Experimental Investigation and Parametric Optimization of EN-8 Steel using Dry Turning for Enhanced Surface Finish

BY:

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Thesis submitted to the Department of Design and Manufacturing Engineering

School of Mechanical, Chemical, and Material Engineering

Office of Graduate Studies

Adama Science and Technology University

Jan 2021

Adama, Ethiopia

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A thesis submitted in partial fulfillment of the requirements for the degree of

MSc in Manufacturing Engineering

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We, the undersigned members of the Board of Examiners of the final open defense by **Kirubel Tadele Weldgbrel** have read and evaluated his thesis entitled “**Experimental Investigation and Parametric Optimization of EN-8 Steel using Dry Turning for Enhanced Surface Finish**” and examined the candidate. Therefore, this is to certify that the thesis has been accepted in partial fulfillment of the requirement of the Degree of Master of Science in Manufacturing Engineering.

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TO

MY MOTHER MESERET LULU

Candidate Declaration

I declare that the thesis entitled **"Experimental Investigation and Parametric Optimization of EN-8 Steel using Dry Turning for Enhanced Surface Finish"** submitted in partial fulfillment of the requirements for the award of the degree of Masters of Science in Manufacturing Engineering is an authentic record of my work carried out, under the advisor **Moera Gutu Jiru (Ph.D.)** and co-advisor **B K Singh** (Ph.D.)**,** Mechanical Design and Manufacturing Engineering Program, Adama Science and Technology University, Adama, Ethiopia. I have not submitted the matter embodied in this thesis for the award of any other degree or diploma. All relevant resources of information used in this thesis have been duly acknowledged.

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This is to certify that the above statement made by the candidate is correct to the best of my Knowledge and belief. This thesis has been submitted for examination with my approval.

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Abstract

In machining parts, it is most important to determine the optimal machining parameters to achieve the desired product quality. Therefore, it is essential to investigate the effect of cutting parameters on surface roughness in a machining operation to accomplish the desired quality of an item. The thesis focuses on optimizing the cutting parameters such as cutting speed, feed rate, and depth of cut on surface roughness. The cutting parameters were optimized by turning process using the response surface methodology method. The surface roughness is selected as response variables and the workpiece is estimated by using a surface roughness analyzer (Profilometer). This study focuses on the development of optimization models to analyze the influence of machining parameters on surface roughness and to obtain the optimal machining parameters leading to minimum surface roughness during the turning of EN-8 steel using cemented carbide cutting tools. The outcome of data analysis in the environment of the Design-Expert version 11 and Minitab 19 software is presented and discussed. The developed models are compared using relative error and the results are validated using the experimental confirmation tests. The minimum surface roughness at optimum tuning parameters in this study was obtained. The result of variance indicates that the contribution of cutting speed, feed rate, and depth of cut was 3.11%, 7.69%, and 76.36%, respectively. It has been found that the predictive model provides optimum machining parameters. The results of the proposed model provide improvement in surface roughness over the best experimental run. The 3D surface and contour plots constructed during the study can be used for choosing the optimal machining parameters to obtain particular surface roughness values. The optimal machining parameters indicate that the depth of cut is the most significant machining parameter followed by the cutting speed and feed rate in surface roughness. The confirmation experiments were performed to facilitate the verification of the obtained feasible optimal machining parameters (v = 375 m/min, f = 0.287 mm/rev and d = 1 mm) for the surface roughness and the optimized surface roughness obtained is (Ra) 5.113 μm. The results reveal that the developed predictive models provide a close relation between the predicted values and the experimental surface roughness values.

Keywords: Response Surface Methodology, Surface Roughness, EN-8 steel

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Nomenclature

2FI	Two-factor interaction
α	clearance angle
γ	rake angle
μ	Mean
µm	Micrometer
Adj	Adjusted
AISI	American Iron and Steel institute
Al	Aluminum
Al_2O_3	Aluminum oxide
ASME	American Society of Mechanical Engineers
ANN	Artificial Neural Network
ANOVA	Analysis of variance
B	fiber orientation angle
BHN	Brinell hardness Number
C40	Carbon steel
CC	Central Composite
CCD	Central Composite Design
CI	Confidence interval
CNC	Computer Numerical Control
C.V	Coefficient of Variation
CVD	Chemical vapor deposition
d	depth of cut
d	Diameter
D	Diameter of tool
da	axial depth of cut
df	Degrees of freedom
DOE	Design of experiment
DP	Dynamic Programing
dr	radial depth of cut
EN	European standard
et al.	And others
F-value	Residual mean square
f	feed
f*	feed
ft	feed/tooth
FANUC	Factory automation numerical control
FFT	Fourier transform
g/min	Gram Per Minute
GA	Genetic Algorithm
GRA	Gray relational analysis
H	Hot hardness
HRB	Brinell hardness
HRC	Hardness
HSS	High-Speed Steels
i.e.	that is to say
lt	lubricant temperature
K	approach angle
kW	kilowatt
LP	Linear Programing
M	Milling
m	Meter
MATLAB	Matrix Laboratory
Max	Maximum

MDN	Maraging steel
mm	Millimeter
mm/rev	revolution of per minute
MPa	Mega pascal
MRR	Material removal rate
mt	machining tolerance
N	number of inserts
NAK	Hardness
NC	Numerical Control
NLP	Non-Linear Programing
OEM	Original Equipment Manufacturer
P	Steel plate
p-value	Probability
PI	Prediction intervals
Pred	Predicted
PRESS	Predicted residual error sum of squares
PVD	Physical vapor deposition
r	tool nose radius
R	Variation
Ra	Roughness Average
Ra	Surface roughness
Ra	Average variation from the mean line
RMR	Resting metabolic rate
Rpm	Revolutions per minute
Rq	Root mean square
RSM	Response Surface Methodology
Rt	Highest peak to the deepest valley
Rz	Roughness Depth
Rz	Average Rt over a given length
S.C	Share Company
S.S	Stainless
S/N	Signal to Noise ratio
SAE	Society of Automotive Engineers
SCEA	side cutting edge angle
SF	Surface Finish
SiC	Silicon carbide
SKD	Tool steel
St	steel
Std. Dev	Standard deviation
T	Turning
t	time (min)
t	Thickness in mm
Ti	Titanium
TiN	Aluminum
v	cutting speed

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

Machining is a flexible procedure generally used in the manufacturing industry to process raw materials of different types to impart shape and finish to items. While commonly used as an optional molding process (essential molding being finish using casting, forming, and so on). It is additionally regularly used as an across-the-board essential procedure for prototyping. It is a manufacturing process that helps provide shape, dimensions, and in some cases, properties to the raw material to produce an intended component.

It is a variety of material removal forms in which a cutting instrument removes undesirable material from a workpiece to deliver the ideal shape. However, the dynamic reaction of a machining framework is frequently decayed by surface quality. The surface quality is one among the foremost specified customer requirements, and therefore the major indicator of surface quality on machined parts is surface roughness (Lauro *et al.* 2014).

Surface finish is one of the most important quality characteristics in manufacturing industries, which influences the performance of mechanical parts as well as production cost. In recent times, modern industries are trying to achieve high-quality products in a very short time with less operator input. For that purpose, the computer numerically controlled (CNC) machine tools with automated and flexible manufacturing systems have been implemented. In the manufacturing industries, various manufacturing processes are adopted to remove the material from the workpiece. Out of these, turning is the first most common method for metal cutting because of its ability to remove materials faster with reasonably good surface quality (Sahoo, 2011).

In a turning operation, it's a crucial task to select cutting parameters for achieving high cutting performance. Usually, the specified cutting parameters are determined by supported experience or by the use of a handbook (Quintana & Ciurana 2011). Cutting parameters are reflected in surface roughness, surface texture, and dimensional deviations of the product. Surface roughness, which is used to determine and evaluate the quality of a product, is one of the main quality attributes of a turning product. Surface roughness is a measure of the technological quality of a product and an element that greatly influences manufacturing cost. It describes the geometry of the machined surfaces and combined them with the surface texture.

Producing good quality, appropriate surface finish, and geometry is essential for the machined workpiece. The surface finish or surface texture based on (ASME, 1985) is defined as geometrical irregularities of solid materials surface while surface roughness is defined as the more delicate irregularities of the surface texture, usually resulting from the inherent action of the assembly process, such as feed marks produced during machining.

This research aims to investigate the effects of cutting parameters on the resulting surface roughness in the turning operation of EN-8 steel material. The specific products from this steel are shafts, cam, bolt, stud, gear, so on. It was essential to optimize this material due to the quick-wear of components under dynamic load. In the present work, models are developed to predicate the surface roughness with the assistance of Response surface methodology, Design of experiments (Montgomery, 2017). The response surface methodology (RSM) may be practical, accurate, and straightforward for implementation. The study of the most important variables affecting the quality characteristics and a plan for conducting such experiments is called the design of experiments (Myers *et al.*, 2016).

The experimental data is used to develop mathematical models for second-order models using regression methods. Analysis of variance is used to verify the validity of the model. RSM optimization procedure has been used to optimize the output responses of surface roughness. On selected material, a different trial with different parameters level carried experiment, and finally, to verify the predicted value, a confirmation test is conducted based on an experiment. The research has completed a fractional experiment design that allows considering different levels of cutting parameters (cutting speed, feed rate, depth of cut) on the measured dependent variable (surface roughness). The ability to control the process for the better quality of the product is significant (Kassab and Khoshnaw, 2007).

1.2 Motivation of research

During the internship of about a month and a half in Dire Dawa Food Complex S.C., I have observed that parts such as shafts, gears, cam, keys, bolts and parts of machines like pump and cylinders wears so fast due to the dynamic load and poor surface finish. Due to such reasons, machined parts in their machine shops were harmed and damaged a few times and substituted with another machined part. This medium occurred because of its poor surface finish the apparatus wears during the groundwater siphoning strategy. This ground breaks down the outside of the rigging pump (vein), and smart prompts wear, finally, out of limit. This way, the cost of remachining and replacing worn out parts to give indications of progress surface finished ought to be the center. Achieving this perfect surface quality is an incredible sign of the capacity conduct of a section.

The primary inspiration driving this work is the requirement for constraining the surface roughness related to cutting parameters and improve the portion from quick wear and damage, expressly through scouring, break, and pits formed on the subsurface of the part, which in turn will reduce the cost of maintenance and time of shutdown.

1.3 Surface roughness overview

Surface roughness refers to deviation from the nominal surface of the third up to the sixth request. Worldwide models are deviation by characterized a request (Benardos and Vosniakos, 2003). First-and second-request deviations refer to frame, i.e., flatness, circularity. Furthermore, to waviness, respectively, and are due to machine tool errors, deformation of the workpiece, erroneous setups and clamping, vibration, and workpiece material inhomogeneities. Third-and fourth-request deviations refer to rare grooves, and to breaks and frailties, which are associated with the shape and state of the cutting edges, chip formation, and process kinematics. Fifth-and sixth request deviations refer to workpiece material structure, which is related to physical-chemical components following abreast of a grain and lattice scale (slip, diffusion, oxidation, residual stress). Diverse request deviations are superimposed and structure the surface roughness profile as shown in Figure 1-1.

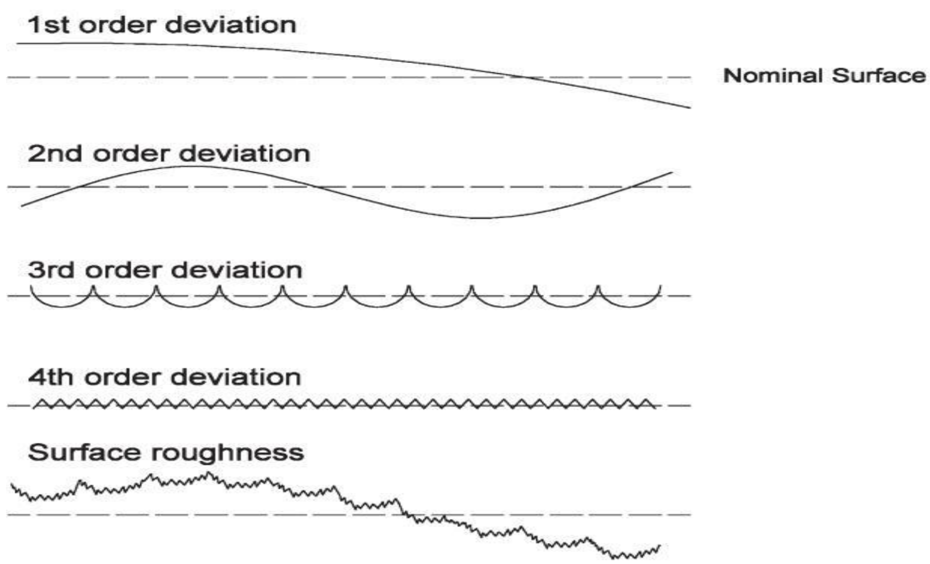


Figure 1-1 Surface form deviations (Benardos and Vosniakos, 2003)

1.4 Surface finish general ideas

Building prints get out a considerable number of things in their endeavor to ensure the part that gets made matches the creator's expectation. Besides measurements and resistances, another significant callout is surface finishing.

Surface finishing is a magnitude of the overall texture of a surface that is characterized by surface roughness and waviness of the surface. Surface finishing when it expects to incorporate each of the three qualities was keep away from perplexity since engineers regularly allude to surface roughness as surface finishing. Another term, analogous to the surface roughness is surface topology.

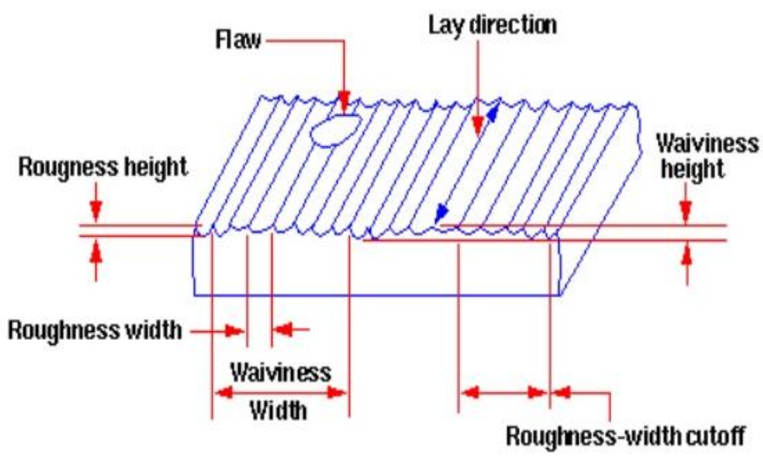


Figure 1-2 Surface characteristics and terminology (Vorbuger and Raja, 1990)

1.5 Types of surface

A surface may be a boundary that separates an object from another object or substance. The surface divide into three subgroups (Vorburger and Raja, 1990):

- **Real surface**

  It is the actual boundary of an object. It deviates from the nominal surface because of the procedure that has made the surface. The deviation additionally relies upon the properties, composition, and structure of the material.

- **Measured surface**

  It is a representation of the real surface acquired with some estimating tool. This qualification is made, and no estimation will give the exact real surface.

- **Nominal surface or ideal**

  It is the proposed surface, is a hypothetical, geometrically perfect surface that does not exist practically speaking, yet it is average of the irregularities that are superimposed on it. The nominal/idea surface does exclude expected surface roughness.

1.6 Statement of the problem

Surface quality in machining technique is related to surface roughness. If there is un-optimized surface roughness, there will be a higher chance of occurrence of defects such as wear of parts, huge pinnacles, and valley formation, which results from part incapable of serving for the arranged period. In this manner, surface roughness can reduce the surface quality which results in high cost. In turning operation, cutting parameters are frequent issues, which impact the result of machining and explicitly the surface finish. The surface roughness issue is subjected to parameters such as depth of cut, cutting speed, and feed rate.

Because of the expanding request of higher exactness parts for its useful perspective and production price reduction, it is crucial to examine and investigate the cutting parameters that influence the surface roughness in the metal turning operation. Furthermore, inappropriate choice of machining parameters makes cutting tools wear and break rapidly just as monetary misfortunes, i.e., harmed workpiece and dismissed item quality. In this manner, the target of the present research is to work on the turning operation of EN-8 steel grade material and to overcome the stated problems with a modeling technique for the prediction of surface roughness.

1.7 Objective of the study

In this section, the general and specific objectives of the thesis are discussed and presented.

1.7.1 General objective

The general objective of this thesis is to experimentally investigate and parametrically optimize dry turning operation of EN-8 steel to produce a smooth and enhanced surface finish.

1.7.2 Specific objective

The specific objectives of this thesis are:

- Investigating the variation of surface roughness with varying parameters (cutting parameters).
- Experimental investigation of surface roughness of EN-8 steel material using turning operation.
- Investigating the variation of surface roughness with response variables.

- Development of predictive and optimization models to determine the optimum machining parameters leading to minimum surface roughness.

1.8 Scope of the study

The scope of the research work is on a turning machine with its corresponding cutting parameters and the effect of cutting speed, feed rate and depth of cut will be studied during the turning of EN-8 steel using carbide cutting tools. A turning operation carried out and surface roughness measurement (Profilometer) used for analysis. Finally, this work focuses on the effect of cutting parameters on surface roughness.

1.9 Significance of the study

Establishing a machining investigation to find out the cutting parameters on surface roughness in a turning operation with quality material that will produce a good surface finish of the product, which leads to an increase in the profit is significant.

The thesis has the following significance:

- This study comes with an alternative way of implementing an investigation of cutting parameters on surface roughness, turning the operation of EN-8 steel material to produce a smooth surface finish.
- The system works on bits of help to maintain the stability of dimensional accuracy, increase the precision of the product, obtain a better surface finish, and reduces the friction factors in the movable joint.

So, the thesis can help as input for large scale production to produce a smooth surface finish. Furthermore, the result of the research will open an opportunity for further application of the optimization technique.

1.10 Organizations of the thesis

The thesis consists of five chapters that entitled in the investigation of cutting parameters on surface roughness for the turning operation of EN-8 steel material.

Chapter one: begins with an introduction in which the background of the study is briefly pointed out, and definition, fundamental principles, machining process, and others.

Chapter two: A review of relevant research publications in the investigation to find out the cutting parameters on surface roughness in a turning operation is presented. Available investigation of cutting parameters on surface roughness in turning operation models are studied to find the research gap in this chapter. The need for developing a new investigation of cutting parameters on surface roughness in turning the operation of EN-8 steel has been justified.

Chapter three: describes the experimental setup and plan, which is carried out to establish a relationship between machining performance (surface roughness) and machining parameters (cutting speed, feed rate, and depth of cut). The surface roughness is the selected measured response variables.

Chapter four: the relationship between machining parameters and surface roughness is obtained by using RSM. Optimum machining parameters leading to minimum surface roughness are achieved by using RSM. Confirmation experiments are conducted to verify the results.

Chapter five: summarizes the optimization research work completed in this investigation, and future research directions are discussed.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

In this part, accessible past works identified with this examination are reviewed inside the domain of the present analysis. In the metal cutting process, its effects are commonly reduced by appropriate choice of procedure parameters. The determination of optimization cutting parameters is a significant issue for each machining procedure to upgrade the nature of the machined item, reduce the machining cost, and increase the production rate.

To achieve these issues, the researcher proposes models that attempt to reproduce the conditions during machining and set up circumstances and logical results connection between different factors and wanted item qualifies—the introduction of each approach by giving minimized data that best suit their need and detail prerequisites. This chapter sets the background for this study. It is an assessment of the present state of the art of the wide and complex field of modeling and optimization of machining operations and their application in conventional machining processes.

2.2 Turning operation

A conventional lathe with its principal components is shown in Figure 2-1. This versatile machine tool, which is usually called the engine lathe, is mainly used for low to medium production. The term “engine” dates from the time when these machines were powered with overhead belts and pulleys, driven by steam engines. Nowadays, various types of automation have been added to the lathes to improve efficiency and accuracy for repetitive operations.

A conventional lathe consists of a horizontal bed or base supporting all other major components. The headstock, which is fixed to the bed, is provided with motors, pulleys, and V-belts that rotate the spindle, which rotates the workpiece at various speeds. Levers on the front of the headstock are to select the speeds of rotational. The headstock has a hollow spindle to which the work holding devices, such as chucks and collets, are attached. Opposite the headstock is the tailstock, which can slide along the ways and be clamped at any position. A center is mounted in the tailstock to support the other end of a long workpiece. A short workpiece is typically supported only by the chuck (Nee, 2015).

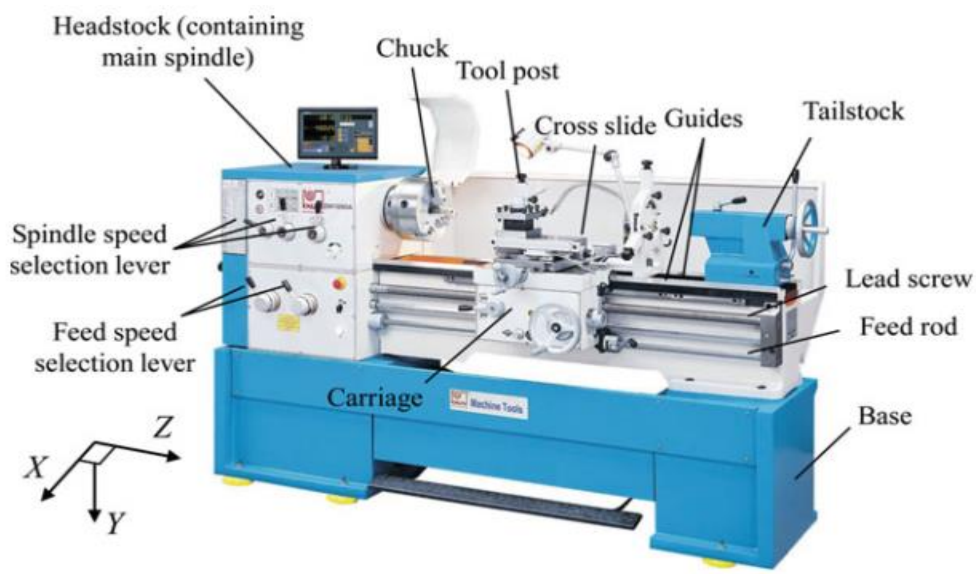


Figure 2-1 Conventional lathe machine (Nee, 2015)

2.3 Optimization techniques used in machining

Many advancement methods have been created by researchers to decide optimal cutting conditions for machining operations. Extensively, these might classify as (i) conventional optimization techniques and (ii) non-conventional optimization techniques, as shown in Figure 2-2.

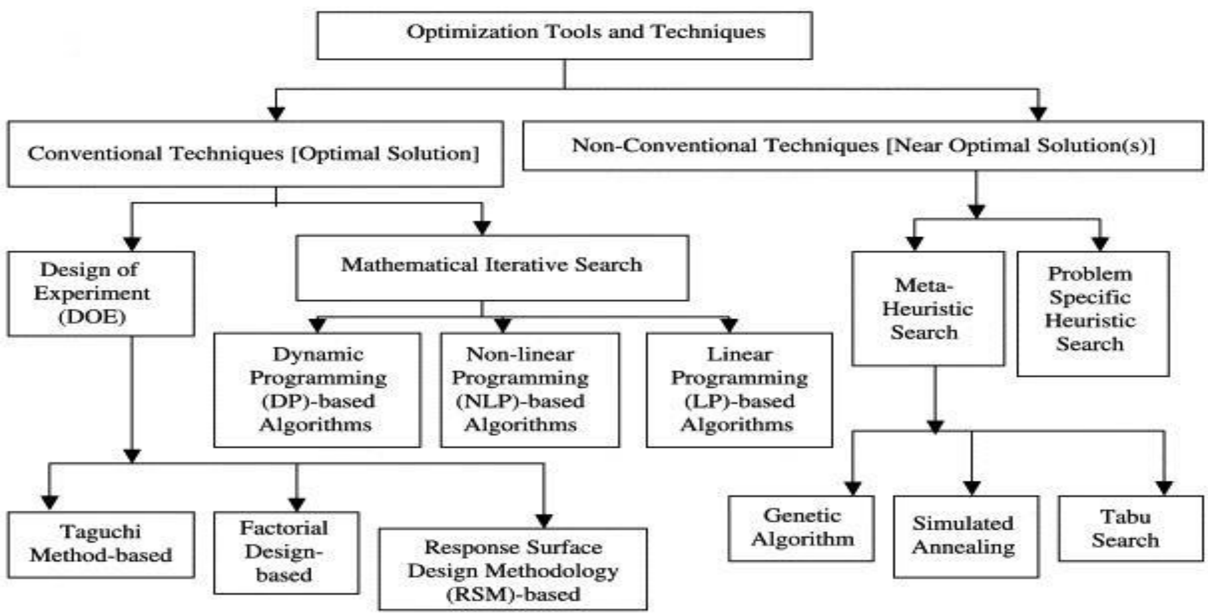


Figure 2-2 Conventional and non-conventional optimization techniques (Mukherjee and Ray, 2006)

2.3.1 Conventional optimization techniques

These systems depend on deterministic algorithms with specific standards for moving from one answer to the other. These algorithms have effectively applied to many engineering design problems. Extensive literature exists on the optimization of machining processes to mainly concentrating on minimum cost and maximum production rate.

Asilturk and Akkus (2011) used the Taguchi method for optimizing turning parameters to minimize surface roughness. The statistical methods of signal to noise ratio and the analysis of variance were applied to research the consequences of cutting speed, feed rate, and depth of cut on surface roughness. Results indicated that the feed rate was the most significant factor affecting surface roughness.

Neseli *et al.* (2011) applied response surface optimization during turning of AISI 1040 Steel with Al_2O_3 coated insert tools. The results revealed the optimal combination of tool nose radius, approach angle, and rake angle for better surface roughness.

Aouici *et al.* (2012) used desirability function analysis in RSM to determine the optimum values of cutting speed, feed rate, workpiece hardness, and depth of cut during the hard turning of AISI H11 steel with cubic boron nitride inserts. Results revealed that the best surface roughness is achieved at the lower feed rate and the higher cutting speed.

Chinchanikar and Choudhury (2013) used a desirability function approach in RSM to determine optimum cutting conditions. It found that the use of lower feed value, lower depth of cut, and limiting the cutting speed while turning 35 and 45 HRC AISI 4340 steel ensures minimum cutting forces, minimum surface roughness, and better tool life.

Campatelli *et al.* (2014) used RSM to analyze the effect of cutting speed, feed rate, radial, and axial depth of cut on energy consumption during the milling of carbon steel. The optimal values of the radial engagement and feed to minimize the specific energy associated with the efficiency of the cutting were 1 mm and 0.12 mm/tooth, respectively.

Conventional optimization techniques are generally gradient-based, and they present numerous restrictions in application to complex machining models (Rao, 2011). To overcome these issues, analysts have proposed non-conventional techniques.

2.3.2 Non-conventional optimization techniques

These algorithms are stochastic with probabilistic progress rules. These strategies are mainly founded on biological, molecular, or neurological marvels that copy the allegory of collective natural advancement or potentially the social conduct of species. To copy the proficient conduct of these species, different researchers have created computational frameworks that look for quick and robust answers for complex optimization issues. Subsequently, numerous new algorithms dependent on random search strategies used in taking care of machining advancement issues (Rao, 2011).

Zain *et al.* (2010) used a genetic algorithm for assessing the optimal cutting conditions for minimum surface roughness. A regression model is used to define goal work. Low feed rate, high cutting speed, and high outspread rake edge lead to bring down surface roughness.

Fu *et al.* (2012) advanced the cutting parameters during high-speed milling of NAK80 shape steel. An experiment dependent on Taguchi's technique was performed. The ideal cutting parameters were acquired utilizing grey relational analysis. The critical part investigation was applied to assess the loads with the goal that their relative weights can depict. The outcomes indicated that grey relational analysis combined with principal component analysis could effectively anticipate the optimal combination of cutting parameters, and the proposed methodology can be a helpful tool to reduce the cutting force.

Zain *et al.* (2012) used ANN combined with GA to scan for a lot of ideal cutting condition directs that lead toward the base estimation of surface roughness. Three machining cutting conditions considered in this examination were feed, radial rake angle, and speed. The used approach reduced the surface roughness esteem contrasted with the experimental, ANN, response surface methods, and regression.

Yan and Li (2013) presented a multi-objective optimization strategy dependent on weighted grey relational analysis and RSM to upgrade the cutting parameters during milling of medium carbon steel with carbide tools to accomplish the maximum material removal rate, minimum surface roughness, and minimum cutting energy. The outcomes demonstrated that the width of the cut was the most impacting parameter pursued by feed rate, spindle speed, and depth of cut. The experimental results showed that GRA combined with RSM is a helpful device for multi-objective optimization of cutting parameters.

2.4 Surface roughness and the effect of cutting parameters

Numerous variables influence the presentation of the turning process, additionally influence the surface finish quality (surface roughness). The surface roughness of a turning workpiece is reliant on process parameters and tool geometry (cutting edge, side cutting edge, nose radius, and rake angle, so on). What is more, it also relies upon a few different exogenous factors, such as; vibration between the workpiece, auxiliary tooling, workpiece machine tool used and lubricant used, cutting tool, and machine tool (He *et al.*, 2018).

Surface roughness in turning operation is, for the most part, influenced by the accompanying three cutting parameters: depth of cut, feed rate, and cutting speed. Surface roughness is also affected by workpiece material, cutting tool material, tool geometry, so on. Thus, to obtain the desired output, the correct combination of the factors is most vital. Along these lines, the essential goal of this exploration work is to examine the impact of the accompanying three cutting parameters of turning operation: feed rate, depth of cut, and cutting speed surface roughness of carbon steel bar and in this way to advance the cutting parameters (factors) to get the base surface roughness.

Detailed literature reviews on various cutting parameters and most significant of those parameters on surface roughness have discussed below:

Taguchi analyzes the configuration used to optimize turning parameters and get the lowest degree level of surface roughness parameters. The investigation result showed that the feed rate and the associated impact between feed rate and cutting rate were the most influential factors over the Ra. A few researchers do not just concentrate on the investigation of the part, yet additionally of the tool, which plays an essential job in deciding the cutting condition, and therefore, in the surface roughness (Dutta & Narala, 2021).

The cutting rate has an incredible impact on the roughness pursued by the depth of cut, and feed has no essential effect on surface roughness found by using the Taguchi method. The low depth of cut, low depth of cut, and low feed rate to get a better surface finish under dry turning action recommended (Noordin *et al.*, 2017).

It has been seen that cutting velocity, nose radius, and feed rate have higher duty surface roughness, while the hardness of work material and depth of cut has less massive responsibility surface roughness (Sijo and Biju, 2014).

The impact of feed rate, cutting speed, depth of cut and geometry of the tool on the average roughness acquired in hard turning bronze parts. The result revealed that the tool radius and the feed rate were the most dominant factors in Ra has been assessed (Pereira *et al.*, 2017).

2.5 Turning operation and surface roughness

Turning operations using a single-point cutting tool has been one of the most established and well-known strategies for metal cutting. It has supplanted granulating in a few applications with decreased lead time without influencing the surface quality. One of the essential aspects which widely studied in turning is cutting parameters and surface roughness of the workpiece.

Optimization process parameters are incredibly huge while investigating the procedure ability of any machining operation. Dry machining (no cutting fluid; avoid the problem of cutting fluid contamination, disposal, and filtration) of steel caused most tool wear and surface roughness, and wet machining did not show considerable improvement.

Ghani *et al.* (2004) optimized cutting parameters in end processing when machining hardened steel under semi-finishing and finishing conditions of feed rate, depth of cut, and rapid cutting speed. The examination of the outcome shows that the ideal blend for low resultant cutting force and good surface finish was high cutting speed, low feed rate, and low depth of cut. The investigation shows that the Taguchi technique was reasonable to take care of the expressed issue with the least number of preliminaries as contrasted and a full factorial structure.

Palanisamy *et al.* (2007) worked in improvement dependent on ground-breaking powerful artificial intelligence called GA. The aftereffect of the work shows how an unpredictable improvement issue is dealt with by a genetic algorithm and converges very quickly. Experimental end milling tests have been performed on mild steel to quantify cutting force using milling tool dynamometer, surface roughness, and vibration using an FFT analyzer for the enhanced cutting parameters in a Universal milling machine utilizing an HSS cutter. The outcomes demonstrate that the enhanced parameters equipped for machining the workpiece all the more proficiently with the better surface finish.

Kumaragurubaran *et al.* (2013) worked on turning tasks of EN-9 steel with various cutting parameters such as depth of cut, feed, and cutting speed and indicated that the turning activity extraordinarily impacted by response parameters including surface roughness and metal removal rate. In mainly, surface roughness was researched utilizing the L9 symmetrical exhibit utilizing

Taguchi's design of experiments with various cutting parameters of EN-9 of turning parameters and upgraded by S/N proportion and broke down by ANOVA's.

Maiyar *et al.* (2013) researched the parameter improvement of end milling with multi-response criteria dependent on the Taguchi symmetrical exhibit with the grey relational analysis. Nine experimental run dependents on an L9 symmetrical exhibit of the Taguchi method performed. A grey relational analysis is used to solve the multiple performance characteristics. Moreover, the ANOVA was additionally applied to distinguish the most critical factor. At last, affirmation tests were performed to examine the experimental outcomes and created models. Experimental results have demonstrated that machining execution at the last processing procedure can be improved adequately through their approach.

Pratyusha *et al.* (2013) worked with the impacts of different processing parameters such as depth of cut, feed rate, and spindle speed on the surface roughness of finished components. The tests were led on AISI 304 S.S. plate material on a vertical processing machine utilizing carbide embeds and by utilizing Taguchi's system, including the L9 symmetrical cluster. The examination of the mean and difference system is used to think about the essentialness of each machining parameter surface roughness.

Saraswat *et al.* (2014) worked streamline in turning of mild steel in turning activities on mild steel, and because of that, the blend of the ideal degrees of the elements gotten to get the least surface roughness. The ANOVA and Sign-to-Noise proportions were used to think about the exhibition qualities in turning activity. Their examination also shows that the anticipated qualities and determined qualities were extremely close, which demonstrates that the created model can utilize to foresee the surface roughness in the turning activity of mild steel. Taguchi technique has embraced the plan of experimental, and results have been by limiting S/N proportion. Optimizing of the surface roughness was finished utilizing the Taguchi method, and the Prescient condition was acquired. An affirmation test was then performed, which delineated that the chose parameters and prescient conditions were precise inside the cutoff points of the estimation tool.

Sangwan *et al.* (2015) introduced a methodology for deciding the ideal machining parameters prompting the least surface roughness by coordinating ANN and GA. A feed-forward neural system was created by gathering the input acquired during the turning of the Ti-6Al-4V titanium combination. The MATLAB tool stash has been used for preparing and testing a neural system model. The anticipated outcomes utilizing ANN show an exceptional understanding of the anticipated qualities and experimental qualities. Further, GA was incorporated with the neural system model to decide the ideal machining parameters prompting the least surface roughness. The examination of this investigation demonstrates that the ANN-GA approach is equipped for foreseeing the ideal machining parameters.

Kumar *et al.* (2016) considered the parametric enhancement under the consistent progression of coolant. The machining cutting parameters (depth of cut, cutting speed, and feed rate) were upgraded to assess high material removal rate and least surface roughness. The response surface technique translated the examination input with the assistance of the structure of the test. ANOVA shows the various parameters which give the critical sway on the estimations of surface roughness and material removal rate.

Panshetty *et al.* (2016) advanced CNC processing Process Parameters to give a superior surface finish and high MRR. As Taguchi's method decreases the quantity of experimental, it is used for streamlining machining parameters. It was applied to discover the impact of different machining parameters such as depth of cut, feed rate, speed on the surface finish, and MRR. MINITAB-14 software has been used to investigate the outcome. Ra was estimated, and the MRR esteems determined to decide ideal levels.

Padma *et al.* (2017) optimized the machining parameters for the turning of EN 9 carbon steel on the machine utilizing a mix of the Taguchi and the Dark Social Investigation to yield base cutting forces and anticipated least surface irregularity. Procedure parameters picked were the cutting speed, a feed, the depth of cut, and a choice cutting liquid. The ANOVA has also been used to assess the most effective handling parameters that were caused by the experiment. The inversion conditions are also set up between a procedure parameter and the response. The outcomes that demonstrate the depth of cut were a significant factor in that influencing a cutting force and the surface roughness.

Ribeiro *et al.* (2017) centered on manufacturing parameters that impact the surface quality of hardness metallic material. In their work, the impacts of differing four parameters in the processing procedure were used, in particular, cutting speed, feed rate, radial depth, and axial depth. The impact of every parameter in surface irregularity was then obtained by applying the ANOVA to experimental data. Their examination also serves to decide the commitment of each machining parameters and their cooperation for surface roughness. Additionally, the outcomes show that the spiral cutting depth and the communication between the outspread and hub depth of cut were essential parameters, being their commitments for the minimization surface roughness about 30% and 24%, respectively.

Prasadraju *et al.* (2017) used Taguchi's experimental design technique. An L9 orthogonal array, Taguchi method, and ANOVA used to define the experimental layout to examinations the impact of every parameter on the machining characteristics and to predict the optimal decision for each milling parameter such as feed rate, depth of cut, and cutting speed. In the cutting process, streamlining of cutting parameters is viewed as a fundamental tool for development in the yielding nature of an item just as decreasing the general production time.

Fedai *et al.* (2018) examined the impact of machining parameters on the different surface roughness characteristics (Ra, Rq, and Rz) in the milling of AISI 4140 steel experimentally investigated. Feed rate, cutting speed, depth of cut, and the number of supplements considered as control factors; Ra, Rz, and Rq considered as response factors. Additionally, the percent commitments of the control factors surface roughness were gotten to be the depth of cut (3.29 %, number of inserts (71.89 %), cutting velocity (5.08%), and feed (19.74 %). Minimum surface roughness esteems for Ra, Rz, and Rq were acquired by using the multi-objective Taguchi technique.

Karthikeyan *et al.* (2018) improved the process parameters such as cutting speed, feed, and depth of cut to accomplish the least surface roughness and least cutting force separately and combinedly by utilizing Taguchi – Dark investigation. From their examination, it was discovered that the joined least surface roughness and cutting force could be achieved under the states of 900 rpm of axle speed, 0.2 mm/fire up of feed, and 0.25 mm of the depth of cut.

Kumar *et al.* (2019) studied the impacts of effects of the parameters of primary end milling process such as cutting speed, radial angle, cutting feed rate, cutting condition, axial depth of cut, and tool geometry helix angle on Ra by the plan of investigations during CNC end milling of Al 7068 Aluminum. All the experiments were done under dry cutting conditions, and the tests were thought of according to the requirements of requisites of response surface methodology. All the importance of end milling process parameters on the Ra resolved with the assistance of ANOVA investigation. Mathematical models for surface roughness Ra, which have been planned with the help of reaction second request surface technique. In the end, the parameters such as helix angle, cutting speed, and radial rake angle of surface roughness seen as the best through the results.

Kumar *et al.* (2019) used to discover the ideal cutting parameters in milling operation of AISI 1005 steel utilizing TiN covered tool. Three cutting parameters, i.e., feed rate, spindle speed, and depth of cut, were optimized with consideration of Ra and MRR. Analyses have been performed dependent on the L9 symmetrical cluster. The impact of the cutting parameter was dissected utilizing ANOVA, and the outcomes show that the depth of cut and feed rate impacts the responses the most. Moreover, the affirmation test has led to dependent on the ideal parameter to legitimize the outcomes. Surface roughness and MRR got at ideal process parameters were 2.97 mm and 0.96923 g/min separately.

Table 2-1 Summary of literature review on surface roughness

No.	**Author Name**	**Years**	**Operation and Machine**	**Materials**	**Optimization Techniques**	**Input Parameters**	**Response Variables**
1	Ghani *et al.*	2004	Milling	AISI H13	Taguchi	cutting speed, feed rate, and depth of cut	Surface Roughness
2	Palanisamy *et al.*	2007	Milling	Mild Steel	GA	feed rate, depth of cut, cutting speed	Surface Roughness
3	Kumaraguruba ran *et al.*	2013	Turning	EN-9	DOE	cutting speed, feed, and depth of cut	Ra and MRR
4	Maiyar *et al.*	2013	Milling	Inconel 718	Taguchi, GRA	cutting speed, feed rate, and depth of cut	Surface Roughness
5	Pratyusha *et al.*	2013	Milling	AISI 304	Taguchi	spindle speed, feed rate, and depth of cut	Surface Roughness
6	Saraswat *et al.*	2014	Turning	Mild Steel	Taguchi	depth of cut, feed rate, and spindle speed	Surface Roughness
7	Sangwan *et al.*	2015	Turning	TI-6AL-4V	ANN-GA	cutting speed, feed rate, and depth of cut	Surface Roughness

8	Kumar *et al.*	2016	Milling	EN18	RSM	cutting speed, feed rate, and depth of cut	Ra and MRR
9	Panshetty *et al.*	2016	Milling	Al 7075	Taguchi	speed, feed rate, and depth of cut.	Ra and MRR
10	Padma *et al.*	2017	Turning	EN 9	GRA	cutting speed, feed, and depth of cut	Surface Roughness
11	Ribeiro *et al.*	2017	Milling	Hardened Steel	Taguchi	cutting speed, feed rate, and depth of cut	Surface Roughness
12	Prasadraju *et al.*	2017	Milling	Mild steel	Taguchi	spindle speed, feed rate, and depth of cut	Surface Roughness
13	Fedai *et al.*	2018	Milling	AISI 4140	Taguchi	depth of cut, feed rate, and cutting speed	Surface Roughness
14	Karthikeyan *et al.*	2018	Turning	EN24	Taguchi- Grey	cutting speed, feed, and depth of cut	Surface Roughness
15	Kausika *et al.*	2018	Milling	Al7068	RSM	cutting speed, feed, and depth of cut	Surface Roughness
16	Kumar *et al.*	2019	Milling	AISI 1005	Taguchi	spindle speed, depth of cut, and feed rate	Ra and MRR

2.6 Response surface design methodology

Accordingly, surface methodology, the elements that are considered as most significant, is used to fabricate a polynomial model in which the independent factor is the examination's response. To locate the worldwide least of the reaction explores that 'prune' the reaction surface is structured and the gradient of the response surface used along with the steepest ascent algorithm as follows (Garcia and Phillips, 1995).

2.6.1 Linear RSM model

i. Select the factors to investigate.

ii. Design and run a two-level factorial experiment in a localized region of the response surface.

iii. Compute the estimates of the effects and thereby calculate the coefficients of the linear model:

$$Y = b_0 + b_1X_1 + b_2X_2 + \ldots + b_nX_n. \quad (2.1)$$

where Y is the corresponding response. The terms $b_0, b_1, b_2, \ldots b_n$ are the second-order regression coefficients and the terms $x_1, x_2, \ldots x_n$ is the independent input parameters

iv. Select a reference factor to use as a guide in determining the appropriate steps along the direction of each factor to continue moving along the path of steepest ascent.

v. Select a few experimental conditions along the path of steepest ascent and run trials to determine if the response continues to increase. If the response ceases to increase, a new path should generate.

If a new path is needed, design, and run a new two-level factorial experiment. All previous steps repeated until no substantial improvement in the response obtained. If substantial improvement is obtained, exponential RSM model will be conducted.

2.6.2 Exponential RSM model

i. Design and run a three-level factorial experiment in the region where the path of the steepest ascent yields no substantial improvement in the response.

ii. Compute the coefficients of the model:

$$Y = b_0 + b_1X_1 + b_2X_2 + \ldots + b_{11}X^2_1 + b_{22}X^2_2 + \ldots + b_{12}X_1X_2 + \ldots + b_{n\text{-}1},\ nX_{n\text{-}1}X_n. \quad (2.2)$$

iii. Using the above model, determine the nature of the stationary point of the response surface. The stationary point is one where the gradient vanishes.

The sequential nature of RSM enables the experimenter to find out about the procedure or framework under the investigation proceeds. This ensures through the span of the RSM application the experimenter will learn: (i) the proper choice of experimental designs; (ii) the approximating function required; (iii) the location of the region of the optimum; (iv) the location of the region of the optimum; and (v) regardless of weather changes on the responses or any of the procedure variables are required (Myers *et al.*, 2016).

Even though accurate models have developed, there are still issues to be dealt with. Some instances such as high accuracy machining, where surface roughness is of great importance, are still under investigation, and factors such as the cutting tool's deflection or the thermal conditions must introduce to future models for a more realistic depiction of surface roughness creation. The integration of the existing models to a more comprehensive advisory system, which could be used by a machine tool operator, for example, could be another beneficial and practical application.

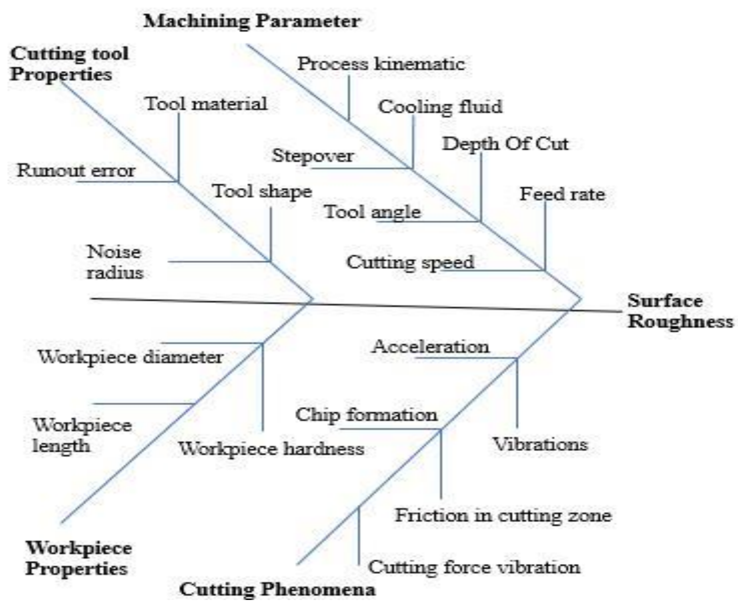


Figure 2-3 Parameters affecting surface roughness (Benardos and Vosniakos, 2003)

2.7 Summary of literature review

From the above literature review, it observed that most of the researchers had taken input parameters such as speed, feed, and depth of cut, while some have taken, machine time, tool length, tool vibration, nose radius, lubricant, so on to find out their impact on performance parameters including surface roughness, MRR, tool wear, and tool life.

Most researchers conclude that parameters that have a significant effect on the surface finish are cutting speed followed by the depth of cut. Other authors observed that the depth of cut is the significant factor followed by cutting speed. Also, the nose radius has a significant effect on obtaining a better finish.

The literature review reveals that researchers have focused on various investigate of the effects of cutting parameters on the resulting surface roughness to determine optimal cutting conditions. RSM most widely used as it offers enormous information from even a small number of the experiment, and even it is possible to analyze the influence of independent parameters on performance characteristics. The various authors have used the Taguchi method, RSM, genetic algorithm, grey relation analysis, so on. as optimization techniques. Table 2-2 suggests that turning is the most commonly used machining process. It has been observed that most of the researchers have used steel as workpiece material. Steel is one of the widely researched materials in machining for more than the last half a century, but there is a renewed interest in the application of steel because of its sustainability 100% recyclable and almost indefinite life cycle (Kant and Sangwan, 2014).

Table 2-2 Summary of literature review

No.	**Author**	**Mp**	**Machining Parameters**	**Workpiece Material**	**Predictive technique**	**OT**
1	Abhang and Hameedullah (2012)	T	f (0.05,0.10,0.15) d (0.2,0.4,0.6) lt (10,30,50)	EN-31 Steel	-	Taguchi
2	Aouici *et al.* (2012)	T	v (120,180,240) f (0.08,0.12,0.16) d (0.15,0.3,0.45) h (40,45,50)	AISI H11 steel	RSM	RSM
3	Asilturk and Akkuş (2011)	T	v (90,120,150) f (0.18,0.27,0.36) d (0.2,0.4,0.6)	Hardened AISI 4140	-	Taguchi
4	Benardos and Vosniakos (2002)	M	v (300,500,700) ft (0.08,0.14,0.2) d (0.25,0.75,1.2)	Aluminum alloy	ANN	Taguchi
5	Bhattacharya *et al.* (2009)	T	v (58,96,151,240) f (0.045,0.1,0.125,0.16) d (1,1.2,1.5,2)	AISI 1045 Steel	-	Taguchi
6	Bhirud *et al.* (2017)	M	v (2000,3000,4000) f (20,60,100) d (0.5,1.5,2.5) N (2,4)	Al 6063	SF	Taguchi
7	Chinchanikar and Choudhury (2013)	T	v (100,200,300) for 35 HRC v (100,150,200) for 45 HRC f (0.1,0.2,0.3) d (0.5,1.5,2.5)	AISI 4340 steel	RSM	RSM

8	Correia and Davim (2011)	T	v (345,410,470) f (0.075,0.15,0.25) r (0.4,0.8)	AISI 1045 steel	-	-
9	Fedai *et al.* (2018)	M	v (175,250,325) f (0.08,0.12,0.16) d (0.5,1,1.5) N (1,2,3)	AISI 4140	RA	Taguchi
10	Ghani *et al.* (2004)	M	v (224,280,355) f (0.1,0.16,0.25) d (0.3,0.5,0.8)	AISI H13	RA	Taguchi
11	Karthikeyan et al. (2018)	T	v (410, 660, 900) f (0.2, 0.25, 0.3) d (0.25, 0.5, 0.75)	EN-24	-	Taguchi - Grey
12	Kausika *et al.* (2018)	M	v (1500,2000,2500,3000,3500) f (0.02,0.03,0.04,0.05,0.06) da (1,1.5,2,2.5,3) dr (4,8,12,16,20) α (25,30,35,40,45)	Al7068	RA	RSM
13	Kumar et al. (2016)	M	v (1000-5000) f (200-2500) d (0.2-1)	EN-18	RA	RSM
14	Kumar *et al.* (2019)	M	v (1000,1250,1500) f (100,150,200) d (0.25,0.5,0.75)	AISI 1005	RA	Taguchi
15	Kumaran and Stephen (2015)	M	v (100,150,200) f (0.2,0.25,0.3) d (0.2,0.3,0.4)	EN-19/EN-31	SF	ANOV A
16	Lakshmi1 and Subbaiah (2012)	M	v (100,150,200) f (0.2,0.25,0.3) d (0.2,0.3,0.4)	EN-24	SF	RSM
17	Lalwani et al. (2008)	T	v (44.5,83,144.5) f (0.039,0.104,0.210,0.216) d (0.2)	MDN250 steel	RSM	-
18	Mahdavinejad and Saeedy (2011)	T	v (100,125,150,175,200) f (0.2,0.3,0.4)	AISI 304 stainless steel	RA	-

19	Maiyar *et al.* (2013)	M	v (25,50,75) f (0.06,0.09,0.12) d (0.2,0.4,0.6)	Inconel 718	RA	GRA
20	Mandal *et al.* (2011)	T	v (140,280,480) f (0.5,1.0,1.5) d (0.24,0.18,0.12)	AISI 4340 steel	RA	Taguchi
21	Noordin *et al.* (2004)	T	v (240,300,375) f (0.18,0.23,0.28) SCEA (-3,0,-5)	AISI 1045 Steel	RSM	-
22	Padma *et al.* (2017)	T	v (450, 720, 910) f (0.02, 0.078, 0.26) d (0.4, 0.98, 1.2)	EN-9	-	GRA
23	Palanisamy *et al.* (2007)	M	v (20-40) f (0.05-0.3) d (0.5-2.5)	Mild Steel	RA	GA
24	Panshetty *et al.* (2016)	M	v (1600,3200,4800) f (165,320,475) d (0.6,0.8,1)	Al 7075	RA	Taguchi
25	Prasadraju *et al.* (2017)	M	v (1000,1250,1500) f (100,150,200) d (0.25,0.5,0.75)	Mild steel	RA	Taguchi
26	Pratyusha *et al.* (2013)	M	v (3.6,3.62,3.16) f (3.45,3.64,3.31) d (3.54,3.33,3.53)	AISI 304	RA	Taguchi
27	Reddy and Rao (2005)	M	v (150,200,250) f *(200,300,400) da (20) r (0.4,0.8,1.2)	AISI 1045 steel	RSM	GA
28	Ribeiro *et al.* (2017)	M	v (200,300) f (0.1,0.3) da (0.1,0.35) dr (1,2)	Hardened Steel	RA	Taguchi
29	Sahin and Motorcu (2005)	T	v (181,208,240, 276, 317) f (0.1,0.13,0.15, 0.18, 0.21) d (0.36,0.43,0.50, 0.58, 0.66)	AISI 1040 mild steel	RSM	-

30	Sangwan *et al.* (2015)	T	v (80,180,180,280) f (0.06, 0.13, 0.21, 0.13) d (0.5, 0.5, 0.75, 0.5)	TI-6AL-4V	-	ANN-GA
31	Saraswat *et al.* (2014)	T	v (58.9, 86.3, 113.8) f (0.1, 0.2, 0.3) d (0.4, 0.6, 0.8)	Mild Steel	-	Taguchi
32	Singh *et al.* (2013)	T	v (410, 660, 900) f (0.2, 0.25, 0.3) d (0.25, 0.5, 0.75)	EN-9	-	MRR
33	Yalcin *et al.* (2013)	M	v (100,130) f (0.05,0.1) d (1.25, 2)	AISI 1050 steel	ANN	Taguchi

MP– Machining process, OT – Optimization technique

2.8 Literature Gap

A lot of research has been done in past and a survey on critical controllable turning parameters for the lathe machines such as cutting speed, feed, depth of cut, tool geometry, tool, and workpiece material, which affect the desired output including, surface finish, tool wear, tool life and performance are studied. But a little research has been done on optimization of surface roughness on cutting parameters of different EN carbon steel grades and a few works are available for different materials to show contrasting results – few authors observed that cutting speed is the most significant factor followed by the depth of cut (Aggarwal *et al.*, 2008; Bhattacharya *et al.*, 2009; Bhushan, 2013). Other authors (Fratila and Caizar, 2011; Hanafi *et al.*, 2012) observed that the depth of cut is the significant factor followed by cutting speed. Therefore, more studies need to be carried out to observe the influence of machining parameters on performance characteristics. A generalized relationship between the machining parameters and the process performance is hard to model accurately mainly due to the nature of the complicated stochastic process mechanisms in machining. This work is an attempt to fill this gap in the research. Machining is still an open field of research after the last some years of research mainly because of the changes in machining technology, materials, and the advancement in the modeling and optimization techniques as well as the advancements in computational technology.

CHAPTER THREE

MATERIALS AND METHODOLOGIES

3.1 Introduction

This study was performed to investigate the cutting parameters on surface roughness in using the turning operation of EN-8 steel. This section aims to present the details of the experimental procedures and material used for the study. Furthermore, machines and instruments are discussed with supporting photographs and schematic diagrams.

3.1.1 Experimental Procedure

In this experimental procedure, the overall stages of the experimental investigation and parametric optimization of cutting parameters on surface roughness in the turning operation of EN-8 steel shown in Figure 3-1.

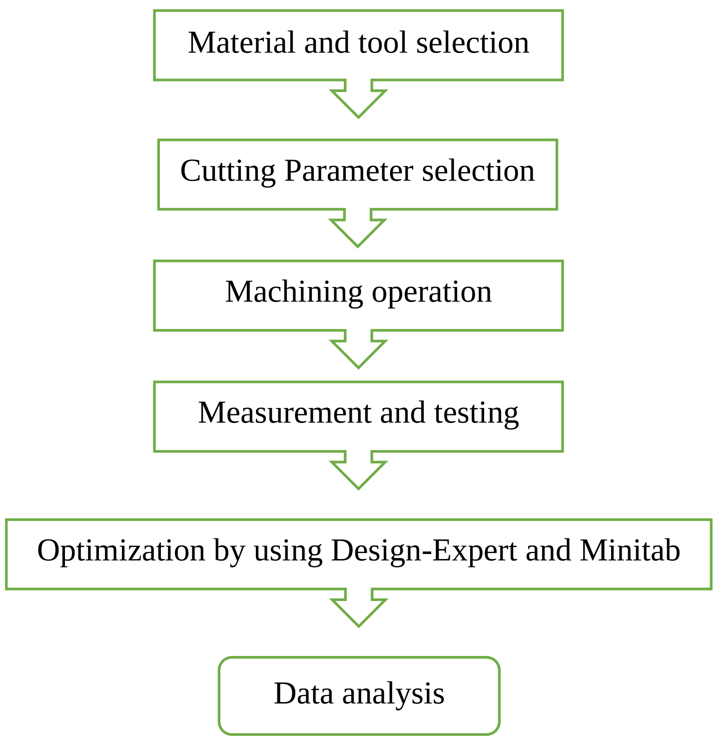


Figure 3-1 Experimental scheme

3.1.2 Equipment used

A conventional lathe machine was used for experimental study for cutting parameters on surface roughness. The turning machine with the model of URSUS 200 was used for this study. The sample material for the research is EN-8 steel. The workpiece is estimated by using a surface roughness analyzer (Profilometer) and it is used to measure average roughness. Generally, the equipment used for the study are;

i. Conventional lathe model URSUS 200
ii. EN-8 steel material
iii. Cemented carbide tool
iv. Profilometer

3.2 Material selection

A machine tool selection is a significant dynamic procedure for many manufacturing companies. Inappropriately choice machines can adversely influence the general execution of a generation framework. The quality, cost, and speed of manufacturing strongly depend on the type of machine tool used.

In this material selection section specifications of the turning machine, selection of workpiece material and carbon steel EN-8 steel chemical composition, EN-8 medium carbon steel mechanical properties, and hardness, and specification of the workpiece are discussed.

3.2.1 Specification of turning machine

The specification material for the research is a conventional lathe. The size and durable construction of the turning machine give tremendous support to handle large and more massive machine without damaging itself. It provides flexible computer control options for cutting purposes and assures accurate cuts.

The primary use of a conventional lathe is to make sure concentric work is produced; this enables the workpiece to be transferred between machining (inspection) operations with no loss of accuracy. A part could also be turned during a lathe, sent off for hardening and tempering, then ground between centers during a cylindrical grinder. The preservation of concentricity between the turning and grinding operations is crucial for quality work. A conventional lathe model URSUS 200 model (Figure 3-2) was used in the turning experiment.

In this investigation, an attempt was made to find out the cutting parameters on surface roughness in turning the operation of EN-8 steel.

Figure 3-2 Conventional lathe machine, URSUS 200 model

Table 3-1 Specification of lathe model URSUS 200

Center distance (mm)	1.500
Max. swing over bed (mm)	420
Max. swing over cross slide (mm)	210
Spindle bore (mm)	52
R.P.M.	35 - 1.500 (16x)
kW	5
Volts	380
Cycles	50

3.2.2 Selection of workpiece material

The sample material for the research is EN-8 steel. There is a renewed interest in the application of this steel because of its sustainability. It is 100% recyclable and almost has an indefinite life cycle. EN-8 steel is one of the steel grades widely used in different industries (construction, transport, automotive, power, so on). The chemical composition and mechanical properties of the EN-8 steel are given in Table 3-4 and Table 3-5 respectively.

EN-8 are steel grades in BS 970-1955 standard, which is a standard for wrought steel for mechanical and allied engineering purposes. It defines requirements for carbon and carbon-manganese, free-cutting, alloy, and stainless steels usually supplied in the bright, cold finished condition.

The material of the workpiece used was EN-8 steel for the analysis. EN-8 steel chosen since it used for the manufacturing of medium size parts such as gears, shafts, spindles, shafts, and general machine components including cylinders, sprockets, cams, small gears, crankshafts, machine tools, grinding balls for ball mills, keys, pulleys, ball race rings, bolts, and nuts, so on Which are the significant results of the mechanical industry. The machining of these parts requires additional time because of size. We know as the hour of machining increases, the temperature of the cutting zone additionally expands, which effectively affects work material and tools. So, to improve the machining, EN-8 steel is chosen.

EN-8 carbon steel is a common medium carbon and medium tensile steel, with improved strength over mild steel, through-hardening medium carbon steel. EN-8 carbon steel is also readily machinable in any condition. Proper heat treatment results on sections more significant than 65mm may still be achievable, but it should be noted that a fall-off in mechanical properties would be apparent approaching the center of the bar. It is therefore recommended that larger sizes of EN-8 steel materials are supplied in the untreated condition and that any heat treatment is carried out after initial stock removal. This should achieve better mechanical properties towards the core.

EN-8 engineering steel is unalloyed carbon steel with reasonable tensile strength. It can be flame or induction hardened and is a readily machinable material. When heat-treated, EN-8 offers moderate wear resistance. Steel EN8 materials in its heat-treated forms possesses good homogenous metallurgical structures, giving consistent machining properties. The EN-8 steel with effective heat treatment viz., tempering at 300^{o}C can be used for structural applications requiring better fatigue, then it is cooled in air, when subjected to cyclical loading in their routine operations (Ravindran *et al.*, 2021). Any heat treatment is carried out after initial stock removal. This should achieve better mechanical properties towards the core.

Table 3-2 Experimental conditions

Machine	Turning Machine
Work Specimens	EN-8 steel
Hardness	180-280 HB
Environment	Dry Machining
Condition	Tempered

3.2.2.1 EN-8 carbon steel grade equivalents

Other steel grades in DIN, JIS standards are similar and equivalent to EN-8 steel, as follows: European standard (including Germany DIN, British BSI, French AFNOR, and other EU member state standards) C40 steel equivalent to Chinese GB standards, Japanese JIS standards, and ISO standards, so on.

Table 3-3 EN-8 material equivalent steel-grades (steelnumber.com, 2020)

EU EN	USA -	Germany DIN,WNr	Japan JIS	France AFNOR	England BS	Italy UNI	China GB	Poland PN	Czechia CSN	Russia GOST	Inter ISO
C40 (1.0511)	1038 1040	1.0511 C40 Ck40	S40C	AF60C40 AF60C45 XC42HI	070M40 080M40 EN-8	C40	40	40	12041	40	C40 C40E4

3.2.3 Carbon steel EN-8 chemical composition

The workpiece material selected for examination is the EN-8 steel is an unalloyed medium carbon steel. EN-8 medium carbon steel finds wide varieties of application such as rollers, forging, forming and molding dies, die making industries, blanking, and forming tools. This steel can provide greater strength and wear resistance.

Table 3-4 Chemical composition of EN 8 steel (Selvam and Senthil, 2016)

Element	Standard (wt%)	Actual (wt%)
Sulfur, S	0.045	0.04
Phosphorus, P	0.045	0.04
Molybdenum, Mo	0.10	0.10
Carbon, C	0.36	0.44
Silicon, Si	0.40	0.40
Chromium, Cr	0.40	0.25
Nickel, Ni	0.40	0.25
Manganese, Mn	0.65	0.60

3.2.4 EN-8 medium carbon steel mechanical properties and hardness

The following table gives the EN-8 steel mechanical properties such as diameter and hardness.

Table 3-5 Mechanical properties of EN-8 steel (Metals4u.co.uk., 2020)

Sample ID	**Diameter (mm)**	**Area (mm^2)**	**Yield Stress MPa**	**Tensile Stress MPa**	**Hardness**
Solid, Round	50	1,963.495	280	550	152/207

3.2.5 Specification of the workpiece

The total length to be machined during each reading is 30 mm. 25 mm length on each side is provided for clamping the workpieces into the three-jaw chuck. Each piece was used to perform one experiment. A pre-cut of 1 mm depth was performed on each workpiece before actually turning using a different cutting tool. This is done to remove the rust or hardened top layer from the surface and to minimize any effect of non-homogeneity on the experimental results.

Table 3-6 Specification of the workpiece

Dimension (mm)	50*55
Weight (kg)	0.771
Density (kg/m^3)	7850

Figure 3-3 Sample of the workpiece material

3.3 Selecting of cutting tool

A cutting tool is any tool that wants to remove metal from the workpiece using shear deformation. Frequently, it also refers to a tool bit. To perform an effective cutting operation, the cutter must be made from a material harder than the work material to be cut. Also, the tool must be ready to withstand the heat generated during the machining process. The tool must have a specific geometry (known as tool geometry) for effective cutting and smooth surface finish. In this selecting of cutting tool single-point cutting tools, cemented carbide, tool geometry recommended cutting conditions, and dry machining are discussed.

3.3.1 Single-point cutting tools

They are those having one sharp cutting edge attached to the shank. The cutting edge is intended to create a machined surface on the workpiece, perform cutting, and produce chips. The cutting tool is held in a tool post fastened to the cross slide. The assembly of the cross slide and tool post is referred to as the carriage. The carriage is designed to slide along the guides to feed the tool parallel to the axis of rotation and the guides are tracks along which the rides of carriage. They are made with great precision to achieve a high degree of parallelism relative to the axis of spindle.

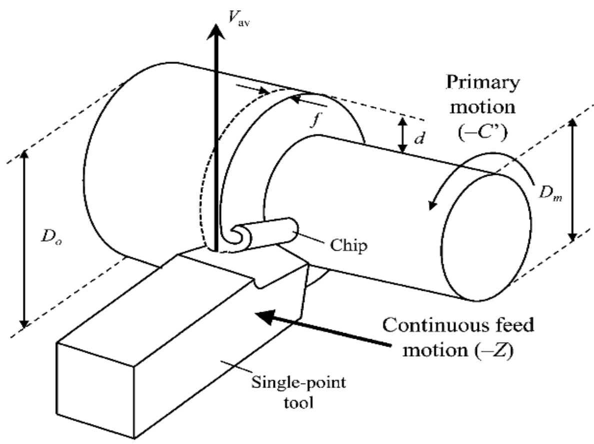


Figure 3-4 Turning on conventional lathe single-point cutting tool

3.3.2 Cemented carbide

Cemented carbide tools are formed by pressing a mixture of tungsten carbide and cobalt together in a hydraulic press and then heating the compact in a hydrogen atmosphere. Tungsten carbide is an extremely hard substance. Cobalt acts as a binder for the hard carbide grains. Most of the cemented carbides used today are made predominantly from the carbides of tungsten, titanium, and tantalum, usually with cobalt as the binder metal.

Cemented carbide is used in metal-forming applications because they combine high compressive strength, good abrasion resistance, high elastic modulus, good impact, and shock resistance, and the ability to take and retain a good surface finish. Typical applications in this category include drawing dies, hot and cold rolling of strips and bards, cold heading dies, forward and back extrusion punches, swaging hammers and mandrels, and can-body punches and dies.

The Anti-chatter tool is shown in Figure 3-5, a narrow land with 5- 10° negative relief is provided at the side flank beside the cutting edge. Similarly, the side rake can also be made negative for a small portion of the rake face adjoining the cutting edge. These features make tools to reduce vibration/ chatter. The turning is done using a cemented carbide tool mounted in a lathe tool holder that is then mounted in the tool spindle on the machine.

Figure 3-5 Cemented carbide tool

3.3.3 Tool geometry

The tool angles have essential functions in cutting operations. The rake angle controls the strength of the tooltip and chip flow direction. Positive rake angles improve the cutting operation by reducing temperatures and forces, but reduce the tool strength, as the small angle may cause the cutting edge to chip away. In the general case of oblique cutting, there are two rake angles, namely, side and back rake angles. As cutting takes place on the side of the tool, the side rake angle is of primary importance. The back-rake angle also affects the ability of the tool to shear the work material and form the chip. The relief angle controls the tool interfacing with the workpiece. Too large a relief angle may cause the tool to chip off, while too small an angle may result in high frictional forces due to rubbing between the flank surface and workpiece, causing excessive flank wear. The cutting-edge angle affects the chip formation, tool strength, and cutting forces. The nose radius affects the surface finish and tooltip strength. A smaller radius creates a rougher surface finish on the workpiece and a weaker tooltip. However, the large radius can lead to excessive force and tool vibrations.

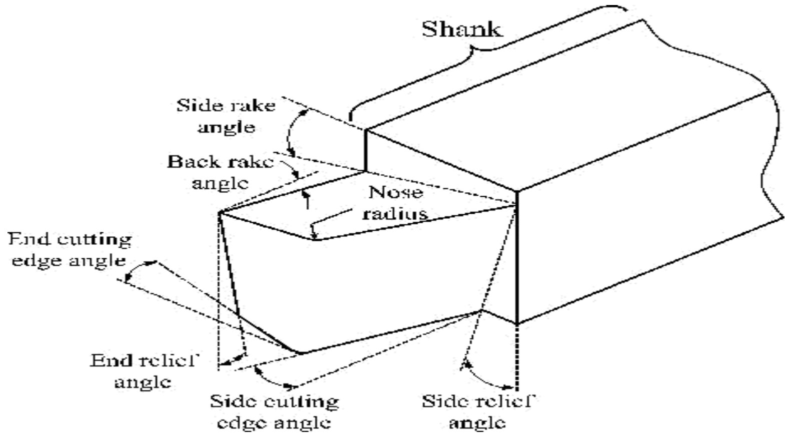


Figure 3-6 Geometry of single-point cutting tool

3.3.4 Cutting conditions

Cutting conditions play an important role in the efficient use of a machine tool. To represent favorably and endorse or encourage as an appropriate choice on cutting conditions. The use of recommended cutting conditions for turning is appropriate.

Table 3-7 Recommended cutting conditions for turning (Mistu, 1994)

Work Material			**Recommended Cutting Condition and Grades**			
			Depth of cut (mm)	**Feed rate (mm/min)**	**Coolant**	**Recommended Spindle Speed and Grades**
Mild Steel	≤ 160 HB	*Light cutting*	≤1.0	≤0.3	Dry	290 (235 - 335)
		Medium cutting	1 - 6	0.4 (0.2 – 0.6)	Dry	350 (260 - 440)
Carbon Steel	160 280 HB	*Light cutting*	≤1.0	≤0.3	Dry	280 (210 - 355)
		Medium cutting	1 – 5	0.3 (0.1 – 0.5)	Dry	330 (220 - 440)
Alloy Steel	280	*Light cutting*	≤1.0	≤0.3	Water Soluble Oil	180 (120 - 230)

	350 HB	*Medium cutting*	1 – 4	0.3 (0.2 – 0.4)	Water Soluble Oil	170 (120 - 210)

3.3.5 Dry machining

Dry machining can provide a cost advantage and machine-tool flexibility if big sumps are not required. In this study, it is used because dry machining is becoming more prevalent in turning. In drilling, coolant is required because the tool has prolonged material exposure, and to evacuate fluid is essential for chips. Furthermore, in dry turning, a big producer of shafts and gears, does not apply any coolant because all its machines are fully automated, and there is no manual handling of parts, so heat build-up is not an issue.

Dry machining represents a more valuable alternative, especially in terms of cost savings and environmental sustainability. It can provide a machine-tool flexibility and cost advantage if big sumps are not required.

3.4 Machine parameters selection

In this optimization of surface roughness, three cutting parameters were included: feed rate, cutting speed, and depth of cut considered to be critical cutting parameters for turning of EN-8 steel. These cutting parameters are some of the essential parameters which affect the surface roughness. In the turning process, the parameters such as feed rate, cutting speed, and depth of cut are optimized for better surface finish.

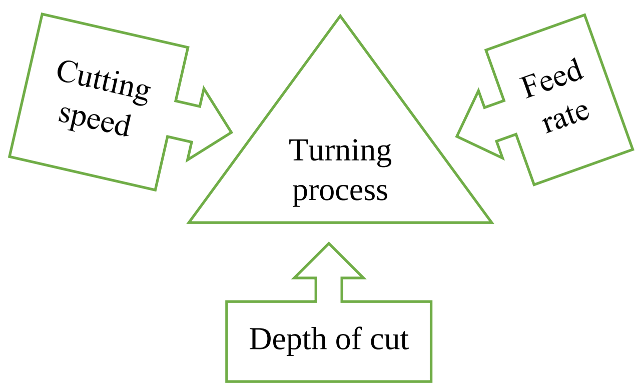


Figure 3-7 Factors affecting the turning process

In this machine parameters selection, cutting speed, feed rate, depth of cut, surface roughness, and machining parameters, and their levels are discussed.

3.4.1 Cutting speed

Cutting speed effects tool life significantly. Increasing cutting speed increases cutting temperature and results in shortening life of tool. Cutting speed varies depending on the hardness and type of the work material. Selecting a tool grade suitable is necessary for the cutting speed.

The relative motion of the workpiece past the cutting edge is cutting speed, which is calculated from the following relation.

$$v = \frac{\pi * Dm * n}{1000} \text{ (m/min)} \quad (3.1)$$

Where Dm (mm): Workpiece diameter

n (min^{-1}): Rpm of the cutter / Main Axis Spindle Speed

v (m/min): Cutting Speed

π, Pi: 3.14

Cutting parameters (cutting speed) for EN-8 steel were selected depending on the recommended cutting parameters, which are given in Table 3-7, and the range was taken to get the accurate results since the maximum difference was at maximum range.

Table 3-8 Cutting speed parameters and their levels

Factor	**Symbol**	**Level 1**	**Level 2**	**Level 3**
Cutting speed (m/min)	*v*	220	292	375

3.4.2 Feed rate

The feed-in a turning machine is defined as the rate with which the workpiece advances under the cutter. The feed per minute is defined by the distance the work advances in one minute. It is expressed in mm/min.

$$f = \frac{l}{n} \text{ (mm/rev)} \quad (3.2)$$

Where f (mm/rev): Feed per tooth

l (mm/min): Cutting Length per min

z: Insert number

Cutting parameters (feed rate) for EN-8 steel were selected depending on the recommended cutting parameters, which are given in Table 3-7, and the range was taken to get the accurate results since the maximum difference was at maximum range.

Table 3-9 Feed rate parameters and their levels

Factor	**Symbol**	**Level 1**	**Level 2**	**Level 3**
Feed rate (mm/min)	*f*	0.1	0.2	0.3

3.4.3 Depth of cut

The depth of cut in turning is the thickness of the material removed in one pass of the work undercutter. It is the perpendicular distance measured between the original and final surface of the workpiece and expressed in mm.

$$d = \frac{(d1-d2)}{2} \tag{3.3}$$

d1 = diameter of the work surface before machining

d2 = diameter of the work surface after machining

Cutting parameters (depth of cut) for EN-8 steel were selected depending on the recommended cutting parameters, which are given in Table 3-7, and the range was taken to get the accurate results since the maximum difference was at maximum range.

Table 3-10 Depth of cut parameters and their levels

Factor	**Symbol**	**Level 1**	**Level 2**	**Level 3**
Depth of cut (mm)	*d*	1	1.5	2

3.4.4 Machining parameters and their levels

The choice of machining parameters was made by taking into account the capacity/limiting cutting conditions of the turning, tool manufacturer’s catalog, experimental time and cost into account, and the values taken by researchers in the literature. Cutting speed, feed rate, and depth of cut are the input parameters chosen for the research. The cutting speed (A) [rev/min] is the rotational speed of the lathe machine spindle or the work-piece. Feed rate (B) [mm/rev] is the speed of the cutting tool relative to that of the workpiece as the tool takes a cut along the axis of the workpiece. The depth of cut (C) [mm] is the thickness of the material removed in one pass of the work undercutter. The performance characteristics chosen to investigate the effect of machining parameters is surface roughness. Cutting parameters for EN-8 steel were selected depending on the recommended cutting parameters, which are given in Table 3-7, and the range was taken to get the accurate results since the maximum difference was at maximum range.

Table 3-11 Machining parameters and their levels

Factor	Symbol	Level 1	Level 2	Level 3
Cutting speed (m/min)	v	220	292	375
Feed rate (mm/min)	f	0.1	0.2	0.3
Depth of cut (mm)	d	1	1.5	2

3.5 Response variables

The surface roughness is the selected response variables. The surface roughness, as a measure of surface texture, is the vertical deviations of a real surface from its ideal form. A significant deviation is taken as a rough surface, while a small deviation is taken as a smooth surface. Thus, surface roughness sees as the high frequency, short wavelength component of surface measured, which determines how a real object will interact with its environment. Rough surfaces wear faster and have a higher coefficient of friction than smooth surfaces. Again, the roughness of a surface [micron, µm, or µmm] may form nucleation sites for cracks or corrosion, promote adhesion, and may be very expensive to control in manufacturing.

3.5.1 Profilometer

The most practical way of determining the surface roughness is to measure the surface roughness, which is defined as the irregularities that remained on the surface after the machining process. The average roughness Ra used in the present study. Ra is measured using a surface roughness testing instrument, which has a probe at one end. During measuring 1mm was set as the cut of length.

Whatever may be the manufacturing process flat surface and the smooth cannot obtain. The machine elements or parts retain the surface irregularities left after manufacturing. The surface of a part is exterior or boundary, and the surface irregularities consist of many small valleys and wedges that deviate from a hypothetical nominal surface. These irregularities are responsible to a greater extent for the appearance of a surface and its suitability (Kumaran and Stephen, 2015).

Surface roughness value is measured by roughness tester and is denoted as *Ra*.

Figure 3-8 Taylor and Hobson profilometer used to measure surface roughness (*AASTU, Department of Material Engineering*)

3.6 Response surface methodology

Response surface methodology is a collection of mathematical and statistical techniques useful for developing, improving, and optimizing processes. It also has essential applications in the development, formulation, and design of new products, as well as in the improvement of existing product designs.

The most extensive applications of RSM are in the industrial world, particularly in situations where several input variables potentially influence some performance measure or quality characteristic of the product or process. This performance measure or quality characteristic is called the response. It is typically measured on rank, sensory responses, although attribute responses and continuous scales are not unusual. The input variables are sometimes called independent variables, and they are subject to the control of the engineer or scientist, at least for purposes of a test or an experiment (Myers *et al.*, 2016).

3.6.1 Mathematical model

Engineering experiments aim at determining the conditions that can lead to optimum performances. One of the methodologies for obtaining optimum performance is the Response Surface Methodology (RSM). RSM, developed by (Box and Draper, 1987), is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which several variables influence the response of interest and the objective is to optimize the response. It is a sequential experimentation strategy for empirical model building and optimization. By conducting experiments and applying regression analysis, a model of the response to independent input variables can be obtained. A near-optimal point can then be deduced based on the model of the response. RSM is often applied in the characterization and optimization of processes. In RSM, it is possible to represent independent process parameters in quantitative form as:

$$Y = f(X_1, X_2, X_3, \ldots\ldots X_n) \pm \varepsilon \quad (3.4)$$

where Y is the response, f is the response function, ε is the experimental error, and X1, X2, X3, ……, Xn are independent parameters. Y is plotted to get the response surface. The form of f is unknown and may be very complicated. Therefore, RSM aims at approximating f by a suitable lower ordered polynomial in some regions of the independent process variables. If the response can be well modeled by a linear function of the independent variables, the function equation (3.4) can be written as:

$$Y = b_0 + b_{1x1} + b_{2x2} + b_{3x3}, \ldots\ldots b_{nxn} \pm \varepsilon \quad (3.5)$$

However, if a curvature appears in the system, then a higher-order polynomial such as quadric model (equation (3.6)) may be used:

$$Y_u = b_0 + \sum_{i=1}^{n} bixi + \sum_{i=1}^{n} bijx^2i + \sum_{i<j}^{n} bijxj \quad (3.6)$$

where Y is the corresponding response and xi (1, 2, …, n) is the independent input parameters. The terms b_0, b_1, b_2, so on. are the second-order regression coefficients. The second term contributes to the linear effect, the third term contributes to the higher-order effects, and the fourth term contributes to the interactive effects of the input parameters. The values of the coefficients are estimated by using the responses collected (Y1, Y2…, Yn) through the design points (n) by applying the least square technique. This equation can be rewritten in terms of the three variables:

$$Y = b_0 + b_{1x1} + b_{2x2} + b_{3x3} + b_{11}x_1^2 + b_{22}x_2^2 + b_{33}x_3^2 + b_{12x1x2} + b_{13x1x3} + b_{23x2x3} \quad (3.7)$$

The objective of using RSM is not only to investigate the response over the entire factor space but also to locate the region of interest where the response reaches its optimal or near-optimal value. A careful study of the response surface model provides a combination of factors giving the best response. The response surface method is a sequential process, and the methodology used for the modeling can be summarized, as shown in Figure 3-9.

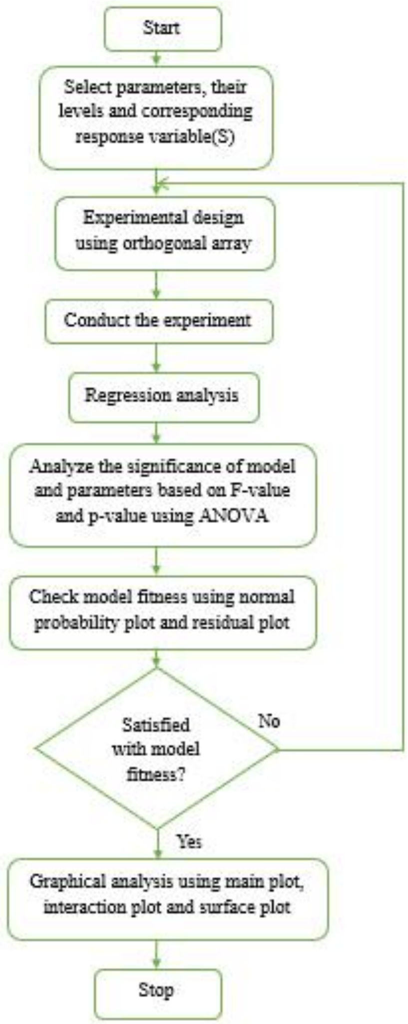


Figure 3-9 Outline of response surface methodology used

3.6.2 Predictive models using response surface methodology

Derringer and Suich (1980) proposed the method of desirability function analysis associated with RSM. This method is based on the reduced gradient algorithm, which starts with multiple solutions and finally obtains the maximum value of the desirability to determine the optimal solution (Maji *et al.*, 2013). The desirability function is based on the idea that the quality of a product or process that has many features is completely unacceptable if one of them is outside the “desirable” limit (Candioti *et al.*, 2014). Several researchers have used desirability function analysis to optimize surface roughness (Bhushan, 2013; Hessainia *et al.*, 2013; Sait *et al.*, 2009; Sarıkaya and Gullu, 2014). In the single objective minimization problem, the first step of the desirability function analysis is to calculate the desirability index (d) using equation (3.8). The scale of the desirability function ranges between 0 and 1. If d = 0 or approaches 0, then the response is completely unacceptable, and if d = 1 or approaches to 1, then the response is perfectly on the target value. There are three types of individual desirability functions: a) the larger, the better, b) the smaller, the better, and c) the nominal, the better. In this study, the desirability function was selected as the smaller, the better because minimum surface roughness is to be achieved with the optimization of machining parameters. The desirability function for the single objective minimization problem is given below:

$$d = 1 \ if \ y \leq y_{min}$$

$$d = \left(\frac{y - y_{max}}{y_{min} - y_{max}}\right), y_{min} \leq y \leq y_{max} \quad (3.8)$$

$$d = 0 \ if \ y \geq y_{max}$$

Where the y is the value of the output during optimization processes, y min and y max are the lower tolerance limit and the upper tolerance limit in the response parameter experimental data.

The individual response optimization analysis has been performed for achieving the minimum surface roughness based on the predicted mathematical model given by equation (4.1).

3.7 Experimental setup

The experiments had performed in a conventional lathe machine and the cutting tool used was cemented carbide cutters. The detailed information on chemical composition and mechanical properties and specification of EN-8 steel is provided in Table 3-4 and Tables 3-5 respectively. The experiment is made in Addis Ababa Metals and Engineering Corporation (METEC).

Figure 3-10 Experimental setups

3.7.1 Experiment plan

The experiment was performed to investigate the effect of input parameters on response. The design of the experiment (DOE) has a significant effect on the approximate accuracy and cost of the response surface. The experiment of 27 runs was randomized by using Design of Experiment. DOE evaluated as the response to the model fitted. The design data is evaluated by running the twenty-seven samples through turning operation and calculate the measuring of the surface roughness using a profilometer. The machining of a cutting parameter is given in Table 3-11.

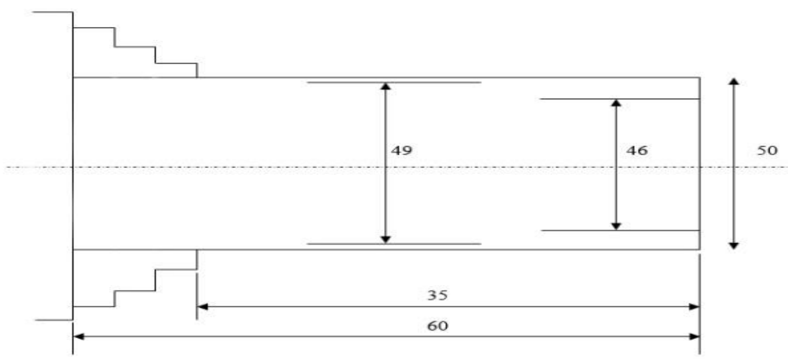
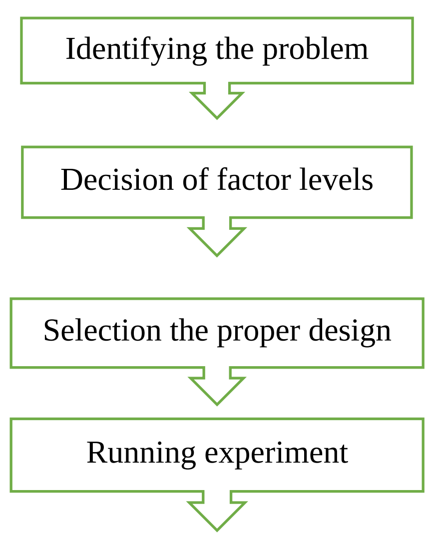


Figure 3-11 Detailed drawings of the cylindrical bar used in experimentation (All dimensions are in mm)

3.8 Research methodology

The research carried out for this section is experimental planning, design of experiment, modeling of surface roughness, surface roughness measurement. By using the materials mentioned above through the following method, the experimental work would be continued. The steps that must follow to apply the RSM method correctly shown in the Figure 3-12.



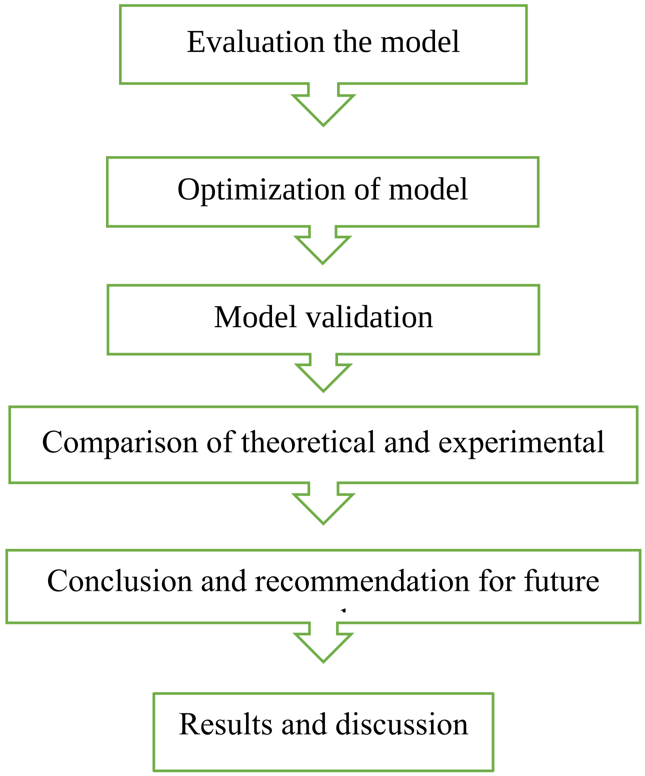


Figure 3-12 Response surface methodology design procedure

In this research methodology design of the experiment, the procedure of turning experiments, studying surface roughness measurement, and data generated from the turning experiment are discussed.

3.8.1 Design of experiment

In the design of experiment techniques, RSM attempts to minimize the assess experimental error, make a qualitative estimation of parameters, optimize values of parameters, number of runs or trials, and make inference regarding the effect of parameters on the characteristics of a process. The main idea of RSM is to use a sequence of designed experiments to obtain an optimal response. The experiment was designed to allow us to estimate an interaction and even quadratic effects, and therefore give us an idea of the shape of the response surface we are investigating. To observe the most influential process parameters in the turning process, namely cutting speed, feed, and depth of cut each at three levels considered in the case of this thesis.

For these reasons, RSM, based on CC-DOE, was selected. Therefore, it is used in this work to model, predict, and optimize *Ra*. As a mathematical and statistical technique, it developed for the treatment of problems involving a response of interest as a function of several variables. It is one of the ways machining process modeling and analysis can achieve to facilitate its optimization. Its application requires machining response *Y* to defined as (Sahoo, 2011):

$$Y = \varphi\ (x1, x2, \ldots, xi) \pm e \tag{3.9}$$

where $\varphi\ (x1, x2, \ldots, xi)$ is the response surface function in the form of a polynomial model, $x1$ is the process variables and is the residual or experimental error. The second-order polynomial or quadratic model may, therefore, written as:

$$\begin{aligned} \varphi &= \varphi\ (x_1, x_2, \ldots, X_k) \\ &= (Y \pm e) \qquad (3.10) \\ &= b_o + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} {x_i}^2 + \sum_{i=1}^{k} b_{ij} x_i x_j \end{aligned}$$

Equation (3.10) is a multiple regression model. In this form, it has constant, linear, square, and cross-product terms. It can, satisfactorily, be used to correlate dependent variables, φ_j, with independent variables, x_i. Several techniques for DOE are available for use to estimate the coefficients of the regression models.

The Central Composite (CC) was selected for the design of the turning experiment. Analysis of variance (ANOVA) was used to validate the developed models and also to predict the effect of selected factors A, B, and C on the response characteristics *Ra*. Optimization of the coded and actual response functions, Ra (A, B, C), subject to constraints as determined by the limits of the factors A, B, and C, was performed as appropriate using a standard optimization technique. The RSM was implemented in the Design-Expert software version 11 environment.

Figure 3-13 Twenty-seven specimen work-piece

3.8.2 The procedure of turning the experiment

In the setup for the turning experiment shown in Figure 3-2, twenty-seven (27) specimen work-piece of EN-8 steel round bars (Figure 3-13) were turned on the conventional lathe with a carbide tool insert (Figure 3-5). The run order, as generated from Design Expert 11 software based on CC-DOE, is given in Table 3-12.

Table 3-12 Experimental layouts

No.	**A: Cutting speed (m/min)**	**B: Feed rate (mm/min)**	**C: Depth of cut (mm)**
1	220	0.1	1
2	220	0.1	1.5
3	220	0.1	2
4	220	0.2	1
5	220	0.2	1.5
6	220	0.2	2
7	220	0.3	1
8	220	0.3	1.5
9	220	0.3	2
10	292	0.1	1
11	292	0.1	1.5
12	292	0.1	2
13	292	0.2	1
14	292	0.2	1.5
15	292	0.2	2
16	292	0.3	1
17	292	0.3	1.5
18	292	0.3	2
19	375	0.1	1
20	375	0.1	1.5
21	375	0.1	2
22	375	0.2	1

23	375	0.2	1.5
24	375	0.2	2
25	375	0.3	1
26	375	0.3	1.5
27	375	0.3	2

3.8.3 Surface roughness measurement

The final workpiece used for measuring the surface roughness is shown in Figure 3-14. The surface roughness of the finished surface is measured by placing the workpiece on a rectangular block over a cast-iron surface plate after each cut (Figure 3-15). After the setup was ready, trial cuts were taken, and equipment was calibrated to ensure that the part quality adhered to the quality requirements of the Original Equipment Manufacturer (OEM) and to compare the stability of the machining process to that of the OEM’s. The equipment was calibrated by measuring the known diameter of a high precision spherical ball. Figure 3-15 shows the surface roughness profile, measured on the spherical ball. The stability of the experimental setup compared to the OEM’s recommended specification. Once the stability of the setup was confirmed, the experiments conducted and the surface roughness was measured at three equally spaced locations around the circumference of the workpiece to obtain the statistically significant data for the test, and then the mean of measurements was calculated. Thus, probable observation errors were kept relatively small. The specifications of the measuring setup presented in Table 3-13.

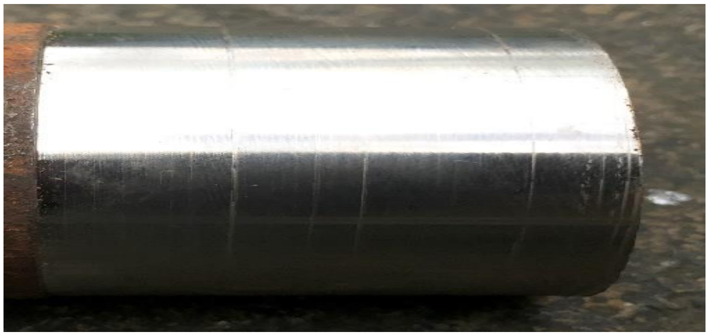


Figure 3-14 Workpiece used for measuring the surface roughness

Table 3-13 Specifications of the surface roughness measurement instrument

Factor	**Specification**
Nominal measuring range	1 mm
Resolution	16 nm

Speed of traverse	1 mm/sec – 10 mm/sec
Make	Taylor Hobson
Pickup	Inductive type
Model	Form Talysurf Intra
Parameters measurable	Ra/Rz/Rt

There are many different surface roughness parameters, which include average variation from the mean line (Ra), the highest peak to the deepest valley (Rt), and the average Rt over a given length (Rz). Ra is universally recognized and the most widely used parameter for roughness as it can easily measure by graphical processes (Correia and Davim, 2011). Besides, Ra values are more accurate than the Rt and Rz values because it considers the averages of peaks and valleys on the surface. Hence, Ra was selected as a measuring parameter for surface roughness. The machining parameters and the corresponding measured Ra are given in Table 3-14.

Figure 3-15 Profilometers used to measure surface roughness

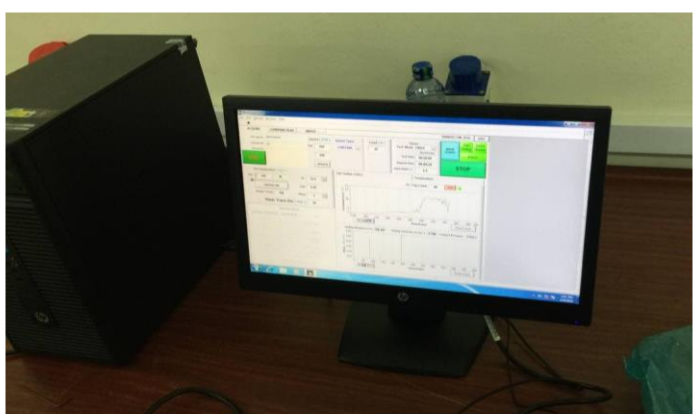


Figure 3-16 Typical surface roughness observed at different cutting conditions

After finalizing the experimental setup and developing the experimental procedure, the next step is to develop a predictive and optimization model based on the collected experimental data. The following chapters provide the development of predictive and optimization models using the collected experimental data of this chapter.

CHAPTER FOUR

RESULT AND DISCUSSION

4.1 Introduction

After completing the machining operation, the response parameter that is the surface roughness was measured. Statistical analysis was performed on the optimum result obtained for attaining main effects. The experimental study was conducted to evaluate the effect of cutting parameters, namely cutting speed, feed rate, and depth of cut on the surface quality of EN-8 steel during the turning process. This step determines the effect of various process parameters to achieve desired surface roughness. The results for each experiment were discussed in this chapter. Table 4-1 shows the design layout for the turning experiment conducted as well as the response data generated. The experiment was conducted in a controlled environment to minimize errors. The design of the experiment was used to identify the optimum cutting parameters and to identify the most influential parameters. The outcome of data analysis in the environment of the Design-Expert version 11 and Minitab 19 software is presented and discussed.

This section aims to present the details of the result and discussion used for the study. Furthermore, predictive and optimization models are discussed with supporting photographs and schematic diagrams.

4.1.1 Measured surface roughness

Measurements of Ra data were taken at three (3) different locations, 120^{o} from each other, on the machined surface using a surface roughness tester (Figure 3-15), and the average values were recorded. The measured Ra has given in Table 4-1.

For all the three runs the maximum and minimum surface roughness values were found to be 15.22 and 4.792μm respectively.

Table 4-1 Measured surface roughness at L_{27} full factorial machining parameters

No.	A: Cutting speed (m/min)	B: Feed rate (mm/min)	C: Depth of cut (mm)	Surface roughness (µm)			
				Run 1	Run 2	Run 3	Average
1	220	0.1	1	13.313	13.496	13.261	13.357
2	220	0.1	1.5	7.592	7.629	7.584	7.602
3	220	0.1	2	7.230	7.218	7.422	7.290
4	220	0.2	1	13.977	15.222	10.776	13.325
5	220	0.2	1.5	7.577	7.824	8.868	8.090
6	220	0.2	2	8.252	8.274	8.297	8.274
7	220	0.3	1	14.150	13.335	12.095	13.193
8	220	0.3	1.5	9.368	9.699	9.985	9.684
9	220	0.3	2	9.409	9.250	9.089	9.249
10	292	0.1	1	9.156	9.167	9.015	9.113
11	292	0.1	1.5	7.010	7.015	6.945	6.990
12	292	0.1	2	8.214	8.203	8.160	8.192
13	292	0.2	1	6.916	7.246	6.374	6.845
14	292	0.2	1.5	6.215	6.10	7.379	6.565
15	292	0.2	2	8.083	8.082	8.130	8.098
16	292	0.3	1	7.076	7.106	7.149	7.110
17	292	0.3	1.5	6.853	6.841	6.831	6.842
18	292	0.3	2	11.066	11.075	11.100	11.080
19	375	0.1	1	5.158	4.792	5.316	5.089
20	375	0.1	1.5	7.074	7.021	7.115	7.070
21	375	0.1	2	11.571	11.564	11.515	11.550
22	375	0.2	1	5.496	5.487	5.503	5.495
23	375	0.2	1.5	6.211	6.225	6.220	6.219
24	375	0.2	2	13.524	13.558	13.501	13.528
25	375	0.3	1	5.156	5.139	5.117	5.137
26	375	0.3	1.5	8.936	8.928	8.889	8.918
27	375	0.3	2	14.733	14.698	14.848	14.760

4.1.2 Data generated from the turning experiment

Data collection plays a significant role in the statistical analysis of any field, as it decides the progression of the analysis to the best or worst. A proper and suitable data collection leads to better results from the analysis. In such a focus, it is very much essential to choose a well suitable data collection technique for the analysis. In this work, Data collection for the turning process is selected for proceeding with Response surface methodology design, i.e., a second-order quadratic model. The values predicted using the model in the turning of EN-8 steel using a carbide cutting tool has been shown in Table 4-2.

Table 4-2 Data generated from the turning experiment

Run	Factor 1 A: Cutting speed (m/min)	Factor 2 B: Feed rate (mm/min)	Factor 3 C: Depth of cut (mm)	Response Surface roughness (μm)
1	220	0.1	1	13.357
2	220	0.1	1.5	7.602
3	220	0.1	2	7.290
4	220	0.2	1	13.325
5	220	0.2	1.5	8.090
6	220	0.2	2	8.274
7	220	0.3	1	13.193
8	220	0.3	1.5	9.684
9	220	0.3	2	9.249
10	292	0.1	1	9.113
11	292	0.1	1.5	6.990
12	292	0.1	2	8.192
13	292	0.2	1	6.845
14	292	0.2	1.5	6.565
15	292	0.2	2	8.098
16	292	0.3	1	7.110
17	292	0.3	1.5	6.842
18	292	0.3	2	11.080
19	375	0.2	1	5.089
20	375	0.2	1.5	7.070
21	375	0.2	2	11.550
22	375	0.1	1	5.495
23	375	0.1	1.5	6.219
24	375	0.	2	13.528
25	375	0.3	1	5.137
26	375	0.3	1.5	8.918
27	375	0.3	2	14.760

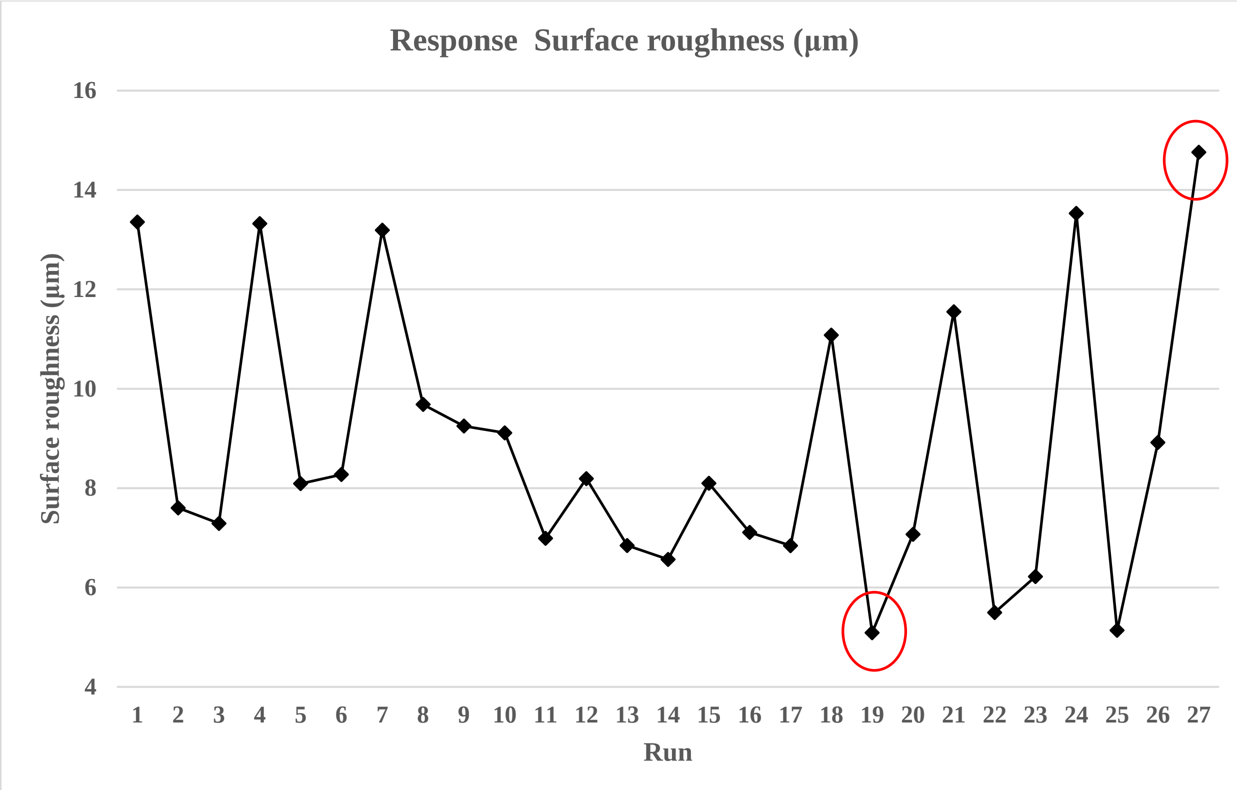


Figure 4-1 Minimum and maximum surface roughness

On average the minimum surface roughness was found to be 5.089µm whereas the maximum surface roughness is 14.760µm.

4.2 Surface roughness data

This analysis deals with the finding the investigation of cutting parameters on surface roughness in turning the operation of EN-8 steel using cemented carbide cutting tool in turning for the different values of cutting speed, feed rate, and depth of cut. The selection of experimental design is a decision-making process that decides the degree of validity of the desired model in finding optimal cutting parameters. This work is carried out using a Response surface methodology. Central Composite Design (CCD) method comes under the Response surface methodology.

A central composite design is an experimental design, useful in response surface methodology, for building a second-order (quadratic) model for the response variable. The response surface design is better, as it generates a second-order quadratic model of regression, which is a better predictive model than a first-order quadratic model. In this work, CCD has been applied for the experimental investigation.

4.2.1 Model summary statistics

In the process of model selection, cubic Model is aliased as, the central composite matrix provides too few unique design points to determine all the terms in the cubic model. It's set up only for the quadratic model.

Table 4-3 Model summary statistics

Source	Std. Dev.	R^2	Adjusted R^2	Predicted R^2	PRESS	
Linear	2.81	0.1113	-0.0046	-0.2993	265.23	
2FI	1.50	0.7803	0.7144	0.5995	81.77	
Quadratic	**0.6593**	**0.9638**	**0.9446**	**0.9136**	**17.63**	**Suggested**
Cubic	0.7282	0.9740	0.9325	0.7873	43.42	Aliased

For each source of terms, the quadratic probability Prob > F falls below 0.05. So far, Design-Expert is indicating (via bold highlighting) the quadratic model looks best – these terms are significant, but adding the cubic order terms will not significantly improve the fit. (Even if they were significant, the cubic terms would be aliased, so they wouldn't be useful for modeling purposes).

4.2.2 Analysis of variance

The ANOVA is where the descriptive statistics and statistical tests are presented. In general, look for low p-values to identify important terms in the model. The p-values to determine if the model explains a significant portion of the variance. Table 4-5 shows ANOVA results for the linear [A, B, C] quadratic [A^2, B^2, C^2] and interactive [(A × B), (A × C), (B×C)] factors. The sum of squares is used to estimate the square of deviation from the mean. Mean squares are estimated by dividing the sum of squares by degrees of freedom. F-value, which is a ratio between the regression mean square and the mean square error, is used to measure the significance of the model under investigation concerning the variance of all the terms, including the error term at the desired significance level. Usually, F > 4 means that the change of the design parameter has a significant effect on the response variable. P-value or probability value is used to determine the statistical significance of results at a confidence level. In this study, the significance level of $\alpha = 0.05$ is used, i.e., the results are valid for a confidence level of 95%. Table 4-5 shows the p-values, the significance levels associated with the F-values for each source of variation. If the p-value is less than 0.05, then the corresponding factor (source) has a statistically significant contribution to the response variable. If the p-value is more than 0.05, then it means the effect of a factor on the response variable is not statistically significant at a 95% confidence level.

Table 4-4 Analysis of variance results

Source	Sum of Squares	Df	Mean Square	F-value	p-value	Contribution%
Model	6.75	9	21.86	6.74	< 0.0001	21.62
A-Cutting speed	0.97	1	5.3	1.19	0.0528	3.11
B-Feed rate	2.4	1	8.4	19.33	0.0004	7.69
C-Depth of cut	23.84	1	12.07	27.77	< 0.0001	76.36
AB	0.16	1	0.1646	0.3787	0.0564	0.51
AC	0.75	1	127.77	2.97	0.4901	2.40
BC	0.63	1	8.63	1.85	0.7003	2.02
A^2	0.51	1	13.51	3.08	0.3022	1.63
B^2	0.57	1	1.62	3.72	0.0505	1.83
C^2	0.33	1	22.33	0.38	0.8059	1.06
Residual	1.06	17	0.4346			3.40
Total	31.22	26				

The Model F-value of 6.75 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise. P-values less than 0.0500 indicate model terms are significant. In this case, A, B, C, AC, BC, A^2, C^2 are significant model terms. Values greater than 0.1000 indicate the model terms are not significant. If there are many insignificant model terms (not counting those required to support hierarchy), model reduction may improve the model.

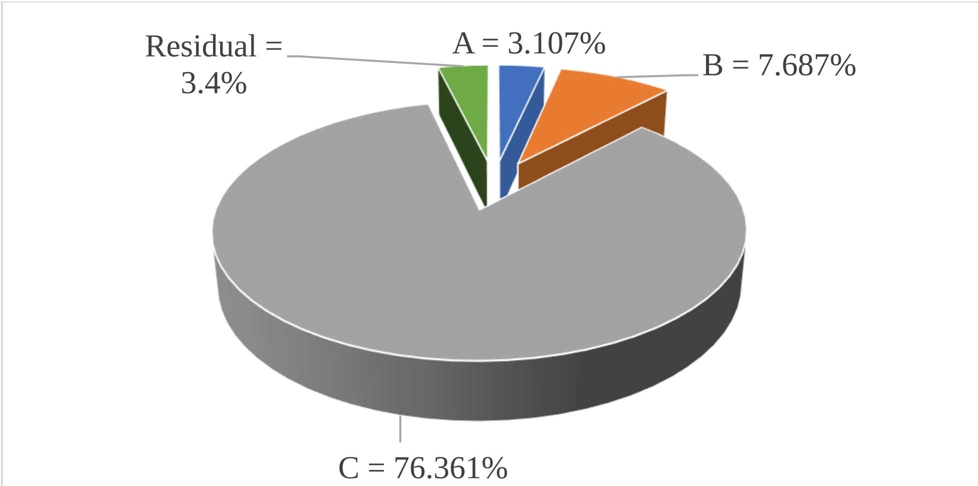


Figure 4-2 Percentage contribution of cutting parameters on surface roughness

The percentage contribution of each term is also shown in Figure 4-2. Depth of cut (C) was found to be the most significant factor for Ra, which explains the 76.36% contribution of the total variation. The next contribution to Ra comes from the feed rate with a contribution of 7.69%. The cutting speed, quadratic [A^2, B^2, C^2] and interactions [(A × B), (A × C), (B ×C)] do not have statistical significance because they have a much lower level of contribution and their p-value is also more than the confidence level.

4.2.3 Fit Statistics

Table 4-5 Fit Statistics summary

Std. Dev.	0.6593	**R^2**	0.9638
Mean	8.84	**Adjusted R^2**	0.9446
C.V. %	7.46	**Predicted R^2**	0.9136
		Adequate Precision	25.3881

The other important term is the coefficient of determination R^2, which is defined as the ratio of the explained variation to the total variation and is a measure of the degree of fit. As R^2 approaches unity, the response model fitness with the actual data improves. The value of $R^2 = 0.9136$ indicates that the model explains 91.36% of the total variations. The adjusted R^2 is a statistic used to adjust the "size" of the model, i.e., the number of factors (machining parameters). The model explains the value of the R^2 (Adj.) = 0.9446 indicating 94.46% of the total variability after considering the significant factors. R^2 (Pred.) = 0.9136 is in good agreement with the R^2 (Adj.) and shows that the model would be expected to explain 91.36% of the variability in new data.

The Predicted R^2 of 0.9136 is in reasonable agreement with the Adjusted R^2 of 0.9446; i.e., the difference is less than 0.2. Adequate Precision measures the signal to noise ratio. A ratio greater than 4 is desirable. The adequate ratio is 25.388 indicates an adequate signal. This model can be used to navigate the design space.

4.2.4 Model fitness check

The examination of residuals has investigated the adequacy of the modal. The residuals, which are the differences between the respective observed response and the predicted response, are examined using normal probability plots of the residuals and the plots of the residuals versus the predicted response. If a model is adequate, the points on the normal probability plots of the residuals should form a straight line. Figure 4-3 reveals that the residuals are not showing any particular trend, and the errors are distributed normally. The residual versus the predicted response plot in Figure 4-4 also shows that there is no obvious pattern and unusual structure.

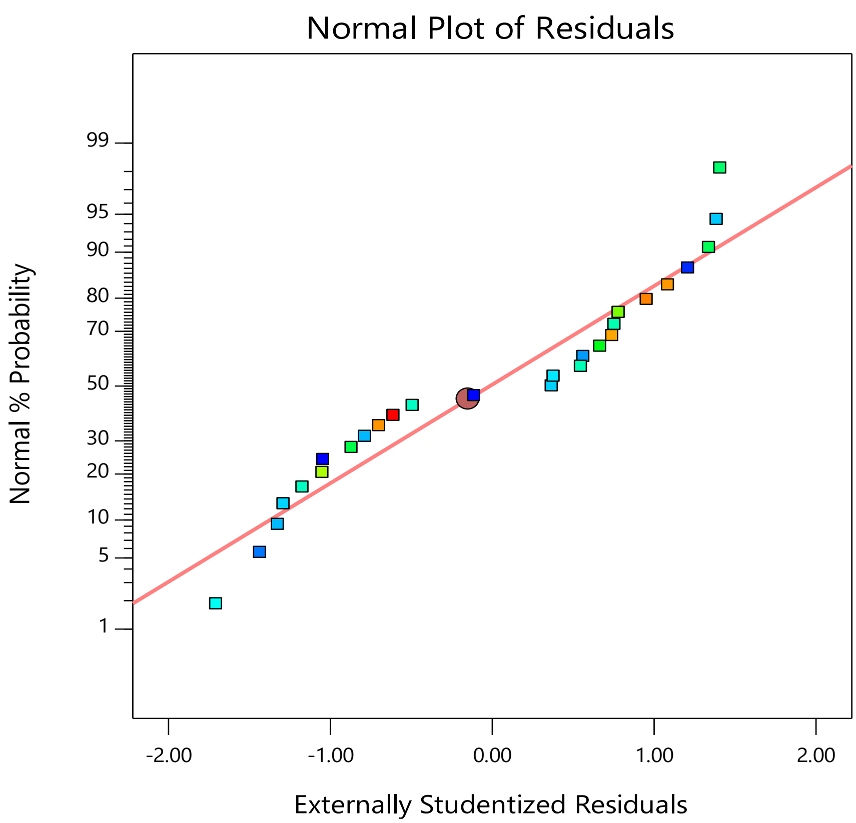


Figure 4-3 Normal probability plot of residuals for surface roughness

4.2.5 Parametric influence on surface roughness

Theoretically, surface roughness is a function of feed rate and nose radius. However, in practice, cutting speed, depth of cut, and tool wear also affect surface roughness. Since the inserts used in the experiments have identical nose radius values, the effect of nose radius was not investigated in this study. The effect of tool wear was neglected as a new cutting edge was used for each experiment, and wear did not reach high levels enough to affect the surface roughness.

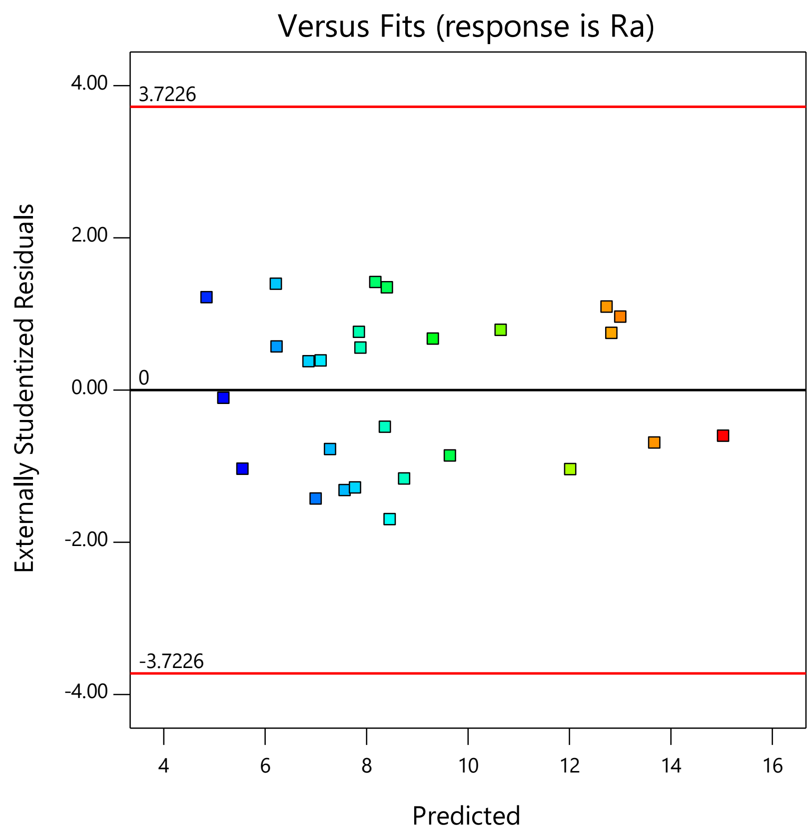


Figure 4-4 Plot of residual versus fitted surface roughness values

The main effects of machining parameters are shown in Figure 4-5. Depth of cut has the greatest effect on surface roughness. The effect of feed rate is very less, and the effect of cutting speed is negligible, as seen in Figure 4-5. Even after a 900% increase in cutting speed, no considerable change was noticed. An increase in cutting speed improves surface quality. This result supports the argument that high cutting speeds reduce cutting forces, giving better surface finish (Sarıkaya and Gullu, 2014). The best surface quality values can be achieved at low feed rates and high cutting speeds. Sahin and Motorcu (2005) also demonstrated that surface roughness increases with an increase in feed rate and decreases with an increase in cutting speed during the cutting of EN-8 steel using a cemented carbide cutting tool.

However, Cetin *et al.* (2011) indicated that the effects of feed rate and depth of cut are more effective than cutting speed on reducing the forces and improving the surface finish.

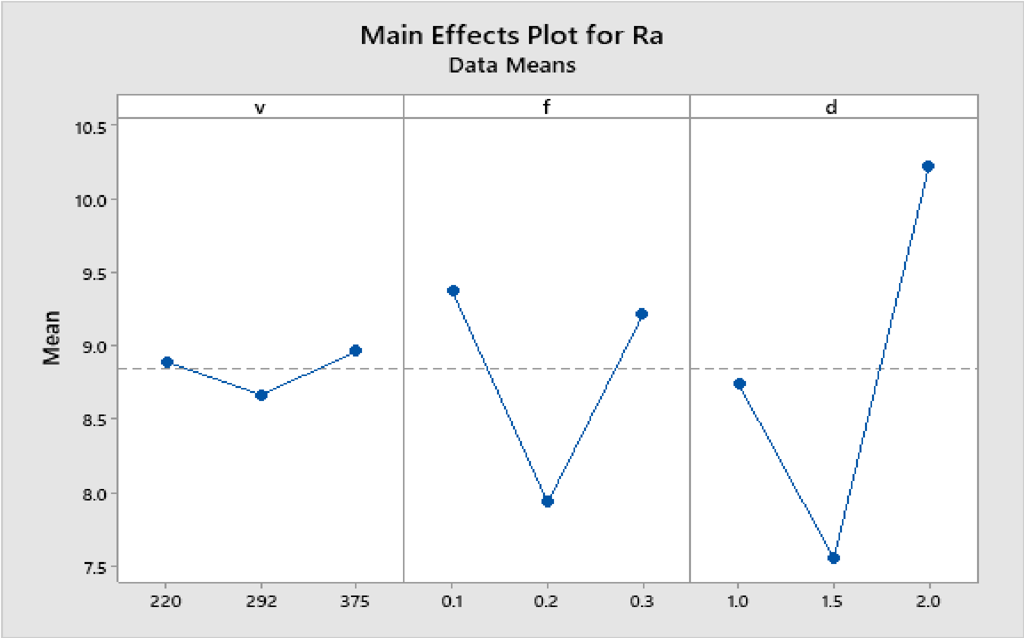


Figure 4-5 Main effect plot of surface roughness

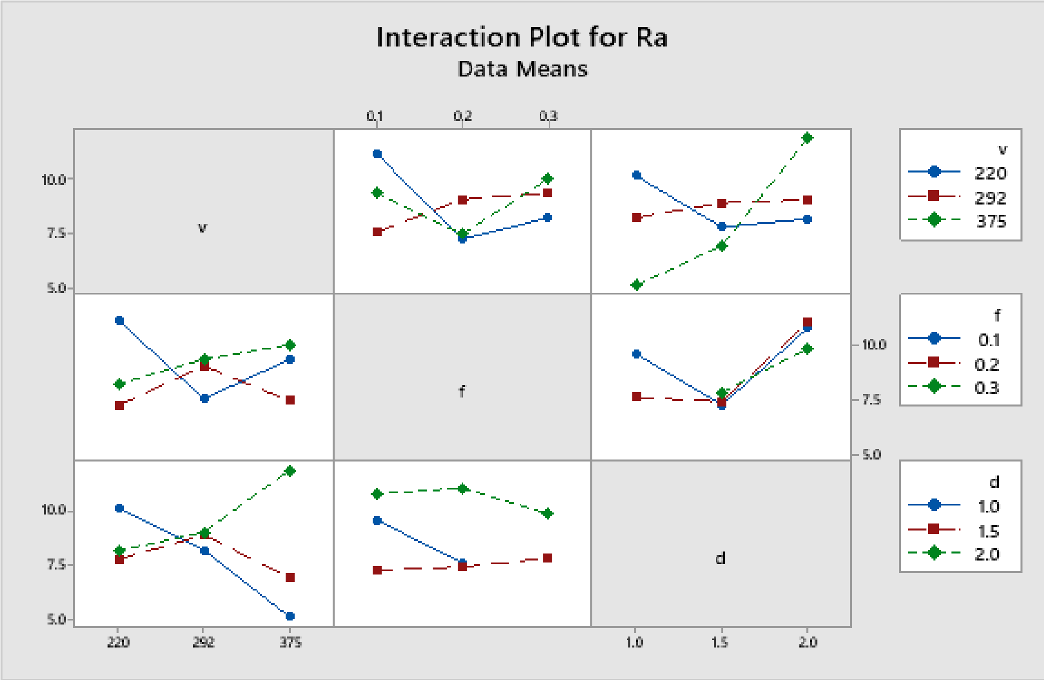


Figure 4-6 Interaction plot of surface roughness

The interaction plot for surface roughness is shown in Figure 4-6. This figure clearly shows that the surface roughness is high with a variation of feed rate at any depth of cut (row 3 column 2) and any cutting speed (row 1 column 2) as the minimum surface roughness is close to 5 μm for level 1 depth of cut and all levels of feed rate and cutting speed, and the maximum surface roughness is more than 7.5 μm for level 3 depth of cut and all levels of feed rate and cutting speed. The variation of feed rate has a negligible effect on surface roughness for feed rate (row 2 column 3) as the spacing between the lines is very small.

4.2.6 Validation of the proposed predictive models

The results obtained from the proposed predictive modeling techniques of RSM are shown in Table 4-7. The relative percentage error between the fitted values predicted and the experimental values of the surface roughness are computed using the following equation.

$$Relative\ Error\ (\%) = \frac{[Predicted\ value\ -\ Experimental\ value]}{\text{Experimental Value}} X100$$

Table 4-6 Predicted values and relative errors for modeling techniques of RSM for surface roughness

Experiment No.	Surface roughness (μm)		Relative Error (%)
	Experimental	Predicted	
1	13.357	12.891	3.489
2	9.113	8.508	6.639
3	5.495	5.821	5.933
4	13.325	12.497	6.214
5	13.193	12.319	6.625
6	6.845	6.737	1.578
7	5.137	5.603	9.071
8	5.089	5.43	6.701
9	7.11	7.453	4.824
10	6.99	7.164	2.489
11	7.602	7.832	3.026
12	6.565	6.294	4.128
13	7.07	7.576	7.157
14	8.09	7.548	6.700
15	9.684	8.916	7.931

16	6.842	7.287	6.504
17	8.918	8.365	6.201
18	6.219	6.837	9.937
19	8.098	7.653	5.495
20	7.29	7.414	1.701
21	11.55	11.67	1.039
22	14.76	14.54	1.491
23	8.274	7.806	5.656
24	13.528	12.368	8.575
25	8.192	7.928	3.223
26	11.08	10.499	5.244
27	9.249	10.065	8.823

Table 4-6 and Figure 4-6 show the relative errors for the modeling techniques.

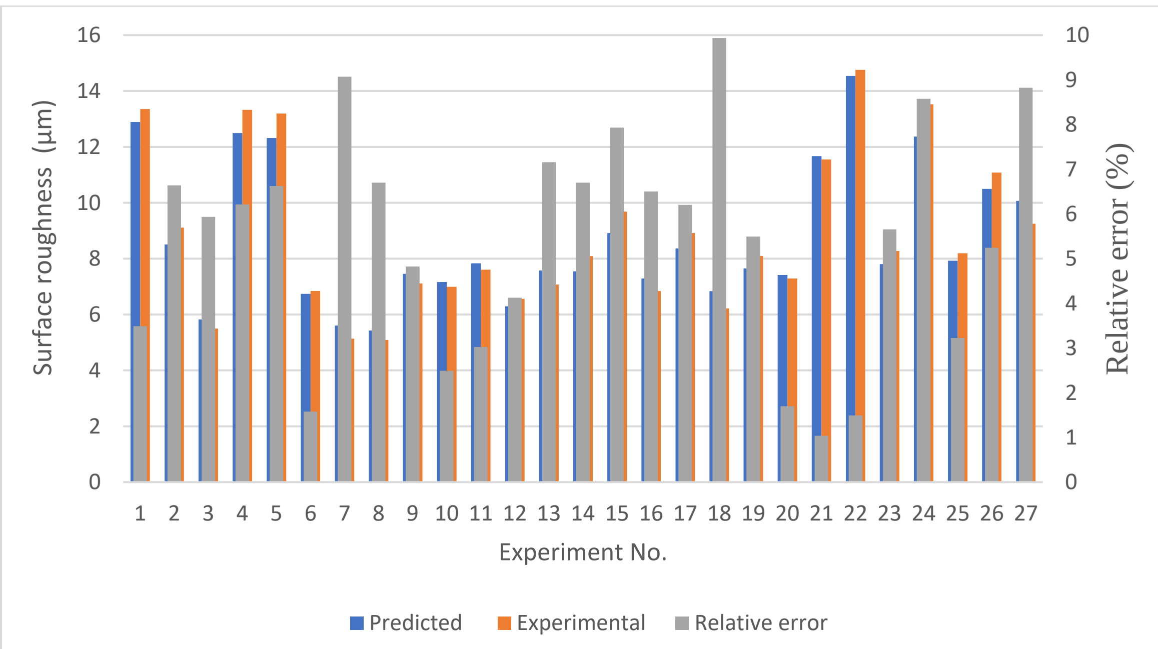


Figure 4-7 Deviation of surface roughness predicted values from the experimental values

The maximum relative error of 9.937% is obtained and which is caused by measurement error and accuracy of profilometer used.

4.3 Surface roughness optimization using response surface methodology

After developing predictive models to predict the surface roughness, the next logical step is surface roughness optimization with respect to cutting conditions. The selection of optimum cutting conditions has always been a challenge in machining. Low surface roughness values can be achieved by adjusting cutting conditions with the help of appropriate optimization methods. Therefore, the process parameters are defined in the standard optimization format to be solved by optimization algorithms.

The optimal response plot is generated using MINITAB software.

Response Optimization: Ra

Table 4-7 Parameters

Response	Goal	Lower	Target	Upper	Weight	Importance
Ra	Target	4.5801	5.089	14.76	1	1

Table 4-8 Starting Values

Variable	v (m/min)	f (mm/min)	d (mm)
Setting	260.15	0.1	1.202

Desirability is simply a mathematical method to find the optimum. Desirability is an objective function that ranges from zero outside of the limits to one at the goal. The numerical optimization finds a point that maximizes the desirability function. A desirability of 1.00 means the goals were easy to reach and better results may be available. Consider making the goals more difficult or adding new criteria for less critical responses and even factors. The ultimate goal is not to maximize the desirability value. The factor settings that result in the highest desirability scores indicate there is an island of acceptable outcomes. It is quite possible for there to be multiple islands (local optima) to explore.

Table 4-9 Optimized solution

Solution	v (m/min)	f (mm/min)	d (mm)	Ra Fit (µm)	Composite Desirability
1	375	0.287879	1	5.09575	0.999302

The value is completely dependent on how closely the lower and upper limits are set relative to the actual optimum. The goal of optimization is to find a good set of conditions that will meet all the goals, not to get to a desirability value of 1.0.

Table 4-10 Optimal machining parameters

Variable	**v (m/min)**	**f (mm/min)**	**d (mm)**
Setting	375	0.287879	1

Optimal machining parameters obtained are cutting speed of 375 m/min at a feed rate of 0.287 mm/min and 1 mm depth of cut.

Table 4-11 Optimized surface roughness

Response	**Fit**	**SE Fit**	**95% CI**	**95% PI**
Ra	5.10	3.76	(-2.83, 13.02)	(-4.72, 14.91)

The optimized surface roughness obtained is (Ra) 5.10 µm. The desirability value is 0.9993, which is very close to 1.0.

Table 4-12 Response optimization for surface roughness

Response	**Goal**	**Optimum Combination**			**Lower**	**Target**	**Upper**	**Predicted**	**Desirability**
		v (m/min)	f (mm/min)	d (mm)					
Ra	Min.	375	0.287	1	5.089	5.089	14.76	5.10	0.9993

Figure 4-8 shows the surface roughness optimization plots for parameters v, f, and d. Each column of the graph corresponds to a factor. Each row of the graph corresponds to the response. Each cell of the graph shows how the response changes as a function of one of the factors, while all other factors remain fixed. The numbers displayed at the top of a column show the current factor level settings and the high and low settings of a factor in the experimental design.

The current optimal parameter settings are: cutting speed of 375 m/min, the feed rate of 0.287 mm/min Furthermore, the depth of the cut of 1 mm for achieving the minimum surface roughness.

The composite desirability (D) is displayed in the upper left corner of the graph. The label above composite desirability refers to the current setting and changes interactively with the factor settings. The optimal response plot is generated using MINITAB software. The vertical lines inside the graph represent current optimal parametric settings. The horizontal dotted lines represent the current response values.

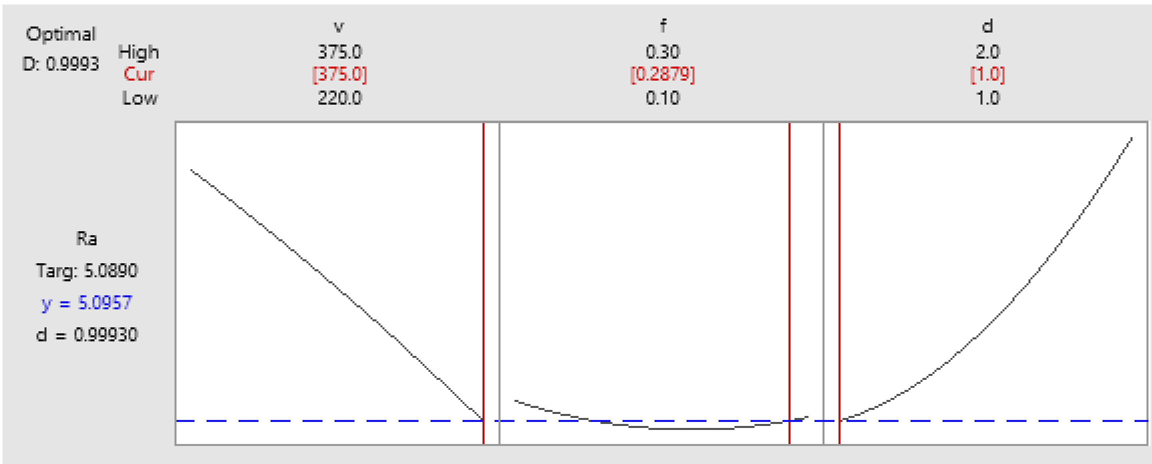


Figure 4-8 Response optimization plot for surface roughness

4.3.1 Combined effect

The combined effect of feed rate and cutting speed on surface roughness

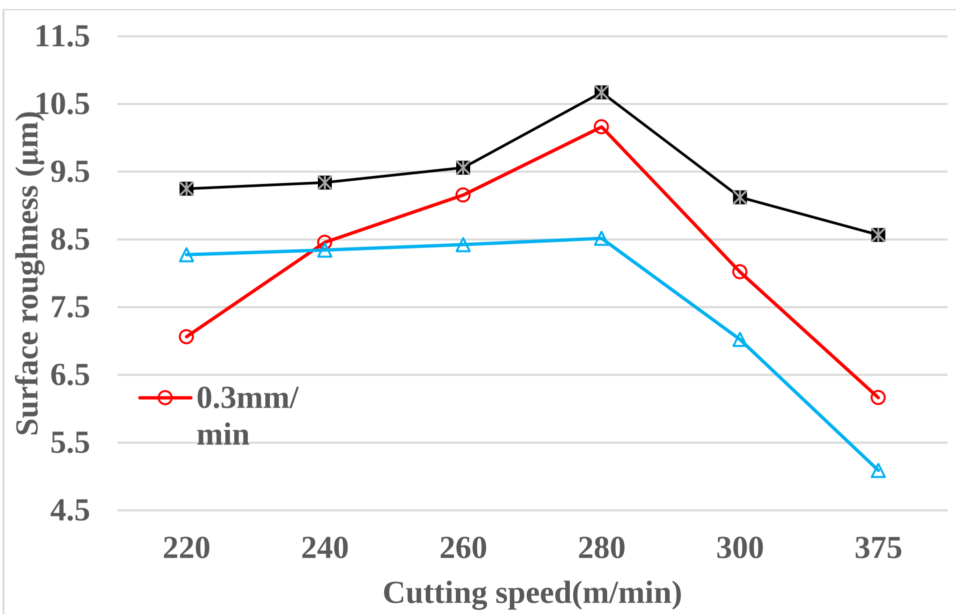


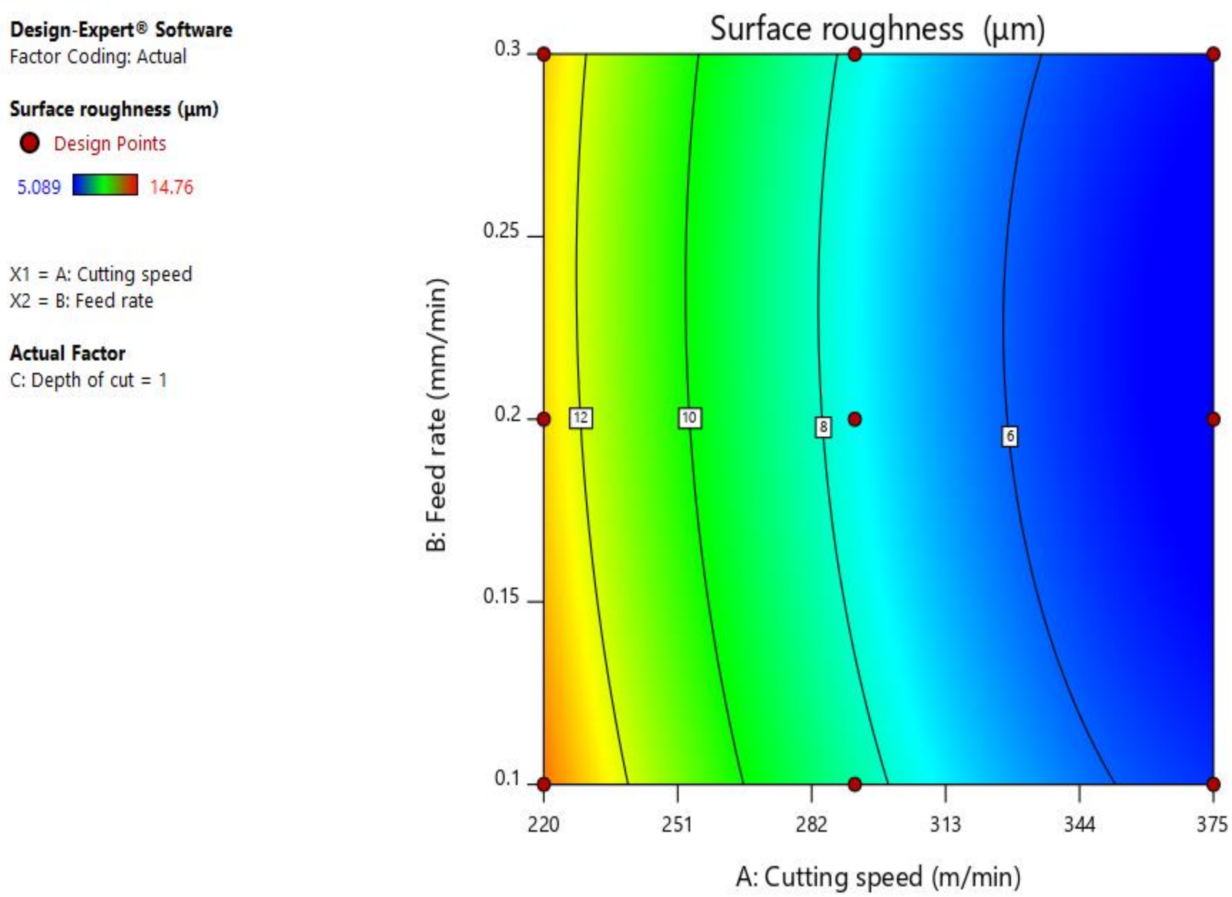
Figure 4-9 Combined effects on surface roughness

Figure 4-9 shows that 3 different combined effect feed rate and the minimum result is found at 0.2 feed rate, at 375 cutting speed and Min Ra = 5.089μm.

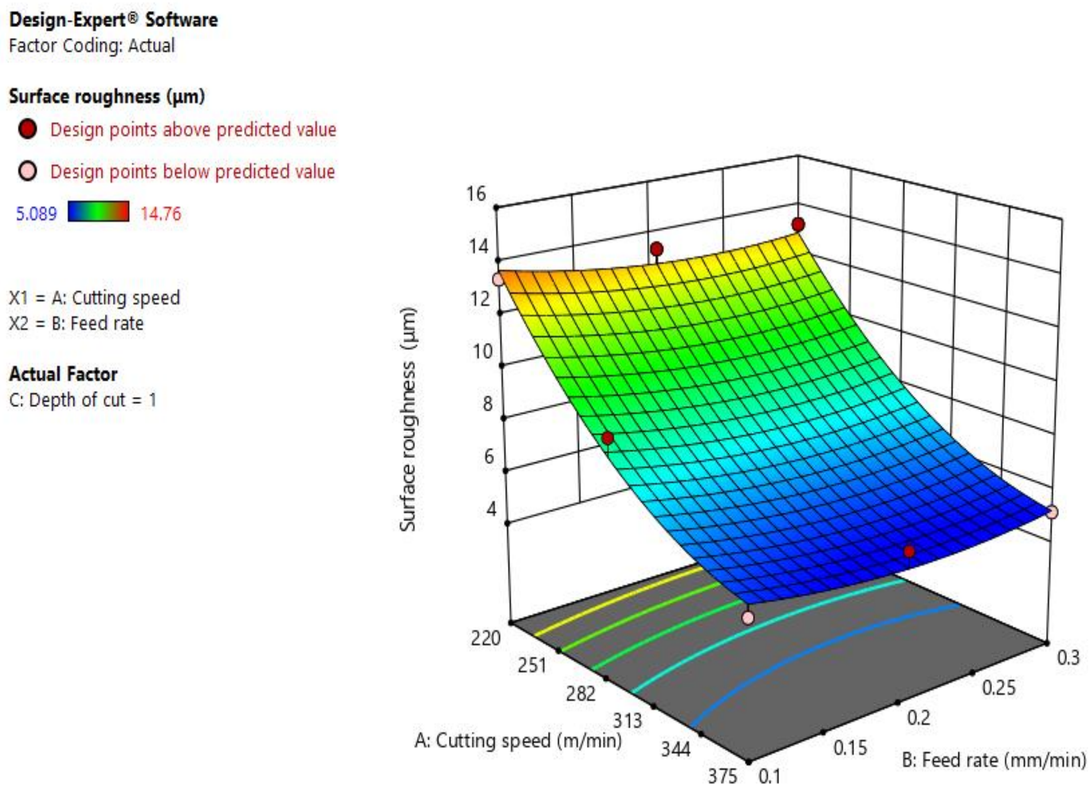
4.3.2 The interaction contour plot

The 2D, 3D surface and contour plots for the respective cutting parameters and surface roughness are shown in the Figure 4-10, 411 and 4-12. However, this plot is useful to find the optimum values of cutting speed and feed rate at a particular value of surface roughness and depth of cut. These 3D surface plots can be used for estimating the surface roughness values for any suitable combination of the input parameters, namely cutting speed, feed rate, and depth of cut.

Figure 4-10 shows the surface and contour plots for surface roughness at 1 mm depth of cut. It is observed that the surface roughness increases with decreases in cutting speed at a lower feed rate and decreases with an increase in feed rate. While at a higher feed rate, the surface roughness decreases with an increase in cutting speed.



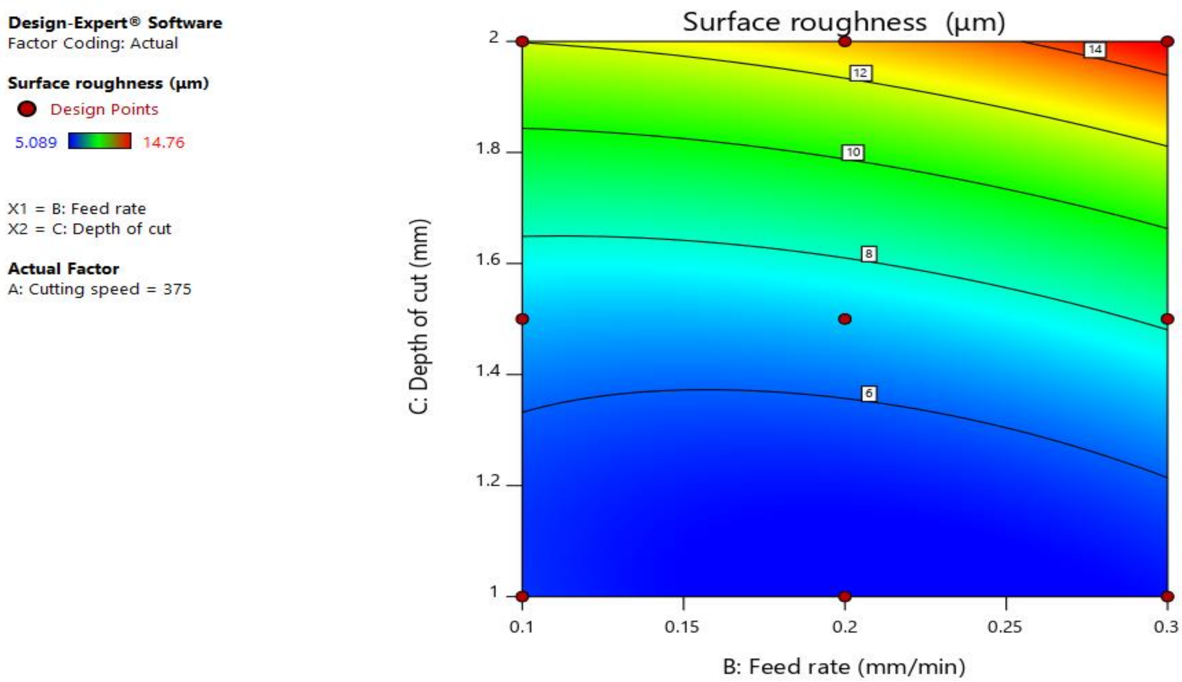
(A)



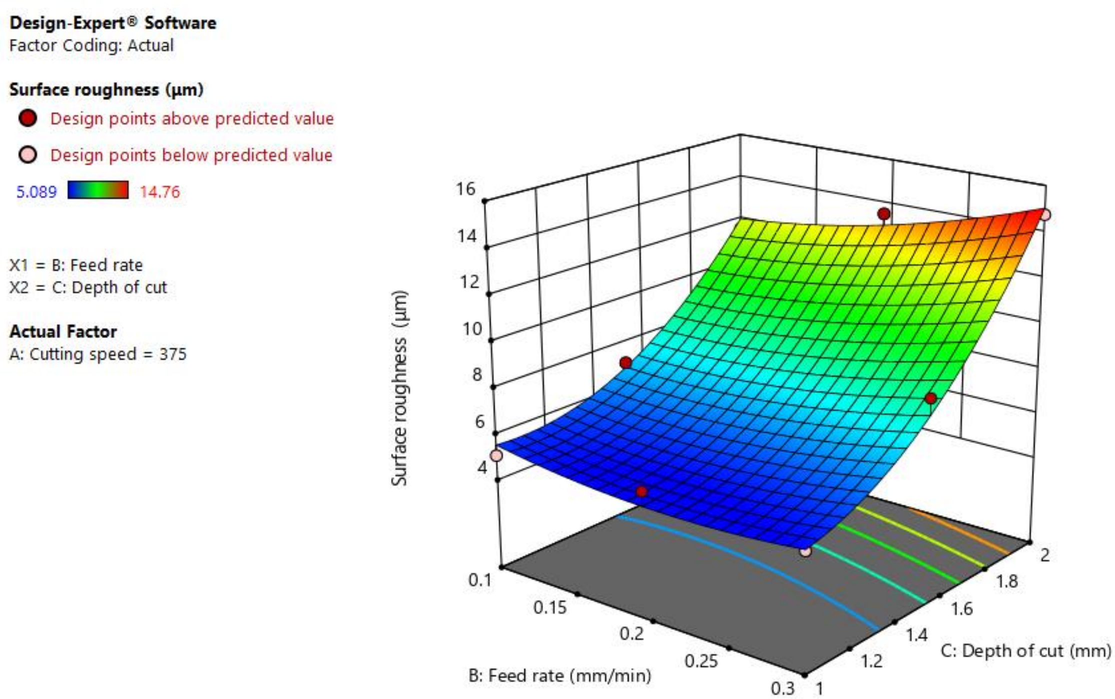
(B)

Figure 4-10 Surface and contour plot of Ra for varying cutting speed and feed rate at 1 mm depth of cut (A) 2D view and (B) 3D view

Figure 4-11 shows the surface and contour plots for surface roughness at a cutting speed of 375 m/min. It reveals that surface roughness increases with an increase in depth of cut, and feed rate has less significant effect. Figure 4-12 shows the surface and contour plots for surface roughness at a feed rate of 0.287 mm/min. At minimum depth of cut and maximum cutting speed the surface roughness is minimum. At maximum depth of cut maximum cutting speed the surface roughness is high. At minimum depth of cut and minimum cutting speed surface roughness is maximum.

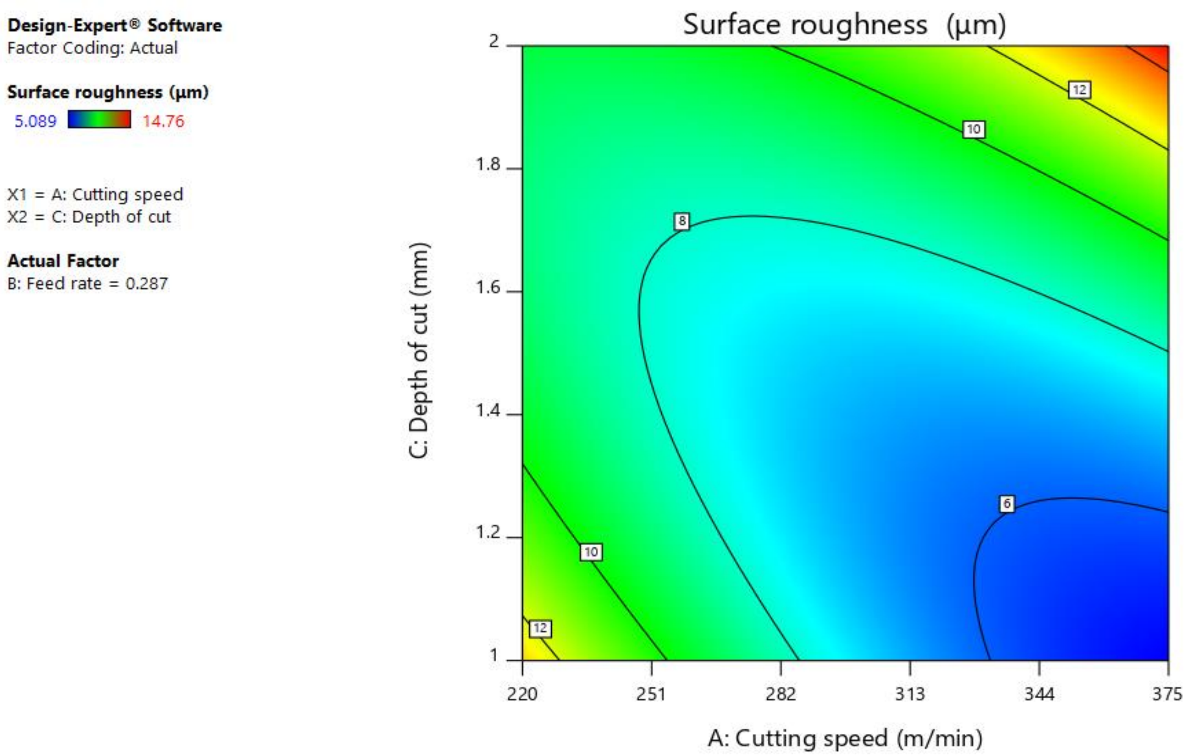


(A)

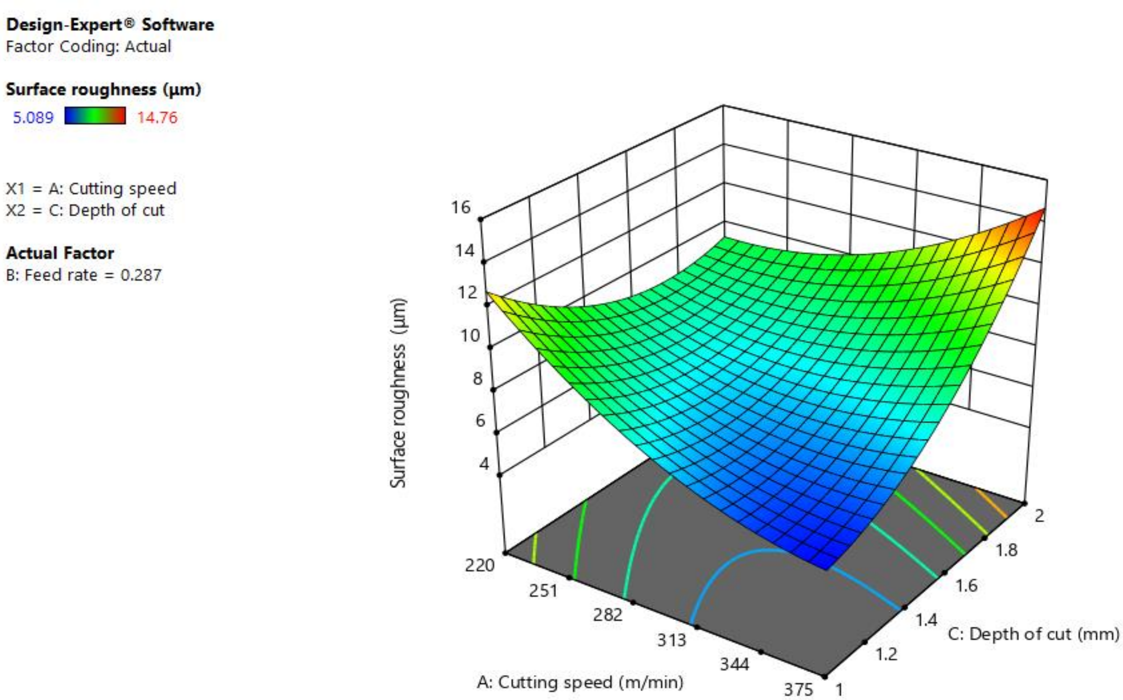


(B)

Figure 4-11 Surface and contour plot of Ra for varying feed rate and depth of cut at 375 m/min cutting speed (A) 2D view and (B) 3D view


Design-Expert® Software
Factor Coding: Actual
Surface roughness (µm)
5.089
14.76
X1 = A: Cutting speed
X2 = C: Depth of cut
Actual Factor
B: Feed rate = 0.287
Surface roughness (µm)
C: Depth of cut (mm)
A: Cutting speed (m/min)
220
251
282
313
344
375
1
1.2
1.4
1.6
1.8
2
6
8
10
12

(A)


Design-Expert® Software
Factor Coding: Actual
Surface roughness (µm)
5.089
14.76
X1 = A: Cutting speed
X2 = C: Depth of cut
Actual Factor
B: Feed rate = 0.287
Surface roughness (µm)
A: Cutting speed (m/min)
C: Depth of cut (mm)
4
6
8
10
12
14
16
220
251
282
313
344
375
1
1.2
1.4
1.6
1.8
2

(B)

Figure 4-12 Surface and contour plot of Ra for varying cutting speed and depth of cut at 0.287 mm/min feed rate (A) 2D view and (B) 3D view

4.4 Predicted values

Predicted values of surface roughness from the developed mathematical model and the experimental values are shown in Figure 4-13 and Table 4-13. The comparison of predicted and measured values shows that the predicted values of the surface roughness are very close to measured values.

The mathematical model for the surface roughness prediction based on the experimental results given in Table 4-4 is developed using equation (3.7). The developed mathematical model to predict Ra is:

$$Ra = 41.4 - 0.075\ v - 9.6\ f - 30.3\ d - 0.000028\ v^2 + 45\ f^2 + 4.39\ d^2 - 0.027\ v*f + 0.0625\ v*d + 0.1\ f*d \quad (4.1)$$

Table 4-13 Experimental and predicted values of surface roughness

Experiment No.	Surface roughness (μm)	
	Experimental	Predicted
1	13.357	12.891
2	9.113	8.508
3	5.495	5.821
4	13.325	12.497
5	13.193	12.319
6	6.845	6.737
7	5.137	5.603
8	5.089	5.43
9	7.11	7.453
10	6.99	7.164
11	7.602	7.832
12	6.565	6.294
13	7.07	7.576
14	8.09	7.548
15	9.684	8.916
16	6.842	7.287

17	8.918	8.365
18	6.219	6.837
19	8.098	7.653
20	7.29	7.414
21	11.55	11.67
22	14.76	14.54
23	8.274	7.806
24	13.528	12.368
25	8.192	7.928
26	11.08	10.499
27	9.249	10.065

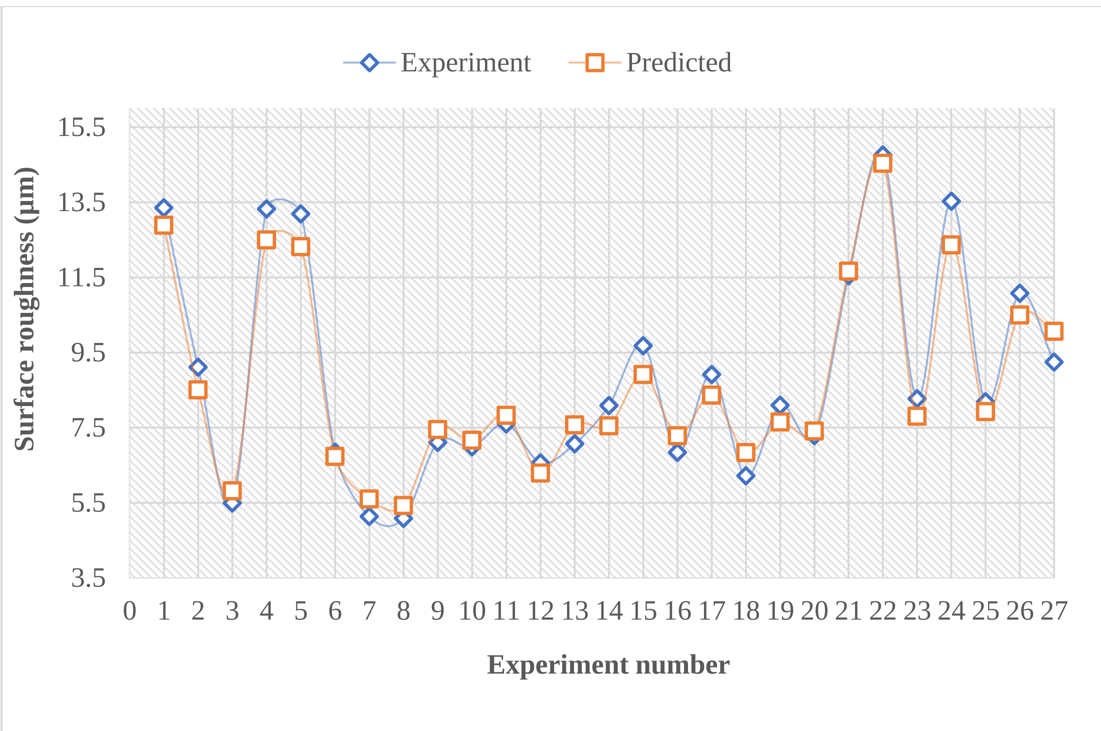


Figure 4-13 Experimentally measured and predicted values of surface roughness

The comparison of predicted and measured values shows that the predicted values of the surface roughness are very close to measured values and the same result were reported by Girish Kant (2016).

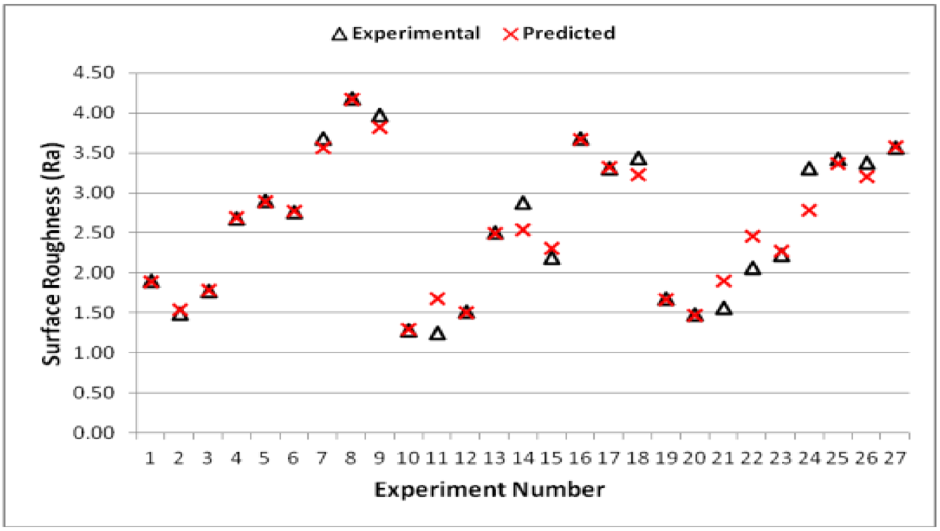


Figure 4-14 Experimentally measured and predicted values of surface roughness by Kant (2016)

4.5 Parameter optimization

The surface roughness (Ra) is undesirable and uncontrollable quality characteristics of a turning process. As such, they are to be minimized to improve on product quality subject to constraints determined by the design limits of the process variables. Figure 4-12, therefore, gives the optimum setting of cutting speed of 375 m/min at a feed rate of 0.287 mm/min and 1 mm depth of cut. These would be required to minimize Ra to a value of 5.10 µm with the desirability of 0.9993, all within the selected design space. This is confirmed by the contour and surface plots of the figures are Figures 4-10, 4-11, and 4-12.

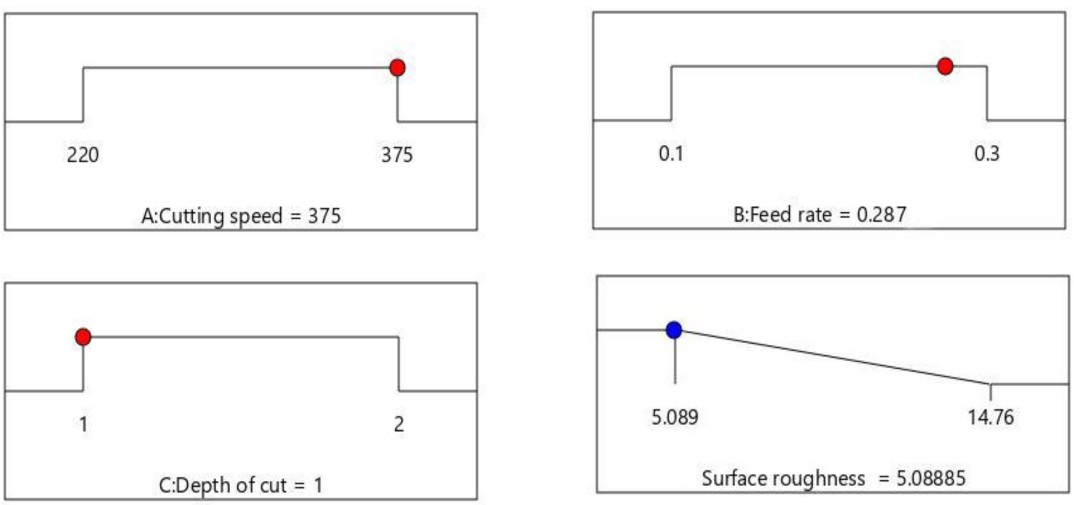


Figure 4-15 Results of parameter optimum

4.6 Experimental confirmation

The confirmation experiments were performed to facilitate the verification of the obtained feasible optimal machining parameters (v = 375 m/min, f = 0.287 mm/rev and d = 1 mm) for the surface roughness. The results of the confirmation run for the response Ra are listed in Table 4-14. The error between the predicted and the confirmation results is 3.403%.

Table 4-14 Confirmation results for surface roughness

Optimum cutting parameters			**Surface roughness (µm)**					**Validation error (%)**
v **(m/min)**	***f*** **(mm/min)**	**d (mm)**	**Experimental**				**Predicted**	
			Run 1	**Run 2**	**Run 3**	**Average**		
375	0.287	1	5.10	5.118	5.122	5.113	4.939	3.403

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This chapter presents an investigation of cutting parameters on surface roughness for the turning operation of EN-8 steel. It has been found that the predictive model provides optimum machining parameters. The results of the proposed model provide improvement in surface roughness over the best experimental run. It has been observed that the depth of cut is the main influencing machining parameter for the minimization of surface roughness by the feed rate and the cutting speed. The 3D surface and contour plots constructed during the study can be used for choosing the optimal machining parameters to obtain particular values of surface roughness these can be used by the machine tool manufacturers to provide the range of cutting speeds, feed rate, and depth of cut for a particular application.

RSM is best modeling as it learns the best fit of models. It has better performance in optimization and enhancement of surface finish. Confirmations experiments carried out using the optimum machining parameters show that the developed predictive and optimization model can be used for turning of EN - 8 steel within 3.403% error. The minimum value of surface roughness obtained is 5.113µm. Optimal cutting conditions for turning operation o EN-8 steel for better surface finish of 5.113 µm was found to be 1mm, 375m/min, and 0.287mm/min for depth of cut, cutting speed and feed rate respectively.

This paper presents the findings of an experimental investigation into the effect of cutting speeds, feed rate, and depth of cut on the surface roughness.

5.2 Recommendation

Based on the results and conclusion found from this study, the researcher forwards the following recommendations:

- The experiment was originally planned to be conducted with the involvement of vibration during a machining operation. Due to the unavailability of the measuring device (accelerometer), difficulties to measure cutting forces without a dynamometer, and the experiment was conducted on cutting parameters only. The application of vibration and cutting forces on the same tool works for the same domain of cutting parameters, and its effect on surface roughness could be studied and analyzed.

- Various parameters and their interactions can extend the study, and the mechanical properties studies can also be carried out.

5.3 Scope for future work

In this research, only one parameter has been studied following their effects. further researches can be carried out to:

i. In this study, carbon steel has been used. This can further be extended to other materials to study the effect of surface roughness under the same cutting parameters.
ii. This work was limited to a single response only. However, a multi-response optimization of machining parameters for surface roughness techniques can be used and analyzed.
iii. Analyses the effect of cutting forces exerted and tool wear rate during the cutting operation.
iv. Study and compare the differences in performance characteristics on the same work sample after heat treatment so on.
v. Future research work may be directed towards applying response surface methodology and genetic algorithm to optimization of cutting parameters, which was beyond the scope of this research, as it was mainly focused on the identification of the most significant influencing factors.

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APPENDIX

Response Surface Regression: Ra versus v, f, d

Coded Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	7.38	1.66	4.44	0.000	
v	-0.216	0.730	-0.30	0.771	1.28
f	0.036	0.925	0.04	0.969	2.05
d	0.759	0.973	0.78	0.446	2.27
v*v	-0.17	1.32	-0.13	0.902	1.37
f*f	0.45	1.41	0.32	0.756	1.60
d*d	1.10	1.41	0.78	0.447	1.59
v*f	-0.21	1.11	-0.19	0.851	1.99
v*d	2.42	1.28	1.90	0.075	1.88
f*d	0.01	1.28	0.01	0.996	2.19

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
2.74217	37.38%	4.23%	0.00%

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	9	76.307	8.4786	1.13	0.396

Linear	3	8.367	2.7891	0.37	0.775
v	1	0.656	0.6563	0.09	0.771
f	1	0.012	0.0117	0.00	0.969
d	1	4.580	4.5801	0.61	0.446
Square	3	6.648	2.2161	0.29	0.829
v*v	1	0.118	0.1185	0.02	0.902
f*f	1	0.751	0.7508	0.10	0.756
d*d	1	4.550	4.5503	0.61	0.447
2-Way Interaction	3	32.892	10.9640	1.46	0.261
v*f	1	0.273	0.2729	0.04	0.851
v*d	1	27.087	27.0873	3.60	0.075
f*d	1	0.000	0.0002	0.00	0.996
Error	17	127.831	7.5195		
Lack-of-Fit	7	24.800	3.5429	0.34	0.915
Pure Error	10	103.031	10.3031		
Total	26	204.138			

Fits and Diagnostics for Unusual Observations

Obs	**Ra**	**Fit**	**Resid**	**Std Resid**	
5	13.19	7.90	5.29	2.28	R

R Large residual

Response Optimization: Ra

Parameters

Response	Goal	Lower	Target	Upper	Weight	Importance
Ra	Target	4.5801	5.089	14.76	1	1

Starting Values

Variable	Setting
v	260.15
f	0.1
d	1.202

Solution

Solution	v	f	d	Ra Fit	Composite Desirability
1	375	0.287879	1	5.09575	0.999302

Multiple Response Prediction

Variable	Setting
v	375
f	0.287879
d	1

Response	Fit	SE Fit	95% CI	95% PI
Ra	5.10	3.76	(-2.83, 13.02)	(-4.72, 14.91)