperatures than CVD-coated inserts, and that MQL further enhanced performance, particularly for cutting force with CVD tools and for temperature with PVD tools. Agrawal and Patil [21] evaluated aloe-vera-oil MQL versus a commercial cutting oil when machining M2 steel and found that MQL with aloe vera oil as a base fluid reduced surface roughness by about 6.7% and slightly reduced tool wear compared to the conventional oil. Gordana et al. [22], reviewed the turning of C45E carbon steel at higher feeds and speeds, concluded that MQL generally yields more favorable cutting force, wear rate, and surface roughness than conventional lubrication, while also being cost-effective and environmentally benign.

Further refinements to MQL delivery systems include the use of textured tools and the optimization of nozzle placement. Liu et al. [23] proposed a Coupling Response Surface Methodology (CRSM) framework for Ti-6Al-4V turning under MQL, integrating Taguchi design and RSM; they reported that FR is the main factor affecting both machining force and surface finish, and that optimal conditions correspond to low values of both DC & FR, and high values of cutting speed. Masoudi et al. [24] studied AISI 1050 steel with nozzles directed at rake face, flank face, and both faces under conditions such as dry, wet, and MQL and showed that MQL, particularly when applied to the rake face, significantly reduced cutting force, face roughness of rake, and wear rate of tool, with the benefits becoming more pronounced at higher workpiece hardness. In high-performance applications with textured tools, Sivaiah et al. [25] demonstrated that hybrid-textured or micro-pit-textured carbide tools combined with MQL can reduce cutting temperature by up to about 36%, flank wear

MQL with conventional fluids as cutting fluids (MQLCF)

by nearly 59%, and surface roughness by up to 54%, while increasing material-removal rate by around 27% compared with untextured tools or conventional conditions. Singh et al. [26] used an RSM-based central composite design for Hastelloy C-276 under vegetable-oil MQL. They identified optimal parameter combinations that minimize CT, SR, and chip reduction coefficient. In contrast, Bhadoria and Bartarya [27] showed that MQL with ceramic inserts for EN31 steel turning can achieve very low surface roughness and flank wear, enabling high-speed, high-feed cutting without sacrificing surface quality.

Taken together, these investigations confirm that MQL with conventional cutting fluids is an effective near-dry lubrication strategy for turning, capable of substantially reducing surface finish, temperature, and tool edge wear relative to the condition of dry cutting and, in many cases, matching or outperforming flood cooling in regard to surface integrity and TW. The outcomes also underscore that MQL's effectiveness depends on an appropriate choice of workpiece–tool combination, cutting parameters, tool coatings or textures, and careful design of the MQL system (nozzle position, pressure, and flow), thereby motivating the need for systematic experimental design and optimization in MQL-based turning research. The comparative analysis in Table 2.1 is structured by the cutting-fluid type and the lubrication mode employed in each study, along with the corresponding critical observations.

Table 2.1 Comparative evaluation of published articles related to MQL with conventional cutting fluid

Researchers	Cutting fluids types	Method of lubrication	Main findings	Year
Dhar et al. [8]	NM	MQL, dry, wet	MQL has improved CT, TW, and SR compared to both dry and wet machining; this method demonstrates reduced dimensional deviation.	2006
Dhar et al. [9]	NM	MQL, dry, wet	MQL lowered SR and TW and improved dimensional accuracy relative to dry and wet conditions.	2006
Bruni et al. [10]	Vegetable oil	MQL, dry, wet	MQL didn't provide a clear advantage over dry cutting in terms of TW or SR.	2006
Dhar et al. [11]	Mobil Cut-102	MQL, dry	MQL reduced CF by approximately 5-15%, and CT, SR, TW, and dimensional deviation were also reduced compared with dry machining.	2007

MQL with conventional fluids as cutting fluids (MQLCF)

Davim et al. [12]	Emulsion oil Microtrend 231L	MQL, wet	Only small differences in SR and CP were observed between MQL and wet lubrication for the conditions studied.	2007
Khan et al. [13]	Vegetable oil	MQL, dry, wet	Vegetable-oil-based MQL lowered chip-tool CT by about 10%, achieved smaller SR and TW, and removed the built-up edge compared to dry and wet cutting.	2009
Hwang and Lee [14]	NM	MQL, wet	MQL offered lower SR and CF than wet machining.	2010
Leppert [15]	Biodegradable vegetable oil	MQL, dry, emulsion	MQL produced improved SR and CF relative to dry and emulsion cooling, with satisfactory ST.	2011
Che Haron et al. [16]	NM	MQL	ANOVA showed that FR is the most influential parameter on SR under MQL turning of Inconel 718.	2011
Leppert [17]	Accu-Lube LB 8000 oil	MQL, dry, emulsion	MQL had little effect on CF compared with dry and emulsion cooling, but clearly reduced SR and suppressed the formation of built-up edge.	2012
Lohar and Nanavaty [18]	Cutting oil	MQL, dry, wet	Relative to dry and wet cutting, MQL reduced CF by about 40%, CT by 36%, and SR by 30%.	2013
Hadad and Sadeghi [19]	Ester oil (RS 1642)	MQL, dry, wet	MQL lowered CT, CF, and SR, and nozzle position strongly influenced CT and SR.	2013
Gordana et al. [22]	NM	MQL, wet	MQL proved to be an effective and more promising solution than the current dry-sliding alternative for achieving favorable CF, TW, and SR, with lower machining cost and environmental impact.	2013
Liu et al. [23]	Vegetable oil	MQL, dry, wet	In Ti-6Al-4V machining under MQL, increasing CS and DC increased CF, while SR was mainly affected by CS.	2013
Saini et al. [20]	Soluble cutting oil	MQL, dry	PVD-coated carbide inserts produced lower CF and tool-tip CT than CVD-coated inserts, and MQL further improved CF for CVD tools and CT for PVD tools.	2014
Masoudi et al. [24]	Ester oil	MQL, dry, wet	MQL significantly reduced CF, SR, and TW, with the best performance obtained when the nozzle was directed towards the rake face.	2017

MQL with mono nanofluids as cutting fluids (MQNFs)

Agrawal, and Patil [21]	Aloe vera oil, & Servo cut S oil	MQL.	Aloe-vera-oil MQL lowered SR by about 6.7% compared with the commercial oil, with SR decreasing as CS increased, and also slightly reduced TW.	2018
Sivaiah et al. [25]	Emulsion-based flood	MQL	A hybrid-textured PVD-coated carbide tool under MQL reduced CT, TW, and SR by approximately 36%, 59% and 46% compared with an un-textured tool.	2019
Sivaiah et al. [28]	Emulsion-based flood	MQL, wet	Compared to untextured tools with MQL, textured tools with MQL generated lower CT, TW, and SR. Also, MQL requires less fluid than conventional flood coolant, which offers greater environmental advantages.	2020
Singh et al. [26]	Vegetable oil	MQL, wet, dry	Vegetable-oil MQL yielded lower CT, SR, and chip reduction coefficient than dry and wet conditions, and an RSM-based CCD model was used to identify optimal cutting parameters.	2021
Bhadoria and Bartarya [27]	Servocut s	MQL, dry	Ceramic inserts under MQL produced the lowest SR and TW, enabling higher CS and feeds without loss of surface quality compared with dry machining.	2021
Sivaiah et al. [29]	Emulsion-based flood	MQL.	For AISI 304 steel, with a carbide tool and a circular micro-pit-textured surface, using MQL, the optimum setting was obtained by the weighted grey relational model, which reduced TW and SR and significantly increased the material removal rate.	2021

Concise review articles specifically addressing minimum-quantity lubrication with conventional cutting fluids have been reported in the literature [2], [3], [30]. These works provide focused assessments of MQL performance compared with dry and flood cooling across the major machining processes of turning, drilling, grinding, and milling.

2.5 MQL with mono nanofluids as cutting fluids (MQNFs)

In recent years, MQL combined with mono nanofluids (MQLNFs) has been widely investigated as a means to enhance cooling and lubrication in turning and other machining processes, owing to the superior mechanical and tribological properties imparted by mono-type nanoparticles dispersed in traditional base oils compared with dry, wet, oil-only

MQL with mono nanofluids as cutting fluids (MQNFs)

MQL conditions, and traditional wet conditions.

Krishna et al. [31] showed that boric-acid nanofluids prepared using SAE-40 and Coconut oil immensely improve CT, surface quality, and average tool wear (flank) in the turning process of AISI 1040 medium carbon steel, with the coconut-oil nanofluid performing better than the mineral-oil-based system. Rao et al. [32] reported that CNT-based nanofluids improved cutting forces, temperatures, surface integrity, and tool life, up to 2% CNT loading, in AISI 1040 turning, beyond which no further benefit was observed. For Inconel 600, Vasu and Reddy [33] demonstrated that MQL with Al_2O_3 nanofluids (4-6 v%) provided better temperature dissipation, lower cutting forces, reduced average tool wear, and improved surface quality than both dry and conventional MQL, with Taguchi analysis confirming the dominant effect of feed rate on roughness and DC on thermal-mechanical responses.

Several studies demonstrate significant benefits of oxide- and carbon-based nanofluids for ferrous alloys. Khandekar et al. [34] reported that 1 wt% Al_2O_3 nanofluid in turning AISI 4340 reduced cutting force by up to about 50% and surface roughness by roughly 55% relative to dry cutting, and by around 30% relative to conventional emulsions. Amrita et al. [35] found that mist lubrication using 0.5 wt% nano-graphite in soluble oil substantially reduced cutting forces and tool wear for both carbide and HSS tools under dry, flood, and HSS coolant conditions in turning of AISI 1040 steel, and subsequent work [36] showed that graphite, boric acid, and MoS_2 nanofluids in emulsifier oil could be tuned such that MoS_2 provided the best force and wear response, whereas boric acid gave superior heat dissipation. Sayuti et al. [37] optimized SiO_2 -mineral-oil nanofluid MQL for AISI 4140 using Taguchi design and fuzzy logic, identifying 0.5 wt% nanoparticles with certain air pressure values and nozzle inclinations. Thus, the selected pair, as aforementioned, achieved optimal performance for minimizing tool wear and improving surface finish.

Copper and other metal-oxide nanofluids have also shown strong potential. Shabgard et al. [38] observed that adding 1 wt% CuO to the soluble oil decreased both CF and SR by approximately 24% and 49%, respectively, in AISI 4340 turning compared with dry and base-fluid conditions. Khalil et al. [39] reported a reduction in TW and an increase in tool life during mild steel machining when using an Al_2O_3 nanofluid MQL. Ganesan et al. [40] demonstrated that Cu-nanofluid MQL during H11 steel turning reduced SR by

MQL with mono nanofluids as cutting fluids (MQNFs)

approximately 40% and TW by approximately 66%, with RSM-based models confirming the statistical significance of these improvements. Das et al. [41] later showed that among several nanofluids (ZnO, CuO, Fe₂O₃, Al₂O₃) for AISI 4340, CuO yielded the lowest CF, least flank wear, and best SR under MQL.

Carbonaceous nanofluids and mixed carbide/nitride systems have been widely optimized using statistical and soft-computing tools. Sharma et al. [42] showed that MWCNT nanofluid MQL outperformed conventional MQL for AISI D2 steel, in terms of temperature and surface roughness—subsequent studies by researchers, Sharma et al. [43] and [44] on TiO₂- and Al₂O₃-based nanofluids in vegetable-oil–water emulsions for AISI 1040 turning reported substantial reductions in tool wear (up to roughly 60%) and cutting force (up to about 60%), along with 25–50% reductions in surface roughness and improved silver-coloured, curled segmented chips, in contrast with conditions of dry, mist, and wet turning. Gupta et al. [45] used RSM, PSO, and BFO to optimize Al₂O₃, MoS₂, and graphite nanofluids for Ti-grade-2 turning, finding that graphite-based nanofluids gave the best overall reductions in machining force, temperature, tool wear, and roughness.

Optimization-oriented studies further underline the role of process design in exploiting MQLNFs. Paturi et al. [46] showed that WS₂-based nanofluid MQL in Inconel 718 turning reduced surface roughness by about 35% relative to conventional MQL, with Taguchi–ANOVA models identifying optimal parameter windows. Rapeti et al. [47] used Taguchi L27 & GRA to optimize MoS₂ nanofluids in coconut, canola, and sesame oils for AISI 1040, concluding that coconut oil + 0.5% MoS₂ at CS: 40 m/min, and FR: 0.14 mm/rev provided the most suitable multi-response performance and was economically viable. Patole and Kulkarni [48] applied Grey Relational Analysis to MWCNT-based nanofluids in AISI 4340 turning and found that nanofluid-MQL lowered the SR, and also the CF compared with other lubrication strategies, with ANOVA trends closely matching GRA results. Singh et al. [49] used RSM and ANOVA to show that higher concentrations of graphene nanoplatelets in Servo-Cut-oil nanofluids were particularly effective in lowering CT and SR in AISI 304 turning at elevated speeds and feeds.

Additional work has addressed different alloys and comparative cooling modes. Joshi et al. [50] demonstrated that Al₂O₃–vegetable-oil nanofluid MQL significantly improved the surface roughness of Inconel 600 over both dry cutting and plain-oil MQL, and developed a

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predictive model based on Taguchi analysis. Vishnu et al. [51] compared dry, flood, and Al_2O_3 nanofluid MQL conditions in EN353 steel turning, showing that while flood cooling gave the best absolute performance, MQL nanofluid results were very close, with clear advantages in cost, environmental impact, and operator health. Pasam et al. [52] reported that boric acid and MoS_2 nanofluids in coconut oil outperformed their corresponding microfluids at higher cutting speeds for AISI 1040, with MoS_2 yielding superior improvements in forces, temperature, roughness, and wear, although microfluids remained more economical. Sivalingham et al. [53] used an atomized graphite– MoS_2 spray to improve Inconel 718 machinability, achieving 17-34% better surface roughness, lower wear, longer tool life, and reduced machining cost compared with dry cooling.

Finally, recent studies have extended MQNFs to residual-stress control and hard-to-cut alloys. Venkatesan et al. [54] showed that hBN nanofluids in coconut oil under MQL, especially at 0.25 wt% concentration with PVD-coated tools, significantly lowered CF, TW, and SR during Hastelloy turning, in contrast to dry conditions and CVD-coated tools. Ramanan et al. [55] examined that 1% Al_2O_3 NF MQL used in machining of Incoloy 800 enhanced fluid wettability, markedly decreased cutting force and surface quality, and slowed average TW compared with cutting modes of dry, flood, and conventional MQL. Nikouei et al. [56] demonstrated that TiO_2 -based nanofluids in Inconel 718 turning can appreciably lower tensile residual stress (from about 11% to 20%), indicating an additional benefit of MQL-NFs beyond immediate force and temperature reductions. To enable a comprehensive review of research on nanofluid-assisted MQL, the surveyed studies are systematically classified in Table 2.2 according to workpiece material, cutting tool material, nanoparticle type, size and morphology, base fluid, and the key reported findings.

Table 2.2 Comparative evaluation of studies related to MQL contains mono-nanofluid

Researchers	Types of NPs with size (nm)	Base fluid types	Main findings	Year
Krishna et al. [31]	Nanoboric acid (50)	SAE-40 oil and coconut oil	Nanofluids reduced machining temperature, TW, and SR, with coconut-oil-based nanofluid performing better than SAE-40 oil.	2010
Rao et al. [32]	CNT (NM)	NM.	CNT nanofluid reduced CT and TW, with the best performance observed up to 2% CNT addition.	2011

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Vasu and Reddy [33]	Al ₂ O ₃ (NM)	Vegetable oil (Coolube 2210)	MQL with Al ₂ O ₃ nanofluid improved machining performance; FR mainly affected SR, while DC strongly influenced CT, feed force, and CF.	2012
Khandekar et al. [34]	Al ₂ O ₃ (NM)	Servo cut-S	Adding 1 wt% Al ₂ O ₃ nanofluid reduced TW, CF, and SR compared with dry machining & conventional fluid machining.	2012
Amrita et al. [35]	Graphite (<80)	Soluble oil	Nano-graphite in soluble oil lowered CF and TW, with improvement in CT, TW & CF overall.	2013
Amrita et al. [36]	Graphite (80), boric acid (100), MoS ₂ (100)	Emulsifier oil	Among the tested nanoparticles, MoS ₂ gave the best TW and CF performance, while boric acid showed the best heat dissipation.	2014
Sayuti et al. [37]	SiO ₂ (5-15)	Mineral oil	SiO ₂ nanolubricant MQL minimized TW and SR at 0.5 wt% concentration with suitable nozzle orientation.	2014
Shabgard et al. [38]	CuO (NM.)	Soluble CF	CuO nanofluid reduced CF and SR compared with soluble oil and dry machining.	2014
Khalil et al. [39]	Al ₂ O ₃ (NM.)	Soluble cutting oil	Al ₂ O ₃ nanofluid reduced TW and improved tool life.	2015
Sharma et al. [42]	MWCNT (NM)	SAE. 20W40 oil	MWCNT nanofluid lowered CT, SR, and TW.	2015
Sharma et al. [43]	TiO ₂ (NM)	Vegetable oil-water emulsion	TiO ₂ nanofluid significantly reduced TW, CF, and SR compared with dry and mist machining.	2016
Sharma et al. [44]	Al ₂ O ₃ (45)	Vegetable oil-water emulsion	The Al ₂ O ₃ nanofluid produced similar improvements, with strong reductions in TW, CF, and SR.	2016
Gupta et al. [45]	Al ₂ O ₃ (40), MoS ₂ (40), Graphite (40)	Vegetable oil	Graphite-based nanofluids gave the best overall multi-response improvement in CF, CT, TW, and SR.	2016
Paturi et al. [46]	Tungsten disulfide WS ₂ (NM)	Emulsifier oil	WS ₂ -assisted MQL reduced SR compared with conventional MQL.	2016
Rapeti et al. [47]	MoS ₂ (NM)	Coconut oil, sesame oil, and canola oil	Coconut oil + 0.5% MoS ₂ provided the most suitable all-around machining performance, minimizing CF, CT, TW, and SR.	2016
Padmini et al. [57]	MoS ₂ (NM)	Coconut oil, sesame	MoS ₂ NF + coconut oil improved the fluid's thermal properties and reduced CF CT, TW, and SR.	2016

MQL with mono nanofluids as cutting fluids (MQNFs)

		oil, and canola oil		
Patole and Kulkarni [48]	MWCNT (15)	Ethylene glycol	MWCNT nanofluid improved machining performance, lowering SR and CF.	2017
Sharma et al. [58]	SiO ₂ (10)	Vegetable oil-water emulsion	SiO ₂ nanofluid reduced TW and SR and produced smoother chips.	2017
Singh et al. [49]	Graphene nanoplatelets (30–40)	Servo Cut S oil	High graphene nanoplatelet % concentration reduced CT and SR, especially at high CS and low FR/DC.	2018
Joshi et al. [50]	Al ₂ O ₃ (NM)	Vegetable oil	The surface quality improved significantly with Al ₂ O ₃ nanofluid machining compared with dry machining and simple MQL machining.	2018
Vishnu et al. [51]	Al ₂ O ₃ (NM)	Water	Flooded cooling gave the best thermal performance, though MQL with Al ₂ O ₃ showed only a small difference and remained environmentally preferable.	2018
Pasam et al. [52]	Boric acid (100) and MoS ₂ (90)	Coconut oil	Nanofluids outperformed microfluids at higher CS, and MoS ₂ was more effective than boric acid.	2018
Ganesan et al. [40]	Copper (50)	Ethylene glycol	Copper nanofluid reduced SR and TW and improved chip morphology.	2018
Sivalingam et al. [53]	Graphite (30-45), and MoS ₂ (10-15)	Vegetable oil	Graphite–MoS ₂ spray improved SR, TL, and machining cost relative to dry cooling.	2020
Das et al. [41]	ZnO, CuO, Fe ₂ O ₃ , and Al ₂ O ₃ (NM)	Deionized water	The CuO nanofluid exhibited the lowest CF, the lowest TW, and the best surface finish among the tested nanofluids.	2020
Venkatesan et al. [54]	hBN (30-100)	Coconut oil	hBN nanofluid with MQL and PVD-coated tools improved CF, TW, and SR.	2020
Ramanan et al. [55]	Al ₂ O ₃ (20)	Semi-synthetic soluble oil	1% Al ₂ O ₃ nanofluid improved wettability and significantly reduced CF, TW, and SR.	2021
Nikouei et al. [56]	TiO ₂ (10, 30, 50)	Water	TiO ₂ nanofluid reduced residual stress substantially.	2021

Significant review studies [42], [59], [60], [61], [62] and have examined nanofluid preparation, nanoparticle concentration, and the use of nanofluids in MQL, with particular

MQL with hybrid nanofluids as cutting fluids (MQHyNFs)

attention to machining performance indicators such as CF, CT, SR, TW, and chip morphology. These reviews cover major machining processes, including turning, milling, grinding, and drilling, and consistently compare nanofluid-assisted MQL with conventional MQL, dry machining, and wet lubrication systems.

2.6 MQL with hybrid nanofluids as cutting fluids (MQHyNFs)

Hybrid nanofluids have recently attracted considerable attention as cutting fluids in MQL because they can combine the beneficial effects of two types of nanoparticles, thereby improving both cooling and lubrication in the interface zone between the cutting tool & work part. In the published literature, several researchers have reported that hybrid nanofluids generally outperform dry machining, conventional MQL with base oil, and, in some cases, even mono nanofluid systems in regards of CF, CT, SR, and TW.

Sharma et al. [63] investigated Al_2O_3 – MoS_2 hybrid nanofluids in the AISI 304 steel turning and reported noticeable reduction in CF components and SR at nanoparticle concentrations between 0.25 and 1.25 v%. Singh et al. [64] studied graphene nanoplatelets dispersed in an Al-based nanofluid and found improvements in thermal conductivity, viscosity, wear resistance, and wettability, along with reductions in SR and CF. Similarly, Sharma et al. [65] showed that Al_2O_3 –GnP hybrid nanofluids produced lower pin wear and friction coefficient than alumina nanofluids, while also reducing cutting temperature and tool wear during AISI 304 turning.

Hybrid nanofluid MQL has also demonstrated encouraging results in the machine turning of hard-to-cut materials. Jamil et al. [66] proclaimed that Al_2O_3 –MWCNT hybrid nanofluids in vegetable oil improved SR, CF, and tool life during tungsten alloy turning. However, cryogenic cooling still gave a slightly lower cutting temperature. Yildirim [67] compared several cooling strategies for Inconel 625 turning and found that the combination of liquid nitrogen with a 0.5 v% hBN nanofluid provided the most favorable overall machining performance in regards of surface improvement and TW. Thakur et al. [68] and [69] further confirmed that hybrid nanofluids such as Al_2O_3 –CuO perform better than mono nanofluids in EN24 steel turning, reducing the coefficient of friction, temperature, tool wear, force, and surface quality. Their optimization studies also indicated that the hybrid nanofluid condition offered the best overall multi-response performance.

MQL with hybrid nanofluids as cutting fluids (MQHyNFs)

Other studies have reinforced these findings across different workpiece materials and nanoparticle combinations. Gugulothu et al. [70] observed that CNT–MoS₂ hybrid nanofluids in sesame oil reduced friction, machining forces, and surface quality in AISI 1040 steel turning, with higher concentrations also lowering cutting temperature and average tool wear. Zaman et al. [71] reported that Al₂O₃–MWCNT hybrid nanofluid MQL improved cutting temperature and surface quality in Ti-6Al-4V turning, with feed rate emerging as the dominant factor influencing roughness; likewise, Kumar et al. [72] found that Cu–Zn hybrid nanofluids reduced CT and SR in Inconel 718 turning versus dry machining and vegetable-oil MQL. In AISI 1018 steel turning, Kumar et al. [73] also reported that CuO–ZnO hybrid nanofluids improved surface finish, with feed rate playing the most meaningful role in the output response. Table 2.3 provides a comprehensive analysis of studies on MQL combined with hybrid nanofluids, considering the NP type and size, the base fluid, the characterization method, and principal findings reported in each study.

Table 2.3 Comparative evaluation of research studies on MQL using hybrid nanofluids

Researchers	Types of NPs with size (nm)	Base fluid types	Tech. of Char.	Main findings	Year
Sharma et al. [63]	Al ₂ O ₃ + MoS ₂ (45, 30)	Vegetable oil	TEM	Lower friction and pin wear were observed when the hybrid Al ₂ O ₃ –MoS ₂ nanofluid was used instead of Al ₂ O ₃ NF. It was observed that lower CF and SR values were achieved with the hybrid nanofluid.	2017
Singh et al. [64]	Al ₂ O ₃ + GnP (45, 11-15)	Servo oil	TEM	The incorporation of Al ₂ O ₃ –GnP hybrid nanoparticles enhanced thermal conductivity and reduced the coefficient of friction. A significant reduction in CF and SR was achieved with the hybrid nanofluid.	2017
Sharma et al. [65]	Al ₂ O ₃ + GnP (NM)	Conventional fluid	TEM, SEM	Low friction and pin wear were observed when both nanofluids were used at increasing concentrations; however, the hybrid nanofluid demonstrated superior performance. It also resulted in lower TW and CT compared to Al ₂ O ₃ nanofluid.	2018
Jamil et al. [66]	Al ₂ O ₃ + MWCNT (30, 10-30)	Vegetable oil	NM	HyNF-assisted MQL conditions reduced SR and CF while improving tool life compared to cryogenic cooling. However,	2019

MQL with hybrid nanofluids as cutting fluids (MQHyNFs)

				cryogenic cooling provided a lower CT than hybrid nanofluid MQL.	
Yildirim [67]	hBN + Al ₂ O ₃ (70, 70)	Vegetable oil	SEM	The hBN-based hybrid nanofluid exhibited superior heat-transfer characteristics. Significant reductions in CT, SR, and TW were achieved, especially when combined with MQL and liquid nitrogen.	2019
Thakur et al. [68]	Al ₂ O ₃ + CuO (NM.)	Soluble oil	NM.	The hybrid Al ₂ O ₃ –CuO nanofluid exhibited the lowest friction coefficient compared to mono nanofluids. It also resulted in minimum SR, CT, and TW with MQL conditions.	2019
Thakur et al. [69]	Al ₂ O ₃ + CuO (30, 50)	Soluble oil	TEM	The addition of nanoparticles improved thermal conductivity. The HyNF under MQL drastically reduced SR, CT, and the coefficient of friction.	2019
Kumar et al. [72]	Cu + Zn (NM)	Groundnut oil	TEM, XRD	The hybrid Cu–Zn nanofluid improved wettability and heat-transfer characteristics, thereby reducing SR, tool-tip damage, and TW.	2020
Kumar et al. [73]	CuO + ZnO (NM)	Coconut oil and Palm oil	NM	The hybrid CuO–ZnO nanofluid reduced SR compared with dry machining. FR was identified as the most influential parameter affecting SR.	2020
Gugulothu, and Pasam [70]	MWCNT + MoS ₂ (30, 30)	Sesame oil	NM	The hybrid MWCNT–MoS ₂ nanofluid enhanced thermal properties and significantly reduced CF, SR, CT, and TW compared to conventional and dry cutting.	2020
Zaman et al. [71]	Al ₂ O ₃ + MWCNT (50, 8-15)	Cutting oil	NM	CT reduced as nanoparticle concentration increased, with CS being the most influential factor. FR had the strongest effect on SR, while higher DC and tool vibration led to increased SR	2020

Concise reviews of MQL with hybrid nanofluids (HyNFs), effects of key input parameters on machining performance, including thermal conductivity, specific heat, and coefficient of friction, were analyzed. These studies also comprehensively examine output responses, including CF, CT, chip morphology, SR, and TW.

Numerous investigators have explored various applications of MQL in turning operations

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using different cutting fluids that serve as both coolants and lubricants, including conventional cutting fluids, vegetable oils, soluble cutting oil, and emulsion oil. To enhance turning efficiency by improving thermal and mechanical properties [76] and to mitigate the working and health concerns associated with cutting fluids, many published articles have focused on nanofluids applied through MQL. Table 2.4 presents a comparative evaluation of cutting fluids and their concerned nano-additives.

Table 2.4 Comparative evaluation of cutting fluids and relevant nano-additives

Cutting Fluid	Normal cutting Fluid	Vegetable Oil	Soluble cutting oil	Emulsion Oil	Water
Al ₂ O ₃	[34], [44]	[33], [45], [50]	[39]	-	[51]
Boric Acid	-	[31], [52], [77]	-	[31], [36]	-
Graphite	-	[45]	[35]	[36]	-
SiO ₂	-	[58]	[37]	-	-
MWCNT	[32]	[48]	-	[42]	-
CuO	-	-	[38]	-	-
TiO ₂	-	[43], [45]	-	-	-
MoS ₂	-	[47], [52], [57]	-	[36]	-
Tungsten disulfide WS ₂	-	-	-	[46]	-
Copper	-	[40]	-	-	-
Graphene Nanoplatelets	-	-	-	[49]	-

2.7 Statistical Analysis

The literature review examines a wide range of cutting fluids used in various machining operations. Key aspects highlighted include machining characteristics, process performance, experimental process analysis, methods of preparation, methodologies of characterization, and the working medium, with a focus on research published over the past ten years. The cited works are primarily drawn from conference proceedings and prominent journals published by Elsevier, Taylor & Francis, and Springer.

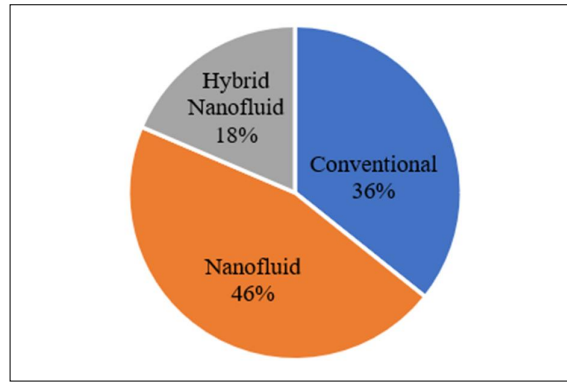


Figure 2.1 Published research categorized by work based on cutting fluids

The total count of published works, categorized according to the nature of the research, is presented in Figure 2.1. Over the past decade, numerous experimental studies using various cutting fluids have been published. Figure 2.2 shows the number of articles that utilized conventional fluids, nanofluids, and hybrid nanofluids as cutting fluids under MQL from 2015 to 2025.

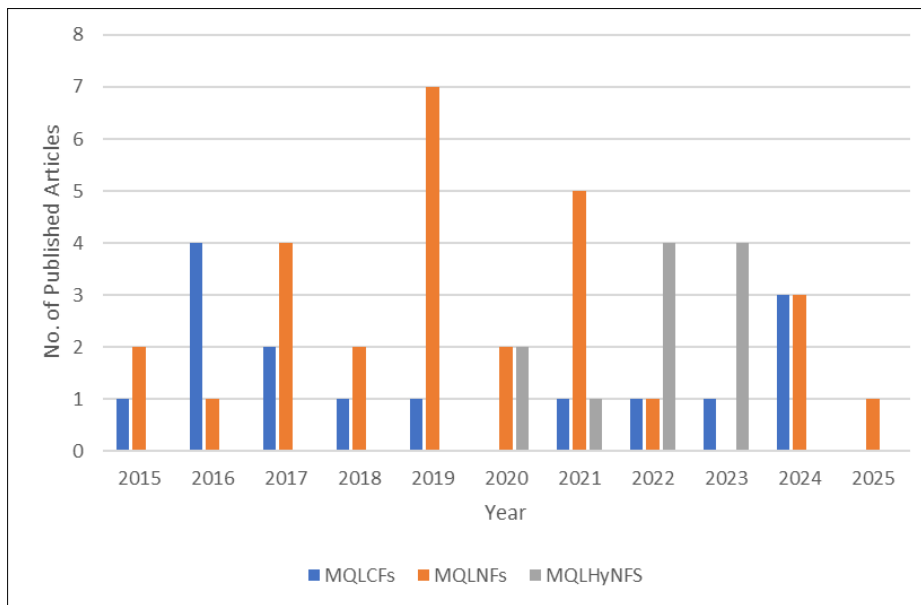


Figure 2.2 Number of published works between 2015 and 2025

The analysis shows that research trends on conventional fluids have declined over time. The use of nanofluids as cutting fluids peaked mid-decade, while hybrid nanofluids have now become the dominant emerging trend in fluid applications. Figure 2.3 presents the number of research studies that used specific workpiece materials together with particular types of cutting fluids. As illustrated, AISI 1040 medium-carbon steel is the most commonly used

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workpiece material, while hybrid nanofluid is the least frequently employed cutting fluid in the reviewed studies.

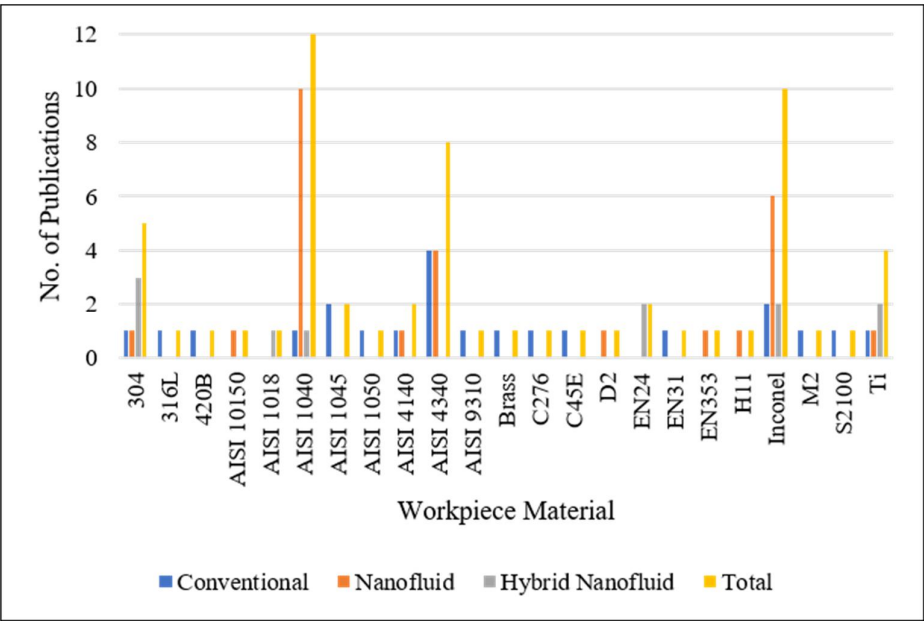


Figure 2.3 Number of published works with workpiece materials types

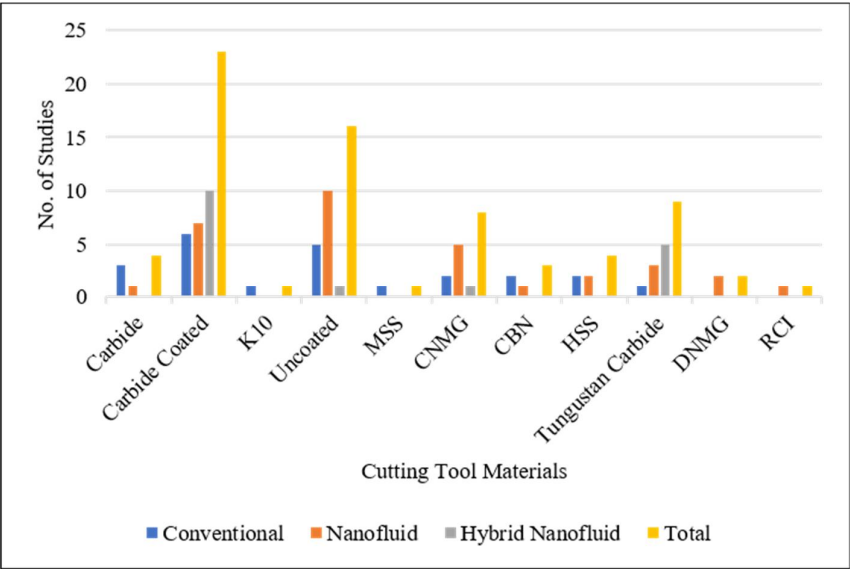


Figure 2.4 Number of published articles with various tool materials varieties

Figure 2.4 presents a summary of research using a variety of tool materials. From the statistics, we find that most of the published papers used HyNFsMQL as the cutting fluid, AISI 1040 medium-carbon steel as the component material, and tungsten carbide with carbide coatings as the cutting tool material. The accumulated evidence suggests that this

Research Gap

specific combination-hybrid nanofluid under MQL, AISI 1040 medium carbon steel workpiece, carbide-coated tungsten carbide tool, demonstrates particularly high effectiveness for diverse turning operations.

2.8 Research Gap

Despite extensive research on nanofluid-assisted machining, most studies either investigate a single nanofluid, focus on different work materials, or do not apply multi-response statistical optimization within a unified experimental framework.

Notably, no research has systematically examined Al_2O_3 -ZnO hybrid nanofluids under various MQL conditions in AISI 1040 steel turning by varying the mixing ratio and nanoparticle concentration, while concurrently modeling CF, CT, and SR using RSM with a Box–Behnken experimental design.

Existing hybrid-nanofluid studies also rarely isolate the relative contributions of Al_2O_3 and ZnO, even though Al_2O_3 is one of the most widely used nanoparticles in MQL owing to its strong tendency to form a lubricating tribofilm at the interface junction of the cutting tool & workpiece.

2.9 Motivation of Research

This proposed work is motivated by the need to improve the thermo-mechanical performance and sustainability of turning operations beyond what is achievable with conventional cutting fluids & standard MQL technology. The condition of flood cooling with mineral oil or emulsion-based fluids can control cutting temperature and surface integrity, but it incurs high fluid consumption, disposal costs, and significant environmental and health concerns; even conventional MQL with base oils cannot fully eliminate these drawbacks or consistently maintain low forces, temperatures, and roughness over a wide range of machining conditions. At the same time, industries increasingly demand higher productivity, tighter dimensional tolerances, and better surface integrity on difficult-to-machine alloys, which intensifies the thermal and mechanical loading at the interface junction between the cutting tool & component and exposes the limitations of existing cooling–lubrication practices.

Problem Formulation

Nanofluid-assisted MQL has emerged as a promising alternative, as mono- and hybrid nanofluids can enhance thermal conductivity, film strength, and anti-wear behavior, thereby reducing CF, CT, SR, and TW during turning, milling, drilling, and grinding. However, the current literature is fragmented: most studies focus on specific materials, single-nanoparticle systems, or narrow parameter windows, and only a few simultaneously compare mono- and hybrid nanofluids, optimize cutting conditions using systematic design of experiments, and develop predictive tools such as ANN models within a coherent framework. There remains a clear gap in the development of an integrated, experimentally validated methodology that links nanoparticle type and concentration, MQL delivery, and cutting parameters to multiple performance indices (force, temperature, roughness, tool wear) in turning. Addressing this gap by developing statistically optimized and ANN-supported models for MQL with mono- and hybrid nanofluids will provide reliable guidelines for selecting eco-friendly cutting fluids and machining conditions, thereby reducing costs and environmental impact while surfaceimproving productivity and surface integrity in industrial turning applications.

2.10 Problem Formulation

The existing MQL turning literature on conventional and mono-nanofluids still leaves key gaps regarding medium-carbon steels such as AISI 1040. AISI 1040 medium-carbon steel is chosen as the work material because of its extensive use in shafts, axles, and similar automotive and general-engineering parts, its moderate machinability, and its sensitivity to lubrication conditions. In particular, Al_2O_3 -ZnO hybrid nanofluids have not been systematically evaluated under MQL across multiple mixing ratios and concentrations while jointly modeling cutting force, cutting temperature, and surface roughness. Al_2O_3 -ZnO hybrid nanofluid was chosen because Al_2O_3 provides a strong lubricating tribofilm that lowers cutting force and surface roughness, while ZnO offers superior heat removal and cutting-zone temperature reduction; together, at appropriate mixing ratio and concentration, they give the most balanced improvement in thermo-tribological performance under MQL turning of AISI 1040 steel. Most studies compare only one or two cooling strategies, limiting clear selection among dry, wet, mono-nanofluid MQL, and hybrid-nanofluid MQL. Moreover, there is a lack of unified frameworks that combine statistically designed experiments, RSM, ANOVA, multi-response desirability optimization, and ANN-based prediction to capture the strong nonlinear and interaction effects among cutting parameters,

Scope and Objectives

cooling conditions, and nanofluid composition. This motivates a focused study to fill these gaps and quantitatively establish the benefits of an Al_2O_3 -ZnO hybrid nanofluid (HyNF) MQL for turning AISI 1040 steel.

2.11 Scope and Objectives

The turning process is a subtractive machining operation in which a workpiece spins on a lathe while a stationary cutting tool moves linearly to remove excess material. In this process, heat is generated as mechanical energy is converted into thermal energy due to permanent plastic deformation and friction. In conventional turning, fluids are generally used to reduce heat generation, lower friction, and improve surface profile. The constraints associated with flood cooling can be overcome by using wet machining instead of cutting fluids. MQL has emerged as a promising near-dry machining approach for reducing fluid usage while maintaining acceptable cooling plus lubrication at the cutting zone. Over the past decade, nanofluids combined with minimum quantity lubrication (MQL) have been proposed and developed as a new class of cooling methods to achieve improved heat transfer and superior lubrication in turning operations.

2.11.1 Scope of Research

The study yields the following research findings:

1. Application of Al_2O_3 and ZnO mono nanofluids and Al_2O_3 -ZnO hybrid nanofluids to improve the thermo-tribological properties of MQL during turning of medium carbon AISI 1040 steel.
2. Composition of stable, properly dispersed mono and hybrid NFs using a standardized two-step method (weighing, magnetic stirring, and ultrasonication) with SAE-40 oil as the base fluid.
3. Study of parameters influence-NP concentration (0-2 wt%), Al_2O_3 :ZnO mixing ratio in hybrid nanofluids, CS, FR, and DC on CF, CT, and SR under MQL.
4. Comparative study of dry cutting, wet cooling, mono-NF MQL, and hybrid-NF MQL to identify lubrication conditions that most effectively improve machinability and

Scope and Objectives

surface integrity for AISI 1040 steel.

5. Identification of the optimum cutting-fluid strategy that delivers the best combined improvement in output responses under MQL turning of AISI 1040 steel.
6. To develop ANN models to predict CF, CT, and SR from cooling condition, nanofluid composition, and cutting parameters, thereby capturing the complex and nonlinear performance trends of nanofluid-assisted MQL turning.

2.11.2 Research Objectives

The objectives of this research are as follows:

1. To experimentally investigate the effects of cutting speed, feed, and depth of cut on turning performance under different cooling strategies (dry, wet, simple MQL, MQL with mono nanofluid, and MQL with hybrid nanofluid).
2. To compare dry, wet, MQL+wet, MQL+mono nanofluid, and MQL+hybrid nanofluid conditions about cutting temperature, cutting force, and surface roughness.
3. To determine the optimum cutting-fluid strategy and operating parameters for MQL-assisted turning, using multi-response optimization based on the measured performance indicators.
4. To develop and train Artificial Neural Network (ANN) models and identify the most accurate ANN architecture for predicting turning performance under different cooling conditions.

CHAPTER 3. EXPERIMENTATION AND ARTIFICIAL NEURAL NETWORK

This research work is separated into two main phases: (i) experimental work, and (ii) ANN model development. The experimental work stage includes experimental design using the RSM-based Box–Behnken method, setup of the experimental apparatus, selection of cooling conditions, and nanofluid preparation. The second phase involves developing, training, and simulating multiple ANN models to predict performance under various cooling conditions.

3.1 Design of Experiments (DOE)

Design of Experiments (DOE) is a systematic statistical approach employed to design, execute, and analyze experiments, enabling efficient evaluation of the effects of multiple input factors on a given response. Its main purpose is to identify significant factors, study interactions, and optimize the process with fewer trials than testing one factor at a time.

Core ideas

- **Factors** are the controllable input variables.
- **Levels** are the selected values of those factors.
- **Responses** are the measured outputs of interest.
- **Randomization, replication, and blocking** are used to improve reliability and reduce bias.

DOE helps reveal interactions between factors that may be missed in simpler testing, making it especially useful for complex engineering and machining problems. It also improves efficiency by extracting more information from a fixed number of experiments.

RSM is a set of mathematical and statistical techniques designed to model and analyze problems where a response of interest is influenced by multiple variables, with the goal of optimizing that response. In engineering applications, the actual relationship between output

Experimental Design and Conditions

responses and process variables is typically unknown. It is therefore approximated with an empirical regression model, often a second-order polynomial. This allows the researcher to evaluate the individual effects of the factors, their interactions, and possible curvature in the response surface, and to resolve the factor settings that lead to optimum performance.

In practice, RSM is applied after selecting the important factors through experimentation, and it helps evaluate main, interaction, and quadratic effects with relatively few runs. Graphical tools such as contour plots and 3D response surfaces are commonly used to interpret the model and locate the optimum settings. Because of its efficiency and ability to capture complex process behavior, RSM is widely used in machining, material processing, and other engineering optimization studies.

A three-variable Box–Behnken design was introduced by Box and Behnken (1960), and its geometric representation is also provided in Figure 3.1. The design is spherical, with all experimental points located on the surface of a sphere of radius.

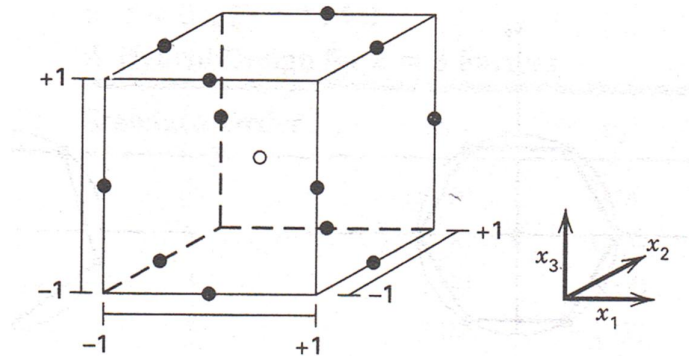


Figure 3.1 A Box – Behnken design for three factors [78]

A key characteristic of the Box–Behnken design is that it excludes points at the vertices of the available region of cubic design defined by the variables' upper and lower limits. This feature is beneficial when corner-point combinations are difficult, costly, or impossible to test due to practical or physical constraints.

3.2 Experimental Design and Conditions

This research utilizes a Box–Behnken Design (BBD) within the framework of RSM to investigate how three input variables (cutting speed: CS, feed rate: FR, and depth of cut: DC) affect cutting force: CF, cutting temperature: CT, and surface roughness: SR across all 13

Experimental Design and Conditions

cooling conditions during AISI 1040 steel turning. Input factors with three levels are given in Table 3.1. The selected ranges of cutting speed, feed rate, and depth of cut are chosen to reflect practical, stable machining conditions for MQL-assisted turning of AISI 1040 steel, while avoiding excessive tool wear, thermal instability, and poor surface integrity. The Box-Behnken design is selected over the Central Composite Design (CCD) because it is more efficient for three-factor optimization and does not require extreme corner points, which can be risky or impractical in machining experiments. For three factors at three levels, the BBD requires 15 experimental runs (12 edge points and 3 center points) listed in Table 3.2, and the run order is fully randomized to minimize systematic bias; repeated center runs provide an estimate of pure error, enabling a Lack-of-Fit test in the ANOVA based on the coded factor levels given in Table 3.1.

Table 3.1 RSM Box-Behnken Method input parameters with their coded factor levels

Input factors	-1	0	1
Cutting Speed (m/min)	31.71	69.63	107.55
Feed (mm/rev)	0.11	0.18	0.25
Depth of Cut (mm)	0.2	0.4	0.6

Table 3.2 Box-Behnken Design experimental runs

Test Run	A: CS (m/min)	B: FR (mm/rev)	C: DC (mm)
1	69.63	0.25	0.2
2	69.63	0.11	0.6
3	31.71	0.18	0.6
4	107.55	0.18	0.2
5	107.55	0.25	0.4
6	69.63	0.25	0.6
7	107.55	0.11	0.4
8	69.63	0.18	0.4
9	69.63	0.18	0.4
10	69.63	0.18	0.4
11	31.71	0.11	0.4
12	31.71	0.25	0.4
13	31.71	0.18	0.2
14	107.55	0.18	0.6
15	69.63	0.11	0.2

3.3 Experimental Setup Preparation

The performance of turning parameters for different cooling cases was carried out using the experimental setup illustrated in Figure 3.2. The experimental setup for this study was prepared on a center lathe (Banka 35–750 geared type) for straight turning of AISI 1040 steel bars with dimensions of $\text{Ø}50 \times 300$ mm, and the material's chemical composition is given in Table 3.3. An external MQL system was integrated, comprising an SAE-40 oil reservoir, compressed-air supply, air–oil mixing chamber, pressure-control valve, and a 2-



Figure 3.2 Experimental setup along with MQL system

mm nozzle delivering nanofluid at 360 ml/h and 3 bar towards the tool–chip interface. Deskar TNMG160408 CQ LF9218 carbide inserts were mounted in a tool holder, and the tool insert with geometry and specifications is shown in Table 3.4.

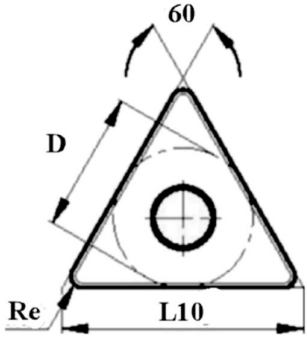
Table 3.3 Workpiece chemical composition (%)

Fe	C	Si	Mn	P	S	Cr	Mo	Ni
Balance	0.4-0.45	0.05-0.35	0.7-0.9	0.027	0.017	0.232	0.08	0.048

Experimental Setup Preparation

To prevent tool wear from biasing experiments on force, temperature, and roughness, the turning in each experiment was performed with a new cutting edge to establish an identical baseline free of flank-wear influence.

Table 3.4 Tool insert geometry with specifications

	
ISO Number	TNMG160408 CQ LF9218
Manufacturer	Deskar
Tool Group	TNMG-CQ
Rake face	Positive
Insert Size (D)	12.7 mm
Length of Insert Cutting Edge (L10)	16.5 mm
Insert Thickness	4.76 mm
Corner Radius (Re)	1.2 mm
Insert Hole Size	3.81 mm

The input factors were set according to the given Box–Behnken design matrix. The strain-gauge-based bridged-form lathe tool dynamometer for measuring cutting force [79]. To quantify the output responses, a Fluke 62 Max+ (with 0.8 surface emissivity value) was used for apparent surface temperature monitoring of the cutting tool-workpiece interface zone at a measurement length of 200 mm from the cutting zone of the machine with a laser point without being obstructed by chips, and a Mitutoyo SJ-210 portable tester was used for post-process surface roughness analysis. The calibration certificates for these measuring devices are presented in Appendix A. After that, the setup was verified by trial runs under dry and wet conditions before nanofluid experiments. Table 3.5 provides specifications of experiments and cutting conditions.

Selection of Cooling Cases

Table 3.5 Details of experimentation and cutting conditions

Workpiece	
Material	AISI 1040 steel
Size	50 mm (Diameter) × 300 mm (Length)
Cutting fluid	
Cutting fluid	SAE-40 oil
Nanoparticle	
Aluminum Oxide (Al ₂ O ₃)	30-50 nm
Zinc Oxide (ZnO)	30-50 nm
Weight fraction of nanoparticles	0%, 1%, 2%
Input machining parameters	
Cutting speed (CS)	31.71, 69.63, and 107.55 m/min
Feed rate (FR)	0.11, 0.18, and 0.25 mm/rev
Depth of cut (DC)	0.2, 0.4, and 0.6 mm
MQL	
Nozzle diameter	2 mm
Nano fluid discharge	360 mL/hr
Air Pressure	3 bar
Machine tools and measuring devices	
Lathe	Banka 35 750 geared type
Cutting tool (insert)	Deskar TNMG160408 CQ LF9218
Cutting force	Dynamometer strain gauge-based bridged form type
Cutting temperature	Fluke 62 Max+ digital infrared thermometer
Surface Roughness	Mitutoyo SJ-210 portable tester

3.4 Selection of Cooling Cases

Thirteen cooling cases were selected for the study based on findings from the available literature review, prior experience, and requirements of the optimization methodology. The detailed experimental conditions for these cases are presented in Table 3.6.

Nanofluid Preparation

Table 3.6 Various cooling cases selected for experimental work

Case	Case Details
Case-A	Dry
Case-B	Wet conventional cutting fluid
Case-C	Wet SAE40 cutting fluid
Case-D1	MQL + 1% wt Al ₂ O ₃ mono NF as a cutting fluid
Case-D2	MQL + 2% wt Al ₂ O ₃ mono NF as a cutting fluid
Case-E1	MQL + 1% wt ZnO mono NF as a cutting fluid
Case-E2	MQL + 2% wt ZnO mono NF as a cutting fluid
Case-F1	MQL + 1% wt (Al ₂ O ₃ /ZnO, 25/75) hybrid NF as a cutting fluid
Case-F2	MQL + 2% wt (Al ₂ O ₃ /ZnO, 25/75) hybrid NF as a cutting fluid
Case-G1	MQL + 1% wt (Al ₂ O ₃ /ZnO, 50/50) hybrid NF as a cutting fluid
Case-G2	MQL + 2% wt (Al ₂ O ₃ /ZnO, 50/50) hybrid NF as a cutting fluid
Case-H1	MQL + 1% wt (Al ₂ O ₃ /ZnO, 75/25) hybrid NF as a cutting fluid
Case-H2	MQL + 2% wt (Al ₂ O ₃ /ZnO, 75/25) hybrid NF as a cutting fluid

3.5 Nanofluid Preparation

Stable and homogeneous nanofluid preparation is critical to achieving desirable thermal performance. The stability of a nanofluid mainly depends on the prevention of particle agglomeration and the maintenance of uniform particle suspension within the base fluid. If these conditions are not properly maintained, the heat transfer characteristics may deteriorate considerably. Because the particles are nanoscale, effective dispersion is essential to prevent sedimentation and ensure consistent performance during testing.

Two different nano-additives, Aluminium Oxide (Al₂O₃) and Zinc Oxide (ZnO) with size range of 30-50 nm [9], [10], were utilized in the current experimental study. All nanoparticles were supplied by Platonic Nanotech Private Limited, Jharkhand, India. The

Nanofluid Preparation

nanoparticle mass calculation required to perform experimental runs is provided in Appendix B. The corresponding total weight of each nanoparticle required to prepare 120 ml of working medium across all cases is presented in Table 3.7. The nanoparticle specifications and characterization data for the purchased nanoparticles are provided in Appendix C.

Table 3.7 List of each cooling case required mass (gm) of nanoparticles

Case	%Weight Concentration	Weight of Al ₂ O ₃ (gm)	Weight of ZnO (gm)	Total particles weight (gm)
Case-A	-	-	-	0.0
Case-B	-	-	-	0.0
Case-C	-	-	-	0.0
Case-D1	1%	1.2	-	1.2
Case-D2	2%	2.4	-	2.4
Case-E1	1%	-	1.2	1.2
Case-E2	2%	-	2.4	2.4
Case-F1	1%	0.3	0.9	1.2
Case-F2	2%	0.6	1.8	2.4
Case-G1	1%	0.6	0.6	1.2
Case-G2	2%	1.2	1.2	2.4
Case-H1	1%	0.9	0.3	1.2
Case-H2	2%	1.8	0.6	2.4

Nanofluids were prepared using the two-step method, which involved three major stages: (1) mass measurement of the nanoparticles, (2) mechanical stirring to disperse them in the base fluid, and (3) ultrasonication to obtain a stable and homogeneous suspension.

Nanofluid Preparation

3.5.1 Mass Measurement

For nanofluid preparation, measuring the mass of nanoparticles involves accurately weighing the required amount before dispersing them into the base fluid. This is typically done using a high-precision ultrasonic weight gauge, so the target concentration 0-2 wt%, as reported in the major investigations, 0-2 wt% was found to be optimum [44], [80], [81], [82].

3.5.2 Mechanical Stirring Process

The mixture of nanoparticles and SAE-40 oil, used as the base fluid, was continuously stirred for 2 hours in a magnetic stirrer. The device of the mechanical magnetic stirrer, which was used in the process of nanofluid composition, is shown in Figure 3.3.



Figure 3.3 Mechanical magnetic stirrer

3.5.3 Ultrasonic Homogenization Process

An ultrasonic homogenizer was used to sonicate the nanofluids for 2 hours after stirring. This procedure's ultrasonic homogenizer is illustrated in Figure 3.4.



Figure 3.4 Ultrasonic homogenizer

3.6 Experimental Methodology

The unified research methodology employed for the evaluation of performance via experimentation is outlined in Figure 3.5.

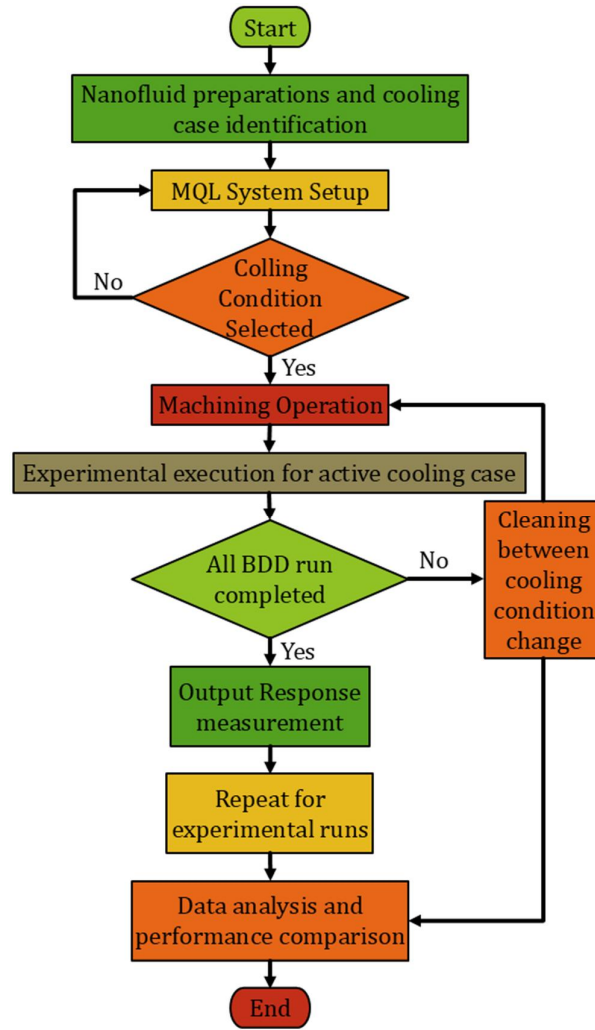


Figure 3.5 Flowchart for experimental procedure

3.7 Artificial Neural Network (ANN)

Training of various ANN models was performed using the complete experimental dataset collected across the thirteen cooling conditions. Of the 195 data points, 80% were randomly selected for training, and 20% were reserved for testing. Prediction performance was assessed based on errors expressed regarding MSE, NMSE, MAE, and MARD. A total of 190 ANN architectures were developed, trained, and simulated in MATLAB 2014a. The

Artificial Neural Network (ANN)

input parameters included cutting condition, Al₂O₃ proportion, ZnO proportion, cutting speed, feed rate, and depth of cut, while the target outputs were cutting force, cutting temperature, and surface roughness. The optimal ANN model was selected based on its ability to achieve low prediction error and a high coefficient of determination (R^2) simultaneously.

3.7.1 Data Selection

The performance prediction for cooling cases using ANN was conducted on data from 13 cooling cases. From the total experimental data, 80% (156 data points) were selected for training, and 20% (39 data points) for validation via randomization. The quantities of data designated for training as well as validation purposes are written down in Table 3.8.

Table 3.8 ANN model data identification

Sr. No.	Experimental data	No. of data
01	Case-A Dry	15
02	Case-B Wet Conventional Fluid	15
03	Case-C Wet SAE40	15
04	Case-D1 MQL + 1% wt Al ₂ O ₃	15
05	Case-D2 MQL + 2% wt Al ₂ O ₃	15
06	Case-E1 MQL + 1% wt ZnO	15
07	Case-E2 MQL + 2% wt ZnO	15
08	Case-F1 [MQL + 1% wt (Al ₂ O ₃ /ZnO, 25/75)]	15
09	Case-F2 [MQL + 2% wt (Al ₂ O ₃ /ZnO, 25/75)]	15
10	Case-G1 [MQL + 1% wt (Al ₂ O ₃ /ZnO, 50/50)]	15
11	Case-G2 [MQL + 2% wt (Al ₂ O ₃ /ZnO, 50/50)]	15
12	Case-H1 [MQL + 1% wt (Al ₂ O ₃ /ZnO, 75/25)]	15
13	Case-H2 [MQL + 2% wt (Al ₂ O ₃ /ZnO, 75/25)]	15
Total Experimental data		195

Artificial Neural Network (ANN)

3.7.2 Input and Output Parameters

The seven input variables-cutting condition (dry/wet MQL), Al_2O_3 and ZnO nanoparticle concentrations, cutting speed, feed rate, and depth of cut-were used to predict three output responses: CF, CT, and SR. These inputs and outputs formed the training dataset for the ANN model and simulations.

3.7.3 Different ANN Model Architectures

The Neural Network Toolbox (nn tool) in MATLAB R2014a was used to create an ANN with a hidden layer. Five different network types were evaluated: (1) Feed-forward backpropagation, (2) Cascade-forward backpropagation, (3) Elman-backpropagation, (4) Feed-forward distributed time delay, and (5) Generalized regression (with 1 to 5 variables). MSE and SSE were chosen as performance functions (2 variables). The transfer functions TRANSIG and PURELIN were employed, with 5-50 neurons in the hidden layer in increments of 5, resulting in 10 variations in the number of hidden-layer neurons. A total of 190 ANN models have been generated for performance prediction, as listed in Table 3.9.

Table 3.9 Various ANN model architectures

Neural Network	Performance function	Transfer function	No. of neurons at hidden layer	Model
Feed-forward backprop	MSE	TRANSIG	5 to 50 (in a gap of 5)	N1P1T1 to N1P1T10
Cascade-forward backprop	MSE	TRANSIG	5 to 50 (in a gap of 5)	N2P1T1 to N2P1T10
Elman-backprop	MSE	TRANSIG	5 to 50 (in a gap of 5)	N3P1T1 to N3P1T10
Feed-forward distributed time delay	MSE	TRANSIG	5 to 50 (in a gap of 5)	N4P1T1 to N4P1T10

Artificial Neural Network (ANN)

Generalized regression	MSE	TRANSIG	Spread constant 1 to 5	N5P1T1 to N5P1T5
Feed-forward backprop	SSE	TRANSIG	5 to 50 (in a gap of 5)	N1P2T1 to N1P2T10
Cascade-forward backprop	SSE	TRANSIG	5 to 50 (in a gap of 5)	N2P2T1 to N2P2T10
Elman-backprop	MSE	TRANSIG	5 to 50 (in a gap of 5)	N3P2T1 to N3P2T10
Feed-forward distributed time delay	SSE	TRANSIG	5 to 50 (in a gap of 5)	N4P2T1 to N4P2T10
Generalized regression	SSE	TRANSIG	Spread constant 1 to 5	N5P2T1 to N5P2T5
Feed-forward backprop	MSE	PURELIN	5 to 50 (in a gap of 5)	N1P1P1 to N1P1P10
Cascade-forward backprop	MSE	PURELIN	5 to 50 (in a gap of 5)	N2P1P1 to N2P1P10
Elman-backprop	MSE	PURELIN	5 to 50 (in a gap of 5)	N3P1P1 to N3P1P10
Feed-forward distributed time delay	MSE	PURELIN	5 to 50 (in a gap of 5)	N4P1P1 to N4P1P10
Generalized regression	MSE	PURELIN	Spread constant 1 to 5	N5P1P1 to N5P1P5
Feed-forward backprop	SSE	PURELIN	5 to 50 (in a gap of 5)	N1P2P1 to N1P2P10
Cascade-forward backprop	SSE	PURELIN	5 to 50 (in a gap of 5)	N2P2P1 to N2P2P10
Elman-backprop	MSE	PURELIN	5 to 50 (in a gap of 5)	N3P2P1 to N3P2P10

Artificial Neural Network (ANN)

Feed-forward distributed time delay	SSE	PURELIN	5 to 50 (in a gap of 5)	N4P2P1 to N4P2P10
Generalized regression	SSE	PURELIN	Spread constant 1 to 5	N5P2P1 to N5P2P5

3.7.4 ANN Models Training

The developed ANN models were trained using the designated input and output data, which were processed such that the Neural Network (nn) tool initially partitions the available data into three subsets: training, testing, and validation. The training set adjusts the network's weights and biases; the validation set is monitored throughout training to identify overfitting and determine early stopping points; and the testing set evaluates the final model's performance. The training process proceeds sequentially: first, the ANN model is trained, then it is validated, and finally it is tested using the selected performance function.

3.7.5 Simulation of ANN Models

After sets of training, the ANN models generate predicted outcomes through simulation. During simulation, the validation input data are fed into the trained model to obtain performance predictions. The output produced by the model, referred to as the decided target data in the simulation, represents the values for predicted data for that specific model. This predicted output is then compared with the corresponding experimental results using statistical error metrics to evaluate the model's predictive accuracy.

3.7.6 Calculation of Statistical Errors for ANN-Models

To analyze the ability of the ANN model to predict cooling conditions, the following statistical metrics were calculated using mathematical methods, Eq. (3.1) for MSE, Eq. (3.2) for NMSE, Eq. (3.3) for MAE, Eq. (3.4) for MARD, and Eq. (3.5) for coefficient of correlation (R^2).

$$MSE = \frac{1}{n} \sum_{i=1}^n (V_{p,i} - V_{a,i})^2 \quad (3.1)$$

$$NMSE = \frac{1}{n} \sum_{i=1}^n \frac{(V_{p,i} - V_{a,i})^2}{\left(\frac{1}{n} \sum_{i=1}^n V_{p,i}\right) \left(\frac{1}{n} \sum_{i=1}^n V_{a,i}\right)} \quad (3.2)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |V_{p,i} - V_{a,i}| \quad (3.3)$$

$$MARD = \frac{1}{n} \sum_{i=1}^n \left| \frac{V_{p,i} - V_{a,i}}{V_{a,i}} \right| \quad (3.4)$$

$$R^2 = 1 - \left\{ \frac{\sum_{i=1}^n (V_{p,i} - V_{a,i})^2}{\sum_{i=1}^n (V_{p,i} - \bar{V}_a)^2} \right\} \quad (3.5)$$

where $V_{a,i}$ is the i -th experimental (actual) value, $V_{p,i}$ is the corresponding predicted value from the ANN model, and n is the total count of data points.

3.7.7 Method of procedure for Developing ANN Models

The unified research methodology employed for the evaluation of performance through the ANN model adheres to a systematic procedure, as depicted in Figure 3.6.

Artificial Neural Network (ANN)

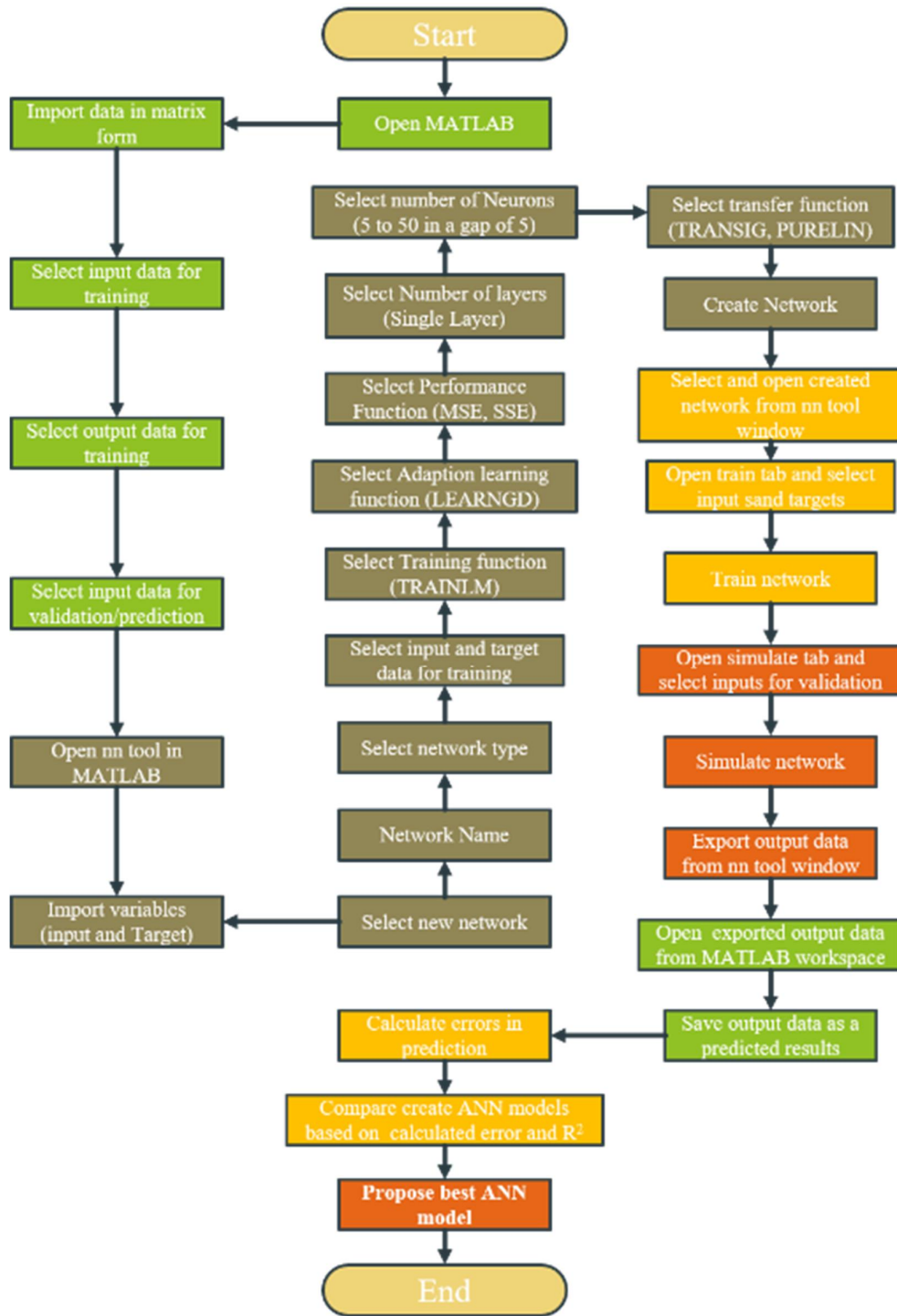


Figure 3.6 Systematic procedure for developing ANN models

CHAPTER 4. RESEARCH METHODOLOGY

This complete research investigation has been organized into four distinct parts: (i) Literature Review, (ii) Experimental Work, (iii) Optimization, and (iv) ANN Model Development. The experimental work subparts are DoE using the RSM-based Box-Behnken method, experimental setup preparation, selection of cooling cases, and nanofluid preparation. Optimization is used to identify the optimal cutting conditions and cooling medium combination that minimizes the output responses while ensuring practical applicability and improved overall machining quality. The ANN model was developed by creating, training, and simulating multiple models to predict cooling performance. The stepwise actions and sub-actions are described as follows:

4.1 Review of Literature

The unified research methodology adopted for the literature review, which establishes the foundation of this study, is presented below:

1. To examine and compare literature related to different cutting fluids that are used in MQL turning. This will include conventional cutting fluids and vegetable oils.
2. To investigate and review literature related to mono and hybrid NFs applied in MQL processes, including base fluid types, nanoparticle types, nanoparticle concentration levels, nanoparticle dimensions, preparation methodologies, and characterization techniques.
3. To conduct a literature study and analysis on cooling condition prediction using ANN for optimization purposes, covering the process of creating, training, and simulating, and related aspects.
4. To perform statistical analysis of the literature review by analyzing per year publication trends, workpiece material usage, tool material usage, nanofluid application in specific machining operations, preparation methods utilized, and characterization techniques employed.

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5. To formulate a problem statement based on the outcomes of the carried out review of literature and identified research gaps.
6. To define clear and specific research objectives of the study as a whole research work based on the problem statement and literature findings.

4.2 Experimental Work

The unified research methodology utilized to carry out performance assessment via experimentation is outlined below:

1. Prepare the nanofluid as mentioned in the subsection on nanofluid preparation and identification of cooling cases by calculating the required mass of Al_2O_3 and ZnO for 1 and 2 wt% concentrations for each of the thirteen cases (A–H2) using the 120 ml volume of base oil.
2. Fill the external MQL reservoir with the prepared nanofluid, connect the compressed-air line, and set the pressure-control valve to 3 bar. Adjust the nozzle (2 mm diameter) to direct the aerosol jet precisely toward the cutting tool-workpiece interface, and set the discharge rate to 360 ml/h for the nanofluid.
3. Start the spindle and feed, activate the chosen cooling condition (dry, wet, MQL with base oil, mono nanofluid, or hybrid nanofluid), and perform a single straight turning pass for each design point.
4. Experiment with the active cooling case, select the ranges of cutting speed, feed rate, and depth of cut according to the corresponding BBD run.
5. Measure and record the three-output response cutting force (CF), cutting temperature (CT) at a fixed position with the IR thermometer during cutting, and surface roughness (SR) along the machined surface using the SJ 210.
6. Clean the tool, workpiece surface, and MQL lines when changing from one cooling condition to another to avoid cross-contamination.
7. Repeat Steps 1-6 for all 15 Box–Behnken runs in each cooling case (A–H2), generating a total of 195 experimental data sets.

4.3 Optimization

The unified research methodology adopted for optimization of the cooling condition using the Desirability Function Approach (DFA) is described below:

1. To identify and select the cooling conditions to be evaluated, including dry machining, wet machining, base-oil MQL, mono NF-assisted MQL, and hybrid NF-assisted MQL.
2. To record output experimental responses associated with each cooling condition.
3. To transform each response into an individual desirability value based on the goal of minimizing the response.
4. To combine the individual value of desirability into a single overall desirability score for each cooling condition.
5. To rank the cooling conditions according to their overall desirability scores and identify the best-performing condition.
6. To identify the optimum cooling case based on optimization for the highest desirability value and the most favorable machining performance.
7. To validate optimum cooling condition results using the experimental data.

4.4 Artificial Neural Network (ANN)

The complete methodology for investigating cooling case performance predictions using an artificial neural network (ANN) is outlined below:

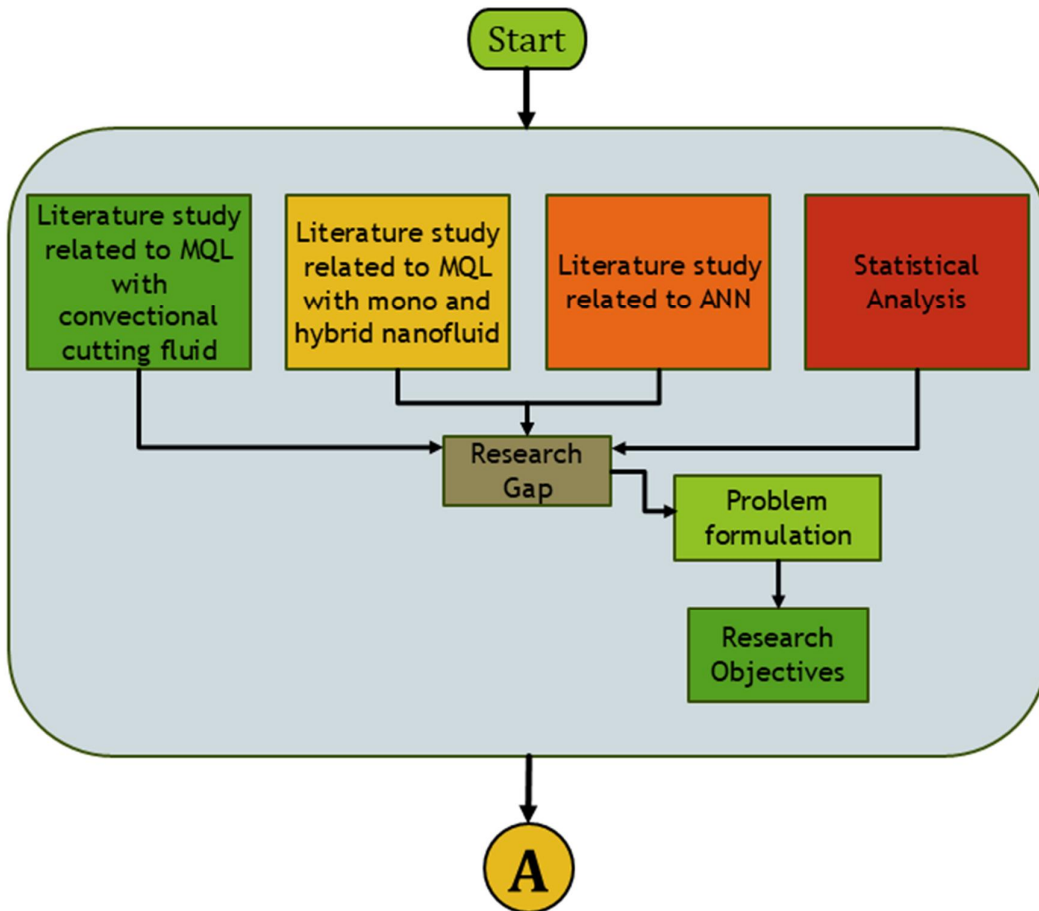
1. To partition the experimental dataset into two separate subsets: 80% for training purposes and 20% for validating purposes of the ANN model.
2. To identify and choose suitable input and output parameters from the available variables of experimental work.
3. To train the developed various ANN architectures using the obtainable training data.

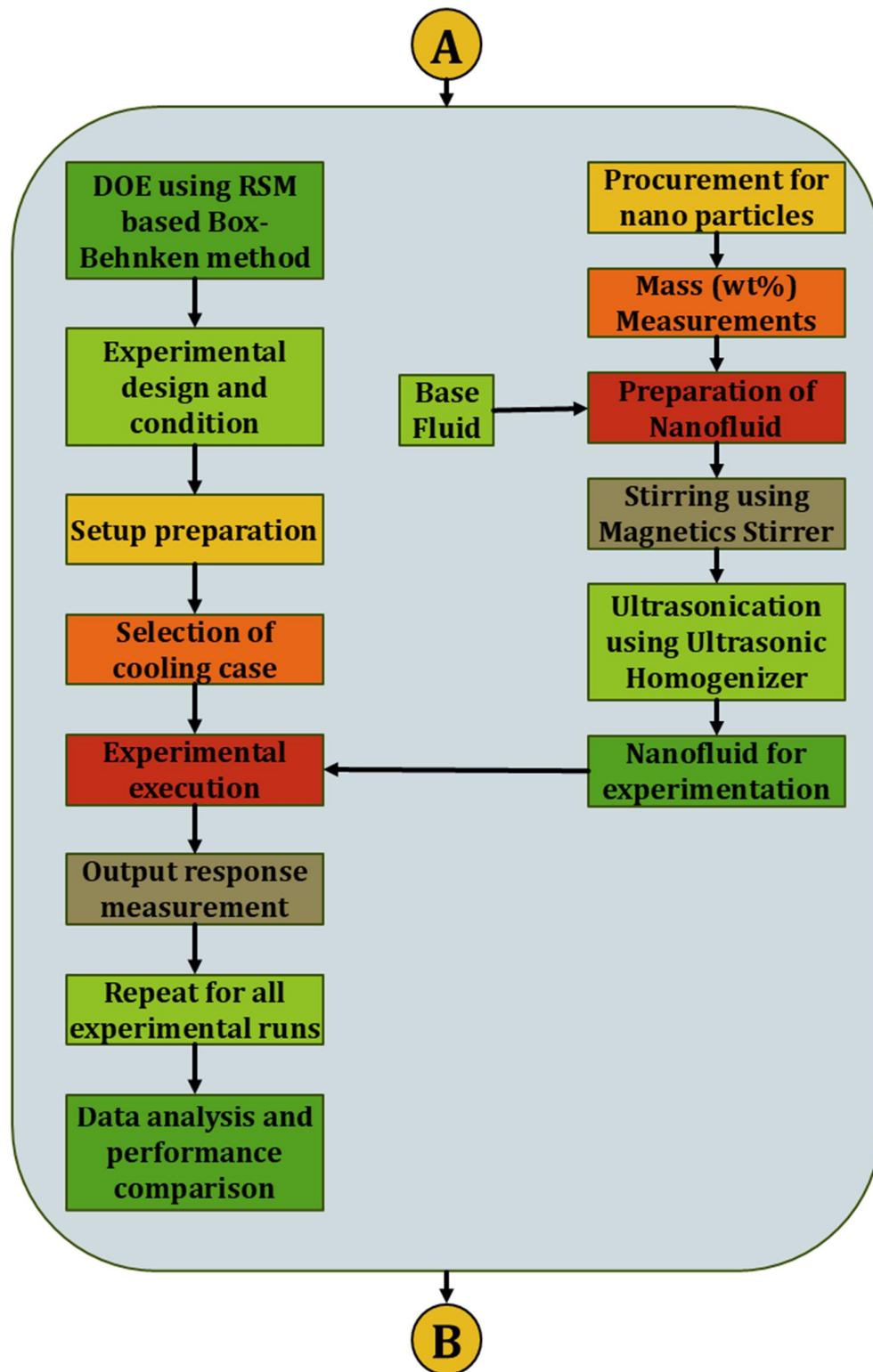
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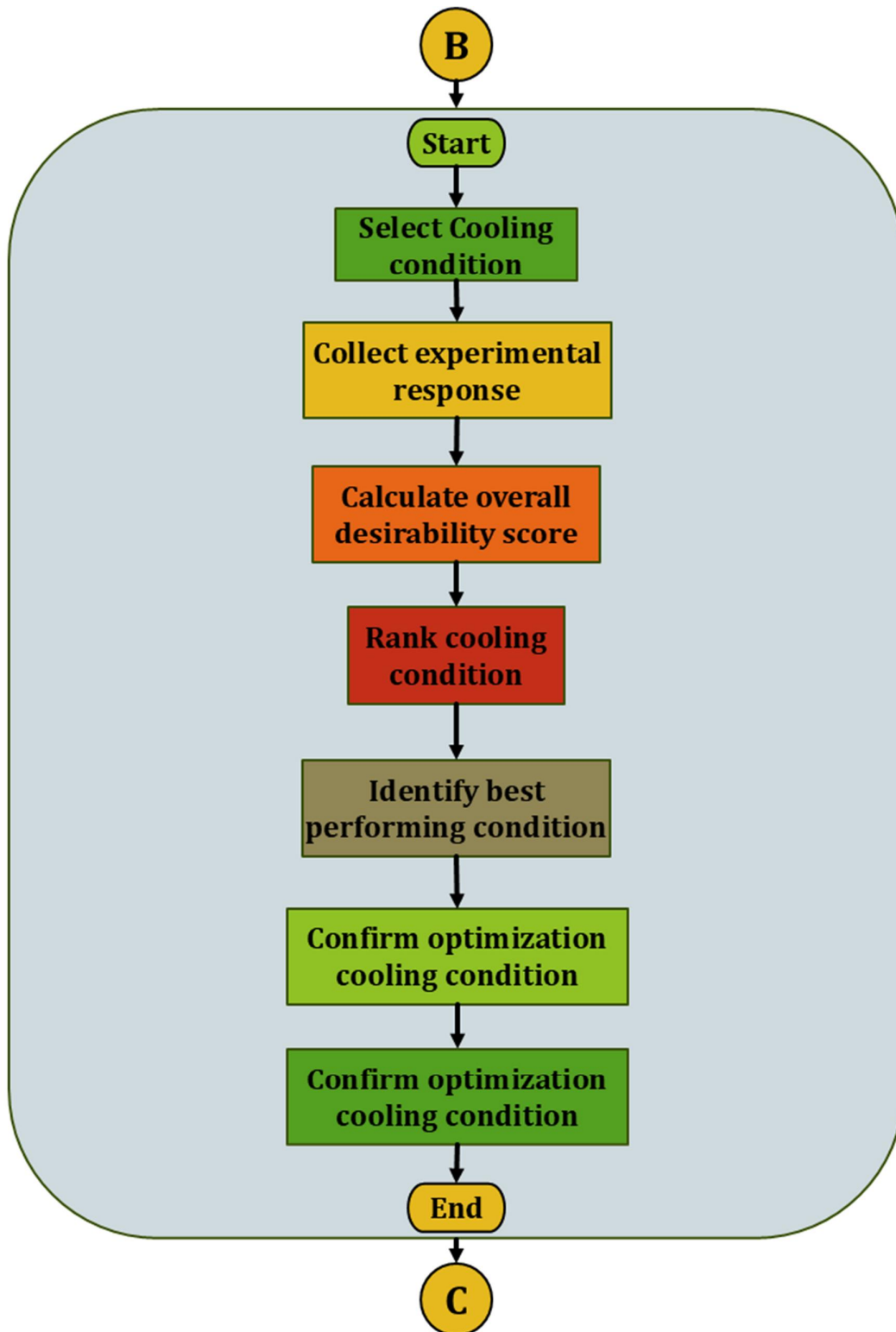
4. To evaluate and confirm the validity of the trained ANN architecture models for the performance prediction of the cooling cases.
5. To compute MSE, NMSE, MAE, MARD, and R^2 ; determine the best combination suitable for ANN.
6. To recommend the best model based on minimal prediction errors and a high coefficient of determination.

4.5 Research Methodology Flowchart

The research methodology is illustrated graphically in flowchart format and is given in Figure 4.1.







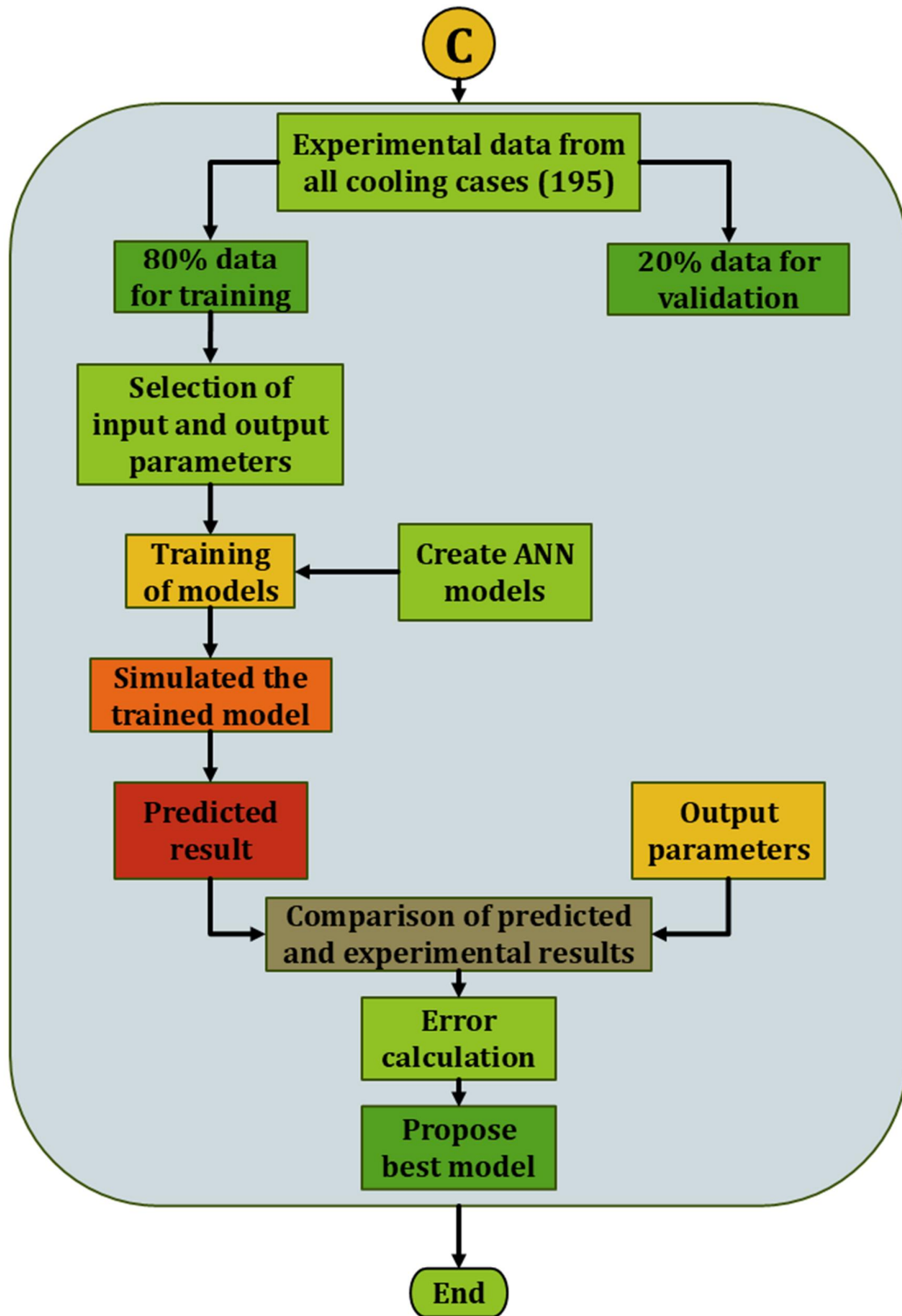


Figure 4.1 Flow chart for the complete research methodology

CHAPTER 5. RESULT AND DISCUSSION

This chapter begins with the results and provides an interpretation of the experimental and computational findings of the present study. Initially, the variable effects of cutting speed (CS), feed rate (FR), depth of cut (DC), and various cooling cases/conditions (dry, conventional MQL, mono NF MQL, and HyNF MQL, i.e., Case-A to H2) on cutting force: CF, CT, and SR are analyzed using the RSM-based Box–Behnken design. The acceptability of the developed models is then assessed through ANOVA and diagnostic checks. Subsequently, desirability-based multi-response optimization is employed to identify the optimal machining and lubrication conditions, and the corresponding confirmation experiments are discussed. Finally, the performance of the selected ANN architectures in predicting machining responses under various cooling conditions is evaluated and compared with RSM results to highlight the predictive capability of the proposed models.

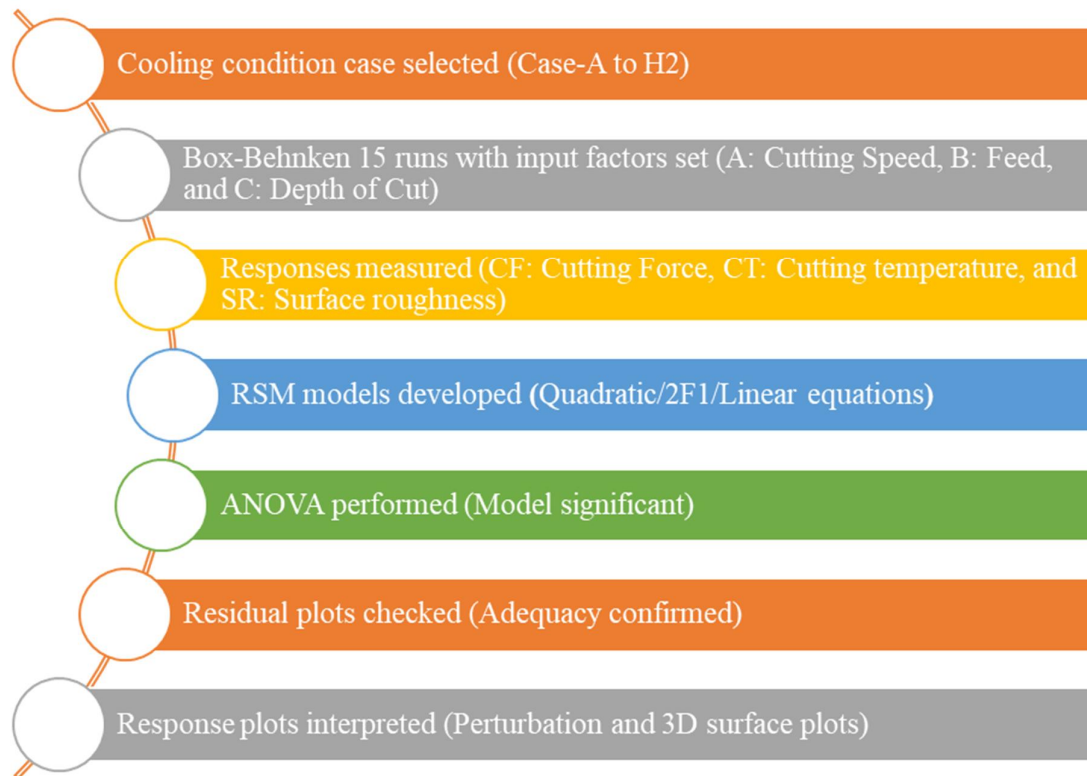


Figure 5.1 Steps followed for Design of Experiments (DOE) using RSM-based BBD

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Design of Experiments (DOE) facilitates the study of operations by providing a structured, statistical framework for varying multiple process factors simultaneously and measuring their impact on output, rather than changing one factor at a time. The steps followed for the Design of Experiments using RSM-based Box–Behnken Design (BBD) are illustrated in Figure 5.1.

5.1 Case-A Dry Cutting

First, the specific cooling condition, i.e., Case-A, was selected, and the corresponding 15-run Box–Behnken design was executed with the input factors. For every run, output responses were measured and compiled into the design matrix as given in Table 5.1. These data were applied to build the RSM models-quadratic for cutting force and cutting temperature, 2FI for surface roughness- where applicable. Insignificant terms in the initial RSM model were systematically identified from ANOVA results and removed, thereby simplifying the regression equation without sacrificing predictive capability. Eliminating these statistically meaningless interactions or higher-order terms reduces overfitting. It improves the numerical stability of the coefficients, allowing the final model to represent the true response surface more clearly over the design space.

Table 5.1 Box Behnken 15 runs for Case-A

Test Run	Input parameters			Output parameters		
	A: CS	B: FR	C: DC	CF	CT	SR
	m/min	mm/rev	mm	N	°C	µm
1	31.71	0.11	0.40	150.34	95.50	3.289
2	69.63	0.18	0.40	204.28	97.00	3.166
3	31.71	0.18	0.20	163.48	60.67	3.130
4	69.63	0.11	0.60	336.67	140.20	3.610
5	31.71	0.18	0.60	534.48	160.67	4.514
6	69.63	0.18	0.40	192.90	95.84	3.246
7	107.55	0.25	0.40	166.72	92.22	1.750
8	69.63	0.25	0.60	508.00	154.00	3.231
9	107.55	0.18	0.20	63.75	61.33	2.811
10	69.63	0.18	0.40	197.81	92.84	3.256
11	69.63	0.25	0.20	104.64	62.33	3.438
12	69.63	0.11	0.20	66.98	48.84	2.586
13	107.55	0.11	0.40	125.82	100.00	3.650

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14	31.71	0.25	0.40	333.44	109.00	4.491
15	107.55	0.18	0.60	456.03	160.43	2.504

5.1.1 Cutting Force

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.2, ANOVA table for cutting force shows that the model's quadratic nature makes feed, depth of cut, and the quadratic effect of depth of cut very meaningful. The coded equation for the cutting force in the final regression model is given in Eq. (5.1).

Table 5.2 Cutting force ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	338900	42367.29	204.13	< 0.0001	significant
A-Cut Speed	17059.79	17059.79	82.20	0.0001	
B-Feed	23433.86	23433.86	112.91	< 0.0001	
C-DOC	257900	257900	1242.50	< 0.0001	
AB	5055.32	5055.32	24.36	0.0026	
BC	4466.88	4466.88	21.52	0.0035	
A ²	1962.52	1962.52	9.46	0.0218	
B ²	2752.71	2752.71	13.26	0.0108	
C ²	25466.32	25466.32	122.70	< 0.0001	
Residual	1245.30	207.55			
Lack of Fit	1180.19	295.05	9.06	0.1018	not significant
Pure Error	65.12	32.56			
Cor Total	340200				

Cutting force (CF)

$$\begin{aligned}
 &= 198.33 + 46.18 \times A + 54.12 \times B + 179.54 \times C \\
 &- 35.55 \times A \times B + 33.42 \times B \times C + 23.05 \times A^2 - 27.30 \times B^2 \\
 &+ 83.05 \times C^2
 \end{aligned} \quad (5.1)$$

Figure 5.2 presents the perturbation impact of the studied factors on CF. The results show that the CF increases with increasing DC, decreases with increasing CS, and increases slightly with increasing FR.

Figure 5.3 demonstrates the 3D response surface plot of the CS and feed. The graph shows

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that the minimum CF occurs at a CS of 107.55, a FR of 0.18, and a DC of 0.2. The maximum CF is obtained at a CS of 31.71, a FR of 0.18, and a DC of 0.6.

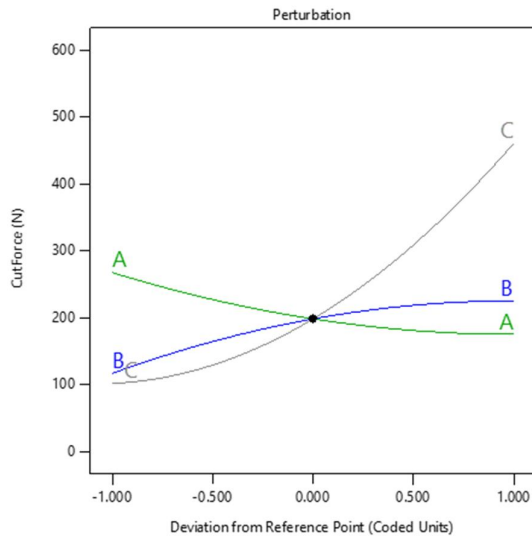


Figure 5.2 Cutting force perturbation plot

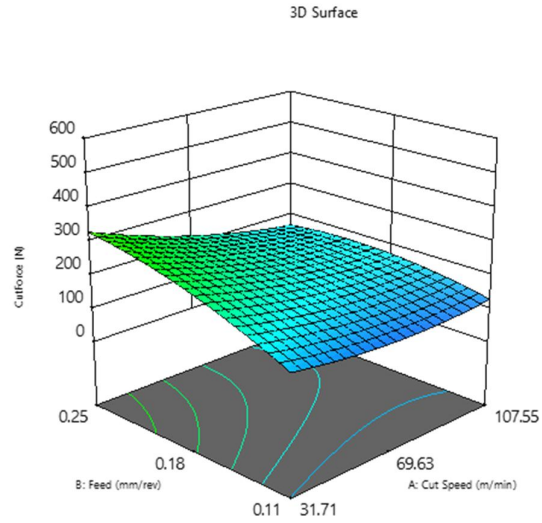


Figure 5.3 Cutting force 3D response surface plot

5.1.2 Cutting Temperature

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.3, ANOVA for cutting temperature indicates that, because the model is quadratic, the DC is highly significant. The final regression model's coded equation for cutting temperature is given in Eq. (5.2).

Table 5.3 Cutting temperature ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	18970.76	3161.79	171.16	< 0.0001	significant
A-Cut Speed	17.57	17.57	0.9513	0.3580	
B-Feed	136.24	136.24	7.37	0.0264	
C-DOC	18252.28	18252.28	988.04	< 0.0001	
AB	113.21	113.21	6.13	0.0384	
A ²	177.02	177.02	9.58	0.0148	
C ²	305.35	305.35	16.53	0.0036	
Residual	147.79	18.47			
Lack of Fit	138.57	23.09	5.01	0.1757	not significant

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Pure Error	9.22	4.61			
Cor Total	19118.55				

$$\begin{aligned}
 \text{Cutting temperature (CT)} \\
 = 93.54 - 1.48 \times A + 4.13 \times B + 47.77 \times C - 5.32 \times A \times B \quad (5.2) \\
 + 6.90 \times A^2 + 9.07 \times C^2
 \end{aligned}$$

Regarding Figure 5.4 the perturbation plot displays the impact of input factors on the CT. It is observed that CT increases with increasing DC, whereas it decreases slightly with increasing CS and FR.

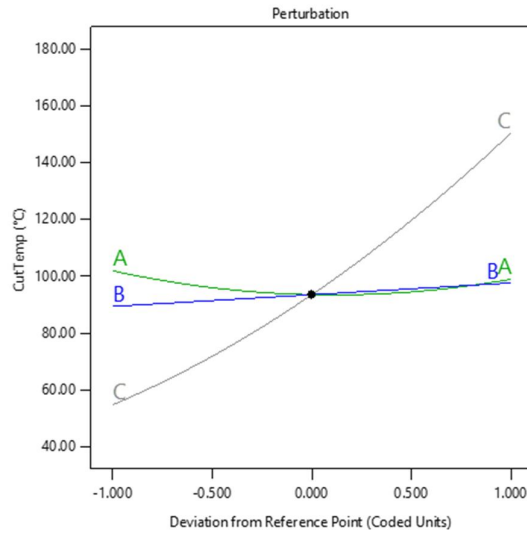


Figure 5.4 Cutting temperature perturbation plot

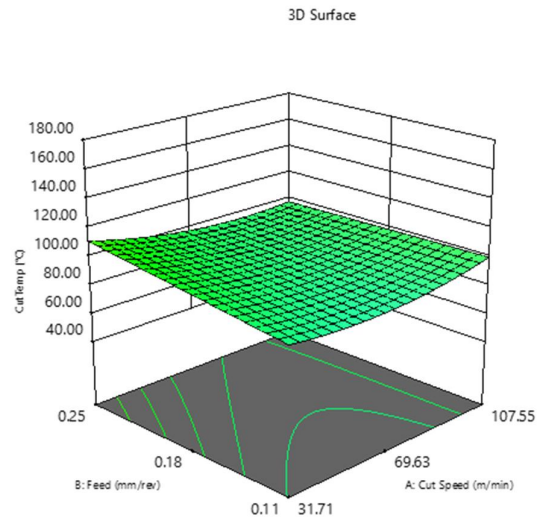


Figure 5.5 Cutting temperature 3D response surface plot

Figure 5.5 shows a 3D response surface plot for CS and feed. Based on this plot, the minimum CT was reached when the CS is 69.63, and feed is 0.11, and DC is 0.2, whereas the CT is maximum when the CS is 31.71, and feed is 0.18, and DC is 0.6.

5.1.3 Surface Roughness

The software identifies a 2FI model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.4, ANOVA for SR indicates that the CS and cutting speed-feed interaction are significant, as expected, because the model is 2FI. The coded equation of the surface roughness from the final regression model is shown in Eq. (5.3).

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Table 5.4 Surface roughness ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	6.73	1.12	44.85	< 0.0001	significant
A-Cut Speed	2.77	2.77	110.88	< 0.0001	
B-Feed	0.0063	0.0063	0.2524	0.6289	
C-DOC	0.4486	0.4486	17.94	0.0029	
AB	2.41	2.41	96.25	< 0.0001	
AC	0.7152	0.7152	28.61	0.0007	
BC	0.3788	0.3788	15.15	0.0046	
Residual	0.2000	0.0250			
Lack of Fit	0.1951	0.0325	13.22	0.0720	not significant
Pure Error	0.0049	0.0025			
Cor Total	6.93				

Surface roughness (SR)

$$\begin{aligned}
 &= 3.24 - 0.5886 \times A - 0.0281 \times B + 0.2386 \times C \\
 &- 0.7756 \times A \times B - 0.4228 \times A \times C - 0.3077 \times B \times C
 \end{aligned} \quad (5.3)$$

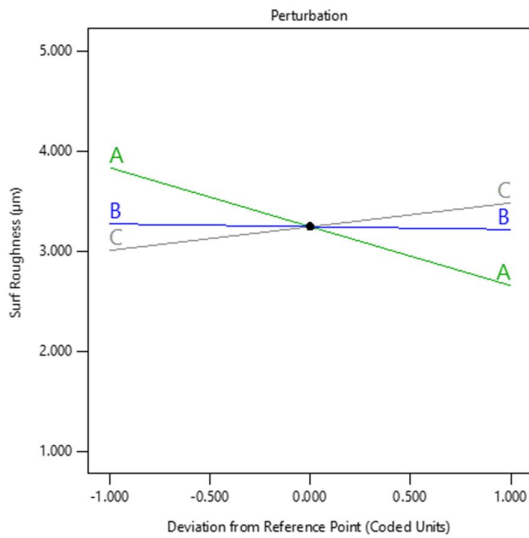


Figure 5.6 Surface roughness perturbation plot

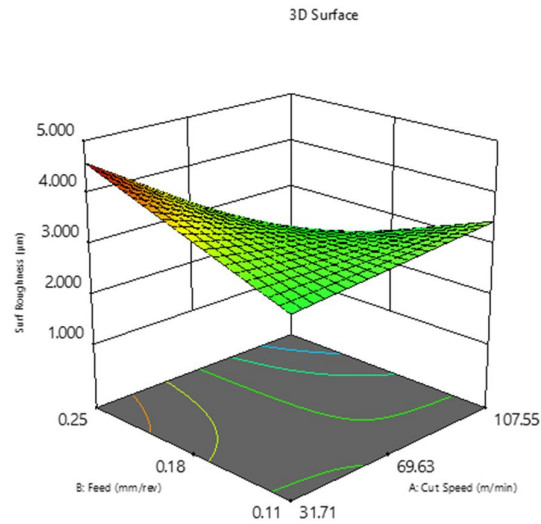


Figure 5.7 Surface roughness 3D response surface plot

Figure 5.6 shows the perturbation plot for the influence of the input factors upon SR. It shows that SR decreases as CS increases, increases as DC increases, and decreases slightly as FR increases. Figure 5.7 shows the 3D response surface plot of CS and FR. According to this figure, the minimum SR occurs at a CS of 107.55 and a FR of 0.25 at a DC of 0.4, whereas

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the maximum SR occurs at a CS of 31.71 and a FR of 0.18 at a DC of 0.6.

Table 5.5 Model adequacy metrics for Case-A output responses

Type	Cutting Force	Cutting Temperature	Surface Roughness
R ²	0.9963	0.9923	0.9711
Adjusted R ²	0.9915	0.9865	0.9495
Predicted R ²	0.9664	0.9590	0.8501

As presented in Table 5.5, the R² and adjusted R² for all responses are very high and consistent, confirming a good fit for all models. The predicted R² values are also very close to the adjusted R² values, indicating that the model performs well on the experimental results.

5.2 Case-B Wet Conventional Fluid

First, the specific cooling condition, i.e., Case-B, was selected, and the corresponding 15-run Box–Behnken design was executed with the input factors. For each run, output responses were measured and compiled into the design matrix, as shown in Table 5.6. These data have then been used to build RSM models: linear for cutting force and temperature, and quadratic for surface roughness. Insignificant terms in the initial RSM model were systematically identified from ANOVA results and removed, thereby simplifying the regression equation without sacrificing predictive capability. Eliminating these statistically meaningless interactions or higher-order terms reduces overfitting. It improves the numerical stability of the coefficients, allowing the final model to represent the true response surface more clearly over the design space.

Table 5.6 Box Behnken 15 runs for Case-B

Test Run	Input parameters			Output parameters		
	A: CS	B: FR	C: DC	CF	CT	SR
	m/min	mm/rev	mm	N	°C	µm
1	31.71	0.11	0.40	117.68	32.33	3.803
2	69.63	0.18	0.40	201.63	43.33	4.150
3	31.71	0.18	0.20	80.12	31.33	3.681
4	69.63	0.11	0.60	228.41	38.33	3.805
5	31.71	0.18	0.60	398.85	44.00	4.318
6	69.63	0.18	0.40	230.46	50.00	4.140
7	107.55	0.25	0.40	456.03	62.33	3.500

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8	69.63	0.25	0.60	562.24	63.67	4.214
9	107.55	0.18	0.20	88.26	34.33	4.001
10	69.63	0.18	0.40	168.39	50.67	4.096
11	69.63	0.25	0.20	201.04	42.67	3.659
12	69.63	0.11	0.20	42.46	30.33	4.046
13	107.55	0.11	0.40	130.73	48.00	4.033
14	31.71	0.25	0.40	261.55	47.33	4.073
15	107.55	0.18	0.60	424.35	65.00	3.887

5.2.1 Cutting Force

The software identifies a linear model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.7, the ANOVA table for cutting force reveals that the coded values for feed and depth of cut are highly meaningful, since a coded quadratic model is used. The coded final regression equation for cutting force is given in Eq. (5.4).

Table 5.7 Cutting force ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	296200	148100	48.20	< 0.0001	significant
B-Feed	115600	115600	37.62	< 0.0001	
C-DOC	180600	180600	58.78	< 0.0001	
Residual	36868.66	3072.39			
Lack of Fit	34938.56	3493.86	3.62	0.2357	not significant
Pure Error	1930.10	965.05			
Cor Total	333000				

$$\text{Cutting force (CF)} = 239.48 + 120.20 \times B + 150.24 \times C \quad (5.4)$$

Figure 5.8 presents the plot of perturbation and the sensitivity to input variables for the CF. From the plot, it can be observed that CF increases with increasing feed and DC.

Figure 5.9 shows the 3D response surface plot of CS and FR. It can be observed from this graph that CS 69.63, FR 0.11, and DC 0.2 give the minimum CF, and CS 69.63, FR 0.25, and DC 0.6 give the maximum CF.

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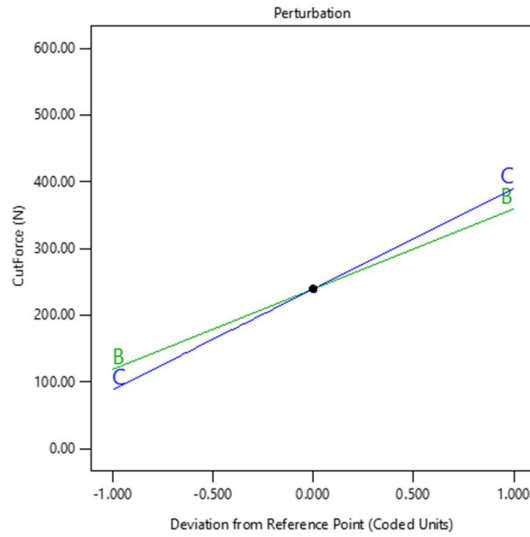


Figure 5.8 Cutting force perturbation plot

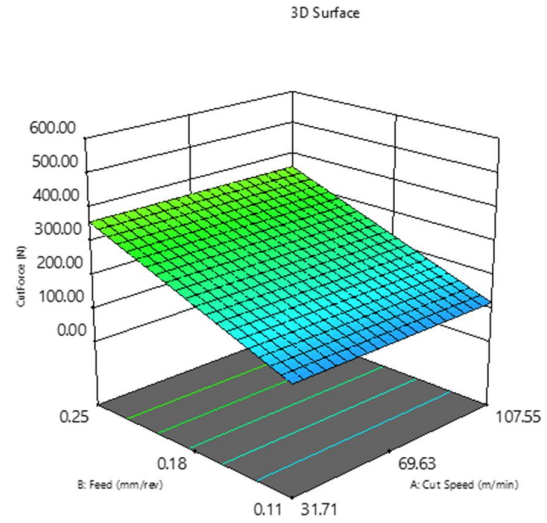


Figure 5.9 Cutting force 3D response surface plot

5.2.2 Cutting Temperature

The software identifies a linear model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

According to Table 5.8, the cutting temperature ANOVA table, the FR, and DC are highly meaningful due to the linear model. The final coded regression model equation for cutting temperature is given by Eq. (5.5).

Table 5.8 Cutting temperature ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	1588.69	529.56	22.71	< 0.0001	significant
A-Cut Speed	373.56	373.56	16.02	0.0021	
B-Feed	561.13	561.13	24.06	0.0005	
C-DOC	654.01	654.01	28.05	0.0003	
Residual	256.52	23.32			
Lack of Fit	223.63	24.85	1.51	0.4607	not significant
Pure Error	32.89	16.44			
Cor Total	1845.21				

$$\text{Cutting temperature (CT)} = 45.58 + 6.83 \times A + 8.38 \times B + 9.04 \times C \quad (5.5)$$

Figure 5.10 contains a perturbation plot that describes the influence of input factors on the CT. It is found that the CT increases as every input parameter increases.

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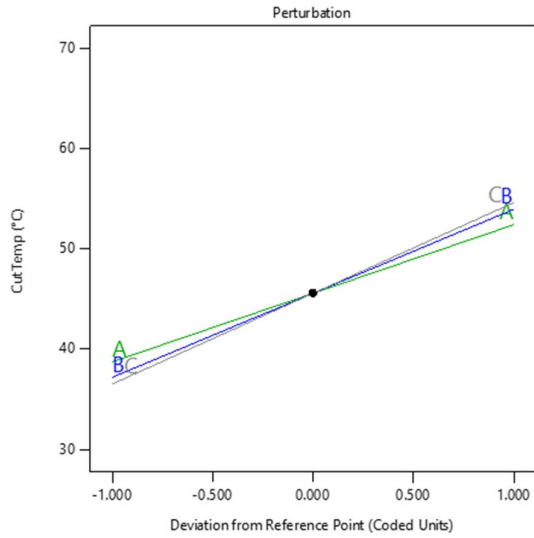


Figure 5.10 Cutting temperature perturbation plot

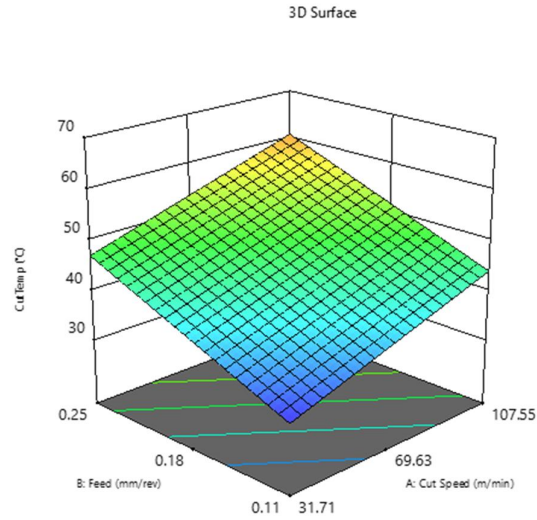


Figure 5.11 Cutting temperature 3D response surface plot

The 3D response surface plot of CS and feed is presented in Figure 5.11. The minimum CT is reached at CS = 69.63, feed = 0.11, and DC = 0.2, whereas the maximum CT is achieved at CS = 107.55, feed = 0.18, and DC = 0.6.

5.2.3 Surface Roughness

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical meaningfulness, as evidenced by a p-value < 0.05.

According to Table 5.9, the ANOVA of surface roughness, the terms feed, cutting speed-feed interaction, cutting speed-depth of cut, feed-depth of cut, cutting speed, and feed (quadratics) would have greater significance than the others, since a quadratic model is used. Eq. (5.6) gives the coded equation for surface roughness in the final regression model.

Table 5.9 ANOVA table for surface roughness

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	0.7111	0.0889	18.04	0.0012	significant
A-Cut Speed	0.0258	0.0258	5.23	0.0622	
B-Feed	0.0073	0.0073	1.48	0.2692	
C-DOC	0.0876	0.0876	17.78	0.0056	
AB	0.1612	0.1612	32.73	0.0012	
AC	0.1410	0.1410	28.63	0.0017	

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BC	0.1581	0.1581	32.10	0.0013	
A ²	0.0490	0.0490	9.94	0.0197	
B ²	0.0899	0.0899	18.25	0.0052	
Residual	0.0296	0.0049			
Lack of Fit	0.0279	0.0070	8.45	0.1086	not significant
Pure Error	0.0017	0.0008			
Cor Total	0.7406				

Surface roughness (SR)

$$\begin{aligned}
 &= 4.10 - 0.0568 \times A - 0.0302 \times B + 0.1046 \times C \\
 &- 0.2007 \times A \times B - 0.1878 \times A \times C + 0.1988 \times B \times C \\
 &- 0.1145 \times A^2 - 0.1556 \times B^2
 \end{aligned} \tag{5.6}$$

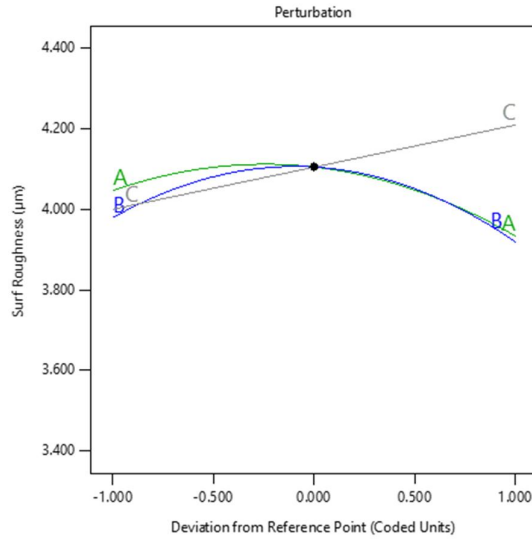


Figure 5.12 Surface roughness perturbation plot

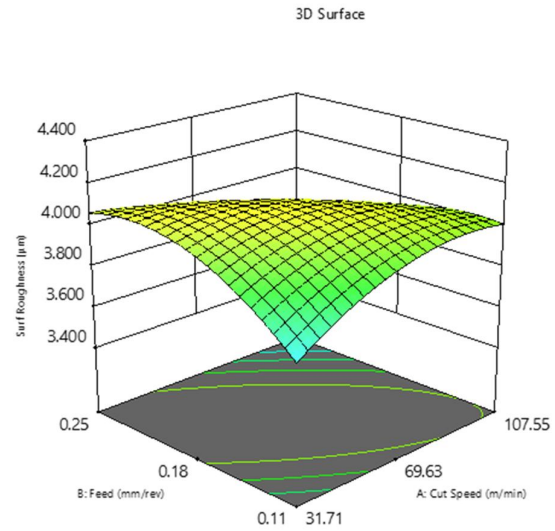


Figure 5.13 Surface roughness 3D response surface plot

Figure 5.12 presents the perturbation plot of input factors on SR. R value increases as DC increases, whereas the SR value decreases with increasing CS and feed. The 3D response surface plot of CS and feed is presented in Figure 5.13 below. In this plot, the SR can be minimized at a CS of 107.55, a feed of 0.25, and a cutting depth of 0.4. However, the SR could be at its maximum at a CS of 31.71, a feed of 0.18, and a cutting depth of 0.6.

As shown in Table 5.10, both the R^2 and adjusted R^2 values are consistently high across all responses and exhibit minimal variation, indicating a strong model fit for all responses. It can also be observed that the predicted R^2 values are not significantly different from the

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adjusted R^2 values, implying that the model can be used to predict the experimental results.

Table 5.10 Model adequacy metrics for Case-B output responses

Type	Cutting Force	Cutting Temperature	Surface Roughness
R^2	0.9111	0.8610	0.9676
Adjusted R^2	0.8869	0.8231	0.9094
Predicted R^2	0.8293	0.7295	0.5130

5.3 Case-C Wet SAE-40 Cutting Fluid

First, the specific cooling condition, i.e., Case-C, was selected, and the corresponding 15-run Box–Behnken design was executed with the input factors. For each run, the output responses are compiled into the design matrix as shown in Table 5.11. These results were then used to create RSM models (quadratic for cutting force, cutting temperature, and surface roughness). Insignificant terms in the initial RSM model were systematically identified from ANOVA results and removed, thereby simplifying the regression equation without sacrificing predictive capability. Eliminating these statistically meaningless interactions or higher-order terms reduces overfitting. It improves the numerical stability of the coefficients, allowing the final model to represent the true response surface more clearly over the design space.

Table 5.11 Box Behnken 15 runs for Case-C

Test Run	Input parameters			Output parameters		
	A: CS	B: FR	C: DC	CF	CT	SR
	m/min	mm/rev	mm	N	°C	µm
1	31.71	0.11	0.40	354.72	77.00	4.250
2	69.63	0.18	0.40	645.59	106.00	2.613
3	31.71	0.18	0.20	109.54	51.67	5.086
4	69.63	0.11	0.60	495.25	105.67	2.547
5	31.71	0.18	0.60	531.25	85.67	5.260
6	69.63	0.18	0.40	648.93	107.00	2.579
7	107.55	0.25	0.40	477.31	101.00	3.186
8	69.63	0.25	0.60	668.54	117.33	4.517
9	107.55	0.18	0.20	67.86	63.33	3.820
10	69.63	0.18	0.40	660.31	113.00	2.639
11	69.63	0.25	0.20	170.64	69.33	4.563
12	69.63	0.11	0.20	81.69	55.67	4.089
13	107.55	0.11	0.40	473.97	73.75	1.678

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14	31.71	0.25	0.40	702.67	77.58	5.200
15	107.55	0.18	0.60	501.82	124.00	2.150

5.3.1 Cutting Force

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.12, cutting force ANOVA data, based on the quadratic model, it can be found that feed, DC, the interaction between cutting speed and feed, and the quadratic influence of cutting speed and DC are very meaningful. The coded equation of the final regression model for cutting force is presented in Eq. (5.7).

Table 5.12 Cutting force ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	727600	90953.80	322.88	< 0.0001	significant
A-Cut Speed	3925.53	3925.53	13.94	0.0097	
B-Feed	47051.76	47051.76	167.03	< 0.0001	
C-DOC	390300	390300	1385.68	< 0.0001	
AB	29690.39	29690.39	105.40	< 0.0001	
BC	1778.32	1778.32	6.31	0.0457	
A ²	37239.64	37239.64	132.20	< 0.0001	
B ²	8870.50	8870.50	31.49	0.0014	
C ²	228100	228100	809.82	< 0.0001	
Residual	1690.18	281.70			
Lack of Fit	1571.20	392.80	6.60	0.1358	not significant
Pure Error	118.98	59.49			
Cor Total	729300				

Cutting force (CF)

$$\begin{aligned}
 &= 651.61 - 22.15 \times A + 76.69 \times B + 220.89 \times C \\
 &- 86.15 \times A \times B + 21.09 \times B \times C - 100.43 \times A^2 - 49.01 \times B^2 \\
 &- 248.56 \times C^2
 \end{aligned} \quad (5.7)$$

Figure 5.14 presents the CF response to input factors in a perturbation plot. It is found that CF increases with increases in feed and DC, and increases slightly with moderate speed. The 3D response surface plot for CS and feed is shown in Figure 5.15. In this graph, the minimum CF occurs at a CS of 107.55, a feed of 0.18, and a DC of 0.2. On the other hand, the maximum

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CF is obtained at a CS of 31.71, a feed of 0.25, and a DC of 0.4.

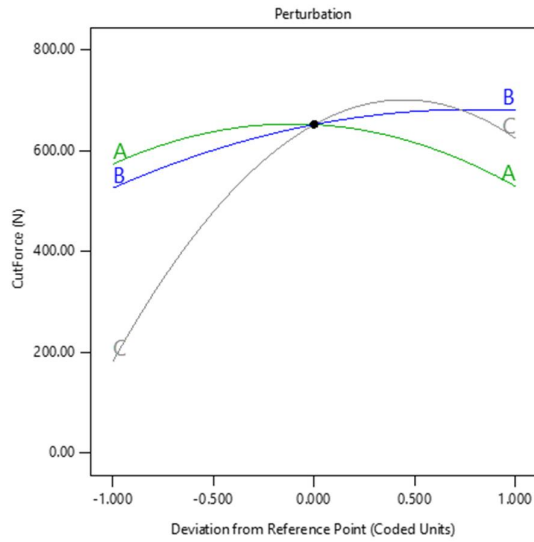


Figure 5.14 Cutting force perturbation plot

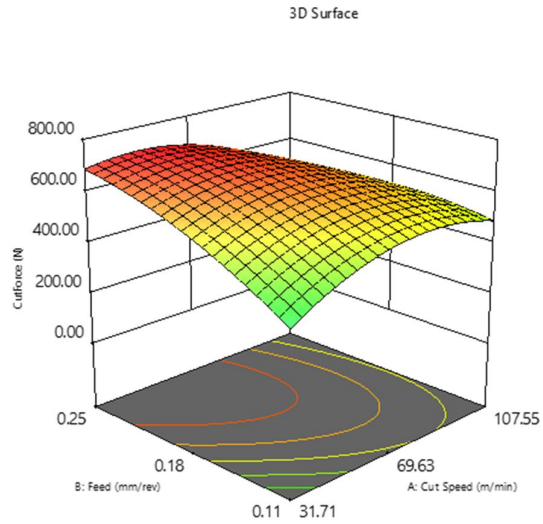


Figure 5.15 Cutting force 3D response surface plot

5.3.2 Cutting Temperature

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

According to the ANOVA data in Table 5.13, for cutting temperature, as the model is linear, feed and DC make meaningful contributions. The final regression model coded equation for cutting temperature is given by Eq. (5.8).

Table 5.13 Cutting temperature ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	7560.96	945.12	39.65	0.0001	significant
A-Cut Speed	615.36	615.36	25.82	0.0023	
B-Feed	353.29	353.29	14.82	0.0085	
C-DOC	4640.38	4640.38	194.69	< 0.0001	
AB	177.82	177.82	7.46	0.0341	
AC	177.78	177.78	7.46	0.0341	
A ²	955.15	955.15	40.07	0.0007	
B ²	387.95	387.95	16.28	0.0068	
C ²	481.22	481.22	20.19	0.0041	
Residual	143.01	23.83			

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Lack of Fit	114.34	28.59	1.99	0.3607	not significant
Pure Error	28.67	14.33			
Cor Total	7703.97				

Cutting temperature (CT)

$$= 108.67 + 8.77 \times A + 6.65 \times B + 24.08 \times C + 6.67 \times A \times B \quad (5.8)$$

$$+ 6.67 \times A \times C - 16.08 \times A^2 - 10.25 \times B^2 - 11.42 \times C^2$$

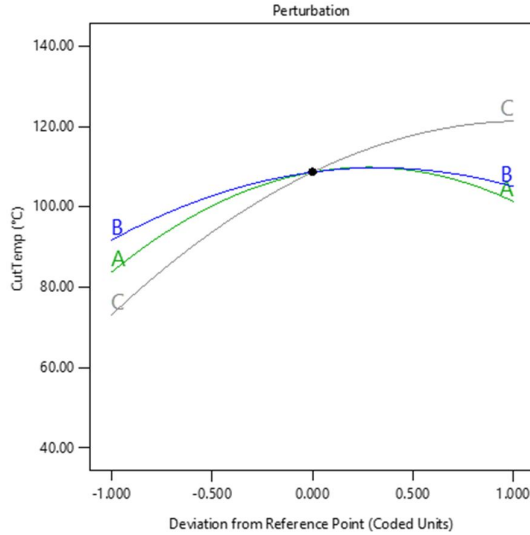


Figure 5.16 Cutting temperature perturbation plot

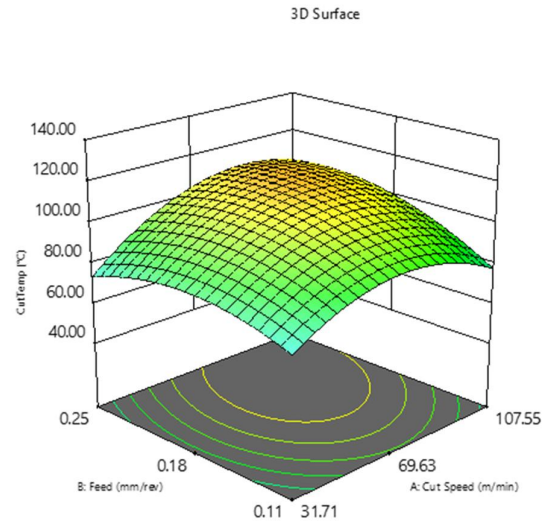


Figure 5.17 Cutting temperature 3D response surface plot

The perturbation plot displayed in Figure 5.16 is used to analyze the contribution of input parameters to the CT. As can be seen, as we increase the DC, CT increases; likewise, as we increase the CS and FR, CT increases slightly.

Figure 5.17 shows a 3D response surface plot of CS vs. feed. From this response surface plot, the minimum CT occurs at a CS of 31.71 and a feed of 0.18, with the same DC (0.2). The maximum CT occurs at a CS of 107.55 and a FR of 0.18, with a DC of 0.6.

5.3.3 Surface Roughness

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.14, ANOVA results for surface roughness revealed that, since the model used

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was quadratic, the meaningful variables are cutting speed, feed, cutting speed-depth of cut interaction, feed-depth of cut interaction, and the quadratic influence of all inputs. The coded equation for surface roughness of the final regression model is presented in Eq. (5.9).

Table 5.14 Surface roughness ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	20.01	2.22	1322.51	< 0.0001	significant
A-Cut Speed	10.04	10.04	5972.87	< 0.0001	
B-Feed	3.00	3.00	1786.49	< 0.0001	
C-DOC	1.19	1.19	707.60	< 0.0001	
AB	0.0778	0.0778	46.31	0.0010	
AC	0.8501	0.8501	505.74	< 0.0001	
BC	0.5590	0.5590	332.57	< 0.0001	
A ²	1.15	1.15	686.14	< 0.0001	
B ²	0.6178	0.6178	367.56	< 0.0001	
C ²	3.05	3.05	1817.27	< 0.0001	
Residual	0.0084	0.0017			
Lack of Fit	0.0066	0.0022	2.46	0.3021	not significant
Pure Error	0.0018	0.0009			
Cor Total	20.02				

$$\begin{aligned}
 \text{Surface roughness (SR)} &= 2.61 - 1.12 \times A + 0.6127 \times B - 0.3856 \times C \\
 &+ 0.1395 \times A \times B - 0.4610 \times A \times C + 0.3738 \times B \times C \\
 &+ 0.5589 \times A^2 + 0.4091 \times B^2 + 0.9096 \times C^2
 \end{aligned} \quad (5.9)$$

Figure 5.18 presents the perturbation plot of the effect of inputs on SR. As can be noticed, SR increases linearly with increasing feed. At the same time, it decreases as the CS and DC increase.

Figure 5.19 displays a 3D response surface plot for CS and FR. According to this plot, the minimum SR occurs at a CS of 107.55, a FR of 0.11, and a DC of 0.4. The maximum SR occurs at a CS of 31.71, a FR of 0.18, and a DC of 0.6.

As presented in Table 5.15, the R² and adjusted R² are comparable across all responses and well above 0.94. Hence, the models are fitted well. Further, the predicted R² values are all close to the adjusted R², indicating good predictive models.

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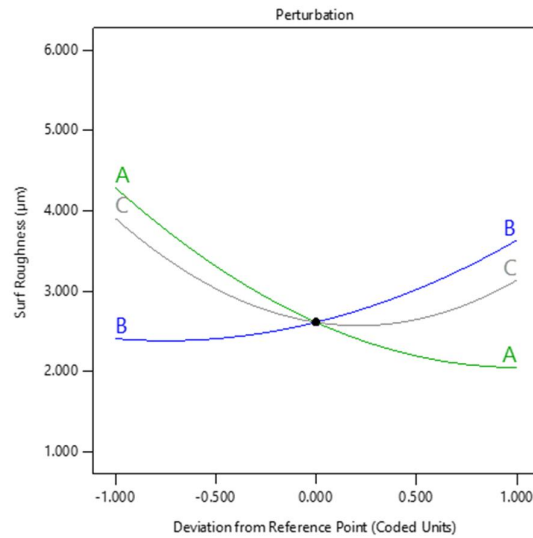


Figure 5.18 Surface roughness perturbation plot

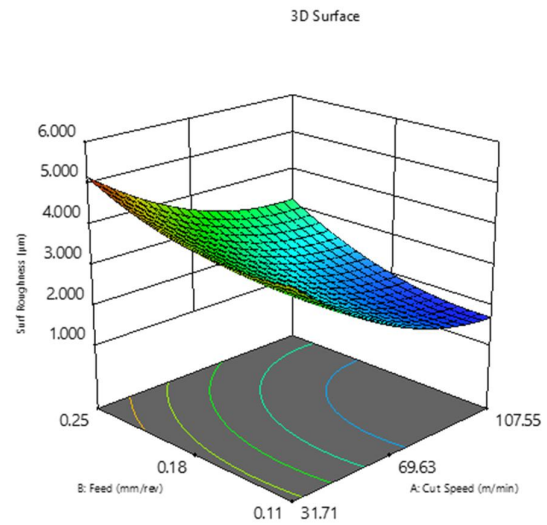


Figure 5.19 Surface roughness 3D response surface plot

Table 5.15 Model adequacy metrics for Case-C output responses

Type	Cutting Force	Cutting Temperature	Surface Roughness
R ²	0.9977	0.9816	0.9996
Adjusted R ²	0.9937	0.9484	0.9988
Predicted R ²	0.9660	0.7562	0.9945

5.4 Case-D1 MQL+ 1% wt Al₂O₃ Mono Nanofluid as a Cutting Fluid

First, the specific cooling condition, i.e., Case-D1, was selected, and the corresponding 15-run Box–Behnken design was executed with the input factors. For each run, output responses were measured and compiled into the design matrix, as shown in Table 5.16. These input variable values were used to build RSM models (quadratic for cutting force, cutting temperature, and surface roughness). Insignificant terms in the initial RSM model were systematically identified from ANOVA results and removed, thereby simplifying the regression equation without sacrificing predictive capability. Eliminating these statistically meaningless interactions or higher-order terms reduces overfitting. It improves the numerical stability of the coefficients, allowing the final model to represent the true response surface more clearly over the design space.

Table 5.16 Box Behnken 15 runs for Case-D1

Test	Input parameters	Output parameters
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Run	A: CS	B: FR	C: DC	CF	CT	SR
	m/min	mm/rev	mm	N	°C	µm
1	31.71	0.11	0.40	129.16	52.67	5.464
2	69.63	0.18	0.40	201.04	66.00	5.510
3	31.71	0.18	0.20	101.80	52.67	4.623
4	69.63	0.11	0.60	277.05	79.33	5.628
5	31.71	0.18	0.60	398.46	95.67	6.054
6	69.63	0.18	0.40	217.42	63.50	5.579
7	107.55	0.25	0.40	369.43	89.33	2.252
8	69.63	0.25	0.60	498.49	106.33	4.053
9	107.55	0.18	0.20	165.05	61.67	3.300
10	69.63	0.18	0.40	209.18	66.50	5.572
11	69.63	0.25	0.20	214.09	69.33	4.757
12	69.63	0.11	0.20	62.08	51.67	4.934
13	107.55	0.11	0.40	150.34	49.00	3.882
14	31.71	0.25	0.40	296.96	66.33	5.114
15	107.55	0.18	0.60	464.17	108.00	2.368

5.4.1 Cutting Force

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.17, ANOVA for cutting force indicates that, due to the quadratic nature of the model, feed and depth of cut are highly meaningful. The final regression model's coded equation for cutting force is given in Eq. (5.10).

Table 5.17 Cutting force ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	238900	47780.16	126.66	< 0.0001	significant
A-Cut Speed	6194.90	6194.90	16.42	0.0029	
B-Feed	72263.99	72263.99	191.57	< 0.0001	
C-DOC	149900	149900	397.43	< 0.0001	
A ²	1973.12	1973.12	5.23	0.0480	
C ²	9101.93	9101.93	24.13	0.0008	
Residual	3394.96	377.22			
Lack of Fit	3260.84	465.83	6.95	0.1316	not significant
Pure Error	134.12	67.06			

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Cor Total	242300				
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Cutting force (CF)

$$= 211.62 + 27.83 \times A + 95.04 \times B + 136.89 \times C + 23.05 \times A^2 + 49.50 \times C^2 \quad (5.10)$$

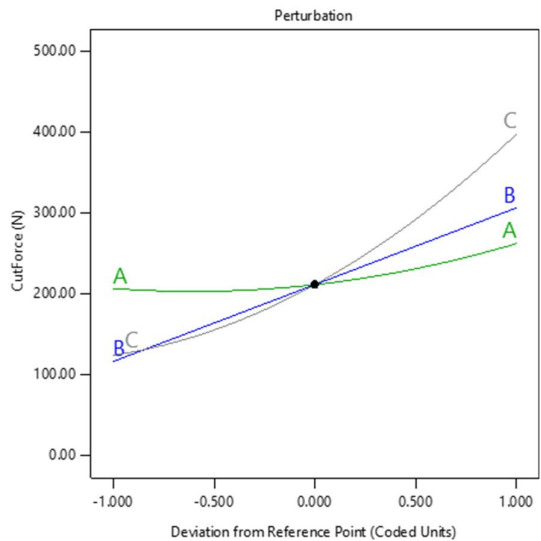


Figure 5.20 Cutting force perturbation plot

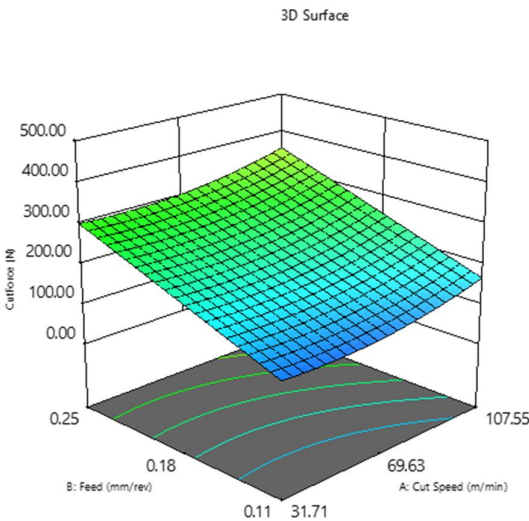


Figure 5.21 Cutting force 3D response surface plot

Figure 5.20 illustrates the influence and disturbance from the input variables upon the CF. The plot clearly demonstrates that the CF increases with increasing feed and DC. As CS increases, the CF increases slightly.

Figure 5.21 shows the 3D response surface between CS and feed. It was found that the lowest CF occurs at 69.63 CS, 0.11 feed, and 0.2 DC, while the highest CF occurs at 69.63 CS, 0.25 feed, and 0.6 DC.

5.4.2 Cutting Temperature

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical meaningfulness, as evidenced by a p-value < 0.05.

With reference to ANOVA for cutting temperature in Table 5.18, feed rate, depth of cut, and the quadratic effect of depth of cut are all statistically meaningful because the model is quadratic. The coded equation of the final regression model of cutting temperature is given

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in Eq. (5.11).

Table 5.18 Cutting temperature ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	5228.41	1045.68	69.74	< 0.0001	significant
A-Cut Speed	206.72	206.72	13.79	0.0048	
B-Feed	1216.89	1216.89	81.16	< 0.0001	
C-DOC	2964.50	2964.50	197.73	< 0.0001	
AB	177.78	177.78	11.86	0.0074	
C ²	662.52	662.52	44.19	< 0.0001	
Residual	134.94	14.99			
Lack of Fit	129.77	18.54	7.18	0.1277	not significant
Pure Error	5.17	2.58			
Cor Total	5363.34				

Cutting temperature (CT)

$$= 64.76 + 5.08 \times A + 12.33 \times B + 19.25 \times C + 6.67 \times A \times B \quad (5.11) \\ + 13.32 \times C^2$$

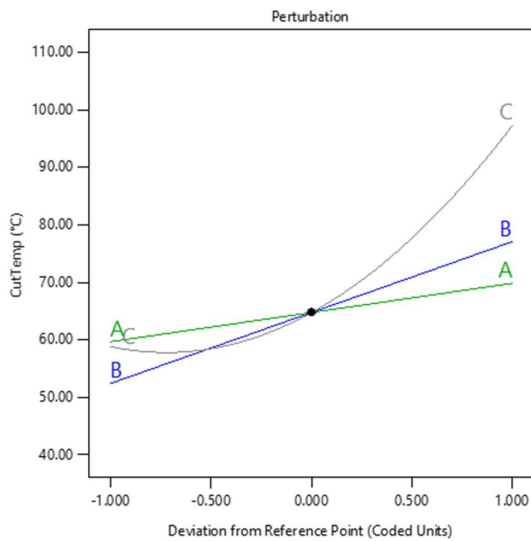


Figure 5.22 Cutting temperature perturbation plot

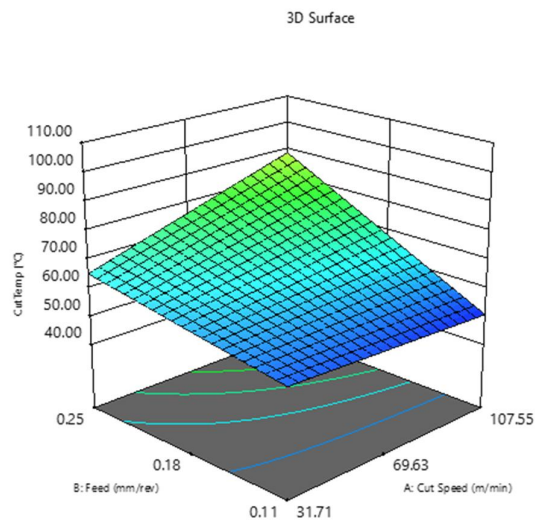


Figure 5.23 Cutting temperature 3D response surface plot

Figure 5.22 illustrates the perturbational influences of the input parameters on the CT. From the plot, we can see that the CT rises significantly with increasing DC and increases linearly with increasing CS and FR. Figure 5.23 shows the 3D response surface to CS and feed. 107.55 CS, 0.11 feed, and 0.4 DC give minimum CT, while 107.55 CS, 0.18 feed, and 0.6

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DC give maximum CT.

5.4.3 Surface Roughness

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.19, ANOVA for surface roughness indicates that, because the model is quadratic, cutting speed and its quadratic effect are more meaningful. The final regression model's coded equation for surface roughness is presented in Eq. (5.12).

Table 5.19 Surface roughness ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	19.97	2.22	136.03	< 0.0001	significant
A-Cut Speed	11.17	11.17	684.82	< 0.0001	
B-Feed	1.74	1.74	106.76	0.0001	
C-DOC	0.0300	0.0300	1.84	0.2330	
AB	0.4096	0.4096	25.11	0.0041	
AC	1.40	1.40	85.68	0.0002	
BC	0.4888	0.4888	29.97	0.0028	
A ²	4.20	4.20	257.29	< 0.0001	
B ²	0.3536	0.3536	21.68	0.0056	
C ²	0.5953	0.5953	36.50	0.0018	
Residual	0.0816	0.0163			
Lack of Fit	0.0786	0.0262	17.99	0.0531	not significant
Pure Error	0.0029	0.0015			
Cor Total	20.05				

$$\begin{aligned} \text{Surface roughness (SR)} &= 5.55 - 1.18 \times A - 0.4665 \times B + 0.0612 \times C \\ &- 0.3200 \times A \times B - 0.5911 \times A \times C - 0.3496 \times B \times C \\ &- 1.07 \times A^2 - 0.3094 \times B^2 - 0.4015 \times C^2 \end{aligned} \quad (5.12)$$

Figure 5.24 presents a plot of the perturbation of input parameters affecting SR. SR decreases with increasing CS and FR, while it slightly increases at medium values of DC.

Figure 5.25 displays the 3D response surface plot of the CS versus feed. From the response surface plot of SR versus CS and feed, SR has a minimum at a CS of 107.55, a FR of 0.25,

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and a DC of 0.4. In comparison, the maximum SR was observed at a CS of 69.63, a FR of 0.18, and a DC of 0.4.

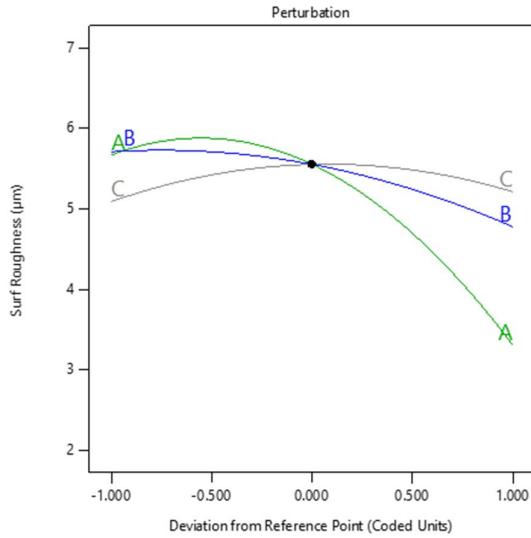


Figure 5.24 Surface roughness perturbation plot

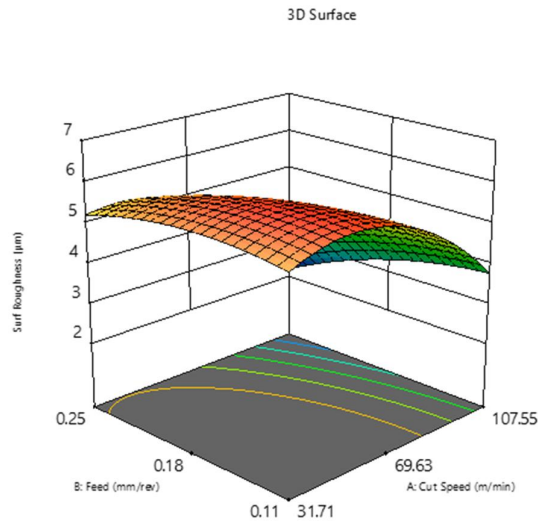


Figure 5.25 Surface roughness 3D response surface plot

The below Table 5.20 shows the R^2 and adjusted R^2 values for all responses, which are both very high and very similar, indicating that the models are a very good fit to the data. All predicted R^2 values also align well with the adjusted R^2 values, indicating the models' reliability in predicting experimental outputs.

Table 5.20 Model adequacy metrics for Case-D1 output responses

Type	Cutting Force	Cutting Temperature	Surface Roughness
R^2	0.9939	0.9827	0.9959
Adjusted R^2	0.9830	0.9517	0.9886
Predicted R^2	0.9103	0.7370	0.9369

5.5 Case-D2 MQL + 2% wt Al_2O_3 Mono Nanofluid as a Cutting Fluid

First, the specific cooling condition, i.e., Case-D2, was selected and the corresponding 15-run Box–Behnken design was executed with input factors. For every run, output responses were measured and compiled into the design matrix as given in Table 5.21. The generated data was subsequently utilized to construct RSM models (quadratic nature) for cutting force, cutting temperature, and surface roughness. Insignificant terms in the initial RSM model were systematically identified from ANOVA results and removed, thereby

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simplifying the regression equation without sacrificing predictive capability. Eliminating these statistically meaningless interactions or higher-order terms reduces overfitting. It improves the numerical stability of the coefficients, allowing the final model to represent the true response surface more clearly over the design space.

Table 5.21 Box Behnken 15 runs for Case-D2

Test Run	Input parameters			Output parameters		
	A: CS	B: FR	C: DC	CF	CT	SR
	m/min	mm/rev	mm	N	°C	µm
1	31.71	0.11	0.40	178.19	61.72	3.608
2	69.63	0.18	0.40	158.58	65.00	3.010
3	31.71	0.18	0.20	143.87	47.89	3.513
4	69.63	0.11	0.60	367.76	93.50	2.097
5	31.71	0.18	0.60	516.53	90.33	2.939
6	69.63	0.18	0.40	174.86	64.67	2.967
7	107.55	0.25	0.40	395.52	93.20	3.666
8	69.63	0.25	0.60	621.08	109.00	2.822
9	107.55	0.18	0.20	152.01	67.67	2.996
10	69.63	0.18	0.40	161.82	65.00	2.922
11	69.63	0.25	0.20	194.47	66.89	3.251
12	69.63	0.11	0.20	102.97	55.67	2.939
13	107.55	0.11	0.40	134.06	70.67	3.400
14	31.71	0.25	0.40	357.96	68.33	4.100
15	107.55	0.18	0.60	572.04	103.00	2.591

5.5.1 Cutting Force

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.22, cutting force ANOVA data shows feed, depth of cut, and the quadratic term of depth of cut as very meaningful as a result of the quadratic form of the model. The coded equation of the final regression model for cutting force is presented in Eq. (5.13).

Table 5.22 Cutting force ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	424200	60597.62	77.99	< 0.0001	significant
A-Cut Speed	407.22	407.22	0.5241	0.4926	

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B-Feed	77230.60	77230.60	99.40	< 0.0001	
C-DOC	275300	275300	354.35	< 0.0001	
BC	6546.06	6546.06	8.43	0.0229	
A ²	14629.00	14629.00	18.83	0.0034	
B ²	5445.26	5445.26	7.01	0.0331	
C ²	51485.31	51485.31	66.26	< 0.0001	
Residual	5438.76	776.97			
Lack of Fit	5290.22	1058.04	14.25	0.0669	not significant
Pure Error	148.54	74.27			
Cor Total	429600				

Cutting force (CF)

$$= 165.08 + 7.13 \times A + 98.25 \times B + 185.51 \times C + 40.51 \times B \times C + 62.94 \times A^2 + 38.40 \times B^2 + 118.08 \times C^2 \quad (5.13)$$

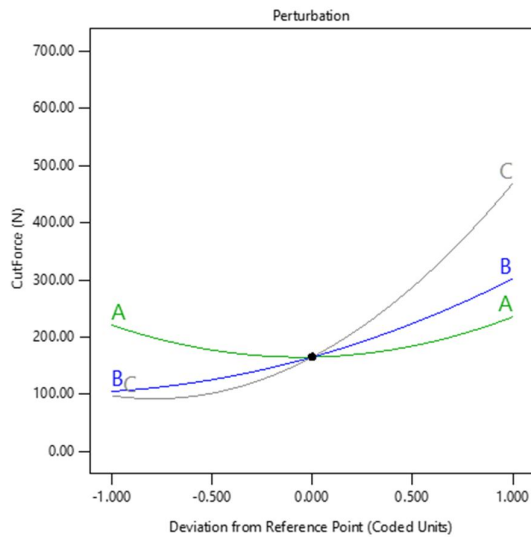


Figure 5.26 Cutting force perturbation plot

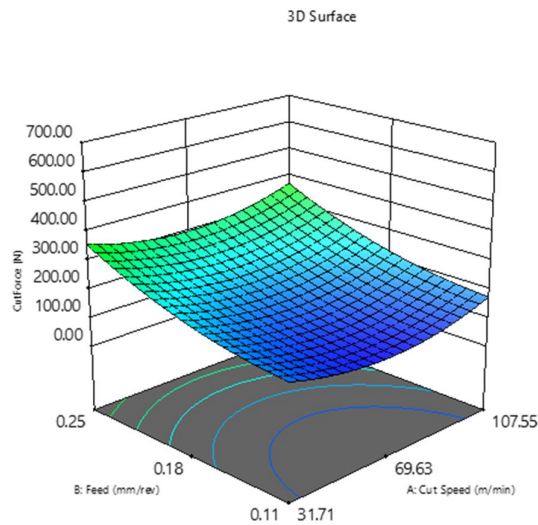


Figure 5.27 Cutting force 3D response surface plot

Figure 5.26 presents the perturbation plot displaying the effect of the various input factors on CF. The CF increases as both feed and cut depth increase, with a very small increase observed at both lower and higher CSs.

Figure 5.27 shows the 3D response surface between CS and feed. Minimum CF occurred at 69.63 CS, 0.11 feed, 0.2 DC, and maximum CF occurred at 69.63 CS, 0.25 feed, 0.6 DC.

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5.5.2 Cutting Temperature

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical meaningfulness, as evidenced by a p-value < 0.05.

From Table 5.23, ANOVA for cutting temperature shows that, since it's quadratic in nature, cutting speed, feed, depth of cut, interaction of cutting speed and feed, quadratic of feed, and quadratic of depth of cut are meaningful. The coded equation for the cutting temperature is the final regression model, given in Eq. (5.14).

Table 5.23 Cutting temperature ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	4621.20	513.47	1575.48	< 0.0001	significant
A-Cut Speed	548.74	548.74	1683.72	< 0.0001	
B-Feed	390.18	390.18	1197.20	< 0.0001	
C-DOC	3109.45	3109.45	9540.76	< 0.0001	
AB	63.36	63.36	194.41	< 0.0001	
AC	12.64	12.64	38.78	0.0016	
BC	4.57	4.57	14.03	0.0134	
A ²	19.11	19.11	58.62	0.0006	
B ²	147.31	147.31	452.00	< 0.0001	
C ²	373.59	373.59	1146.30	< 0.0001	
Residual	1.63	0.3259			
Lack of Fit	1.56	0.5185	14.00	0.0674	not significant
Pure Error	0.0741	0.0370			
Cor Total	4622.83				

$$\begin{aligned}
 \text{Cutting temperature (CT)} &= 64.89 + 8.28 \times A + 6.98 \times B + 19.71 \times C + 3.98 \times A \times B \\
 &- 1.78 \times A \times C + 1.07 \times B \times C + 2.27 \times A^2 + 6.32 \times B^2 \\
 &+ 10.06 \times C^2
 \end{aligned} \quad (5.14)$$

Figure 5.28 displays the perturbation influence of input factors on CT. From the figure, we see that the CT increases significantly with cutting depth and increases slightly with CS and FR.

Figure 5.29 displays the 3D response surface plot for CS and feed. It can be obtained that the minimum CT occurs at a CS of 31.71, a feed of 0.18, and a DC of 0.2. Otherwise, the maximum CT occurs at a CS of 69.63, a feed of 0.25, and a DC of 0.6.

RESULT AND DISCUSSION

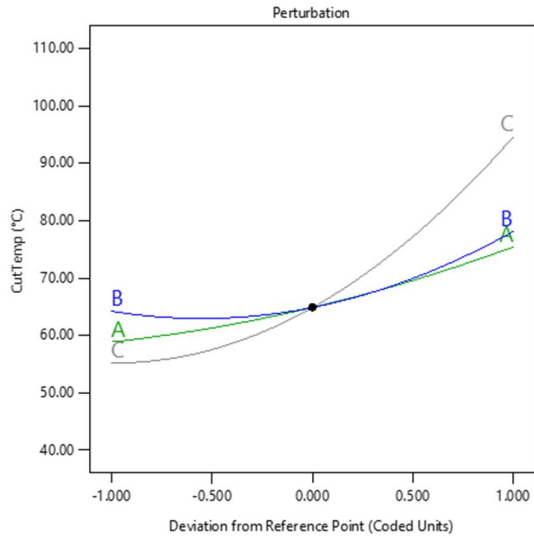


Figure 5.28 Cutting temperature perturbation plot

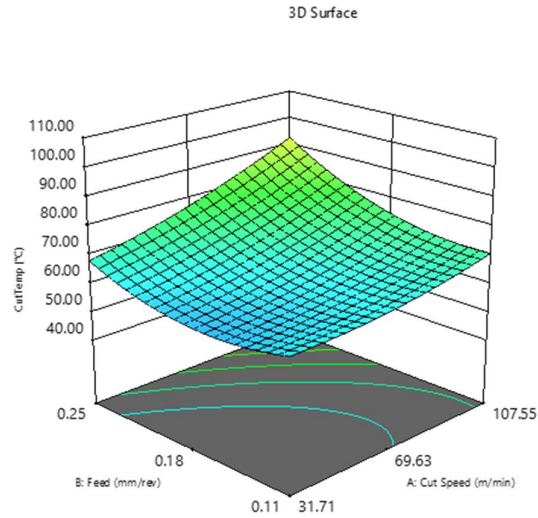


Figure 5.29 Cutting temperature 3D response surface plot

5.5.3 Surface Roughness

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.24, the ANOVA data for surface roughness show that, because the model is quadratic in nature, the DC and the quadratic effect of CS and DC are more meaningful. The regression model's coded equation of the surface roughness is shown below in Eq. (5.15).

Table 5.24 Surface roughness ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	3.27	0.4668	64.98	< 0.0001	significant
A-Cut Speed	0.2841	0.2841	39.55	0.0004	
B-Feed	0.4025	0.4025	56.02	0.0001	
C-DOC	0.6332	0.6332	88.13	< 0.0001	
BC	0.0426	0.0426	5.93	0.0451	
A ²	0.8499	0.8499	118.29	< 0.0001	
B ²	0.2257	0.2257	31.42	0.0008	
C ²	0.7040	0.7040	97.99	< 0.0001	
Residual	0.0503	0.0072			
Lack of Fit	0.0464	0.0093	4.83	0.1803	not significant
Pure Error	0.0038	0.0019			

RESULT AND DISCUSSION

Cor Total	3.32				
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$$\begin{aligned}
 \text{Surface roughness (SR)} &= 2.97 - 0.1885 \times A + 0.2243 \times B - 0.2813 \times C \\
 &+ 0.1032 \times B \times C + 0.4798 \times A^2 + 0.2473 \times B^2 - 0.4367 \times C^2
 \end{aligned}
 \tag{5.15}$$

The perturbation plot describing the impact of the input factors on SR is displayed in Figure 5.30. As is apparent, the SR increases slightly with the increasing FR, but decreases with increasing DC, and increases with increasing CS.

Figure 5.31 presents the 3D response surface of CS and feed. The best and worst SR were produced at 69.63 CS, 0.11 feed, and 0.6 DC, and at 31.71 CS, 0.25 feed, and 0.4 DC, respectively.

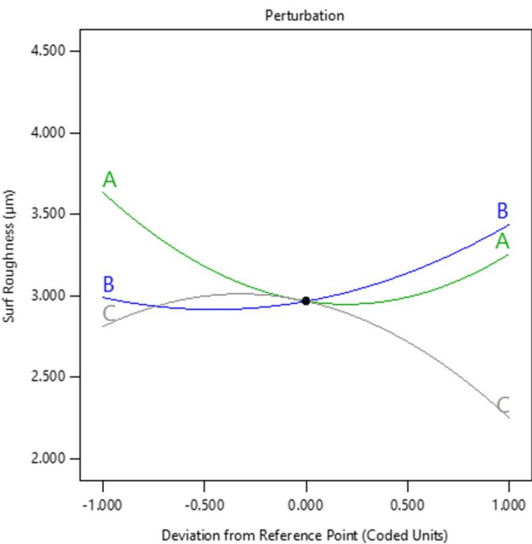


Figure 5.30 Surface roughness perturbation plot

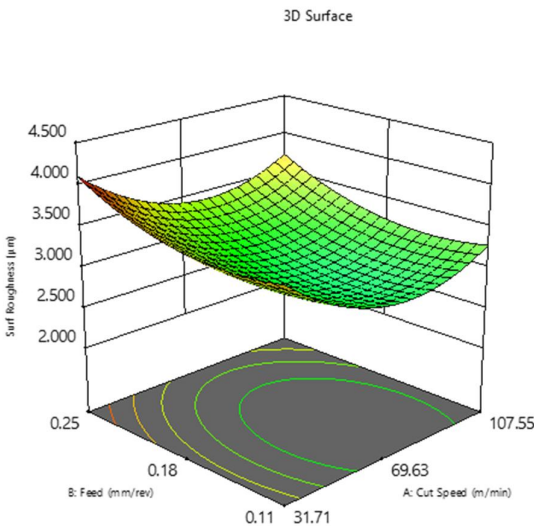


Figure 5.31 Surface roughness 3D response surface plot

Table 5.25 presents the R^2 and adjusted R^2 for each response. Both R^2 and adjusted R^2 are high and close to each other for each response, indicating that the models fit well. Also, the predicted R^2 values match well with the adjusted R^2 values, indicating that the models' predictions are trustworthy.

Table 5.25 Model adequacy metrics for Case-D2 output responses

Type	Cutting Force	Cutting Temperature	Surface Roughness
R^2	0.9925	0.9996	0.9908
Adjusted R^2	0.9791	0.9990	0.9743

RESULT AND DISCUSSION

Predicted R ²	0.8852	0.9946	0.8691
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5.6 Case-E1 MQL + 1% wt ZnO Mono Nanofluid as a Cutting Fluid

First, the specific cooling condition, i.e., Case-E1, was selected and the corresponding 15-run Box–Behnken design was executed with input factors. For each run, output responses were measured and compiled into the design matrix, as shown in Table 5.26. These results were then used to design RSM models (2FI) for the cutting force and linear models for the cutting temperature and surface roughness, respectively. Insignificant terms in the initial RSM model were systematically identified from ANOVA results and removed, thereby simplifying the regression equation without sacrificing predictive capability. Eliminating these statistically meaningless interactions or higher-order terms reduces overfitting. It improves the numerical stability of the coefficients, allowing the final model to represent the true response surface more clearly over the design space.

Table 5.26 Box Behnken 15 runs for Case-E1

Test Run	Input parameters			Output parameters		
	A: CS	B: FR	C: DC	CF	CT	SR
	m/min	mm/rev	mm	N	°C	µm
1	31.71	0.11	0.40	148.77	46.83	2.996
2	69.63	0.18	0.40	233.70	55.27	4.159
3	31.71	0.18	0.20	122.59	45.27	2.460
4	69.63	0.11	0.60	196.14	54.93	4.321
5	31.71	0.18	0.60	398.85	55.87	5.000
6	69.63	0.18	0.40	243.51	56.54	4.159
7	107.55	0.25	0.40	269.69	60.87	5.395
8	69.63	0.25	0.60	421.70	58.13	6.100
9	107.55	0.18	0.20	135.63	52.17	3.540
10	69.63	0.18	0.40	250.08	56.73	4.223
11	69.63	0.25	0.20	147.11	55.67	3.988
12	69.63	0.11	0.20	88.26	46.67	2.020
13	107.55	0.11	0.40	156.91	56.47	3.867
14	31.71	0.25	0.40	346.48	53.03	4.712
15	107.55	0.18	0.60	307.25	60.47	5.892

RESULT AND DISCUSSION

5.6.1 Cutting Force

The software identifies a 2FI model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.27, ANOVA data for cutting force shows that, the feed and depth of cut are meaningful, which is caused by the 2FI model nature.

Table 5.27 Cutting force ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	142800	28563.78	55.60	< 0.0001	significant
A-Cut Speed	2708.59	2708.59	5.27	0.0473	
B-Feed	44237.15	44237.15	86.11	< 0.0001	
C-DOC	86186.94	86186.94	167.77	< 0.0001	
AC	2737.42	2737.42	5.33	0.0464	
BC	6948.81	6948.81	13.53	0.0051	
Residual	4623.40	513.71			
Lack of Fit	4487.54	641.08	9.44	0.0991	not significant
Pure Error	135.86	67.93			
Cor Total	147400				

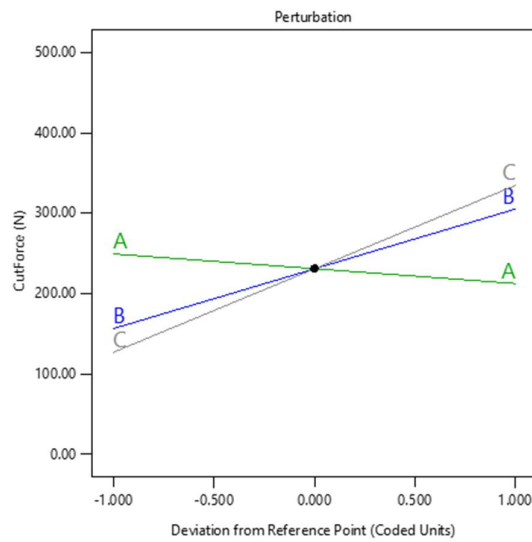


Figure 5.32 Cutting force perturbation plot

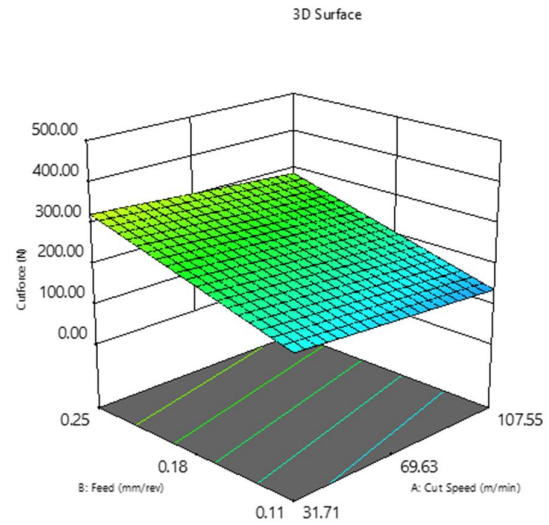


Figure 5.33 Cutting force 3D response surface plot

The coded equation of the regression model for cutting force is given in Eq. (5.16).

RESULT AND DISCUSSION

$$\begin{aligned} \text{Cutting force (CF)} \\ = 231.11 - 18.40 \times A + 74.36 \times B + 103.79 \times C \\ - 26.16 \times A \times C + 41.68 \times B \times C \end{aligned} \quad (5.16)$$

Error! Reference source not found. presents the perturbation plot, which shows the sensitivity of CF on input factors. It is observed that CF increases with increasing feed and DC, but decreases slightly with increasing CS.

The 3D response surface plot for CS and feed is presented in **Error! Reference source not found.**. From the plot, the minimum CF occurred at a CS of 69.63, feed of 0.11, and DC of 0.2, whereas the maximum CF occurred at the same CS of 69.63 but with a higher feed of 0.25 and DC of 0.6.

5.6.2 Cutting Temperature

The software identifies a linear model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value less than 0.05.

From Table 5.28, ANOVA data for cutting temperature show that, because the model is linear, CS, feed, and depth of cut are meaningful. The coded equation for cutting temperature is given in Eq. (5.17).

Table 5.28 Cutting temperature ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	279.63	93.21	26.10	< 0.0001	significant
A-Cut Speed	104.88	104.88	29.37	0.0002	
B-Feed	64.98	64.98	18.20	0.0013	
C-DOC	109.77	109.77	30.74	0.0002	
Residual	39.28	3.57			
Lack of Fit	38.01	4.22	6.64	0.1377	not significant
Pure Error	1.27	0.6362			
Cor Total	318.91				

$$\text{Cutting temperature (CT)} = 54.33 + 3.62 \times A + 2.85 \times B + 3.70 \times C \quad (5.17)$$

Regarding Figure 5.34 presents the perturbation plot is the output that represents the impact of input factors on the CT. It is observed that the higher the input factors, the higher the CT.

RESULT AND DISCUSSION

Figure 5.35 illustrates the 3D response surface plot for the CS and feed. The minimum CT is achieved at a CS of 31.71, a FR of 0.18, and a cutting depth of 0.2. The maximum CT is achieved at a CS of 107.55, a FR of 0.25, and a cutting depth of 0.4.

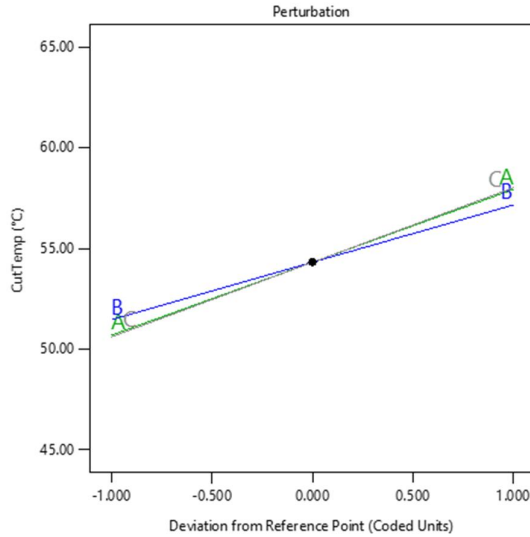


Figure 5.34 Cutting temperature perturbation plot

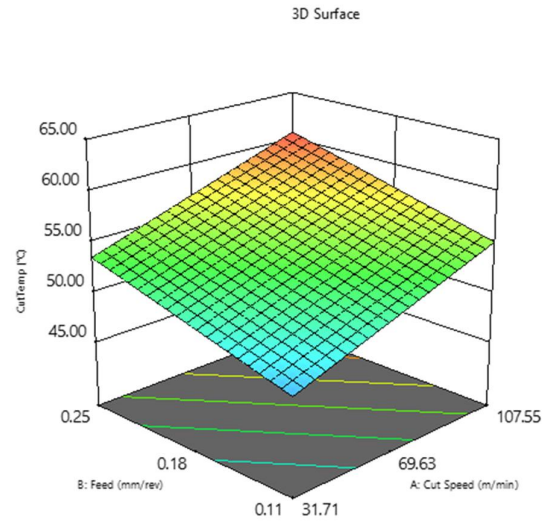


Figure 5.35 Cutting temperature 3D response surface plot

5.6.3 Surface Roughness

The software identifies a linear model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.29, ANOVA data for surface roughness suggests that, since the model is linear, CS, feed, and depth of cut are highly meaningful. The final coded regression equation for surface roughness is given by Eq. (5.18).

Table 5.29 Surface roughness ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	18.49	6.16	439.14	< 0.0001	significant
A-Cut Speed	1.55	1.55	110.72	< 0.0001	
B-Feed	6.11	6.11	435.46	< 0.0001	
C-DOC	10.82	10.82	771.23	< 0.0001	
Residual	0.1544	0.0140			
Lack of Fit	0.1516	0.0168	12.41	0.0768	not significant
Pure Error	0.0027	0.0014			
Cor Total	18.64				

RESULT AND DISCUSSION

$$\text{Surface roughness (SR)} = 4.19 + 0.4407 \times A + 0.8740 \times B + 1.16 \times C \quad (5.18)$$

Figure 5.36 illustrates the perturbation plot of the input variables. From the plot, it can be observed that SR increases as input factors increase.

Figure 5.37 shows the 3D response surface between CS and FR. At 69.63 CS, 0.11 feed, and 0.2 DC, SR is minimum, while at 69.63 CS, 0.25 feed, and 0.6 DC, SR is maximum.

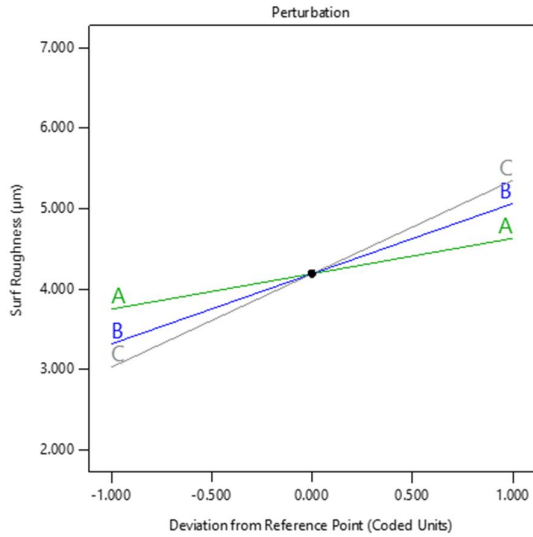


Figure 5.36 Surface roughness perturbation plot

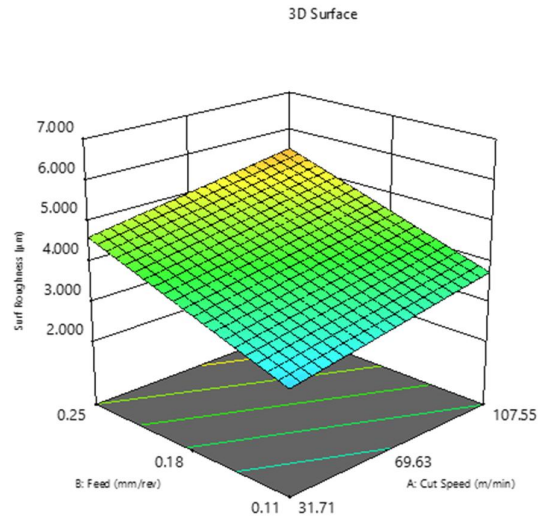


Figure 5.37 Surface roughness 3D response surface plot

In Table 5.30, the R^2 and adjusted R^2 values are shown for all responses, both being high and close together, indicating a good fit of the models. The predicted R^2 value closely aligns with the adjusted R^2 value, which supports confidence in the models' ability to predict experimental outcomes.

Table 5.30 Model adequacy metrics for Case-E1 output responses

Type	Cutting Force	Cutting Temperature	Surface Roughness
R^2	0.9809	0.8768	0.9917
Adjusted R^2	0.9665	0.8432	0.9895
Predicted R^2	0.9129	0.7723	0.9824

RESULT AND DISCUSSION

5.7 Case-E2 MQL+ 2% wt ZnO Mono Nanofluid as a Cutting Fluid

First, the specific cooling condition, i.e., Case-E2, was selected, and the corresponding 15-run Box–Behnken design was executed with the input factors. For each run, output responses were measured and compiled into the design matrix, as shown in Table 5.31. The derived data then formed the RSM models: linear for cutting force and quadratic for both cutting temperature and surface roughness. Insignificant terms in the initial RSM model were systematically identified from ANOVA results and removed, thereby simplifying the regression equation without sacrificing predictive capability. Eliminating these statistically meaningless interactions or higher-order terms reduces overfitting. It improves the numerical stability of the coefficients, allowing the final model to represent the true response surface more clearly over the design space.

Table 5.31 Box Behnken 15 runs for Case-E2

Test Run	Input parameters			Output parameters		
	A: CS	B: FR	C: DC	CF	CT	SR
	m/min	mm/rev	mm	N	°C	µm
1	31.71	0.11	0.40	172.11	60.33	3.373
2	69.63	0.18	0.40	276.56	101.67	3.298
3	31.71	0.18	0.20	143.87	50.33	3.382
4	69.63	0.11	0.60	313.82	101.67	4.319
5	31.71	0.18	0.60	397.18	74.00	4.519
6	69.63	0.18	0.40	280.09	101.33	3.399
7	107.55	0.25	0.40	357.96	84.00	2.430
8	69.63	0.25	0.60	444.55	90.00	4.738
9	107.55	0.18	0.20	147.11	64.33	2.200
10	69.63	0.18	0.40	284.01	98.67	3.310
11	69.63	0.25	0.20	208.79	63.67	3.749
12	69.63	0.11	0.20	83.36	52.33	3.267
13	107.55	0.11	0.40	184.67	84.67	2.210
14	31.71	0.25	0.40	318.73	67.67	4.239
15	107.55	0.18	0.60	375.90	96.67	3.169

5.7.1 Cutting Force

The software identifies a linear model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

RESULT AND DISCUSSION

From Table 5.32, the ANOVA data for cutting force, it can be found that feed and depth of cut are meaningful because of the linear model. The final coded regression equation for cutting force is expressed below in Eq. (5.19).

Table 5.32 Cutting force ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	153900	76949.48	363.67	< 0.0001	significant
B-Feed	41481.10	41481.10	196.04	< 0.0001	
C-DOC	112400	112400	531.29	< 0.0001	
Residual	2539.12	211.59			
Lack of Fit	2511.32	251.13	18.07	0.0536	not significant
Pure Error	27.80	13.90			
Cor Total	156400				

$$\text{Cutting force (CF)} = 265.91 + 72.01 \times B + 118.54 \times C \quad (5.19)$$

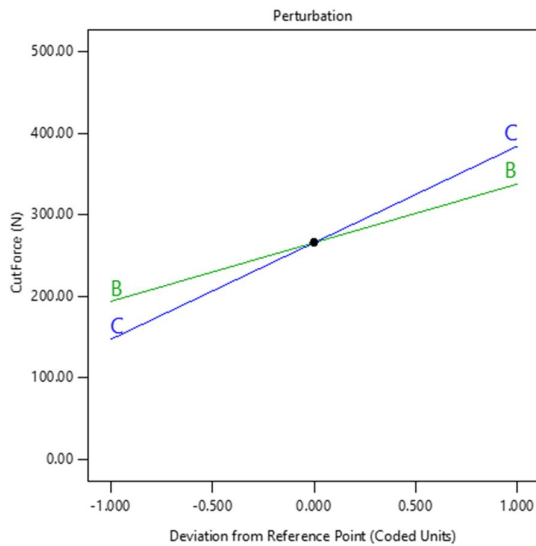


Figure 5.38 Cutting force perturbation plot

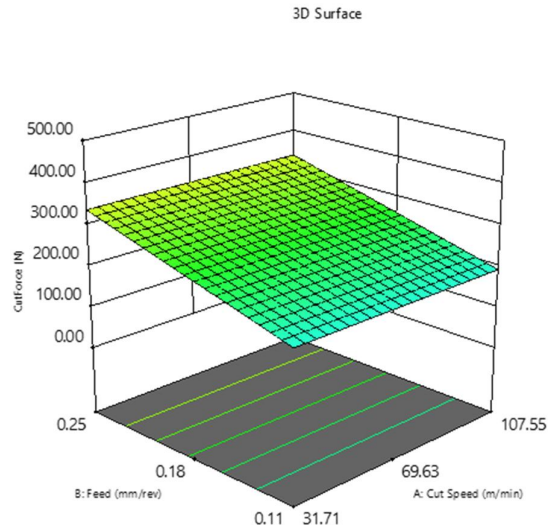


Figure 5.39 Cutting force 3D response surface plot

Figure 5.38 presents the perturbation plot illustrating the influence of input parameters on CF. It is clear that CF increases as the feed and DC increase.

The 3D response surface plot of CS vs feed is shown in Figure 5.39. It is observed that for the minimum CF, the CS is 69.63, feed is 0.11, and DC is 0.2, whereas for maximum CF, the CS is 69.63, feed is 0.25, and DC is 0.6.

RESULT AND DISCUSSION

5.7.2 Cutting Temperature

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.33, ANOVA data for cutting temperature shows that, because the model is quadratic, the cut depth and the quadratic effect of cut speed are meaningful.

Table 5.33 Cutting temperature ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	4789.01	684.14	49.55	< 0.0001	significant
A-Cut Speed	747.56	747.56	54.14	0.0002	
B-Feed	5.01	5.01	0.3631	0.5658	
C-DOC	2167.02	2167.02	156.93	< 0.0001	
BC	132.25	132.25	9.58	0.0174	
A ²	943.60	943.60	68.33	< 0.0001	
B ²	399.57	399.57	28.94	0.0010	
C ²	646.87	646.87	46.85	0.0002	
Residual	96.66	13.81			
Lack of Fit	91.25	18.25	6.75	0.1340	not significant
Pure Error	5.41	2.70			
Cor Total	4885.67				

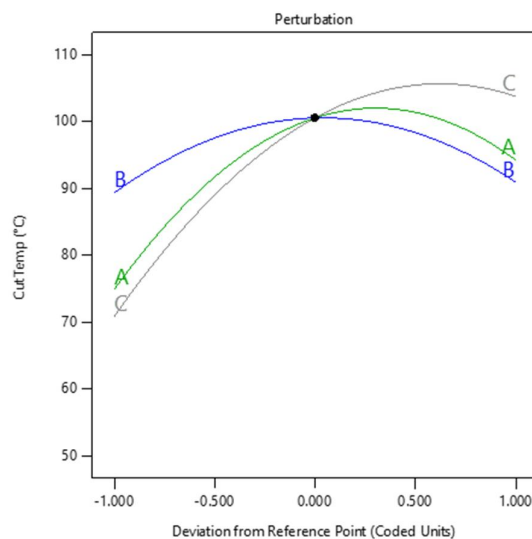


Figure 5.40 Cutting temperature perturbation plot

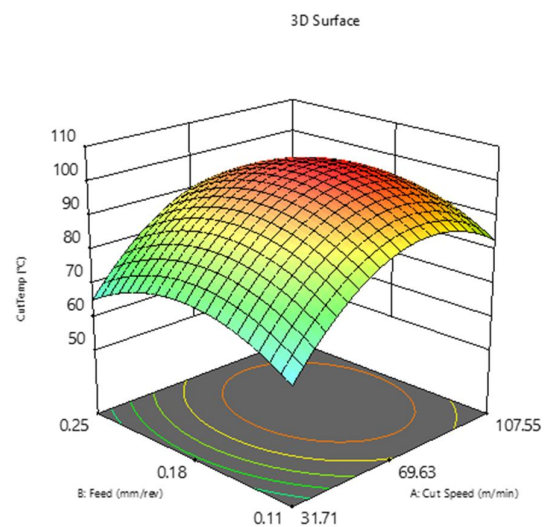


Figure 5.41 Cutting temperature 3D response surface plot

RESULT AND DISCUSSION

The coded equation of the final regression model for cutting temperature is given in Eq. (5.20).

$$\begin{aligned} \text{Cutting temperature (CT)} \\ = 100.56 + 9.67 \times A + 0.7916 \times B + 16.46 \times C - 5.75 \times B \times C \quad (5.20) \\ - 15.99 \times A^2 - 10.40 \times B^2 - 13.24 \times C^2 \end{aligned}$$

Figure 5.40 presents the perturbation plot of the input factors influencing CT. As seen in the graph, as CS and DC increase, CT rises; both low and high FRs reduce it. Figure 5.41 shows the 3D response surface plot between CS and feed. The minimum CT is obtained at a CS of 31.71, feed of 0.18, and DC of 0.2, whereas the maximum CT is obtained at a CS of 69.63, feed of 0.11, and DC of 0.6.

5.7.3 Surface Roughness

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical meaningfulness, as evidenced by a p-value < 0.05.

From Table 5.34, ANOVA data for surface roughness, cutting speed, depth of cut, and the squares of depth of cut and cutting speed were statistically meaningful due to the quadratic model. The final regression-coded equation for surface roughness is given in Eq. (5.21).

Table 5.34 Surface roughness ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	8.53	1.22	198.01	< 0.0001	significant
A-Cut Speed	3.79	3.79	615.14	< 0.0001	
B-Feed	0.4935	0.4935	80.18	< 0.0001	
C-DOC	2.15	2.15	349.08	< 0.0001	
AB	0.1043	0.1043	16.95	0.0045	
A ²	0.8752	0.8752	142.19	< 0.0001	
B ²	0.1690	0.1690	27.46	0.0012	
C ²	0.8100	0.8100	131.60	< 0.0001	
Residual	0.0431	0.0062			
Lack of Fit	0.0370	0.0074	2.45	0.3148	not significant
Pure Error	0.0060	0.0030			
Cor Total	8.57				

RESULT AND DISCUSSION

Surface roughness (SR)

$$= 3.34 - 0.6880 \times A + 0.2484 \times B + 0.5183 \times C \quad (5.21)$$

$$- 0.1615 \times A \times B - 0.4869 \times A^2 + 0.2140 \times B^2 + 0.4684 \times C^2$$

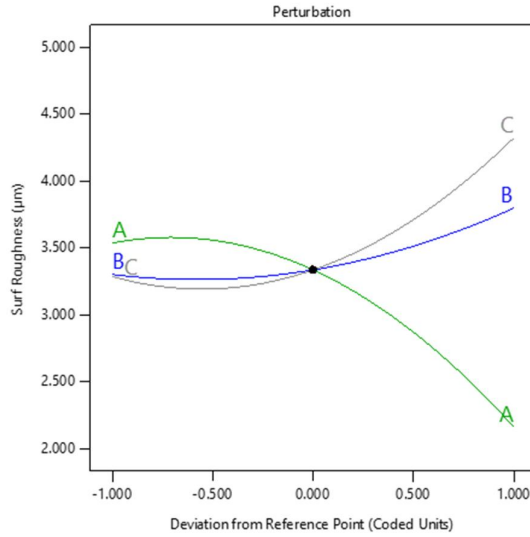


Figure 5.42 Surface roughness perturbation plot

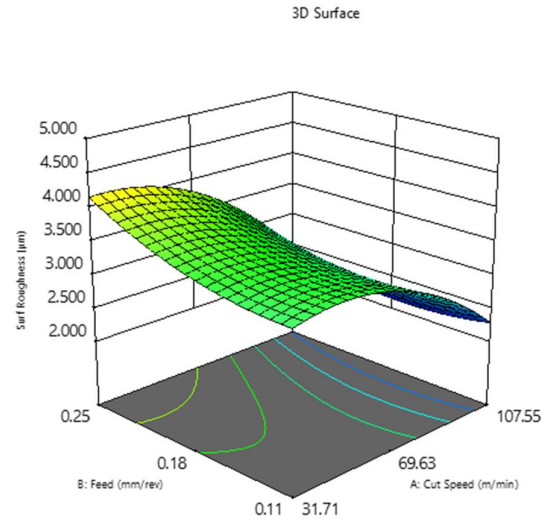


Figure 5.43 Surface roughness 3D response surface plot

Figure 5.42 illustrates the perturbation plot of the input factors influencing SR. The plot shows that SR increases with increasing FR and DC, and decreases with increasing CS.

The 3D response surface between CS and feed is shown in Figure 5.43. The minimum SR is found to be achieved at 107.55 CS, 0.18 feed, and 0.2 DC, and the maximum SR is observed at 69.63 CS, 0.25 feed, and 0.6 DC.

As shown in Table 5.35, the values of R^2 and adjusted R^2 for all responses are high and close to each other, suggesting the models have a good fit. The predicted R^2 also appears close to the adjusted R^2 , suggesting that the models are good at predicting experimental results.

Table 5.35 Model adequacy metrics for Case-E2 output responses

Type	Cutting Force	Cutting Temperature	Surface Roughness
R^2	0.9847	0.9873	0.9880
Adjusted R^2	0.9805	0.9645	0.9665
Predicted R^2	0.9713	0.8126	0.8176

RESULT AND DISCUSSION

5.8 Case-F1 1% wt ($\text{Al}_2\text{O}_3/\text{ZnO}$, 25/75) Hybrid Nanofluid as a Cutting Fluid

First, the specific cooling condition, i.e., Case-F1, was selected, and the corresponding 15-run Box–Behnken design was executed with the input factors. For every run, output responses were measured and compiled into the design matrix as given in Table 5.36. From this data, RSM models were developed: a linear model for cutting force and quadratic models for cutting temperature and surface roughness. Insignificant terms in the initial RSM model were systematically identified from ANOVA results and removed, thereby simplifying the regression equation without sacrificing predictive capability. Eliminating these statistically meaningless interactions or higher-order terms reduces overfitting. It improves the numerical stability of the coefficients, allowing the final model to represent the true response surface more clearly over the design space.

Table 5.36 Box Behnken 15 runs for Case-F1

Test Run	Input parameters			Output parameters		
	A: CS	B: FR	C: DC	CF	CT	SR
	m/min	mm/rev	mm	N	°C	μm
1	31.71	0.11	0.40	147.11	52.00	3.070
2	69.63	0.18	0.40	214.09	68.33	3.864
3	31.71	0.18	0.20	142.20	55.83	3.907
4	69.63	0.11	0.60	263.12	67.93	4.167
5	31.71	0.18	0.60	282.15	53.67	4.191
6	69.63	0.18	0.40	223.60	68.53	3.892
7	107.55	0.25	0.40	243.51	74.79	4.219
8	69.63	0.25	0.60	380.32	65.00	4.900
9	107.55	0.18	0.20	143.87	64.67	3.091
10	69.63	0.18	0.40	218.40	69.33	3.860
11	69.63	0.25	0.20	165.05	65.73	4.256
12	69.63	0.11	0.20	86.60	55.50	2.820
13	107.55	0.11	0.40	147.11	69.67	2.621
14	31.71	0.25	0.40	253.31	59.00	3.826
15	107.55	0.18	0.60	313.82	73.67	5.027

5.8.1 Cutting Force

The software identifies a linear model as the most appropriate fit for the data. This model

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demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.37, ANOVA data for cutting force reveal that the linear terms (feed and depth of cut) are highly meaningful, as the model is linear. The coded equation for cutting force in the final regression model is presented in Eq. (5.22).

Table 5.37 Cutting force ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	81372.86	40686.43	140.49	< 0.0001	significant
B-Feed	19826.60	19826.60	68.46	< 0.0001	
C-DOC	61546.26	61546.26	212.52	< 0.0001	
Residual	3475.25	289.60			
Lack of Fit	3429.87	342.99	15.12	0.0636	not significant
Pure Error	45.38	22.69			
Cor Total	84848.11				

$$\text{Cutting force (CF)} = 214.95 + 49.78 \times B + 87.81 \times C \quad (5.22)$$

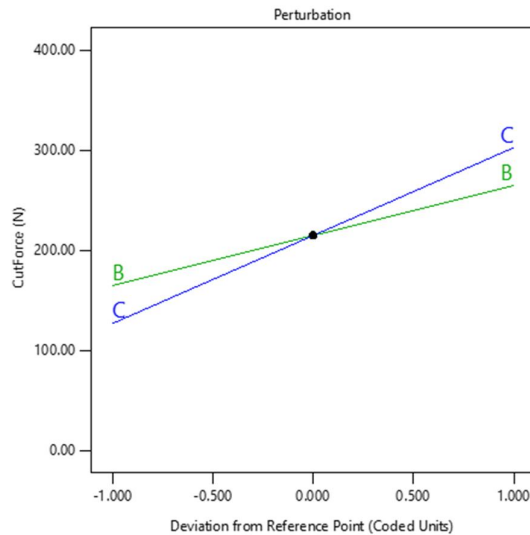


Figure 5.44 Cutting force perturbation plot

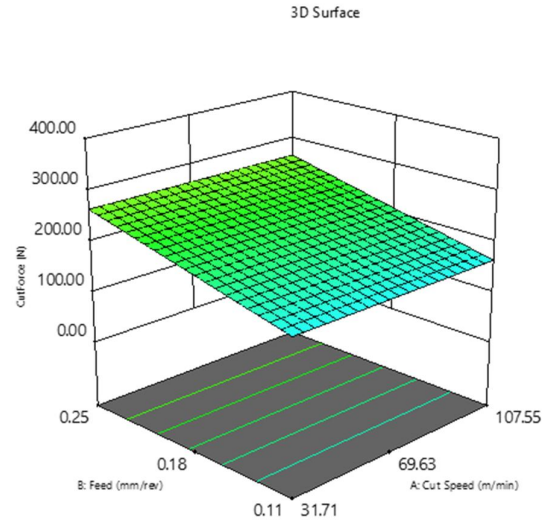


Figure 5.45 Cutting force 3D response surface plot

Figure 5.44 presents the perturbation plot, which reveals how the input parameters affect CF. From the plot, it is apparent that the CF increases with both increasing feed and DC.

Figure 5.45 shows the CS-feed 3D response surface plot. According to this 3D response surface plot, the minimum CF occurs at a CS of 69.63, a FR of 0.11, and a DC of 0.2. On

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the contrary, the maximum CF appears at a CS of 69.63, a FR of 0.25, and a DC of 0.6.

5.8.2 Cutting Temperature

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.38, ANOVA for cutting temperature indicates that, due to the quadratic nature of the model, CS is highly meaningful, and all other parameters are also meaningful (p-value < 0.05).

Table 5.38 Cutting temperature ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	733.49	91.69	55.12	< 0.0001	significant
A-Cut Speed	485.01	485.01	291.56	< 0.0001	
B-Feed	47.16	47.16	28.35	0.0018	
C-DOC	42.94	42.94	25.81	0.0023	
AC	31.17	31.17	18.74	0.0049	
BC	43.30	43.30	26.03	0.0022	
A ²	38.41	38.41	23.09	0.0030	
B ²	9.98	9.98	6.00	0.0499	
C ²	46.52	46.52	27.97	0.0019	
Residual	9.98	1.66			
Lack of Fit	9.42	2.36	8.41	0.1091	not significant
Pure Error	0.5600	0.2800			
Cor Total	743.47				

The final regression model's coded equation for cutting temperature is given in Eq. (5.23).

$$\begin{aligned} \text{Cutting temperature (CT)} \\ = 68.73 + 7.79 \times A + 2.43 \times B + 2.32 \times C + 2.79 \times A \times C \quad (5.23) \\ - 3.29 \times B \times C - 3.23 \times A^2 - 1.64 \times B^2 - 3.55 \times C^2 \end{aligned}$$

Figure 5.46 presents a perturbation plot showing how the input parameters affect CT. It is noted that CT rises with increasing CS and only moderately with increases in FR and DC.

Figure 5.47 shows the 3D response surface plot for CS and feed. From the graph, the minimum CT occurs at a CS of 31.71, a FR of 0.11, and a DC of 0.4. On the other hand, the maximum CT occurs at a CS of 107.55, a FR of 0.25, and a DC of 0.4.

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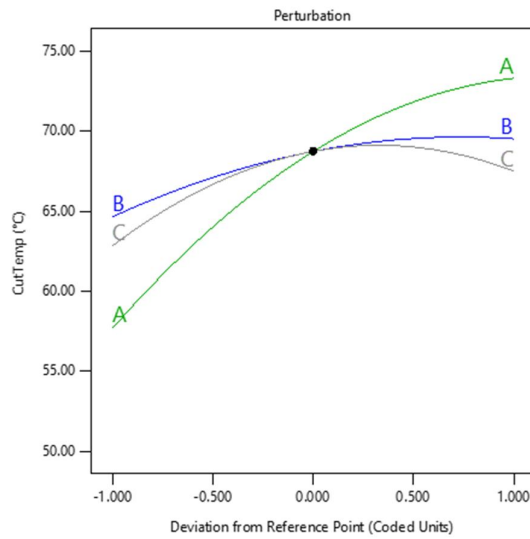


Figure 5.46 Cutting temperature perturbation plot

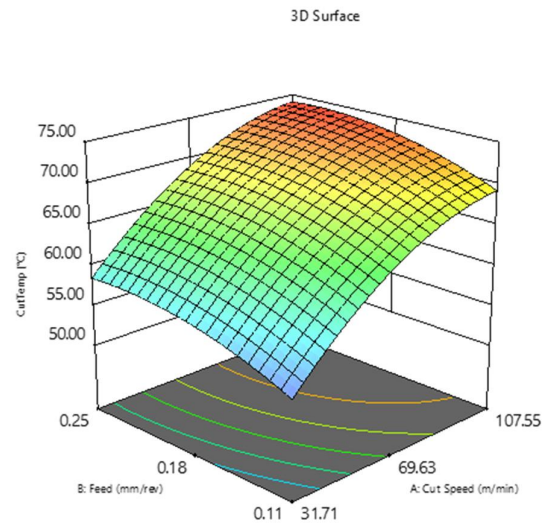


Figure 5.47 Cutting temperature 3D response surface plot

5.8.3 Surface Roughness

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical meaningfulness, as evidenced by a p-value < 0.05.

From Table 5.39, ANOVA data for surface roughness, feed rate, depth of cut, cutting speed-depth of cut interaction effect, and depth of cut-depth of cut quadratic effect are meaningful because of the quadratic equation. The coded equation for surface roughness in the final regression model is given by Eq. (5.24).

Table 5.39 Surface roughness ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	6.75	0.7505	308.50	< 0.0001	significant
A-Cut Speed	0.0002	0.0002	0.0703	0.8014	
B-Feed	2.56	2.56	1051.18	< 0.0001	
C-DOC	2.22	2.22	911.30	< 0.0001	
AB	0.1772	0.1772	72.86	0.0004	
AC	0.6820	0.6820	280.35	< 0.0001	
BC	0.1233	0.1233	50.69	0.0008	
A ²	0.1623	0.1623	66.72	0.0004	
B ²	0.1919	0.1919	78.90	0.0003	

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C^2	0.5671	0.5671	233.13	< 0.0001	
Residual	0.0122	0.0024			
Lack of Fit	0.0116	0.0039	12.67	0.0740	not significant
Pure Error	0.0006	0.0003			
Cor Total	6.77				

Surface roughness (SR)

$$\begin{aligned}
 &= 3.87 - 0.0046 \times A + 0.5654 \times B + 0.5264 \times C \\
 &+ 0.2105 \times A \times B + 0.4129 \times A \times C - 0.1756 \times B \times C \\
 &- 0.2097 \times A^2 - 0.2280 \times B^2 + 0.3919 \times C^2
 \end{aligned} \quad (5.24)$$

Figure 5.48 illustrates the perturbation plot analyzing the impact of input factors on SR. The figure shows that as the feed and the DC increase, SR increases, with an upward trend at intermediate CS.

Figure 5.49 shows the 3-D response surface diagram of SR against CS and feed. The minimum SR is at 107.55 CS, 0.11 feed, and 0.4 DC. And the maximum SR at 107.55 CS, 0.18 feed, and 0.6 DC.

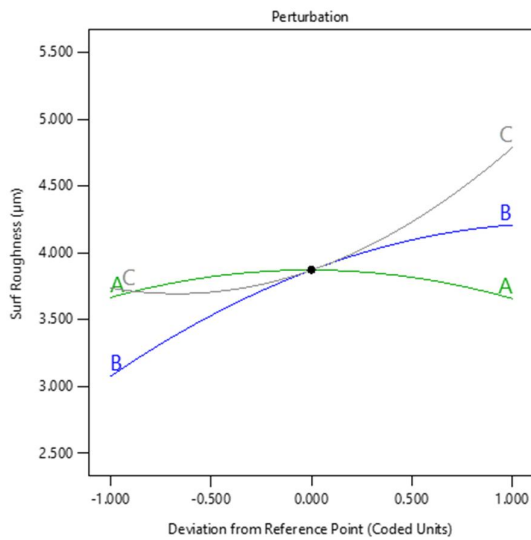


Figure 5.48 Surface roughness perturbation plot

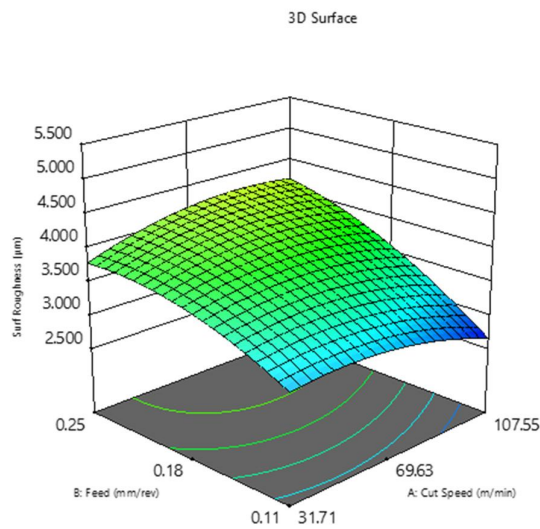


Figure 5.49 Surface roughness 3D response surface plot

Table 5.40 presents all the R^2 and adjusted R^2 values for the entire response, which are relatively high and in close agreement, implying a good model fit. Predicted R^2 values are also in reasonable agreement with adjusted R^2 values, suggesting good model predictability.

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Table 5.40 Model adequacy metrics for Case-F1 output responses

Type	Cutting Force	Cutting Temperature	Surface Roughness
R ²	0.9599	0.9878	0.9982
Adjusted R ²	0.9489	0.9657	0.9950
Predicted R ²	0.9151	0.8145	0.9725

5.9 Case-F2 2% wt (Al₂O₃/ZnO, 25/75) Hybrid Nanofluid as a Cutting Fluid

First, the specific cooling condition, i.e., Case-F2, was selected, and the corresponding 15-run Box–Behnken design was executed with the input factors. For each run, output responses were measured and compiled into the design matrix, as shown in Table 5.41. The data thus collected were then used to generate RSM models-2FI for cutting force, quadratic for both cutting temperature and surface roughness, where appropriate. Insignificant terms in the initial RSM model were systematically identified from ANOVA results and removed, thereby simplifying the regression equation without sacrificing predictive capability. Eliminating these statistically meaningless interactions or higher-order terms reduces overfitting. It improves the numerical stability of the coefficients, allowing the final model to represent the true response surface more clearly over the design space.

Table 5.41 Box Behnken 15 runs for Case-F2

Test Run	Input parameters			Output parameters		
	A: CS	B: FR	C: DC	CF	CT	SR
	m/min	mm/rev	mm	N	°C	µm
1	31.71	0.11	0.40	124.75	41.67	2.625
2	69.63	0.18	0.40	227.23	47.17	4.166
3	31.71	0.18	0.20	143.87	54.67	6.124
4	69.63	0.11	0.60	173.29	43.63	3.303
5	31.71	0.18	0.60	291.86	53.29	4.230
6	69.63	0.18	0.40	238.60	50.50	4.136
7	107.55	0.25	0.40	258.22	46.00	3.167
8	69.63	0.25	0.60	441.32	53.33	3.944
9	107.55	0.18	0.20	137.30	56.38	4.480
10	69.63	0.18	0.40	240.27	49.33	3.769
11	69.63	0.25	0.20	124.25	46.00	5.918

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12	69.63	0.11	0.20	98.07	50.33	4.066
13	107.55	0.11	0.40	171.62	53.83	2.659
14	31.71	0.25	0.40	366.59	53.83	4.654
15	107.55	0.18	0.60	346.48	56.00	4.682

5.9.1 Cutting Force

The software identifies a 2FI model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.42, ANOVA of cutting force shows that feed and depth of cut are meaningful, as the model is a 2FI. The coded equation of the final regression model for cutting force is presented in Eq. (5.25).

Table 5.42 Cutting force ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	139300	27868.04	57.57	< 0.0001	significant
A-Cut Speed	22.56	22.56	0.0466	0.8339	
B-Feed	48461.07	48461.07	100.11	< 0.0001	
C-DOC	70209.59	70209.59	145.04	< 0.0001	
AB	6025.24	6025.24	12.45	0.0064	
BC	14621.72	14621.72	30.21	0.0004	
Residual	4356.57	484.06			
Lack of Fit	4255.80	607.97	12.07	0.0786	not significant
Pure Error	100.77	50.39			
Cor Total	143700				

Cutting force (CF)

$$= 222.58 - 1.68 \times A + 77.83 \times B + 93.68 \times C - 38.81 \times A \times B \quad (5.25) \\ + 60.46 \times B \times C$$

Figure 5.50 illustrates the perturbing effect of input factors on the CF. It can be inferred from the plot that the CF increases linearly with increases in feed and DC, and slightly decreases with increases in CS.

Figure 5.51 This is the 3D response surface graph of CS against feed. The minimum CF is obtained under the condition of 69.63 CS, 0.11 feed, and 0.2 DC. Conversely, the maximum CF is obtained at a CS of 69.63, a feed of 0.25, and a DC of 0.6.

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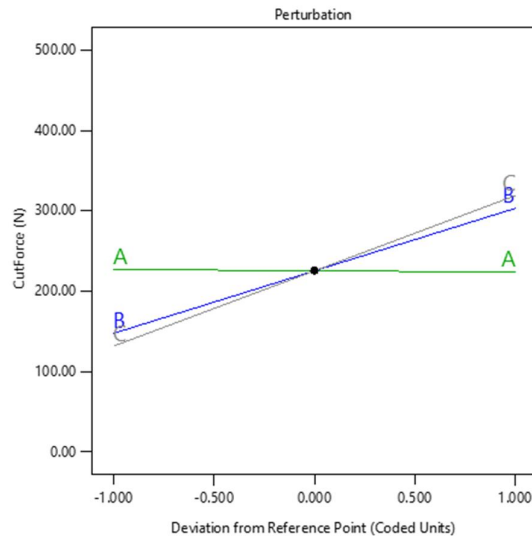


Figure 5.50 Cutting force perturbation plot

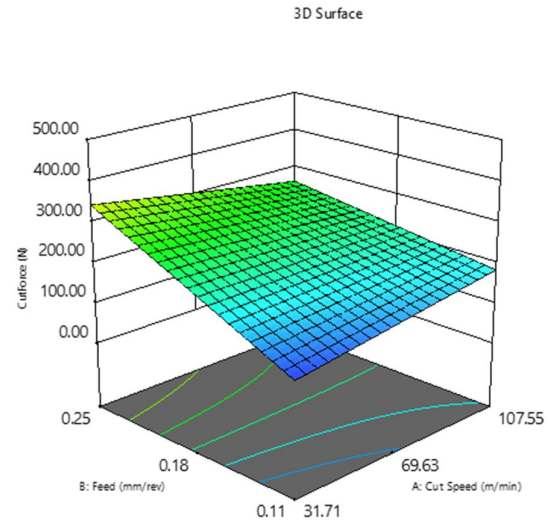


Figure 5.51 Cutting force 3D response surface plot

5.9.2 Cutting Temperature

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p -value < 0.05 .

From Table 5.43, ANOVA data for cutting temperature, the interaction term between CS and FR is highly meaningful due to the quadratic model. Besides that, all factors except depth of cut are meaningful (p -value < 0.05). The final regression model's coded equation for cutting temperature is given in Eq. (5.26).

Table 5.43 Cutting temperature ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	291.41	36.43	32.07	0.0002	significant
A-Cut Speed	9.58	9.58	8.44	0.0272	
B-Feed	11.76	11.76	10.35	0.0182	
C-DOC	0.1596	0.1596	0.1405	0.7207	
AB	99.93	99.93	87.98	< 0.0001	
BC	49.23	49.23	43.35	0.0006	
A ²	40.12	40.12	35.32	0.0010	
B ²	44.32	44.32	39.02	0.0008	
C ²	28.70	28.70	25.27	0.0024	
Residual	6.82	1.14			

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Lack of Fit	1.09	0.2732	0.0955	0.9743	not significant
Pure Error	5.72	2.86			
Cor Total	298.22				

Cutting temperature (CT)

$$= 49.00 + 1.09 \times A + 1.21 \times B - 0.1413 \times C - 5.00 \times A \times B \quad (5.26) \\ + 3.51 \times B \times C + 3.30 \times A^2 - 3.46 \times B^2 + 2.79 \times C^2$$

Figure 5.52 presents the plot of perturbation showing the sensitivity of the input factors on CT. The CT decreases at moderate CS and DC, and increases at moderate FR. Figure 5.53 shows the 3D response surface plot of CS versus feed. From this plot, the minimum CT occurs when the CS is 31.71, the FR is 0.11, and the DC is 0.4; The maximum CT occurs when the CS is 107.55, the FR is 0.18, and the DC is 0.2.

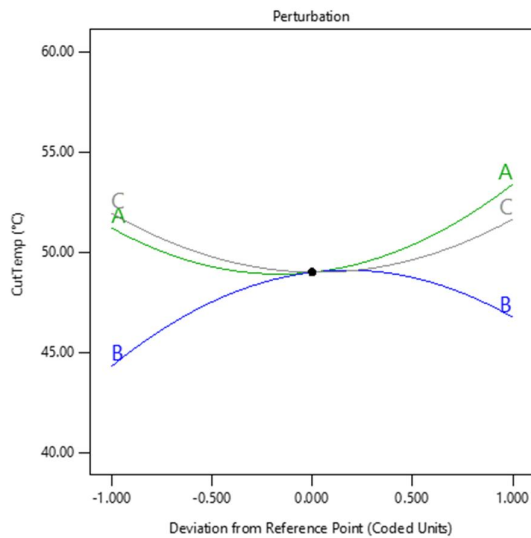


Figure 5.52 *Cutting temperature perturbation plot*

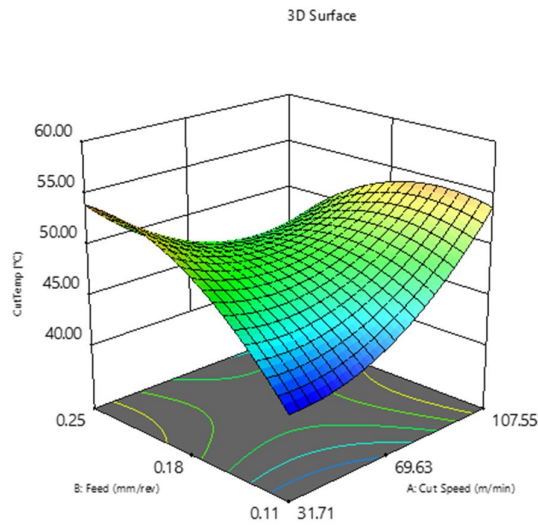


Figure 5.53 *Cutting temperature 3D response surface plot*

5.9.3 Surface Roughness

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.44, ANOVA data of surface roughness shows that since the model is a complex quadratic model the input variables; cutting speed-feed interaction, cutting speed-depth of cut interaction, feed-depth of cut interaction and feed-depth of cut quadratic effect have a significance at high level. The coded equation of the final regression model for surface

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roughness is given in Eq. (5.27).

Table 5.44 Surface roughness ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	13.82	1.73	38.23	0.0001	significant
A-Cut Speed	0.8749	0.8749	19.36	0.0046	
B-Feed	3.16	3.16	69.94	0.0002	
C-DOC	2.45	2.45	54.27	0.0003	
AB	0.5789	0.5789	12.81	0.0117	
AC	1.10	1.10	24.30	0.0026	
BC	0.3668	0.3668	8.12	0.0292	
B ²	1.58	1.58	35.00	0.0010	
C ²	3.35	3.35	74.18	0.0001	
Residual	0.2712	0.0452			
Lack of Fit	0.1737	0.0434	0.8913	0.5896	not significant
Pure Error	0.0975	0.0487			
Cor Total	14.10				

Surface roughness (SR)

$$\begin{aligned}
 &= 3.97 - 0.3307 \times A + 0.6286 \times B - 0.5537 \times C \\
 &\quad - 0.3804 \times A \times B + 0.5240 \times A \times C - 0.3028 \times B \times C \\
 &\quad - 0.6526 \times B^2 + 0.9501 \times C^2
 \end{aligned} \tag{5.27}$$

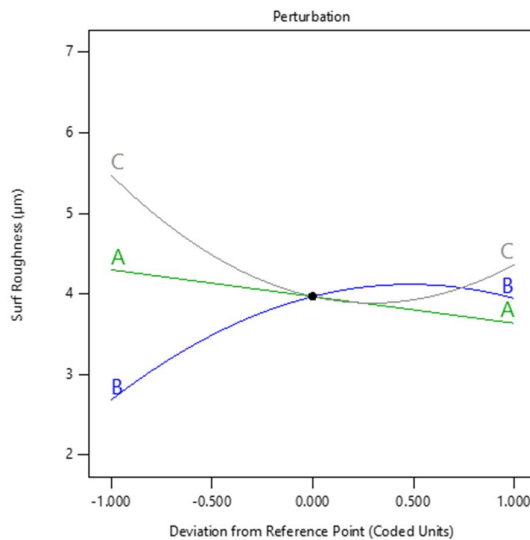


Figure 5.54 Surface roughness perturbation plot

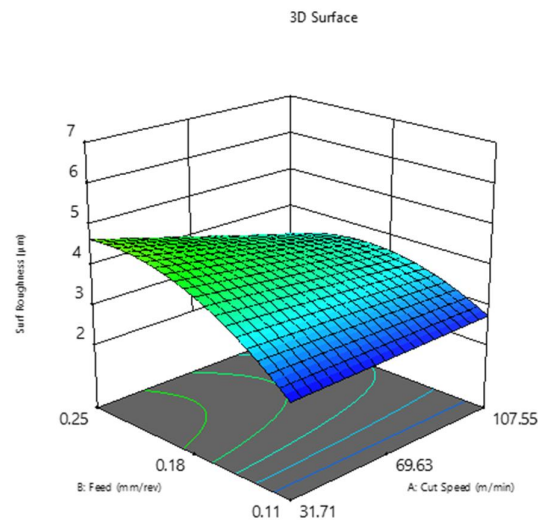


Figure 5.55 Surface roughness 3D response surface plot

Figure 5.54 presents a perturbation plot, representing the impact of the input parameters on

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SR. It is evident from the plot that SR is directly proportional to CS and attains its minimum value at an intermediate DC. In contrast, it is inversely proportional to FR.

Figure 5.55 shows the 3D response surface plot of CS against feed. Based on this plot, the minimum SR occurs at a CS of 31.71, a FR of 0.11, and a DC of 0.4. The maximum SR occurs at a CS of 31.71, a FR of 0.18, and a DC of 0.2.

As shown in Table 5.45, the R^2 and adjusted R^2 values for all responses are high and quite similar, indicating that the models fit the data well. Also, the predicted R^2 value is quite similar to the adjusted R^2 value, suggesting that the models can reliably predict the experimental results.

Table 5.45 Model adequacy metrics for Case-F2 output responses

Type	Cutting Force	Cutting Temperature	Surface Roughness
R^2	0.9762	0.9780	0.9828
Adjusted R^2	0.9583	0.9383	0.9518
Predicted R^2	0.8845	0.9115	0.8197

5.10 Case-G1 1% wt (Al_2O_3/ZnO , 50/50) Hybrid Nanofluid as a Cutting Fluid

First, the specific cooling condition, i.e., Case-G1, was selected, and the corresponding 15-run Box–Behnken design was executed with the input factors. For every run, output responses were measured and compiled into the design matrix as given in Table 5.46. Based on these results, RSM models of (quadratic) cutting force, 2FI of cutting temperature, and quadratic surface roughness were built. Insignificant terms in the initial RSM model were systematically identified from ANOVA results and removed, thereby simplifying the regression equation without sacrificing predictive capability. Eliminating these statistically meaningless interactions or higher-order terms reduces overfitting. It improves the numerical stability of the coefficients, allowing the final model to represent the true response surface more clearly over the design space.

Table 5.46 Box Behnken 15 runs for Case-G1

Test Run	Input parameters			Output parameters		
	A: CS	B: FR	C: DC	CF	CT	SR
	m/min	mm/rev	mm	N	°C	μm

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1	31.71	0.11	0.40	166.72	46.83	3.790
2	69.63	0.18	0.40	237.04	58.00	4.242
3	31.71	0.18	0.20	127.49	49.17	3.699
4	69.63	0.11	0.60	282.93	64.67	4.690
5	31.71	0.18	0.60	424.94	58.33	5.496
6	69.63	0.18	0.40	245.18	60.33	3.958
7	107.55	0.25	0.40	253.31	63.33	3.645
8	69.63	0.25	0.60	511.63	71.67	5.700
9	107.55	0.18	0.20	99.74	42.00	4.849
10	69.63	0.18	0.40	235.37	60.27	4.475
11	69.63	0.25	0.20	148.58	40.83	3.853
12	69.63	0.11	0.20	98.07	55.50	4.590
13	107.55	0.11	0.40	166.72	58.87	4.131
14	31.71	0.25	0.40	287.64	50.17	3.990
15	107.55	0.18	0.60	416.80	78.00	4.656

5.10.1 Cutting Force

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.47, ANOVA of cutting force shows that feed and depth of cut are meaningful because the model is quadratic. The final coded equation of cutting force is given in Eq. (5.28).

Table 5.47 Cutting force ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	211400	52846.55	171.44	< 0.0001	significant
B-Feed	29612.22	29612.22	96.07	< 0.0001	
C-DOC	168900	168900	547.94	< 0.0001	
BC	7938.20	7938.20	25.75	0.0005	
C ²	4932.18	4932.18	16.00	0.0025	
Residual	3082.49	308.25			
Lack of Fit	3027.42	378.43	13.74	0.0696	not significant
Pure Error	55.07	27.54			
Cor Total	214500				

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$$\begin{aligned} \text{Cutting force (CF)} \\ = 227.42 + 60.84 \times B + 145.30 \times C + 44.55 \times B \times C \\ + 36.35 \times C^2 \end{aligned} \quad (5.28)$$

Figure 5.56 shows the impacts of perturbing the input factors on the CF. It is clear that increasing the FR and the DC increases the CF.

Figure 5.57 illustrates the 3D response surface between CS and feed. The CF is at a minimum of 69.63 CS, 0.11 feed, and 0.2 cutting depth, and at a maximum of 69.63 CS, 0.25 feed, and 0.6 cutting depth.

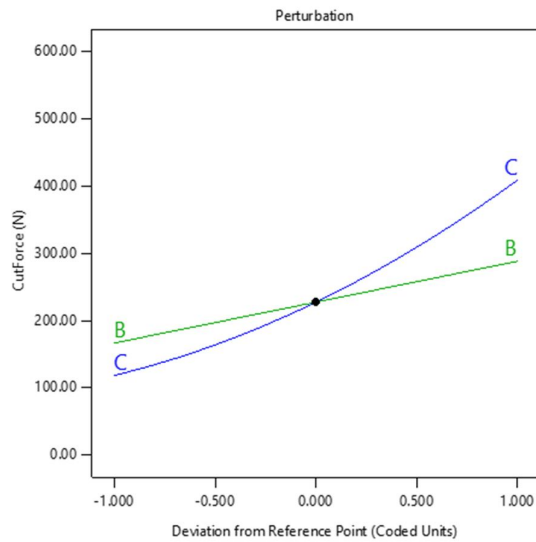


Figure 5.56 Cutting force perturbation plot

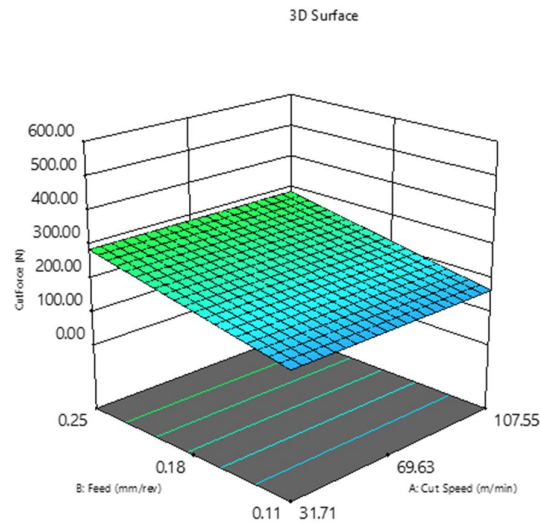


Figure 5.57 Cutting force 3D response surface plot

5.10.2 Cutting Temperature

The software identifies a 2FI model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.48, ANOVA for the cutting temperature shows that, as the design is 2FI, the depth of cut is highly meaningful, and cutting speed, cutting speed × depth of cut, and feed × depth of cut are meaningful. The coded regression equation for cutting temperature is given in Eq. (5.29).

Table 5.48 Cutting temperature ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
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Model	1381.70	276.34	24.68	< 0.0001	significant
A-Cut Speed	177.66	177.66	15.87	0.0032	
B-Feed	0.0022	0.0022	0.0002	0.9891	
C-DOC	906.67	906.67	80.97	< 0.0001	
AC	180.01	180.01	16.07	0.0031	
BC	117.36	117.36	10.48	0.0102	
Residual	100.78	11.20			
Lack of Fit	97.25	13.89	7.87	0.1173	not significant
Pure Error	3.53	1.76			
Cor Total	1482.49				

Cutting temperature (CT)

$$= 57.20 + 4.71 \times A + 0.0167 \times B + 10.65 \times C + 6.71 \times A \times C + 5.42 \times B \times C \quad (5.29)$$

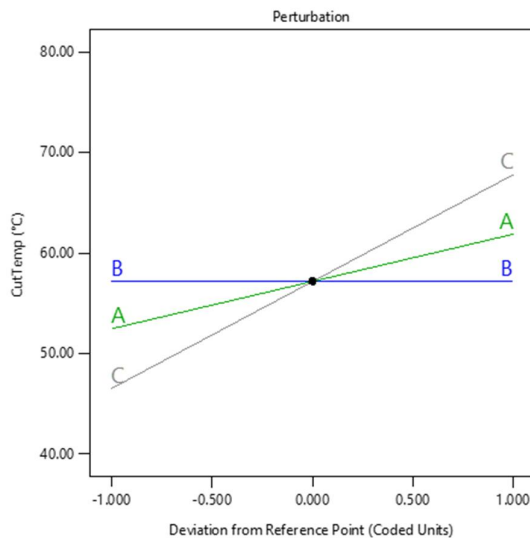


Figure 5.58 *Cutting temperature perturbation plot*

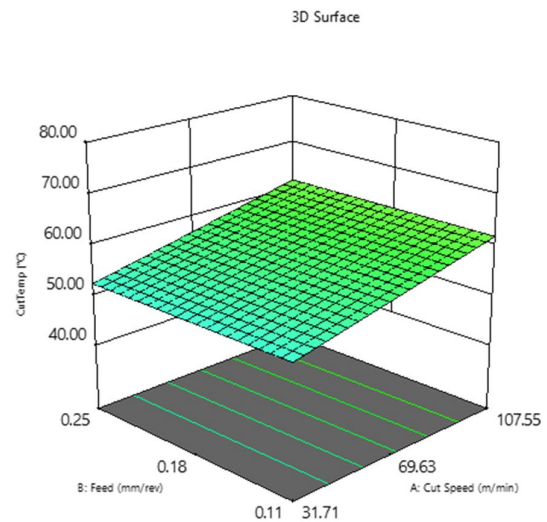


Figure 5.59 *Cutting temperature 3D response surface plot*

Figure 5.58 presents the perturbation plot showing the influence of these input parameters on the CT. From this figure, the CT increases with increasing CS and DC, while decreasing slightly with increasing FR.

Figure 5.59 shows the 3D response surface plot between CS and feed. The minimum CT obtained from the 3D response surface plot is at 69.63 of CS, 0.25 of feed, and 0.2 of DC, whereas the maximum CT is at 107.55 of CS, 0.18 of feed, and 0.6 of DC.

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5.10.3 Surface Roughness

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.49, the ANOVA data of surface roughness shows that, owing to the intricate quadratic equation of the model, the meaningful variables are depth of cut, the interactions between cutting speed and depth of cut, feed and depth of cut, and the quadratic effect of depth of cut. The coded equation of the final regression model for surface roughness is listed in Eq. (5.30).

Table 5.49 Surface roughness ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	4.96	0.8266	12.87	0.0010	significant
A-Cut Speed	0.0117	0.0117	0.1826	0.6804	
B-Feed	0.0000	0.0000	0.0003	0.9856	
C-DOC	1.58	1.58	24.54	0.0011	
AC	0.9900	0.9900	15.41	0.0044	
BC	0.7630	0.7630	11.88	0.0087	
C ²	1.62	1.62	25.20	0.0010	
Residual	0.5139	0.0642			
Lack of Fit	0.3800	0.0633	0.9460	0.5957	not significant
Pure Error	0.1339	0.0670			
Cor Total	5.47				

$$\begin{aligned} \text{Surface roughness (SR)} \\ = 4.03 + 0.0383 \times A - 0.0017 \times B + 0.4439 \times C \\ - 0.4975 \times A \times C + 0.4367 \times B \times C + 0.6584 \times C^2 \end{aligned} \quad (5.30)$$

Figure 5.60 presents the perturbation influence of the input factors on SR. The graph shows a slight rise in SR with increasing CS and FR, but a significant increase with increasing DC.

Figure 5.61 illustrates the 3D response surface plot of CS against feed. It has been found that the minimum SR occurs at a CS of 107.55, a feed of 0.25, and a DC of 0.4, while the maximum SR occurs at a CS of 69.63, a feed of 0.25, and a DC of 0.6.

As shown in Table 5.50, all R² and adjusted R² values are quite high and close together, indicating the models have a very good fit. Moreover, predicted R² values are quite close to

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the adjusted R^2 values, implying the models have good predictive ability.

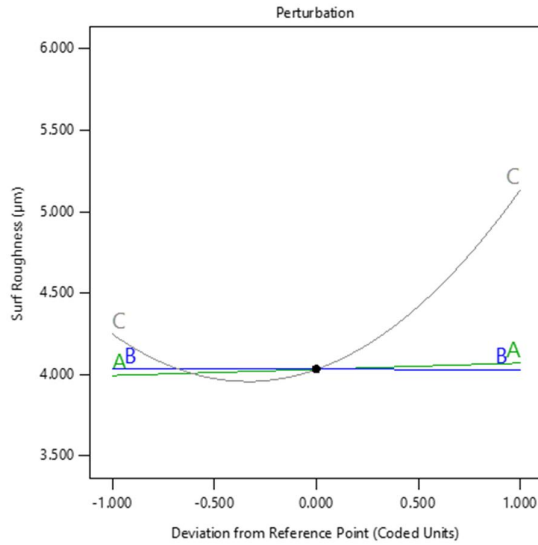


Figure 5.60 Surface roughness perturbation plot

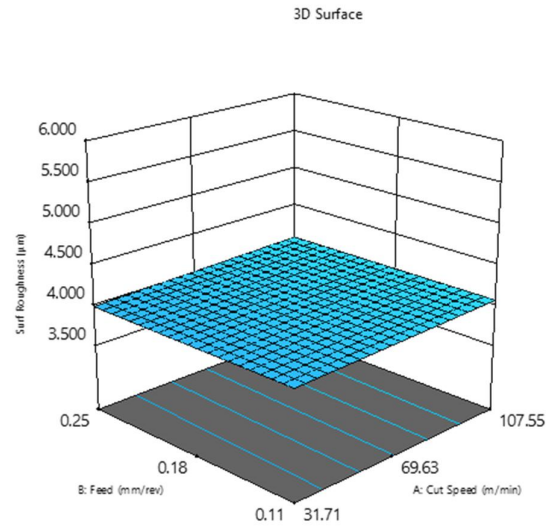


Figure 5.61 Surface roughness 3D response surface plot

Table 5.50 Model adequacy metrics for Case-G1 output responses

Type	Cutting Force	Cutting Temperature	Surface Roughness
R^2	0.9942	0.9322	0.9634
Adjusted R^2	0.9837	0.8814	0.8976
Predicted R^2	0.9101	0.6952	0.7514

5.11 Case-G2 2% wt ($\text{Al}_2\text{O}_3/\text{ZnO}$, 50/50) Hybrid Nanofluid as a Cutting Fluid

First, the specific cooling condition, i.e., Case-G2, was selected and the corresponding 15-run Box–Behnken design was executed with input factors. For each run, output responses were measured and compiled into the design matrix, as shown in Table 5.51. Based on these findings, the data were utilized to create the RSM models: quadratic for cutting force, cutting temperature, and surface roughness, where appropriate. Insignificant terms in the initial RSM model were systematically identified from ANOVA results and removed, thereby simplifying the regression equation without sacrificing predictive capability. Eliminating these statistically meaningless interactions or higher-order terms reduces overfitting. It improves the numerical stability of the coefficients, allowing the final model to represent the true response surface more clearly over the design space.

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Table 5.51 Box Behnken 15 runs for Case-G2

Test Run	Input parameters			Output parameters		
	A: CS	B: FR	C: DC	CF	CT	SR
	m/min	mm/rev	mm	N	°C	µm
1	31.71	0.11	0.40	191.24	57.00	2.341
2	69.63	0.18	0.40	269.69	77.17	3.031
3	31.71	0.18	0.20	107.88	45.40	3.661
4	69.63	0.11	0.60	290.09	75.17	4.303
5	31.71	0.18	0.60	354.72	61.83	4.933
6	69.63	0.18	0.40	289.31	80.13	2.891
7	107.55	0.25	0.40	232.13	70.83	2.571
8	69.63	0.25	0.60	377.57	66.17	5.560
9	107.55	0.18	0.20	94.83	60.17	3.836
10	69.63	0.18	0.40	286.07	79.17	3.001
11	69.63	0.25	0.20	124.25	58.27	3.939
12	69.63	0.11	0.20	88.26	48.90	3.750
13	107.55	0.11	0.40	181.43	69.40	2.572
14	31.71	0.25	0.40	253.31	54.00	3.051
15	107.55	0.18	0.60	406.99	81.60	4.301

5.11.1 Cutting Force

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.52, ANOVA for cutting force shows that depth of cut is extremely meaningful and feed, and quadratic term of depth of cut are meaningful (p-value < 0.05) since the model is quadratic in nature. The coded equation for the final regression model for cutting force is listed in Eq. (5.31).

Table 5.52 Cutting force ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	141900	47292.70	75.89	< 0.0001	significant
B-Feed	6976.80	6976.80	11.20	0.0065	
C-DOC	128600	128600	206.31	< 0.0001	
B ²	6340.85	6340.85	10.18	0.0086	
Residual	6854.55	623.14			
Lack of Fit	6633.41	737.05	6.67	0.1372	not significant

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Pure Error	221.14	110.57			
Cor Total	148700				

$$\text{Cutting force (CF)} = 258.50 + 29.53 \times B + 126.77 \times C - 41.21 \times B^2 \quad (5.31)$$

Figure 5.62 illustrates the perturbation influence of input variables on the CF. From the graph, CF increases linearly with an increase in the DC and slightly increases with an increase in the FR.

Figure 5.63 shows CS versus feed 3D response surface. The minimal value of CF occurs when the CS is 69.63, feed is 0.11, and DC is 0.2, and the maximal value of CF occurs when the CS is 107.55, feed is 0.18, and DC is 0.6.

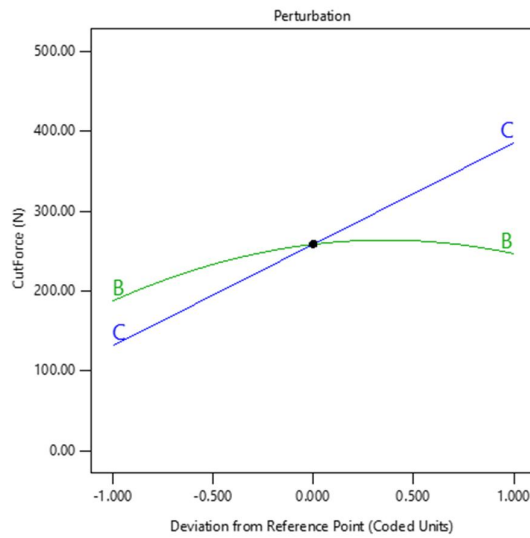


Figure 5.62 Cutting force perturbation plot

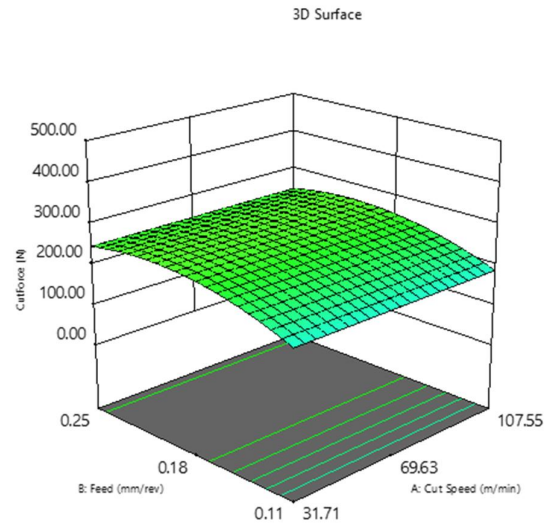


Figure 5.63 Cutting force 3D response surface plot

5.11.2 Cutting Temperature

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.53, ANOVA data of cutting temperature shows that the cutting temperature model is a quadratic equation; cutting speed, depth of cut, and the quadratic effect of all input parameters are extremely meaningful. The final regression model's coded equation for cutting temperature is given in Eq. (5.32).

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Table 5.53 Cutting temperature ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	1890.14	270.02	88.19	< 0.0001	significant
A-Cut Speed	508.27	508.27	166.01	< 0.0001	
B-Feed	0.1800	0.1800	0.0588	0.8154	
C-DOC	648.60	648.60	211.84	< 0.0001	
BC	84.33	84.33	27.54	0.0012	
A ²	233.04	233.04	76.11	< 0.0001	
B ²	240.43	240.43	78.53	< 0.0001	
C ²	274.85	274.85	89.77	< 0.0001	
Residual	21.43	3.06			
Lack of Fit	16.85	3.37	1.47	0.4516	not significant
Pure Error	4.58	2.29			
Cor Total	1911.57				

Cutting temperature (CT)

$$= 78.82 + 7.97 \times A - 0.1500 \times B + 9.00 \times C - 4.59 \times B \times C \quad (5.32)$$

$$- 7.94 \times A^2 - 8.07 \times B^2 - 8.63 \times C^2$$

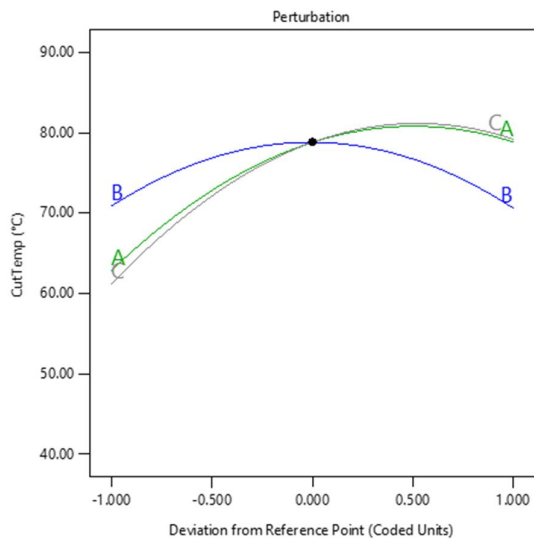


Figure 5.64 Cutting temperature perturbation plot

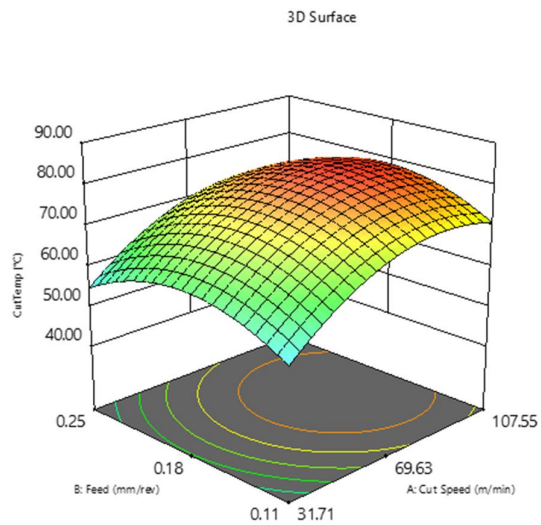


Figure 5.65 Cutting temperature 3D response surface plot

Figure 5.64 presents a perturbation plot for input factors and their impact on CT. It is noted that the CT is elevated as the CS and DC increase. It is also noted that the CT increased at an average FR.

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Figure 5.65 shows the 3D response surface plot between CS and feed. From the above plot, the minimum CT is achieved at a CS of 31.71, a feed of 0.18, and a DC of 0.2. For the maximum CT, the CS and feed are 107.55 and 0.18, respectively, with a DC of 0.6.

5.11.3 Surface Roughness

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.54, ANOVA data for surface roughness: because the quadratic model is complicated, the quadratic effect of DC is meaningful, and feed and DC are meaningful.

Table 5.54 Surface roughness ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	10.96	3.65	39.09	< 0.0001	significant
B-Feed	0.5801	0.5801	6.21	0.0299	
C-DOC	1.91	1.91	20.47	0.0009	
C ²	8.46	8.46	90.58	< 0.0001	
Residual	1.03	0.0934			
Lack of Fit	1.02	0.1130	20.69	0.0469	significant
Pure Error	0.0109	0.0055			
Cor Total	11.98				

The final regression equation in coded form is listed in Eq. (5.33).

$$\text{Surface roughness (SR)} = 2.78 + 0.2693 \times B + 0.4890 \times C + 1.51 \times C^2 \quad (5.33)$$

Figure 5.66 illustrates the effects of perturbations to input variables on SR. The graph shows that SR is an increasing function of FR and increases substantially with decreases and increases in DC.

Figure 5.67 presents the 3D response surface between the CS and the feed. The minimum SR was obtained at a CS of 31.71, a feed of 0.11, and a DC of 0.4. The maximum SR was obtained at a CS of 69.63, a FR of 0.25, and a DC of 0.6.

Table 5.55 presents the R² and adjusted R² values for all responses; both are high, indicating a good model fit. The predicted R² values also correlate well with adjusted R².

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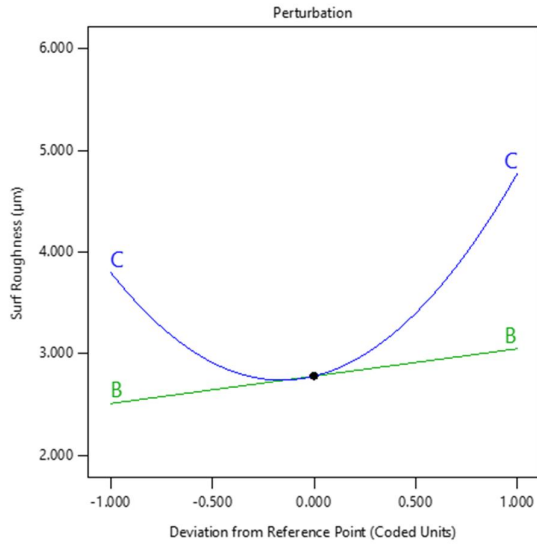


Figure 5.66 Surface roughness perturbation plot

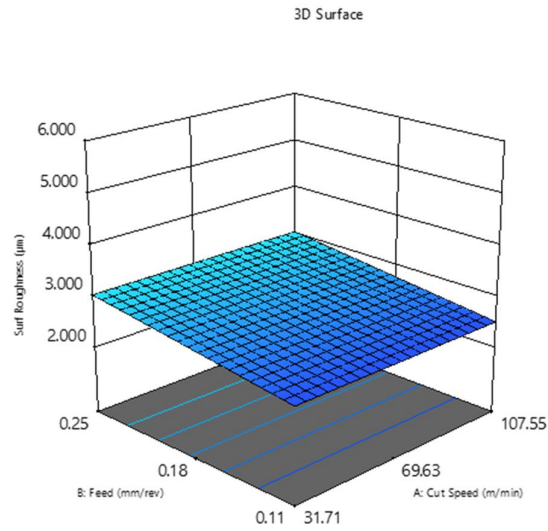


Figure 5.67 Surface roughness 3D response surface plot

Table 5.55 Model adequacy metrics for Case-G2 output responses

Type	Cutting Force	Cutting Temperature	Surface Roughness
R ²	0.9852	0.9946	0.9910
Adjusted R ²	0.9586	0.9850	0.9748
Predicted R ²	0.7838	0.9470	0.8683

5.12 Case-H1 1% wt (Al₂O₃/ZnO, 75/25) Hybrid Nanofluid as a Cutting Fluid

First, the specific cooling condition, i.e., Case-H1, was selected and the corresponding 15-run Box–Behnken design was executed with input factors. For each run, output responses were measured and compiled into the design matrix, as shown in

Table 5.56. These data were then used to formulate the RSM models: linear for cutting force and cutting temperature, quadratic for surface roughness. Insignificant terms in the initial RSM model were systematically identified from ANOVA results and removed, thereby simplifying the regression equation without sacrificing predictive capability. Eliminating these statistically meaningless interactions or higher-order terms reduces overfitting. It improves the numerical stability of the coefficients, allowing the final model to represent the true response surface more clearly over the design space.

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Table 5.56 Box Behnken 15 runs for Case-H1

Test Run	Input parameters			Output parameters		
	A: CS	B: FR	C: DC	CF	CT	SR
	m/min	mm/rev	mm	N	°C	µm
1	31.71	0.11	0.40	201.04	55.14	2.459
2	69.63	0.18	0.40	343.25	72.33	2.536
3	31.71	0.18	0.20	142.20	45.33	3.437
4	69.63	0.11	0.60	374.33	92.76	1.600
5	31.71	0.18	0.60	467.50	90.26	2.760
6	69.63	0.18	0.40	329.22	73.00	2.567
7	107.55	0.25	0.40	393.95	86.31	3.082
8	69.63	0.25	0.60	590.09	109.55	3.157
9	107.55	0.18	0.20	137.30	59.00	2.900
10	69.63	0.18	0.40	348.15	74.00	2.506
11	69.63	0.25	0.20	228.50	52.33	3.900
12	69.63	0.11	0.20	63.75	47.33	2.850
13	107.55	0.11	0.40	222.62	72.33	2.000
14	31.71	0.25	0.40	408.66	76.72	4.020
15	107.55	0.18	0.60	536.54	106.00	1.721

5.12.1 Cutting Force

The software identifies a linear model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.57, the ANOVA data of cutting force, it can be known that the feed and depth of cut are statistically meaningful because the linear model is used for cutting force. The final coded regression equation for cutting force is shown in Eq. (5.34).

Table 5.57 Cutting force ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	315900	158000	316.09	< 0.0001	significant
B-Feed	72096.31	72096.31	144.26	< 0.0001	
C-DOC	243900	243900	487.93	< 0.0001	
Residual	5997.21	499.77			
Lack of Fit	5804.22	580.42	6.02	0.1509	not significant
Pure Error	192.99	96.49			
Cor Total	321900				

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$$\text{Cutting force (CF)} = 319.14 + 94.93 \times B + 174.59 \times C \quad (5.34)$$

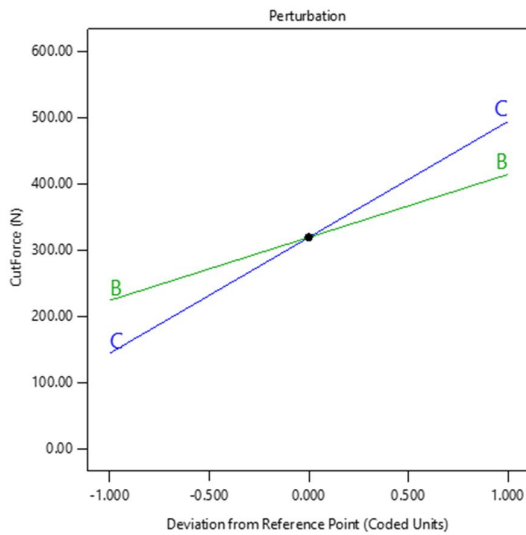


Figure 5.68 Cutting force perturbation plot

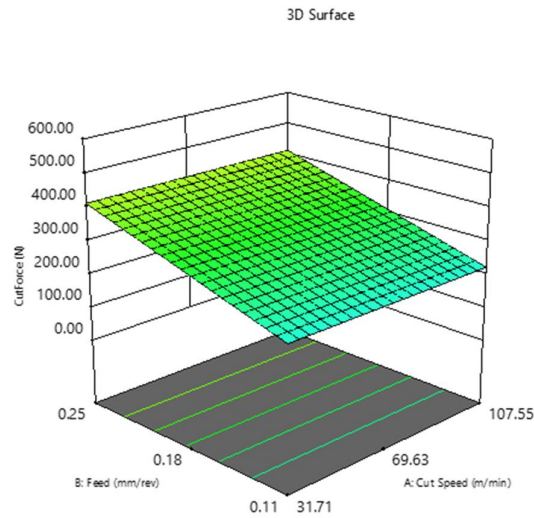


Figure 5.69 Cutting force 3D response surface plot

Figure 5.68 presents the perturbation plot showing the influence of the input factors. It can be observed that the CF is proportional to increasing feed and DC.

Figure 5.69 shows the 3D response surface plot for CS versus feed. From this plot, it can be seen that the minimum CF occurs at a value of 69.63, a CS of 0.11, and a 0.2 DC. But the maximum CF occurs at a CS of 69.63, a feed of 0.25, and a DC of 0.6.

5.12.2 Cutting Temperature

The software identifies a linear model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.58, the result of ANOVA on cutting temperature shows that speed of cut, DC, and feed have become quite meaningful as the model is linear. The final coded equation for cutting temperature is shown in Eq. (5.35).

Table 5.58 Cutting temperature ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	5537.93	1845.98	177.60	< 0.0001	significant

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A-Cut Speed	394.66	394.66	37.97	< 0.0001	
B-Feed	411.08	411.08	39.55	< 0.0001	
C-DOC	4732.19	4732.19	455.28	< 0.0001	
Residual	114.33	10.39			
Lack of Fit	112.93	12.55	17.83	0.0542	not significant
Pure Error	1.41	0.7037			
Cor Total	5652.26				

$$\text{Cutting temperature (CT)} = 74.16 + 7.02 \times A + 7.17 \times B + 24.32 \times C \quad (5.35)$$

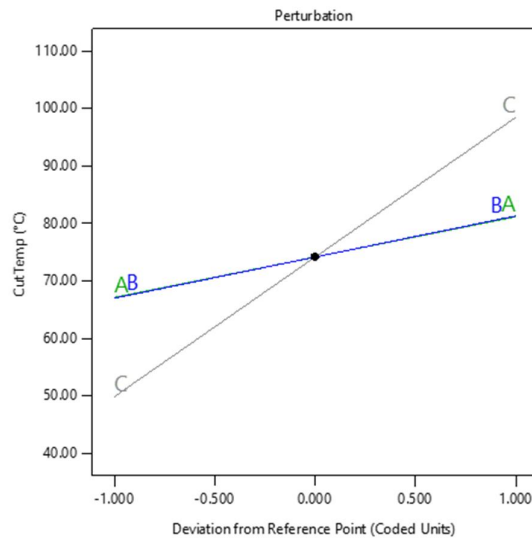


Figure 5.70 Cutting temperature perturbation plot

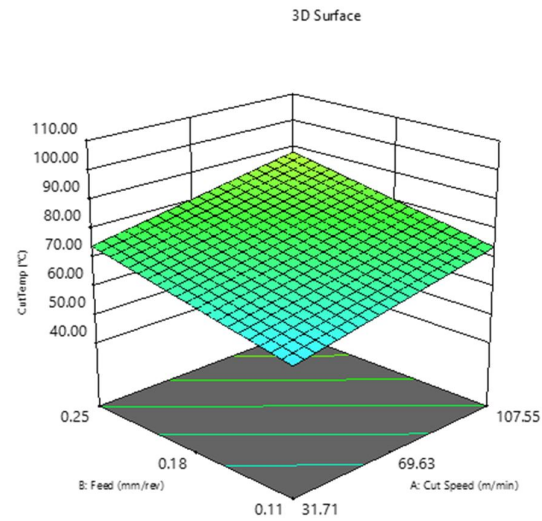


Figure 5.71 Cutting temperature 3D response surface plot

Figure 5.70 illustrates the influence of input factors, clearly showing that the CT increases with increasing DC and shows a minor increase with CS and FR. It also shows how the CT depends upon varying input parameters.

Figure 5.71 presents a 3D response surface between CS and feed. CT at the minimum value is obtained by CS at 31.71, FR at 0.18, and DC at 0.2, and CT at the maximum value is obtained by CS at 69.63, FR at 0.25, and DC at 0.6.

5.12.3 Surface Roughness

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

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Based on ANOVA data on surface roughness from Table 5.59, it's remarkable that CS, FR, DC, and the quadratic effect of FR are highly meaningful, as indicated by the quadratic model equation.

Table 5.59 Surface roughness ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	6.87	0.7633	454.40	< 0.0001	significant
A-Cut Speed	1.10	1.10	657.24	< 0.0001	
B-Feed	3.45	3.45	2050.92	< 0.0001	
C-DOC	1.85	1.85	1102.17	< 0.0001	
AB	0.0574	0.0574	34.19	0.0021	
AC	0.0630	0.0630	37.50	0.0017	
BC	0.0642	0.0642	38.20	0.0016	
A ²	0.0306	0.0306	18.20	0.0080	
B ²	0.2557	0.2557	152.22	< 0.0001	
C ²	0.0222	0.0222	13.20	0.0150	
Residual	0.0084	0.0017			
Lack of Fit	0.0065	0.0022	2.34	0.3131	not significant
Pure Error	0.0019	0.0009			
Cor Total	6.88				

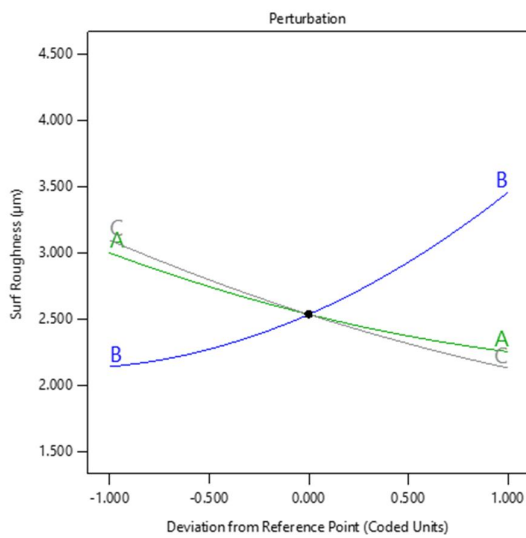


Figure 5.72 Surface roughness perturbation plot

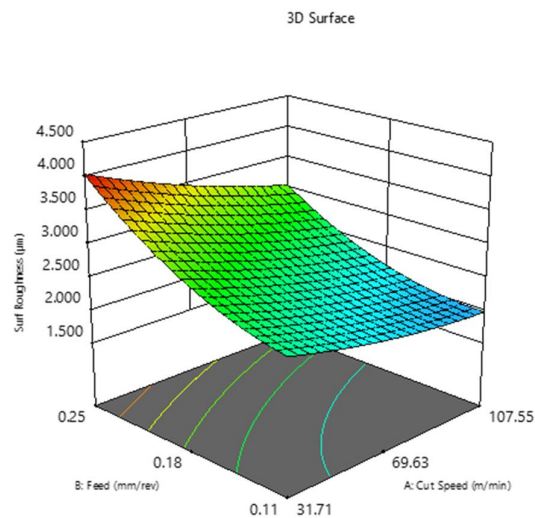


Figure 5.73 Surface roughness 3D response surface plot

The equation in coded units of the final regression model of surface roughness is shown in Eq. (5.36).

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$$\begin{aligned} \text{Surface roughness (SR)} &= 2.54 - 0.3715 \times A + 0.6562 \times B - 0.4811 \times C \\ &\quad - 0.1198 \times A \times B - 0.1255 \times A \times C + 0.1267 \times B \times C \\ &\quad + 0.0910 \times A^2 + 0.2632 \times B^2 + 0.0775 \times C^2 \end{aligned} \quad (5.36)$$

Figure 5.72 presents the perturbation plot showing the influence of the input factors upon SR. It is clear from the graph that SR increases with FR, whereas it decreases with CS and DC.

Figure 5.73 displays a 3D response surface plot, with CS and feed. From this plot, it is possible to note that the minimum SR was obtained at a CS of 69.63, feed of 0.11, and DC of 0.6, and the maximum SR was obtained at a CS of 31.71, feed of 0.25, and DC of 0.4.

Table 5.60 shows that the R^2 and adjusted R^2 values are high and exhibit little disparity across all responses, indicating that the models are well-fitted. Moreover, the predicted R^2 values are sufficiently close to the adjusted R^2 values, signifying that these models could reliably predict the experimental results.

Table 5.60 Model adequacy metrics for Case-H1 output responses

Type	Cutting Force	Cutting Temperature	Surface Roughness
R^2	0.9833	0.9798	0.9988
Adjusted R^2	0.9788	0.9743	0.9966
Predicted R^2	0.9690	0.9575	0.9842

5.13 Case-H2 2% wt ($\text{Al}_2\text{O}_3/\text{ZnO}$, 75/25) Hybrid Nanofluid as a Cutting Fluid

First, the specific cooling condition, i.e., Case-H2, was selected and the corresponding 15-run Box–Behnken design was executed with input factors. For every run, output responses were measured and compiled into the design matrix as given in Table 5.61. These data were employed to estimate RSM models-quadratic for cutting force, cutting temperature, and surface roughness. Insignificant terms in the initial RSM model were systematically identified from ANOVA results and removed, thereby simplifying the regression equation without sacrificing predictive capability. Eliminating these statistically meaningless interactions or higher-order terms reduces overfitting. It improves the numerical

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stability of the coefficients, allowing the final model to represent the true response surface more clearly over the design space.

Table 5.61 Box Behnken 15 runs for Case-H2

Test Run	Input parameters			Output parameters		
	A: CS	B: FR	C: DC	CF	CT	SR
	m/min	mm/rev	mm	N	°C	µm
1	31.71	0.11	0.40	143.87	40.66	3.150
2	69.63	0.18	0.40	230.46	51.23	5.364
3	31.71	0.18	0.20	161.82	50.83	3.725
4	69.63	0.11	0.60	196.14	61.20	4.305
5	31.71	0.18	0.60	426.60	60.27	4.562
6	69.63	0.18	0.40	250.08	52.63	5.316
7	107.55	0.25	0.40	243.51	56.40	4.350
8	69.63	0.25	0.60	487.11	71.27	4.980
9	107.55	0.18	0.20	156.91	58.47	4.207
10	69.63	0.18	0.40	254.98	53.17	5.305
11	69.63	0.25	0.20	166.72	52.80	3.964
12	69.63	0.11	0.20	104.64	51.60	3.160
13	107.55	0.11	0.40	158.58	50.77	4.562
14	31.71	0.25	0.40	353.05	42.53	4.461
15	107.55	0.18	0.60	395.52	77.03	5.484

5.13.1 Cutting Force

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.62, ANOVA for cutting force indicates that, due to the quadratic nature of the model, depth of cut is highly meaningful. Furthermore, the feed and feed-depth-of-cut interaction effect is meaningful, as the p-value is < 0.05. The final coded equation of cutting force obtained from regression analysis is as follows in Eq. (5.37).

Table 5.62 Cutting force ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	170200	56723.26	37.84	< 0.0001	significant
B-Feed	52352.64	52352.64	34.93	0.0001	
C-DOC	104700	104700	69.86	< 0.0001	

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BC	13098.27	13098.27	8.74	0.0131	
Residual	16488.37	1498.94			
Lack of Fit	16151.75	1794.64	10.66	0.0886	not significant
Pure Error	336.62	168.31			
Cor Total	186700				

$$\text{Cutting force (CF)} = 248.67 + 80.90 \times B + 114.41 \times C + 57.22 \times B \times C \quad (5.37)$$

Figure 5.74 illustrates the perturbation influence of input variables on the CF. From this graph, it is observed that the CF increases linearly with the increase of feed and DC.

The response surface is shown in 3D in Figure 5.75, which shows the relationship between CS and FR. The minimum CF occurs at a CS of 69.63 and a FR of 0.11, and a 0.2 DC, whereas the maximum CF occurs at a CS of 69.63 and a FR of 0.25 and a 0.6 DC.

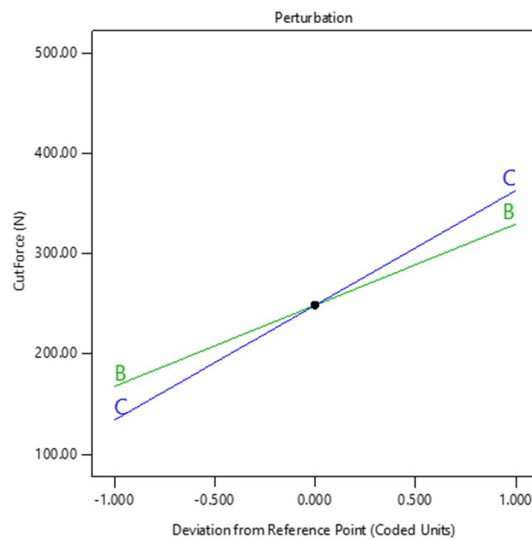


Figure 5.74 Cutting force perturbation plot

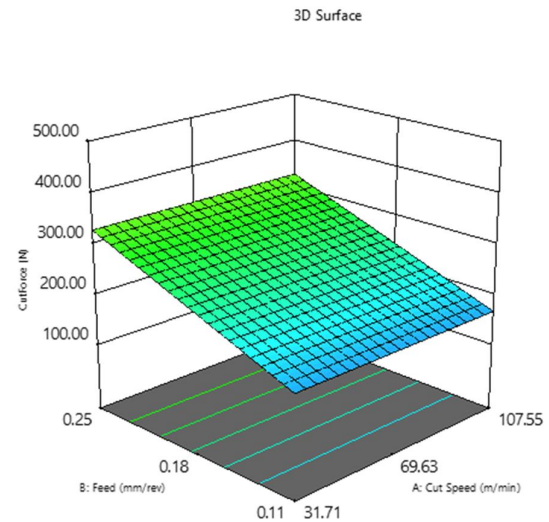


Figure 5.75 Cutting force 3D response surface plot

5.13.2 Cutting Temperature

The software identifies a linear model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.63, cutting temperature is subject to ANOVA data and it can be found that (because of the quadratic effect in the model) CS and depth of cut and (because it is squared) the depth of cut are all meaningful. The final coded regression model's equation for cutting

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temperature is given in Eq. (5.38).

Table 5.63 Cutting temperature ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	1251.68	178.81	101.73	< 0.0001	significant
A-Cut Speed	292.58	292.58	166.45	< 0.0001	
B-Feed	44.04	44.04	25.05	0.0016	
C-DOC	392.98	392.98	223.57	< 0.0001	
AC	20.85	20.85	11.86	0.0108	
BC	19.67	19.67	11.19	0.0123	
B ²	45.61	45.61	25.95	0.0014	
C ²	413.87	413.87	235.45	< 0.0001	
Residual	12.30	1.76			
Lack of Fit	10.31	2.06	2.07	0.3573	not significant
Pure Error	1.99	0.9970			
Cor Total	1263.98				

Cutting temperature (CT)

$$= 51.63 + 6.05 \times A + 2.35 \times B + 7.01 \times C + 2.28 \times A \times C \quad (5.38) \\ + 2.22 \times B \times C - 3.50 \times B^2 + 10.56 \times C^2$$

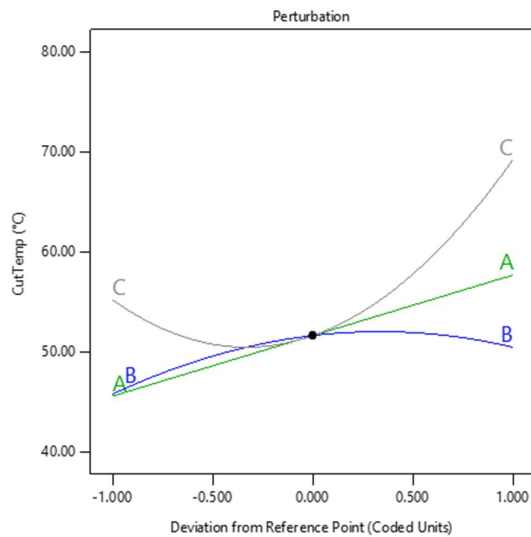


Figure 5.76 Cutting temperature perturbation plot

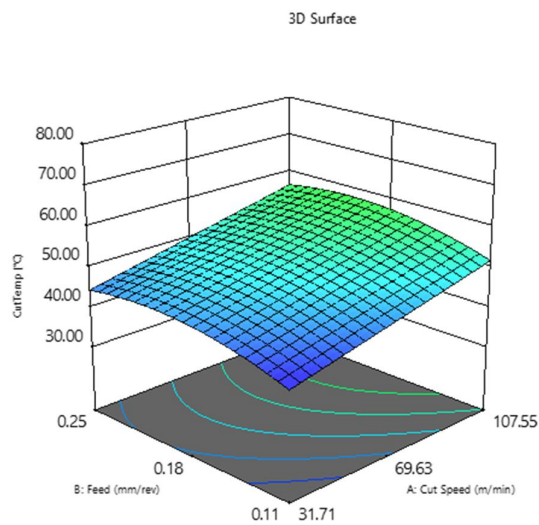


Figure 5.77 Cutting temperature 3D response surface plot

Figure 5.76 presents the perturbation plot showing the influence of the input factors on the CT. The results revealed that CT rises with increasing CS and is lowest at a medium DC.

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Furthermore, CT decreases slightly as the FR increases.

Figure 5.77 shows the 3D response surface plot for CS and feed. From this plot, the CT is minimal at a CS of 31.71, a feed of 0.11, and a DC of 0.4. And the CT is maximal at a CS of 107.55, a feed of 0.18, and a DC of 0.6.

5.13.3 Surface Roughness

The software identifies a quadratic model as the most appropriate fit for the data. This model demonstrates high statistical significance, as evidenced by a p-value < 0.05.

From Table 5.64, ANOVA data of surface roughness indicates that model is quadratic nature, all input factors, interaction effect of cutting speed-feed and all quadratic input factors are highly meaningful. Coded equation for surface roughness in the final regression model is shown in Eq. (5.39).

Table 5.64 Surface roughness ANOVA table

Source	S. Sq.	M. Sq.	F-value	p-value	
Model	7.87	0.9841	228.46	< 0.0001	significant
A-Cut Speed	0.9151	0.9151	212.43	< 0.0001	
B-Feed	0.8312	0.8312	192.95	< 0.0001	
C-DOC	2.28	2.28	530.32	< 0.0001	
AB	0.5804	0.5804	134.73	< 0.0001	
AC	0.0483	0.0483	11.20	0.0155	
A ²	0.5987	0.5987	138.98	< 0.0001	
B ²	2.33	2.33	541.85	< 0.0001	
C ²	0.6869	0.6869	159.47	< 0.0001	
Residual	0.0258	0.0043			
Lack of Fit	0.0239	0.0060	6.06	0.1465	not significant
Pure Error	0.0020	0.0010			
Cor Total	7.90				

$$\begin{aligned}
 \text{Surface roughness (SR)} &= 5.33 + 0.3382 \times A + 0.3223 \times B + 0.5344 \times C \\
 &- 0.3809 \times A \times B + 0.1098 \times A \times C - 0.4027 \times A^2 \\
 &- 0.7951 \times B^2 - 0.4313 \times C^2
 \end{aligned} \tag{5.39}$$

The values of input factors' effect on SR are presented in the perturbation plot illustrated in

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Figure 5.78. It can be clearly seen from the plot that the SR increases with the value of all input factors, but begins decline after a moderate level of FR is reached.

Figure 5.79 shows the 3D response surface between the CS versus feed. The smallest SR is achieved at 31.71, a FR of 0.11, and a DC of 0.4, and the greatest SR is gained at 107.55, a FR of 0.18, and a DC of 0.6.

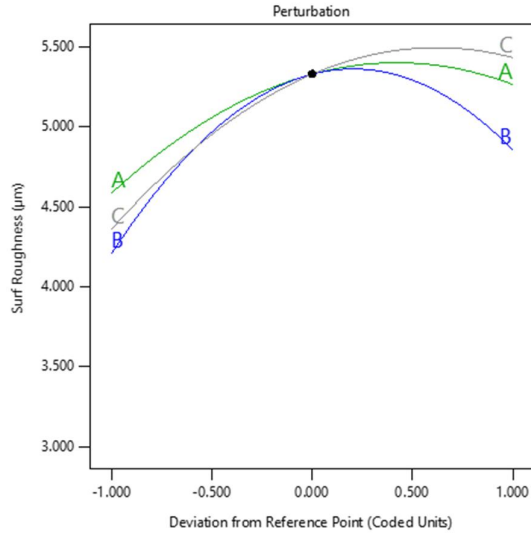


Figure 5.78 Surface roughness perturbation plot

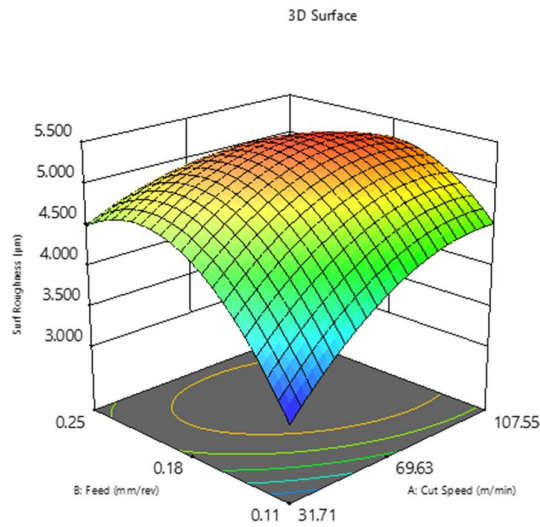


Figure 5.79 Surface roughness 3D response surface plot

As shown in Table 5.65, all responses have high R^2 and Adjusted R^2 values, indicating excellent model fit. Predicted R^2 values are also close to Adjusted R^2 values.

Table 5.65 Model adequacy metrics for Case-H2 output responses

Type	Cutting Force	Cutting Temperature	Surface Roughness
R^2	0.9879	0.9970	0.9973
Adjusted R^2	0.9662	0.9916	0.9923
Predicted R^2	0.8319	0.9737	0.9595

The primary outcomes obtained from DOE employing RSM include:

- From ANOVA:
 - The p-value is < 0.05 : the factor is meaningful; it has a true impact on the response.
 - The factor which has p-value is found to be more than 0.05, it is not found

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meaningful and its effect is considered weak or uncertain.

- A higher value of F usually means that the factor has a significant effect on the response.
- The insignificance of nanoparticle wt% in linear form but significance in quadratic form indicates a non-monotonic, curved relationship, implying an optimum wt% exists within the tested range. This reflects the trade-off in nanofluid-based MQL, where moderate concentrations enhance lubrication and thermal performance, while excessive loading causes agglomeration or viscosity issues that degrade the response.
- From model adequacy metrics:
 - Most of R^2 values are higher than 0.95, and some higher than 0.98, which show the proposed models fit most of the variance of responses.
 - Adjusted R^2 values are only slightly lower than R^2 , showing that additional terms (interaction and quadratic) are justified and not just overfitting.
 - Predicted R^2 remains high (generally above 0.8), which supports good predictive capability for new combinations within the design space.
- From residuals and model graphs:
 - For all responses, the normal probability plots of residuals are approximately linear. Thus, the residuals are approximately normal.
 - Residuals vs. predicted plots show random scatter without obvious patterns, supporting same variance and independence of errors.
 - The perturbation plots showed smooth and monotonic variations of each response with respect to individual factors, without abrupt oscillations, further supporting the robustness of the fitted models across the design space.
 - The 3D response surface behaves smoothly and matches the experimental data trends, which is consistent with a good model fit across the design region.

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➤ From cooling condition cases:

- **Dry cutting (Case A):** Typically exhibits higher cutting temperatures and poorer surface roughness. Cutting force is moderate, but because both T and Ra are worse.
- **Wet cutting with conventional fluids (Cases B, C):** Produces a substantial reduction in cutting temperature versus dry for the same input parameters, with forces often in a comparable range. However, surface roughness values are not consistently the lowest and remains higher than MQL-nanofluid cases.
- **MQL mono nanofluids (D1, D2: Al₂O₃; E1, E2: ZnO):** Offer improved cooling and sometimes reduced cutting force compared to wet, especially at moderate feeds and lower DoC. Surface roughness generally improves compared to dry and can be competitive with wet, but is still not uniformly minimal at all input combinations.
- **MQL hybrid nanofluids (F1/F2, G1/G2, H1/H2):** These cases show the most balanced behaviour:
 - ✓ Forces that are comparable to or slightly better than wet cutting.
 - ✓ Temperatures much lower than dry and comparable to or modestly higher than wet.
 - ✓ Roughness often significantly lower than both dry and conventional wet, with several runs at Ra near or below 2–3 µm even at moderate feeds.

➤ From input parameters:

- **Cutting speed (A)** tends to decrease roughness at moderate speeds in lubricated conditions but may increase temperature; force behavior with speed is more complex but often decreases slightly with increasing speed in many machining studies.
- Increasing speed changes chip formation and reduces built-up edge, so surface roughness improves at moderate speeds, especially with lubrication; however,

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plastic deformation and sliding occur faster, so heat generation surpasses heat dissipation and cutting temperature rises, while cutting force often drops slightly due to thermal softening of the workpiece.

- o **Feed (B)** is the strongest driver for increasing both cutting force and surface roughness for almost all cutting conditions, increased feed deteriorated all three responses while productivity increased in certain situations.
 - o Feed directly sets undeformed chip thickness and theoretical cusp height, so higher feed produces thicker chips, larger shear area and steeper feed marks, which significantly increase the cutting force and surface roughness. Higher MRR, higher contact pressure leads to higher cutting temperature.
 - o **Depth of cut (C)** considerably increases the cutting force and generally increases cutting temperature and SR values, especially at higher feed values, irrespective of the case.
 - o Depth of cut enlarges chip cross-section and tool–work contact length, so the load on the tool and the frictional contact area increase almost proportionally, making cutting force highly sensitive to depth of cut.
 - o The larger engaged volume generates more heat and promotes tool/work deflection and ploughing, which tend to elevate temperature and roughness at the higher depth (0.6 mm).
- From the nanoparticle and its concentration:
- o Al_2O_3 nanofluid consistently yielded lower surface roughness (R_a) due to superior tribological mechanisms: its high hardness forms a durable tribofilm at the tool-chip interface.
 - o ZnO nanofluid influenced cutting temperature more strongly due to its superior heat conduction capability, dissipating thermal energy efficiently at higher cutting speeds.
 - o Furthermore, spherical nanoparticles enable micro-rolling motion, slashing friction by 25-40% [44], which enhances tribological performance and reduces

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cutting force.

- o Nanoparticles at moderate concentrations (e.g., 1 wt%) improve the thermal conductivity and form tribofilm at the tool & chip interface, and hence reduce friction and heat generation. Also, > 1.5-2 wt% elevates viscosity, promotes agglomeration.
- o The impact of nanofluid thermophysical properties on lubrication performance is evident in the way Al_2O_3 and ZnO are chosen to increase thermal conductivity while preserving dispersion stability and sprayability, enabling efficient heat removal and temperature reduction at the cutting zone. The 1-2 wt% concentration window is selected to avoid the excessive viscosity, agglomeration and nozzle clogging observed at higher loadings, so that the 1 wt% Al_2O_3 -ZnO hybrid nanofluid achieves the best combined improvements in cutting force, temperature and surface roughness.
- o A comparative summary for both nanoparticles is given in Table 5.66.

Table 5.66 Comparative summary of both nanoparticles

Aspect	Al_2O_3	ZnO
Dominant strength	Better cutting force and surface roughness reduction	Better cutting temperature reduction
Typical effect of wt%	Clear moderate; too high wt% increases viscosity and force/roughness	Similar moderate behavior; strong effect on temperature
Sensitivity to cutting speed	Strong influence on temperature in both; Al_2O_3 gives lower forces at moderate speeds	High-speed performance enhanced by superior heat transfer
Best use-case	When priority is low, force and high surface finish	When priority is aggressive cooling and thermal control

5.14 Comparison of Cooling Cases

To compare the thirteen cooling cases on a common basis, a multi-response desirability index [83] approach was employed. For each case, the Box–Behnken RSM models for output responses were first used to identify the best-performing region within the design space, and the corresponding response values were converted into individual ‘smaller-is-better’ desirability functions ranging from 0 to 1. An overall desirability index was then calculated

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as the geometric mean of the three single-response desirabilities, assigning equal importance to force, temperature, and roughness; this composite index enabled a direct, quantitative ranking of all cooling cases and the selection of the most suitable lubrication strategy for simultaneous minimization of the three outputs.

The minimum CF, CT, and SR values in each case (from DoE tables) are used. For each response Y in a given case, a “smaller-is-better” desirability between 0 and 1 is defined is:

$$d = \frac{Y_{max} - Y}{Y_{max} - Y_{min}} \quad (5.40)$$

where Y_{max} and Y_{min} are the worst and best values across all 13 cases for that response.

Then, for each case, an overall desirability was calculated as the geometric mean:

$$D = (d_{CF}, d_{CT}, d_{SR})^{1/3} \quad (5.41)$$

From this calculation, rank the thirteen cases in descending order of the overall desirability D . The ranking of cases by overall desirability D is shown in Table 5.67.

Table 5.67 Ranked multi-response performance (global minima basis)

Rank	Cooling Condition Case	Global-min F (N)	Global-min T (°C)	Global-min Ra (μm)	Overall D
1	Case-H1 [MQL + 1% wt (Al ₂ O ₃ /ZnO, 75/25)]	63.75	45.33	1.6	0.621
2	Case-A Dry	63.75	48.84	1.75	0.472
3	Case-G2 [MQL + 2% wt (Al ₂ O ₃ /ZnO, 50/50)]	83.36	45.4	2.341	0.468
4	Case-E1 MQL + 1% wt ZnO	88.26	46.67	2.02	0.45
5	Case-D1 MQL + 1% wt Al ₂ O ₃	62.08	49	2.252	0.423
6	Case-D2 MQL + 2% wt Al ₂ O ₃	102.97	47.89	2.097	0.342
7	Case-H2 [MQL + 2% wt (Al ₂ O ₃ /ZnO, 75/25)]	104.64	40.66	3.15	0.321
8	Case-E2 MQL + 2% wt ZnO	83.36	50.33	2.05	0.317
9	Case-C Wet SAE40	67.86	51.67	1.678	0.22
10	Case-G1 [MQL + 1% wt (Al ₂ O ₃ /ZnO, 50/50)]	98.07	42	3.645	0.102
11	Case-B Wet Conventional Fluid	42.46	31.33	3.659	very low D (poor Ra)

A desirability-based multi-response optimization (equal weighting of output responses, smaller is better) identifies Case-H1 (MQL + 1 wt% hybrid Al₂O₃/ZnO, 75/25) as the most suitable overall lubrication condition among the 13 tested cases. Case-H1 stands out as it

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combines very low Ra (global best, 1.600 μm) with moderately low force and temperature compared with other nanofluid and conventional cooling cases.

5.15 Multi-Objective Optimization and Validation

After comparison of all thirteen cooling cases was completed, Case-H1 was identified as the most suitable cooling case among them, and the next step is to reach the optimum condition.

The Desirability Function Analysis (DFA) approach was chosen for multi-response numerical optimization [84], [85], [86] due to its direct interaction with the predictive models obtained from the Box-Behnken design method, which enables determining the optimal solutions within a continuous design space compared to only ranking discrete experimental designs. The optimization procedure under software involves two variables: Importance (Ii), that denotes the importance levels (graded 1-5) of the responses that are used to find the global desirability (D) based on the weighted geometric mean formula, and Weight (wi), that controls the degree of curve of the individual desirability where values greater than one mean higher standard should be met.

Initially, mathematical models for output responses were formulated. Each response was regarded as “lower the better” with a specified lower bound, an upper bound, and a target value set for each response. Desirability functions were calculated for each response before calculating their composite desirability (D). Parameters related to process variables (input factors) were optimized by maximizing D.

The optimization combination was set up with three design variables: A, B, and C, restricted to ranges $31.71 \leq A \leq 107.55$ m/min, $0.11 \leq B \leq 0.25$, and $0.2 \leq C \leq 0.4$ mm. For all of the RSM-based three responses, which include cutting force $CF(A, B, C)$, cutting temperature $CT(A, B, C)$, and surface roughness $SR(A, B, C)$, minimum values were selected with equal weightings. At the same time, the optimization was performed using the maximum-desirability function $D(A, B, C)$.

Weights were assigned based on the premise that surface finish is the primary quality requirement in finish turning, followed by cutting force, which relates to tool life and stability, and then temperature, as is commonly adopted in multi-objective machining optimization [87], [88].

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Weights are assigned to output responses:

- ✓ SR: weight = 0.5
- ✓ CF: weight = 0.3
- ✓ CT: weight = 0.2

As discussed earlier, at higher cutting speeds, temperature rises, but surface finish improves in MQL-lubricated cases due to increased chip flow and reduced built-up edge. An increase in feed generally increases Ra and force significantly in all cases. Therefore, for minimizing all three outputs, low feed is favorable. A higher increase in cutting force with an increase in depth of cut occurs in all circumstances; a corresponding increase in temperature and surface roughness frequently occurs.

Constraint conditions of input variables, namely, A, B, and C, are to be within the required set goal, while the constraint conditions of output responses, namely, CF, CT, and SR, are to be minimized. Table 5.68 shows constraint criteria for parameters to get the optimum level.

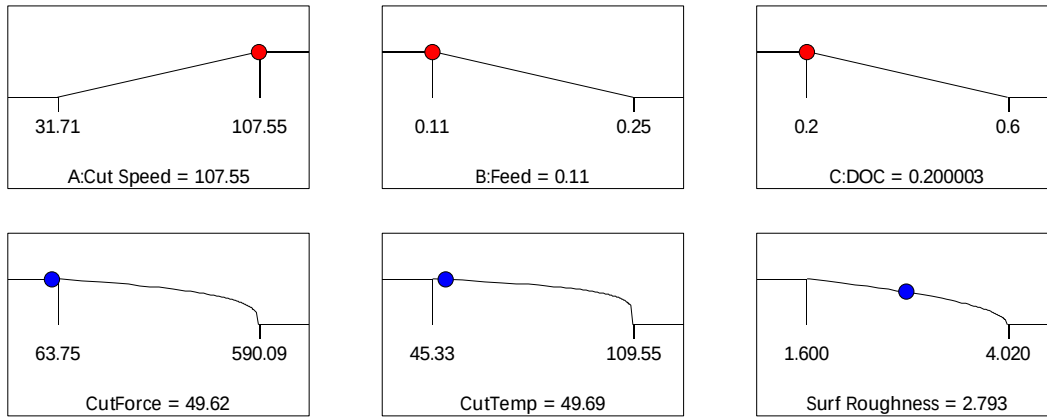
Table 5.68 Criteria table for optimum condition

Parameter	Goal	Lower Limit	Upper Limit	Weight
A: Cutting Speed	maximize	31.71	107.55	1
B: Feed	minimize	0.11	0.25	1
C: Depth of Cut	minimize	0.2	0.6	1
CF: Cutting Force	minimize	63.75	590.08	0.3
CT: Cutting Temperature	minimize	45.33	109.55	0.2
SR: Surface Roughness	minimize	1.6	4.02	0.5

Out of 34 available optimization solutions, the solution with the maximum value of desirability is selected. The optimal conditions at a high desirability value of 0.943 for Cutting Force (49.62 N), Cutting Temperature (49.69 °C), and Surface Roughness (2.793 μm) are as follows: Cutting Speed 107.55, Feed Rate 0.11, and Depth of Cut 0.2.

A ramp graph with the maximum value of desirability for the predicted output response for selected input factors is shown in Figure 5.80. For optimum condition of output response at C = 0.2 mm, the predicted value of output responses has been shown in a contour plot with

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Desirability = 0.943
Solution 1 out of 34

Figure 5.80 Ramp graph with maximum value of desirability

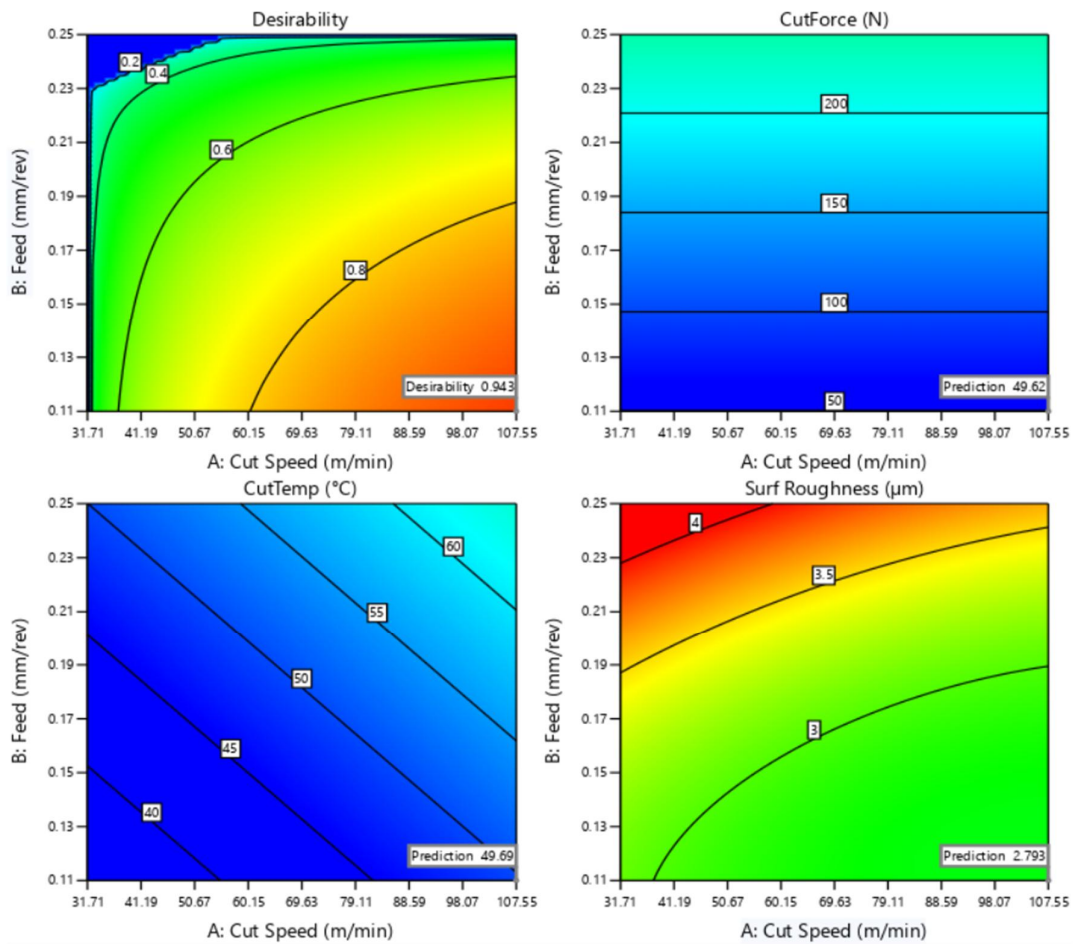


Figure 5.81 Contour plot for the predicted value of output responses with input variables

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the input factors in Figure 5.81.

Once the optimal parameter values have been identified, the final task is to validate the predicted outputs through a validation experiment. The validating experiment aims to verify conclusions derived in the statistical analysis stage and the improvement of measured output performance using the optimum level. For Case-H1 as a cooling method, the optimum condition, with a high desirability value of 0.943, for CF, CT, and SR is as follows: A of 107.55 m/min, B of 0.11mm/rev, and C of 0.2 mm.

Once the optimal parameter values have been identified, the final task is to validate the predicted outputs through a validation experiment. The validating experiment aims to verify conclusions derived in the statistical analysis stage and the improvement of measured output performance using the optimum level. For Case-H1 as a cooling method, the optimum condition, with a high desirability value of 0.943, for CF, CT, and SR is as follows: A of 107.55 m/min, B of 0.11mm/rev, and C of 0.2 mm.

Table 5.69 indicates that the experimentation runs extract the expected and actual answers and compare them with the predicted value. The percentage errors between experimental means and RSM predictions were 8.23% (cutting force), 6.83% (temperature), and 3.56% (surface roughness).

Table 5.69 Validation table with percentage error

Output Parameter	Predicted value by RSM	Mean experiment value	Percentage error (%)
Cutting Force	49.62	54.07	8.23
Cutting Temperature	49.69	53.33	6.83
Surface Roughness	2.793	2.896	3.56

The percentage errors between the predicted and mean experimental values are within acceptable accuracy. It confirms the high predictive accuracy of the developed RSM models.

5.16 Performance Prediction of Cooling Cases Using ANN

A new fully-connected artificial neural network (ANN) model has been designed to predict the cooling condition performance. The selected input variables encompass cutting condition (dry and wet), MQL, Al₂O₃ proportion, ZnO proportion, and three input factors. Performance

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evaluation of cooling conditions was conducted based on three output responses. As a result, input variables were considered as the aforementioned variables and cooling cases performances calculated were used as target parameters. For each target performance parameter, separate artificial neural network (ANN) models were developed using different combinations of input variables. The best ANN architecture for each case was selected based on statistical performance indices and error analysis.

In statistical plots, when data points are positioned near the $Y = X$ line, the neural network demonstrates high-precision predictions; smaller scatter about this line is desirable to indicate good model fit. This spread is measured by the correlation coefficient R^2 : values of R^2 close to 1 indicate a strong agreement between ANN-predicted values and experimental measurements. A common issue when working with relatively small datasets is overfitting, where the ANN learns noise instead of the underlying relationship and therefore loses its generalisation capability. One simple way to detect overfitting is to monitor the prediction error and correlation coefficient on the independent test data. When the correlation coefficients for training, validation and test subsets are all high and of similar magnitude, it confirms that overfitting has not occurred and that the selected ANN model generalises well to unseen data.

A systematic architecture search was carried out by varying network type, performance function, transfer function and number of hidden neurons, resulting in 190 different ANN models. The network types tested were: feedforward backpropagation, cascade forward, Elman recurrent feed forward distributed time delay and generalized regression network; performance functions were MSE and SSE; transfer functions were TANSIG and PURELIN; and the number of hidden neurons was varied between 5 and 50 in steps of 5.

All models were trained in MATLAB 2014a using the Levenberg–Marquardt algorithm (TRAINLM) with gradient descent adaptation, and their performance was compared in terms of MSE, MAE, MAPE and determination coefficient R^2 . For each group of architectures, the model with the lowest error indices and highest R^2 was retained as the best candidate.

ANN models developed based on network type is showing in Figure 5.82. It is required that MSE, MAE & MAPE errors should be as low as possible and R^2 should be as high as possible. So, it can be seen that a feed-forward distributed time delay network gives optimum results for the performance prediction of the cooling condition.

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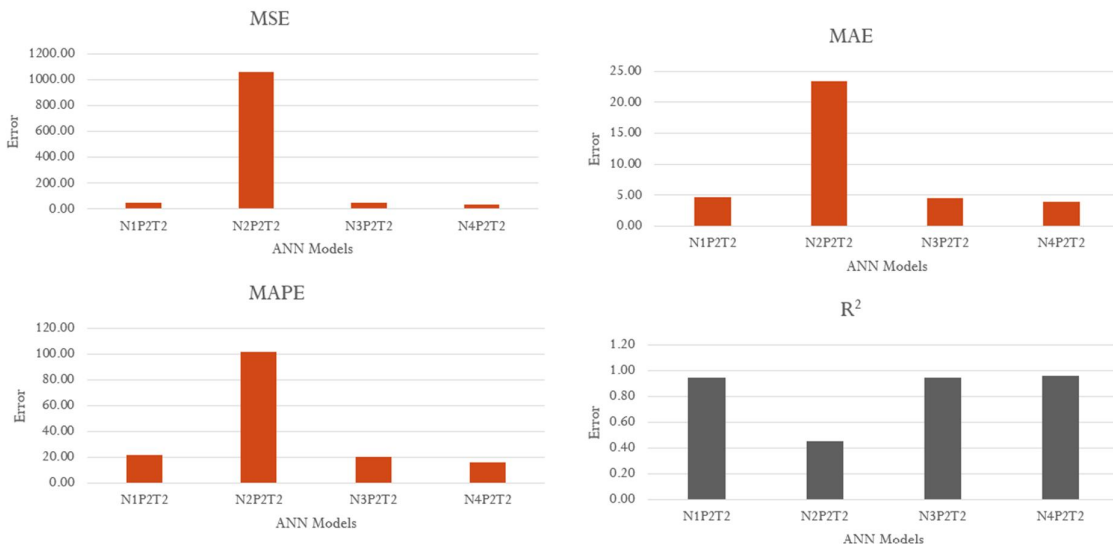


Figure 5.82 ANN models developed based on network type

ANN models developed based on the performance function are showing in Figure 5.83. So, it can be seen that the SSE performance function with low MSE, MAE & MAPE errors and high R^2 gives optimum results for the performance prediction of cooling conditions.

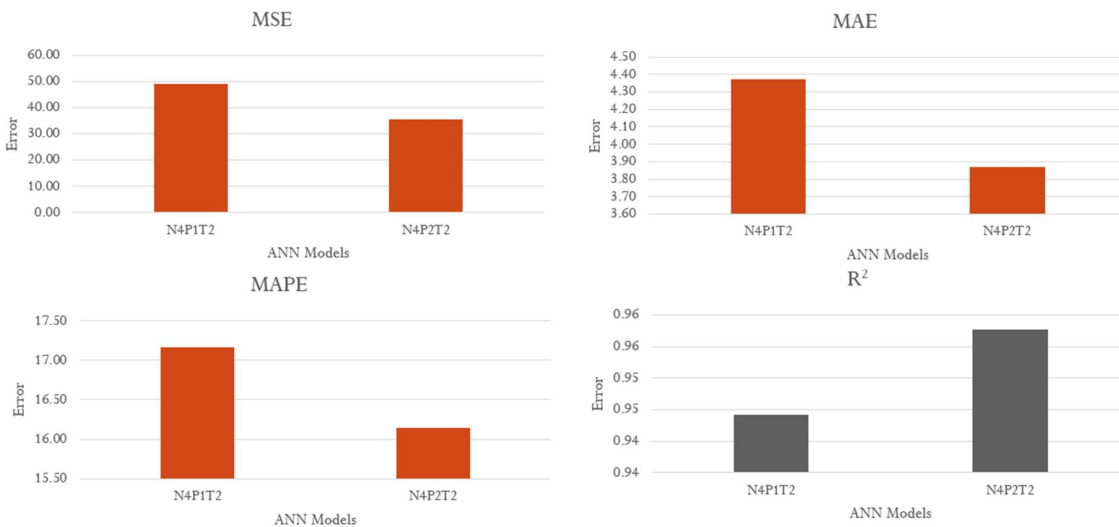


Figure 5.83 ANN models developed based on performance function

ANN models developed based on the transfer function are showing in Figure 5.84. So, it can be seen that TRANSIG transfer with low MSE, MAE & MAPE errors and high R^2 gives optimum results for the performance prediction of cooling conditions.

ANN models developed according to varying numbers of neurons are illustrated in Figure 5.85. So, it can be seen that 10 neurons with low MSE, MAE & MAPE errors and high R^2

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give optimum results for the performance prediction of cooling conditions.

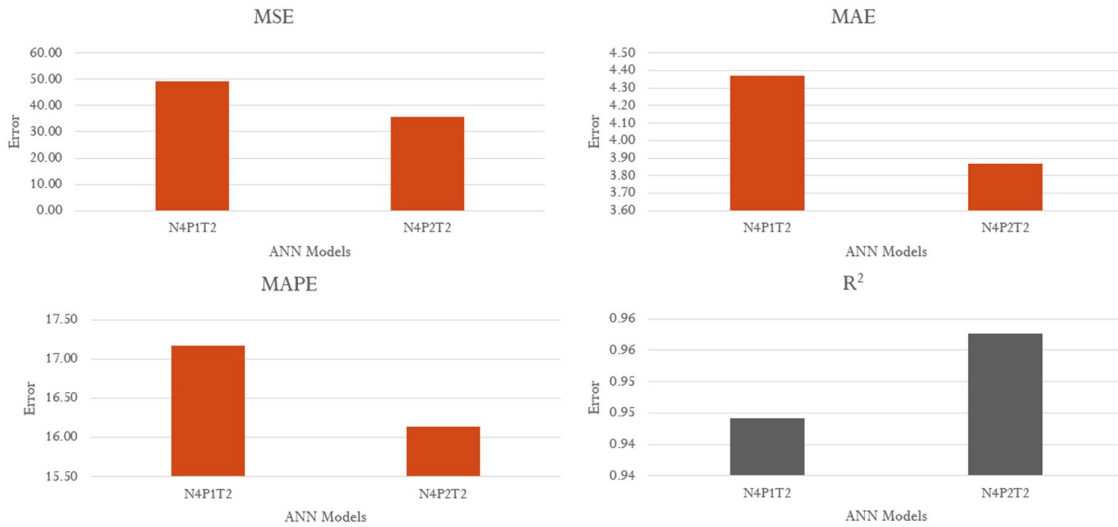


Figure 5.84 ANN models developed based on the transfer function

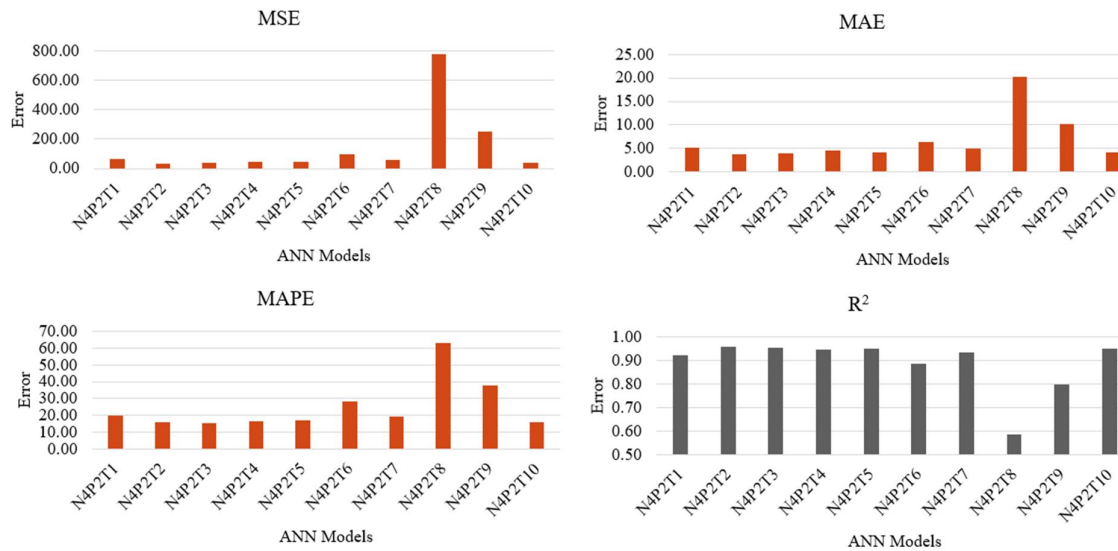


Figure 5.85 ANN models developed according to neuron count

The comparative error and correlation coefficient analysis showed that the predicted N4P2T2 model (Figure 5.86) - corresponding to a feed-forward distributed time-delay network with SSE performance function, TANSIG transfer function, and the hidden layer with 10 neurons, yielded the most favorable configuration, with the smallest MSE, MAE, and MAPE, and the highest R^2 (≈ 0.95 - 0.96) among all candidates.

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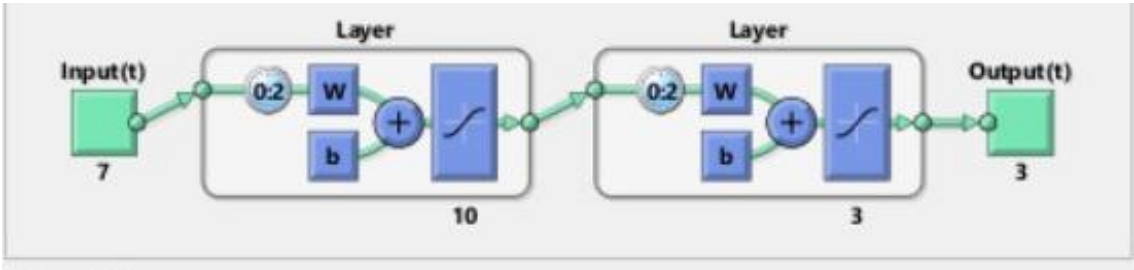


Figure 5.86 N4P2T2 ANN model

Training-state plots for the selected N4P2T2 model in Figure 5.87 showed smooth convergence of the validation SSE, with the best validation performance reached after about 28 epochs and no signs of divergence or severe overfitting, as indicated by the limited number of validation failures.

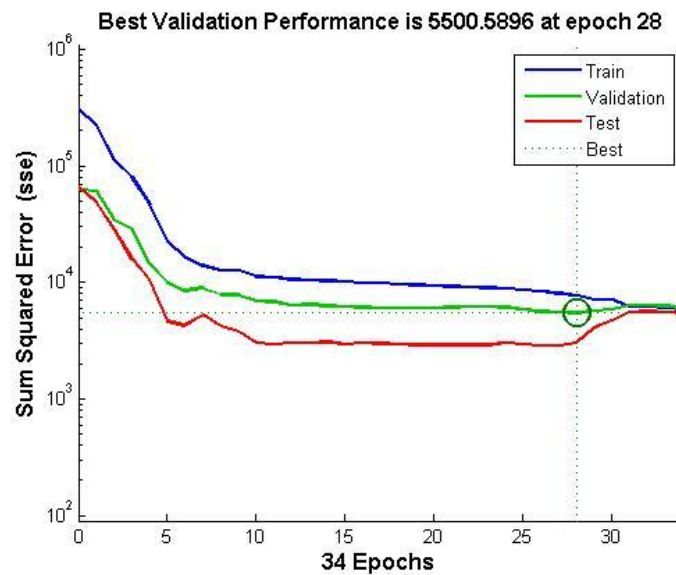


Figure 5.87 Training state plots for the selected N4P2T2 ANN model

CHAPTER 6. CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

In the present work, experimental and ANN-based investigations were carried out on AISI 1040 turning under thirteen cooling strategies, ranging from dry and wet cutting to MQL with Al_2O_3 , ZnO , and Al_2O_3 - ZnO hybrid nanofluids, where RSM-based Box–Behnken models and multi-response desirability optimization were used to quantify and optimize output responses, and an ANN model was subsequently developed and selected based on minimum prediction error and high R^2 for reliable prediction of cooling-condition performance.

1. The RSM-based Box–Behnken designs were applied independently to all thirteen cooling conditions (Cases A-H2), and ANOVA confirmed that the models for cutting force, cutting temperature, and surface roughness are statistically significant in every case. The models exhibit high R^2 and adjusted R^2 (typically above 0.95), with acceptable predicted R^2 ; normal probability and residual–predicted plots show no serious violations of normality or constant variance; and perturbation and response-surface plots closely follow experimental trends, demonstrating that the RSM models are satisfactory and reliable.
2. Feed rate and depth of cut are the main elements leading to increased cutting force, cutting temperature, and surface roughness. Conversely, the cutting speed had a moderate yet significant and more complex effect. Higher feed markedly increases chip thickness, leading to large rises in force, temperature, and roughness, while higher depth of cut mainly amplifies cutting force via larger chip cross-section and contact length and also tends to increase temperature and roughness; cutting speed tends to improve R_a at moderate levels by reducing built-up edge but raises temperature and slightly lowers force due to thermal softening.
3. Selection between Al_2O_3 and ZnO nanofluids can be made on the basis that Al_2O_3 is

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preferable for surface integrity and lower forces. At the same time, ZnO is more effective for thermal management at high speed. Al₂O₃ nanofluid yields consistently lower surface roughness and cutting force due to its tribological behavior (formation of a load-bearing tribofilm and micro-rolling/polishing effect), whereas ZnO-based nanofluids reduce cutting temperature more strongly thanks to higher thermal conductivity; an intermediate concentration around 1 wt% gives the best overall performance, while higher loadings (1.5-2 wt%) increase viscosity and agglomeration, degrading lubrication.

4. A multi-response desirability index with equal weighting of output responses (smaller is better) ranks MQL with 1 wt% hybrid Al₂O₃-ZnO (75/25, Case H1) as the most suitable lubrication condition among the thirteen cases. Case H1 provides the globally lowest surface roughness (about 1.6 μm) together with moderately low force and temperature compared with both mono-nanofluid and conventional conditions, demonstrating a clear synergistic effect between Al₂O₃ and ZnO nanoparticles on mechanical (force, Ra) and thermal (temperature) performance.
5. Desirability Function Analysis coupled with RSM identified the optimal cutting parameters for Case-H1 when cutting speed is 107.55 m/min, feed is 0.11 mm/rev, and depth of cut is 0.2 mm. Confirmation experiments at this setting showed low prediction errors (about 8.23% for cutting force, 6.83% for cutting temperature, and 3.56% for surface roughness), confirming that the developed RSM models and DFA-based optimization provide accurate and practically useful predictions.
6. At the same optimum input condition, Case H1 (hybrid nanofluid MQL) achieves reductions of approximately 25.1%, 18.26% and 16.33% in cutting force, cutting temperature, and surface roughness, respectively, when compared with dry cutting (Case A).
7. Among all ANN architectures evaluated, the best-performing model for predicting cooling-condition performance is the N4P2T2 configuration, i.e., a feed-forward distributed time-delay network with TANSIG transfer function and 10 hidden layer neurons.

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6.2 Future scope

Results are limited to the tested ranges of speed, feed, and depth of cut, one workpiece, one tool, and one MQL setup, and only consider force, temperature, and roughness; tool wear, residual stresses, nanofluid stability, and full cost/environmental assessment were not evaluated.

Future research may extend the present work by exploring wider ranges of cutting parameters, different tool geometries and wear conditions, and hard-to-machine alloys and coated tools, as well as by generalizing the methodology to other machining processes, including milling, drilling, and grinding. In parallel, nanofluid formulations can be further optimized by varying nanoparticle concentration, employing alternative base oils, and developing more complex systems such as tri-hybrid nanoparticle mixtures to enhance stability, cooling, and lubrication performance.

Furthermore, integrating advanced optimization schemes and AI-based predictive models with comprehensive sustainability, economic, and health-impact assessments would support the industrial-scale implementation of hybrid nanofluid MQL as a practical, green machining technology and a sustainable manufacturing approach.

List of References

- [1] A. J. P, A. Xavior, and R. Scholar, ““Influence Of Nano Lubrication In Machining Operations-A Review,”” *Mater. Today Proc.*, vol. 5, pp. 11185–11192, 2018, doi: 10.1016/j.matpr.2018.01.142.
- [2] V. S. Sharma, G. Singh, and K. Sorby, “A review on minimum quantity lubrication for machining processes,” *Materials and Manufacturing Processes*, vol. 30, no. 8, pp. 935–953, Aug. 2015, doi: 10.1080/10426914.2014.994759.
- [3] A. K. Sharma, A. K. Tiwari, and A. R. Dixit, “Effects of Minimum Quantity Lubrication (MQL) in machining processes using conventional and nanofluid-based cutting fluids: A comprehensive review,” Jul. 20, 2016, *Elsevier Ltd.* doi: 10.1016/j.jclepro.2016.03.146.
- [4] N. Madanchi, D. Kurle, M. Winter, S. Thiede, and C. Herrmann, “Energy efficient process chain: The impact of cutting fluid strategies,” *Procedia CIRP*, vol. 29, pp. 360–365, 2015, doi: 10.1016/j.procir.2015.02.056.
- [5] I. P. Okokpujie, C. A. Bolu, O. S. Ohunakin, E. T. Akinlabi, and D. S. Adelekan, “A review of recent application of machining techniques, based on the phenomena of CNC machining operations,” in *Procedia Manufacturing*, Elsevier B.V., 2019, pp. 1054–1060. doi: 10.1016/j.promfg.2019.06.056.
- [6] L. V. Suryam, A. V. Pradeep, S. V. Satya Prasad, and P. Prasanna Kumari, “Functioning mechanism of nanomaterials and significance on machinability: A review,” in *Materials Today: Proceedings*, Elsevier Ltd, 2019, pp. 560–563. doi: 10.1016/j.matpr.2019.07.733.
- [7] A. NALBANDH, N. CHAVDA, and R. BUMATARIA, “Current research aspects in minimum quantity lubrication for turning operations: Cutting fluid as mono and hybrid nanofluid,” *Sigma Journal of Engineering and Natural Sciences – Sigma*

List of References

- Mühendislik ve Fen Bilimleri Dergisi*, vol. 44, no. 2, pp. 1344–1368, Apr. 2026, doi: 10.14744/sigma.2026.2041.
- [8] N. R. Dhar, M. Kamruzzaman, and M. Ahmed, “Effect of minimum quantity lubrication (MQL) on tool wear and surface roughness in turning AISI-4340 steel,” *J. Mater. Process. Technol.*, vol. 172, no. 2, pp. 299–304, 2006, doi: 10.1016/j.jmatprotec.2005.09.022.
- [9] N. R. Dhar, M. W. Islam, S. Islam, and M. A. H. Mithu, “The influence of minimum quantity of lubrication (MQL) on cutting temperature, chip and dimensional accuracy in turning AISI-1040 steel,” *J. Mater. Process. Technol.*, vol. 171, no. 1, pp. 93–99, Jan. 2006, doi: 10.1016/j.jmatprotec.2005.06.047.
- [10] C. Bruni, A. Forcellese, F. Gabrielli, and M. Simoncini, “Effect of the lubrication-cooling technique, insert technology and machine bed material on the workpart surface finish and tool wear in finish turning of AISI 420B,” *Int. J. Mach. Tools Manuf.*, vol. 46, no. 12–13, pp. 1547–1554, 2006, doi: 10.1016/j.ijmachtools.2005.09.007.
- [11] N. R. Dhar, M. T. Ahmed, and S. Islam, “An experimental investigation on effect of minimum quantity lubrication in machining AISI 1040 steel,” *Int. J. Mach. Tools Manuf.*, vol. 47, no. 5 SPEC. ISS., pp. 748–753, 2007, doi: 10.1016/j.ijmachtools.2006.09.017.
- [12] J. P. Davim, P. S. Sreejith, and J. Silva, “Turning of brasses using minimum quantity of lubricant (MQL) and flooded lubricant conditions,” *Materials and Manufacturing Processes*, vol. 22, no. 1, pp. 45–50, 2007, doi: 10.1080/10426910601015881.
- [13] M. M. A. Khan, M. A. H. Mithu, and N. R. Dhar, “Effects of minimum quantity lubrication on turning AISI 9310 alloy steel using vegetable oil-based cutting fluid,” *J. Mater. Process. Technol.*, vol. 209, no. 15–16, pp. 5573–5583, 2009, doi: 10.1016/j.jmatprotec.2009.05.014.
- [14] Y. K. Hwang and C. M. Lee, “Surface roughness and cutting force prediction in MQL and wet turning process of AISI 1045 using design of experiments,” *Journal of*

List of References

- Mechanical Science and Technology*, vol. 24, no. 8, pp. 1669–1677, 2010, doi: 10.1007/s12206-010-0522-1.
- [15] T. Leppert, “Effect of cooling and lubrication conditions on surface topography and turning process of C45 steel,” *Int. J. Mach. Tools Manuf.*, vol. 51, no. 2, pp. 120–126, 2011, doi: 10.1016/j.ijmachtools.2010.11.001.
- [16] C. H. Che Haron, J. A. Ghani, M. S. Kasim, T. K. Soon, A. I. Gusri, and M. A. Sulaiman, “Surface integrity of Inconel 718 under MQL condition,” in *Advanced Materials Research*, 2011, pp. 1667–1672. doi: 10.4028/www.scientific.net/AMR.150-151.1667.
- [17] T. Leppert, “Surface layer properties of AISI 316L steel when turning under dry and with minimum quantity lubrication conditions,” *Proc. Inst. Mech. Eng. B J. Eng. Manuf.*, vol. 226, no. 4, pp. 617–631, Apr. 2012, doi: 10.1177/0954405411429894.
- [18] D. V. Lohar and C. R. Nanavaty, “Performance Evaluation of Minimum Quantity Lubrication (MQL) using CBN Tool during Hard Turning of AISI 4340 and its Comparison with Dry and Wet Turning,” *Bonfring International Journal of Industrial Engineering and Management Science*, vol. 3, no. 3, pp. 102–106, 2013, doi: 10.9756/bijiems.4392.
- [19] M. Hadad and B. Sadeghi, “Minimum quantity lubrication-MQL turning of AISI 4140 steel alloy,” *J. Clean. Prod.*, vol. 54, pp. 332–343, 2013, doi: 10.1016/j.jclepro.2013.05.011.
- [20] A. Saini, S. Dhiman, R. Sharma, and S. Setia, “Experimental estimation and optimization of process parameters under minimum quantity lubrication and dry turning of AISI-4340 with different carbide inserts,” *Journal of Mechanical Science and Technology*, vol. 28, no. 6, pp. 2307–2318, 2014, doi: 10.1007/s12206-014-0521-8.
- [21] S. M. Agrawal and N. G. Patil, “Experimental study of non edible vegetable oil as a cutting fluid in machining of M2 Steel using MQL,” in *Procedia Manufacturing*, Elsevier B.V., 2018, pp. 207–212. doi: 10.1016/j.promfg.2018.02.030.

List of References

- [22] Globočki. Lakić. Gordana, Sredanović. Branislav, Kramar. Davorin, Nedić. Bogdan, and Kopač. Janez, “Effects of Using of Mql Technique in Metal,” in *13th International Conference on Tribology*, 2013, pp. 292–301.
- [23] Z. Q. Liu, J. Xu, S. Han, and M. Chen, “A coupling method of response surfaces (CRSM) for cutting parameters optimization in machining titanium alloy under minimum quantity lubrication (MQL) condition,” *International Journal of Precision Engineering and Manufacturing*, vol. 14, no. 5, pp. 693–702, 2013, doi: 10.1007/s12541-013-0093-z.
- [24] S. Masoudi, A. Vafadar, M. Hadad, and F. Jafarian, “Experimental investigation into the effects of nozzle position, workpiece hardness, and tool type in MQL turning of AISI 1045 steel,” *Materials and Manufacturing Processes*, vol. 33, no. 9, pp. 1011–1019, Jul. 2018, doi: 10.1080/10426914.2017.1401716.
- [25] P. Sivaiah, V. Ajay Kumar G, M. Singh M, and H. Kumar, “Effect of novel hybrid texture tool on turning process performance in MQL machining of Inconel 718 superalloy,” *Materials and Manufacturing Processes*, vol. 35, no. 1, pp. 61–71, Jan. 2020, doi: 10.1080/10426914.2019.1697444.
- [26] G. Singh, V. Aggarwal, and S. Singh, “Experimental investigations into machining performance of Hastelloy C-276 in different cooling environments,” *Materials and Manufacturing Processes*, vol. 36, no. 15, pp. 1789–1799, 2021, doi: 10.1080/10426914.2021.1945099.
- [27] N. S. Bhadoria and G. Bartarya, “On the improvement in process performance of ceramic inserts during hard turning in MQL environment,” *Materials and Manufacturing Processes*, 2021, doi: 10.1080/10426914.2021.1967978.
- [28] P. Sivaiah, M. Guru Prasad, M. Singh M, and B. Uma, “Machinability evaluation during machining of AISI 52100 steel with textured tools under Minimum Quantity Lubrication—A comparative study,” *Materials and Manufacturing Processes*, vol. 35, no. 15, pp. 1761–1768, Nov. 2020, doi: 10.1080/10426914.2020.1802034.
- [29] P. Sivaiah, V. Ajay kumar G, K. Lakshmi Narasimhamu, and N. Siva Balaji, “Performance improvement of turning operation during processing of AISI 304 with

List of References

- novel textured tools under minimum quantity lubrication using hybrid optimization technique,” *Materials and Manufacturing Processes*, 2021, doi: 10.1080/10426914.2021.1967977.
- [30] Mst. Nazma Sultana, N. Ranjan Dhar, and P. Binte Zaman, “A Review on Different Cooling/Lubrication Techniques in Metal Cutting,” *American Journal of Mechanics and Applications*, vol. 7, no. 4, p. 71, 2019, doi: 10.11648/j.ajma.20190704.11.
- [31] P. V. Krishna, R. R. Srikant, and D. Nageswara Rao, “Experimental investigation on the performance of nanoboric acid suspensions in SAE-40 and coconut oil during turning of AISI 1040 steel,” *Int. J. Mach. Tools Manuf.*, vol. 50, no. 10, pp. 911–916, Oct. 2010, doi: 10.1016/j.ijmachtools.2010.06.001.
- [32] S. N. Rao, B. Satyanarayana, and K. Venkatasubbaiah, “Experimental estimation of tool wear and cutting temperatures in MQL using cutting fluids with CNT inclusion,” *International Journal of Engineering Science and Technology*, vol. 3, no. 4, pp. 2928–2931, Apr. 2011.
- [33] V. Vasu and G. P. K. Reddy, “Effect of minimum quantity lubrication with Al₂O₃ nanoparticles on surface roughness, tool wear and temperature dissipation in machining Inconel 600 alloy,” in *Proceedings of the Institution of Mechanical Engineers, Part N: Journal of Nanoengineering and Nanosystems*, Mar. 2012, pp. 3–15. doi: 10.1177/1740349911427520.
- [34] S. Khandekar, M. R. Sankar, V. Agnihotri, and J. Ramkumar, “Nano-cutting fluid for enhancement of metal cutting performance,” *Materials and Manufacturing Processes*, vol. 27, no. 9, pp. 963–967, Sep. 2012, doi: 10.1080/10426914.2011.610078.
- [35] M. Amrita, R. R. Srikant, A. V. Sitaramaraju, M. M. S. Prasad, and P. V. Krishna, “Experimental investigations on influence of mist cooling using nanofluids on machining parameters in turning AISI 1040 steel,” *Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology*, vol. 227, no. 12, pp. 1334–1346, Dec. 2013, doi: 10.1177/1350650113491934.

List of References

- [36] M. Amrita, S. A. Shariq, M. Manoj, and C. Gopal, "Experimental investigation on application of emulsifier oil based nano cutting fluids in metal cutting process," *Procedia Eng.*, vol. 97, pp. 115–124, 2014, doi: 10.1016/j.proeng.2014.12.231.
- [37] M. Sayuti, A. A. D. Sarhan, and F. Salem, "Novel uses of SiO₂ nano-lubrication system in hard turning process of hardened steel AISI4140 for less tool wear, surface roughness and oil consumption," *J. Clean. Prod.*, vol. 67, pp. 265–276, Mar. 2014, doi: 10.1016/j.jclepro.2013.12.052.
- [38] M. R. Shabgard, M. J. Zenjanab, and R. Azarafza, "Experimental study on the influence of CuO nanofluid on surface roughness and machining force in turning of AISI 4340 steel," *Modares Mechanical Engineering*, vol. 14, no. 2, pp. 27–33, 2014.
- [39] A. N. M. Khalil, M. A. M. Ali, and A. I. Azmi, "Effect of Al₂O₃ Nanolubricant with SDBS on Tool Wear During Turning Process of AISI 1050 with Minimal Quantity Lubricant," *Procedia Manuf.*, vol. 2, no. February, pp. 130–134, 2015, doi: 10.1016/j.promfg.2015.07.023.
- [40] K. Ganesan, M. Naresh Babu, M. Santhanakumar, and N. Muthukrishnan, "Experimental investigation of copper nanofluid based minimum quantity lubrication in turning of H 11 steel," *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, vol. 40, no. 3, 2018, doi: 10.1007/s40430-018-1093-9.
- [41] A. Das, S. K. Patel, M. Arakha, A. Dey, and B. B. Biswal, "Processing of hardened steel by MQL technique using nano cutting fluids," *Materials and Manufacturing Processes*, vol. 36, no. 3, pp. 316–328, 2021, doi: 10.1080/10426914.2020.1832688.
- [42] P. Sharma, B. S. Sidhu, and J. Sharma, "Investigation of effects of nanofluids on turning of AISI D2 steel using minimum quantity lubrication," *J. Clean. Prod.*, vol. 108, pp. 72–79, Dec. 2015, doi: 10.1016/j.jclepro.2015.07.122.
- [43] A. K. Sharma, A. K. Tiwari, R. K. Singh, and A. R. Dixit, "Tribological Investigation of TiO₂ Nanoparticle based Cutting Fluid in Machining under Minimum Quantity Lubrication (MQL)," *Mater. Today Proc.*, vol. 3, no. 6, pp. 2155–2162, 2016, doi: 10.1016/j.matpr.2016.04.121.

List of References

- [44] A. K. Sharma, R. K. Singh, A. R. Dixit, and A. K. Tiwari, "Characterization and experimental investigation of Al₂O₃ nanoparticle based cutting fluid in turning of AISI 1040 steel under minimum quantity lubrication (MQL)," *Mater. Today Proc.*, vol. 3, no. 6, pp. 1899–1906, 2016, doi: 10.1016/j.matpr.2016.04.090.
- [45] M. K. Gupta, P. K. Sood, and V. S. Sharma, "Optimization of machining parameters and cutting fluids during nano-fluid based minimum quantity lubrication turning of titanium alloy by using evolutionary techniques," *J. Clean. Prod.*, vol. 135, pp. 1276–1288, 2016, doi: 10.1016/j.jclepro.2016.06.184.
- [46] U. M. R. Paturi, Y. R. Maddu, R. R. Maruri, and S. K. R. Narala, "Measurement and Analysis of Surface Roughness in WS₂ Solid Lubricant Assisted Minimum Quantity Lubrication (MQL) Turning of Inconel 718," *Procedia CIRP*, vol. 40, pp. 138–143, 2016, doi: 10.1016/j.procir.2016.01.082.
- [47] P. Rapeti, V. K. Pasam, K. M. Rao Gurram, and R. S. Revuru, "Performance evaluation of vegetable oil based nano cutting fluids in machining using grey relational analysis-A step towards sustainable manufacturing," *J. Clean. Prod.*, vol. 172, pp. 2862–2875, Aug. 2016, doi: 10.1016/j.jclepro.2017.11.127.
- [48] P. B. Patole and V. V. Kulkarni, "Experimental investigation and optimization of cutting parameters with multi response characteristics in MQL turning of AISI 4340 using nano fluid," *Cogent Eng.*, vol. 4, no. 1, 2017, doi: 10.1080/23311916.2017.1303956.
- [49] R. K. Singh *et al.*, "Influence of graphene-based nanofluid with minimum quantity lubrication on surface roughness and cutting temperature in turning operation," *Mater. Today Proc.*, vol. 5, pp. 24578–24586, 2018, doi: 10.1016/j.matpr.2018.10.255.
- [50] K. K. Joshi, R. K. Behera, and Anurag, "Effect of minimum quantity lubrication with Al₂O₃ Nanofluid on Surface Roughness and its prediction using hybrid fuzzy controller in turning operation of Inconel 600," 2018. doi: 10.1016/j.matpr.2018.06.449.

List of References

- [51] A. V. Vishnu, P. J. Kumar, and M. Venkata Ramana, "Comparison among Dry, Flooded and MQL Conditions in Machining of EN 353 Steel Alloys-An Experimental Investigation," *Mater. Today Proc.*, vol. 5, pp. 24954–24962, 2018, doi: 10.1016/j.matpr.2018.10.296.
- [52] V. K. Pasam, R. R. Srikant, and S. Gugulothu, "Comparing the performance & viability of nano and microfluids in minimum quantity lubrication for machining AISI1040 steel," in *Materials Today: Proceedings*, Elsevier Ltd, 2018, pp. 8016–8024. doi: 10.1016/j.matpr.2017.11.486.
- [53] V. Sivalingam *et al.*, "Use of Atomized Spray Cutting Fluid Technique for the Turning of a Nickel Base Superalloy," *Materials and Manufacturing Processes*, vol. 36, no. 3, pp. 373–380, 2021, doi: 10.1080/10426914.2020.1832687.
- [54] K. Venkatesan, S. Devendiran, K. Nishanth Purusotham, and V. S. Praveen, "Study of machinability performance of Hastelloy-X for nanofluids, dry with coated tools," *Materials and Manufacturing Processes*, vol. 35, no. 7, pp. 751–761, May 2020, doi: 10.1080/10426914.2020.1729990.
- [55] K. V. Ramanan, S. Ramesh Babu, M. Jebaraj, and K. Nimel Sworna Ross, "Face turning of Incoloy 800 under MQL and nano-MQL environments," *Materials and Manufacturing Processes*, vol. 36, no. 15, pp. 1769–1780, 2021, doi: 10.1080/10426914.2021.1944191.
- [56] S. M. Nikouei, M. R. Razfar, and M. Khajehzadeh, "Influence of nanoparticles' size on Inconel 718 machining induced residual stresses," *Materials and Manufacturing Processes*, 2021, doi: 10.1080/10426914.2021.2016821.
- [57] R. Padmini, P. Vamsi Krishna, and G. Krishna Mohana Rao, "Effectiveness of vegetable oil based nanofluids as potential cutting fluids in turning AISI 1040 steel," *Tribol. Int.*, vol. 94, pp. 490–501, Feb. 2016, doi: 10.1016/j.triboint.2015.10.006.
- [58] A. K. Sharma, A. K. Tiwari, A. R. Dixit, and R. K. Singh, "Investigation into Performance of SiO₂ Nanoparticle Based Cutting Fluid in Machining Process," *Mater. Today Proc.*, vol. 4, no. 2, pp. 133–141, 2017, doi: 10.1016/j.matpr.2017.01.006.

List of References

- [59] Y. Shokoohi and E. Shekarian, “Application of nanofluids in machining processes-A review,” 2016.
- [60] Z. Said *et al.*, “A comprehensive review on minimum quantity lubrication (MQL) in machining processes using nano-cutting fluids,” *International Journal of Advanced Manufacturing Technology*, vol. 105, no. 5–6, pp. 2057–2086, Dec. 2019, doi: 10.1007/s00170-019-04382-x.
- [61] V. Singh, A. K. Sharma, R. K. Sahu, and J. K. Katiyar, “State of the art on sustainable manufacturing using mono/hybrid nano-cutting fluids with minimum quantity lubrication,” *Materials and Manufacturing Processes*, pp. 1–37, Feb. 2022, doi: 10.1080/10426914.2022.2032147.
- [62] A. Khudaiwala, R. L. Patel, and R. Bumataria, “Recent developments in thermal management of light-emitting diodes (LEDs): A review,” *Journal of Thermal Engineering*, vol. 10, no. 2, pp. 517–540, Mar. 2024, doi: 10.18186/thermal.1457052.
- [63] A. K. Sharma, R. K. Singh, A. R. Dixit, and A. K. Tiwari, “Novel uses of alumina-MoS₂ hybrid nanoparticle enriched cutting fluid in hard turning of AISI 304 steel,” *J. Manuf. Process.*, vol. 30, pp. 467–482, Dec. 2017, doi: 10.1016/j.jmapro.2017.10.016.
- [64] R. K. Singh, A. K. Sharma, A. R. Dixit, A. K. Tiwari, A. Pramanik, and A. Mandal, “Performance evaluation of alumina-graphene hybrid nano-cutting fluid in hard turning,” *J. Clean. Prod.*, vol. 162, pp. 830–845, Sep. 2017, doi: 10.1016/j.jclepro.2017.06.104.
- [65] A. K. Sharma, A. K. Tiwari, A. R. Dixit, R. K. Singh, and M. Singh, “Novel uses of alumina/graphene hybrid nanoparticle additives for improved tribological properties of lubricant in turning operation,” *Tribol. Int.*, vol. 119, no. September 2017, pp. 99–111, 2018, doi: 10.1016/j.triboint.2017.10.036.
- [66] M. Jamil *et al.*, “Effects of hybrid Al₂O₃-CNT nanofluids and cryogenic cooling on machining of Ti-6Al-4V,” *International Journal of Advanced Manufacturing Technology*, vol. 102, no. 9–12, pp. 3895–3909, 2019, doi: 10.1007/s00170-019-03485-9.

List of References

- [67] Ç. V. Yıldırım, “Experimental comparison of the performance of nanofluids, cryogenic and hybrid cooling in turning of Inconel 625,” *Tribol. Int.*, vol. 137, pp. 366–378, Sep. 2019, doi: 10.1016/j.triboint.2019.05.014.
- [68] A. Thakur, A. Manna, and S. Samir, “Performance Evaluation of Different Environmental Conditions on Output Characteristics During Turning of EN-24 Steel,” *International Journal of Precision Engineering and Manufacturing*, vol. 20, no. 10, pp. 1839–1849, Oct. 2019, doi: 10.1007/s12541-019-00179-w.
- [69] A. Thakur, A. Manna, and S. Samir, “Experimental investigation of nanofluids in minimum quantity lubrication during turning of EN-24 steel,” *Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology*, vol. 234, no. 5, pp. 712–729, May 2019, doi: 10.1177/1350650119878286.
- [70] S. Gugulothu and V. K. Pasam, “Experimental investigation to study the performance of CNT/MoS₂ hybrid nanofluid in turning of AISI 1040 steel,” *Australian Journal of Mechanical Engineering*, 2020, doi: 10.1080/14484846.2020.1756067.
- [71] P. B. Zaman, M. I. H. Tusar, and N. R. Dhar, “Selection of appropriate process inputs for turning Ti-6Al-4V alloy under hybrid Al₂O₃-MWCNT nano-fluid based MQL,” *Advances in Materials and Processing Technologies*, 2020, doi: 10.1080/2374068X.2020.1812324.
- [72] M. Sandeep Kumar, V. Vasu, and A. Venu Gopal, “Investigation of Influence of Hybrid Nanofluid/MQL on Surface Roughness in Turning Inconel-718,” *Advances in Applied Mechanical Engineering*, pp. 1137–1145, 2020, doi: http://doi.org/10.1007/978-981-15-1201-8_120.
- [73] M. Sandeep Kumar, V. Murali Krishna, and M. Kumar, “Investigation on influence of Hybrid Biodegradable Nanofluids (CuO-ZnO) on Surface Roughness in Turning AISI 1018 Steel,” 2020. doi: 10.1016/j.matpr.2020.04.477.
- [74] M. H. Esfe, M. Bahiraei, and A. Mir, “Application of conventional and hybrid nanofluids in different machining processes: A critical review,” Aug. 01, 2020, *Elsevier B.V.* doi: 10.1016/j.cis.2020.102199.

List of References

- [75] A. A. Junankar *et al.*, “A Review: Enhancement of turning process performance by effective utilization of hybrid nanofluid and MQL,” *Mater. Today Proc.*, Jun. 2020, doi: 10.1016/j.matpr.2020.05.603.
- [76] H. Hegab, H. A. Kishawy, and B. Darras, “Sustainable cooling and lubrication strategies in machining processes: A comparative study,” in *Procedia Manufacturing*, Elsevier B.V., 2019, pp. 786–793. doi: 10.1016/j.promfg.2019.04.099.
- [77] K. P. Sodavadia and A. H. Makwana, “Experimental Investigation on the Performance of Coconut oil Based Nano Fluid as Lubricants during Turning of AISI 304 Austenitic Stainless Steel,” 2014. [Online]. Available: <http://www.ripublication.com/ijame.htm>
- [78] D. C. Montgomery, *Design and analysis of experiments*, 8th ed. Hoboken NJ: John Wiley & Sons, Inc., 2013.
- [79] S. R. Kandavalli *et al.*, “Application of sophisticated sensors to advance the monitoring of machining processes: analysis and holistic review,” *The International Journal of Advanced Manufacturing Technology*, vol. 125, no. 3–4, pp. 989–1014, Mar. 2023, doi: 10.1007/s00170-022-10771-6.
- [80] F. Günan, T. Kivak, Ç. V. Yıldırım, and M. Sarıkaya, “Performance evaluation of MQL with AL₂O₃ mixed nanofluids prepared at different concentrations in milling of Hastelloy C276 alloy,” *Journal of Materials Research and Technology*, vol. 9, no. 5, pp. 10386–10400, Sep. 2020, doi: 10.1016/j.jmrt.2020.07.018.
- [81] Z. Said *et al.*, “Recent advances on the fundamental physical phenomena behind stability, dynamic motion, thermophysical properties, heat transport, applications, and challenges of nanofluids,” Feb. 02, 2022, *Elsevier B.V.* doi: 10.1016/j.physrep.2021.07.002.
- [82] O. Özbek, N. Altan Özbek, F. Kara, and H. Saruhan, “Effect of vibration and cutting zone temperature on surface topography during hybrid cooling/lubrication assisted machining of Vanadis 10,” *Materials Testing*, vol. 65, no. 9, pp. 1437–1452, Sep. 2023, doi: 10.1515/mt-2023-0057.

List of References

- [83] Fethi Khelifaoui, M. A. Yallese, N. Ouelaa, S. Chihaoui, and S. Belhadi, “Statistical analysis, modeling and multi-objective optimization of parameters intermittent turning process of AISI D3,” *Journal of Mechanical Engineering and Sciences*, pp. 9492–9506, Jun. 2023, doi: 10.15282/jmes.17.2.2023.8.0752.
- [84] R. V Prasad, R. Rajesh, D. Thirumalaikumarasamy, M. Ashokkumar, and S. Rajakumar, “Multi response optimization of HVOF process parameters in low carbon steels,” *Sādhana*, vol. 47, no. 4, p. 265, Dec. 2022, doi: 10.1007/s12046-022-02045-4.
- [85] P. Kanti, K. V. Sharma, K. M. Yashawantha, and S. Dmk, “Experimental determination for viscosity of fly ash nanofluid and fly ash-Cu hybrid nanofluid: Prediction and optimization using artificial intelligent techniques,” *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 47, no. 2, Dec. 2025, doi: 10.1080/15567036.2021.1877374.
- [86] F. Kara, A. Takmaz, Ö. Erkan, and S. Filiz, “Response Surface Method Optimization of Hard Machining with Cryogenically Treated Cutting Tools: Surface Roughness, Cutting Force, Tool Wear, Rietveld Analysis, and Metallurgical Properties,” *Steel Res. Int.*, vol. 96, no. 7, Jul. 2025, doi: 10.1002/srin.202400850.
- [87] A. Ercetin, K. Aslantaş, Ö. Özgün, M. Perçin, and M. P. G. Chandrashekarappa, “Optimization of Machining Parameters to Minimize Cutting Forces and Surface Roughness in Micro-Milling of Mg13Sn Alloy,” *Micromachines (Basel)*, vol. 14, no. 8, p. 1590, Aug. 2023, doi: 10.3390/mi14081590.
- [88] E. M. Gutema, M. Gopal, and H. G. Lemu, “Minimization of Surface Roughness and Temperature during Turning of Aluminum 6061 Using Response Surface Methodology and Desirability Function Analysis,” *Materials*, vol. 15, no. 21, p. 7638, Oct. 2022, doi: 10.3390/ma15217638.

List of Publications

List of Research Paper(s)

1. **A. H. Nalbandh**, N. K. Chavda, and R. K. Bumataria, “Response Surface Methodology-based Modeling and Optimization of AISI 1040 Turning Using Al₂O₃ and ZnO Nanofluids Under Minimum Quantity Lubrication,” *Journal of Environmental Nanotechnology*, vol. 15(1), March, pp. 603–615, 2026. <https://doi.org/10.13074/jent.2026.03.2612063> (Scopus)
2. **A. H. Nalbandh**, N. K. Chavda, and R. K. Bumataria, “Comparative Study of Mono and Hybrid Nanofluids in MQL Turning of AISI 1040 Steel Using Box–Behnken RSM Approach,” *International Journal of Technology & Emerging Research*, vol. 2(4), April, pp. 26–44, 2026. <https://doi.org/10.64823/ijter.2604004> (Academia)
3. **A. H. Nalbandh**, N. K. Chavda, and R. K. Bumataria, “Current research aspects in minimum quantity lubrication for turning operations: Cutting fluid as mono and hybrid nanofluid,” *Sigma Journal of Engineering and Natural Science*, vol. 44(2), April, pp. 1344–1368, 2026. <https://doi.org/10.14744/sigma.2026.2041> (ESCI, Scopus)
4. **A. H. Nalbandh**, N. K. Chavda, and R. K. Bumataria, “Performance Analysis of AISI 1040 Steel Turning Under Al₂O₃–ZnO Hybrid Nanofluid MQL Using Response Surface Methodology - A Step Towards Sustainable Machining,” *Journal of Materials and Engineering*, vol. 4(2), pp. 155–168, 2026. <https://doi.org/10.61552/JME.2026.02.003> (DOAJ)

List of Patent(s)

1. **Nalbandh, A. H.**, Chavda N. K., Bumataria, R. K. Nandaniya M. P., GTU, A System and Method for Minimum Quantity Lubrication Incorporating a Dual-Nanoparticle Cutting Fluid Composition and its Synthesis for Turning Operations, Patent journal: 27/2025 dated: 04/07/2025, No.202521056040A.

Appendices

Appendix A- Calibration Certificate



RMS CONTROLS

(Mfrs/ Dealers in : Electronic Instruments, Sensors, LAB Equipment, PLC Automation Control Panel)
 1/3A, 2nd Floor, 11th Cross Street, Venkateshwara Nagar, Ramapuram, Chennai - 600 089.
 Ph. : 044-24760086, 96772 35931 | E-mail : rmscontrols96@gmail.com web : www.rmscontrols.in

TIN NO. : 33350845642
 GSTIN : 33AUWPM2681F1ZA

LATHE TOOL DYNAMOMETER CALIBRATION CERTIFICATE

Client :
Mr. Altaf H. Nalbandh,
 A-115, Mechanical Engineering Department,
 Government Polytechnic,
 O/P Aerodrome, NH-27,
 Porbandar-360577
 Gujarat

Certificate No. RMS/20/2023-24

Test Instruments Details

Instrument	Lathe Tool Dynamometer
Make	RMS Controls
Model	Strain Gauge Based
Sl. No.	2307001
Capacity	0-500Kgf

Date of Calibration	05.07.2023
Next Due Date	05.07.2024
Temperature	25+/-2°C
Humidity	45% - 55%

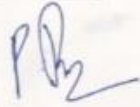
Standard Instruments Details

Certificate No	Make	Model	Description	Traceability	Validity
Cal/E/022	RMS Controls	-----	Prove Ring kg	(NABL)	26.11.2023

Calibration Result

S.NO	PROVE RING MASTER LOAD KGF	X-AXIS(KGF)	Y-AXIS(KGF)	Z-AXIS(KGF)
1	0	0	0	0
2	100.0	100.0	100.0	100.0
3	200.0	200.0	200.5	200.0
4	300.0	300.5	300.0	300.5
5	400.0	400.0	400.0	400.5
6	500.0	500.0	500.5	500.5

Calibrated By. 

Verified By. 
 P. RAJI (Manager)





ULR-CC101421000017739F

Lab ID : 00638/23/1

P. R. CHAVDA

Appendices

Appendix B- Nanoparticles mass calculations

Calculation for weight concentration:

$$\phi_w = \frac{[W_p]}{[W_p + W_b]} \times 100\%$$

For 1.0 w%:

$$\phi_w = \frac{[W_p]}{[W_p + W_b]} \times 100\% = 1.0\% \Rightarrow 100 \times W_p = [W_p + W_b] \Rightarrow \boxed{W_p = \frac{W_b}{99}}$$

For 2.0 w%:

$$\phi_w = \frac{[W_p]}{[W_p + W_b]} \times 100\% = 2.0\% \Rightarrow 100 \times W_p = [W_p + W_b] \Rightarrow \boxed{W_p = \frac{W_b}{98}}$$

Table Property table of different materials as per supplier's data

Property	Al ₂ O ₃	ZnO
Density (g/cm ³)	3.97	4.97

Sample calculation of volume concentration:

For Al₂O₃:

$$\begin{aligned} \phi_v &= \frac{\left[\frac{W_b}{99 \times 3.97} \right]}{\left[\frac{W_b}{99 \times 3.97} + \frac{W_b}{1} \right]} \times 100\% = \frac{\left[\frac{W_b}{393.03} \right]}{\left[\frac{W_b}{393.03} + \frac{W_b}{1} \right]} \times 100\% = \frac{\left[\frac{1}{393.03} \right]}{\left[\frac{1}{393.03} + \frac{1}{1} \right]} \times 100\% \\ &= \frac{1}{1 + 393.03} \times 100\% = 0.25\% \end{aligned}$$

For 120 ml nanofluid, required mass of nanoparticles (Al₂O₃):

$$m_p = \phi_v \cdot \rho_p \cdot V_{nf} = \frac{0.25}{100} \times 3.97 \times 120 = 1.19 \text{ gm} \approx 1.2 \text{ gm}$$

Appendix C- Specifications and characterization of nanoparticles

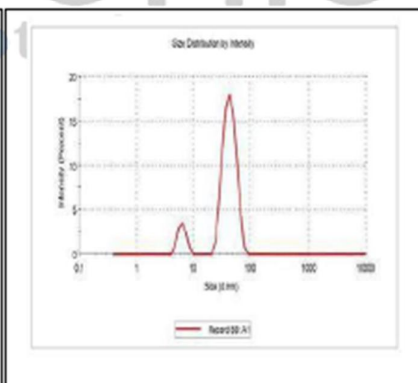
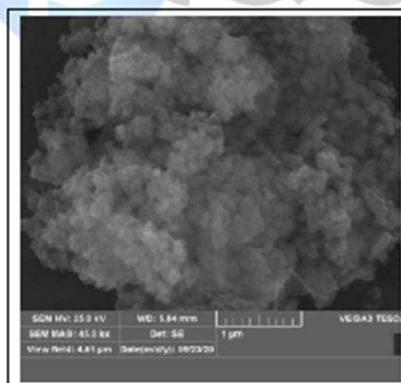
For Aluminium Oxide (Al_2O_3):



**PLATONIC NANOTECH
PRIVATE LIMITED**

TECHNICAL DATA SHEET

SPECIFICATIONS	DESCRIPTION
PURITY	>99%
AVERAGE PARTICLE SIZE	<100 nm
BULK DENSITY	0.6 g/cm ³
SSA	~110 m ² /g
PHYSICAL FORM	POWDER
MORPHOLOGY OF NANOPARTICLE	NEAR SPHERICAL
COLOUR	WHITE
CAS NO	1344-28-1



Platonic Nanotech Private Limited

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CIN NO. U24299JH2017PTC010268

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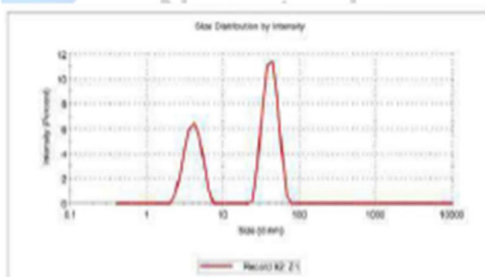
For Zinc Oxide (ZnO):



**PLATONIC NANOTECH
PRIVATE LIMITED**

TECHNICAL DATA SHEET

SPECIFICATIONS	DESCRIPTION
PURITY	> 99%
AVERAGE PARTICLE SIZE	<100 nm
BULK DENSITY	0.55 g/cm ³
SSA	100-110 m ² /g
PHYSICAL FORM	POWDER
MORPHOLOGY OF NANOPARTICLE	NEAR SPHERICAL
COLOUR	WHITE
CAS NO	1314-13-2



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