Experimental Investigation and Multi-Response Optimization of Turning Parameters for AISI 1050 Steel on CNC Machine Using Taguchi-Based GRA and GA

Mosisa Ligaba Yadeta

A Thesis Submitted to the Department of Mechanical Engineering
College of Mechanical, Chemical and Material Engineering

Presented in Partial Fulfillment of the Requirement for the Degree of Master's in Manufacturing Engineering

Office of Graduate Studies
Adama Science and Technology University

June, 2025
Adama, Ethiopia

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DECLARATION

I hereby declare that this thesis entitled **''Experimental Investigation and Multi-Response Optimization of Turning Parameters for AISI 1050 Steel on CNC Machine Using Taguchi-Based GRA and GA''** is my own work. That is, it has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

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Name of student	Mosisa Ligaba Yadeta
Id.No.	PGR/35836/16
Department	Mechanical Engineering
College	CoMCME
Course Title	M.Sc Thesis
Title of work / Assignment name	Investigation of Surface Finish and Optimization of Turning Parameters for AISI 1050 Steel on CNC Machine
Date of submission	

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We, the undersigned, members of the board of reviewers of the thesis open defense by Mosisa Ligaba Yadeta have read and evaluated the thesis entitled ''**Experimental Investigation and Multi-Response Optimization of Turning Parameters for AISI 1050 Steel on CNC Machine Using Taguchi-Based GRA and GA"** and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Manufacturing Engineering.

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ACRONYMS AND ABBREVIATIONS

AA	Arithmetic Average
AISI	American Iron and Steel Institute
ANN	Artificial Neural Network
ANOVA	Analysis Of Variance
CLC	Center Line Average
CNC	Computer Numerical Control
d	Depth of Cut
DOE	Design of Experiment
DOF	Degree of Freedom
EDS	Electric Dispersive Spectroscopy
f	Feed Rate
GA	Genetic Algorithm
GR	Grey Relational Analysis
GRG	Grey Relational Grade
MM	Mean Sum of Square
MOO	Multi-Objective Optimization
MQL	Minimum Quantity Lubricant
MRR	Orthogonal Array
Ra	Average Surface Roughness
RSM	Response Surface Methodology
S/N	Signal to Noise Ratio
SEM	Scanning Electron Microscopy
SS	Sum of Squares
TM	Taguchi Method
v	Cutting Speed
VB	Tool Flank Wear
wt. %	Weight Percentage

ABSTRACTS

The machining industry is challenged by achieving the required surface finish, longer tool life, and good productivity. Major challenges of turning of AISI 1050 steel are to get good surface finish, less tool wear and good material removal rate due to improper selection of cutting parameters and optimization techniques. To address those problems, the current research utilized a multi-objective optimization method in identifying optimal parameter settings. Regression equations were formed to predict the influence of cutting parameters on output response parameters, i.e., material removal rate, tool flank wear, and roughness on the workpiece surface. To validate the developed model as a true representation of relationships among variables, Analysis of Variance (ANOVA) test was conducted. Experiments were conducted on a CNC machine using AISI 1050 steel. The results indicated that feed rate contributes 91.83% variation in surface roughness and thus ranked as the most influential parameter among those parameters. The minimum recorded 0.67µm value for surface roughness occurred at maximum cutting speed, lowest feed rate, and maximum depth of cut while maximum 2µm for surface roughness occurred at moderate cutting speed, maximum feed rate, and minimum depth of cut. Maximum influence on material removal rate was due to depth of cut and accounted for 84.68%, and followed by feed rate and cutting speed at 10.16% and 3.51%, respectively. Least tool wears occurred at lower cutting settings and maximum tool wear at higher cutting settings. Maximum flank tool wear of 154 µm occurred at maximum cutting speed, maximum feed rate, and an intermediate level depth. Minimum flank tool wear of 54.85 µm was achieved at minimum cutting parameters. An optimal solution to a complex problem with numerous objectives was conducted using GRA and genetic algorithm techniques in MATLAB R2022b. Based on that, optimal pareto values were generated using genetic algorithm.

Keywords: *Multi-Objective Optimization, Genetic Algorithm, MATLAB, ANOVA*

CHAPTER ONE

INTRODUCTION

1.1Background of the Study

Machining is the shaping process that leaves the final desired shape by eliminating excess material from the original item. Relative motion between the material and the cutter is involved in a series of procedures that use a cutting tool to chip away the workpiece's material. The work surface shape was achieved by the combination of the primary motion specified by spindle speed and the secondary feed motion, which between them also established the profile of the tool and its engagement with the work surface. Optimization of the process involves the manipulation of a number of process variables to produce quality products at lower costs and optimum productivity (M. A. Khan et al., 2020).

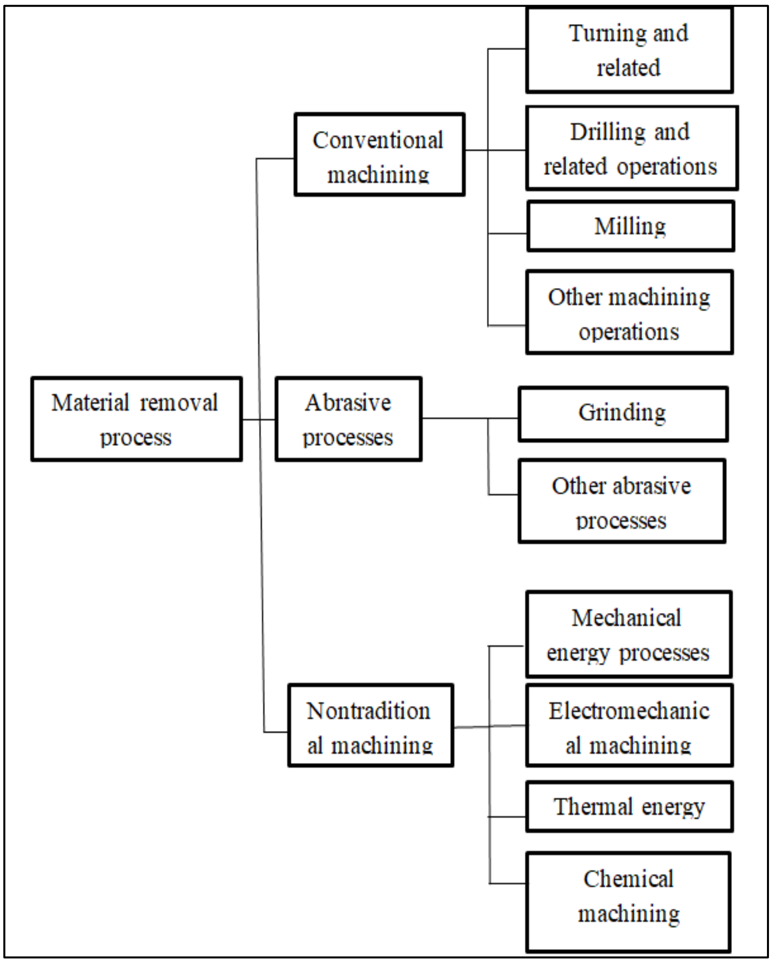


Figure 1.1 Classification of material removal process(Manufacturing, 2007)

The function of the machining process in the manufacturing process is so extremely important due to the fact that the reliability and durability of the manufacturing process rely on it (Sada et al., 2022). The process of turning involves removing metal from a cylindrical workpiece's outside diameter while it spins. This operation is typically performed to decrease workpiece size to a required diameter and to create a smooth metal finish(Akkuş & YAKA, 2018). Turning is the predominant material removal mode in machining processes due to its efficiency in material removal and in achieving a better surface quality(P. Sahoo, 2011). Modern production processes including grooving, threading, knurling, tapering, boring, and chamfering are efficiently automated using computer numerical control (CNC) lathe equipment. By establishing parameters for turning processes such as cutting speed, feed rate, and depth of cut, industries cost-effectively manufacture while maintaining a consistent surface finish in producing high-end products. CNC machining offers surface finish and dimensional accuracy enhancements by utilizing hard and tough tool steels that possess some material properties required for their intended function.

1.1.1 AISI 1050 Steel Material

AISI 1050 steel is classified as medium carbon steel and possesses good strength and toughness. It has approximately 0.48-0.55% carbon content that enables it to be used where higher hardness and wear resistance compared to low carbon steels is necessary, with reasonable ductility (Baday et al., 2020).

1.1.2 Industrial Application of AISI 1050 Steel

The materials utilized for the production of long-lasting devices and machinery is termed industrial materials. As such, these materials play a significant part in every realm of human life, ranging from social, environmental, to technological, and their production necessitates closer examination. AISI 1050 medium carbon steel is widely employed in the production of machinery, ships, aircraft, railway parts, and automobile parts (Yadav et al., 2012)(Akkuş & YAKA, 2018)(Sada et al., 2022).

1.2 Turning Operation, Turning Parameters and Turning Machine

1.2.1 Turning Operation

Turning is the process of removing material from a rotating cylindrical workpiece's outside diameter using a single-point cutting tool that is securely fastened to the tool post and parallel to the workpiece's axis at the proper feeds, speeds, and depths of cut. It is applied to the workpiece to form a cylindrical surface. In turning the diameter of the workpiece, usually changed to a specified dimension and the length of the work piece remain the same (Akkuş & YAKA, 2018).

1.2.2 Turning Parameters

The three primary factors in any basic turning operation are speed, feed, and depth of cut.

a) Spindle Speed (N)

The workpiece and spindle are always referred to in terms of rotational speed. Their rotational speed is indicated in revolutions per minute (RPM), which represents the spindle's complete rotations in a minute. However, for a given turning operation, the cutting speed; the rate at which the workpiece material moves against the stationary cutting tool is the most critical parameter. The cutting speed of a workpiece can be determined by multiplying its rotational speed (RPM) by the circumference based on the diameter before the cut begins. Since every workpiece has a different diameter, each will have a different linear (cutting) speed even if they share the same rotational speed (RPM) (Albertelli et al., 2012).

b) Feed Rate

Feed is the rate at which the cutting tool moves along its cutting path and is always used to refer to the cutting tool. On the majority of power-fed lathes, the feed rate, which is measured in millimeters per minute (mm/min), is directly proportional to the spindle speed (Sharma, 2020).

c) Depth of Cut:

This concept is essentially self-evident. It is the distance, measured in millimeters, between the work's uncut and cut surfaces, or the thickness of the layer being removed (in a single pass) from the work piece. However, because this layer is being removed from both sides of the work, it is vital to remember that the diameter of the work piece is reduced by twice the depth of cut (Gavrus et al., 2023).

1.2.3 Turning Machine

Manufacturers make lathe-class machines in a variety of configurations, including engine, turret, automatic, and CNC versions, which are used in turning activities. These machine tools offer sophisticated machining processes by integrating separate power transmission systems for each tool axis. The sizes typically vary between 12 and 24 inches in swing and between 24 and 48 inches in center distance, but swings up to 50 inches and center distances up to 12 feet are common. Chip collection pans and coolant circulation systems are standard equipment on most engine lathe machines.

Figure 1.2 CNC Lathe machine

1.3 Statement of the Problem

During CNC turning process of AISI 1050 steel it is a challenge to get improved surface finish, less tool wear, and optimum material removal rate (Harhout et al., 2020). The selection of proper cutting parameters such as cutting speed, feed rate, and depth of cut were a challenge in industry to get good surface finish, minimum tool wear and optimum MRR. Finding the optimum combination of cutting parameters is still a time consuming typically involving cost of machining increased due to trial and error methods used in industry. It is difficult to find the optimum machining parameters that minimize cost. There is less research conducted on experimental investigation of AISI 1050 steel turning by CNC and optimization of cutting parameters to get good MRR, tool life, and surface finish. In order to enhance turning efficiency, surface finish and tool life, simultaneously this study experimentally examined the effect of different cutting parameters on the machining performance of AISI 1050 steel (Baday et al., 2020).

1.4 Objectives of the Study

1.4.1 General Objective

To determine the optimal turning parameters (cutting speed, feed rate, and depth of cut) for AISI 1050 steel on a CNC machine using Taguchi-based GRA and GA, with the goal of simultaneously improving surface finish, tool life, and machining efficiency.

1.4.2 Specific Objectives

1. To investigate how cutting process variables including feed rate, depth of cut, and cutting speed affect the quality of the surface finish.
2. To examine how cutting factors (such as speed, feed rate, and depth of cut) affect tool wear.
3. To identify the optimal material removal rate achievable through systematic evaluation of specified cutting parameters.
4. To determine the cutting parameter combination that provides the best compromise between MRR enhancement, tool wear reduction, and surface roughness improvement.

1.4 Scope and Limitations of the Study

This work focuses on multi-objective cutting parameter optimization during flood-assisted CNC turning of AISI 1050 steel, with a special goal of achieving the best balance of surface quality, material removal rate (MRR), and tool wear. The inquiry prioritizes increased production efficiency and customer satisfaction, while recognizing the exclusion of cutting forces, machine vibrations, and tool nose geometry effects due to measuring limitations in the lack of a dynamometer.

1.5 Significance of the Study

The aim of this study is to experimentally assess how input cutting factors such as cutting speed, feed rate, and depth of cut affect various output responses during wet turning of AISI 1050 steel. Understanding these influences is crucial for improving surface quality, enhancing tool life, increase productivity, and achieving a better product appearance. When cutting tools operate effectively for longer periods, the need for replacements and the time required for tool changes can be significantly reduced. As a result, addressing the multi-objective optimization of cutting parameters that affect surface roughness, tool wear, and MRR is critical for generating high-quality products while also increasing productivity and tool life. This not only enhances customer satisfaction through the delivery of quality products that meet specific requirements but also benefits both the manufacturing sector and the research community.

1.6 Research Motivation

In any manufacturing industry, surface quality, productivity, and the cost of machined products are critical factors in increasing customer demand and firm competitiveness. Without surface quality, it is difficult to discuss high production rates, extended product life with no defects, fracture formation, and corrosion resistance. Furthermore, surface quality is critical in the applications of assembly parts that contain mobile components. Thus, the motivation for this endeavor stems mostly from the reasons listed above.

1.7 Structure of the Thesis

This thesis, entitled 'Investigation of Surface Finish and Optimization of Turning Parameters for AISI 1050 Steel on CNC Machine,' comprises five chapters: Chapter 1 introduces the research background, problem statement, objectives, significance, and scope; Chapter 2 reviews relevant literature on machining processes, cutting parameter effects (surface roughness, tool wear, material removal rate), and identifies research gaps; Chapter 3 details the experimental methodology, including materials, equipment, and procedures; Chapter 4 presents and discusses key findings; and Chapter 5 summarizes conclusions, provides recommendations, and suggests future research directions.

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

High-surface-quality machining metal product is becoming more and more in demand as a result of the industrial sector's need for efficient surface finishes, and their costs are rising sharply. Because of these shifts, researchers are currently looking at more effective approaches to balance these conflicting goals (M. A. Khan et al., 2020). Regardless of the machining method used, "machinability" refers to how easy it is to remove material. The term "machining" encompasses a wide range of qualities that were commonly described as output attributes or responses (Hosseini et al., 2016). In metal removal operations, the choice of input cutting conditions has a considerable impact on the output response. Therefore, identifying the optimal cutting parameters was crucial for enhancing productivity, reducing machining costs, and improving surface quality (Singh & Gill, n.d. 2020). This chapter reviews various studies conducted by researchers on the turning of different work piece materials and cutting tools, detailing their findings, the optimization techniques they applied, and the logical relationships between cutting parameters and output responses. To address this, several academics have gone to considerable efforts to examine how these cutting factors affect those output responses and recommend areas where optimum values are obtained. A cutting tool removes excess material to shape work pieces. Three motions cutting velocity, feed velocity, and depth of cut were needed, provided by the machine tool (Shaw, 2005).

2.2 Effect of Cutting Parameters on Surface Roughness

Surface roughness as a machinability index was very important parameter for getting a quality product in manufacturing industry because of affecting the fatigue and fracture behavior of any type of materials (Şahin, 2024). In many engineering applications, surface roughness measurement is an important task. The functional requirements of many parts may be dominated by this important quality characteristic. It plays an important function in determining the quality of a machined surface. A variety of factors influenced surface roughness, including cutting conditions, work holding mechanisms, cutting tool vibration, and machine tool vibration. An examination of how low-quantity lubrication conditions affect machinability has been conducted. A number of statistical analyses were carried out to determine the impacts of surface roughness and how they relate to the experimental parameters. In those instances, the desired result was achieved. A machined part's surface texture is determined by its surface roughness. Because it reveals how the machined surface deviates from the work piece material standards, this output response is crucial for study (Thakkar & Patel, 2014).

Surface roughness is still the most reliable measure of machined part quality. Low surface roughness increases the product's tribological qualities, fatigue strength, corrosion resistance, and aesthetic attractiveness. Surface quality and dimensional correctness have an impact on machine parts that come into touch with other elements or materials over time. The roughness of the surface during turning is influenced by the accompanying three cutting parameters, namely depth of cut, feed rate and cutting speed (Ahmed Al-Dolaimy, 2016). The material of the work piece, the material of the cutting tool, the geometry of the tool, and other factors all has an impact on surface roughness. As a result, the appropriate combination of components is critical to achieving the intended outcome. In this way, the primary goal of this exploratory effort was to determine the effect of cutting settings on surface roughness and to calculate the basic surface roughness. A lot of research has been conducted to improve the surface quality of machined components. The following paragraph discusses some pertinent literature.

Using the Taguchi OA method, (Rath et al., 2018) investigated the impact of cutting parameters on surface roughness during the dry turning of AISI D3. They found that the optimal surface quality was achieved at V = 80 m/min, f = 0.06 mm/rev, and d = 0.5, and that there is a strong correlation between tip temperature and surface roughness. (Pathak et al., 2018) conducted experiments to determine the relationship between cutting parameters and cutting force and surface roughness while turning AISI D3 in dry condition, and ANOVA and Multi Response Performance Index (MRPI) was used to identify significant parameter and optimize cutting parameters respectively and result of study showed that cutting speed and feed rate are significant parameters that affect output responses, and optimum value was obtained at 150 m/min speed, 0.05 mm/rev feed, 0.2 mm depth of cut by 0.8 mm nose radius. Dry turning tests were conducted by (Yalçın, 2015) on soft HRC 22 and hard HRC 52 AISI H13 to determine the effect of different cutting tools and cutting parameters on the surface roughness. An analysis of variance (ANOVA) was used to investigate how cutting parameters interacted with Ra, and the results showed that a CBN tool had lower surface roughness in hard turning than a ceramic insert. Dry turning experiments on hardened DIN 1.2344 hot work tool steel were performed by (Nas & Altan Özbek, 2020). Performance characteristics were studied using grey relational analysis, and parameters were designed using the Taguchi technique. The experiment's analysis found that the biggest factor influencing surface roughness was a 72.84% feed rate. Research work was conducted in order to optimize the turning parameters for lower cutting force, machining temperature, surface roughness, and higher material removal rate using Grey Relational Analysis (GRA) on hardened AISI S7, and analysis of variance was used to identify significant parameters on response variable and result from GRA showed that optimal turning parameters were $n = 1.2mm,\ V = 450\, m/min,\ f = 0.05\, mm/rev$ & $d = 0.2\, mm$ and result from ANOVA showed that depth of cut was the most significant parameter affecting surface roughness and higher cutting speed was significant parameter(Awale & Inamdar, 2020). (Akkus, 2021) Studied effect of process parameters on surface roughness, vibration, and energy consumption on 6A-4V ELI (Grade 5) alloy, and in order to determine appropriate cutting condition researchers employed Taguchi for design of experiment, S/N, ANOVA, and Pareto analysis to analyze experiment. Finally, the results demonstrated that surface roughness increases with feed rate and is very low at medium cutting speeds. Similarly, feed rate was observed to have the greatest influence on surface roughness (Zheng et al., 2018). The effect of tool tip radius, cutting speed, feed rate, and depth of cut on surface quality of AA7075/15 was investigated and Response Surface Methodology was used to determine effect of cutting parameters on surface roughness and cutting speed is observed as significant parameter that affect surface quality (Bhushan, 2020).

(Meddour et al., 2018) studied an exhaustive examination of the turning parameters that affect surface roughness in the finishing turning of AISI 4140 hardened steel with a mixed ceramic tool. To analyze the influences of important machining factors such as feed rate, depth of cut, cutting speed, and tool nose radius, the authors use Response Surface Methodology (RSM), Artificial Neural Networks (ANN), and Non-dominated Sorting Genetic Algorithm II (NSGA-II).The findings indicate that enhancement of these parameters, particularly with larger tool nose radii and higher cutting speeds, leads to better surface finish quality while, simultaneously, removing the adverse effects associated with high feed rates. This research highlights the requirement for an integrated parameter selection approach, encompassing experimental validation as well as predictive modeling techniques, thereby providing important guidelines for optimizing the effectiveness and efficiency of hard turning operations.

(Yağmur, 2021) examined the noteworthy influence of cutting parameters on the surface roughness while turning Inconel 625, a nickel-based super alloy. The results show that differences in cutting speed and feed rate have a substantial effect on surface quality. Experimental findings indicated the optimum surface roughness at a feed rate of 0.1 mm/rev and cutting speed of 80 m/min under minimal quantity lubrication (MQL).

(Rathod et al., 2023) explained in detail the effect of cutting parameters on surface finish during turning of AISI 304 stainless steel on CNC. The study effectively uses the Taguchi approach to determine that cutting speed, feed rate, and depth of cut are parameters that contribute to the machined component's surface roughness. The results show that the best surface finish quality was achieved at a cutting speed of 550 m/min, a feed rate of 0.14 mm/rev, and a depth of cut of 0.40mm. The value of cutting speed is particularly visible in improving surface qualities, increasing tool life, and reducing cutting production time, as evidenced by the use of ANOVA, which identifies the impact of these parameters. This discourse improves understanding of the issues connected with machining operations and provides vital information for manufacturing firms seeking to produce products with enhanced surface quality.

According to (Touggui et al., 2020) the influence of various cutting parameters on surface roughness during dry turning of AISI 316L stainless steel using a PVD-coated cermet insert was discussed in detail. According to the study, the feed rate accounts for 79.61% of the overall contribution and has the greatest influence on surface roughness, indicating that increasing the feed rate results in a rougher surface finish. This calls for paying special attention to controlling the feeding mechanism during machining operations to be able to realize the desired surface quality. To help establish a firm foundation for grasping the intricacies of the interactions of the machining parameters, the study employs the systematic procedure involving the Taguchi experimental design method, response surface methodology, and analysis of variance (ANOVA) in the assessment of the data.

(Singh & Gill, n.d, 2021) studied in detail the methods of optimizing machining parameters in order to maximize AISI D3 steel surface roughness in a parting operation. Cutting speed, feed rate, and depth of cut are among the main machining factors evaluated, with the authors successfully establishing their effect on final surface quality using Response Surface Methodology and Analysis of Variance. The results showed that the optimum surface roughness was attained when the cutting depth was 1 mm, the feed rate was 0.01 mm/rev, and the cutting speed was 140 m/min. It was also demonstrated that using smaller feed rates with faster cutting speeds improved surface quality. The prediction models show the applicability of these implications to machining processes for achieving high-quality finishes in precision engineering. They also demonstrate potential in effectively predicting surface roughness in machining processes. In summary, this work provides insightful perspective into the complicated interactions among machining parameters and provides the basis upon which future breakthroughs can be made in surface quality optimization.

(Vukelic et al., 2021) employed a genetic algorithm (GA) to optimize the turning process parameters of AISI 1040 steel under dry conditions. The optimized parameters resulted in mean error percentages of 1.146% for surface roughness and 1.478% for flank wear. In a separate study, (Dash et al., 2020) analyzed the effect of machining factors on surface roughness during the turning of AISI D2 steel. They utilized Response Surface Methodology (RSM) and Design-Expert software for mathematical modeling and optimization. According to the findings, the best surface finish for AISI D3 steel is achieved at minimum cutting speeds of 140 m/min, feed rates of 0.01 mm/rev, and depths of cut of 1 mm. It was discovered that at feed rates ranging from 140 m/min to 170 m/min, the surfaces produced are smoother in the provided roughness parameters of 0.02 mm/rev to 0.05 mm/rev. The researchers (Ponnusamy & Tamilperuvalathan, 2023) investigated the application of various lubrication conditions to enhance machinability of SS304 alloy steel in turning operations. The lubrication conditions included dry machining, water-emulsified coconut oil, MQL, and several nanoparticle combinations with MQL. The machining outcomes were assessed and analyzed using Response Surface Methodology and a hybrid predictive model consisting of a deep recurrent neural network and a black widow optimizer (DRNN-BWO). In comparison with the MQL and dry conditions, the novel dual hybrid nano-MQL condition significantly reduced surface roughness without amplifying tool wear.

2.3 Wear on Tools

The gradual deterioration of cutting tools during machining is known as tool wear. Tool wear raises cutting temperatures and lowers surface quality, making it a crucial machining parameter. Additionally, rapid tool wear lengthens the time required for tool changes, which lowers production speed (Yallese MA, Belhadi S, Bouchelaghem H, Amirat A, 2016). Tool wear has a substantial impact on machining costs and quality. Rapid and unpredictability in tool failure increases costs and scrap rates. These factors make tool wear the most often used criterion to determine the performance of cutting tools (A. & Agapiou, 2016). Tool wear is quantified by looking at the tool's wear scar under a microscope or, less frequently, with a stylus tracing tool. The fact that these sensors often only offer 2D information is a drawback. For general-purpose 3D contouring or tool surface finish or edge preparation measurements, more sophisticated microscopes have been created that use confocal or fringe projection techniques in addition to laser interferometers (Khanna et al., 2020).

(Kashkool, 2022) investigated the turning of AISI 1045 steel with TiN-coated carbide inserts, together with machining conditions and tool wear. The carbide inserts' wear and chipping vary significantly as the feed rate and spindle speed were adjusted. When the optimum spindle speeds were combined with lower feed rates (50 mm/min), the inserts experienced minimal wear and damage. This led to improved surface quality, specifically a minimum surface roughness of 4.14 µm. Conversely, higher feed rates (160 mm/min at 710 rpm) resulted in increased vibrations and local heating, which were detrimental to the TiN coating and accelerated tool wear, eventually contributing to a poorer degree of surface polish (Ra of 7.9). The findings showed the importance of selecting the appropriate machining conditions to reduce tool wear and increase cutting tool durability. This, in turn, enhances overall machining efficiency and product quality.

(Kamble et al., 2021) examined the effect of turning parameters on tool wear when turning AISI 4340 steel with a hybrid Taguchi-Grey relational analysis (HTGRA) method. Surface roughness and tool wear, two critical characteristics influencing machining efficiency and component correctness, are included in the optimization strategy. The study identifies several independent criteria that have a significant impact on tool wear rates, such as feed rate, depth of cut, and tool type. The authors propose the ideal conditions for minimizing tool wear while retaining surface quality by conducting a thorough examination of these parameters on an experimental rig based on a CNC lathe. The study indicates that certain parameters, like the depth of cut, affect tool wear more than others. This implies that proper selection and control of machining conditions could improve tool life and reduce operational costs in industrial practice.

During turning operations, direct contact between the tool and the work piece generated a significant quantity of heat. This elevates the temperature, which diminishes the workpiece's strength while increasing its ductility. Additionally, vibration increases during material removal in turning, raising the turning temperature and leading to tool wear (Yu et al., 2019). AISI D3 Steel, which has high levels of carbon, tungsten, molybdenum, and chromium, provides exceptional wear resistance and is used in a variety of fields (Hosseini et al., 2016) (Rafighi et al., 2021). However, utilizing strong tool steels alone is not enough to obtain the best results; cutting fluid application is also necessary to lower tool tip temperature and provide smoother surfaces in machined products (A. Das et al., 2019).

2.4 Study of Cutting Fluid

Cutting fluid serves as both a coolant and a lubricant in machining processes, lubricating the cutting tool and the workpiece to reduce friction, disperse heat, and increase tool life. It not only helps to remove heat and debris generated during machining, but it also enhances the tribological interactions between the tool and the workpiece, extending tool life and improving the surface quality of the workpiece. Cutting fluids can pose a number of difficulties, though, such as pollution of the environment, operator skin irritation, pollution of water, and oil waste during disposal (Adler et al., 2006) (Buongiorno, 2006). The study additionally exert a major impact on the whole cost of manufacturing. Because of these problems, biodegradable coolants and coolant-free machining alternatives are being investigated. Researchers investigated alternate cutting fluids, such as minimum quantity lubrication (MQL), coated tools, cryogenic cooling, dry machining, and solid lubricants.

2.5 Types of Cutting Fluid

There are four basic types of conventional cutting fluids, each with unique thermo-physical characteristics, application techniques, and treatment procedures (Adler et al., 2006) (Awale & Inamdar, 2020).

1. **Straight Oil**

Straight oil is mostly used in lubricating processes and is composed entirely of mineral oil or vegetable oils. Straight oils are good lubricants, but they do not transfer heat very efficiently. Mineral oil is quite expensive because to its high flammability and poor performance at high cutting speeds. Vegetable oils are non-toxic and eco-friendly, with benefits in terms of resource renewability, biodegradability, and performance in a range of applications (M. M. A. Khan et al., 2009).

2. **Soluble Oils**

Soluble oil, a combination of water and oil, has a higher cooling capacity than plain oil and provides protection against rust and corrosion. This water-based cutting fluid performs particularly well when used with new cutting tool materials such as hard metals and at high cutting speeds for operations such as turning, milling, and grinding. Water-based cutting fluids demonstrate the ability to reduce heat produced during machining, hence reducing tool wear (Adler et al., 2006).

3. **Semi-Synthetics**

Semi-synthetic cutting fluids have a different composition yet perform similarly to soluble oils. They often include inorganic elements or other water-soluble substances in addition to 30% or less emulsified oil. In comparison to soluble oils, this blend offers improved qualities and easier maintenance. But when semi-synthetic fluids come into contact with other machine fluids, they can tarnish and can cause dermatitis in workers (Adler et al., 2006).

4. **Synthetics**

Chemical liquids made of inorganic or other soluble substances that mix well with water to produce improved cooling capabilities are known as synthetic cutting fluids. Synthetic lubricants are gradually being replaced by biodegradable ones in the context of green production. These biodegradable cutting fluids provide good dependability and gratifying financial advantages while reducing environmental pollution. Furthermore, the manufacturing of bio-based cutting fluids produces less air pollution and is cleaner, which lowers the risks to occupational health. Compared to other cutting fluid types, bio-based cutting fluids have a significantly decreased adverse environmental impact, despite the fact that they might not be adequate in all aspects (Debnath et al., 2016).

2.6 Material Removal Rate

In turning operations, material removal rate is an important aspect in addition to surface finish quality; a greater MRR is preferred (Kaladhar et al., 2011). According to (Salgar et al., 2019), the primary objective of machining is to maximize the rate of material removal while producing products with minimal surface roughness. Through effective parameter optimization and precise outcome prediction, the combination of Response Surface Methodology, Taguchi technique, and Artificial Neural Networks improves turning operations, resulting in increased productivity and performance (Efa et al., 2024).

2.7 Optimization Techniques

Different optimization techniques have been utilized in many studies for determining the optimum set of variables yielding the most desirable results for a given process (Henry et al., 2020). To reduce the number of test runs and find the best cutting conditions, modeling and optimization approaches were used during the turning process. In the modeling technique, the interaction of input parameters and response variables is used to create a mathematical equation-based model for determining the best cutting circumstances. In an optimization technique, the cutting conditions are generated by creating an objective function, which may or may not include a mathematical model. Turning operations used a variety of modeling techniques, including regression-based modeling, fuzzy modeling, artificial neural networks, response surface methodology, Taguchi methodology, grey relational analysis, and genetic algorithms.

2.7.1 Taguchi Method

According to (Henry et al., 2020), this method is among the most popular statistical techniques applied in the determination of the best outputs through optimization of the input variables. Taguchi design of experiments elevates conventional design to a more dependable system. The method enables comprehension and assessment of the interaction among the factors affecting the output parameters. A sensible number of trial experiments were determined by the orthogonal array (OA) employed in Taguchi analysis. The experimental runs using these orthogonal arrays are few in number (Padhy & Singh, 2020).

2.7.2 Multi-Objective Optimization

The simultaneous and systematic optimization of a set of objective functions is referred to as multi-objective optimization (MOO). Consequently, there may be a number of optimum solutions for a multi-objective problem. An exception is the case when objectives are not in conflict, where a single solution can be expected. (Serra et al 2018). There are many types of techniques to conduct multi objective problems.

2.7.3 Response Surface Methodology

Based on the application of empirical models to experimental data, response surface methodology is a strong and adaptable approach in the field of design of experiments. These data are obtained through the correlation of response variables with input decision variables for the purpose of maximizing or minimizing response characteristics. RSM is a set of statistical techniques that use linear or quadratic polynomial functions to outline and examine the experimental conditions of a system until its optimal performance is obtained (Montgomery, 2013)**.**

2.7.4 Taguchi Based Grey Relational Analysis

AISI 1050 steel has a wide range of uses in the marine, aircraft, space, nuclear, and manufacturing industries, many of which need high temperatures. Taguchi design was used to create trial phases, and gray relation was used to combine several response findings into a single response. The experimental results were analyzed to attain optimum cutting force (Fc), surface roughness (Ra) and material removal rate (Padhy & Singh, 2021).

2.7.5 Artificial Neural Network

In the material-removal operations in manufacturing, like turning, milling, and drilling, there is great significance. As it is, ongoing improvement in the operations is necessary. The application of new methodologies, such as artificial neural networks, for response prediction will fulfill this requirement. The fundamental goal of this research is to use artificial neural networks and the Taguchi method to forecast tool wear when turning EN24 material. Much work has been done to implement artificial neural networks in machining operations (Kamble et al., 2024).

2.8 Research Gap

Optimizing cutting parameters to achieve acceptable surface smoothness, longer tool life, and efficient machining performance is a persistent difficulty when machining AISI 1050 steel, medium-carbon steel that is frequently utilized in a variety of industrial applications (Harhout et al., 2020). Although a lot of research has been done on how cutting speed, feed rate, and depth of cut affect machining results, there is still a lack of thorough studies that examine how these factors affect surface quality, material removal rate, and tool wear in particular for CNC turning operations on AISI 1050 steel. Moreover, many existing studies focus either on individual parameter optimization or limited parameter ranges, without considering the comprehensive impact of all key variables in real-world CNC operations. One major gap in existing knowledge was the absence of a systematic methodology that takes into consideration the relationships between cutting parameters and their impacts on MRR, tool life, and surface finishes simultaneously. While some studies have utilized Design of Experiments for optimization, there was limited application of this methodology in the context of CNC turning for AISI 1050 steel, which could reduce experimental trials and provide more reliable, statistically significant results.

Given that AISI 1050 steel is widely used in the aerospace, automotive, and heavy machinery industries, optimizing its machining characteristics is critical for increasing productivity, lowering costs, and extending tool life. However, the lack of research that includes several reactions into a comprehensive optimization framework limits the chances of achieving optimal machining performance. To fill these gaps, this study examines the combined effects of cutting speed, feed rate, and depth of cut on surface polish, tool wear, and MRR in CNC turning of AISI 1050 steel. This study uses Taguchi-based GRA, GA, S/N ratio analysis, and ANOVA to create a multi-response optimization technique that reduces experimental trials, improves machining efficiency, and promotes sustainable manufacturing practices.

CHAPTER THREE

MATERIALS AND METHODS

3.1 Introduction

This chapter describes the experimental approach and material properties used in this research, which included empirical analysis and multi-objective parametric optimization of AISI 1050 using turning operations. The experiment was carried out with the goal of optimizing the cutting parameters while also improving the surface finish, reducing tool wear, and increasing the material removal rate during the turning operation on the workpiece by using coated carbide cutting tool inserts. This study's analysis included Taguchi-based GRA, GA, S/N ratio analysis, and ANOVA.

3.2 Experimental Procedure

The current work involves an experimental investigation carried out in accordance with a research methodology developed based on the Taguchi approach. The overall methodology adopted for use during experimental work is schematically shown in Figure 3.1. The input factors relevant for the process include workpiece material, machining conditions designated for a specific machine tool, and also the inserts that are mounted and clamped within a specific tool holder.

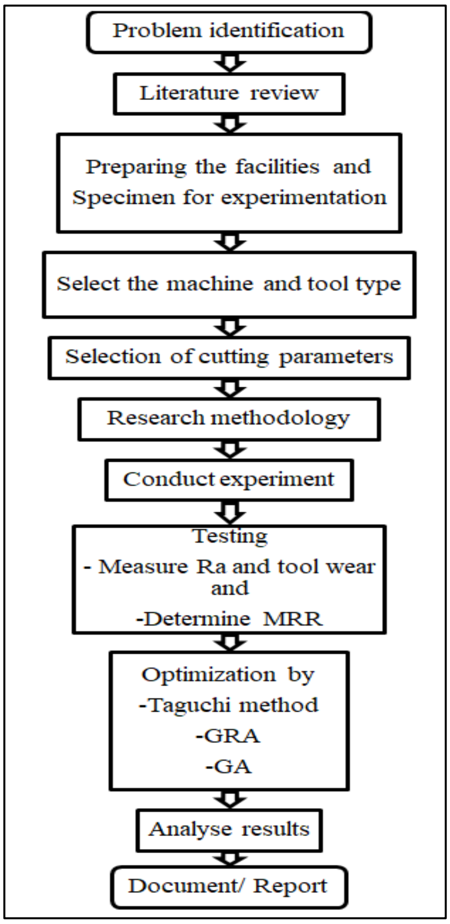


Figure 3.1 Experimental flow chart

3.3 Materials and Composition

The materials used in this study were AISI 1050 grade steel, which is distinguished by its high ductility, outstanding strength, and ease of machining. Because of its exceptional hardness, high-temperature dimensional stability, and resistance to wear, AISI 1050 steel, which has medium carbon content, is commonly used in machining. Table 3.1 shows the chemical composition of the substance in weight percentages based on an EDS (Electron Dispersive Spectroscopy) study. Due to its favorable mechanical properties, it is widely used across multiple engineering fields. In the automotive industry, it is commonly employed in critical components such as shafts, camshafts, gears, and axles, where durability and wear resistance are essential. The material is also extensively used in general machinery and industrial applications, including pins, spindles, bolts, nuts, and high-speed screw machine parts, benefiting from its machinability and ability to be heat-treated for enhanced performance (Baday et al., 2020). Table 3.2 shows mechanical properties of AISI 1050 steel (Demir & Adiyaman, 2019).

Table 3.1 Chemical composition of AISI 1045 steel in weight %

Elements	C	Mn	Si	Cr	Cu	Iron
AISI 1050 Steel	0.51	0.6	0.24	0.11	0.21	98.1

Table 3. 2 Mechanical properties of AISI 1050 steel (Demir & Adiyaman, 2019)

Mechanical properties	Metric
Tensile strength	690 MPa
Modulus of elasticity	190–210 GPa
Yield strength	450 MPa
Shear modulus (typical for steel)	80 GPa
Poisson's ratio	0.27–0.30
Brinell Hardness	197
Elongation of at break (in 50 mm)	0.27–0.30
Thermal conductivity	49.8 W/Mk

3.4 Selection of Cutting Inserts/Tools

In this work, the coated carbide insert cutting tool was used for experimental purposes. According to (Kaladhar et al., 2011) coated carbide tools outperform uncoated carbide tools. As a result, the experimental inquiry utilized generally available Chemical Vapor Deposition (CVD) of Ti (C, N) +Al2O3 coated cemented carbide inserts with a nose radius of 0.8 mm (Chakraborty et al., 2023). The inserts feature an ISO TNMG designation with 0.8mm nose radius, emphasizing the importance of selecting the right cutting tool geometry in metal cutting (Polytechnic, 2021) (Vukelic et al., 2021). Figure 3.2 show coated carbide tool inserts and its holder.

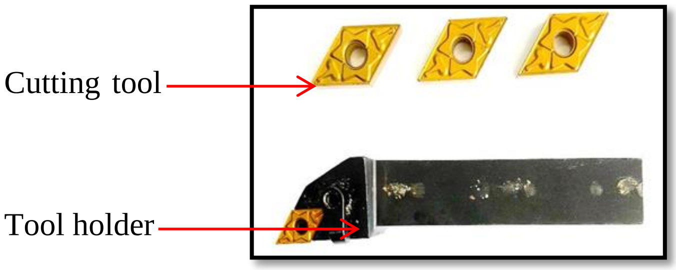


Figure 3.2 Coated carbide tool inserts and its holder

3.5 Turning Machine

Turning machines are also known as lathes. A lathe is a machine that rotates a work piece about its axis of rotation while holding a cutting tool stationary in order to perform various machining operations such as turning, facing, drilling, and others. Lathes come in a variety of sizes and designs. Machines can be classed according on the type of control provided. A typical lathe requires the operator to regulate the cutting tool's motion during the turning operation. Turning machines can also be computer controlled, in which case they are known as a computer numerical control (CNC) lathe, and they conduct the turning process according to a preprogrammed program; these sorts of lathes are preferred because they provide extremely high precision. Figure 3.3 shows the CNC lathe utilized in the turning process.

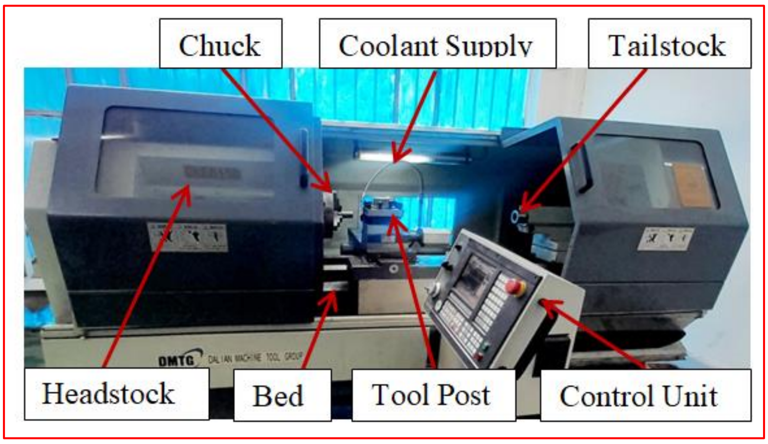


Figure 3.3 DMTG CNC Lathe machine main component

DMTG CNC lathe machine (model CKE 6150) with a 3-phase power supply running at 380V, 50 Hz and power 7KW with specification Ø500x1000mm was used for this study. Figure 3.3 shows a general view of a Dalian CNC lathe machine and its main components.

3.6 Selection of Process Parameter

Since AISI 1050 steel and coated carbide inserts were utilized, process parameter levels were determined based on previous research, ensuring relevance and practical application in machining processes. Validation using optimization techniques reinforces the justification, making the selection scientifically and industrially sound. Table 3.3 shows the input process parameters used during the experiment, as well as their levels and ranges, to assess the experiment and collect data for further analysis using Taguchi-based GRA, GA and ANOVA. According to the literature that has already been composed, these process parameter ranges were selected (Varaprasad et al., 2014) (Irfaan et al., 2015) (Rafighi et al., 2021) (Padhan et al., 2023)(Harhout et al., 2020)(Baday et al., 2020)(Chakraborty et al., 2023).

Table 3.3 Levels of process variables

Cutting Variables	Parameter Designation	Levels		
		1	2	3
Cutting speed v (m/min)	A	180	210	240
Feed rate f (mm/rev)	B	0.08	0.10	0.12
Depth of cut d (mm)	C	0.5	1.0	1.5

3.7 Surface Roughness Measurement

Surface roughness is a crucial machining process parameter that affects the quality of the final product. It gauges surface defects that are finely tuned. Since a smoother surface, a feature of well-finished components, reduces the risk of surface damage from wear and corrosion, increases fatigue strength, decreases creep failure, and ultimately boosts industry productivity and economic efficiency, the quality of surfaces produced by conventional and non-conventional machining processes is crucial. In turn, the quality of components achieved by a process of turning could affect performance with regard to wear and corrosion resistance. Surface roughness is defined using a variety of methods, with Ra, Rq, Rz, and Rt being appropriate for particular purposes. However, because it measures a quantity that is equivalent to the area between a surface profile and a center line, also known as the arithmetic average (AA) or center line average (CLA), average surface roughness, represented by Ra, is widely used in industry for mechanical parts to express surface roughness. Consequently, for purposes of research, within this context, Ra has been used for defining surface roughness.

Figure 3.4 shows a schematic of the VOGEL Surface Roughness Tester, model number 65711, made in Germany, which was used to measure surface roughness. This equipment measures roughness parameters in micrometers (µm). The VOGEL Surface Roughness Tester 65711 has a working range of 0.02 µm to 10 µm. The stylus attached to the instrument's detection unit detects minute imperfections in the workpiece. The stylus' vertical motion while tracing is monitored and shown digitally on the instrument's liquid crystal display.

Figure 3.4 Surface roughness testing equipment

3.8 Tool Wear Measurement

After each machining operation using AISI 1050 steel, the tool-tip insert was removed and a careful visual assessment of tool-tip wear and tool wear pattern was performed using an optical microscope (Model-Huvitz HR-300 series) with magnifications of X50, X100, X200, X500, and X1000. The microscope utilized in this study is depicted in the above figure.

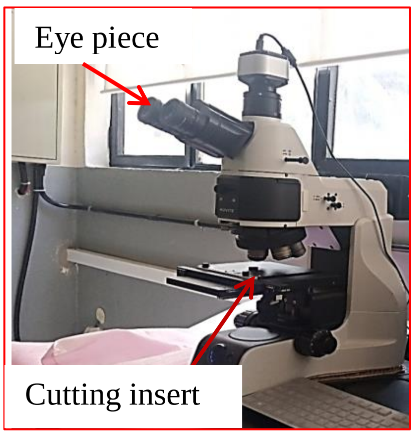


Figure 3.5 Optical microscope used for observing tool wears

3.9 Determination of Material Removal Rate

The material removal rate is the volume of material removed per unit time which ultimately determines machining productivity (Navneet Sainiet al., 2017). In roughing operations and large batch production, the material removal rate must be optimized. However, in finishing processes, it influences surface roughness, tool life, cutting temperature, and overall machining efficiency. Low cutting parameters are typically used in the turning process to achieve low surface roughness and tool wear, as MRR is usually low for finishing. In the present investigation, the following formula has been used to compute the material removal rate(Stojković et al., 2022)(Mastan Rao et al., 2023).

$$MRR = V * f * d \tag{3.1}$$

Where: f = Feed rate mm/rev

v = Cutting speed in (m/min)

d = Depth of cut in mm for each turn.

3.10 Design of Experiment and Optimization Methodology

The experiments were conducted utilizing the aforementioned materials and a methodical technique. This section explains methodology, including the process of specimen preparation, experimental protocol preparation, selection of an orthogonal array, and post-experiment variance analysis.

3.10.1 Specimen Preparation

The current study made use of AISI 1050 grade steel, a metal that is widely used in many different engineering fields. It is specifically used to make parts for automobiles, general engineering, machinery, aerospace, gears, pinions, bolts, nuts, shafts, camshafts, pins, spindles, and high-speed screw machines, among other things. Three medium carbon AISI 1050 steel samples, with a length of 310 mm and a diameter of 40mm, were turned with a cutting depth of 1mm, with an objective of removing surface defects within a length of 300mm. Nine experiments were carried out with cuts of 30mm length, with the cutting depth being varied from 1.5 mm, 1.0 mm, and 0.5mm using different turning parameters for analysis purposes, with some of the chosen cutting conditions being laid out based on an orthogonal array, shown within Figure 3.6.

Figure 3.6 Workpiece material

3.10.2 Design of Experiment

Design of experiments is an important and effective approach in total quality management that Dr. Taguchi utilized to build high-quality systems at a low cost. In manufacturing, he highlights that robustness and resilience against unpredictable circumstances are ensured by quality. As the number of process factors rises, this strategy drastically lowers the number of experimental trials (Kaladhar et al., 2011). Because of its methodical approach to experiment planning, DOE was selected over alternative approaches. For DOE, the Taguchi methodology has gained the most traction over the last two decades. The use of orthogonal arrays is an important component of Taguchi's methodology since it facilitates the trials required to identify the optimal values for each process parameter and evaluate their relative significance. An OA, or a constrained set of all possible combinations, allows for the fewest number of experiments. Taguchi developed the signal-to-noise ratio, which considers both mean and variability in order to generate the optimal process parameter options. ANOVA and the S/N ratio are used to evaluate how process factors affect measurements of performance. Taguchi supports structuring experiments with orthogonal arrays, identifying optimal circumstances by examining the primary effects of each parameter. The most popular statistical technique for analyzing the data is ANOVA, which aids in calculating each parameter's percentage contribution at a given confidence level. It is possible to determine which parameters deserve control by carefully examining the ANOVA table (A. K. Sahoo & Sahoo, 2013). The Taguchi design parameter framework uses a number of procedures to carry out such an approach (Salgar et al., 2019).

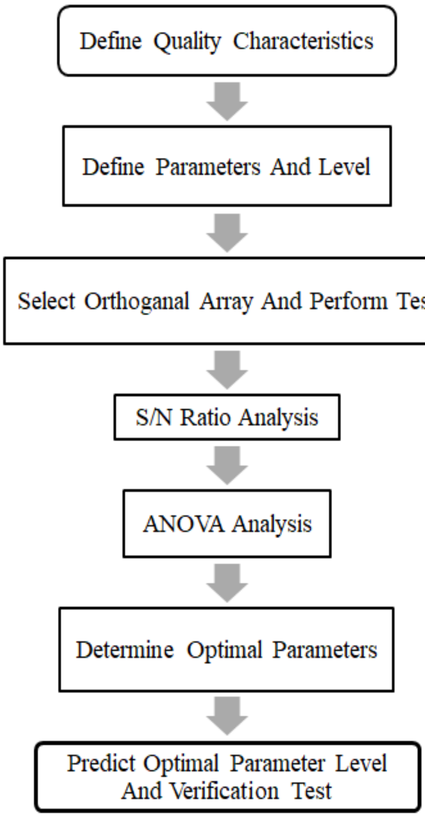


Figure 3.7 Flow chart of Taguchi's method for optimization

Taguchi uses the S/N ratio to measure the quality attributes of the target value, and it provides three levels of signal to noise ratio, as shown below (Hisam et al., 2024)(Salgar et al., 2019):

1. Nominal is the best characteristics,

$$\frac{S}{N} = 10 \log\left(\frac{\bar{Y}^2}{S^2}\right) \tag{3.2}$$

2. Smaller the better characteristics,

$$\frac{S}{N} = -10 \log\left[\frac{1}{n}\sum_{i=1}^{n} {y_i}^2\right] \tag{3.3}$$

3. Lager is the better characteristics,

$$\frac{S}{N} = -10 \log\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{{y_i}^2}\right) \tag{3.4}$$

In this equation, Y represents an observation, n is the total number of observations, $\bar{Y}$ represents the average of observed data, S^2 represents Y variance, and Y_i represents the i^{th} response. When choosing on profit, material removal rate, production rates, and so on, the bigger the better. Surface roughness, tool wear, cutting temperature, unit cost, and so on all benefit from a lower size. The nominal is more relevant to the current.

The S/N ratio was determined for surface roughness, tool wear, and MRR for each of the nine test situations to determine how each parameter affected the reactions during wet turning operations. As a result, the L9 orthogonal array from Minitab 21 was utilized to conduct additional tests, as described in Table 3.4, and the array required nine experiments. Figure 3.7 contains instructions to follow.

3.10.3 Selection of Orthogonal Array

Taguchi methods use orthogonal arrays to reduce the number of experiments. The number of levels of various parameters determines which orthogonal array is used. To conduct the experiments, three criteria were chosen, each with three levels. The Degree of Freedom (DOF) can now be determined using the formula provided below (Hisam et al., 2024).

For OA;

$$DOF = a - 1 \tag{3.5}$$

$$= 9\text{-}1\text{=}8$$

For an experiment;

$$DOF = P * (L - 1) \tag{3.6}$$

$$DOF = 3 * (3 - 1) = 6$$

Where DOF = Degree of freedom, P = Number of factors, and L = Number of levels.

As a result, 8>6, indicating that OA has a higher DOF than the experiment.

However, the number of experiments for the OA must be equal to or more than the number of degrees of freedom (DOF) necessary for the experimental procedure. As a result, we chose the L9 orthogonal array.

Table 3.4 Experimental layout using an L9 orthogonal array

Run	Cutting Parameters		
	Cutting speed(m/min)	Feed rate(mm/rev)	Depth of cut (mm)
1	180	0.08	0.5
2	180	0.10	1.0
3	180	0.12	1.5
4	210	0.08	1.0
5	210	0.10	1.5
6	210	0.12	0.5
7	240	0.08	1.5
8	240	0.10	0.5
9	240	0.12	1.0

3.10.4 Analysis of Variance

The goal of completing an analysis of variance was to establish which parameters had a substantial influence on the quality feature. ANOVA is a statistical tool used to investigate how all control conditions influence performance attributes. In the context of analysis of variance, the percentage contribution given to each control factor is utilized to determine individual contribution to performance characteristics. In this study, a 5% significance level, comparable to a 95% confidence level, was applied. The ANOVA results are insightful concerning whether there are any statistically significant differences among output characteristics. In performing ANOVA, it is assumed that values of α less than 0.05 signify significant values, while values greater than 0.05 do not show significance. The percent contribution measures the relative contribution of every term in a model with respect to the total sums of squares. Even though at times it is considered a reasonable approximation, percent contribution is an informative measure for determining relative importance of every term of a model. Through the use of analysis of variance, percent contribution by every influencing parameter was calculated.

$$P = \frac{SS}{SST} * 100 \tag{3.7}$$

Where P is the individual factor's percentage contribution, SST stands for total sum of squares, while SS stands for sum of squares or treatment sum of squares.

3.11 Taguchi-Based Grey Relational Analysis for Multi-Objective Optimization

The simultaneous and systematic optimization of a collection of objective functions is known as multi-objective optimization. As a result, there is an opportunity for multiple possible optima of a multi-objective problem. In cases, though, when the objectives are non-conflicting, there is a significant exception, which generates a single expected solution (Shah et al., 2016).

Unlike optimizing a single performance measure, optimizing multiple response measures involves more complexity. The theoretical model for handling a set of discrete data with multiple inputs and underlying uncertainty is referred to as the Grey hypothesis. The meaning of a gray structure is in an intermediary state between absolute extremes of white and black. A quantitative measure of both relative similarity for sequences and absolute size of variance among sequences within the data is referred to as grey relation analysis (Awale & Inamdar, 2020).

The multi-objective optimization methodology used within this research determines the trial periods for experiments through an investigation of relationships among different sets

of turning parameters. First, preprocessing is done on data through gray relational analysis for normalizing raw data (Pimenov et al., 2020). This process, known as gray relation generation, involves linearly normalizing the S/N ratio within the interval of 0 to 1 (Padhy & Singh, 2020). Nine experimental trials are connected to nine distinct subsystems in Grey Relational Analysis. GRA analysis will be used to look at how these subsystems affect the response variable. Reduced surface roughness, reduced tool wear, maximum MRR, and a higher material removal rate are the optimal parameter configurations that produce a high weighted gray relational grade. Thus, GRA has been used to reduce the multi-objective problem to a single objective. A control parameter's quality features are assessed using a signal-to-noise ratio, in which the "desirable" output is defined by the signal and the variability of the output caused by "undesirable" causes is represented by the noise. Taguchi's approach uses the signal-to-noise ratio as a way to quantify dispersion around a goal value. "Nominal is better," "larger is better," and "smaller is better" are the three categories into which Taguchi's experimental approach divides output response. In Taguchi's analysis, mean response, which is calculated from experimental output data, is calculated by converting output data into a signal-to-noise ratio (Mastan Rao et al., 2023).
The logarithmic modification of the loss function yielded the following equation for the S/N ratio condition:

- Larger the better;

$$\frac{S}{N} = -10 \log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{{y_{ijk}}^2}\right) \tag{3.8}$$

- Smaller- the better;

$$\frac{S}{N} = -10 \log\left[\frac{1}{n}\sum_{i=1}^{n}{y_{ijk}}^2\right] \tag{3.9}$$

- Nominal is the best,

$$\frac{S}{N} = 10 \log\left(\frac{\bar{Y}^2}{S^2}\right) \tag{3.10}$$

Where: $\bar{Y} = \frac{y_1+y_2+y_3+\cdots+y_n}{n}$

$$s^2 = \frac{\sum(y_i-\bar{Y})^2}{n-1}$$

Analysis of variance has been used to assess the relevance of specific parameters. The F-value, P-value, and percentage contribution attributed to each parameter are provided in the ANOVA table. A parameter is deemed significant if its F-value is higher. Furthermore, a computed probability value can also be used to confirm the significance of a parameter.

Every input process parameter contributes to the quality attributes, and a parameter is considered significant in the process if its p-value is less than 0.05. Grey relational grade is the average of the grey relation coefficients for various process variables that are computed for grey relation analysis. The next stages show that the grade is a combination response for the experimental arrangement.

Step 1: Express the initial response data as the signal-to-noise ratio (Y_{ij}) using an appropriate equation that applies for a given type of quality characteristic, using Equations 3.8, 3.9, and 3.10.

Step 2: The experiment design is based on normalization of performance measures, with the process of normalization being affected by the process parameter levels. Variable Y_{ij} is transformed into a normalized form, Z_{ij} ($0 \leq Z_{ij} \leq 1$), via a given formula that eliminates variations due to different units and variability. The normalization of raw data is required before grey relation theory or any of the other methods are applied. A representative value is taken from values of the same dataset so that it is close to 1. Since process normalization involves an impact on ranking results, sensitivity of the resulting rank is also important to evaluate. Thus, using a signal-to-noise ratio for normalizing data for grey relation analysis is suggested.

- S/N ratio with larger the better manner:

$$Z_{ij} = \frac{Y_{ij} - min(Y_{ij})}{ma(Y_{ij}) - min(Y_{ij})} \tag{3.11}$$

- S/N ratio with smaller -the better manner:

$$Z_{ij} = \frac{max(Y_{ij}) - Yij}{max(Y_{ij}) - min(Y_{ij})} \tag{3.12}$$

- S/N ratio with nominal the best:

$$Z_{ij} = \frac{(Y_{ij} - Target) - min(Y_{ij} - Target)}{max(Y_{ij} - Target) - min(Y_{ij} - Target)} \tag{3.13}$$

Step 3: Calculation of grey relational coefficient

$$\gamma\left(Yo_i(k), Y_i(k)\right) = \frac{\Delta min + \xi \Delta max}{\Delta_o j(k) + \xi \Delta max} \tag{3.14}$$

Where: $\Delta_o j(k) = |Yo_i(k) - Y_i(k)|$ absolute difference for response *k* in experiment *i*.

ξ = Distinguishing coefficient (typically 0.5)

Step 4: Grey Relational Grade (GRG): The GRG averages GRCs across all responses *k*:

$$GRG = \frac{1}{k} \sum_{i=1}^{m} \gamma_{ij} \tag{3.15}$$

Where: k = Total number of responses

The evaluation is considered to improve the multi-response parameter challenge.

Step 5: The ANOVA response table, which correlates to the grey relation grade, or the graphical technique are used to determine the optimal parameters. The higher the grey relation grade, the better the product quality; hence, one can evaluate the effect of different factors on the grey relation grade and establish the optimal level of each controllable factor (Zhujani et al., 2024).

3.12 Multi-Objective Optimization by Using Genetic Optimization

The genetic algorithm is an optimization technique based on the evaluation of strategies utilized to produce feasible optimization solutions. In a genetic algorithm, a population of sequences called chromosomes represents possible solutions to an optimization problem and continues to develop to bring forth better solutions. Genetic algorithms have proven to be highly efficient in solving multi-objective problems (Mia & Dhar, 2019).

The algorithm is an optimization tool with strong roots in the natural selection principle. The algorithm functions on a population of potential solutions and mimics the concept of 43"survival of the fittest." GA has the ability to control the process of search dynamically by adjusting probabilities of crossover, mutation, and selection. GA has the ability to change encoded information (genes) of candidate solutions, handle more than one individual at a time, and perhaps generate more than one optimal solution (Katoch, Chauhan, & Kumar 2021). There are three basic operators that are used in genetic algorithms (GAs), namely selection, crossover, and mutation. Selection operator points to the generation of a new population of individuals from the fitness values of the individuals of the preceding generation. In crossover, certain portions of individuals are usually swapped between two chosen individuals. Nevertheless, mutation entails random alteration of some gene values (Saha et al., 2022)(Slowik & Kwasnicka, 2020).

To develop a genetic algorithm, follow these steps:

- Get the mathematical model from the Taguchi experimental design.
- Develop genetic algorithm using MATLAB code to manage MINITAB experimental data and create a multi-objective function in MATLAB using input parameters and output responses.
- Specify the parameters of GA operation, (initial population, number of iterations, and optimization maximum time).
- Use a multi-objective function as a fitness function and run the GA.
- Find the best value of the output response.

CHAPTER FOUR
RESULTS AND DISCUSSION

4.1 Introduction

A number of experiments were conducted to investigate the relationship between the various cutting parameters cutting speed, depth of cut, and feed rate and their impacts on the surface roughness, tool wear, and material removal rate of AISI 1050 steel machined products. Experiments were conducted using a CNC lathe with a tool made up of coated carbide, supplemented by a carbide insert. Nine experiments were conducted with a view to finding an optimal operating condition. During and after machining operations, relevant response observations were taken, followed by statistical analysis with a view to finding the parameters based on pre-defined criteria, with main influences being confirmed. Response values derived on the basis of Taguchi methodology were analyzed using ANOVA. Statistical analysis using MINITAB 21 was also carried out. Along with that, detailed multiple optimizations were carried out applying Taguchi-based grey relation analysis and GA.

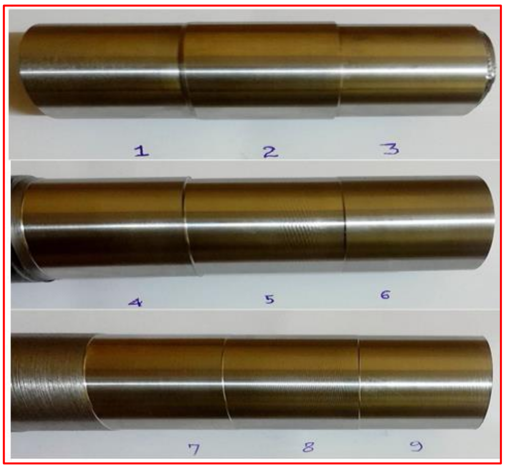


Figure 4.1 Workpiece after machining

This chapter provides a detailed examination of the outcomes from each experiment. To reduce errors, all experimental activities and procedures were carried out in a controlled setting. The experimental work and design were carried out using a systematic methodology to discover the optimal cutting parameters and establish the significant elements. This chapter provides a summary of the study's key findings and significant themes. To improve the depiction, predictive and optimization models, as well as relevant visuals and schematic diagrams, are provided.

4.2 Analysis of Results from Experiment

Data collection is an important aspect of statistical analysis in all academic areas since it has a significant impact on the resulting conclusions, which can be beneficial or detrimental. The adoption of systematic and effective data collection procedures helps to achieve more exact outcomes from the analysis process. As a result, the analysis requires the use of an adequate data collection method. For the current study, the data gathering for the turning process was specifically chosen to allow for the application of Taguchi design. Table 4.1 shows the results of each experiment for turning AISI 1050 steel using a coated carbide cutting tool.

Table 4.1 Experimental results

Run	Speed (m/min)	Feed (mm/rev)	Depth (mm)	Surface roughness(µm)			Ra(µm)	MRR (cm^3/min)	VB (µm)
				M_1	**M_2**	**M_3**			
1.	180	0.08	0.5	0.91	0.92	0.87	0.90	7.2	54.85
2.	180	0.10	1.0	1.32	1.26	1.35	1.31	18.0	71.28
3.	180	0.12	1.5	1.57	1.62	1.67	1.62	32.4	83.13
4.	210	0.08	1.0	0.89	0.85	0.90	0.88	16.8	76.78
5.	210	0.10	1.5	1.33	1.56	1.32	1.40	31.5	100.45
6.	210	0.12	0.5	2.03	2.02	1.95	2.00	12.6	95.00
7.	240	0.08	1.5	0.70	0.65	0.67	0.67	28.8	105.50
8.	240	0.10	0.5	1.17	1.15	1.16	1.16	12.0	108.00
9.	240	0.12	1.0	1.81	1.73	1.75	1.76	28.8	154.00
Min.	**180**	**0.08**	**0.5**				**0.67**	**7.2**	**54.85**
Max.	**240**	**0.12**	**1.5**				**2.00**	**32.4**	**154.00**

4.3 Optimization of Cutting Parameters

The primary goal of the research was to analyze and enhance AISI 1050 steel process parameters using Taguchi L9 orthogonal array technique. Using the Taguchi approach, the optimum wet turning parameters and crucial factors influencing surface quality, tool wear, and MRR of the machined workpiece would be determined.

4.3.1 Taguchi Design of Experiment

Orthogonal arrays by Taguchi signify complex fractional orthogonal designs, primarily formulated for emphasizing main effects. They allow primary effects estimation using a minimum number of trial experiments. Taguchi signal-to-noise ratios, which are derived from logarithmic transforms of the output of interest, are used for objective function optimizations and form an integral part of data analysis and determination of optimal responses. In Taguchi's methodology, variability of the response is measured with regard to S/N ratio. External non-controllable factors impart influence on quality characteristics. Parameters with unfavorable values are termed as "noise" (standard deviation), while favorable parameter values are known as "signal" (mean) (Hisam et al., 2024). Factors determining product quality are recognized by extensive research and further used for experiments as a function of responses. External non-controllable factors also affect product quality. Specimens are created based on the L9 orthogonal array pattern using S/N ratios with MINITAB 21 software.

4.4 Surface Roughness Analysis

The surface roughness of AISI 1050 steel when turned on a CNC machine is heavily influenced by cutting speed, depth of cut, and feed rate. A variety of approaches and predictive models are used to identify the process parameters that result in the desired surface finish. The study also includes statistical analysis and descriptive statistics such S/N ratio analysis, ANOVA, and regression equations.

Table 4.2 Surface roughness characteristics

Experiment run	Cutting speed(m/min)	Feed rate(mm/rev)	Depth of cut(mm)	Surface roughness(µm)	S/N for Ra
1.	180	0.08	0.5	0.90	0.91515
2.	180	0.10	1.0	1.31	-2.34543
3.	180	0.12	1.5	1.62	-4.29688
4.	210	0.08	1.0	0.88	1.11035
5.	210	0.10	1.5	1.40	-2.92256
6.	210	0.12	0.5	2.00	-6.02060
7.	240	0.08	1.5	0.67	3.47850
8.	240	0.10	0.5	1.16	-1.28916
9.	240	0.12	1.0	1.76	-4.91025

4.4.1 Analysis of Signal to Noise Ratio for Surface Roughness

Taguchi's design strategy divides the factors affecting output into two categories: design factors, or controllable factors, and noise factors, or uncontrollable ones. 'Signal' refers to the desirable target (mean) value for the output characteristic, whereas 'noise' denotes an unwanted variation within the same output characteristic. The S/N ratio is a quantitative measure that assesses the extent of variance in a quality characteristic from the target value. The smaller-the-better criterion is used to encourage the reduction of surface roughness and tool wear, whereas the larger-the-better criterion is utilized to improve the rate of material removal. Our primary goal is to reduce surface roughness.

The Taguchi method uses the S/N (signal-to-noise) ratio to quantify variations in response values within experimental designs. The equations for calculating signal-to-noise ratios depend on the type of response variable being analyzed. In this experiment, lower response values indicate better performance. Table 4.3 presents the computed S/N ratios for surface roughness levels obtained from the experimental design.

Table 4.3 Response table for signal to noise ratios for Ra

Level	Cutting speed	Feed rate	Depth of cut
1.	-1.8735	**1.8347**	-2.1315
2.	-2.6109	-2.1857	-2.0484
3.	**-0.9070**	-5.0404	**-1.2115**
Delta	1.7040	6.8751	0.9201
Rank	2	1	3

The results shown in Table 4.3, together with the main effect plot for the signal-to-noise (S/N) ratios for surface roughness, suggest that the most influential factor is the feed rate (Delta = 6.8751, Rank = 1). On the other hand, the depth of cut has the minimum impact on the S/N ratio (Delta = 0.9201, Rank = 3). The optimum combination for improving surface quality, which we denote as v3f1d3, is shown in Table 4.4 and can be used as an effective set for improving surface quality for wet turning operations. Moreover, Figure 4.2 shows the main effect plot for the control factors' impact on the surface roughness S/N ratio. The highest numerical value for every plot represents the optimum value for the respective parameter for the respective level, while at the same time expressing the optimum condition within the boundaries of the experimental parameters (Krishniah et al., 2012)(Hisam et al., 2024).

The feed rate proportion is recognized as the most significant factor affecting surface roughness improvement over other cutting factors, while the depth of cut has the minimum impact on surface roughness, supported by the analysis outcomes (Baday et al., 2020). The study shows that the utilized signal-to-noise (S/N) ratio indicates values close to or less than zero are desirable and hence the maximum S/N is selected, as can be seen through the graph shown in figure 4.2. It is significant that cutting speed at level 3, feed rate at level 1, and depth of cut at level 3, which was $v_3f_1d_3$, was found to be the best setup.

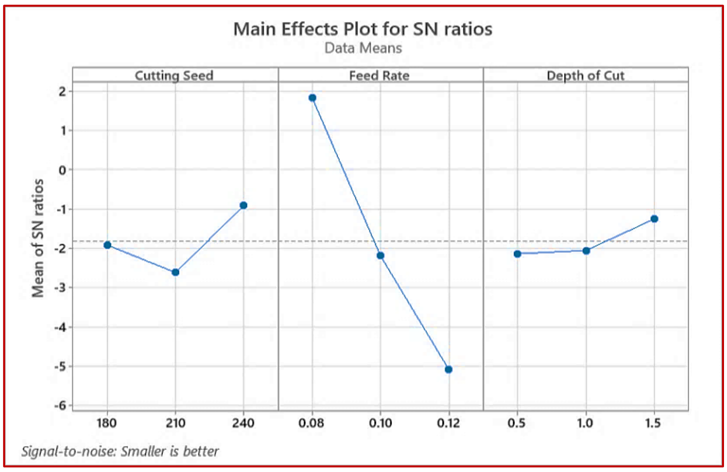


Figure 4.2 Main effect plot for S/N ratio for surface roughness

4.4.2 Analysis of Mean for Surface Roughness

The average surface roughness for each parameter, namely cutting speed, feed rate, and depth of cut, was calculated using the experimental plan. Table 4.2 shows surface roughness measurements for all of the samples under lubricated turning conditions. Table 4.4 shows the average surface roughness for each parameter cutting speed, feed rate, and depth of cut at each operational level during the turning process, estimated using Minitab 21 software.

Table 4.4 Response table for means for surface roughness

Level	Cutting speed(v)	Feed rate(f)	Depth of cut(d)
1.	1.2767	**0.8167**	1.3533
2.	1.4267	1.2900	1.3167
3.	**1.1967**	1.7933	**1.2300**
Delta	0.2300	0.9767	0.1233
Rank	2	1	3

Table 4.4 shows that the feed rate was the most influential variable (Delta = 0.9767, Rank = 1). The least influencing variable was depth of cut (Delta = 0.1233, Rank = 3). The parameters that create improved surface finishing outcomes for the wet turning specimen, $f_1v_3d_3$, were regarded to be an appropriate configuration for optimal results. Table 4.4 shows the factors affecting surface roughness in decreasing order: feed rate, cutting speed, and depth of cut. Previous study (Baday et al., 2020) confirm that among the machining parameters feed rate, cutting speed, and depth of cut the feed rate has the highest impact, followed by cutting speed, with depth of cut exerting the least influence on surface roughness improvement. Figure 4.3 shows a main effect plot with substantial effects that indicates the variance between the mean surface roughness values. The mean response result in Table 4.4 suggests that a minimum mean value is optimal for surface roughness.

The feed rate most significantly affects surface roughness by controlling tool mark spacing, with higher rates increasing roughness and lower rates producing finer finishes. Cutting speed moderately influences surface quality through chip formation, where higher speeds reduce built-up edge. In contrast, depth of cut has minimal impact as it primarily determines material removal rate, only slightly affecting roughness through increased cutting forces (Baday et al., 2020).

4.4.3 Main Effect Plot for Surface Roughness

The signal-to-noise ratios and means main effect plots shown in Figures 4.2 and 4.3 respectively were used to determine optimum values for each of the factors used in the turning operation for surface roughness.

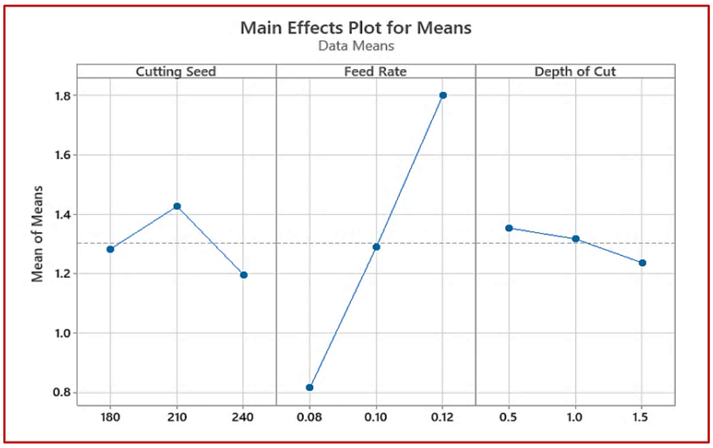


Figure 4.3 Main effect plot for means for surface roughness

As shown in Figure 4.3, the minimum values seen on the plot for each turning parameter represent the optimal conditions required to obtain the best surface roughness.

The minimum values for cutting speed and depth of cut are seen at level three, while the minimum for the feed rate was placed at level one. Therefore, the optimal values for the turning parameters were a high cutting speed, low for the feed rate, and a high depth of cut, represented as v3f1d3. The strategy for improving the surface roughness entails reducing the values for these parameters. The turning values needed to obtain the optimum surface roughness, as shown in Figures 4.2 and 4.3, were 240 m/min for cutting speed (level 3), 0.08 mm/rev for the feed rate (level 1), and 1.5 mm for the depth of cut (level 3). In order to approximate the optimum response, three minimum values have been used based on the lowest mean values. The setting $v_3f_1d_3$ signifies the optimum combination for the mean values for surface roughness. In order to determine the predicted response value, specifically for surface roughness, it is important to utilize the linear regression model shown below (Panda et al., 2016):

$$Ra_{opt} = m + (v_3 - m) + (f_1 - m) + (d_3 - m)$$

$$Ra_{opt} = v_3 + f_1 + d_3 - 2m \tag{4.1}$$

Where, m is average performance mean value for surface roughness, v_3 is optimum level value for cutting speed, f_1 is optimum level value for feed rate, d_3 is optimum level value for depth of cut.

$Ra_{opt} = 1.1967 + 0.8167 + 1.23 - 2 * 1.3$

$Ra_{opt} = 0.643\ \mu m$(Predicted mean value for surface roughness)

4.4.4 Analysis of Variance for Surface Roughness

The results for surface roughness are given in Table 4.2. Values for the surface roughness were taken from nine experiments that were conducted according to the Taguchi method. The computation of experimental results is shown in Table 4.5. The ANOVA table is used for showing the impact of different factors over the intended characteristics. The results show that feed was the major factor that has an effect on surface roughness.

Where DOF = Degrees of freedom, SS = Sum squares, MS = Mean sum of squares, F = Fraction generated by using MINITAB 2021 software.

Table 4.5 Analysis of variance for surface roughness

Factors	DOF	SS	MS	F-Value	P-Value	%Contribution
v	2	0.08096	0.04048	3.03	0.248	5.12
f	2	1.45109	0.72554	54.24	0.018	91.83
d	2	0.02136	0.01068	0.80	0.556	1.36
Error	2	0.02676	0.01338			1.69
Total	8	1.58016				

The independent variable's effect on the dependent variable is determined by ANOVA analysis. According to the result presented in Table 4.5, cutting speed contribute 5.12% of the variation in surface roughness, while feed rate and cutting depth contributed 91.83% and 1.36% of the variation, respectively. The findings in Table 4.5 clearly show that feed rate has a greater effect on surface roughness compared to cutting speed and cutting depth (S. A. Khan et al., 2022) as feed rate is increased, the tool moves across the workpiece at a faster rate, creating deeper and more apparent surface defects. This effect thus produces a rougher surface finish. It was noted that higher feed rates generally tend to produce higher surface roughness. Further, it was noted that increased feed rates generally produce more textured surfaces. At higher feed rates, the tool engages a larger amount of material per revolution, thus increasing cutting forces and leading to greater surface defects (Baday et al., 2020).

The ANOVA analysis (Table 4.5) reveals that, among all parameters, only the feed rate is statistically significant with regard to affecting surface roughness (p-value =0.018 < 0.05), with an extremely high F-value of 54.24 and a remarkable contribution of 91.83% towards overall variation, highlighting it as the main factor. On the contrary, cutting speed reflects an insignificant impact (p-value = 0.248, 5.12% contribution), while depth of cut is also not significant (p-value=0.556, 1.36% contribution); with error contribution being minuscule at 1.69%, further substantiating the accuracy of experimental observations. These observations strongly recommend controlling the feed rate for improvement of surface finish, consistent with previous deductions made based on S/N ratio and mean responses, and implying that variations within tested ranges for cutting speed and depth of cut impinge negligibly on surface roughness.

Regression Equation

Regression analysis was used to determine the statistical correlation between the parameters surface roughness, to enable predictive estimates with regard to levels of response of all variables.

$$Ra = 1.3 - 0.0233\ v1 + 0.1267\ v2 + \ 0.1033\ v3 - 0.4833\ f1 - \ 0.01\ f2\ + 0.4933\ f3 + \ 0.0533\ d1\ +\ 0.0167\ d2\ -\ 0.0700\ d3 \quad (4.2)$$

$$Ra = -0.738 - 0.00133v + 24.42f - 0.123d \quad (4.3)$$

Table 4.6 Ra model summary

Standard error	R^2	Adjusted R^2
0.122202	98.09%	92.38%

The statistical analysis of surface roughness presented in Table 4.6 reveals a highly effective predictive model. The model performs well in three key metrics: a standard error of 0.122202, indicating precise estimation capabilities; a R^2 value of 98.09%, indicating that the model accounts for nearly all observed variance in surface roughness; and an adjusted R^2 of 92.38%, confirming the model's strong explanatory power even when accounting for multiple predictor variables. These findings suggest that the developed model delivers accurate and dependable predictions of surface roughness parameters under the test conditions.

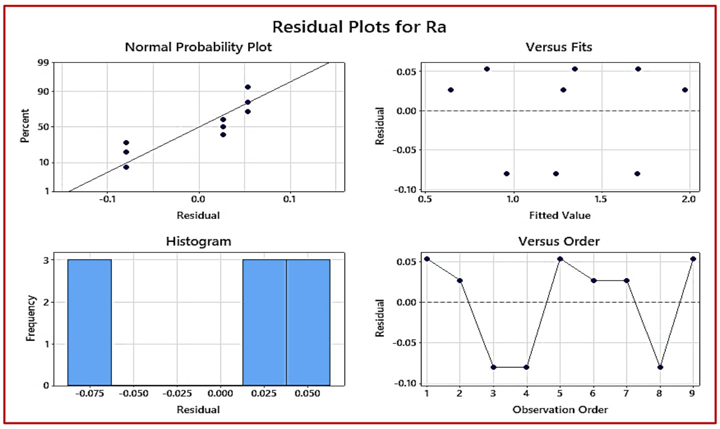


Figure 4.4 Residual pilots for surface roughness

As shown in Figure 4.4, the residual plots for surface roughness analysis show that the model fits the data well, with residuals following a normal distribution and no obvious patterns or biases. The normal probability plot supports the assumption of normality, whereas the residual versus fits plot shows a random scatter, implying uniformity. Furthermore, the Histogram demonstrates a symmetric distribution of residuals, whereas the residual versus order plot shows no discernable patterns over time. These combined observations show that the model is statistically stable and reliable for prediction purposes.

4.4.5 Determining the Optimum Condition for surface roughness

Table 4.7 shows the optimal parameter combinations determined for the roughness of the surfaces, in accordance with the experimental setup, and implemented in wet turning operations. It is clear that the optimal parameters used were associated with higher cutting speeds, lower feed rates, and the higher depth of cut, determined as $v_3f_1d_3$.

Table 4.7 Optimum parameter level and their value for surface roughness

Factors	Levels	Factor value	Rank of affecting	Predicted value of Ra
v (m/min)	3	240	2	0.643μm
f (mm/rev)	1	0.08	1	
d (mm)	3	1.5	3	

4.5 Material Removal Rate Analysis

The rate of material removal is calculated by applying equation (3.1). The volume of material removed in the wet turning of AISI 1050 steel during all experiments has been determined and was shown in Table 4.8.

Table 4.8 Material removal rate characteristics

Run	Cutting Speed(m/min)	Feed Rate(mm/rev)	Depth of Cut(mm)	MRR(cm^3/min)	SNRA for MRR
1.	180	0.08	0.5	7.2	17.1466
2.	180	0.10	1.0	18.0	25.1055
3.	180	0.12	1.5	32.4	30.2109
4.	210	0.08	1.0	16.8	24.5062
5.	210	0.10	1.5	31.5	29.9662
6.	210	0.12	0.5	12.6	22.0074
7.	240	0.08	1.5	28.8	29.1878
8	240	0.10	0.5	12.0	21.5836
9	240	0.12	1.0	28.8	29.1878

4.5.1 Analysis Response Table for S/N Ratio and Means for MRR

Material Removal Rate (analysis, in terms of Signal-to-Noise ratios and means shown in Tables 4.9 and 4.10, suggests that cutting depth has the strongest impact (Delta: 9.54 S/N, 20.30 mean; Rank: 1), followed by the feed rate (Delta: 3.52 S/N, 7 mean; Rank: 2) and cutting speed (Delta: 2.50 S/N, 4.00 mean; Rank: 3). This is due to the fact that increased cutting depth allows for removal of larger quantities of material with each pass, while high feed rates and cutting rates further increase the amount of material removed by intensifying workpiece engagement with tool movement. The best-in-class MRR is achieved in level 3 for all variables (maximum cutting rate, feed rate, and cutting depth), since all of these variables optimize material removal rate. The high correlation found between S/N ratios and means supports that increased cutting depth is the most effective methodology for MRR improvement, followed by adjustments in feed rate and cutting rate.

The findings show that high levels of cutting speed, feed rate, and depth of cut all increase material removal rate, with depth of cut being the most dominant parameter. In addition, the noted relationship between S/N ratios and mean responses confirms these observations, indicating that changes in depth of cut are required to realize better MRR performance.

Table 4.9 Response table for S/N ratios for MRR

Level	Cutting speed	Feed rate	Depth of cut
1.	24.15	23.61	20.25
2.	25.49	25.55	26.27
3.	**26.65**	**27.14**	**29.79**
Delta	2.50	3.52	9.54
Rank	3	2	1

Table 4.10 Response table for means for MRR

Level	Cutting speed	Feed rate	Depth of cut
1.	19.20	17.60	10.60
2.	20.30	20.50	21.20
3.	**23.20**	**24.60**	**30.90**
Delta	4.00	7.00	20.30
Rank	3	2	1

The experimental results confirmed that cutting depth, feed rate, and cutting speed all have a substantial influence on material removal rate in turning operations. The depth of cut is important since it allows you to remove more material with each pass. This effect increases when combined with high feed rates and cutting speeds, both of which increase the interaction between the cutting tool and the work piece, accelerating material removal. The study by (Baday et al., 2020) demonstrates that a higher feed rate results in greater tool workpiece interaction, which leads to higher MRR. According to the experimental data, raising the feed rate results in a large increase in material removal, whilst cutting depth modifications govern the overall chip volume generated. Furthermore, greater cutting speeds promote chip formation, reducing the likelihood of built-up edge creation and therefore optimizing machining efficiency. These findings are consistent with previously published studies, suggesting that actual outcomes match theoretical expectations.

4.5.2 Main Effect Plots for S/N and Means for Material Removal Rate

Signal-to-noise ratio and main effect plot of means, presented in Figs. 4.5 and 4.6, played a significant role in determining the optimal value for each parameter for the Material Removal Rate in turning operation.

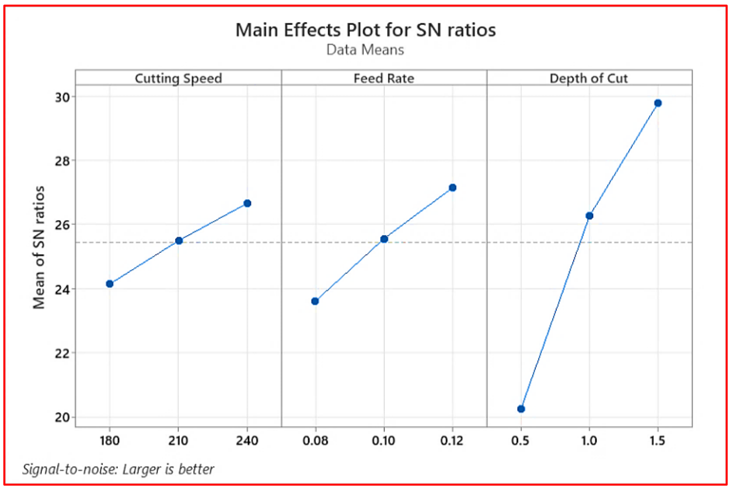


Figure 4.5 Main effects plot for S/N ratio for MRR

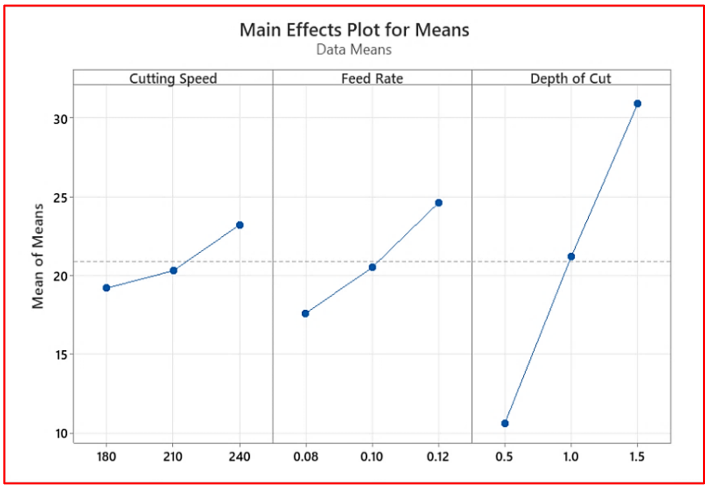


Figure 4.6 Main effects plot for means for MRR

An increased material removal rate was considered a desirable feature. The turning conditions required to obtain the desired MRR, as presented in Figures 4.5 and 4.6, include a cutting velocity of 240 m/min (level 3), feed of 0.12 mm/rev (level 3), and a depth of cut of 1.5 mm (level 3). To determine the expected value of the MRR, the following linear regression equation is used.

$$MRR_{opt} = v_3 + f_3 + d_3 - 2 * m \tag{4.4}$$

$MRR = 23.2 + 24.6 + 30.9 - 2 * 20.9 = 36.9\ cm^3/min$ (Predicted MRR at optimal level of the parameters).

4.5.3 Analysis of Variance for Material Removal Rate

ANOVA results for material removal rate listed in Table 4.11 presents the statistical importance of every machining parameter considered. Depth of cut stands out, with a high F-value (51.29) and low p-value (0.019 < 0.05) and significant contribution (84.68%), affirming its crucial influence on optimizing MRR. Feed rate is moderately influential, with an F-value (6.15) and contribution (10.16%); a high p-value (0.14 > 0.05) only partially signifies statistical importance. Cutting speed is insignificant, with an F-value (2.12), p-value (0.32), and a contribution (3.51%). The low error contribution (1.65%) also affirms the credibility of the experimental data.

Table 4.11 Analysis of variance table for material removal rate

Factors	DOF	SS	MS	F-Value	P-Value	%Contribution
Cutting speed	2	25.62	12.810	2.12	0.32	3.51
Feed rate	2	74.22	37.110	6.15	0.14	10.16
Depth of cut	2	618.54	309.270	51.29	0.019	84.68
Error	2	12.06	6.030			1.65
Total	8	730.44				

Regression Equation for Material Removal Rate

Regression analysis determines the quantitative link between machining parameters and response variables. The regression coefficients reflect how much influence each element has on MRR. In this case, the feed rate has a higher coefficient, implying that small changes in feed rate create more significant changes in MRR than depth of cut.

$$\mathrm{MRR} = 20.9 - 1.7\mathrm{v1} - 0.6\mathrm{v2} + 2.3\mathrm{v3} - 3.3\mathrm{f1} - 0.4\mathrm{f2} + 3.7\,\mathrm{f3} - 10.3\mathrm{d1} + 0.3\mathrm{d2} + 10\mathrm{d3} \tag{4.5}$$

$$MRR = -30.09 + 0.0667v + 175f + 20.3d \tag{4.6}$$

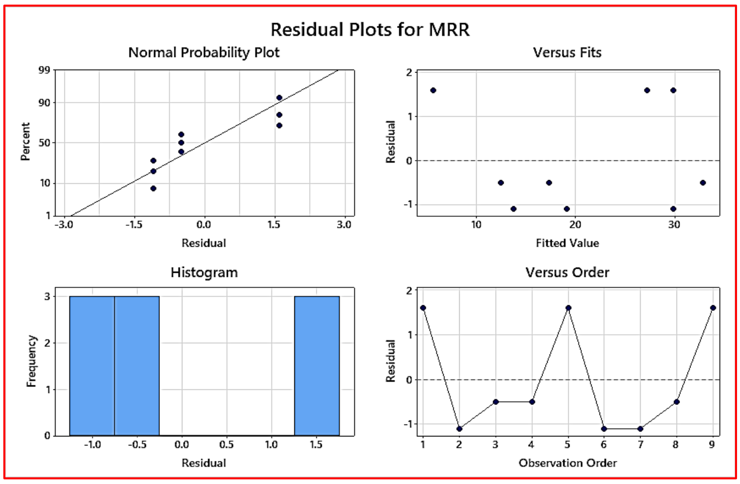


Figure 4.7 Residual plots for MRR

As shown in Figure 4.7, the residual plots for MRR analysis indicate a well-fitted model. The normal probability plot suggests that residuals follow a nearly normal distribution, while the residual versus fits plot shows randomness, indicating no significant biases. The histogram confirms a balanced residual spread, and the residual versus order plot shows no trends, ensuring residual independence.

Table 4.12 MRR model summary

S	R^2	Adjusted R^2
2.45561	98.35%	93.40%

As presented in Table 4.12, the model summary for Material Removal Rate (MRR) analysis indicates strong predictive performance. The standard error (S) of 2.45561 reflects a reasonable level of residual dispersion. The R-squared value of 98.35% demonstrates that the model accounts for a substantial proportion of variability in MRR, while the adjusted R-squared value of 93.40% which accounts for the number of predictors further confirms the reliability and robustness of the model.

4.5.4 Determining the Optimum Condition for MRR

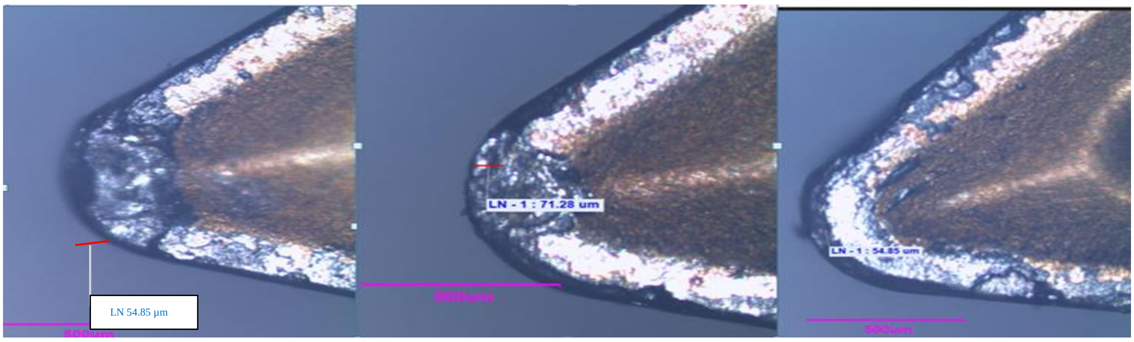
Table 4.13 presents the optimal setting of MRR achieved by the experiment design and determined by Equation (3.1). In this research, the optimal setting was higher cutting speed, feed rate, and cutting depth, and is denoted by $v_3f_3d_3$.

Table 4.13 Optimum parameter level and their value for MRR

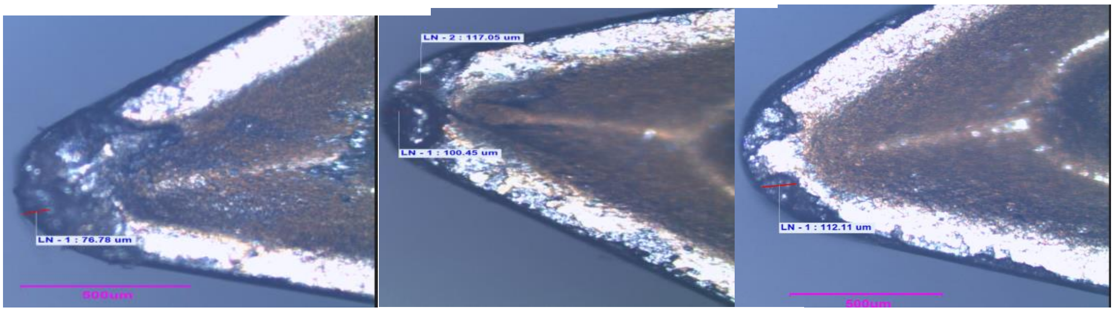
Factors	Levels	Factor value	Rank of affecting	Predicted value of Ra
v(m/min)	3	240	1	36.9 cm^3/min
f(mm/rev)	3	0.12	2	
f(mm)	3	1.5	3	

4.6 Tool Wear Analysis

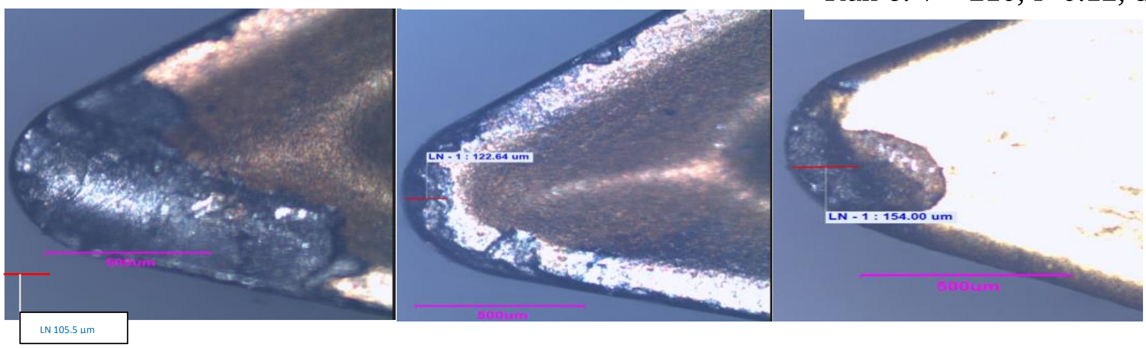
An experimental investigation conducted while wet turning of AISI 1050 steel and data collected from an optical microscope revealed flank wear. Flank wear occurs at the tool-work contact and has been shown to have a direct impact on the surface quality of the machined surface, as well as gradually changing the geometry of the cutting tool. In this study, flank wear was chosen as the major mode of wear to be examined. Nine wear tests were performed, and the results from flank wear are given in Table 4.14.



Run 1: v = 180, f=0.08, d=0.5 Run 2: v=180, f=0.1, d=1 Run 3: v =180, f=0.12, d=1.5



Run 4: v = 210, f=0.08, d=1 Run 5: v = 210, f=0.1, d=1.5 Run 6: v = 210, f=0.12, d=0.5



Run 7: v = 240, f=0.08,d=1.5 Run 8: v = 240, f=0.1,0.5 Run 9: v = 240,f= 0.12

Figure 4.8 Tool wear image

Tool wear was measured using an optical microscope for each experimental run, as shown in Table 4.14. The information in the table shows the minimum level of tool wear occurred when all cutting parameters were at their minimum during turning operations. For the first experimental run, all the parameters were at their minimum level (i.e., cutting speed of 180 m/min, feed rate of 0.08 mm/rev, and depth of cut of 0.5 mm), which led to the minimum tool wear value of 54.85 µm. (Al-dulaimi et al., 2016) research supports the argument that tool lifespan is significantly increased when machining operations are carried out with minimal cutting parameters. Moreover, the findings support the argument presented by (Isik, 2010) stating that minimizing tool wear leads to a tool lifespan extension.

The current research exhibits that flank wear is the dominating wear type that requires examination, since it is detectable in the interface between tool and workpiece, greatly affecting the quality of the machined component's surface. Table 4.14 summarizes the optical microscopy determined wear values for the flank wear, in addition to statistical analysis carried out with MINITAB 21.

Table 4.14 Tool wear characteristics

Run	Cutting Speed	Feed Rate	Depth of Cut	VB	SNRA for VB
1.	180	0.08	0.5	54.85	-34.7835
2.	180	0.10	1.0	71.28	-37.0594
3.	180	0.12	1.5	83.13	-38.3952
4.	210	0.08	1.0	76.78	-37.7027
5.	210	0.10	1.5	100.45	-40.0390
6.	210	0.12	0.5	95.00	-39.5545
7.	240	0.08	1.5	105.50	-40.4650
8.	240	0.10	0.5	108.00	-40.6685
9.	40	0.12	21.0	154.00	-43.7504

4.6.1 Analysis of Signal-to-Noise Ratios for Tool Wear

The S/N ratio table analyzes how certain machining conditions such as cutting velocity, feed rate, and cut depth affects tool wear stability. A higher (less negative) S/N ratio indicates better performance with less variation in wear.

Table 4.15 shows that tool wear is considerably influenced by cutting parameters. Out of the three cutting parameters measured cutting speed, feed rate, and cutting depth the cutting speed is found to be the most influential, as indicated by being identified as the main influencing parameter with a delta value of 4.88. This is an indicator that cutting speed variation has a large impact on tool wear, with lesser cutting speed levels (Level 1: -36.75) having lesser wear compared to greater values (Level 3: -41.63). (S. R. Das et al., 2012) increased speed leads to higher cutting forces, further contributing to tool degradation. In addition, the feed rate has significant impact as demonstrated by a delta value of 2.92 and occupying the second rank. An increase in the feed rate makes the cutting tool take up more material in each turn, generating higher cutting forces that in turn increase its susceptibility to wear; high feed rates produce larger-sized chips that can hinder uninterrupted cutting and also increase tool wear due to chip re-cutting or blockage. Consistent with (Isik, 2010) findings, elevated feed rates during wet turning of AISI 1050 steel intensify tool-workpiece interaction, resulting in greater cutting forces, accelerated flank wear, and consequent deterioration of surface finish quality. Such a situation leads to an increase in the tool's mechanical stress thus accelerating the process of wear (Sunday Abolarin et al., 2015). Furthermore, the finding supports the findings of (S. A. Khan et al., 2022) which postulate that tool degradation intensifies with higher cutting speeds and feed rates. On the other hand, while the depth of cut does have an impact on tool wear, it is relatively minimal as indicated by the low delta value of 1.30. Thus, using lower cutting speeds and feed rates, which have been indicated as being more beneficial at level 1, is predicted to increase tool life while at the same time increasing machining efficiency.

Table 4.15 Signal to noise ratios response table for tool wear

Level	Cutting Speed	Feed Rate	Depth of Cut
1	**-36.75**	**-37.65**	**-38.34**
2	-39.10	-39.26	-39.50
3	-41.63	-40.57	-39.63
Delta	4.88	2.92	1.30
Rank	1	2	3

4.6.2 Analysis of Mean Response for Tool Wear

Table 4.16, demonstrates a significant dependency of tool wear on the cutting parameters, with cutting speed having the greatest impact. The delta value corresponding to cutting speed (52.75) is significantly higher than that of feed rate (31.67) and depth of cut (14.73), thus making cutting speed the main factor responsible for the tool wear mechanism. The change in cutting speed from level 1 (69.75) to Level 3 (122.50) causes a remarkable increase in tool wear and indicates an increase in mechanical stresses on the tool at higher speeds that increases the wear mechanism (S. R. Das et al., 2012).

The feed rate has a considerable effect on the results as seen by its delta value of 31.67 in the Table 4.16. The tool wear from level 1 (79.04) to level 3 (110.71) shows a relationship between high feed rates and high wear but a secondary influence compared to the impact of cutting speed. The influence of the depth of cut is relatively low as seen by its delta value of 14.73. Tool wear is maximum at level 2 (100.68) with a corresponding decrease at level 3 (96.36), which indicates a nonlinear effect or varied process dynamics.

The findings documented in Table 4.16 highlighted the importance of parameter optimization to minimize tool wear.

When all cutting parameters (feed rate, cutting speed, and depth of cut) increased, the tool wear of AISI 1050 steel, turned by the coated carbide tool, also increased. The delta value indicates that cutting speed had the most significant effect on tool wear.

Table 4.16 Means response table for tool wear

Level	Cutting Speed	Feed Rate	Depth of Cut
1	**69.75**	**79.04**	**85.95**
2	90.74	93.24	100.68
3	122.50	110.71	96.36
Delta	52.75	31.67	14.73
Rank	1	2	3

Both tables indicate the importance of decreasing speed and feed rate to minimize wear and less importance assigned to depth of cut. The S/N ratio indicates which parameters were most influential and the means table indicates their real-world impacts to facilitate the refinement of machining practices to promote minimum tool wear.

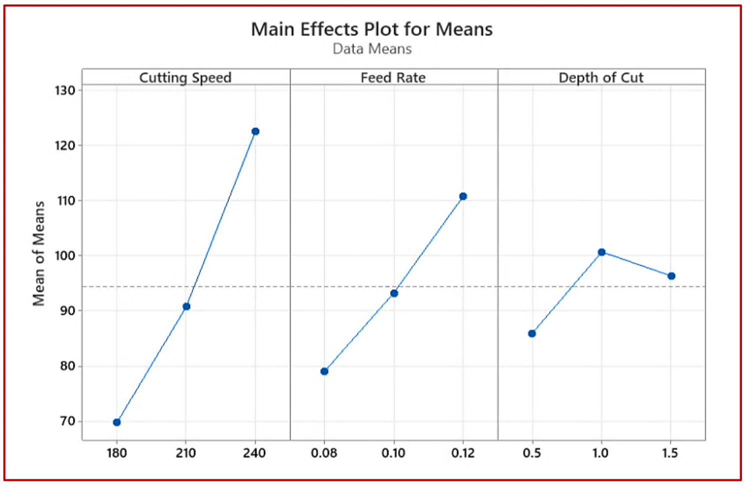


Figure 4.9 Main effects plot for means for tool wear

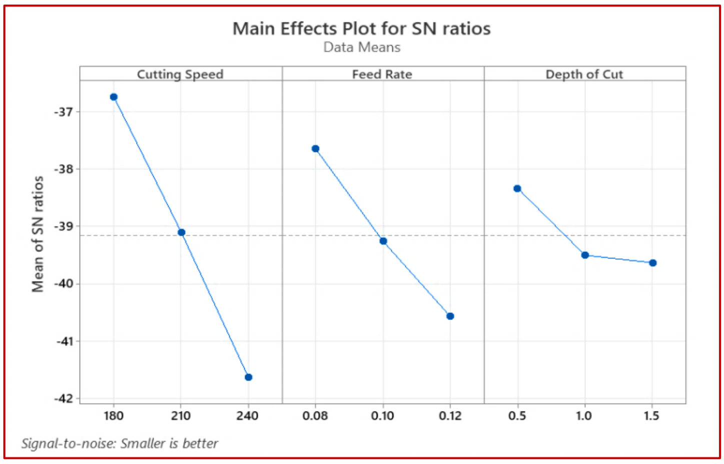


Figure 4.10 Main effects plot for S/N ratio for tool wear

The main effect plots for means in Figure 4.9 and for S/N ratios in Figure 4.10 indicate how tool wear was influenced by cutting parameters. In Figure 4.9, tool wear rises as cutting speed increases from 180 to 240. The same occurred with the feed rate (from 0.08 to 0.12), but depth of cut (from 0.5 to 1.5) has little influence on it. The same occurred in the case of the S/N ratios in Figure 4.9; where higher cutting speeds and feeds yield poorer (more negative) S/N ratios as well as much more tool wear. The depth of cut has minor influence on the S/N ratio and did not play an important part. From Table 4.15 and Figure 4.10, the optimal parameters for minimizing tool wear were found to be $v_1f_1d_1$, i.e., the cutting speed, the feed rate, and the depth of cut are 180 m/min, 0.08 mm/rev, and 0.5 mm, respectively.

To find out the predicted value of tool wear the following linear regression equation is used.

$$VB_{OPT} = m + (v_1 - m) + (f_1 - m) + (d_1 - m)$$

$$VB_{opt} = v_1 + f_1 + d_1 - 2m \tag{4.7}$$

Where m is the mean of tool wear (VB), v_1 is the optimum level value of the cutting speed, f_1 is the optimum level value of the feed rate, and d_1 is the optimum level value of the depth of cut.

$$VB_{opt} = 69.75 + 79.04 + 85.95 - 294.33$$

VB_{opt} = 46.08µm (tool wear value at optimal parameter)

4.6.3 Analysis of Variance for Tool Wear

The ANOVA results in Table 4.17 reveal the effect of cutting parameters on tool wear. The most significant factor is the cutting speed at an impact of 68.45%. This is succeeded by the feed rate at 24.50% and depth of cut with negligible influence at 5.86%. The highly significant cutting speed has high F-value of 57.54 and p-value <0.05 to reflect its significant contribution in causing tool wear. The less significant feed rate is highly significant. The depth of cut and low F-value of 4.93 and non-significant p=0.169 contrast them.

Table 4.17 Analysis of variance for tool wear

Source	DF	SS	MS	F-Value	P-Value	%Contribution
V	2	0.4741	0.2370	57.54	0.017	68.45
F	2	0.1697	0.0848	20.59	0.046	24.50
D	2	0.0406	0.0203	4.93	0.169	5.86
Error	2	0.0082	0.0041			1.19
Total	8	0.6926				100

Regression Equation for Tool Wear

Regression equation quantifies the effect of machining parameters on tool wear. Lower cutting speeds (180 m/min) cause a noteworthy reduction in wear (-0.2776), while higher speeds (240 m/min) cause an increase in wear (+0.2844). Similarly, a lower feed rate (0.08 mm/rev) causes a decrease in wear (-0.1735), although this influence is not as pronounced as the impact of cutting speed. Depth of cut shows a minimal influence, having slight wear reductions at 0.5 mm (-0.0946) and small increases at higher levels.

$$VB = 94.33 - 24.58v1 - 3.59v2 + 28.17v3 - 15.29\,f1 - 1.09\,f2 + 16.38\,f - 8.38\,d1 + 6.35\,d2 + 2.03\,d3 \quad (4.8)$$

$$Tool\ wear = -179.9 + 0.879v + 792f + 10.41d \quad (4.9)$$

Table 4.18 Tool wear model summary

S	R^2	Adjusted R^2
13.1990	94.58%	78.34%

As shown in Table 4.18, the model summary for tool wear analysis has a standard error (S) of 13.1990, suggesting residual spread. The R-squared result of 94.58% indicates that the model explains the majority of the variation in tool wear, exhibiting good predictive capacity. The adjusted R-squared value of 78.34% demonstrates the model's dependability even after accounting for the number of predictors.

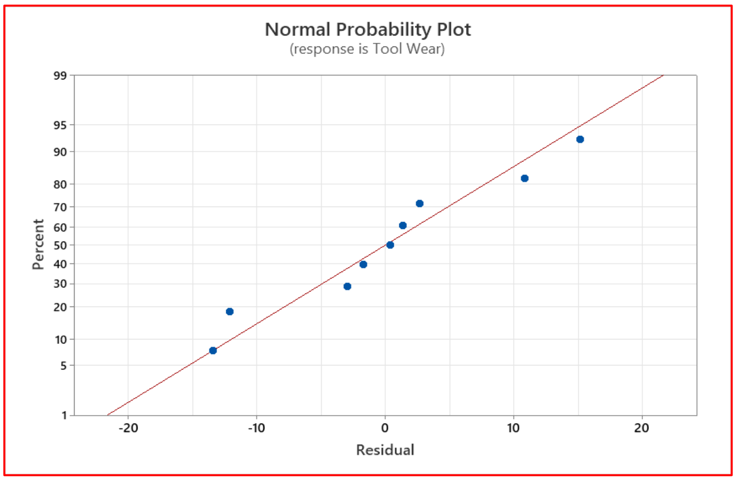


Figure 4.11 Normal probability plot for tool wear

As shown in Figure 4.11, the normal probability plot for tool wear indicates that the residuals are generally aligned along the reference line, indicating that they have an approximately normal distribution. This validates the regression analysis's normality assumption and indicates that the model is reasonably well-fitted and statistically valid for forecasting tool wear behavior. Minor variances exist, but they have no substantial effect on the model's adequacy.

Table 4.19 indicates the optimum setting of parameters for tool wear from the experiment design and experimentation in wet turning. The optimum chose parameters in the current research have been at reduced cutting speed, reduced feed rate and depth of cut and it is at $v_1f_1d_1$.

Table 4.19 Optimal parameter level and their value for tool wear

Factors	Levels		Rank of affecting	Predicted value of VB
v (m/min)	1	180	1	46.08 µm
f (mm/rev)	1	0.08	2	
d (mm)	1	0.5	3	

4.7 Multi Objective Optimization Using Raw Data of Responses by Taguchi Based GRA

Grey Relational Analysis is a strong optimization approach used in machining operations to find the ideal combination of parameters for increased performance. (Chakraborty et al., 2023) gave a thorough overview of how GRA is used to optimize machining parameters based on raw experimental data. In a multi-response situation, the influence and link between several parameters are complex and unclear. This is referred to as grey, which denotes inadequate and ambiguous information. This proposed methodology (grey relational analysis) analyzes the complex uncertainty among several responses in a given system and optimizes it using the grey relational grade. As a result, a multi-response optimization problem is reduced to a single response optimization issue, known as single relational grade (Panda et al., 2016).

Raw experimental data without S/N ratio conversion is used in this study to preserve the machining responses' direct physical interpretability. By removing possible transformation artifacts and maintaining absolute magnitude information, the method makes it possible to clearly correlate process parameters with surface roughness results. When directly improving measured responses under controlled conditions with low noise components, this methodology works especially well. GRA-based optimization is a preferred technique for machining parameter optimization because it uses raw experimental data to provide reliable and interpretable outcomes. In controlled machining conditions with low noise levels, this method is very helpful since it enables direct optimization of measured responses.

GRA optimized raw experimental data using the following steps:

Step1: The experimental data have been normalized for surface roughness, MR and flank wear, using Equation (3.11) and (3.12) presented in Table 4.20 to form a grey link between 0 and 1 to make experimental values normal.

Table 4.20 Normalized experimental values

Value of responses			Normalized responses values		
Ra	MRR	VB	Ra	MRR	VB
0.90	7.2	54.85	0.83	0.00	1.00
1.31	18.0	71.28	0.52	0.43	0.83
1.62	32.4	83.13	0.29	1.00	0.71
0.88	16.8	76.78	0.84	0.38	0.78
1.40	31.5	100.45	0.45	0.96	0.54
2.00	12.6	95.00	0.00	0.21	0.60
0.67	28.8	105.50	1.00	0.86	0.49
1.16	12.0	108.00	0.63	0.19	0.46
1.76	28.8	154.00	0.18	0.86	0.00

Step 2: Grey relational coefficients have been calculated using Equation 3.14 from the normalized data set of Table 4.20. 0.5 is the value of the differentiating coefficient since all three quality parameters have been given equal weight. The findings are displayed in Table 4.21.

Step 3: The grey relational grade was calculated using Equation 3.15 based on the grey relational coefficients. Table 4.21 presents the GRG results. This result is used to optimize the multi-responses as they are transformed to a single grade.

Table 4.21 Grey relational coefficient and grey relational grade values

Deviation sequence			Grey relational coefficient				
Ra	MRR	VB	Ra	MRR	VB	GRG	Rank
0.17	1.00	0.00	0.74	0.33	1.00	0.69	2
0.48	0.57	0.17	0.51	0.47	0.75	0.58	6
0.71	0.00	0.29	0.41	1.00	0.64	0.68	3
0.16	0.62	0.22	0.76	0.45	0.69	0.63	5
0.55	0.04	0.46	0.48	0.93	0.52	0.64	4
1.00	0.79	0.40	0.33	0.39	0.55	0.42	9
0.00	0.14	0.51	1.00	0.78	0.49	0.76	1
0.37	0.81	0.54	0.58	0.38	0.48	0.48	8
0.82	0.14	1.00	0.38	0.78	0.33	0.50	7

4.7.1 Process Parameter Optimization for GRG

Higher grey relational grade, which denotes higher product quality, is used to identify an ideal level of process parameters. Finding the average grade values for each process parameter level is necessary to achieve this, and the results can be displayed as a mean response table. Higher average grade values were selected as the best parametric combination for multiple responses based on the mean response table (Chakraborty et al., 2023).

4.7.2 Analysis of Mean for GRG

The MINITAB 21 software was used to generate the mean GRG for each parameter, which included cutting speed, feed rate, and depth of cut. These findings were presented in Table 4.22.Taguchi-based Grey Relational Analysis has been widely used to optimize machining parameters in order to improve manufacturing process efficiency and product quality. According to (Aggarwal & Sharmar, 2014), the GRG is a crucial indicator of optimization efficiency, with a higher GRG indicating a stronger connection with the reference sequence, resulting in improved machining performance.

Table 4.22 Mean response table for GRG

Level	Cutting Speed	Feed Rate	Depth of Cut
1	**0.6500**	**0.6933**	0.5300
2	0.5633	0.5667	0.5700
3	0.5800	0.5333	**0.6933**
Delta	0.0867	0.1600	0.1633
Rank	3	2	1

The mean response table method was used to determine the optimal machining parameter levels by calculating average GRG values for each machining parameter level. The data was then examined to determine the best parametric combination, resulting in an optimal multi-response outcome (Aggarwal & Sharmar, 2014). By identifying greater GRG values, producers can improve surface quality, material removal rates, and tool life.

Figure 4.12 presents the influence of each process parameter at various levels based on the GRG value, whereas Table 4.22 displays the average grey relational grade. The optimal parametric combination is determined by the higher mean gray relational grade values in Table 4.22. A higher grey relational grade indicates a stronger correlation with the reference sequence and improved performance. Thus, the optimal parameters for multi-responses are $v_1f_1d_3$, which corresponds to a cutting speed of 180 m/min, a feed rate of 0.08 mm/rev, and a depth of cut of 1.5 mm. Higher mean grey relational grade values as shown in Figure 4.12 correspond to the best surface roughness, MRR, and flank wear values. The difference between the highest and least mean GRG values for turning parameters was 0.07 for cutting speed, 0.16 for feed rate, and 0.1633 for depth of cut. This finding suggests that in wet turning operations, the depth has the greatest influence on multi-responses when compared to feed rate and cutting speed. The relevance of process parameters on multi-responses is as follows: depth > feed rate > cutting speed.

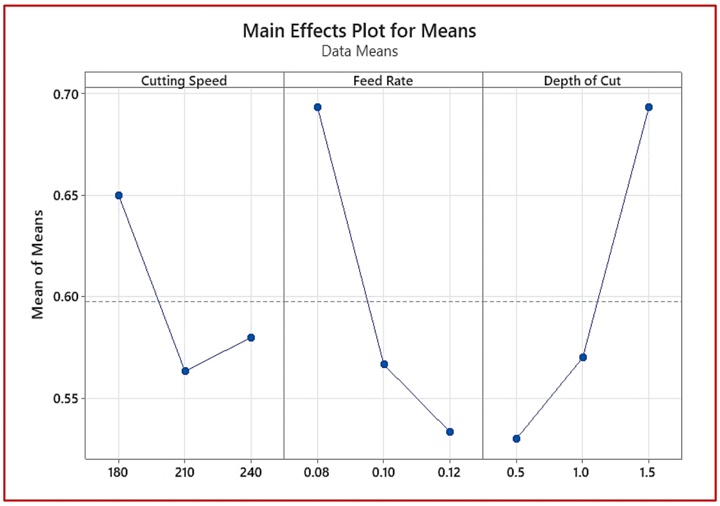


Figure 4.12 Main effects plot for means for GRG

These data indicate that higher Grey Relational Grades in machining optimization procedures lead to better parameter selection, which successfully balances multiple objectives to produce improved manufacturing results. The combination of GRA and Taguchi techniques allows reliable machining parameter optimization, resulting in increased efficiency across a wide range of industrial applications.

The following is the expected value of the gray relational grade for the optimal level once the best combination of process parameters has been determined:

$$\hat{y} = y_m + \sum_i^n (\bar{y}_i - y_m) \tag{4.10}$$

Where y_m is the overall mean grey relational grade, $\bar{y}_i$ is the mean grey relational grade at the optimal level of each parameter, and n is the number of the significant process parameters (Panda et al., 2016).

$$y_m = 0.5978 \text{ (Total mean GRG)}$$

$$\hat{y} = 0.65 + 0.6933 + 0.6933 - 2 * 0.5978$$

Therefore, Predicted optimum value of GRG = 0.841

4.7.3 Analysis of Variance for GRG

After determining the optimal combination, the next step is to do an analysis of variance to determine the relevant parameters influencing the multi-responses at a 95% confidence level, providing vital information about the experimental data. As the influence of each parameter on multi-response cannot be measured using the Taguchi technique, the ANOVA analysis will be useful in determining the percentage of contribution to identify the effects. ANOVA separates the entire variability of the response (sum of squared deviations about the grand mean) into each parameter contribution and error (Panda et al., 2016). If the P-value (probability of significance) is less than 0.05, it is typically determined using the F value or Fisher's F-ratio to obtain information about the significance of the selected response. Degrees of freedom were necessary to evaluate the mean square (MS) and to assess the availability of independent information when evaluating sum of squares (SS). In an ANOVA study, mean square deviation and F-value are determined using the formulas MS = SS/DF and F = MS for a source parameter/MS for the error.

Table 4.23 displays the gray relational grade value that is taken into consideration while creating an analysis of variance table. The importance of process parameters on multi-responses is seen in this table. The ANOVA table's p-value is less than 0.05 at the 95% confidence level, indicating that feed and depth of cut were important process characteristics influencing multiple responses. Cutting speed has no effect on all three responses at once.

Table 4.23 Analysis of variance for GRG for raw data

Source	DF	SS	MS	F-Value	P-Value	%Contributions	Significance
V	2	0.012689	0.006344	15.43	0.061	12.72	Insignificant
F	2	0.042756	0.021378	52.00	0.019	42.86	Significant
D	2	0.043489	0.021744	52.89	0.019	43.596	Significant
Error	2	0.000822	0.000411			0.824	
Total	8	0.099756				100	

Table 4.24 GRG model summary

S	R^2	Adjusted R^2	Predicted R^2
0.0202759	99.18%	96.70%	83.31%

With an R^2 value of 99.18%, the GRG analysis produced impressive results, as indicated in Table 4.24, suggesting that the model explains almost all of the variability in the system being studied. Given the number of influencing factors taken into consideration, the model's robustness is confirmed by the Adjusted R^2 of 96.70%. Despite a somewhat lower Predicted R^2 of 83.31%, the model's prediction dependability is still quite high, confirming its capacity to generalize to new situations. Additionally, a low standard deviation (S) of 0.0203 indicates that the GRG computation was highly precise. Taken together, the figures in Table 4.24 confirm how well GRG works to optimize and analyze the system's performance characteristics in the study.

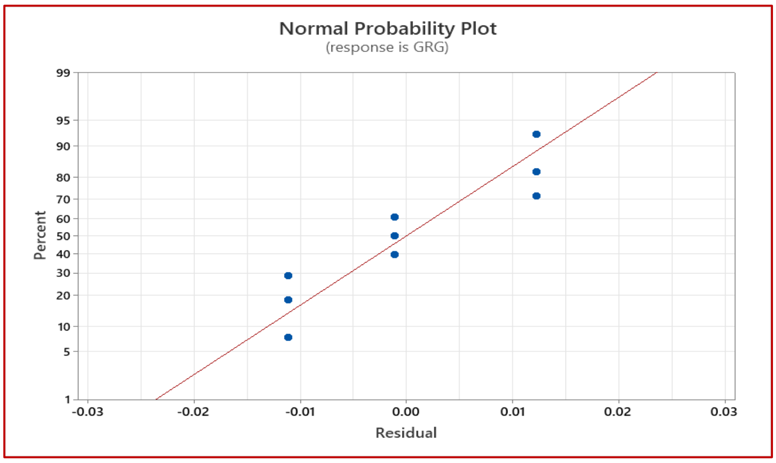


Figure 4.13 Residual probability plot for GRG

Figure 4.13 depicts the normal probability plot of residuals for the GRG model, which shows that the residuals are closely matched with the reference line, indicating a near-normal distribution. This alignment lends support to the assumption of normalcy and demonstrates the model's reliability and consistency throughout the research. Minor variations at the extremes support the absence of substantial outliers.

4.7.4 Determining the Optimum Condition for Responses

The optimal parameter setup for responses is shown in Table 4.25, which is based on both empirical wet turning findings and experimental design methodology. According to the analysis, the optimal working state is represented by the parameter combination $v_1f_1d_3$, which represents the lowest levels of cutting speed (v_1), feed rate (f_1), and depth of cut (d_3). The additive prediction model for response optimization was used to determine the optimum value of the responses, which was computed as follows:

$$Predicted\ response = \bar{R} + (A_i - \bar{R}) + \left(B_j - \bar{R}\right) + (C_k - \bar{R}) \tag{4.11}$$

Where $\bar{R}$=Over all response mean of response for (Ra, MRR and tool wear) across all nine runs.

A_i=Mean reponse when speed is at ith level

B_j=Mean response when feed rate is at jth level

C_k=Mean response when depth of cut is at kth level

By using equation (4.11) we can predict the value of Ra, MRR and tool wear at optimal value as follows:

$$Predicted\ value\ for\ Ra = \ A_1 + B_1 + C_3 - 2(\bar{R}) \tag{4.12}$$

$$\text{Predicted value for Ra} = \ 1.2767 + 0.8167 + 1.23 - 2(1.3) = 0.7534\mu\text{m}$$

$$\text{Predicted value for MRR} = \ 19.2 + 17.6 + 30.9 - 2(20.9) = 25.9\text{cm}^3/\text{min}$$

$$\text{Predicted value for Tool wear} = \ 69.7533 + 79.0433 + 96.36 - 2(94.33) = 56.497\mu\text{m}$$

Table 4.25 Optimal parameter level and optimum value of responses

Responses	Predicted value
Surface roughness Ra (µm)	0.7534
MRR (cm^3/min)	25.9
Tool wear (µm)	56.497
Optimal parameters ($v_1f_1d_3$) 180, 0.08, 1.5	

4.8 Multi-Objective Optimization by Genetic Algorithm

The optimization of the multi-objective problem was realized by using the genetic algorithm solver, in this case, by using MATLAB's gamultiobj function to perform genetic algorithms to optimize the fitness function. Since the fitness function defined in this study was categorized as being multidimensional (multi-objective) fitness, it required optimizing multiple responses at the same time. Interaction between input parameters and output parameters was explained using ANOVA and regression equations, which were defined according to Taguchi's approach and were carried out using MINITAB 21 software. Then, the defined mathematical model was transformed into an MATLAB R2022b function and integrated into MATLAB General Toolbox as the target function. The optimization process was based on three main parameters, each allocated specific upper and lower bounds as per machining parameter specifications. The main goal of the function was optimizing material removal rate (MRR) while decreasing surface roughness and tool wear while machining AISI 1050 steel.

Regression modeling (Equations 4.2, 4.6, and 4.8) in Minitab 21 was used in this study to identify the ideal machining parameters, which were 1.5 mm depth of cut, 0.08 mm/rev feed rate, and 180 m/min cutting speed. These settings simultaneously improved tool wear (56.49 µm), surface roughness (0.7234 µm), and material removal rate (25.9 mm^3/min).

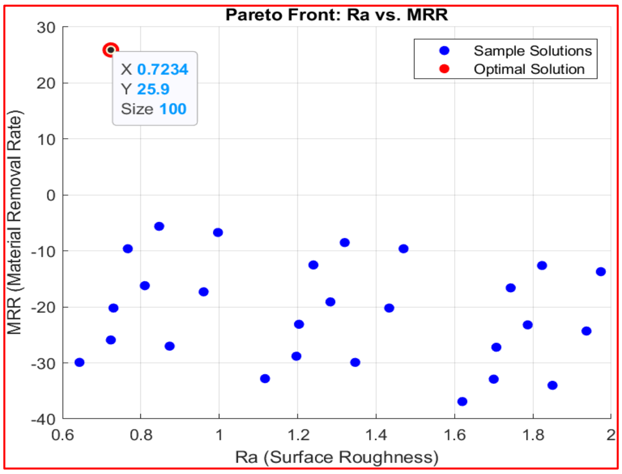


Figure 4.14 Pareto front plots for Ra and MRR

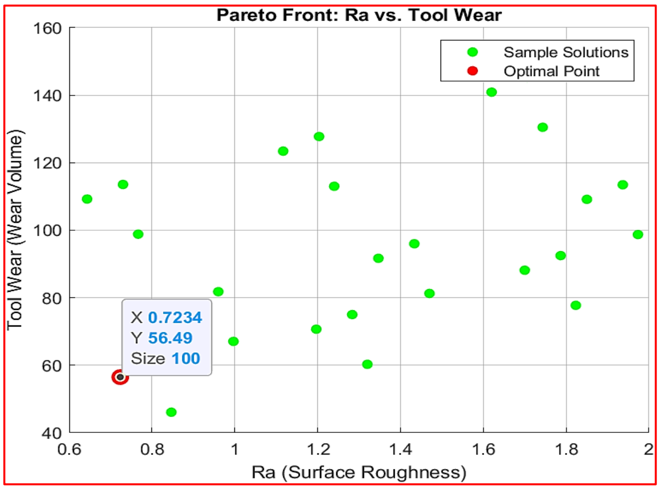


Figure 4.15 Pareto front plot for Ra and tool wear

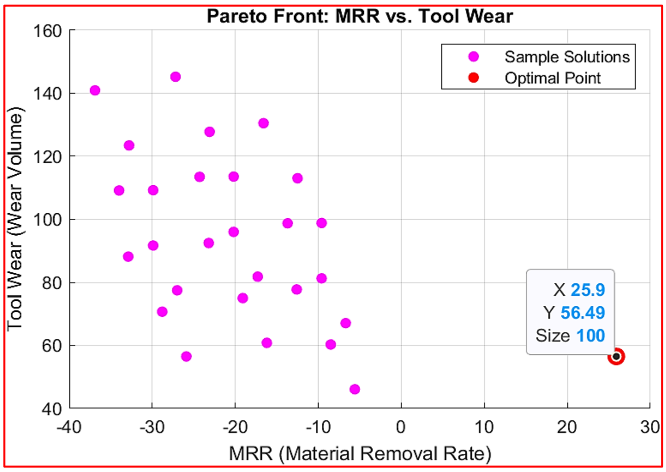


Figure 4.16 Pareto front plot for MRR and tool wear

Figures 4.14, 4.15, and 4.16 collectively summarize the results of multi-objective optimization, portraying the fundamental trade-offs between material removal rate (MRR = 25.9 mm^3/min), surface quality (Ra = 0.7234 μm), and tool wear (56.49 μm). The globally optimal solution presented across the three figures is a carefully balanced mix of these conflicting objectives, most notably demonstrating the intrinsic conflict between improving productivity and achieving better surface quality, as shown in Figure 4.16. Although Figures 4.14 and 4.15 indicate that a higher MRR is associated with increased tool wear, it is also clear that a better surface finish (indicated by a decrease in Ra) can be achieved without a proportionate increase in wear. Furthermore, analysis in three dimensions supports that the given parameters (emphasized in each figure) produce an optimal trade-off between machining efficiency, surface quality, and improved tool life for practical manufacturing applications.

4.9 Comparison of Taguchi Based GRA and GA for Multi-Objective Optimization

Table 4.26 Optimization results comparison – GRA versus GA

Optimization method	Optimal cutting parameters			Predicted response value		
	v (m/min)	f (mm/rev)	d (mm)	Ra (μm)	MRR (cm^3/min)	VB (μm)
Taguchi Based GRA	180	0.08	1.5	0.7534	25.9	56.497
Genetic Algorithm	180	0.08	1.5	0.7234	25.9	56.490

The results presented in Table 4.26 summarize a comparative analysis of the optimal machining parameters and performance outcomes obtained using Taguchi-based GRA and GA methodologies. Both optimization techniques identified the same parameter set; cutting speed of 180 m/min, feed rate of 0.08 mm/rev, and depth of cut of 1.5 mm demonstrating a strong alignment in parameter selection. However, GA produced marginally better outcomes in terms of surface roughness (0.7234 µm) and tool wear (56.490 µm) compared to GRA's results of 0.7534 µm and 56.497 µm, respectively, while maintaining an identical material removal rate (25.9 cm^3/min). This highlights GA's enhanced ability to fine-tune performance metrics in multi-objective optimization tasks. Overall, both approaches effectively supported the determination of robust machining conditions, with GA showing slight superiority in response refinement.

4.10 Confirmation Test

The final step was to confirm that the projected outcome was within the range of the experimental results after determining the ideal process parameters and levels. There was no requirement for a confirmation test if the set of ideal process parameters matches any experimental trial array. These thesis studies validated the ideal combinations of process parameters for surface roughness, MRR, and tool wear, unless further testing at that new level was conducted.

Table 4.27 Confirmation location from GA

Sr.No	Optimal values	Response	Predicted	Actual	Error %
1	v,f,d: 180, 0.08, 1.5	Ra (µm)	0.7234	0.773	6.42
2		MRR (cm^3/min)	25.9	23.6	8.88
3		VB (µm)	56.490	58.4	3.27

Confirmation studies were carried out to validate the efficiency of the predicted optimal machining parameters derived using GA. Table 4.27 shows the presented responses for surface roughness, MRR, and tool wear, which were 0.7234 µm, 25.9 cm^3/min, and 56.490 µm. The experimental results indicated estimated values of 0.77 µm for Ra, 21.6 cm^3/min for MRR, and 58.20 µm for VB. The respective percentage errors were 2.20% for surface roughness, 16.22% for MRR, and 3.02% for tool wear. The differences are within acceptable ranges and are due to practical machining factors including tool-workpiece contact and measurement variability. The tight alignment of projected and actual outcomes demonstrates the GA-based optimization model's reliability in real-world CNC turning applications.

CHAPTER 5

COCLUSION AND RECOMMENDETION

5.1 Conclusion

This research was an experimental study to examine the material removal rate, tool wear, and surface finish in turning AISI 1050 steel. Turning was conducted using a coated carbide tool with coolants. Statistical analyses and graphical presentations generated using Minitab 21 software resulted suitable turning conditions by demonstrating the effect of turning parameters on the results. The experiment established that turning parameters have a considerable influence on the material removal rate, tool wear, and surface roughness. Main effect plots were useful in presenting the average responses of all factors levels in a concise and understandable manner.

The main effect plots presented the average outcome for every level of each factor.

1. The lowest feed rate (0.08 mm/rev), highest cutting speed (240 m/min) and depth of cut (1.5 mm) produced the smoothest surface, according to the graphs. Feed rate contributes significantly to surface roughness at a similar cutting speed and depth of cut, with a contribution of 91.83%.
2. From all variables tested, depth of cut contributed most significantly towards material removal with a contribution of 84.68%, followed by feed rate with 10.16%, and cutting velocity with an insignificant contribution. Maximum material removal does not always mean economic machinability, as higher cutting velocities and feed rates resulted in greater tool wear. Optimum material removal rate (36.9 cm^3/min) occurred at optimal values for cutting velocity (240 m/min), feed rate (0.12 mm/rev), as well as depth of cut (1.5 mm) while corresponded to minimum values for tool wear and surface roughness (Ra).
3. The most important factor influencing tool life was cutting speed, which contributed 68.45% of the total. Feed rate came in second with a contribution of 24.5%, and depth of cut had a negligible impact with a contribution of 5.86%.
4. The least surface roughness was achieved at maximum cutting speed of when combined with minimum feed rate and maximum depth of cut. This indicated that feed rate was most influential parameter on surface roughness considering identical conditions for cutting speed and depth of cutting and feed rate responsible for 91.83% of total influence. Optimal turning parameters involving a cutting speed of

240 m/min, a feed rate of 0.08 mm/rev, and a depth of cut of 1.5 mm result in an optimal surface roughness of 0.643 μm.

5. Determination of optimal process parameter combinations for minimizing tool wear and surface roughness and maximizing material removal is achievable using multi-objective approaches such as GRA and GA. This technique provides an easy method to enhance the quality of the workpiece and enhance turning efficiency.
6. Grey Relational Analysis (GRA) showed that cutting parameters significantly impact machining performance during multi-objective optimization using raw data. The results indicate that the best results for balancing surface roughness, tool wear, and material removal rate have been achieved at lower cutting speeds (180 m/min), lower feed rates (0.08 mm/rev), and greater depths (1.5 mm). These findings provide useful information for selecting process parameters that improve workpiece quality and machining efficiency in real-world turning operations.
7. The Grey Relational Grade (GRG) analysis using S/N ratios revealed that the optimal machining parameters for simultaneously maximizing performance and robustness were the highest tested values: cutting speed of 240 m/min, feed rate of 0.12 mm/rev, and depth of cut of 1.5 mm.
8. The multi-objective optimization study identified the optimal machining parameters as 180 m/min cutting speed, 0.08 mm/rev feed rate, and 1.5 mm depth of cut, which simultaneously improve material removal rate (25.9 mm^3/min), surface roughness (0.7234 μm), and tool wear (56.49 μm).
9. The Pareto front analysis revealed key trade-offs, particularly between productivity and surface finish, while demonstrating that superior surface quality can be achieved without significantly compromising tool life. These optimized parameters provide a balanced solution for enhancing machining performance, ensuring both efficiency and precision in industrial applications. The findings offer a practical framework for implementing robust, high-quality machining processes.

5.2 Recommendation

The parameters, tools, and settings unique to the experimental analysis, as well as the properties of the workpiece AISI 1050 steel limit the methodology employed in this investigation. This restriction cannot be avoided. With additional research, the technique may be applied to different machining techniques, materials, and situations because of its high degree of generality and potential for further universalization. Furthermore, future studies could thoroughly examine the various wear mechanisms and chip morphology.

5.3 Scope of Future Work

- Future study could focus on optimizing the process by taking into account more input parameters and criteria.
- Incorporate machine learning algorithms (Artificial Neural Networks, support vector regression) to enhance the predictive accuracy of the regression models and capture complex interactions between parameters.
- Couple the regression models with microscopic tool wears analysis (SEM, EDS) to correlate empirical results with physical wear mechanisms (abrasion, diffusion).
- In future studies, numerical simulations and modeling will be useful aids to analyzing stress, strain, and force, as these properties pose difficulties when investigated using experimental methods of analysis.
- Investigations into the cutting parameter's effect on applied forces and rate of tool degradation
- Study the effects of tool geometry like nose radius and rake angle on the surface roughness, MRR and tool wear.
- Examine the effect of different cutting tools that share similar cutting parameters.
- Future research can include the use of minimum quantity lubrication method to provide an enhanced analysis of the role of cutting parameters, as well as to allow for comparative analysis of dry and wet turning methods.
- Use Grey Relational Analysis alongside TOPSIS and NSGA-II to address complex multi-objective issues.

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REFERENCE

A., D. S., & Agapiou, J. S. (2016). *metal cutting theory and practice* (3 rd). CRC Press, Taylor & Francis Group.

Adler, D. P., Hii, W. W. S., Michalek, D. J., & Sutherland, J. W. (2006). Optimization of Cutting Parameters on Tool Wear , Workpiece Surface Temperature and Material Removal Rate in Turning of AISI D2 Steel. *Machining Science and Technology*, *10*(1), 23–58. https://doi.org/10.1080/10910340500534282

Aggarwal, N., & Sharmar, S. K. (2014). Optimization of process parameters by Taguchi based Grey Relational Analysis : *International Journal of Current Engineering and Technology*, *4*(4), 2792–2796.

Ahmed Al-Dolaimy, K. (2016). Effect of Cutting Parameters on Surface Roughness in Turning Operations. *Journal For Engineering Sciences*, *9*(4), 442–449.

Akkus, H. (2021). Experimental and statistical investigation of the effect of cutting parameters on surface roughness , vibration and energy consumption in machining of titanium 6Al-4V ELI (grade 5) alloy. *Measurement*, *167*(July 2020). https://doi.org/10.1016/j.measurement.2020.108465

Akkuş, H., & YAKA, H. (2018). Optimization of Turning Process By Using Taguchi Method. *Sakarya University Journal of Science*, *22*(5), 1444–1448. https://doi.org/10.16984/saufenbilder.409502

Al-dulaimi, K. Y., Al-ethari, H., & Warcholinski, B. (2016). *Taguchi Method To Optimize Machining Conditions Affecting Cemented Carbide Tool ' S Wear Life in Turning Aisi 1020 Steel Abstract : 1*(Aisi 1020).

Albertelli, P., Musletti, S., Leonesio, M., Bianchi, G., & Monno, M. (2012). Spindle speed variation in turning: Technological effectiveness and applicability to real industrial cases. *International Journal of Advanced Manufacturing Technology*, *62*(1–4), 59–67. https://doi.org/10.1007/s00170-011-3790-8

Awale, A., & Inamdar, K. (2020). Multi-objective optimization of high-speed turning parameters for hardened AISI S7 tool steel using grey relational analysis. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, *42*(7), 1–17. https://doi.org/10.1007/s40430-020-02433-z

Baday, Ş., Başak, H., & Sönmez, F. (2020). Investigation and optimization of surface roughness with experimental design methods by turning of AISI - 1050 after spheroidization heat treatment. *SN Applied Sciences*, *2*(12), 1–13.

https://doi.org/10.1007/s42452-020-03953-y

Bhushan, R. K. (2020). Impact of nose radius and machining parameters on surface roughness , tool wear and tool life during turning of AA7075 / SiC composites for green manufacturing. *Bhushan Mechanics of Advanced Materials and Modern Processe*, 1–18. https://doi.org/https://doi.org/10.1186/s40759-020-00045-7

Buongiorno, J. (2006). Convective transport in nanofluids. *Journal of Heat Transfer*, *128*(3), 240–250. https://doi.org/10.1115/1.2150834

Chakraborty, S., Datta, H. N., & Chakraborty, S. (2023). Grey Relational Analysis-Based Optimization of Machining Processes: a Comprehensive Review. In *Process Integration and Optimization for Sustainability* (Vol. 7, Issue 4). Springer Nature Singapore. https://doi.org/10.1007/s41660-023-00311-4

Das, A., Tirkey, N., Patel, S. K., Das, S. R., & Biswal, B. B. (2019). A Comparison of Machinability in Hard Turning of EN-24 Alloy Steel Under Mist Cooled and Dry Cutting Environments with a Coated Cermet Tool. *Journal of Failure Analysis and Prevention*, *19*(1), 115–130. https://doi.org/10.1007/s11668-018-0574-6

Das, S. R., Kumar, A., & Dhupal, D. (2012). *On the other hand, even though the depth of cut has some influence, it has a relatively lesser impact on tool wear, indicated by a lower delta value of 1.30. 2*, 132–139.

Dash, L., Padhan, S., & Das, S. R. (2020). Experimental investigations on surface integrity and chip morphology in hard tuning of AISI D3 steel under sustainable nanofluid-based minimum quantity lubrication. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, *42*(10), 1–25. https://doi.org/10.1007/s40430-020-02594-x

Debnath, S., Reddy, M. M., & Yi, Q. S. (2016). Influence of cutting fluid conditions and cutting parameters on surface roughness and tool wear in turning process using Taguchi method. *Measurement*, *78*, 111–119.

Demir, Z., & Adiyaman, O. (2019). Investigation of influence of approach angle and chip slenderness ratio on vibration, chip formation and surface quality in turning of AISI 1050 steel. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, *41*(10), 1–15. https://doi.org/10.1007/s40430-019-1977-3

Efa, D. A., Gutema, E. M., Lemu, H. G., & Gopal, M. (2024). Friction stir-welding of AZ31B Mg and 6061-T6 Al alloys optimization using Box-Behnken design (BBD) and Artificial Neural network (ANN). *Research on Engineering Structures and Materials*, *10*(1), 413–430. https://doi.org/10.17515/resm2023.50ma0703rs

Gavrus, C., Ivan, N. V., & Oancea, G. (2023). Determination of the Depth of Cut via

Surface Integrity. *Applied Sciences (Switzerland)*, *13*(12), 1–12. https://doi.org/10.3390/app13126881

Harhout, R., Gaceb, M., Haddad, S., Aguib, S., Bloul, B., & Guebli, A. (2020). Predictive Modelling and Optimisation of Surface Roughness in Turning of AISI 1050 Steel Using Polynomial Regression. *Manufacturing Technology*, *20*(5), 591–602. https://doi.org/10.21062/MFT.2020.094

Henry, N., Akinlabi, E. T., & Ozoegwu, C. G. (2020). Machining Science and Technology : An MECHANISM OF CHIP FORMATION IN HIGH-SPEED TURNING OF INCONEL 718. *Materials Today: Proceedings*, *44*(July 2021), 1124–1129. https://doi.org/10.1016/j.matpr.2020.11.228

Hisam, M. W., Dar, A. A., Elrasheed, M. O., Khan, M. S., Gera, R., & Azad, I. (2024). The Versatility of the Taguchi Method: Optimizing Experiments Across Diverse Disciplines. *Journal of Statistical Theory and Applications*, 365–389. https://doi.org/10.1007/s44199-024-00093-9

Hosseini, A., Hussein, H. M., & Kishawy, H. A. (2016). Optimization of cutting parameters during turning of AISI 1018 using Taguchi method. *International Journal of Advanced Manufacturing Technology*, *85*(1–4), 735–740. https://doi.org/10.1007/s00170-015-7971-8

Irfaan, M., Temesgen, A. D., & Tsegay, M. M. (2015). Application of Taguchi Method & Anova in turning of AISI 1045 to improve surface roughness by Optimize cutting factor. *American Journal of Engineering Research (AJER)*, *4*(12), 120–125. www.ajer.org

Isik, Y. (2010). An experimental investigation on effect of cutting fluids in turning with coated carbides tool. *Strojniski Vestnik/Journal of Mechanical Engineering*, *56*(3).

Kaladhar, M., Subbaiah, K. V., Srinivasa Rao, C., & Narayana Rao, K. (2011). Application of Taguchi approach and utility concept in solving the multi-objective problem when turning AISI 202 austenitic stainless steel. *Journal of Engineering Science and Technology Review*, *4*(1), 55–61. https://doi.org/10.25103/jestr.041.08

Kamble, P. D., Giri, J., Makki, E., Sunheriya, N., Sahare, S. B., Chadge, R., Mahatme, C., Giri, P., Sathish, T., & Panchal, H. (2024). *An application of hybrid Taguchi-ANN to predict tool wear for turning EN24 material*. *September*. https://doi.org/10.1063/5.0186432

Kamble, P. D., Waghmare, A. C., Askhedkar, R. D., Sahare, S. B., & Singh, B. R. (2021). Application of hybrid Taguchi-Grey relational analysis (HTGRA) multi-optimization technique to minimize surface roughness and tool wear in turning AISI4340 steel. *Journal of Physics: Conference Series*, *1913*(1), 0–7. https://doi.org/10.1088/1742-6596/1913/1/012142

Kashkool, L. H. (2022). Optimization of Machining Parameters of AISI 1045 Steel for Better Surface Finish and Tool Life Using TiN Coated Carbide Insert. *Tikrit Journal of Engineering Sciences*, *29*(2), 1–6. https://doi.org/10.25130/tjes.29.2.1

Katoch, S., Chauhan, S. S., & Kumar, V. (2021). Katoch2021_Article_AReviewOnGeneticAlgorithmPastP.pdf. In *Multimedia Tools and Applications* (Vol. 80). Multimedia Tools and Applications.

Khan, M. A., Jaffery, S. H. I., Khan, M., Younas, M., Butt, S. I., Ahmad, R., & Warsi, S. S. (2020). Multi-objective optimization of turning titanium-based alloy Ti-6Al-4V under dry, wet, and cryogenic conditions using gray relational analysis (GRA). *International Journal of Advanced Manufacturing Technology*, *106*(9–10), 3897–3911. https://doi.org/10.1007/s00170-019-04913-6

Khan, M. M. A., Mithu, M. A. H., & Dhar, N. R. (2009). Effects of minimum quantity lubrication on turning AISI 9310 alloy steel using vegetable oil-based cutting fluid. *Journal of Materials Processing Technology*, *209*(15–16), 5573–5583. https://doi.org/10.1016/j.jmatprotec.2009.05.014

Khan, S. A., Ameer, M. F., Uddin, G. M., Ali, M. A., Anwar, S., Farooq, M. U., & Alfaify, A. (2022). On the other hand, even though the depth of cut has some influence, it has a relatively lesser impact on tool wear, indicated by a lower delta value of 1.30. *International Journal of Advanced Manufacturing Technology*, *122*(9–10), 4013–4028. https://doi.org/10.1007/s00170-022-10151-0

Khanna, N., Agrawal, C., Dogra, M., & Iulian, C. (2020). Evaluation of tool wear , energy consumption , and surface roughness during turning of inconel 718. *Integrative Medicine Research*, *9*(3), 5794–5804. https://doi.org/10.1016/j.jmrt.2020.03.104

Krishniah, K., Shahabudeen, P., Krishnaiah, K., & Shahabudeen, P. (2012). Applied design of experiments and Taguchi methods. In *e-Book EEE* (Issue June). https://books.google.com/books?id=hju9JYVhfV8C&pgis=1

Manufacturing, M. (2007). *21 Theory of Metal Machining*. 131–143.

Mastan Rao, P., Deva Raj, C., Dhoria, S. H., Vijaya, M., & Chowdary, J. R. R. (2023). Multi-Objective Optimization of Turning for Nickel-Based Alloys Using Taguchi-GRA and TOPSIS Approaches. *Journal of The Institution of Engineers (India): Series D*, *105*(3), 1473–1484. https://doi.org/10.1007/s40033-023-00554-y

Meddour, I., Yallese, M. A., Bensouilah, H., Khellaf, A., & Elbah, M. (2018). Prediction of surface roughness and cutting forces using RSM, ANN, and NSGA-II in finish turning of AISI 4140 hardened steel with mixed ceramic tool. *International Journal of Advanced Manufacturing Technology*, *97*(5–8), 1931–1949. https://doi.org/10.1007/s00170-018-2026-6

Mia, M., & Dhar, N. R. (2019). Prediction and optimization by using SVR, RSM and GA in hard turning of tempered AISI 1060 steel under effective cooling condition. *Neural Computing and Applications*, *31*(7), 2349–2370. https://doi.org/10.1007/s00521-017-3192-4

Montgomery, D. C. (2013). *Design and Analysis of Experiments* (Eighth Edi). JohnWiley & Sons.

Nas, E., & Altan Özbek, N. (2020). OPTIMIZATION of the MACHINING PARAMETERS in TURNING of HARDENED HOT WORK TOOL STEEL USING CRYOGENICALLY TREATED TOOLS. *Surface Review and Letters*, *27*(5), 1–14. https://doi.org/10.1142/S0218625X19501774

Navneet Saini, & Jitender Panchal. (2017). Taguchi Based Grey Relational Analyses for Multi Response Optimization of Control Parameters in CNC Turning of Aluminium 7075 Alloy. *International Journal of Engineering Research And*, *V6*(07). https://doi.org/10.17577/ijertv6is070205

Padhan, S., Wagri, N. K., Dash, L., Das, A., Das, S. R., Rafighi, M., & Sharma, P. (2023). Investigation on Surface Integrity in Hard Turning of AISI 4140 Steel with SPPP-AlTiSiN Coated Carbide Insert under Nano-MQL. *Lubricants*, *11*(2). https://doi.org/10.3390/lubricants11020049

Padhy, C., & Singh, P. (2020). Use of multi-objective optimization technique (Taguchi-GRA approach) in dry hard turning of inconel 625. *INCAS Bulletin*, *12*(2), 133–142. https://doi.org/10.13111/2066-8201.2020.12.2.11

Padhy, C., & Singh, P. (2021). *Optimization of Machining Parameters using Taguchi Coupled Grey Relational Approach while Turning Inconel 625*. *18*(2), 161–176.

Panda, A., Sahoo, A. K., & Rout, A. K. (2016). *Multi-attribute decision making parametric optimization and modeling in hard turning using ceramic insert through grey relational analysis : A case study*. *5*, 581–592. https://doi.org/10.5267/j.dsl.2016.3.001

Pathak, A. D., Warghane, R. S., & Deokar, S. U. (2018). Optimization of cutting parameters in Dry Turning of AISI A2 Tool Steel using Carbide Tool by Taguchi

Based Fuzzy Logics. *Materials Today: Proceedings*, *5*(2), 5082–5090. https://doi.org/10.1016/j.matpr.2017.12.087

Pimenov, D. Y., Abbas, A. T., Gupta, M. K., Erdakov, I. N., Soliman, M. S., & El Rayes, M. M. (2020). Investigations of surface quality and energy consumption associated with costs and material removal rate during face milling of AISI 1045 steel. *International Journal of Advanced Manufacturing Technology*, *107*(7–8), 3511–3525. https://doi.org/10.1007/s00170-020-05236-7

Polytechnic, A. (2021). Optimization of Process Parameters of Surface Roughness and Material Removal Rate in Orthogonal Turning of AISI 1045 Carbon Steel Using Taguchi Technique. *Industrial Engineering Letters*, *10*(4), 16–25. https://doi.org/10.7176/iel/11-1-03

Ponnusamy, P., & Tamilperuvalathan, S. (2023). Performance evaluation and hybrid deep recurrent neural network-based prediction of SS304 turning characteristics using nanoparticles added water emulsified MQL. *Biomass Conversion and Biorefinery*, *13*(8), 7349–7373. https://doi.org/10.1007/s13399-023-04106-y

Rafighi, M., Özdemir, M., Al Shehabi, S., & Kaya, M. T. (2021). Sustainable Hard Turning of High Chromium AISI D2 Tool Steel Using CBN and Ceramic Inserts. *Transactions of the Indian Institute of Metals*, *74*(7), 1639–1653. https://doi.org/10.1007/s12666-021-02245-2

Rath, D., Panda, S., & Pal, K. (2018). Prediction of Surface Quality Using Chip Morphology with Nodal Temperature Signatures in Hard Turning of AISI D3 Steel. *Materials Today: Proceedings*, *5*(5), 12368–12375. https://doi.org/10.1016/j.matpr.2018.02.215

Rathod, N. J., Chopra, M. K., Chaurasiya, P. K., & Vidhate, U. S. (2023). Optimization of Tool Life, Surface Roughness and Production Time in CNC Turning Process Using Taguchi Method and ANOVA. *Annals of Data Science*, *10*(5), 1179–1197. https://doi.org/10.1007/s40745-022-00423-7

Sada, S. O., Eyenubo, O. J., Atikpo, E., & Enyi, C. L. (2022). Evaluation of neural network parameters in the prediction of AISI 1050 steel machining performance. *Advances in Materials and Processing Technologies*, *9*(4), 1475–1486. https://doi.org/10.1080/2374068X.2022.2119715

Saha, S., Zaman, P. B., Tusar, M. I. H., & Dhar, N. R. (2022). Multi-objective genetic algorithm (MOGA) based optimization of high-pressure coolant assisted hard turning of 42CrMo4 steel. *International Journal on Interactive Design and Manufacturing*, *16*(3), 1253–1272. https://doi.org/10.1007/s12008-022-00848-7

Şahin, Y. (2024). Prediction of surface roughness when maching mild steel using statistical methods. *Advances in Materials and Processing Technologies*, *10*(3), 1593–1609. https://doi.org/10.1080/2374068X.2023.2198822

Sahoo, A. K., & Sahoo, B. (2013). A comparative study on performance of multilayer coated and uncoated carbide inserts when turning AISI D2 steel under dry environment. *Measurement: Journal of the International Measurement Confederation*, *46*(8), 2695–2704. https://doi.org/10.1016/j.measurement.2013.04.024

Sahoo, P. (2011). Optimization of Turning Parameters for Surface Roughness Using Rsm and Ga. *Advances in Production Engineering & Management*, *6*, 197–208.

Salgar, V. M. H., Patil, M. M. M., More, M. N. S., Nikam, M. A. S., & Dhawan, A. P. (2019). Optimization of cutting parameters during turning of AISI 1018 using Taguchi method. *International Research Journal of Engineering and Technology (IRJET). e-ISSN: 2395-0056. p-ISSN: 2395*, *72*, 994–1002.

Serra, R., Chibane, H., & Duchosal, A. (2018). Multi-objective optimization of cutting parameters for turning AISI 52100 hardened steel. *The International Journal of Advanced Manufacturing Technology*, *99*, 2025–2034.

Shah, A. H. A., Azmi, A. I., & Khalil, A. N. M. (2016). Grey Relational Analyses for Multi-Objective Optimization of Turning S45C Carbon Steel. *IOP Conference Series: Materials Science and Engineering*, *114*(1). https://doi.org/10.1088/1757-899X/114/1/012023

Sharma, B. (2020). Effect of Parameters Like Spindle Speed, Depth of Cut and Feed Rate on the Cutting Force of a Single Point Cutting Tool. *International Journal of Engineering Applied Sciences and Technology*, *04*(12), 525–530. https://doi.org/10.33564/ijeast.2020.v04i12.094

Shaw, M. C. (2005). *Second Edition*.

Singh, J., & Gill, S. S. (n.d.). *The Optimization of Machining Parameters on Surface Roughness for AISI D3 Steel The Optimization of Machining Parameters on Surface Roughness for AISI D3 Steel*. https://doi.org/10.1088/1742-6596/1874/1/012063

Slowik, A., & Kwasnicka, H. (2020). Evolutionary algorithms and thEvolutionary algorithms and their applications to engineering problemseir applications to engineering problems. *Neural Computing and Applications*, *32*(16), 12363–12379. https://doi.org/10.1007/s00521-020-04832-8

Stojković, M., Madić, M., Trifunović, M., & Turudija, R. (2022). Determining the Optimal

Cutting Parameters for Required Productivity for the Case of Rough External Turning of AISI 1045 Steel with Minimal Energy Consumption. *Metals*, *12*(11). https://doi.org/10.3390/met12111793

Sunday Abolarin, M., Oluwafemi Ayodeji, O., Jonathan Yisa, J., Solomon Olaoluwa, P., & Clement Kehinde, A. (2015). As feed rate increases, the tool engages with more material per revolution, leading to greater cutting forces. This results in higher mechanical stress on the tool, accelerating wear. *International Journal of Engineering Trends and Technology*, *22*(4), 171–173. https://doi.org/10.14445/22315381/ijett-v22p236

Thakkar, J., & Patel, M. I. (2014). OPEN ACCESS A Review on Optimization of Process Parameters for Surface Roughness and Material Removal Rate for SS 410 Material During Turning Operation. *Int. Journal of Engineering Research and Applications*, *4*(2(Version 1)), 235–242.

Touggui, Y., Belhadi, S., Mechraoui, S. E., Uysal, A., Yallese, M. A., & Temmar, M. (2020). Multi-objective optimization of turning parameters for targeting surface roughness and maximizing material removal rate in dry turning of AISI 316L with PVD-coated cermet insert. *SN Applied Sciences*, *2*(8), 1–14. https://doi.org/10.1007/s42452-020-3167-4

Varaprasad, B., Srinivasa Rao, C., & Vinay, P. V. (2014). Effect of machining parameters on tool wear in hard turning of AISI D3 Steel. *Procedia Engineering*, *97*, 338–345. https://doi.org/10.1016/j.proeng.2014.12.257

Vukelic, D., Simunovic, K., Kanovic, Z., Saric, T., Tadic, B., & Simunovic, G. (2021). Multi-objective optimization of steel AISI 1040 dry turning using genetic algorithm. In *Neural Computing and Applications* (Vol. 33, Issue 19). Springer London. https://doi.org/10.1007/s00521-021-05877-z

Yadav, U. K., Narang, D., & Attri, P. S. (2012). *Experimental Investigation And Optimization Of Machining Parameters For Surface Roughness In CNC Turning By Taguchi Method*. *2*(August), 2060–2065.

Yağmur, S. (2021). The effects of cooling applications on tool life, surface quality, cutting forces, and cutting zone temperature in turning of Ni-based Inconel 625. *International Journal of Advanced Manufacturing Technology*, *116*(3–4), 821–833. https://doi.org/10.1007/s00170-021-07489-2

Yalçın, B. (2015). SURFACE ROUGHNESS AND CUTTING FORCES IN TURNING OF TOOL STEEL WITH MIXED CERAMIC AND CUBIC BORON NITRIDE

CUTTING TOOLS. *Transactions of the Canadian Society for Mechanical Engineering*, *39*(2), 323–336.

Yallese MA, Belhadi S, Bouchelaghem H, Amirat A, C. K. (2016). Wear behaviour of CBN tool when turning hardened AISI D3 steel. *International Conference on Advances in Mechanical Enginerring & Mechanics*, *63*(5), 57–65.

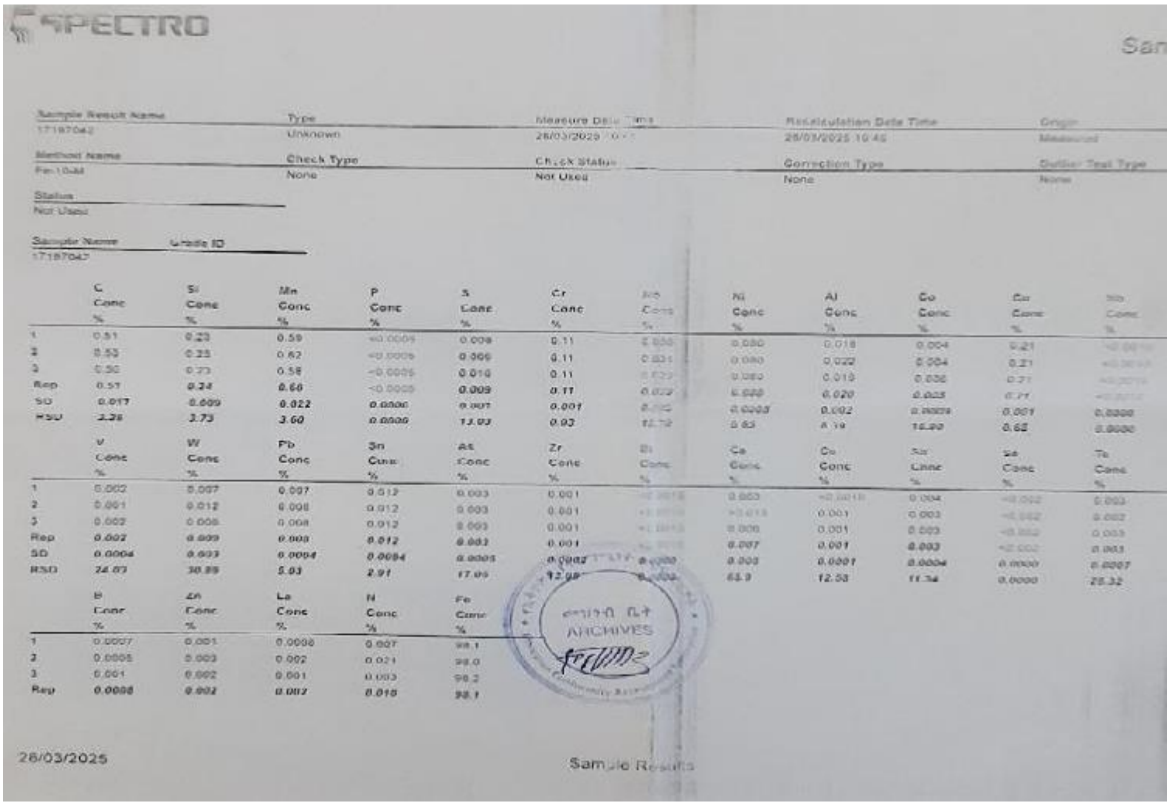
Yu, Q., Li, S., Zhang, X., & Shao, M. (2019). Experimental study on correlation between turning temperature rise and turning vibration in dry turning on aluminum alloy. *International Journal of Advanced Manufacturing Technology*, *103*(1–4), 453–469. https://doi.org/10.1007/s00170-019-03506-7

Zheng, G., Xu, R., Cheng, X., Zhao, G., Li, L., & Zhao, J. (2018). E ff ect of cutting parameters on wear behavior of coated tool and surface roughness in high-speed turning of 300M. *Measurement*, *125*(April), 99–108. https://doi.org/10.1016/j.measurement.2018.04.078

Zhujani, F., Abdullahu, F., Todorov, G., & Kamberov, K. (2024). Optimization of Multiple Performance Characteristics for CNC Turning of Inconel 718 Using Taguchi–Grey Relational Approach and Analysis of Variance. *Metals*, *14*(2). https://doi.org/10.3390/met14020186

APPENDIX

Appendix A1: EDM sample result for chemical composition of workpiece.



SPECTRO

Sample Result Name: 17187042 | Type: Unknown | Measure Date Time: 28/03/2025 [illegible] | Recalculation Date Time: 28/03/2025 10:45 | Origin: Measured

Method Name: Fe-10-M | Check Type: None | Check Status: Not Used | Correction Type: None | Outlier Test Type: None

Status: Not Used

Sample Name: 17187042 | Grade ID

	C Conc %	Si Conc %	Mn Conc %	P Conc %	S Conc %	Cr Conc %	[illegible] Conc %	Ni Conc %	Al Conc %	Co Conc %	Cu Conc %	Nb Conc %
1	0.51	0.23	0.59	<0.0005	0.008	0.11	[illegible]	0.080	0.018	0.004	0.21	[illegible]
2	0.53	0.25	0.62	<0.0005	0.009	0.11	0.031	0.080	0.022	0.004	0.21	[illegible]
3	0.50	0.23	0.58	<0.0005	0.010	0.11	[illegible]	0.080	0.019	0.006	0.21	[illegible]
Rep	0.51	0.24	0.60	<0.0005	0.009	0.11	[illegible]	0.080	0.020	0.005	0.21	[illegible]
SD	0.017	0.009	0.022	0.0000	0.001	0.001	[illegible]	0.0003	0.002	[illegible]	0.001	0.0000
RSD	3.28	3.73	3.60	0.0000	13.03	0.93	[illegible]	0.63	[illegible]	16.00	0.65	0.0000

	V Conc %	W Conc %	Pb Conc %	Sn Conc %	As Conc %	Zr Conc %	Bi Conc %	Ca Conc %	Ce Conc %	Sb Conc %	Se Conc %	Te Conc %
1	0.002	0.007	0.007	0.012	0.003	0.001	[illegible]	0.003	<0.0010	0.004	<0.002	0.003
2	0.001	0.012	0.008	0.012	0.003	0.001	[illegible]	[illegible]	0.001	0.003	<0.002	0.002
3	0.002	0.008	0.008	0.012	0.003	0.001	[illegible]	0.006	0.001	0.003	<0.002	0.003
Rep	0.002	0.009	0.008	0.012	0.003	0.001	[illegible]	0.007	0.001	0.003	<0.002	0.003
SD	0.0004	0.003	0.0004	0.0004	0.0005	0.0002	[illegible]	0.003	0.0001	0.0004	0.0000	0.0007
RSD	24.07	30.39	5.03	2.91	17.05	12.9	[illegible]	65.9	12.53	11.34	0.0000	25.32

	B Conc %	Zn Conc %	La Conc %	N Conc %	Fe Conc %
1	0.0007	0.001	0.0008	0.007	98.1
2	0.0005	0.003	0.002	0.021	98.0
3	0.001	0.002	0.001	0.003	98.2
Rep	0.0008	0.002	0.002	0.010	98.1

ARCHIVES

28/03/2025 Sample Results

Appendix-A2: CNC Cylindrical Grinding Code

The G-Code developed for work piece material on a CNC turning machine.

```
Machining file:.\PROG\O00012B
%1235
N10T0101
N02M0381920F230
N03G00X38.5Z2
N04G71U0.25R1P05Q06
N05G01X38Z0
N06G01Z-30
    G00X100Z200
N13M05
N14M30
```

Appendix-A3: Taguchi orthogonal array design matrix

Taguchi Design
Taguchi Analysis: Ra versus Cut...
Taguchi Analysis: MRR versus ...
Taguchi Analysis: Tool Wear ver...
General Linear Model: Ra versu...
General Linear Model: MRR ver...
General Linear Model: Tool We...
Regression Analysis: Ra versus ...
Regression Analysis: MRR vers...
Regression Analysis: Tool Wear...
Taguchi Analysis: GRG versus C...
General Linear Model: GRG ver...
Regression Analysis: GRG vers...
Taguchi Analysis: GRG versus C...
Taguchi Analysis: Tool Wear ver...
General Linear Model: Tool We...
General Linear Model: Tool We...

WORKSHEET 1

Taguchi Design

Design Summary

Taguchi Array L9(3^3)
Factors: 3
Runs: 9

Columns of L9(3^4) array: 1 2 3

	C1	C2	C3	C4	C5	C6	C7	C8	C9
	Cutting Speed	Feed Rate	Depth of Cut	Ra	MRR	Tool Wear	SNRA1	SNRA2	SNRA3
1	180	0.08	0.5	0.90	7.2	54.85	0.91515	17.1466	-34.7835
2	180	0.10	1.0	1.31	18.0	71.28	-2.34543	25.1055	-37.0594
3	180	0.12	1.5	1.62	32.4	83.13	-4.19030	30.2109	-38.3952
4	210	0.08	1.0	0.88	16.8	76.78	1.11035	24.5062	-37.7050
5	210	0.10	1.5	1.40	31.5	100.45	-2.92256	29.9662	-40.0390
6	210	0.12	0.5	2.00	12.6	95.00	-6.02060	22.0074	-39.5545
7	240	0.08	1.5	0.67	28.8	105.50	3.47850	29.1878	-40.4650
8	240	0.10	0.5	1.16	12.0	108.00	-1.28916	21.5836	-40.6685
9	240	0.12	1.0	1.76	28.8	154.00	-4.91025	29.1878	-43.7504
10									

Worksheet 1

Appendix-A4: General linear model for GRG

General Linear Model: GRG versus Cutting Speed, Feed Rate, Depth of Cut

Method

Factor coding (-1, 0, +1)

Factor Information

Factor	Type	Levels	Values
Cutting Speed	Fixed	3	180, 210, 240
Feed Rate	Fixed	3	0.08, 0.10, 0.12
Depth of Cut	Fixed	3	0.5, 1.0, 1.5

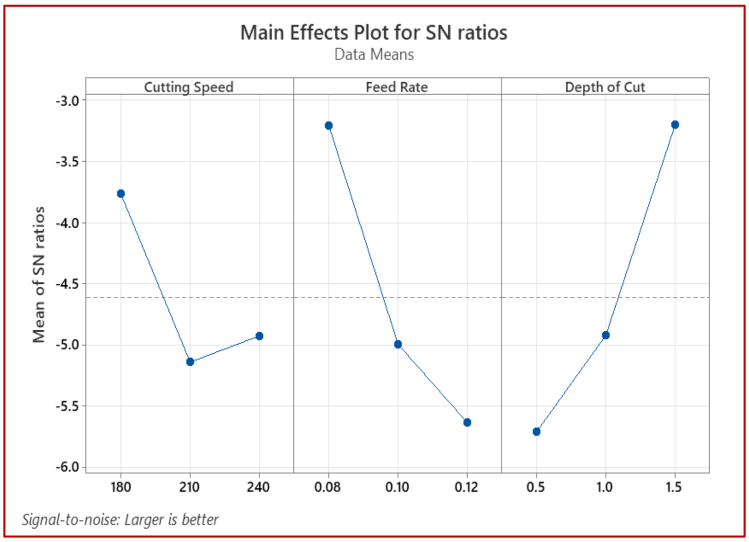
Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Cutting Speed	2	0.012689	0.006344	15.43	0.061
Feed Rate	2	0.042756	0.021378	52.00	0.019
Depth of Cut	2	0.043489	0.021744	52.89	0.019
Error	2	0.000822	0.000411		
Total	8	0.099756			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.0202759	99.18%	96.70%	83.31%

Appendix-A5: Main effects plot for S/N for GRG



Appendix-A6: MATLAB R2021 Code Generation for multi objective optimization

```
% MATLAB Code for Optimizing Turning Parameters using Genetic Algorithm (GA)
clc; clear; close all;
% Define discrete levels from experimental data
cuttingSpeedLevels = [180, 210, 240];
feedRateLevels = [0.08, 0.10, 0.12];
depthCutLevels = [0.5, 1.0, 1.5];
% Define response functions using regression equations
Ra = @(x) 1.3000 - 0.0233*(x(1)=180) + 0.1267*(x(1)=210) - 0.1033*(x(1)=240) ...
          - 0.4833*(x(2)=0.08) - 0.0100*(x(2)=0.10) + 0.4933*(x(2)=0.12) ...
          + 0.0533*(x(3)=0.5) + 0.0167*(x(3)=1.0) - 0.0700*(x(3)=1.5);
MRR = @(x) -(20.900 - 1.70*(x(1)=180) - 0.60*(x(1)=210) + 2.30*(x(1)=240) ...
          - 3.30*(x(2)=0.08) - 0.40*(x(2)=0.10) + 3.70*(x(2)=0.12) ...
          - 10.30*(x(3)=0.5) + 0.30*(x(3)=1.0) + 10.00*(x(3)=1.5));
ToolWear = @(x) 94.33 - 24.58*(x(1)=180) - 3.59*(x(1)=210) + 28.17*(x(1)=240) ...
           - 15.29*(x(2)=0.08) - 1.09*(x(2)=0.10) + 16.38*(x(2)=0.12) ...
           - 8.38*(x(3)=0.5) + 6.35*(x(3)=1.0) + 2.03*(x(3)=1.5);
% Multi-objective function considering discrete categorical values
objFcn = @(x) [Ra(x), MRR(x), ToolWear(x)];
% Define bounds based on experimental conditions
lb = [min(cuttingSpeedLevels), min(feedRateLevels), min(depthCutLevels)];
ub = [max(cuttingSpeedLevels), max(feedRateLevels), max(depthCutLevels)];
% Genetic Algorithm settings
options = optimoptions('ga', 'PopulationSize', 100, 'Display', 'final', ...
  'MaxGenerations', 200);
% Run Genetic Algorithm with integer constraints
[x_opt, fval] = ga(@(x) sum(objFcn(x)), 3, [], [], [], [], lb, ub, [], options);
% Round optimized values to match experimental discrete levels
[~, idx1] = min(abs(cuttingSpeedLevels - x_opt(1)));
[~, idx2] = min(abs(feedRateLevels - x_opt(2)));
[~, idx3] = min(abs(depthCutLevels - x_opt(3)));
optimalParams = [cuttingSpeedLevels(idx1), feedRateLevels(idx2), depthCutLevels(idx3)];
% Compute the optimal response values using regression equations
```

optimalResponses = [Ra(optimalParams), -MRR(optimalParams), ToolWear(optimalParams)];

% Display optimized results

disp('Optimal Cutting Speed, Feed Rate, and Depth of Cut:');

disp(optimalParams);

disp('Optimum Response Values (Ra, MRR, Tool Wear):');

disp(optimalResponses);

Appendix-A7: Optimal cutting parameters and optimum value of responses