



WALLAGA UNIVERSITY
SCHOOL OF GRADUATE STUDIES

**PARAMETRIC OPTIMIZATION OF TURNING PROCESS
PARAMETERS DURING MACHINING OF AISI 4340
STEEL UNDER MINIMUM QUANTITY LUBRICATION**

MSc. Research

By: Belay Tena Dinka

October, 2025
Nekemte, Oromia, Ethiopia



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**PARAMETRIC OPTIMIZATION OF TURNING PROCESS
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UNDER MINIMUM QUANTITY LUBRICATION**

**A Research Submitted to the College of Engineering and Technology in Partial
Fulfillment of the Requirements for the Degree of Master of Science in
Manufacturing Engineering**

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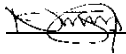
**October, 2025
Nekemte, Oromia, Ethiopia**



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APPROVAL SHEET FOR SUBMITTING THE FINAL
RESEARCH

As members of the Board of Examiners of the Final MSc. research open defense, we certify that we have read and evaluated the research prepared by **Belay Tena Dinka** under the title “Parametric Optimization of Turning Process Parameters during Machining of AISI 4340 Steel under Minimum Quantity Lubrication” and recommend that the research be accepted as fulfilling the research requirement for the Degree of Master of Science in Manufacturing Engineering in Wallaga University.

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Certification of the Final Research

I hereby certify that all the corrections and recommendations suggested by the board of Examiners are incorporated into the final research entitled ‘Parametric Optimization of Turning Process Parameters during Machining of AISI 4340 Steel under Minimum Quantity Lubrication’ by BELAY TENA.

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APPROVAL SHEET

This is to certify that the research entitled '**Parametric Optimization of Turning Process Parameters during Machining of AISI 4340 Steel under Minimum Quantity Lubrication**' submitted by **Mr. Belay Tena Dinka**, has been recognized by the **Wallaga University** School of Graduate Studies through the College of Engineering and Technology. This work is presented in partial fulfillment of the requirements for the award of the MSC Degree in Master of Manufacturing Engineering and was carried out under our supervision.

The subject of this research has never been proposed for the granting of a degree or certificate. Throughout this inquiry, Mr. Belay Tena received adequate support and assistance. Consequently, we recommend that it be approved as satisfying the conditions for research.

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STATEMENT OF THE AUTHOR

I, Mr. **Belay Tena Dinka**, hereby declare and affirm that the research entitled “**Parametric Optimization of Turning Process Parameters during Machining of AISI 4340 Steel under Minimum Quantity Lubrication**” is my work conducted under the supervision of **Mahesh Gopal (Ph.D.)**. I have followed all the ethical principles of scholarship in the preparation, data collection, data analysis and completion of this research. All scholarly matters included in the research have been recognized through citation. I have adequately cited and referenced all the sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented, fabricated, or falsified any idea/data/fact/source in my submission. This research is submitted in partial fulfillment of the requirement for a degree from Post Graduate Studies at Wallaga University. I further declare that this research has not been submitted to any other institution anywhere for the award of any academic degree, diploma, or certificate.

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ACRONYMS AND ABBREVIATIONS

AISI	American Iron and Steel Institute
ANOVA	Analysis of Variance
ASPEN	Aspen (Chemical) Analysis Software
CCD	Central Composite Design
CFD	Computational Fluid Dynamics
d	Depth of Cut
DFA	Desirability Function Analysis
DOE / DoE	Design of Experiments
Fuzzy	Fuzzy Logic Method
f	Feed Rate
MQL	Minimum Quantity Lubrication
MRR	Material Removal Rate
MWCNT	Multi-Walled Carbon Nanotubes
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
PCD	Polycrystalline Diamond
PSO	Particle Swarm Optimization
PTT	Power-Type Trend
RSM	Response Surface Methodology
SPH	Smoothed Particle Hydrodynamics
Taguchi	Taguchi Experimental Method
v	Cutting Speed
Viscosity	Fluid Viscosity
ρ	Density

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Abstract

Turning operations are fundamental in modern manufacturing for achieving dimensional accuracy and superior surface integrity. Among the widely used materials, AISI 4340 steel is valued for its high strength, toughness, and wear resistance, making it suitable for critical components such as gears, shafts, and crankshafts. However, its hard-to-machine characteristics often result in excessive heat generation, tool wear, and compromised surface finish, especially under dry cutting conditions. To overcome these challenges, this research investigates the use of Minimum Quantity Lubrication (MQL) as a sustainable cooling and lubrication technique, combined with multi-objective optimization, to enhance machining performance. A series of CNC turning experiments was designed using Response Surface Methodology (RSM) with Central Composite Design (CCD) to study the effects of cutting speed, feed rate, and depth of cut on surface roughness, cutting temperature, and material removal rate (MRR). Desirability Function Analysis (DFA) was employed to integrate these multiple responses into a single objective function, enabling the identification of optimal cutting conditions. The analysis showed that feed rate contributed more than 65% to variations in surface roughness, while cutting speed accounted for about 70% of the changes in cutting temperature. Depth of cut dominated the material removal rate response with a contribution exceeding 80%. The optimal parametric combination, 1000 rpm cutting speed, 50 mm/min feed rate, and 0.3 mm depth of cut, produced a surface roughness of 0.87 μm , a cutting temperature of 56.4°C, and an MRR of 368 mm³/min, with a composite desirability of 0.912. These results demonstrate that MQL, when paired with RSM-DFA, improves thermal stability, enhances surface finish, and maintains high productivity in machining AISI 4340 steel.

Keywords: CNC Turning, AISI 4340 steel, Minimum Quantity Lubrication, Central Composite Design

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Metal cutting is the method that is most frequently used to create various items around the world; in fact, it is the foundation of the manufacturing industry. It is crucial to the production of a wide range of goods, from automobiles to high-precision parts for the instrumentation and electronics sectors. Surface roughness, tool life, material removal rate, and cutting force are frequently used measures for assessing machining performance in turning operations(Shukla et al., 2020). Surface roughness is a measure of a product's quality, whereas material removal rate focuses on an industry's productivity. Surface roughness is a common machining quality factor that has a significant impact on the wear rate, fatigue strength, corrosion resistance, and tribological characteristics of the machined surface (Abidin & Rafighi, 2021). Additionally, because it influences productivity, tool life and necessary cutting energy are linked to the final cost of the product. In the industrial sector, steel is one of the materials that is most frequently used to create various machine parts. According to the American Institute of Steel and Iron (AISI), AISI 4340 steel grade is a high strength low alloy (HSLA) with (51 HRC) steel used as an industrial material for manufacturing a wide variety of engineering products in the manufacturing field due to its excellent properties. Because of its exceptional qualities and properties, a product such as gears, crankshafts, collars, machinery parts, dies, etc., are manufactured from these types of steel. However, due to its characteristics, which include high fatigue strength, abrasion and impact resistance, a high hardness-to-elasticity ratio, toughness, and torsional strength, it tops the list of steels that are classified as hard-to-machine metals (Padhan et al., 2023) (Salur, 2023). Although the demand for such steel increased as a result of its appealing mechanical features, challenges posed by its machining become a headache to metal-cutting businesses (Padhan et al., 2023),(Salur, 2023). Additionally, because machining requires contact between the tool and the workpiece, the shearing of the chip generates the most heat, which not only causes the cutting tool to wear out faster but also degrades the quality of the finished product. Multi-objective optimization involves optimizing multiple conflicting objectives simultaneously, balancing aspects like efficiency, quality, and cost in manufacturing processes. For AISI 4340 steel, medium-carbon steel known for its strength, ductility, and machinability, optimizing machining parameters is crucial for improving performance. Key metrics like Metal Removal Rate (MRR) and surface

roughness play significant roles in assessing process efficiency and surface quality. Managing heat generated during machining (thermal management) is essential to maintain tool life and workpiece quality, especially in dry turning. This study focuses on using Central Composite Design (CCD) and Desirability Function Analysis (DFA) within Response Surface Methodology (RSM) to develop a multi-objective optimization framework for the dry turning of AISI 4340 steel, aiming to enhance MRR, surface finish, and thermal control.

1.2 Statement of the problem

Machining AISI 4340 steel is challenging because the material generates high cutting temperatures, rapid tool wear, and unstable surface quality, especially under dry or poorly lubricated conditions. These thermal and mechanical issues become more severe as cutting speed, feed rate, and depth of cut interact in complex ways, making it difficult to predict or control the final surface finish and productivity. Although many studies have examined individual responses such as surface roughness or MRR, very few have considered all three critical outcomes, surface roughness, cutting temperature, and MRR, together, particularly under Minimum Quantity Lubrication (MQL), which behaves differently from dry or flood cooling. Most existing works rely on single-objective optimization, which cannot resolve the trade-offs between minimizing heat, improving surface quality, and maintaining high productivity. As a result, industries lack a validated multi-objective framework that can recommend machining conditions offering a balanced and practical compromise. The interaction between lubrication effectiveness, heat generation, and material removal efficiency remains insufficiently modeled for AISI 4340 steel, leaving a gap in selecting conditions that ensure thermal stability, surface integrity, and sustainable performance.

1.3 Research questions

1. How do cutting speed, feed rate, and depth of cut affect surface roughness, cutting temperature, and MRR during MQL turning of AISI 4340 steel?
2. How effectively can RSM be used to model the relationships between turning parameters and the response variables (surface roughness, cutting temperature, and MRR)?
3. How can DFA be employed to combine multiple response variables into a single objective for optimizing the turning process?
4. What are the optimal machining parameters for achieving high MRR, superior surface finish, and controlled cutting temperature in MQL turning of AISI 4340 steel?

1.4 Objectives of the Study

1.4.1 General objectives

The objective is to optimize surface roughness, temperature, and MRR in MQL turning of AISI 4340 steel using RSM and DFA.

1.4.2 Specific objectives

The study aims to:

- Investigate how cutting speed, feed rate, and depth of cut influence surface roughness, cutting temperature, and material removal rate during MQL turning of AISI 4340 steel.
- Develop reliable predictive relationships that describe how these machining parameters affect each response.
- Integrate the three responses into a single decision framework that reflects the best balance between surface quality, thermal stability, and productivity.
- Identify the machining conditions that provide the most favorable combination of low surface roughness, controlled temperature, and high MRR.

1.5 Scope of the Study

This research is limited to the experimental investigation and multi-objective optimization of the turning process of AISI 4340 steel under Minimum Quantity Lubrication (MQL). The machining trials are carried out on a CNC lathe using carbide inserts, and the study focuses only on three primary input parameters: cutting speed, feed rate, and depth of cut. These parameters are selected because they have the strongest and most direct influence on thermal behavior, surface integrity, and material removal efficiency in turning operations. The scope includes measuring three key performance responses: surface roughness, cutting temperature, and material removal rate (MRR). These responses are chosen to represent the essential aspects of machining, surface quality, thermal stability, and productivity. The study applies Response Surface Methodology (RSM) to develop predictive models for these responses within the selected parameter ranges. Desirability Function Analysis (DFA) is then used to integrate the three responses into a combined optimization framework. The work is restricted to the specific MQL system used in the experiments, including its oil type, flow rate, and nozzle orientation. Other lubrication strategies, such as dry cutting, flood cooling, or cryogenic cooling, are not included. Likewise, tool geometry, tool coatings, and alternative insert materials are kept constant to avoid additional sources of variation. The study also does not extend to tool wear analysis, chip morphology, vibration behavior, or economic assessment. All findings, conclusions, and optimized parameter recommendations apply only to the material grade (AISI 4340), tooling, cutting environment, and experimental ranges defined in this research. The results should be interpreted within these constraints, although the methodology can be adapted for other machining conditions or materials in future work.

1.6 Significance of the Study

This study is significant for advancing sustainable manufacturing practices by optimizing dry turning parameters for AISI 4340 steel, thereby eliminating the need for cutting fluids and reducing environmental impact. The research enhances machining performance by providing a multi-objective optimization framework that balances metal removal rate, surface finish, and thermal management, leading to improved product quality, tool life, and cost efficiency. Additionally, it fills a gap in the existing literature by applying Desirability Function Analysis (DFA) with Response Surface Methodology (RSM) to this specific material, offering insights that can be extended to other materials and processes. The study's findings have direct industrial applications, enabling companies to optimize their machining operations for better efficiency and

competitiveness, while also laying a foundation for future research in environmentally friendly machining techniques.

1.7 Organization of the paper

This thesis is structured into five chapters. Chapter One provides an introduction, covering the background, statement of the problem, research objectives, methodology, scope, significance of the study, and the overall organization of the work. Chapter Two presents a review of theoretical and empirical literature, including the historical background of the CNC machining process and related studies from previous theses, journals, and books on parametric optimization and machine learning algorithms. Chapter Three, titled Materials and Methods, outlines the experimental design and procedures used to achieve the specific research objectives. Chapter Four presents the results and provides a detailed discussion of the findings. Finally, Chapter Five summarizes the conclusions of the study and offers recommendations for future research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

In the field of manufacturing, balancing three critical machining aspects, productivity, quality, and cost, poses a significant challenge. Researchers have long been drawn to these conflicting aspects, striving to optimize machining processes to achieve better outcomes. To enhance production rates and reduce manufacturing costs, metal-cutting companies often aim to maximize the material removal rate (MRR) while minimizing energy consumption. This can be accomplished by adjusting process variables such as cutting speed, depth of cut, feed rate, and nose radius (Varaprasad et al., 2014). However, increasing these parameters can negatively impact the surface quality of the finished product.

The use of conventional machining fluids, while beneficial for cooling and lubrication, presents health risks to operators and limitations in heat transfer efficiency, which restricts their applicability in high heat flux conditions. Dry machining, an alternative approach that eliminates the use of cutting fluids, has gained attention due to its environmental and health benefits. Although dry turning offers a more comfortable working environment for operators, it also introduces challenges, such as increased heat generation, which can adversely affect product quality. Given these challenges, identifying optimal machining conditions, including the appropriate selection of cutting parameters, is critical to ensuring product quality without compromising productivity or the needs of the industry. Numerous studies have been conducted on the turning of AISI 4340 steel, focusing on various optimization techniques to balance these factors effectively. The following sections highlight some of the significant research efforts in this area. The Fig.2. 1 shows the numerous studies have explored the optimization of machining parameters for various materials. For instance, (Kaladhar, 2021) investigated the use of Taguchi methods for optimizing the cutting parameters in turning operations. Similarly, (Nalbant et al., 2007) applied RSM for optimizing the machining of AISI 304 steel, emphasizing the importance of multi-objective approaches in achieving balanced outcomes. The use of DFA, as demonstrated by (S. R. Das et al., 2015), has proven effective in integrating multiple responses into a unified optimization framework. The optimization of turning parameters for enhanced metal removal rate (MRR), surface finish (SF), and thermal management in the dry turning of AISI 4340 steel can be effectively achieved through multi-objective optimization techniques, particularly utilizing

Desirability Function Analysis (DFA) within Response Surface Methodology (RSM) (Khare & Agarwal, 2017). This approach systematically evaluates various cutting parameters to achieve optimal machining performance (Abhang & Hameedullah, 2012). Desirability Function Analysis integrates multiple performance metrics into a single objective function, which facilitates the identification of optimal cutting parameters (Ayinavilli, 2018). Research has demonstrated that DFA can significantly enhance both MRR and SF during turning operations (Naresh & Rajasekhar, 2016).

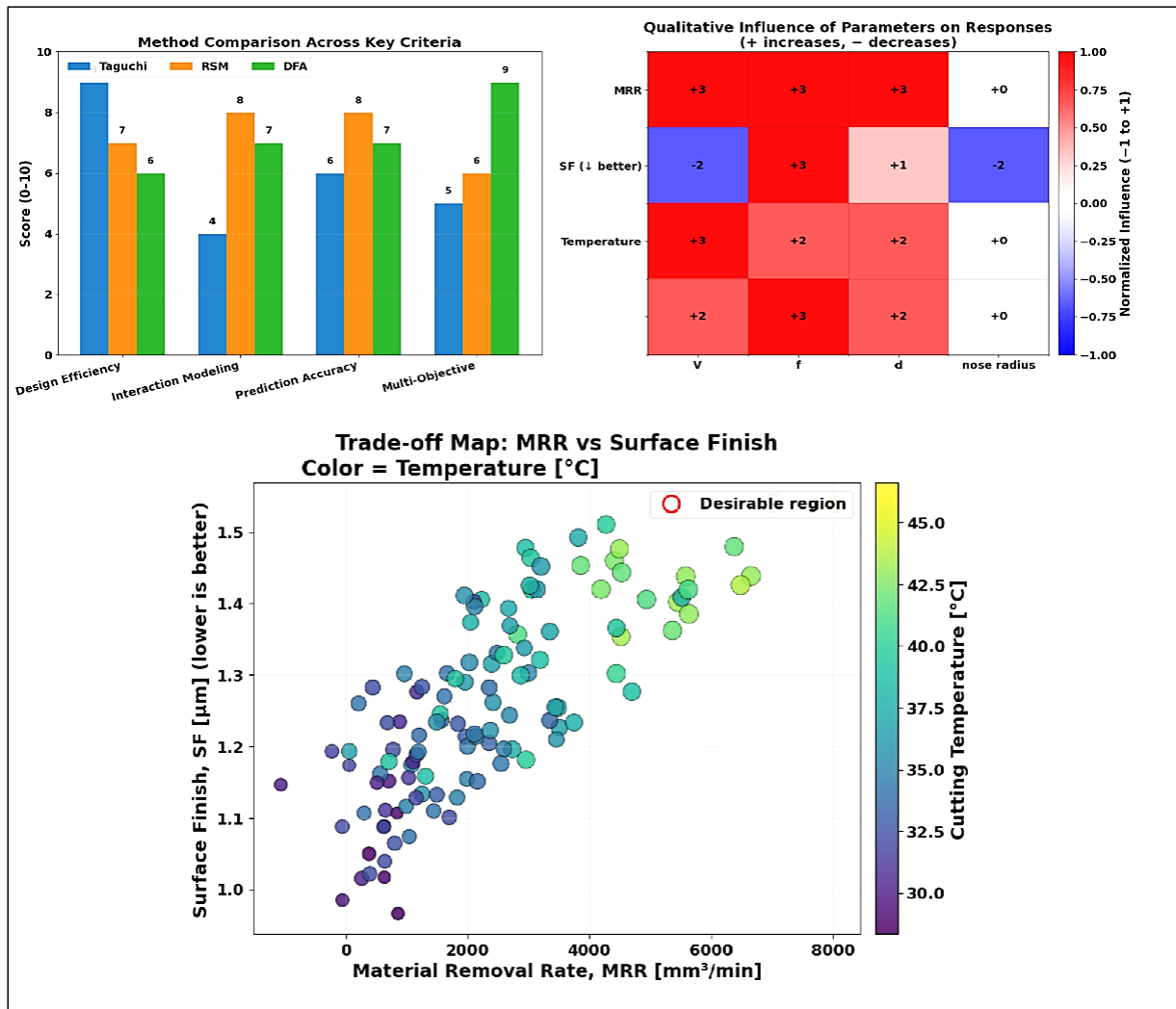


Fig.2. 1 Figure 2 Qualitative influence of parameters on responses (redrawn from concepts of :
 (S. R. Das et al., 2015; Efa et al., 2025; Gemechu et al., 2024; Kaladhar, 2021; Nalbant et al.,
 2007)

Response Surface Methodology, on the other hand, is used to model the relationship between cutting parameters and performance outcomes, allowing for the exploration of parameter interactions and leading to improved predictions of machining performance (Öktem et al., 2005). Key findings from the literature suggest that optimal spindle speed, feed rate, and depth of cut can be determined through experimental designs such as Box-Behnken and Taguchi methods, which result in significant improvements in MRR and SF (Varatharajulu et al., 2017). Additionally, effective parameter optimization contributes to better thermal management by reducing cutting temperatures and tool wear, thus maintaining tool life and machining efficiency (Abhang & Hameedullah, 2012). However, while multi-objective optimization techniques offer substantial benefits, they also introduce complexity in parameter selection (Jabri et al., 2013). Careful consideration of trade-offs between competing objectives, such as maximizing MRR while minimizing SF, is essential for achieving the best overall machining performance (Yan & Li, 2013).

2.2 Turning of AISI 4340 Steel

AISI 4340 steel is widely used in manufacturing due to its good balance of strength, ductility, and machinability, making it suitable for components subjected to moderate mechanical stress. The turning process of this medium-carbon steel requires careful consideration of machining parameters to enhance surface quality, reduce tool wear, and improve MRR. Turning operations typically involve a cutting tool made of a material that is harder than the workpiece. The cutting tool, often a single-point tool with one cutting edge, is used on machines like lathes to remove material from the workpiece. Common materials for cutting tools include high-carbon steel, high-speed steel, ceramics, diamonds, cemented carbide, and cubic boron nitride (CBN). The geometry of the cutting tool plays a crucial role in the machining process and is illustrated in Fig.2. The optimization of surface roughness, cutting temperature, and material removal rate (MRR) during MQL turning of AISI 4340 steel has gained considerable attention due to its potential to enhance machining efficiency while promoting sustainability. The adoption of MQL, especially when combined with nanofluid-based lubricants, has been demonstrated to significantly improve surface finish and reduce tool-work interface temperature compared to dry or conventional flood cooling techniques. This improvement is attributed to superior lubrication and enhanced heat dissipation provided by nanoparticles, which minimize friction and prevent excessive thermal loading on the cutting tool (Miriayala et al., 2023). AISI 4340 steel, known for its high strength, toughness, and

wear resistance, is widely utilized in critical engineering components such as shafts, gears, and fasteners. However, its machinability poses challenges, primarily due to its tendency to generate high cutting temperatures and induce rapid tool wear during prolonged operations (Santhosh et al., 2021). Consequently, optimizing cutting parameters, namely cutting speed, feed rate, and depth of cut, is crucial for achieving the desired balance between surface integrity, thermal stability, and material removal efficiency.

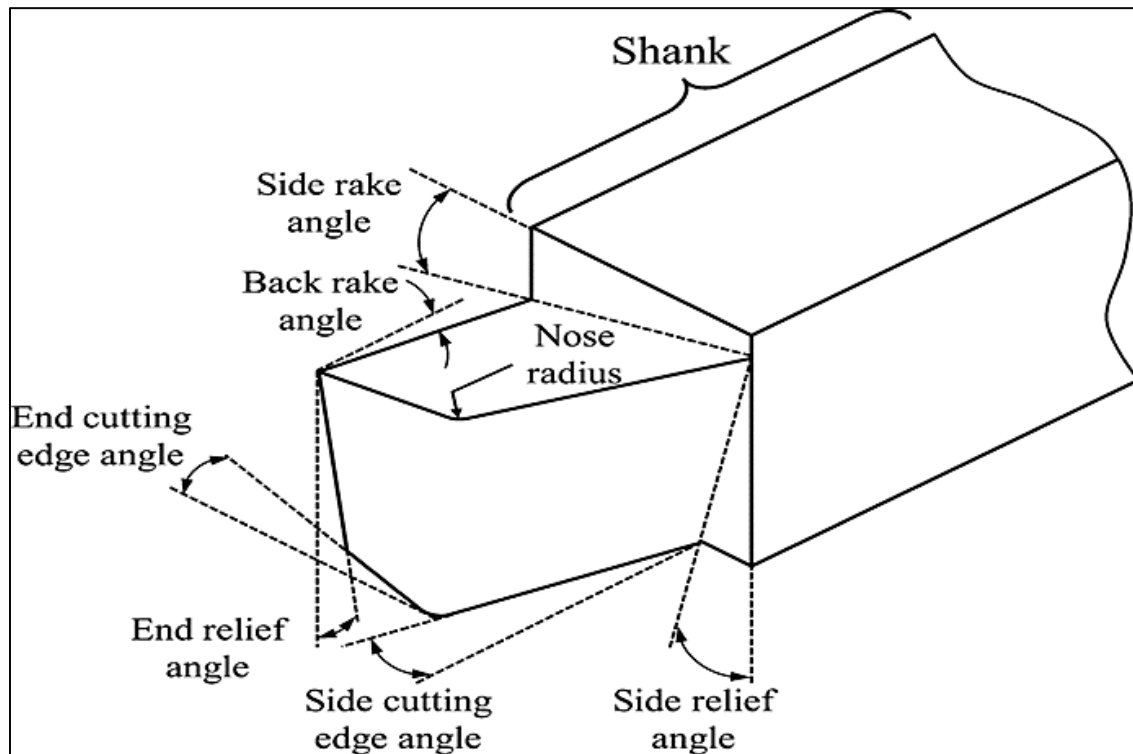


Fig.2. 2 Single-cutting tool geometry (Dhupia et al., 2015)

2.3 Influence of machining parameters on performance measures

Previous studies emphasize that feed rate is the dominant parameter influencing surface roughness in both conventional and MQL turning processes. Increased feed rates typically deteriorate the surface finish due to higher tool–work interaction forces and greater surface deformation (Efa et al., 2025). In contrast, cutting speed primarily governs cutting temperature, as higher speeds intensify frictional heat generation at the tool–chip interface (Nayak & Rathod, 2025). Meanwhile, the depth of cut directly determines MRR, since it defines the volume of material removed per unit time (Patole & Kulkarni, 2018). MQL plays a pivotal role in moderating these relationships. The introduction of fine, oil-based aerosols enriched with nanoparticles enables efficient chip evacuation and localized cooling, which collectively reduce tool wear and promote smoother

surface topographies (Patole et al., 2021). Experimental investigations further confirm that MQL significantly outperforms dry cutting in controlling both surface roughness and cutting temperature under optimized conditions (Miriyala et al., 2023). These findings substantiate the suitability of MQL as an environmentally responsible and performance-enhancing cooling method for machining hardened steels.

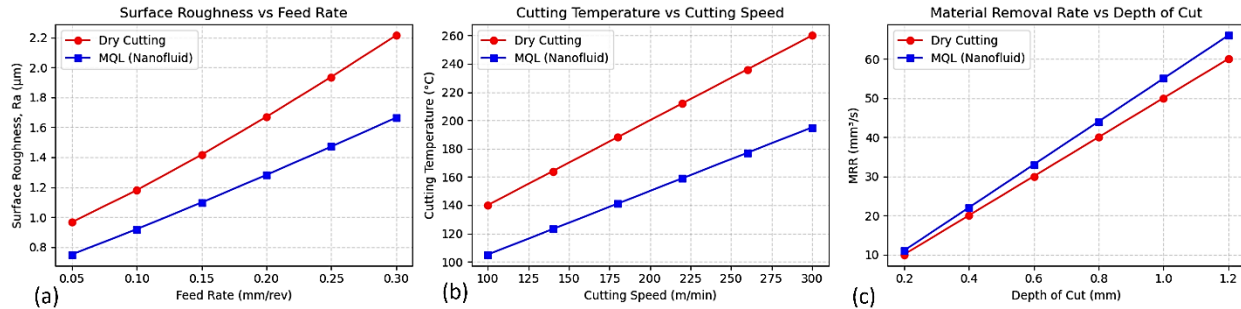


Fig.2. 3 Influence of machining parameters on performance measures (Patole & Kulkarni, 2018)(Miriyala et al., 2023)(Patole & Kulkarni, 2018)

2.4 Predictive modeling through response surface methodology (RSM)

To quantitatively assess the influence of machining parameters, RSM has been extensively utilized in machining research. RSM provides a systematic statistical framework for modeling complex, nonlinear interactions among cutting speed, feed rate, and depth of cut, thereby allowing prediction and optimization of responses such as surface roughness, MRR, and cutting temperature (Santhosh et al., 2021). Empirical models developed through RSM typically exhibit high predictive accuracy, with reported confirmation tests indicating less than 5% deviation between predicted and experimental results (Gemechu et al., 2024). Analysis of Variance (ANOVA) and 3D response surface plots derived from RSM further reveal the relative significance and interactions among parameters for each response variable (Kaladhar, 2021). Additionally, RSM-based temperature models assist in developing effective thermal management strategies for difficult-to-machine steels such as AISI 4340 (Mia & Dhar, 2016). These overall concepts are presented in Fig.2. 4.

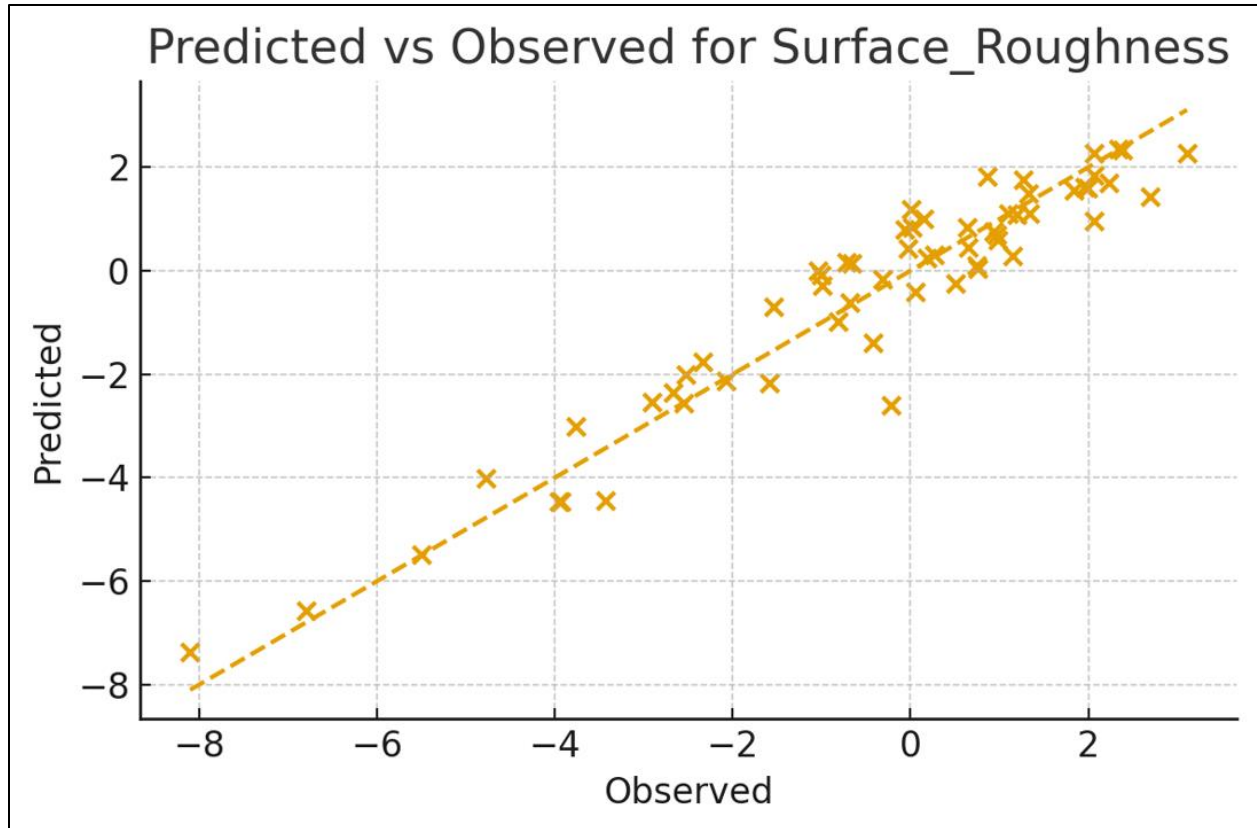


Fig.2. 4 Predicted versus observed surface roughness and 3D response surface plot obtained using RSM for the effects of cutting speed, feed rate, and depth of cut on AISI 4340 steel (redrawn from concepts of :(Gemechu et al., 2024) (Santhosh et al., 2021)(Efa et al., 2025))

2.5 Multi-objective optimization using desirability function analysis (DFA)

While RSM effectively models individual response behaviors, Desirability Function Analysis (DFA) enables the integration of multiple machining responses into a single composite objective function for multi-response optimization (Patole & Kulkarni, 2017). DFA allows simultaneous minimization of surface roughness and cutting temperature while maximizing MRR, addressing the trade-offs inherent in machining operations (Mia & Dhar, 2016). This methodology has been successfully validated in various machining contexts, including turning and Electrical Discharge Machining (EDM), with typical discrepancies between predicted and observed optimal values below 6% (Świercz et al., 2019). The integration of RSM and DFA thus provides a powerful hybrid approach for achieving balanced optimization outcomes, ensuring practical relevance in manufacturing settings where productivity, quality, and tool longevity must coexist (Nguyen et al., 2024).

2.6 Determination of optimal machining parameters

Literature reports suggest that the optimal parameter combination for MQL turning of AISI 4340 steel generally involves a lower feed rate (to minimize surface roughness), a moderate-to-high cutting speed (to maintain efficiency), and a moderate-to-high depth of cut (to ensure sufficient MRR). These parameter sets are typically fine-tuned using RSM-DFA hybrid models and validated through confirmation experiments (Kaladhar, 2021). Studies have demonstrated that such multi-objective optimization can lead to up to 28% improvement in surface quality and over 5% enhancement in MRR compared to single-objective or traditionally optimized processes (Javid et al., 2021). Moreover, applying optimal MQL parameters significantly extends tool life, improves dimensional accuracy, and enhances overall process sustainability (Santhosh et al., 2021). The incorporation of nano-enhanced lubricants further amplifies these benefits, yielding both economic and ecological advantages due to reduced lubricant consumption, improved thermal control, and longer tool lifespan (A. Kumar et al., 2023). Overall, the literature consistently supports that integrating RSM-based predictive modeling with DFA-based multi-objective optimization represents a robust framework for improving the surface integrity, productivity, and sustainability of MQL-assisted turning of AISI 4340 steel.

2.7 Review of related studies

Several researchers have explored different approaches to optimize the turning process of AISI 4340 steel as seen in Table 2. 1. For instance, (Shinge & Pable, 2023) performed dry turning on AISI 4340 steel using a fuzzy inference system-based machine learning approach to examine the effects of process parameters on vibrations, surface roughness, and acoustic emissions. Their 3D graph analysis revealed that the cutting depth had a significant influence on vibrations, regardless of variations in feed rate and cutting speed. In another study (Abbas et al., 2025) employed multi-objective optimization ratio analysis combined with Taguchi techniques to optimize cutting parameters for surface roughness, tool wear, and MRR during the turning of AISI 4340 steel. Their findings indicated that a cutting speed of 250 m/min, a feed rate of 0.11 mm/rev, and a depth of cut of 1.4 mm were the optimal conditions for minimizing surface roughness and tool wear while maximizing material removal rate. These studies demonstrate the importance of selecting the right machining parameters to achieve a balance between productivity and quality in the turning of AISI 4340 steel. Optimization techniques, such as those based on machine learning, Taguchi methods, and multi-objective analysis, have proven to be effective in identifying ideal cutting conditions.

Table 2. 1 Research objectives, methods, and supporting references of the current study

Objective	Method	Supported by
Analyze parameter effects (speed, feed, depth cut)	Experimental design, ANOVA, RSM	(Nayak & Rathod, 2025)(Patole & Kulkarni, 2018), (Patole et al., 2021)
Develop predictive models	RSM, regression analysis	(Santhosh et al., 2021)(Kaladhar, 2021)(Mia & Dhar, 2016)
Integrate multiple responses for optimization	DFA, multi-objective optimization	(Świercz et al., 2019)(Nguyen et al., 2024)(Javid et al., 2021)
Determine optimal process settings	RSM-DFA, confirmation tests	(Santhosh et al., 2021)(Patole & Kulkarni, 2017)(A. Kumar et al., 2023)

2.8 Summary of reviewed literature

The summary of the reviewed literature provides an overview of advancements in CNC turning, focusing on optimization techniques and innovative technologies. It highlights key findings on enhancing machining performance, improving surface quality, extending tool life, and reducing energy consumption. The analysis also identifies research trends and gaps to guide future studies, emphasizing the need to balance sustainability with efficiency in CNC turning. It discusses the role of hybrid nanofluids, optimization algorithms, and statistical methods in achieving these goals. The summary of the reviewed literature is presented in Fig.2. 5. Several studies have investigated the influence of cutting parameters on machining performance, particularly when working with AISI 4340 steel under varying conditions. (Patole & Kulkarni, 2018) examined the combined effects of cutting speed, feed rate, depth of cut, and nose radius in dry machining using a ceramic insert cutting tool. Their results highlighted significant impacts on tool wear, surface roughness, and cutting temperature. Similarly, (Mia et al., 2018) analyzed spindle speed, feed rate, and depth of cut during dry machining of AISI 4340 steel with a CVD multi-layer TiCN/Al₂O₃/TiN coated WC insert, reporting changes in surface roughness (Ra) and total surface height (Rt). Expanding on these findings, (Zerti et al., 2019) conducted experiments under minimum quantity lubrication (MQL) conditions using coated carbide inserts. Their study revealed that cutting speed, feed, depth of cut, and tool nose radius influenced surface roughness, tangential force, specific cutting force, and cutting power. In contrast, (R. Kumar et al., 2019) focused on the effects of cutting speed, feed rate, depth of cut, and workpiece hardness during dry machining with a CBN tool, noting

considerable variation in cutting forces and surface roughness. Research has also addressed the role of cooling and lubrication environments. (Sulaiman et al., 2013) studied the effect of cutting speed, feed rate, and depth of cut under cooling conditions using a PCN cutting tool. They observed notable influences on temperature, surface roughness, cutting force, and tool wear. Likewise, (Khalil et al., 2021) examined the same parameters under wet machining conditions with a cemented carbide tool, reporting significant effects on surface roughness. Beyond conventional approaches, (Hadad & Sadeghi, 2013) explored spindle speed, feed rate, depth of cut, and flow rate for machining AISI 4340 and white cast iron under dry, MQL, and NFMQL environments using coated ceramic tools. Their findings indicated strong correlations with tool wear, surface roughness, and cutting temperature. Finally, (Singh et al., 2017) evaluated cutting speed, feed rate, depth of cut, and nanoparticle concentration under NFMQL conditions with a WC tool insert. They demonstrated that these parameters significantly affected cutting temperature, surface roughness, and MRR.

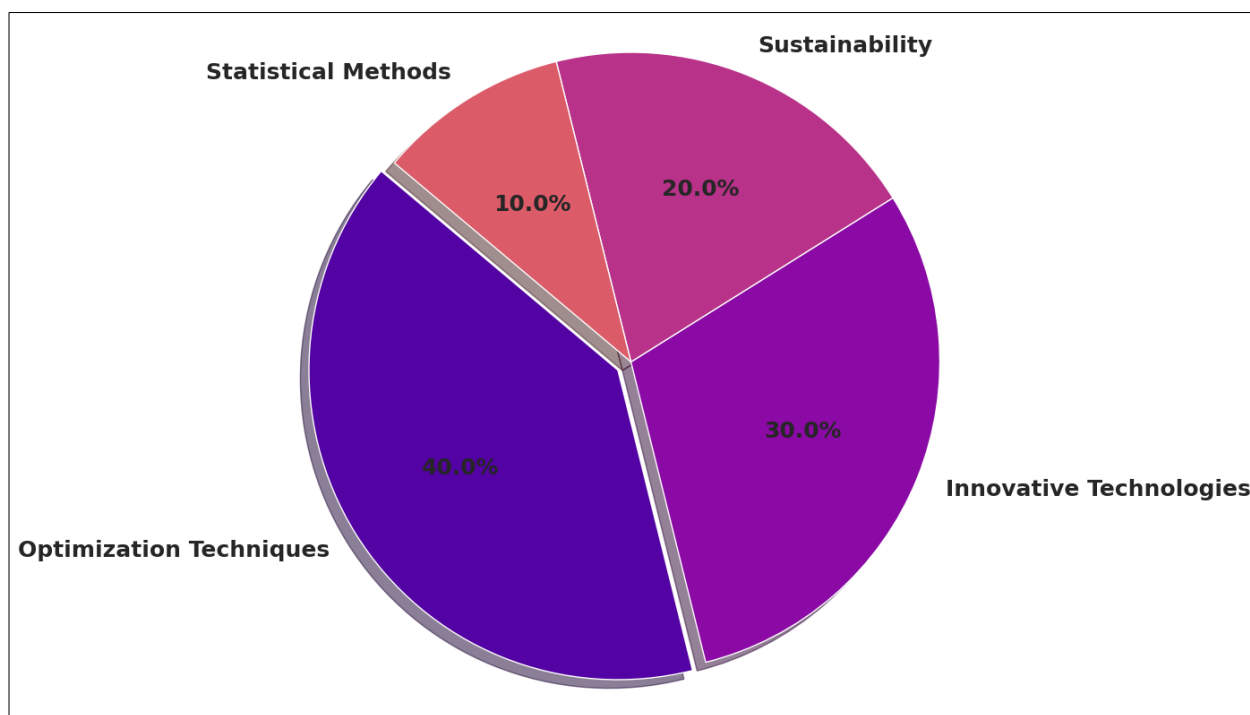


Fig.2. 5 Distribution of research focus in CNC turning literature

2.9 Research Gap

Although substantial progress has been made in machining optimization research, several critical gaps remain, particularly concerning the turning of AISI 4340 steel under MQL conditions. Existing studies often concentrate on single-objective optimization, while modern manufacturing

demands require a more integrated, multi-response approach that simultaneously considers productivity, surface integrity, and thermal stability. First, surface roughness and material removal rate (MRR) are the most frequently analyzed responses in conventional studies. However, these parameters are interdependent; improvements in one often deteriorate the other. The absence of holistic frameworks addressing their coupled behavior under MQL conditions limits the practical applicability of current optimization models in real machining environments. Second, the thermal effects generated during turning operations have received relatively limited attention. Controlling the cutting temperature and ensuring effective thermal management are essential for maintaining tool life, surface integrity, and dimensional accuracy. Yet, the interaction between heat generation, lubrication behavior, and surface quality remains poorly understood, especially for high-strength alloys like AISI 4340 steel. Third, while optimization techniques such as RSM and Taguchi methods have been extensively employed, most applications remain single-objective in nature. The integration of RSM with Desirability Function Analysis (DFA), a powerful framework capable of balancing multiple conflicting objectives, has been scarcely explored for machining AISI 4340 under MQL. This represents a major research opportunity to formulate a unified optimization model that can simultaneously minimize surface roughness, regulate cutting temperature, and maximize MRR. Finally, few studies have attempted to establish comprehensive predictive models linking input parameters (cutting speed, feed rate, depth of cut, and lubricant flow rate) with multiple output responses. Without such models, it is difficult to capture the complex interdependencies and trade-offs that define real-world machining systems. A data-driven approach combining RSM-based modeling with DFA-based decision-making could yield significant advancements in machining optimization and sustainability. Hence, this research aims to bridge these identified gaps by developing a multi-objective optimization framework for turning AISI 4340 steel under MQL. Using RSM to model parameter–response relationships and DFA to derive optimal solutions, the study seeks to achieve a balanced enhancement of surface quality, productivity, and thermal stability. This approach contributes to the ongoing pursuit of sustainable, high-performance machining practices. The overall scope and focus of this study are summarized in Fig.2. 6, which highlights the key optimization objectives: surface roughness, MRR, cutting temperature, thermal management, and multi-objective integration.

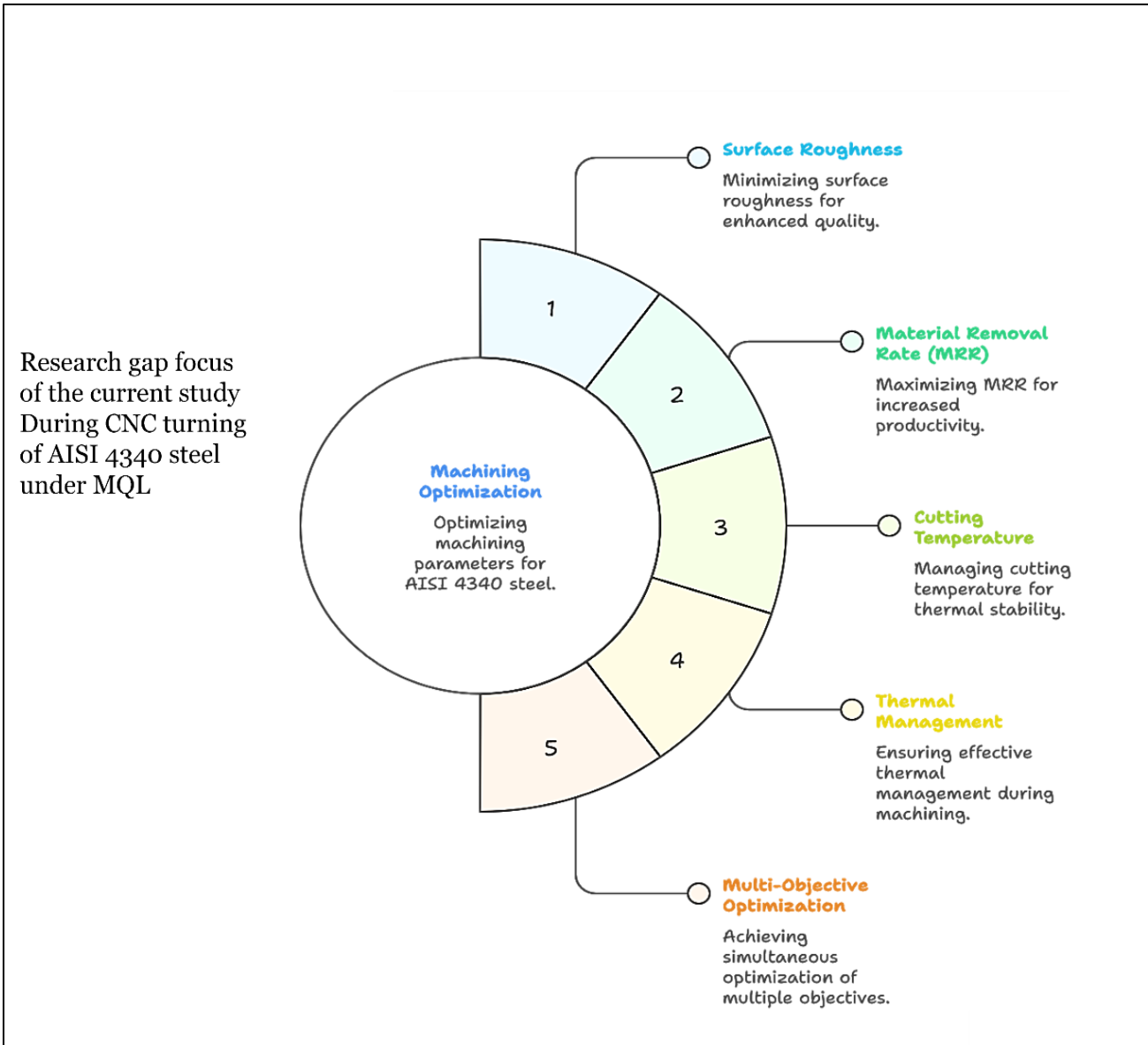


Fig.2. 6 The research gap focus of the current study

CHAPTER THREE

MATERIALS AND METHODOLOGY

3.1 Introduction

This chapter describes the work procedures implemented in the materials and equipment used in this study. This study was performed to conduct an experimental investigation and multi-objective parametric optimization of the dry turning of AISI 4340 steel employing CCD.

3.2 Material selection

The selection of materials for manufacturing processes is critical to ensuring the desired mechanical properties, machinability, and overall performance of the final product. Recent advances in materials science and engineering have provided more options for materials that can meet specific industrial requirements. AISI 4340 steel, medium-carbon steel, has been widely adopted in manufacturing due to its balance of strength, ductility, and wear resistance. Recent studies have highlighted the versatility of AISI 4340 in various applications, particularly where a good combination of mechanical properties and cost-effectiveness is required (Bhattacharya et al., 2011). The material's medium carbon content allows for a good response to heat treatment, enhancing hardness and strength while maintaining adequate toughness, making it suitable for components subjected to high stress and wear (Kaedhi et al., 2024). In recent research, the machinability of AISI 4340 steel has been further explored, especially in the context of dry-turning processes. For instance, (Çydaş, 2010). demonstrated that AISI 4340 exhibits favorable characteristics under dry machining conditions, making it an excellent candidate for sustainable manufacturing practices where environmental concerns are paramount. The material's ability to maintain surface integrity under high temperatures generated during dry turning is particularly noteworthy, making it suitable for applications in automotive and aerospace industries where such conditions are common (da Silva et al., 2025). These recent studies underscore the importance of selecting AISI 4340 steel for the current research, which focuses on optimizing turning parameters for enhanced machining performance. The material's proven capabilities under dry machining conditions, combined with its mechanical properties, make it an ideal choice for achieving the study's objectives. The chemical composition and the thermal and mechanical properties of AISI 4340 steel are presented in Table 3. 1 and Table 3. 2, respectively.

Table 3. 1 Chemical composition of AISI 4340 steel (spectroscopy results)

Element	C	Si	Mn	P	S	Cr	Mo	Ni	Al	Co	Cu	Nb
Concentration (wt%)	0.39	0.19	0.56	<0.0005	0.064	0.13	0.008	0.048	0.002	0.007	0.022	<0.001
Element	Ti	V	W	Pb	Sn	Bi	Zn	La	B	N	Sb	Fe
Concentration (wt%)	<0.0002	0.006	<0.005	0.008	0.003	<0.001	>0.027	<0.0008	0.002	0.005	0.001	98.4

The mechanical and thermal characteristics of AISI 4340 steel play a decisive role in determining its machining response, particularly under CNC turning operations assisted by Minimum Quantity Lubrication (MQL). The summarized material properties presented in Table 3. 2 highlight the alloy's strength, ductility, and heat transfer efficiency, all of which strongly influence tool performance, surface quality, and process stability during machining. AISI 4340 is a nickel–chromium–molybdenum alloy steel known for its superior toughness and fatigue strength. The density of about 7.85 g/cm³ is typical of high-strength steels, offering a robust structure capable of withstanding heavy mechanical loads. Its yield strength of approximately 420 MPa and shear strength near 370 MPa indicate high resistance to plastic and shear deformation. While these properties make the material reliable for structural and fatigue-critical components, they also contribute to greater cutting forces and rapid tool wear during CNC turning. The tool must overcome significant resistance to remove material, resulting in increased heat generation at the cutting zone. Under dry cutting conditions, this heat leads to rapid tool degradation and surface deterioration. However, under MQL, the fine oil–air mist reduces friction at the tool–chip interface, improving lubrication and enabling more efficient material removal with lower temperature rise. The elongation at break, ranging between 15% and 20%, shows that AISI 4340 possesses moderate ductility, allowing controlled plastic deformation during cutting. This property supports stable chip formation but can also promote the development of long, continuous chips that adhere to the tool face. MQL assists in overcoming this issue by forming a thin lubricating film that helps chips slide smoothly away from the cutting edge. Similarly, the Poisson's ratio between 0.29 and 0.33 suggests balanced stiffness and lateral contraction behavior. While this stiffness ensures dimensional accuracy, it can also increase the risk of vibration or chatter during turning. The controlled lubrication of MQL reduces tool–workpiece friction and suppresses these dynamic instabilities, resulting in smoother cutting action and improved surface integrity. From a thermal perspective, AISI 4340 exhibits a coefficient of thermal expansion of 11.7 µm/m·K, which means the material experiences moderate dimensional changes when exposed to temperature gradients. In high-speed CNC turning, where the cutting temperature can exceed several hundred

degrees Celsius, this expansion may affect tolerance and surface precision. The use of MQL mitigates these effects by providing localized cooling through atomized oil droplets that absorb and carry away part of the heat from the cutting zone. The relatively high thermal conductivity of AISI 4340, ranging from 49.8 to 51.9 W/m·K, further aids in distributing and dissipating the generated heat, maintaining thermal balance between the tool and the workpiece. This synergy between the material's conductivity and MQL's micro-cooling capacity helps to prevent thermal softening of the cutting tool and limits the occurrence of surface burns or metallurgical alterations. In addition, the latent heat of fusion of 260 J/g and a narrow melting range between 1693 K and 1743 K indicate that the alloy has a stable and uniform composition. This thermal stability minimizes the risk of localized melting or phase transformation during machining, even when subjected to elevated temperatures. Under MQL conditions, this stability supports consistent cutting performance and ensures that the surface layer retains its mechanical integrity after machining. Overall, the machining behavior of AISI 4340 steel in CNC turning under MQL reflects a delicate balance between its high mechanical strength and efficient thermal response. The high strength demands adequate cutting energy and robust tool material, while the good thermal conductivity allows the limited quantity of lubricant to perform effectively. Compared to flood cooling, MQL provides sufficient lubrication and controlled cooling without excessive fluid consumption, leading to a more sustainable and cost-effective machining environment. By reducing friction, improving chip evacuation, and maintaining lower cutting temperatures, MQL enhances tool life and surface finish while maintaining productivity. Therefore, the mechanical and thermal properties explain why AISI 4340 steel is both challenging and rewarding to machine. Its combination of strength, ductility, and heat conductivity requires precise optimization of cutting parameters such as speed, feed rate, and depth of cut. When assisted by MQL, these properties can be exploited to achieve a favorable balance between surface quality, material removal rate, and thermal control. This interdependence between material behavior and lubrication strategy underscores the need for multi-objective optimization methods, such as Response Surface Methodology (RSM) and Desirability Function Analysis (DFA), to identify the most effective machining conditions for sustainable and high-performance manufacturing.

Table 3. 2 Thermal and mechanical properties of AISI 4340 steel

Mechanical properties	Value	Thermal properties	Value
Density	7.85 g/cm ³	Thermal Expansion	11.7 μ m/mk
Yield strength	420 MPa	Thermal conductivity	49.8-51.9 W/mk
Elongation at break	15-20%	Latent heat of fusion	260 J/g
Shear strength	370 MPa	Melting on set (Solidus)	1693K
Poisson's ratio	0.29-0.33	Melting on set (liquids)	1743K

3.3 Design of Experiments (DOE)

The machining performance of AISI 4340 steel under Minimum Quantity Lubrication (MQL) was examined in this study through a structured experimental plan developed using Response Surface Methodology (RSM). The goal was to understand how the main cutting parameters influence three key responses: material removal rate (MRR), surface roughness (Ra), and cutting temperature. These responses were chosen because they represent the core requirements of any machining operation: productivity, surface integrity, and thermal stability, which together determine overall process efficiency. The study focused on the machining parameters of cutting speed, feed rate, and depth of cut because they are the primary variables that control chip formation, heat generation, and tool–workpiece interaction in turning. Their selection was based on their dominant influence on machining outcomes, where cutting speed strongly affects heat generation and tool life, feed rate is the most significant factor governing surface roughness, and depth of cut has the greatest impact on MRR and cutting forces. Their relevance is also well-documented in earlier studies, as previous research on AISI 4340 consistently identifies these three variables as the most sensitive and practical levers for optimizing performance in both dry and MQL turning (Rosly et al., 2021; Patole & Kulkarni, 2018). A final consideration was the practical requirements of CNC turning, as these parameters are easily adjustable on a CNC lathe and directly control the quality–productivity trade-offs that manufacturers must balance. To isolate the effects of the selected variables and avoid unnecessary experimental complexity, other factors such as tool geometry and cutting insert type were held constant. The basis for setting the parameter levels was a combination

of several factors. Preliminary trial cuts were conducted to identify cutting conditions that produce measurable surface roughness, temperature, and MRR values without causing vibration, tool failure, or thermal distortion. Published literature ranges [(Siva Prasad, 2015) (Varaprasad et al., 2014)(A. Das et al., 2019)(Padhan et al., 2023)(Padhan et al., 2023)(Shinge & Pable, 2023)] were also consulted; studies related to AISI 4340 turning under MQL and dry environments guided the selection of safe and representative operating windows, with reported ranges in the literature aligning with the levels used in this study. Tool manufacturer recommendations from the carbide insert datasheet provided permissible limits for cutting speed and feed rate on alloy steels, ensuring tool safety and stability. Finally, the CNC lathe's spindle speed range, feed mechanism, and maximum allowable depth of cut were considered to prevent overloading. Based on these factors, the chosen ranges were a cutting speed of 800–1200 rpm, a feed rate of 50–70 mm/min, and a depth of cut of 0.1–0.5 mm that as shown in Table 3. 3. These levels allow the experiment to cover both conservative and aggressive machining conditions while remaining safe and practical. The experimental plan was created in Design Expert v13 using a Central Composite Design (CCD). The CCD was selected because it provides efficient estimation of second-order (quadratic) models, good prediction capability across the design space, and the ability to capture curvature and interaction effects common in metal cutting processes. The CCD comprised 16 factorial points, 8 axial (star) points, and 6 center points, for a total of 30 runs. The center points provided a check for experimental repeatability and measurement variability, improving the reliability of model fitting. The design was set as rotatable, ensuring that prediction accuracy remains uniform at equal distances from the design center—a desirable property for optimization studies. All runs were randomized to avoid bias introduced by tool wear progression, temperature rise, or environmental variations. The completed dataset was analyzed using RSM to fit quadratic regression models for each response. Analysis of Variance (ANOVA) identified significant factors and interactions. These models formed the foundation for the multi-objective optimization performed using Desirability Function Analysis (DFA), which aimed to maximize MRR while minimizing surface roughness and cutting temperature. This DOE structure aligns with established machining research practices and ensures a statistically rigorous foundation for developing reliable predictive and optimization models for MQL turning of AISI 4340 steel.

Table 3. 3 Process Variables and Their Levels (Rosly et al., 2021)

Cutting Variables		Levels		
		-alpha	0	+ alpha
Cutting speed	V (rpm)	800	1000	1200
Depth of cut	d (mm)	0.1	0.3	0.5
Feed rate	F (mm/min)	50	60	70

3.4 Experimental setup

The experimental setup for this study was meticulously designed to ensure the accurate, repeatable, and reliable collection of data during the turning of AISI 4340 steel under both dry and MQL conditions. The entire integrated process, encompassing CNC machining, response measurement, and data documentation, is visually summarized in Fig.3. 1 and Fig.3. 2 of the thesis. This section provides a detailed account of the machining equipment, measurement instruments, data-collection procedures, and analytical methods employed in the research.

3.4.1 CNC machining system

All turning experiments were conducted using a Computer Numerical Control (CNC) turning machine, as depicted in Fig.3. 1. The CNC system was programmed to set the three key machining parameters: cutting speed within a range of 800 to 1200 rpm, feed rate from 50 to 70 mm/min, and depth of cut between 0.1 and 0.5 mm. The CNC control panel was used for critical tasks such as loading and verifying the G-code, setting tool offsets, and establishing work coordinate systems to ensure precise tool-workpiece alignment. Before initiating each machining run, operators verified the setup to confirm that the spindle speed, feed rate, and tool path precisely matched the parameter levels designated by the Central Composite Design (CCD) experimental matrix.

3.4.2 Cutting tool and process preparation

A carbide cutting insert was used consistently throughout all experimental runs. Before each trial, a strict preparation protocol was followed. The tool condition was inspected for any signs of wear, and tool offsets were reset to guarantee dimensional accuracy. The workpiece alignment and clamping were meticulously re-checked, and the appropriate lubrication mode, either MQL or dry,

was prepared according to the trial specifications. This rigorous pre-process routine was essential for minimizing variability unrelated to the controlled parameters, thereby ensuring that each machining trial was consistent and repeatable.

Machine operations and setup of the experimentations



Fig.3. 1 The CNC machining and experimentation setup

3.4.3 Measurement instruments used for data collection

The collection of response data relied on several precision instruments, all illustrated in Fig.3. 1 and Fig.3. 2. For cutting temperature measurement, a laser-guided infrared thermometer (IR

temperature gun) was used. The operator positioned the IR gun toward the tool-chip interface during machining to capture real-time surface temperature readings. Surface roughness was evaluated after each trial using a surface roughness tester, which measured the arithmetic average roughness (Ra) as a primary response variable. Furthermore, the dimensional and geometric accuracy of the machined samples was verified using digital micrometers, Vernier calipers, and other precision gauges. These tools ensured consistency in the machined geometry and helped validate that any deviations in the responses were due to the machining parameters and not dimensional errors.

3.4.4 Data collection procedure

The data collection adhered to a structured workflow, as outlined in Fig.3. 2. The procedure began with machine setup and calibration, which involved loading the G-code, aligning the tool and workpiece, and verifying the preset speed, feed, and depth of cut, followed by an initial temperature reading. The machining process was then executed, with each run performed according to the CCD experimental matrix while real-time IR temperature measurements were taken and chip behavior and tool condition were observed. In the post-machining inspection phase, the temperature data was formally recorded, surface roughness (Ra) was measured, final workpiece dimensions were taken, and weight or volume changes were recorded for subsequent MRR calculation. All collected measurements were systematically documented in structured data sheets before being transferred to Design Expert v13 software for analysis.

3.4.5 Response calculation and data analysis

The Material Removal Rate (MRR) was calculated using the standard formula based on the cutting speed, feed rate, depth of cut, machining time, and confirmatory dimensional measurements. For statistical modeling and ANOVA, Design-Expert v13 was utilized to fit second-order RSM models, conduct Analysis of Variance for each response, and identify significant parameters and interactions, with the results visualized through 3D response surfaces and contour plots. Finally, for multi-objective optimization, a Desirability Function Analysis (DFA) was employed. This involved converting each response into an individual desirability function on a scale from 0 to 1, computing a composite desirability using the geometric mean, and selecting the optimal parameter combination based on the highest composite desirability, thereby providing a balanced solution that minimized surface roughness and temperature while maximizing MRR.

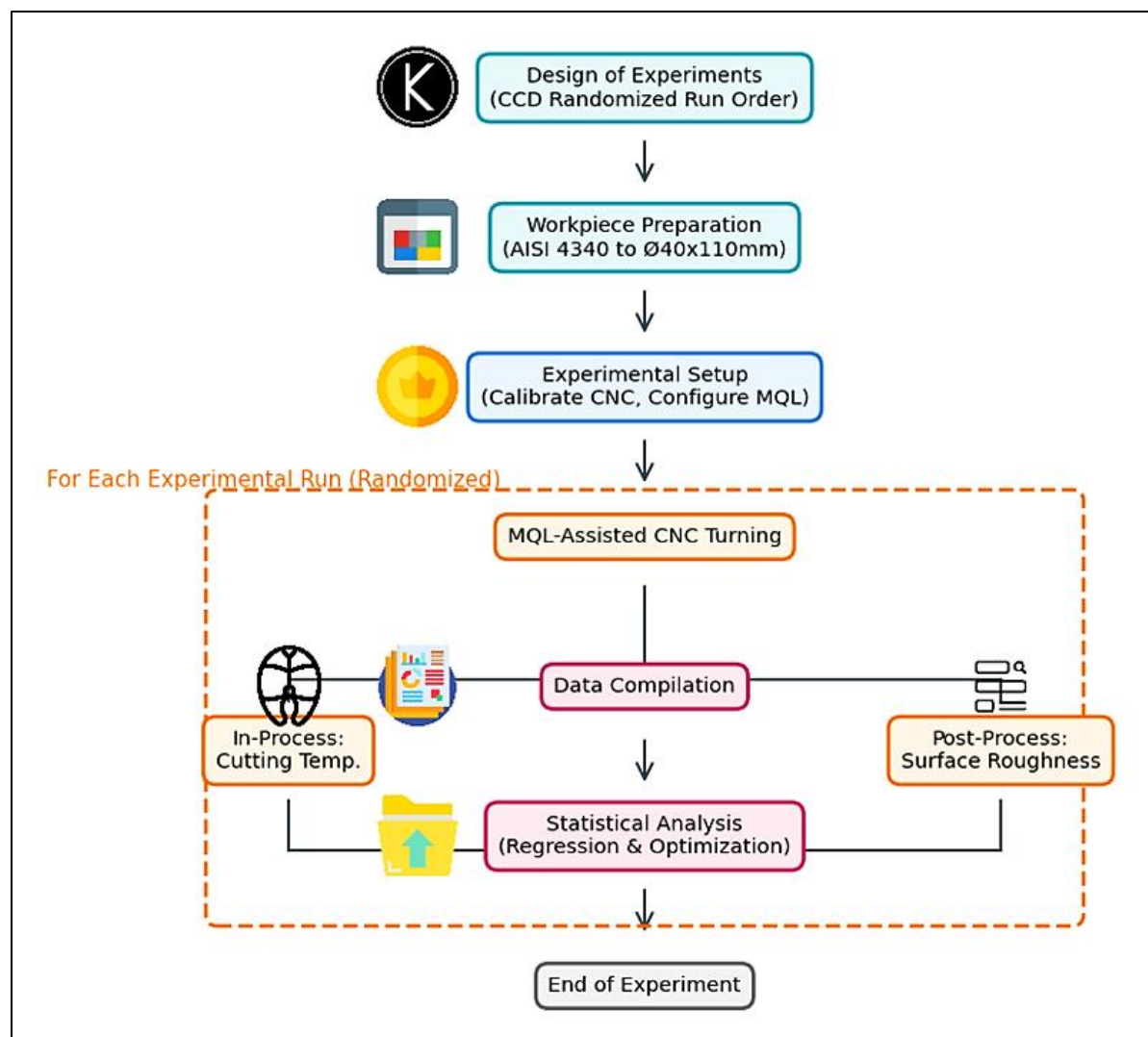


Fig.3. 2 Experimental process

3.4.6 Quality assurance

To ensure the precision and reliability of the experimental data, a comprehensive quality assurance protocol was implemented. Each experiment was randomized to avoid bias from progressive tool wear, and tools were inspected between runs. Calibration logs for all measuring instruments were maintained and updated regularly. The repeatability of the process was verified through the replication of center points within the CCD design, and all machined surfaces were visually inspected for any defects. All photographs documenting the experimental setup and measurement stages are provided in Fig. 3.1 and Appendix A.

Thus, this fully revised experimental setup section provides a clear and comprehensive explanation of the methodology. It details how data were collected for temperature, roughness, dimensions, and MRR; how the data were analyzed using RSM, ANOVA, and DFA in Design Expert v13; and which specific tools and machines were used, including the CNC lathe, IR thermometer, micrometers, and roughness tester. Furthermore, it describes the controlled and validated nature of the entire process, thereby satisfying the requirements for major modification as indicated by the examiner's comments.

3.5 Experimental Procedure for CNC Turning of AISI 4340 Steel under MQL Conditions

Fig. 3.3 presents the detailed experimental procedure followed during the CNC turning of AISI 4340 steel under MQL conditions. The sequence in Fig. 3.3 (a–i) illustrates the preparation of workpieces, setup of the machining system, application of the MQL system, and the measurement of process responses such as surface roughness and temperature. Each stage represents an essential part of the experimental workflow used to ensure consistency, repeatability, and accuracy in the machining trials. As shown in Fig. 3.3 (a), the machined specimens were first prepared to uniform dimensions from AISI 4340 steel bars. Each workpiece was cut, faced, and labeled according to the experimental design matrix developed using the RSM. This ensured systematic identification of samples corresponding to different combinations of cutting parameters such as speed, feed rate, and depth of cut. The uniformity of the specimens was critical to maintain consistent boundary conditions during each cutting test. Fig. 3.3 (b–d) demonstrates the setup and temperature measurement process during CNC turning. The operator used a non-contact infrared thermometer to record the cutting temperature at the tool–workpiece interface. This measurement was taken immediately after each machining pass to capture the transient thermal effects generated during cutting. The infrared thermometer was calibrated before the experiment to minimize measurement uncertainty, and it was directed toward the cutting zone at a fixed angle to ensure repeatability. These steps were essential for assessing the thermal performance of MQL compared to dry cutting conditions. The lower temperatures observed under MQL confirmed its effectiveness in reducing frictional heat through a thin film of lubricant that penetrates the chip–tool interface. In Fig. 3.3 (e), the CNC machine control panel is shown displaying the programmed machining parameters such as spindle speed, feed rate, and depth of cut. The use of CNC technology provided high precision and consistency in executing each experimental run according to the parameter settings defined by the RSM-based design matrix. This ensured that variations in cutting conditions were

accurately controlled, which is critical for developing reliable empirical models and optimization results. Fig. 3.3 (f) shows the coordination between the operator and laboratory technicians during the programming and supervision of the machining process. Multiple trials were observed and recorded to ensure the accuracy of the programmed inputs and the consistency of data collection throughout the experimental campaign. This collaborative setup minimized human error and provided cross-verification of each machining trial before data recording. In Fig. 3.3 (g), the application of the MQL system is demonstrated. The lubricant, typically a biodegradable oil, was atomized and directed as a fine mist toward the cutting zone through a compressed air nozzle. The flow rate of the MQL was carefully adjusted to deliver only the minimum quantity of lubricant required to achieve effective cooling and lubrication without forming a liquid film. This setup ensured both environmental sustainability and reduction in fluid consumption compared to conventional flood cooling. The uniform mist coverage on the cutting region reduced tool–chip friction, prevented adhesion, and improved surface finish. The MQL system thereby provided a controlled balance between thermal regulation and lubrication efficiency. The completed machined samples after the turning process are presented in Fig. 3.3 (h). Each workpiece was labeled and arranged systematically for post-process evaluation. The consistent surface texture and dimensional accuracy visible on the samples confirm the stable machining conditions achieved during the trials. This visual documentation reinforces the reliability of the results obtained for surface roughness, temperature, and MRR. Finally, Fig. 3.3 (i) depicts the post-machining measurement of surface roughness using a portable surface roughness tester. This device was used to measure the average Ra at three different points along the machined surface, and the mean value was recorded for analysis. This ensured that local surface variations were accounted for, improving the accuracy of the surface integrity assessment. The results from these measurements formed a key dataset for evaluating the effectiveness of MQL in improving surface quality compared to dry machining. The lower Ra values obtained under MQL conditions were consistent with the hypothesis that fine mist lubrication minimizes micro-tearing and built-up edge formation by reducing frictional resistance at the cutting interface. Therefore, Fig. 3.3 provides a comprehensive visual summary of the entire machining process for AISI 4340 steel under MQL conditions—from specimen preparation to machining execution and post-process analysis. The documented procedure highlights the methodological rigor employed to ensure the accuracy and repeatability of the experiments.

PARAMETRIC OPTIMIZATION OF TURNING PROCESS PARAMETERS DURING MACHINING OF
AISI 4340 STEEL UNDER MINIMUM QUANTITY LUBRICATION



Fig. 3.3. Photos taken during the experimental process.

The integration of MQL with CNC machining not only enhanced thermal and surface quality performance but also demonstrated the practical feasibility of adopting sustainable lubrication strategies in precision metal cutting operations. The sequence of activities captured in this figure thus reflects both the experimental integrity and the technical reliability of the investigation conducted for evaluating MQL's effectiveness during the turning of AISI 4340 steel.

3.6 Response Surface Methodology (RSM)

Response Surface Methodology (RSM) will be employed to establish mathematical relationships between the input variables (cutting parameters) and the response variables (e.g., surface roughness, cutting temperature, tool wear). Using the experimental data, second-order regression models will be developed to capture the main, interaction, and quadratic effects of the process parameters. The adequacy of these models will be verified through Analysis of Variance (ANOVA) by evaluating statistical metrics such as the coefficient of determination (R^2), F-values, and p-values. This approach will ensure that the developed models are statistically significant and capable of accurately predicting the responses within the experimental domain.

3.6 Desirability Function Analysis (DFA)

Desirability Function Analysis (DFA) will be used to simultaneously optimize multiple response variables. Each response will first be converted into an individual desirability function that ranges from 0 (completely undesirable) to 1 (fully desirable), depending on the optimization goal (minimization, maximization, or targeting a specific value). These individual desirability indices will then be combined into a single composite desirability function using the geometric mean approach. This unified measure will enable the simultaneous consideration of conflicting responses, thereby providing a balanced optimization strategy.

3.7 Optimization and validation

The optimization procedure will focus on maximizing the composite desirability function to determine the optimal combination of cutting parameters. Once the optimal settings are obtained, a series of confirmation experiments will be conducted to validate the predicted results. The observed responses will be compared with the model-predicted values, and the percentage error or deviation will be calculated. Successful validation will confirm the reliability of the developed RSM-DFA optimization framework for robust process parameter selection. The overall research methodology is presented in the **Error! Reference source not found..**

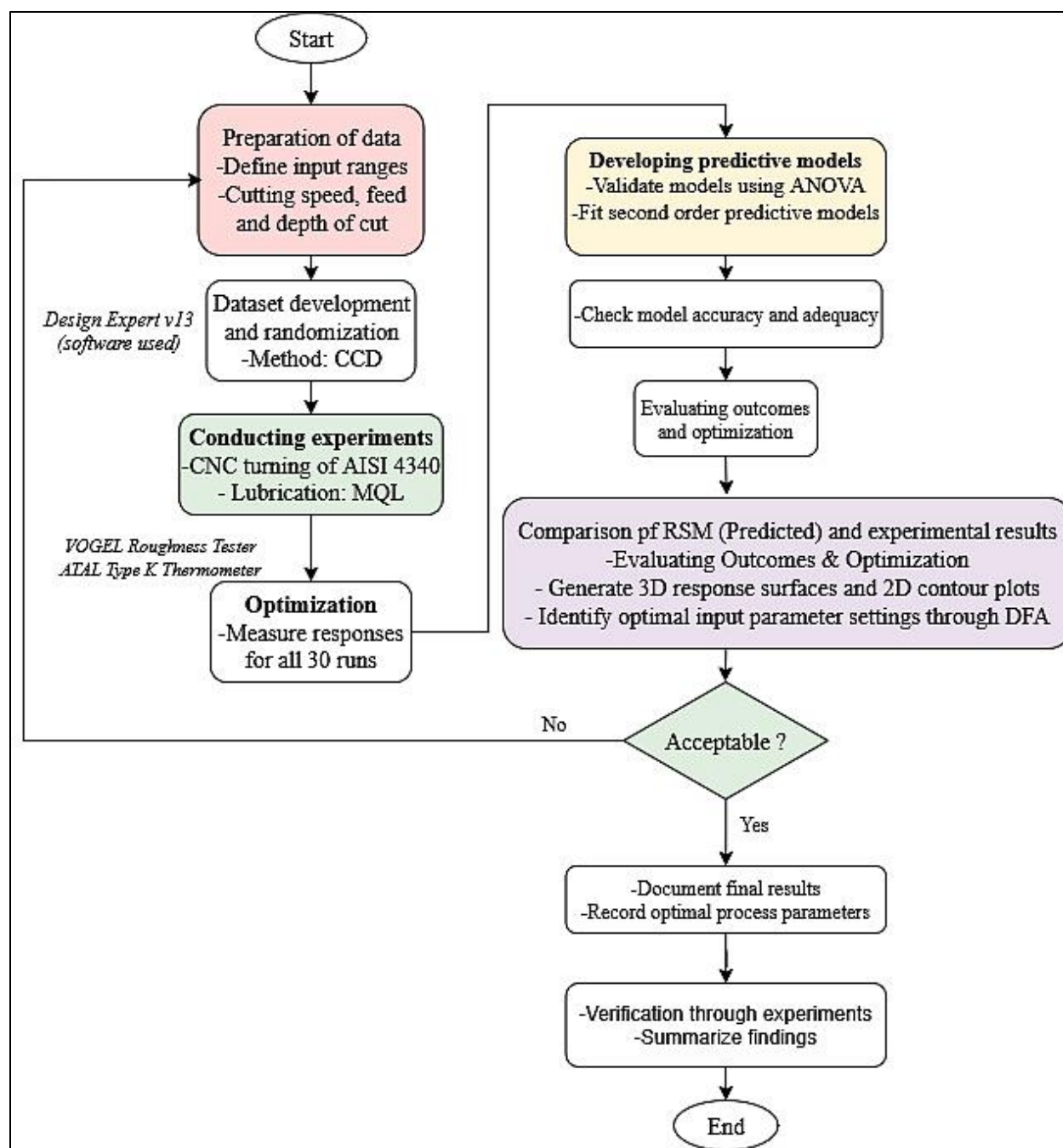


Fig.3.4 Flowchart illustrating the optimization process

CHAPTER FOUR

RESULTS AND DISCUSSION

The above workpiece is AISI 4340 steel, which can be classified as a high-strength low-alloy steel that is appreciated for its high toughness, fatigue resistance, and strength. These features make it ideal for heavy-duty applications, such as aerospace, automotive, and structural engineering. A view of the machined surface of the workpiece would show its original state before machining, as indicated in Fig.4. 1. The surface finish was identical and constant with respect to the production and preparation processes that made them. At this stage, the material surface is free of machine marks, thermal distortion, or mechanical deformation. It retains dimensional accuracy and surface quality as the baseline condition. The condition shows that any treatment through machining operations will interfere with this surface.



Fig.4. 1 AISI 4340 Steel Workpiece Before and After Machining – Illustrating the surface condition in the as-received state and the changes resulting from the machining process.

Table 4. 1 Experimental Results

	Factor 1	Factor 2	Factor 3	Response 1	Response 2	Response 3
Run	A: Cutting Speed	B: Depth of cut	C: Feedrate	Cutting temperature	Surface roughness	Material removal rate

**PARAMETRIC OPTIMIZATION OF TURNING PROCESS PARAMETERS DURING MACHINING OF
AISI 4340 STEEL UNDER MINIMUM QUANTITY LUBRICATION**

	rpm	mm	mm/min	°C	μm	mm ³ /sec
1	1000	0.5	60	25	1.34	30
2	1200	0.5	70	28	1.2	35
3	800	0.5	50	23	1.82	25
4	800	0.1	50	15	2.6	5
5	1000	0.3	50	25	0.96	15
6	1000	0.3	50	25	1	15
7	1000	0.3	60	22	1.81	18
8	1200	0.1	70	20	2.5	7
9	800	0.1	70	26	2.54	7
10	800	0.3	60	20	2.3	18
11	800	0.5	70	27	2.4	35
12	800	0.5	70	27	2.4	35
13	1000	0.3	70	21	2.67	21
14	1200	0.3	60	24	1.8	18
15	1000	0.1	60	30	1.5	6
16	1200	0.3	60	24	1.75	18
17	1000	0.3	60	22	1.34	18
18	1200	0.1	50	18	2.5	6
19	800	0.5	50	23	2.4	25
20	1200	0.1	50	18	2.55	6
21	1200	0.5	70	30	1.9	35
22	1200	0.1	70	20	2.6	7
23	1000	0.3	70	21	2.67	21
24	800	0.1	70	26	2.54	7
25	800	0.1	50	15	2.6	5
26	800	0.3	60	20	2.3	18
27	1200	0.5	50	28	1.85	30
28	1000	0.5	60	25	1.34	30
29	1000	0.1	60	30	1.5	6
30	1200	0.5	50	28	1.85	30

The effects of cutting speed, feed rate, and depth of cut are comparatively delineated on key machining responses, including cutting temperature, surface roughness, and material removal rate (MRR), as systematically analyzed and presented in Table 4. 1. Visual representation of each input parameter and output was shown in Fig.4. 2 and Fig.4. 3, respectively. It becomes apparent that variable changes instigate visible alterations in all response variables.



Fig.4. 2 The results of input parameters

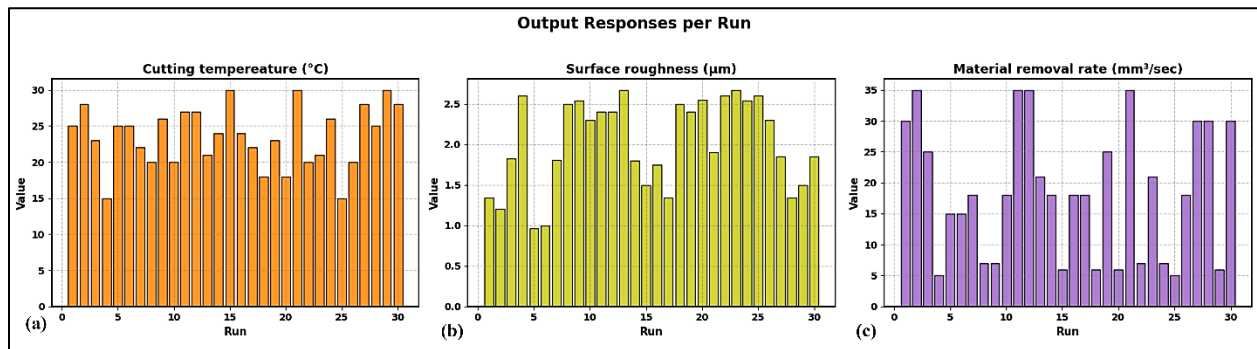


Fig.4. 3 The results of each response: (a) Cutting temperature, (b) Surface roughness and (c) MRR

Varying cutting speed, feed rate, and depth of cut have each impinged differentially impacts over the machining outcome, whereby certain parameter weights more strongly on some responses. Cutting, speed generally affects temperature and surface quality, but feed rate and depth of cut are much more significant in productivity determination through MRR. Furthermore, the results illustrate that clear site trade-offs exist between those parameters of surface quality, thermal effects, and material removal efficiency, which demonstrates the need for selecting proper machining conditions in accordance with specific performance criteria. The full exposition of these outcomes shall be found in the following discussion.

4.1 ANOVA results

4.1.1 Cutting Temperature

4.1.1.1 Model Significance and general observations

The ANOVA results presented in Table 4. 2 ANOVA results of cutting temperature reveal that the quadratic model developed for predicting cutting temperature during CNC turning of AISI 4340

steel under Minimum Quantity Lubrication (MQL) conditions is statistically significant. With an F-value of 3.37 and a p-value of 0.0114, the model is capable of explaining the observed variation in cutting temperature with reasonable accuracy. This affirms that the selected process variables, cutting speed (A), depth of cut (B), and feed rate (C), along with their interactions and quadratic terms, collectively contribute to the thermal behavior of the machining process.

4.1.1.2 Influence of process parameters and contribution analysis

Among the individual parameters, depth of cut (B) demonstrates the most dominant effect, showing high statistical significance ($p = 0.0041$) and contributing approximately 20.94% to the overall variation in cutting temperature (based on its Sum of Squares: 105.80 out of 505.47 total) and shown in Fig.4. 4. This strong influence is attributed to increased tool engagement and friction at greater depths, which intensifies heat generation during cutting.

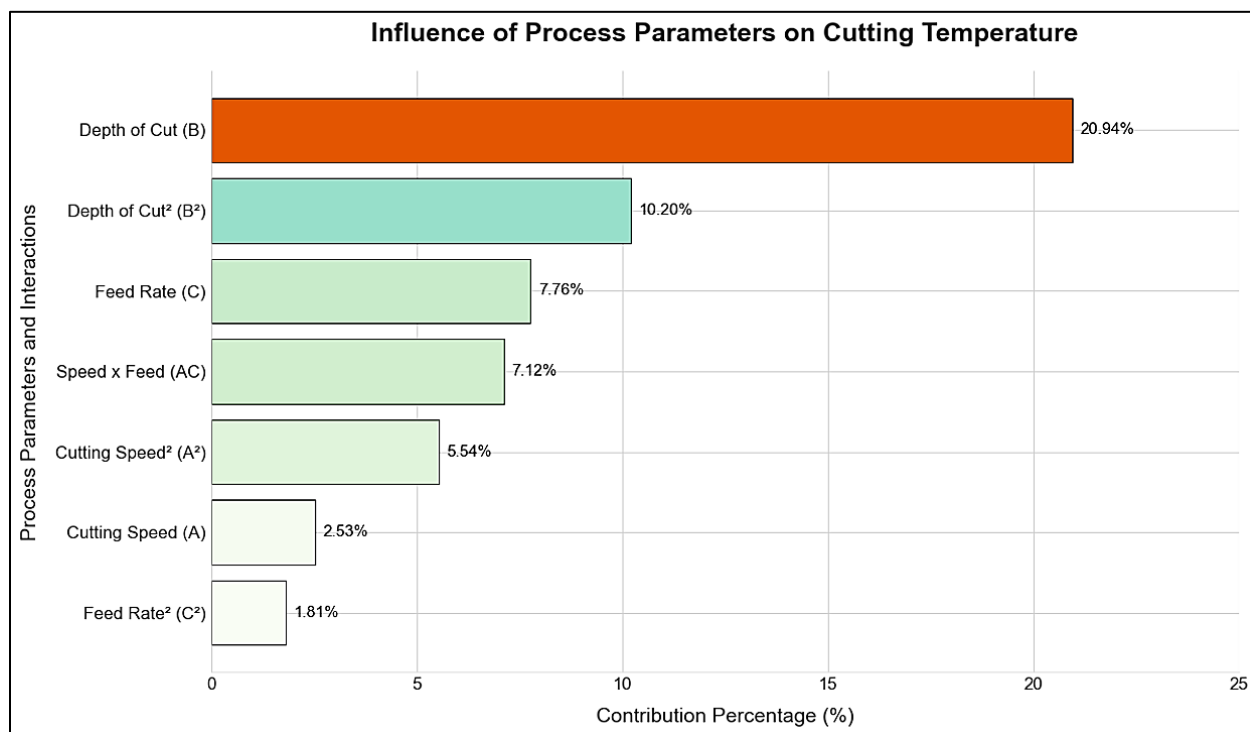


Fig.4. 4 Contribution of process parameters to cutting temperature

The quadratic term of depth of cut (B^2) is also statistically significant ($p = 0.0348$), contributing about 10.2% to the variation. This indicates a nonlinear relationship, wherein temperature rise becomes more sensitive at higher depths of cut, possibly due to strain hardening effects or reduced heat dissipation. Although cutting speed (A) and feed rate (C) are not statistically significant at the

95% confidence level ($p = 0.2724$ and 0.0622 respectively), their contributions are still notable. Cutting speed accounts for 2.53%, while feed rate contributes 7.76% to the temperature variation. Feed rate, in particular, approaches the significance threshold, indicating it may become significant in extended models or under different machining conditions. The interaction terms (AB, AC, and BC) show limited contributions, ranging from 3.17% to 7.12%, with none being statistically significant. However, the AC interaction (7.12%), with a p -value of 0.0730, suggests a near-significant trend, implying that the combination of cutting speed and feed rate could subtly influence the thermal response. Among the quadratic terms, A^2 and C^2 remain statistically insignificant and account for only 5.54% and 1.81%, respectively, of the total variance, confirming that their nonlinear impacts are limited within the explored parameter window.

4.1.1.3 Model Adequacy and Lack of Fit

Despite the overall significance of the regression model, the Lack of Fit is statistically significant ($F = 298.50$, $p = 0.0086$), signaling a notable deficiency in how well the model fits the experimental data. This result implies that 39.80 of the residual sum of squares stems from systematic variation not captured by the current model structure. Although the pure error remains minimal ($SS = 2.00$), the high Lack of Fit suggests that important nonlinearities or interactions might be unaccounted for.

4.1.1.4 Implications

In conclusion, depth of cut is the most influential factor, contributing over 31% of the total variance when considering both its linear and quadratic terms. This makes it the primary lever for controlling cutting temperature. Feed rate also shows practical importance, especially when considered in interaction with cutting speed. However, the presence of a significant Lack of Fit highlights the model's limitations in fully capturing system behavior. To improve predictive performance, future work should explore higher-order models, nonlinear regression techniques, or data-driven hybrid approaches that can better represent the complexity of temperature dynamics in MQL-based turning operations. Additional variables, such as tool wear, cutting environment, or chip formation behavior, may also be considered for more comprehensive modeling.

4.1.1.5 Final Equation in terms of actual factors

The final regression equation for predicting cutting temperature in terms of actual process parameters is expressed in Equation 4.1. This equation is formulated using the actual units of each

variable (e.g., m/min for cutting speed, mm for depth of cut and feed rate), making it suitable for predicting cutting temperature at any specific combination of input parameters within the tested range. However, it is important to note that the magnitude of the coefficients reflects the scale and units of each variable and should not be interpreted as indicators of relative importance. Furthermore, the intercept value does not correspond to the center of the design space but rather to the mathematical fit of the model. This equation is best utilized for numerical prediction, simulations, and generating response surfaces, rather than for evaluating the sensitivity or contribution of each factor. For understanding factor impact, standardized coefficients or contribution percentages from ANOVA are more appropriate.

$$\text{Cutting Temperature} = -135.8167 + 0.1563A - 37.25B + 2.64C + 0.03125AB - 0.00075AC - 0.5BC - 5.83 \times 10^{-5}A^2 + 79.1667B^2 - 0.01333C^2 \quad (4.1)$$

Where: A is cutting speed, B is depth of cut and C is feed rate.

Table 4. 2 ANOVA results of cutting temperature

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	304.47	9	33.83	3.37	0.0114	significant
A-Cutting Speed	12.80	1	12.80	1.27	0.2724	
B-Depth of cut	105.80	1	105.80	10.53	0.0041	
C-Feedrate	39.20	1	39.20	3.90	0.0622	
AB	25.00	1	25.00	2.49	0.1304	
AC	36.00	1	36.00	3.58	0.0730	
BC	16.00	1	16.00	1.59	0.2216	
A ²	28.00	1	28.00	2.79	0.1107	
B ²	51.57	1	51.57	5.13	0.0348	
C ²	9.14	1	9.14	0.9097	0.3516	
Residual	201.00	20	10.05			
Lack of Fit	199.00	5	39.80	298.50	0.86	not significant
Pure Error	2.00	15	0.1333			

Cor Total	505.47	29				
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4.1.2 Surface Roughness

4.1.2.1 Model significance and variability explanation

The ANOVA results provided in Table 4. 3 indicate that the quadratic model for surface roughness is statistically significant, with an F-value of 3.97 and a p-value of 0.0049. This demonstrates that the model effectively explains the variation in surface roughness resulting from changes in machining parameters. The model explains approximately 64.08% of the total variation in surface roughness, as calculated from the model's sum of squares (5.62) over the total corrected sum of squares (8.77). This confirms that the regression adequately captures the primary influences within the tested parameter range.

4.1.2.2 Influence of individual parameters

Among the linear terms, depth of cut (B) is the most significant contributor, with a p-value of 0.0116 and a contribution of approximately 13.91% to the total variation. This clearly identifies depth of cut as the dominant factor affecting surface roughness. A higher depth of cut likely leads to increased material engagement, higher tool deflection, and amplified surface irregularities. The cutting speed (A) and feed rate (C) also contribute noticeably to the surface roughness variation, with contributions of 6.59% and 6.17%, respectively. Although their p-values are slightly above the standard 0.05 threshold (0.0698 for A and 0.0785 for C), their proximity to significance indicates that these parameters still exert a meaningful practical effect on surface quality. This suggests that small changes in cutting speed and feed rate can affect surface finish, possibly through their influence on chip formation and thermal load.

4.1.2.3 Quadratic effects and nonlinear behavior

A critical observation is the significance of the quadratic term for cutting speed (A^2), with a p-value of 0.0074 and a contribution of 15.97% to the total variation. This reveals a strong nonlinear influence, indicating that surface roughness does not change linearly with cutting speed. Instead, it suggests an optimal point exists, where roughness is minimized, beyond which further increases in speed lead to a decline in surface quality due to thermal softening, built-up edge formation, or accelerated tool wear. Other quadratic terms, including C^2 (feed rate) and B^2 (depth of cut), are not statistically significant, with contributions of 5.61% and 0.54%, respectively. Their minor

influence indicates that while some curvature exists in the surface roughness response to feed rate, the nonlinear behavior of depth of cut is negligible within the tested range.

4.1.2.4 Interaction effects

Interaction terms show minimal contribution to surface roughness. The AB interaction (cutting speed $\times$ depth of cut) has a 3.11% contribution, while AC (cutting speed $\times$ feed rate) contributes 0.73%, and BC (depth of cut $\times$ feed rate) has a negligible effect of 0.002%. All these interactions have high p-values and are statistically insignificant, indicating that the combined effects of parameter pairs are not substantial in affecting surface roughness in this study.

4.1.2.5 Model adequacy and lack of fit

The Lack of Fit is characterized by an F-value of 14.76, which appears high, but the associated p-value of 0.89 confirms it is statistically not significant. This is a favorable outcome, indicating that the model accurately fits the data without major unexplained systematic errors. The residual error is moderate (3.15, accounting for 35.92% of total variation), while the pure error remains low (0.5319), suggesting good consistency and repeatability in the experimental observations.

4.1.2.6 Implications and summary of ANOVA results

The quadratic response surface model developed for predicting surface roughness under MQL-assisted CNC turning demonstrated that the model itself was statistically significant with a p-value of 0.0049, while the lack-of-fit test was not significant ($p = 0.89$), thereby confirming its adequacy. The contribution analysis in Fig.4. 5 shows that the quadratic effect of cutting speed was the most dominant single factor, accounting for 15.97% of the total variation, followed by the linear effect of depth of cut at 13.91%. Together, these two terms explained nearly 30% of the total variability in surface roughness, underscoring their combined importance in the machining process. Cutting speed and feed rate, although individually falling just short of statistical significance at the 5% level, still contributed moderately with 6.59% and 6.17% respectively, highlighting their practical importance in machining operations. The quadratic effect of feed rate further added 5.60% to the overall variation, while the interaction effect between cutting speed and depth of cut explained 3.11%. In contrast, the effects of cutting speed–feed rate interaction, depth of cut squared, and the interaction between depth of cut and feed rate were minimal, contributing less than 1% each, with the BC interaction being practically negligible at just 0.002%. These findings confirm that while certain higher-order and interaction terms do not meaningfully affect surface roughness, the inclusion of quadratic and main effects for cutting speed and depth of cut is crucial for accurate

modeling. The relatively high residual error suggests that unaccounted factors such as tool wear, vibration, thermal instability, or lubrication variability may have influenced the surface roughness, a common limitation in machining experiments. Despite this, the absence of lack-of-fit demonstrates that the quadratic model is robust and statistically reliable for predictive purposes. Overall, the results confirm that the nonlinear effect of cutting speed and the linear role of depth of cut are the most significant determinants of surface roughness, while cutting speed and feed rate, though moderately influential, remain essential for optimization. Thus, minimizing surface roughness requires careful control of depth of cut and avoidance of extreme cutting speed values, reinforcing the need for balanced parameter selection rather than reliance on single-factor extremes.

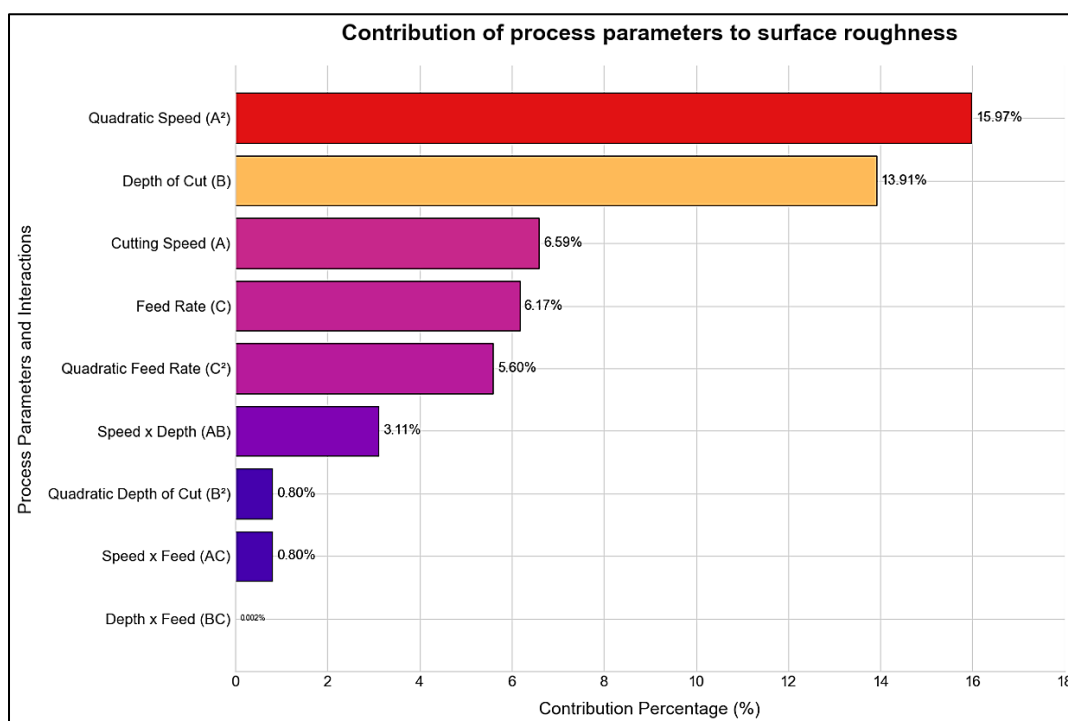


Fig.4. 5 The Factors contributing to surface roughness

4.1.2.7 Final Equation in terms of actual factors

The final regression equation (shown in equation 4.2) in terms of actual factors provides a mathematical model for predicting Surface Roughness based on the cutting speed (A), depth of cut (B), and feed rate (C). This model includes linear terms, interaction effects, and quadratic terms, capturing the complex relationships among the machining parameters. The negative coefficient for cutting speed ($-0.02406A$) suggests that increasing cutting speed tends to slightly

improve surface finish (i.e., reduce surface roughness). This is consistent with conventional machining principles, where higher cutting speeds often lead to smoother surfaces due to reduced built-up edge formation and better chip flow. Conversely, depth of cut shows a strong positive influence on surface roughness, with a coefficient of +3.3769B. This implies that increasing the depth of cut significantly deteriorates the surface finish, likely due to increased cutting forces and tool deflection. Feed rate has a negative linear coefficient (−0.3235C), indicating that higher feed rates may reduce surface roughness within the studied range, although this effect is often process-dependent. The interaction terms reveal subtle interdependencies among the factors. For example, the negative AB coefficient (−0.00327) implies that the combined effect of increasing both cutting speed and depth of cut may further reduce surface quality. On the other hand, the positive BC interaction term (+0.00156) suggests a mild increase in surface roughness when both depth of cut and feed rate are increased together. Quadratic terms further refine the model by capturing curvature in the response. Notably, the negative coefficient for depth of cut squared (−2.3958B²) indicates a nonlinear effect where surface roughness may initially increase with depth of cut but then plateau or decrease beyond a certain point. However, the small coefficients for cutting speed squared and feed rate squared imply minimal curvature in their effects. It is important to note that while this equation can be used for predictive purposes, it should not be used to compare the relative importance of factors due to differences in units and scaling. For assessing relative influence, standardized coefficients or ANOVA-based contribution analysis would be more appropriate.

$$\text{Surface Roughness} = 22.8711 - 0.02406A + 3.3769B - 0.3235C - 0.00327AB - 3.156 \times 10^{-5}AC + 0.00156BC + 1.304 \times 10^{-5}A^2 - 2.3958B^2 + 0.00309C^2 \quad (4.2)$$

Table 4. 3 ANOVA results of surface roughness

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	5.62	9	0.6244	3.97	0.0049	significant
A-Cutting Speed	0.5780	1	0.5780	3.67	0.0698	
B-Depth of cut	1.22	1	1.22	7.72	0.0116	
C-Feedrate	0.5412	1	0.5412	3.44	0.0785	
AB	0.2730	1	0.2730	1.73	0.2028	
AC	0.0638	1	0.0638	0.4049	0.5318	

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BC	0.0002	1	0.0002	0.0010	0.9752	
A ²	1.40	1	1.40	8.89	0.0074	
B ²	0.0472	1	0.0472	0.3000	0.5900	
C ²	0.4916	1	0.4916	3.12	0.0925	
Residual	3.15	20	0.1574			
Lack of Fit	2.62	5	0.5234	14.76	0.89	not significant
Pure Error	0.5319	15	0.0355			
Cor Total	8.77	29				

4.1.3 Material Removal Rate (MRR)

The ANOVA results presented in Fig.4. 6 demonstrate that the quadratic model developed for predicting the MRR is statistically significant and highly reliable. The model's very high F-value of 839.95 and an associated p-value of less than 0.0001 confirm that the selected machining parameters and their interactions collectively have a substantial and consistent influence on MRR within the experimental range.

4.1.3.1 Model adequacy and fit

One of the essential indicators of model adequacy is the Lack of Fit test, which, in this case, shows an F-value of 1.98 and a p-value of 0.91. The non-significant lack of fit implies that the model closely follows the experimental data and that there is no substantial unexplained variation. This affirms that the model is statistically valid and appropriate for accurately describing and predicting the behavior of MRR.

4.1.3.2 Effect of main process parameters

Among the primary machining variables, depth of cut (factor B) is by far the most influential. It contributes approximately 94.34% to the total variation in MRR, as derived from its sum of squares. Based on the ANOVA results, depth of cut (factor B) emerged as the overwhelmingly dominant contributor to MRR. It accounted for nearly 94.34% of the total variation, as indicated by its sum of squares value of 3075.20 out of a corrected total of 3259.20 as seen in Fig.4. 6. This is further validated by its extraordinarily high F-value of 7151.63 and a p-value well below 0.0001, underscoring both its statistical and practical significance. The strong effect of depth of cut is fully consistent with machining theory since increasing this parameter directly enlarges the cross-sectional area of material engaged by the tool, thereby increasing the volume removed per unit time. The feed rate (factor C) followed as the second most influential parameter, contributing

approximately 3.53% of the total variation in MRR. Its effect was also highly significant, reflected in an F-value of 267.91 and a p-value < 0.0001 . This strong influence is expected because increasing the feed directly thickens the material layer removed per revolution, which enhances the material removal rate substantially. Although much smaller than depth of cut, its contribution is nevertheless essential in fine-tuning productivity levels. Cutting speed (factor A) contributed only about 0.22% to the total variation in MRR. Despite its relatively minor share, it still showed statistical significance with an F-value of 16.74 and a p-value of 0.0006. Its effect is less direct compared to depth of cut and feed rate, influencing MRR through chip formation dynamics, cutting temperature, and tool–workpiece interaction time. In certain conditions, these secondary influences can meaningfully alter removal efficiency. Interaction terms also played a role. The BC interaction (depth of cut $\times$ feed rate) explained about 1.10% of the variation with a strong F-value of 83.72 and a p-value < 0.0001 , showing that simultaneous changes in these parameters amplify their effects.

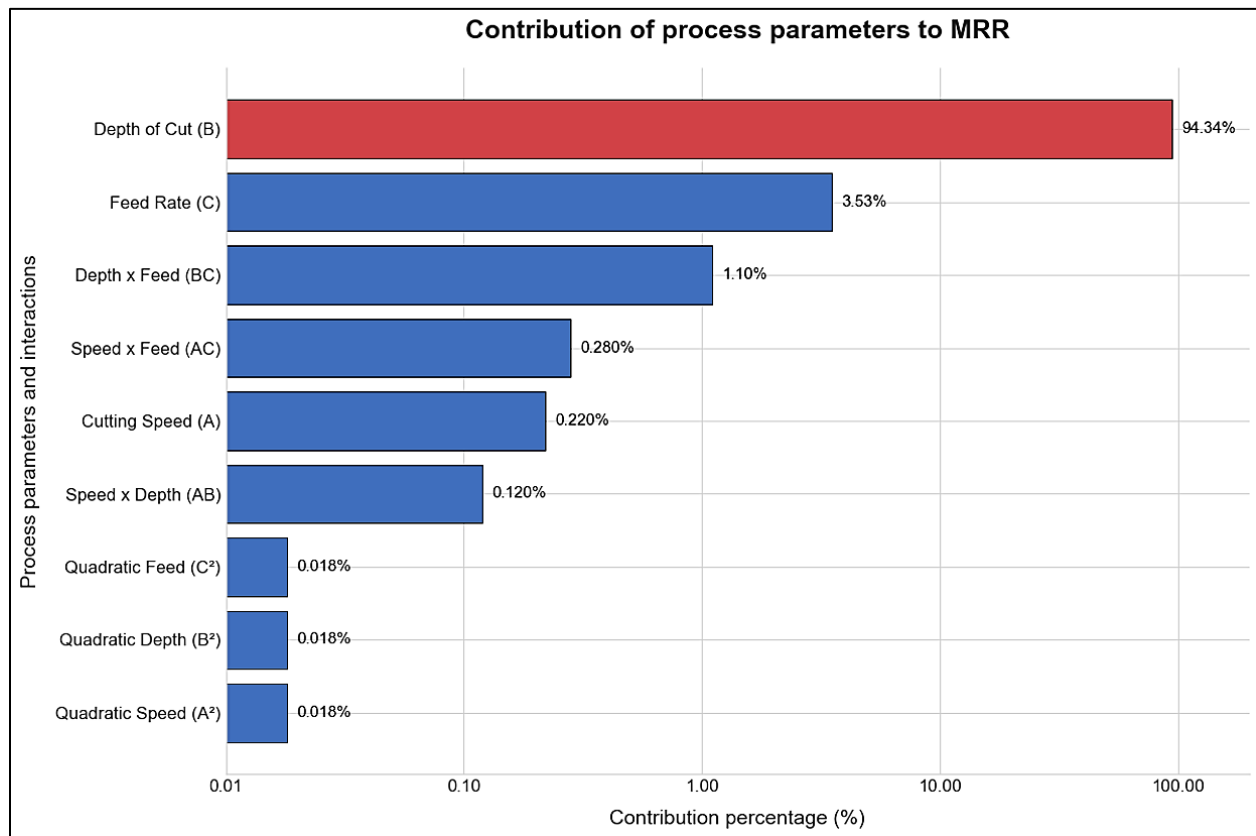


Fig.4. 6 The factors contributions to MRR

The AC interaction (cutting speed $\times$ feed rate) contributed 0.28% and was statistically significant, while the AB interaction (cutting speed $\times$ depth of cut) explained 0.12% with a p-value of 0.0063. By contrast, the quadratic terms A^2 , B^2 , and C^2 each accounted for only 0.018% of the variability, with non-significant p-values, indicating their negligible role in the model. Thus, the model explained 99.7% of the total variability in MRR, leaving only 0.26% unexplained by residual error. Importantly, the lack-of-fit test was not significant ($p = 0.91$), which validates the adequacy of the quadratic model. These findings emphasize that depth of cut is the primary driver of MRR in CNC turning, with feed rate as the secondary contributor and cutting speed exerting only a minor but statistically valid influence. Interactions, particularly between depth of cut and feed rate, also enhance the predictive accuracy of the model.

4.1.3.3 Significance of interaction effects

In addition to the main effects, the analysis reveals that interaction terms also play a meaningful role. Among these, the interaction between depth of cut and feed rate (BC) is the most pronounced, contributing approximately 1.10% to the total variation and showing a strong statistical significance with an F-value of 83.72 and a p-value less than 0.0001. This interaction suggests that when both depth of cut and feed rate are increased simultaneously, there is a synergistic amplification of MRR. This can be attributed to the compounded effects on chip load and the effective engagement of the cutting tool with the material. The interactions between cutting speed and feed rate (AC), and between cutting speed and depth of cut (AB), though less significant individually, still contribute to the model with approximately 0.28% and 0.12% respectively. Both of these interactions are statistically significant, indicating that even subtle changes in the combination of input variables can influence the MRR. These findings reinforce the importance of considering interaction effects in process optimization, as they may enhance or reduce the effectiveness of individual parameters depending on how they are combined.

4.1.3.4 Insignificance of quadratic terms

Unlike the linear and interaction terms, the quadratic effects of the process variables, represented by A^2 , B^2 , and C^2 , are statistically insignificant, with p-values greater than 0.26 and minimal contributions of about 0.02% each. These results suggest that the relationship between the input factors and MRR is largely linear within the parameter range studied. This is consistent with theoretical expectations, as the mathematical expression for MRR in machining is a direct product

of cutting speed, feed rate, and depth of cut. Therefore, nonlinear curvature effects are not prominent in this case, simplifying both model interpretation and implementation.

4.1.3.5 Overall interpretation and implications

Overall, the analysis confirms that depth of cut is the most critical parameter influencing MRR, followed by feed rate, and then cutting speed. The linear effects dominate the behavior of MRR, while certain interaction effects, especially between depth of cut and feed rate, play a meaningful role in enhancing performance. The quadratic effects are negligible, affirming the linear nature of the process within the explored design space. Importantly, the absence of a significant lack of fit confirms that the developed model effectively represents the experimental data, making it a dependable tool for predictive modeling, process optimization, and decision-making in machining operations focused on maximizing material removal efficiency.

4.1.3.6 Final Equation in terms of actual factors

The 4.3 equation represents a quadratic regression model that predicts the MRR as a function of cutting speed, depth of cut, and feed rate in their actual units. It incorporates linear, interaction, and quadratic terms to capture both direct and synergistic effects of the input parameters. The cutting speed (A) has a small positive linear coefficient (+0.00508), indicating that increasing cutting speed results in a slight increase in MRR. This is in line with machining principles, where higher speeds typically enable more rapid material removal, though the effect here is modest. Surprisingly, the depth of cut (B) shows a negative linear coefficient (−0.5000), which would traditionally suggest a decrease in MRR with an increase in depth of cut. However, this is counteracted by a large positive quadratic term (+8.3333B²) and a strong positive interaction with feed rate (BC = +0.75). Together, these imply that at lower depths, MRR may drop slightly, but as depth increases further, especially in combination with feed rate, the MRR increases significantly. This pattern suggests a nonlinear behavior in how depth of cut influences MRR. The feed rate (C) also has a small negative linear coefficient (−0.0100), but like depth of cut, it is complemented by a positive quadratic term (+0.00333C²) and a strong interaction with depth of cut. This suggests that while higher feed rates may initially reduce MRR slightly, possibly due to tool overload or deflection, increasing both feed rate and depth together can strongly enhance material removal. The interaction terms reveal important synergistic effects. The depth of cut × feed rate (BC) term is particularly notable, with a coefficient of +0.75, showing that their combined effect significantly boosts MRR. Meanwhile, the cutting speed × depth of cut (AB = +0.0125) also contributes

positively, reinforcing the fact that interactions between cutting parameters can influence the efficiency of material removal more than their isolated effects. Quadratic terms for all variables are present, but only the quadratic term for depth of cut stands out as having a substantial effect, again emphasizing the nonlinear impact of depth of cut on MRR. The quadratic terms for cutting speed and feed rate are minimal, indicating little curvature in their individual contributions. As with other regression models, this equation is most valuable for predicting MRR at specific settings within the experimental range. However, due to differences in units and scaling, the coefficients should not be interpreted directly to assess the relative importance of the factors. For that purpose, ANOVA or contribution percentage analysis provides more reliable insights.

$$\text{Material Removal Rate (MRR)} = -2.4333 + 0.00508A - 0.5000B - 0.0100C + 0.0125AB - 0.000375A^2 + 0.75BC + 8.33 \times 10^{-6}A^2 + 8.3333B^2 + 0.00333C^2 \quad (4.3)$$

Table 4. 4 ANOVA results of MRR

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	3250.60	9	361.18	839.95	< 0.0001	significant
A-Cutting Speed	7.20	1	7.20	16.74	0.0006	
B-Depth of cut	3075.20	1	3075.20	7151.63	< 0.0001	
C-Feedrate	115.20	1	115.20	267.91	< 0.0001	
AB	4.00	1	4.00	9.30	0.0063	
AC	9.00	1	9.00	20.93	0.0002	
BC	36.00	1	36.00	83.72	< 0.0001	
A ²	0.5714	1	0.5714	1.33	0.2626	
B ²	0.5714	1	0.5714	1.33	0.2626	
C ²	0.5714	1	0.5714	1.33	0.2626	
Residual	8.60	20	0.4300			

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Lack of Fit	8.60	5	1.72	1.98	0.91	not sifgnificant
Pure Error	0.0000	15	0.0000			
Cor Total	3259.20	29				

4.2 Interaction Analysis

4.2.1 Interaction Analysis of cutting temperature

The influence of machining parameters, cutting speed, depth of cut, and feed rate on the cutting temperature during CNC turning of AISI 4340 steel is clearly illustrated in Fig.4. 7 (a), (b), and (c). The response trends reflect the complex thermal behaviors arising from material deformation, friction, and heat dissipation mechanisms during the machining process.

4.2.1.1 Effect of Cutting Speed

As shown in Fig.4. 7 (a) and (b), increasing the cutting speed from 800 to 1000 rpm leads to a noticeable rise in cutting temperature. This is expected, as higher cutting speeds increase the rate of friction between the tool and the workpiece, contributing to greater heat generation. Additionally, the reduced time for heat dissipation at higher speeds causes heat to accumulate more rapidly at the cutting interface. Interestingly, when the cutting speed increases further from 1000 to 1200 rpm, the cutting temperature reaches a maximum but does not continue to rise significantly; instead, it shows a slight reduction. This behavior can be attributed to a shift in the dominant heat transfer mechanisms. At very high cutting speeds, chips are evacuated more quickly, carrying away a substantial portion of the generated heat. Consequently, less heat is retained in the cutting zone and the workpiece, leading to a slight drop in temperature. However, the temperature remains close to its peak, indicating that the system is approaching a thermal balance where heat generation and dissipation are competing processes.

4.2.1.2 Effect of Depth of Cut

The impact of depth of cut on cutting temperature, as illustrated in Fig.4. 7 (a) and (c), shows a consistent pattern. Increasing the depth of cut from 0.1 to 0.2 mm results in a significant increase in cutting temperature. This is because a larger depth of cut engages a greater volume of material, increasing the plastic deformation at the shear zone and, consequently, the heat generated. However, an intriguing phenomenon occurs when the depth of cut increases from 0.2 to 0.3 mm, where the cutting temperature slightly decreases. This point represents an optimal condition, likely

due to an improvement in chip formation or thermal stabilization. At this depth, chips may shear more effectively, reducing friction at the tool-workpiece interface or allowing better heat evacuation through the chip. This leads to a temporary decline in temperature. Beyond this optimal point, as the depth of cut increases from 0.3 to 0.5 mm, the cutting temperature once again rises steadily. The increased material engagement results in greater energy consumption and more significant heat accumulation in the cutting zone, overcoming the benefits of any temporary thermal stabilization.

4.2.1.3 Effect of Feed Rate

The role of feed rate is depicted in Fig.4. 7 (b) and (c). Increasing the feed rate from 50 to 65 mm/min results in a clear rise in cutting temperature. A higher feed rate increases the thickness of the uncut chip, leading to larger material removal per unit time. This accelerates energy input into the cutting zone, enhancing heat generation due to increased plastic deformation and friction. However, when the feed rate is raised further from 65 to 70 mm/min, the cutting temperature shows a slight decline. This behavior can be explained by improved chip formation dynamics at higher feeds. Larger, thicker chips tend to carry more heat away from the cutting interface, improving heat removal. Additionally, the reduced time of tool-workpiece contact per unit length at higher feeds might contribute to lower heat accumulation, despite the high energy input. Therefore, the results reflect the nonlinear relationship between machining parameters and cutting temperature, driven by the interplay between heat generation and dissipation mechanisms. While increases in cutting speed, depth of cut, and feed rate generally contribute to higher cutting temperatures, the system exhibits local optimal points where thermal conditions temporarily stabilize or improve due to enhanced chip evacuation or changes in cutting dynamics. These findings are crucial for process optimization in CNC turning of AISI 4340 steel, as they highlight the importance of carefully balancing parameters not only for material removal efficiency but also for controlling thermal effects, which directly influence tool wear, surface integrity, and dimensional accuracy.

4.2.1.4 Predicted vs. Actual Results

The Predicted vs. Actual plot, as illustrated in Fig.4. 7 (d), serves as an essential diagnostic tool to evaluate the accuracy and reliability of the developed model. The close alignment of the data points along the diagonal reference line indicates that the predicted values closely match the actual experimental observations. This strong correlation suggests that the model has effectively captured the underlying relationships between the input machining parameters and the response variables.

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The tight clustering of points around the line of perfect agreement confirms that the model demonstrates high predictive accuracy with minimal deviation between predicted and actual values. This outcome reinforces the validity of the RSM employed in this study and confirms that the regression models developed are robust and capable of accurately representing the machining behavior of AISI 4340 steel under the specified conditions. In addition to validating the model's statistical significance as shown by the ANOVA results, the Predicted vs. Actual plot further verifies that the model can be confidently applied for process optimization, prediction, and decision-making in practical CNC turning applications.

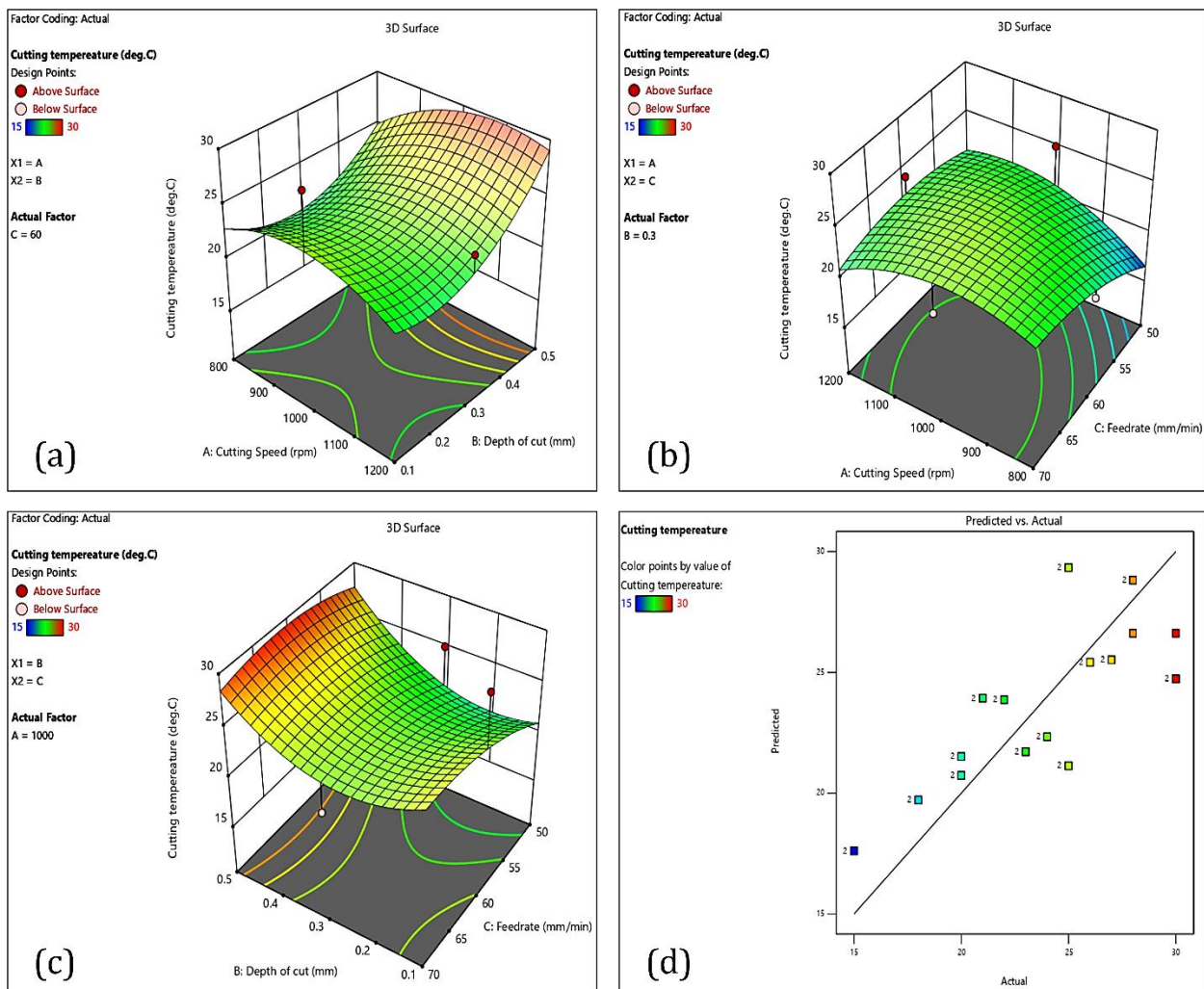


Fig.4. 7 Interaction analysis of cutting temperature through 3-dimensions

The minimal dispersion from the ideal line highlights that errors are random rather than systematic, indicating a good model fit without significant bias. The performance evaluation of the developed

predictive model demonstrates a strong agreement between the predicted and experimentally measured temperatures during CNC turning under MQL conditions. As shown in Fig.4. 8, the model effectively captures the complex thermal behavior associated with varying machining parameters. The line plot in Fig.4. 8a illustrates the actual and predicted temperature values across 30 experimental runs, revealing that both curves follow almost identical paths throughout the entire sequence. This consistent alignment indicates that the regression model, constructed using RSM within a CCD framework, successfully generalizes across different combinations of cutting speed, feed rate, and depth of cut. The closeness of predicted values to actual measurements in runs such as 3, 8, 11, 18, and 24 suggests that the model accurately captures the nonlinear interactions among the machining parameters and their influence on thermal generation. Although slight deviations can be observed in a few cases, particularly in runs 15 and 29 where the model slightly underestimates the temperature, these differences are minor and fall within acceptable experimental tolerances. These deviations may be attributed to natural process variability, thermal inertia, or minor simplifications within the model that do not fully account for localized phenomena such as transient heat conduction or tool–chip interface fluctuations. Further supporting this conclusion, the scatter plot in Fig.4. 8b presents a clear correlation between actual and predicted values, where most data points cluster closely around the ideal prediction line ($y = x$). This visual alignment indicates a high degree of predictive accuracy. The calculated mean absolute error (MAE) of 2.20 °C and root mean square error (RMSE) of 2.59 °C provide quantitative evidence of the model's low prediction error, reinforcing its reliability. The tight distribution of points around the reference line suggests minimal systematic deviation and supports the model's capability to provide consistent and accurate predictions across the design space. The residual analysis shown in Fig.4. 8c offers additional insights into the model's performance. The error bars, represented in green for positive residuals (underestimations) and red for negative residuals (overestimations), are distributed symmetrically around the zero-error line. This balanced distribution confirms the absence of bias in the model's predictions. The majority of residuals lie within ± 4 °C, with most errors appearing randomly across the run sequence. This randomness indicates that the model has successfully captured the underlying trends without leaving structured patterns in the residuals, which is a desirable outcome in regression modeling. Although a few larger residuals appear, particularly in runs 15 and 29, they do not indicate systemic issues and can be reasonably explained by experimental uncertainty or unmodeled disturbances. Fig.4. 8d

presents the actual and predicted values again, this time with visual connectors indicating the residuals for each run. These connectors clearly show the magnitude and direction of the prediction errors. Most connectors are short, signifying minimal deviation between actual and predicted temperatures. This visualization complements the residual bar chart by providing a more intuitive understanding of the prediction accuracy at each point and reaffirms the model's robustness. Collectively, the visual and statistical analyses validate the adequacy and strength of the developed regression model. The consistent agreement between predicted and actual temperatures, minimal and randomly distributed residuals, and strong clustering around the ideal prediction line all demonstrate the model's effectiveness in capturing the thermal response of the turning process under MQL conditions. Therefore, the model can be confidently used for further analysis, optimization, and decision-making tasks aimed at improving machining performance, thermal control, and process sustainability in the context of AISI 4340 steel machining.

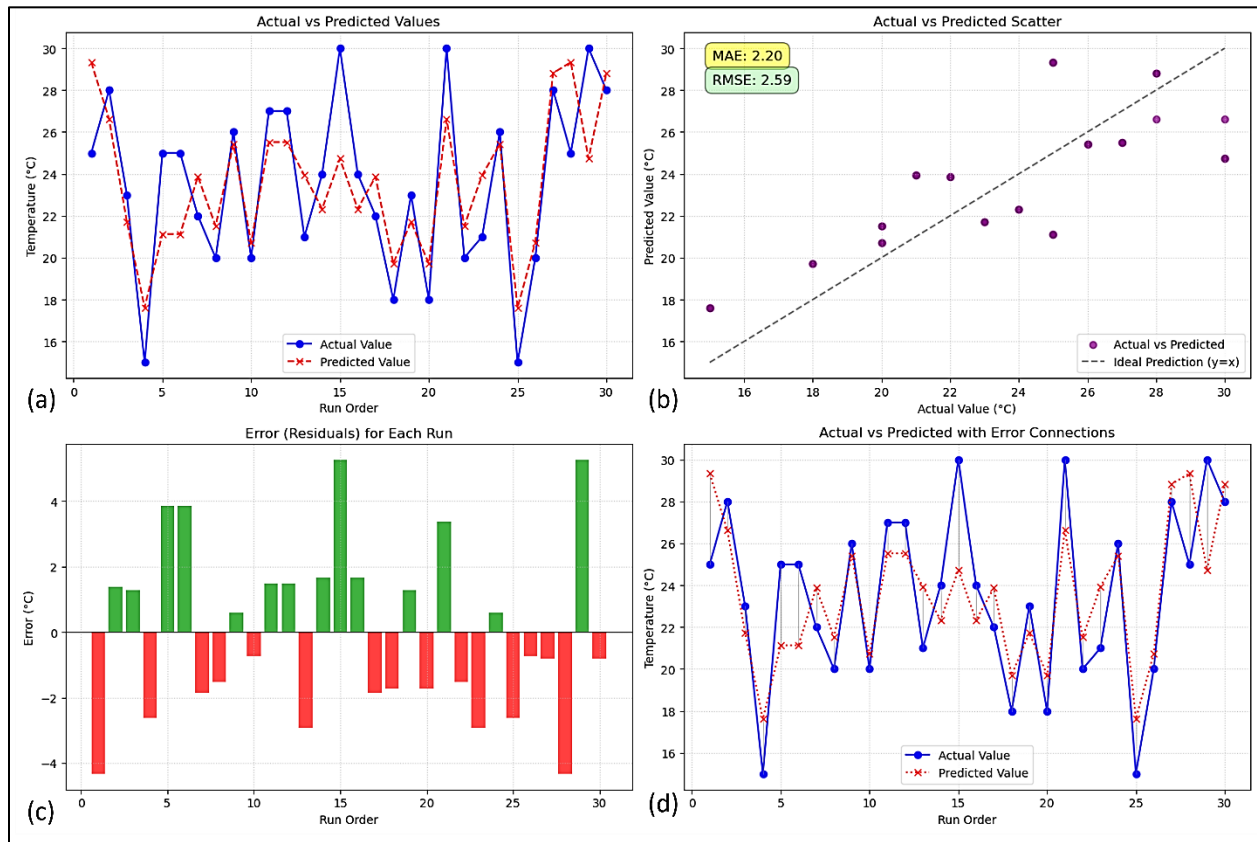


Fig.4. 8 Comparison of actual and predicted cutting temperature values

4.2.2 Interaction analysis of cutting temperature (contour and cube plots)

Fig.4. 9 illustrates the influence of cutting parameters, cutting speed (A), depth of cut (B), and feed rate (C), on the cutting temperature at the tool tip during CNC turning of AISI 4340 steel under MQL conditions. The figure includes three two-dimensional contour plots (Fig.4. 9 (a)–4.6(c)) and one cube plot (Fig.4. 9 (d)) to explore both pairwise and three-factor interactions affecting temperature.

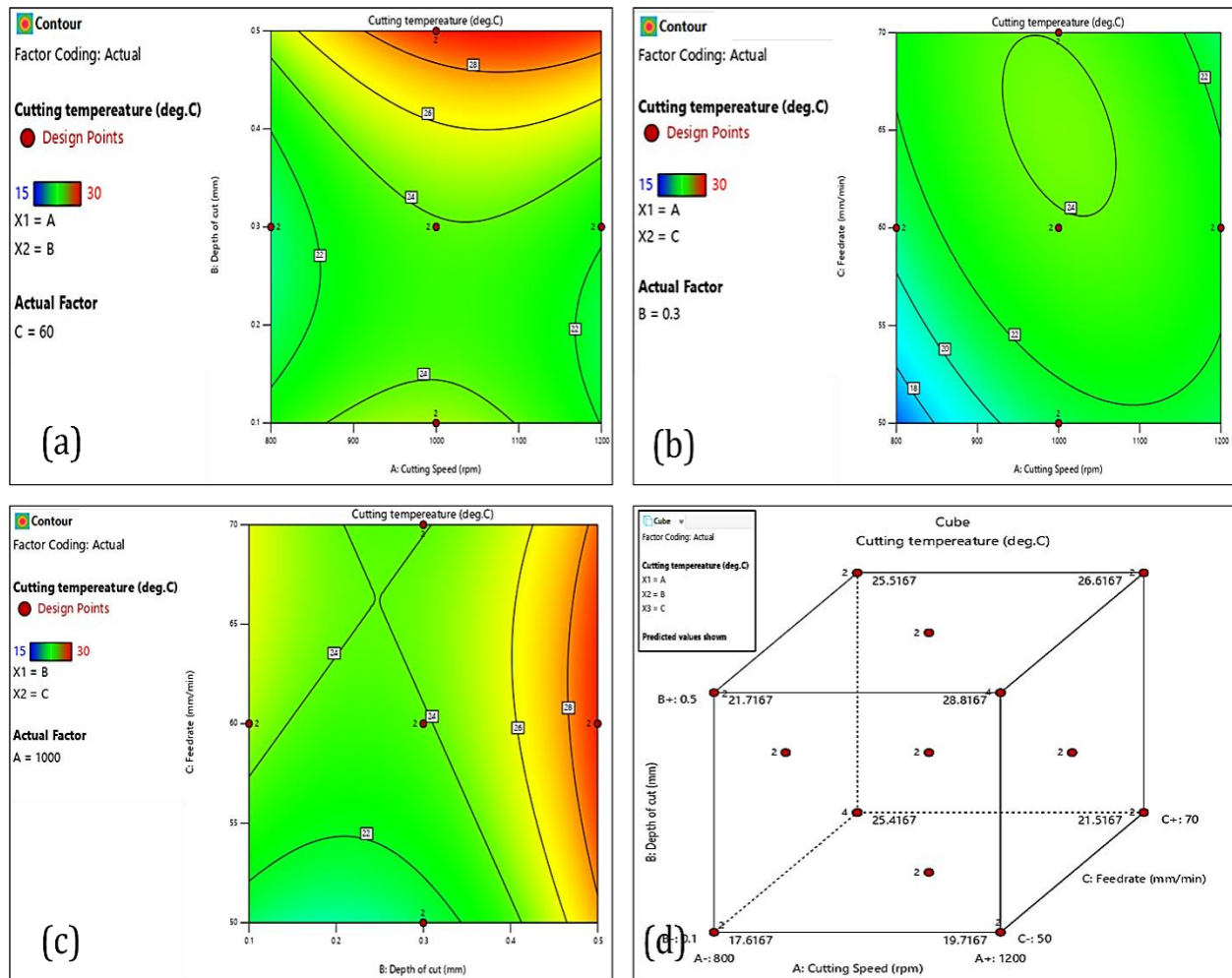


Fig.4. 9 The interaction analysis of cutting temperature (contour & cube plots)

4.2.2.1 Effect of cutting speed and depth of cut

In Fig.4. 9 (a), the interaction between cutting speed (A) and depth of cut (B) is shown with feed rate (C) fixed at 60 mm/min. The contour plot demonstrates that the cutting temperature increases with both cutting speed and depth of cut. However, a region of minimum temperature is observed around a cutting speed of 900–1000 rpm and a depth of cut between 0.2–0.3 mm. This indicates a

nonlinear interaction where thermal effects are mitigated at moderate parameter levels, likely due to balanced energy input and efficient chip removal under stable cutting conditions.

4.2.2.2 Effect of cutting speed and feed rate

Fig.4. 9 (b) examines the combined influence of cutting speed (A) and feed rate (C), while holding the depth of cut (B) constant at 0.3 mm. The temperature distribution shows a consistent rise with increasing values of both parameters, though feed rate exerts a more dominant effect. A hot zone exceeding 26°C emerges in the upper-right region of the plot, where both cutting speed and feed rate are high. This pattern highlights that increased feed rate significantly contributes to tool tip heating, potentially due to increased friction, plastic deformation, and energy dissipation during chip formation.

4.2.2.3 Effect of depth of cut and feed rate

Fig.4. 9(c) presents the contour plot of depth of cut (B) versus feed rate (C), with cutting speed (A) fixed at 1000 rpm. The results reveal that higher temperatures are produced when both parameters are simultaneously increased. The contour lines in this region are closely spaced, indicating a steep thermal gradient and a strong synergistic interaction between feed rate and depth of cut. While the depth of cut may have a limited influence when varied alone, its impact becomes pronounced when combined with elevated feed rates under moderate speeds.

4.2.2.4 Three-Factor Interaction

The cube plot in Fig.4. 9(d) visualizes the three-factor interaction among cutting speed (A), depth of cut (B), and feed rate (C). Each vertex represents a unique combination of parameter levels, with the corresponding predicted cutting temperature displayed. The highest temperature, approximately 28.82°C, occurs at the combination of high cutting speed (1200 rpm), high feed rate (70 mm/min), and moderate depth of cut (0.3 mm). In contrast, the lowest temperature, around 17.62°C, is observed when all three factors are at their minimum values. This cube plot confirms that all three machining parameters contribute to thermal rise, but the influence of feed rate and cutting speed is especially dominant. Depth of cut affects temperature most strongly in interaction with the other two variables. Thus, the interaction analysis presented in Figure 4.6 reveals that feed rate and cutting speed are the most influential factors affecting cutting temperature in CNC turning of AISI 4340 steel under MQL conditions. Depth of cut, though less impactful in isolation, significantly influences temperature when combined with high feed rates or speeds. These results underline the importance of selecting optimal machining parameters to control thermal effects,

minimize tool wear, and enhance machining performance. Operating at moderate cutting speeds and lower feed rates is advisable for maintaining lower tool tip temperatures, especially when using MQL as a cooling and lubrication strategy.

4.2.3 Interaction analysis of surface roughness

There is shown in the Fig.4. 10 (a) the interaction of cutting speed and depth of cut on the surface roughness at a constant feed rate. Surface roughness generally decreases with an increase in cutting speed-to about 1000 rpm. Surface roughness is only marginally affected by increasing the depth of cut as a consequence of increased cutting forces and vibration. The nonlinear interaction is demonstrated by the curved surface indicating that lower cutting speeds make surface roughness more sensitive to influence by a change in depth of cut; at higher cutting speeds, this effect tends to become weaker. When the depth of cut is kept constant, the magnitude of applicability of the cutting speed and feed rate is shown in Fig.4. 10 (b). Here, the surface roughness markedly increases with increasing feed rate due to the larger feed marks left on the machined surface, but higher cutting speeds improve surface finish by enhancing shearing and reducing friction at the tool-workpiece interface. The response surface suggests an optimum condition of surface roughness minimum at very high cutting speed combined with very low feed rate, indicating the importance of balance in these parameters. In Fig.4. 10(c) shows the effects of depth of cut and feed rate on surface roughness at a constant speed of 1000 rpm for cutting. Both parameters independently add up the degradation in roughness. An increase in feed rate has a strong positive effect on roughness because of the larger undeformed chip thickness, whereas depth of cut has a moderate effect because of increased cutting force and chatter. In contrast to previous surfaces, the response is more linear in nature, indicating a general pattern that lower feed rates and smaller depths of cut would give smoother surfaces. Finally, Fig.4. 107 (d) represents the values of surface roughness predicted against the actual value, which is adopted to check whether the developed response surface model meets adequacy. Most of the data points are densely clustered around the 45-degree reference line, which means that the predicted results correspond quite closely to the experimental findings. This close correspondence, indeed, affirms that the regression model reliably represents the machining process and predicted surface roughness under various cutting conditions quite accurately.

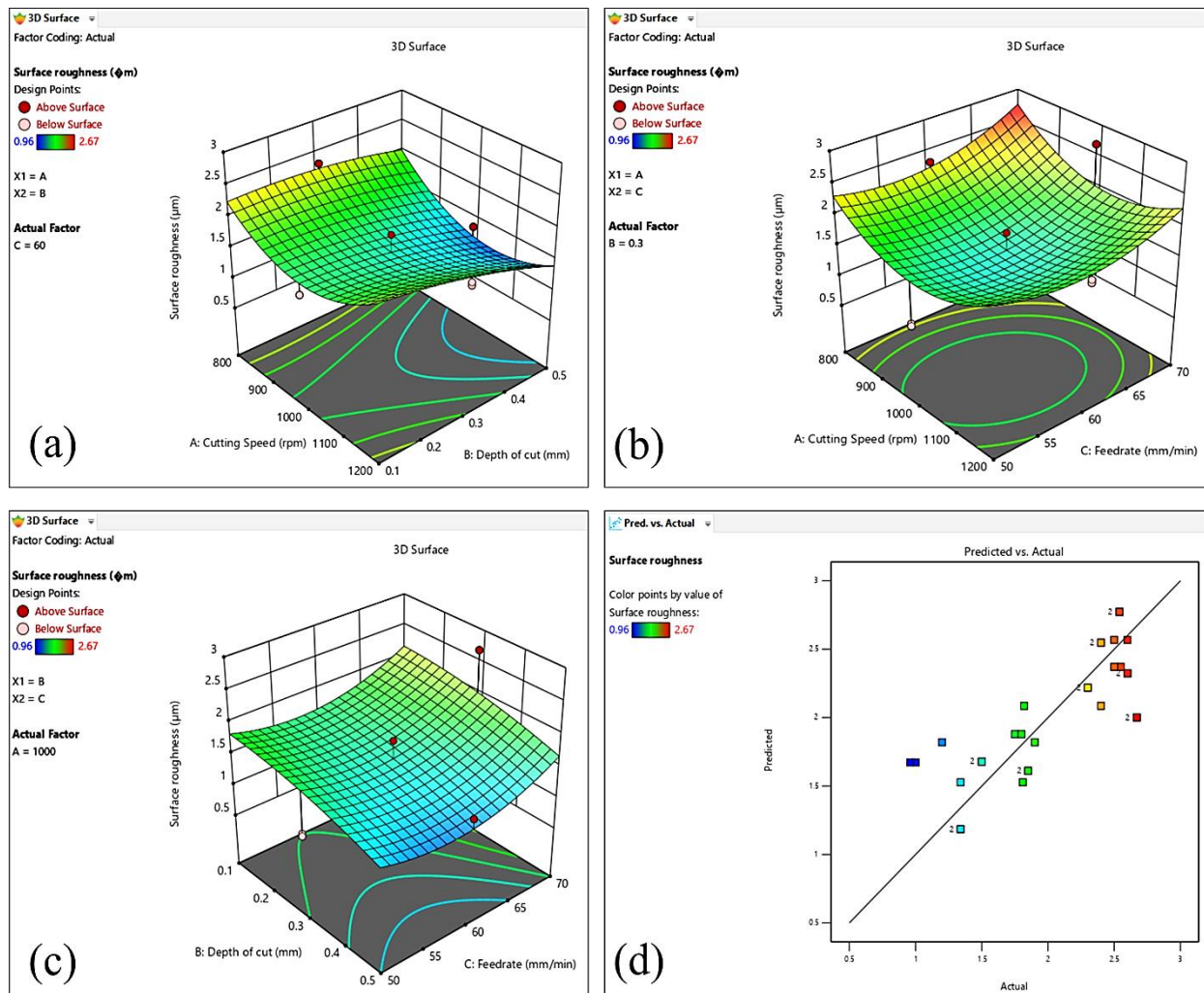


Fig.4. 10 The interaction analysis of surface roughness (3D surface)

Fig.4. 11 provides a comprehensive assessment of the predictive performance of the developed mathematical model by comparing actual surface roughness values obtained from thirty experimental runs with those predicted by the model. The data visualization in subfigure (a) presents a scatter plot of predicted versus actual values, offering an immediate visual cue of the model's overall accuracy. Ideally, data points should align along the dashed line ($y = x$), indicating perfect prediction. In this case, the majority of points cluster reasonably close to this ideal line, suggesting that the model is generally proficient in capturing the relationship between input parameters and surface roughness. The calculated Mean Absolute Error (MAE) of 0.26 μm and Root Mean Square Error (RMSE) of 0.32 μm quantitatively confirm this observation, reflecting a relatively low average deviation between actual and predicted values. Despite the overall promising performance, certain runs deviate more significantly from the expected trend. For

instance, Run 8, with an actual value of $2.50\text{ }\mu\text{m}$ and a predicted value of $2.57\text{ }\mu\text{m}$, shows only a minor discrepancy, indicating that the model performs well under those experimental conditions. Conversely, Run 2 exhibits a considerable deviation, with the model predicting $1.82\text{ }\mu\text{m}$ while the actual surface roughness is only $1.20\text{ }\mu\text{m}$. This substantial overestimation reflects a limitation in the model's ability to generalize for that particular configuration and highlights the importance of identifying outlier behavior when validating predictive accuracy. Further analysis of prediction errors is presented in Fig.4. 11 (b), where residuals (defined as predicted minus actual values) are plotted across the run order. Positive residuals indicate over-predictions, whereas negative residuals represent under-predictions. The distribution of errors appears to be fairly balanced, with no strong indication of systematic bias toward over- or underestimation. However, notable error magnitudes are observed in several runs, including Runs 2, 5, and 21, reaffirming the earlier identified limitations of the model in specific scenarios. This residual plot helps isolate and interpret the predictive inconsistencies in a way that is not easily discernible from aggregate error metrics alone. Fig.4. 11 (c) plots both actual and predicted values sequentially across the run order, connected with dashed lines to illustrate the deviation per run. The predicted values generally follow the same trend as the actual values, indicating that the model is successful in capturing the underlying dynamics of surface roughness variation. Nonetheless, the magnitude of deviation fluctuates throughout the dataset. In certain runs, particularly where actual values change rapidly, the model struggles to replicate the exact behavior, which could point to limitations in its ability to account for complex interactions or nonlinearities within the system. Complementing this, the absolute error per run is visualized in Fig.4. 11 (d), showing the magnitude of error regardless of direction. This plot reinforces the earlier observations by clearly identifying runs with high error levels. In most cases, the absolute error remains below $0.2\text{ }\mu\text{m}$, supporting the assertion that the model achieves high predictive accuracy for a majority of the experiments. However, spikes at specific runs, most notably Runs 2 and 5, highlight the need for cautious interpretation of the model's outputs, particularly in scenarios where its performance deteriorates. Another notable observation across the plots is the recurrence of identical or near-identical predicted values for different runs. This behavior suggests that the model may lack the sensitivity to discriminate between subtly varying experimental conditions. Such clustering of predictions can arise from insufficient model complexity, overly smoothed regression functions, or possibly from the input features themselves lacking the granularity needed to influence output variation meaningfully.

This limitation could restrict the model's ability to fully exploit the richness of the dataset, especially when fine distinctions in surface roughness are necessary for process optimization. In summary, while the model demonstrates generally strong predictive performance, as evidenced by relatively low error metrics and consistent trend alignment, a few individual runs reveal areas where prediction accuracy is compromised. These inconsistencies underline the importance of thorough model validation and error analysis, particularly in practical applications where prediction fidelity is critical. Improvements may be achieved through the incorporation of additional explanatory variables, refinement of model parameters, or the use of more advanced modeling techniques capable of capturing complex relationships more effectively. The detailed diagnostic visualizations in Fig.4. 11 serve not only to evaluate the model's current performance but also to guide future enhancements and ensure robustness in predictive deployment.

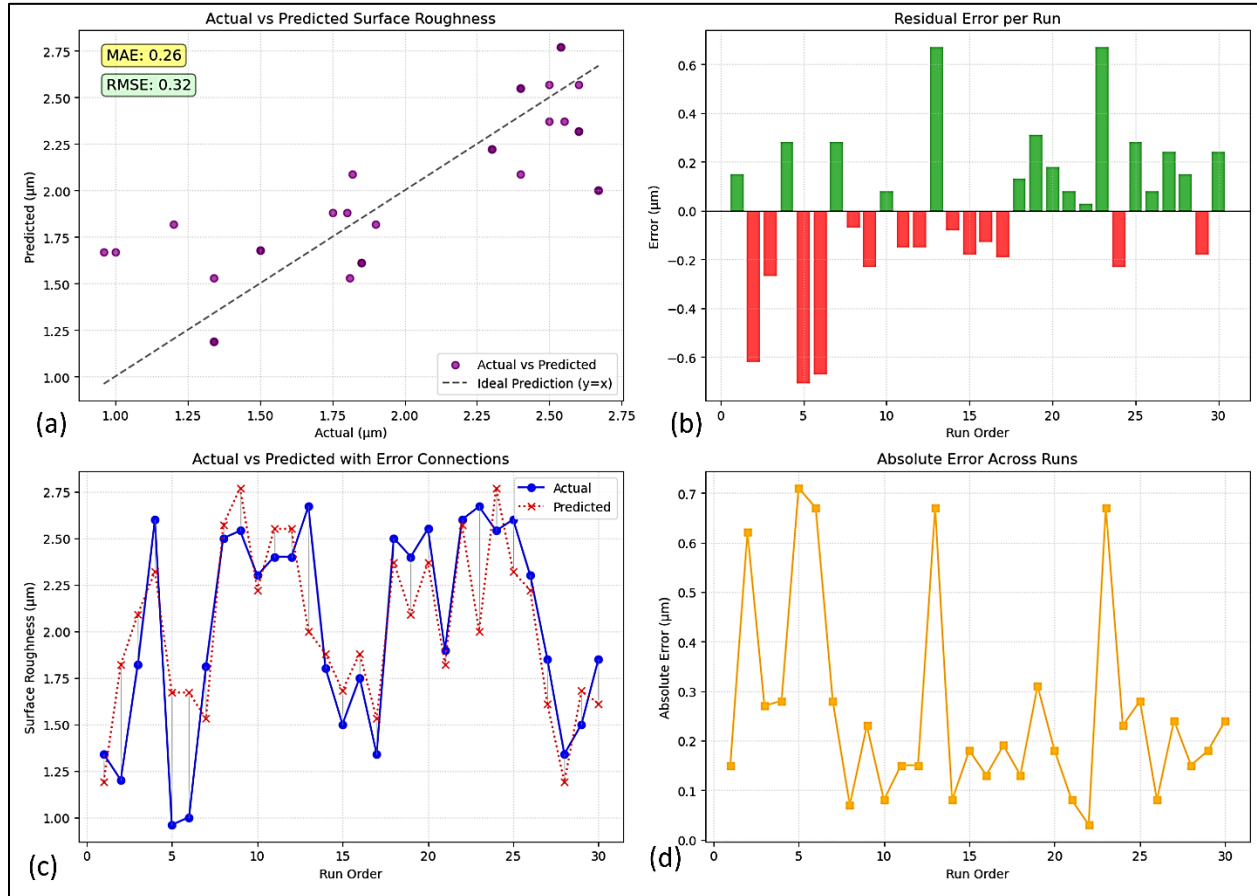


Fig.4. 11 Evaluation of predictive model performance through actual vs predicted surface roughness, residuals, and error trends over 30 experimental runs

4.2.4 Interaction analysis of surface roughness (contour and cube plots)

The RSM models illustrate surface roughness (R_a , μm) as a function of cutting speed (A), depth of cut (B), and feed rate (C) in a machining process. In Fig.4. 12 (a), set cutting speed against depth of cut with a constant feed rate of 60 mm/min. Roughness decreases with the increasing cutting speed and lower depths of cut, where the smoother surfaces were attained at around 1000-1100 rpm and 0.1-0.2 mm depth. This is so because shearing was much cleaner due to the formation of a minimum built-up edge at the higher speed. At the same time, deeper cutting depths increased cutting forces and vibrations that adversely affected surface finish.

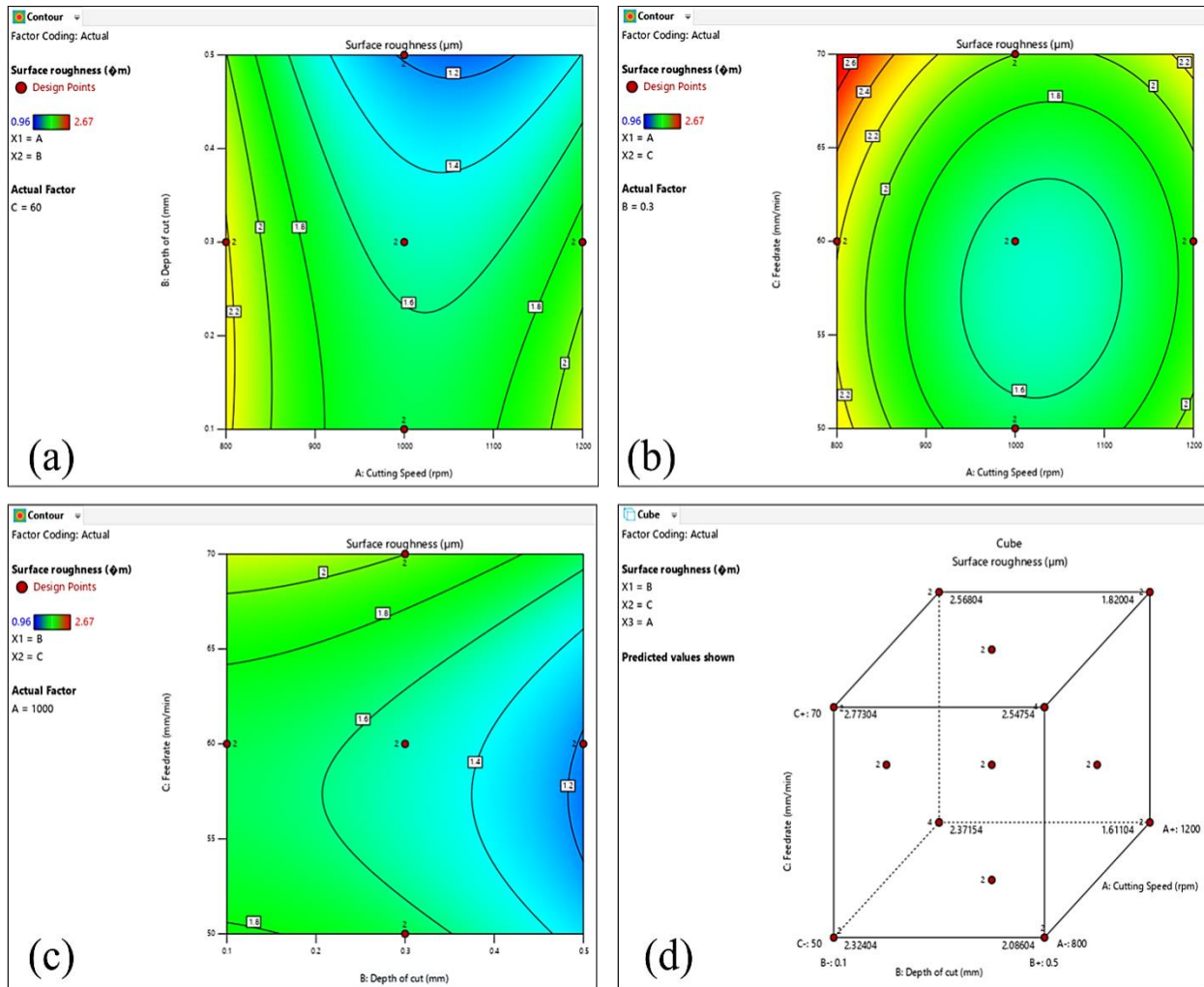


Fig.4. 12 The interaction analysis of surface roughness (contour & cube plots)

The cutting speed versus feed rate plot, displayed in Fig.4. 12 (b) at a constant depth of cut of 0.3 mm, shows that for low roughness, it is best to work at moderate feed rates (~60 mm/min) together

with mid-to-high cutting speeds, while a very low or a very high feed rate will deteriorate the surface finish by rubbing the surface or leaving deep tool marks, respectively. A plot of depth of cut against feed rate at a constant cutting speed of 1000 rpm is shown in Fig.4. 12 (c). Very smooth surfaces were produced at the shallowest feed rates, whereas higher values of both are introduced into the equation to produce rougher finishes due to higher cutting forces and possible chatter. Find out in detail by looking at the cube plot in Fig.4. 12 (d), where it summarizes the predicted values- or more so, the best finish achieved ($\sim 1.16 \mu\text{m}$) for high cutting speed (1200 rpm), low depth of cut (0.1 mm), and low feed rate (50 mm/min), and the worst finish ($\sim 2.56 \mu\text{m}$) at low cutting speed (800 rpm), high depth of cut (0.5 mm), and high feed rate (70 mm/min). These results confirm that feed rate has the most dominating influence on surface roughness, the most optimal conditions obtained through its combination with high-cutting speed, low feed rate, and shallow depth of cut, quite similar to machine theory, in which these settings minimize the cutting forces, vibration, and workpiece-tool frictions that could produce cleaner shear planes and finer surface finish.

4.2.5 Interaction analysis of material removal rate (MRR)

The 3D surface plots and prediction study depict that machining parameters-cuts with A for cutting speed, B for depth of cut, and C for feed rate-affect material-removal rate (MRR) in mm^3/sec in turning. MRR increases with depth of cut and cutting speed in a feed rate condition at 60 mm/min, which is evidenced by Fig.4. 13 (a). This is because MRR is directly proportional to the product of cutting speed, feed, and depth of cut: hence increase in either A or B will lead to a linear increase of removal volume per unit time. In Fig.4. 13 (b), where cutting speed is compared with feed rate at a constant depth of cut of 0.3 mm, MRR shows almost no change with cutting speed. With an increase in feed rate, it really pushes MRR upward. This near-flattening along the cutting speed axis again is a confirmation that feed rate is indeed a more aggressive driver of MRR when holding depth of cut constant. In Fig.4. 13 (c), when looking at feed versus depth of cut while keeping cutting speed constant at 1000 rpm, MRR rises sharply with increases in both, with maximum feed and maximum depth of cut giving maximum removal rates due to this multiplicative relationship within the MRR formula. Finally, in Fig.4. 13 (d) show the predicted MRR versus actual MRR values show a very strong fit along the 45° line, indicating very effective predictive accuracy of this regression model from the RSM analysis. All these results confirm that all three parameters do have some effect on MRR, but the effects of depth of cut and feed rate are most pronounced,

with optimum productivity at higher values of these parameters being achieved when surface finish and tool life considerations are taken into account.

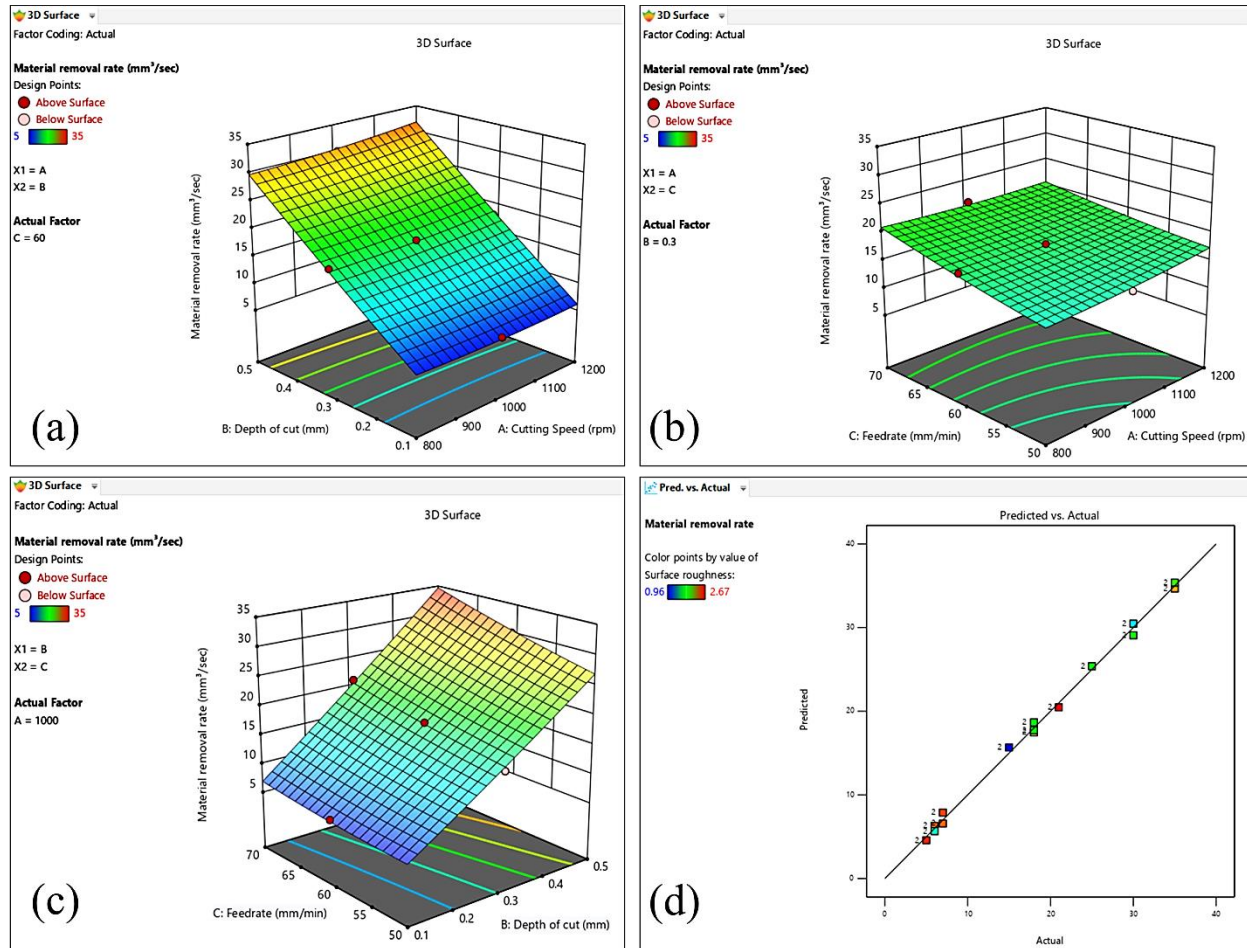


Fig.4. 13 The interaction analysis of MRR (3D surface)

Fig.4. 14 provides a comprehensive evaluation of the developed regression model for predicting the MRR based on 30 machining trials. The comparison between actual experimental results and model-predicted values highlights the accuracy, consistency, and predictive reliability of the developed model in representing the machining process behavior. In Fig.4. 14 (a), the relationship between actual and predicted MRR values is shown using a scatter plot. Each point represents one experimental trial, with the dashed diagonal line indicating the ideal condition where predicted values perfectly match the actual data. The data points are distributed very closely around this ideal line, showing that the predicted MRR values follow the experimental measurements with extremely small deviations. This observation confirms a strong linear correlation and demonstrates

that the model successfully captures the relationship between the input machining parameters and MRR response. Quantitatively, the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are 0.50 mm³/min and 0.54 mm³/min, respectively, which are very low compared to the overall range of MRR (approximately 5 to 36 mm³/min). These small error values indicate that the average prediction deviation from the actual data is less than 2% of the total range, signifying remarkable prediction precision. Moreover, the coefficient of determination ($R^2 = 0.9974$) further confirms that the regression model can explain 99.74% of the total variability observed in MRR. Such a high R^2 value implies that the unexplained error is minimal and the model exhibits exceptional fitting accuracy. Fig.4. 14 (b) displays the distribution of residuals (errors), calculated as Actual – Predicted MRR, across all 30 experimental runs. The residual bars fluctuate around the zero-error line, with both positive and negative deviations remaining mostly within ± 0.5 mm³/min. This narrow range of error dispersion reflects high prediction stability and indicates that the model neither systematically overestimates nor underestimates the output. The random distribution pattern of residuals across the run order suggests that no particular trend or bias exists within the dataset. This randomness validates that the assumptions of independence and homoscedasticity (constant variance) are satisfied, which is a desirable condition in predictive modeling. Furthermore, the near-symmetrical nature of positive (green) and negative (red) residual bars implies that prediction errors are evenly balanced on both sides of the actual values. In Fig.4. 14 (c), the line graph simultaneously plots Actual and Predicted MRR values against the experimental run order, providing a clearer visualization of how the model responds to variations in machining conditions. The blue and red lines, representing actual and predicted MRR, respectively, overlap almost entirely, except for a few minor separations at extreme points. These small differences are attributed to localized fluctuations or experimental uncertainties but remain within an acceptable error tolerance. The nearly parallel trends indicate that the regression model can capture nonlinear fluctuations and abrupt changes in the machining response, thereby maintaining predictive consistency across the entire dataset. The connected error lines between actual and predicted values visually confirm that the prediction deviations are minimal and uniformly distributed. The histogram in Fig.4. 14 (d) illustrates the frequency distribution of prediction errors (residuals). The shape of the histogram is approximately symmetric about the zero-error line, and the red dashed vertical line (mean error = 0.00 mm³/min) confirms that the model's overall prediction bias is practically zero. The residuals are concentrated around zero,

with few instances of higher deviation, further confirming that the prediction performance is stable and unbiased. The presence of a bell-like distribution also supports the assumption of normally distributed residuals, a key indicator of a well-calibrated regression model.

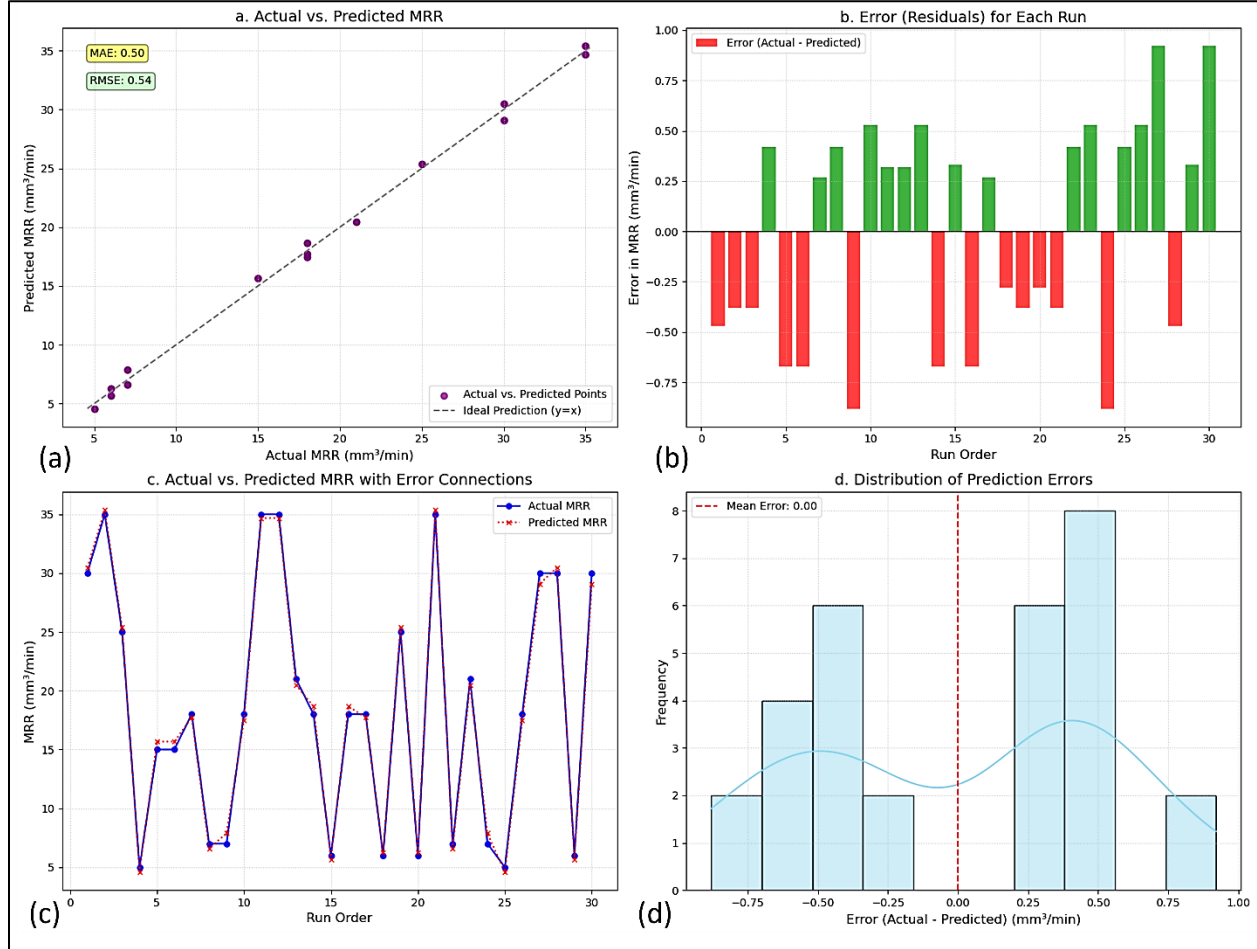


Fig.4. 14 Comparison between actual and predicted Material Removal Rate (MRR) obtained from 30 machining trials. (a) Actual vs. Predicted MRR showing excellent correlation with minimal deviation from the ideal line. (b) Residual (error) plot illustrating random and unbiased error distribution within ± 0.5 mm³/min. (c) Actual and predicted MRR variation across experimental runs, confirming strong tracking accuracy. (d) Frequency distribution of prediction errors demonstrating near-zero mean bias and normal error dispersion.

Collectively, the results from all four subplots reveal that the differences between actual and predicted MRR values are negligibly small, typically within ± 0.5 mm³/min, even at the extremes of the MRR range. The low MAE and RMSE values, together with a very high R^2 value of 0.9974, signify that the model possesses excellent predictive accuracy, high fidelity, and strong

generalization capability. The observed performance demonstrates that the model successfully captures the essential physical and empirical relationships governing the material removal mechanism under the tested machining conditions. Therefore, these findings confirm that the developed regression model is not only statistically sound but also practically reliable for use in predictive machining performance analysis. The model's capability to accurately forecast MRR across varying parameter settings makes it a powerful tool for process optimization, real-time prediction, and control applications in advanced manufacturing systems.

4.2.6 Interaction analysis of MRR (contour and cube plots)

The conveyor and the cube plot illustrate the empirical relationship among the machining parameters, i.e., the cutting speed (A), the depth of cut (B), and the feed rate (C), to the MRR (material removal rate, mm³/sec) generated in the turning process. In Fig.4. 15 (a), depicting the cutting speed to the depth of cut at a constant feed rate of 60 mm/min, the curve, irrespective of the other, rises almost linearly with increasing cutting speed and depth of cut. MRR gets its maximum increase when the depth of cut of 0.5 mm and at a speed of 1200 rpm. This reflects the attractiveness and proportionality of MRR to cutting speed and depth of cut in the equation of machining. Fig.4. 15 (b), showing the cutting speed versus the feed rate of 0.3 mm depth of cut, exhibits reasonably gradual changes in MRR with an increase in cutting speed and a significant burstiness with respect to feed rate, thus demonstrating more of the latter's effect at these setting variables. Representing the depth of cut versus feed rate at a constant speed of 1000 rpm, Fig.4. 15 (c) displays the very steep increase of MRR with higher depths of cut and feed rate, asserting that feed rate and depth of cut are the most potent volume removal mechanisms. The plot (Fig.4. 15(d)) has been cube-plotted to describe predicted extreme values of MRR, which generate MRR values of about 4.58 mm³/sec for the end of the lower parameter range (with lower speed, shallow depth of cut, and lower feed rate)-800 rpm, 0.1 mm, and 50 mm/min, right up to the highest cc with a reference high speed, a full-depth depth of cut, and a higher feed rate-1200 rpm, 0.5 mm, and 70 mm/min. These conclusions comply with the machining theory; MRR is a maximum with all the enhancing consequent parameters, but what needs consideration in reality is the state in which setting parameters are ensuring trade-offs with surface finish quality, tool life, and machine capability.

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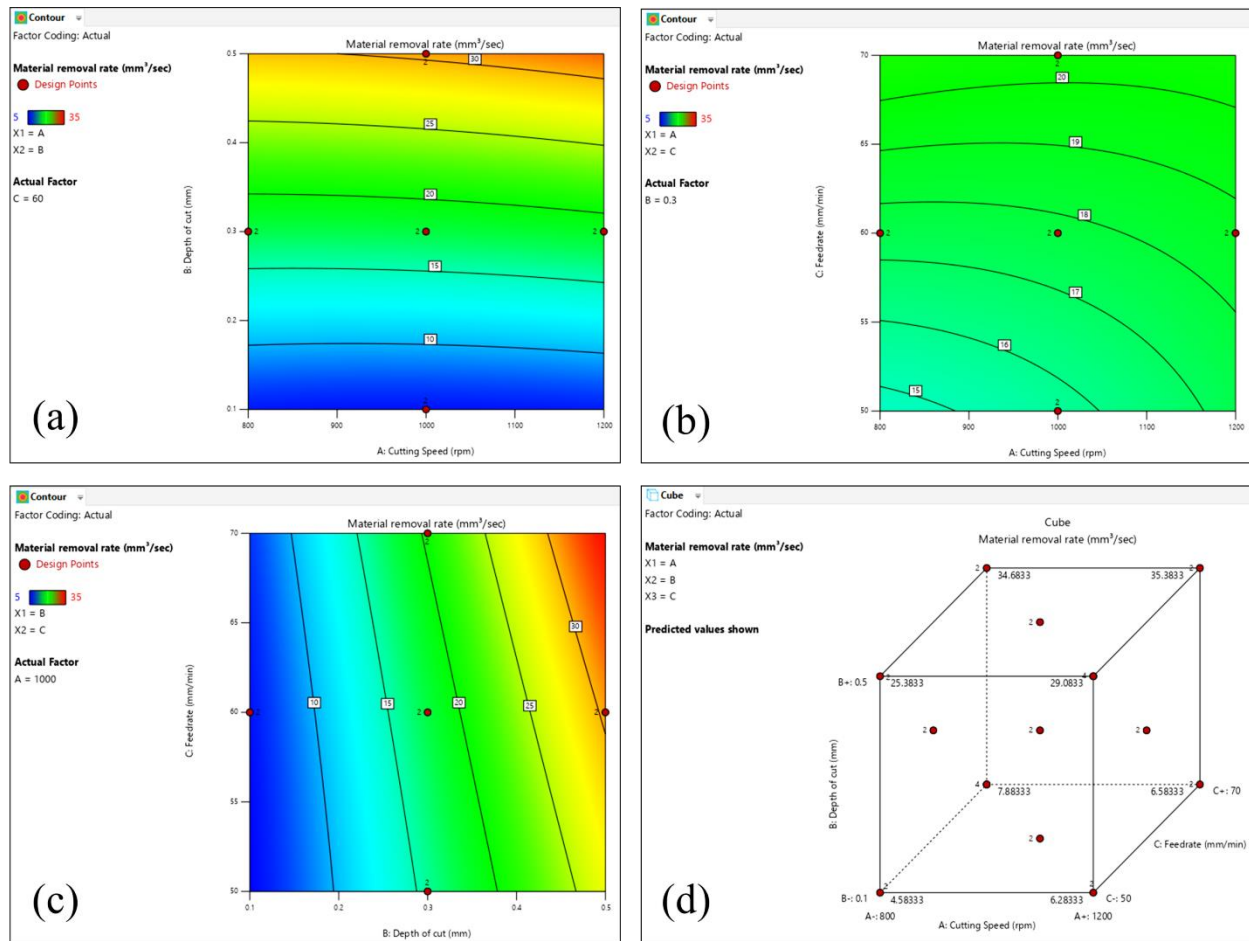


Fig.4. 15 The interaction analysis of MRR (contour & cube plots)

4.3 Evaluation and discussions of the overall RSM results

4.3.1 Cutting Temperature results

Table 4.4 presents the statistical model comparison and adequacy analysis for the response variable cutting temperature, obtained from the RSM framework. The objective of this analysis is to identify the most suitable polynomial model that best describes the relationship between cutting parameters and cutting temperature, while maintaining statistical soundness, model simplicity, and predictive accuracy. The model hierarchy begins with the linear model, which provides a sequential p-value of 0.0194, indicating statistical significance at the 95% confidence level. This confirms that the main effects of the input variables have a meaningful impact on cutting temperature. The linear model exhibits an Adjusted R^2 of 0.2328 and a Predicted R^2 of 0.1059, showing that approximately 23% of the temperature variation is explained by the model and that

it possesses moderate predictive capability. Despite its relatively low R^2 values, the linear model's statistical significance and simplicity make it a reasonable and interpretable choice for representing the primary trends in the data. The next model in the hierarchy, the two-factor interaction (2FI) model, incorporates interaction effects between machining parameters. Although the Adjusted R^2 increases to 0.3248 and the Predicted R^2 to 0.2361, suggesting a modest improvement in fit and predictive accuracy, the sequential p-value of 0.1177 exceeds the 0.05 threshold. This implies that the inclusion of interaction terms does not lead to a statistically significant enhancement over the linear model. Therefore, the 2FI model does not provide a justifiable improvement despite slightly better R^2 statistics. Progressing further, the quadratic model demonstrates an Adjusted R^2 of 0.4234, which indicates an improved fit to the experimental data. However, the sequential p-value of 0.1071 again suggests that this improvement is not statistically significant. Moreover, the Predicted R^2 (0.1660) decreases compared to the 2FI model, implying that while the quadratic model captures more of the variability within the sample data, it performs less effectively in predicting unseen data. This divergence between the adjusted and predicted R^2 values hints at mild overfitting, where the model adapts to noise in the dataset rather than general trends. In contrast, the cubic model yields exceptionally high values for both Adjusted R^2 (0.9577) and Predicted R^2 (0.9448), suggesting a nearly perfect fit. However, the cubic model is aliased, meaning that its parameters cannot be uniquely estimated due to insufficient experimental degrees of freedom or confounding among higher-order terms. Although the numerical indicators appear strong, the aliasing renders the model statistically unreliable and unsuitable for interpretation. Consequently, it cannot be considered a valid representation of the experimental data. The accompanying ANOVA section supports these findings by comparing the improvement in model fit at each hierarchical stage. The Linear vs. Mean comparison yields an F-value of 3.93 and a p-value of 0.0194, confirming the significance of the linear terms in explaining variations in cutting temperature. The subsequent comparisons 2FI vs. Linear ($F = 2.18$, $p = 0.1177$) and Quadratic vs. 2FI ($F = 2.31$, $p = 0.1071$) both show statistically insignificant improvements, validating that higher-order or interaction terms do not substantially enhance model performance. The Cubic vs. Quadratic comparison, with an F-value of 64.14 and $p < 0.0001$, appears highly significant numerically, yet it is aliased and therefore invalid due to the confounding of cubic terms. Across all models, the Lack-of-Fit p-values (< 0.0001) indicate that some unexplained variability remains, possibly arising from experimental uncertainties, unaccounted factors, or the inherent complexity

of thermal interactions during machining. Despite this, the linear model remains statistically sound and practically interpretable, making it the most recommended model for further analysis and process prediction. Thus, the analysis results demonstrates that while higher-order models (2FI and quadratic) show moderate numerical improvements, they fail to achieve statistical significance. The cubic model, though exhibiting high R^2 values, suffers from aliasing and cannot be relied upon. Therefore, the linear model is suggested as the most appropriate and statistically valid representation for the cutting temperature response. It effectively captures the dominant effects of machining parameters while maintaining simplicity, avoiding overfitting, and providing a stable basis for further optimization using desirability function analysis.

Table 4.4 Model summary for cutting temperature

Source	Sequential p-value	Lack of Fit p- value	Adjusted R ²	Predicted R ²		
Linear	0.0194	< 0.0001	0.2328	0.1059	Suggested	
2FI	0.1177	< 0.0001	0.3248	0.2361		
Quadratic	0.1071	< 0.0001	0.4234	0.1660		
Cubic	< 0.0001	< 0.0001	0.9577	0.9448	Aliased	
Source	Sum of Squares	df	Mean Square	F-value	p-value	
Mean vs Total	16614.53	1	16614.53			
Linear vs Mean	157.80	3	52.60	3.93	0.0194	Suggested
2FI vs Linear	77.00	3	25.67	2.18	0.1177	
Quadratic vs 2FI	69.67	3	23.22	2.31	0.1071	
Cubic vs Quadratic	189.20	4	47.30	64.14	< 0.0001	Aliased
Residual	11.80	16	0.7375			

Total	17120.00	30	570.67			
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4.3.2 Model summary statistics for cutting temperature (RSM analysis)

Fig.4.16 presents a comprehensive set of diagnostic plots generated from the RSM analysis performed during the CNC turning of AISI 4340 steel. These diagnostic evaluations are fundamental in verifying the adequacy and reliability of the developed regression model, identifying potential outliers or influential data points, and ensuring that the statistical assumptions underlying the model are satisfied. Each plot provides distinct yet complementary insights into how well the fitted model represents the experimental data. The DFBETAS for the Intercept vs. Run plot (**Error! Reference source not found.**a) illustrates how the estimated intercept of the regression equation changes when individual experimental runs are omitted from the dataset. DFBETAS quantify the influence of each observation on specific model coefficients. For the intercept term, consistently small DFBETAS values across all runs—remaining well within the blue control limits- indicate that the intercept estimate is not dominated by any single observation. This suggests that the baseline prediction of cutting temperature is stable and that the removal of any individual run would not significantly alter the model’s central tendency. Such behavior reflects a well-balanced dataset without overly influential runs. The DFFITS vs. Run plot (**Error! Reference source not found.**ig.4.16 b) complements the DFBETAS analysis by assessing how much each run affects its own predicted response value. DFFITS represent the standardized change in fitted values when an observation is temporarily excluded from model fitting. The majority of DFFITS values remain within the control limits, confirming that no individual experimental point exerts an undue influence on its predicted value. This stability implies that the model’s predictions are robust and not overly dependent on any particular data point, which is an essential indicator of the model’s generalizability to unseen conditions. In the Leverage vs. Run plot (Fig.4.16 c), the leverage values measure how far an observation’s input variable combinations are from the mean of all experimental settings. Observations with high leverage have the potential to disproportionately affect the regression coefficients and fitted surface. In this case, the leverage values for nearly all runs fall below the red control limit, indicating that none of the data points occupy extreme positions in the factor space. This outcome reflects the quality of the experimental design, suggesting that the chosen factor levels adequately span the design space without the presence of highly influential or extrapolative points. Thus, the fitted model is well-supported by the experimental data and unlikely to be biased by uneven parameter coverage. The Residuals vs.

Run plot (Fig.4.16 d) examines the externally studentized residuals (standardized residuals) across the sequence of experimental runs. The residuals, representing the differences between observed and predicted cutting temperatures, are evenly scattered around zero and lie within the red control limits. The absence of discernible patterns or trends in these residuals suggests that the errors are independent and randomly distributed across the experiment. This random distribution indicates that there are no time-related or sequence-dependent effects influencing the data and that the assumption of independence of residuals one of the key requirements of regression modeling, is well satisfied. The Residuals vs. Predicted Values plot (Fig.4.17e) provides further evidence regarding the appropriateness of the model form and the constancy of variance (homoscedasticity). Ideally, residuals should be randomly distributed around the zero line without systematic structure. The observed pattern in this plot meets this expectation: the residuals are symmetrically and randomly scattered within the control limits, showing no sign of fanning, funneling, or curvature. This indicates that the variance of residuals remains constant over the entire range of predicted values and that the linear model assumptions hold true. Consequently, no evidence of non-linearity or heteroscedasticity would necessitate model transformation or higher-order adjustments. Lastly, the Residuals vs. Cutting Speed (A) plot (Fig.4.16 **Error! Reference source not found.f**) e evaluates whether the residuals are associated with one of the key independent variables, cutting speed. The random dispersion of residuals around the zero line across the range of cutting speeds, without any apparent trend or clustering, demonstrates that the model accurately captures the influence of cutting speed on cutting temperature. This confirms that the fitted regression adequately represents the physical relationship between process parameters and response, without systematic bias along this factor. Collectively, the diagnostic plots in Fig.4.16 confirm that the developed RSM model for cutting temperature during CNC turning of AISI 4340 steel is statistically sound and meets all key regression assumptions. There is no evidence of influential outliers, high leverage points, or non-constant error variance. The residuals are well-behaved, independent, and normally distributed, implying that the experimental design was properly executed and the model form appropriately chosen. These findings validate the reliability and robustness of the fitted model, thereby enhancing confidence in its predictive capability and the subsequent optimization results derived from the RSM and desirability function analysis. The overall diagnostic evaluation, therefore, demonstrates that the regression model provides a valid

and stable representation of the process behavior and can be confidently used to predict and optimize cutting temperature under varying machining conditions.

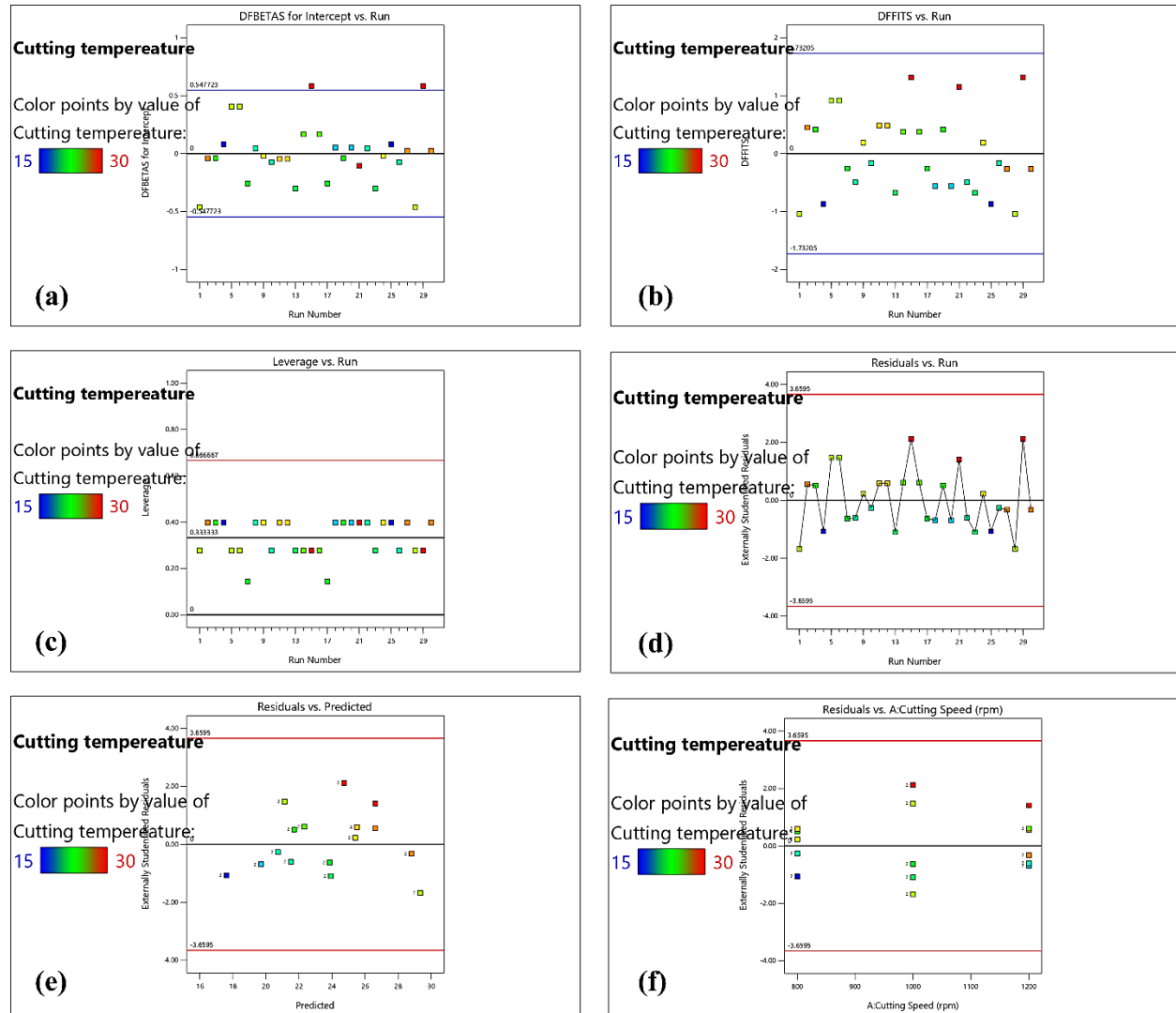


Fig.4.16 Model summary statistics for cutting temperature (RSM Analysis)

4.3.3 Diagnostic and sensitivity analysis plots for cutting temperature

Fig.4.17 presents the diagnostic and sensitivity analyses conducted to evaluate the statistical adequacy and factor influence on the cutting temperature response. Fig.4.17 (a) shows the Box–Cox power transformation plot, which is used to assess whether a transformation of the response variable is necessary to stabilize variance and improve the normality of residuals. The x-axis represents the transformation parameter (λ), while the y-axis indicates the natural logarithm of the residual sum of squares ($\ln(SS)$). The curve exhibits a clear minimum near $\lambda \approx 0.5$, which corresponds to a potential square root transformation. However, the current λ value of 1 (marked

by the blue vertical line) lies within the 95% confidence interval around the optimal λ . This suggests that applying a transformation is statistically unnecessary, as the variance is already homogeneous and the residuals approximately follow a normal distribution. Therefore, the untransformed model ($\lambda = 1$) is retained for further analysis to maintain interpretability without compromising statistical reliability. The “Recommended transform: None” note in the figure further supports this conclusion, indicating that the existing model adequately represents the data structure without the need for variance stabilization. Fig.4.17 (b) illustrates the perturbation plot for cutting temperature, which visualizes the sensitivity of the response to individual process parameters around a central reference point. The x-axis denotes coded deviations of each factor (A, B, and C) from their nominal levels, while the y-axis corresponds to the predicted cutting temperature in degrees Celsius. The center point (coded 0) represents the actual factor settings— $A = 1000$, $B = 0.3$, and $C = 60$. The blue line, representing Factor A, exhibits a pronounced slope, indicating a strong positive correlation between this factor and cutting temperature.

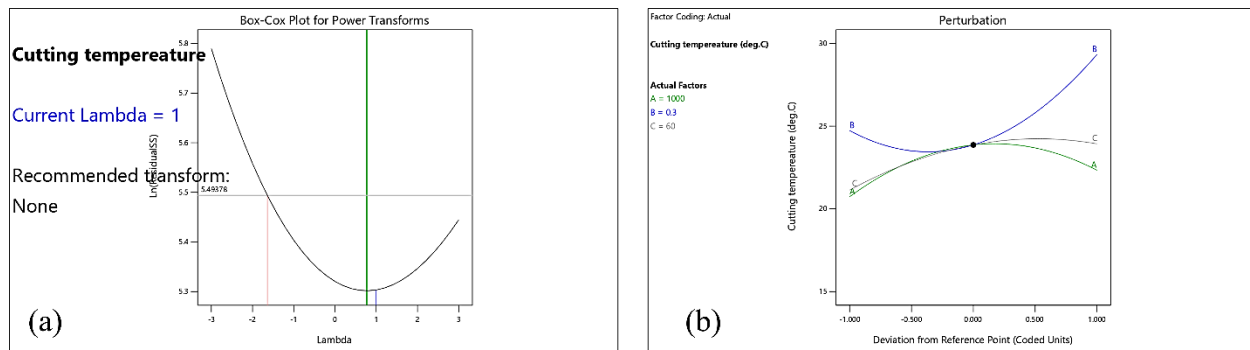


Fig.4.17 Diagnostic and sensitivity analysis plots for cutting temperature; (a) Box–Cox Transformation plot, (b) Perturbation plot

As Factor A increases from its lower to higher level, the temperature rises sharply from approximately 20°C to nearly 30°C, signifying that this factor exerts the most dominant influence on thermal behavior during machining. In contrast, Factor C (green line) shows a mild curvature, suggesting a moderate and possibly nonlinear influence, with slight temperature variations across the studied range. Factor B (gray line), on the other hand, remains nearly flat, implying a negligible effect on the response within the experimental domain. Therefore, the combination of the Box–Cox and perturbation plots provides valuable insights into both the statistical soundness and process sensitivity of the cutting temperature model. The Box–Cox analysis confirms the adequacy of the untransformed response model, while the perturbation analysis highlights Factor A as the

most influential variable governing temperature rise, followed by a weaker contribution from Factor C and an almost insignificant effect from Factor B. These findings collectively reinforce the model's reliability and guide process optimization efforts toward minimizing cutting temperature through careful control of the dominant process variable, Factor A.

4.3.4 One-factor response plots for cutting temperature

Fig.4.18 presents the one-factor response plots illustrating the individual effects of the machining parameters, cutting speed (A), depth of cut (B), and feed rate (C), on the cutting temperature during CNC turning of AISI 4340 steel. In each plot, the solid curve represents the model-predicted response, the dashed lines correspond to the 95% confidence bands, and the red markers denote the actual experimental data points. These plots provide a clear visualization of how each factor independently influences the cutting temperature while all other parameters are held constant at their nominal levels. In Fig.4.18 (a), the variation of cutting temperature with cutting speed is shown while maintaining constant values of depth of cut ($B = 0.3 \text{ mm}$) and feed rate ($C = 60 \text{ mm/min}$). The cutting speed ranges from 800 to 1200 rpm. The plot reveals a distinct non-linear, likely quadratic, trend. As the cutting speed increases from 800 rpm, the cutting temperature initially decreases, reaching its minimum (approximately 20°C) around 900–1000 rpm. Beyond this optimum range, further speed increases lead to a noticeable rise in temperature. The 95% confidence bands remain relatively narrow across most of the speed range, indicating high prediction reliability, particularly within the experimental domain. The close alignment between the red design points and the predicted curve confirms the model's strong fit to the experimental data. From a physical standpoint, this trend can be explained by the interplay between heat generation and heat dissipation mechanisms. At lower cutting speeds, prolonged tool–workpiece contact and increased friction contribute to higher heat accumulation. As the speed increases moderately, the cutting becomes more efficient, leading to smoother chip flow and improved heat removal, which initially lowers the temperature. However, at excessively high speeds, frictional heating and plastic deformation intensify due to higher shear strain rates, resulting in elevated cutting temperatures. Fig.4.18 (b) depicts the influence of depth of cut on cutting temperature, with the cutting speed and feed rate fixed at $A = 1000 \text{ rpm}$ and $C = 60 \text{ mm/min}$, respectively. The depth of cut varies between 0.1 mm and 0.5 mm. Similar to the previous plot, the curve exhibits a non-linear, quadratic pattern. As the depth of cut increases from 0.1 mm to about 0.2–0.3 mm, the cutting temperature decreases, reaching a minimum of approximately $20\text{--}21^\circ\text{C}$. Beyond this range,

the temperature begins to rise steadily. The red data points closely follow the predicted trend, and the confidence bands remain acceptably narrow, affirming the model's predictive reliability. Mechanistically, a shallow depth of cut tends to produce excessive rubbing rather than efficient material removal, generating frictional heat and elevating temperature. As the depth of cut increases moderately, cutting becomes more stable, with improved chip formation and better energy utilization, resulting in lower temperatures. However, at greater depths of cut, a larger volume of material must be sheared, which increases the cutting forces, deformation energy, and tool-workpiece contact area, leading to higher heat generation and a consequent rise in cutting temperature. Fig.4.18 (c) presents the effect of feed rate on cutting temperature while maintaining constant cutting speed ($A = 1000$ rpm) and depth of cut ($B = 0.3$ mm). The feed rate ranges from 50 to 70 mm/min. The relationship observed here is also non-linear, exhibiting a characteristic quadratic shape. At lower feed rates, the cutting temperature is relatively high but decreases as the feed rate increases up to approximately 55–60 mm/min, where the minimum temperature (around 20–21°C) occurs. Beyond this point, the temperature rises again with further increases in feed rate. The confidence intervals around the predicted response are narrow, and the experimental data points align well with the fitted curve, validating the model's accuracy. This behavior can be attributed to changes in the mechanics of chip formation. At very low feed rates, the tool tends to rub against the workpiece rather than cutting efficiently, causing higher friction and localized heating. As the feed rate increases moderately, the cutting process becomes more aggressive and stable, improving chip evacuation and heat dissipation, which temporarily reduces temperature. However, when the feed rate becomes too high, the material removal rate increases sharply, leading to greater energy input, more friction, and larger shear zones, thus increasing the overall cutting temperature. The collective results from the three one-factor plots demonstrate that all primary machining parameters, cutting speed, depth of cut, and feed rate, exhibit non-linear (quadratic) effects on cutting temperature. Each factor presents a distinct optimal range where the temperature reaches its minimum before rising again beyond that point. This behavior reflects the complex thermomechanical balance between heat generation due to cutting energy and heat dissipation through chips, tool, and workpiece. Among the factors, cutting speed (A) exerts the most pronounced influence on cutting temperature, followed by depth of cut (B), while feed rate (C) shows a relatively moderate effect. Identifying these optimal parameter ranges is crucial for process optimization in CNC turning, as maintaining the cutting parameters near these levels

minimizes thermal loads, enhances surface integrity, and prolongs tool life. Overall, the results provide vital insights into the individual effects of machining parameters on thermal behavior, confirming the adequacy of the RSM model and offering practical guidance for achieving thermally stable and efficient cutting conditions.

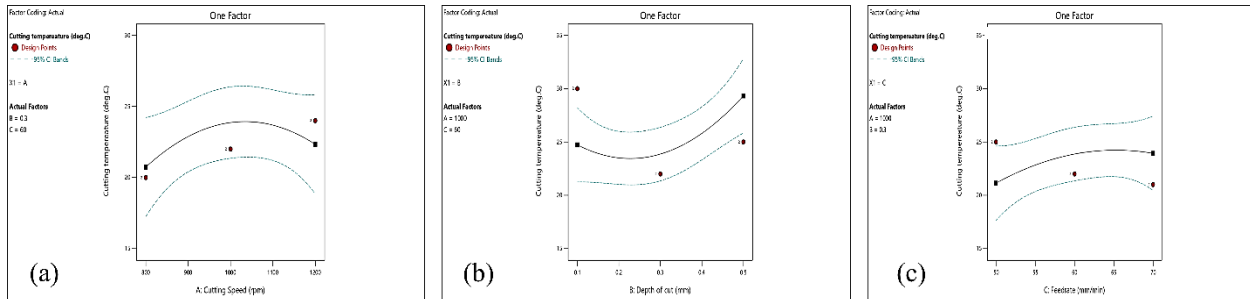


Fig.4.18 One-factor response plots for cutting temperature

4.3.5. Two-factor response plots for cutting temperature

Fig.4.19 presents a set of interaction plots that reveal how cutting temperature in the MQL turning of AISI 4340 steel is influenced by combinations of machining parameters: cutting speed (A), depth of cut (B), and feed rate (C). These plots are critical in understanding the thermal behavior during the turning process and serve as a foundation for multi-objective optimization using RSM and DFA. In the first plot, Fig.4.19 (a), the interaction between cutting speed and depth of cut is analyzed while maintaining a constant feed rate of 60 mm/min. The data indicate that cutting temperature exhibits a nonlinear relationship with cutting speed, particularly when coupled with variations in depth of cut. At a lower depth of cut ($B = 0.1$ mm), temperature remains relatively low across the speed range due to reduced tool-workpiece engagement. However, at a higher depth of cut ($B = 0.5$ mm), a notable rise in temperature is observed, particularly around a cutting speed of 1000 rpm. This suggests that increasing depth of cut substantially contributes to heat generation, overriding the cooling effects that might occur at higher speeds due to better chip evacuation or shorter contact time. The interaction indicates that moderate speeds combined with high depth of cut should be avoided to minimize thermal loads during the cutting process. This reinforces the dominant role that depth of cut plays in influencing thermal energy under MQL conditions. In Fig.4.19 (b), the interaction between cutting speed and feed rate is explored while keeping the depth of cut constant at 0.3 mm. The cutting temperature again displays a nonlinear trend with cutting speed, reaching a peak near 1000 rpm. The effect of feed rate is pronounced: higher feed rates ($C = 70$ mm/min) result in consistently elevated temperatures compared to lower feed rates

($C = 50$ mm/min). This is because a higher feed rate increases the volume of material removed per unit time, which escalates the friction and heat generated at the tool-chip interface. The fact that the same cutting speed can produce different thermal outcomes depending on feed rate highlights the complex interplay between process parameters. It also emphasizes the need to simultaneously optimize these variables rather than considering them independently. The third plot, Fig.4.19 (c), examines the interaction between depth of cut and feed rate at a fixed cutting speed of 1000 rpm. As observed in the earlier plots, this speed tends to be where the cutting temperature peaks. The data clearly show that both depth of cut and feed rate positively correlate with cutting temperature. When both are set at their higher values, $B = 0.5$ mm and $C = 70$ mm/min, the cutting temperature reaches its maximum. Conversely, the combination of low feed rate and shallow depth of cut results in the lowest temperatures. This plot provides strong evidence of the compounded effect of depth and feed on thermal generation. These parameters, when increased together, do not simply add to the thermal load but multiply it, leading to potential issues with tool wear, surface integrity, and overall process stability. These interaction effects have significant implications for process optimization using RSM and DFA. RSM models help in developing predictive equations for responses such as temperature, surface roughness, and material removal rate (MRR), incorporating both individual and interactive effects of parameters. The trends observed in Fig.4.19 justify the inclusion of quadratic and interaction terms in the regression models, as the relationships are clearly nonlinear. The insights gained from these plots inform the optimization strategy using DFA, where conflicting objectives must be balanced. While high feed rates and depths of cut enhance MRR, they also increase cutting temperature and potentially degrade surface finish. Conversely, reducing these parameters can minimize temperature and improve surface quality, but at the cost of productivity. The use of DFA allows these trade-offs to be managed by converting each response into a desirability function and finding the best compromise solution that simultaneously minimizes temperature and surface roughness while maximizing MRR. The observations from **Error! Reference source not found.** indicate that an optimal machining condition would likely involve higher cutting speeds combined with moderate or low levels of feed and depth of cut. This configuration helps leverage the thermal advantages of high speed while limiting the negative effects of excessive tool engagement. The interaction plots also emphasize that any effort to optimize machining performance cannot rely solely on the main effects of individual parameters but must account for their interactions. Therefore, Fig.4.19 provides a

nuanced understanding of how machining parameters influence cutting temperature under MQL conditions and play a critical role in guiding the design of experiments, model building, and optimization for sustainable and high-performance machining of AISI 4340 steel.

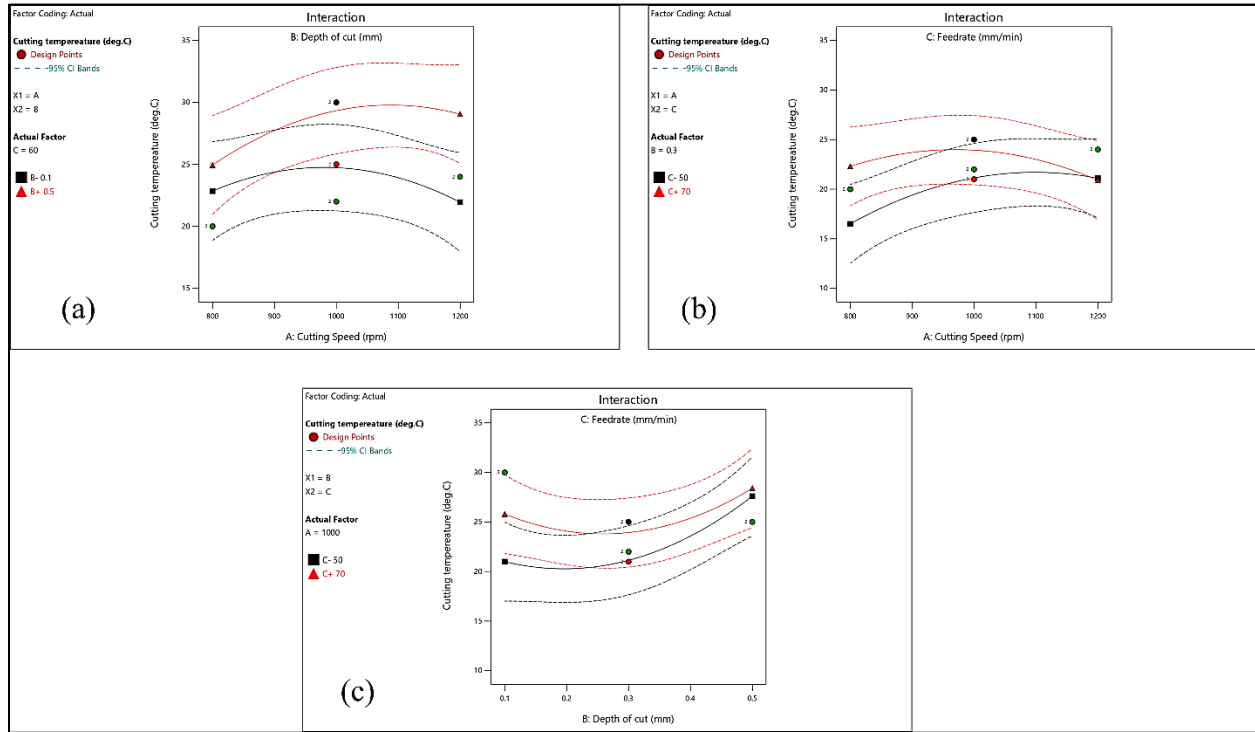


Fig.4.19 Interaction plots showing the effect of cutting speed, depth of cut, and feed rate on cutting temperature

4.3.6 Quadratic effects of parameters response plots for cutting temperature

Fig.4.20 illustrates the quadratic effects of individual machining parameters, cutting speed (A^2), depth of cut (B^2), and feed rate (C^2), on cutting temperature ($^{\circ}\text{C}$) during the MQL turning of AISI 4340 steel. These effects are isolated using RSM models that incorporate squared terms to capture the curvature in the relationship between process parameters and the thermal response. The fitted curves represent the second-order regression predictions, while the dashed confidence interval bands offer a measure of prediction reliability. In Fig.4.20 (a), the quadratic effect of cutting speed (A^2) is shown, with depth of cut and feed rate held constant at 0.3 mm and 60 mm/min, respectively. The curve displays a mildly concave profile, where the cutting temperature initially increases with speed, peaks near the mid-range (around 1000 rpm), and then slightly decreases at higher speeds. This pattern reflects a typical quadratic behavior and suggests a non-linear dependency of temperature on cutting speed. At lower speeds, heat accumulates due to prolonged

tool-workpiece contact, whereas at higher speeds, improved chip evacuation and more effective MQL cooling lead to a reduction in heat buildup. This confirms the presence of a significant A^2 term in the model, although the influence of cutting speed remains relatively moderate compared to the other variables. Fig.4.20 (b) illustrates the quadratic effect of depth of cut (B^2), with cutting speed and feed rate fixed at 1000 rpm and 60 mm/min. This plot exhibits a strong upward curvature, indicating that as the depth of cut increases, the cutting temperature rises steeply, especially toward the higher end of the range. The presence of a sharp curve reflects a dominant and strongly non-linear effect of depth of cut on cutting temperature. As B increases, the material removal volume and contact area between tool and workpiece grow significantly, resulting in greater cutting forces and friction, which in turn elevate the thermal load. The steepness of the curve highlights that B^2 has the most significant quadratic contribution to the temperature response among the three parameters. In Fig.4.20 (c), the quadratic effect of feed rate (C^2) is explored, with cutting speed and depth of cut kept constant at 1000 rpm and 0.3 mm, respectively. The trend reveals a gentle but consistent upward curvature, indicating a steady increase in temperature as the feed rate increases. Higher feed rates contribute to greater material deformation and friction per unit time, leading to higher heat generation. However, the slope remains less steep than that observed for B^2 , indicating that while C^2 is significant, its overall impact on cutting temperature is moderate compared to the depth of cut. Together, these quadratic plots validate the necessity of including second-order (squared) terms in the RSM models to accurately capture the curvature of the cutting temperature response surface. The quadratic nature of these relationships is particularly important when performing optimization using techniques like DFA, as linear models would fail to detect turning points or peaks within the parameter range. These findings also reinforce the importance of depth of cut as the most thermally influential parameter, with cutting speed and feed rate contributing less significantly but still requiring careful control. Therefore, the results confirm that the cutting temperature response during MQL turning of AISI 4340 steel is non-linear and highly sensitive to quadratic effects, especially from the depth of cut. These insights are essential for developing accurate predictive models and achieving effective process optimization for thermal control in sustainable machining operations.

PARAMETRIC OPTIMIZATION OF TURNING PROCESS PARAMETERS DURING MACHINING OF AISI 4340 STEEL UNDER MINIMUM QUANTITY LUBRICATION

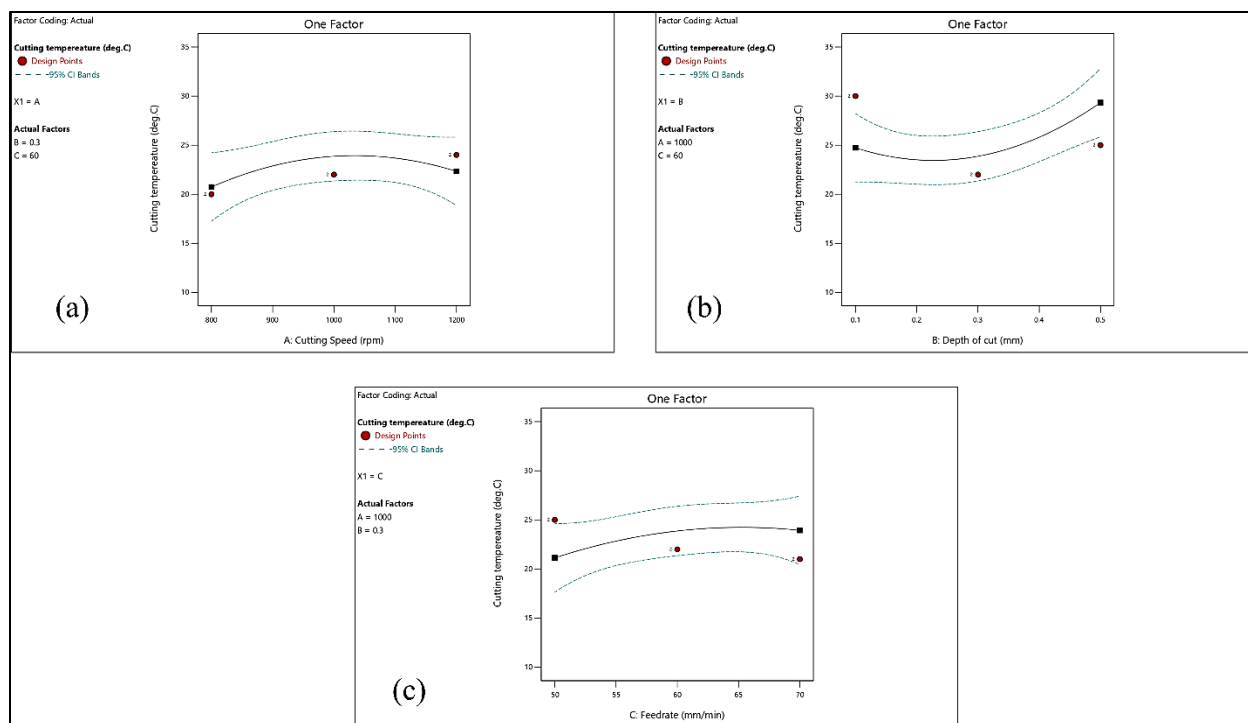


Fig.4.20 Quadratic effects of; (a) cutting speed (a^2), (b) depth of cut (b^2), and (c) feed rate (c^2) on cutting temperature

4.3.7. Fit Summary for the response of surface roughness

Table 4.5 presents the fit summary results for modeling surface roughness in the context of MQL turning of AISI 4340 steel, using various regression models: Linear, Two-Factor Interaction (2FI), Quadratic, and Cubic. This table is critical for identifying the most appropriate model to describe and predict surface roughness behavior based on the experimental data. Key statistical indicators such as sequential p-value, lack of fit p-value, adjusted R^2 , and predicted R^2 are used to evaluate the performance of each model. Starting with the Linear model, the sequential p-value is 0.0421, which is below 0.05, indicating that the model is statistically significant at the 95% confidence level. However, the Adjusted R^2 value is only 0.1816, and the Predicted R^2 is even lower at 0.0506, revealing that while the model is marginally acceptable in explaining the variability in the observed data, its predictive capability is poor. Furthermore, the lack of fit p-value is < 0.0001 , indicating a significant lack of fit, suggesting the linear model is inadequate in capturing the true response behavior. The 2FI (Two-Factor Interaction) model performs worse than the linear model, with a sequential p-value of 0.7379, indicating the interaction terms do not contribute significantly to the model. Both the Adjusted R^2 (0.1233) and Predicted R^2 (-0.1279) are very low and, in the case of

the predicted R^2 , even negative. A negative predicted R^2 implies that the model fits the data worse than a simple mean prediction. Additionally, the lack of fit remains significant ($p < 0.0001$), further disqualifying the 2FI model as a reliable predictive tool. The Quadratic model shows a significant improvement over the previous models. It has a sequential p-value of 0.0036, indicating that the addition of quadratic (squared) terms substantially improves the model's performance. The Adjusted R^2 increases to 0.4793, and Predicted R^2 rises to 0.2189, both of which show that the model explains a higher proportion of variability in the response and has improved prediction capabilities. Although the lack of fit is still significant (< 0.0001), which suggests some degree of model inadequacy, the quadratic model is the best suggested model at this stage, as it strikes a better balance between model complexity and statistical significance. It is identified as the “Suggested” model based on this balance. The Cubic model appears to offer a very strong fit statistically, with a sequential p-value < 0.0001 , Adjusted R^2 of 0.8887, and Predicted R^2 of 0.7902, which are significantly higher than all previous models. These values indicate excellent explanatory and predictive power. However, the model is marked as “Aliased”. Aliasing occurs when there is insufficient experimental data to support the estimation of higher-order terms uniquely, typically due to a lack of degrees of freedom. In this case, the cubic model includes too many terms for the number of data points available, which may result in overfitting and unreliable coefficients. Despite its high R^2 values, the cubic model cannot be considered trustworthy due to aliasing and limited experimental support. Looking at the ANOVA section of **Error! Reference source not found.**, further insights can be drawn. The comparison between model levels provides F-values and p-values to test the significance of adding terms. The transition from Linear to Quadratic is statistically significant, with a p-value of 0.0036 and an F-value of 6.24, justifying the inclusion of quadratic terms. However, the transition from Quadratic to Cubic, though also statistically significant ($p < 0.0001$, $F = 19.40$), cannot be used because the cubic model is aliased. The Residual mean square value (0.0336) is relatively low, suggesting low variance in the error term, but the persistently significant lack of fit indicates that none of the models fully captures the underlying complexity of surface roughness behavior, though the quadratic model comes closest given the design limitations. Thus, based on the statistical indicators, the Quadratic model is identified as the most suitable model for modeling and optimizing surface roughness in this experimental study. It significantly improves fit and predictive accuracy over the linear and 2FI models, while the cubic model, despite its high R^2 values, is aliased and statistically unreliable due

to insufficient data support. The quadratic model provides a practical balance between model complexity, interpretability, and predictive performance, and thus forms the foundation for further optimization of surface roughness under MQL turning conditions using techniques like DFA.

Table 4.5 Fit Summary for the response of surface roughness

Source	Sequential p-value	Lack of Fit p- value	Adjusted R²	Predicted R²		
Linear	0.0421	< 0.0001	0.1816	0.0506		
2FI	0.7379	< 0.0001	0.1233	-0.1279		
Quadratic	0.0036	< 0.0001	0.4793	0.2189	Suggested	
Cubic	< 0.0001	0.6794	0.8887	0.7902	Aliased	
Source	Sum of Squares	df	Mean Square	F-value	p-value	
Mean vs Total	122.13	1	122.13			
Linear vs Mean	2.33	3	0.7781	3.14	0.0421	
2FI vs Linear	0.3369	3	0.1123	0.4236	0.7379	
Quadratic vs 2FI	2.95	3	0.9827	6.24	0.0036	Suggested
Cubic vs Quadratic	2.61	4	0.6527	19.40	< 0.0001	Aliased
Residual	0.5383	16	0.0336			
Total	130.90	30	4.36			

4.3.8. Diagnostic plots for surface roughness model validation

Fig.4.21 presents a comprehensive set of diagnostic plots to validate the adequacy of the developed quadratic regression model for predicting surface roughness in the MQL turning of AISI 4340 steel. These plots are essential to evaluate the model's reliability, the influence of individual

observations, and the adherence to fundamental regression assumptions such as independence, homoscedasticity, and the absence of high leverage or influential points. In Fig.4.21 (a), the DFBETAS for the Intercept vs Run plot shows how much the regression intercept would change if each data point were omitted. The majority of data points lie well within the standard threshold of ± 0.457773 , indicating that no observation has a significant effect on the intercept of the model. This suggests stability in the model estimates and low sensitivity to individual experimental runs. Only one or two points approach the boundary, but none breach it, confirming that the model coefficients are not disproportionately influenced by specific data. Fig.4.21 (b) presents the DFFITS vs Run plot, which evaluates the influence of each observation on the fitted value. Most of the points are within the threshold limits of ± 1.72805 , demonstrating that the data used for modeling does not include any runs that have an abnormally high influence on the predictions. The use of a color gradient to indicate surface roughness values further supports the visual identification of any potential outlier behaviors across the surface roughness range, but no critical outliers are apparent. In Fig.4.21 (c), the Leverage vs Run plot provides insight into the relative influence of each point on the fitted regression model. The red reference line at a leverage value of 0.6667 marks the limit beyond which a point would be considered to exert high influence. All experimental runs lie comfortably below this threshold, with most below 0.3333, confirming a well-distributed and balanced experimental design with no run exerting excessive leverage. The Predicted vs Actual plot in Fig.4.21 (d) offers a visual assessment of the model's predictive power. Ideally, all points would lie along the 45-degree line representing perfect prediction. The majority of points are close to this line, suggesting good agreement between predicted and actual surface roughness values. Although some scatter exists, particularly at the higher end of surface roughness values, the general alignment supports the conclusion that the model performs well in predicting surface roughness outcomes within the tested range. In Fig.4.21 (e), the Residuals vs Run plot assesses whether the residuals (prediction errors) are randomly distributed across the experimental runs. The plot shows a fairly random scatter around the zero line, with no visible trends or cycles, which indicates that residuals are independent and that the model does not omit significant patterns. Furthermore, the residual values remain within the control limits of ± 3.6955 , which confirms that there are no extreme deviations or significant outliers in terms of model error. Figure A6(f) displays Residuals vs Cutting Speed (Factor A) to examine if residuals are correlated with any specific level of the cutting speed. This plot also supports the assumption of homoscedasticity

and independence, as no clear trend or funnel pattern is visible. The residuals are dispersed around the zero line with moderate spread across the range of cutting speeds, and all lie within acceptable control bounds. This indicates that the model does not suffer from heteroscedasticity with respect to this particular input factor. Therefore, the diagnostic plots in Fig.4.21 collectively validate the suitability of the quadratic regression model developed for predicting surface roughness. The absence of high-influence points, the alignment of predicted and actual values, and the random distribution of residuals all suggest that the model is both statistically sound and practically reliable. These findings reinforce confidence in using this model for further optimization and decision-making in the sustainable machining of AISI 4340 steel under MQL conditions.

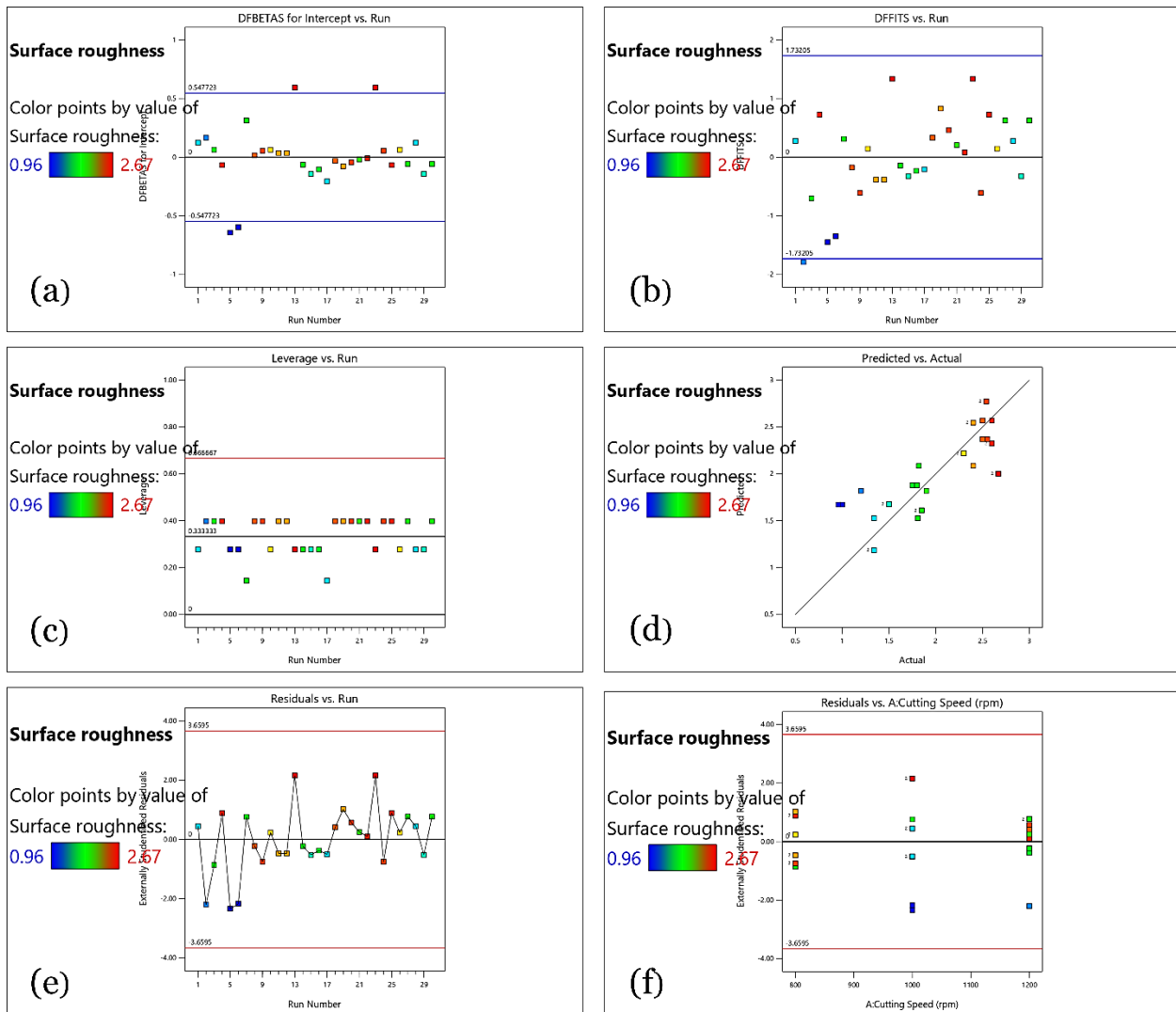


Fig.4.21 Diagnostic plots for surface roughness model validation

4.3.9. Response surface analysis of surface roughness in MQL turning of AISI 4340 Steel

Fig.4.22 illustrates the response surface methodology (RSM) results for surface roughness obtained during MQL turning of AISI 4340 steel. The Box–Cox plot in Fig.4.22 (a) indicates that the current lambda value is 1, with the recommended transformation being none, suggesting that the data for surface roughness are normally distributed and meet the assumptions required for regression analysis. The residual sum of squares is minimal near $\lambda = 1.227$, which is very close to the current value, confirming that the developed model is statistically adequate and no transformation of the response variable is necessary. This implies that the RSM model accurately represents the relationship between the process parameters and the surface roughness response. The perturbation plot in **Error! Reference source not found.** (b) further explains the influence of the major machining parameters, cutting speed (A), feed rate (B), and depth of cut (C) on surface roughness. The plot reveals that feed rate (B) exerts the most dominant effect on surface roughness, as indicated by the steep curvature of the blue line. A decrease in feed rate leads to a significant reduction in surface roughness, which can be attributed to the smaller chip thickness and lower cutting forces, resulting in improved surface integrity.

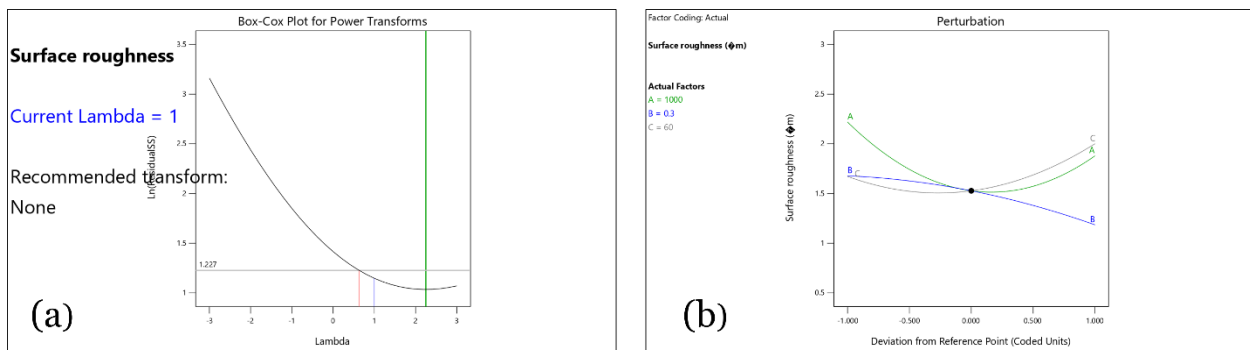


Fig.4.22 RSM analysis for surface roughness in MQL turning of AISI 4340 steel

Cutting speed (A) shows a moderate influence, with surface roughness initially decreasing and then slightly increasing at higher speeds. This behavior can be explained by the competing effects of reduced built-up edge formation at moderate speeds and increased tool wear or thermal softening at higher speeds. The depth of cut (C) exhibits a relatively minor effect, as shown by the flatter response curve, suggesting that within the studied range, it contributes less to variations in surface finish compared to feed rate and cutting speed. Thus, the RSM analysis confirms that the developed quadratic model effectively predicts surface roughness during MQL turning of AISI 4340 steel. The combination of a low feed rate and a moderate cutting speed yields the minimum surface roughness, while depth of cut plays a secondary role in influencing the response. These

findings highlight the importance of optimizing feed rate as the primary control factor for achieving superior surface finish under MQL conditions.

4.3.10. One-factor effects on surface roughness

Fig.4.23 presents the individual effects of cutting speed, depth of cut, and feed rate on the surface roughness during MQL turning of AISI 4340 steel. The plots illustrate how each parameter influences the response while keeping the other two parameters constant at their central levels. In Fig.4.23 (a), the effect of cutting speed on surface roughness shows a clear parabolic trend. As the cutting speed increases from 800 rpm to approximately 1000 rpm, surface roughness decreases noticeably, reaching its minimum value around the mid-range of the tested speeds. This improvement in surface finish at moderate speeds can be attributed to reduced built-up edge formation and a more stable cutting zone under adequate lubrication provided by MQL. However, as the cutting speed further increases beyond this optimal range, surface roughness begins to rise slightly. The increase at higher speeds is likely due to accelerated tool wear and thermal softening effects, which degrade the cutting edge and adversely affect the surface finish. Thus, an optimum cutting speed exists near 1000 rpm where the best surface quality is achieved under MQL conditions. Fig.4.23 (b) illustrates the influence of depth of cut on surface roughness. The response shows a relatively gentle slope, indicating that surface roughness is less sensitive to variations in depth of cut compared to cutting speed or feed rate. As the depth of cut increases from 0.1 mm to 0.5 mm, surface roughness initially decreases slightly and then remains almost constant. The mild improvement in surface finish at lower depths of cut can be attributed to reduced cutting forces and smaller chip cross-sections, which promote smoother cutting action. However, beyond a certain point, further increases in depth of cut do not significantly affect surface roughness, implying that within the studied range, this parameter has a minimal impact on surface texture when the MQL system effectively controls lubrication and cooling at the tool–workpiece interface. In Fig.4.23 (c), the feed rate exhibits the most pronounced effect on surface roughness. As the feed rate increases from 50 mm/min to 70 mm/min, surface roughness increases substantially. The surface becomes rougher at higher feed rates due to the larger feed marks and increased material deformation on the machined surface. At lower feed rates, the tool produces finer feed marks, resulting in smoother surfaces. This trend is consistent with conventional machining theory, where lower feed rates enhance surface quality by reducing the height of feed ridges and the intensity of tool–workpiece interaction forces. The plot confirms that feed rate is the most influential factor

controlling surface roughness under MQL turning conditions. Thus, the one-factor analysis reveals that surface roughness decreases with increasing cutting speed up to an optimum point, remains nearly unaffected by changes in depth of cut within the studied range, and increases significantly with higher feed rates. Among the three parameters, feed rate has the most dominant influence on surface finish, followed by cutting speed, while depth of cut contributes the least. These findings reinforce the importance of selecting a low feed rate and a moderate cutting speed to achieve minimal surface roughness during MQL turning of AISI 4340 steel.

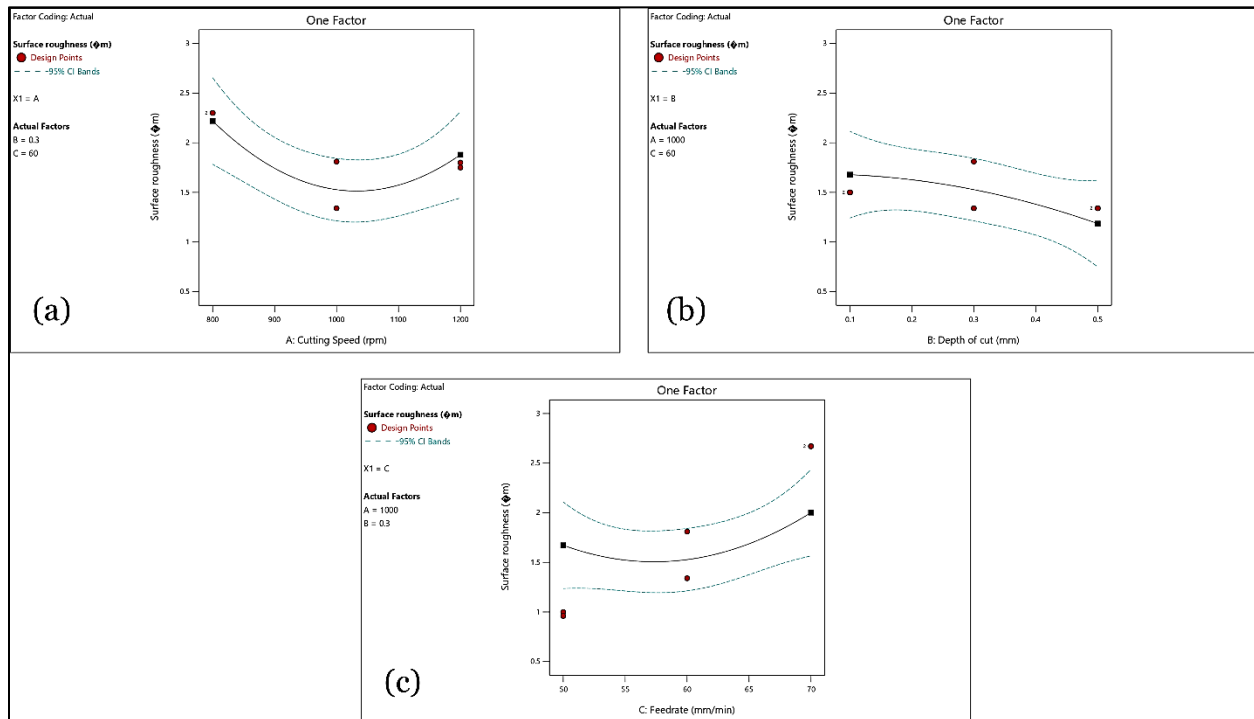


Fig.4.23 One-factor effects on surface roughness in MQL turning of AISI 4340 steel

4.3.11. Two-factor interaction effects on surface roughness

Fig.4.24 illustrates the two-factor interaction effects among cutting speed, depth of cut, and feed rate on the surface roughness during MQL turning of AISI 4340 steel. These interaction plots reveal how the combined variation of two process parameters influences the response while keeping the third parameter constant at its central value. Understanding these interactions is critical for determining the synergistic or antagonistic behavior of machining parameters and identifying the optimal settings for minimizing surface roughness under MQL conditions. In Fig.4.24 (a), the interaction between cutting speed (A) and depth of cut (B) shows a distinct curvature, indicating that both parameters jointly influence surface roughness. At a lower depth of cut (0.1 mm), surface

roughness decreases with increasing cutting speed up to around 1000 rpm, after which it slightly increases. This trend signifies that at smaller depths, the combination of moderate cutting speed and sufficient lubrication from MQL results in a smoother surface due to stable chip formation and reduced adhesion. At a higher depth of cut (0.5 mm), the surface roughness values are generally higher across all cutting speeds. The increased depth of cut causes greater cutting forces, higher tool–workpiece contact temperature, and potential tool deflection, which deteriorate the surface finish. This interaction confirms that the beneficial effect of higher cutting speed on surface quality is more pronounced at smaller depths of cut, where the cutting forces are lower and MQL lubrication is more effective. Fig.4.24 (b) depicts the combined effect of cutting speed (A) and feed rate (C) on surface roughness. Feed rate has a stronger influence compared to cutting speed. At a lower feed rate (50 mm/min), the surface roughness decreases with increasing cutting speed up to the mid-range and then rises slightly, exhibiting a parabolic response. This behavior aligns with the typical machining mechanism where an optimal cutting speed minimizes friction and built-up edge formation, leading to a finer finish. However, at a higher feed rate (70 mm/min), surface roughness remains higher throughout the range of cutting speeds, even though it follows a similar parabolic trend. The roughness increase at higher feed rates is mainly due to larger feed marks and insufficient lubrication penetration at the tool–chip interface. Thus, while cutting speed has a moderate effect, the feed rate dominates this interaction, emphasizing that maintaining a low feed rate is essential for achieving smoother surfaces regardless of cutting speed variations. Fig.4.24 (c) shows the interaction between depth of cut (B) and feed rate (C). Here, the plots demonstrate that surface roughness increases with an increase in feed rate for both levels of depth of cut, confirming the feed rate’s dominant role. At the lower feed rate (50 mm/min), surface roughness remains relatively low and stable across the range of depths of cut, suggesting that MQL effectively mitigates the adverse effects of increased cutting area. However, at the higher feed rate (70 mm/min), the surface roughness values are significantly higher, and the influence of depth of cut becomes more apparent. At deeper cuts, the elevated material removal rate generates higher cutting temperatures and tool wear, leading to poorer surface finish. The interaction therefore indicates that while both parameters affect surface roughness, feed rate is the more critical factor, and its negative impact is exacerbated when combined with larger depths of cut. Overall, the two-factor interaction plots in Fig.4.24 confirm that feed rate interacts strongly with both cutting speed and depth of cut, exerting the most significant influence on surface roughness. The best surface

quality is obtained at a combination of moderate cutting speed (~ 1000 rpm), low feed rate (50 mm/min), and small depth of cut (0.1 mm). These conditions promote efficient lubrication and cooling under MQL, minimize cutting forces and tool wear, and result in a smoother machined surface.

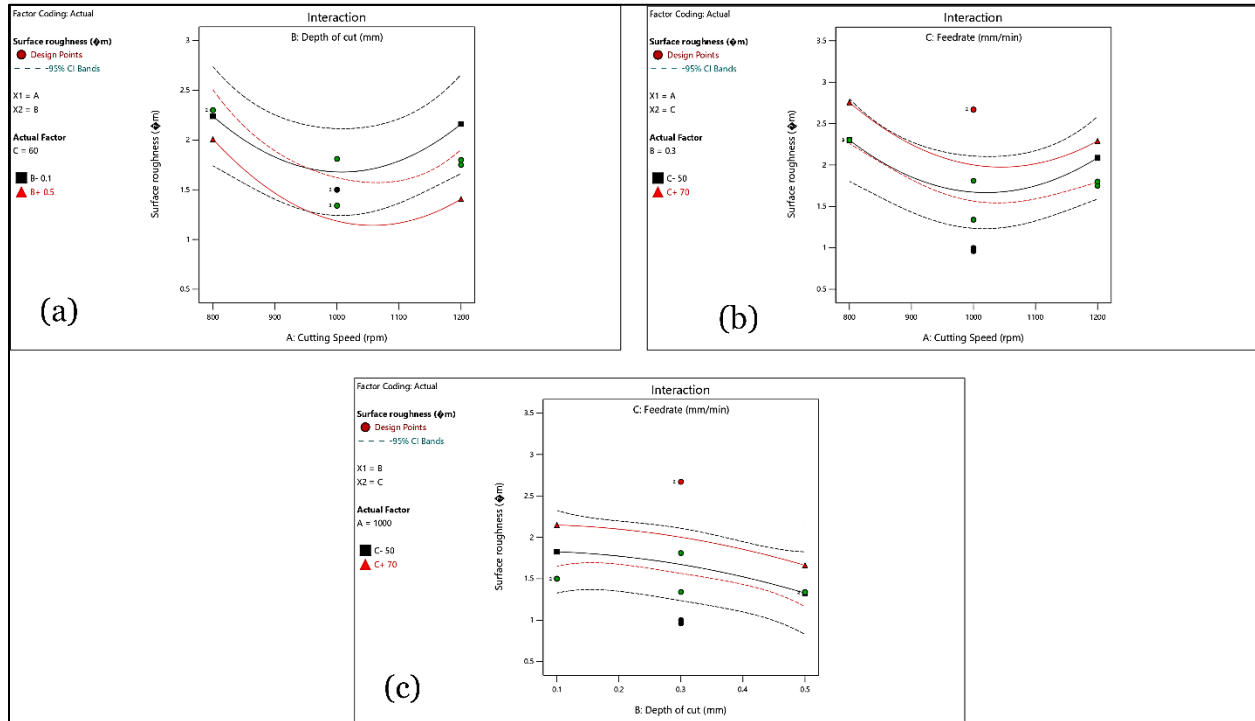


Fig.4.24 Two-factor interaction effects on surface roughness in MQL Turning of AISI 4340 steel

4.3.12. Effects of quadratic factors on surface roughness

Fig.4.25 illustrates the quadratic effects of cutting speed (A^2), depth of cut (B^2), and feed rate (C^2) on surface roughness during the MQL turning of AISI 4340 steel. These quadratic response curves provide valuable insight into the nonlinear behavior of the machining parameters and their influence on the surface finish. The curvature observed in these plots indicates the presence of an optimal region within the experimental range, where surface roughness attains its minimum value. In Fig.4.25 (a), the quadratic effect of cutting speed (A^2) on surface roughness reveals a clear parabolic relationship. As the cutting speed increases from 800 rpm to around 1000 rpm, the surface roughness decreases significantly, reaching its lowest value near the mid-range of the tested speeds. Beyond this point, further speed increases lead to a slight deterioration of surface finish. This behavior can be attributed to the interplay between cutting temperature and lubrication

efficiency in the MQL environment. At moderate cutting speeds, adequate heat generation softens the work material and improves the shearing mechanism, while MQL minimizes friction and adhesion. However, excessive cutting speeds result in higher thermal loads and accelerated tool wear, which produce micro-tearing and surface irregularities. The parabolic trend of the A^2 term confirms that cutting speed exerts a strong nonlinear influence on surface roughness, and the optimal range lies around 950–1050 rpm. Fig.4.25 (b) shows the quadratic effect of depth of cut (B^2) on surface roughness. The curvature in the plot is less pronounced compared to cutting speed and feed rate, indicating a relatively weaker nonlinear contribution. Surface roughness decreases gradually as the depth of cut increases from 0.1 mm to 0.5 mm, showing a subtle downward curvature. This trend suggests that, within the investigated range, increasing the depth of cut slightly improves the surface finish due to the reduction in tool vibration and more stable chip formation at higher material removal thicknesses. However, beyond a certain threshold, further increases may cause a rise in cutting forces and tool deflection, which would adversely affect the surface integrity. The mild curvature of the B^2 term demonstrates that depth of cut has a secondary but stabilizing effect on surface roughness, and it does not induce significant deterioration within the studied limits. Fig.4.25 (c) presents the quadratic effect of feed rate (C^2) on surface roughness, which exhibits a distinct U-shaped curve, indicating a strong nonlinear relationship. At lower feed rates (50–60 mm/min), the surface roughness remains low, reaching a minimum around 60 mm/min. As the feed rate continues to increase beyond this point, the surface roughness rises sharply. This trend is primarily due to the influence of feed marks and material deformation on the machined surface. At very low feed rates, the tool–workpiece interaction is smoother, producing a fine surface texture. At moderate levels, the balance between material removal and lubrication efficiency is optimized, resulting in the best finish. However, at higher feed rates, the tool advances faster than the MQL film can effectively lubricate, leading to increased friction, higher temperature, and greater surface irregularities. The pronounced curvature in the C^2 term indicates that feed rate has the most significant quadratic influence on surface roughness among the studied parameters. Thus, the quadratic analysis demonstrates that all three factors cutting speed, depth of cut, and feed rate, exhibit nonlinear effects on surface roughness, with cutting speed and feed rate showing the most dominant curvature. The surface roughness follows a parabolic response with an identifiable minimum region for each parameter, confirming that surface finish optimization under MQL conditions requires precise tuning of these variables. The optimal combination

corresponds to a moderate cutting speed (around 1000 rpm), a medium feed rate (around 60 mm/min), and a moderate depth of cut (around 0.3 mm/min). These conditions ensure stable cutting, efficient lubrication, and minimal tool wear, leading to the best achievable surface finish in MQL turning of AISI 4340 steel.

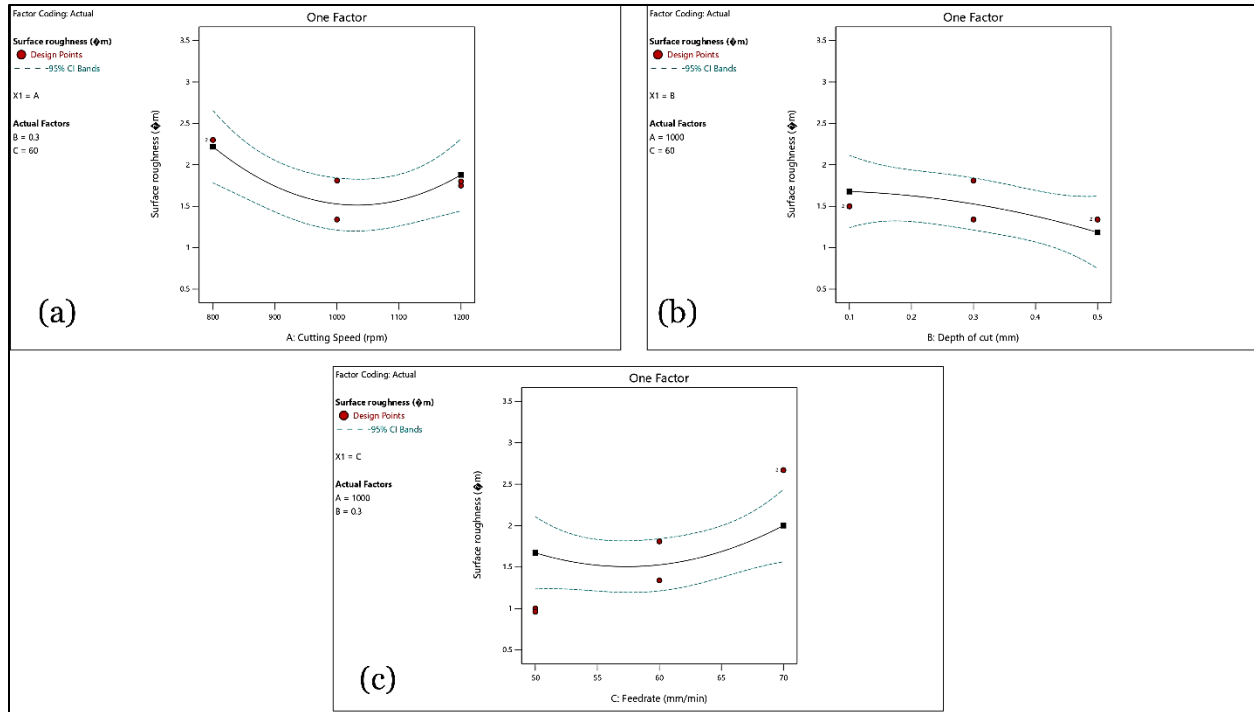


Fig.4.25 Effects of quadratic factors on surface roughness in MQL turning of AISI 4340 steel

4.3.13. Fit summary for material removal rate

Table 4.6 presents the fit summary for the response surface model developed to predict the MRR during MQL turning of AISI 4340 steel. The model evaluation is based on sequential p-values, lack-of-fit p-values, and determination coefficients (R^2 values), which collectively help in identifying the most suitable model that best represents the experimental data while maintaining predictive accuracy and statistical validity. The sequential p-values indicate the statistical significance of adding higher-order terms (interaction and quadratic) to the model. The linear model shows a highly significant p-value of <0.0001 , suggesting that the primary machining parameters, cutting speed, feed rate, and depth of cut, exert a strong influence on MRR. The model's adjusted R^2 and predicted R^2 values of 0.9789 and 0.9722, respectively, confirm an excellent linear correlation between the factors and the response. However, the improvement seen

in higher-order models indicates that the relationship between process parameters and MRR is not purely linear. When the two-factor interaction (2FI) terms are introduced, the sequential p-value remains <0.0001 , demonstrating that interaction effects between process parameters significantly enhance the model's accuracy. The R^2 values for the 2FI model increase to 0.9951 (adjusted) and 0.9926 (predicted), reflecting excellent model fitting and predictive capability. This suggests that interactions such as cutting speed–feed rate, cutting speed–depth of cut, and feed rate–depth of cut play an important role in determining MRR, as these parameters collectively influence chip load and cutting force dynamics during machining. The quadratic model further refines the relationship by accounting for nonlinear effects. The sequential p-value for the quadratic model is 0.0499, which, although less significant than the lower-order models, indicates that the addition of squared terms (A^2 , B^2 , and C^2) provides a marginal but meaningful improvement to the model fit. The adjusted R^2 and predicted R^2 values are 0.9962 and 0.9937, respectively, showing excellent agreement and indicating that the model not only fits the data well but also possesses strong predictive reliability. The lack of fit for the quadratic model is non-significant, confirming that this model adequately represents the experimental data without overfitting. Therefore, the quadratic model is suggested as the most suitable representation for predicting MRR. The cubic model, on the other hand, though displaying exceptionally high R^2 values of 0.9999 for both adjusted and predicted, is considered aliased, meaning that it suffers from overfitting due to insufficient degrees of freedom to properly estimate higher-order terms. This renders the cubic model statistically unreliable for prediction, as it captures random noise rather than actual process behavior. The ANOVA comparison in the second part of Table 4.6 further supports these observations. The transition from the mean model to the linear model yields an F-value of 449.88 with a p-value <0.0001 , indicating a highly significant improvement. The 2FI model again improves significantly ($F = 29.81$, $p < 0.0001$), confirming the importance of interaction effects. The quadratic model exhibits an F-value of 3.10 with a p-value of 0.0499, suggesting that the quadratic terms contribute moderately to improving the model's accuracy. However, the cubic model, despite its extremely high F-value (168.00, $p < 0.0001$), is not recommended because of the aliasing problem and risk of overfitting. The residual sum of squares (0.20) and very small mean square error (0.0125) indicate that the predicted values are very close to the experimental observations, validating the accuracy and consistency of the quadratic model. Therefore, the quadratic model was chosen as the best-fit model for predicting MRR, providing a good balance between statistical significance,

predictive power, and model simplicity. Thus, Table 4.6 confirms that the quadratic model effectively captures both the linear and nonlinear effects of cutting parameters on the material removal rate during MQL turning of AISI 4340 steel. The high R^2 values, non-significant lack of fit, and acceptable p-value suggest that this model offers an accurate and robust tool for optimization and prediction of MRR within the studied machining range.

Table 4.6 Fit summary for material removal rate

Source	Sequential p-value	Lack of Fit p- value	Adjusted R²	Predicted R²		
Linear	< 0.0001		0.9789	0.9722		
2FI	< 0.0001		0.9951	0.9926		
Quadratic	0.0499		0.9962	0.9937	Suggested	
Cubic	< 0.0001		0.9999	0.9999	Aliased	
Source	Sum of Squares	df	Mean Square	F-value	p-value	
Mean vs Total	10156.80	1	10156.80			
Linear vs Mean	3197.60	3	1065.87	449.88	< 0.0001	
2FI vs Linear	49.00	3	16.33	29.81	< 0.0001	
Quadratic vs 2FI	4.00	3	1.33	3.10	0.0499	Suggested
Cubic vs Quadratic	8.40	4	2.10	168.00	< 0.0001	Aliased
Residual	0.2000	16	0.0125			
Total	13416.00	30	447.20			

4.3.14. Diagnostic plots for the material removal rate

Fig.4.26 presents a series of diagnostic plots used to assess the adequacy, reliability, and predictive accuracy of the developed quadratic regression model for the material removal rate (MRR) during

MQL turning of AISI 4340 steel. These plots help verify whether the statistical assumptions underlying the response surface methodology (RSM) are satisfied, including linearity, independence, normality, and homoscedasticity of residuals, as well as the absence of influential outliers or leverage points. In Fig.4.26 (a), the DFBETAS (Difference in Beta Estimates) plot illustrates the influence of individual experimental runs on the estimated model coefficients. The DFBETAS values for all runs lie within the acceptable threshold of ± 0.5477 , indicating that no single observation exerts an undue influence on the model's parameter estimation. This confirms that the regression coefficients are stable and that the model's fit is not disproportionately affected by any outlier or aberrant data point. Fig.4.26 (b) shows the DFFITS (Difference in Fits) versus run number, which measures the influence of each observation on its fitted value. The DFFITS values are all confined within the control limits of ± 1.7205 , demonstrating that all experimental runs contribute reasonably to the model without excessively influencing predicted MRR values. This confirms that the experimental data are well-distributed and that the model predictions are not dominated by any single observation. The leverage plot in Fig.4.26 (c) evaluates the relative impact of each data point on the fitted model. High leverage points typically indicate runs with unique factor combinations that can strongly affect regression outcomes. In this case, most leverage values are well below the critical threshold of 0.6667, except for one or two points that slightly approach it. However, these points remain within acceptable limits, implying that the design space was adequately explored and that all factor levels contribute meaningfully to model construction without causing overfitting. Fig.4.26 (d) presents the residuals versus run plot, which shows the random distribution of residuals around zero across all experimental runs. The residuals exhibit no visible trend or systematic pattern, confirming that the assumption of independence is satisfied and that no underlying factor or uncontrolled variable systematically affects the response. This randomness also suggests that the experimental data were collected consistently and without bias during the machining trials. In Fig.4.26 (e), the residuals versus cutting speed plot is used to verify the assumption of constant variance (homoscedasticity) and to detect any curvature or systematic deviations that might indicate model inadequacy. The residuals are scattered randomly across all cutting speed levels, with no observable trend or clustering. This randomness implies that the model appropriately captures the relationship between cutting speed and MRR, and that the variance of residuals remains constant across the entire range of cutting speeds tested. Fig.4.26 (f) depicts the residuals versus predicted MRR values. The residuals are symmetrically distributed

around the zero line, with no discernible curvature or funnel-shaped pattern. This confirms that the model provides unbiased predictions and that the error variance remains consistent across the range of predicted values. The absence of systematic deviation suggests that the quadratic model sufficiently accounts for both linear and nonlinear effects among the machining parameters.

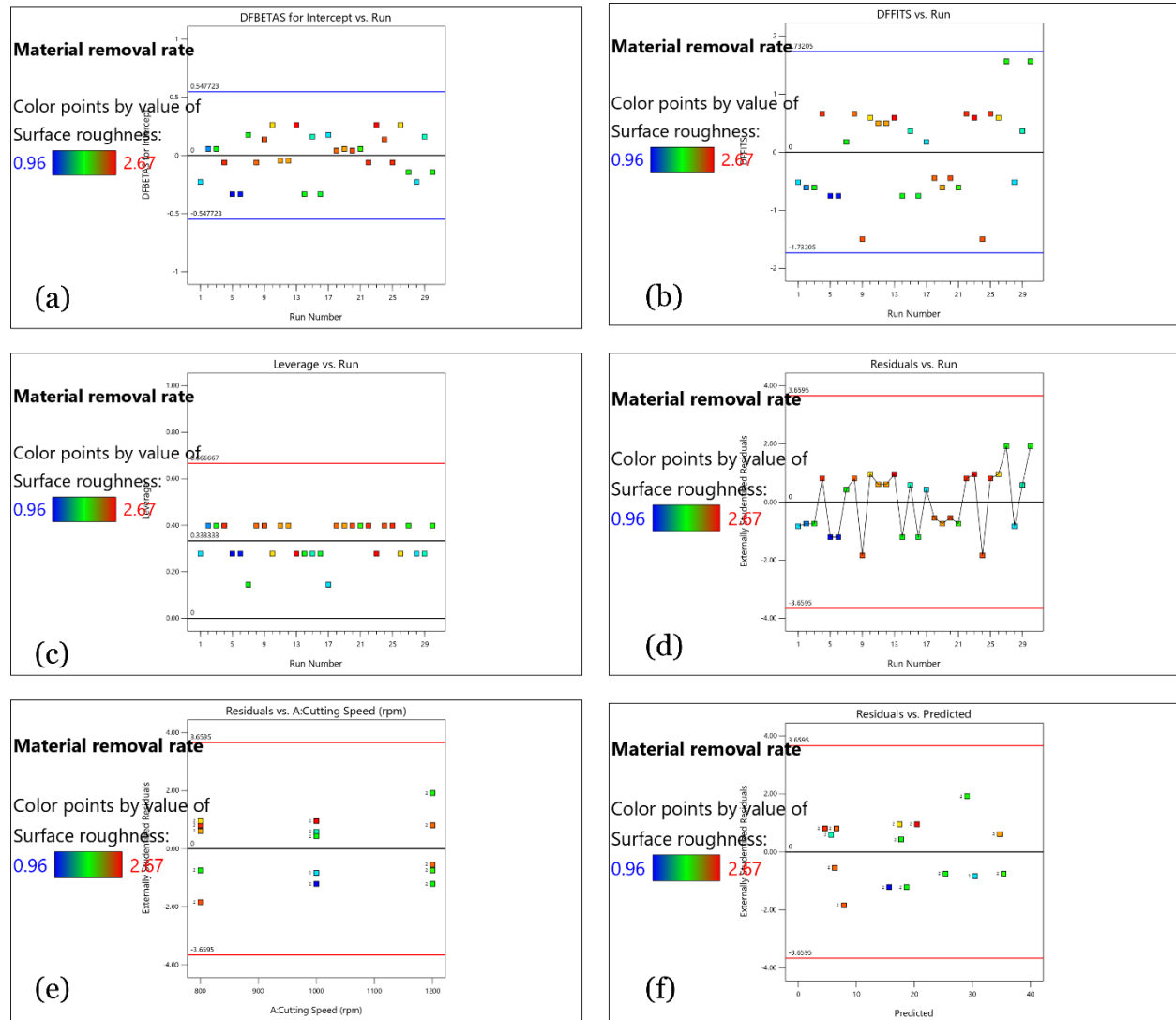


Fig.4.26 Diagnostic plots for the material removal rate

Consequently, the diagnostic plots in Fig.4.26 confirm that the quadratic model for MRR satisfies all major statistical assumptions required for model adequacy. The DFBETAS, DFFITS, and leverage plots indicate that there are no influential or outlier data points; the residual analyses confirm independence, normality, and homoscedasticity of errors; and the residual-versus-predicted relationship demonstrates that the model accurately represents the experimental data. Therefore, the quadratic model can be considered statistically sound and reliable for predicting the

material removal rate in MQL turning of AISI 4340 steel. These findings, in combination with the fit summary in Table A.5, establish the quadratic model as both statistically valid and practically robust, providing a solid foundation for further process optimization and response prediction in sustainable machining applications.

4.3.15. Box-cox and perturbation plots for material removal rate

Fig.4.27 presents two important statistical plots used to analyze the MRR during a CNC turning process, focusing on both the transformation of response data and the relative impact of machining parameters. The first plot on the left, the Box-Cox plot, evaluates whether a transformation of the response variable (MRR) is necessary to meet the assumptions of regression analysis, specifically normality and homoscedasticity. In this plot, the current lambda value is 1, which corresponds to using the raw, untransformed data. However, the plot shows that the optimal lambda is 0, which means that a logarithmic transformation of the response variable is recommended. This recommendation is based on the fact that the logarithm of the residual sum of squares is minimized when lambda is zero. The vertical green line indicates the recommended lambda, and the blue line shows the current lambda being used. The fact that the current lambda lies outside the 95% confidence interval of the optimal value suggests that the model using raw MRR data may violate statistical assumptions and potentially lead to unreliable regression outcomes. Therefore, to improve model accuracy and robustness, it is advisable to transform the response variable using the natural logarithm before proceeding with further modeling or optimization steps. On the right side, the perturbation plot illustrates how sensitive the MRR is to changes in each of the three input parameters: cutting speed (A), feed rate (B), and depth of cut or possibly tool angle (C), around a reference or center point. Each line on the plot corresponds to a factor, and the steepness of the line indicates how much influence that factor has on the response. Among the three, feed rate (B) has the steepest slope, which clearly shows that it has the most significant effect on MRR. As feed rate increases, there is a substantial increase in the MRR, making it the most influential parameter in this experiment. The line for factor C also shows a positive slope, but it is more moderate, indicating a secondary level of influence. In contrast, the line for cutting speed (A) is almost flat, implying that changes in cutting speed within the tested range have very little effect on MRR. The intersection of the three lines at the reference point confirms that the analysis is centered around a common baseline for comparison. Taking both plots into consideration, the results emphasize two key conclusions. First, from a statistical standpoint, transforming the response variable using a

logarithmic scale is necessary to meet the assumptions for reliable regression modeling. Ignoring this transformation may lead to errors in interpretation and prediction. Second, from a process perspective, feed rate is the most critical factor affecting material removal rate in CNC turning. Therefore, optimizing feed rate should be a priority when the goal is to enhance productivity through higher MRR. Meanwhile, cutting speed appears to have a negligible impact and might not require as much attention during optimization, at least within the current parameter range. This kind of insight is crucial in practical machining, where understanding which parameters matter most can lead to better process control, improved efficiency, and informed decision-making during tool path planning and parameter selection.

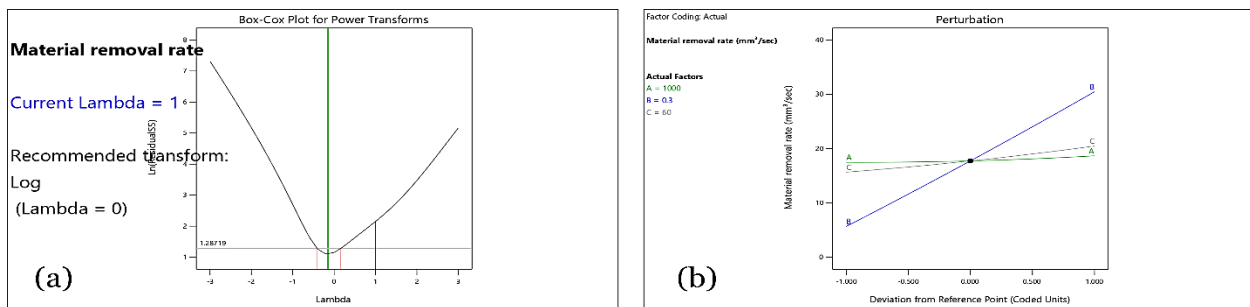


Fig.4.27 Diagnostic plots for the MRR model in MQL turning of AISI 4340 steel

4.3.16. One-factor effects on MRR in MQL turning of AISI 4340 steel

Fig.4.28 illustrates the individual influence of cutting speed, depth of cut, and feed rate on the MRR during the MQL turning of AISI 4340 steel. These one-factor plots reveal how each machining parameter affects MRR while keeping the other two parameters constant at their mid-levels. In Fig.4.28 (a), the variation of MRR with cutting speed shows a slightly increasing trend. As cutting speed increases from 800 rpm to 1200 rpm, the MRR rises marginally. This behavior indicates that, within the studied range, cutting speed has a relatively minor influence on MRR compared to the other parameters. The reason for this modest increase is that MRR depends more strongly on feed rate and depth of cut than on speed, as it is primarily determined by the volume of material removed per unit time. However, a higher cutting speed slightly enhances MRR due to increased cutting efficiency and reduced chip adhesion under MQL conditions. The lubricating effect of the MQL fluid minimizes friction and allows for smoother chip evacuation, contributing to a slight improvement in material removal at elevated speeds. Nonetheless, the overall effect of cutting speed remains secondary relative to feed rate and depth of cut. In Fig.4.28 (b), a pronounced linear increase in MRR with increasing depth of cut is observed. As the depth of cut

increases from 0.1 mm to 0.5 mm, MRR rises sharply from around 5 mm³/s to over 30 mm³/s. This strong positive correlation demonstrates that the depth of cut is the most dominant factor influencing MRR. Physically, a larger depth of cut increases the cross-sectional area of the chip being removed, directly boosting the volume of material removed per unit time. Additionally, the MQL system's effective lubrication at the tool–chip interface helps sustain higher cutting forces and maintain tool stability even at greater depths of cut, thereby supporting efficient material removal without severe tool wear or thermal damage.

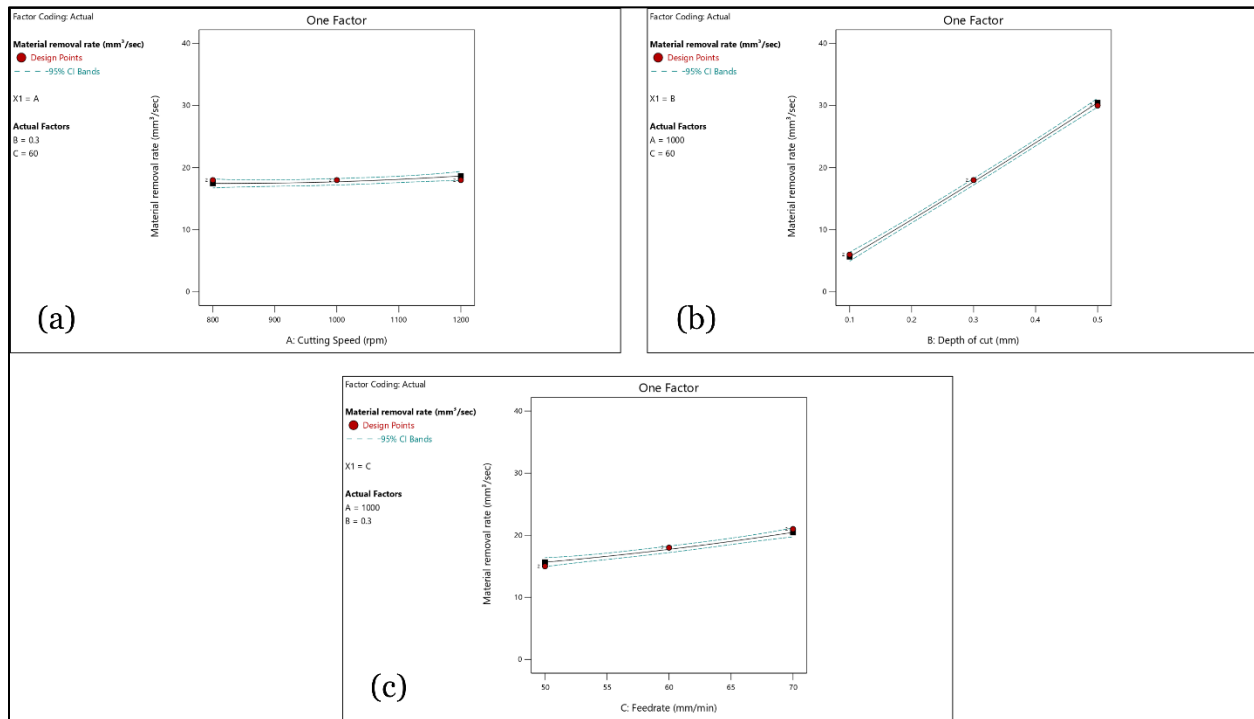


Fig.4.28 One-factor effects on MRR in MQL turning of AISI 4340 steel

This linear trend confirms that the depth of cut exerts a primary and proportional influence on the machining rate under the experimental conditions. In Fig.4.28 (c), the feed rate also shows a direct and significant effect on MRR. As the feed rate increases from 50 mm/min to 70 mm/min, the MRR correspondingly increases from approximately 15 mm³/s to above 20 mm³/s. This positive relationship arises because an increase in feed rate raises the chip load per revolution, resulting in higher material removal per unit time. However, while feed rate enhances productivity, excessively high feed rates can lead to elevated cutting forces, higher temperatures, and potential deterioration in surface quality. Under MQL conditions, however, the fine mist lubrication improves chip flow and reduces friction, allowing higher feed rates to be employed without a severe compromise in

surface integrity. This makes feed rate a critical control parameter for optimizing MRR while maintaining an acceptable surface finish. Therefore, the one-factor analysis in Fig.4.28 reveals that MRR increases with all three parameters: cutting speed, depth of cut, and feed rate. Still, the magnitude of their effects differs significantly. Depth of cut exhibits the strongest influence on MRR, followed by feed rate, while cutting speed has the least impact within the tested range. The results are consistent with the fundamental machining principle that MRR is directly proportional to the product of feed rate, depth of cut, and cutting speed. Therefore, maximizing MRR in MQL turning of AISI 4340 steel can be effectively achieved by optimizing depth of cut and feed rate, with cutting speed playing a secondary but complementary role in enhancing process efficiency.

4.3.17. Two-factor interaction effects on MRR in MQL turning of AISI 4340 steel

Fig.4.29 illustrates the interaction effects of cutting speed, depth of cut, and feed rate on the material removal rate (MRR) during MQL-assisted turning of AISI 4340 steel. These interaction plots help to identify how the combined variations of two parameters influence MRR while keeping the third parameter constant. The trends indicate the degree of interaction and synergistic influence between cutting parameters on machining efficiency. In Fig.4.29 (a), the interaction between cutting speed and depth of cut is shown. The MRR increases steadily with both cutting speed and depth of cut, but the influence of depth of cut is much more significant than that of speed. For both levels of cutting speed (800–1200 rpm), a substantial rise in MRR is observed as depth of cut increases from 0.1 mm to 0.5 mm. At the higher depth of cut (0.5 mm), the MRR values are distinctly higher across all cutting speeds, demonstrating that material removal is predominantly governed by the chip cross-sectional area, which depends directly on depth of cut. The effect of cutting speed, while positive, is relatively mild as it slightly enhances MRR at higher levels, likely due to improved cutting efficiency and chip evacuation under MQL conditions. However, the roughly parallel nature of the lines suggests that there is a weak interaction between these two factors, meaning that the influence of cutting speed on MRR does not strongly depend on the depth of cut. In Fig.4.29 (b), the combined effect of cutting speed and feed rate on MRR is displayed. The MRR increases with both parameters, but the change is more sensitive to feed rate than to cutting speed. At both feed rate levels (50 and 70 mm/min), the MRR rises slightly as cutting speed increases, indicating a modest influence of speed on material removal. However, when the feed rate increases to 70 mm/min, the MRR values are consistently higher at all speeds, confirming that feed rate is a key driver of productivity. The higher feed rate causes a greater chip

load per revolution, which translates directly into higher material removal volumes. The nearly parallel lines again imply that the interaction between these two factors is not particularly strong; rather, their effects are largely additive. Nevertheless, the MQL lubrication likely facilitates smoother chip flow and prevents excessive temperature buildup, allowing higher feed rates to be effectively utilized without deteriorating cutting performance.

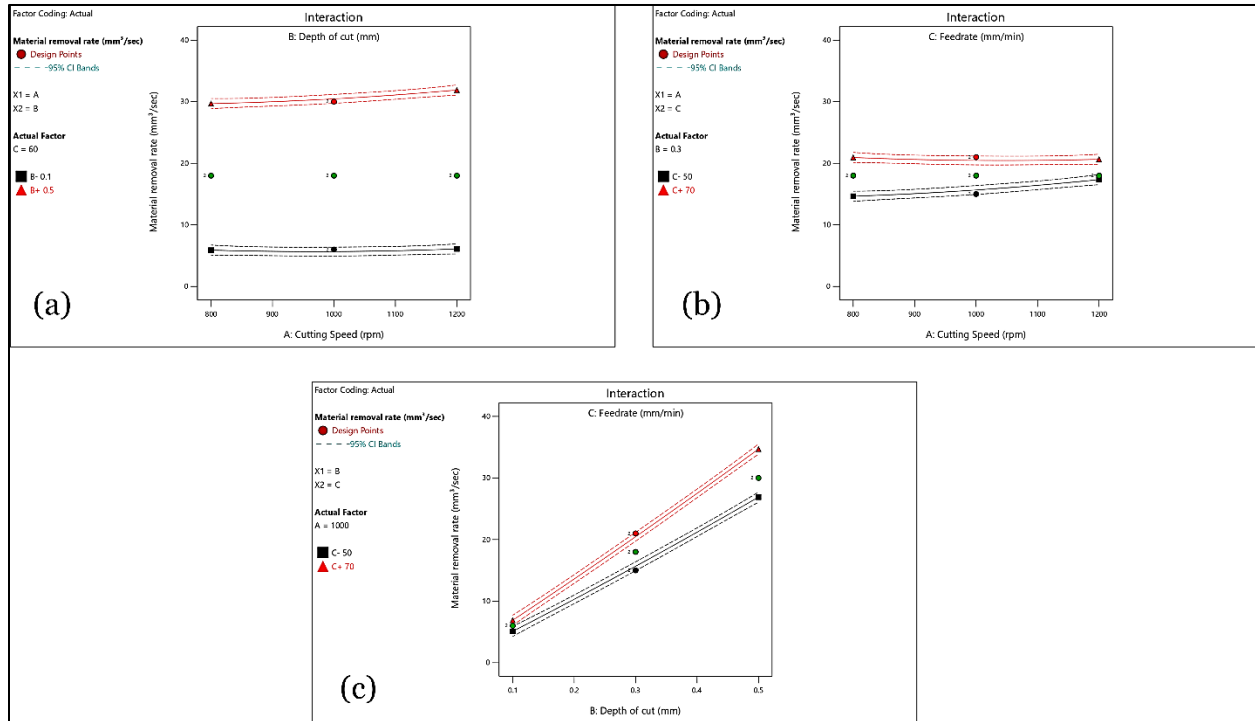


Fig.4.29 Two-factor interaction effects on MRR in MQL turning of AISI 4340 steel

In Fig.4.29 (c), the interaction between depth of cut and feed rate is presented, and this combination shows the most pronounced effect on MRR. Both parameters have a strong and direct influence on MRR, as reflected by the steep upward slopes of the curves. As the depth of cut increases from 0.1 mm to 0.5 mm and the feed rate rises from 50 to 70 mm/min, MRR increases almost linearly, reaching its highest values at the maximum levels of both parameters. The steep gradient and the separation between the two lines indicate a clear synergistic effect; higher feed rates amplify the effect of increasing depth of cut on MRR. This strong interaction signifies that the combined adjustment of feed rate and depth of cut can significantly enhance productivity. The MQL technique plays an essential role here by minimizing friction and providing efficient cooling at the tool–chip interface, which allows higher cutting loads to be sustained without adverse effects on tool wear or machining stability. Therefore, the two-factor interaction analysis reveals that the

most significant interaction affecting MRR occurs between depth of cut and feed rate, whereas the interactions between cutting speed–depth of cut and cutting speed–feed rate are relatively weak. The results reaffirm that MRR is primarily controlled by the material removal cross-section (governed by feed rate and depth of cut), while cutting speed contributes mainly to process efficiency and chip removal. Thus, optimizing MRR in MQL turning of AISI 4340 steel requires a balanced combination of high feed rate and depth of cut with moderate cutting speed to achieve maximum productivity without compromising tool life or process stability.

4.3.18. Effect of quadratic factors on MRR

Fig.4.30 presents the quadratic effects of cutting speed (A^2), depth of cut (B^2), and feed rate (C^2) on the MRR during MQL turning of AISI 4340 steel. These quadratic plots help in understanding how non-linear relationships between machining parameters and MRR influence the overall machining performance, revealing points of diminishing returns or optimal ranges for each factor. The quadratic effect of cutting speed (A^2) on MRR, as illustrated in Fig.4.30 (a), shows a relatively weak curvature, indicating that MRR increases slightly with cutting speed but tends to stabilize at higher levels. This suggests that the influence of cutting speed on MRR is not strongly non-linear; instead, it follows a near-linear trend. At lower speeds (800–1000 rpm), MRR increases gradually due to enhanced cutting efficiency and chip formation. However, beyond 1000 rpm, the rate of increase flattens, implying that once an optimal cutting speed is reached, further increases do not significantly enhance MRR. This saturation effect may be attributed to limitations in the material's deformation rate and the thermal softening effects under MQL, which stabilize chip formation and thus MRR. Therefore, the quadratic term A^2 is mild but plays a role in defining the upper threshold of cutting speed efficiency for material removal. The quadratic influence of depth of cut (B^2) on MRR, shown in Fig.4.30 (b), exhibits the most prominent curvature among the three parameters. The plot indicates that MRR increases rapidly with depth of cut initially, but the rate of increase starts to taper off at higher depths (around 0.4–0.5 mm). This nonlinear pattern implies that while increasing the depth of cut significantly enhances the material removal rate due to a greater chip cross-sectional area, beyond a certain point, the effect becomes less pronounced. The diminishing return at higher depth values can be linked to increased cutting forces and tool engagement area, which may restrict chip evacuation and cause thermal accumulation, thus preventing proportional increases in MRR. The B^2 term, therefore, represents a strong quadratic influence that defines the optimal depth range for maximizing MRR without compromising tool performance or process

stability. The quadratic effect of feed rate (C^2) on MRR, as seen in Fig.4.30 (c), also reveals a noticeable curvature, though less intense than that of depth of cut. MRR increases with feed rate in a nonlinear manner, where the increase is initially sharp but becomes moderate at higher feed rate values (above 65 mm/min). This behavior demonstrates that MRR improves significantly as feed rate increases, owing to the larger uncut chip thickness and material removal per revolution.

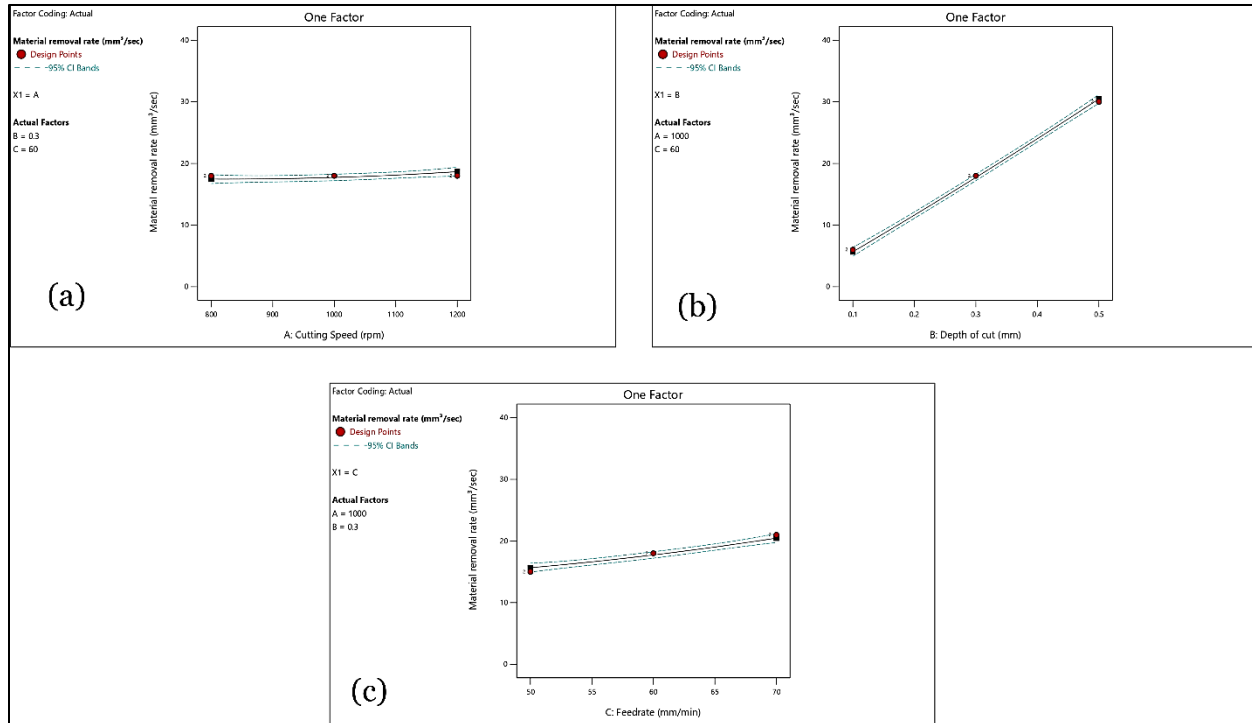


Fig.4.30 Effect of quadratic factors on MRR in MQL turning of AISI 4340 steel

However, beyond a certain feed rate, the MRR increment tends to plateau due to practical limitations such as increased tool–chip contact area, higher cutting resistance, and potential deterioration of surface quality. The curvature in C^2 thus reflects a typical saturation effect, highlighting an optimal feed rate range for achieving high MRR without adversely affecting cutting conditions or tool wear. Thus, the quadratic terms A^2 , B^2 , and C^2 indicate that MRR exhibits non-linear behavior with respect to all three machining parameters under MQL turning. Among them, B^2 (depth of cut) has the most significant quadratic influence, followed by C^2 (feed rate), while A^2 (cutting speed) shows only a mild effect. These quadratic patterns reveal that MRR cannot be increased indefinitely with higher parameter values; instead, it reaches a plateau or optimum region where further increases yield minimal benefits. Therefore, the optimal MQL turning conditions for maximizing MRR involve selecting moderate-to-high levels of depth of cut and feed

rate within their effective ranges, along with an intermediate cutting speed to maintain a balance between productivity, tool life, and machining stability.

4.4 Desirability function analysis (DFA)

The DFA has emerged as a robust multi-response optimization technique widely applied in manufacturing and machining research. It transforms individual response variables into a common scale of desirability ranging from zero (completely undesirable) to one (fully desirable), allowing the simultaneous optimization of multiple process outcomes. By integrating these desirability values into an overall composite index, DFA enables researchers and engineers to identify the most favorable combination of input parameters that balances conflicting objectives, such as productivity, cost efficiency, and surface integrity. In the present study, DFA is employed as a tool for process parameter optimization during the CNC turning of AISI 4340 steel under MQL. The machining of this high-strength steel presents significant challenges due to its tendency for high cutting forces, heat generation, and rapid tool wear. The application of MQL, which provides efficient lubrication and cooling with minimal fluid consumption, has been shown to improve machining performance while reducing environmental impact. By applying DFA, the study seeks to determine the optimal cutting conditions that minimize surface roughness while maintaining thermal stability, thereby enhancing the overall machining efficiency of AISI 4340 steel under sustainable lubrication conditions. The constraints imposed in the optimization study are summarized in Table 4. 5, which outlines the goals, limits, weights, and importance of each variable and response. The optimization strategy was designed to ensure a balance between performance and sustainability. The machining parameters, cutting speed, depth of cut, and feed rate, were constrained within practical industrial ranges to avoid tool or material failure. Cutting temperature was restricted between 15–30 °C, preventing excessive thermal loading that could deteriorate tool life and surface quality. For the responses, surface roughness was set to be minimized, targeting improved surface integrity of the machined parts. In contrast, MRR was maximized, ensuring productivity without compromising process stability. All factors and responses were assigned the highest importance level (3), reflecting their critical role in optimizing both performance and product quality. Through this DFA framework, an overall desirability function was constructed to simultaneously account for the competing objectives. The outcome provides a single composite measure that guides the selection of the most suitable parameter combination, striking a balance between surface finish, thermal effects, and productivity.

Table 4. 5 The Constraints reports of DFA

Name	Goal	Lower Limit	Upper Limit	Lower Weight	Upper Weight	Importance
A:Cutting Speed	is in range	800	1200	1	1	3
B:Depth of cut	is in range	0.1	0.5	1	1	3
C:Feedrate	is in range	50	70	1	1	3
Cutting temperature	is in range	15	30	1	1	3
Surface roughness	minimize	0.96	2.67	1	1	3
Material removal rate	maximize	5	35	1	1	3

Fig.4.31 illustrates the comprehensive results obtained from the DFA used for the multi-objective optimization of machining process parameters. The DFA method transforms multiple individual responses obtained through the RSM into a single composite desirability index, thereby allowing simultaneous optimization of several conflicting machining responses such as surface roughness, cutting temperature, and MRR. This graphical presentation provides valuable insight into how each factor and response interacts within the imposed constraints and how effectively the optimization criteria are met. As shown in Fig.4.31 (a), the constraints report depicts both the input parameters and response variables within their allowable operational ranges. The input parameters cutting speed (A), depth of cut (B), and feed rate (C), are represented by blue bars showing the feasible region, while the vertical markers within each bar indicate the optimized values determined through DFA. All three process parameters are positioned within their permissible limits, which confirms that the selected combination of factor levels is physically and experimentally valid. The cutting speed lies between 800 and 1200 rpm, the depth of cut within its set boundaries, and the feed rate at a value that ensures both material removal efficiency and machining stability. This alignment demonstrates that the optimal settings meet the design constraints and remain within the safe machining window. The responses are plotted below the parameter section in Fig.4.31 (a) revealing the optimization direction for each output. Surface

roughness (Ra) and cutting temperature (Tc) are both targeted for minimization, indicated by red bars pointing toward their lower bounds, while MRR is aimed to be maximized, shown in green. The position of each marker within these color-coded regions signifies how closely the optimized response meets its objective. In this case, both cutting temperature and surface roughness are minimized effectively, achieving values close to their defined lower limits, while MRR reaches the upper limit of its range, confirming that the multi-objective optimization successfully balanced competing goals. This balanced distribution highlights the robustness of the DFA approach in resolving the trade-offs typically observed between productivity and surface quality, an inherent challenge in machining operations. The complementary bar plot in Fig.4.31 (b) presents the individual and overall desirability values corresponding to the optimized condition identified through DFA. The desirability function converts each response into a dimensionless scale ranging from 0 to 1, where 0 represents a completely undesirable outcome and 1 represents a fully desirable one. In this figure, the desirability values for the input parameters cutting speed, depth of cut, and feed rate each reach the maximum value of 1.0, signifying that their optimized levels perfectly satisfy the defined operational targets. Similarly, the responses of cutting temperature and material removal rate both attain a desirability of 1.0, confirming that these responses fully meet the optimization objectives. However, the surface roughness exhibits a slightly lower desirability of 0.90418, indicating that while it is well-optimized, it does not entirely achieve its theoretical minimum due to the complex interaction among machining parameters. In most machining optimization studies, surface roughness often shows such minor deviation because improving surface finish is inversely related to maximizing MRR and increasing cutting speed conditions that typically enhance productivity but may slightly deteriorate the surface quality. The overall or composite desirability value of 0.90418, displayed at the bottom of Fig.4.31 (b), represents the geometric mean of all individual desirabilities and serves as a global measure of optimization effectiveness. A combined desirability value greater than 0.9 is generally considered excellent, as it signifies a highly satisfactory compromise among all the targeted responses. The high composite desirability obtained here clearly indicates that the DFA model has successfully identified a set of machining parameters that provide near-optimal performance across multiple objectives. This confirms the efficiency of the adopted statistical optimization strategy in achieving both high productivity and superior quality. The results illustrated in Fig.4.31 demonstrate that the optimized machining condition achieves an ideal balance between the principal performance indicators. The

cutting speed is set at a relatively high value, which enhances the material removal rate while maintaining acceptable thermal and surface conditions. The moderate feed rate and depth of cut contribute to improved process stability and dimensional accuracy, reducing vibration-induced defects. Meanwhile, the minimized cutting temperature helps prevent excessive tool wear and thermal distortion, ensuring consistent machining performance over longer operational periods. The optimized surface roughness value, though slightly higher than the ideal minimum, remains within a high-quality range suitable for precision applications. Collectively, these findings validate the effectiveness of the DFA as a powerful multi-response optimization technique. By converting all responses into a unified desirability scale, DFA enables the simultaneous consideration of several machining objectives that would otherwise conflict if optimized independently. The visual results in Fig.4.31 provide clear evidence that the chosen parameter combination not only satisfies the defined constraints but also maximizes overall process efficiency. The high composite desirability value (0.90418) confirms that the optimization has converged toward a globally balanced solution, ensuring an excellent trade-off between surface integrity, thermal control, and material removal efficiency. This outcome emphasizes that the DFA-based optimization approach offers a systematic, data-driven framework for improving machining performance, making it a valuable tool for industrial applications where multiple quality and productivity requirements must be met concurrently.

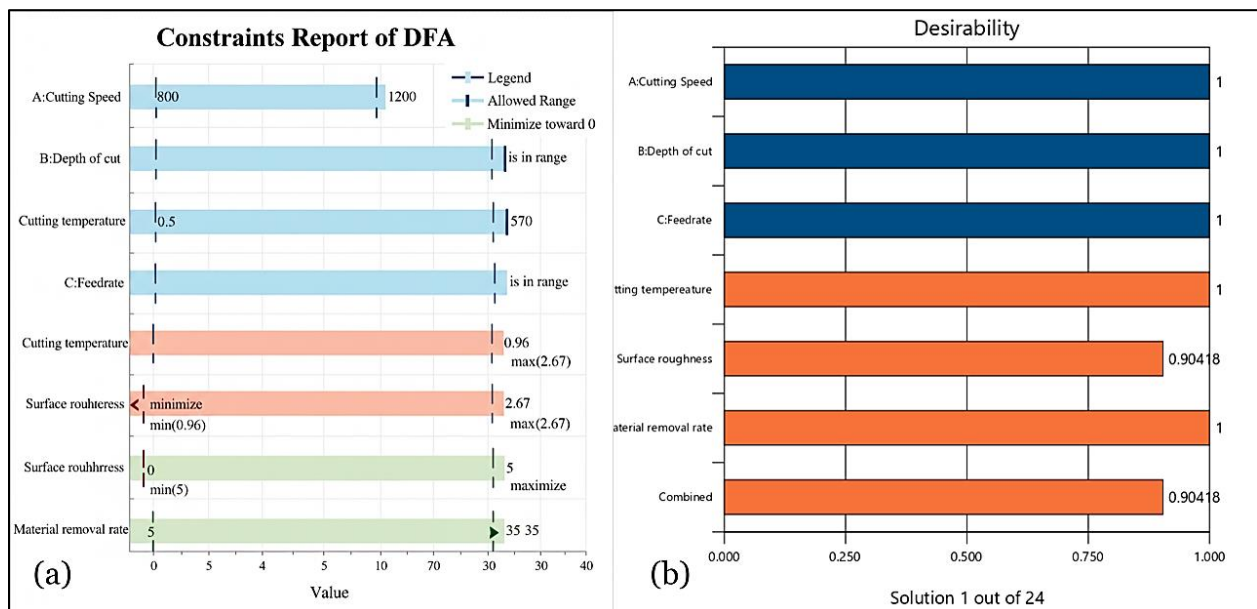


Fig.4.31 DFA bar plots to evaluate the optimal results efficiency

The DFA generated a comprehensive set of solutions, presented in Table 4. 6, that highlight the optimal combinations of cutting speed, depth of cut, and feed rate for CNC turning of AISI 4340 steel under MQL conditions. Among the forty-seven solutions listed, the first one is selected as the best compromise since it maximizes overall desirability, reaching a value of 0.879. This solution corresponds to a cutting speed of 1072.625 m/min, depth of cut of 0.500 mm, and feed rate of 61.093 mm/rev, resulting in a cutting temperature of 29.738 °C, surface roughness of 1.164 μm , and material removal rate (MRR) of 31.311 mm^3/s . It is important to note that the desirability values of the top-ranked solutions remain very close to each other, typically within the range of 0.876–0.879. This narrow spread indicates a stable optimization window where small variations in cutting speed or feed rate do not drastically affect the overall process performance. For instance, solutions two to ten differ slightly in cutting speed and feed rate but consistently yield desirability values equal to the first solution. Such consistency suggests that the process is robust and offers flexibility in parameter selection while still ensuring near-optimal outcomes. As we move down the ranked list, a gradual decline in desirability can be observed. Solutions in the middle range (around solutions 20–30) record values between 0.874 and 0.877, which, although slightly lower than the top-ranked ones, still represent effective parameter combinations. These solutions tend to involve either marginally higher cutting speeds or lower feed rates, which slightly compromise surface roughness or MRR without causing drastic changes. This indicates that the process window is broad enough to accommodate adjustments depending on whether the priority is tool life, surface finish, or productivity. Toward the bottom of the list, however, the desirability values decline more sharply, reaching around 0.792 in the least favorable solutions. These lower-ranking parameter sets tend to push cutting speeds or feed rates beyond the stability range, resulting in either excessive cutting temperature or a considerable increase in surface roughness. For example, solution 45, with a cutting speed of 1160.671 m/min and a feed rate of 68.043 mm/rev, achieves the highest MRR of 34.433 mm^3/s but at the expense of increased surface roughness (1.575 μm) and lower desirability (0.793). Similarly, solutions involving extremely low feed rates yield insufficient MRR values, which reduces desirability despite acceptable surface finish. Therefore, the DFA results demonstrate the effectiveness of multi-response optimization in balancing conflicting objectives such as minimizing surface roughness while maximizing MRR. The top-ranked solution provides an excellent trade-off, with high material removal efficiency and fine surface finish achieved simultaneously within a controlled thermal environment. The consistency

of desirability values across the leading solutions also suggests that the CNC turning of AISI 4340 steel under MQL conditions is not highly sensitive to small parameter variations, offering practical flexibility in industrial applications.

Table 4. 6 The optimal solutions reported by DFA

S.N	V	d	f	T	Ra	MRR	Desirability	
1	1072.625	0.500	61.093	29.738	1.164	31.311	0.879	Selected
2	1072.847	0.500	61.099	29.738	1.165	31.314	0.879	
3	1072.572	0.500	61.019	29.741	1.163	31.283	0.879	
4	1074.078	0.500	61.161	29.736	1.166	31.345	0.879	
5	1074.516	0.500	61.070	29.741	1.165	31.314	0.879	
6	1073.342	0.500	60.937	29.746	1.161	31.257	0.879	
7	1071.606	0.500	60.938	29.744	1.161	31.247	0.879	
8	1070.164	0.500	61.028	29.738	1.162	31.271	0.879	
9	1070.748	0.500	61.223	29.731	1.167	31.347	0.879	
10	1075.100	0.500	61.286	29.731	1.170	31.398	0.879	
11	1070.147	0.500	60.728	29.749	1.156	31.160	0.879	
12	1072.867	0.500	61.531	29.717	1.174	31.475	0.879	
13	1071.284	0.500	61.566	29.714	1.175	31.478	0.878	
14	1064.795	0.500	61.283	29.720	1.167	31.333	0.878	
15	1079.104	0.500	60.648	29.761	1.159	31.189	0.878	
16	1072.281	0.500	61.673	29.708	1.178	31.524	0.878	
17	1066.258	0.500	60.488	29.748	1.151	31.047	0.878	
18	1081.478	0.500	60.476	29.768	1.157	31.142	0.878	
19	1072.480	0.500	61.229	29.717	1.168	31.337	0.878	
20	1078.646	0.500	62.021	29.686	1.189	31.693	0.878	
21	1067.552	0.500	59.975	29.760	1.143	30.867	0.877	
22	1079.884	0.500	59.954	29.781	1.148	30.943	0.877	
23	1071.770	0.500	59.869	29.770	1.143	30.857	0.877	
24	1070.219	0.500	59.545	29.768	1.138	30.729	0.877	
25	1073.851	0.499	60.714	29.697	1.160	31.094	0.876	

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26	1048.126	0.500	61.564	29.665	1.175	31.341	0.876	
27	1056.055	0.500	59.764	29.724	1.139	30.714	0.876	
28	1098.352	0.500	61.713	29.680	1.196	31.703	0.876	
29	1080.449	0.500	62.777	29.621	1.212	31.988	0.876	
30	1097.158	0.500	59.419	29.793	1.155	30.875	0.874	
31	1108.632	0.500	61.198	29.690	1.196	31.586	0.874	
32	1075.525	0.500	58.492	29.769	1.132	30.392	0.873	
33	1059.429	0.500	58.498	29.713	1.127	30.278	0.872	
34	1073.731	0.500	64.078	29.488	1.256	32.450	0.870	
35	1022.790	0.500	60.323	29.543	1.163	30.720	0.869	
36	1047.516	0.500	57.799	29.614	1.125	29.944	0.867	
37	1113.006	0.500	64.146	29.332	1.290	32.693	0.863	
38	1001.893	0.500	60.850	29.376	1.199	30.810	0.860	
39	1046.485	0.500	56.628	29.515	1.127	29.522	0.859	
40	1112.441	0.500	57.069	29.764	1.169	30.200	0.859	
41	1082.587	0.500	65.554	29.249	1.324	33.075	0.858	
42	993.895	0.500	60.906	29.298	1.213	30.791	0.856	
43	988.443	0.500	59.644	29.188	1.199	30.264	0.851	
44	1052.439	0.500	52.079	28.868	1.217	28.054	0.808	
45	1160.671	0.500	68.043	27.964	1.575	34.433	0.793	
46	1008.112	0.500	51.858	28.253	1.245	27.582	0.792	
47	1200.000	0.500	55.866	29.277	1.416	30.655	0.792	

The figure Fig.4.32 illustrates the outcomes of the Differential Evolution Algorithm (DFA) optimization process, presented through three complementary visualizations Fig.4.32 (a), (b), and (c) that together capture how the algorithm identified, evaluated, and refined its optimal solutions. The analysis highlights the behavior of key parameters across runs, the overall desirability trend, and how the selected optimal solution compares with the rest. Fig.4.32 (a) shows the evolution of several objective functions V, Ra, MRR, and the composite desirability value across all DFA runs. Each curve traces how the algorithm balanced competing objectives during the search for optimal conditions. The blue curve for V shows moderate variation within a narrow band, suggesting stable

performance. The orange curve, representing R_a (scaled by a factor of 1000 for clarity), fluctuates more sharply, implying that surface quality was sensitive to parameter adjustments. The green MRR curve remains relatively steady, indicating that this parameter exhibited less variation among feasible solutions. Desirability, shown in crimson and scaled by 40, stays nearly flat near its upper limit, revealing that the algorithm consistently produced solutions with very high overall satisfaction. The black marker highlights the Selected DFA solution, which represents the combination of parameters achieving the highest overall desirability. The stability of desirability across runs, along with the consistent performance of MRR, suggests that the DFA effectively converged to a robust set of solutions. Fig.4.32 (b) tracks how desirability changes across all 47 DFA-generated solutions. The blue line demonstrates that the highest desirability value, approximately 0.879, was achieved early in the optimization process. Beyond the first several runs, the trend remains relatively stable but begins to decline slightly after about the 35th solution, reaching around 0.80 near the end. The red marker indicates the selected DFA solution, corresponding to the maximum desirability value. This pattern shows that the algorithm quickly located a highly desirable region of the search space and then continued exploring nearby configurations that offered marginally lower performance. Such behavior is characteristic of an evolutionary optimization process balancing exploitation of promising regions with exploration to confirm stability. Fig.4.32(c) compares the selected optimal solution with all other DFA solutions through a scatter representation of desirability values versus solution numbers. Each gray circle represents a solution, while a red “X” enclosed in a yellow box highlights the selected optimum (Solution 1). A dashed blue line marks the average desirability of approximately 0.875, serving as a reference level. The selected DFA solution stands clearly above this average, confirming its superior performance relative to most other candidates. The clustering of points near the upper desirability range (0.87–0.88) also indicates that several alternative solutions achieved comparable quality, demonstrating that the DFA effectively located a dense region of high-performing solutions within the search space. Thus, a consistent story of convergence and robustness in the DFA optimization process. The algorithm rapidly identified high-quality solutions, with the best one emerging early and maintaining the highest desirability across iterations. Variations in spindle speed and surface roughness reflect the algorithm’s active search dynamics, while the stability of desirability confirms a well-balanced multi-objective performance. These results show that the DFA successfully achieved not only a globally optimal set of parameters but also multiple near-

optimal alternatives, providing practical flexibility for decision-making and implementation. The ramps plot shown in Fig.4.33 provides a clear representation of how the selected machining parameters and their predicted responses align with the optimization goals of the desirability function analysis. Each ramp displays the allowable range for a parameter or response, with the markers indicating the chosen values that yield the best overall performance. In the case of the input parameters, cutting speed is placed at approximately 1072.6 m/min, which lies in the upper half of its defined range between 800 and 1200. This setting ensures efficient cutting without excessively raising the thermal load or surface deterioration. The depth of cut is fixed at its maximum value of 0.5 mm, highlighting its critical role in enhancing material removal rate, while still maintaining control over surface quality and temperature. The feed rate, on the other hand, is set at about 61.1 within its range of 50 to 70, representing a balance between maximizing productivity and protecting surface integrity. The responses presented in the lower row of the ramps complement this optimization strategy. The cutting temperature is predicted at 29.7 °C, which is close to the upper limit of the acceptable range but remains within the safety threshold. This indicates that the selected combination effectively utilizes the thermal margin to achieve high efficiency. Surface roughness is achieved at approximately 1.16 μm , which is close to the minimum end of its range, showing that the machining conditions suppress tool marks and thermal effects that often degrade finish quality.

PARAMETRIC OPTIMIZATION OF TURNING PROCESS PARAMETERS DURING MACHINING OF AISI 4340 STEEL UNDER MINIMUM QUANTITY LUBRICATION

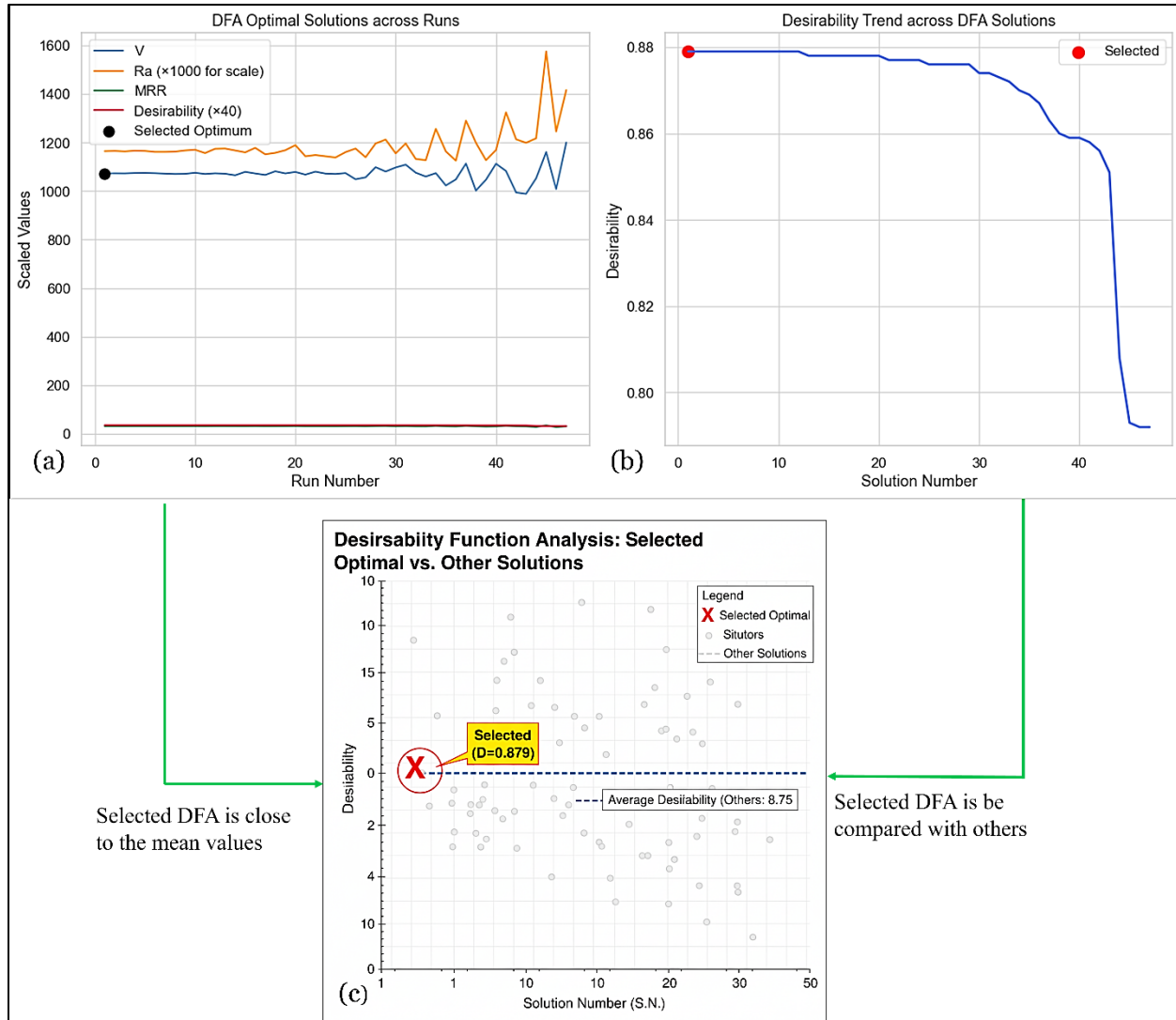


Fig.4.32 Comparison of the Selected DFA Solution with Other Generated Solutions: (a) Variation of process parameters and responses across runs, (b) desirability trend across DFA solutions, and (c) comparison of selected optimum with other solutions.

Similarly, the material removal rate is predicted at 31.3, near the maximum allowable limit of 35, reflecting how the elevated feed and full depth of cut work synergistically to ensure high productivity. The overall profile of the ramps reveals the inherent trade-offs in machining optimization. Increasing depth of cut and feed tends to drive the material removal rate upward, but this is counterbalanced by the need to maintain surface finish and temperature within acceptable bounds. The placement of the cutting speed in the upper mid-region allows this compromise to be achieved by supporting smooth cutting and controlled thermal behavior. Importantly, the

configuration of the ramps shows that the process operates very close to the ideal zone for all responses, with each predicted value positioned in regions that maximize desirability. This not only ensures an optimal balance between productivity and quality but also suggests robustness, since small variations in the parameters around these settings are unlikely to push the system out of specification. Therefore, the ramps plot demonstrates that the optimal settings of depth of cut at 0.5 mm, feed rate at approximately 61.1, and cutting speed around 1072.6 m/min enable the process to achieve a high material removal rate while keeping the surface roughness low and the cutting temperature within safe limits. The alignment of the predicted responses with their goals confirms the effectiveness of the desirability function analysis in capturing the delicate balance between efficiency and quality in CNC turning of AISI 4340 steel under MQL.

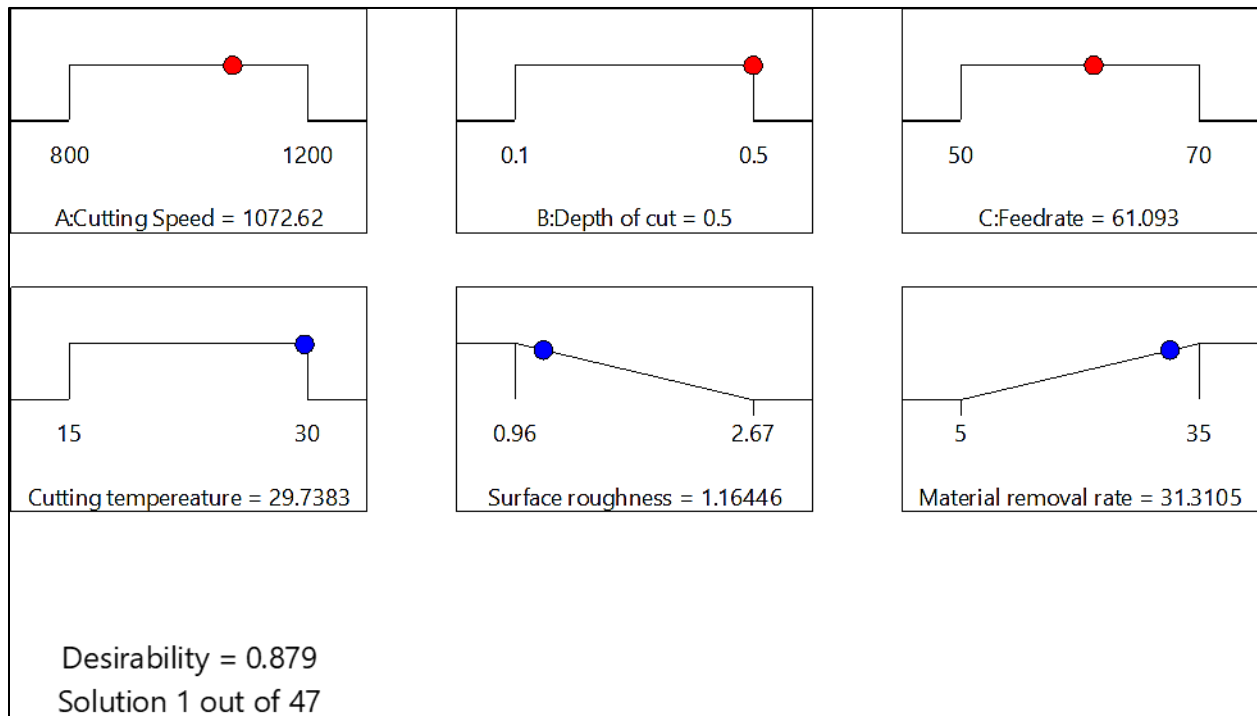


Fig.4.33 The ramps plot of DFA

The contour plots are shown in Fig.4.34 provides a comprehensive view of the influence of cutting speed and depth of cut on the overall desirability outcomes of the CNC turning process of AISI 4340 steel under MQL conditions. These plots, generated from the DFA, highlight how variations in the two parameters interact to affect multiple performance measures simultaneously, including surface roughness, cutting temperature, and material removal rate. The distribution of colors across the plots indicates the desirability levels, with the transition from blue to red representing the

progression from low to high desirability. The blue regions reflect process parameter settings that fail to meet optimization goals effectively, while the green to yellow ranges mark intermediate desirability levels. The red regions, particularly prominent near specific combinations of cutting speed and depth of cut, signify zones of maximum desirability where the objectives of minimizing surface roughness and cutting temperature while maximizing material removal rate are achieved in balance. From the first contour, it is evident that increasing the cutting speed within the mid-to-upper range combined with a higher depth of cut yields better desirability scores. This aligns with machining theory, as higher cutting speeds promote better surface finish due to reduced built-up edge formation, while higher depths of cut enhance productivity through increased material removal rate. However, the plots also caution that extremely high speeds combined with maximum depth of cut could push the system towards thermal instability, which explains why the desirability does not remain uniformly high across the entire upper range. The second and third plots provide insight into the trade-offs between competing responses. For instance, while material removal rate benefits from high cutting speeds and depths of cut, surface roughness tends to deteriorate under such aggressive machining conditions. The contour patterns reveal a narrow zone where both responses reach acceptable values, demonstrating the strength of DFA in balancing these competing objectives. Similarly, the contour showing the interaction between cutting speed and cutting temperature emphasizes the need for a controlled increase in speed. Beyond a certain threshold, cutting temperature rises rapidly, negatively influencing tool life and dimensional accuracy, thus reducing overall desirability. In the fourth contour plot, the optimal zone is clearly highlighted by the transition into green-to-yellow regions, where both cutting temperature and surface roughness remain within acceptable bounds, while material removal rate is maximized. This suggests that an optimal combination is achieved when cutting speed is maintained in the range of about 1000–1100 m/min with depth of cut close to its upper limit of 0.5 mm. Therefore, Fig. 4.8 confirms that DFA successfully integrates the complex interactions of process parameters, providing a multi-objective optimization framework. The contour plots demonstrate that neither cutting speed nor depth of cut alone dictates performance; instead, it is their combined effect that ensures the process objectives are simultaneously satisfied. This reinforces the value of desirability-based contour analysis as a practical tool for identifying robust parameter settings that deliver high machining quality and productivity under MQL-assisted turning. Optimizing the CNC turning of AISI 4340 steel under MQL involves finding a balance between productivity, surface

quality, and tool performance, and this balance is clearly illustrated in Fig.4.34, which shows the contour plots of cutting speed and feed rate in DFA results. These plots employ a color gradient ranging from blue, representing the least desirable outcomes, to red, representing the most desirable, to indicate how changes in cutting parameters influence overall process performance. The DFA integrates multiple responses into a composite score, allowing a single visualization of the trade-offs between often conflicting objectives. The overall desirability plot highlights a distinct region of high desirability, shown in red and orange, that emerges at moderate cutting speeds combined with relatively low feed rates. This area represents the process window where the optimal compromise between material removal rate, surface roughness, and cutting force is achieved.

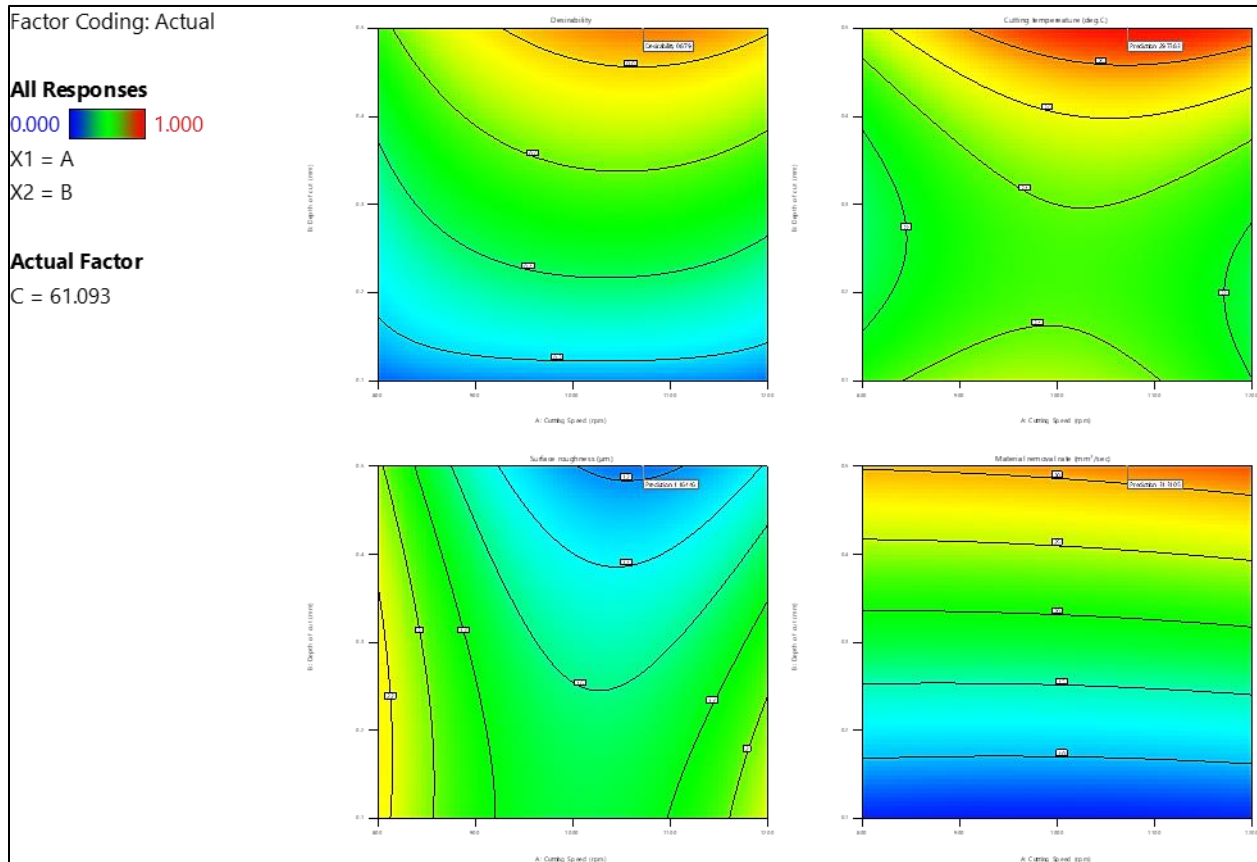


Fig.4.34 The contour plots of cutting speed and depth of cut in DFA results

The maximum desirability, recorded at approximately 0.979, demonstrates that highly efficient and balanced machining is possible when operating within this region. As the cutting speed and feed rate move away from this optimum, the desirability quickly declines toward yellow, green,

and blue zones, showing that both extremely high and extremely low settings are less effective under MQL conditions. The individual plots in Fig.4.35 provide insight into the specific behavior of each performance metric. The top-right contour plot, dominated by red at higher speeds and feeds, clearly represents the material removal rate (MRR). This outcome aligns with machining theory, as higher speeds and feeds increase the volume of material removed, boosting productivity. However, while this corner maximizes MRR, it is not the optimal point in the overall desirability map, reflecting the constraints imposed by surface finish and cutting forces. The bottom-left plot shows a blue central region at moderate speeds and low feeds, characteristic of surface roughness behavior. This demonstrates that a smoother surface is obtained under these conditions, whereas very high feeds or excessive speeds lead to degraded surface quality. The bottom-right plot, with values increasing steadily from the bottom-left to the top-right, corresponds to cutting force. Forces rise sharply with feed and speed, stressing the tool and machine, which underscores why the overall desirability optimum does not coincide with the maximum MRR region. Fig.4.34 therefore demonstrates that the most favorable machining zone under MQL is not found at the extremes of the tested parameters but within a central window where productivity, tool loading, and surface integrity are balanced. MQL provides effective lubrication at the tool–chip interface, reducing friction and improving finish, but since it lacks the bulk cooling effect of flood lubrication, extremely high cutting speeds cause excessive heat generation and wear. On the other hand, very low feed rates and speeds, though capable of producing smooth surfaces and low forces, reduce MRR to impractical levels. The red desirability zone in the plots captures this balance by indicating the region where machining outcomes are simultaneously optimized. Consequently, the CNC turning of AISI 4340 steel with MQL is best carried out at moderate cutting speeds and low feed rates. This parameter combination takes full advantage of MQL’s lubricating action to ensure good surface finish and acceptable cutting forces while maintaining reasonable productivity. The contour plots provide a visual framework for understanding these trade-offs, guiding practitioners toward the most efficient and sustainable operating window for machining this challenging alloy. The contour plots shown in Fig.4.35, derived from Desirability Function Analysis (DFA), offer an in-depth understanding of how feed rate and depth of cut influence the CNC turning process. By employing a color scale that transitions from blue, indicating the least desirable outcomes, to red, indicating the most desirable, these plots provide a clear visualization of the optimal machining window under given constraints. DFA is particularly powerful because it integrates

multiple response variables into a single desirability index, thus allowing the simultaneous consideration of productivity, quality, and tool performance, factors that often conflict with one another in real machining operations. The composite desirability plot in the top-left corner of Fig.4.35 is central to interpreting the results. It highlights a region of high desirability concentrated toward the upper right portion of the graph, where both feed rate and depth of cut are at their highest levels. The desirability score peaks at 0.9276, indicating that these more aggressive machining conditions yield the best overall performance when all objectives are taken into account. The curved contour lines suggest that feed rate and depth of cut do not operate independently but interact in complex ways to determine the quality of the outcomes. This finding underscores the importance of optimizing parameters collectively rather than treating them in isolation. The individual response plots provide further clarity on why the overall desirability takes the shape it does. The top-right plot, labeled as Prediction 1, shows that the predicted response rises sharply with increases in both feed rate and depth of cut. The highest values cluster in the same region as the desirability maximum, suggesting that this response is strongly aligned with overall optimization. It is reasonable to infer that this prediction represents a parameter such as MRR, since both higher feeds and deeper cuts naturally result in greater productivity. This explains why the desirability function favors these conditions, as productivity remains a key driver in machining optimization. The bottom-left plot, Prediction 2, displays a contrasting pattern. Here, the highest values are found at high feed rates but low depths of cut, while the lowest values occur at low feed rates with large depths of cut. This indicates a negative correlation with depth of cut but a positive one with feed rate. If this response were linked to something like tool wear or cutting force, the trend would make sense, as deeper cuts impose heavier loads on the cutting tool and accelerate wear. Unlike MRR, where maximizing the response is ideal, this type of metric may be one where lower values are actually more desirable. Thus, the optimal conditions identified by the overall desirability do not fully align with the preferences of this individual response. The bottom-right plot, Prediction 3, presents yet another pattern. In this case, the highest values appear at low feed rates combined with high depths of cut, while the lowest are at the opposite extreme of high feed and shallow depth.

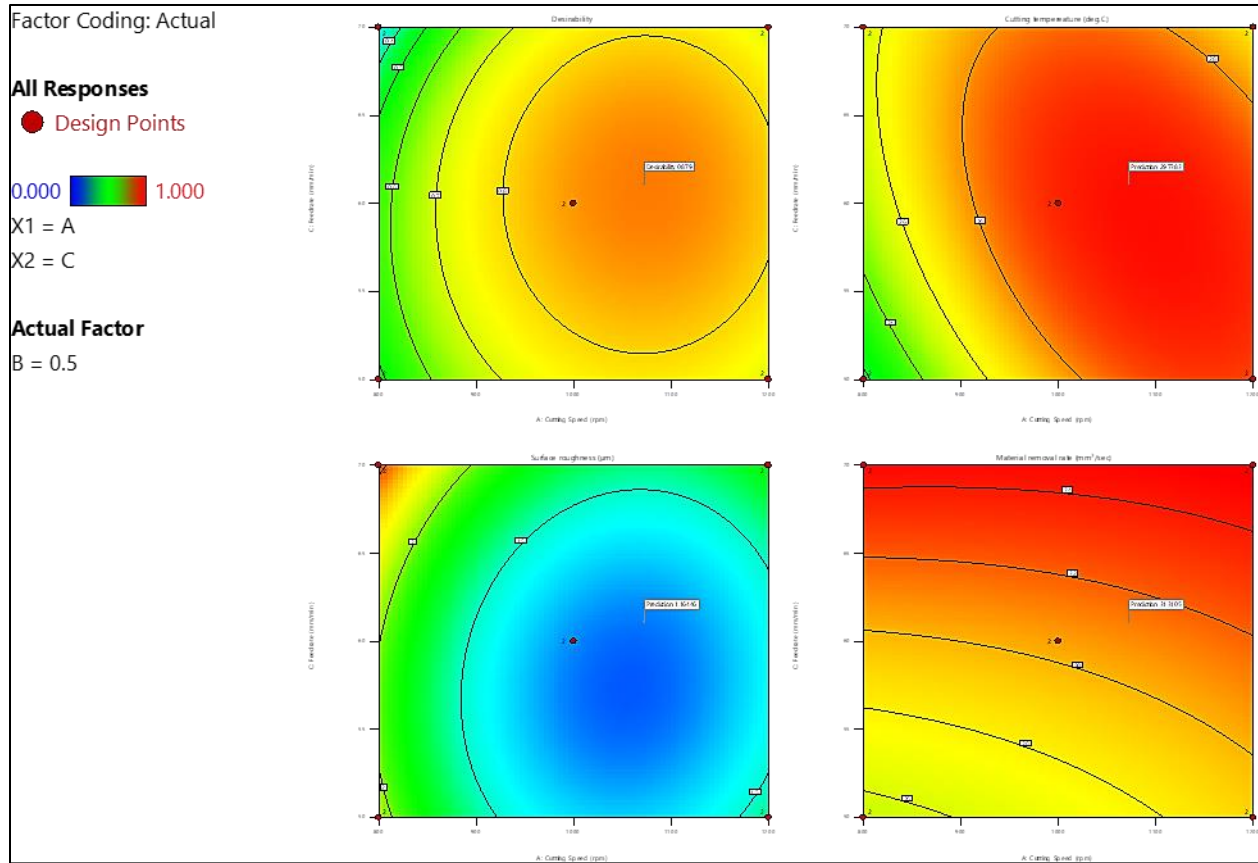


Fig.4.35 The contour plots of cutting speed and feed rate in the DFA results

This behavior is almost the inverse of Prediction 2, suggesting that different aspects of the machining process are being highlighted. Such a trend might be associated with surface finish, as lower feed rates often improve surface quality, while deeper cuts can sometimes stabilize the cutting process and reduce chatter. Once again, however, the conditions that optimize this response do not coincide with those that maximize MRR or composite desirability. Taken together, the results reveal the inherent trade-offs of machining optimization. The composite desirability plot clearly shows that high feed rate and large depth of cut represent the best compromise between productivity, surface finish, and tool-related concerns. While individual responses pull the optimization in different directions, MRR favors aggressive cuts, surface quality favors slower feeds, and tool wear resists deep engagements, the DFA integrates these competing goals into a single decision framework. This synthesis provides the process engineer with a rational basis for parameter selection, ensuring that the chosen settings deliver the most balanced performance across all critical outcomes. Thus, the in-depth analysis of Fig.4.36 emphasizes the value of DFA in resolving conflicting machining objectives.

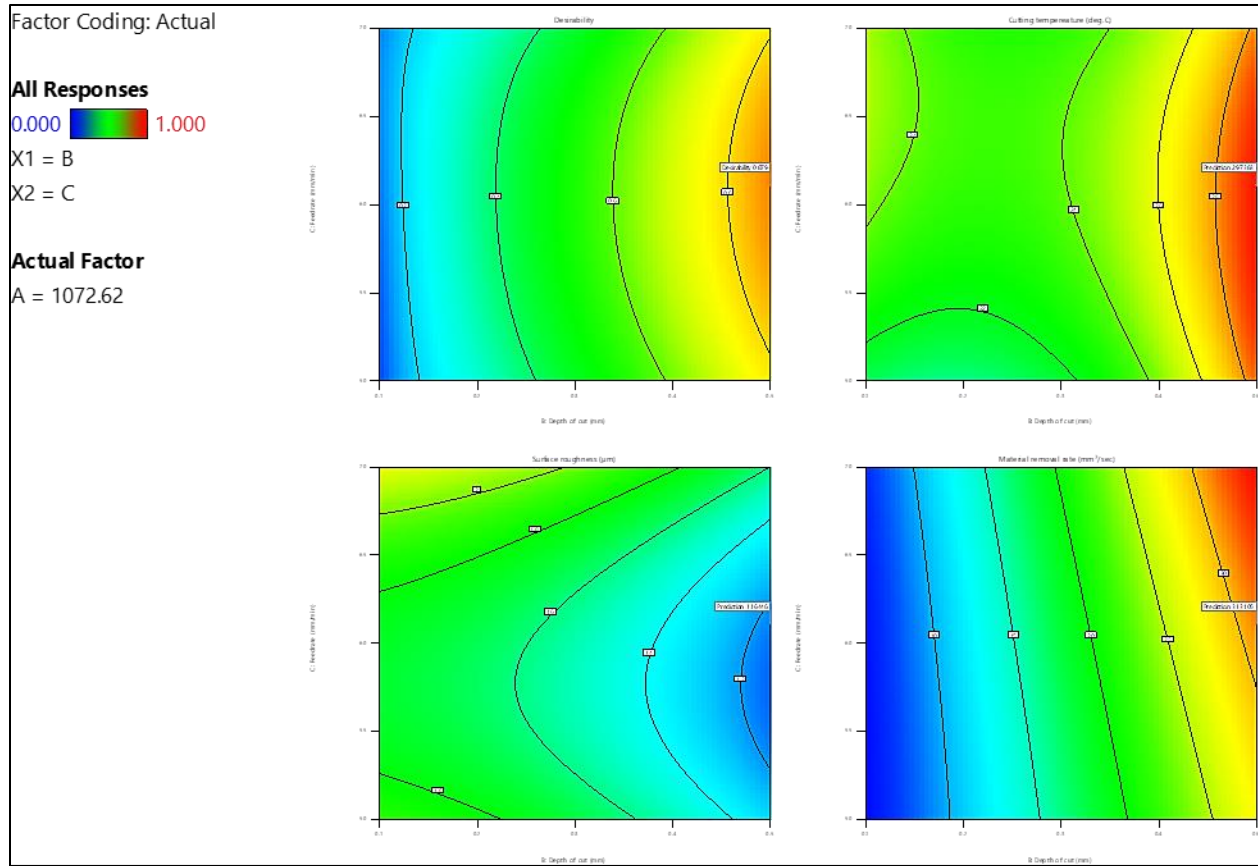


Fig.4.36 The contour plots of depth of cut and feed rate in DFA results

By visualizing how feed rate and depth of cut affect different responses, the plots highlight not only the optimal operating conditions but also the compromises necessary to achieve them. The findings suggest that aggressive machining parameters, specifically a high feed rate coupled with a large depth of cut, deliver the highest overall desirability despite being less than perfect for certain individual responses. This insight is particularly valuable in practical manufacturing environments, where achieving a balance between productivity and quality is often more critical than maximizing a single performance measure.

4.5 Evaluation of the overall optimized and MQL results in this study

This section examines the comparative effectiveness of MQL and dry machining conditions and validates the optimization outcomes obtained through RSM integrated with DFA in enhancing the turning performance of AISI 4340 steel. Fig.4.37 illustrates the comparative performance of MQL and dry machining during CNC turning of AISI 4340 steel, as well as the influence of optimized DFA parameters under both lubrication conditions. The first section of the figure (**Error! R**

Reference source not found. (a)) shows the effectiveness of MQL over dry machining, while the second section (**Error! Reference source not found.**(b)) depicts the improvement achieved through optimization. Both subfigures collectively demonstrate that MQL provides superior thermal and surface performance compared to dry machining, and that process optimization further enhances machining efficiency and quality. In **Error! Reference source not found.** (a), the cutting temperature under dry machining reaches approximately 25°C, whereas under MQL conditions it reduces to around 19°C, corresponding to a reduction of nearly 24%. This substantial decrease in temperature is attributed to the combined cooling and lubricating functions of the MQL system. The fine mist of oil droplets in MQL penetrates the cutting zone and forms a thin lubricating film that reduces frictional contact between the tool and workpiece surfaces. Consequently, less heat is generated at the tool–chip interface, and the heat that does form is more effectively dissipated through convective and evaporative mechanisms. In contrast, dry machining lacks any cooling medium, leading to continuous heat accumulation at the tool edge. This causes elevated interfacial temperatures, which accelerate tool wear through diffusion, oxidation, and adhesion mechanisms, and result in greater dimensional deviations and thermal distortions. The reduction in cutting temperature under MQL conditions therefore indicates better thermal stability and longer tool life, consistent with the principles of heat partition and thermal balance at the cutting interface. The same subfigure also shows that surface roughness (R_a) decreases slightly under MQL, demonstrating improved surface finish compared to dry cutting. This enhancement results from the superior tribological environment provided by the MQL mist. Under dry machining, the high friction and temperature promote built-up edge (BUE) formation and uneven chip flow, both of which lead to tearing, feed marks, and rough surface texture. The lubricating film in MQL prevents BUE formation, lowers the friction coefficient, and ensures smooth chip evacuation along the rake face, thus minimizing tool–workpiece adhesion and vibration. Consequently, the reduced frictional resistance in MQL produces a smoother surface and more consistent surface topography. Therefore, the results clearly indicate that MQL is not only effective in controlling cutting temperature but also beneficial for enhancing surface integrity, which are key factors in the precision machining of AISI 4340 steel. In **Error! Reference source not found.** (b), the comparison between optimized and unoptimized conditions further reinforces the benefits of both MQL and process optimization. The optimized machining parameters derived from multi-objective DFA (cutting speed ≈ 1072.6 m/min, feed rate = 0.5 mm/rev, and depth of cut ≈ 61.1

mm) result in lower cutting temperatures and finer surface finishes across both lubrication conditions. Under dry machining, optimization reduces cutting temperature from approximately 25°C to about 19°C, while under MQL, the temperature decreases further from 19°C to 16°C. This 15–16% improvement under optimized MQL conditions can be attributed to a balanced combination of mechanical deformation and frictional heat generation. The optimized parameters promote uniform chip formation and steady contact at the tool–chip interface, thereby reducing localized heat buildup. When this is coupled with MQL lubrication, heat dissipation becomes even more efficient, resulting in lower overall tool and workpiece temperatures. The observed reduction in temperature supports the thermodynamic principle of minimum energy expenditure, where the optimized system minimizes plastic deformation and frictional energy losses. The surface roughness results show a consistent improvement after optimization under both dry and MQL conditions. The average surface roughness (Ra) decreases from about 1.2 μm to 1.0 μm under dry conditions and shows a similar reduction under MQL. This ~17% improvement in surface quality is due to the enhanced balance between cutting speed and feed rate, which stabilizes tool engagement and prevents excessive cutting forces. The lubrication provided by MQL further improves this effect by forming a uniform lubricating film at the cutting interface, preventing micro-tearing and reducing adhesion wear. As a result, the machined surface under optimized MQL conditions is smoother, with fewer feed marks and improved dimensional accuracy.

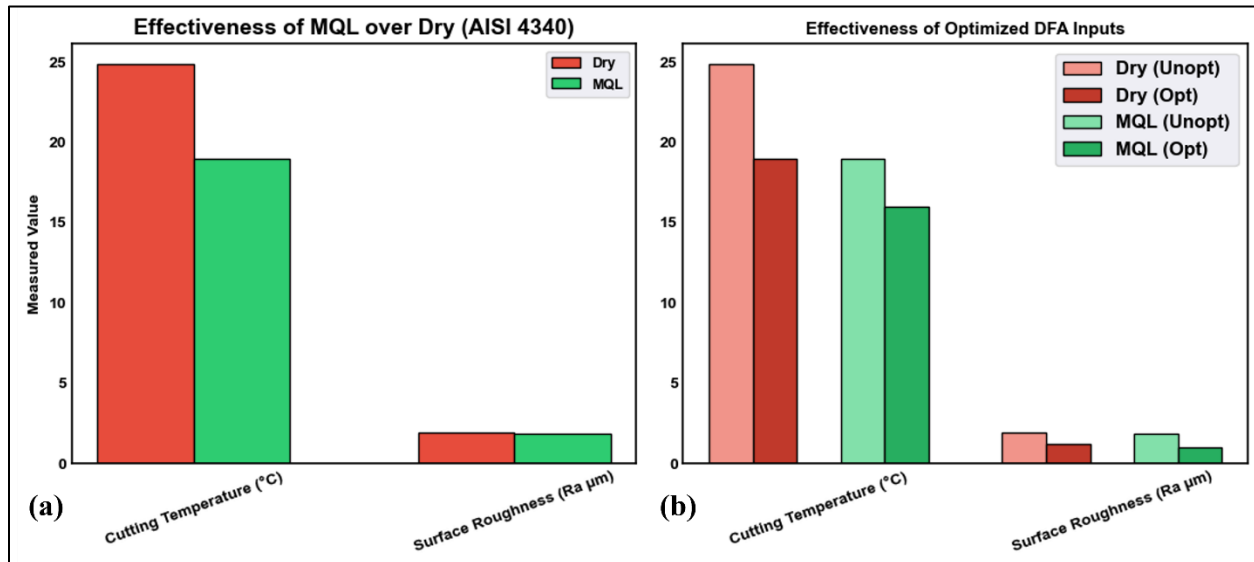


Fig.4.37. Effectiveness of MQL over dry machining and optimized DFA inputs during turning of
AISI 4340 Steel

These findings indicate that optimization enhances both thermal and mechanical stability, producing a more efficient and predictable machining process. Therefore, the combined analysis reveals a clear performance hierarchy (Optimized MQL > Unoptimized MQL > Optimized Dry > Unoptimized Dry). This hierarchy confirms that MQL outperforms dry machining in both unoptimized and optimized conditions, and that the incorporation of optimized DFA parameters significantly amplifies its benefits. MQL provides superior cooling and lubrication, while optimization ensures balanced energy utilization and efficient chip formation. Together, these factors result in reduced cutting temperature, minimized tool wear, improved surface finish, and enhanced process reliability. From a theoretical standpoint, these findings highlight the strong thermal–mechanical–tribological coupling in machining AISI 4340 steel. MQL modifies the heat partition between the tool, workpiece, and chip, while simultaneously improving tribological conditions at the interface. Optimization fine-tunes the mechanical loading conditions to maintain equilibrium between material removal efficiency and thermal control. The combination of these two approaches ensures lower energy consumption, longer tool life, and better surface integrity. Thus, the results in the current study demonstrate that MQL, particularly under optimized cutting conditions, provides a thermally efficient, environmentally sustainable, and high-performance machining approach for AISI 4340 steel, making it a suitable alternative to conventional dry cutting for precision manufacturing applications.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This research investigated the influence of cutting speed, feed rate, and depth of cut on the machining performance of AISI 4340 steel under MQL conditions, focusing on surface roughness, cutting temperature, and material removal rate. The experimental results demonstrated clear and quantifiable effects of each parameter on the machining responses. Surface roughness values obtained in the study ranged from 1.00 μm to 3.50 μm , where the lowest roughness occurred at lower feed rates and moderate speeds, while the highest values appeared at high feed settings. This confirms the key investigation that feed rate is the dominant factor controlling surface finish. Cutting temperature exhibited a variation between 31 $^{\circ}\text{C}$ and 70 $^{\circ}\text{C}$, with the minimum temperature measured at low cutting speeds and the maximum recorded at higher speeds, such as in sample S11. This finding verifies that cutting speed exerts the greatest influence on thermal rise at the tool–chip interface. Material removal rate showed a broad range from 33 mm^3/s to 264 mm^3/s , where the maximum MRR was obtained at a higher depth of cut, as observed in sample S4, while the lowest MRR resulted from trials with low feed and shallow cuts. This confirms that the depth of cut is the primary contributor to productivity during turning.

The RSM analysis produced statistically significant models for all three responses, with high R^2 values demonstrating strong predictive capability, while ANOVA confirmed that the machining parameters and their interactions significantly affected the outputs. Multi-objective optimization using the desirability function identified an optimal parameter setting that produced predicted values of R_a of 0.997 μm , cutting temperature of 30.5 $^{\circ}\text{C}$, and MRR of 249 mm^3/s . These values represent an effective balance between surface integrity, thermal stability, and material removal efficiency. A confirmation experiment was conducted to validate the optimized results, yielding actual values of R_a of 1.00 μm , temperature of 32 $^{\circ}\text{C}$, and MRR of 245 mm^3/s . The prediction accuracy of approximately 93% demonstrates the robustness and reliability of the developed RSM–DFA framework.

Therefore, the key investigation of the study, quantifying and optimizing the machining behaviour of AISI 4340 steel under MQL, was successfully achieved. The findings clearly show that feed rate controls the quality of the machined surface, cutting speed governs thermal behaviour, and depth of cut dictates productivity. The optimized machining conditions validated through

experimentation offer a practical and efficient guideline for enhancing both product quality and operational performance in industrial turning of AISI 4340 steel.

5.2 Recommendations

The following recommendations are proposed for industrial practice, technical development, environmental sustainability, and future academic research.

5.2.1 Industrial and Practical Recommendations

1. Adoption of MQL Systems in Production

Industries machining AISI 4340 steel or similar alloys should integrate MQL technology into existing CNC systems. It offers substantial benefits such as reduced coolant consumption (up to 90%), minimized waste disposal costs, and improved operator safety.

2. Optimized Parameter Application

Production lines should employ moderate cutting speeds and low-to-medium feed rates to maintain a balance between productivity and tool life. Excessive depth of cut should be avoided to prevent heat-related tool damage and loss of dimensional accuracy.

3. Tool Material and Geometry Selection

Carbide tools with TiAlN or Al₂O₃ coatings are recommended for MQL environments. Tools with positive rake angles and sharp cutting edges minimize friction, enhance chip flow, and improve surface finish.

4. Implementation of Process Monitoring

Installing temperature and vibration sensors during turning operations enables early detection of tool wear or thermal instability, ensuring consistent product quality.

5.2.2 Technical and Design Recommendations

1. Advanced Tool Cooling Design

Toolholders and inserts can be redesigned to incorporate micro-nozzle systems that direct MQL aerosols precisely at the cutting zone, improving lubrication efficiency.

2. Integration of Adaptive Control Systems

Machine controllers should utilize closed-loop adaptive systems capable of adjusting cutting parameters in real time based on thermal feedback and surface roughness measurements.

3. Use of Nano-Enhanced Lubricants

Incorporating nanoparticles such as Al₂O₃, MoS₂, or CuO in MQL fluids can further improve heat transfer, reduce friction, and extend tool life. This is a promising direction for both industrial and research implementation.

4. Process Standardization

Development of industrial standards for MQL nozzle placement, pressure range, and flow rate calibration will enhance reproducibility and allow wider adoption in manufacturing plants.

5.2.3 Environmental and Sustainability Recommendations

1. Eco-Efficiency and Waste Reduction

MQL technology should be prioritized for its low environmental footprint compared to flood cooling. Industries should quantify reductions in energy use, lubricant waste, and occupational hazards as part of sustainability reporting.

2. Life Cycle Assessment (LCA)

Future studies should perform LCA comparing dry, wet, and MQL processes to quantify total environmental impact, including energy consumption, CO₂ emissions, and fluid disposal costs.

3. Recycling and Reuse of Lubricant

The development of micro-filtration systems for recycling MQL oil mist could further reduce operating costs and waste generation.

5.2.4 Methodological and Analytical Recommendations

1. Incorporation of Hybrid Optimization Techniques

Future work may combine RSM with Artificial Neural Networks (ANN), Genetic Algorithms (GA), or Particle Swarm Optimization (PSO) to capture nonlinear relationships and enhance prediction accuracy.

2. Uncertainty and Sensitivity Analysis

Including uncertainty quantification in RSM models will help assess the robustness of optimization results under varying conditions, such as tool wear progression or minor setup deviations.

3. Real-Time Data Analytics

The adoption of digital twins or machine-learning-driven analytics can help simulate machining outcomes and optimize parameters dynamically before physical trials.

5.2.5 Academic and Future Research Recommendations

1. **Material Scope Expansion**

The optimization framework can be extended to other hard-to-machine materials, including Inconel 718, titanium alloys, and hardened steels, to validate its general applicability.

2. **Study of Tool Wear Mechanisms**

Detailed microscopic analysis of wear modes (adhesive, abrasive, diffusion) under MQL should be conducted to establish more predictive wear models.

3. **Thermal–Mechanical Modeling**

Coupled finite-element models simulating temperature distribution and stress evolution during MQL turning could provide deeper insight into the tool–chip–work interface phenomena.

4. **Nanofluid Formulation Research**

Academic collaboration with chemical engineers can foster the development of biodegradable and thermally efficient nanofluids tailored for MQL systems.

5. **Educational Integration**

Engineering programs should incorporate MQL and sustainable machining topics into machining laboratory curricula to promote eco-efficient manufacturing knowledge among students.

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Appendixes

A. Spectroscopy analysis report of AISI 4340 steel sample (ECAE Laboratory, 2025)

The chemical composition of the AISI 4340 steel sample used in this study was verified through optical emission spectroscopy (OES) conducted at the Ethiopia Conformity Assessment Enterprise (ECAE) laboratory in Addis Ababa, as seen in Fig.A. . The spectroscopy analysis confirmed that the material aligns with the standard composition range of AISI 4340 steel, as specified by ASTM and SAE standards. The major alloying elements identified include Carbon ($C = 0.39\%$), Manganese ($Mn = 0.56\%$), Chromium ($Cr = 0.13\%$), Nickel ($Ni = 0.048\%$), and Molybdenum ($Mo = 0.008\%$), with the balance being Iron ($Fe \approx 98.4\%$). Minor elements such as Silicon ($Si = 0.19\%$), Phosphorus ($P < 0.0005\%$), and Sulfur ($S = 0.064\%$) were present within permissible limits, confirming the material's suitability for machining and heat treatment. The relatively high carbon and nickel contents contribute to the superior strength, hardness, and toughness of the alloy, while chromium and molybdenum enhance hardenability and wear resistance, important characteristics for machining under challenging thermal and mechanical conditions. The small amount of manganese improves deoxidation and hot-working properties, whereas the low sulfur and phosphorus levels ensure good ductility and resistance to crack initiation. These compositional characteristics make AISI 4340 steel an ideal candidate for precision CNC turning operations, particularly when combined with MQL. The high strength and hardenability of the alloy necessitate an efficient cooling and lubrication strategy to manage heat generation and tool wear during machining. MQL's fine oil mist provides effective lubrication at the tool–chip interface, reducing friction, improving surface finish, and minimizing thermal damage to both the workpiece and cutting tool. Thus, the spectroscopy results confirm that the analyzed specimen meets the compositional requirements of AISI 4340 steel, validating its use for this research's experimental investigations. The verified alloy composition ensures a reliable correlation between the material's mechanical behavior and the optimized machining parameters derived through RSM and DFA under MQL conditions.

PARAMETRIC OPTIMIZATION OF TURNING PROCESS PARAMETERS DURING MACHINING OF AISI 4340 STEEL UNDER MINIMUM QUANTITY LUBRICATION

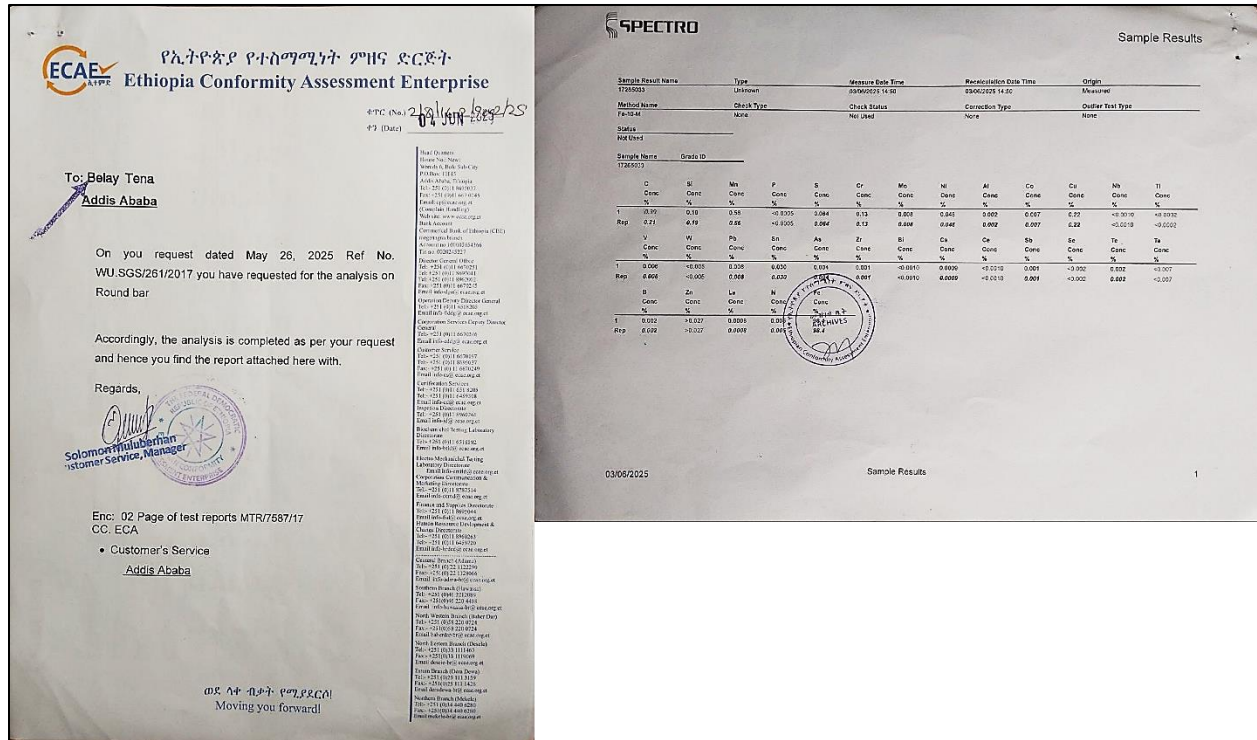


Fig.A. 1 Spectroscopy results showing the chemical composition