2022-03

Multi-Objective Process Parameter Optimization of Hot turning on 316 Stainless Steel Using Taguchi and Grey Relational Analysis

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FACULTY OF MECHANICAL AND INDUSTRIAL ENGINEERING

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March 2022

Bahir Dar, Ethiopia

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A thesis submitted to the school of research and graduate studies of Bahir Dar Institute of Technology, BDU in partial fulfilment of requirements for the degree

Of

Master of Science in mechanical engineering

In the faculty of mechanical and industrial engineering.

Advisor Name: Teshome Mulatie, Ph.D.

March 2022

BAHIR DAR, ETHIOPIA

BAHIR DAR UNIVERSITY

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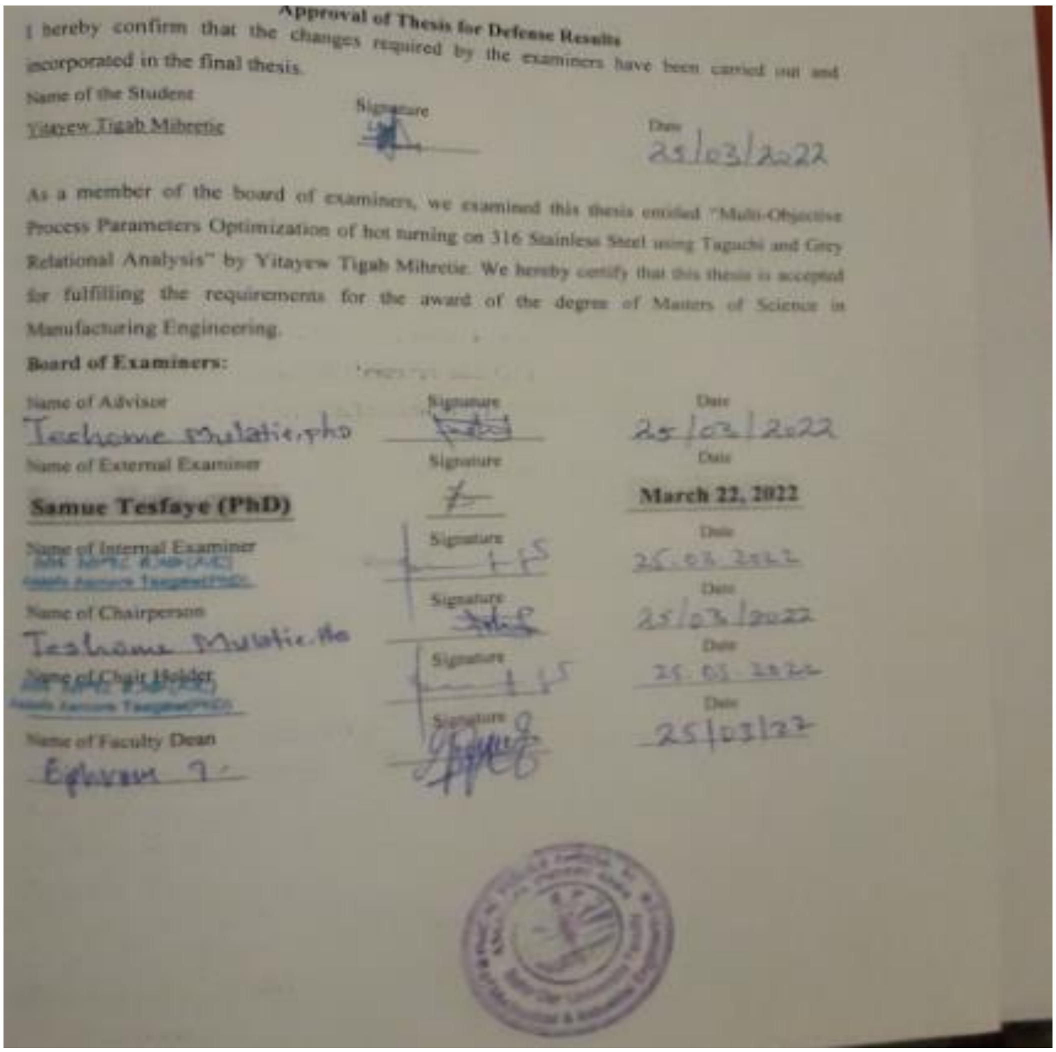
Thesis Approval sheet



Approval of Thesis for Defense Results

I hereby confirm that the changes required by the examiners have been carried out and incorporated in the final thesis.

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As a member of the board of examiners, we examined this thesis entitled "Multi-Objective Process Parameters Optimization of hot turning on 316 Stainless Steel using Taguchi and Grey Relational Analysis" by Yitayew Tigab Mihretie. We hereby certify that this thesis is accepted for fulfilling the requirements for the award of the degree of Masters of Science in Manufacturing Engineering.

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DECLARATION

I hereby declare that the work which is being presented in this thesis entitled **Multi-Objective Process Parameter Optimization of Hot turning on 316 Stainless Steel usingTaguchi and Grey Relational Analysis**, is original work of my own, has not been presented for a degree of any other university and all the resource of material used for this have been fully acknowledged.

ACKNOWLEDGEMENT

First of all, I would like to thank the **God**, who gave me the commitment to pass various obstacles and come up with the accomplishment of this thesis.

First and foremost, I'd want to express my gratitude to my adviser, Dr. Teshome Mulatie, for his support, encouragement, motivation, patience, and vast knowledge. His guidance was inevitable and without his help, I would not accomplish at the given time.

I would like to thank Mr. Gize Melkamu from the Amhara metal and machine technology enterprise to facilitate the roughness testing machine and giving important feedback in my work.

Finally, yet importantly, I would like to extend a special word of thanking Bahir Dar Institute of Technology for fully sponsoring.

ABSTRACT

Hot turning was a relatively new technology for improving the surface roughness and material removal rate of hardened stainless steels. These material are difficult to be turning whether using conventional or unconventional methods and also facing constraint (like low surface quality and low material removal rate) which lead to high costs and decrease productivity. Hot turning was a procedure for turning hardened stainless steels that was distinguished by its heat capabilities. As a result, increasing the operating temperature was one of the variable and available heating strategies that may be used to warm the cutting zone of the work piece, which helps to soften such zones and make the turning operation easier by reducing their hardness and strength. The experiment was carried out on stainless steel rods with a diameter of 30mm. Cutting speed, feed rate, depth of cut, and tool types were all used as process factors. Process parameters also optimized making use of mixed L16 orthogonal arrays were established with different cutting speed (53.694,120.576,157.314,188.4),federate (0.238,0.302,0.416,0.512mm/rev) depth of cut(0.4,0.6,0.8,1.0mm),types of tool(diamond and carbide tool) and grey relational analysis method with a larger better quality characteristics. In order to evaluate the important process parameters, an ANOVA was used. Cutting speed and depth of cut become significant as a result of this study. Cutting speed 157.314m/min, feed rate 0.512mm/rev, depth of cut 1mm, and tool type's diamond tool were determined using an ANOVA analysis. The heating techniques are oxy-acetylene gas and heating temperature are control by MLX90614 temperature sensor with Arduino. The findings of five confirmatory tests show that the average values of the grey relational grade are within the 95% confidence interval for the experiment is 0.637, which is in range of the 95 confidence interval and achieved surface roughness and material removal rate of 5.731 µm and 80.540cm^3/mm respectively. As a result, the confirmatory experiment tests show that this is the safest experiment.

Keyword: AISI316; hot machining; surface roughness; orthogonal array; ANOVA; Grey relational; Multi-objective.

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LIST OF ABBREVIATIONS

ANOVA	Analysis of Variance
AISI	American Iron and steel Institute
CNC	Computer Numerical Control
D	Diameter
DFA	Desirability Functional Analysis
GRA	Grey Relational Analysis
GRC	Grey Relational Coefficient
GRG	Grey Relational Grade
HRc	Rockwell Hardness
HSS	High Speed Steel
HSTR	HighStrength Temperature-resistant
MRR	Material Removal Rate
OHNS	Oil hardened non Shrinkage Steel
RPM	Revolution Per Minute
RSM	Response Surface Methodology
TiAlN	Titanium Aluminium Nitride

LIST OF SYMBOLS

C	Carbon
Cr	Chromium
Mn	Manganese
Ni	Nickel
p	phosphoresce
S	Sulfur
Si	Silicon
S/N	Signal to noise ratio
μGRG	Predicted mean of Grey relational Grade
ξ	Grey relational coefficient

LIST OF APPENDICES

1. INTRODUCTION

1.1 .Background

Turning is the process of removing metal from the outside diameter of a spinning cylindrical work item. It's used to reduce the diameter of a work piece to a certain size and smooth off the metal's surface. Because the work piece is frequently turned, the sizes of adjacent areas of the work piece vary. The machining procedure of turning generates cylindrical pieces(Tesfaye, 2017).

Precipitation hardenable martensitic stainless steel has incredible advantages in aerospace industries (particularly in actuator parts for modern aircrafts), nuclear industries, chemical, petrochemical, gears, pumps, food processing, paper and general metalworking industries(Ganta & Chakradhar, 2014b).

Hot turning is one of the most recent procedures for improving the machinability and surface polish of hardened steels. These materials are difficult to process, whether using traditional or unconventional methods, and they are also constrained (e.g., Cutting tool wear is excessive, material removal rate is low, and surface quality is poor, among other things.), resulting in high costs and poorer productivity(Mohammed et al., 2020).

The basic of hot turning operation is to first soften the work piece is by preheating and thereby shear strength gets reduced in the vicinity of the shear zone. The use of hot machining has become very useful in the machining of high strength temperature-resistant (HSTR) alloys. Hot machining has two functions to perform, one, to machine some HSTR alloys which are un Machninable in the conventional machining method. Second, to improve tool life this eventually improves the production rate. There are various techniques of hot turning which are subjected to requirements. The penetration of heat should be such that the shear zone is appreciably affected. Input rate of heat must be commendably high, so as to temperature sufficiently and quickly. Thermal damage done to work piece through distortion should be minimum. The installation and operation cost should be minimum. The operators in the operation should take safety measures into account (Singh, 2017a).

The beneficial manufacturing of the components of excessive hard materials can be substantial in terms of reduced cost of machining and lead time as compared to the traditional way which involves metal machining in annealed state followed by Heat Treatment, and then finishing operations like grinding and polishing operations, which in turn consumes lots of effort, time and workspace. Machining of high hard materials through conventional processes is restricted due to excessive tool wear of cutting tools and undesired surface finish quality. So for a qualitative and productive process, the positive interest for hot machining process is being moderately developed in production technology (Patel et al., 2014).

The primary principle of hot turning is to soften the work piece by preheating it, lowering the shear strength in the shear zone. In the machining of high strength temperature-resistant (HSTR) metals, hot machining has proven to be particularly useful. Surface finish and material removal rate are two critical parameters in the manufacturing business that must be considered to ensure product aesthetic appeal as well as increased efficiency. To get a better surface smoothness and a higher material removal rate, the cutting parameters must be appropriately established before the operation begins. Spindle speed, feed rate, and depth of cut are all variables that can be set up ahead of time to manage the cutting process(VENKATESWARLU & SURESH, 2019a).

Cutting Speed (v): A tool's cutting speed is the rate at which metal is extracted from the work material by the tool. In a lathe, it is the peripheral speed in m/min of the work part.

$V=\frac{\pi DN}{1000}$(m/min) (1)

Where D, is diameter of work piece (mm) and

N, is spindle speed (rpm).

Feed (f): In lathe work, the feed of the cutting tool is the distance the tool advances in mm for each turn of the work piece.

$$Fm=f.N \text{ (mm/min)} \quad (2)$$

Where, Fm is the feed (mm/min

f is the feed in mm per rev and

N is the spindle speed in RPM.

Depth of cut (d): The perpendicular distance measured in millimeters from the machined surface to the uncut surface of the work piece is known as the depth of cut.

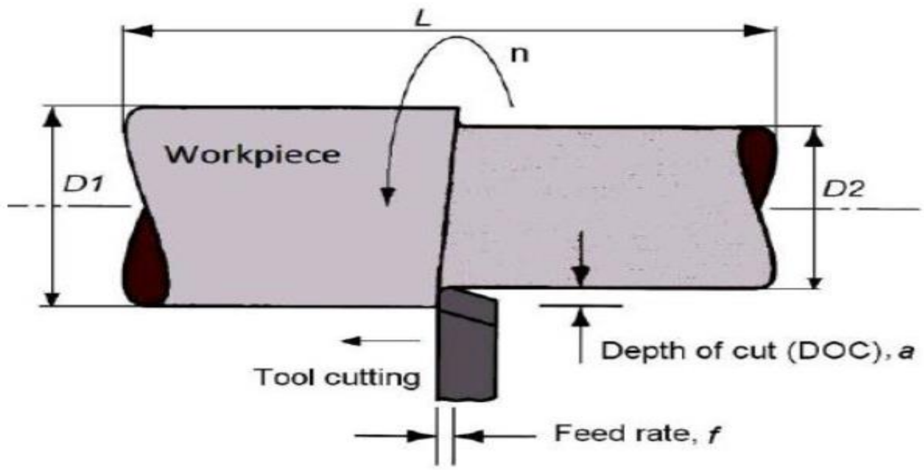


Figure 1.1:Schematic Diagram of the Orthogonal Metal cutting configuration

Electrical resistance, plasma heating, laser heating, gas flame heating, friction heating, and furnace heating are some of the heating techniques employed in the hot machining process(Parida & Maity, 2018). It is vital to select the optimum heating method to optimally heat the materials when rotating. Incorrect heating can produce undesirable changes in the work piece while also raising the cost. This research employs the gas flame heating technology.

Some of the advantages of hot machining are as follows:

- Reducing the mechanical characteristics of work piece materials to facilitate machining.
- Increasing the cutting speed, feed, and depth of cut to select higher machining settings.
- Reducing tool wear.
- Increasing productivity.

- Eliminating cutting fluid application.
- Reducing total production cost.

The drawbacks of hot machining are listed below.

- Require more safety precaution because of heating equipment

1.1.1. Types of material

Super alloys, High Chromium white CI, Ceramic Materials, Hyper chrome CI alloys, Cr-Mo white CI, Hardened steel, High Manganese steel, NH4 (Ni-hard steel), Hardened steel, High Manganese steel, NH4 (Ni-hard steel), Hardened steel, High Manganese steel, NH4 (Ni-hard steel), Hardened steel, High Manganese steel, NH4 (Ni- Materials often machined include stainless steel, S-816 alloy, X-alloy, Timken 16-25-6, Navy Grade Steel, Inconel-X, Ni-Cr Steel, and tungsten, molybdenum, titanium, and tantalum alloys (Senthilvelan, 2011).

Due to its superior corrosion resistance, strength, and machinability properties, AISI316 stainless steel is now the most common and widely used material in the maritime and automotive industries. As a result, the purpose of this study is to find the optimal process parameters for the target materialsfor surface roughness and material removal rate.

1.1.2.Taguchi method

Traditional experimental design methodologies are cumbersome and difficult to implement. Furthermore, when the number of process parameters grows, these methods necessitate a high number of experiments. To reduce the amount of tests required, Taguchi developed the Taguchi experimental design approach, a powerful tool for developing high-quality systems. The Taguchi technique employs an orthogonal array design to investigate the whole parameter space with a limited number of experiments. Taguchi recommends calculating the average response for each array run, as well as analyzing variation using a signal-to-noise ratio (S/N) that is acceptable for the situation(Sharma & Bhambri, 2012).

1.1.3. Grey relational analysis

In the Grey relational analysis, the quality characteristics are first standardized, ranging from zero to one. This process is known as Grey Relational Generation. The Grey Relational Coefficient is then calculated using normalized experimental data to show the correlation between the desired and actual experimental data. Then, by averaging the Grey relational coefficients for selected responses, the overall Grey Relational Grade (GRG) is calculated.

The determined GRG determines the multiple response process' overall performance characteristic. Using the Grey relational technique, a multiple response process optimization problem is reduced to a single response process optimization problem. The best parametric combination, resulting in the highest Grey relational grade, is then examined. The Taguchi approach can be used to determine the best factor setting for maximizing the overall Grey relational grade(Sharma & Bhambri, 2012).

The normalized surface roughness should follow the smaller-the-better (SB) criterion .The normalized material elimination rate in Grey relational generation should follow the larger-is-better (LB) criterion.

1.2 .Statement of the problem

Materials with extremely high hardness and shear strength are required to fulfill modern industrial needs. Traditional ways of machining such materials have proven to be prohibitively expensive.Stainless steel (316) was used in applications where parts must be extensively machined. Nuts and bolts, screws, gears, aviation fittings, bushings, and shafts are examples of these applications. Because stainless steel (316) has a high hardness and shear strength, it is difficult to cut with traditional methods, which diminish surface polish, reduce material removal rate, reduce tool life, increase power consumption, and increase tool wear, all of which raise manufacturing costs. To solve this problem, hot machining was the ideal option for turning operations, because in hot machining, a component or the entire work piece is heated before or during the machining process and heating temperature are control using temperature sensor with Arduino. When high-hardness materials are heated, they soften, resulting in better machinability, higher production rates, better surface roughness, lower power consumption, higher metal removal rates, and longer tool life. Cutting speed, feed rate, depth of cut, and cutting tool types were all used as process factors. Using a mixed L16 orthogonal array and the taguchi based grey relational analysis methods, the process parameters were also optimized. In order to evaluate the important process parameters, an ANOVA was used.

1.3 . Objective

1.3.1 . General objective

The main objective of this research was optimize the process parameters of hot turning on 316 stainless steel material for improving the surface roughness and material removal rate.

1.3.2 . Specific objectives

The following specific objectives were created in order to achieve the overarching goal.

- Determine the optimum level settings of parameters, using grey based Taguchi method,
- Investigate the effect of process parameters on surface roughness and material removal rate,
- Identify significant parameters using ANOVA and validate using a Confirmatory test

1.4 . Research Question

The study's goal was to discover answers to the following questions:

i. What are the process parameters that give good surface roughness and high Material removal rate for 316 stainless steel material?
ii. What are the most critical process parameters for the study?

1.5 .Significance of the Study

The study's importance might be expressed in terms of the information it will provide to industry sectors and research centers. Theoretical and practical parts of the subject are both beneficial.

The following is the theoretical significance:

The literature on improving mechanical property and process parameter theories that is currently available; identifies theoretical gaps; and fills the gaps in the existing literature.

The following are the research's practical implications:

It determines the most effective process parameters. The study's findings will aid other companies in implementing hot machining in their operations.

1.6 .Scope of the study

The purpose of this research was to increase the surface roughness and metal removal rate of hot turning by optimizing process parameters. Cutting speed, feed rate, depth of cut, and cutting tool type are all elements to consider. The Taguchi method and Grey relational analysis are used to analyze the experiment. The experiment is carried out on a lathe machine using a hot-turned 316 stainless steel bar with a diameter of 30 mm.

The study's experimental work was done at the Faculty of Mechanical and Industrial Engineering at Bahir Dar Institute of Technology, and the samples will be inspected at the Amhara metal and machine technology firm.

1.7 .Limitation of the study

Based on existing industry need, the study solely looked at 316 stainless steel materials.

1.8 . Research methodology

To fulfill the predetermined goals in this study, the thesis structures contain the following conceptual setups (Figure 1.1). In the experimental work, the effect of important process parameters on the target materials' surface roughness and material removal rate must be investigated.

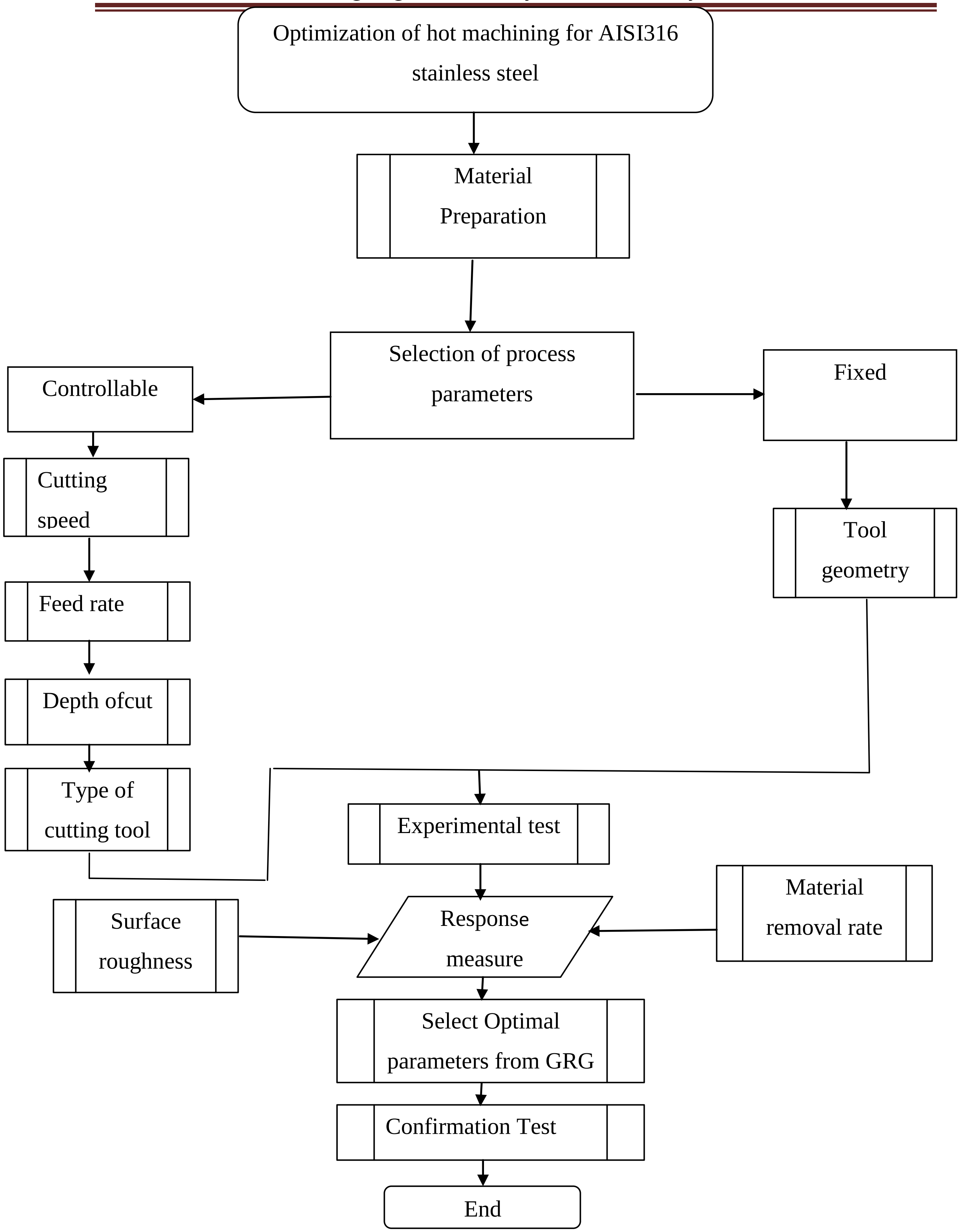


Figure 1.2: Research methodology

2. LITERATURE REVIEW

This chapter covers the basics of hot machining. The major parameters of hot turning will be defined, and various journals on the effects of cutting speed, feed rate, depth of cut, cutting tool kinds, and hot machining heating temperature will be summarized.

2.1 .Overview of hot machining

Hot turning is one of the most recent procedures for improving the machinability and surface polish of hardened steels. These materials are difficult to machine, regardless of whether traditional or unconventional methods are used, and they also face restrictions (such as high cutting tool wear, low material removal rate, poor surface quality, and so on), resulting in high costs and decreased productivity (Mohammed, 2020).

According to earlier tests, the majority of the power consumed during turning operations is due to material shearing and plastic deformation of the metal removed. Because the shear strength and hardness of engineering materials both decrease with rising temperature, it was projected that increasing the work piece's temperature would lower the amount of power required for machining. And, as a result, increase tool life(Rajopadhye et al., 2009).

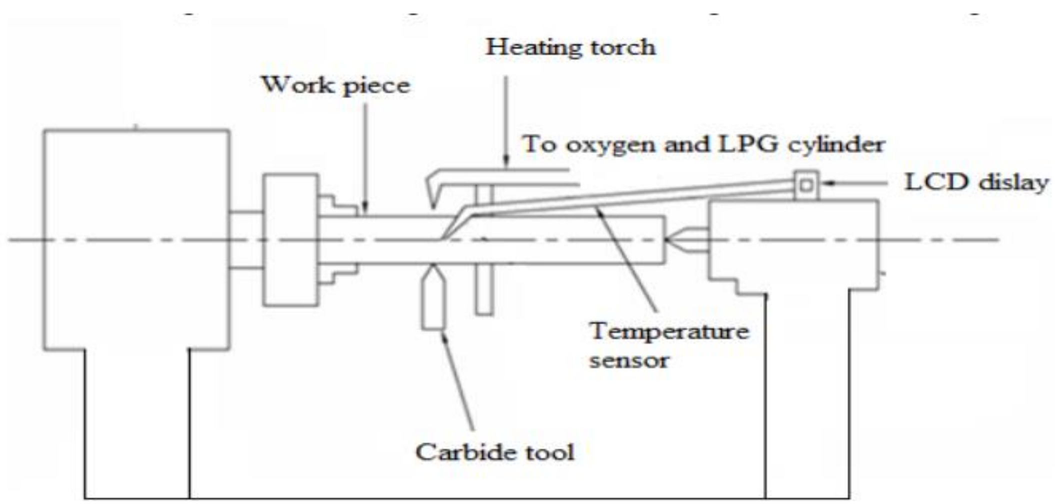


Figure 2.1: Experimental setup(Rajopadhye et al., 2009).

2.2 .Process parameters of hot turning

Taguchi divided factors into two categories: controllable and fixed. A controllable factor is one whose values may be set and controlled throughout the experiment as well as in the end product or process design. Fixed factors, on the other hand, are variables that have an impact on the outcome of a product or process but are not typically maintained at particular values throughout the manufacturing process or application time (Roy, 2010). Based on the availability of materials and tools, parameters are categorized as controllable or fixed in this study.

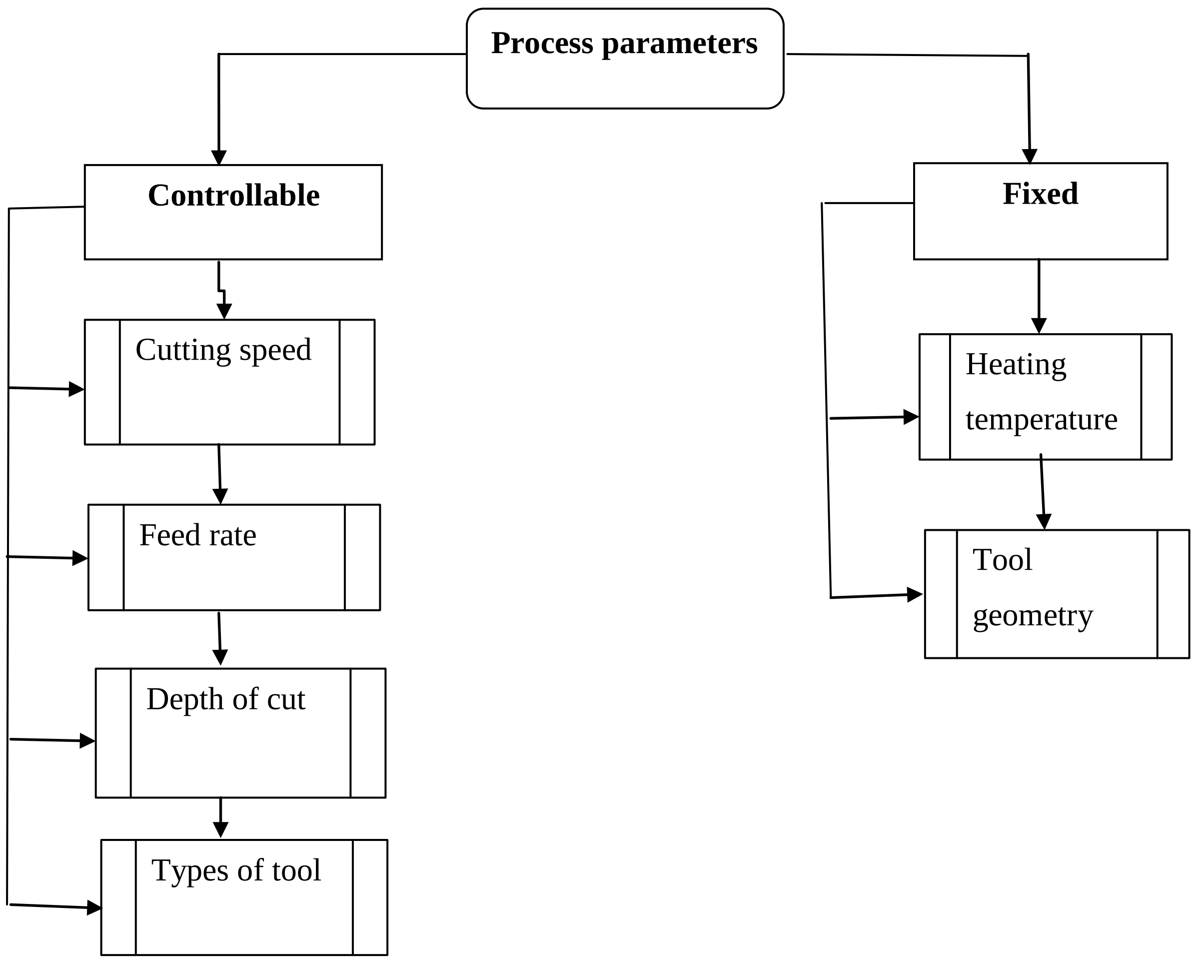


Figure 2.2: Hot turning process parameters

Hot turning surface roughness and material removal rate are influenced by the process parameters stated above. As a result, optimizing the process was the greatest option for achieving excellent roughness quality.

2.2.1. Spindle speed

The experiment was conducted on conventional lathe. The temperature is controlled using an infrared thermometer and a flame heating system. The statistical analysis is done by Taguchi method. Taguchi designs are a powerful and effective technique to make things that work consistently and optimally in a wide range of situations. To assign the objects chosen for the experiment, the Taguchi method advises using orthogonal array designs. A Taguchi experiment's L9 orthogonal array is chosen for four parameters. (Speed, feed rate, depth of cut, and temperature) with three levels in order to optimize the hot machining turning settings on the lathe, (low, medium, and high). In hot machining of AISI 4140 steel materials, optimizing the cutting conditions for surface roughness, material removal rate, and tool wear. According to grey relational analysis, the best process parameters for surface roughness, material removal rate, and tool wear include high cutting speed (125m/min), low feed (0.10mm/ rev), medium depth of cut (0.6 mm), and a pre-heating temperature of 220^{0}c. Surface roughness rose by 3.34 percent, and material removal rate and tool wear improved by 0.91 percent and 13.34 percent, respectively, utilizing Grey Taguchi analysis(Singh, 2017a).

An experimental investigation is carried out using Grey relational analysis (GRA) and desirability function analysis to maximize performance metrics (surface roughness and material removal rate) in hot machining operations (DFA). The trials are carried out on a CNC lathe with AISI D3 tool steel as the work material and a PVD coated TNMG-HM tool based on the Taguchi L18 orthogonal array design as the tool material. The work piece is heated with a butane torch flame, which is a more cost-effective manner than other hot machining heating procedures. Surface roughness and material removal rate performance were investigated in relation to spindle speed, feed, and cut depth. The composite desirability index and grey relational analysis are used to find the ideal turning parameters (SURESH, 2019).

In AISI 52100 steel hot machining, optimizing the cutting conditions for surface roughness (Ra). Hot machining experiments were performed on lathe machine. For hot machining of Bearing Steel, the experiment was carried out on an auto feed lathe using a Tungsten Carbide cutting tool. The temperature was controlled using a thermocouple and a furnace heating system. Different samples were obtained by employing tool cutting speeds of 25.43, 58.87and 90.903 m/min, and feed rate 0.265, 0.344and 0.430mm/rev, with the temperature of the work piece 200^0c, 400^0c and 600^0c.As a result, hot machining process gives good surface finish at high cutting speed, high temperature and low feed rate and it is also advantageous in terms of reduced cutting and feeding forces. Cutting speed of 965rpm, depth of cut of 0.8 mm, feed rate of 0.265 mm/rev, and temperature of 600^0C offer the best results(Modh et al., 2011b). The combination of nickel and molybdenum in Inconel 625 alloy provides corrosion resistance. Inconel 625 is therefore widely used in the maritime and biomedical industries. Different samples were obtained by employing tool rotational speeds of 35, 60 and 100 m/min, feed rate 0.07, 0.10, and 0.15mm/rev, depth of cut 0.3, 0.5 and 1.0mm.

In the current study, the cutting parameters in hot machining of Inconel 625 were optimized using principal component analysis and Taguchi's method. The research yielded the following conclusions.

•When the above-mentioned optimization technique is used to the hot machining of Inconel-625 alloy, the outcome is a superior surface finish, lower power, and a lower coefficient value chip reduction.

•The optimal cutting conditions are Vc = 100 m/min, f = 0.07 mm/rev, and ap = 1 mm.

•Cutting speed has been found to have the greatest impact on reactions when compared to other variables(Parida et al., 2020).

In the hot turning of Ni-Hard nickel-based alloys with carbide tools, cutting variables such as cutting speed, feed rate, depth of cut, and preheating temperature were investigated in terms of flank wear and cutting power. The Grey relational based Taguchi optimization approach was applied to improve flank wear and power as output responses.

The Grey Relational Analysis (GRA) method is used to establish the grey relational grade, and the best setting parameter is identified as a result. The feed rate is 0.13 mm/rev, the cut depth is 0.2 mm, and the temperature is 200^{0}c when the cutting speed is 16.49 m/min(Parida & Maity, 2016).

In hot machining of 15-5PH martensitic stainless steel with a hardness of 40 HRC, the average surface roughness (Ra) and metal removal rate (MRR) were optimized. On a lathe machine, hot machining trials were carried out with a K313 carbide tool insert. In the studies, the Taguchi L18 orthogonal array was used. Using the statistical methods of signal-to-noise (S/N) ratio and analysis of variance, the optimum process parameters, such as speed feed, depth of cut, and work piece temperature, and its impact on performance indicators like surface roughness and metal removal rate were explored (ANOVA). The feed rate has the largest impact on surface roughness, according to the findings of the study. Material removal rate was primarily influenced by cutting speed and feed rate.

• Experiments performed at 120 m/min cutting speed, 0.2 mm/rev feed rate, 0.4 depth of cut, and 250^{0}C temperature yielded the minimum Ra values of 0.49 m during hot machining of 15-5PH stainless steel.

• Maximum MRR values were obtained during hot machining of 15-5PH stainless steel at 120 m/min, 0.4 mm/rev feed rate, 0.6 depth of cut, and 250^{0}C temperature.

• ANOVA was used to explore the effects of the parameters on surface roughness and metal removal rate. Feed rate and cutting speed were determined to be the most important characteristics, whereas work piece temperature and depth of cut were found to be the least important (Ganta & Chakradhar, 2014a).

2.2.2. Feed rate

To meet modern industrial demands, materials with extremely high hardness and shear strength are necessary. Traditional methods of machining such materials have proven to be prohibitively expensive, as these materials have a major impact on tool life. Hot machining is preferred to reduce tool wear and improve surface smoothness. An analysis of the impact of cutting settings on a variety of performance metrics obtained during hot turning operations (material removal rate and work piece surface roughness). The experiments were carried out on oil hardened non-shrinkage steel (OHNS) utilizing a Titanium Aluminum Nitride coated carbide insert (TiAlN) as the tool and a Taguchi method to heat the work piece (Rajeshkannan et al., 2017b).

Optimizing the cutting parameters for the average surface roughness (Ra) and metal removal rate in hot machining of 15-5PH stainless steel (MRR). On a lathe machine, hot machining trials were carried out with a K313 carbide tool insert. The Taguchi L27 orthogonal array was used in the research.

Various samples were obtained with tool rotational speeds of 31, 77, and 120 m/min, feed rates of 0.2, 0.3, and 0.4mm/rev, cut depths of 0.4, 0.8, and 1mm, and work piece temperatures of 200^0c, 400^0c, and 600^0cdegrees Celsius. As a result, cutting speed (31m/min), feed rate (0.4mm/rev), depth of cut (0.4mm), and work piece temperature (400^0c) will produce the best results while hot machining 15-5PH stainless steel utilizing multi response optimization with grey relational analysis. According to the ANOVA results, cutting speed is the most important component, accounting for 46.42 percent of the contribution ratio. In hot machining of 15-5PH stainless steel, the feed rate has a 30.23 percent influence on the surface roughness and metal removal rate, whereas the depth of cut has a 12.19 percent influence (Ganta & Chakradhar, 2014b).

For performing hot machining, the selected material should be hard enough that at elevated temperature it should maintain the strength. As a result, the work piece material is chosen to be AISI 4140. A round bar with a diameter of 50mm and a length of 280mm is used. The material is heat treated by tempering at and oil quenched and having hardness of 50 HRc (Rockwell hardness).Various samples were obtained with tool cutting speeds of 30.80 and 125 m/min, feed rates of 0.1, 0.15, and 0.20 mm/rev, and cut depths of 0.04, 0.06, and 0.08mm with work piece temperatures of 55^0c, 110^0c, and 220^0c. As a consequence, Best parameter combinations for optimum surface roughness are: Speed (A) is set to level 3 (125 m/min), feed (B) is set to level 2 (0.15 mm/rev), depth of cut (c) is set to level 1 (0.4 mm), and temperature (D) is set to level 3. (220^0C).

1. Cutting speed, followed by feed, depth of cut, and temperature, is the most important characteristic for a greater material removal rate value.

2. The following are the best parameter combinations for optimum material removal rate: Speed (A) at level 3 (125m /min), feed (B)at level 3(0.20mm /rev) , depth(C) of cut at level 3(0.8mm)and temperature(D) at level 2(110^0C)(Singh, 2017b).

Using taguchi orthogonal array, the statistical method is utilized to analyze and optimize hot machining process parameters in a lathe machine. The work piece was tested with EN-8 steel. During the method, the input parameters include speed, feed, and cut depth. The output parameters are surface quality.At high cutting speeds, high temperatures, and low feed rates, the hot machining process produces a superior surface finish. Furthermore, In terms of surface roughness, it is favorable. During the hot machining process, the cutting speed is 300 rev/min, the depth of cut is 0.8 mm, the feed is 0.111 mm/rev, and the temperature is 500^0c for optimal results(Patel et al., 2014).

In this investigation, EN 36 Steel specimens were machined on a lathe under a variety of cutting conditions, including surface temperatures, cutting speeds, and feed rates. Cutting force, feed force, and surface roughness were investigated in relation to machining parameters such as cutting speed (21.352, 33.912, 51.119, 78.5, and 121.204), feed rate (0.245, 0.287,0.344,0.382, and 0.430), and temperature (200, 300, 400, 500, and 600°C) at a constant depth of cut of 0.8 mm. The Taguchi Design of Experiments yielded the greatest results in the experimental investigation. In present study, Analysis found that varying parameters are affected in different way for different response. To find the best cutting parameters, an ANOVA analysis was employed. Cutting force and Feed force decrease as temperature, cutting speed, and feed rate increase, achieving optimal outcomes. Temperature is the most critical control factor for cutting force and feed force. The advantages of hot machining include a low cutting force and a low feed force(Kamdar & Patel, 2012).

2.2.3. Depth of cut

For hot machining of 15-5PH stainless steel, the cutting settings were optimized for average surface roughness (Ra) and metal removal rate (MRR). Hot machining experiments were carried out using a lathe machine and a K313 carbide tool insert. The Taguchi L27 orthogonal array was employed in the studies.

Various samples were obtained with tool rotational speeds of 31, 77, and 120 m/min, feed rates of 0.2, 0.3, and 0.4mm/rev, cut depths of 0.4, 0.8, and 1mm, and work piece temperatures of 200, 400, and 600 degrees Celsius. As a result, cutting speed (31m/min), feed rate (0.4mm/rev), depth of cut (0.4mm), and work piece temperature (400^0c) will produce the best results while hot machining 15-5PH stainless steel utilizing multi response optimization with grey relational analysis. According to the ANOVA results, cutting speed is the most important component, accounting for 46.42 percent of the contribution ratio. In hot machining of 15-5PH stainless steel, the feed rate has a 30.23 percent influence on the surface roughness metal removal rate, while the depth of cut has a 12.19 percent influence(Ganta & Chakradhar, 2014b).

At 200°C, 400°C, and 600°C, the impact of machining factors such as cutting speed on cutting force, feed force, and surface roughness was investigated (Vs) , feed rate (fs), and depth of cut (ap). The greatest findings in the experimental study were obtained employing a Design of Experiment with full factorial design. The best cutting settings were determined using an ANOVA analysis. At high cutting speeds, high temperatures, and low feed rates, as well as modest cutting and feed forces, the hot machining process produces a superior surface polish.

Cutting at 965 rev/min with a depth of cut of 0.8 mm, a feed rate of 0.265 mm/rev, and a temperature of 600^0C produces the best results(Modh et al., 2011a).

Cutting parameters such as cutting speed (Vs), feed rate (fs), and depth of cut (ap) machining parameters such as cutting speed 29.68,73.04, and 113.1m/mm, feed rate 0.25, 0.375, and 0.381mm/rev, depth of cut 0.4,0.8, and 1mm, and temperature at 200^0C, 400 ^{0}C, and 600^0C hot turning of 316 stainless steel are investigated. Taguchi strategies can be used to produce the best results in the experimental investigation. Cutting speed, feed rate, and cut depth have an impact on the performance metric, tool wear (VB), are studied using an orthogonal array and analysis of variance at 200°C, 400°C, and 600°C hot turning (ANOVA).Using a multiple linear regression equation, optimal cutting parameters were discovered for each performance measure, as well as the link between the parameters and the performance indicator. Based on the findings of a study in which AISI 316 stainless steel with WC inserts was employed.

In 200^0C hot turning of 316 SS, cutting speed and depth of cut are statistically significant elements impacting tool wear, accounting for 11.765 percent and 16.214 percent of the total variance, respectively. The feed rate and depth of cut are statistically significant variables in 400^0C hot turning of 316 SS, explaining 5.02 percent and 5.02 percent of the total variation, respectively. Cutting speed and depth of cut are statistically significant parameters for 600^0C hot turning of 316SS, accounting for 11.61 percent and 15.45 percent of total variance, respectively(Ranganathan & Senthilvelan, 2010).

2.2.4. Types of tool

High-speed tool steel, cobalt-base alloys, cemented carbides, ceramic, polycrystalline cubic boron nitride, and polycrystalline diamond are some of the cutting tool materials used in machining operations. Different Machining applications require different Cutting Tool Materials. All of the following features should be present in the ideal cutting tool material:

- ✓ Harder than the work it is cutting
- ✓ High temperature stability
- ✓ Resists wear and thermal shock
- ✓ Impact resistant

Some cutting tool materials are: Carbon steel, high-strength steel (HSS), cast cobalt alloys, carbides, coatings, cermets, silicon nitride, cubic boron nitride, and other materials are used.

2.2.5. Heating temperature

Cutting force, feed force, and surface roughness were investigated at 200^0C, 400^0C, and 600^0C under the impact of machining parameters such as cutting speed (Vs), feed rate (fs), and depth of cut (ap). A Design of Experiment using full factorial design yielded the most significant findings in the experimental study. The best cutting settings were determined using an ANOVA analysis. The results generated in the hot machining process provide a good surface polish at high cutting speeds, high temperatures, and low feed rates, as well as low cutting and feed forces.

For optimal results, set the cutting speed to 965 rev/min, the depth of cut to 0.8 mm, the feed rate to 0.265 mm/rev, and the temperature to 600^0C(Modh et al., 2011a).

Cutting variables including cutting speed (Vs), feed rate (fs), and cut depth (dc) all have an effect (ap) Cutting speeds of 29.68, 73.04, and 113.1m/mm, feed rates of 0.25, 0.375, and 0.381mm/rev, depths of cut of 0.4, 0.8, and 1mm, and temperatures of 200^0C, 400^0C, and 600^0C hot turning of 316 stainless steel are all explored on tool wear. The best results in the experimental inquiry can be attained using Taguchi process. At 200°C, 400°C, and 600°C hot turning, the combined impacts of three cutting parameters, namely cutting speed, feed rate, and depth of cut, on the performance measure, tool wear (VB), are evaluated using an orthogonal array and analysis of variance (ANOVA). Using a multiple linear regression equation, optimal cutting parameters were discovered for each performance measure, as well as the relationship between the parameters and the performance measure. Based on the results of a study that used AISI 316 stainless steel with WC inserts.

For 200^0C hot turning of 316 SS, cutting speed and depth of cut are statistically significant factors impacting tool wear; they account for 11.765 percent and 16.214 percent of overall variance, respectively. In 400^0C hot turning of 316 SS, the feed rate and depth of cut are statistically significant characteristics, explaining 5.02 percent and 5.02 percent of the total variation, respectively. Cutting speed and depth of cut are statistically significant parameters in 600^0C hot turning of 316SS, explaining 11.61 percent and 15.45 percent of the total variation, respectively(Ranganathan & Senthilvelan, 2010).

The experiment is conducted on conventional lathe. An infrared thermometer and a flame heating system are used to regulate the temperature. Taguchi method is used for statistical analysis. Taguchi designs are a powerful and successful method for creating objects that perform consistently and optimally in a variety of conditions. The Taguchi approach suggests employing orthogonal array designs to assign the items chosen for the experiment. A Taguchi experiment's A L9 orthogonal array is chosen for four parameters (speed, feed rate, depth of cut, and temperature) with three levels in order to optimize the hot machining turning settings on the lathe (low, medium, and high).

In hot machining of AISI 4140 steel materials, optimizing the cutting conditions for surface roughness, material removal rate, and tool wear. According to grey relational analysis, the best process parameters for surface roughness, material removal rate, and tool wear include high cutting speed (125m/min), low feed (0.10mm/ rev), medium depth of cut (0.6 mm), and a pre-heating temperature of 220^0c. Surface roughness rose by 3.34 percent, and material removal rate and tool wear improved by 0.91 percent and 13.34 percent, respectively, utilizing Grey Taguchi analysis(Singh, 2017a).

Cutting variables such as cutting speed, feed rate, depth of cut, and preheating temperature were evaluated in terms of flank wear and cutting power when hot turning Ni-Hard nickel-based alloys with carbide tools. To improve flank wear and power as output responses, the Grey relational based Taguchi optimization approach was used. The grey relational grade is determined using the Grey Relational Analysis (GRA) method, and the appropriate setting parameter is determined as a result. The best results are obtained when the cutting speed is 16.49 m/min, the feed is 0.13 mm/rev, the cut depth is 0.2 mm, and the temperature is 200^0C(Parida & Maity, 2016).

In hot machining of 15-5PH martensitic stainless steel with a hardness of 40 HRC, the average surface roughness (Ra) and metal removal rate (MRR) were optimized. On a lathe machine, hot machining trials were carried out with a K313 carbide tool insert. The Taguchi L18 orthogonal array was used in the research. The ideal process parameters, such as speed feed, depth of cut, and work piece temperature, and their effect on performance metrics, such as surface roughness and metal removal rate, were investigated using statistical methods such as signal-to-noise (S/N) ratio and analysis of variance (ANOVA). According to the study's findings, the feed rate has the greatest impact on surface roughness. Material removal speed is primarily influenced by cutting speed and feed rate.

• Experiments were carried out at a cutting speed of 120 m/min, a feed rate of 0.2 mm/rev, and a cut depth of 0.4 mm and 250^{0}C temperature yielded the minimum Ra values of 0.49 m during hot machining of 15-5PH stainless steel.

• Maximum MRR values were obtained during hot machining of 15-5PH stainless steel at 120 m/min, 0.4 mm/rev feed rate, 0.6 depth of cut, and 250^{0}C temperature.

• ANOVA was used to explore the effects of the parameters on surface roughness and metal removal rate. . Feed rate and cutting speed were determined to be the most important characteristics, whereas work piece temperature and depth of cut were shown to be the least important (Ganta & Chakradhar, 2014a).

Oxy acetylene heating is one of the best choices for hot machining because it requires low-cost equipment, the heat transfer to the work piece is very low, despite the fact that the gross heat available and the energy transfer density will be low, and the metallurgical damage to the work piece will be minimal. The flame was created using the torch's nozzle. To allow for flexible movement of the heat source while machining, an unique attachment was employed to move the torch positioned on the carriage. The distance between the torch and the work piece is 25 mm during all of the testing. Pressure regulators were used to modify and maintain acetylene and oxygen flow rates, resulting in a neutral flame that was employed throughout the machining process (R.Rajeshkannan et al., 2017).

2.3 .Summary of Literature Review and Research Gaps

The following are the major findings of the research:-

- The utilization of different parameters impart various results. From the kinds of literature reviewed it could be clearly seen that feed rate, depth of cut and heating temperature magnitudes depends on levels cutting speed .
- The most significant process factors for attaining the minimum surface roughness and highest material removal rate are cutting speed, feed rate, and depth of cut.

- Cutting speed, feed rate, cut depth, and heating temperature were the focus of the majority of previous research. This clearly shows thatthe researches in the area of hot turning process parameters improvement were limited and require further study of other parameters. For this reason, improvement of hot turning process parameters will be further examined and evaluated in this research.

3. MATERIALS AND METHODS

This chapter goes into the materials and instruments involved in the hot turning and testing of the specimen in great detail. The methodology section describes the experimental and optimization strategies. The study's experimental flowchart is depicted in the diagram below.

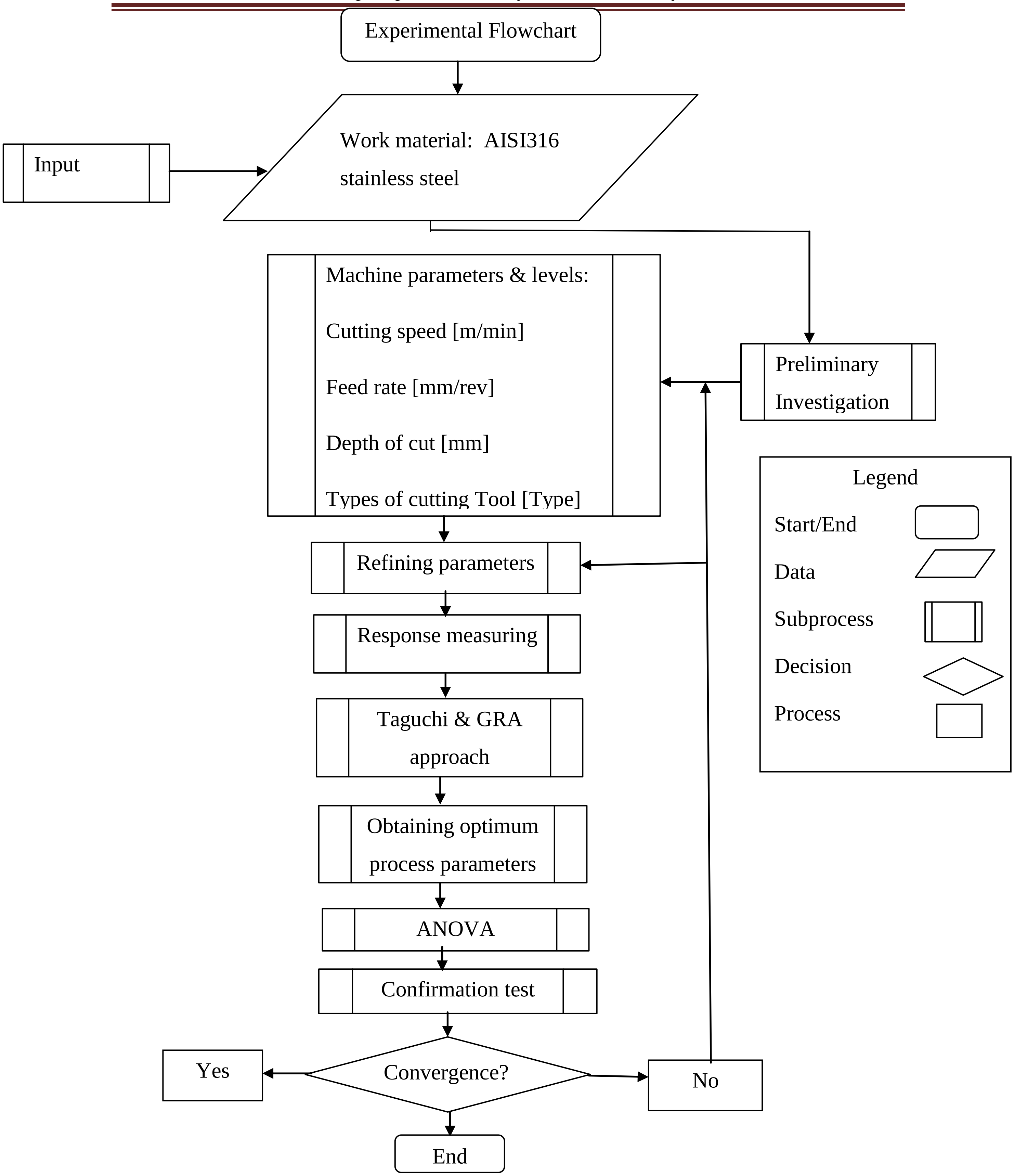


Figure 3.1: A research framework

3.1 .Material

3.1.1. Work piece material

In this experiment, the work piece is a round bar made of commercial AISI 316 stainless steel with a diameter of 30 mm and a length of 150 mm. Machine tool parts such as spindles, shafts, and shanks, as well as vehicle goods, are typical applications for these materials. Table3.1 shows the results of a SPECTROMAXx machine used to determine the chemical composition of the metal.

Figure 3.2:Stainless steel bars

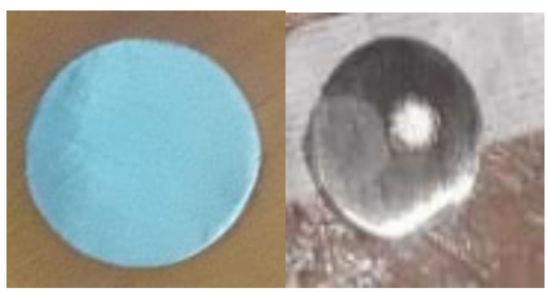


Figure 3.3: Before and after testing of chemical composition test

Table3.1 :AISI 316 stainless steel chemical composition

Material	C	Cr	Ni	Mn	Si	P	S
AISI316	0.08%	16-18%	10-14%	2.00%	0.75%	0.045%	0.03%

Table 3.2:Mechanical properties of 316 stainless steel

Material	Tensile Strength [MPa]	Yield Strength [MPa]	Hardness [HV]	
			Rockwell B	Brinell (HB)
316 stainless steel	515	205	95	217

3.1.2. Cutting tool material

High-speed tool steel, cobalt-base alloys, cemented carbides, ceramic, polycrystalline cubic boron nitride, and polycrystalline diamond are some of the cutting tool materials used in machining operations. Different Machining applications require different Cutting Tool Materials. All of the following features should be present in the ideal cutting tool material:

- ✓ Harder than the work it is cutting
- ✓ High temperature stability
- ✓ Resists wear and thermal shock
- ✓ Impact resistant

Some cutting tool materials are: Carbon steel, high-strength steel (HSS), cast cobalt alloys, carbides, coatings, cermets, silicon nitride, cubic boron nitride, and other materials are used. Then select the diamond tool and carbide tool because the material was hardened material.

3.2 .Experimental Machines and setups

3.2.1. LatheMachine

In this study, used IT200BLlathe machine as a hot machining. The machine specifications are listed below the table:

Table 3.3: IT200BLlathe machine specification(From machine manual)

N^o	Part Name	Unit	Specification
1	Center height on the bed	mm	200
2	Swing over saddle	mm	210
3	Swing over bed	mm	400
4	Swing over gap	mm	550
5	Center distance	mm	1000
6	Spindle speed	N^o	12
7	Spindle hole diameter	mm	58
8	Diameter of standard chuck	mm	200
9	Leadscrew diameter	mm	32
10	Screw pitch	mm	6
11	Weight	Kg	1800

Figure 3.4: Lathe machine

3.2.2. Temperature measuring device

In today's industrial world, temperature measurement serves a wide range of needs and applications.

Temperature sensor

Sensors that sense the temperature of a medium are known as temperature sensors. Types of temperature sensor was non-contact MLX90614 temperature sensor that can be used to measure the temperature of a particular object ranging from -70^{0}c to 382.2^{0}c.the sensor uses IR rays to measure the temperature of the object without any physical contact and communicates to the microcontroller using the 12c protocol.

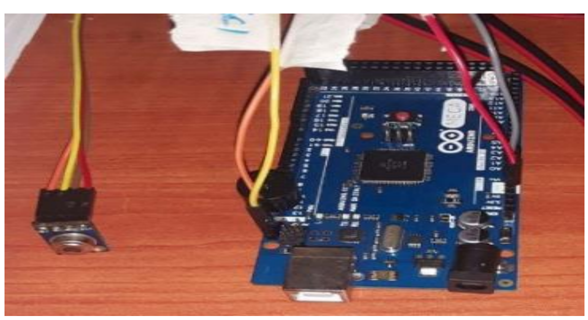


Figure 3.5:MLX90614Temperature sensor with Arduino

3.2.3.Experimental works

Because it is the most often used in the industries, a 316 stainless steel bar was chosen as the target material. All specimens were cut to 150 mm lengths using a power hacksaw that will be used throughout cutting procedures. In addition, Measure the roughness of the specimen after it has been flipped. Temperatures were measured using a mlx90614temperature sensor with Arduino during hot turning.

The following plan of experiment was used to achieve the goal of the current study.

The Center Lathe is being inspected and prepared for machining.

- ✓ To acquire the desired dimension of the work pieces, cut AISI316 stainless steel bars with a power hacksaw and perform first turning operations in a lathe.
- ✓ Straight turning operations on specimens in a range of cutting settings, including process control elements including cutting speed, feed, depth of cut, and cutting tool types.
- ✓ Calculating material removal rate of each machined specimen.
- ✓ Surface roughness is measured with a JB-4C roughness tester.

The experiment works with the lathemachine. The experimental setup is displayedin Figure 3.6 below:

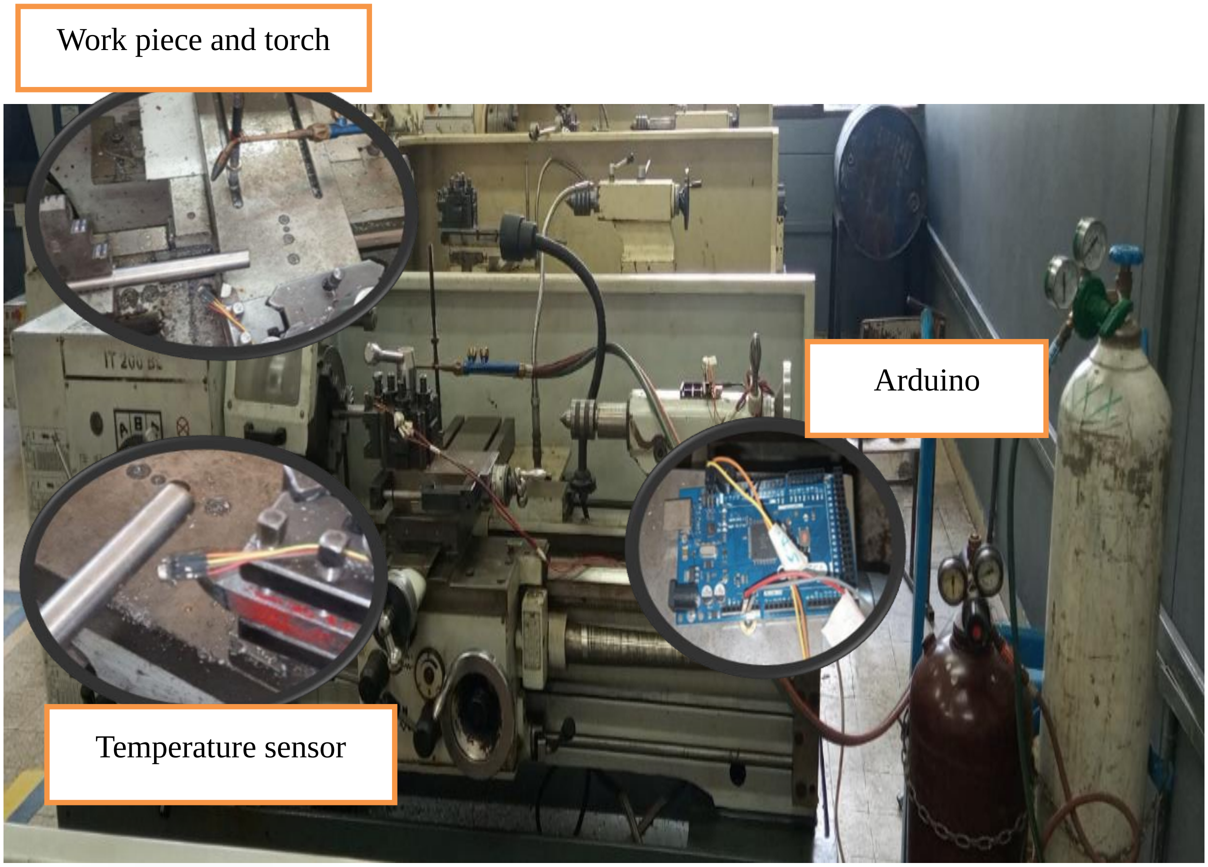


Figure 3.6: Experimental setup

The experiment was conducted on a lathe machine for hot turning operation of 316stainless steel using a carbide and diamond cutting tool. The temperature was controlled by an MLX90614 temperature sensor with Arduino.

The workpiece's surface roughness was measured using a JB-4C roughness tester, and the cut length was 0.8mm, with the material removal rate estimated using the formula.

Where MRR stands for volume of material removal rate (cm3/min), vc for cutting speed (m/min), fS for feed rate (mm/rev), and dP for cut depth (mm) (Ganta & Chakradhar, 2014b).

3.3 .Inspection and testing

3.3.1. Surface roughness

Because surface roughness has a substantial impact on mechanical part performance as well as production costs, it is a vital indicator of product quality. Surface roughness has an impact on mechanical variables like as fatigue, corrosion resistance, creep life, and so on. Friction, wear, light reflection, and heat transmission are some of the other functional qualities of parts that are affected.

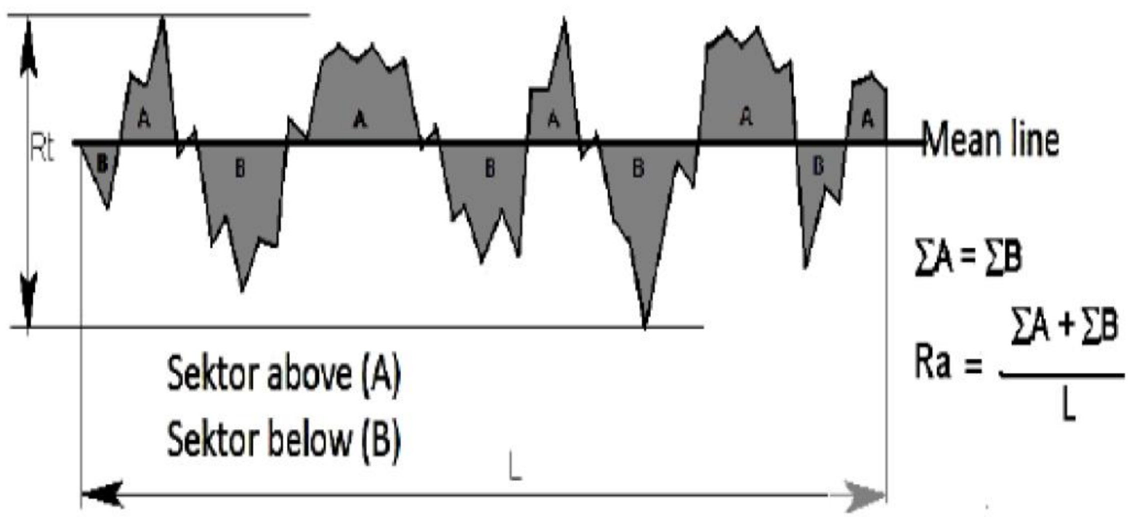


Figure 3.7:The Mean Arithmetic Deviation (Ra) and Total Roughness are computed using the following parameter definitions (Rt).

JB-4C Roughness testing machine

The JB-4C Roughness Test Meter is a profile measurement equipment with a probe design. It may be used to measure the surface of a variety of parts, including flat, inclination, cylinder, round, spherical, grooves, and bores. It is also applicable for measuring roughness of roll path, either outer or inner of bearing. It can be used to determine the surface roughness contour as well as to measure elements like the outline of peaks and valleys and the work piece's TP steps. The gadget is easy to use and has a good level of accuracy, repeatability, and stability, among other things.

Computers and measurement software are included in the equipment. , as well as an advanced noise-free mechanical positioning device that can be selected to be measured at various positions and set various measuring the length of the automatic measurement, as well as an assessment segment sampled data up to 4000 points.

The surface roughness tester is used to determine the surface roughness of a work piece. After machining, the work piece is placed on a v-block, the roughness tester probe is placed on the work piece, and the play button is pressed; the roughness of the area is displayed on the LED screen, and the value is recorded. Similarly, three different areas of the work item's roughness are measured. The roughness of the work item is determined by the average of the three numbers. The cutoff distance for JB-4C surface roughness measurement apparatus was 0.08, 0.25, 0.8 and 2.5mm.

Figure 3.8:JB-4C roughness testing machine

Figure 3.9: Surface roughness test of specimen

3.3.2. Material removal rate test

The Material Removal Rate (MRR) in turning operations is the volume of material/metal removed per unit time in mm3/min. With each turn of the work piece, a ring-shaped layer of material is removed. MRR can be calculated using the formula below.

$$MRR = v.\ f\ .a\ (\text{cm}^3/\text{min}) \quad (3)$$

Where: Cutting speed is V, feed rate is f, and cutting depth is a.

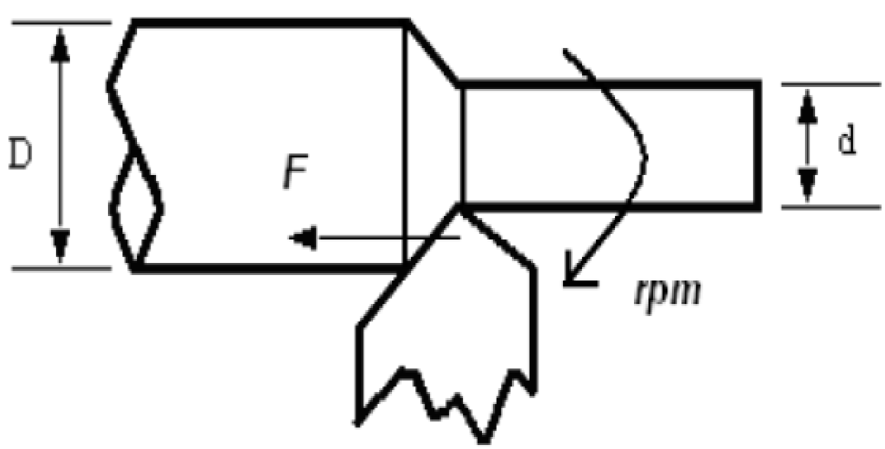


Figure 3.10: Material removal rate in turning

3.4 .Methods

3.4.1. Determination of working limits of parameters

To discover which process parameters are statistically significant and influence the study's response, an analysis of variance (ANOVA) can be used. ANOVA was used by several scholars to find parameters of how much percent contributed to the study's answer.

3.4.2. Determination of working limits of levels

The cutting speed, feed rate, and depth of cut for the target material of 316 stainless steel were determined using available literature, and the levels were chosen based on their frequency, i.e. which level magnitudes are frequently used by scholars, and the level magnitudes that impart the highest response value were chosen

3.4.3. Determination of working of cutting speed

Table 3.4: Optimize cutting speed with its responses

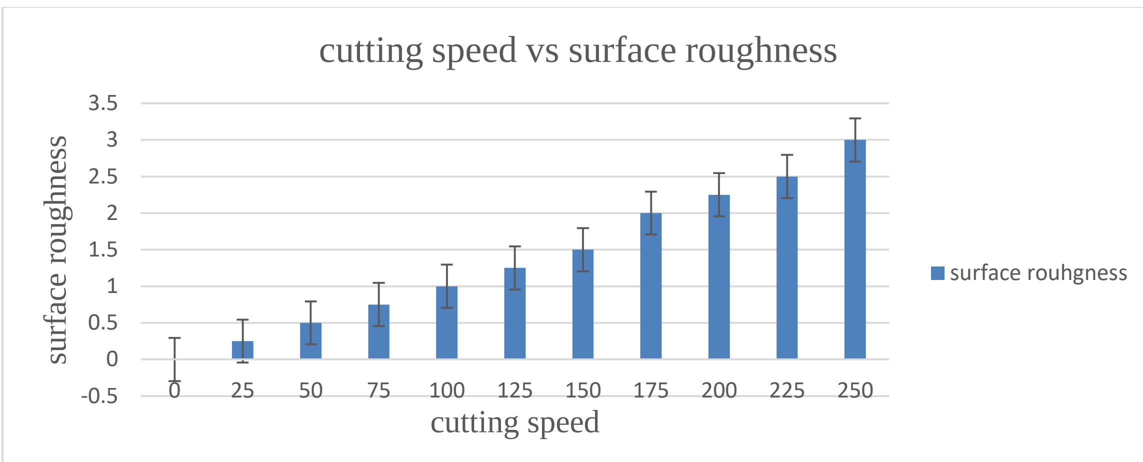
No	Title	Material	Initial RPM	Optimized RPM	Result	Reference
1	An experimental investigation to optimize the process parameters of AISI 52100 steel in hot machining	AISI 52100 steel	25.43,58.87 and 90.903m/min	90.903 m/min	Ra=1.24um	(Modh et al., 2011a)
2	An Experimental Investigation of Hot Machining Performance Parameters using Oxy-Acetylene gas setup	15-5PH stainless steel	31 , 77 and 120m/min	120 m/min	Ra=0.49 µm	(Ganta & Chakradhar, 2014a, 2014b)
3	Investigation of Hot Machining Process on Oil Hardened Non Shrinking Steel Using TiAlN Coated Carbide Tool	oil hardened non shrinkage steel (OHNS)	0.293, 0.418 and 0.523RPM	0.418RPM	Ra=0.78 µm	(Rajeshkannan et al., 2017a)

4	Multi-objective optimization of hot machining of 15-5PH stainless steel using grey relation analysis	15-5PH stainless steel	31,77and 123m/min	31m/min	4.30 µm 4.96cm^3/min	(Ganta & Chakradhar, 2014b)
5	Experimental Investigation of Machining Parameters of EN 36 Steel using Tungsten Carbide Cutting Tool during Hot Machining	EN 36 Steel	21.352 , 33.912 , 51.119 , 78.5 and 121.204m/min	121.204 m/min	Ra=1.75 µm	(Kamdar & Patel, 2012)
6	Multi-response optimization of machining parameters in hot turning using grey analysis	stainless steel (type316)	29.68,73.04 and 113.1m/min	113.1 m/min	Ra=3.6µm	(Ranganathan & Senthilvelan, 2011)
7	Optimization for hot turning operations with multiple performance characteristics	manganese steel	22 ,46 and75 m/min	22m/min	Ra=0.47 µm	(Tosun & Ozler, 2004)

The magnitude of the parameters is determined by the frequency with which the scholars are most frequently employed. The criteria that were chosen for this inquiry are listed in the table below.

Table 3.5: Selected cutting speed

Cutting speed	90.903	120	31	121.204	113.1	22
Roughness	1.24	0.49	4.30	1.75	3.6	0.47
MRR			4.96		43.100	
Frequency	1x	1x	1x	1x	1x	1x



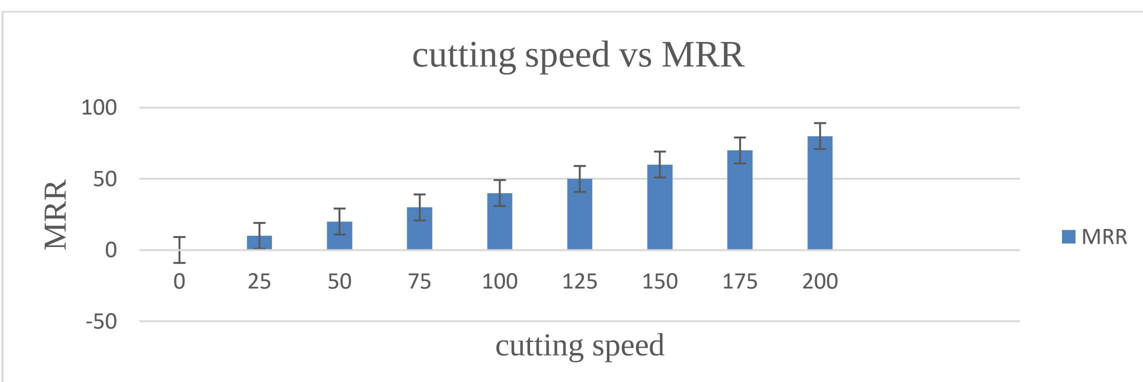


Figure 3.11: Surface roughness and Material removal rate are affected by cutting speed.

Based on the above table, the magnitude gap is not equal .The rationale for this is that scholars accomplish the lowest surface roughness at various cutting speeds and the highest material removal rate at various cutting speeds. Then select 53.694,120.576,157.314and 188.4 cutting speed magnitude for hot turning of 316 stainless steel based on materials, machine and scholars.

3.4.4. Determination of working of feed rate

The feed rate level magnitudes are chosen based on the spindle speed magnitudes chosen.

Table 3.6: Optimize feed rate with its responses

No	Title	Material	Initial feed rate [mm/rev]	Optimized feed rate with cutting speed	Result	Reference
1	Investigation of Hot Machining Process on Oil Hardened Non Shrinking Steel Using TiAlN Coated Carbide Tool	OHNS steel	0.05,0.5 and 1	0.16 @250 rpm	Ra=0.78µm	(Rajeshkannan et al., 2017a)
2	Multi-objective optimization of hot machining of 15-5PH stainless steel using grey relational analysis	15-5PH	0.2,0.3 and 0.4	0.4@31m/min	Ra=4.30 µm MRR=4.96cm/min	(Ganta & Chakradhar, 2014b)

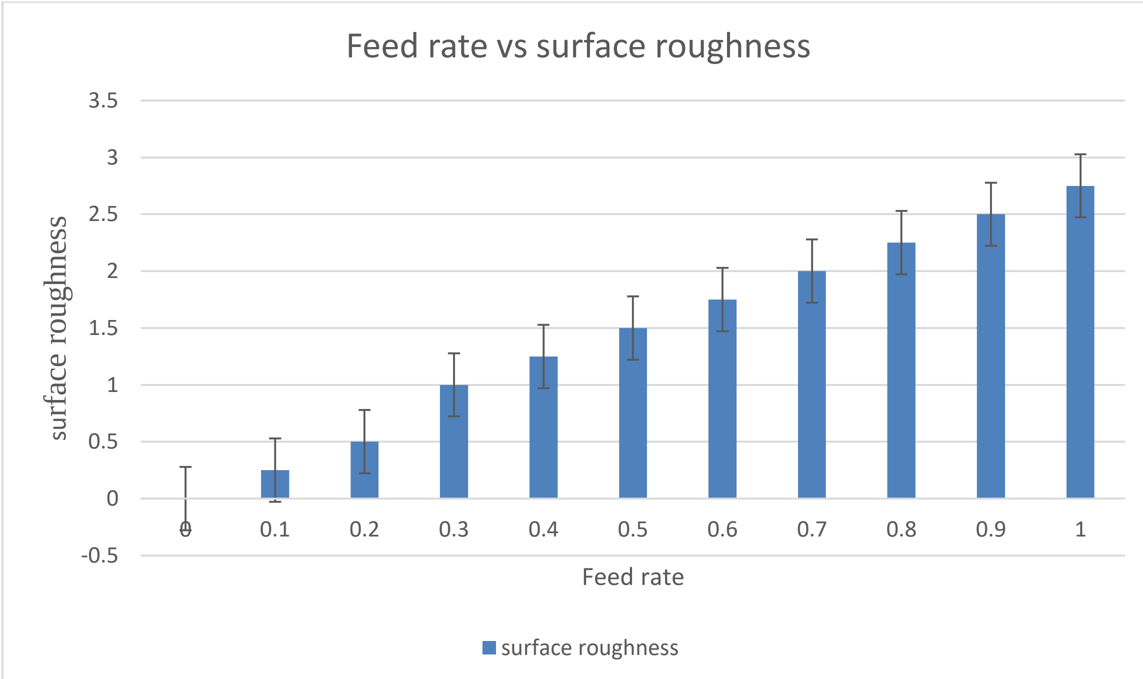
3	Studies on machining parameters of hot machining process using AISI4140 material	AISI4140 material	0.1, 0.15 and 2.0	0. 15 @125m/min	Ra=1.4 μm MRR=5870.18 mm / min	(Singh, 2017a)
4	Multi-response optimization of machining parameters in hot turning using grey analysis	stainless steel (type 316)	0.25,0.376 and 0.381	0.381 @113.1 m/min	Ra=3.6 μm	(Ranganathan & Senthilvelan, 2011)
5	An Experimental Investigation of Hot Machining Performance Parameters using Oxy-Acetylene gas setup	15-5PH stainless steel	0.2 , 0.3 and 0.4	0.2@120 m/min	Ra=0.49 μm	(Ganta & Chakradhar, 2014a)

6	Optimization of hot turning parameters using principal component analysis method	Inconel 625	0.07, 0.10 and 0.15	0.07@ 100 m/min	Ra=0.551 µm	(Parida et al., 2020)
7	An experimental investigation to optimize the process parameters of AISI 52100 steel in hot machining	AISI 52100 steel	0.265, 0.344 and 0.430	0.265@ 90.903m/min	Ra=1.24um	(Modh et al., 2011a)
8	Optimisation for hot turning operations with multiple performance characteristics	manganese steel	0.1 0.2 and 0.4	0.1 @22 m/min	Ra=0.47um	(Tosun & Ozler, 2004)

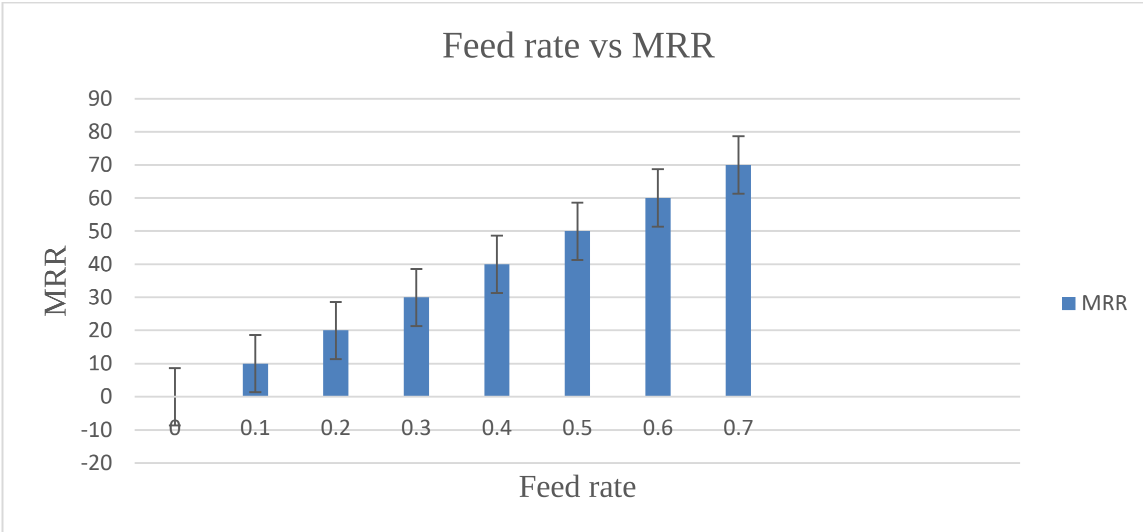
Table 3.7:Selected feed rate

Feed rate	0.16	0.4	0.15	0.381	0.2	0.07	0.265	0.1
Surface roughness	0.78	4.30	1.4	3.6	0.49	0.551	1.24	0.47
MRR		4.96	5870.18	43.66				
cutting speed	250	31	125	113.1	120	100	90.903	22
cutting speed frequency	1x	1x	1x	1x	1x	1x		

All feed rate magnitude and range of intervals are different. Therefore, based on the above-selected cutting speed,based on machine and based on scholars being select the feed rate offour levels such as 0.238, 0.302, 0.416 and 0.512 mm/rev. Levels range of intervals should be not equalmagnitude gaps because of machine setting.



(a) Surface roughness



(b)MRR

Figure 3.12: Effect of feed rate withsurface roughness and MRR

3.4.5. Determination of working of depth of cut

Table 3.8:Optimized depth of cut with its responses

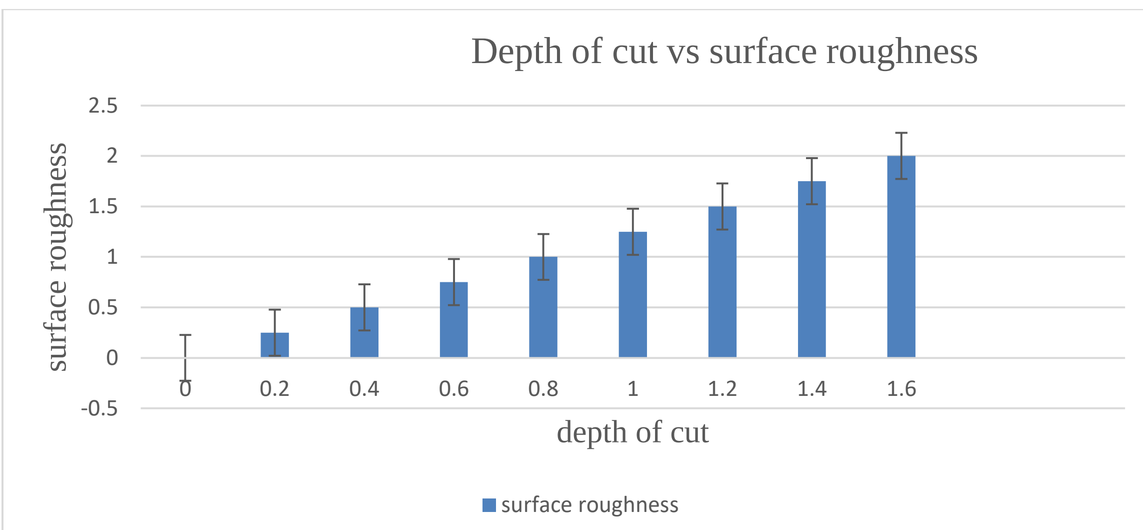
No	Title	Material	Initial depth of cut [mm]	Optimized depth of cut with cutting speed [mm]	Result	Reference
1	studies on machining parameters of hot machining process using AISI4140 material	AISI4140	0.4,0.6 and 0.8	0.4@125 and 0.8@125	Ra=1.4 µm MRR=5870.18mm^3/min	(Singh, 2017a)
2	Optimization of hot turning parameters using principal component analysis method	Inconel 625	0.3, 0.5 and 1.0	1@100	Ra=0.551 µm	(Parida et al., 2020)
3	Multi-response optimization of machining parameters in hot turning using grey analysis	316stainles steel	0.4,0.8 and 1	1@113.1	Ra=3.6µm, and	(Ranganathan & Senthilvelan, 2011)
4	Optimization for hot turning operations with	manganese steel	0.5 ,1.5 and 2.5	0.5@22	Ra=0.47 µm	(Tosun & Ozler, 2004)

	multiple performance characteristics					
5	DFA & GRA based multi objective optimization duringhot machining of AISI D3 tool steel using TNMG insert	AISI D3 tool steel	0.5,1.0 and1.5	1.5@43.96	Ra=0.29 µm, MRR =1492.53 mm^3/min	(VENKATESWARLU & SURESH, 2019b)
6	An Experimental Investigation of Hot Machining Performance Parameters using Oxy-Acetylene gas setup	15-5PH stainless steel	0.4,0.6 and 0.8	0.6@120	Ra=0.49 µm	(Ganta & Chakradhar, 2014a)
7	Experimental investigation of Material removal rate in CNC turning using Taguchi method	C34000 (Medium brass alloy	0.10 , 0.15 and 0.20	0.2@55	MRR=8.78 mm^3/min	(Hassan et al., 2012)

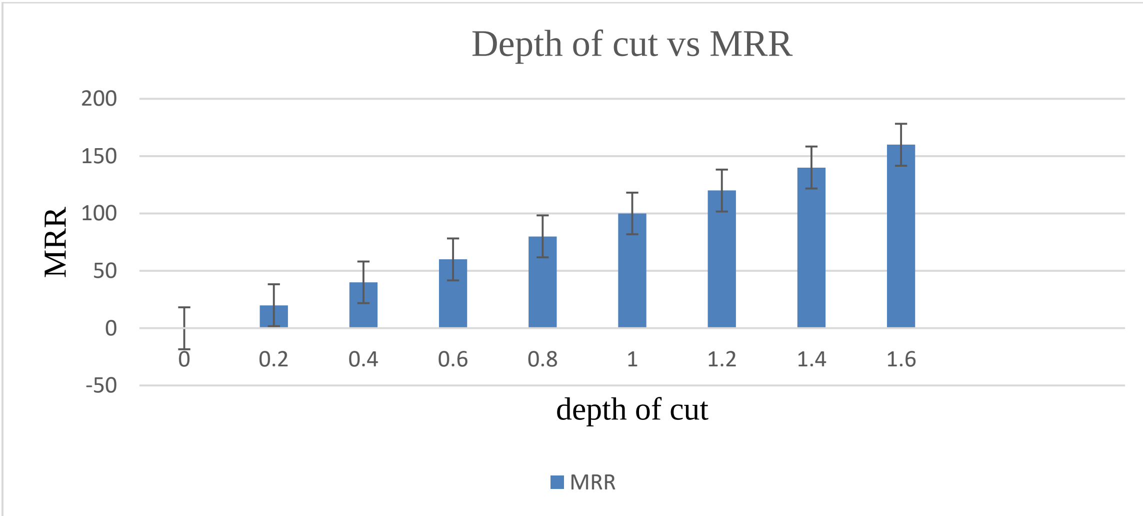
Table 3.9: Selected depth of cut

Depth of cut	0.4	1	0.5	1.5	0.6	0.2
Surface roughness	1.4	3.6	0.47	0.29	0.49	
MRR	5870.18	43.100		1492.53		8.78
cutting speed	125	113.1	22	43.96	120	55
cutting speed frequency	1x	1x	1x	1x	1x	1x

All depth of cut magnitude and range of intervals are different. Therefore, based on the above-selected cuttingspeed, machine and scholars being select the depth of cut of four levels such as 0.4,0.6,0.8 and 1.0mm.level range of intervals should be a divided in equal magnitude gaps. Therefore, equally, divided the above levels of gaps with an interval of 0.2mm.The selection of the level of depth of cut is based on materials, machine and scholars.



(b) Surface roughness



(c) material removal rate

Figure 3.13: Effect of depth of cut with surface roughness and MRR

3.4.6. Determination of working of heating temperature

Table 3.10: Optimized depth of cut with its responses

No	Title	Material	Initial heating temperature [^{0}c]	Optimized heating temperature with cutting speed [^{0}c]	Result	Reference
1	Multi-objective optimization of hot machining of 15-5PH stainless steel using grey relation analysis	15-5PH stainless steel	200,400 and 600	400@31	4.30 µm 4.96cm^3/min	(Ganta & Chakradhar, 2014b)
2	Multi-response optimization of machining parameters in hot turning using grey analysis	316stainles steel	200,400 and 600	400@113.1	3.6µm	(Ranganathan & Senthilvelan, 2011)
3	Performance evaluation and parametric optimization of hot machining process on	EN-8 steel	100,200,300,400 and 500	500@303		(Patel et al., 2014)

	EN-8material					
4	An Experimental Investigation of Hot Machining Performance Parameters using Oxy-Acetylene gas setup	15-5PH stainless steel	150,250 and 350	250@120	Ra=0.49 µm	(Ganta & Chakradhar, 2014a)
5	An experimental investigation to optimize the process parameters of AISI 52100 steel in hot machining	AISI 52100 steel	200,400 and 600	600@90.903	Ra=1.24um	(Modh et al., 2011a)(
6	An experimental investigation to optimize multi-response characteristics of Ni-Hard material using hot machining	Ni-Hard nickel	200,300 and 400	200@16.49		(Parida & Maity, 2016)

Table 3.11: Selected heating temperature

Temperature	400	400	500	250	600	200
Surface roughness	4.30	3.6		0.49	1.24	
MRR	4.96	43.100				
cutting speed	31	113.1	303	120	90.903	16.49
Heating temperature frequency	2x		1x	1x	X1	X1

Based on the above table and scholars same scholars are uses heating temperatures are 400^0c and 200^0c heating temperature. Then select 300^0c as heating temperature for hot turning of 316 stainless steel materials. Because of the average temperature ofthe above tableused and based on materials and scholars.Oxy acetylene heating techniques are selected and the distance between the torch and work piece is 25mm in based on scholars and to control the heating temperature by using Arduino.

3.5 .Optimization Techniques

The machining engineer tries to select turning parameters based on prior experience when determining the appropriate hot turning procedure for a given set of properties, however a number of experimental trials may be conducted, particularly for new projects, eventually leading to the definition of the optimal turning parameters. This process consumes more time and expensive(Dhas & Dhas, 2012). There are many strategies or procedures for determining process parameters, however the methods shown below are suitable and commonly used by scholars to investigate the process parameters optimization of hot turning on 316 stainless steel materials.

3.5.1. Taguchi method

The Taguchi method is a systematic approach to using the experimental design process to generate and improve things. To obtain high quality without increasing expenses, the Taguchi technique focuses on the optimization of process parameters. The Taguchi method evaluates the findings using a statistical measure of performance known as signal-to-noise (S/N). This S/N ratio is used to determine which control levels are ideal for dealing with noise (Pankaj Sharma, 2012).

3.5.2. Response surface methodology (RSM)

To explore the link between a large number of explanatory variables and one or more response variables, the response surface method is utilized. The primary principle of RSM is to obtain an optimal response through a series of carefully prepared tests. RSM is made up of three parts: an experimental design to identify an approximation model between input and output variables, statistical modeling, and response optimization (Dhas & Dhas, 2012).

3.5.3. Genetic algorithm (GA)

The Genetic Algorithm is a strategy for getting the optimal answer by simulating Darwin's natural selection process in biological evolution. GA is used to discover the circumstances that are near-optimal for hot machining. To begin, the GA uses a predetermined length of binary strings made up of and instead of input variables. Second, GA looks for a set of potential answers. As a result, it is particularly effective in locating a global optimal point by preventing it from being converted to a local optimum point. Finally, the GA employs the value of a fitness function that is neither continuous nor differentiable. Finally, rather than being deterministic, the GA's transition rule is probabilistic(Dhas & Dhas, 2012).

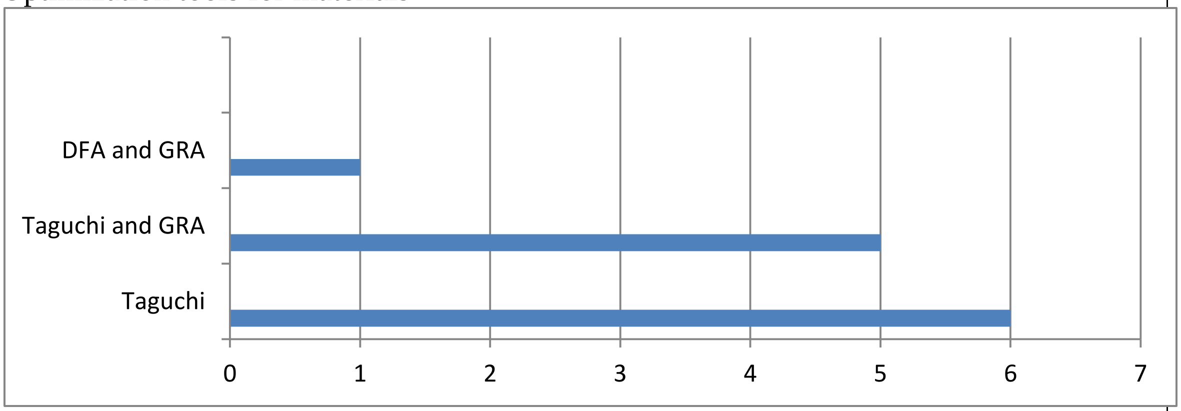
Table 3.12:Optimization techniques for materials

NO	Parameter	Optimization techniques	materials	references
1	Cutting speed ,feed rate ,depth of cut and temperature	Taguchi and GRA	AISI 52100 steel	(Modh et al., 2011a)
2	Cutting speed ,feed rate and depth	Taguchi	Medium brass	(Hassan et al., 2012)

	of cut		alloy (C34000)	
3	Cutting speed ,feed rate ,depth of cut and temperature	Taguchi	AISI 316 stainless steel	(Senthilvelan2, 2010)
4	Cutting speed ,feed rate ,depth of cut and temperature	Taguchi and GRA	15-5PH martensitic stainless steel	(Ganta & Chakradhar, 2014b)
5	Cutting speed ,feed rate and depth of cut	Taguchi	EN-8 steel	(Patel et al., 2014)
6	spindle speed, feed and depth of the cut	DFA & GRA	AISI D3 TOOL STEEL	(SURESH, 2019)
7	cutting speed, feed and depth of the cut	Taguchi	oil hardened non shrinkage steel	(Rajeshkannan et al., 2017b)
8	Surface temperatures, Cutting speeds and Feed rates	Taguchi	EN 36 Steel	(Kamdar & Patel, 2012)
9	speed, feed rate, depth of cut and temperature	Taguchi	AISI4140	(Singh, 2017a)
10	Cutting speed, feed rate, depth of cut	Taguchi and GRA	Inconel 625	(Parida et al., 2020)
11	speed, feed, depth of cut and preheating temperature	Taguchi and GRA	MMCs	(M R jadhavandu a dabade,2016)
12	cutting speed, feed rate, depth of cut and preheating temperature	Taguchi and GRA	Ni-Hard nickel based alloy	(Parida & Maity, 2016)

In the current investigations, 12 journal publications (Table 3.12) are evaluated to determine the optimum optimization tools for hot machining parameters and materials. Six papers have utilized the Taguchi approach to optimize their parameters, five articles have used a combination of Taguchi and GRA, and one article has used the DFA and GRA optimization strategy.

Optimization tools for materials



Frequency

	Taguchi	Taguchi and GRA	DFA and GRA
Frequency	6	5	1

Figure 3.14: Optimization techniques for hot turning of 316 stainless steel

Application of optimization approaches to AISI316 materials during hot machining Scholars frequently employed Taguchi, Taguchi, and GRA tools to improve hot machining settings for AISI316 materials, as seen in the diagram above. The Taguchi approach, on the other hand, is limited to mono objective replies. Correspondingly. As a result, the initial optimization strategy is ineffective for the challenges in the current study. Optimization based on a wide range of criteria becomes simple and successful when Taguchi and grey relational analysis are coupled. As a result, the Taguchi-based GRA approach is an appropriate strategy for optimizing the selected hot turning parameters for 316 stainless steel in the current study.

3.6 .Design of Experiments

Design of experiment approach was one of the most successful and practical statistical quality control techniques for investigating the individual and interaction impacts of process factors. DOE approaches can be a valuable aspect of a comprehensive system optimization, resulting in definite system design or redesign suggestions. Experiment planning, conducting experiments, and fitting models to the outcomes are all part of these procedures. An essential ingredient in applying DOE methods is the use of experimental design can have a large influence on the accuracy and the construction cost of the approximations. Several experimental design techniques have been used to aid in the selection of appropriate design points(Ranganathan & Senthilvelan, 2010).

Table 3.13:Processparameters and levels

Level	Cutting speed [m/min]	Feed rate [mm/rev]	Depth of [mm]	Types of tool
1	53.694	0.238	0.4	Diamond Tool
2	120.576	0.302	0.6	Carbide Tool
3	157.314	0.416	0.8	
4	188.400	0.512	1	

3.6.1. Selection of Orthogonal array

One of the first steps in establishing the best hot turning circumstances is to choose an orthogonal array. The characteristics of the study were cutting speed, feed rate, depth of cut, and cutting tool kinds. In addition, four levels were created for each parameter. As a result, for the parameters and levels we chose previously, the mixed L16 orthogonal array is a good design. This 15-degree-of-freedom orthogonal array was employed in sixteen testing runs.

The process parameters and levels employed in the L16 orthogonal array architecture are listed in Table 3.14.

Table 3.14: Process parameters and their levels

Ex. No	cutting Speed [m/min]	Feed rate [mm/rev]	Depth ofCut [mm]	Types of cutting tool
1	53.694	0.238	0.4	Diamond Tool
2	53.694	0.302	0.6	Diamond Tool
3	53.694	0.416	0.8	Carbide Tool
4	53.694	0.512	1	Carbide Tool
5	120.576	0.238	0.6	Carbide Tool
6	120.576	0.302	0.4	Carbide Tool
7	120.576	0.416	1	Diamond Tool
8	120.576	0.512	0.8	Diamond Tool
9	157.314	0.238	0.8	Diamond Tool
10	157.314	0.302	1	Diamond Tool
11	157.314	0.416	0.4	Carbide tool
12	157.314	0.512	0.6	Carbide Tool
13	188.400	0.238	1	CarbideTool
14	188.400	0.302	0.8	Carbide Tool
15	188.400	0.416	0.6	Diamond Tool
16	188.400	0.512	0.4	Diamond Tool

4. RESULTS AND DISCUSSION

4.1 .Introduction

This chapter presents the overall findings of the testing using the Taguchi and Grey relational analysis method. The experiment's purpose was to find the best surface roughness and rate of material removal for 316 stainless steel.

4.2 . Experimental results

Table 4.1 shows the effects of process parameters on surface roughness and material removal rate output response characteristics. The MINITAB 18 software was used to perform statistical analysis on the data.

A series of machining tests were conducted to assess the effect of turning parameters on the surface roughness and material removal rate of 316 stainless steel. Table 4.1 shows the results of experiments on the surface roughness and material removal rate of 316 stainless steel materials with varied process settings.

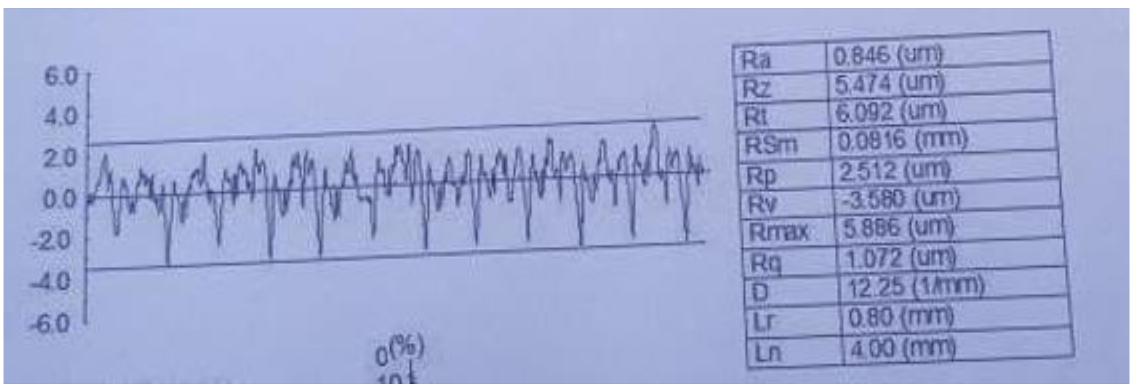
Table 4.1: Experimental result

Ex. No	**Cutting Speed [m/min]**	**Feed rate [mm/rev]**	**Depth of Cut [mm]**	**Types of cutting tool**	**Surface Roughness Ra[μm]**	**Material removal rate[cm^3/min]**
1	53.694	0.238	0.4	Diamond T	1.358	5.11
2	53.694	0.302	0.6	Diamond T	1.566	9.72
3	53.694	0.416	0.8	Carbide. T	1.717	17.86
4	53.694	0.512	1	Carbide .T	4.971	27.49
5	120.576	0.238	0.6	Carbide .T	1.383	17.21
6	120.576	0.302	0.4	Carbide .T	1.574	14.56
7	120.576	0.416	1	Diamond T	5.731	50.15
8	120.576	0.512	0.8	Diamond T	0.846	49.38
9	157.314	0.238	0.8	Diamond T	1.365	29.95
10	157.314	0.302	1	Diamond T	1.829	47.50
11	157.314	0.416	0.4	Carbide. T	4.765	26.17

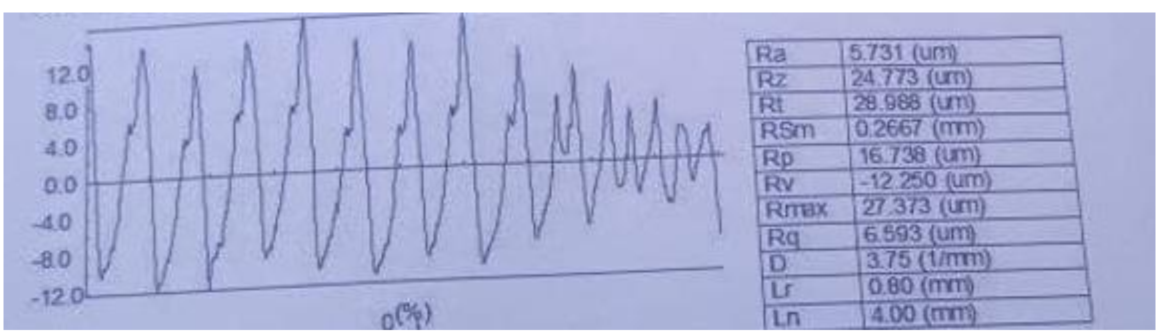
12	157.314	0.512	0.6	Carbide. T	1.15	48.32
13	188.400	0.238	1	Carbide. T	1.358	44.83
14	188.400	0.302	0.8	Carbide. T	1.945	45.51
15	188.400	0.416	0.6	Diamond T	1.064	47.02
16	188.400	0.512	0.4	Diamond T	1.814	38.58

4.2.1. Surface roughness

The test was conducted for stainless steel (316). With a cutting speed of 120.576 m/min, a feed rate of 0.512 mm/rev, a depth of cut of 0.8 mm, and a diamond tool, a minimum surface roughness of 0.846 μm was obtained. The largest surface roughness was 5.731μ m when cutting with a diamond tool at a speed of 120.576 m/min with a feed rate of 0.416 mm/rev and a depth of cut of 1mm.



(a)



(b)

Figure 4.1: Minimum (a) and maximum (b) surface roughness results

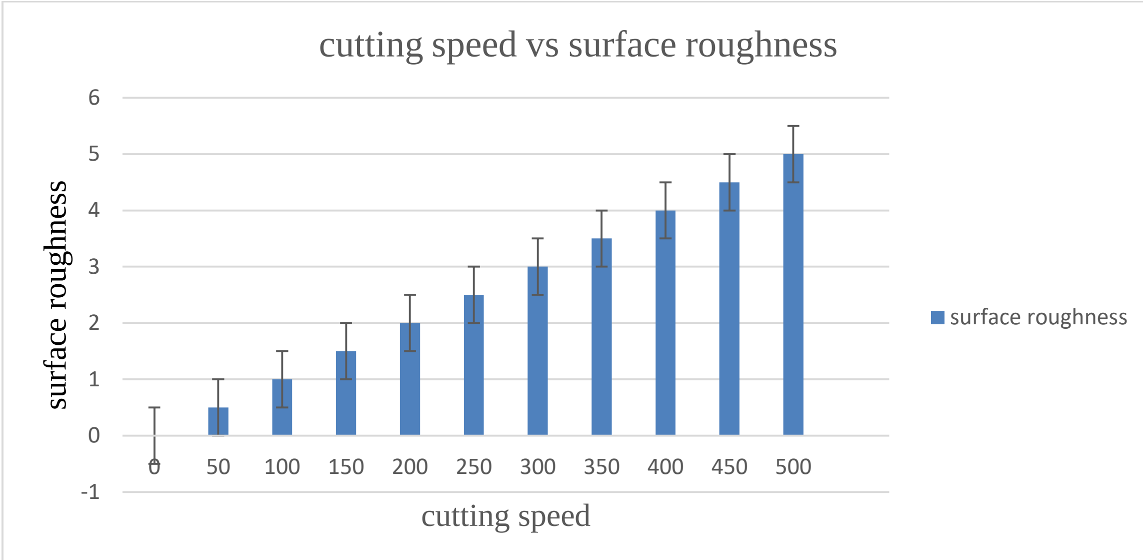


Figure 4.2: Relationship b/n cutting speed and surface roughness

4.2.2. Material removal rate

With a cutting speed of 120.576 m/min, a feed rate of 0.416 mm/rev, a depth of cut of 1, and a tool type of diamond tool mm, a higher material removal rate of 50.15 cm3/min was achieved. With a cutting speed of 53.694 m/min, a feed rate of 0.238 mm/rev, a depth of cut of 0.4mm, and a diamond tool, a minimum material removal rate of 5.11 cm3/min was achieved. The highest material removal rate is achieved by combining the fastest cutting speed with the highest feed rate and depth of cut. Cutting speed, feed rate, and cut depth all influence the rate of material removal.

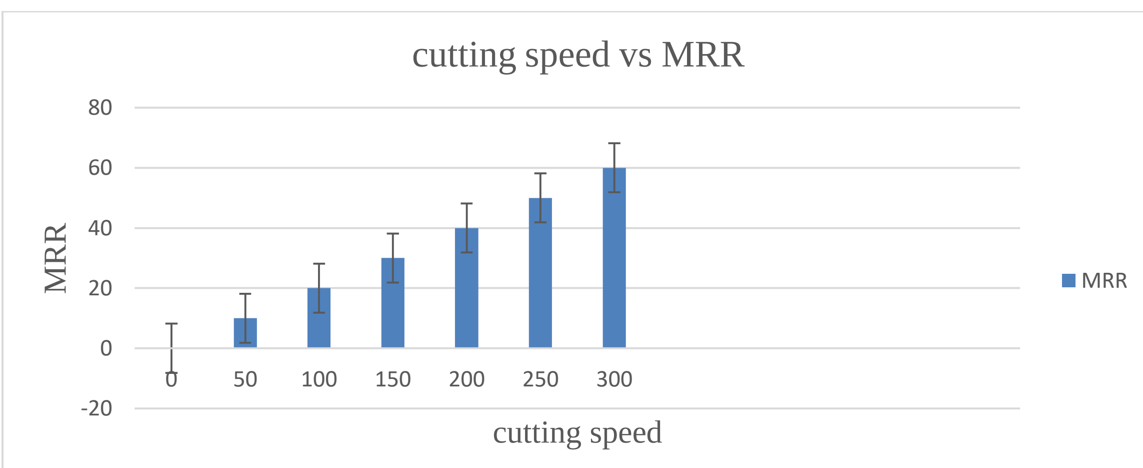


Figure 4.3: Relationship b/n cutting speed and material removal rate

4.3 .Taguchi-based grey analysis

The signal-to-noise (S/N) ratio can be computed in three ways using the Taguchi technique: Greater is preferable, nominal is preferable, and smaller is preferable. The selection of a suitable S/N ratio, on the other hand, necessitates some practical experience and comprehension of the process. The purpose of this study is to figure out how to have the best surface roughness with the least amount of material removal. As a result, a S/N ratio of smaller is better in roughness and larger is better in material removal rate was chosen. It was calculated using the equation below. (Kasman, 2013).

$$\frac{S}{N}(\eta) = -10log10\,\frac{1}{n}\sum_{i=1}^{n}\quad \frac{1}{y2\;ijk}\;(5)$$

Where the letter n stands for the number of replications. And yijk is the response value of the ith performance characteristic in the jth experiment at the kthtrial. The results of surface roughness, material removal rate, and S/N ratios are shown in Table 4.2.

Table 4.2: Experimental results with its S/N ratio

No	Surface roughness [µm]	Material removal rate [cm^3/mm]	S/NRa	S/NMRR
1	1.358	5.11	-2.658	14.168
2	1.566	9.72	-3.896	19.753
3	1.717	17.86	-4.695	25.038
4	4.971	27.49	-13.929	28.783
5	1.383	17.21	-2.816	24.716
6	1.574	14.56	-3.940	23.263
7	5.731	50.15	-15.165	34.005
8	0.846	49.38	1.453	33.871
9	1.365	29.95	-2.703	29.528
10	1.829	47.50	-5.244	33.534
11	4.765	26.17	-13.561	28.356

12	1.15	48.32	-1.214	33.683
13	1.358	44.83	-2.658	33.031
14	1.945	45.51	-5.778	33.162
15	1.064	47.02	-0.539	33.446
16	1.814	38.58	-5.173	31.727

4.4 . Grey relational analysis

When employing the Taguchi approach, only one parameter is optimized. (i.e. Mono-objective optimization). Taguchi combined with a grey relational analysis method may easily and successfully optimize various parameters (Kumar, 2013). When dealing with multi-response situations, GRA (grey relational analysis) is a beneficial tool. This kind of analysis is used to solve complex interconnections between multi-objective replies. For maximizing numerous responses, GRA includes seven phases (Vijayan et al., 2012).The following actions were taken in this research:

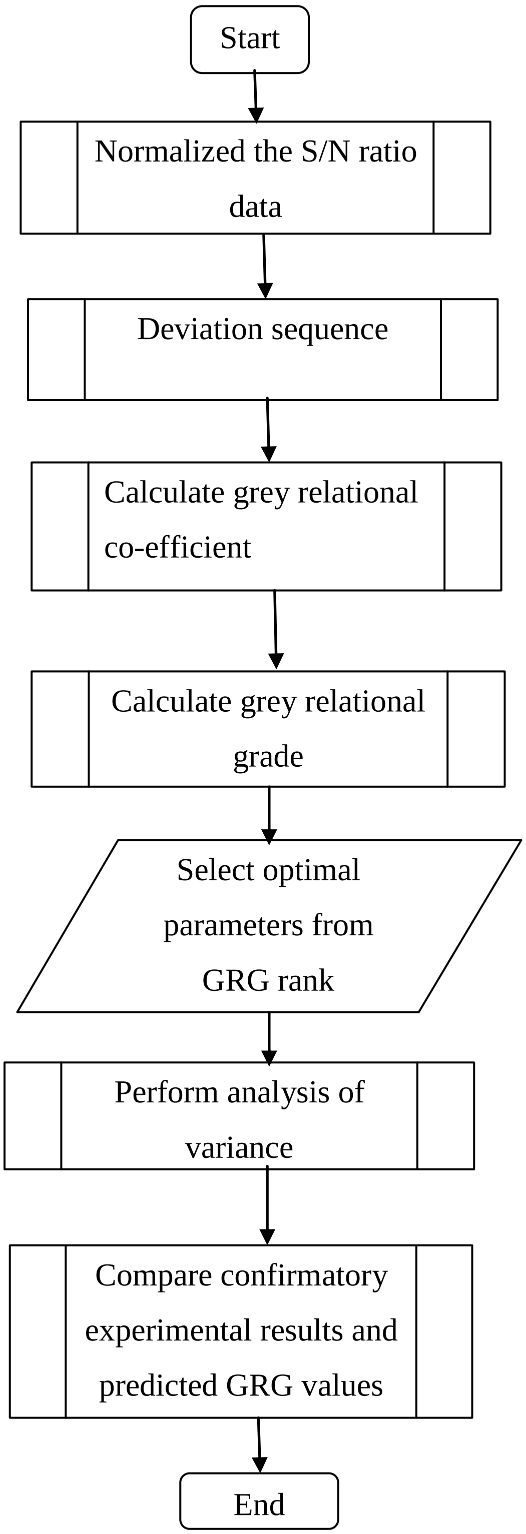


Figure 4.4: Grey relational analysis steps to improve multiple responses

4.4.1. Data normalization

It's a technique that changes the original sequence into a comparable one, and it's one of the first phases in the grey relational analysis approach. As a result, the outcomes of the experiment are standardized to a range of zero to one. This strategy is required when the sequence scatter range is too broad or the sequence target direction is modified. (Rao & Kalyankar, 2014). Larger is better features are meant for normalizing to scale the answer into an appropriate range by the following formula if the response is to be maximized.(Kasman, 2013). To analysis grey rational grade for material removal rate (MRR), it is identified as larger is better for MRR and the term is expressed as

$$\boldsymbol{x}i(\mathrm{k}) = \frac{\boldsymbol{x}\mathrm{i}^0(\mathrm{k}) - \min \boldsymbol{x}\mathrm{i}^0(\mathrm{k})}{\mathrm{ma}\boldsymbol{x}\mathrm{i}^0(\mathrm{k}) - \min \boldsymbol{x}\mathrm{i}^0(\mathrm{k})} \quad (6)$$

For surface roughness, it is smaller is better, the term expressed as

$$\boldsymbol{x}i(\mathrm{k}) = \frac{\mathrm{ma}\boldsymbol{x}\ \boldsymbol{x}\mathrm{i}^0(\mathrm{k}) - \boldsymbol{x}\mathrm{i}^0(\mathrm{k})}{\max \boldsymbol{x}\mathrm{i}^0(\mathrm{k}) - \min \boldsymbol{x}\mathrm{i}^0(\mathrm{k})} \quad (7)$$

Where the reference sequence is xi0 (k), xi*(k) is the sequence after data preprocessing (Comparability sequence), max xi0 (k) is the largest value in the reference sequence, min xi0 (k) is the smallest value in the reference sequence, I = 1, 2, m; k = 1, 2..., n; m is the number of experiments and n is the number of experimental data, and n is the number of experimental data.

4.4.2. Calculation of deviation sequences and grey relational Coefficients

Using the following approach, the grey relational coefficient, ξi (k), is derived from the normalized data. The GRC is used to highlight how the reference and comparability sequences are related.To aggregate the data obtained from the equations, the GRC (ξ) is employed. (Kumar, 2013).

$$\Delta_{0\mathrm{i}}(\mathrm{k}) = \|\mathrm{x}_{0^*}(\mathrm{k}) - \mathrm{x}_{\mathrm{i}^*}(\mathrm{k})\| \quad (8)$$

$$\xi(x_{0^*}(k), x_{0^*}(k)) = \frac{\Delta_{min}(k) + \xi\Delta_{max}(k)}{\Delta_{0i}(k) + \xi\Delta_{max}(k)} \quad (9)$$

Where Δ_{oi} (k) is the deviation sequence of the reference sequence x_o* (k) and comparability sequence x_i* (k) and ξ is the distinguishing coefficient that takes a value between 0 and 1, and the value of ξ = 0.5 is taken from the calculation result. It is necessary to calculate the deviation sequences before calculating the GRC, as stated in equation (9). The deviation sequences are calculated using an equation (8). As a result, values of 0.5 for grey connection coefficients are used.

Principal Component Analysis

The Principal Component Analysis (PCA) has been used to eliminate the response correlation. This matrix consists of Eigen values, Eigenvectors and quality characteristics contributions. The elements of the array for multiple performance characteristics listed in Table 4.3-4.5 represent the grey relational coefficient matrix and determine the corresponding Eigen value.

Table 4.3: Eigen values and explained variation (appendices 7)

Principal component	**Eigen values**	**Explained variation (%)**
Surface roughness	1.0690	53.4
Material removal rate	0.9310	46.6

The principal component with the highest Eigen values is chosen to replace the original responses for further analysis. In this case, the highest Eigen values were obtained in the surface roughness first principal component. Then, the contribution of each individual quality characteristic for the first principal components was shown in Table4.4.

Table 4.4: The eigenvector for principal component (appendices 7)

Quality characteristics	Eigenvector	
	1st principal	2nd principal
Surface roughness	0.707	-0.707
Material removal rate	0.707	0.707

Table 4.5: Quality characteristic contribution

Surface roughness	0.4999
Material removal rate	0.4999

Therefore, the grey relational coefficients values are taken ξ=0.5 was used.

Table 4.6:Data normalization and deviation sequence

Step 1:Data normalized			**Step 2:Deviation sequence**	
No	**Ra**	**MRR**	**Ra**	**MRR**
1	0.200	0.000	0.800	1.000
2	0.322	0.282	0.678	0.718
3	0.370	0.548	0.630	0.452
4	0.926	0.737	0.074	0.263
5	0.257	0.532	0.743	0.468
6	0.325	0.458	0.675	0.542
7	1.000	1.000	0.000	0.000
8	0.000	0.993	1.000	0.007
9	0.250	0.774	0.750	0.226
10	0.403	0.976	0.597	0.024
11	0.904	0.715	0.096	0.285
12	0.160	0.984	0.840	0.016
13	0.247	0.951	0.753	0.049
14	0.435	0.957	0.565	0.043
15	0.120	0.972	0.880	0.028
16	0.399	0.885	0.601	0.115

4.4.3. Calculation of grey relational grades

The degree of correlation between the reference and comparability sequences is indicated by the grey relational grade. A weighted average of multi-objective grey relational coefficients makes up the grey relational grade.(Kumar, 2013). It is determined as the following equation: the grey relational coefficient results for the experimental layout are shown in table 4.7.After averaging the grey relational coefficient, the grey relational grade $\gamma i(x_0^*, x_{1*})$ can be obtained as

$$\gamma i(x_0^*, x_{1*}) = \frac{1}{n}\sum_{i=1}^{n} wi\xi\ (x_0^*(k), x_i^*(k))\ (10)$$

Where $\gamma i(x_0^*, x_{1*})$ is the GRG for the i^{th} experiment, wi is the weighting value of the i^{th} performance characteristics and n is the numbers of performance characteristics.

Table 4.7. Shows the experimental results for grey relational grade and order using the experimental layout. The higher value of the grey relational grade represents the stronger relational degree between the reference sequence x_0 (k) and the given sequence x_i(k).

Table 4.7: GRC and GRG

Step 3;Grey relational coefficient			**Step 4:Grey relational grade and it is rank**	
No	**Ra**	**MRR**	**GRG**	**Rank**
1	0.385	0.718	0.551	16
2	0.424	0.410	0.417	15
3	0.442	0.525	0.484	12
4	0.871	0.655	0.763	2
5	0.402	0.516	0.459	13
6	0.425	0.480	0.453	14
7	1.000	1.000	1.000	1
8	0.333	0.987	0.660	7
9	0.400	0.689	0.544	11
10	0.456	0.955	0.705	4
11	0.838	0.637	0.738	3
12	0.373	0.968	0.671	6
13	0.399	0.911	0.655	8
14	0.470	0.922	0.696	5
15	0.362	0.947	0.654	9
16	0.454	0.813	0.634	10

Average GRG=0.5171

4.4.4. Determination of the optimal level of each parameter

The response table for grey relational analysis is determined using GRG's main effect analysis, as shown in Table 4.8, for each factor level, this determines the average of each response characteristic. The highest minus the lowest average of each element is the delta static. Minitab assigns ranks to ideal parameters based on delta values; for example, the highest delta value is rated 1, the second highest delta value is ranked 2, and so on. The mean response is the average value of the performance characteristic for each parameter at various levels, and these ranks represent the relative relevance of each element to the answer.

Table 4.8: Main effects of GRG

Level	**cuttingspeed [A]**	**Feed rate [B]**	**Depth of cut [C]**	**Types of tool [D]**
1	0.5075	0.5060	0.5477	0.6225*
2	0.6430	0.5677	0.5503	0.6149
3	0.6645*	0.7190*	0.5960	
4	0.6597	0.6820	0.7808*	
Delta	0.1570	0.2130	0.2330	0.0076
Rank	3	2	1	4

* indicates the optimal value in each parameters

Figure 4.5: Main effects of grey relational grade (GRG)

Table 4.8 shows the greatest GRG value for each parameter and the marked points in Figure 4.5, Cutting speed (A3) of 157.314 m/min, feed rate (B3) of 0.416 mm/rev, depth of cut (C4) of 1 mm, and types of tool (D1) of diamond tool are specified as an optimal parameter combination for the many performance characteristics. According to the findings in Table 4.8, cutting speed has the greatest impact on surface roughness and material removal rate.

4.4.5. Performing analysis of variance

To test if the factors were significant, the analysis of variance (ANOVA) was utilized. The impact of the variables on the grey relational grade was investigated using the ANOVA results. When the P-value for a factor falls below 0.05 at a 95% confidence level and the F-value reading from an ANOVA table is greater than the F-value reading from a standard table, the factor or parameter is considered significant (Kumar, 2013), Statistical software with an ANOVA analysis tool is used to determine which parameter has a significant impact on performance metrics. Table 4.9 shows the ANOVA results for the grey relationship grade.

Table 4.9: ANOVA results for a grey relational grade (GRG)

Source	DF	Adj SS	Adj MS	F-value	P-value	Contribution	remark
v	3	0.0669	0.0223	2.58	0.149	17.51%	In significant
F.R	3	0.1174	0.0391	4.52	0.055	30.72%	In significant
D.C	3	0.1459	0.0486	5.62	0.035	38.18%	significant
T.T*	1	0.0519	0.0086				In significant
Error	6	0.05170	0.0103				
Error pooled	7	0.0561	0.0104			13.59%	
Total	16	0.899				100.00%	
F0.05(1,7)=5.59;						**F0.05(3,7)=4.35**	

S=0.093042, **S-sq=**86.41%,**R-sq(adj)**=66.04%

*Indicates the parameters that was pooled

V: spindle Speed, F.R: Feed rate, D.C: depth of cut, T.T: types of cutting tool.

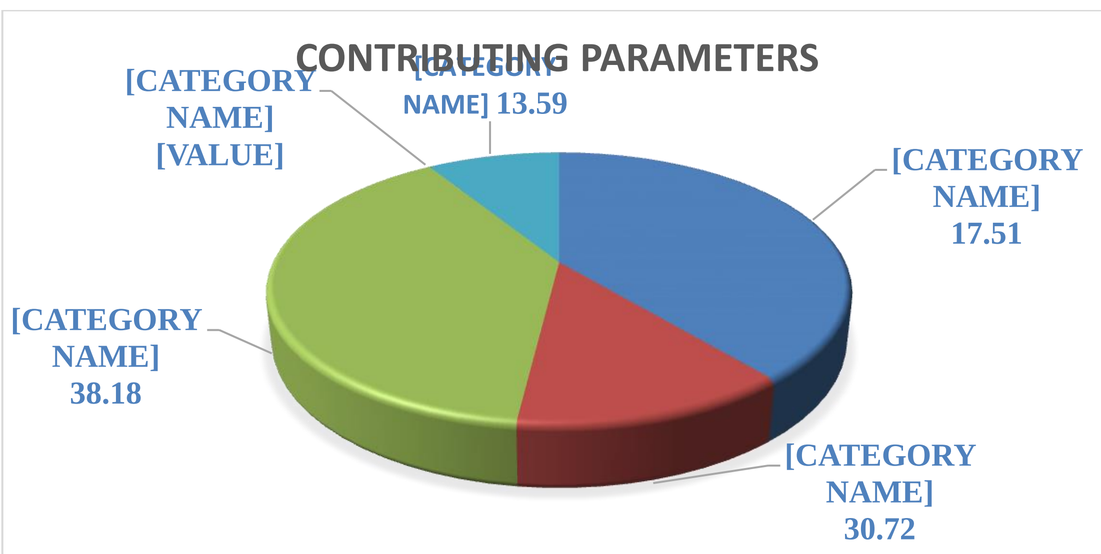


Figure 4.6: Contribution of each turning parameters in ANOVA

The ANOVA results, two parameters i.e., feed rate and depth of cut are significant parameters because each parameter P-value is less than 0.05 and F-values are greater than the standard reading F-value. In addition, the feed rate (30.72%) and the depth of cut (38.18%) both contribute a proportion of the total. Because it is related to uncertain or uncontrollable circumstances, the total error can be used to determine whether or not an experiment is feasible and sufficient. As stated in Table 4.9, the overall error for contribution is 13.82 percent, indicating the proposed optimization approach.

4.4.6. Confirmation experiment

Five samples were subjected to a confirmation test under ideal conditions for hot turning parameters. :C4(depth of cut 1mm).A 95% confidence interval for the predicted mean of grey relational grade (μGRG) on a confirmation test was calculated using the following equation(Kumar, 2013).

$$\mu A3C4 = IGRG + (C4 - IGRG) \qquad (11)$$

Where IGRG = 0.637, the mean values of grey relational grade with parameters at optimal levels are C, respectively, while the total mean of grey relational grade is IGRG. They are the two most important process variables.

$$\mu C4 = 0.637 + (0.780 - 0.637) = 0.7808$$

The following equation is used to calculate the expected mean of the grey relationship grade in the confirmation test: On a confirmation run, the confidence interval for the predicted mean is calculated using the equation below.

$$CI = \mu \pm \sqrt{F\alpha;\ (1;\ fe) * Ve\left(\frac{1}{neff} + \frac{1}{r}\right)} \qquad (12)$$

Where Fα; (1, *fe*) = F0.05; (1, 7) = 5.59 (F-Table in the Appendices 3)

α = Risk = 0.05

fe = Error DOF = 7 (F-Table in the Appendices 3)

Ve = Error adjusted mean square (Table 4.6) = 0.0087

neff = effective number of replications

, R = number of replications for confirmation experiment = 5.

The effective number of replications (neff) is also determined using the following formula:

$$neff = \frac{Tn}{1+Ts} = \frac{16}{1+3} = 4 \quad (13)$$

Where *neff* = is mathematically expressed

Tn = Total number of experiments = 16

Ts = the sum of the total degree of freedom of significant factors

Therefore, the calculated CI is

$$CI=0.7888 \pm \sqrt{5.59 \, * \, 0.0088\left(\frac{1}{4} + \frac{1}{5}\right)}$$

CI=

The projected optimal grey relational grade has a 95% confidence interval of:

$$(\mu - CI) < \mu < (\mu + CI) \quad (14)$$

$$= (0.780 - 0.178) < \mu < (0.78 + 0.178)$$

$$= \mathbf{0.602} < \mu < 0.958$$

Table 4.10: Confirmation test results

Optimal combination	**The response of quality characteristics**				
A3B4C4D1	**Ra**	**$Ra_{S/N}$**	**MRR**	**$MRR_{S/N}$**	**GRG**
Replication 1	5.731	-15.165	80.544	38.121	1.000
Replication 2	5.73	-15.163	80.54	38.120	0.874
Replication 3	5.72	-15.148	80.53	38.119	0.563
Replication 4	5.71	-15.133	80.52	38.118	0.416

Replication 5	5.701	-15.119	80.51	38.117	0.333
Average	**5.718**		**80.528**		**0.637**
Mean of GRG for confirmation test=0.637					

At 95% of the confidence interval of the confirmation result of GRG at optimal condition is between 0.602 and 0.958.If the predicted and observed GRG values of the multiple performance parameters are close to each other, the effectiveness of the optimal condition can be ensured. The expected outcomes were confirmed five times at the ideal condition in order to put the theory to the test. The grey relational grade for the experiment is 0.637, which is in range of the 95 confidence interval and achieved surface roughness and material removal rate of 5.731 µm and 80.540cm^3/mm respectively. As a result, the confirmatory experiment tests reveal that the experiment is the safest.

Table 4.11: The following are the results of the confirmation tests:

	Optimal parameters	
	Predicted	**Confirmation result**
Setting level	**A3B3C4D1**	**A3B3C4D1**
Surface roughness		5.731
Material removal rate		80.540
Grey relational grade	**0.7808**	**0.637**

5. CONCLUSION, RECOMMENDATIONAND FUTURE WORK

5.1 .Conclusion

The effect of surface roughness and material removal rate when turning stainless steel on a lathe machine was effectively explored using the Taguchi method in this study. As a result of the Experimental and Analytical Results, the following conclusions were made.

- Based on experimental result the optimal parameters was achieved at a Cutting speed of 157.314 m/min, feed rate of 0.416 mm/rev, depth of cut of 1 mm, and diamond tool.
- From the experiment and AVOVA, one can conclude that the depth of cut are significant influences on the hot turning of 316 stainless steel.
- Depth of cut have significant characteristics at a 95% confidence interval, according to ANOVA results. Depth of cut each contributed 37.716% and 38.18% respectively.
- From observation and verification of the experiment, the optimum values of the turning parameters to reduce surface roughness and highest material removal rate are cutting speed of 157.314 m/min, feed rate of 0.512 mm/rev, depth of cut of 1 mm, and diamond tool and heating temperature of 300^0c are control in temperature sensor with Arduino are preferred.

5.2 .Recommendation

This study was successful in generating the best response with the least amount of money and time. It's also worth noting that design quality can be improved by increasing the quality and productivity of company-wide activities. The best tests for machining process quality monitoring are surface finish and material removal rate. Surface finish, in particular, has a significant impact on product quality and is a crucial factor to consider when evaluating machining precision. In addition, The Taguchi Method was well-suited to industrial applications. But it may also be utilized for scientific research, and it stresses a mean performance characteristic value close to the target value rather than a value within particular set limitations, resulting in improved performance.

5.3 .Future work

In this thesis work analysis process parameters such as surface roughness and material removal rate in turning of stainless steel on lathe machine, it can be further studied by performing experiments for a better results in addition to that other influencing factor is not studied in this paper.so the following research areas are recommended for future studies.

- The same experiment can be performed by changing parameters tool geometry and work piece material etc, or by taking different level.
- Optimum stand-off distance for flame can be obtained by varying stand-off distance of the torch.

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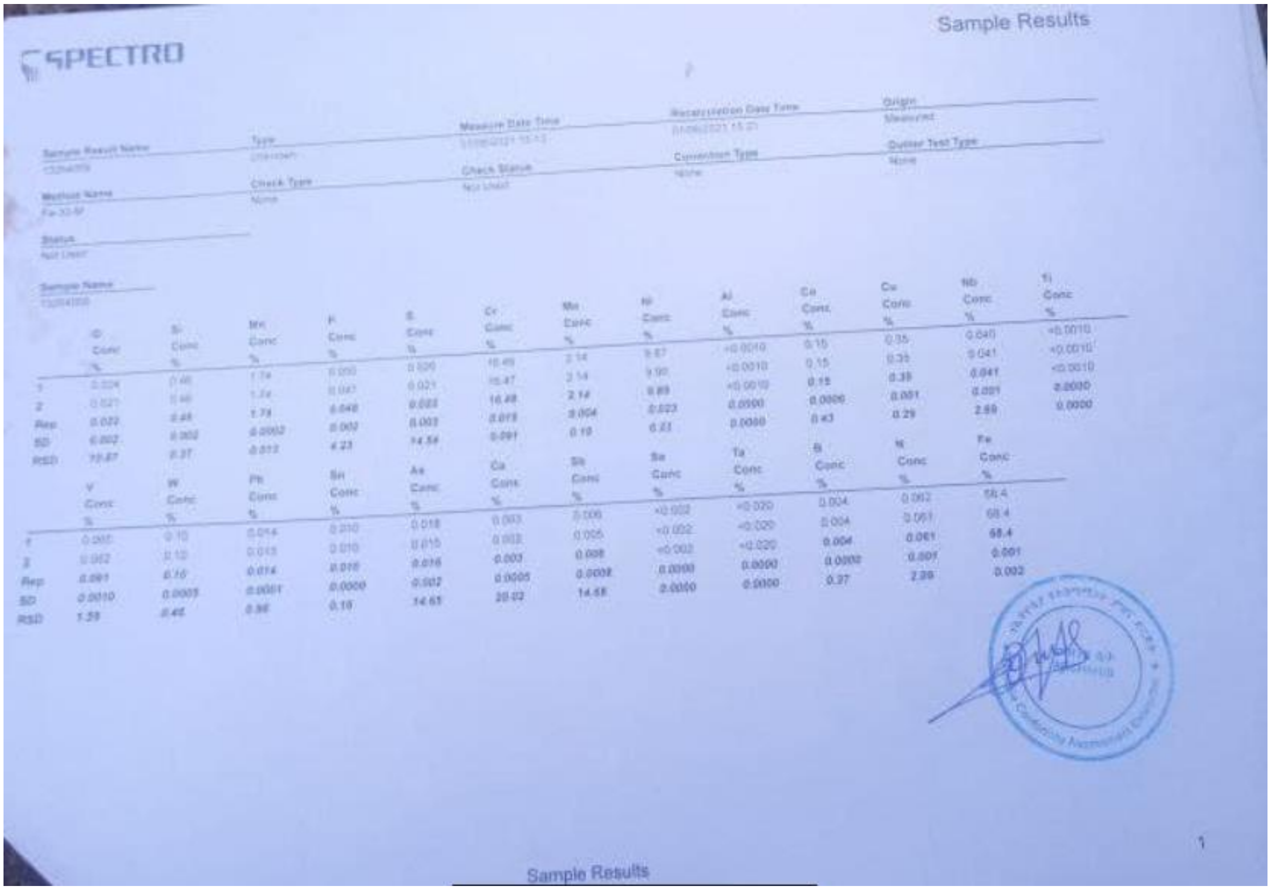
APPENDICES

Appendices1: Chemical composition result



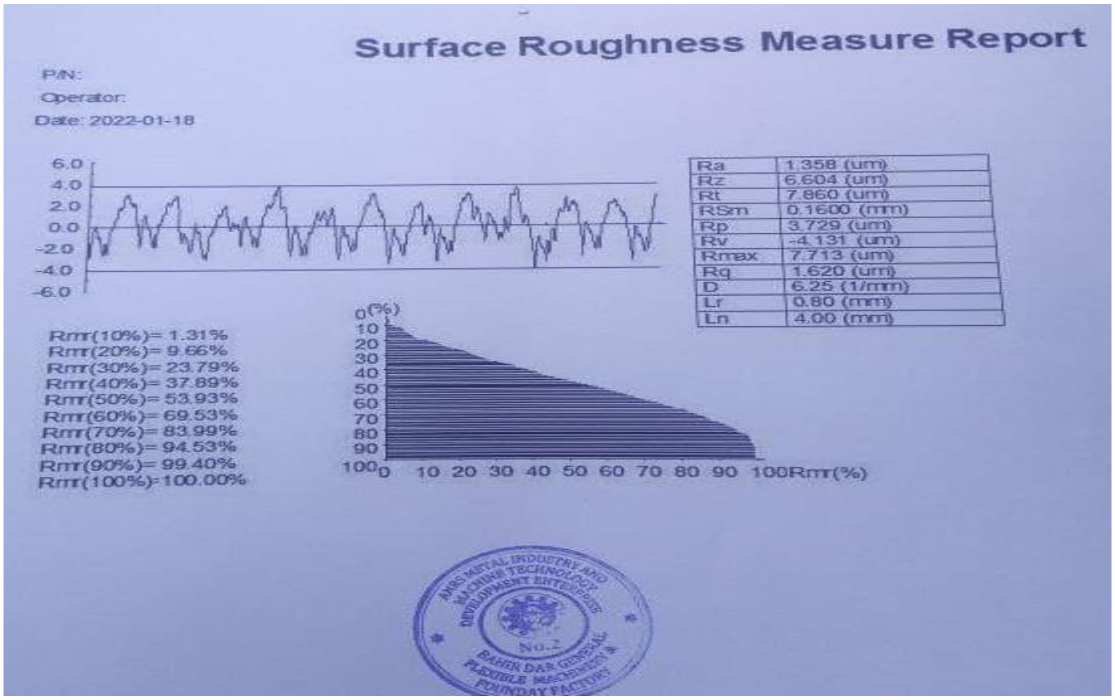
SPECTRO — Sample Results

	C Conc %	Si Conc %	Mn Conc %	P Conc %	S Conc %	Cr Conc %	Mo Conc %	Ni Conc %	Al Conc %	Co Conc %	Cu Conc %	Nb Conc %	Ti Conc %
1	0.024	0.46	1.74	0.050	0.020	16.49	2.14	9.87	<0.0010	0.15	0.35	0.040	<0.0010
2	0.021	0.46	1.74	0.047	0.021	16.47	2.14	9.90	<0.0010	0.15	0.35	0.041	<0.0010
Rep	0.022	0.46	1.74	0.048	0.023	16.48	2.14	9.89	<0.0010	0.15	0.35	0.041	<0.0010
SD	0.002	0.002	0.0002	0.002	0.003	0.015	0.004	0.023	0.0000	0.0006	0.001	0.001	0.0000
RSD	11.87	0.37	0.013	4.23	14.54	0.091	0.19	0.23	0.0000	0.43	0.29	2.69	0.0000

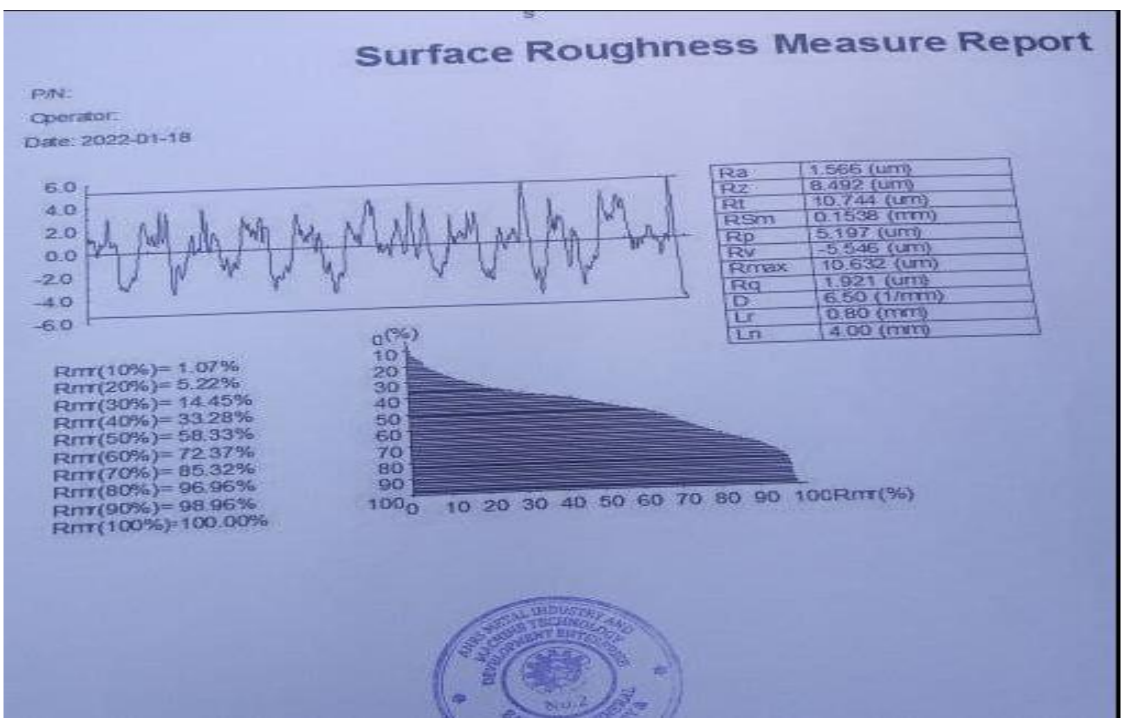
	V Conc %	W Conc %	Pb Conc %	Sn Conc %	As Conc %	Ca Conc %	Sb Conc %	Se Conc %	Ta Conc %	B Conc %	N Conc %	Fe Conc %
1	0.060	0.10	0.014	0.010	0.018	0.003	0.006	<0.002	<0.020	0.004	0.062	68.4
2	0.062	0.10	0.013	0.010	0.015	0.002	0.005	<0.002	<0.020	0.004	0.061	68.4
Rep	0.061	0.10	0.014	0.010	0.016	0.003	0.006	<0.002	<0.020	0.004	0.061	68.4
SD	0.0010	0.0005	0.0001	0.0000	0.002	0.0005	0.0008	0.0000	0.0000	0.0000	0.001	0.001
RSD	1.59	0.46	0.96	0.10	14.61	20.02	14.58	0.0000	0.0000	0.27	2.20	0.002

Appendices 2: Roughness test result

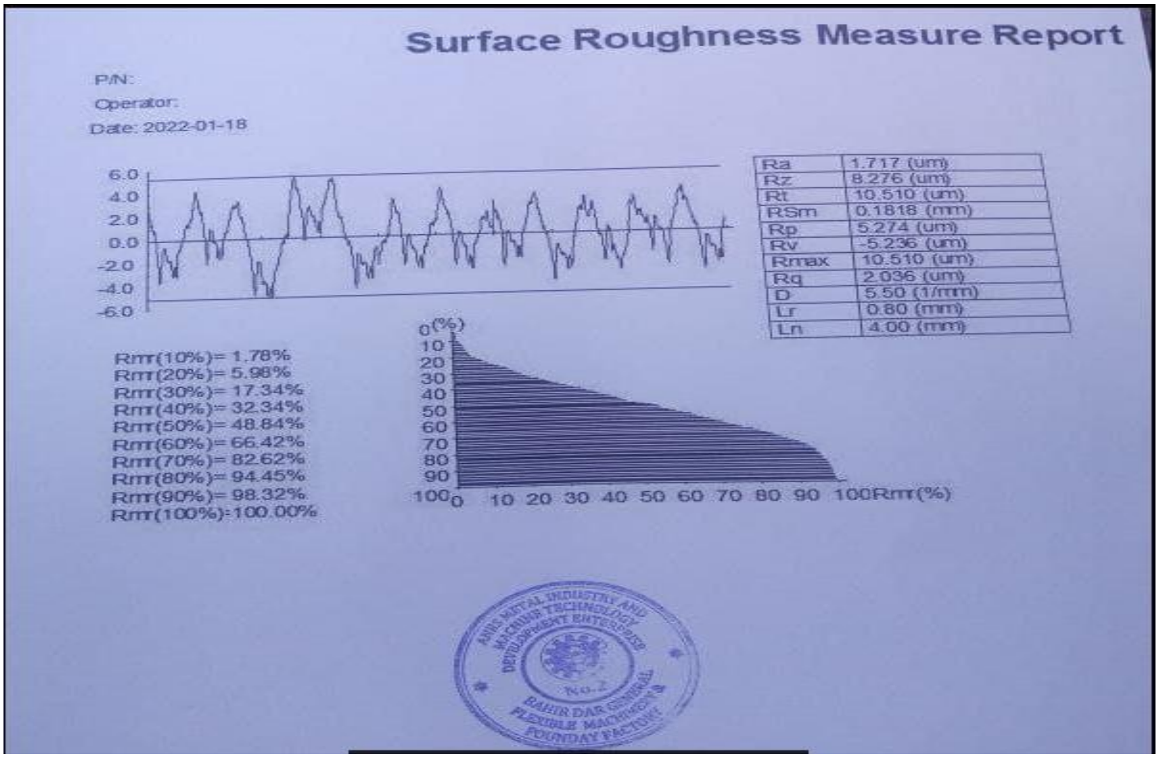
Experiment 1



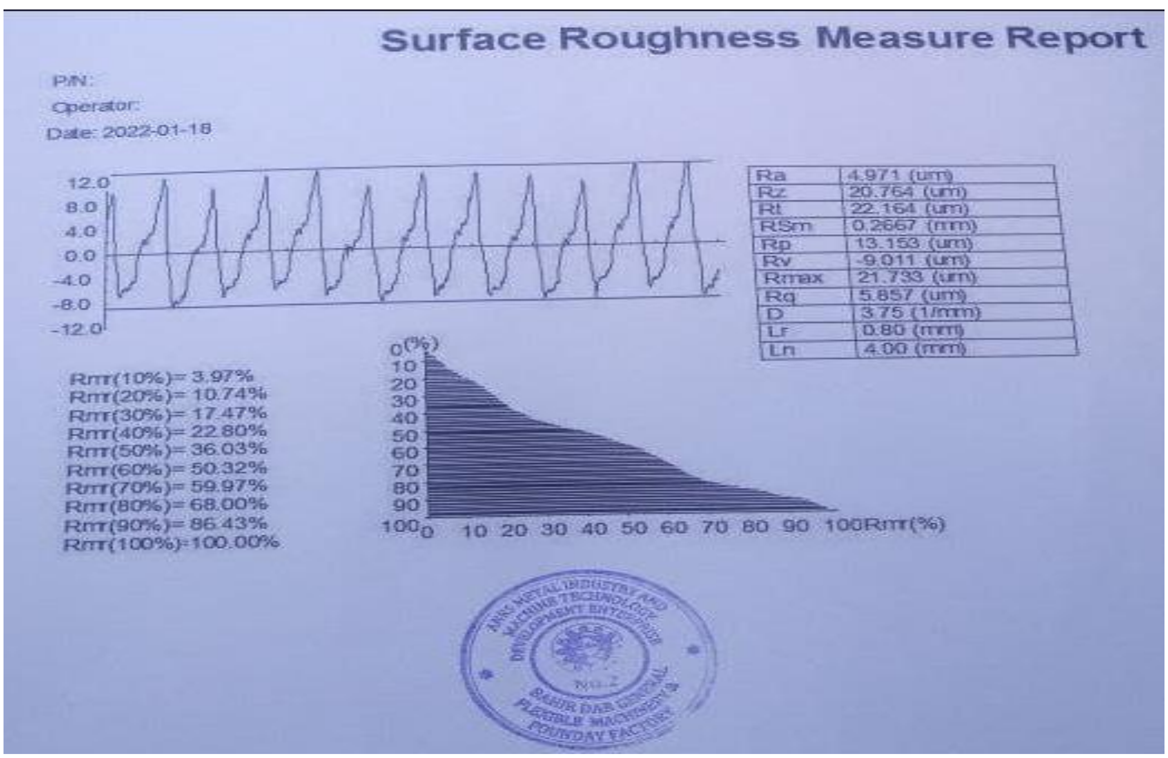
Experiment 2



Experiment 3



Experiment 4



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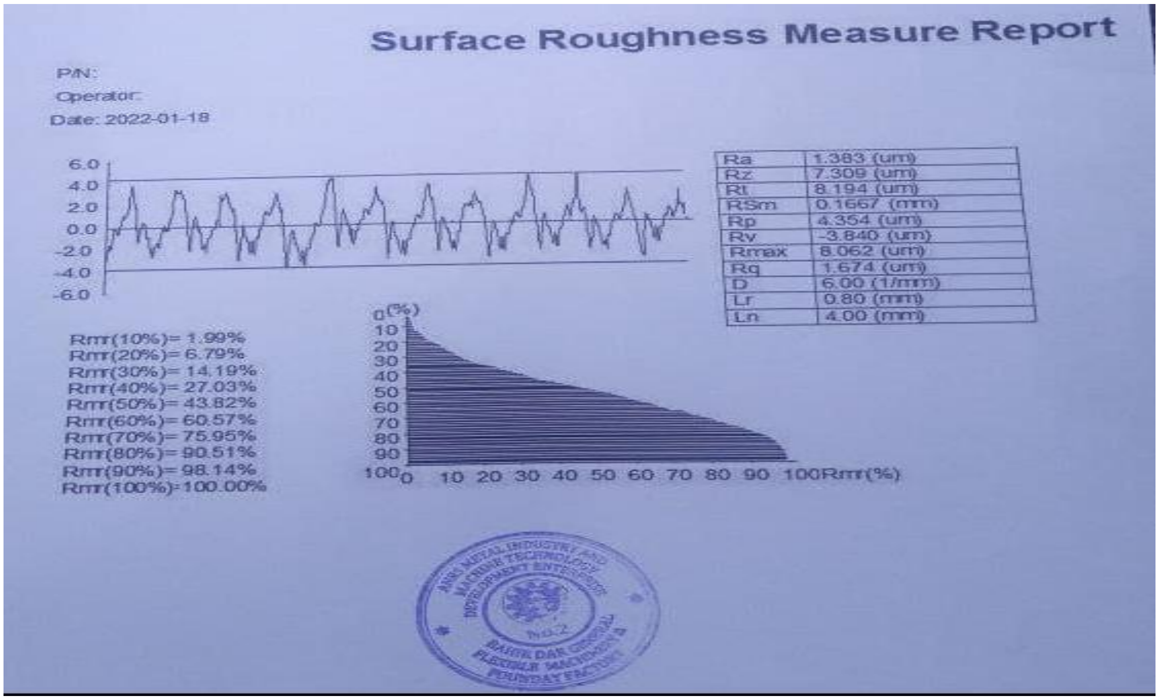

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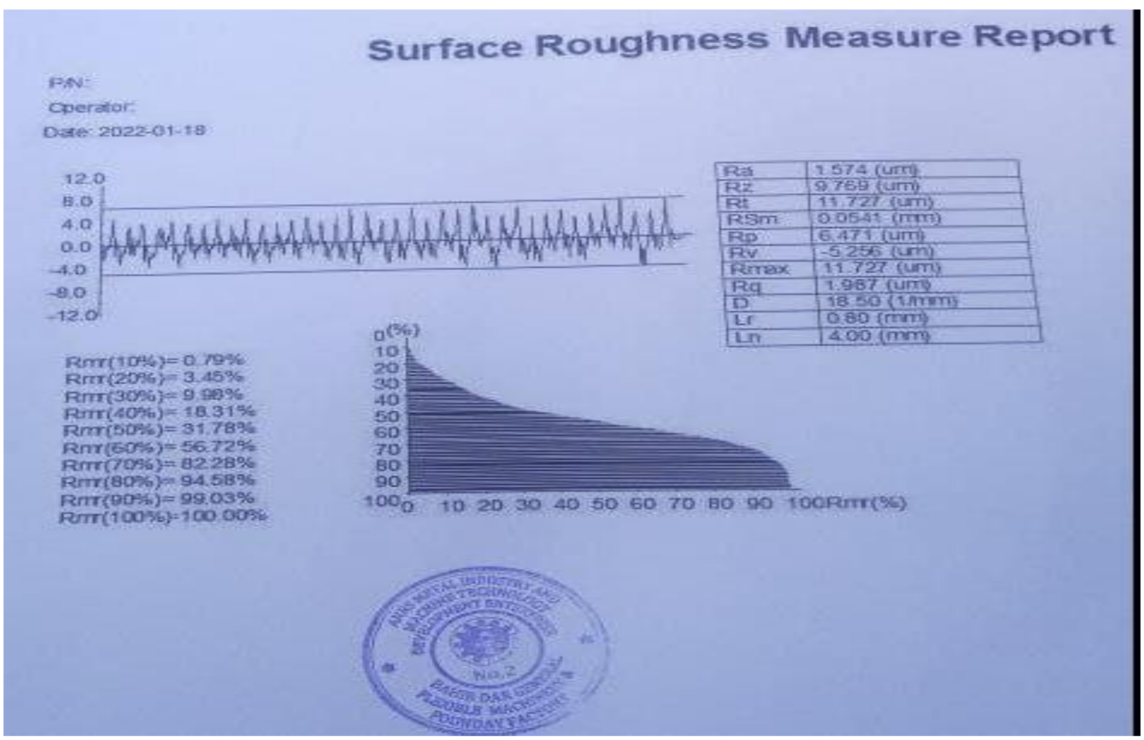

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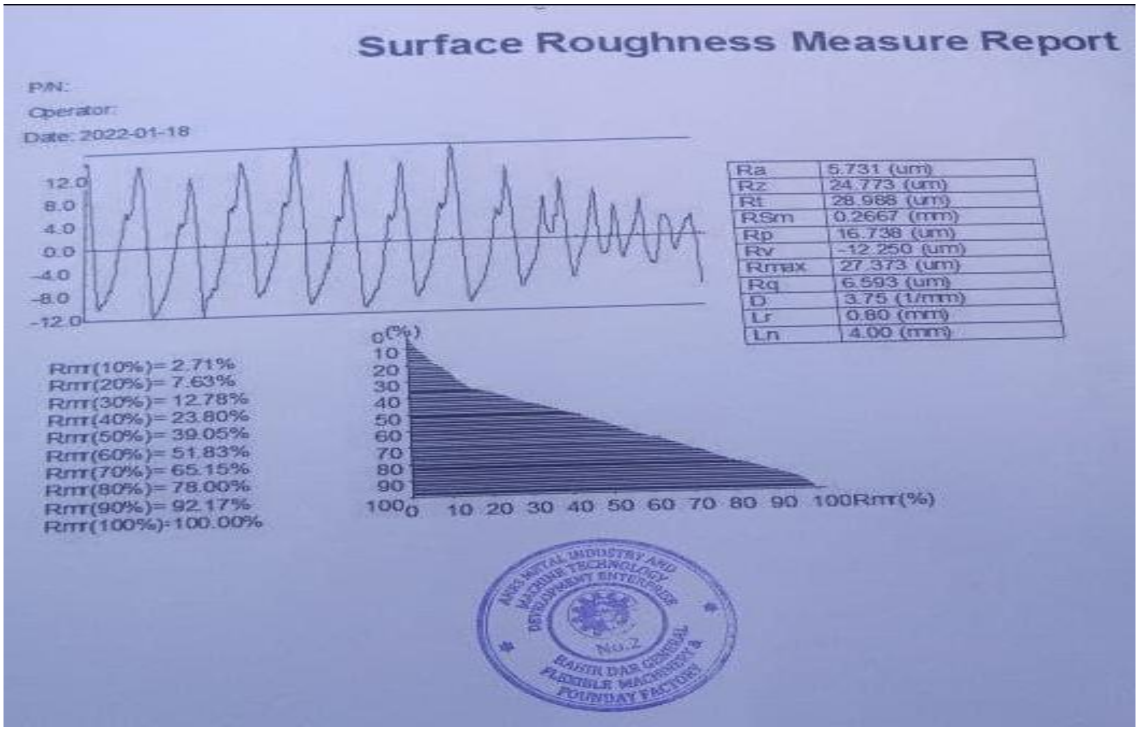
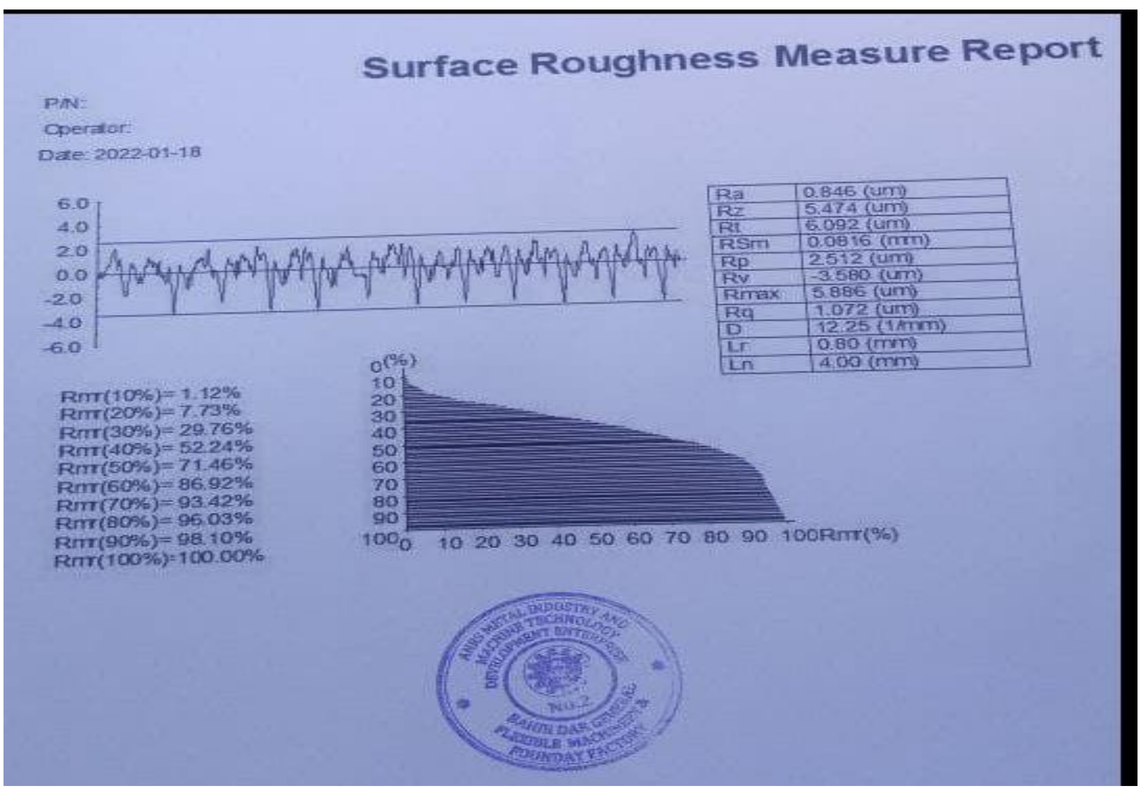
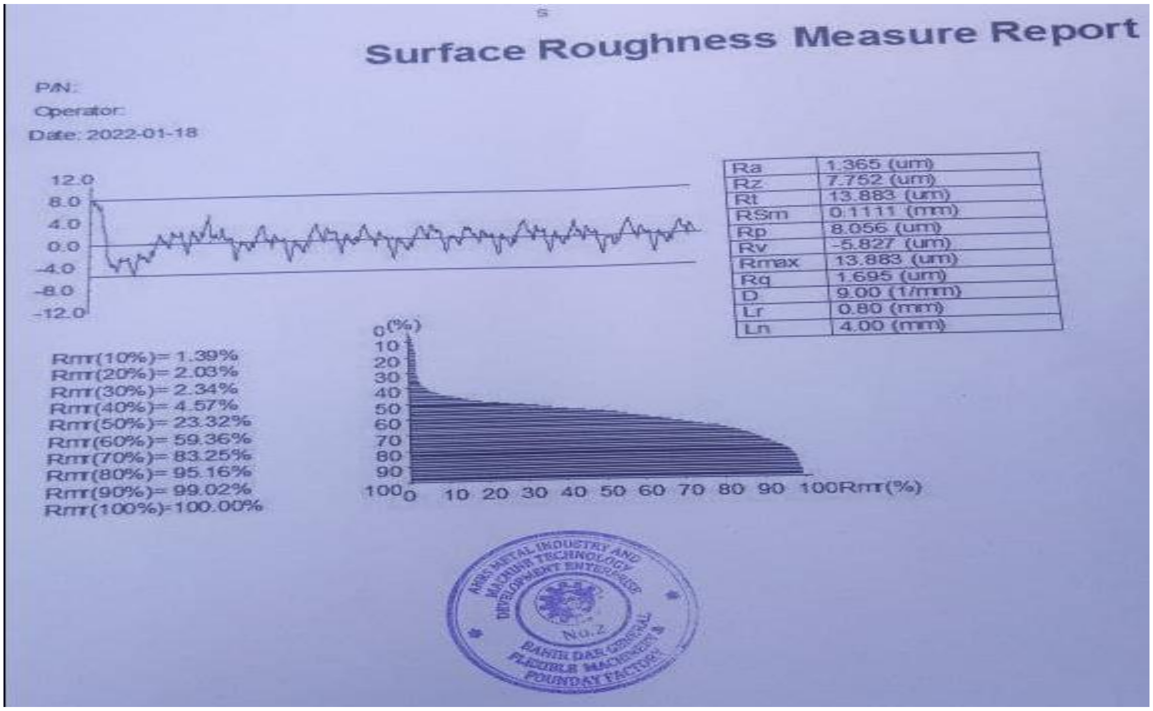


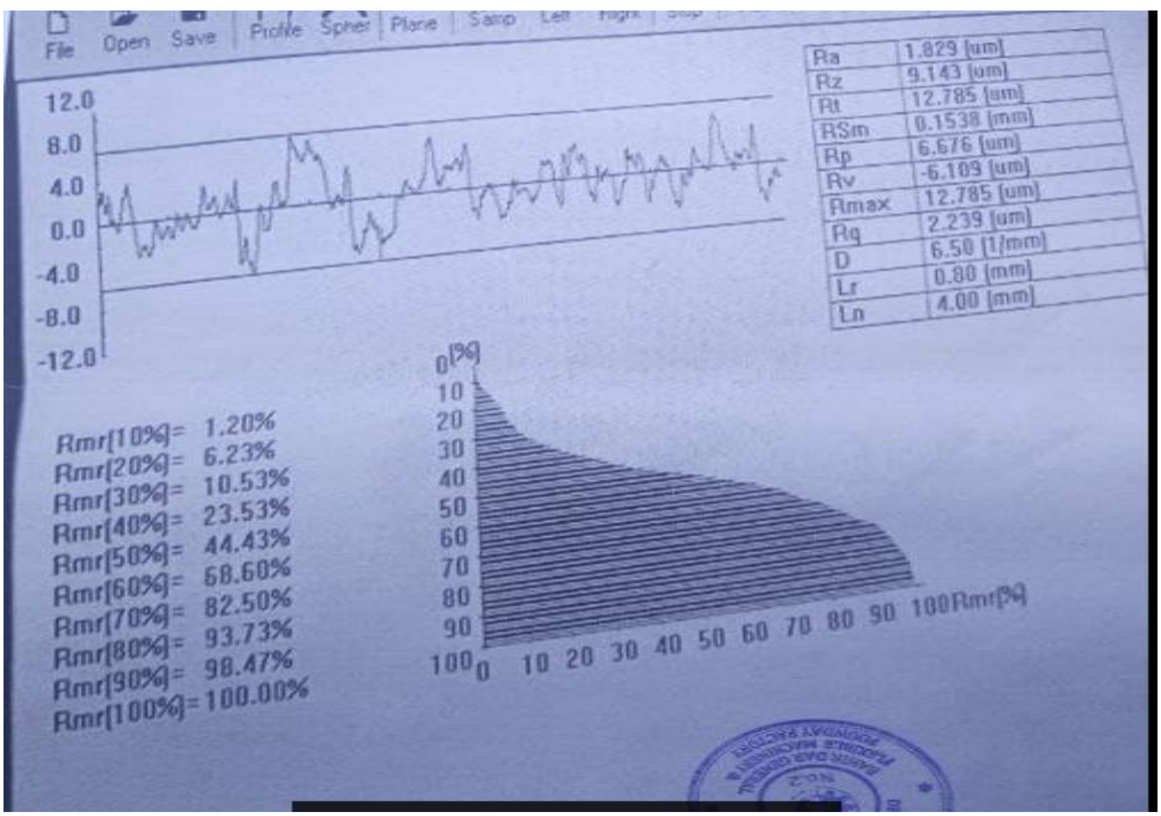
Experiment 8



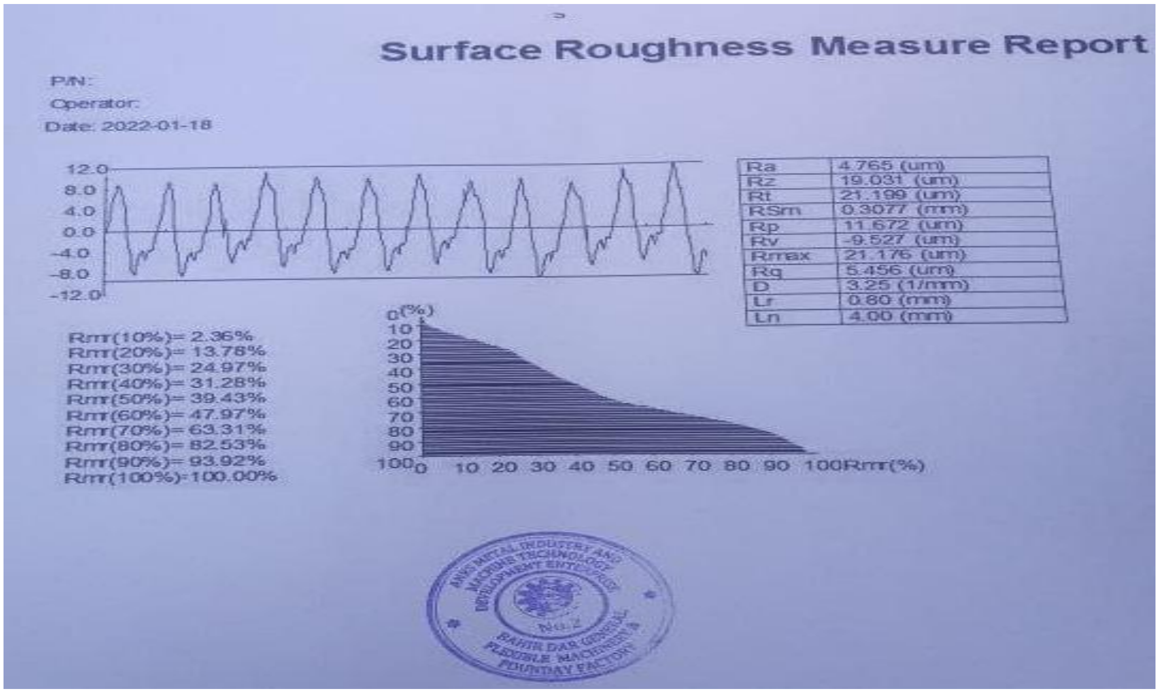
Experiment 9



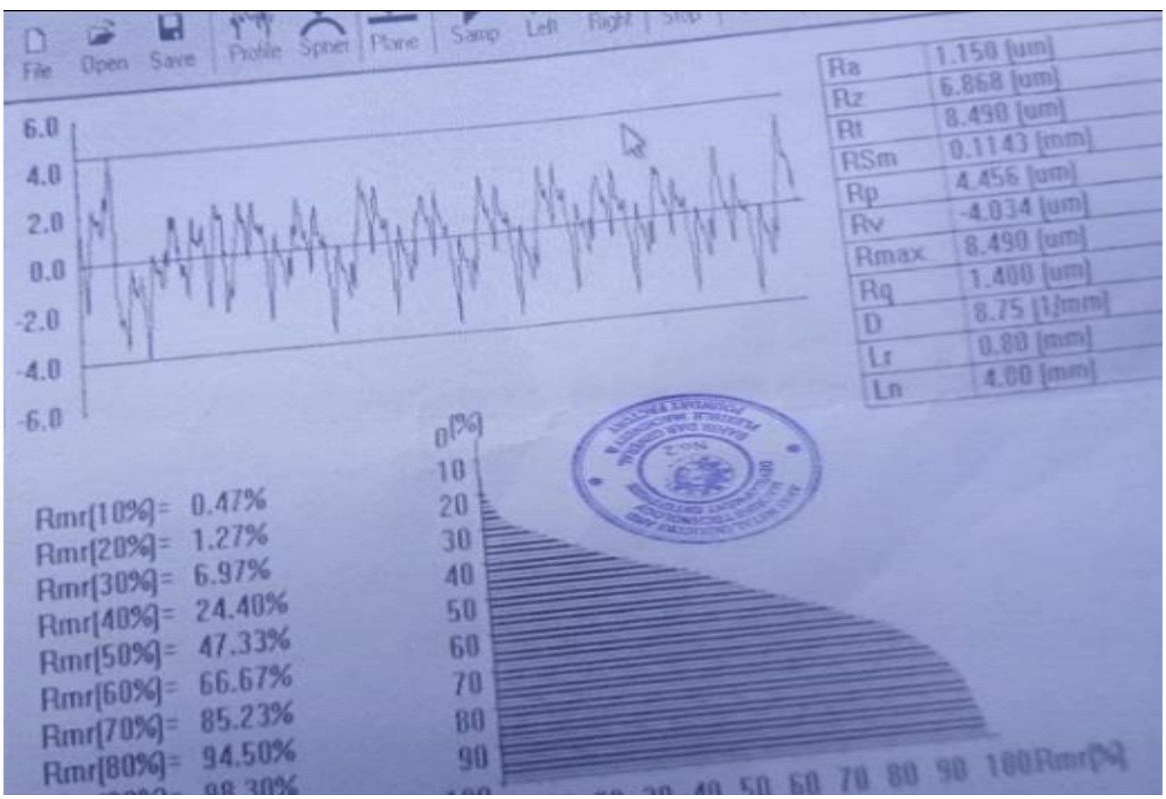
Experiment 10



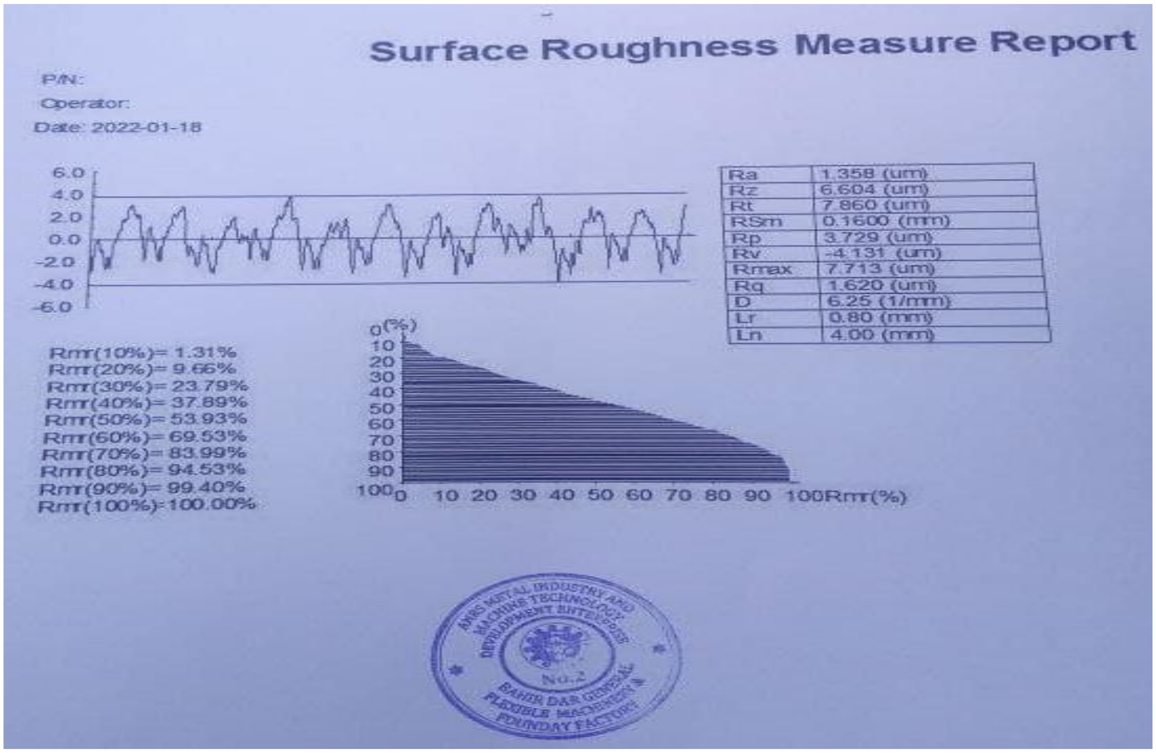
Experiment 11



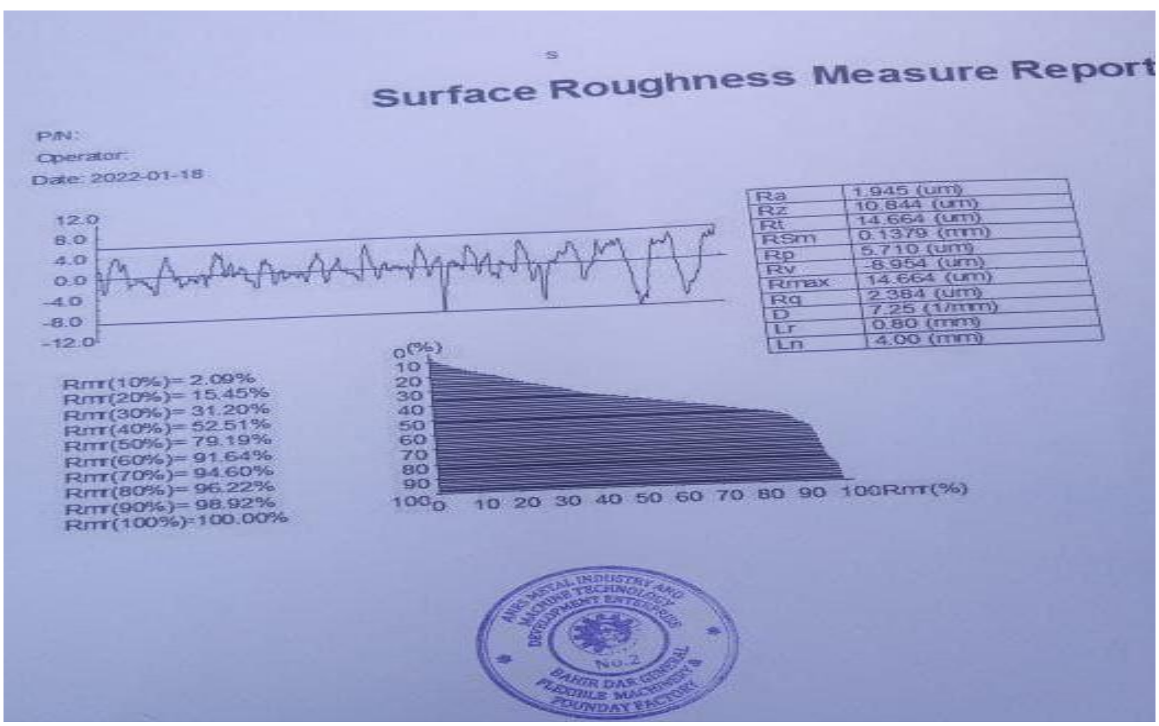
Experiment 12



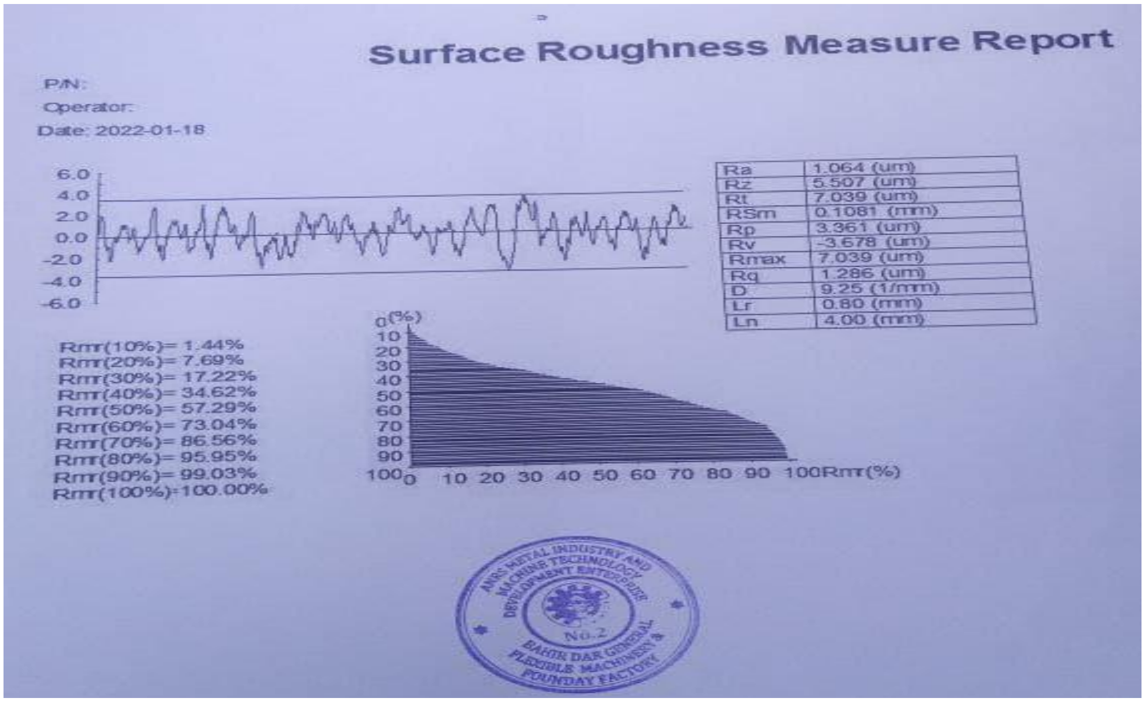
Experiment 13



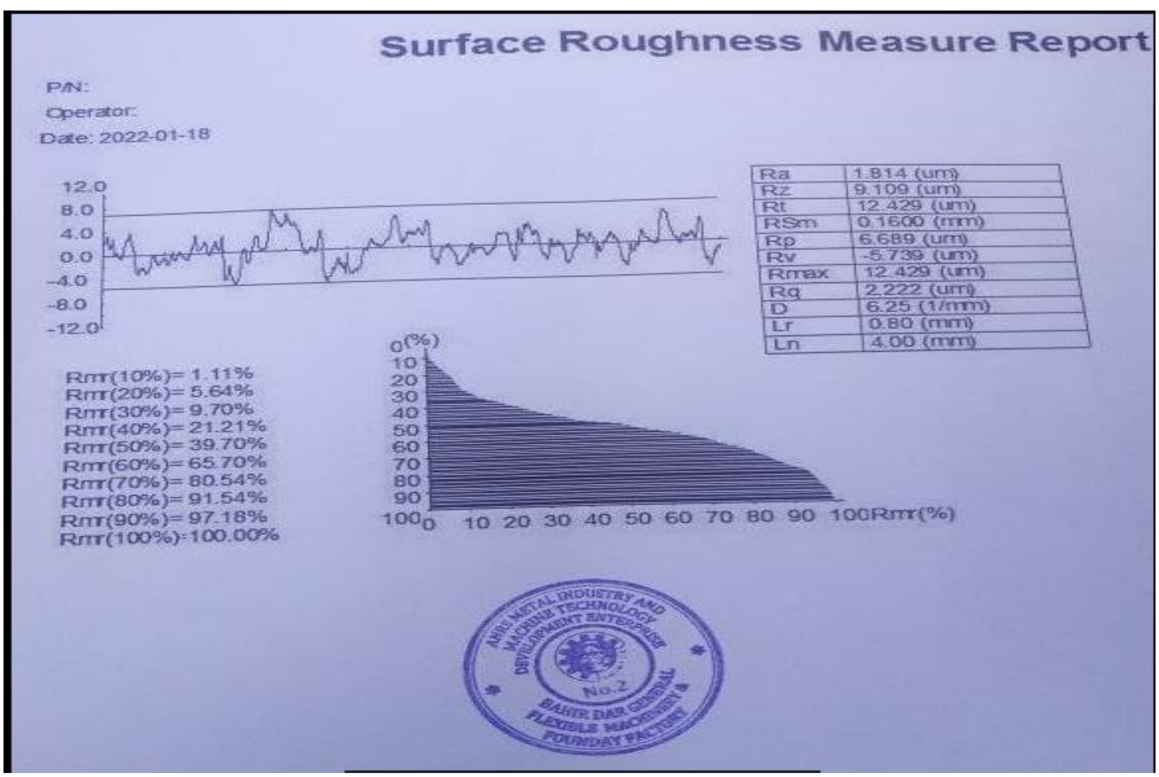
Experiment 14



Experiment 15



Experiment 16



Appendices 3: F-Table

TABLE E

F critical values

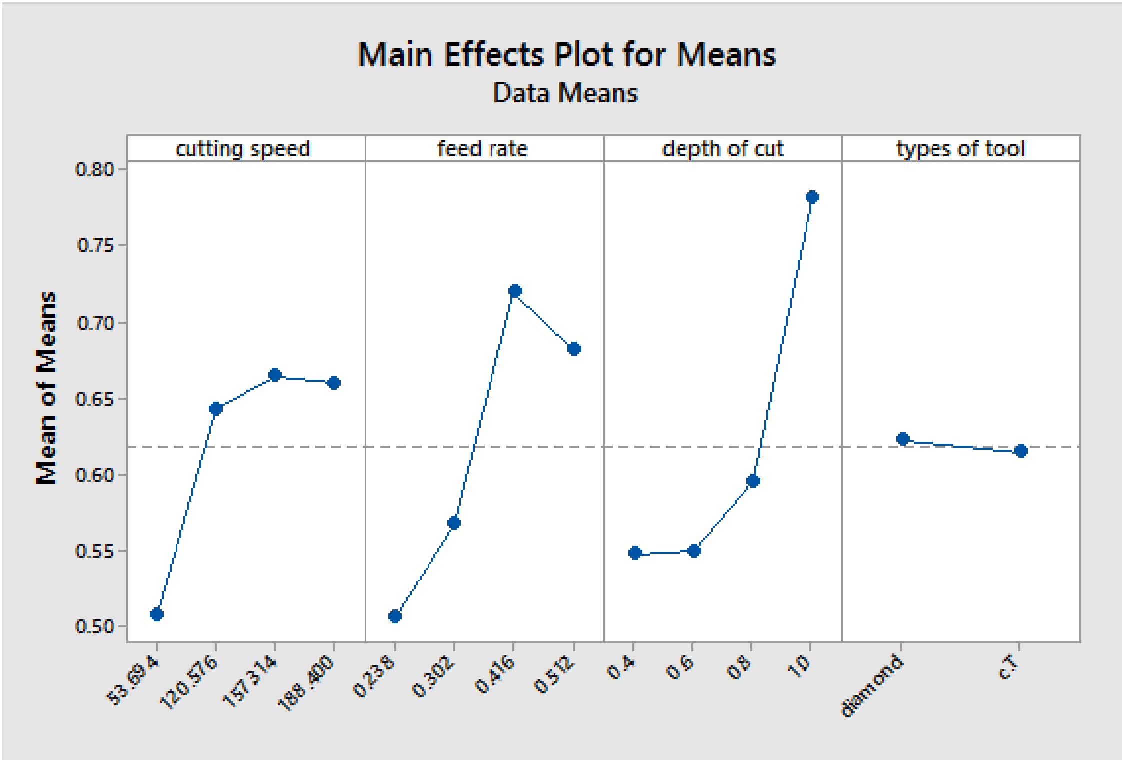
Degrees of freedom in the denominator		Degrees of freedom in the numerator								
	p	1	2	3	4	5	6	7	8	9
1	.100	39.86	49.50	53.59	55.83	57.24	58.20	58.91	59.44	59.86
	.050	161.45	199.50	215.71	224.58	230.16	233.99	236.77	238.88	240.54
	.025	647.79	799.50	864.16	899.58	921.85	937.11	948.22	956.66	963.28
	.010	4052.2	4999.5	5403.4	5624.6	5763.6	5859.0	5928.4	5981.1	6022.5
	.001	405284	500000	540379	562500	576405	585937	592873	598144	602284
2	.100	8.53	9.00	9.16	9.24	9.29	9.33	9.35	9.37	9.38
	.050	18.51	19.00	19.16	19.25	19.30	19.33	19.35	19.37	19.38
	.025	38.51	39.00	39.17	39.25	39.30	39.33	39.36	39.37	39.39
	.010	98.50	99.00	99.17	99.25	99.30	99.33	99.36	99.37	99.39
	.001	998.50	999.00	999.17	999.25	999.30	999.33	999.36	999.37	999.39
3	.100	5.54	5.46	5.39	5.34	5.31	5.28	5.27	5.25	5.24
	.050	10.13	9.55	9.28	9.12	9.01	8.94	8.89	8.85	8.81
	.025	17.44	16.04	15.44	15.10	14.88	14.73	14.62	14.54	14.47
	.010	34.12	30.82	29.46	28.71	28.24	27.91	27.67	27.49	27.35
	.001	167.03	148.50	141.11	137.10	134.58	132.85	131.58	130.62	129.86
4	.100	4.54	4.32	4.19	4.11	4.05	4.01	3.98	3.95	3.94
	.050	7.71	6.94	6.59	6.39	6.26	6.16	6.09	6.04	6.00
	.025	12.22	10.65	9.98	9.60	9.36	9.20	9.07	8.98	8.90
	.010	21.20	18.00	16.69	15.98	15.52	15.21	14.98	14.80	14.66
	.001	74.14	61.25	56.18	53.44	51.71	50.53	49.66	49.00	48.47
5	.100	4.06	3.78	3.62	3.52	3.45	3.40	3.37	3.34	3.32
	.050	6.61	5.79	5.41	5.19	5.05	4.95	4.88	4.82	4.77
	.025	10.01	8.43	7.76	7.39	7.15	6.98	6.85	6.76	6.68
	.010	16.26	13.27	12.06	11.39	10.97	10.67	10.46	10.29	10.16
	.001	47.18	37.12	33.20	31.09	29.75	28.83	28.16	27.65	27.24
6	.100	3.78	3.46	3.29	3.18	3.11	3.05	3.01	2.98	2.96
	.050	5.99	5.14	4.76	4.53	4.39	4.28	4.21	4.15	4.10
	.025	8.81	7.26	6.60	6.23	5.99	5.82	5.70	5.60	5.52
	.010	13.75	10.92	9.78	9.15	8.75	8.47	8.26	8.10	7.98
	.001	35.51	27.00	23.70	21.92	20.80	20.03	19.46	19.03	18.69
7	.100	3.59	3.26	3.07	2.96	2.88	2.83	2.78	2.75	2.72
	.050	5.59	4.74	4.35	4.12	3.97	3.87	3.79	3.73	3.68
	.025	8.07	6.54	5.89	5.52	5.29	5.12	4.99	4.90	4.82
	.010	12.25	9.55	8.45	7.85	7.46	7.19	6.99	6.84	6.72
	.001	29.25	21.69	18.77	17.20	16.21	15.52	15.02	14.63	14.33

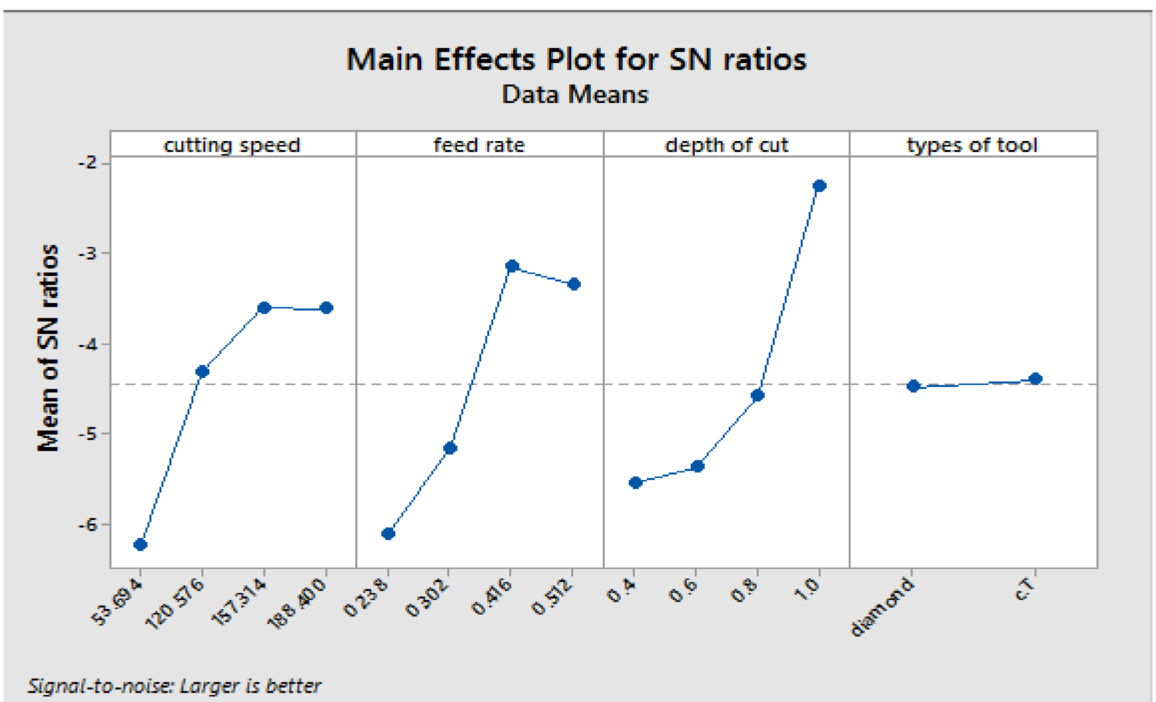
Degrees of freedom in the denominator	p	Degrees of freedom in the numerator 1	2	3	4	5	6	7	8	9
8	.100	3.46	3.11	2.92	2.81	2.73	2.67	2.62	2.59	2.56
	.050	5.32	4.46	4.07	3.84	3.69	3.58	3.50	3.44	3.39
	.025	7.57	6.06	5.42	5.05	4.82	4.65	4.53	4.43	4.36
	.010	11.26	8.65	7.59	7.01	6.63	6.37	6.18	6.03	5.91
	.001	25.41	18.49	15.83	14.39	13.48	12.86	12.40	12.05	11.77
9	.100	3.36	3.01	2.81	2.69	2.61	2.55	2.51	2.47	2.44
	.050	5.12	4.26	3.86	3.63	3.48	3.37	3.29	3.23	3.18
	.025	7.21	5.71	5.08	4.72	4.48	4.32	4.20	4.10	4.03
	.010	10.56	8.02	6.99	6.42	6.06	5.80	5.61	5.47	5.35
	.001	22.86	16.39	13.90	12.56	11.71	11.13	10.70	10.37	10.11
10	.100	3.29	2.92	2.73	2.61	2.52	2.46	2.41	2.38	2.35
	.050	4.96	4.10	3.71	3.48	3.33	3.22	3.14	3.07	3.02
	.025	6.94	5.46	4.83	4.47	4.24	4.07	3.95	3.85	3.78
	.010	10.04	7.56	6.55	5.99	5.64	5.39	5.20	5.06	4.94
	.001	21.04	14.91	12.55	11.28	10.48	9.93	9.52	9.20	8.96
11	.100	3.23	2.86	2.66	2.54	2.45	2.39	2.34	2.30	2.27
	.050	4.84	3.98	3.59	3.36	3.20	3.09	3.01	2.95	2.90
	.025	6.72	5.26	4.63	4.28	4.04	3.88	3.76	3.66	3.59
	.010	9.65	7.21	6.22	5.67	5.32	5.07	4.89	4.74	4.63
	.001	19.69	13.81	11.56	10.35	9.58	9.05	8.66	8.35	8.12
12	.100	3.18	2.81	2.61	2.48	2.39	2.33	2.28	2.24	2.21
	.050	4.75	3.89	3.49	3.26	3.11	3.00	2.91	2.85	2.80
	.025	6.55	5.10	4.47	4.12	3.89	3.73	3.61	3.51	3.44
	.010	9.33	6.93	5.95	5.41	5.06	4.82	4.64	4.50	4.39
	.001	18.64	12.97	10.80	9.63	8.89	8.38	8.00	7.71	7.48
13	.100	3.14	2.76	2.56	2.43	2.35	2.28	2.23	2.20	2.16
	.050	4.67	3.81	3.41	3.18	3.03	2.92	2.83	2.77	2.71
	.025	6.41	4.97	4.35	4.00	3.77	3.60	3.48	3.39	3.31
	.010	9.07	6.70	5.74	5.21	4.86	4.62	4.44	4.30	4.19
	.001	17.82	12.31	10.21	9.07	8.35	7.86	7.49	7.21	6.98
14	.100	3.10	2.73	2.52	2.39	2.31	2.24	2.19	2.15	2.12
	.050	4.60	3.74	3.34	3.11	2.96	2.85	2.76	2.70	2.65
	.025	6.30	4.86	4.24	3.89	3.66	3.50	3.38	3.29	3.21
	.010	8.86	6.51	5.56	5.04	4.69	4.46	4.28	4.14	4.03
	.001	17.14	11.78	9.73	8.62	7.92	7.44	7.08	6.80	6.58
15	.100	3.07	2.70	2.49	2.36	2.27	2.21	2.16	2.12	2.09
	.050	4.54	3.68	3.29	3.06	2.90	2.79	2.71	2.64	2.59
	.025	6.20	4.77	4.15	3.80	3.58	3.41	3.29	3.20	3.12
	.010	8.68	6.36	5.42	4.89	4.56	4.32	4.14	4.00	3.89
	.001	16.59	11.34	9.34	8.25	7.57	7.09	6.74	6.47	6.26
16	.100	3.05	2.67	2.46	2.33	2.24	2.18	2.13	2.09	2.06
	.050	4.49	3.63	3.24	3.01	2.85	2.74	2.66	2.59	2.54
	.025	6.12	4.69	4.08	3.73	3.50	3.34	3.22	3.12	3.05
	.010	8.53	6.23	5.29	4.77	4.44	4.20	4.03	3.89	3.78
	.001	16.12	10.97	9.01	7.94	7.27	6.80	6.46	6.19	5.98
17	.100	3.03	2.64	2.44	2.31	2.22	2.15	2.10	2.06	2.03
	.050	4.45	3.59	3.20	2.96	2.81	2.70	2.61	2.55	2.49
	.025	6.04	4.62	4.01	3.66	3.44	3.28	3.16	3.06	2.98
	.010	8.40	6.11	5.19	4.67	4.34	4.10	3.93	3.79	3.68
	.001	15.72	10.66	8.73	7.68	7.02	6.56	6.22	5.96	5.75

Appendices 4: Main Effects of GRG Table

Level	cutting speed	feed rate	depth of cut	types of tool
1	0.5075	0.5060	0.5477	0.6225
2	0.6430	0.5677	0.5503	0.6149
3	0.6645	0.7190	0.5960	
4	0.6597	0.6820	0.7808	
Delta	0.1570	0.2130	0.2330	0.0076
Rank	3	2	1	4

Appendices 5: Main Effects of GRG and S/N ratio plots





Appendices 6: ANOVA Table for GRG

Source	DF	Adj SS	Adj MS	F-Value	P-Value
cutting speed	3	0.06695	0.022318	2.58	0.149
feed rate	3	0.11746	0.039152	4.52	0.055
depth of cut	3	0.14598	0.048660	5.62	0.035
Error	6	0.05194	0.008657		
Total	15	0.89916			

Appendices 7: Eigen analysis of the correlation matrix and vectors

Eigen analysis of the Correlation Matrix

Eigenvalue	1.0690	0.9310
Proportion	0.534	0.466
Cumulative	0.534	1.000

Eigenvectors

Variable	**PC1**	**PC2**
Ra	0.707	-0.707
MRR	0.707	0.707

Appendices 8: Arduino program

InfraredTemprature_for_machine

```
#include <Wire.h>
#include <Adafruit_MLX90614.h>

Adafruit_MLX90614 mlx = Adafruit_MLX90614();
int buzzer=11;


float low_temp=280.0;
float high_temp=300.0;

void setup()
{

  Serial.begin(9600);
  pinMode(buzzer,OUTPUT);
  mlx.begin();
}

void loop()
{
    float temp = mlx.readObjectTempC();
    Serial.println(" ");
    Serial.print("Temp: ");
    Serial.println(temp);



     if (temp<=low_temp)
     {
       Serial.println("Lower Temprature");
       digitalWrite(buzzer,HIGH);
     }


     else if (temp>=high_temp)
     {
       Serial.println("High Temprature");
       digitalWrite(buzzer,HIGH);
     }
     delay(1000);
 }
```