



WALLAGA UNIVERSITY
SCHOOL OF GRADUATE STUDIES

**EXPERIMENTAL INVESTIGATION AND MULTI-
OBJECTIVE PARAMETRIC OPTIMIZATION DURING
TURNING OF AISI 1045 USING CCD**

MSc. Thesis

By: Yohannes Senbeto Abdissa

May 2025

Nekemte, Oromia, Ethiopia



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**A Thesis 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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May, 2025

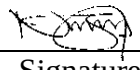
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APPROVAL SHEET FOR SUBMITTING THE FINAL
THESIS

As members of the Board of Examining of the Final MSc. thesis open defense, we certify that we have read and evaluated the thesis prepared by Yohannes Caenorhabditis under the title “Experimental Investigation and Multi-Objective Parametric Optimization Turning of AISI 1045 using CCD” and recommend that the thesis be accepted as full filling the thesis requirement for the Degree of Master of Science in Manufacturing Engineering in Wallaga University.

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Certification of the Final Thesis

I hereby certify that all the corrections and recommendations suggested by the board of Examiners are incorporated into the final thesis entitled ‘Experimental Investigation and Multi-Objective Parametric Optimization during Turning of AISI 1045 using CCD’ by Yohannes Senbeto Abdissa.

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APPROVAL SHEET

This is to certify that the thesis entitled ‘**Experimental Investigation and Multi-Objective Parametric Optimization during Turning of AISI 1045 using CCD**’ submitted by **Mr. Yohannes Senbeto Abdissa**, 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 the course of this inquiry, Mr. Yohannes Senbeto Abdissa 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. **Yohannes Senbeto Abdissa**, affirm that the thesis entitled "Experimental Investigation and Multi-Objective Parametric Optimization during Turning of AISI 1045 using CCD" is my original work, completed under the supervision of **Dr. Moera Gutu (PhD)**. Throughout the preparation, data collection, analysis, and completion of this thesis, I have adhered to all ethical standards of scholarship. I have properly acknowledged all sources and citations within the thesis. I confirm that I have not misrepresented, fabricated, or falsified any ideas, data, facts, or sources in my work. This thesis is submitted in partial fulfillment of the requirements for a degree from the Post Graduate Studies at Wallaga University. I further declare that this work has not been submitted to any other institution for the award of any academic degree, diploma, or certificate.

I understand that any violation of these principles may lead to disciplinary actions by the University and could also result in legal consequences from the sources that were improperly cited or from whom permission was not obtained when necessary.

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ACRONYMS AND ABBREVIATIONS

AISI.....	American Iron and Steel Institute
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
CBN	Cubic Boron Nitride
CNC	Computer Numerical controlled
CVD	Chemical Vapor Deposition
DOC	Depth of Cut
DoE.....	Design of Experiment
f	Feed Rate
FEM	Finite Elemental Method
GA	Genetic Algorithm
GRA	Grey Relational Analysis
HRC	Rockwell Hardness
MOO	Multi-Objective Optimization
MRPI.....	Multi-Response Performance Index
MRR.....	Material Removal Rate
n.....	Tool Nose Radius
OA.....	Orthogonal Array
MQL.....	Minimum quantity Lubricant
NFMQL	Nanofluid Minimum quantity Lubricant
PCBN	Boron Nitride
PVD.....	Physical Vapor Deposition
Ra	Arithmetic Surface Roughness
RSM.....	Response Surface Methodology
SEM.....	Scanning Electron Microscope
S/N.....	Signal to Noise Ratio
V.....	Cutting Speed

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Abstract

The primary challenges in metalworking industries revolve around enhancing productivity and product quality, particularly in machining processes. Machining, a critical finishing method, shapes workpiece materials to specified dimensions and surface finish. However, achieving optimal product quality while minimizing lead time and cost remains a key issue in these industries. This research addresses these challenges by focusing on experimental investigation and parametric optimization in turning processes. The study aims to improve product quality, reduce machining time and cost, and establish optimal cutting conditions. Key cutting parameters, including cutting speed, depth of cut, feed rate, and Minimum Quantity Lubrication (MQL), are considered, with a specific focus on understanding the impact of MQL and other cutting parameters on the machining process. A multi-objective optimization model of the various parameters was created with Response Surface Methodology (RSM) in Design Expert 13 using a desirability approach, which generally understands the impacts of the input process parameters. Cutting speed was the most influential factor on surface roughness (ANOVA), showing a U-shaped trend with an optimal range of 160–170 m/min; depth of cut and feed rate contributed 20–30% and 15–25%, respectively, with optimal feed at 1.00 mm and 0.08 mm/rev to minimize tool marks and vibration. Cutting speed accounted for 93.8% of cutting temperature (optimal at 164.570 m/min), while feed rate had the highest impact on MRR (57.64%), followed by depth of cut (26.79%) and cutting speed (7.92%), with improved MRR observed as depth increased from 0.6 mm to 1.0 mm.

Keywords: Multi-Objective Optimization, Response Surface Methodology, ANN

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Machining is a process of shaping operations to remove excess material from an initial workpiece prior to the desired final shape. Machining covers a group of processes that remove chips or sometimes shavings from the workpiece material using a cutting tool that requires relative motion between the cutter and the workpiece material. The relative motion required to obtain the desired geometry of the work surface was obtained through the relative motions between the primary motion (i.e., spindle speed) and a secondary feed motion combined through the tool profile and how deep the tool penetrated into the surface of the work. In production, optimizing the machining process means optimizing the process parameters to yield high-quality products, while also achieving best productivity and lowest cost in production (Khan et al., 2020). Turning is the material removal operation most frequently employed in the machining industry because it can remove the material efficiently and yield a superior surface finish (Sahoo, 2011). Turning as a machining operation generally refers to a group of machining operations that share a similar mode of material removal. Specifically, Turning defines the role of computer Numerical Control (CNC) lathe machines as advanced manufacturing tools capable of performing operations like grooving, threading, knurling, tapering, boring, and chamfering. In the pursuit to manufacturing in an economical way, industries will consider factors affecting yielding cost-effective modes of manufacturing, when making decisions on turning processing parameters like spindle velocity, feed rate, or depth of cut that ensure consistent surface texture in the production of high-quality products (Panwar et al., 2020). Using CNC machining to promote better surface finish and dimensional accuracy, manufacturers rely on tough and hard tool steels; however, they must ensure that the tool steel meets the specific material characteristics to use for their intended purpose (Kahrobaee& Kashefi, 2015). AISI D3 Steel provides excellent wear resistance with chromium, tungsten, molybdenum, and carbon contents (Hosseini et al., 2016), (Rafighi et al., 2021) and (Zerti et al., 2019). Obviously while the use of tough tool steels helps to obtain better results, it is often important to apply cutting fluid to minimize tool tip temperature while enhancing the surface finish of the machined part (A. Das et al., 2019). Likewise, combining Response Surface Methodology (RSM), Genetic Algorithms (GA) and Artificial Neural Networks (ANN) to improve turning processes, allows for optimal process parameters to be developed while being predictive of

outcomes can increase overall performance and productivity (Efa, 2024). (Vukelic et al., 2021) optimized turning process parameters in a dry environment for AISI 1040 steel using GA for optimal process parameters which resulted in flank wear average error of 1.478% and surface roughness average error of 1.146% to be obtained for experimental turning. Examining the influence of machining parameters on surface roughness while turning AISI D2 steel, (Khalil et al., 2021) based their mathematical modeling and optimization on a response surface methodology using Design-Expert software. The study revealed that, for AISI D3 steel, surface finish quality is optimized at low cutting speed (140m/min), low feed (0.01mm/rev), and with minimal depth of cut (1mm), while to ensure cleanliness, the rough required feed rate, with desirable surface condition, is between 0.02mm/rev to 0.05mm/rev at feed rates anywhere between 140m/min to 170m/min. The researchers, (Ponnusamy& Tamilperuvalathan, 2023) tried to enhance the machinability of SS304 alloy steel with lubrication conditions, using dry machining, water-emulsified coconut oil (MQL), and mixtures of nanoparticles added to the MQL. The machining results were modeled and analyzed with RSM and a hybrid deep recurrent neural network-black widow optimizer (DRNN-BWO) prediction model. Surface roughness was highly improved with the proposed dual hybrid nano-MQL condition compared to the dry and MQL conditions and tool wear was also reduced.

1.2 Statement of the problem

Today's manufacturing and machining industries deal with several important challenges. These include being less expensive to produce, being more efficient, being higher quality, and reducing negative effects on the environment. It is not easy to achieve all of these simultaneously. Generally, the interaction of processes combined with major uncertainty forces practitioners back to trial-and-error and frequent testing, especially when addressing conflict in objectives. A poorly suited strategy could lead to too many costly experiments to understand the process. As a result, identifying a compromise between the number of tests to run and the amount of useful information gained with each test is important. This is why research is often about using simulations, prediction models, and optimization. These approaches can save resources while improving productivity (Vukelic et al., 2021). It is important to put focus on try to manage the external influences when machining hard steels to construct a peaceful and unwavering turning process. Machining conditions must be carefully selected such as speed, feed rate, and depth of cut. Hard materials also require some form of cooling or lubrication to manage excessive heat in the cutting tool. Total

loss of cutting ability has been observed after dry machining. However, the use of a cutting fluid demonstrates only modest cooling, cutting fluids can result in longer tool life compared to dry machining, particularly when machining hardened steels (A. Das et al., 2019). However, using too much cutting fluid in the traditional way can lead to extra costs, lower productivity, health risks for operators, and environmental damage (Mia et al., 2018). To solve this problem, the Minimum Quantity Lubrication (MQL) technique has been introduced. MQL uses a very small amount of fluid and has proven to be highly effective in reducing tool wear, improving surface finish, and lowering cutting temperatures (Naresh Babu et al., 2019).

1.3 Research questions

1. What are the optimal input process parameters for achieving Surface Quality and increased productivity during the CNC turning process?
2. What influence do the cutting parameters and MQL have on the temperature that is generated at the tooltip?
3. What does the AISI 1045 steel chip analysis resemble?
4. What are the outcomes machining with save tool life?

1.4 Objectives of the Study

1.4.1 General objectives

The primary objective of this research is to conduct an Experimental Investigation and Multi-Objective Parametric Optimization during the Turning of AISI 1045 using CCD

1.4.2 Specific objectives

1. To optimize cutting process parameters to get a better surface finish while turning AISI 1045 steel using oil based MQL.
2. To examine the influence of cutting parameters on the temperature and surface roughness
3. To determine the optimum material removal rate for the selected cutting parameters.
4. To study the optimal cutting parameter values using a machine learning approach.

1.5 Scope of the Study

This study focuses on optimizing multiple cutting conditions at the same time to find the best combination for improving surface finish, material removal rate, and tool tip temperature during the turning of AISI 1045 steel using a CNC lathe with oil-based Minimum Quantity Lubrication (MQL). The intention is to provide a higher level of customer satisfaction and a better level of

production. But there are aspects of cutting force, vibrations of the machine, and the effects of tool nose radius on surface quality and production volume that are not included in this project because such vibrations and forces can only be measured accurately by using special tools such as a dynamometer, which was not, had access to for this work.

1.6 Significance of the Study

This research is conducted to investigate different parameters applied in dry cutting, such as spindle speed, feed rate, and depth of cut, as well as oil-based Minimum Quantity Lubrication (MQL) in order to establish the effect of changing parameters, during the turning process of AISI 1045 steel. It is known that using MQL lubrication will improve surface finish, minimize heat, enhance corrosion resistance, and provide the final product with a superior shine complexion. Processing of cutting tools leads to optimal performance, which extends cutting tool life and minimizes the number of times they are constantly either rebuild or replaced, reducing time and cost. Studies have shown that MQL provides better results than dry machining practices, wet machining practices, and other MQL practices. These results make developing the respective cutting conditions important to manage for reduced surface roughness increases tool life and overall productivity. All of **this aid** in ensuring the finished product quality is satisfactory to customers. Ultimately, the research will serve both the industry and the research community, by showcasing how each parameter affects the outcome of their processing goals by using machine learning optimization to identify the best outcome with various settings and allowing the user/manufacturers a range of similarly suitable values to select for their individual business objectives.

1.7 Organization of the paper

The thesis is divided into four main chapters. Chapter one provides an introduction to the study that includes a background, problem statement, objectives, methodology, scope, organization of the thesis, and significance. Chapter Two provides both theoretical and practical literature discussing the history of CNC machining and previous studies (such as theses and journal articles and books), especially the study of parameter research and machine learning techniques. Chapter Three describes their materials and methods used to carry out the research to achieve the specific goals of the study. Chapter Four contains conclusion and recommendation of the research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

A number of industries have begun demanding metal products with high quality and low-cost finishes. As the demand for higher quality surface finishes has arisen, researchers have begun developing better ways to design processes to meet these often incompatible demands (Khan et al., 2020). Machinability describes the ability of a process to make material removal, regardless of the machining process used. Machining can refer to a constellation of characteristics usually termed; responses or output parameters. In metal removal, the result is primarily dependent upon selecting the appropriate input-cutting parameters. It is therefore, essential to determine the optimal cutting settings in order to reduce machining costs, improve surface quality, and increase productivity. This chapter discusses the work of various researchers who studied turning of; materials and cutting tools, identified findings, optimization methods and made connections between the cutting parameters and their output results.

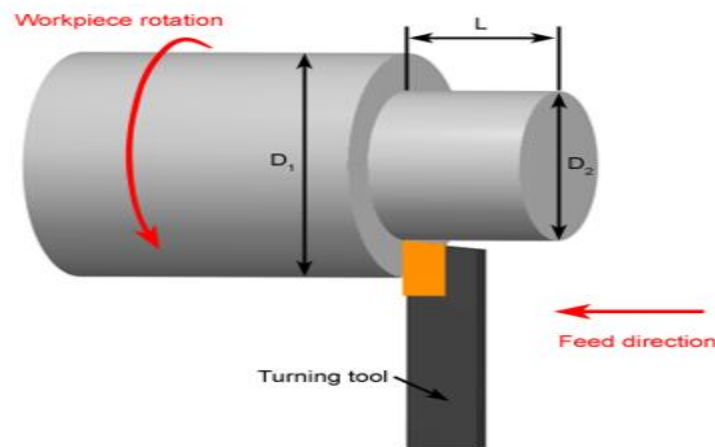


Fig.2. 1 Single tool turning process

To combat this, many researchers have taken significant steps to study how those cut parameters affected those output responses and suggest locations of optimum points. A cutting tool removes material to define the shape of workpieces. Three motions cutting velocity, feed velocity, and depth of cut exist to describe these operations completing the needs of the machine tool, illustrated in Fig.2. 1. This turning tool is a single-point cutter example. Many other single-point tools in the list may not function as single-point tools unless specific requirements are in place.

2.2 Studies on the MQL cutting fluid

Cutting fluid is used in machining to reduce friction, manage heat, and extend the life of tools by lubricating both the cutting tool and workpiece. Minimum Quantity Lubrication (MQL) is a type of cutting fluid designed to improve heat transfer, lubrication, and the efficiency of material removal, potentially enhancing machining performance and surface quality. However, using large amounts of cutting fluids in traditional machining methods leads to higher costs, reduced productivity, health risks for operators, and environmental concerns (Mia et al., 2018). To address these issues, MQL has become a popular and effective solution for reducing tool wear, surface roughness, and cutting temperature. Studies have shown the benefits of MQL in various machining processes. For example, (Naresh Babu et al., 2019) explored the use of graphene nanoparticles in MQL while turning AISI 1045 steel, finding that MQL reduced surface roughness, tool wear, and temperature. (Dash et al., 2020) noted that MQL provides effective cooling and lubrication, which improves safety, cleanliness, and productivity, while also being more environmentally friendly. In their work, (Touggui et al., 2021) compared the turning of AISI 304 stainless steel with various lubrication methods, including both dry and MQL conditions, with significant advantages in both surface roughness and cutting temperature of MQL. They also noted a benefit in the reduction of cutting temperature with MQL compared to dry methods. (Singh et al., 2017) demonstrated that the addition of graphene nanoparticles to the MQL could appreciably lower values of surface roughness and temperature during the turning of AISI 304 stainless steel, providing a significant improvement in processing efficiency. (Kr et al., 2021) performed experiments to evaluate the effect of hybrid alumina-graphene based MQL while turning Ti-6Al-4V alloy, showing positive improvement in values of cutting temperature and surface roughness. (Gupta & Korkmaz, 2023) studied the sustainable machining performance using MQL and hBN-enriched nano-MQL using Bohler K490 steel, and actually reported reduced tool wear by value of 26.9% over dry conditions. (Shinge & Pable, 2023) focused on the nanotube addition to MQL while milling AISI D3 tool steel; they found that better control in cutting temperature values was obtained using MQL, and TiO₂ reduced the cutting temperature even more. (Usluer et al., 2023) analyzed different hybrid MQL conditions in an orthogonal cutting process and determined that their nano-fluid MQL conditions resulted in the lowest cutting forces and temperatures; these changes will contribute to reducing machining cost and carbon footprint.

In their joint study, (Arifuddin et al., 2023) studied the effectiveness of Al₂O₃ nano-cutting fluid in the turning of Al 7075 aluminum alloy turning; the results indicated that greater concentrations of Al₂O₃ were shown to reduce the temperature during cutting, improve surface finish, and extend tool life. In addition, (Khatai et al., 2023) studied a dual-nozzle MQL system with ZnO MQL for hard turning of AISI 52100 bearing steel and reported significant reductions in tool flank wear. It was further reported that the dual-nozzle had an even better performance regarding tool wear depending on the cutting parameters applied during the turning process.

2.3 Summary of Reviewed Literature

The summary of the reviewed articles, enriched with key concepts and insights, is presented comprehensively in [Table 2. 1](#). This table serves as a condensed repository of pertinent information extracted from the literature, encapsulating significant findings, methodologies, and theoretical frameworks discussed across the various studies

Table 2. 1 Summary of Reviewed Literature

S/N	Input parameter	Material	Cutting Condition	Cutting tool	Output Response	Author (year)
1	Effect of Cutting speed, feed, and depth of cut	AISI D3 tool steel	Wet condition	Cement d carbide	Surface Roughness	(Khalil et al., 2021)
2	Effect of Cutting speed, federate, and depth of cut.	AISI D2 workpiece material	In cooling condition	PCN cutting tool	Temperature, surface roughness, cutting force and tool wear	(Zhang, J et al.,2023)
3	Cutting speed, feed rate, depth of cut, hardness of work piece	AISI H13 steel	Dry	CBN tool	Cutting forces, surface roughness	(Kumar et al., 2019)
4	Cutting speed, feed rate, depth of cut, concentration of np	AISI 304 stainless steel	NFMQL	WC tool inset	Cutting temperature, surface roughness, tool wear	(Singh et al., 2017)
5	spindle speed, feed rate, depth of cut, flow rate	Nickel, chromium, white cast iron	Dry, MQL, NFMQL	Coated ceramic tool	Tool wear, surface roughness, cutting temperature	(Kivak et al. 2020)
6	Cutting speed, feed rate, depth of cut, nose radius	AISI D3 tool steel	Dry	Ceramic insert cutting tool	Tool wear, surface roughness, cutting temperature	(Patole & Kulkarni, 2018)
7	Speed, depth of cut, feed rate	AISI 1045 steel	MQL	MQL with grapheme, nano-particles	Reduced surface roughness, tool wear, and temperature, making MQL a promising alternative for turning.	Naresh Babu et al. (2019)

8	Cutting speed, feed, depth of cut, tool nose radius	AISI 4340 steel	NFMQL	Coated carbide inserts	surface roughness, tangential force, specific cutting force and cutting power	(Zerti et al., 2019)
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2.4 Research Gap

Several scholars have extensively investigated the cutting parameters for lathe machines in the past, focusing on how factors such as spindle speed, feed, depth of cut, tool geometry, and hardness of material, all affect the surface quality and general efficiency of machined products. This research has shown that these parameters can affect surface finish, tool wear, and tool failure on various materials. Difficulties associated with turning AISI 1045 steel while machining with conventional cutting fluid and dry machining. Problems associated with the creation of a common language for sustainable manufacturing for both industry and research centers. There is limited work on determining the optimum values using the machine learning approach method following oil based MQL in AISI 1045 steel turning. Additionally, there has been no simultaneous optimization of the influence of machining input parameters on Surface roughness, tool-tip temperature, MRR. Consequently, this research work will be mainly focused on experimental investigations using ANN machine learning algorithms based on MQL CNC Turning to evaluate Surface roughness, tool-tip temperature and MRR.

CHAPTER THREE

MATERIALS AND METHODOLOGY

3.1 Introduction

This chapter presents the work methods applied to the equipment and materials used in this experiment. This study was completed for Experimental Investigations and Multi-Objective Parametric Optimization when Turning AISI 1045 using CCD.

3.2 Material selection

AISI 1045 steel, renowned for its high carbon and chromium content, is widely utilized in the machining process due to its exceptional wear resistance, hardness, and dimensional stability at high temperatures (Hosseini et al., 2016), (Rafighi et al., 2021), (Zerti et al., 2019). Hence, this research utilized AISI 1045 steel specimens with a diameter of 40mm and a length of 110mm, conducting three experiments on each face of the workpiece. The mechanical and physical properties of the material are presented in [Table 3. 1](#) and [Table 3. 2](#). The study employs the VOGEL Surface Roughness Tester (65711) to measure surface roughness, which has a capacity ranging from 0.02 μ m to 10 μ m. Additionally, the ATAL Infrared Type K Thermometer thermal imaging camera is planned to record the tool tip temperature. Furthermore, a carbide insert is utilized during CNC turning operation due to its durability, wear resistance, and thermal stability (Kurt et al., 2015), (Ferreira et al., 2016) and (Kumar et al., 2019). The experimental investigation is planned to utilize a DMTG CNC lathe machine (model CKE 6150) equipped with a 3-phase power supply operating at 380V and a frequency of 50 Hz.

Table 3. 1 Chemical composition of AISI 1045 steel

Elements	C	Mn	Si	Cr	S	P	Iron
Amount (wt. %)	0.43 - 0.50	0.60 -0.90	0.15-0.35	11-13.5	0.05	0.04	Balance

Table 3. 2 Thermal and Mechanical Properties of AISI 1045 steel

Mechanical properties	Value	Thermal properties	Value
Density	7.85 g/cm ³	Thermal Expansion	11.7 μ m/mk
Tensile strength	565 MPa	Thermal conductivity	51.9 W/mk
Elongation at break	16 %	Latent heat of fusion	250 KJ/kg
Yield strength	310 MPa	Melting on set (Solidus)	1783 K
Poisson's ratio	0.30	Melting on set (liquids)	1783 K

3.3 Design of Experiment and Optimization Methodology

3.3.1 Response Surface Methodology (RSM)

The Response Surface Methodology (RSM) approach is a methodology used to model and assess the interaction of numerous input variables on the response variables under consideration, thus revealing the amount of influence each independent parameter has on the response parameters. RSM is often used to explore values for response parameters and for the investigation of the relationship between response parameters and variable parameters in a design or product experiment (Singh et al., 2017). Here, RSM is employed to optimize machining conditions regarding optimized tool tip temperature and surface roughness study in CNC turning. The term RSM is also important as it not only provides the investigator with the relationships among the variables being considered but to also be able to visualize what impact each factor has directly on the response being measured. RSM provides a methodical path to exploring design of experiments. This is beneficial to engineering and manufacturing processes.

3.3.2 Optimization Process Overview

The optimization process begins by establishing definitive objectives and proposed hypotheses of the research, then identifying parameters which are crucial to the optimization process. In the optimal case, preliminary data will be obtained from previous studies or initial experimental trails and cleansed thoroughly prior to further analysis. Cleaning the data is a step which involves removing inconsistencies, missing values and/or outliers, thereby maintaining data reliability. The optimization process has been diagrammed in [Fig.3. 1](#) as a flow chart for better clarity.

3.3.3 Data Preparation

As a subset of preparation, the data preparation process involves completely assembling a dataset that realistically represents the range and variation in process parameters. Randomization is employed to reduce bias, effectively manipulating the experimental runs so that they are less likely to be affected by external factors. This step is fundamental to establishing a sound experimental design that will closely/accurately represent the influence of the objects of study.

3.3.4 Experimental Design

In this research, the Central Composite Design (CCD) under RSM was applied to improve the machining operation. The Box-Behnken Design was chosen as it is effective in determining

quadratic relationships (without consideration of extreme points) and can reduce the amount of run time as they can sample fewer experimental runs. The Box-Behnken Design establishes levels of each parameters, under which the parameters would vary under three conditions to study the parameters' effect on responses i.e., the input parameters and ranges were chosen based on literature (Varaprasad et al., 2014; S. R. Das et al., 2015; Rafighi et al., 2021; Padhan et al., 2023; Salur, 2023). Table 3. 3shows the input process parameters, levels, and ranges used in this experiment to look into the experiment further and to get results for subsequent analysis using ANN and GA as seen in Fig. 3.1.

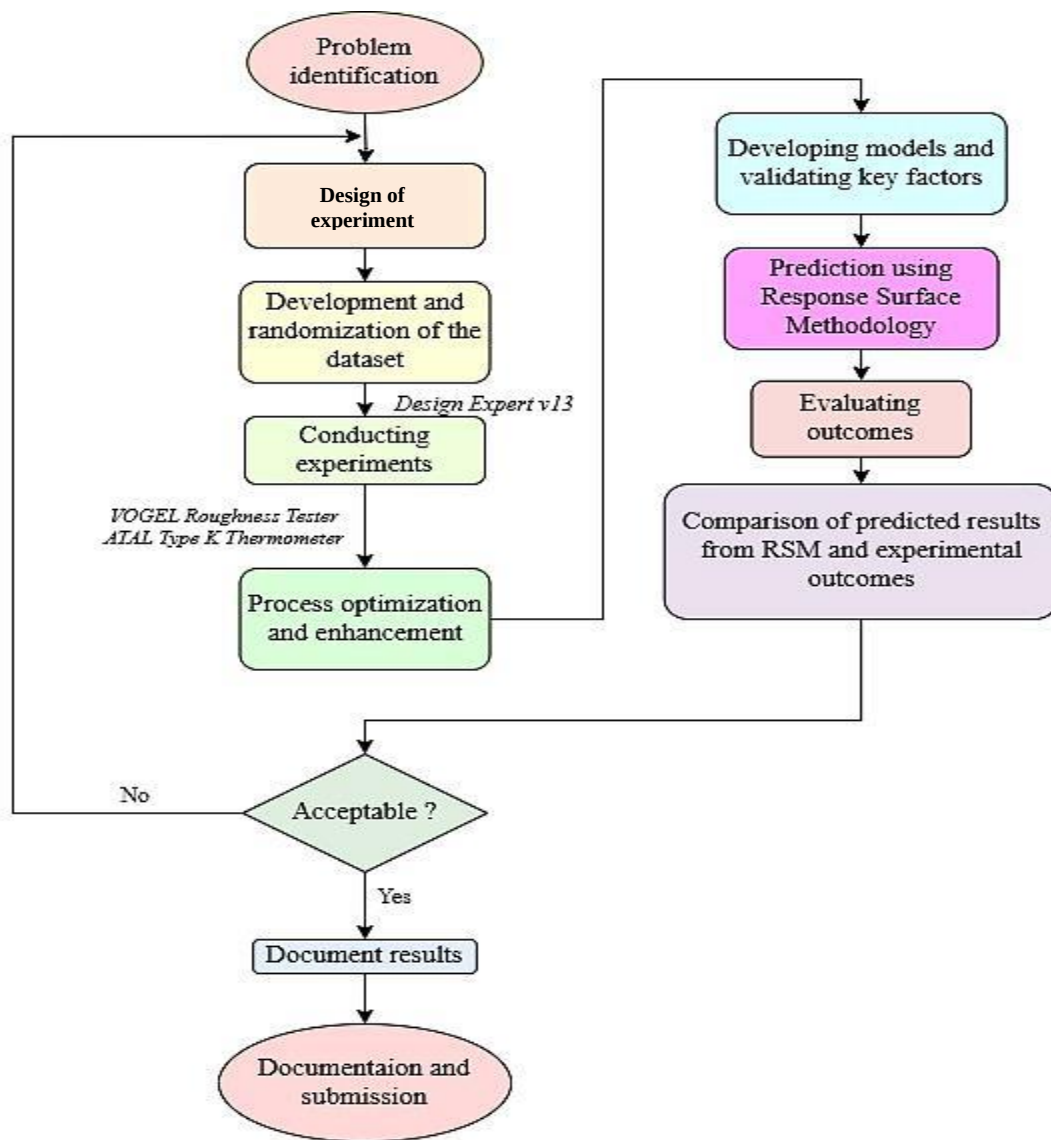


Fig.3. 1 Flowchart illustrating the optimization process

Table 3. 3 Process Variables and their levels

Cutting Variables		Levels		
		-alpha	0	+ alpha
Cutting speed	V (m/min)	155	165	175
Depth of cut	d (mm)	0.6	0.8	1.0
Feed rate	F (mm/rev)	0.04	0.06	0.08

RSM is the main approach of this study; method will be highlighted as a capable method, applicable in a variety of contexts. The ANN provides fairly robust answers to the complex problems by way of learning from data and improving their predictions in the training step (Efa et al., 2024). Future work where the ANNs are integrated with Genetic Algorithms (GA) will also be taken into consideration toward the ability to improve the predictive ability of optimization models.

3.3.5 Experimental Procedure

The experimental runs are performed precisely in line with the randomized experimental design generated by the software to ensure assured testing. The VOGEL Roughness Tester and the ATAL Type K Thermometer are crucial instruments used in the experiment to monitor the surface roughness value and the tool tip temperature, respectively. Fig.3. 2 illustrates an experimental set up used in this research. The data collected from these instruments will then be used in the optimization process.

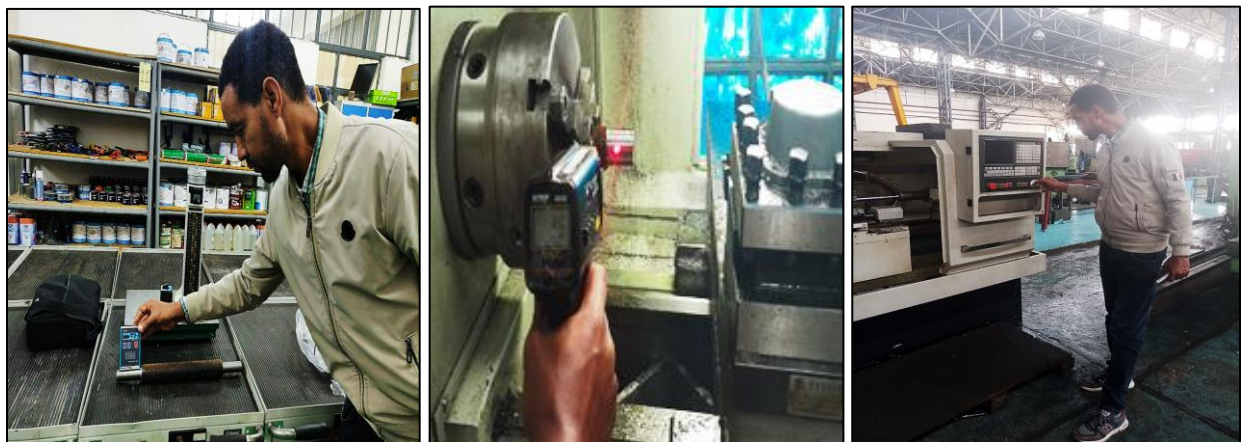


Fig.3. 2 Experimental Setup and CNC Turning Operations

3.3.6 Data Analysis and Optimization

RSM is used to optimize the parameters aimed at minimizing surface roughness and retaining tool tip temperature. The experimental data are further scrutinized through the optimization algorithms supplied in Design Expert v13 software. In this investigation, RSM is used to construct predictive models; an Analysis of Variance (ANOVA) is carried out to check significance for the factors and their interaction. This Investigation is deemed very important, as it not only collects such information to refine the model, but it gives us a clearer understanding of the effect of each factor on the process.

3.3.7 Validation and Finalization

After developing the predictive model, RSM is used to predict responses such as surface roughness and tool tip temperature. In order to check the predicted values, experiments will be performed based on the optimized parameters. The predicted values will be compared with the experimental data obtained from the trials and the error margins will be derived to evaluate the reliability of this model. In case the error margins are within an acceptable range, the results will be accepted and concluded; otherwise the researchers will modify the parameter settings and repeat the above process, until refined to a preferred accuracy. Once satisfactory results have occurred, the optimized process parameters and associated responses will be recorded in a final report for dissemination. The report will, of course, include the conclusions of this research, plus recommendations for subsequent improvement and new emerging research frontiers.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

The gathered experimental data on cutting temperature, surface roughness, and Material Removal Rate (MRR) is invaluable for understanding how machining conditions affect performance. In fact, the data captures the complex correlations between key parameters, and the subsequent effect on machining results. Cutting temperature is one of the clearest indicators of how the tool conditions are related to tool life and the work, the quality of the surface. All three-process parameter (cutting speed, feed rate, and depth of cut) affect cutting temperature, but this also, in turn, affects both surface quality and MRR. Cutting temperature can increase and cause thermal deformation while the original material could be softened, which can make the surface quality rougher, but could also make the MRR higher. The surface roughness also demonstrates how sensitive the surface can be to simple modifications in machining settings. A good surface finish is important to high tolerances applications, and [Table 4. 1](#) shows how differences in combinations of cutting parameters affect surface finish, focusing on interaction between feed rate and depth of cut. [Fig.4. 1](#) presents the distribution of process parameters numerically and visually to identify the relationships between the inputs and responses. The MRR results indicate that the tradeoff of selecting machining parameters is to ensure maximum efficiency of material removal and preserving a level of quality of machining. Even though higher MRR equals higher productivity, high MRR increases productivity, especially if is uncontrolled lowering both surface integrity and tool life. This data indicates the need to optimize the cutting parameters to obtain the desired surface finish and MRR by adjusting the performance of each of them negatively.

Table 4. 1 Cutting Temperature, Surface Roughness, and MRR Outcomes with Input Parameters

	Factor 1	Factor 2	Factor 3	Response 1	Response 2	Response 3
Run	Cutting Speed	Depth of Cut	Feed rate	Cutting Temperature	Surface Roughness	Metal Removal Rate
	m/min	mm	mm/rev	°C	μm	mm ³ /min
1	165	0.8	0.06	430	3.25	792
2	155	1	0.08	365	4	1245

3	165	0.8	0.04	428	3.28	528
4	155	0.6	0.04	365	4.1	378
5	175	1	0.04	455	4.5	706
6	155	1	0.04	365	4	617
7	165	0.8	0.08	430	3.3	1059
8	155	0.6	0.08	365	4.25	743
9	175	1	0.08	455	4.5	1398
10	155	0.8	0.06	365	4.1	744
11	165	0.8	0.04	430.8	3.28	528
12	155	0.8	0.06	365	4.06	744
13	155	1	0.04	365	4	621
14	155	0.6	0.08	365	4.05	742
15	165	0.8	0.06	430	3.25	792
16	175	1	0.04	455	4.5	706
17	165	0.6	0.06	430	3.2	594
18	175	0.8	0.06	455	4.55	840
19	175	0.8	0.06	455	4.55	840
20	175	0.6	0.04	455	4.5	418
21	165	1	0.06	430	3.15	990
22	165	0.8	0.08	430	3.3	1055
23	155	0.6	0.04	365	4.1	378
24	155	1	0.08	365	4	1255
25	175	0.6	0.04	455	4.5	418
26	175	0.6	0.08	455	4.5	848
27	165	1	0.06	430	3.15	990
28	165	0.6	0.06	430	3.2	594
29	175	0.6	0.08	455	4.5	848

30	175	1	0.08	455	4.5	1398
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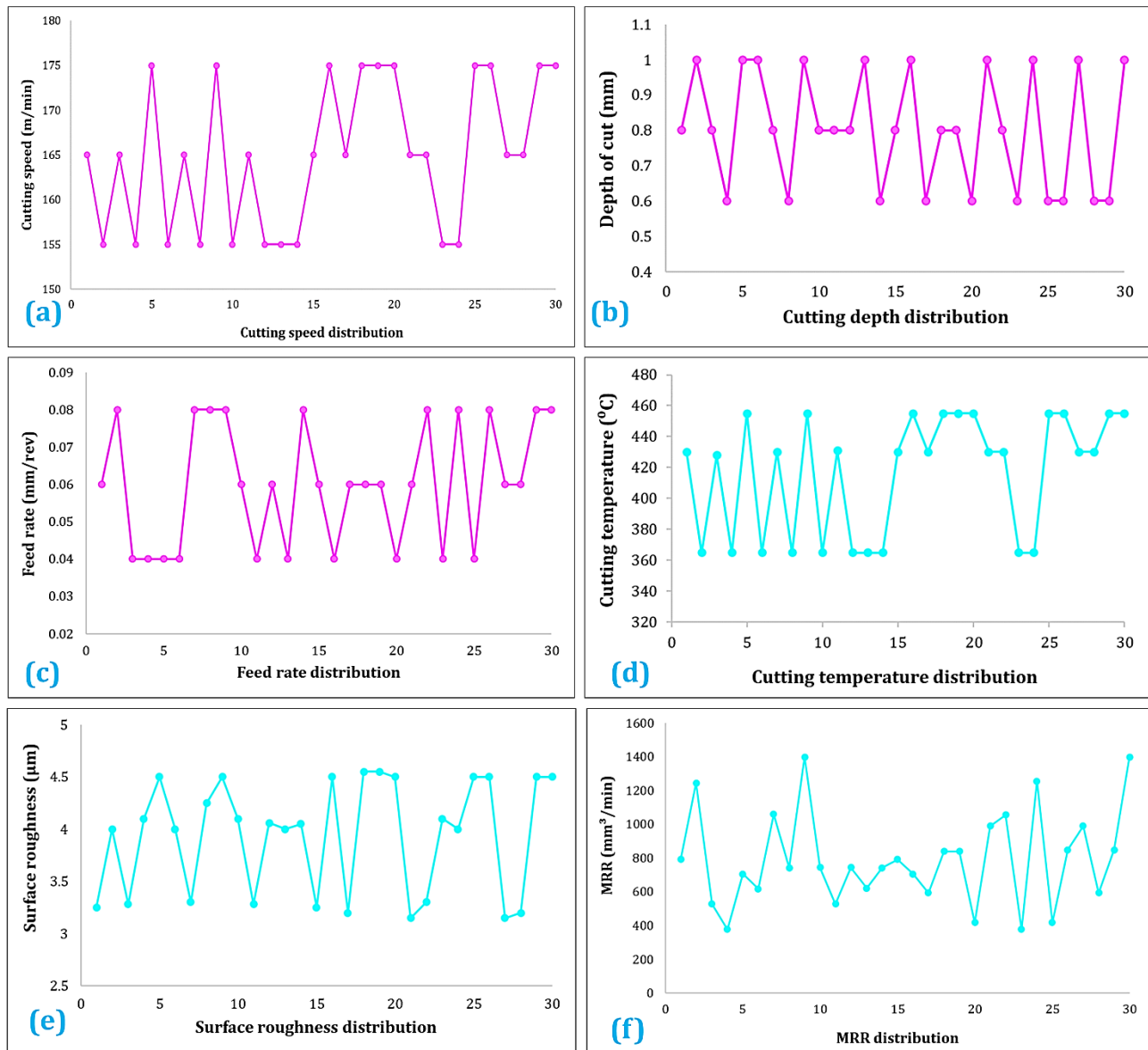


Fig.4. 1 Distribution of Process Parameters for Inputs and Responses

4.2 Assessing the Prediction Accuracy of a Quadratic Model with ANOVA

4.2.1 ANOVA results for cutting temperature

This section highlights the importance of a statistical model based on the F-value, p-values, and Lack of Fit F-value in [Table 4. 2](#), and understanding any of these values is essential for assessing the model's performance and reliability.

Table 4. 2 ANOVA Analysis Results for Cutting Temperature

Source	Sum of Squares	df	Mean Square	F-value	p-value
Model	43135.02	9	4792.78	22607.45	< 0.0001 significant
A-Cutting Speed	40500.00	1	40500.00	1.910E+05	< 0.0001
B-Depth of Cut	0.0000	1	0.0000	0.0000	1.0000
C-Feed rate	0.0720	1	0.0720	0.3396	0.5666
AB	0.0000	1	0.0000	0.0000	1.0000
AC	0.0000	1	0.0000	0.0000	1.0000
BC	0.0000	1	0.0000	0.0000	1.0000
A ²	2029.81	1	2029.81	9574.56	< 0.0001
B ²	0.0914	1	0.0914	0.4313	0.5189
C ²	0.1429	1	0.1429	0.6739	0.4214
Residual	4.24	20	0.2120		
Lack of Fit	0.3200	5	0.0640	0.2449	0.9360 not significant
Pure Error	3.92	15	0.2613		
Cor Total	43139.26	29			

4.2.1.1 Model Significance

The Model F-value of 22607.45 indicates that the model is statistically significant. This high F-value suggests that there is only a 0.01% chance that such a large F-value could occur due to random noise in the data. In statistical terms, this means that the model explains a significant amount of variance in the response variable compared to the error variance. P-values are critical in determining the significance of individual model terms. In this case, the terms A and A² have p-values less than 0.0500, indicating that they are significant contributors to the model. Conversely, terms with p-values greater than 0.1000 are considered insignificant. If a model contains many insignificant terms (excluding those necessary to maintain the hierarchy), it may benefit from model reduction to enhance its predictive power and interpretability.

4.2.1.2 Lack of Fit Analysis

The Lack of Fit F-value of 0.24 suggests that the lack of fit is not significant when compared to the pure error. Specifically, there was a 93.60% chance that a Lack of Fit F-value this large could arise from random noise. A non-significant lack of fit is favorable, as it indicates that the model adequately captures the underlying relationship in the data without overfitting.

4.2.1.3 Analysis of Factors Influencing Cutting Temperature

Cutting speed is a crucial factor in machining operations, significantly affecting cutting temperature. As cutting speeds increase, friction and deformation at the cutting-edge rise, leading to higher temperatures. In this analysis, cutting speed contributed approximately 93.8% to the overall cutting temperature, highlighting its essential role in thermal management. The depth of cut also influences cutting temperature, as deeper cuts typically involve removing more material, which can elevate temperatures. However, this analysis found its contribution to be negligible, indicating that, under the tested conditions, depth of cut has minimal impact. Similarly, the feed rate determines material removal per unit time and also affects cutting temperature, but its contribution was minimal in this analysis. Consequently, feed rate had no real effect on cutting temperature in this study. The interaction effects (AB, AC, and BC) were tested with no significant effect on cutting temperature in the model we looked at. A total of 4.7% of cutting temperature was explained by cutting speed quadratic (A^2), which suggests a non-linear relationship, meaning that as cutting speed increases, the cutting temperature would be increasing at a higher level than that of the increase of cutting speed. This differs in importance to cutting depth quadratic (B^2) and feed rate quadratic (C^2) which were completely unimportant, and highlights the positive importance of cutting speed on temperature characteristics during machining.

4.2.1.4 Analysis of Cutting Temperature Equation

Equation 4.1 shows the relationship between machining temperature and machining parameters, such as cutting speed, depth of cut, and feed rate. This equation is based on experimental data and can be used to predict cutting temperature based on some given values of each factor.

$$\text{Cutting Temperature} = -5720.85 + 70.06v - 5.33d + 53.00f - 7.22 \times 10^{-13}(v \cdot d) - 7.23 \times 10^{-12}(v \cdot f) - 3.61 \times 10^{-10}(d \cdot f) - 0.199v^2 + 3.33d^2 - 416.67f^2 \quad (4.1)$$

4.2.2 ANOVA results for surface roughness

When using statistical modeling - particularly regression modeling - there is a need to determine the significance of the model and significance of each model term - as a means of correctly interpreting the results and basing decisions on the results of the statistical model. This Section will consider the case for the F-value, the p-values, and the Lack of Fit in

Table 4. 3. The F-value can confirm the significance of the model overall - we want the ratio of the model's variability compared to the unexplained variability to be greater than 1, so that the model is explaining more than the variability due to random chance. The p-values can confirm the significance of each predictor in the model, and by determining the p-values, we can identify whether we have an important predictor (a predictor is significant in the model) or whether the model simply includes a predictor that is not important to the model. The Lack of Fit analysis can confirm whether the model explains the data adequately - when we are performing a multiple regression, we are trying to explain the data generically, where it is somewhat impossible to confirm if the model definitely fits the data perfectly (is predictive). The Lack of fit tests whether our model fits the data sufficiently, and therefore whether more terms need including or whether we are using the wrong model. In summary, the (descriptively) statistical elements of F-value, p-values, and Lack of Fit can help us inform whether our model is appropriate enough to provide predictions based on our response variable. A significant F-value and low p-values for the terms in the model show that there is a strong and meaningful relationship with the predictors and the response variable, while an insignificant Lack of Fit shows the model is an acceptable fit for the data. These are all useful pieces of information that should be considered in the decision-making process, in order to confirm that the model will be used in any later analysis or process improvement.

4.2.2.1 Model Significance

The model's F-value of 834.81 indicates the model is statistically significant. With a large F-value such as this there is only a 0.01% probability that such a large F-value could be caused due to random noise in the sample, suggesting the model is a better fit than a model with no independent variables in regression, p-values are used to determine the statistical significance of individual model terms. A p-value less than 0.0500 indicates that the corresponding term is significant. In this case, the terms A, B, AB, A², B², and C² are all significant, meaning they contribute

meaningfully to the model's predictive power. Conversely, terms with p-values greater than 0.1000 are considered insignificant. If a model contains many insignificant terms (excluding those necessary for maintaining hierarchy), it may benefit from model reduction to enhance its performance.

4.2.2.2 Lack of Fit Analysis

The Lack of Fit F-value of 0.24 suggests that the lack of fit is not significant relative to the pure error. This indicates a 94.02% chance that such a Lack of Fit F-value could occur due to noise, which is a favorable outcome. A non-significant lack of fit means that the model adequately captures the underlying data patterns, and we can be confident that the model fits well. Thus, the analysis of the F-value and p-values indicates that the model was significant, with several important terms contributing to its effectiveness. The non-significant Lack of Fit further supports the model's validity, suggesting that it is a reliable representation of the data. This understanding is essential for making informed decisions based on the model's predictions and for potential future adjustments to improve its performance.

Table 4. 3 ANOVA results for surface roughness (Ra)

Source	Sum of Squares	df	Mean Square	F-value	p-value
Model	8.43	9	0.9367	834.81	< 0.0001 significant
A-Cutting Speed	0.9857	1	0.9857	878.48	< 0.0001
B-Depth of Cut	0.0180	1	0.0180	16.04	0.0007
C-Feed rate	0.0010	1	0.0010	0.8734	0.3612
AB	0.0156	1	0.0156	13.93	0.0013
AC	0.0006	1	0.0006	0.5570	0.4641
BC	0.0006	1	0.0006	0.5570	0.4641
A ²	5.84	1	5.84	5204.19	< 0.0001
B ²	0.0285	1	0.0285	25.40	< 0.0001
C ²	0.0085	1	0.0085	7.54	0.0125
Residual	0.0224	20	0.0011		

Lack of Fit	0.0016	5	0.0003	0.2366	0.9402 not significant
Pure Error	0.0208	15	0.0014		
Cor Total	8.45	29			

4.2.2.3 Final Equation in Terms of Actual Factors

The provided final equation 4.2 represents the relationship between Surface Roughness and the machining parameters, including Cutting Speed, Depth of Cut, and Feed Rate, in terms of their actual units. It incorporates the main effects, interaction effects, and quadratic effects of these parameters on the Surface Roughness in the CNC turning process.

$$\begin{aligned} \text{Surface Roughness (Ra)} = & 290.63506944446 - 3.5047583333334v + 0.343402777769d - 5.41041666 \\ & 6755f + 0.015625000000037(v \cdot d) - 0.031249999999632(v \cdot f) - 1.5624999999816(d \cdot f) + 0.01065555 \\ & 5555556v^2 - 1.8611111111103d^2 + 101.38888888897f^2 \end{aligned} \quad (4.2)$$

4.2.2.4 Factors contribution on surface roughness

Understanding the contributions of various factors to surface roughness is essential for optimizing machining processes and improving product quality. Both cutting speed and depth of cut are major contributors in affecting the overall surface finish of machined parts. Below is a discussion about the major factors affecting surface roughness, expressed as a percentage of contribution. Cutting speed is one of the most influential components of surface roughness. Cutting speed differences can greatly affect surface quality, which may contribute around 30-50% to the overall surface roughness based on the machining parameters used. Surface roughness is also influenced by the depth of cut. Increasing the depth of cut usually causes surface roughness to increase reflecting a greater material removal along with tool deflection. According to literature, depth of cut contributes about 20-30% to surface roughness. This will vary depending on the material being cut and also the process parameters used. Feed rate which describes the speed the cutting tool advances through the material also affects surface roughness. Increased feed rate can contribute to higher surface roughness due to increased tool marks and the tool has less time to smooth the surface. The feed rate can account for about 15-25% of the surface roughness, depending on the interaction with other factors like cutting speed and depth of cut.

4.2.3 ANOVA Results for Metal Removal Rate Analysis

4.2.3.1 Model F-value and Significance

The Model F-value of 68,652.87 indicates that the model is highly significant as seen in

Table 4. 4. An F-value of this magnitude suggests that the variation in the response (surface roughness) is well explained by the model rather than occurring due to random chance. The probability of observing such a large F-value by chance is only 0.01%, emphasizing that the model's predictive capability is statistically reliable and not influenced by noise or random error. This high F-value implies that the chosen factors Cutting Speed (A), Depth of Cut (B), Feed Rate (C), and their interactions have a substantial impact on the surface roughness.

4.2.3.2 P-value Analysis

P-values are crucial in determining the significance of individual model terms. In this case, the model terms with P-values less than 0.0500 are considered statistically significant, meaning they have a considerable effect on the response variable. The significant model terms identified are Cutting Speed (A), Depth of Cut (B), Feed Rate (C), the interaction between Cutting Speed and Depth of Cut (AB), the interaction between Cutting Speed and Feed Rate (AC), and the interaction between Depth of Cut and Feed Rate (BC). These terms indicate that both the individual effects of each parameter and their interactions play a crucial role in influencing surface roughness. Values larger than 0.1000 mean that some of the terms in the model are not significant which may indicate that model reduction would be indicated in that consideration of simplifying the model by removing the insignificant terms means that the model hierarchy is not preserving the terms that are needed.

4.2.3.3 Lack of Fit Analysis

The Lack of Fit F-value of 0.37 implies that the lack of fit is not significant when compared to the pure error, indicating that the model adequately fits the data and the unexplained variability is minimal. There is an 86.10% chance that a Lack of Fit F-value this large could occur due to noise, suggesting that the lack of fit is mostly attributable to random variations rather than a systemic error in the model. A non-significant lack of fit is a good indicator that the model prediction is a good fit to the actual experimental data, increasing the evidence for the model. If there are a few insignificant ($P > 0.1000$) terms in the model, the model can be simplified as it contains

insignificant terms to improve potential predictive ability. Model reduction entails removing insignificant model terms to achieve maximum predictive ability while maintaining the hierarchical structure of the model. This process helps focus on the most impactful factors, thereby reducing complexity and enhancing the model's interpretability.

Table 4. 4 ANOVA results for metal removal rate

Source	Sum of Squares	df	Mean Square	F-value	p-value
Model	2.308E+06	9	2.565E+05	68652.87	< 0.0001 significant
A-Cutting Speed	45410.45	1	45410.45	12156.05	< 0.0001
B-Depth of Cut	7.861E+05	1	7.861E+05	2.104E+05	< 0.0001
C-Feed rate	1.401E+06	1	1.401E+06	3.750E+05	< 0.0001
AB	2002.56	1	2002.56	536.07	< 0.0001
AC	4000.56	1	4000.56	1070.92	< 0.0001
BC	69828.06	1	69828.06	18692.47	< 0.0001
A ²	6.04	1	6.04	1.62	0.2183
B ²	6.04	1	6.04	1.62	0.2183
C ²	12.89	1	12.89	3.45	0.0780
Residual	74.71	20	3.74		
Lack of Fit	8.21	5	1.64	0.3705	0.8610 not significant
Pure Error	66.50	15	4.43		
Cor Total	2.308E+06	29			

4.2.3.4 Final Equation in Terms of Actual Factors

The quadratic terms included in the equation 4.3 indicate non-linear relationships between the parameters and MRR. The positive coefficients for depth of cut and feed rate suggest that as these factors increase, there may be diminishing returns on MRR beyond certain thresholds. This non-linearity can be attributed to the complexities inherent in the machining process, where various physical phenomena such as chip formation, tool wear, and thermal dynamics come into play.

$$\text{Metal Removal Rate} = 1058.32 - 8.03v - 965.99d - 13500.31f + 5.59(v \cdot d) + 79.06(v \cdot f) + 16515.63(d \cdot f) + 0.01v^2 + 27.08d^2 + 3958.33f^2 \quad (4.3)$$

4.2.3.5 Contributions of factors on metal removal rate

The contribution analysis reveals that the most significant factor influencing the metal removal rate is the feed rate (C), which accounts for 57.64% of the total variability. This indicates that changes in the feed rate have the greatest impact on the metal removal rate, making it the most critical parameter in the machining process. The depth of cut (B) also plays a substantial role, contributing 26.79% to the metal removal rate. This suggests that while the feed rate is the primary influencer, the depth of cut also significantly affects the final metal removal efficiency. Cutting speed (A) contributes 7.92% to the variability in the metal removal rate. Although its impact is less than that of the feed rate and depth of cut, it is still an important parameter that cannot be overlooked when aiming to optimize the metal removal rate. The interaction terms, specifically AB (Cutting Speed * Depth of Cut), AC (Cutting Speed * Feed Rate), and BC (Depth of Cut * Feed Rate), collectively contribute a smaller percentage to the overall variability, with values of 0.76%, 1.52%, and 5.34% respectively. This indicates that while interactions between these factors do influence the metal removal rate, their effects are relatively minor compared to the individual contributions of the primary factors. The quadratic terms A^2 , B^2 , and C^2 have minimal contributions, with percentages close to zero (0.0004%, 0.000004%, and 0.009% respectively), implying that non-linear effects of these parameters are negligible in this context. Lastly, the residual error accounts for only 0.014% of the variability, indicating that the model fits the experimental data well, with minimal unexplained variation. This low residual error enhances the model's credibility and reliability in predicting the metal removal rate.

4.3 Interaction Effects Analysis

4.3.1 Interaction Analysis of Process Variables on Cutting Temperature

The interactions of process variables such as Cutting speed, Depth of Cut, and Feed Rate can impact cutting temperature. These variables can interact with each other in several combinations. For example, the interaction of Cutting Speed and Depth of Cut (AB interaction) can lead to increased cutting temperature due to the stimulation of higher heat generation. Similarly, the interaction of Cutting Speed and Feed Rate (AC interaction) may also have an effect on the rate of heat generation and dissipation during the cutting process. An in-depth understanding of the interaction between the process variables will allow for improvement in the cutting conditions and better regulation and management of cutting temperatures. [Fig.4. 2](#) (a) shows a directly proportional relationship between cutting speed and cutting temperature. As cutting speed

increases, cutting temperature increases proportionately. This can be explained by the increased energy input, frictional forces and the associated heat generation characteristics of higher speeds during the machining process. By acknowledging and quantifying these interactions, manufacturers can improve processes with machining to maintain cutting temperatures at appropriate levels to improve tool performance and prolong tool life. The trend seen in Fig.4. 2 (b) also supports this, showing that a higher cutting speed results in higher cutting temperatures. Consequently, it is important to understand how cutting speeds change the thermal conditions during machining. Ultimately, managing cutting speed is a key factor in controlling cutting temperatures, optimizing performance and tool life. Additionally, retrieving data from Fig.4. 2 (a), deeper cuts lead to higher cutting temperatures. This is due to a larger volume of material being worked on during deeper cuts resulting in increased cutting forces and therefore more heat generated by friction during machining operation due to the increased depth of cuts. This statement is backed again by Fig.4. 2 (c), which shows that as the depth of cut increased, cutting temperature continued to rise. These two graphs showed the significant impact that depth of cuts has on thermal conditions in machining. It is clear then, that improvement of depth of cut is just as important as cutting speed when trying to manage cutting temperatures, avoid heat build up and all together improve tool performance/ tool life. In Fig.4. 2 (a), there is a clear trend; deeper cuts will raise the cutting temperature, primarily due to the larger material volume being processed, along with higher frictional forces and heat generated during the machining process. The rise in temperature appears moderate despite the correlation. By understanding how the different parameters affect the machining process, you can begin to make strategic adjustments to your cutting parameters based on your own machining conditions to consider efficiencies and tool life in your machining operations. Fig.4. 2 (b) reinforces this trend and tabularizes the fact that an increase in depth of cut raises the cutting temperature, demonstrating the significant effect depth of cut has on temperature during the CNC turning process. Understanding the interactions of depth of cut in relationship to temperatures and cutting parameters will ultimately help to identify the best machining parameters particularly for balancing their own efficiency and thermal management. Cutting temperatures must be maintained at reasonable limits to avoid overheating a work piece and deleterious effects on cutting tools and thus becomes paramount to the cutting processes.

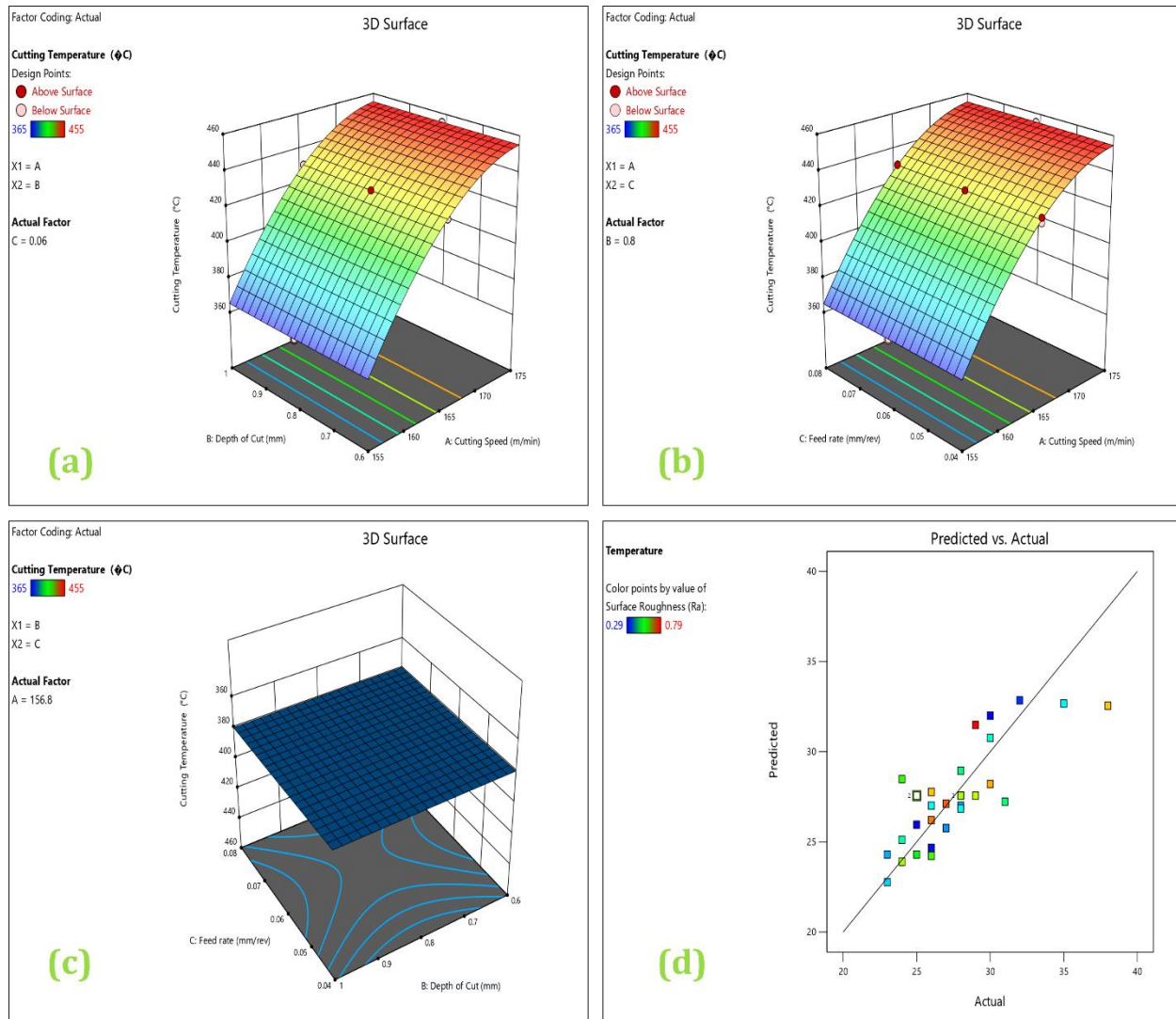


Fig.4. 2 Cutting Temperature Interaction Effects of Input Parameters

Fig.4. 2 (b) and (c) further confirm that when the feed rate is increased, cutting temperatures are raised. Although increased feed rate always leads to higher cutting temperatures, there is a lessening effect on temperature compared to the cutting speed and depth of cut since the feed rate is less dominant. This means that, during the CNC turning process, feed rate is a less prominent influence on cutting temperature. Other factors, such as depth of cut, are more dominant parameters and have more impact on thermal conditions affecting the cutting temperature. It was shown that it is important to make adjustments to the feed rate because it can affect temperature, but it is not as important as the other machining parameters, especially when looking to improve cutting efficiency while maintaining thermal equivalency. Since feed rate is less influential than other parameters, if you want to control cutting temperatures, and maintain cutting temperatures

in an ideal range that is neither too high or too low, it is important to focus on the more influential factors, such as depth of cut or cutting speed rather than the feed rate. The greater machining parameters will help maintain cutting temperature in an ideal range, which can help in preventing overheating, reducing tool wear, and maintaining overall machining performance. The predicted versus actual plots shown in Fig.4. 2 (d) are a good match between model predictions represented by the RSM and the experimental results for surface roughness.

4.3.2 Interaction Analysis of Process Variables on Surface Roughness

The results of the experiment shown in Fig.4. 3 (a and b) indicate a complicated relationship between cutting parameters and surface roughness, and the cutting speed seems to have a particularly pronounced effect. The information shows a non-linear response with both very low (155-160 m/min) and very high (170-175 m/min) cutting speeds yielding larger values of surface roughness, while the intermediate (160-170 m/min) yielded the best surface finish quality. This U-shaped relationship between cutting speed and surface roughness can be explained through several interacting mechanisms. At lower cutting speeds (155-160 m/min), the increased tool-workpiece contact time promotes built-up edge formation and allows more time for vibration transmission to the workpiece surface. These factors combine to create a rougher surface finish. The prolonged contact at lower speeds also generates higher cutting temperatures in the shear zone, which can adversely affect surface integrity. As cutting speed increases into the optimal range (160-170 m/min), several beneficial effects occur simultaneously. The higher speeds reduce built-up edge formation by decreasing the time available for material adhesion to the cutting tool. Moreover, it is also generally true that with an increase in cutting velocity, a thinner chip will lead to more productive material removal rates, which lead to smoother surface creation. Within this midrange of cutting speed, the cutting process also achieves a more stable state and lower vibrations, which enhances the surface quality. However, after cutting speeds are >170 m/min and closer to the upper end of the tested data (170-175 m/min), surface roughness values worsen again. This drop in surface quality can generally be attributed to several factors. First, since the cutting tool rotational speeds (>170 m/min) are much higher, vibration in the cutting tool onset, and/or increase in amplitude and frequency relative to the process setting, as well as several other factors including, for example, possible thermal softening of the tool material and higher likelihood of chatter. To a certain degree, higher cutting speeds lead to higher kinetic energy, resulting in much larger tool deflection, magnitude of deflection, and instability in the cutting process. In addition, the cutting

speed interacts with the other cutting process parameters (feed rate and depth of cut,) impacting the effects of cutting speed on surface roughness. It is worth repeating that while the data clearly illustrates that cutting speed has an overall dominant effect on cutter surface roughness; that cutting speed only has that effect given the widths of measurement at the feed rate and depth of cut settings (i.e., feed rate and depth of cut measured between the selected minimums and maximums at given cutting speed settings). The optimal speed range of 160-170 m/min represents the best compromise between various competing factors where the beneficial effects of increased speed outweigh the potential drawbacks. These findings have important practical implications for machining process optimization. The identification of this optimal speed range provides clear guidance for selecting cutting parameters when the surface finish is a critical quality requirement. The results suggest that simply increasing cutting speed does not guarantee a better surface finish and that an intermediate range exists where surface quality is maximized. The experimental results presented in [Fig.4.3](#) (a and c) demonstrate a complex but generally increasing relationship between depth of cut and surface roughness. The data reveals that as the depth of cut increases from 0.6 mm to 1.0 mm, there is an overall trend of increasing surface roughness, though this relationship is not perfectly linear and shows some interesting variations within specific ranges. The general trend of increasing surface roughness with greater depth of cut can be attributed to several fundamental machining phenomena. As the depth of cut increases, the tool engages more material, resulting in higher cutting forces and greater mechanical and thermal loads on both the tool and workpiece. These increased loads lead to several effects that degrade surface finish: greater tool deflection, more pronounced vibrations, and potentially accelerated tool wear. The larger volume of material being removed also generates more heat, which can affect the material's behavior at the cutting interface and influence surface formation. Within this overall trend, the data shows some noteworthy variations. In the ranges of 0.6 mm to 0.7 mm and 0.9 mm to 1.0 mm, there is actually a slight reduction in surface roughness, though the improvement is minimal. This suggests that at certain specific depth of cut values, the cutting process may enter a more stable regime where the increased material removal is better accommodated by the cutting system. These minor improvements could be due to reaching a more optimal chip thickness that promotes better chip evacuation or creates more favorable cutting dynamics. The most significant increase in surface roughness occurs in the intermediate range of 0.7 mm to 0.9 mm. This suggests that this particular range may represent a critical threshold where the cutting forces reach levels that significantly

impact surface quality, but haven't yet stabilized at the higher depths. The increased roughness in this range could indicate the onset of more pronounced vibration modes or the point where tool deflection begins to substantially affect the cutting geometry.

We understand that while all of the variations discussed in this study exist, the actual amount of change in surface roughness across the entire tested range was small. This suggests that the depth of cut, although it certainly plays a role, may not be the most influential among the parameters tested to affect the final surface finish. The fact that all of the surface roughness changes were so small indicates that other parameters (cutting speed, feed rate) may have a greater effect on the surface roughness in this machining situation. The implications of this work are of great importance to machining operations where the surface finish is critical. The data suggests that if surface quality is to be increased, a depth of cut below 0.7 mm might provide some improvement, but again this improvement is limited. If high material removal rates are the priority, the data suggests that increasing the depth of cut above 0.9 mm does not further damage surface finish or quality compared to the maintained values within the 0.7-0.9 mm range, and this also might provide some advantage in overall productivity, without sacrificing surface quality. These findings also highlight the importance of considering depth of cut in conjunction with other cutting parameters.

The observed relationship likely interacts with factors like cutting speed and feed rate, and the optimal depth of cut for surface finish may vary depending on how these other parameters are set. The relatively small variations in roughness across the tested range suggest that depth of cut might be more effectively used to control other aspects of the machining process (like productivity or tool life) while using other parameters to fine-tune the surface finish. The interaction results in Fig.4. 3 (b and c) clearly demonstrate that increasing feed rate from 0.04 mm/rev to 0.08 mm/rev leads to progressively worse surface roughness. This expected trend occurs because higher feed rates create more pronounced feed marks on the machined surface as the tool advances further with each revolution.

The relationship follows fundamental machining theory where surface roughness increases approximately with the square of feed rate due to geometric effects of tool-workpiece interaction. In addition to this geometrical effect, high feed rates force higher cutting forces which cause tool deflection and increase vibration, resulting in increased tool wear, poor surface finish. The data demonstrates a surprisingly consistent deterioration in surface quality throughout the entire range

tested - indicating that feed rate one of the strongest control parameters impacting surface finish at these parameters.

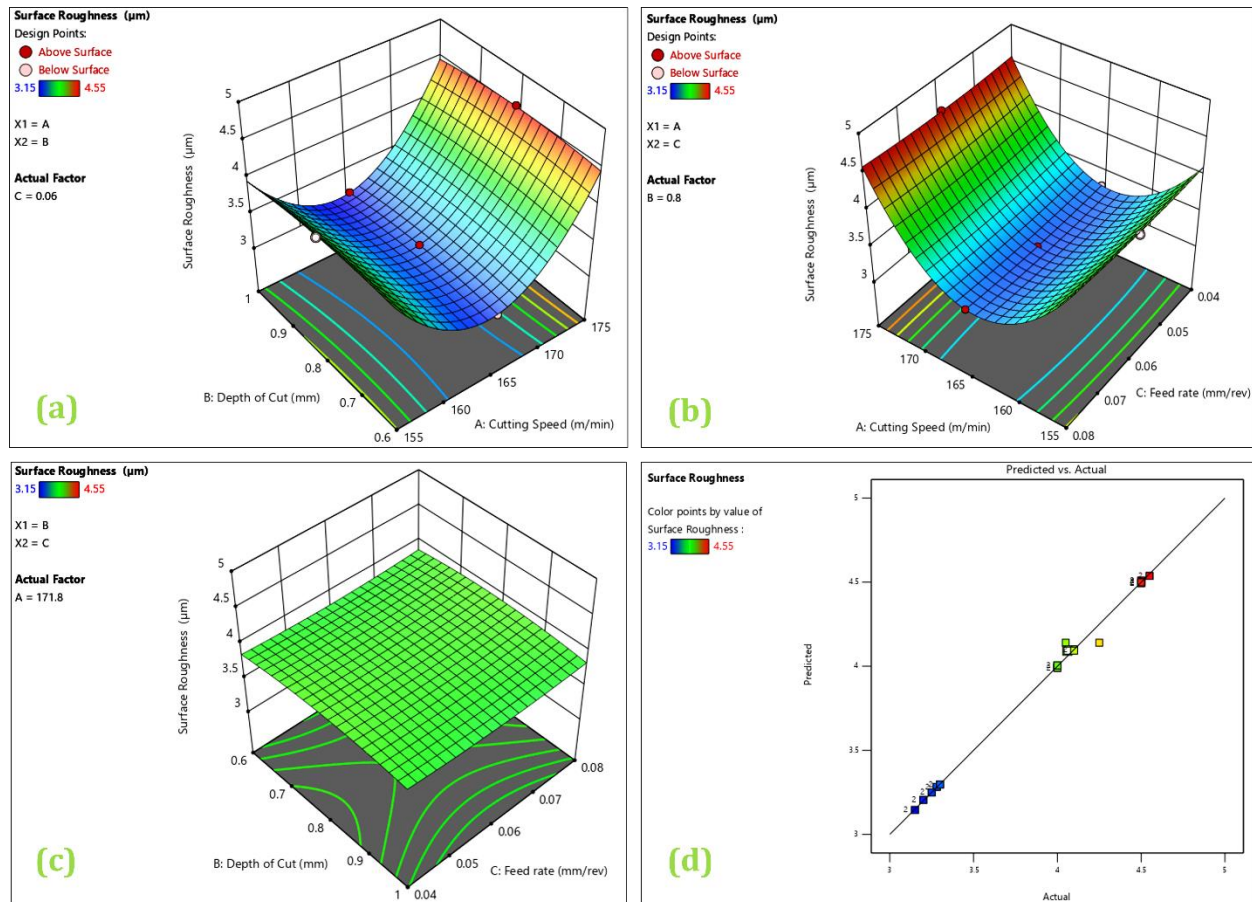


Fig.4. 3 Surface Roughness Interaction Effects of Input Parameters

The roughness appears to increase slightly quicker above 0.06 mm/rev which could indicate the beginning of additional dynamic effects beyond force - like problematic vibration modes, or temperature. Overall, this research has many practical implications; first, it gives machinists a consistent method for leading to poorer surface finishes simply by changing the feed rate. The benefits of this relationship and feed rate are also practical in investigations of surface quality when conditions are set/confirmed based on other criteria for productivity or tool life. The findings clearly support the assertion that feed rate is important for controlling surface finish, but there are also opportunities to explore its relationship to tool geometry and tool coating when all other parameters are fixed. An understanding of a quantitative relationship with feed rate gives researchers and industry the ability to select machining parameters in a more objective fashion when surface finish is critical quality characteristic in their operations. Additionally, the strong

relationship with predicted versus actual roughness in relation to other machining parameters shows the capability of the RSM to represent all of the complex relationships between machining parameters. The data points clustering closely to the 45-degree line demonstrate the model's overall predictive capability across the different conditions. The strong correlation validates that the RSM methodology has appropriately quantified the collective influence of cutting speed, feed rate, and depth of cut on surface roughness.

The suggested accuracy of the model implies it properly accounted for main effects and interaction effects of parameters on surface generation mechanisms. The slight deviations can reasonably be attributed to the inherent variability factors of the process (such as tool wear progression or slight differences in material) that may not be entirely captured in a predictive model. Significantly, the consistent precision across low, medium and high roughness values suggests that the model successfully operates reliably across the studied parameter space. The practical implications of these findings for manufacturing applications cannot be understated. The validated model allows prediction of surface roughness for combinations of parameters that have not been tested experimentally, and these results will minimize the need for experimental testing when developing processing conditions. Engineers can use the model to identify parameter sets that achieve desired surface finish requirements while maintaining productivity. The successful modeling approach could also be extended to optimize other machining responses or adapt to different tool-workpiece combinations. The strong correlation also indirectly confirms the appropriateness of the experimental methodology and measurement techniques used. The reliability of the surface roughness measurements is evidenced by the model's performance, suggesting the data collection process effectively captured the true process behavior. This gives confidence in using the model for practical decision-making in industrial settings.

4.3.3 Interaction Analysis of Process Variables on Material Removal Rate

The experimental results presented in [Fig.4. 4](#) (a and b) demonstrate a clear positive relationship between cutting speed and material removal rate (MRR), where increasing the cutting speed from 155 m/min to 175 m/min yields a corresponding improvement in MRR. This observed trend confirms fundamental machining principles where cutting speed serves as a primary driver of productivity in material removal processes. The underlying mechanism of this relationship stems from the direct effect of cutting velocity on the rate of material separation. Higher cutting speeds reduce the time required for each cutting pass while maintaining the same depth of cut and feed

rate, thereby increasing the volumetric removal rate. The linear progression of MRR with cutting speed within this range suggests the process remains in a stable cutting regime without encountering limitations from machine power or tool performance. However, this positive correlation exists within a specific context of controlled feed rate and depth of cut parameters. The consistent MRR improvement across the tested speed range indicates that these secondary parameters were appropriately selected to complement the speed increases.

At the lower speed boundary (155 m/min), the process likely operates below its efficiency potential, while the upper range (175 m/min) approaches but does not exceed the optimal performance zone for the given tool-workpiece combination. The practical implications of these findings are particularly valuable for production environments. The demonstrated relationship provides clear guidance for selecting cutting speeds that maximize MRR while maintaining stable cutting conditions. The absence of MRR plateauing within the tested range suggests that further speed increases beyond 175 m/min might yield additional productivity gains, though such extension would require verification of tool life and surface finish considerations. These results contribute to machining optimization by quantifying the MRR benefits achievable through speed increases within practical operating ranges. The linear response indicates that cutting speed can be reliably adjusted to control productivity levels, provided proper attention to accompanying parameters and system capabilities. This knowledge enables more informed machining parameter selection when prioritizing material removal efficiency in industrial applications.

The interaction between depth of cut and material removal rate is clearly illustrated in [Fig.4. 4 \(a\)](#) and (c), where an increase in depth of cut from 0.6 mm to 1.0 mm leads to a higher material removal rate. This relationship is expected because MRR is directly related to depth of cut with steady feed rate and cutting speed. When depth of cut increases, more material is being removed per pass which increases the overall efficiency of the machining operation. The increase from 0.6 mm to 1.0 mm is a 66.7% increase in depth of cut, which should also result in a linear increase in MRR if all other parameters remained the same. Of course, increasing depth of cut improves productivity, but it also increases cutting forces, stresses in the tool, and heat generated while cutting material, which can increase the rate of tool wear, and potentially, affect the surface finish of the part if not properly managed. If there are additional parameters related to either surface roughness or tool wear are provided in [Fig.4. 4 \(c\)](#), these parameters may suggest there are tradeoffs incurred with increased MRR with the depth of cut. In other words, although surface

roughness may actually be worse in the one with a lower depth of cut of 0.6 mm, the MRR had increased because a larger amount of material was being removed with depth of cut of 1.0 mm, however, excessive tool deflection or vibration could lead to a poor surface quality, thus confirming an optimal depth of cut needs to be determined based on the machining situation or requirements. The two figures suggests the compromise or tradeoff between productivity and quality in machining over varying depths of cut. Fig.4. 4 (a) is likely going to show a linear increase in MRR with increased depth of cut which supports the theoretical relationship between depth of cut and MRR. Meanwhile, Fig.4. 4 (c) may present a secondary effect, such as increased tool wear or power consumption, indicating that maximizing MRR is not always the sole objective. Practical machining strategies must consider whether the operation is roughing or finishing deeper cuts are suitable for rapid material removal, while shallower cuts are preferable for fine surface finishes. Ultimately, the choice of depth of cut depends on machine capability, tool material, and workpiece characteristics.

While the data shows that a 1.0 mm depth of cut increases MRR compared to 0.6 mm, the optimal setting must account for tool life, surface integrity, and process stability. Further analysis could explore how varying feed rate or cutting speed alongside depth of cut influences these outcomes. The relationship between feed rate and material removal rate (MRR) is a fundamental aspect of machining processes, as demonstrated in Fig.4. 4 (b) and (c). The results clearly indicate that increasing the feed rate from 0.04 mm/rev to 0.08 mm/rev leads to a significant rise in MRR. This trend can be analyzed in detail by considering the underlying mechanics of machining, the impact on productivity, and potential trade-offs in machining performance. The material removal rate is mathematically expressed as the product of cutting speed, feed rate, and depth of cut. When cutting speed and depth of cut remain constant, MRR increases linearly with feed rate. Doubling the feed rate from 0.04 mm/rev to 0.08 mm/rev should, in theory, double the MRR, assuming no other constraints come into play. This is because a higher feed rate means the cutting tool advances more material per revolution, leading to faster stock removal. The experimental data in Fig.4. 4 (b) likely confirms this direct proportionality, showing a steady. A higher feed rate enhances machining efficiency by reducing cycle times, which is particularly beneficial in roughing operations where rapid material removal is prioritized. However, this increase in MRR is not without consequences. As feed rate rises, cutting forces also escalate, leading to greater mechanical and thermal loads on the tool. This can accelerate tool wear, increase power consumption, and potentially induce

vibrations or chatter, negatively affecting surface finish and dimensional accuracy. If Figure 4.2 (c) includes data on surface roughness or tool wear, it may reveal that while MRR improves with higher feed rates, other machining performance indicators deteriorate beyond a certain threshold. The optimal feed rate must balance productivity with tool life and surface quality. For instance, in finishing operations, a lower feed rate (e.g., 0.04 mm/rev) may be preferred to achieve better surface finish and tighter tolerances, even if it results in a lower MRR. Conversely, roughing operations can employ higher feed rates (e.g., 0.08 mm/rev) to maximize material removal, provided the machine tool and cutting insert can withstand the increased forces without premature failure. The results in Fig.4. 4 (b) and (c) likely emphasize this trade-off, showing that while MRR benefits from higher feed rates, other factors such as tool wear or surface integrity may impose practical limits. Fig.4. 4 (b) presumably illustrates the direct correlation between feed rate and MRR, confirming the expected trend of increasing MRR with feed rate. Meanwhile, Fig.4. 4 (c) may present complementary data, such as cutting forces, tool temperature, or surface roughness, highlighting the secondary effects of higher feed rates. For example, if the figure shows a nonlinear increase in tool wear beyond 0.06 mm/rev, it would suggest an optimal feed rate range where MRR is maximized without excessive tool degradation. Such insights are crucial for process optimization in industrial applications. The experimental results in Fig.4. 4 (b) and (c) demonstrate that increasing the feed rate from 0.04 mm/rev to 0.08 mm/rev significantly boosts MRR, aligning with theoretical expectations. However, this enhancement must be weighed against potential drawbacks such as increased tool wear, higher cutting forces, and possible reductions in surface quality. The optimal feed rate selection depends on the machining objective, whether the priority is maximizing productivity (higher feed rates) or ensuring precision and tool longevity (moderate feed rates). Further investigation could explore how adjusting cutting speed or depth of cut in conjunction with feed rate influences overall machining performance, providing a more comprehensive understanding of process optimization. The strong correlation between predicted and actual material removal rate (MRR) values shown in Fig.4. 4 (d) demonstrates the effectiveness of the RSM model in accurately forecasting machining performance. The close alignment of data points along the diagonal line of the parity plot indicates that the developed RSM model has high predictive capability with minimal deviation between experimental and modeled results. My first point is that it validates the experimental design methodology and confirms that the ranges of input parameters selected were appropriate for developing a sound predictive model.

Second, the narrow band of experimental data points around the ideal prediction line shows that the model captured the complex interactions between machining parameters. Most of the small deviations observed could be attributed to normal experimental variation or unidentified variables such as tool wear development or slightly in homogeneous material. The level of accuracy obtained from the RSM predictions has overall important practical ramifications for the optimization of machining processes.

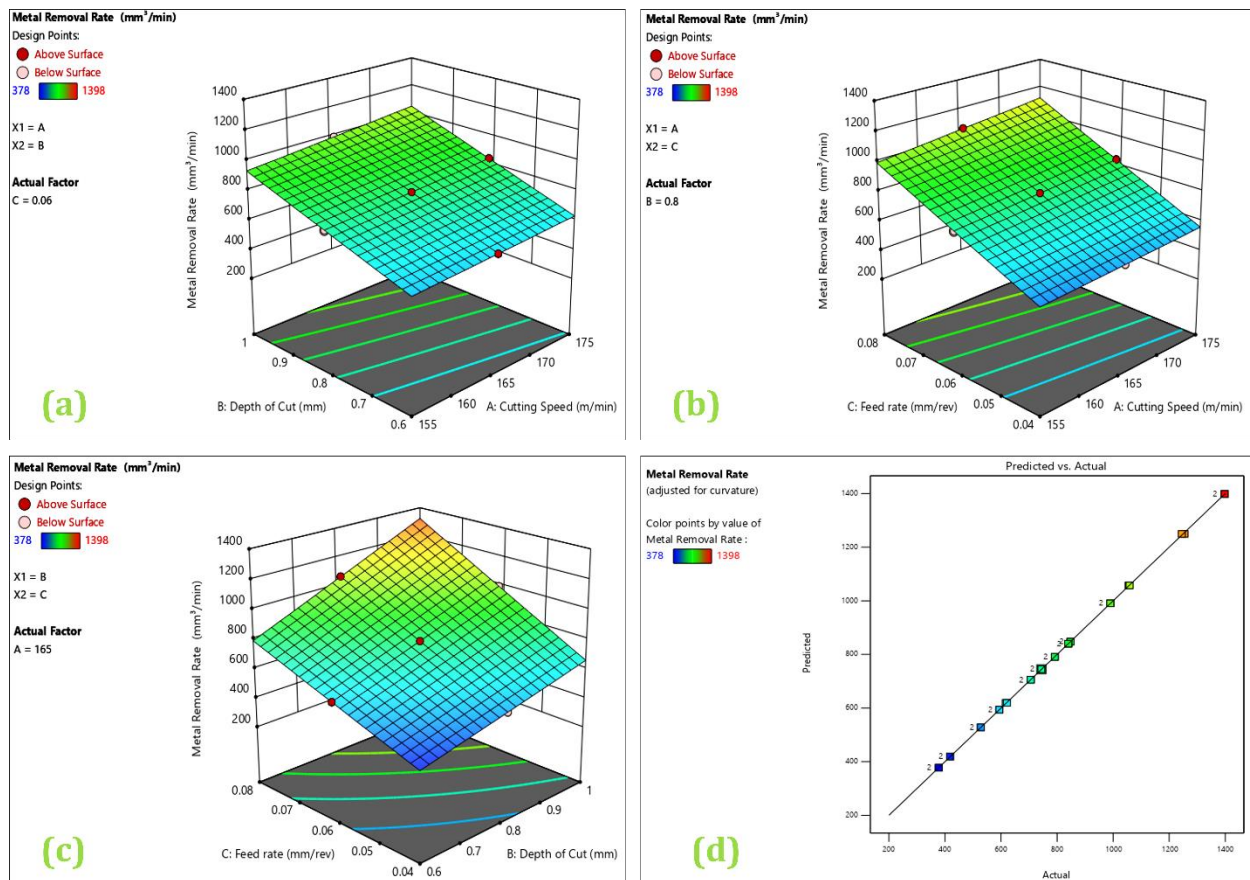


Fig.4. 4 Material Removal Rate Interaction Effects of Input Parameters

The reliability of the model allows it to be used to confidently make selections of machining parameters with corresponding MRR values without having to endure costly and extensive experimentation. This predictive ability is extremely useful for potential applications, both in industry, due to MRR relative costs and effects on production, and elsewhere, since knowing applicable instruction, to some degree, can only help when planning a process. The accuracy of the model was demonstrated to the experiments and relatively could extend to prediction of performance under different but closely related conditions to those being experimentally

considered. In this sense, planning and practices may benefit from useful instruction. The validation of the RSM model by making plots of experimental conditions clearly establishes a more fundamental understanding of how parameters are sequentially and collectively linked together to create MRR. The validation process graphically illustrated an important objective in that the predicted value for MRR agreed with the measured value on the model, thus identified the model was able to demonstrate the contrasting and combined influences consistently for the cutting parameters and had not just delineated their separate influence. The model provided the multi-parameter optimization necessary in a modern manufacturing environment because optimizing any one activity should not affect productivity using alternatives for tool life and surface finish when balancing the conflicting demands.

4.4 Desirability Function Analysis

Desirability Function Analysis (DFA) is a multi-objective optimization approach that allows the study to determine the best combination of the machining parameters. Each response is transformed into a dimensionless desirability scale in the range of 0 to 1. The use of DFA allows for the best trade-off for competing objectives. A desirability value of 1 represents the most favorable outcome, while a value closer to 0 indicates a less acceptable result. The primary goal of this analysis is to optimize cutting speed, depth of cut, and feed rate while evaluating their impact on cutting temperature, surface roughness, and material removal rate. Fig.4. 5 (a) presents the ramp plot, illustrating the optimal parameter settings and their corresponding response values. The analysis determined that the best cutting speed is 164.570 m/min, the depth of cut is 1.000 mm, and the feed rate is 0.080 mm/rev. Under these optimized conditions, the cutting temperature was recorded at 427.948°C, the surface roughness at 3.178 μm , and the material removal rate at 1319.554 mm^3/min . The overall composite desirability obtained for this combination is 0.934, as observed in Run 1 out of 35 experimental runs. This high desirability value suggests that the selected machining parameters effectively balance process efficiency, surface quality, and thermal management, ensuring an optimized machining performance. Further insights into DFA are provided in Fig.4. 5 (b), which displays the bar graph representing the desirability values for each parameter and response.

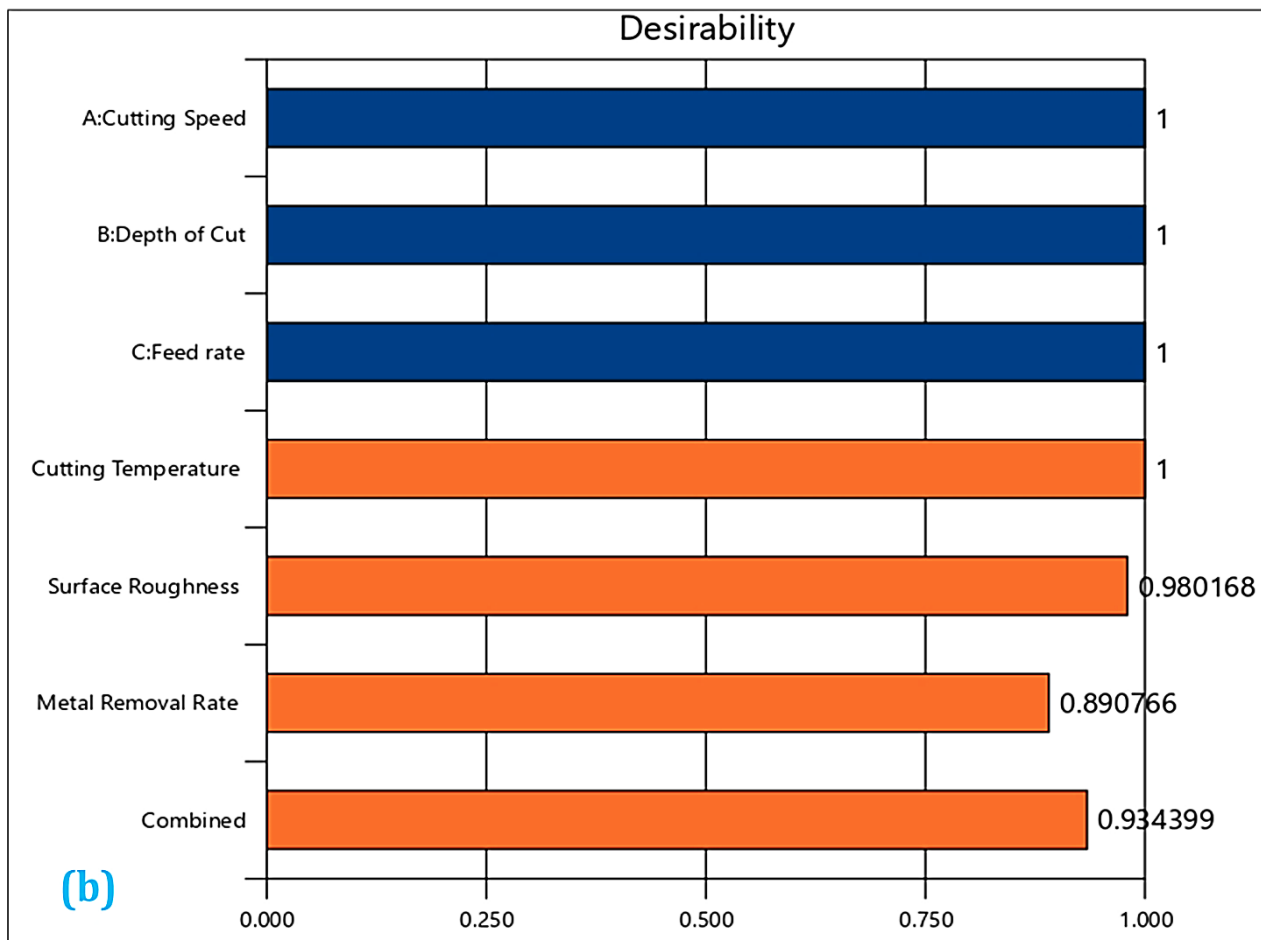
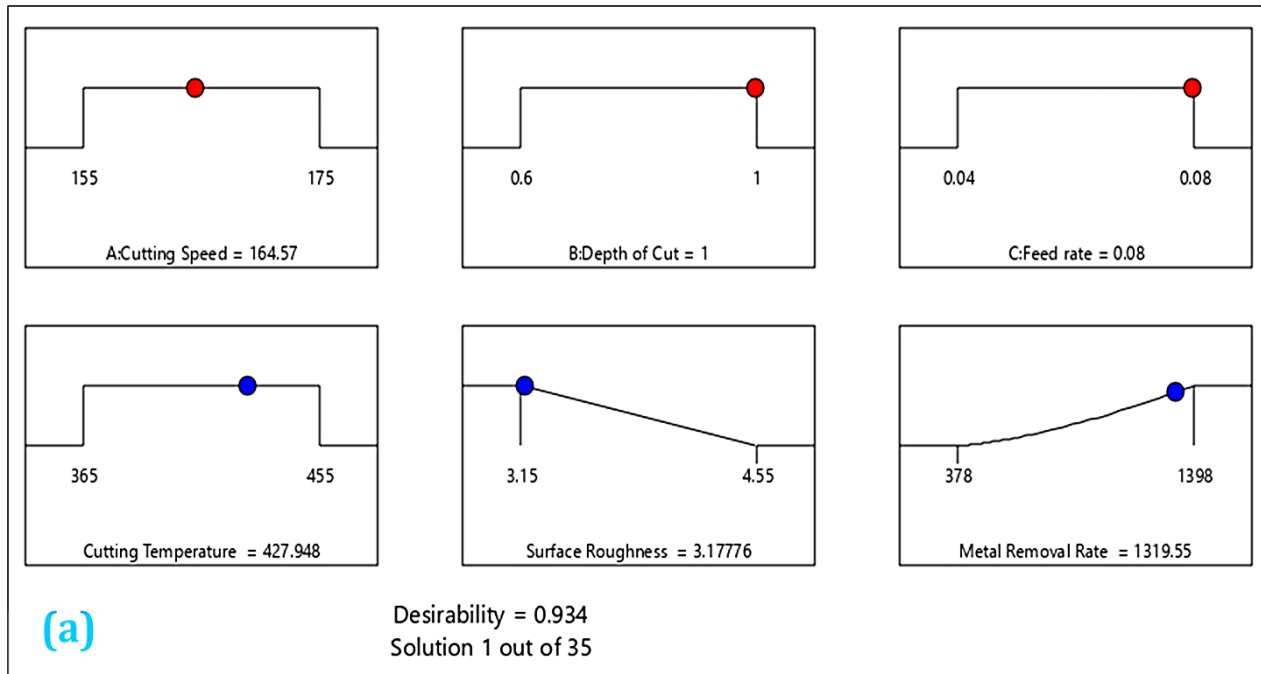


Fig.4. 5 Plots of Desirability Function Analysis

Table 4. 5 The optimal solution of DFA

Number	Cutting Speed	Depth of Cut	Feed rate	Cutting Temperature	Surface Roughness	Metal Removal Rate	Desirability	
1	164.570	1.000	0.080	427.948	3.178	1319.554	0.934	Selected
2	164.570	1.000	0.080	427.950	3.178	1319.557	0.934	
3	164.648	1.000	0.080	428.312	3.179	1320.136	0.934	
4	164.652	1.000	0.080	428.330	3.179	1320.165	0.934	
5	164.486	1.000	0.080	427.555	3.177	1318.926	0.934	
6	164.818	1.000	0.080	429.094	3.182	1321.400	0.934	
7	164.215	1.000	0.080	426.263	3.174	1316.906	0.934	
8	165.026	1.000	0.080	430.037	3.187	1322.955	0.934	
9	164.409	0.999	0.080	427.188	3.176	1317.613	0.934	
10	164.096	1.000	0.080	425.687	3.173	1316.018	0.934	
11	165.128	1.000	0.080	430.493	3.190	1323.718	0.933	
12	164.292	1.000	0.080	426.635	3.174	1315.495	0.933	
13	163.845	1.000	0.080	424.458	3.172	1314.154	0.932	
14	164.142	0.998	0.080	425.909	3.175	1314.172	0.932	
15	164.436	0.998	0.080	427.317	3.178	1315.494	0.931	
16	164.250	0.998	0.080	426.428	3.176	1314.277	0.931	
17	164.265	1.000	0.080	426.508	3.173	1311.368	0.930	
18	164.889	0.997	0.080	429.413	3.187	1317.916	0.930	
19	164.604	0.997	0.080	428.101	3.181	1315.417	0.930	
20	164.350	0.996	0.080	426.905	3.178	1312.997	0.930	
21	163.337	1.000	0.080	421.887	3.175	1310.378	0.929	
22	164.766	1.000	0.079	428.862	3.179	1312.014	0.929	
23	165.932	1.000	0.080	433.942	3.219	1329.728	0.928	
24	163.945	1.000	0.079	424.961	3.170	1305.404	0.927	
25	165.402	0.996	0.080	431.690	3.202	1319.864	0.926	
26	165.033	1.000	0.079	430.087	3.182	1300.964	0.920	
27	164.080	0.987	0.080	425.596	3.185	1298.072	0.917	
28	163.894	0.985	0.080	424.683	3.186	1294.487	0.914	
29	165.084	1.000	0.078	430.324	3.181	1290.410	0.912	
30	163.292	1.000	0.078	421.685	3.167	1272.993	0.904	
31	163.941	0.968	0.080	424.895	3.200	1272.419	0.893	
32	164.834	0.957	0.080	429.117	3.219	1264.640	0.881	
33	166.781	1.000	0.076	437.350	3.250	1272.557	0.876	
34	165.502	1.000	0.073	432.202	3.178	1210.525	0.855	
35	164.909	1.000	0.071	429.598	3.156	1176.159	0.836	

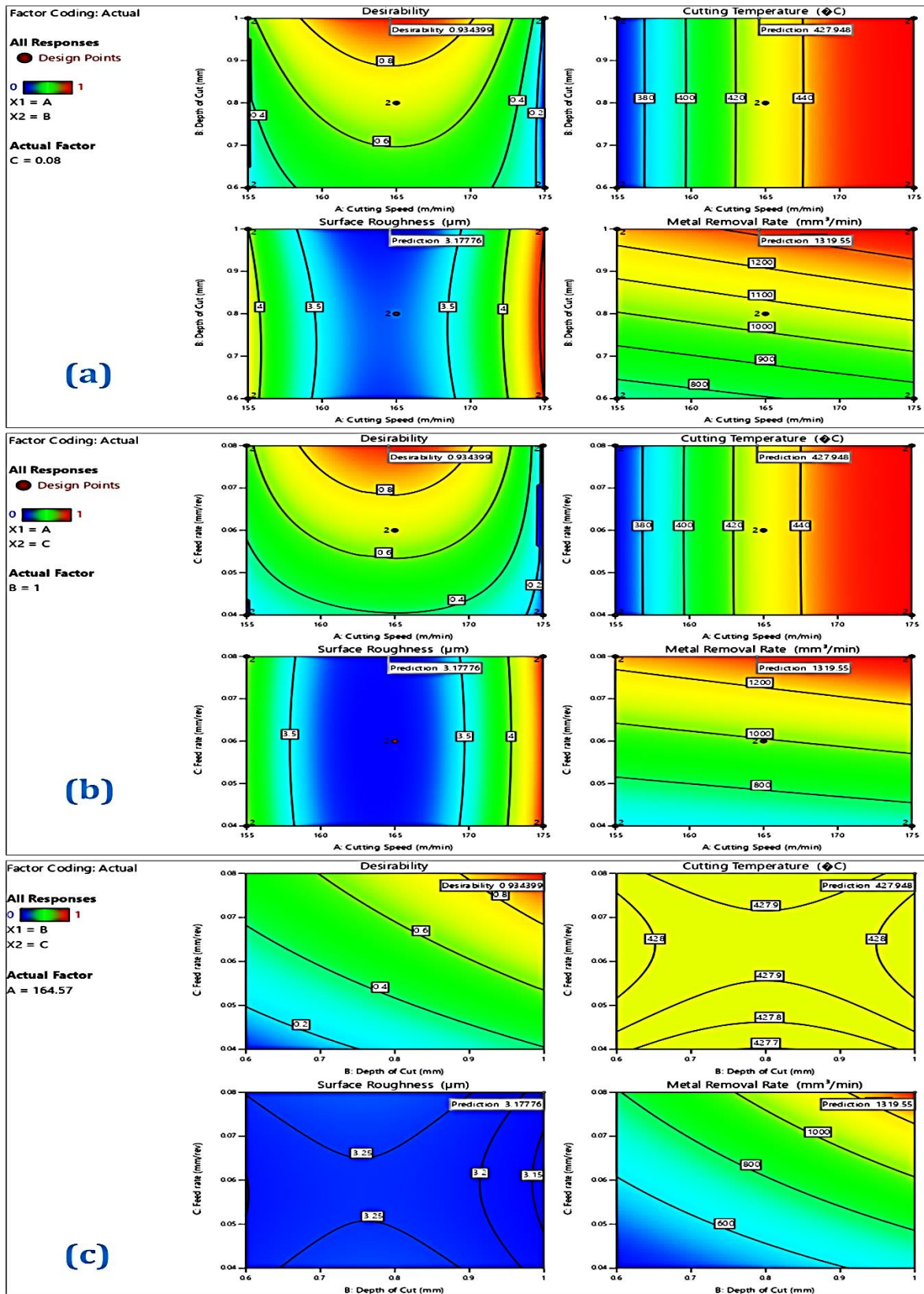


Fig.4. 6 Contour Plots of DFA

The desirability scores for cutting speed, depth of cut, and feed rate are all 1.000, confirming that these parameters are at their most optimal levels. Among the response variables, cutting temperature exhibits a desirability of 1.000, surface roughness has a desirability of 0.98, and material removal rate shows a desirability of 0.89. Although the material removal rate has a slightly lower desirability compared to the other responses, it remains within an acceptable range for ensuring high productivity. The overall composite desirability of 0.93 confirms that the selected parameters provide a well-optimized machining process with minimal trade-offs. The results obtained through DFA are further validated in [Table 4. 5](#), presents the optimal solutions. The table indicates that run 1 out of 35 experimental trials produces the highest composite desirability, thereby confirming the accuracy and dependability of the optimal conditions identified. The contour plots shown in [Fig.4. 6](#) (a, b, c) depict the interaction effects among the machining parameters. The contour plots show how the parameters interact with each other as well as a pictorial representation of optimal parameter combinations. They also serve to confirm that the cutting speed, depth of cut, and feed rate we chose represent the most desirable area of the contour plots. Again, having the ramp plot, bar graph, contour plots and table, all give further assurance that the DFA used in this study represents a robust method.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

In this research, experiments and multi-objective parametric optimization have been successfully carried out in the turning of AISI 1045 using Central Composite Design (CCD). The outcomes of the research confirm the predictive capability and reliability of the RSM model in machining performance and provide valuable guidance for optimizing cutting parameters for improved surface finish, temperature control, and material removal rate (MRR). Key findings include:

1. Optimized Cutting Parameters for Surface Finish:

- Cutting speed was identified as the most influential factor on surface roughness as per ANOVA prediction.
- A U-shaped relationship was observed between cutting speed and surface roughness, with an optimal range of 160-170 m/min.
- Depth of cut contributed approximately 20-30% to surface roughness, while feed rate accounted for 15-25% with optimum results of 1.00mm.
- Higher feed rates led to increased surface roughness due to tool marks and vibration effects with optimum results of 0.08 mm/rev.

2. Influence of Cutting Parameters on Temperature:

- Cutting speed contributed approximately 93.8% to cutting temperature, making it the most significant factor with optimal value of 164.570 m/min.
- Depth of cut and feed rate had minimal impact on cutting temperature under the tested conditions.
- Increased depth of cut and feed rate resulted in higher temperatures, but their influence was secondary to cutting speed.

3. Optimized Material Removal Rate (MRR):

- Feed rate had the highest contribution to MRR (57.64%), followed by depth of cut (26.79%) and cutting speed (7.92%).
- Higher feed rates significantly enhanced MRR but could also lead to increased tool wear and surface roughness.
- Depth of cut increases from 0.6 mm to 1.0 mm, improved MRR, but required careful consideration of tool deflection and vibration.

5. Validation and Model Performance:

- The RSM results showed strong agreement, with no variation between them, confirming the robustness of the optimization approach.
- The RSM model accurately captured interactions between machining parameters, making it a reliable tool for optimizing turning operations.

5.2 Recommendations

1. Process Optimization for Enhanced Performance:

- Cutting speed should be maintained between 160-170 m/min to achieve optimal surface finish and prevent excessive heat generation.
- Depth of cut should be optimized within 0.6-0.9 mm to balance MRR and surface finish quality.
- Feed rates should be carefully selected based on machining objectives; lower feed rates (0.04 mm/rev) are preferable for finishing, while higher feed rates (0.08 mm/rev) can be used for roughing operations.

2. Thermal Management and Tool Wear Mitigation:

- Since cutting speed predominantly affects cutting temperature, thermal control strategies (such as adaptive speed adjustments or optimized lubrication) should be considered.
- Excessive depth of cut and feed rates should be avoided to minimize tool wear and maintain machining efficiency.

3. Industrial and Practical Applications:

- The findings provide a valuable reference for optimizing CNC turning of AISI 1045 in industrial settings.
- Future research can explore alternative lubricants, tool materials, and hybrid machining approaches to further improve machining efficiency.

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Appendixes

A. Images Captured During Experimentation

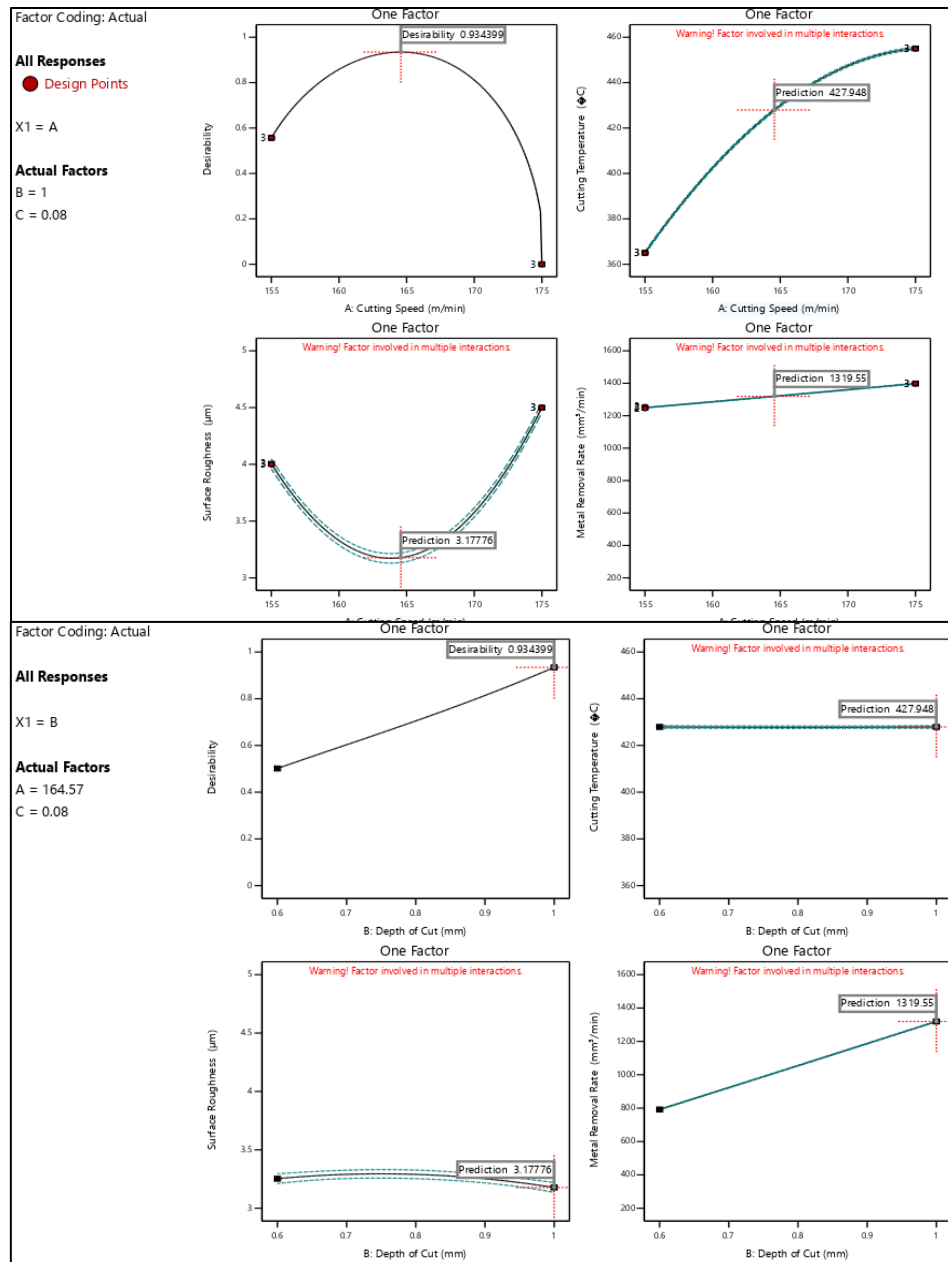
The images taken during the experimental process, displayed in [Fig.A. 1](#), visually depict the different stages and conditions under which the tests were carried out. These images provide essential insights into the setup, tools, workpiece, and machining environment, serving to document the procedures and validate the experimental approach. By capturing crucial moments of the experiment, these images act as valuable references for comprehending the results, ensuring reproducibility, and aiding in the interpretation of the findings.



Fig.A. 1 Images captured during the experiment

B. Visualizing Factors and Responses: Numerical Contour Plot Analysis

Numerical contour plot analysis is a powerful method for visualizing the relationships between different factors and their associated responses in experimental research. By displaying data in a two-dimensional format, contour plots enable researchers to identify trends, interactions, and optimal areas within the parameter space, as shown in [Fig.A. 2](#). This visualization approach improves the understanding of complex data, supporting more informed decision-making and optimization throughout the research process.



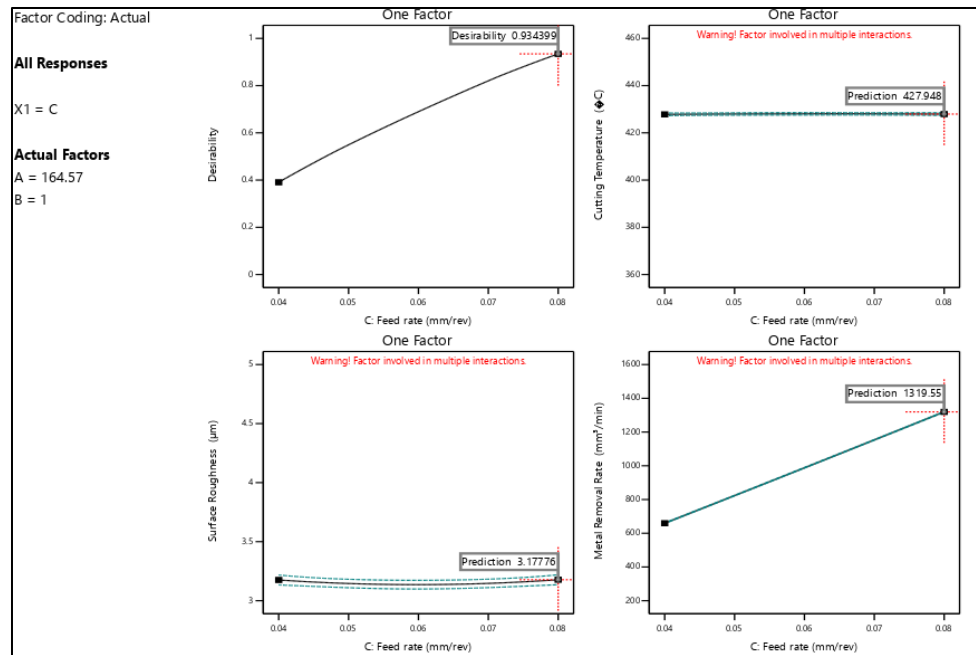
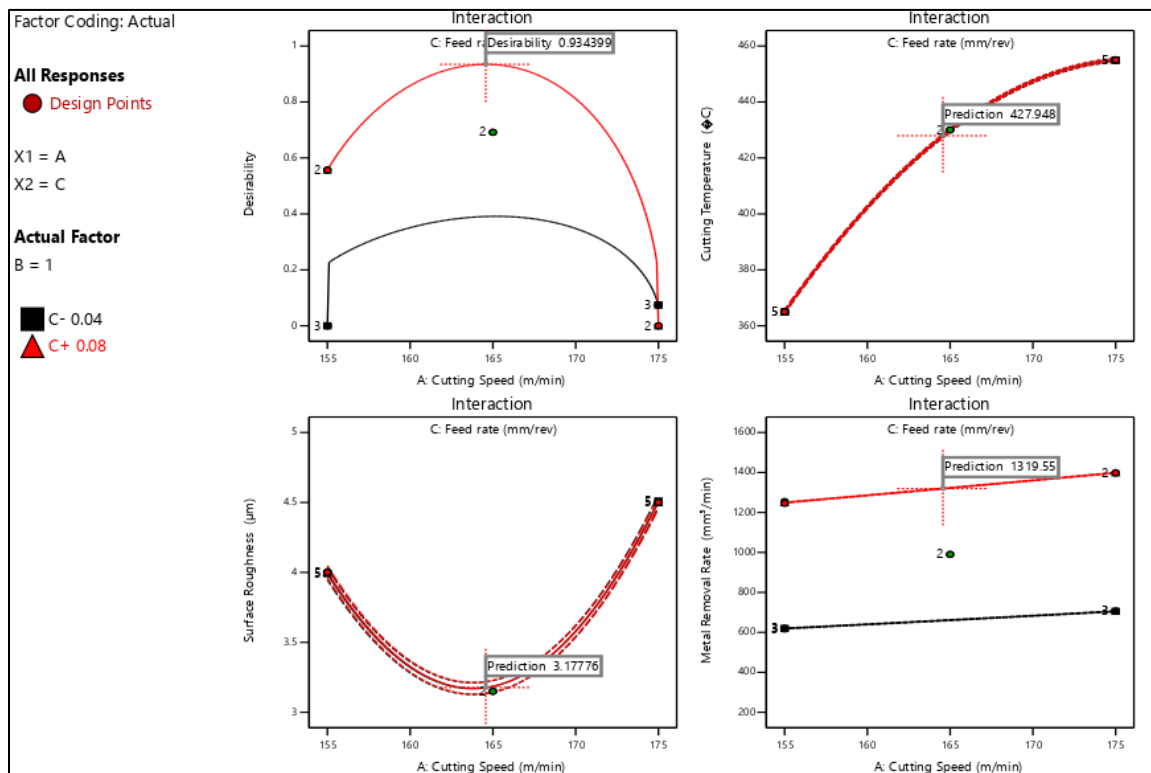
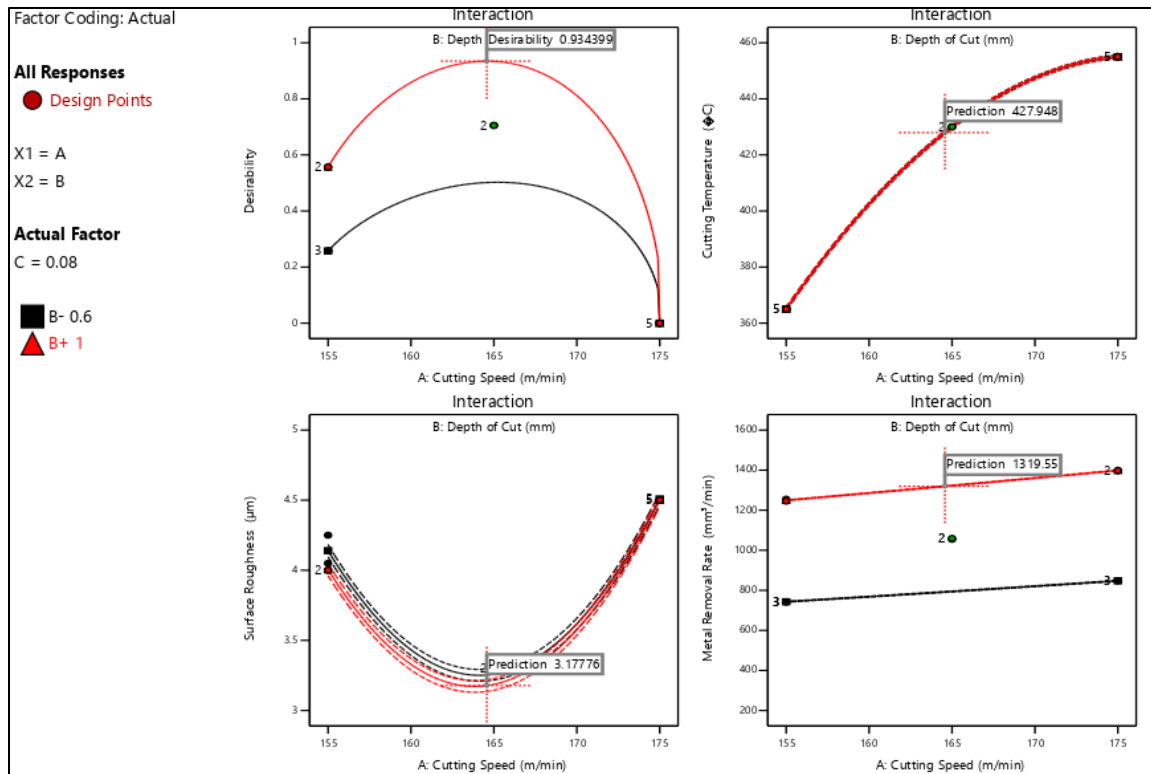


Fig.A. 2 Numerical Contour Plot Analysis of Factors and Responses

C. Numerical Interaction Plots of All Factors and Responses

Numerical interaction plots are an essential analytical tool in experimental research, offering a clear visual depiction of how different factors affect various responses, as shown in Fig.A. 3. These plots highlight the interactions between multiple variables, making it easier to identify important relationships and trends within the data. Understanding these interactions is key to process optimization, as it helps researchers determine the conditions that produce the most favorable results. This visualization improves data interpretation, supports better decision-making, and contributes to achieving the research objectives.



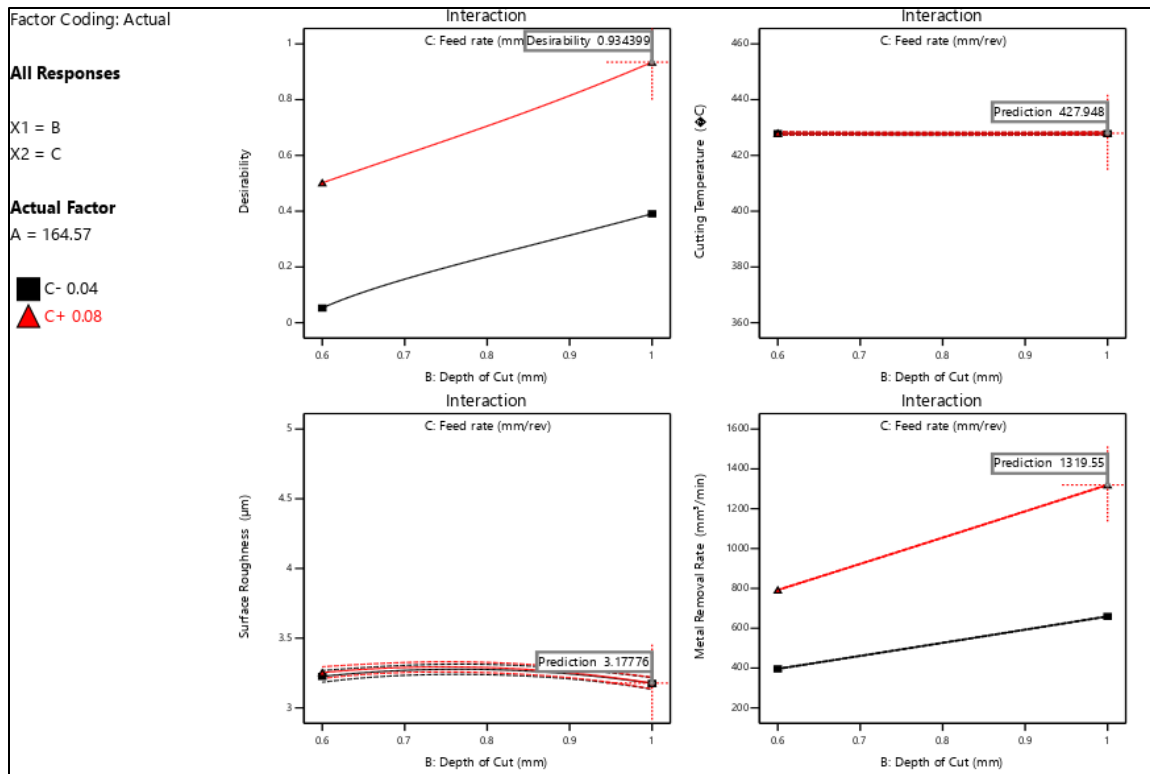


Fig.A. 3 Numerical Interaction Plots of All Factors and Responses

D. Numerical Cube Representation of Optimal Results

The numerical cube representation offers a three-dimensional visualization of the optimal results, displaying the interactions between multiple variables at once, as shown in Fig.A. 4. This approach provides a more thorough understanding of the relationships between factors, making it easier to pinpoint the combination of parameters that produces the best outcomes. By presenting a clear and detailed view of the optimal conditions, the numerical cube supports improved decision-making and process optimization in experimental studies.

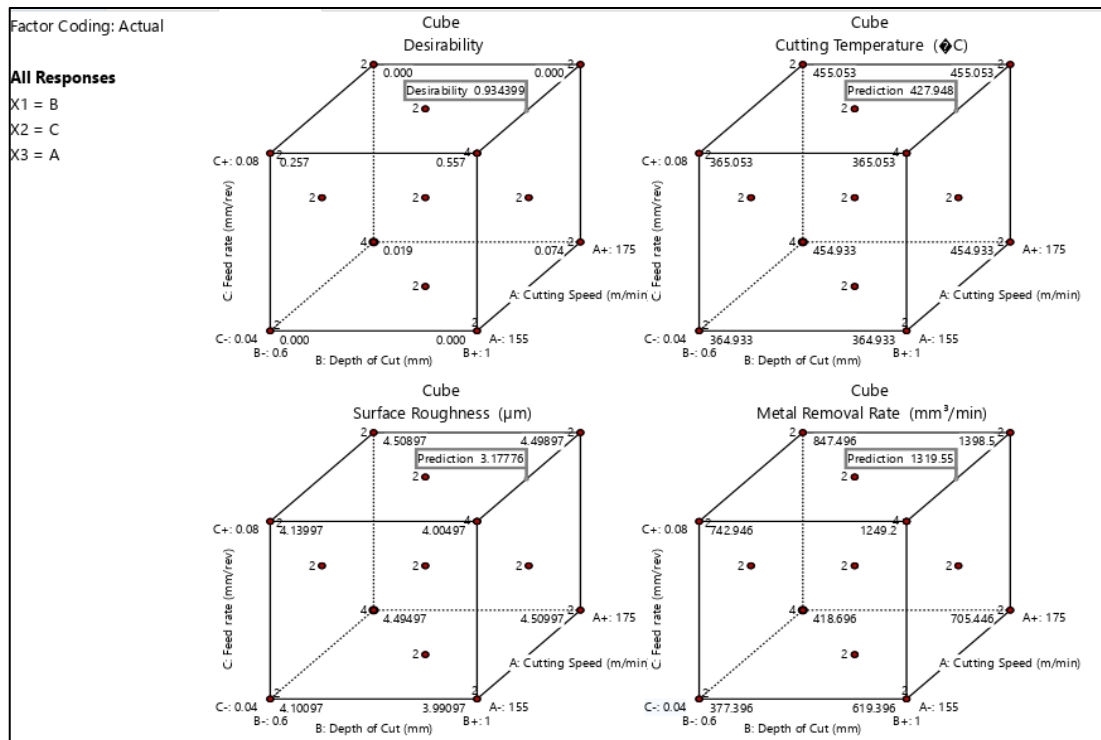


Fig.A. 4 Numerical Cube Representation of Optimal Results

E. Confirmation results of DFA

The validation results of the Desirability Function Analysis (DFA), including two-sided 95% confidence intervals, are presented in [Table A. 1](#).

Table A. 1 Confirmation results of DFA

Analysis	Predicted Mean	Predicted Median	Observed	Std Dev	n	SE Pred	95% PI low	Data Mean	95% PI high
Cutting Temperature	429.893	429.893		0.460435	1	0.492567	428.866		430.921
Surface Roughness	3.24956	3.24956		0.0334967	1	0.0358343	3.17481		3.3243
Metal Removal Rate	791.133	791.133		1.93278	1	2.06766	786.82		795.446