

SQL BASED PREDICTION AND OPTIMIZATION OF CUTTING PARAMETERS IN TURNING: AN ENVIRONMENTAL CONSCIOUS MACHINING APPROACH

*A Project report submitted in partial fulfillment of the requirements
for the award of the degree of*

**Bachelor of Technology
in
Mechanical Engineering**

Submitted by

SUMIT KUMAR MONDAL	319126520048
SALAPU NARASIMHA ANEESH NAIDU	319126520041
VEDULLAVALASA MADHU ABHINAV	319126520058
MUNJETI YOGESHWARA RAO	319126520030
RAKOTI KESAVA CHANDRA SAI KIRAN	319126520039

Under the Esteemed Guidance of

Mr. D.S.S. RAVI KIRAN (PhD), A.M.I.I.E., M.I.I.W

Assistant Professor



DEPARTMENT OF MECHANICAL ENGINEERING

ANIL NEERUKONDA INSTITUTE OF TECHNOLOGY & SCIENCES

(Permanently Affiliated to Andhra University, Approved by AICTE, Accredited by NBA Tier-I, NAAC)

Sangivalasa, Visakhapatnam (District) Andhra Pradesh -India- 531162.

APRIL 2023

DEPARTMENT OF MECHANICAL ENGINEERING
ANIL NEERUKONDA INSTITUTE OF TECHNOLOGY & SCIENCES
(UGC Autonomous & Permanently Affiliated to Andhra University)

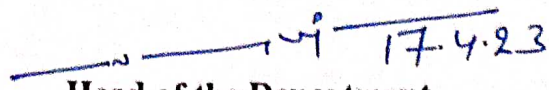


CERTIFICATE

This is to certify that the project report entitled "MQL based prediction and optimization of cutting parameters in turning: An Environmental Conscious Machining Approach" has been carried out by Sumit Kumar Mondal (319126520048), Salapu Narasimha Aneesh Naidu (319126520041), Vedullavalasa Madhu Abhinav (319126520058), Munjeti Yogeshwara Rao (319126520030), Rakoti Kesava Chandra Sai Kiran (319126520039) under the esteemed guidance of Mr. D.S.S. RAVI Kiran, in partial fulfilment of the requirements for the award of the Degree of Bachelor of Technology in Mechanical Engineering by Anil Neerukonda Institute Of Technology & Sciences, Visakhapatnam.


Project Guide

Mr. D.S.S. RAVI KIRAN
Assistant Professor
Dept. Of Mechanical Engineering
ANITS


Head of the Department

Dr. B. NAGARAJU
Professor
Dept. Of Mechanical Engineering
ANITS

THIS PROJECT IS APPROVED BY THE BOARD OF EXAMINERS

Nelharika
INTERNAL EXAMINER *(7/4/23)*

[Signature]
EXTERNAL EXAMINER *(7/4/2023)*

ACKNOWLEDGEMENT

I express immensely my deep sense of gratitude to **Mr. D.S.S. Ravi Kiran**, Assistant professor, Department of Mechanical Engineering, Anil Neerukonda Institute of Technology and Sciences, Sangivalasa, Visakhapatnam, for his valuable guidance and encouragement at every stage of the work made it a successful fulfilment.

We express our sincere thanks to **Mr. R.D.V. PRASAD**, Assistant Professor, Department of Mechanical Engineering, Anil Neerukonda Institute of Technology & Sciences for his valuable suggestions throughout the project.

Also we are very thankful to **Prof. K. Rama Krishna**, Principal, ANITS, **Dr.B.NagaRaju**, Head of the Department, Mechanical Engineering, ANITS, Visakhapatnam.

We immensely express our deep sense of gratitude to the management and technical staff of **Gayatri Vidya Parishad College of Engineering** for providing assistance in carrying out the experiment work.

We express our sincere thanks to the members of Teaching and Non-Teaching staff of the Department of Mechanical Engineering, ANITS, for their co-operation and support to carry on work.

Last but not the least, we like to convey our thanks to all who have contributed directly or indirectly for the completion of this project work.

Sumit Kumar Mondal	319126520048
Salapu Narasimha Aneesh Naidu	319126520041
Vedullavalasa Madhu Abhinav	319126520058
Munjeti Yogeshwara Rao	319126520030
Rakoti Kesava Chandra Sai Kiran	319126520039

ABSTRACT

In recent trends of manufacturing lower lead times and increase demand for good quality parts require the industry to produce the parts manufactured sustainably with high precision, low cost and improve productivity using novel techniques which are economical and Eco-Friendly. In most of the industries they use flooded machining where more cutting fluids are wasted. Even the cutting fluids are affecting the workers. Because in industries toxic cutting fluids are being used.

The current research work deals with the analysis of multi objective optimization of cutting process parameters of materials through the use of both Minimum Quantity Lubrication (MQL) condition using Response Surface Optimization and the prediction method used is Fuzzy logic Optimization. The cutting parameters considered are Speed, Feed and Depth of Cut. While the output parameters considered are MRR , Rt , Ra , Rq and Rz. The type of insert used is a Carbide (Solid Carbide) Single Point Turning tool (SPTT). While cutting fluid used in MQL is Vegetable Oil (Sesame oil) performed at 90, 180 ml/hrs. The experiments were designed using Taguchi's L9 orthogonal array for conducting the experimentation. Analysis of variance is applied to identify the most significant cutting process parameters influencing surface roughness and MRR under MQL conditions.

The prediction / forecasting of responses is a critical part and has high significance in any manufacturing industry. This regression analysis and fuzzy logic approach have been implemented for this purpose. Finally, the best possible combination of cutting parameters are obtained by performing optimization analysis using RSM. The Cutting speed – 100.512(m/min) , Feed – 0.404(mm) , Depth of Cut – 0.9(mm) are found to be best possible combination in the selected range and this has been validated by a confirmation experiment.

TABLE OF CONTENTS

Description	Page No.
ACKNOWLEDGEMENT.....	i
ABSTRACT.....	ii
TABLE OF CONTENTS.....	iii
LIST OF FIGURES.....	vi
LIST OF TABLES.....	xi
LIST OF EQUATIONS.....	xiv
NOMENCLATURE.....	xv
Chapter 1: INTRODUCTION.....	1
1.1 Introduction of Machining.....	1
1.1.1 Types of Machining operations.....	1
1.2 Turning Operation.....	4
1.2.1 Types of Turning Operation.....	5
1.2.2 Dynamics of Turning Operation.....	8
1.2.3 Cutting Parameters of Turning Operation.....	8
1.2.4 Advantages of Turning Operation.....	9
1.3 Cutting Tools.....	9
1.3.1 Role of Cutting Tool.....	10
1.3.2 Types of Cutting Tool.....	10
1.3.3 Single Point Cutting Tool Geometry.....	15
1.4 Cutting Liquids.....	16
1.4.1 Role of Cutting Fluid.....	17
1.4.2 Types of Cutting Fluids.....	17
1.5 MQL.....	19
1.5.1 Introduction.....	19
1.5.2 Functions of MQL.....	20
1.5.3 Benefits of MQL.....	21
1.5.4 Over & Under Lubrication.....	21

1.6 MQL Setups.....	21
1.6.1 External Supply Unit.....	22
1.6.2 Internal Supply Unit.....	23
1.7 Importance of Flow rate in MQL.....	25
1.8 MQL Machine Equipments.....	25
1.8.1 Lathe Machine.....	25
1.8.2 Mist Spray.....	27
1.8.3 Air Compressor.....	28
Chapter 2: LITERATURE REVIEW.....	30
2.1 Literature Review on MQL based experiments.....	30
2.2 Literature Review on Turning Process.....	31
2.3 Literature Review on various Optimization Techniques.....	32
Chapter 3: METHODOLOGY AND MATERIALS.....	34
3.1 Materials used in MQL Experiment.....	34
3.1.1 SS202.....	34
3.1.2 Lathe cone pulley pilot,6', Png-2.....	36
3.1.3 Mist Spray.....	36
3.1.4 Cutting Tool.....	37
3.1.5 Air Compressor.....	38
3.1.6 Surface Roughness Instrument.....	39
3.2 Minitab.....	40
3.2.1 Introduction.....	40
3.2.2 Specifications of Minitab.....	41
3.2.3 Features of Minitab.....	41
3.2.4 Uses & Applications of Minitab.....	42
3.3 ANOVA- DOE.....	42
3.3.1 Introduction to ANOVA.....	42
3.3.2 Formula for ANOVA.....	42
3.3.3 Terms of ANOVA test.....	43

3.3.4 Introduction of DOE.....	46
3.3.5 Terms of DOE.....	46
3.4 Matlab.....	47
3.4.1 Introduction.....	47
3.4.2 Specifications of Matlab 2015.....	48
3.4.3 Rules for using Matlab 2015.....	50
3.4.4 Uses of Matlab R2015.....	51
3.5 Regression Analysis.....	51
3.5.1 Introduction.....	51
3.5.2 Types of Regression Analysis.....	52
3.6 Fuzzy Logic Optimization.....	53
3.6.1 Introduction.....	53
3.6.2 Fuzzy Inference System.....	54
3.7 Response Surface Optimization.....	55
Chapter 4: EXPERIMENTAL DETAILS AND PARAMETERS FOR OPTIMIZATION.....	57
4.1 Experimental Details.....	57
4.2 Optimization Inputs.....	61
4.2.1 Fuzzy engine.....	61
4.2.2 Response surface optimization inputs & outputs.....	63
4.2.3 Response Optimizer Inputs.....	66
Chapter 5: RESULTS AND DISCUSSION.....	67
5.1 Response surface optimization results.....	67
5.2 Response optimizer results	83
5.3 Fuzzy Logic Optimization Results... ..	85
Chapter 6: CONCLUSIONS	106
6.1 Conclusion	106
6.2 Future Scope.....	107
Chapter 7: REFERENCES.....	108

LIST OF FIGURES

Figure No.	Figure Caption	Page No.
Figure 1.1	Drilling Operation...	2
Figure 1.2	Boring Operation on a work piece	2
Figure 1.3	Milling Operation	3
Figure 1.4	Ultrasonic Machining	4
Figure 1.5	Schematic diagram of Electrical Discharge Machining	4
Figure 1.6	Turning Operation	5
Figure 1.7	Step Turning Operation	6
Figure 1.8	Taper Turning Operation	6
Figure 1.9	Chamfer Turning Operation	7
Figure 1.10	Contour Turning Operation	7
Figure 1.11	High Carbon Steel Tool bits	10
Figure 1.12	HSS Tool bits	11
Figure 1.13	Cemented Carbide & Cemented tool bits	11
Figure 1.14	Ceramic glass drill bit	12
Figure 1.15	Cubic Boron Nitride tool bit	12
Figure 1.16	Diamond drill bit	13
Figure 1.17	Single Point Cutting Tool	13
Figure 1.18	Double Point Cutting Tool	14
Figure 1.19	Multi Point Cutting Tool	14
Figure 1.20	Single point cutting tool geometry	15
Figure 1.21	Neat Oil	18
Figure 1.22	Soluble Oil	18
Figure 1.23	Semi synthetic cutting fluid	19
Figure 1.24	Synthetic cutting fluid	19
Figure 1.25	Schematic diagram for MQL process	20
Figure 1.26	Benefits of using MQL	21
Figure 1.27	MQL supply systems	22

Figure 1.28	Principle of MQL with external supply unit	22
Figure 1.29	Use of multiple nozzles for machining under MQL	23
Figure 1.30	MQL internal supply systems	23
Figure 1.31	Nano cutting fluids	24
Figure 1.32	Solid cutting fluids	24
Figure 1.33	Lathe Machine	25
Figure 1.34	Mist Spray setup	27
Figure 1.35	Ultrasonic Mist Spray	28
Figure 1.36	High Pressure Mist Spray	28
Figure 1.37	Air Compressor overview	29
Figure 3.1	SS202 Material	34
Figure 3.2	Lathe (Cone Pulley) pilot, 6', Png-2	36
Figure 3.3	Mist Spray	37
Figure 3.4	CNMG 120404MS	38
Figure 3.5	Air Compressor	38
Figure 3.6	PCE-RT-11 device	39
Figure 3.7	Condition List of Instrument	39
Figure 3.8	Minitab Interface	40
Figure 3.9	Response Surface with no Curvature	46
Figure 3.10	Response Surface with Curvature	47
Figure 3.11	MATLAB user interface overview	48
Figure 3.12	Analyzing and visualizing data	49
Figure 3.13	Regression Optimization Window	52
Figure 3.14	Simple Regression Analysis	52
Figure 3.15	Multiple Regression	53
Figure 3.16	Response Surface Methodology	56
Figure 4.1	Matlab command Window	61
Figure 4.2	Fuzzy Logic Interface	62
Figure 4.3	Membership functions Interface	63

Figure 4.4	Rule editor Interface	63
Figure 4.5	Input and Output values in minitab interface	64
Figure 4.6	Minitab interface for Response Surface optimization	64
Figure 4.7	Defining custom Regression Surface Design Interface	65
Figure 4.8	Analyze Response Surface Design Interface	65
Figure 5.1	Normplot of Residuals for MRR (m^3/min)	68
Figure 5.2	Residuals vs Fits for MRR (m^3/min)	68
Figure 5.3	Normplot of Residuals for Rt (μm)	69
Figure 5.4	Residuals vs Fits for Rt (μm)	70
Figure 5.5	Normplot of Residuals for Ra (μm)	71
Figure 5.6	Residuals vs Fits for Ra (μm)	71
Figure 5.7	Normplot of Residuals for Rq (μm)	72
Figure 5.8	Residuals vs Fits for Rq (μm)	73
Figure 5.9	Normplot of Residuals for Rz (μm)	74
Figure 5.10	Residuals vs Fits for Rz (μm)	74
Figure 5.11	Normplot of Residuals for MRR (m^3/min)	76
Figure 5.12	Residuals vs Fits for MRR (m^3/min)	76
Figure 5.13	Normplot of Residuals for Rt (μm)	77
Figure 5.14	Residuals vs Fits for Rt (μm)	78
Figure 5.15	Normplot of Residuals for Ra (μm)	79
Figure 5.16	Residuals vs Fits for Ra (μm)	79
Figure 5.17	Normplot of Residuals for Rq (μm)	80
Figure 5.18	Residuals vs Fits for Rq (μm)	81
Figure 5.19	Normplot of Residuals for Rz (μm)	82
Figure 5.20	Residuals vs Fits for Rz (μm)	82
Figure 5.21	Optimization plot for workpiece of 180ml/hr	84
Figure 5.22	Optimization plot for workpiece of 90ml/hr	85
Figure 5.23	Fuzzy logic designer	86
Figure 5.24	Fuzzy logic input membership functions for the work piece	86

Figure 5.25	Fuzzy logic output membership functions for the work piece	87
Figure 5.26	Rule editor for the work piece with flowrate of 180ml/hr	88
Figure 5.27	Rule editor for the work piece with flowrate of 90ml/hr	90
Figure 5.28	Rule viewer for the work piece with flowrate of 180ml/hr	91
Figure 5.29	Surface viewer for the work piece with flowrate of 180ml/hr	93
Figure 5.30	Rule viewer for the work piece with flowrate of 90ml/hr	94
Figure 5.31	Surface viewer for the work piece with flowrate of 90ml/hr	95
Figure 5.32	MRR Experimental (180ml/hr) Vs MRR Regression equation value	96
Figure 5.33	Rt Experimental (180ml/hr) Vs Rt Regression equation value	96
Figure 5.34	Ra Experimental (180ml/hr) Vs Ra Regression equation value	96
Figure 5.35	Rq Experimental (180ml/hr) Vs Rq Regression equation value	96
Figure 5.36	Rz Experimental (180ml/hr) Vs Rz Regression equation value	97
Figure 5.37	MRR Experimental (90ml/hr) Vs MRR Regression equation value	97
Figure 5.38	Rt Experimental (90ml/hr) Vs Rt Regression equation value	97
Figure 5.39	Ra Experimental (90ml/hr) Vs Ra Regression equation value	98
Figure 5.40	Rq Experimental (90ml/hr) Vs Rq Regression equation value	98
Figure 5.41	Rz Experimental (90ml/hr) Vs Rz Regression equation value	98
Figure 5.42	MRR Experimental (180ml/hr) Vs MRR Fuzzy generated value	99
Figure 5.43	Rt Experimental (180ml/hr) Vs Rt Fuzzy generated value	99
Figure 5.44	Ra Experimental (180ml/hr) Vs Ra Fuzzy generated value	99
Figure 5.45	Rq Experimental (180ml/hr) Vs Rq Fuzzy generated value	99
Figure 5.46	Rz Experimental (180ml/hr) Vs Rz Fuzzy generated value	100
Figure 5.47	MRR Experimental (90ml/hr) Vs MRR Fuzzy generated value	100
Figure 5.48	Rt Experimental (90ml/hr) Vs Rt Fuzzy generated value	100
Figure 5.49	Ra Experimental (90ml/hr) Vs Ra Fuzzy generated value	101

Figure 5.50	Rq Experimental (90ml/hr) Vs Rq Fuzzy generated value	101
Figure 5.51	Rz Experimental (90ml/hr) Vs Rz Fuzzy generated value	101
Figure 5.52	MRR Regression equation value (180ml/hr) Vs MRR Fuzzy generated value	102
Figure 5.53	Rt Regression equation value (180ml/hr) Vs Rt Fuzzy generated value	102
Figure 5.54	Ra Regression equation value (180ml/hr) Vs Ra Fuzzy generated value	102
Figure 5.55	Rq Regression equation value (180ml/hr) Vs Rq Fuzzy generated value	102
Figure 5.56	Rz Regression equation value (180ml/hr) Vs Rz Fuzzy generated value	103
Figure 5.57	MRR Regression equation value (90ml/hr) Vs MRR Fuzzy generated value	103
Figure 5.58	Rt Regression equation value (90ml/hr) Vs Rt Fuzzy generated value	103
Figure 5.59	Ra Regression equation value (90ml/hr) Vs Ra Fuzzy generated value	104
Figure 5.60	Rq Regression equation value (90ml/hr) Vs Rq Fuzzy generated value	104
Figure 5.61	Rz Regression equation value (90ml/hr) Vs Rz Fuzzy generated value	104

LIST OF TABLES

Table No.	Title of Table	Page No.
Table 3.1	Chemical Composition of SS202	35
Table 3.2	Physical properties of SS202	35
Table 3.3	Mechanical Properties of SS202	35
Table 4.1	Input parameters	57
Table 4.2	Cutting parameters	58
Table 4.3	Material Removal Rate	58
Table 4.4	Surface roughness values for work piece with flow rate of 180ml/hr...	59
Table 4.5	Surface roughness values for work piece with flow rate of 90ml/hr...	59
Table 4.6	Input and Output parameters used for optimization and prediction for work piece with flow rate of 180ml/hr	60
Table 4.7	Input and Output parameters used for optimization and prediction for work piece with flow rate of 90ml/hr	60
Table 5.1	Analysis of Variance of MRR of workpiece with flowrate of 180ml/hr	67
Table 5.2	Modal Summary of Analysis of Variance of MRR of workpiece with flowrate of 180ml/hr	67
Table 5.3	Analysis of Variance of Rt of workpiece with flowrate of 180ml/hr	69
Table 5.4	Modal Summary of Analysis of Variance of Rt of workpiece with flowrate of 180ml/hr	69
Table 5.5	Analysis of Variance of Ra of workpiece with flowrate of 180ml/hr	70
Table 5.6	Modal Summary of Analysis of Variance of Ra of workpiece with flowrate of 180ml/hr	70
Table 5.7	Analysis of Variance of Rq of workpiece with flowrate of 180ml/hr	72
Table 5.8	Modal Summary of Analysis of Variance	72

	of Rq of workpiece with flowrate of 180ml/hr	
Table 5.9	Analysis of Variance of Rz of workpiece with flowrate of 180ml/hr	73
Table 5.10	Modal Summary of Analysis of Variance of Rz of workpiece with flowrate of 180ml/hr	73
Table 5.11	Regression Equation Generated Values For Workpiece Of Flowrate (180ml/Hr)	75
Table 5.12	Analysis of Variance of MRR of workpiece with flowrate of 90ml/hr	75
Table 5.13	Modal Summary of Analysis of Variance of MRR of workpiece with flowrate of 90ml/hr	75
Table 5.14	Analysis of Variance of Rt of workpiece with flowrate of 90ml/hr	77
Table 5.15	Modal Summary of Analysis of Variance of Rt of workpiece with flowrate of 90ml/hr	77
Table 5.16	Analysis of Variance of Ra of workpiece with flowrate of 90ml/hr	78
Table 5.17	Modal Summary of Analysis of Variance of Ra of workpiece with flowrate of 90ml/hr	78
Table 5.18	Analysis of Variance of Rq of workpiece with flowrate of 90ml/hr	80
Table 5.19	Modal Summary of Analysis of Variance of Rq of workpiece with flowrate of 90ml/hr	80
Table 5.20	Analysis of Variance of Rz of workpiece with flowrate of 90ml/hr	81
Table 5.21	Modal Summary of Analysis of Variance of Rz of workpiece with flowrate of 90ml/hr	81
Table 5.22	Regression Equation Generated Values For Workpiece Of Flowrate (90ml/Hr)	83
Table 5.23	Results of Response Optimizer for Workpieces of 180 ml/hr	84

Table 5.24	Results of Response Optimizer for Workpiece of 90 ml/hr	85
Table 5.25	RULES FOR WORKPIECE WITH FLOW RATE OF 180ML/HR	88
Table 5.26	RULES FOR WORKPIECE WITH FLOW RATE OF 90ML/HR	90
Table 5.27	Output values after fuzzy logic optimization for work piece with flow rate of 180ml/hr	92
Table 5.28	Output values after fuzzy logic optimization for work piece with flow rate of 90 ml/hr	94

LIST OF EQUATIONS

Equation No.	Equation Name	Page No.
EQ 4.1	MRR Equation	57
EQ 4.2	Cutting Speed Equation	57
EQ 5.1	Regression Equation in Uncoded Units of MRR of workpiece with flowrate of 180ml/hr	67
EQ 5.2	Regression Equation in Uncoded Units of Rt of workpiece with flowrate of 180ml/hr	69
EQ 5.3	Regression Equation in Uncoded Units of Ra of workpiece with flowrate of 180ml/hr	70
EQ 5.4	Regression Equation in Uncoded Units of Rq of workpiece with flowrate of 180ml/hr	72
EQ 5.5	Regression Equation in Uncoded Units of Rz of workpiece with flowrate of 180ml/hr	73
EQ 5.6	Regression Equation in Uncoded Units of MRR of workpiece with flowrate of 90ml/hr	75
EQ 5.7	Regression Equation in Uncoded Units of Rt of workpiece with flowrate of 90ml/hr	77
EQ 5.8	Regression Equation in Uncoded Units of Ra of workpiece with flowrate of 90ml/hr	78
EQ 5.9	Regression Equation in Uncoded Units of Rq of workpiece with flowrate of 90ml/hr	80
EQ 5.10	Regression Equation in Uncoded Units of Rz of workpiece with flowrate of 90ml/hr	81

NOMENCLATURE

MRR	-	Material Removal Rate
Rt	-	Total height of the roughness profile
Ra	-	Arithmetic average roughness
Rq	-	Root mean square roughness
Rz	-	Mean roughness depth
ANOVA	-	Analysis of Variance
DOE	-	Design of Experiments
DF	-	Degree of Freedom
Adj SS	-	Adjusted Sum of Squares
Adj MS	-	Adjusted Mean Squares

CHAPTER 1

INTRODUCTION

The majority of engineering parts, such as gears, bearings, clutches, tools, screws, and nuts, require precise dimensions, shapes, and smooth surfaces to function properly. However, manufacturing processes like casting and forging often cannot achieve the required accuracy and finish. Therefore, pre-formed parts, known as blanks, must undergo semi-finishing and finishing through machining and grinding to achieve the necessary precision and smoothness. Grinding is essentially a type of machining process.

1.1 Importance of Machining

A critical step in creating high-quality components is machining, which involves progressively eliminating superfluous material from prepared blanks in the form of chips using cutting tools to reach the necessary dimensions and surface qualities. This process is a precision machining operation that results in smooth and accurate surfaces, making it a fundamental process in the manufacturing industry.

Machining involves cutting, shaping, and forming raw materials into their final shapes and sizes, resulting in parts, tools, and instruments that are used in various industries. Metals are typically formed through machining, but other materials such as plastics, wood, ceramics and composites can also be machined. To carry out this process, workshops use advanced tools and equipment such as mills, lathes and drills that use various techniques to cut and shape the material. 3D printers are also used to add material to components. The machining process requires a high level of technical knowledge, expertise and attention to detail to produce parts and components with the required specifications.

1.1.1 Types of Machining Operations

i. Conventional Machining Process

The conventional machining process refers to the use of traditional methods for machining, without employing any advanced techniques. The classic machining method is another name for it. The traditional machining techniques are described here.

- *Drilling Operation*

Drilling operations refer to the process of creating a hole or wellbore in the ground for the extraction of natural resources such as oil, gas, or water. This process involves the use of specialized equipment, including drill bits, drilling rigs, and pumps. The operation begins with the preparation of the drilling site and the assembly of the drilling rig. When machining with a single-point cutting tool vs drilling, the MRR (material removal rate) for drilling is quite high. as shown in Fig 1.1.

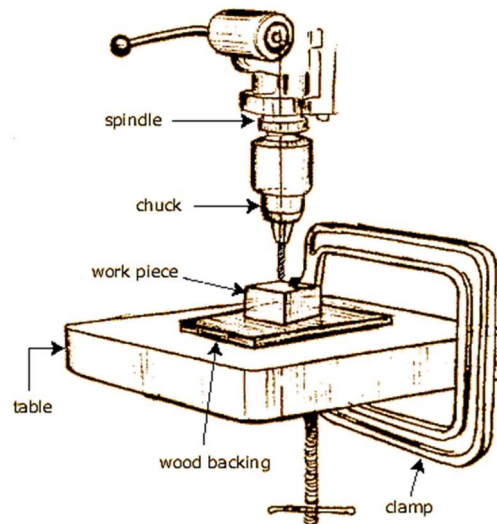


Fig 1.1 Drilling operation

- ***Boring operation***

Boring is a machining technique that employs a specialized cutting tool, akin to a drill bit, to enhance the accuracy of an existing hole in a workpiece. This method involves the removal of material from the internal part of the workpiece. Boring is a versatile technique that can produce holes of varying sizes and degrees of precision. For achieving high levels of accuracy in the size and position of large-diameter holes, boring is often the sole viable machining option available, as shown in Fig 1.2.

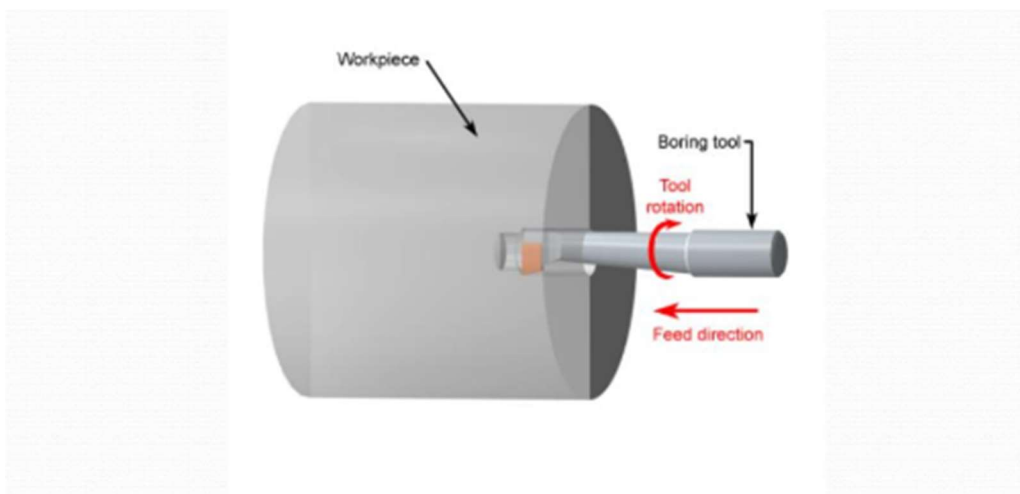


Fig 1.2 Boring operation on a workpiece

- ***Milling Operation***

The process of milling involves the use of revolving cutters that can pierce the work material. You can cut grooves in the material of the workpiece by milling. The workpiece is subjected to the feed motion during the machining process, while the tool rotates primarily. In some circumstances, the rotating tool may execute the primary and feed

motions concurrently while the workpiece remains in place, as shown in Figure 1.3. Common machine tools for milling include milling machines, such as horizontal, vertical, and gantry mills. They can be traditional or CNC machines, and the cutting tool is a spinning milling cutter.

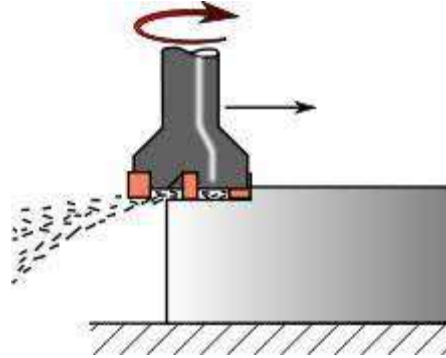


Fig 1.3 Milling Operation

- ***Turning Operation***

It is a lathe operation that is used to remove material from the surface of the workpiece in order to decrease the diameter of the workpiece to the required value. This is referred to as turning.

- ii. **Unconventional Machining Process**

Unconventional machining processes are unique in that they do not involve direct contact between the tool and workpiece, making them distinct from conventional machining processes. These processes represent a more advanced approach to machining.

- ***USM (Ultrasonic Machining)***

Ultrasonic machining is an unconventional method of removing material from a surface by vibrating an instrument against it at high frequency and low amplitude while also utilising small abrasive particles. Both conductive and non-conductive materials, even those that cannot be machined using traditional techniques, can be processed using it. This method is very helpful when cutting fragile materials. The schematic diagram for ultrasonic machining is shown in Fig. 1.4.

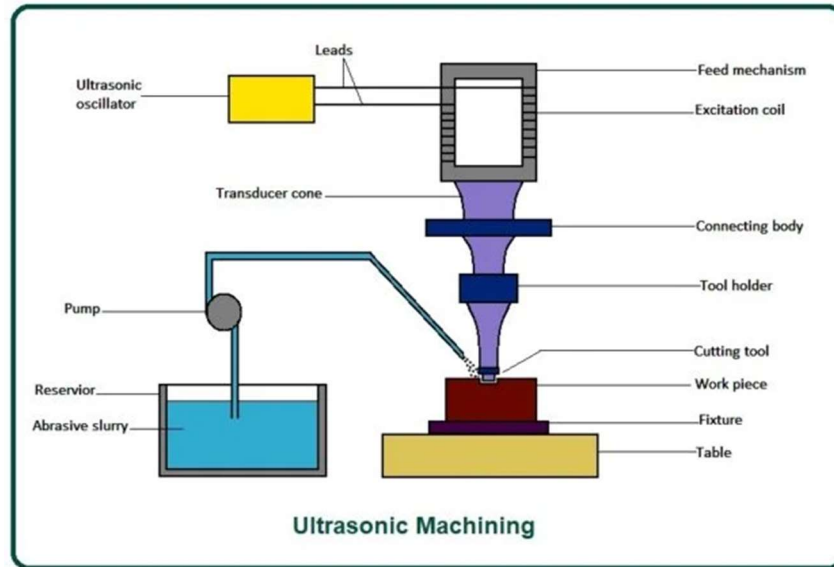


Fig 1.4 Ultrasonic Machining

- ***Electrical Discharge Machining Process***

The Spark Machining technique is another name for this procedure. This method removes material off the surface of the workpiece by local melting or vaporisation, as illustrated in Fig. 1.5, by sparking the tool and the workpiece, which are both submerged in a dielectric liquid.

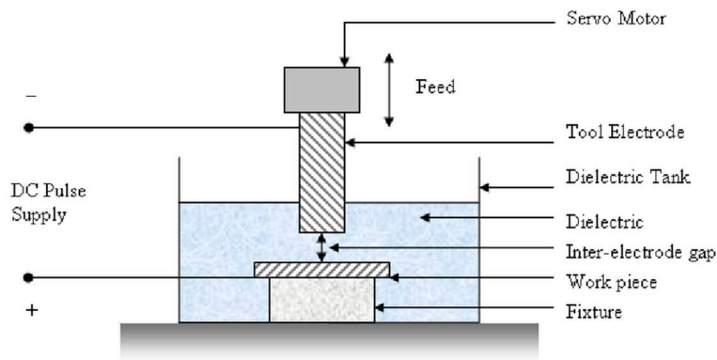


Fig 1.5 Schematic diagram of Electrical Discharge Machining

1.2 Turning Operation

As seen in Fig. 1.6, turning is a type of machining in which material is removed from a spinning workpiece to generate a cylindrical shape using a cutting tool, often a single-point

cutting tool. From straightforward shafts to intricate pieces utilised in the aerospace, automotive, and other sectors, turning activities are crucial in the manufacturing sector.

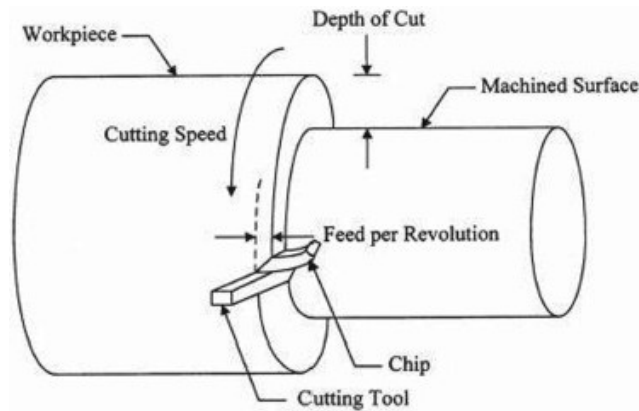


Fig 1.6 Turning operation

Turning is a machining process that can be performed manually using a traditional lathe that requires constant operator supervision. Alternatively, an automated lathe may be used, called a CNC lathe, which requires no operator intervention. Objects that are turned are called "turned parts" or "machined objects." This process can be used to machine cylindrical, conical, face, grooved and threaded surfaces with rotating surfaces.

To generate accurate diameters and depths, turning involves rotating the workpiece while a cutting tool is moved along one, two, or three axes of motion. Turning's primary goal is to reduce the workpiece's diameter to the appropriate size. Turning can be used to create tubular components with different geometries on either the interior or outside of the cylinder. The lathe's centre has to be positioned for the workpiece's diameter to be the same at both ends. In order to turn, the diameter must be trimmed in two stages: roughing and finishing.

1.2.1 Types of Turning Operation

There are different types of turning, such as straight turning, taper turning, profiling, or external grooving. Generally, single-edged tools are used for turning. Let us discuss the types of turning operations.

- ***Plain Turning***

In plain turning, the surface of a cylindrical workpiece is machined to remove excess material. The workpiece is held in a chuck or between centers, and the tool is driven longitudinally by hand or with a motor.

- ***Step Turning***

Step turning is a type of turning operation in which a series of steps of different diameters are created on a workpiece, resulting in a final product that resembles a step as shown in Fig 1.7

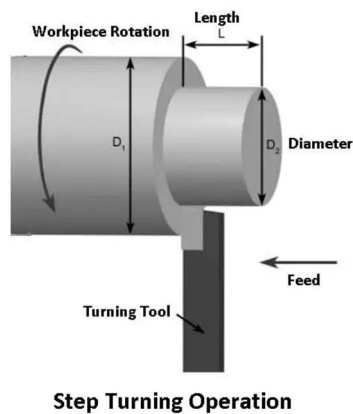


Fig 1.7 Step Turning Operation

- ***Taper Turning***

Taper turning is a machining operation in which the diameter of a cylindrical workpiece is gradually reduced from one end to the other. This can be accomplished by using a compound slide, a taper turning attachment, or by offsetting the tailstock on a lathe as shown in Fig 1.8.

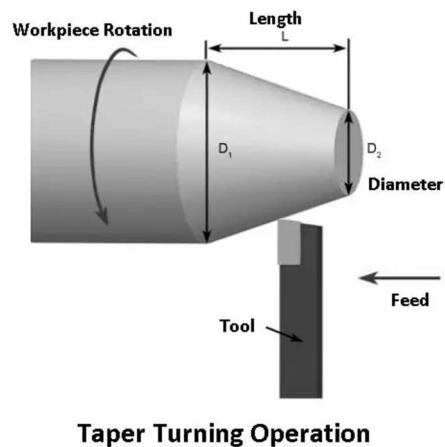


Fig 1.8 Taper Turning

- ***Chamfer Turning***

Chamfering is a machining process in which the end of a workpiece is bevelled, similar to step turning. This process is essential after threading to allow the nut to slide freely over the threaded workpiece. In addition, chamfering removes sharp edges, which significantly reduces the risk of cutting, as depicted in Figure 1.9.

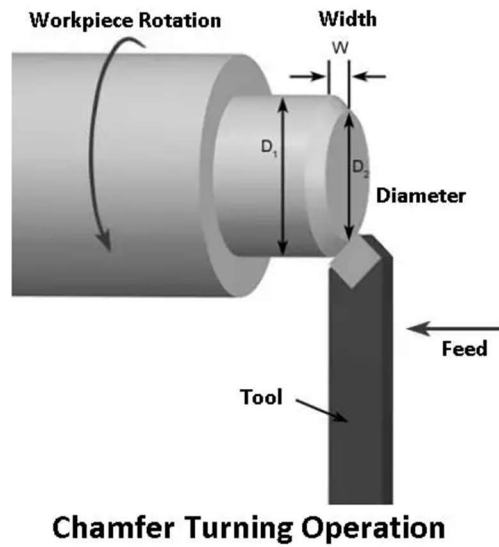


Fig 1.9 Chamfer turning operation

- ***Contour Turning***

In a particular type of turning operation, the cutting tool follows a predetermined axial path geometry to produce specific contours on a workpiece. Contouring tools must make multiple passes to achieve the desired shape on the workpiece. However, it is possible to create the same contour shape in a single pass by using shaping tools, as illustrated in Figure 1.10.

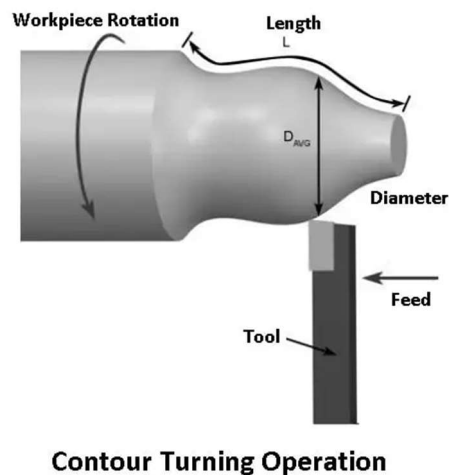


Fig 1.10 Contour Turning Operation

- ***Spherical Generation***

Spherical generation is a process for producing a finished surface by rotating a mould about a fixed axis of rotation. This process requires the use of a hydraulic copying device and a mould on a CNC lathe.

- ***Hard Turning***

The term "hard turning" refers to the process of turning materials with a Rockwell hardness greater than 45, typically after the workpiece has undergone heat treatment. The primary purpose of this process is to replace conventional grinding operations. Hard turning outperforms rough grinding in terms of stock removal alone. However, grinding is preferred for finishing where form and dimensions are critical.

- ***Eccentric Turning***

Eccentric turning is a machining process that involves two axes of rotation, where one axis is offset from the other. To perform this operation, three sets of centre holes are drilled. The workpiece can then be held at these three centres to perform a machining operation on each surface.

1.2.2 Dynamics of Turning Operation

- ***Forces***

The design of machine tools for turning operations relies heavily on the consideration of relative forces that can be absorbed by the machine without leading to notable deflections, vibrations, or chatter. Specifically, the three primary forces to be mindful of during turning are:

- i. **Cutting or tangential force:** The forces exerted on the tooltip during a cutting operation are directed downwards, resulting in an upward deflection of the workpiece. These forces play a vital role in providing the necessary energy for the cutting process.
- ii. **Axial or feed force:** The longitudinal force, also known as the feed force, acts in the direction of the feed of the equipment and causes the tool to move away from the lathe chuck
- iii. **Radial or thrust force:** It acts in a radial direction and pushes the tool away from the workpiece.

- ***Speed***

When it comes to turning operations, the appropriate cutting speed is determined by various factors such as the material of the cutter and workpiece, the hardness of the setup, the rigidity of the machine tool and spindle power, the chosen coolant, among others.

- ***Feed***

The feed in a turning operation refers to the distance that the tool travels through the material in a single revolution and is typically measured in millimeters per revolution (mm/rev).

1.2.3 Cutting parameters

- ***Cutting Feed***

In the context of turning operations, cutting feed refers to the distance that either the cutting tool or the workpiece travels during a single revolution of the spindle. This

measurement is usually expressed in inches per revolution (IPR) and corresponds to the feed per tooth for a multi-tip tool, which is measured in inches per tooth (IPT).

- ***Cutting Speed***

Cutting speed during turning is expressed in feet per minute (SFM) and indicates the speed at which the workpiece surface moves relative to the edges of the cutting tool.

- ***Spindle Speed***

The spindle speed in a turning operation is the number of revolutions per minute (RPM) at which the spindle and workpiece rotate. It is determined by dividing the cutting speed by the circumference of the workpiece.

- ***Feed Rate***

The speed at which the cutting tool moves in relation to the workpiece during a cutting operation is known as the cutting speed and is expressed in inches per minute (IPM).

- ***Axial Depth of Cut***

In a facing operation, the depth of the tool along the workpiece axis during cutting is referred to as axial depth of cut. A higher axial depth of cut will necessitate a reduction in the feed rate to avoid increasing the tool load and reducing the tool's lifespan.

- ***Radial Depth of Cut***

During a turning or boring operation, the depth of the tool changes as it moves across the radius of the workpiece. When dealing with large radial depths, it is crucial to employ a low feed rate to prevent excessive tool load, which can lead to reduced tool life.

1.2.4 Advantages of the turning process

- Every substance may be used in another.
- There is tremendous tolerance.
- The lead time is brief.
- A low-skilled operator is not necessary.
- The rate of material removal may be changed..

1.3 Cutting Tools

The purpose of a cutting tool is to shear off extra layers of material from a workpiece during machining in order to give it the correct form, size, and precision. It depends on different mechanical and other arrangements to provide the relative velocity between the workpiece and the cutting tool required for the cutting operation. It is securely attached to the machine tool.

1.3.1 Role of cutting tool

A cutting tool is a wedge-shaped object with sharp edges that is used to remove extra material from a workpiece in order to shape and size it to the appropriate dimensions. The cutting tool is fixedly attached to the machine tool and moves rather quickly to perform the cutting operation.

Metal cutting tools are utilized in the manufacturing process of metal components for machines. The process involves selective removal of metal to create the desired shape, ranging from simple to complex pieces of varying sizes. With the advancements in technology, metal cutting tools have evolved to be used on computerized numerical control (CNC) machines, which offer high precision and can produce complex parts of different shapes and sizes. Various techniques are used to remove unwanted metal, including single and multiple edge cutting tools, electrical discharge machining, and abrasive cutting using grinding methods.

1.3.2 Types of Cutting tool

The cutting process may vary depending on the conditions under which it is performed, and the cutting tool used may require unique properties in addition to meeting general requirements. The choice of material for a particular application is determined by factors such as the material to be machined, the type of machining, and the quality and quantity of production required.

i. Various types of tool bits

- ***High carbon steel cutting tool***

In the beginning, tool bits were typically manufactured using high carbon steel that was correctly hardened and tempered. This type of steel contained small amounts of silicon, chromium, manganese, and vanadium, which helped to refine the grain size and carbon content to between 0.6% to 1.5%. The maximum hardness that could be achieved with this material was approximately HRC 62. However, it had low wear resistance and hot hardness. Figure 1.11 illustrates a high carbon steel tool bit.



Fig 1.11 High carbon steel tool bits

- ***High-Speed Steel (HSS) cutting tool***

This is another high carbon steel featuring a significant quantity of alloys like chromium and tungsten to increase their hardness and wear resistance. HSS loses its hardness when temperatures hit 650 °C. It is, therefore, advisable to use coolants to increase tool life .Fig 1.12 shows various tool bits of HSS material.



Fig 1.12 HSS tool bits

- ***Cemented Carbide and Cement***

The cemented carbide cutting tool is created using metallurgy method. It is made from tungsten, titanium carbide and tantalum with cobalt as a binder. The most notable thing about the cemented carbide tools is that they are very hard and can be used for cutting at high speed and temperatures as shown in Fig 1.13. For example, you can use them for cutting at temperatures of 1000 °C without losing their properties.



Fig 1.13 Cemented carbide and cemented tool bits

- ***Ceramics***

The common ceramic materials used in cutting tools are silicon nitride and aluminium oxide. When the ceramic material powder is compacted and inserted at very high temperatures, the resulting tools are inert and resistant to corrosion. Therefore, they have high compressive strength. Fig 1.14 depicts ceramic glass drill bit. The ceramics are stable when operating even in temperatures of up to 1800°C and are about 10 times faster than HSS.



Fig 1.14 Ceramic glass drill bit

- ***Cubic Boron Nitride (CBN)***

CBN is the second hardest material and is commonly used in hand machines. They provide high abrasion resistance and utilize abrasive in grinding wheels. They are ideal at speeds of 600-800m/min. Fig 1.15 shows the Cubic Boron Nitride tool bit



Fig 1.15 Cubic Boron Nitride tool bit

- ***Diamond***

This is the hardest material used in tools. It features a high melting point and thermal conductivity. Therefore, it provides excellent abrasion resistance, low thermal expansion, and low friction coefficient. It is considered ideal for machining hard materials like glass, nitrides, and carbides. Fig 1.16 depicts diamond drill bit.



Fig 1.16 Diamond drill bit

ii. Classification of Cutting Tools

One or more projecting cutting edges that take part in simultaneous cutting in a single pass might make up a cutting tool. The category of the cutting tool is:

- ***Single Points Cutting Tool***

A cutting tool with only one primary cutting edge that can remove material in a single pass is referred to as a single-point cutting tool. Typical machining processes involving this tool include turning, shaping, and planing. Usually, it is constructed of strong materials like high-speed steel, high-carbon steel, ceramic, or diamond. There is a larger chance that the cutting edge will break since there is only one cutting edge engaged in the cutting process, which can result in a relatively sluggish rate of material removal. A single point cutting tool's appearance is depicted in Fig. 1.17.

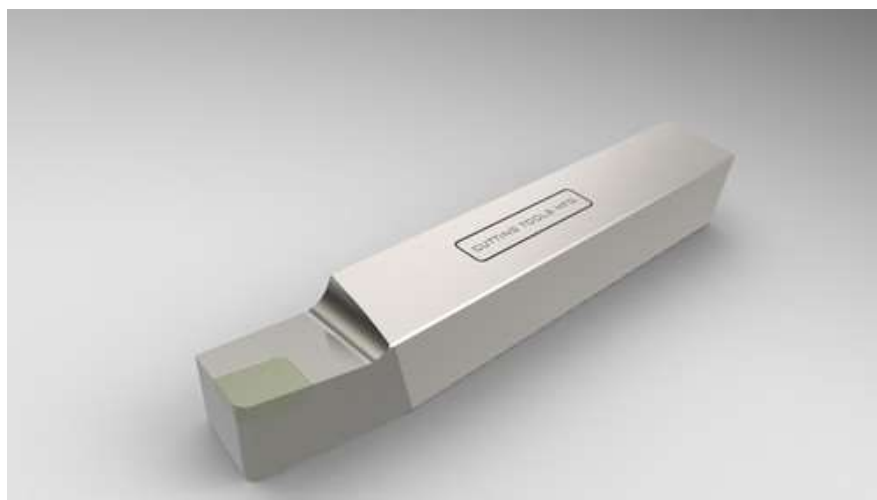


Fig 1.17 Single point cutting tool

- ***Double Point Cutting Tool***

While single-edged tools only have one main cutting edge, double point cutting tools feature two cutting edges that can cut and shear concurrently in a single action. On the other hand, multi-edged tools have more than two cutting blades and may complete many machining operations in one pass. Even though certain cutters are split into two categories, double-tip cutters are also referred to as multi-tip cutters. Figure 1.18 illustrates how a rake face and a flank come together to form cutting edges.

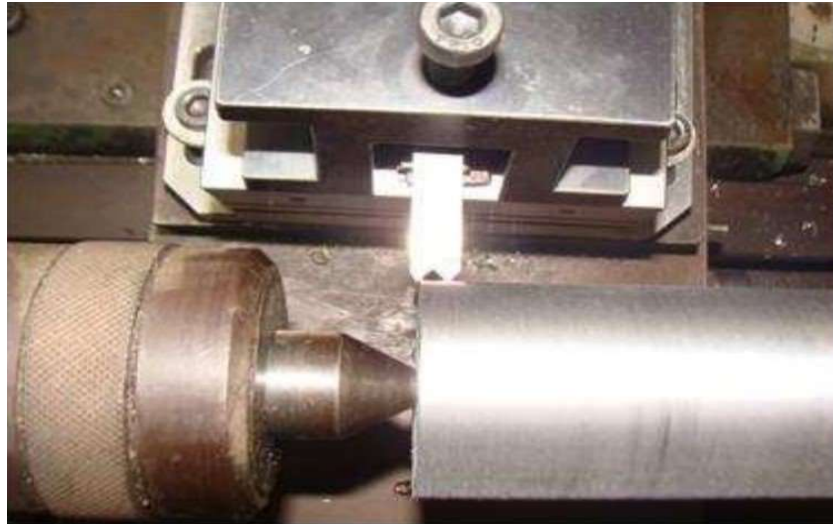


Fig 1.18 Double point cutting tool

- ***Multi-Point Cutting Tools***

A cutting tool with several main cutting edges working together in a single operation is called a multiple cutting tool. Some refer to a cutting tool with two cutting edges as a multiple cutting tool rather than a double cutting tool. The number of cutting edges in a multi-point tool can range from three to several hundred. Unlike a single point tool, a multi-point tool allows multiple cutting edges to be used simultaneously, resulting in more efficient material removal. This is shown in Fig. 1.19.



Fig 1.19 Multi point cutting tool

1.3.3 Single Point Cutting Tool Geometry

There are various components in the cutting tool geometry

1. Shank
2. Flank
3. Face 3/6 single-point cutting tool
4. Heel
5. Nose
6. Nose radius
7. Cutting Edges

Angle:

1. Side Cutting edge angle
2. End cutting edge angle
3. Side relief angle
4. End relief angle
5. Back Rack angle
6. Side rack angle

Here you can see in the Fig1.20:

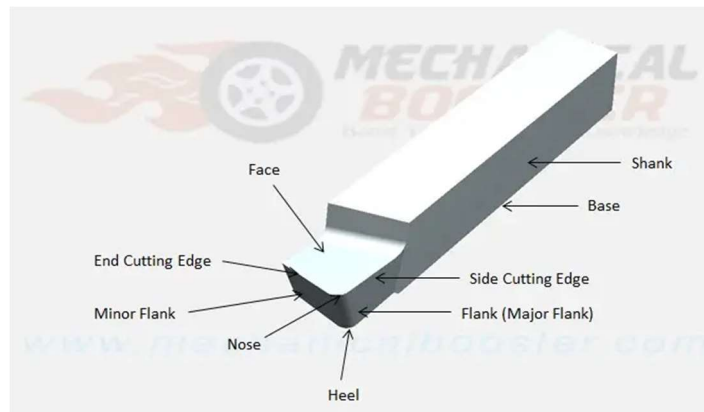


Fig 1.20 Single point cutting tool geometry

1. **The shank:** The tool's primary body is the shank. The tool (i.e., the tool holder) is held by the shank.
2. **Flank:** The flank of the tool is the area below and next to the cutting edge.
3. **Face:** The tool's face is the area where the chips roll over it.
4. **The heel :** is the location where the tool's base and flank converge. It is a curved portion on the tool's base.

5. **Nose:** This location marks the intersection of the side and end cutting edges. 4/6

6. **Nose Radius:** With a sharp tip on the nose, the nose radius offers extended life and a superb surface polish.

7. **Cutting Edge:** This is the edge on the face of the tool that removes material from the workpiece. The tool cutting edge consists of a side cutting edge, an end cutting edge

Angle:

1. **Side cutting edge angle:** this angle is also called the lead angle. This is the angle between the side cutting edge The lead angle is another name for the side cutting edge angle. The angle formed by the side cutting edge and the tool shank is seen here.

2. The angle between the end cutting edge and a line perpendicular to the tool shank is known as the end cutting edge angle.

3. **Side relief angle:** This is the angular relationship between a line perpendicular to the tool's base and measured at right angles to the end flank, and the area of the side flank just below the side cutting edge.

4. **End relief angle:** This is the arc formed by the end flank's part just under the end cutter and a line perpendicular to the tool's base that is measured at a right angle to the flank.

5. **Back rack angle:** This is the angle measured in a plane perpendicular to the side cutting edge between the tool's face and a line parallel to the tool's base.

6. **Side rack angle:** Measured in a plane perpendicular to the tool's base and the side cutter, this angle describes the angle formed between the tool's face and a line that is parallel to the tool's base.

1.4 Cutting Fluids

During machining or cutting operations, cutting fluids are liquids that are commonly applied. These operations can include milling, turning, drilling, and others. The primary purpose of cutting fluids is to remove the heat generated during metal cutting and other machining processes, and they can also serve as lubricants in certain cases. Cutting fluids are used to enhance cutting conditions and prolong the life of cutting tools.

Purpose of cutting fluids

- **Temperature control:** Cutting fluids are used to lessen the friction and heat that are produced between the cutting tool and the workpiece since high temperatures can shorten the tool's lifespan.
- **Lubricating:** The use of cutting fluids reduces friction and cutting forces by lubricating both the cutting tool and the workpiece.
- **Cleaning the Machines:** The removal of chips, particles, and debris that might possibly damage the surface finish is facilitated by the use of cutting fluids.
- Avoid dangerous contamination

Properties of Cutting Fluid

- High stability,
- Good lubricating qualities
- A high flash point
- Strong heat absorption capacity
- neutral characteristics.
- It must be nontoxic and odourless.
- Low viscosity; transparent

1.4.1 Role of Cutting fluids

Cooling lubricants are important fluids used in metalworking processes such as cutting, drilling, milling, and turning to achieve optimum performance and extend the life of the cutting tool and workpiece. Although commonly referred to as coolants or lubricants, metalworking fluids perform a variety of functions beyond simply cooling and lubricating. These fluids are used in machining to reduce the heat generated by the cutting process, which can deform the workpiece and damage the cutting tool. Cutting fluids also lubricate the tool and workpiece to minimize friction and wear of the cutting tool and workpiece. They also contribute to excellent surface finish and precise dimensional control. The composition of cooling lubricants varies depending on the machining operation and the materials involved. Typically, metalworking fluids are made by mixing water and oil with an emulsifier to force mixing. Synthetic fluids can be made by adding additional chemicals to improve their properties. Metalworking fluids are essential in metalworking and perform numerous functions beyond cooling and lubrication. They help minimize heat, reduce friction, improve surface finish and dimensional accuracy, and extend the life of cutting tools and workpieces.

1.4.2 Types of cutting fluids

- ***Neat oils***

Neat cutting oils are formulated from mineral oils blended with additives to improve their performance. They are supplied by the manufacturer without further dilution for use in cutting operations. These oils have excellent lubricating and cutting properties and help prevent corrosion, rust and wear on metal machinery and tools. Figure 1.21 shows an example of a pure cutting oil.



Fig 1.21 Neat Oil

- ***Soluble oils***

Soluble cutting oils, also known as emulsifiable oils, are lubricants used in metalworking to reduce friction and heat during cutting, drilling and grinding. Soluble Cutting Oil is a coolant and lubricant specifically designed for metalworking and machining processes. It is available in various forms such as oils, oil-water emulsions, pastes, gels and mists and can be made from various raw materials such as petroleum distillates, vegetable oils, animal fats and others. Depending on the type of cutting fluid, it is called soluble cutting fluid or soluble cutting oil. An example of a soluble oil is shown in Fig. 1.22.



Fig 1.18 Soluble oil

- ***Semi-synthetic cutting fluids***

Semi-synthetic cutting oils are commonly used in machining operations such as turning, milling, and drilling. They offer several advantages over conventional mineral-based cutting fluids, including improved cooling and lubrication properties, better rust and corrosion protection, and longer tool life. The synthetic component of the oil provides better lubrication, reduces friction and wear, and improves the overall performance of the cutting fluid. The mineral oil component of the oil provides good cooling properties and helps to flush away chips and debris from the cutting zone. Fig 1.23 depicts an example of semi synthetic cutting fluids.



Fig 1.23 semi synthetic cutting fluids.

- ***Synthetic cutting fluids***

Synthetic cutting oil is a type of cutting fluid that is formulated using synthetic base oils instead of mineral oils. Synthetic oils are chemically engineered to have specific properties such as high viscosity index, low volatility, and excellent lubricity. Synthetic cutting oils are commonly used in high-performance machining operations that require high-speed cutting, heavy-duty machining, and tight tolerances. They offer several advantages over conventional mineral-based cutting fluids, including improved thermal stability, better cooling and lubrication properties, and reduced environmental impact. Fig 1.24 shows an example of synthetic cutting fluids.

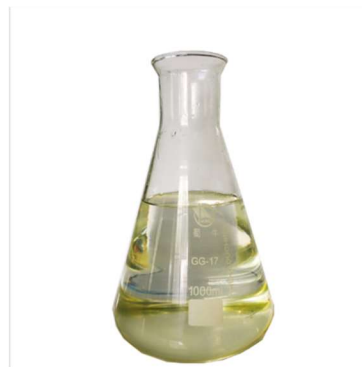


Fig 1.24 Synthetic cutting fluids

1.5 Minimum quantity lubrication (MQL)

1.5.1 Introduction

Minimum Quantity Lubrication (MQL) is a modern method of lubrication that reduces the amount of coolant or lubricant used in machining processes. MQL is a sustainable solution that promotes environmental responsibility by minimizing the amount of waste generated during the machining process. MQL is an innovative lubrication technique that uses a small amount of lubricant or coolant that is directed precisely to the cutting zone of the tool. This minimal amount of lubricant is sufficient to ensure efficient and reliable machining, while also reducing the amount of waste and costs associated with traditional flood lubrication methods. MQL systems can be used with a variety of cutting tools and

materials, including metals, plastics, and composites. The lubricant used in MQL can be either oil or water-based and is delivered to the cutting zone through a series of micro-nozzles or atomizers Fig 1.25 depicts the schematic diagram of MQL process

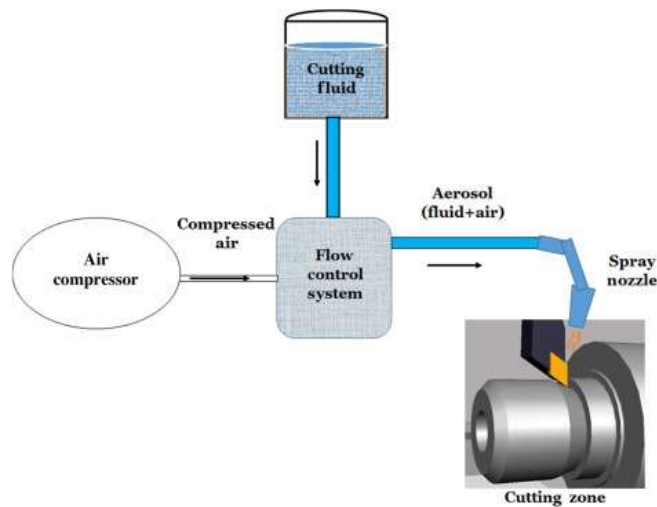


Fig 1.25 Schematic Diagram of MQL process

1.5.2 Functions of MQL

Minimum Quantity Lubrication (MQL) is a metalworking fluid system that provides a significant reduction in the amount of lubricant used during the machining process compared to conventional flood lubrication systems. Instead of using large quantities of lubricant, MQL uses only a few millilitres of lubricant per hour. The lubricant dosage is so precise that it is almost completely consumed during the process. This results in nearly dry workpieces and chips, which reduces health hazards caused by emissions of metalworking fluids on the skin and in the air breathed by employees.

Compared to emulsion lubrication, which may result in considerable wastage due to evaporation and may pose health hazards, MQL is a safer and more environmentally friendly option. With MQL, there is no need for metalworking fluid maintenance, preparation, or disposal, and there is a decrease in the work required to clean the processed pieces. The chips produced during the MQL process are nearly dry, which makes them easy to recycle and reduces oil soiling.

By using MQL, the cost-inflating factors of conventional flood lubrication can be eliminated. The reduction of metalworking fluid quantities used in MQL not only saves money, but also reduces the need for monitoring and maintenance. This makes the machining process more efficient, less hazardous, and more sustainable.

1.5.3 Benefits of MQL

- Efficient, environmentally friendly near-dry machining practises can lead to several types of cost savings and improvements in a manufacturing operation, as shown in Fig. 1.26.

- Significantly reduced fluid/lubricant consumption.
- Safer cutting fluids and lubricants.
- Fewer health hazards for employees.
- Longer tool life.
- Lower fluid disposal cost.
- Faster machining speeds and feeds.
- And a cleaner shop with reduced maintenance.

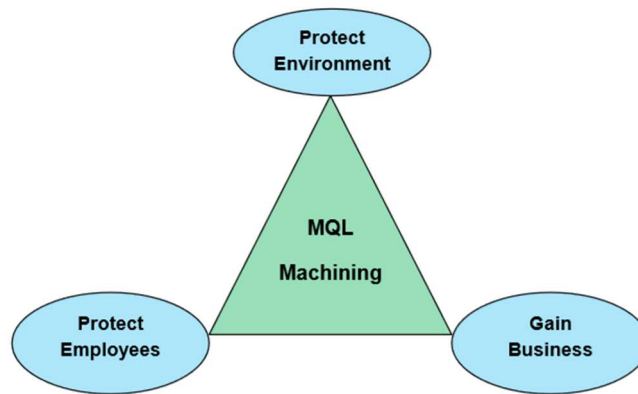


Fig 1.26 Benefits of using MQL

1.5.4 Over- and Under-lubrication:

Insufficient grease in a machine component can lead to its rapid failure, while over-greasing can also have adverse effects. It is crucial to keep in mind that lubricants occupy a specific volume. Too much grease can cause clogs, leading to additional maintenance and downtime. Over-greasing can also result in seal failure, as grease guns can generate high levels of pressure that may harm bearings. Additionally, excess pressure from the lubricant can cause grease to dry and crack, exacerbating the damage to bearings. Ultrasound readings can be used by technicians to determine the optimal amount of grease needed.

1.6 MQL setups

In an NDM/MQL system, aerosol can be introduced into the cutting zone through external nozzles installed in the machine area or internally through channels built into the tool. The choice between external and internal supply units depends on the specific machining operation being performed. Figure 1.27 illustrates different MQL supply systems.

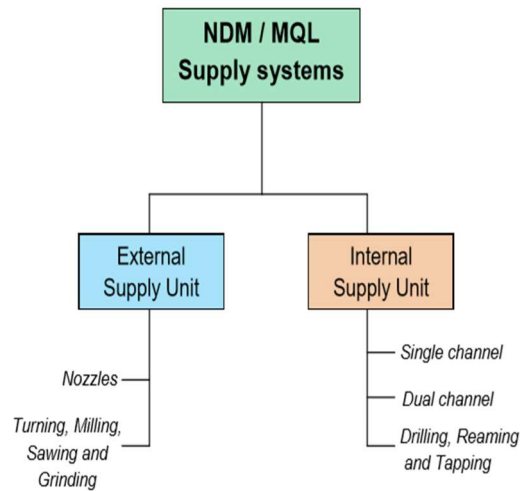


Fig 1.27 MQL supply systems

1.6.1 External supply unit

The coolant reservoir or tank and one or more nozzles are linked by hoses to form the external supply system for MQL. This system includes adjustable air and coolant flow that may be put close to the machine to maximise supply. It is a portable, cost-effective solution for machining tasks including turning, milling, sawing, and grinding. For MQL with an external aerosol supply system, there are two choices. In the first option, the ejector nozzle receives oil and compressed air, and the aerosol develops right behind the nozzle. In the second scenario, MQL employs a standard nozzle similar to one seen in a flooded coolant delivery system. An external atomizer prepares the aerosol, which is then fed into the conventional nozzle, as shown in Fig 1.28.

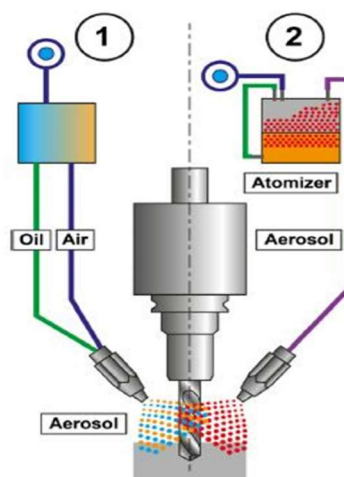


Fig 1.28 Principle of MQL with external supply unit

The use of multiple nozzles for MQL processing is illustrated in Fig. 1.29. The first nozzle injects cutting fluid to minimize friction between the tool and the workpiece, resulting in reduced flank wear. The second nozzle helps with the chip curve caused by the rebonding effect and cools the process. This removes the heat generated in the primary shear zone. The third nozzle ejects fluid to remove heat from the secondary shear zone at the rake face.

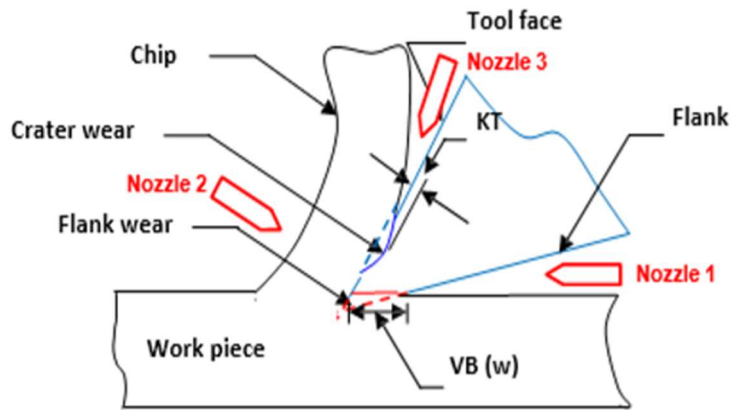


Fig 1.29 Use of multiple nozzles for machining under MQL

1.6.2 Internal supply unit

The single-channel system and the dual-channel system are two different internal supply system types that are depicted in Fig. 1.30. The aerosol mixture is created outside the spindle and delivered through a single channel in the single-channel system. To create the aerosol directly in front of the tool, either as it leaves the spindle or while it is in the tool holder, air and oil are fed independently through the spindle or rotating union in the two-channel system.

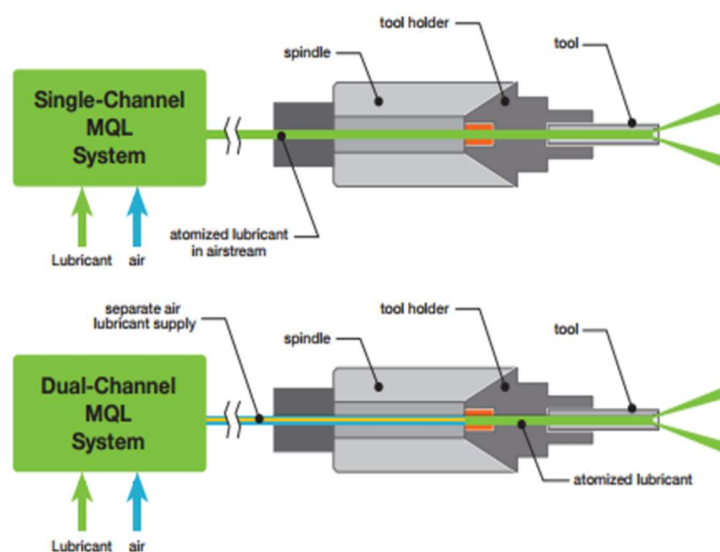


Fig 1.30 MQL internal supply systems

Types of cutting fluids used in MQL

- ***Nano Cutting Fluids***

Nano cutting fluids are a type of cutting fluid that contain nanoparticles, which are particles with sizes ranging from 1 to 100 nanometres. These nanoparticles can be made of various materials, such as ceramics, metals, and polymers, and are added to the cutting fluid to enhance its performance. Fig 1.31 shows various examples of nano cutting fluids

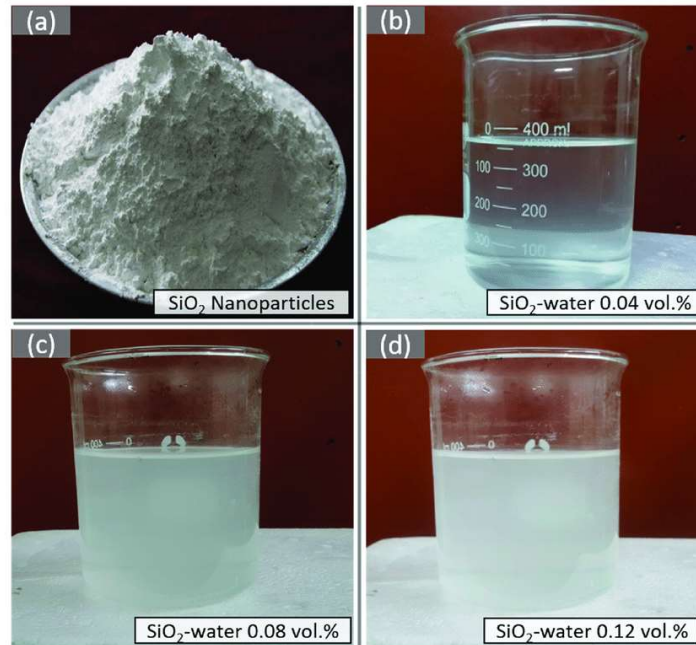


Fig 1.31 Nano Cutting Fluids

- ***Solid cutting fluids***

Solid cutting fluids, also known as dry cutting or near-dry machining, are a type of cutting fluid that come in a solid form, such as a wax or a powder. Unlike traditional liquid cutting fluids, solid cutting fluids do not require a coolant system to apply them during metalworking operations Fig 1.32 depicts an example of solid cutting fluid



Fig 1.32 Solid cutting fluids

1.7 Importance of flowrate in MQL

A minimal quantity of lubricant is applied to a cutting tool or workpiece during machining as part of a process known as minimum quantity lubrication (MQL). The quantity of lubricant delivered to the cutting tool or workpiece and, consequently, the efficacy of the lubrication, are both influenced by the lubricant's flow rate, which is a critical component of MQL. In MQL, the lubricant is delivered as a fine mist or droplets, with the size and frequency of the droplets depending on the flow rate. The droplets may be excessively big and not disperse uniformly throughout the cutting tool or workpiece if the flow rate is too low, resulting in insufficient lubrication and consequent tool wear or damage. On the other side, excessive lubrication may result in problems including chip blockage, poor cutting performance, and more frequent cleaning procedures if the flow rate is too high. Because of this, it's crucial to optimise the flow rate for the particular machining process, taking into consideration elements like cutting speed, tool shape, material qualities, and lubricant properties. By doing so, you may save waste and costs while improving lubrication and machining performance.

1.8 MQL machine equipment

1.8.1 Lathe Machine

A lathe is a machine tool used to form a piece of material by rotating it against a cutting tool. The material is usually held in a chuck attached to a spindle. The spindle rotates the chuck and the material while the cutting tool is stationary or moves against the material to remove it. Lathes are used for a variety of machining operations, including turning, facing, drilling, boring and tapping

Parts of Lathe Machine

A lathe machine consists of several parts as shown in Fig 1.33



Fig 1.33 Lathe Machine

- **Bed:** The bed is the base of the machine and serves as support for all other parts.
- **Headstock:** The headstock contains the spindle and the gear for turning the spindle.
- **Tailstock:** The tailstock is located at the opposite end of the lathe from the headstock and is used to support the other end of the material being machined.
- **Carriage:** The slide holds the cutting tool and can be moved along the bed to make cuts on the material.
- **Chuck:** The chuck holds the material being machined and rotates it against the cutting tool.
- **Cross slide:** The cross slide moves the cutting tool perpendicular to the axis of the lathe, allowing facing and other operations.
- **Cross slide:** The cross slide holds the cutting tool and can be switched to perform angular cuts.

Working of a Lathe Machine

The operation of a lathe includes the following steps The material to be machined is clamped in the chuck and the chuck is attached to the spindle The cutting tool is mounted on the slide or cross slide. The spindle is rotated through the headstock and the cutting tool is moved toward the material. The cutting tool removes material from the material and shapes it as desired. The cutting tool can be moved along the bed and cross slide to make cuts at various positions on the material.

Applications of Lathe Machines

Lathes are used for a broad range of machining operations and are commonly found in machine shops and manufacturing facilities. Some of the common applications of lathe machines include:

- **Turning:** The process of removing material from the surface of a cylindrical workpiece to produce a desired shape.
- **Facing:** The process of removing material from the face of a workpiece to produce a flat surface.
- **Drilling:** The process of making holes in a workpiece with a rotary cutting tool.
- **Boring:** The process of enlarging an existing hole in a workpiece.
- **Tapping:** The process of tapping a cylindrical workpiece.
- **Taper Turning:** The process of creating a conical shape on a workpiece.
- **Knurling:** The process of creating a pattern of small, diamond-shaped impressions on the surface of a workpiece.

1.8.2 Mist Spray

Mist spray is a type of spray that produces a fine mist of liquid particles. It is commonly used for a variety of applications such as in cosmetics, agriculture, cooling systems, and

more. Mist sprays are typically produced through the use of specialized equipment such as misting nozzles or atomizers, which break down a liquid into tiny droplets that can be easily dispersed as shown in Fig 1.34.

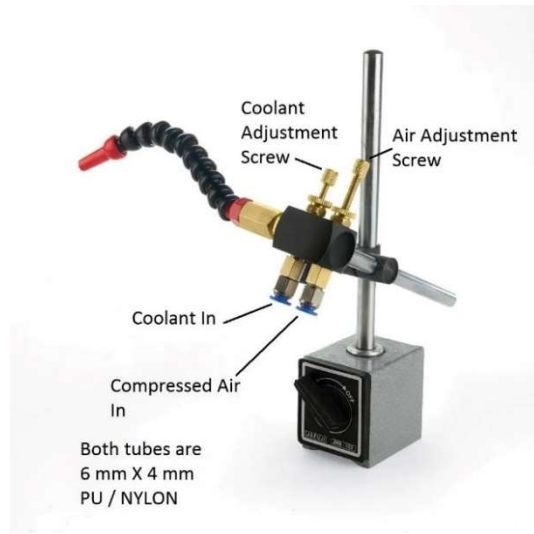


Fig 1.34 Mist Spray set up

Working of Mist Spray

Mist sprays work by atomizing a liquid into a fine mist that can be easily dispersed in the air. The liquid is typically fed through a nozzle or atomizer that uses pressure, ultrasonic vibrations, or other methods to break the liquid into tiny droplets. These droplets are then sprayed out of the nozzle and into the air, where they can be used for a variety of applications.

i. Types of Mist Sprays:

- ***Ultrasonic Mist Sprays***

These types of mist sprays use ultrasonic vibrations to create a fine mist of liquid particles. The vibrations break down the liquid into tiny droplets that are then dispersed into the air as shown in Fig 1.35

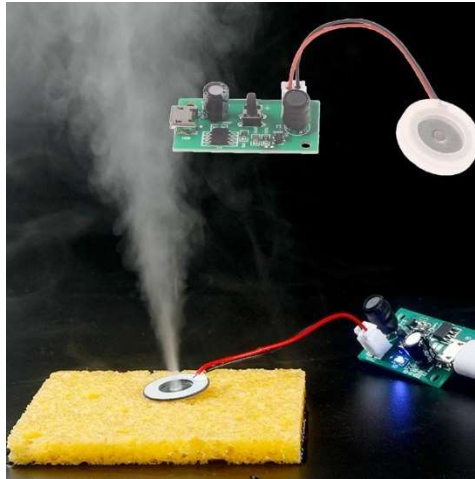


Fig 1.35 Ultrasonic Mist Sprays

- ***Pressure Mist Sprays***

These types of mist sprays use pressure to create a fine mist of liquid particles. The liquid is fed through a nozzle that is designed to create a high-pressure environment, which breaks down the liquid into tiny droplets that are then sprayed into the air as shown in Fig 1.36



Fig 1.36 High pressure mist spray

1.8.3 Air compressor

An air compressor is a mechanical device that is used to compress air and store it in a tank for later use. Air compressors come in different sizes and types, ranging from small, portable units to large industrial-sized models. They are commonly used in various industries, including manufacturing, construction, automotive, and agriculture. Fig 1.37 shows air compressor used during the experiment.



Fig 1.37 Air compressor overview

Use of air compressor in MQL process

- Minimum quantity lubrication (MQL) projects use air compressors to drive pneumatic systems that provide lubrication and cooling for machining processes. MQL is a method of lubricating and cooling metalworking processes using small amounts of oil and air. Compressed air from the compressor is used to atomize the oil into small droplets, which are then sprayed onto the cutting tool and workpiece. The air also helps cool the machining area and reduce the heat generated during the cutting process.
- Air compressors are an essential part of MQL systems because they provide the pressure and flow necessary to atomize and deliver the oil to the cutting tool. They also help regulate the temperature in the machining area to prevent overheating and reduce the risk of damage to the workpiece or cutting tool.

CHAPTER 2

LITERATURE SURVEY

2.1 Literature review on MQL based experiments

Harshit B. Kulkarni *et.al* (2019) [1] In order to evaluate the effects of minimal quantity lubrication (MQL) coolant supply to the traditional flood cooling approach when surface milling Al7075-T6 aerospace aluminium plates with an uncoated carbide tool, the study employed a complete factorial design with ANOVA-based analyses. The spindle speed, feed rate, and depth of cut were taken into consideration in the study. The outcomes demonstrated that, in terms of surface finish (Ra) and lowest temperature (T) values, the MQL technique performed better than dry milling and nanofluid MQL milling. Additionally, decreasing the temperature at the tool-interface without impacting milling performance was a benefit of adding nanoparticles to the coolant.

Jinyang Xu *et.al* (2019) [2] Although minimal quantity lubrication (MQL) is frequently employed in the machining of metallic materials, little research has been done on how it affects the drilling characteristics of composite metal stacks. To close this gap, a research on the drilling of a composite titanium stack made up of sheets of Ti6Al4V and carbon/epoxy laminates T700/FRD-YZR -03 was carried out. Using tungsten carbide twist drills, it looked at how MQL parameters impact drilling pressure, surface form, the severity of drilling flaws, geometric precision of drilling, and tool wear indicators. According to the study, MQL drilling enhanced the cut composite holes' surface morphology but had no impact on the pressure within the holes, the degree of delamination, the severity of drill wear, or the cylindricity defects inside the holes.

E A Rahim *et.al* (2011) [3] In this article, it is suggested that during MQL machining, a little quantity of lubricant be added to the area where the tool and workpiece meet. The study looked at how palm oil and synthetic ester, two different MQL lubricants, affected drilling of Ti-6Al-4V. The findings revealed that dry machining had the shortest tool life, whereas MQL enhanced a number of measured responses, including temperature, thrust, and tool life. Because of its capacity to create a thin coating that permitted boundary lubrication throughout the machining process, palm oil was found to perform better than other oils. In terms of microhardness, surface roughness, and subsurface deformation, palm oil fared better than synthetic ester.

E. A. Rahim *et.al* (2014) [4] The implications of typical mineral-based cutting fluids on the environment, worker health, and machining costs are mentioned by the authors. Alternatives like minimal quantity lubrication (MQL), cryogenic coolants, and dry machining have all showed promise, particularly in terms of prolonging cutting tool life. This study compared the effectiveness of a synthetic ester cutting fluid based on MQL to the dry technique in orthogonal cutting tests. The findings demonstrated that MQL was superior to dry cutting in

terms of lowering the machining process's cutting temperature, cutting force, tool-chip contact time, and chip thickness.

O. Pereira *et.al* (2016) [5] In their study, the authors propose a more efficient machining method that combines cryogenic cooling and minimal amount lubrication. The findings show that this combination strategy extends tool life by over 50%, increases cutting speed by over 30%, and keeps or even enhances cutting forces and surface integrity. The combination of cryogenic and lubricating techniques was determined to establish a compromise between technical and environmental issues after a life cycle study was done to compare other options. Single-system solutions were found to fall short of being complete.

Anuj Kumar Sharma *et.al* (2016) [6] The method of near-dry machining (NDM) or minimal quantity lubrication (MQL), which optimises the spraying of a compressed air-cutting material mixture instead of flood cooling, is covered in the article. The paper looks at a number of research investigations on the MQL approach, including the use of cutting fluids based on nanofluids, vegetable oils, and mineral oils for different machining operations. It describes the MQL technique's workings and assesses how it affects performance metrics. Experimental research has demonstrated that MQL delivers a surface finish that is comparable to wet machining and superior than dry machining. It is a desirable substitute for flux lubrication since it also lowers cutting forces, cutting zone temperature, tool wear, and friction coefficient.

2.2 Literature review on turning processes

E. Budak and E. Ozturk (2011) [7] said that due to the use of numerous cutting tools, parallel turning provides improved productivity. The security of the process is impacted by the dynamic interplay between the instruments, which requires analysis. This research models the kinetics and stability of simultaneous turning processes. The outcomes of the created stable models in the frequency and time domains exhibit fair accord. The possibility of enhanced stability as a result of dynamic tool contact producing an absorber effect on one another is one of the intriguing results. When the expected stability boundaries are compared to the experimental findings, a believable alignment is shown.

Yousef Shokoohi *et.al* (2015) [8] The process of turning is crucial in metal cutting, and the heat produced during this process affects the quality of the final product and energy consumption. A study was conducted to examine the effectiveness of a new cooling technique that involved mixing water, vegetable oil, anti-bacterial agent, and scented essence. The findings indicated that this method resulted in significant improvements in machining parameters, operator health, and environmental concerns. This combined cooling technique has the potential to increase productivity by improving machining quality, reducing costs, and promoting environmental protection.

Alakesh Manna and Sandeep Salodkar (2007) [9] The authors of the paper proposed a procedure for determining optimal machining conditions in a turning operation with the objective of minimizing production costs. They used the Taguchi method to optimize cutting

parameters and establish a mathematical model that relates to the surface roughness height Ra. The model helped to identify the most effective parameter for cost optimization and analyze the effects of different input constraints at the optimal point. The study provides useful graphical representations to understand and evaluate the influences of various parameters on production cost.

2.3 Literature review on various optimization techniques

Gilberto Miller Devós Ganga and Luiz Cesar Ribeiro Carpinetti (2011) [10] The authors of the paper propose a new model to predict supply chain performance by combining fuzzy logic and SCOR model metrics. The model is tested through a quantitative approach, and statistical analysis confirms the causal relationships. The use of fuzzy logic allows dealing with uncertainty and subjectivity in supply chain management. This paper introduces a valuable tool for supply chain performance management.

H.D. Cheng and Huijuan Xu (2000) [11] The authors proposed a new method for adaptive direct fuzzy contrast enhancement that utilizes fuzzy entropy and fuzzy set theory. The objective of this method is to enhance image contrast by determining a criterion for measuring contrast and using it to perform enhancement. Unlike other enhancement methods, this method is directly applied to the image and adjusts the enhancement process based on the image's characteristics. The experimental results demonstrate that the proposed algorithm is successful in enhancing contrast while avoiding over-enhancement. This method presents a new avenue for future research in the fields of image processing, pattern recognition, and computer vision.

Giovanni and Maria (1983) [12] The speaker explained that Response Surface Methodology (RSM) is a statistical approach that utilizes quantitative data obtained from experimental designs to establish and solve multivariate equations. These equations are then represented graphically as response surfaces, which illustrate how the test variables impact the response. By providing insight into the interrelationships among the variables and describing their combined effect on the response, RSM can assist product developers in comprehending ingredient interactions within the product. This understanding can aid in formulating the final product and in anticipating future cost and quality variations.

Marcos Almeida Bezerra *et.al* (2008) [13] The paper discusses the use of response surface methodology (RSM) to optimize analytical methods. It compares various symmetric experimental designs such as three-stage factorial experimental designs, Box-Behnken experimental designs, central composite experimental designs, and Doehlert experimental designs and highlights their applications in analytical chemistry. The paper also discusses the use of desirability functions for multiple response optimization and the use of artificial neural networks for modelling.

Shyam Narayan Pandey and Shahnawaz Alam (2015) [14] In their study, the authors focused on electrical discharge machining, an unconventional machining process used in various

industries to produce high-value parts. In particular, they investigated the effects of electrode material selection on the machining of difficult-to-machine materials with the aim of determining the most suitable material for machining stainless steel-202. To evaluate the performance of different materials, the study considered two important factors: Material removal rate and electrode wear rate.

Ishwer Shivakoti *et.al* (2018) [15] In this article, the process parameters for turning stainless steel-202 were examined using parametric analysis and an ANFIS-based modelling strategy. They employed the Taguchi L16 DOE experimental design with feed rate, spindle speed, and depth of cut as their three turning parameters. Evaluation and analysis of the impacts of process parameters on performance was done for material removal rate (MRR) and surface roughness (Ra) performance. The answers were correctly predicted by the ANFIS-based model, and the outcomes were compared and confirmed.

Gurudatt Ghadi and Dr. Shivakumar S (2016) [16] The goal of this study is to examine the stainless steel (SS 202) TIG welding parameters that are utilised to create pressure vessels and heat exchangers. A non-melting tungsten electrode is utilised in the tungsten arc welding (GTAW) method, which is often employed for a range of metals. Prioritising the welding input parameters and calculating the tensile strength, flexural strength, and BHN value are done using the complete factorial design approach. Tensile, flexural, and hardness tests are used to assess the weldments' qualitative qualities.

G Vignesh *et.al* (2019) [17] The goal of this study was to determine the stainless steel sheet 202's 0.8 mm forming limit during incremental single point sheet forming (SPIF). In the investigation, various process variables including spindle speed, feed rate, and vertical infeed were employed. Additionally, the study measured dislocation density and examined fractograms. Forming limit diagrams (FLDs) based on stress and strain were both produced. Additionally, the corrosion behaviour of specimens that were distorted and those that were not was examined.

SCOPE FROM LITERATURE SURVEY

From the following literature reviews we had come to know about following things:

- MQL based operations helps in utilizing the lubricants in the most efficient manner
- Turning processes showing the possibility of improved stability through dynamic tool contact hence reducing tool wear. So turning operation may give the best output.
- Fuzzy logic optimization along with regression analysis and response surface optimization are best in determining the required output parameters.

CHAPTER 3

MATERIALS AND METHODOLOGY

3.1 Materials used in MQL experiment

3.1.1 SS202

The material selected for the research project is SS202 as our material as shown in Fig 3.1. The properties and applications of the material are discussed below



Fig 3.1 SS202 material

Stainless steel 202 is a type of austenitic stainless steel that contains chromium, nickel, and manganese. It is a lower-cost alternative to other types of stainless steel such as 304 or 316, but it is not as corrosion-resistant and has lower toughness and ductility. Stainless steel 202 is commonly used in appliances, kitchenware, and automotive parts.

Stainless steel 202 is magnetic and has a higher yield strength compared to 304 stainless steel. It also has good formability and is relatively easy to weld, making it suitable for a variety of applications such as kitchenware, appliances, automotive parts, and architectural trim.

However, due to its lower corrosion resistance, stainless steel 202 is not recommended for use in highly corrosive environments or applications exposed to high temperatures. In general, it is a versatile and cost-effective stainless-steel grade that can be a good option for certain applications where corrosion resistance is not the primary concern.

Chemical Composition

The chemical composition of grade 202 stainless steel is outlined in the following table 3.1.

Table 3.1 Chemical Composition of SS202

Element	Content (%)
Fe	68.1
Cr	16.8-18.2
Mn	7.5- 9.5
Ni	4.1-6.6
Si	<1
N	<0.25
C	<0.15
P	<0.060
S	<0.030

Table 3.2 Physical properties of SS202

Properties	Value
Density	7.9 g/cm ³
Melting Point	1454°C (2650°F)
Thermal Conductivity	16.3 W/m·K at 20°C (68°F)
Electrical Resistivity	0.74 μΩ·cm at 20°C (68°F)

Table 3.3 Mechanical Properties of SS202

Properties	Value
Tensile Strength	520 MPa (75 ksi)
Yield Strength	275 MPa (40 ksi)
Elongation At Break	40% in 50 mm (2 in.)
Thermal Expansion Coefficient	(@20-100°C/68-212°F): 11.7 x 10 ⁻⁶ cm/cm°C (6.56 in./in./°F)
Modulus Of Elasticity	(@20°C/68°F): 193 GPa (28 x 10 ⁶ psi)

Applications

- Equipment for restaurants.
- Kitchen tools.
- Sinks.
- Trim for automobiles.
- Architectural elements like doors and windows.
- Train cars.
- Trailers.

3.1.2 Lathe (Cone Pulley) Pilot, 6', Png-2



Fig 3.2 Lathe (Cone Pulley) Pilot, 6', Png-2

Lathe machine used for doing this experiment is **Lathe (Cone Pulley) Pilot, 6', Png-2** shown in Fig 3.2. Table 3.3 shows specification of lathe .

Table 3.3 specifications of Lathe (Cone Pulley) Pilot, 6', Png-2

Maximum Swing Over Bed	250mm
Power Source	Electric
Max Spindle Speed	1000 Rpm
Max Turning Diameter	500 Mm
Material	Ms
Voltage	220-440v
Frequency	50-60 Hz

3.1.3 Mist Spray

Mist spray used in our experiment is shown in Fig 3.3



Fig 3.3 Mist Spray

3.1.4 Cutting tool

Cutting tools are essential for various machining operations, and there are many different types of cutting tools available for different applications. The choice of cutting tool depends on the material being machined, the desired shape and finish, and the cutting conditions.

Cutting tool Used in our Project is CNMG 120404MS as shown in Fig 3.4 and Fig 3.5



Fig 3.5 CNMG 120404MS

CNMG 120404MS is a specific type of cutting tool insert that is commonly used in turning operations. Here's a breakdown of what each part of the code means:

CNMG: This is the ISO code for a turning insert with a rhombic shape.

120404: The first two digits (12) represent the nominal insert length in millimeters. The second two digits (04) represent the nominal insert width in millimeters. The last two digits (04) represent the thickness of the insert in millimeters.

MS: This refers to the specific grade of material that the insert is made from. In this case, MS likely stands for a specific grade of carbide designed for machining steel.

3.1.5 Air compressor



Fig 3.5 Air compressor

3.1.6 Surface Roughness Instrument

Surface roughness instruments are devices used to measure the roughness of surfaces. For this experiment we had carried used PCE-RT-11 device as shown in Fig 3.14

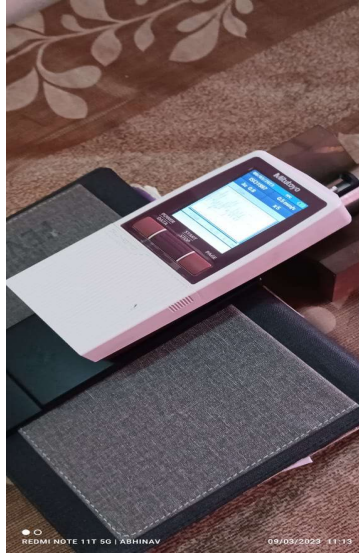


Fig 3.6 PCE-RT-11 device

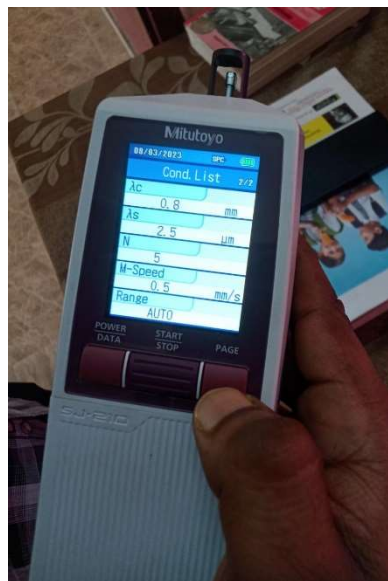


Fig 3.7 Condition List of instrument

Surface Roughness Parameters:

Surface Roughness measurement parameters such as **Ra, Rz, Rp, Rv and Rt.**

Rp: Maximum profile peak height Rv: Maximum profile valley depth Rz: Maximum height of the profile Ra: Arithmetic mean deviation

Other parameters: R_{sk} , R_{ku} , Rq , Rz_{lmax}

3.2 Minitab

3.2.1 Introduction

A variety of fundamental and sophisticated data analysis features are offered by the user-friendly statistical analysis software programme known as Minitab. Because of its straightforward command syntax, individuals with different backgrounds and degrees of expertise may use it with ease. The programme is compatible with the majority of popular workstations, minicomputers, and mainframes in addition to PC and Macintosh systems. It is simple to transition between versions since the worksheet and instructions are consistent across computer systems and versions. The Windows version of Minitab provides a user-friendly interface with pull-down menus and dialog boxes that prompt the user at every step to make statistical analysis more intuitive. Data can be entered into a spreadsheet-like window or imported from other software programs. Minitab's graphics capabilities offer unlimited possibilities for creating visually impressive presentations, and macros allow custom operations for specific applications. A screen shot of the Minitab interface is shown in Figure 3.8.

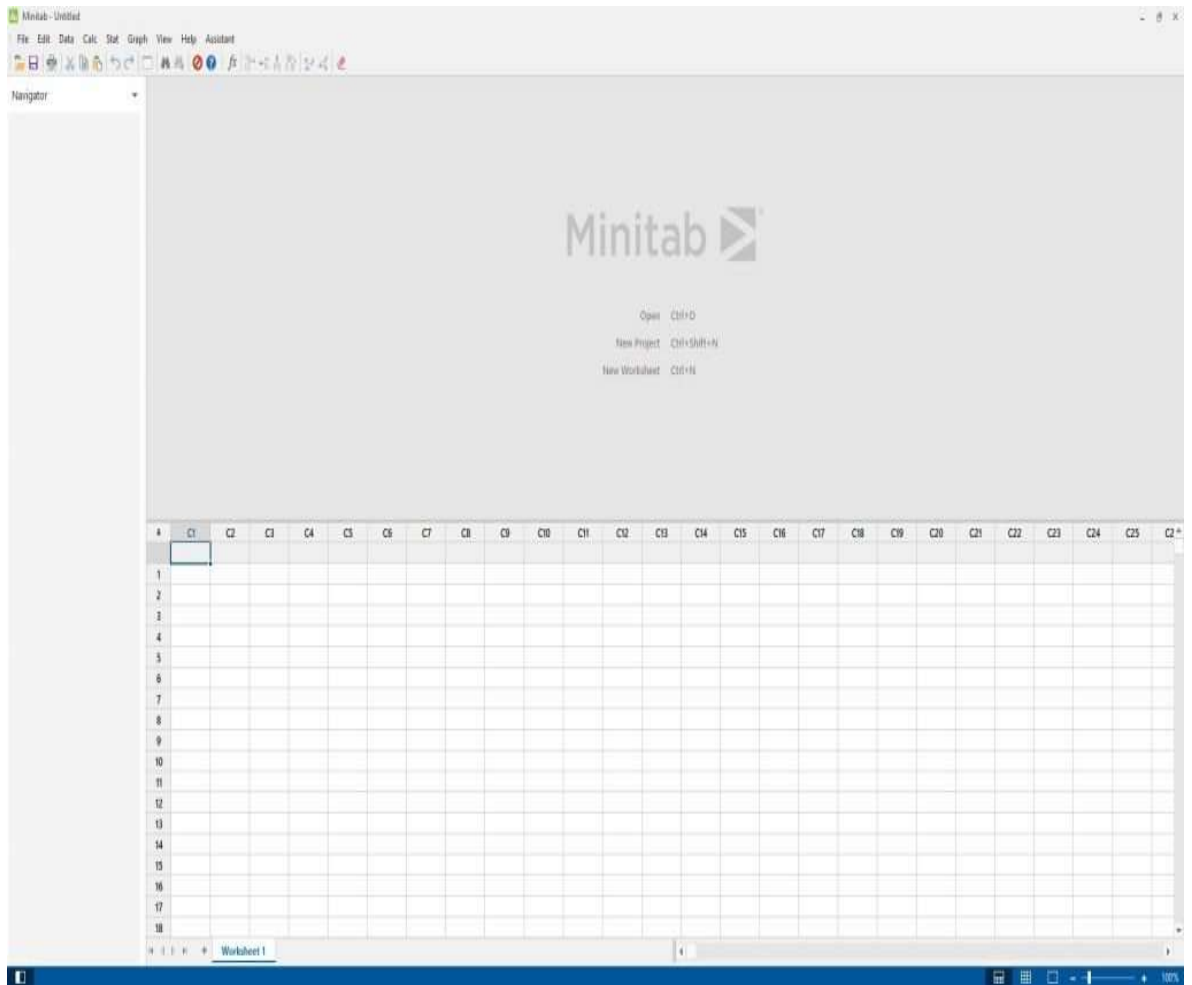


Fig 3.8 Minitab interface

3.2.2 Specifications of MINITAB

- **Operating systems:** Windows 8, Windows 10, Windows 11, MacBook.
- **RAM 32-bit systems** - 1 GB (minimum), 64-bit systems - 2 GB (minimum).
- **PROCESSOR** intel® Pentium® 4 minimum.
- **Hard disk space:** 2 GB (minimum) free space required.
- **Screen resolution:** 1024 x 768 or higher.
- **Connectivity:** Internet connection is required for Minitab installation/activation and help content

3.2.3 FEATURES OF MINITAB

- Assistant
 - i. Hypothesis Tests.
 - ii. Capability Analysis.
 - iii. Control Charts.
- Graphics
 - i. Contour and rotating 3D plots.
 - ii. Automatically updates graphs as data change.
 - iii. Brush graphs to explore points of interest.
- Basic Structures
 - i. Descriptive Statistics.
 - ii. Normality Tests.
 - iii. Outlier Tests.
- Reliability/Survival
 - i. Goodness of fit measures.
 - ii. Accelerated life Testing.
 - iii. Multiple Failure Modes.
- Stimulations and Distributions
 - i. Random Number Generator.
 - ii. Random Sampling.
 - iii. Bootstrapping and Randomization Tests.
- Multivariate
 - i. Factor Analysis.
 - ii. Discriminative Analysis.
 - iii. Cluster Analysis.
- Macros and Customizations
 - i. Python Integration.
 - ii. R Integration.

- iii. Customizable Menus and Toolbars.
 - Time Series and Forecasting
 - i. Time Series Analysis.
 - ii. Trend Analysis.
- iii. Forecast with ARIMA Model.
 - Non Parameters
 - i. Sign Test.
 - ii. Friedman Test.
- iii. Runs Test.

3.2.4 Uses and Application of MINITAB

Minitab has several practical applications, including but not limited to:

- Implementation of Six Sigma projects in various industries and research settings.
- Converting complex data sets into a simplified form.
- Generating graphical output, such as scatter plots, box plots, histograms, etc., to help visualize the data.
- Using it as a tool for learning and conducting statistical research.
- Minitab is a user-friendly and efficient software for inputting, manipulating, and analyzing statistical data, as well as identifying trends, patterns, and solutions to current issues.

3.3 ANOVA-DOE

3.3.1 Introduction to ANOVA

The user-friendly statistical analysis tool known as Minitab provides a number of basic and advanced data analysis functions. People with various educational backgrounds and levels of competence may use it easily because to its simple command syntax. Along with PC and Macintosh operating systems, the application is compatible with the majority of common workstations, minicomputers, and mainframes. Since the worksheet and instructions are the same across computer systems and versions, switching between them is straightforward.

The arithmetic average of a group of variables is referred to as a mean in ANOVA. The overall mean and the sample mean are determined as part of the ANOVA test. The overall mean (\bar{y}) is the average of the sample means from all groups or the mean of all observations, whereas the sample mean (\bar{y}_i) is the average value for a specific group.

3.3.2 Formula for ANOVA

$$F = \text{MSE} / \text{MST}$$

Where: F= F-static (Fisher's Ratio)

MST=Mean sum of squares of variation.

MSE=Mean sum of squares of residual .

3.3.3 TERMS OF ANOVA TESTS

- **MEANS (GRAND AND SAMPLE)**

The F-statistic or F-ratio is a statistical measure that quantifies the degree of difference between the means of different samples or the significance level of their differences. It represents a ratio between the effect size, which is in the numerator, and the variance associated with that effect, which is reflected in the denominator.

$$GM(\mu) = \frac{\mu_1 + \mu_2 + \mu_3 + \dots + \mu_n}{n}$$

- **F-STATISTIC**

The F-statistic or F-Ratio is a statistical measure that quantifies the degree of difference between means of distinct samples or the level of significance of their differences. It represents a ratio of the effect size, which is captured in the numerator, and the variance linked to that effect, which is reflected in the denominator.

$$F = \frac{\text{measure of effect (MSE}_{\text{effect}})}{\text{measure of error (MSE}_{\text{error}})}$$

The F statistic is a measure of the ratio of variances, as it uses variances to explain the effect measure and the error measure. The F-value is always non-negative. When the F-value is greater than 1, it means that the variance caused by the effect is greater than the variance associated with the sampling error. This can be represented as $F > 1$, where the variance caused by the effect is greater than the variance caused by the error. On the other hand, if $F < 1$ means that the variance due to the effect is less than the variance due to the error. When F is equal to 1, it means that the variation due to the effect is equal to the variation due to the error, which is not ideal.

- **SUMS OF SQUARES**

In regression analysis, the sum of squares is a statistical technique used to calculate the dispersion of data points. The F value is also calculated using it in the ANOVA test. It is frequently referred to as variation since it contains information on the standard deviation. The following is the formula for computing the sum of squares.

$$\text{Sum of Squares (SS)} = \sum_{i=0}^n (X_i - \bar{X})^2$$

where:

$X_i = i^{\text{th}}$ term,

$\bar{X} = \text{Grand Mean}$

While calculating the value of F, we need to find SS Total that is equal to the sum of SS_{Effect} and SS_{Error}.

$$\text{SS}_{\text{Total}} = \text{SS}_{\text{Effect}} + \text{SS}_{\text{Error}}$$

- **DEGREES OF FREEDOMS (D_f):**

Degrees of freedom can be defined as the highest number of values that are independent of each other and have the ability to change within a given dataset.

$$D_f = N - 1$$

Where:

$$D_f = \text{Degree of Freedom} \quad N = \text{Number of Values}$$

- **MEAN SQUARED ERROR (MSE):**

By calculating the Mean Squared Error, we can determine the typical amount of error present within a dataset on average. The Mean Squared Error can be obtained by dividing the sum of squares by the degrees of freedom.

$$MSE = \frac{SS}{D_f}$$

- **HYPOTHESIS (ALTERNATE AND NULL):**

A hypothesis is an informed assumption made about a phenomenon. When we are presented with a dataset and asked to make a prediction, we employ certain calculations and arrive at an educated guess, which is essentially a hypothesis. In the context of the ANOVA test, we use two hypotheses - the Null Hypothesis (H₀) and the Alternate Hypothesis (H₁).

$$H_0 = \mu_1 = \mu_2 = \mu_3 = \dots = \mu_n \text{ NULL HYPOTHESIS}$$

$$H_1: \mu_1 \neq \mu_n \text{ ALTERNATE HYPOTHESIS}$$

- **GROUP VARIABILITY (WITHIN GROUP AND BETWEEN GROUP):**

To comprehend the concept of group variability, it's essential to have a clear understanding of what constitutes a group. In the ANOVA test, a group refers to the collection of samples belonging to the independent variable. The variability within the groups and among the individual groups both play a crucial role in determining the overall group variability.

- **Df**

"Df," commonly known as "degrees of freedom," usually pertains to the regression model's degrees of freedom. Degrees of freedom signify the number of independent information units accessible to estimate a parameter within a statistical model.

- **Adj ss**

"ADJ SS" in Response Surface Regression usually stands for "Adjusted Sum of Squares" The sum of squares is a metric that measures the variability in the data that is accounted for by the model. In response surface regression, adjusted sum of squares is a revised form of sum of squares that accounts for the number of predictor variables included in the model.

- **Adj ms**

Generally speaking, "ADJ MS" in response surface regression refers to "Adjusted Mean Squares". Adjusted for the degrees of freedom used to estimate the model parameters, the adjusted mean squares are a measure of the variability in the response variable that can be explained by the predictor variables in the model. The adjusted sum of squares is divided by the degrees of freedom to produce the adjusted mean squares.

- **F value**

The "F-value" is a statistical test statistic used in response surface regression to evaluate the importance of the regression model or specific predictor variables inside the model. The adjusted mean square for the predictor variable or regression model is divided by the mean square of the residuals to determine the F-value. This ratio shows how much of the response variable's variability is explained by the predictor variables in the model as opposed to how much of it is unaccounted for.

- **P value**

Response surface regression uses a statistical metric known as the "p-value" to assess the statistical significance of the regression model as a whole or of each individual predictor variable. If the null hypothesis is true, the p-value shows the likelihood of finding a test statistic that is as severe as what was seen in the data. The null hypothesis in response surface regression is that the regression model or predictor variable(s) have no discernible impact on the response variable.

- **Percentage contribution (% contribution)**

In response surface regression, the "% contribution" represents the percentage of the response variable's variability that each predictor variable in the model contributes to. In terms of explaining the variation in the response variable, this quantifies the importance of each predictor variable. When the sum of the squares explained by each predictor variable in the model is divided by the sum of the squares in the entire model and multiplied by 100, the result is the percentage of the variability in the response variable that is explained by each predictor variable.

3.3.4 Introduction to DOE

An experiment's design comprises a number of planned trials or runs in which the input variables are altered and the resulting effects are tracked. Experimental designs are a systematic method for examining the factors in a process or product that have an impact on the quality of a product in an industrial setting. Improvement projects can be focused to increase product manufacturability, reliability, quality, and performance in the field by identifying the critical process conditions and product components that influence product quality.

3.3.5 Terms of DOE

- **TAGUCHI DESIGN**

A taguchi design is a type of experimental design that aims to improve the consistency of a product or process in its operating environment. The taguchi design approach recognizes that some factors that contribute to variability may be beyond control and are referred to as confounding factors. Rather than attempting to control these factors, Taguchi designs focus on identifying and manipulating controllable factors (control factors) that can minimize the effects of confounding factors. Through experimentation, the confounding factors are intentionally varied to create variability, and optimal settings for the control factors are identified to create a robust process or product that is resistant to variation due to confounding factors. Such an approach leads to a more consistent outcome of a process and ensures consistent performance of a product, regardless of its deployment environment.

- **RESPONSE SURFACE DESIGN**

Response surface design is an advanced experimental technique used for optimizing and understanding a response. It is typically employed after identifying significant factors using screening or factorial designs. The response surface design is particularly useful when there is a possibility of curvature in the response surface. Figures 3.9 and 3.10 depict the variation in the response surface with and without curvature.

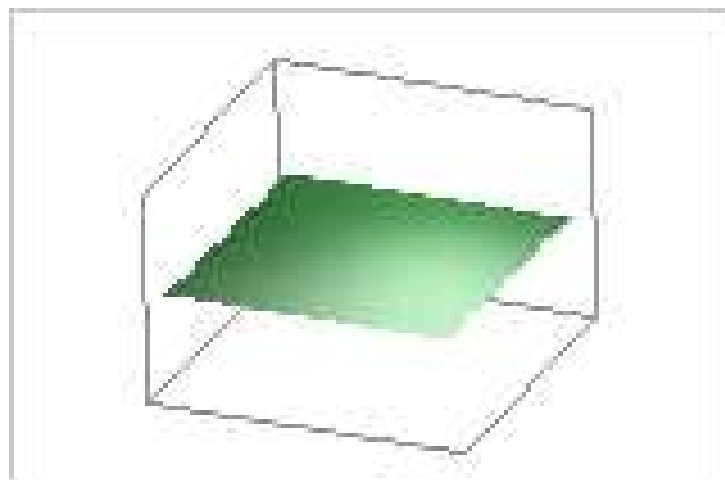


Fig 3.9 Response surface with no curvature

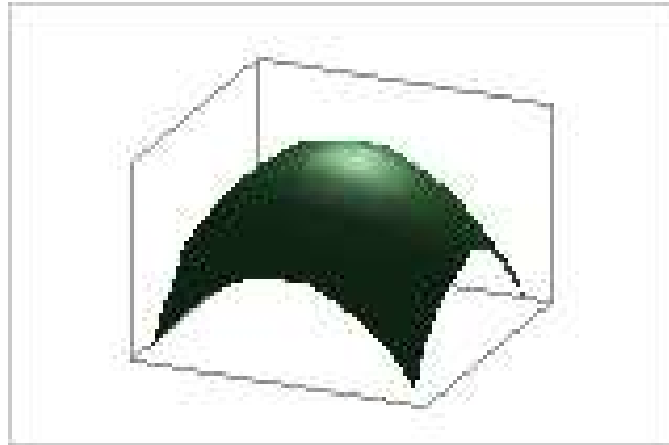


Fig 3.10 Response surface with curvature

Response surface equations and factorial design equations differ in that response surface equations include quadratic terms, which allow for the modeling of curvature in the response surface. This makes response surface equations valuable for several purposes, such as mapping a region of the response surface, identifying the optimal levels of variables for maximizing the response, and determining the appropriate operating conditions for meeting desired specifications. Essentially, response surface equations are a powerful tool for understanding and optimizing responses.

3.4 MATLAB

3.4.1 Introduction

For this experiment we are using MATLAB R2015. MATLAB R2015 is a software program developed by Math Works that provides a powerful platform for numerical computing and data analysis. It is widely used in engineering, science, and mathematics, as well as in various other fields, due to its versatility and ease of use.

MATLAB R2015 includes a comprehensive set of tools for data visualization, data analysis, and numerical computation. It also features an interactive development environment (IDE) that allows users to write and debug their own scripts and functions. The program's syntax is based on the MATLAB language, which is easy to learn and understand.

Some of the key features of MATLAB R2015 include support for parallel computing, machine learning, and deep learning. It also includes a variety of built-in functions and toolboxes for signal processing, image processing, optimization, and statistics. Fig 3.11 shows matlab user interface overview

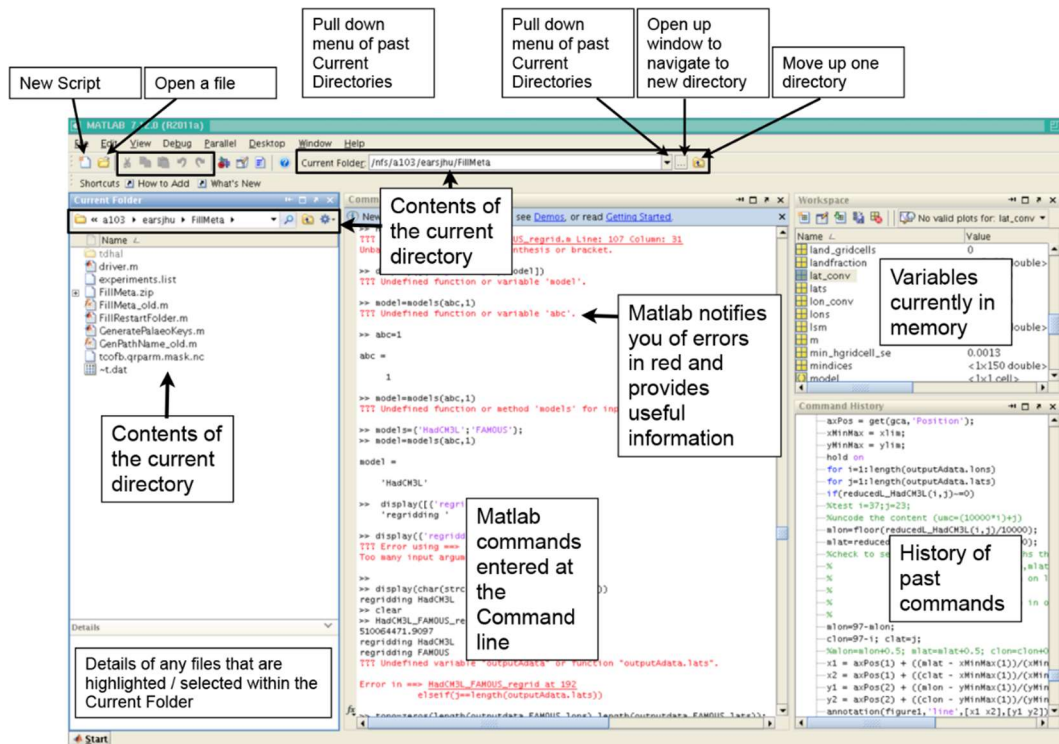


Fig 3.11 MATLAB USER INTERFACE OVERVIEW

3.4.2 Specifications of MATLAB R2015

- System requirements: MATLAB R2015 is available for Windows, Mac, and Linux operating systems. The minimum system requirements are a 64-bit processor and 4 GB of RAM, although higher specifications are recommended for optimal performance.
- Programming language: MATLAB R2015 uses a high-level programming language that allows users to write scripts and functions for numerical computation, data analysis, and visualization. The language is based on matrix operations and includes a wide range of built-in functions for common tasks.
- Toolboxes: MATLAB R2015 includes a range of toolboxes for specific applications, such as signal processing, control systems, and image processing. These toolboxes provide additional functions and features tailored to specific domains.
- Graphics: MATLAB R2015 includes a powerful graphics engine for creating 2D and 3D visualizations of data. The graphics engine supports a wide range of plot types and customization options.
- Fuzzy logic toolbox: MATLAB R2015 includes a fuzzy logic toolbox for designing and simulating fuzzy systems. This toolbox provides functions for defining fuzzy sets, creating fuzzy rules, and evaluating fuzzy systems.
- Simulink: MATLAB R2015 includes Simulink, a block diagram environment for simulating and modeling dynamic systems. Simulink provides a visual interface for designing and simulating complex systems, and includes a wide range of predefined blocks for common tasks.
- Parallel computing: MATLAB R2015 includes built-in support for parallel computing,

allowing users to distribute computations across multiple processors or computers. This can significantly reduce computation time for large-scale problems.

Working

- Data import and manipulation: Users can import data into MATLAB R2015 from various sources, such as spreadsheets or databases. The data can then be manipulated using built-in functions or custom scripts.
- Data visualization: MATLAB R2015 provides a variety of tools for data visualization, including 2D and 3D plots, histograms, and scatter plots shown in Fig 3.12. Users can customize these visualizations using built-in functions or custom scripts.
- Numerical computation: MATLAB R2015 allows users to perform numerical computations on their data, such as matrix operations, differential equations, and optimization. Built-in functions and toolboxes are available for these operations.
- Programming: MATLAB R2015 provides an interactive development environment (IDE) that allows users to write and debug their own scripts and functions. The syntax of MATLAB is similar to other programming languages, making it easy to learn and use.
- Toolboxes: MATLAB R2015 includes a variety of built-in toolboxes that provide additional functionality for various fields such as signal processing, image processing, and statistics.
- Deployment: MATLAB R2015 allows users to deploy their programs as standalone applications or integrate them with other programming languages and applications.

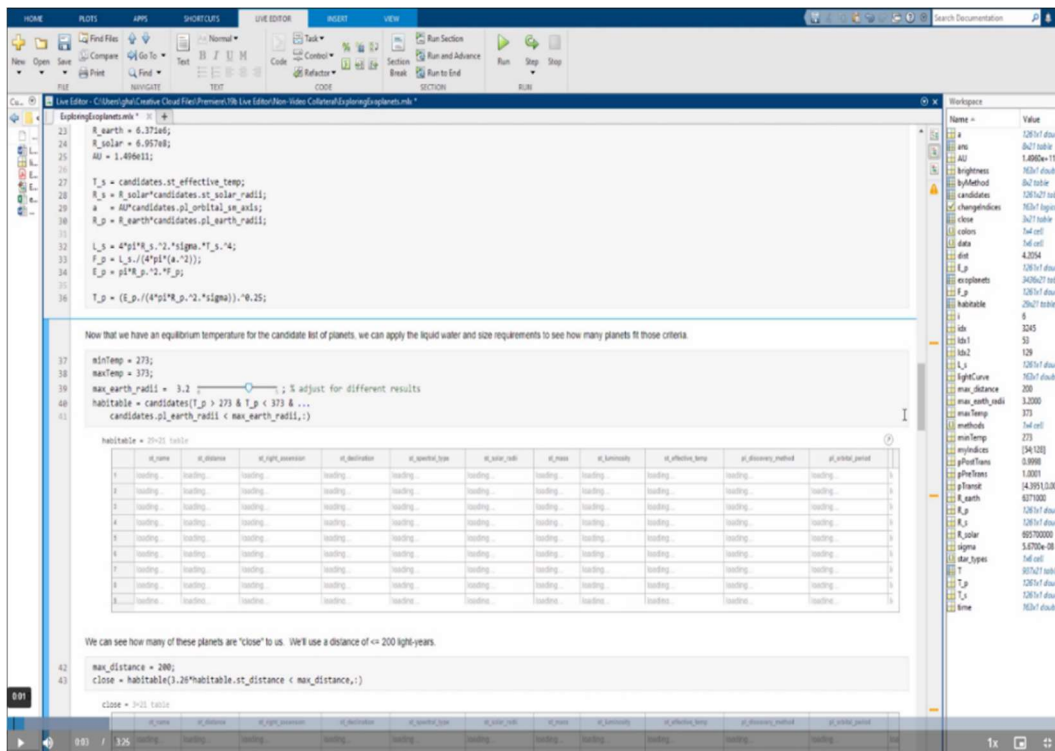


Fig 3.12 Analyzing and visualizing data

Application

MATLAB R2015 has a wide range of applications in various fields due to its versatility and ease of use. Some of the common applications of MATLAB R2015 include:

- **Engineering:** MATLAB R2015 is widely used in engineering for designing, analyzing, and optimizing systems. It is used for signal processing, control systems, robotics, and many other applications.
- **Science:** MATLAB R2015 is used in science for data analysis, modeling, and simulation. It is used in fields such as physics, chemistry, biology, and environmental science.
- **Finance:** MATLAB R2015 is used in finance for data analysis, risk management, and financial modeling. It is used for options pricing, portfolio optimization, and financial forecasting.
- **Education:** MATLAB R2015 is used in education for teaching mathematics, programming, and data analysis. It is used in schools and universities to teach a variety of subjects, including physics, engineering, and economics.
- **Research:** MATLAB R2015 is used in research for data analysis, modeling, and simulation. It is used in various fields such as medicine, psychology, and sociology.
- **Machine learning:** MATLAB R2015 includes machine learning toolboxes that are used for developing and implementing machine learning algorithms. It is used in applications such as image recognition, natural language processing, and predictive analytics.

3.4.3 Rules for using MATLAB R2015

In MATLAB R2015, rules can refer to different things depending on the context. Here are a few examples of how rules are used in MATLAB R2015:

- **Fuzzy logic rules:** In the fuzzy logic toolbox, rules are used to define the relationship between the input and output variables in a fuzzy system. These rules are expressed using linguistic terms and are often represented in the form of if-then statements. For example, a rule might be "if temperature is cold and humidity is high, then the air conditioning should be turned on". The fuzzy logic toolbox in MATLAB R2015 provides functions for adding and removing rules, as well as for adjusting their parameters.
- **MATLAB programming rules:** In MATLAB R2015, rules are used to define the syntax and structure of MATLAB code. These rules ensure that the code is well-formed and can be executed correctly. For example, in MATLAB, the equal sign (=) is used for assignment, while the double equal sign (==) is used for comparison. MATLAB provides a set of programming rules to ensure that code is consistent and easy to understand.
- **Simulink rules:** In Simulink, rules are used to define the behavior of a simulation. These rules specify how the different components of the simulation interact with each other, and how the simulation responds to different inputs. For example, a rule might

be "if the input signal exceeds a certain threshold, then a certain component should be activated".

- Simulink provides a set of rules for designing and simulating complex systems.

3.4.4 Uses of MATLAB R2015

- Data analysis and visualization: MATLAB R2015 provides powerful tools for data analysis, visualization, and exploration. It can be used to import and manipulate data from various sources, perform statistical analysis, and create visualizations such as plots, graphs, and charts.
- Algorithm development: MATLAB R2015 is widely used in the development of algorithms for various applications, such as signal processing, image and video processing, and control systems. It provides a rich set of functions and tools for developing, testing, and debugging algorithms.
- Scientific computing: MATLAB R2015 is used extensively in scientific computing for numerical simulations, modeling, and optimization. It provides a wide range of numerical methods and techniques for solving complex problems in areas such as physics, engineering, and finance.
- Control system design: MATLAB R2015 is commonly used in the design and analysis of control systems. It provides a variety of tools for modeling, simulating, and analyzing control systems, including linear and nonlinear systems, PID controllers, and state-space models.
- Machine learning and deep learning: MATLAB R2015 provides comprehensive support for machine learning and deep learning, including neural networks, support vector machines, decision trees, and clustering algorithms. It allows users to train, test, and deploy machine learning models with ease.
- Image and video processing: MATLAB R2015 is widely used in image and video processing applications. It provides tools for image filtering, segmentation, feature extraction, and object recognition, as well as video processing and analysis.

3.5 Regression Analysis

3.5.1 Introduction

Regression analysis is a statistical technique that aims to explore the relationships between different variables. It involves gathering data on the relevant variables and determining the quantitative impact of one variable on another, as depicted in Fig 3.13. Additionally, the researcher assesses the "statistical significance" of the estimated relationships, which reflects the level of confidence that the estimated relationship is close to the true relationship. While regression analysis has traditionally been used in economic statistics, it is now gaining significance in legal contexts for policy-making and decision-making purposes.

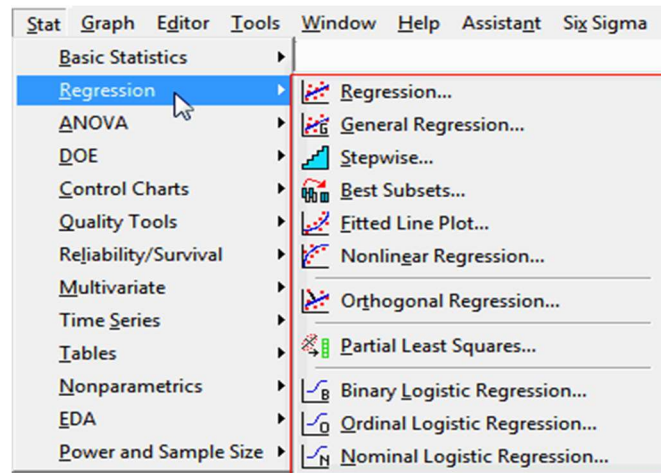


Fig 3.13 Regression optimization window

3.5.2 Types of Regression Analysis

I. Simple Linear Regression

Simple linear regression is a statistical analysis that investigates the association between two continuous variables - one is the response variable (y) and the other is the predictor variable (x). If there is a relationship between the two variables, it becomes possible to make predictions about the response variable based on the predictor variable with a higher degree of accuracy. The regression analysis yields a line of best fit, as depicted in Fig 3.14, which can be utilized to:

- Study how the response variable changes as the predictor variable varies.
- Anticipate the value of the response variable (y) for any given value of the predictor variable (x).

$$Y = a + bX + \epsilon$$

Where:

Y – Variable that is dependent

X – Independent (explanatory) variable

a – Intercept

b – Slope

ϵ – Residual (error)

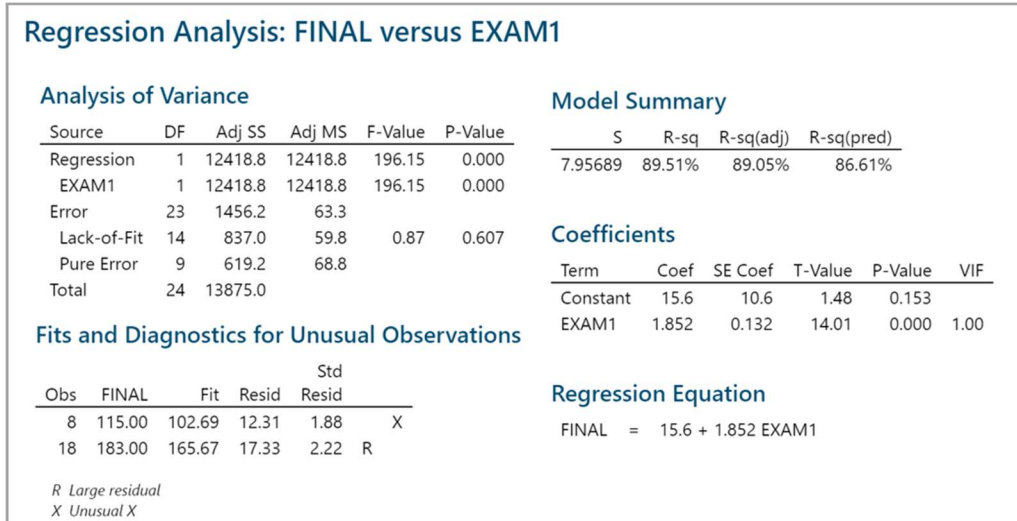


Fig 3.14 Simple Regression Analysis

II. Multiple Linear Regression

Multiple linear regression is a statistical method that examines the linear relationships between a continuous response variable and two or more predictor variables, as illustrated in figure 3.15. When there are many predictor variables, it is advisable to use model-selection techniques like stepwise or best subsets to eliminate any predictors that are not significantly associated with the response variable before fitting the regression model. The equation for multiple linear regression can be expressed as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \epsilon$$

Here, y represents the predicted value of the dependent variable, β_0 is the y -intercept, and β_1 to β_n are the regression coefficients for the independent variables x_1 to x_n , respectively. The coefficients indicate the effect of increasing each independent variable on the predicted value of the dependent variable. The term ϵ represents the model error or the degree of flexibility in the estimate of the dependent variable.

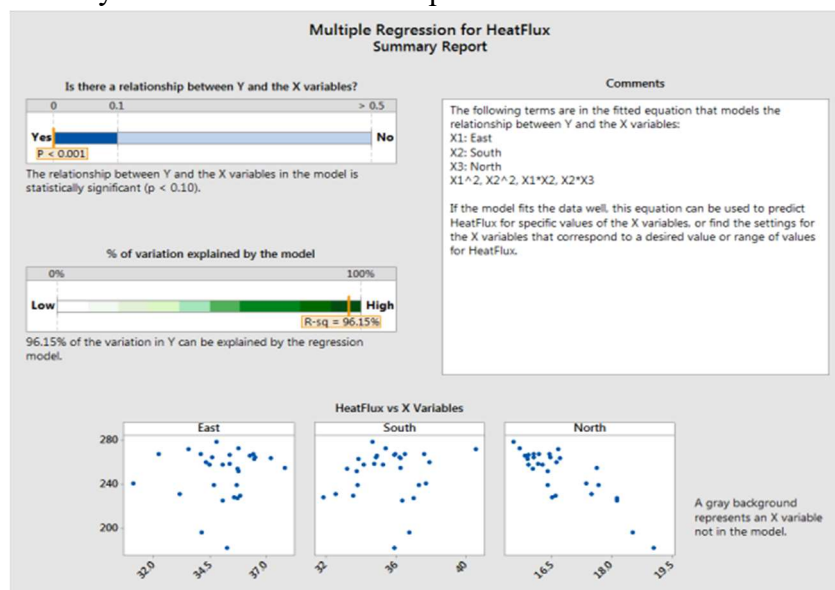


Fig 3.15 Multiple Regression

3.6 Fuzzy Logic Optimization

3.6.1 Introduction

A mathematical framework called fuzzy logic was developed to cope with data imprecision and ambiguity. It is especially helpful in situations when human thinking is necessary and conventional logic and binary true/false values are insufficient. Fuzzy sets, which allow for a degree of membership in a set rather than a binary true/false value, are the foundation of fuzzy logic. Control systems, decision support systems, image processing, medical diagnostics, and robotics are just a few of the areas where fuzzy logic may be used. The two primary varieties of fuzzy inference systems are: Sugeno and Mamdani. Sugeno FIS is more suited for tasks that call for precise control, whereas Mamdani FIS is the more conventional and often used approach. In Mamdani FIS, fuzzy logic is used to design the rules while membership functions are used to fuzzify the input variables. For a clear value, the output variables are defuzzified. In Sugeno FIS, the output variables are created by simply combining the input variables in a linear fashion.

3.6.2 Fuzzy Inference systems

Mamdani-type (1977) and Sugeno-type (1985) fuzzy inference systems are the two basic varieties that may be used. The methods used to derive outputs in these two types of inference systems differ substantially.

Mamdani Fuzzy interference systems

A Mamdani fuzzy inference system (FIS) is a type of fuzzy logic system that uses fuzzy sets and fuzzy rules to reason about uncertain or imprecise information. In a Mamdani FIS, inputs are first mapped to fuzzy sets using fuzzy membership functions. Based on how closely each input variable fits the features of the fuzzy set, the membership function assigns a degree of membership to each input variable for each fuzzy set. The language phrases "very high," "high," "medium," "low," and "very low," which denote the degree of membership of the input variable to each fuzzy set, are typically used to create fuzzy sets. The "if" section of a "if-then" statement, which defines a combination of fuzzy sets for the input variables and the "then" part, specifies a fuzzy set for the output variable, is how Mamdani FIS's fuzzy rules are written. Each rule has a level of certainty attached to it that describes how accurate it is in general.

Advantages of Mamdani FIS over Sugeno FIS:

1. **Interpretability:** Mamdani FIS outputs are fuzzy sets with linguistic labels that are easily interpretable by humans. This makes Mamdani FISs more transparent and easier to explain, which can be an advantage in some applications.
2. **Flexibility:** Mamdani FISs can handle more complex relationships between input variables and output variables compared to Sugeno FISs, which are limited to linear relationships. Mamdani FISs can use a wide variety of membership functions and

fuzzy rules

3. **Ability to handle uncertainty:** Mamdani FISs are more suited for handling uncertainty and vagueness in data due to the use of fuzzy sets and fuzzy logic, which can capture uncertain or imprecise information.
4. **Use of expert knowledge:** Mamdani FISs can incorporate expert knowledge through the use of linguistic rules and fuzzy sets, which can be useful in decision-making applications.
5. **Robustness:** Mamdani FISs are more robust to changes in the input data, as they are based on a fuzzy set of rules rather than a fixed set of mathematical equations.

3.7 Response Surface Optimization

A system's behaviour may be predicted using a model of the system using the mathematical modelling and optimisation approach known as "response surface optimisation." It is especially helpful when the system is complicated and the factors influencing its behaviour are challenging to regulate or directly assess. An overview of response surface roughness optimisation is shown in Fig. 3.16.

Response surface optimization's fundamental premise is to develop a mathematical model that connects the input variables to the desired output variable. This model may be used to identify the ideal input variable values that will produce the intended outcome. A set of experimental data that comprises measurements of the output variables under various situations of the input variables is often used to build the model.

The best input variable values can be found after the model has been developed using a number of optimisation strategies. Utilising a response surface optimizer, a piece of software created expressly to discover the best input variable values based on the model, is one popular strategy.

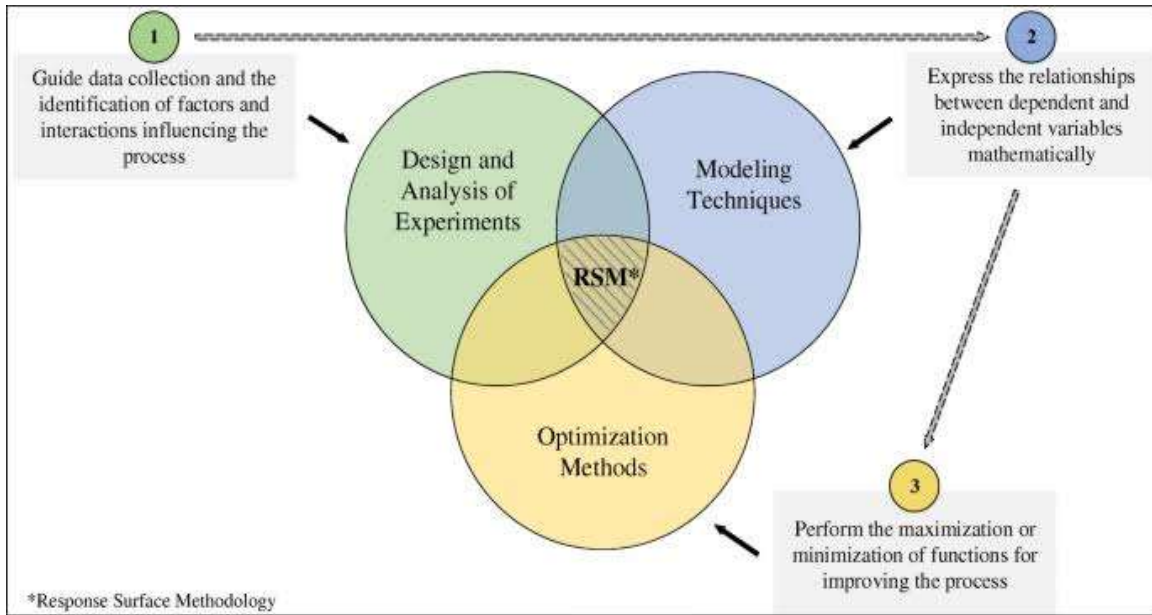


Fig 3.16 Response Surface Methodology

The response surface optimizer works by iteratively adjusting the input variables and using the model to predict the output variable at each step. Based on these predictions, the optimizer makes adjustments to the input variables and continues the process until it converges on the optimal solution.

Response surface optimization is widely used in engineering, physics, chemistry, and other fields where complex systems need to be optimized. It offers a powerful tool for improving the efficiency and effectiveness of systems and processes, and it has been shown to produce significant improvements in a wide range of applications.

CHAPTER 4

EXPERIMENTAL DETAILS AND PARAMETERS FOR OPTIMIZATION

4.1 Experimental Details

In the below table 3.1 we can observe that the input parameters are Speed, Feed and Depth of cut. The 9 set of inputs which are used for machining are given by Taguchi using MINITAB where we have given 3 level of factors. Now coming to the output parameters we have opted for Material removal rate, Surface roughness of the material (Rt, Ra, Rq, Rz).to find out the material removal rate we should first find out the cutting speed

Table 4.1- Input parameters

S.NO	Speed(rpm)	Feed(mm)	DoC(mm)
1	465	0.404	0.3
2	465	0.596	0.6
3	465	0.808	0.9
4	740	0.404	0.6
5	740	0.596	0.9
6	740	0.808	0.3
7	1000	0.404	0.9
8	1000	0.596	0.3
9	1000	0.808	0.6

To find out both the cutting speed and material removal rate we use the below formulas:

$$MRR = v * f * d \text{ (m}^3\text{/min)} \quad \text{----- EQ 4.1}$$

Where,

v = Cutting speed(m/min)

f = Feed(mm)

d = Depth of cut(mm)

$$v = (3.141 * D * N) / 1000 \quad \text{----- EQ 4.2}$$

Where, D = Diameter of the work piece (mm) N = Speed(rpm)

Table 4.2 - Cutting speed

S.NO	Cutting speed(m/min)
1	46.74
2	46.74
3	46.74
4	74.38
5	74.38
6	74.38
7	100.51
8	100.51
9	100.51

As mentioned in the above table 4.2 They are the values of cutting speed for the input parameters which are in the table 4.1. Using the formulas given above we found out the cutting speed.

Table 4.3- Material removal rate

Cutting speed(m/min)	Feed(mm)	DoC(mm)	MRR (m³/min)
46.74	0.404	0.3	5.66
46.74	0.596	0.6	16.71
46.74	0.808	0.9	33.99
74.38	0.404	0.6	18.03
74.38	0.596	0.9	39.90
74.38	0.808	0.3	18.03
100.51	0.404	0.9	36.55
100.51	0.596	0.3	17.97
100.51	0.808	0.6	48.73

The Material Removal Rates for the input parameters are given in above table 4.3

Here we are also including the flowrate in the machining . For one work piece the flowrate of MQL setup is 90ml/hr(table 8) and for another workpiece the flowrate of MQL setup is 180ml/hr (table 7). After completion of the machining for both the workpieces we have used surface roughness tester and noted the values of R_t , R_a , R_q , R_z .

Table 4.4 Surface roughness values for workpiece with flowrate of 180ml/hr

Cutting speed(m/min)	Feed(mm)	DoC(mm)	R_t (μm)	R_a(μm)	R_q(μm)	R_z(μm)
46.74	0.404	0.3	36.0148	5.716	6.756	28.39
46.74	0.596	0.6	16.57	2.123	2.661	12.019
46.74	0.808	0.9	43.485	10.05	11.717	39.377
74.38	0.404	0.6	32.588	5.287	6.542	23.39
74.38	0.596	0.9	43.228	9.266	11.069	38.931
74.38	0.808	0.3	44.02	8.98	10.111	34.84
100.51	0.404	0.9	25.539	4.029	4.932	20.266
100.51	0.596	0.3	45.475	9.912	11.25	38.158
100.51	0.808	0.6	24.795	4.814	5.837	21.955

Table 4.5 Surface roughness values for workpiece with flowrate of 90ml/hr

Cutting speed(m/min)	Feed(mm)	DoC(mm)	R_t (μm)	R_a (μm)	R_q (μm)	R_z (μm)
46.74	0.404	0.3	43.346	9.285	10.304	36.371
46.74	0.596	0.6	37.48	8.318	9.527	32.055
46.74	0.808	0.9	54.134	15.639	16.825	49.587
74.38	0.404	0.6	56.654	9.023	11.831	51.709
74.38	0.596	0.9	40.637	10.026	11.309	37.417
74.38	0.808	0.3	48.085	8.256	9.896	37.249
100.51	0.404	0.9	64.777	9.209	12.673	58.808
100.51	0.596	0.3	43.279	6.464	7.913	31.714
100.51	0.808	0.6	35.418	9.236	10.333	32.984

The above two tables 4.4 and 4.5 represents surface roughness values which we got using surface roughness tester for the workpeices 1 and 2 with flowrate of 180ml/hr and 90 m/hr respectively.

Table 4.6 Input and output parameters used for optimization and prediction for workpiece with flowrate of 180ml/hr

Cutting speed (m/min)	Feed (mm)	DoC (mm)	MRR (m³/min)	R_t (μm)	R_a (μm)	R_q (μm)	R_z (μm)
46.74	0.404	0.3	5.66	36.0148	5.716	6.756	28.39
46.74	0.596	0.6	16.71	16.57	2.123	2.661	12.019
46.74	0.808	0.9	33.99	43.485	10.05	11.717	39.377
74.38	0.404	0.6	18.03	32.588	5.287	6.542	23.39
74.38	0.596	0.9	39.90	43.228	9.266	11.069	38.931
74.38	0.808	0.3	18.03	44.02	8.98	10.111	34.84
100.51	0.404	0.9	36.55	25.539	4.029	4.932	20.266
100.51	0.596	0.3	17.97	45.475	9.912	11.25	38.158
100.51	0.808	0.6	48.73	24.795	4.814	5.837	21.955

Table 4.7 Input and output parameters used for optimization and prediction for workpiece with flowrate of 90ml/hr

Cutting speed(m/min)	Feed(mm)	DoC(mm)	MRR (m³/min)	R_t (μm)	R_a (μm)	R_q (μm)	R_z (μm)
46.74	0.404	0.3	5.66	43.346	9.285	10.304	36.371
46.74	0.596	0.6	16.71	37.48	8.318	9.527	32.055
46.74	0.808	0.9	33.99	54.134	15.639	16.825	49.587
74.38	0.404	0.6	18.03	56.654	9.023	11.831	51.709
74.38	0.596	0.9	39.90	40.637	10.026	11.309	37.417
74.38	0.808	0.3	18.03	48.085	8.256	9.896	37.249
100.51	0.404	0.9	36.55	64.777	9.209	12.673	58.808
100.51	0.596	0.3	17.97	43.279	6.464	7.913	31.714
100.51	0.808	0.6	48.73	35.418	9.236	10.333	32.984

Table 4.6 and 4.7 shows the input and output parameters used for optimization and prediction for both workpieces.

4.2 Optimization inputs

4.2.1 Fuzzy engine

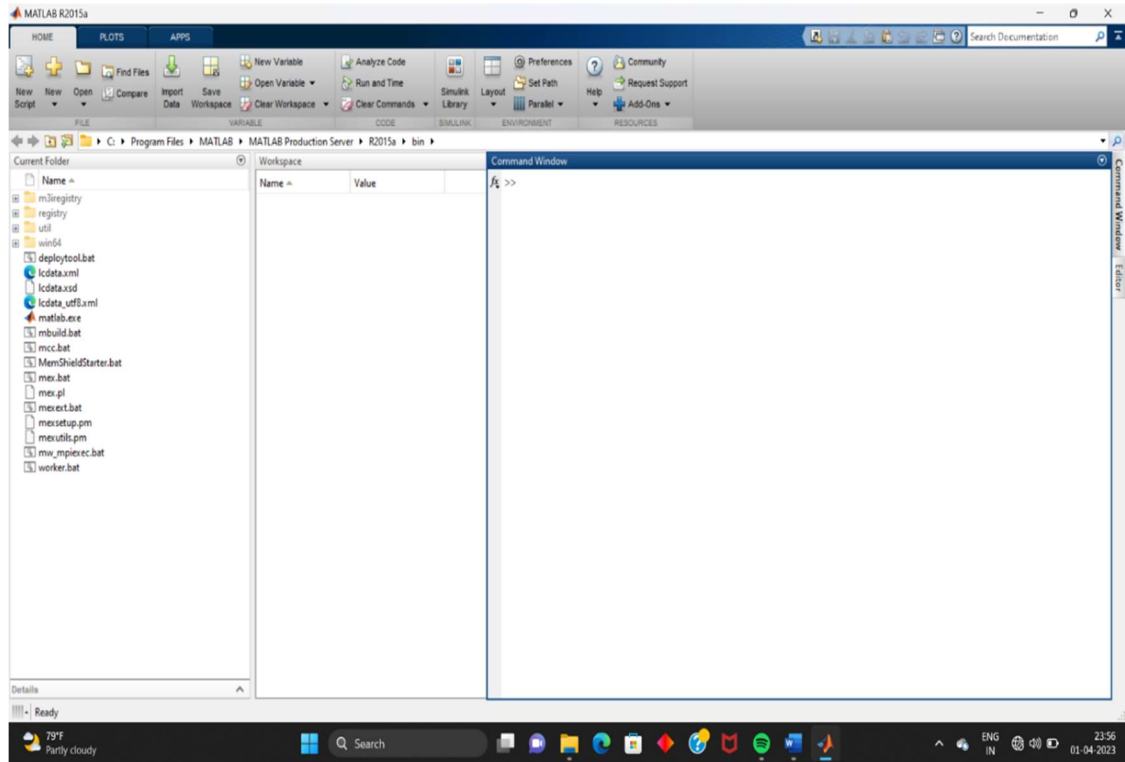


Fig 4.1 Matlab command window

Here from the above Fig 4.1 we can see the command window where we can give commands. As we are doing fuzzy logic optimization we should type fuzzy and click on enter . then a dialog box is displayed . where we can observe input parameter , fuzzy inference system and output parameters

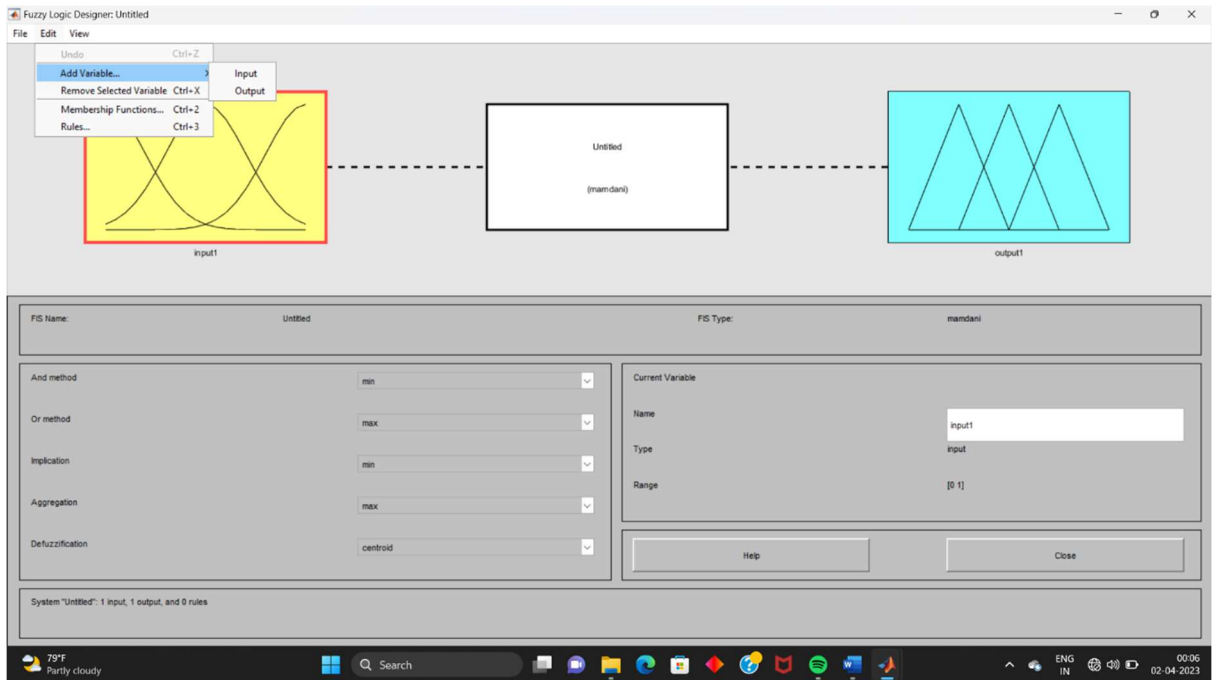


Fig 4.2 Fuzzy Logic Interface

Here from the above Fig 4.2 we can see the input, output parameters and fuzzy inference system. Here we use Mamdani inference system because in most of the literatures Mamdani inference system is used. As you can see in the above figure by clicking on the edit option, some options are displayed. By clicking on 'Add Variable' we can add more input variables and output variables.

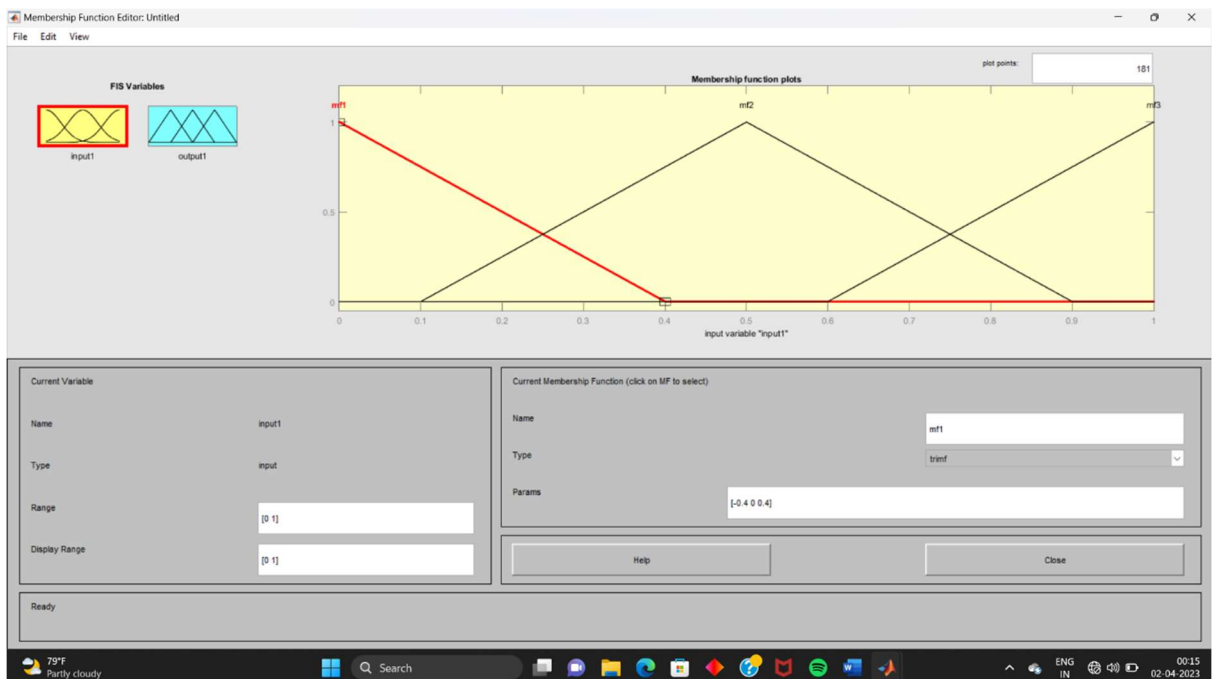


Fig 4.3 Membership functions interface

By clicking on membership functions another window is displayed where we can edit membership functions shown in fig 4.3. We can give names to that membership functions and we can also give range . we can give these names and range for inputs and outputs. Here we can also add membership functions also.

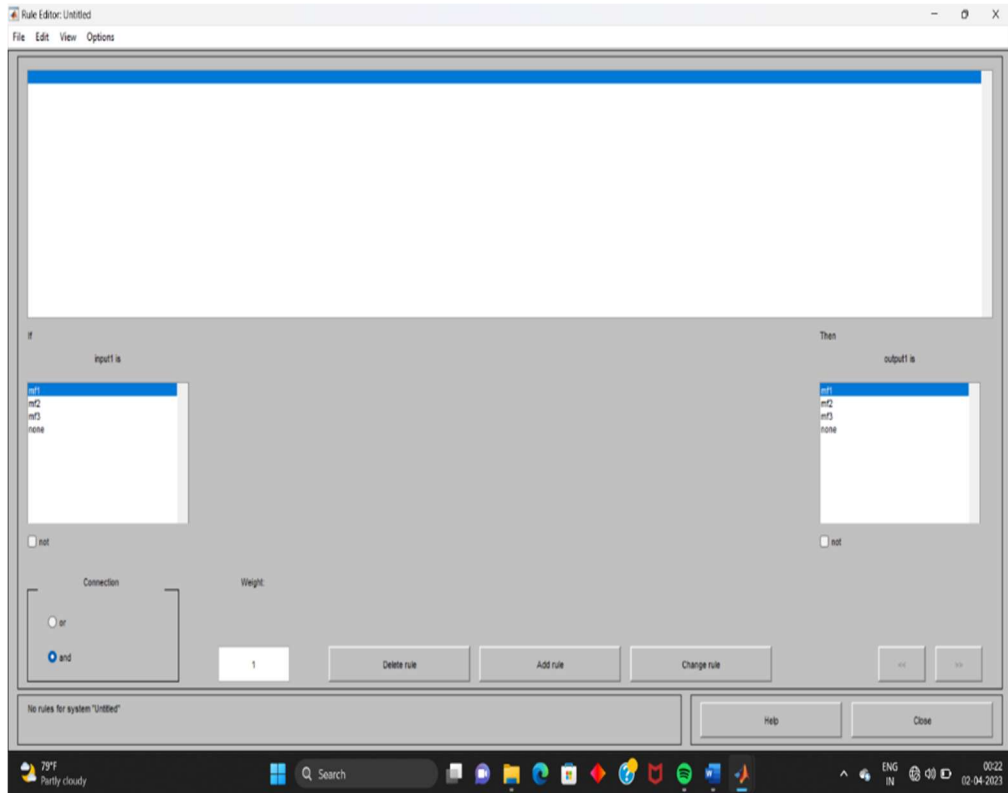


Fig 4.4 Rule editor Interface

The above Fig 4.4 represents the rule editor where we can add rules to train the fuzzy logic system. We need to train the fuzzy logic system with as many as rules to get accurate values. The values given are AI generated values.

4.2.2 RESPONSE SURFACE OPTIMIZATION INPUTS AND OUTPUTS

We use minitab software for response surface optimization. In the below figure we can see the interface of the minitab software after opening it. It almost looks like a excel sheet. To that, we should add our experimental inputs and outputs as shown in the below Fig 4.5

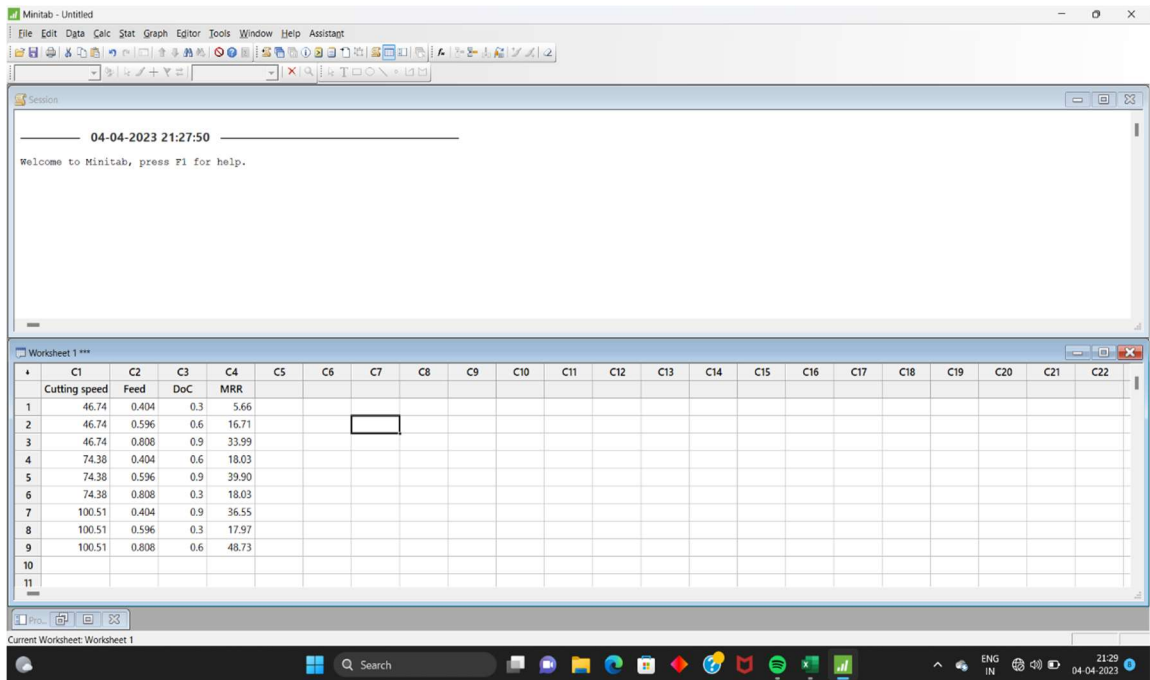


Fig 4.5 Input and output values in Minitab interface

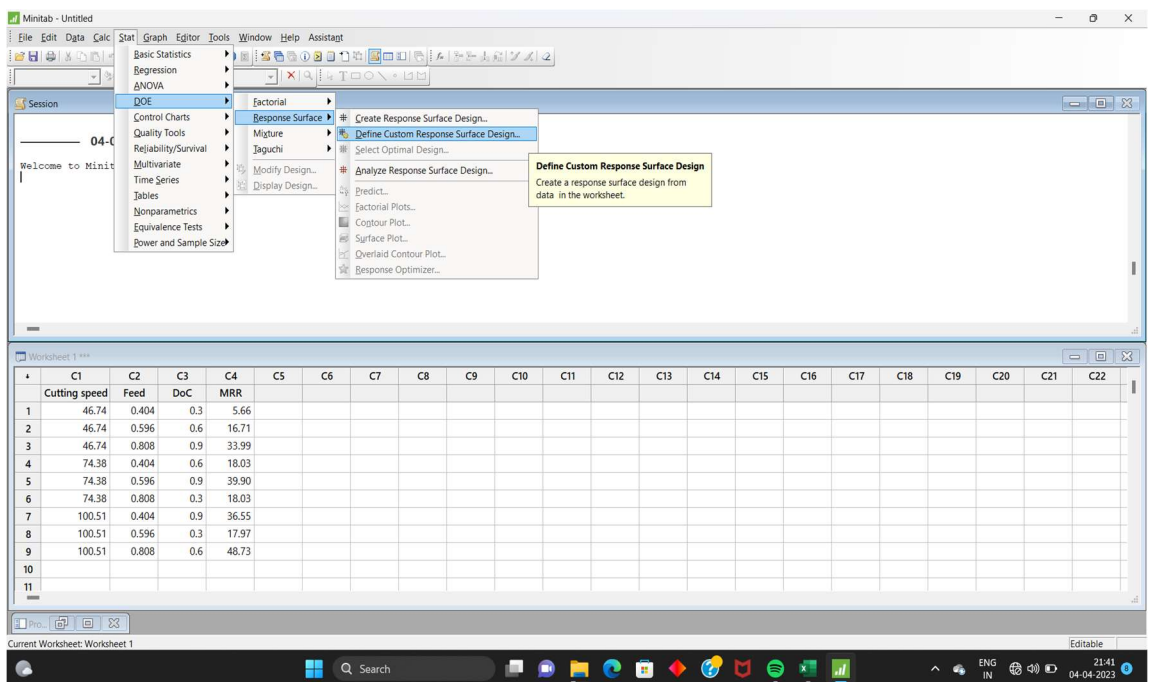


Fig 4.6 Minitab interface for Response Surface optimization

In the above Fig 4.6 we can see that we had given input values like Cutting speed , Feed and Depth of Cut and output parameter like MRR , Rt , Ra , Rq , Rz. Now for optimization we have to click on *Stat* and then we have to click on *DOE* .Now we have to select *Response surface* . In that we have to click on *Define Custom Regression Surface Design*.

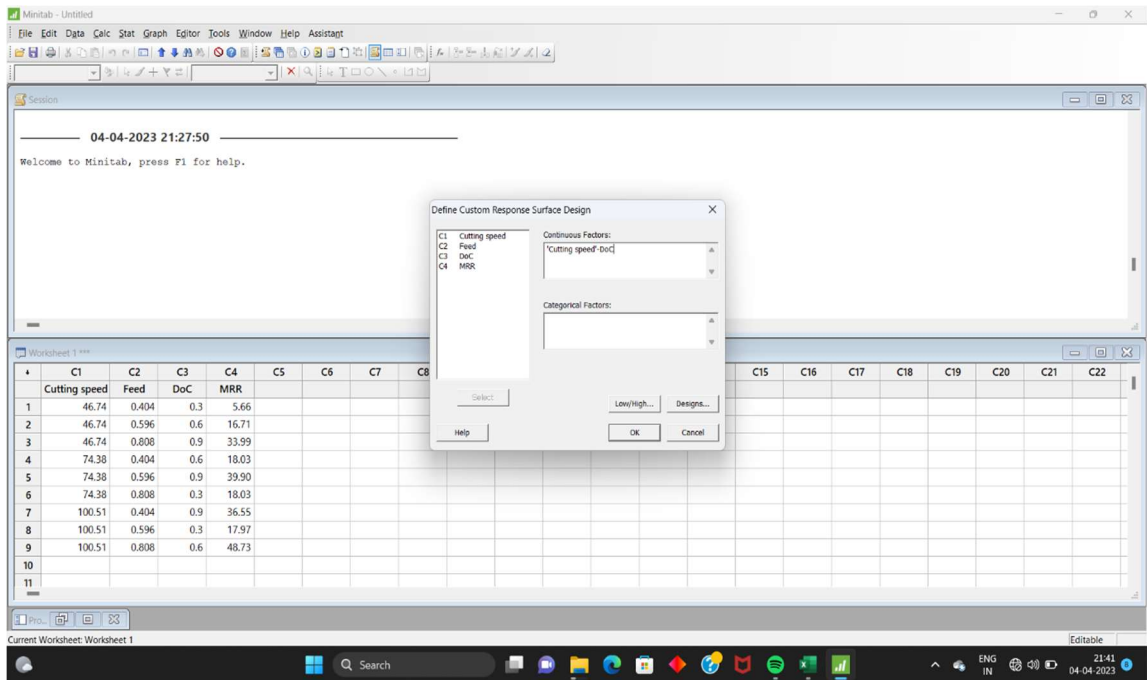


Fig 4.7 Defining custom Regression Surface Design Interface

After clicking on *Define Custom Regression Surface Design* we have to select the input parameters and click on *ok*. Here we have to define only input values. Now we have to click on *Analyze Response Surface Design*. As shown in Fig 4.7

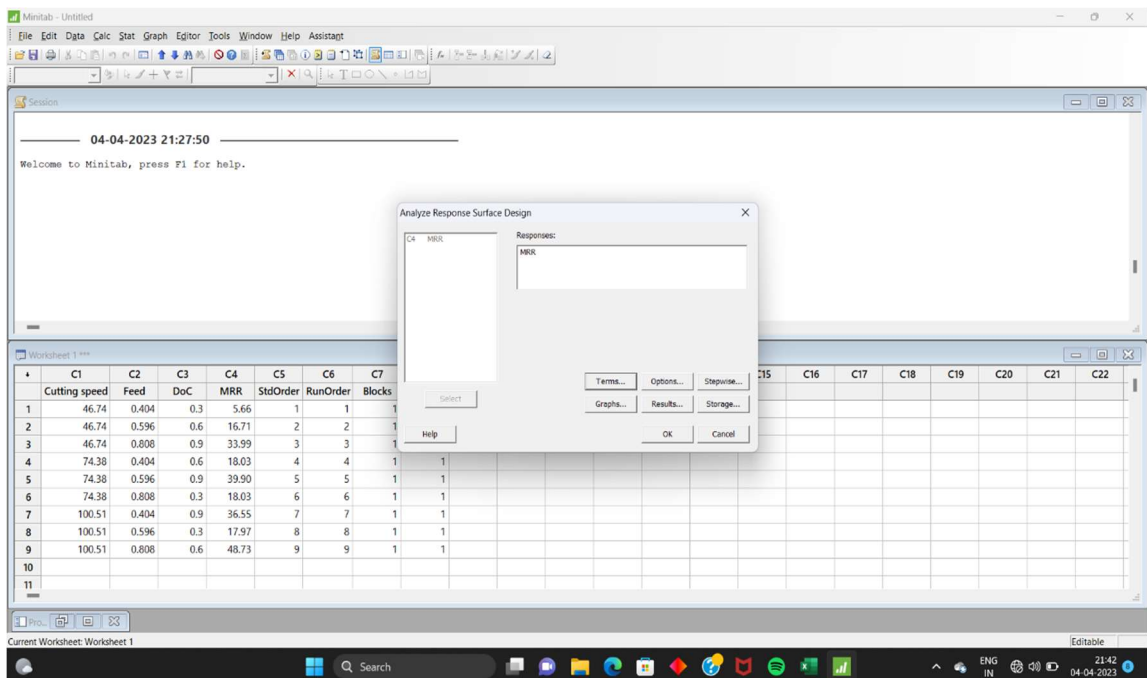


Fig 4.8 Analyse Response Surface Design Interface

In the above Fig 4.8 we can see the dialog box which is opened after clicking on *Analyse Response Surface Design* . Now we have to select the output values like MRR , Rt , Ra , Rq , Rz now we have select the Terms and we have to opted for linear because we have checked the interactions , squares and full quadratic equation . Except in linear in other aspects we haven't got significant values so we have opted for linear type of equation. While selecting the graphs according to our requirement we have selected normplots and scattered plots. Now we have to click on OK. The output that came from the optimization will be continued or discussed in Results and Discussion.

4.2.3 Response Optimizer Inputs

After completing the Response Surface optimization to derive the best cutting parameter we use Response Surface Optimizer. To open the Response Surface Optimizer first click on *Stat-DOE-Response Surface – Response Surface Optimizer*.After clicking on it will show a dialog box as shown in figure 4.9

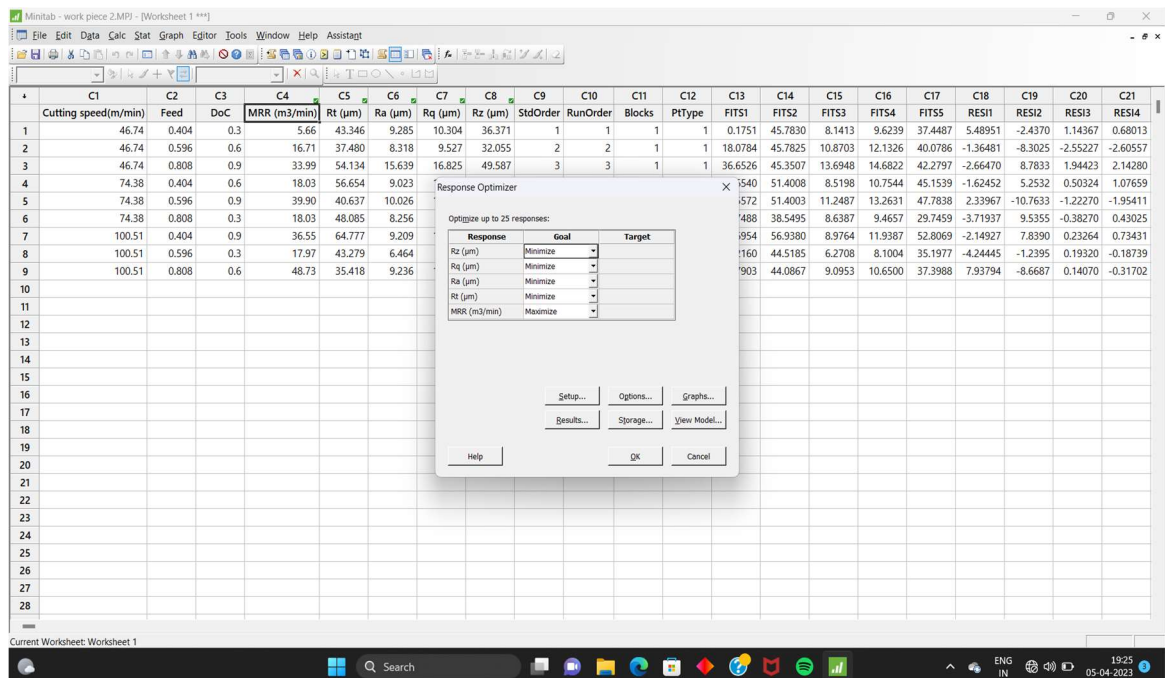


Fig 4.9 Response optimizer interface

In that Dialog box there are is an option named Goal. Here we there are three options to give. They are Minimum, Maximum and Target. For the Surface roughness values (Rt, Ra, Rq, Rz) we should give Minimum and for MRR we should give Maximum. By giving other input functions and clicking on Ok we can get the Optimization plot.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 Response Surface Optimization Results

The below are results and discussion made based on our experimentation and values that came from the optimization part.

RESPONSE SURFACE OPTIMIZATION FOR WORKPIECE WITH FLOWRATE (180ML/HR)

Response Surface Regression: MRR (m³/min) versus Cutting speed(m/min), Feed, DoC

Table 5.1 Analysis of Variance of MRR of workpiece with flowrate of 180ml/hr

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%Contribution
Model	3	1429.0	476.35	16.24	0.005	-
Linear	3	1429.0	476.35	16.24	0.005	-
Cutting speed(m/min)	1	365.1	365.07	12.44	0.017	25.54
Feed	1	275.9	275.86	9.40	0.028	19.24
DoC	1	788.1	788.11	26.86	0.004	55.14
Error	5	146.7	29.34			
Total	8	1575.7				

Table 5.2 Modal Summary of Analysis of Variance of MRR of workpiece with flowrate of 180ml/hr

S	R-sq	R-sq(adi)	R-sq(pred)
5.41644	90.69%	85.11%	61.71%

Regression Equation in Uncoded Units

$$\text{MRR (m}^3\text{/min)} = -38.4 + 0.2901 \text{ Cutting speed(m/min)} + 33.6 \text{ Feed} + 38.20 \text{ DoC} \quad \text{-----EQ 5.1}$$

The above MRR equation is used to find out the regression equation values for MRR of work piece with flowrate of 180ml/hr. The above table discusses about the DF , ADJ Sum of Squares, F value ,P value and % contribution. Using % contribution we can say which factor is most influencing for MRR while doing machining at flowrate of 180ml/hr. Here we can see that DOC is having % contribution of 55.14% that means in this machining part for MRR is mainly effected by DOC . Here R-sq value is much enough to say that our values are enough good for optimization

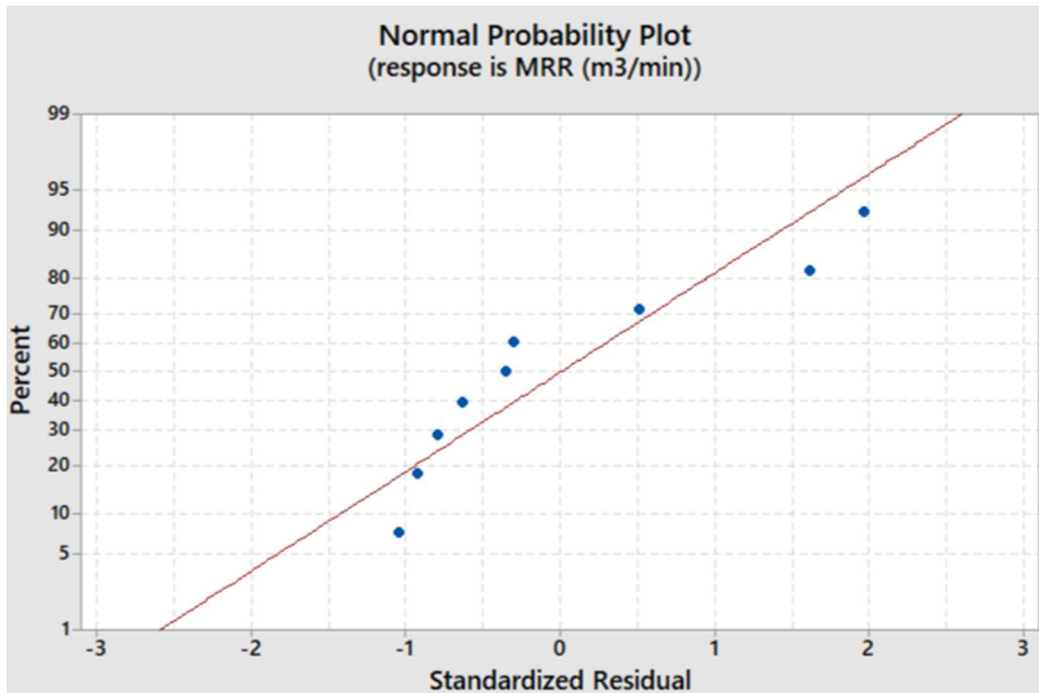


Fig 5.1 Normplot of Residuals for MRR (m3/min)

The above Fig 5.1 represents the Normal Probability plot for MRR value for the workpiece at flow rate of 180ml/hr. Here the blue dots represents the output values. The above figure says that all MRR values are in a linearity line, we can say that all the values are linear with each other.

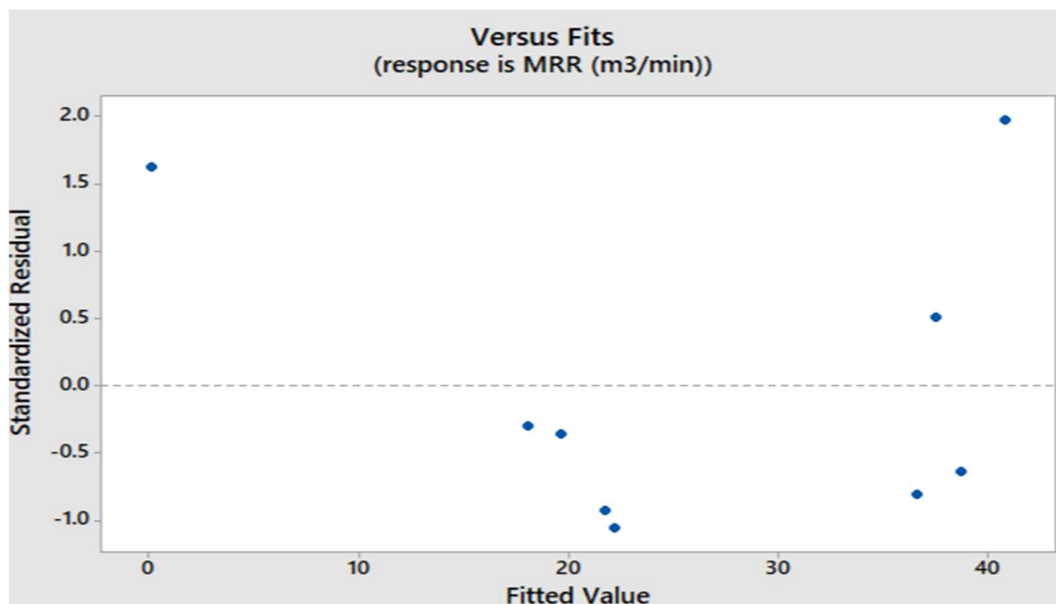


Fig 5.2 Residuals vs Fits for MRR (m3/min)

The above Fig 5.2 represents the versus fits (Scattered plots) In the above figure the blue dots indicate MRR values. It says that for all the 9 experiments the output values are not same. It states that we used 9 different input parameters so for each parameter the output values are different.

Response Surface Regression: Rt (µm) versus Cutting speed(m/min), Feed, DoC

Table 5.3 Analysis of Variance of Rt of workpiece with flowrate of 180ml/hr

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%Contribution
Model	3	83.800	27.933	65.18	0.007	-
Linear	3	83.800	27.933	65.18	0.007	-
Cutting speed(m/min)	1	0.006	0.006	9.00	0.005	0.007
Feed	1	54.500	54.500	86.35	0.002	65.03
DoC	1	29.295	29.295	53.19	0.004	34.95
Error	5	785.947	157.189			
Total	8	869.747				

Table 5.4 Modal Summary of Analysis of Variance of Rt of workpiece with flowrate of 180ml/hr

S	R-sq	R-sq(adi)	R-sq(pred)
12.5375	92.64%	0.00%	0.00%

Regression Equation in Uncoded Units

$$Rt (\mu m) = 30.0 + 0.001 \text{ Cutting speed(m/min)} + 14.9 \text{ Feed} - 7.4 \text{ DoC} \quad \text{-----EQ 5.2}$$

The above Rt equation is used to find out the regression equation values for Rt of work piece with flowrate of 180ml/hr. Here according to the %contribution the feed is the most effecting parameter and cutting speed is the least effecting parameter for Rt value for workpiece with flow rate of 180ml/hr.

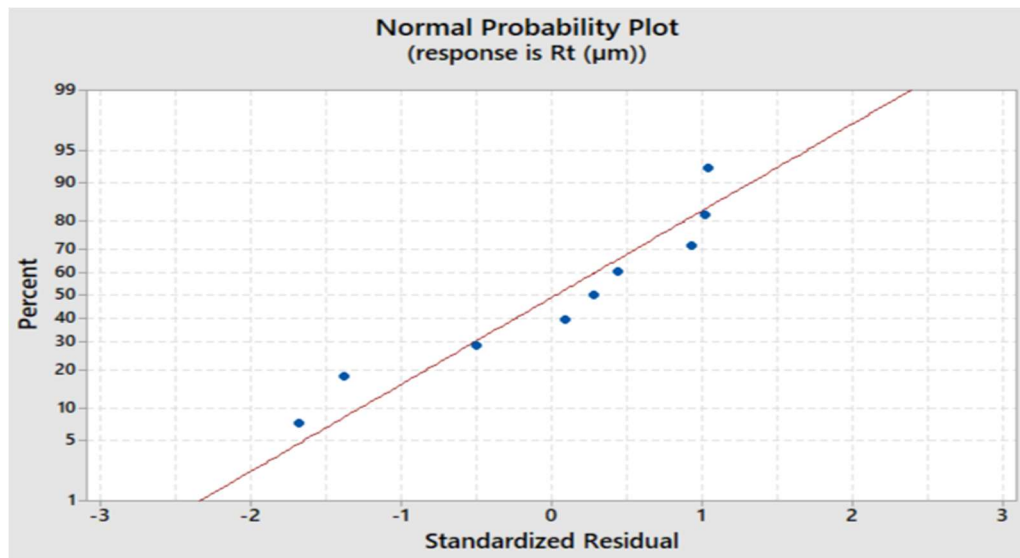


Fig 5.3 Normplot of Residuals for Rt (µm)

The above Fig 5.3 represents the Normal Probability plot for Rt value for the workpiece at flow rate of 180ml/hr. Here the blue dots represents the output values. It also says that all Rt values are very near to the linearity line, we can say that all the values are linear with each other.

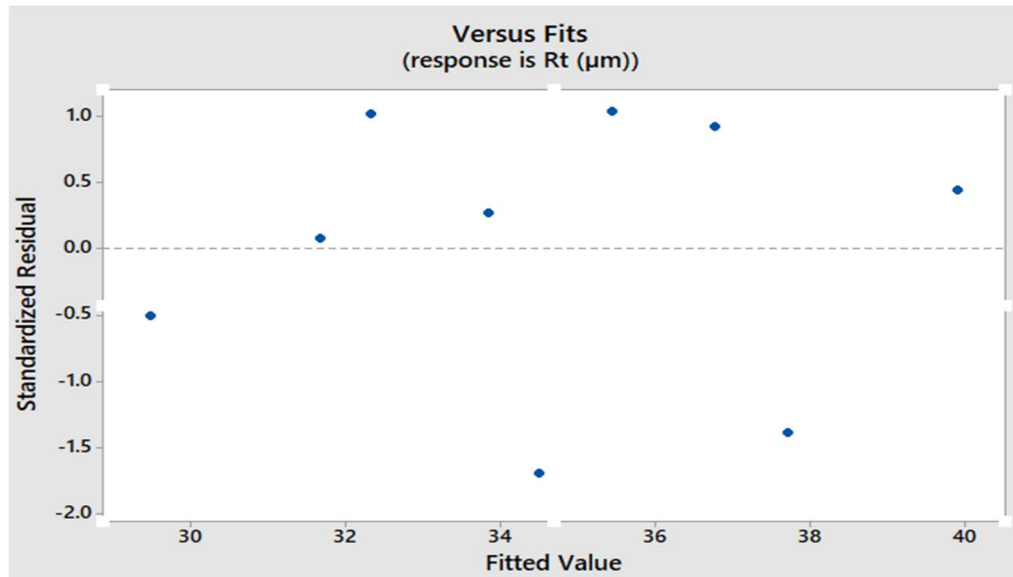


Fig 5.4 Residuals vs Fits for Rt (µm)

The above Fig5.4 represents the versus fits (Scattered plots). In the above figure the blue dots indicate Rt values. It says that for all the 9 experiments the output values are not same. It states that we used 9 different input parameters so for each parameter the output value is different.

Response Surface Regression: Ra (µm) versus Cutting speed(m/min), Feed, DoC

Table 5.5 Analysis of Variance of Ra of workpiece with flowrate of 180ml/hr

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%Contribution
Model	3	13.1720	4.3907	49.40	0.059	-
Linear	3	13.1720	4.3907	4.40	0.059	-
Cutting speed(m/min)	1	0.1547	0.1547	4.01	0.010	1.175
Feed	1	12.7515	12.7515	96.16	0.030	96.80
DoC	1	0.2659	0.2659	8.02	0.002	2.018
Error	5	54.7535	10.9507			
Total	8	67.9255				

Table 5.6 Modal Summary of Analysis of Variance of Ra of workpiece with flowrate of 180ml/hr

S	R-sq	R-sq(adi)	R-sq(pred)
3.30918	85.38%	0.00%	0.00%

Regression Equation in Uncoded Units

$$Ra (\mu m) = 2.32 + 0.0060 \text{ Cutting speed(m/min)} + 7.21 \text{ Feed} - 0.70 \text{ DoC} \quad \text{-----EQ 5.3}$$

The above Ra equation is used to find out the regression equation values for Ra of work piece with flowrate of 180ml/hr. Here according to the %contribution the feed is the most effecting parameter and cutting speed is the least effecting parameter for Ra value for workpiece with flow rate of 180ml/hr.

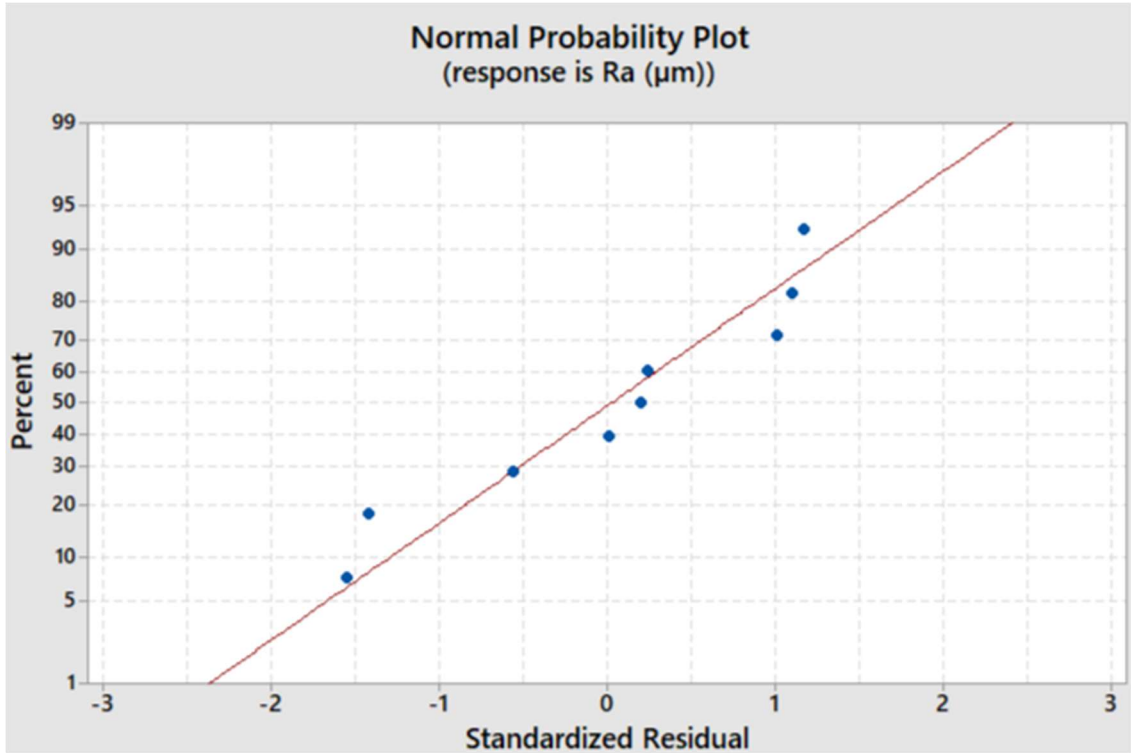


Fig 5.5 Normplot of Residuals for Ra (μm)

The above Fig 5.5 represents the Normal Probability plot for Ra value for the workpiece at flow rate of 180ml/hr. Here the blue dots represents the output values. It also says that all Ra values are very near to the linearity line, we can say that all the values are linear with each other.

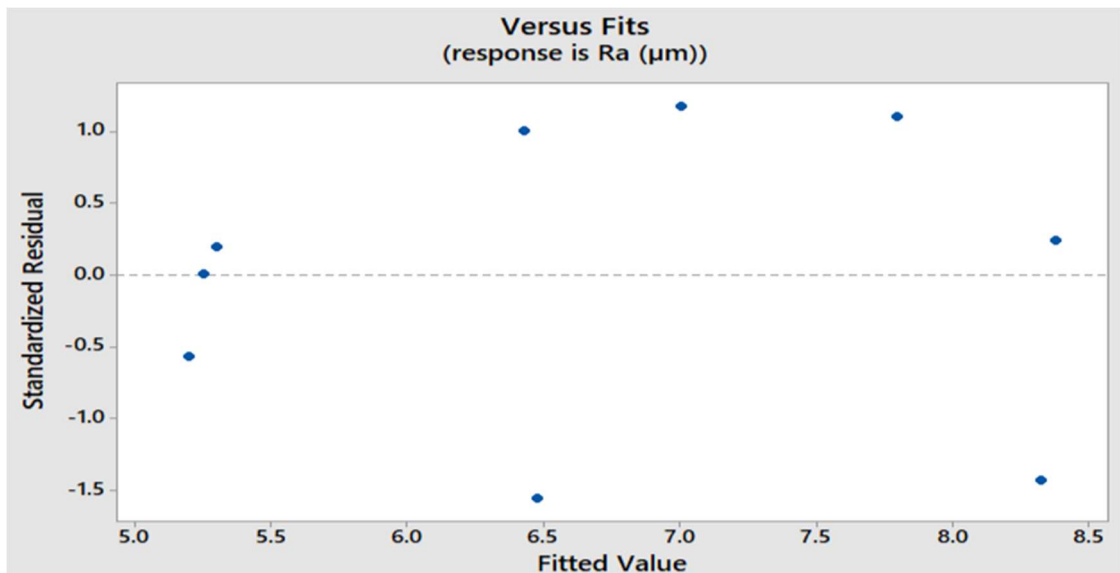


Fig 5.6 Residuals vs Fits for Ra (μm)

The above Fig 5.6 represents the versus fits (Scattered plots). In the above figure the blue dots indicate Ra values. It says that for all the 9 experiments the output values are not same. It states that we used 9 different input parameters so for each parameter the output value is different.

Response Surface Regression: Rq (µm) versus Cutting speed(m/min), Feed, DoC

Table 5.7 Analysis of Variance of Rq of workpiece with flowrate of 180ml/hr

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%Contribution
Model	3	14.8075	4.9358	0.35	0.049	-
Linear	3	14.8075	4.9358	0.35	0.049	-
Cutting speed(m/min)	1	0.1666	0.1666	20.01	0.017	1.125
Feed	1	14.6144	14.6144	138.05	0.052	38.69
DoC	1	0.0265	0.0265	14.00	0.007	0.001
Error	5	69.5750	13.9150			
Total	8	84.3825				

Table 5.8 Modal Summary of Analysis of Variance of Rq of workpiece with flowrate of 180ml/hr

S	R-sq	R-sq(adi)	R-sq(pred)
3.73028	87.55%	0.00%	0.00%

Regression Equation in Uncoded Units

$$Rq (\mu\text{m}) = 2.90 + 0.0062 \text{ Cutting speed(m/min)} + 7.72 \text{ Feed} - 0.22 \text{ DoC} \quad \text{-----EQ 5.4}$$

The above Rq equation is used to find out the regression equation values for Rq of work piece with flowrate of 180ml/hr. Here according to the %contribution the feed is the most effecting parameter and depth of cut is the least effecting parameter for Rq value for workpiece with flow rate of 180ml/hr.

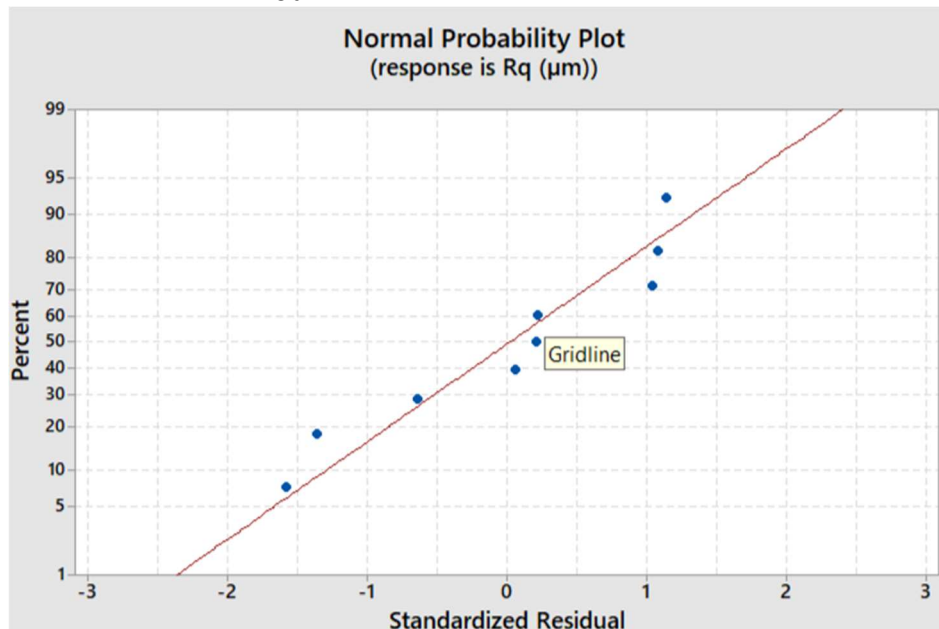


Fig 5.7 Normplot of Residuals for Rq (µm)

The above figure represents the Normal Probability plot for Rq value for the workpiece at flow rate of 180ml/hr. Here the blue dots represents the output values. It also says that all

Rq values are very near to the linearity line, we can say that all the values are linear with each other.

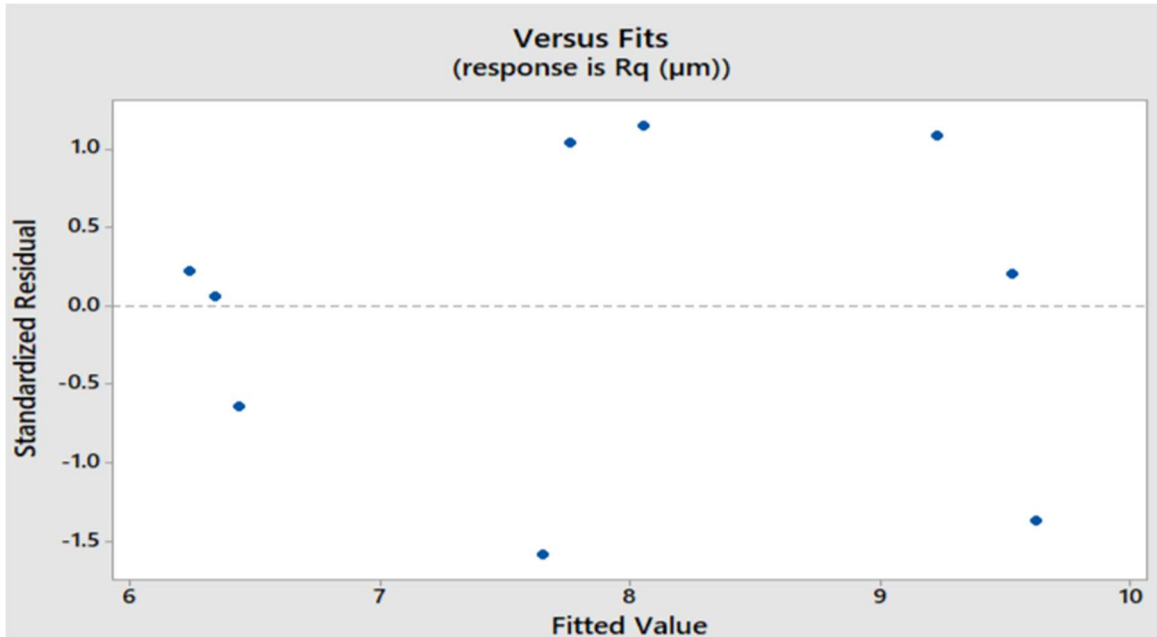


Fig 5.8 Residuals vs Fits for Rq (µm)

The above Fig 5.8 represents the versus fits (Scattered plots). In the above figure the blue dots indicate Rq values. It says that for all the 9 experiments the output values are not same. It states that we used 9 different input parameters so for each parameter the output value is different.

Response Surface Regression: Rz (µm) versus Cutting speed(m/min), Feed, DoC

Table 5.9 Analysis of Variance of Rz of workpiece with flowrate of 180ml/hr

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%Contribution
Model	2	97.069	32.356	69.24	0.065	-
Linear	2	97.069	32.356	69.24	0.065	-
Cutting speed(m/min)	1	0.139	0.139	5.00	0.056	0.0014
Feed	1	95.610	95.610	99.71	0.037	98.496
DoC	1	1.320	1.320	1.01	0.025	1.3598
Error	5	671.826	134.365			
Total	8	768.895				

Table 5.10 Modal Summary of Analysis of Variance of Rz of workpiece with flowrate of 180ml/hr

S	R-sq	R-sq(adi)	R-sq(pred)
11.5916	82.62%	0.00%	0.00%

Regression Equation in Uncoded Units

$$Rz (\mu\text{m}) = 17.2 + 0.006 \text{ Cutting speed(m/min)} + 19.8 \text{ Feed} - 1.6 \text{ DoC} \quad \text{-----EQ 5.5}$$

The above Rz equation is used to find out the regression equation values for Rz of work piece with flowrate of 180ml/hr. Here according to the %contribution the feed is the most effecting parameter and cutting speed is the least effecting parameter for Rz value for workpiece with flow rate of 180ml/hr.

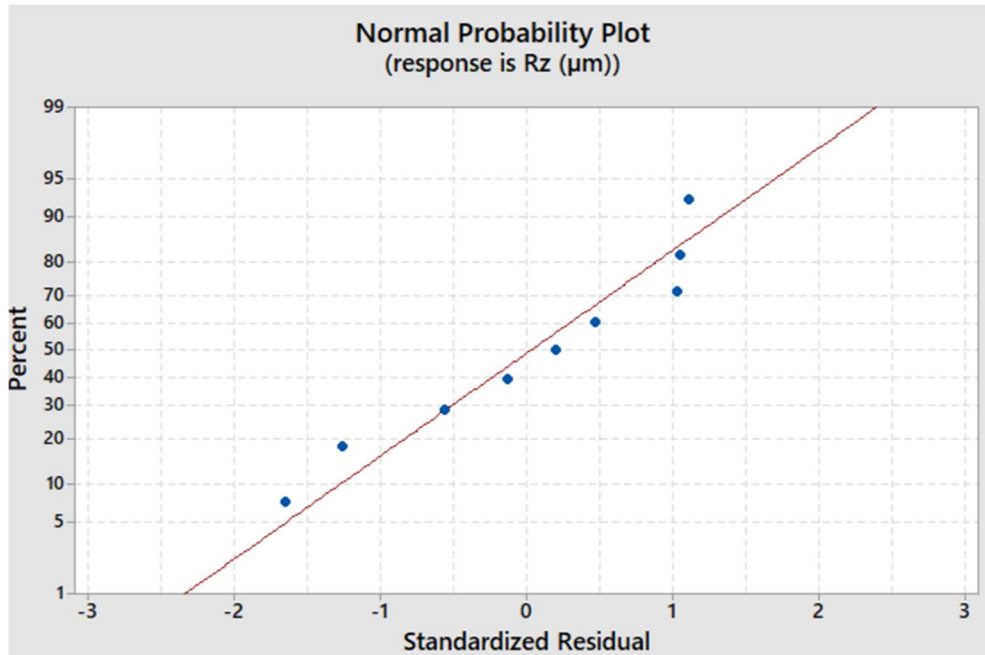


Fig 5.9 Normplot of Residuals for Rz (µm)

The above Fig 5.9 represents the Normal Probability plot for Rz value for the workpiece at flow rate of 180ml/hr. Here the blue dots represents the output values. It also says that all Rz values are very near to the linearity line, we can say that all the values are linear with each other.

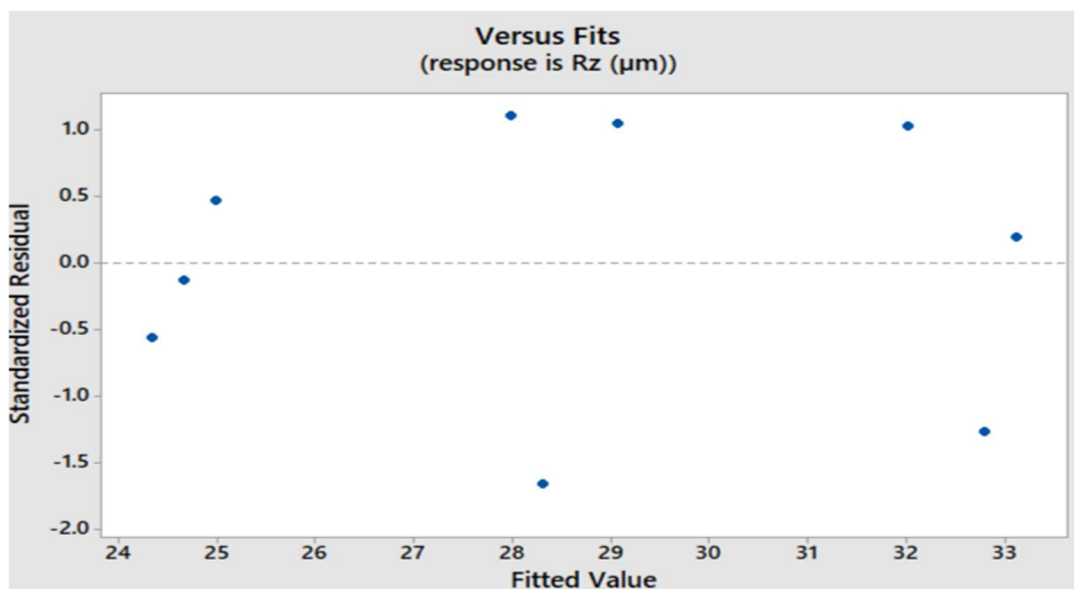


Fig 5.10 Residuals vs Fits for Rz (µm)

The above Fig 5.10 represents the versus fits (Scattered plots). In the above figure the blue dots indicate Rt values. Here the blue dots represents the output values. It says that for all

the 9 experiments the output values are not same. It states that we used 9 different input parameters so for each parameter the output value is different.

Table 5.11 Regression Equation Generated Values For Workpiece Of Flowrate (180ml/Hr)

Cutting speed (m/min)	Feed (mm)	DoC (mm)	MRR (m3/min)	Rt (µm)	Ra (µm)	Rq (µm)	Rz (µm)
46.74	0.404	0.3	0.236	33.846	5.303	6.243	12.343
46.74	0.596	0.6	18.147	34.487	6.478	7.659	15.664
46.74	0.808	0.9	36.73	35.426	7.796	9.23	19.382
74.38	0.404	0.6	19.739	31.654	5.259	6.348	14.715
74.38	0.596	0.9	37.65	32.295	6.433	7.764	18.037
74.38	0.808	0.3	21.853	39.894	8.382	9.533	23.194
100.51	0.404	0.9	38.803	29.46	5.206	6.444	16.932
100.51	0.596	0.3	22.334	36.761	7.01	8.058	21.693
100.51	0.808	0.6	40.917	37.7	8.329	9.629	25.411

The above table represents the values which are generated from using the equations which are given above respectively. So that these values can be used for comparison of experimental values and regression equation generated values.

RESPONSE SURFACE OPTIMIZATION FOR WORKPIECE WITH FLOWRATE (90ML/HR)

Response Surface Regression: MRR (m3/min) versus Cutting speed(m/min), Feed, DoC

Table 5.12 Analysis of Variance of MRR of workpiece with flowrate of 90ml/hr

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%Contribution
Model	3	1429.0	476.35	16.24	0.005	-
Linear	3	1429.0	476.35	16.24	0.005	-
Cutting speed(m/min)	1	365.1	365.07	12.44	0.017	25.54
Feed	1	275.9	275.86	9.40	0.028	19.54
DoC	1	788.1	788.11	26.86	0.004	55.14
Error	5	146.7	29.34			
Total	8	1575.7				

Table 5.13 Modal Summary of Analysis of Variance of MRR of workpiece with flowrate of 90ml/hr

S	R-sq	R-sq(adi)	R-sq(pred)
5.41646	90.69%	85.11%	61.71%

Regression Equation in Uncoded Units

$$\text{MRR (m3/min)} = -38.4 + 0.2901 \text{ Cutting speed(m/min)} + 33.6 \text{ Feed} + 38.20 \text{ DoC} \quad \text{----- EQ 5.6}$$

The above MRR equation is used to find out the regression equation values for MRR of work piece with flowrate of 90ml/hr. The above table discusses about the DF, ADJ Sum of Squares, F value, P value and % contribution. Using % contribution we can say which factor is most influencing for MRR while doing machining at flowrate of 90ml/hr. Here we can see that DOC is having % contribution of 55.14% that means in this machining part for MRR is mainly effected by DOC. Here R-sq value is much enough to say that our values are enough good for optimization

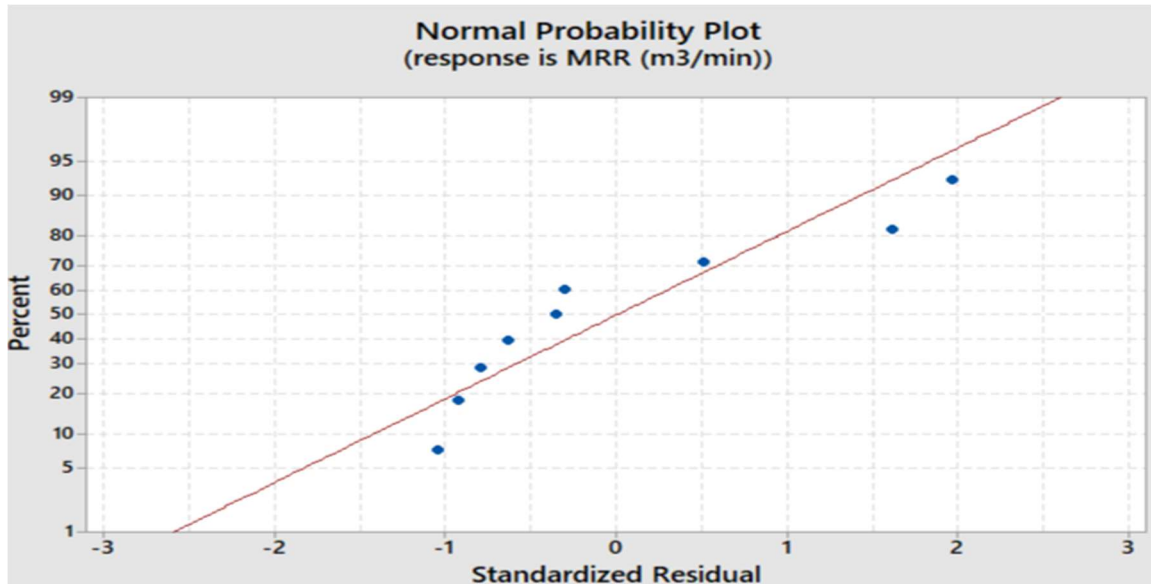


Fig 5.11 Normplot of Residuals for MRR (m3/min)

The above Fig 5.11 represents the Normal Probability plot for MRR value for the workpiece at flow rate of 90ml/hr. Here the blue dots represents the output values. The above figure says that all MRR values are in a linearity line, we can say that all the values are linear with each other.

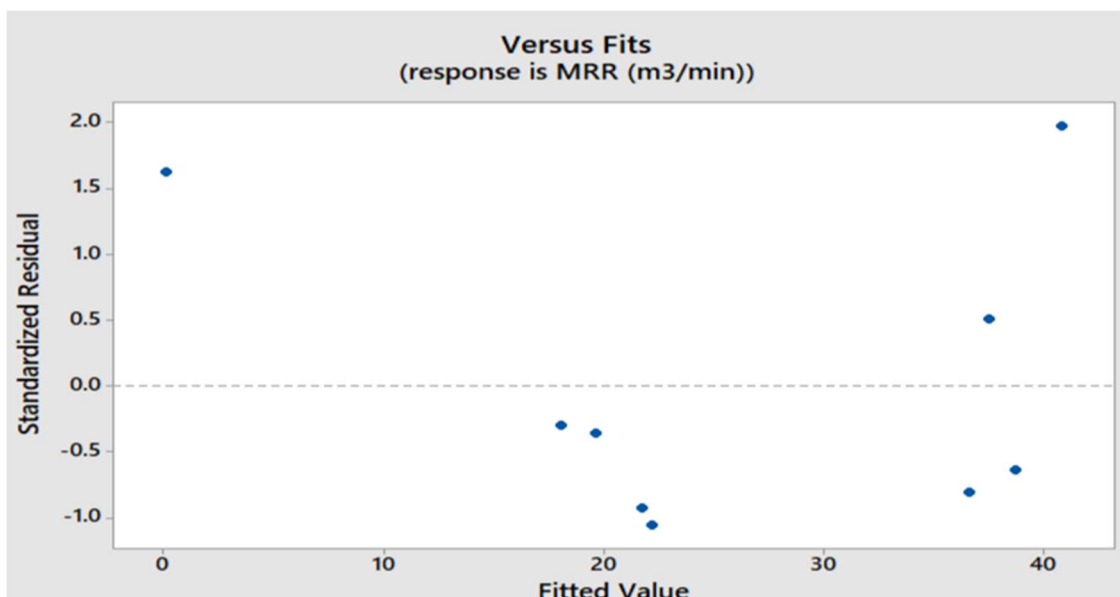


Fig 5.12 Residuals vs Fits for MRR (m3/min)

The above Fig 5.12 represents the versus fits (Scattered plots) In the above figure the blue dots indicate MRR values. It says that for all the 9 experiments the output values are not same. It states that we used 9 different input parameters so for each parameter the output values are different.

Response Surface Regression: Rt (µm) versus Cutting speed(m/min), Feed, DoC

Table 5.14 Analysis of Variance of Rt of workpiece with flowrate of 90ml/hr

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%Contribution
Model	3	229.16	76.39	120.73	0.068	-
Linear		229.16	76.39	120.73	0.068	-
Cutting speed(m/min)	1	12.41	12.41	9.12	0.045	5.415
Feed	1	113.93	113.93	91.09	0.045	49.71
DoC	1	102.82	102.82	80.98	0.058	44.86
Error	5	524.52	104.90			
Total	8	753.68				

Table 5.15 Modal Summary of Analysis of Variance of Rt of workpiece with flowrate of 90ml/hr

S	R-sq	R-sq(adi)	R-sq(pred)
10.2423	73.48%	0.00%	0.00%

Regression Equation in Uncoded Units

$$Rt (\mu m) = 47.9 + 0.053 \text{ Cutting speed(m/min)} - 21.6 \text{ Feed} + 13.8 \text{ DoC} \quad \text{-----EQ 5.7}$$

The above Rt equation is used to find out the regression equation values for Rt of work piece with flowrate of 90ml/hr. Here according to the %contribution the feed is the most effecting parameter , Depth of cut is second most effecting parameter and cutting speed is the least effecting parameter for Rt value for workpiece with flow rate of 90ml/hr.

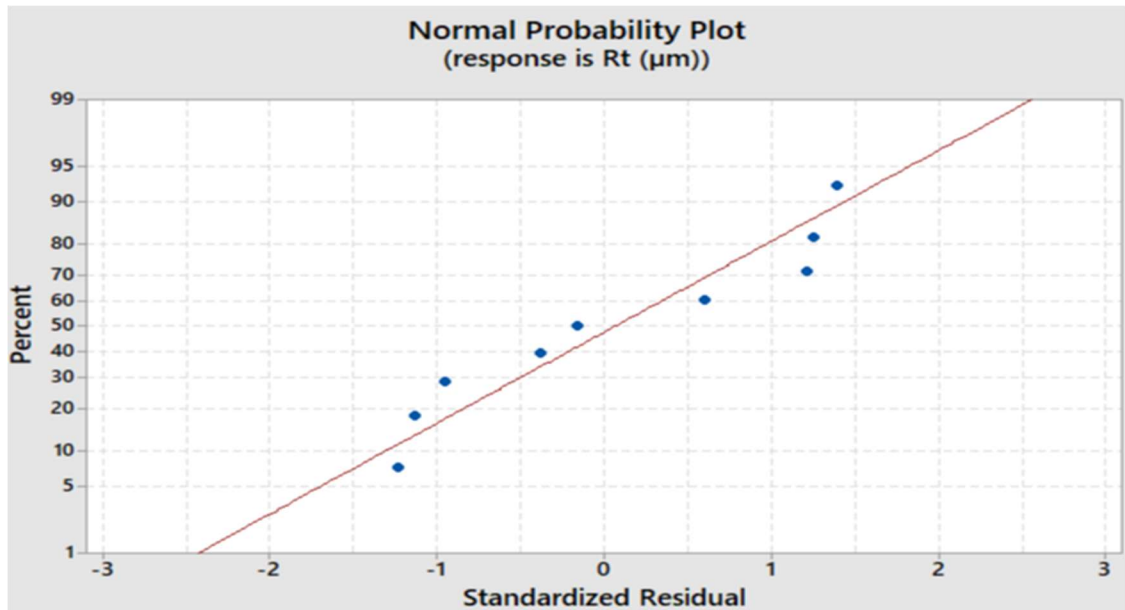


Fig 5.13 Normplot of Residuals for Rt (µm)

The above Fig 5.13 represents the Normal Probability plot for Rt value for the workpiece at flow rate of 90ml/hr. Here the blue dots represents the output values. It also says that all Rt values are very near to the linearity line, we can say that all the values are linear with each other.

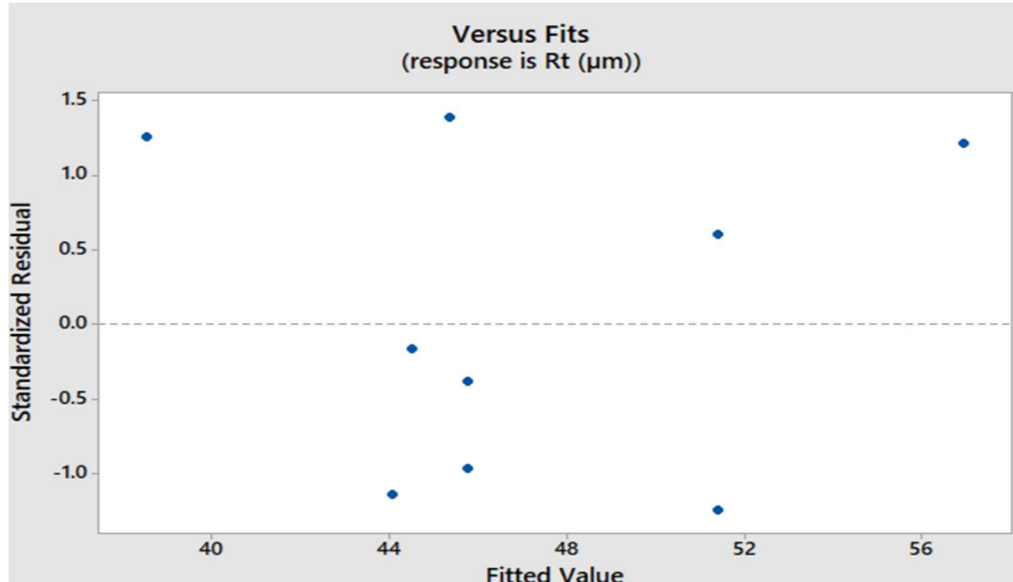


Fig 5.14 Residuals vs Fits for Rt (µm)

The above Fig 5.14 represents the versus fits (Scattered plots). In the above figure the blue dots indicate Rt values. It says that for all the 9 experiments the output values are not same. It states that we used 9 different input parameters so for each parameter the output value is different.

Response Surface Regression: Ra (µm) versus Cutting speed(m/min), Feed, DoC

Table 5.16 Analysis of Variance of Ra of workpiece with flowrate of 90ml/hr

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%Contribution
Model	3	36.946	12.315	41.53	0.049	-
Linear	3	36.946	12.315	41.53	0.049	-
Cutting speed(m/min)	1	11.662	11.662	40.29	0.063	31.565
Feed	1	5.594	5.594	25.06	0.011	15.141
DoC	1	19.689	19.689	79.23	0.043	53.292
Error	5	13.608	2.722			
Total	8	50.554				

Table 5.17 Modal Summary of Analysis of Variance of Ra of workpiece with flowrate of 90ml/hr

S	R-sq	R-sq(adi)	R-sq(pred)
1.64973	73.08%	56.93%	0.00%

Regression Equation in Uncoded Units

$$Ra (\mu m) = 6.82 - 0.0518 \text{ Cutting speed(m/min)} + 4.78 \text{ Feed} + 6.04 \text{ DoC} \quad \text{-----EQ 5.8}$$

The above Ra equation is used to find out the regression equation values for Ra of work piece with flowrate of 90ml/hr. Here according to the %contribution the Depth of cut is the most effecting parameter , cutting speed is the second most effecting parameter and feed is the least effecting parameter for Ra value for workpiece with flow rate of 90ml/hr.

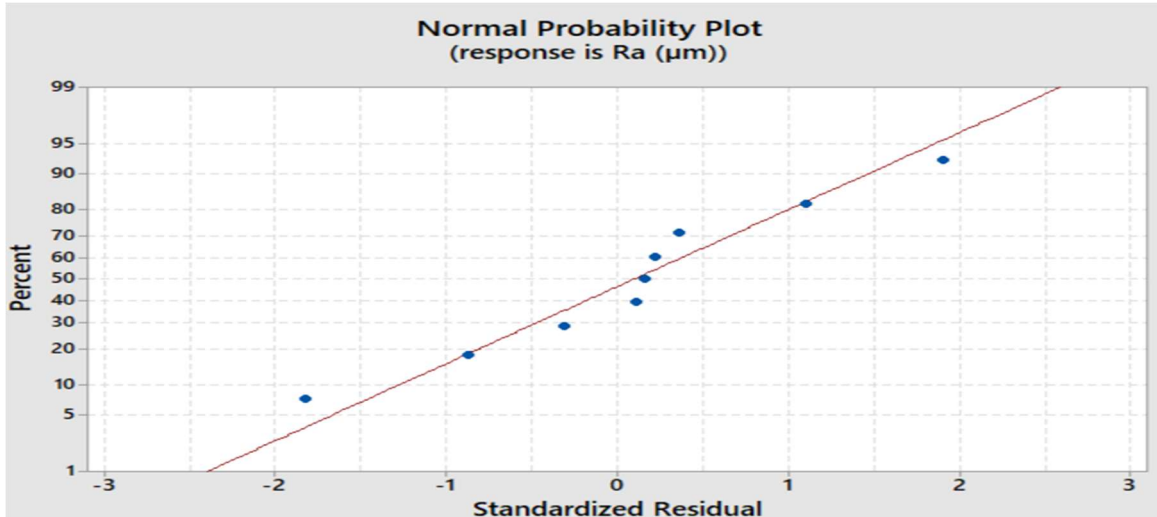


Fig 5.15 Normplot of Residuals for Ra (µm)

The above Fig 5.15 represents the Normal Probability plot for Ra value for the workpiece at flow rate of 90ml/hr. Here the blue dots represents the output values. It also says that all Ra values are very near to the linearity line, we can say that all the values are linear with each other.

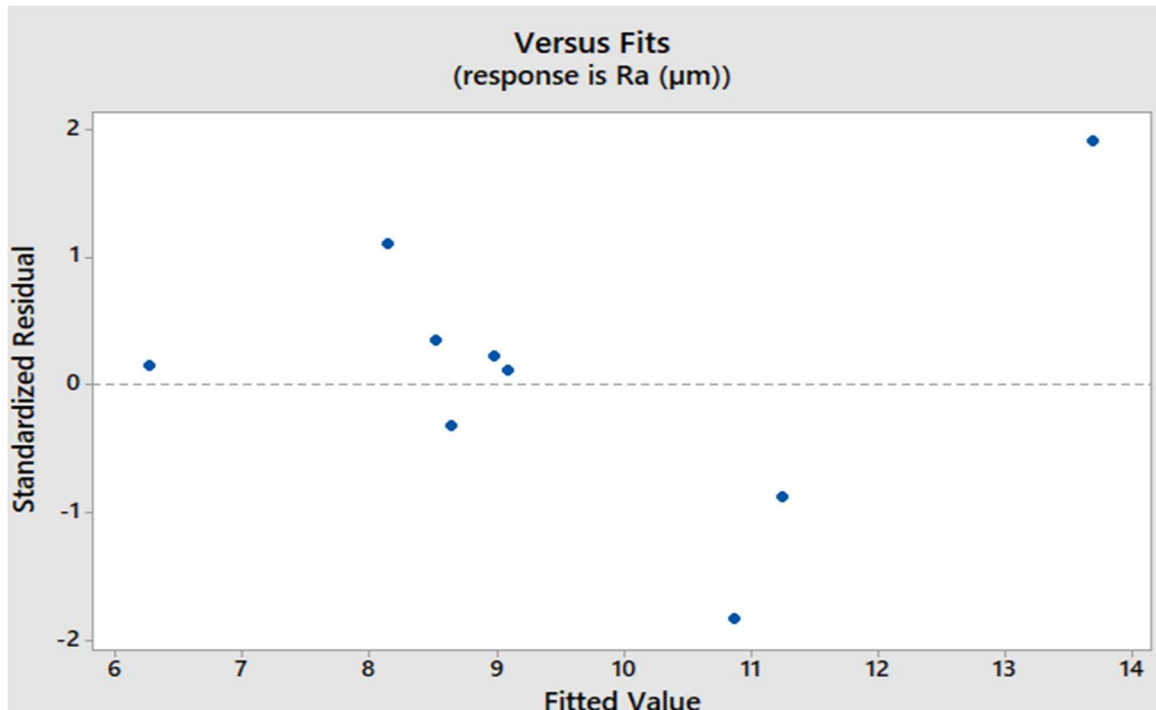


Fig 5.16 Residuals vs Fits for Ra (µm)

The above Fig 5.16 represents the versus fits (Scattered plots). In the above figure the blue dots indicate Ra values. It says that for all the 9 experiments the output values are not same. It states that we used 9 different input parameters so for each parameter the output value is different.

Response Surface Regression: Rq (µm) versus Cutting speed(m/min), Feed, DoC

Table 5.18 Analysis of Variance of Rq of workpiece with flowrate of 90ml/hr

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%Contribution
Model	3	33.394	11.131	36.15	0.024	-
Linear	3	33.394	11.131	36.15	0.024	-
Cutting speed(m/min)	1	5.511	5.511	41.56	0.067	16.502
Feed	1	1.027	1.027	22.29	0.013	3.0754
DoC	1	26.856	26.856	172.59	0.040	80.421
Error	5	17.681	3.536			
Total	8	51.075				

Table 5.19 Modal Summary of Analysis of Variance of Rq of workpiece with flowrate of 90ml/hr

S	R-sq	R-sq(adi)	R-sq(pred)
1.88046	85.38%	84.61%	0.00%

Regression Equation in Uncoded Units

$$Rq (\mu m) = 8.35 - 0.0356 \text{ Cutting speed(m/min)} + 2.05 \text{ Feed} + 7.05 \text{ DoC} \quad \text{-----EQ 5.9}$$

The above Rq equation is used to find out the regression equation values for Rq of work piece with flowrate of 90ml/hr. Here according to the %contribution the depth of cut is the most effecting parameter , cutting speed is second most effecting parameter and feed is the least effecting parameter for Rq value for workpiece with flow rate of 90ml/hr.

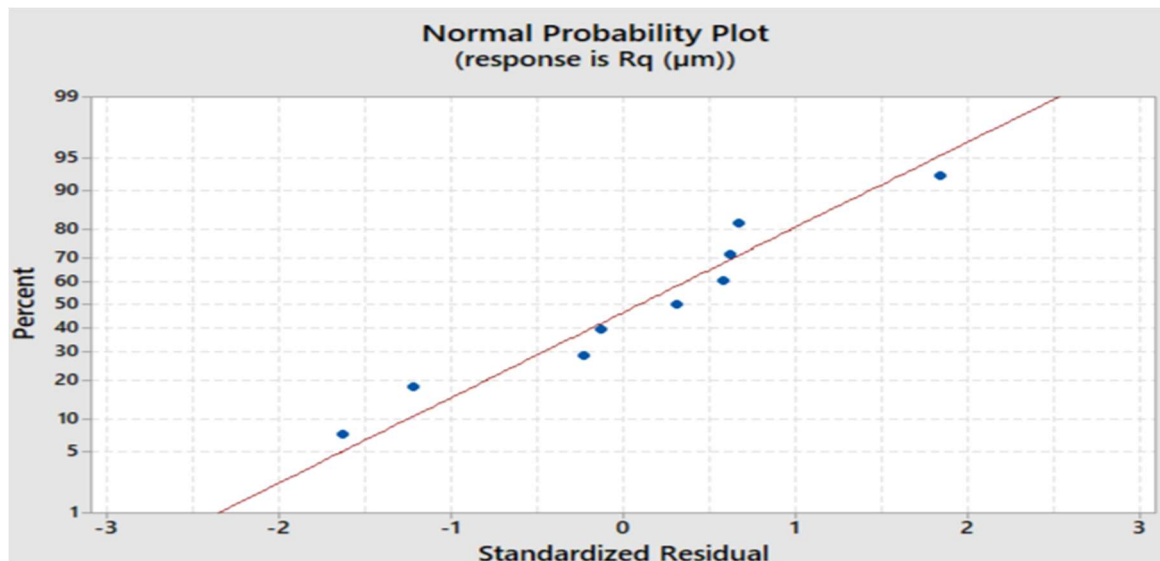


Fig 5.17 Normplot of Residuals for Rq (µm)

The above Fig 5.17 represents the Normal Probability plot for Rq value for the workpiece at flow rate of 90ml/hr. Here the blue dots represents the output values. It also says that all Rq values are very near to the linearity line, we can say that all the values are linear with each other.

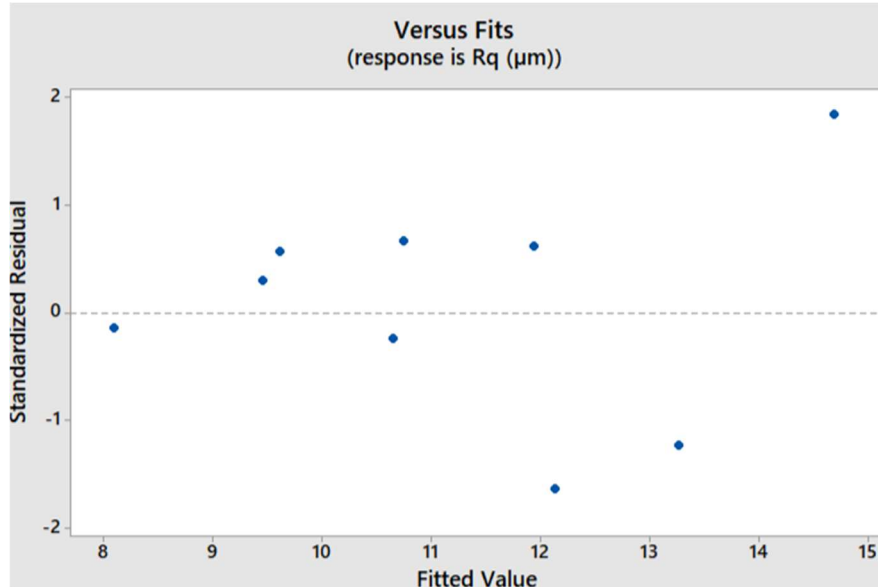


Fig 5.18 Residuals vs Fits for Rq (µm)

The above Fig 5.18 represents the versus fits (Scattered plots). In the above figure the blue dots indicate Rq values. It says that for all the 9 experiments the output values are not same. It states that we used 9 different input parameters so for each parameter the output value is different.

Response Surface Regression: Rz (µm) versus Cutting speed(m/min), Feed, DoC

Table 5.20 Analysis of Variance of Rz of workpiece with flowrate of 90ml/hr

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%Contribution
Model	3	390.929	130.310	99.66	0.060	-
Linear	3	390.929	130.310	99.66	0.060	-
Cutting speed(m/min)	1	5.221	5.221	63.07	0.007	1.335
Feed	1	112.630	112.630	112.43	0.065	28.810
DoC	1	273.078	273.078	322.47	0.021	69.853
Error	5	393.314	78.663			
Total	8	784.243				

Table 5.21 Modal Summary of Analysis of Variance of Rz of workpiece with flowrate of 90ml/hr

S	R-sq	R-sq(adi)	R-sq(pred)
8.86920	89.82%	19.76%	0.00%

Regression Equation in Uncoded Units

$$Rz (\mu\text{m}) = 37.7 + 0.035 \text{ Cutting speed(m/min)} - 21.4 \text{ Feed} + 22.5 \text{ DoC} \quad \text{-----EQ 5.10}$$

The above Rz equation is used to find out the regression equation values for Rz of work piece with flowrate of 90ml/hr. Here according to the %contribution the feed is the most effecting parameter and cutting speed is the least effecting parameter for Rz value for workpiece with flow rate of 90ml/hr.

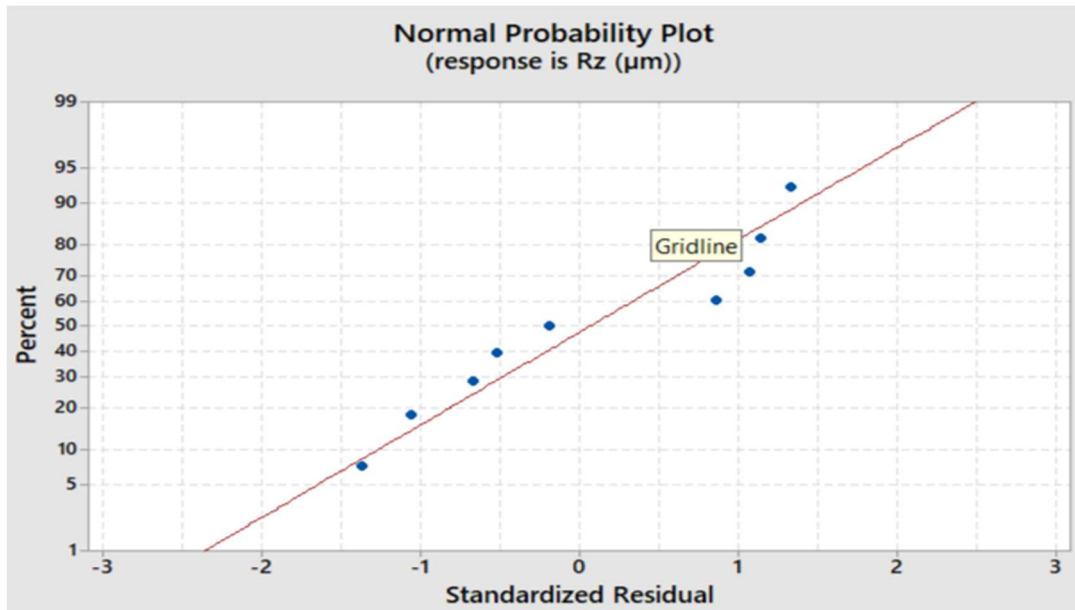


Fig 5.19 Normplot of Residuals for Rz (µm)

The above Fig 5.19 represents the Normal Probability plot for Rz value for the workpiece at flow rate of 180ml/hr. Here the blue dots represents the output values. It also says that all Rz values are very near to the linearity line, we can say that all the values are linear with each other.

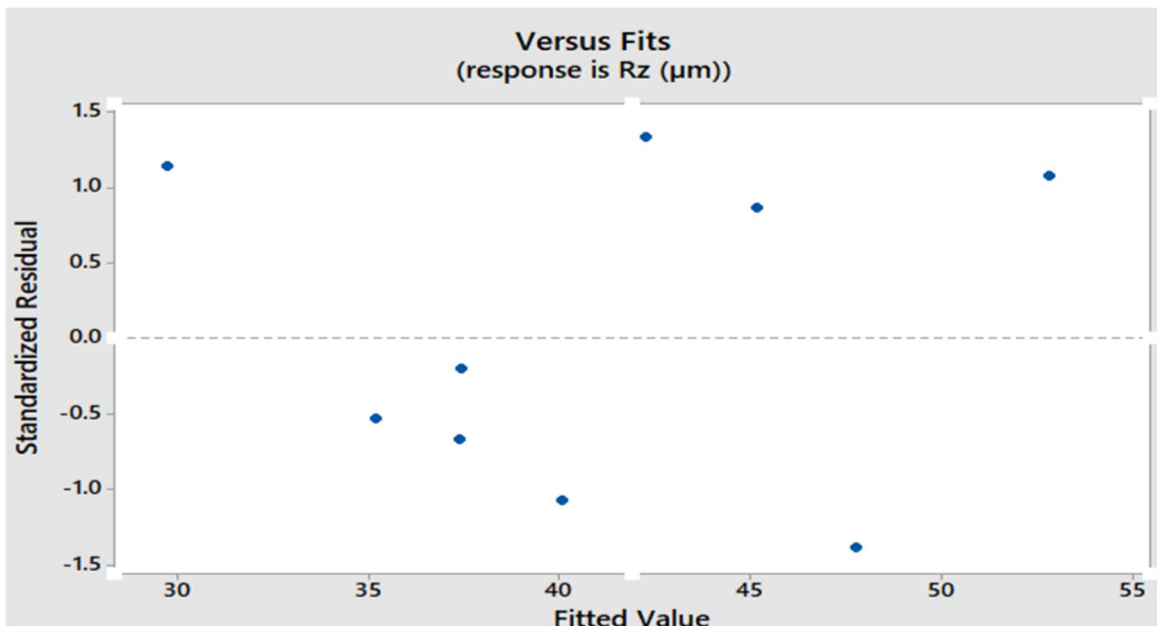


Fig 5.20 Residuals vs Fits for Rz (µm)

The above Fig 5.20 represents the versus fits (Scattered plots). In the above figure the blue dots indicate Rt values. Here the blue dots represents the output values. It says that for all the 9 experiments the output values are not same. It states that we used 9 different input parameters so for each parameter the output value is different.

Table 5.22 Regression Equation Generated Values For Workpiece Of Flowrate (90ml/Hr)

Cutting speed (m/min)	Feed (mm)	DoC (mm)	MRR (m3/min)	Rt (µm)	Ra (µm)	Rq (µm)	Rz (µm)
46.74	0.404	0.3	0.236	45.791	8.142	9.629	37.44
46.74	0.596	0.6	18.147	45.784	10.872	12.138	40.082
46.74	0.808	0.9	36.73	45.344	13.697	14.687	42.295
74.38	0.404	0.6	19.739	51.396	8.522	10.76	45.158
74.38	0.596	0.9	37.65	51.389	11.252	13.269	47.799
74.38	0.808	0.3	21.853	38.529	8.641	9.473	29.762
100.51	0.404	0.9	38.803	56.921	8.981	11.945	52.822
100.51	0.596	0.3	22.334	44.493	6.274	8.109	35.213
100.51	0.808	0.6	40.917	44.054	9.1	10.658	37.427

The above table represents the values which are generated from using the equations which are given above. Some of the values are nearer to the experimental values ,where as some of the values are very much far away when compared with the experimental values . So that these values can be used for comparison of experimental values and regression equation generated values.

5.2 RESPONSE OPTIMIZER RESULTS

RESPONSE OPTIMIZER RESULT FOR WORK PIECE WITH FLOWRATE OF 180ML/HR

After giving the Response Surface Optimizer inputs we click on OK and the results that will be displayed are given below in the figure.

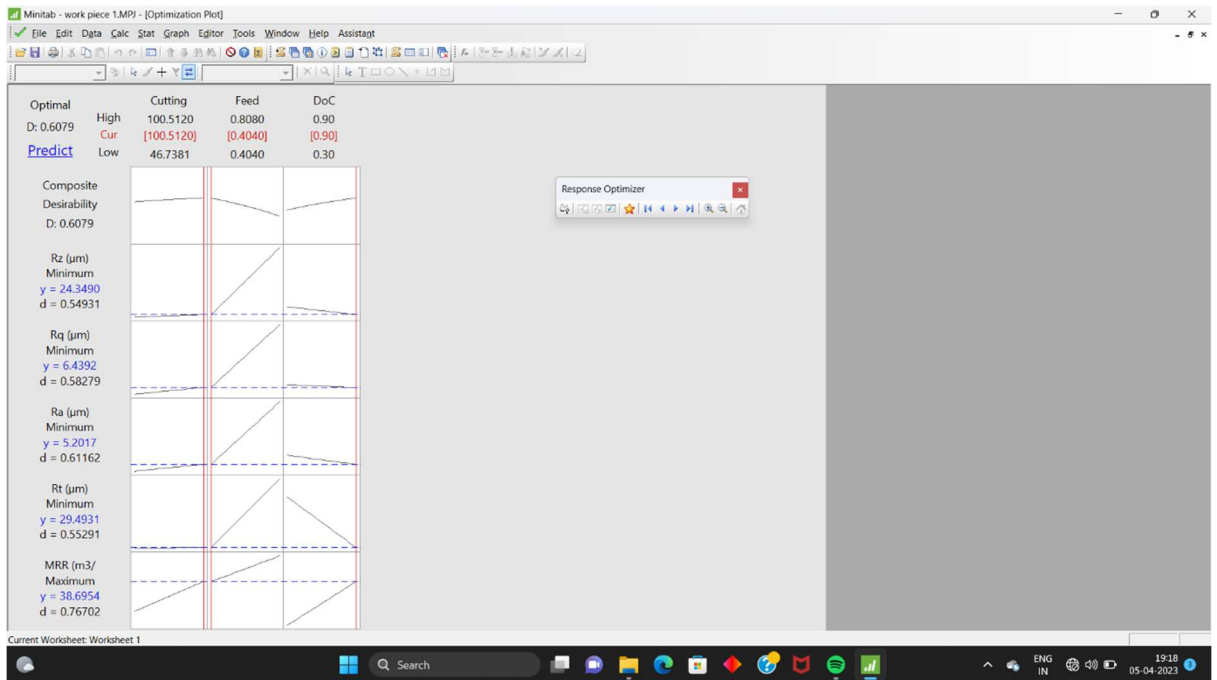


Fig 5.21 Optimization plot for workpiece of 180 ml/hr

Here from the above figure 5.21 we get the best output cutting parameters. They are Cutting speed – 100.512, Feed – 0.404, DOC – 0.90. Using these cutting parameters we did the machining again to get the output parameter values like MRR , Rt , Ra , Rq and Rz.

Table 5.23 Results of Response Optimizer for Workpieces of 180 ml/hr

S.no	Cutting speed (m/min)	Feed (mm)	DoC (mm)	MRR (m3/min)	Rt (µm)	Ra (µm)	Rq (µm)	Rz (µm)
1	100.512	0.404	0.9	36.532	27.684	5.201	5.099	15.201

Above values are the values which are obtained after doing machining for the above cutting parameters. Those cutting parameters are generated after completing the optimization. We did optimization so find out the best cutting parameter among the parameters we did with L9 experiments.

RESPONSE SURFACE OPTIMIZER RESULT FOR WORK PIECE WITH FLOWRATE OF 90ML/HR

After giving the Response Surface Optimizer inputs we click on OK and the results that will be displayed are given below in the figure.

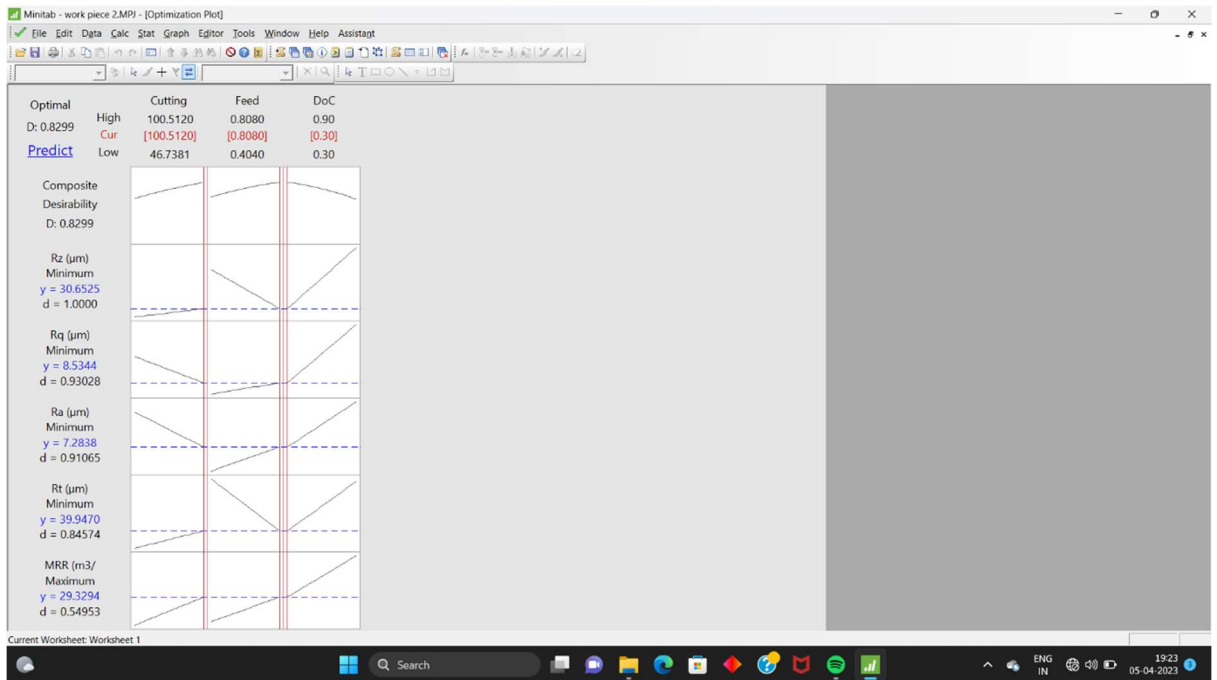


Fig 5.22 Optimization plot for workpiece of 90ml/hr

Here from the above figure 5.22 we get the best output cutting parameters. They are Cutting speed – 100.512, Feed – 0.808, DOC – 0.30. Using these cutting parameters we did the machining again to get the output parameter values like MRR , Rt , Ra , Rq and Rz.

Table 5.24 Results of Response Optimizer for Workpiece of 90 ml/hr

S.no	Cutting speed (m/min)	Feed (mm)	DoC (mm)	MRR (m3/min)	Rt (µm)	Ra (µm)	Rq (µm)	Rz (µm)
1	100.512	0.404	0.9	31.256	38.257	8.354	9.741	32.012

Above values are the values which are obtained after doing machining for the above cutting parameters. Those cutting parameters are generated after completing the optimization. We did optimization so find out the best cutting parameter among the parameters we did with L9 experiments. Here we consider these as best values from our set of experiments based on our Response Surface optimization.

5.3 Fuzzy Logic Optimization Results

We can use fuzzy logic in matlab opening fuzzy logic toolbox. It can be used for analyzing, designing, and simulating fuzzy logic systems. This lets you configure and specify inputs , outputs ,membership functions and rules. As per our requirement we are taking Cutting speed, Feed and Depth of cut as inputs and Material Removal Rate , Rt , Ra , Rq , Rz as our output parameters .To perform a fuzzy logic operation there are two fuzzy inference systems. They are Mamdani and Sugeno. As per our observation in most of the literatures Mamdani fuzzy inference system is used. So, we have also opted for Mamdani system.

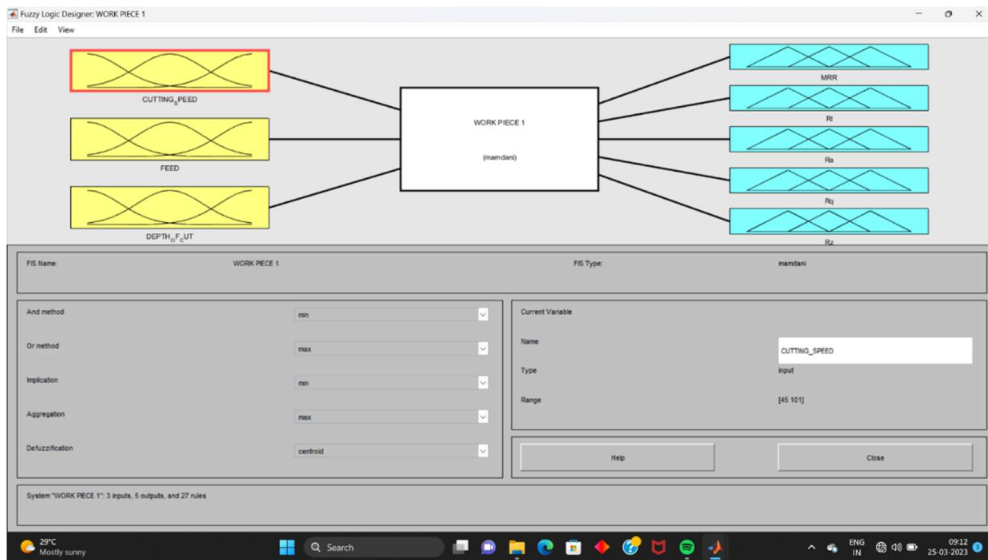


Fig 5.23 Fuzzy logic designer

As you can observe in above Fig 5.23 . We have taken Cutting speed, Feed and Depth of cut as input parameters , Mamdani system as our fuzzy inference system and Material Removal Rate , R_t , R_a , R_q , R_z as our output parameters. In the above figure we added input and output parameters using Add variable which is present in edit which is present on the toolbar. Here we have to define the range of value for the input parameters . So, we have given [45 101] , [0.4 0.85] , [0.2 0.9] as our range values for Cutting speed , Feed and Depth of cut.

Now we click on edit and open membership functions. These membership functions represents the degree of truth in fuzzy logic. They characterize all the information in fuzzy set. Membership functions mainly depend on the users experience rather than users knowledge

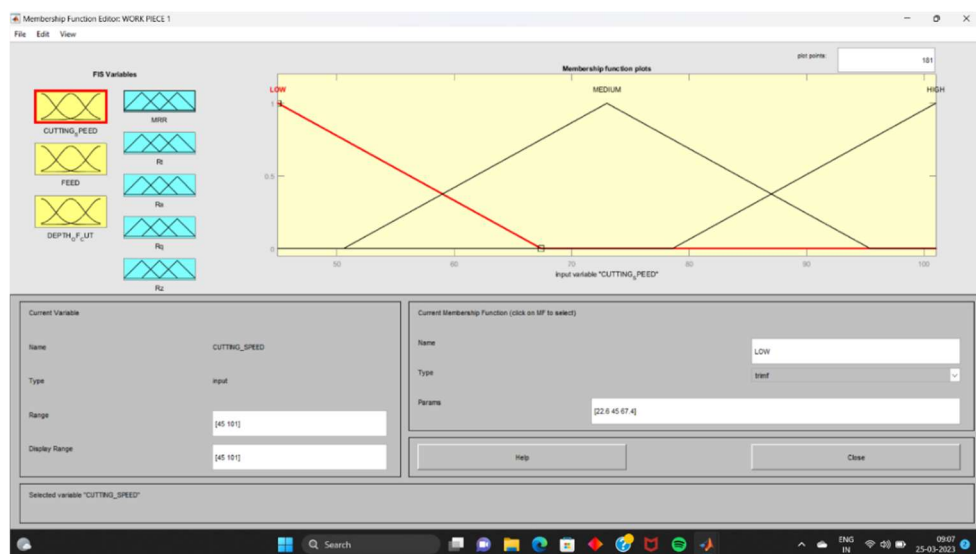


Fig 5.24 Fuzzy logic input membership functions for the work piece

Here in the above Fig 5.24 we are naming the membership functions as Low , Medium and High. So as to divide the range of values of Cutting speed , Feed and Depth of cut into 3 ranges to define the range into Low , Medium And High. Based on the least and highest values of the input parameters they have been divided into 3 ranges . Now we have to give the range of values to the membership functions based on the range of Low , Medium And High.

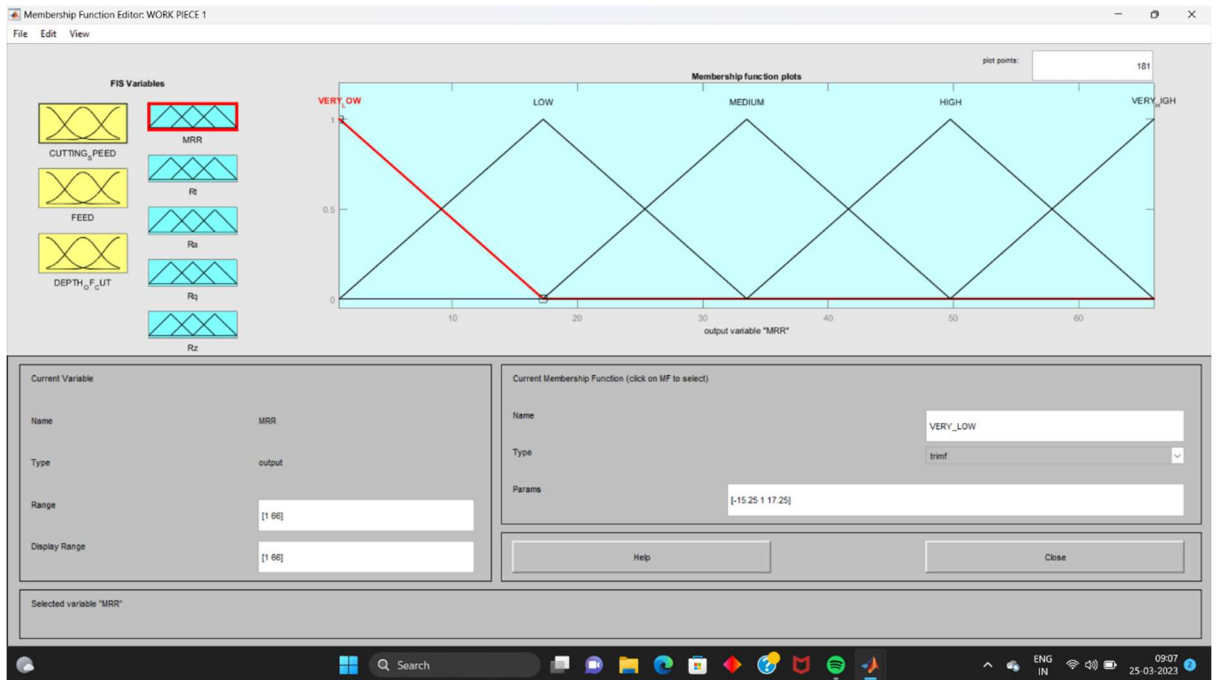


Fig 5.25 Fuzzy logic output membership functions for the work piece

In the above diagram Fig 5.25 we setting up 5 membership functions into Very low , Low , Medium , High and Very high, So it will be much more accurate for the range of input parameters. Based on the least and highest of each and every range they are divided into Very low , Low , Medium High and Very high.

Now we have to give rules . which play the most important role in fuzzy logic optimization . these rules are made by the user based on the input parameters and output parameters. While doing doing experimentation we have created a 9 experiment order based on 3 factors and we did those on two work pieces but with different flow rates . So for each 9 experiments we create a fuzzy logic system . so we create two fuzzy logic systems i.e., a work piece experimentation did at 180ml/hr and another workpiece experimentation did at 90ml/hr.

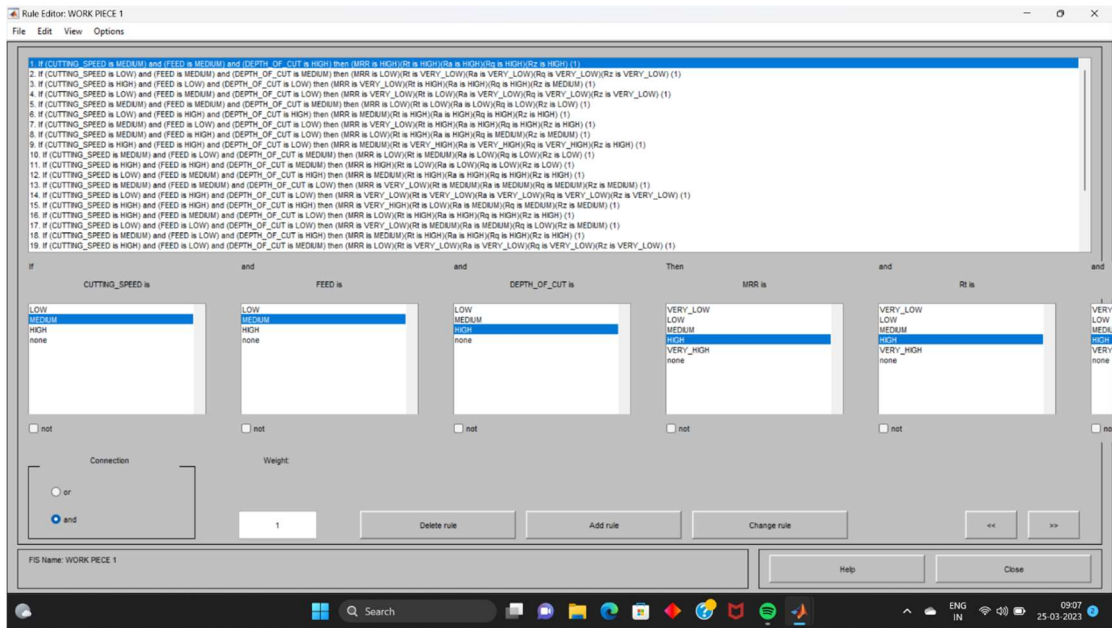


Fig 5.26 Rule editor for the work piece with flowrate of 180ml/hr

The above Fig 5.26 discusses about the rules that are given by using theoretical knowledge which are gained by literatures and journals based upon cutting speed, feed and depth of cut. The above are the rules for workpiece 1, where its flowrate is 180ml/hr.

Table 5.25 RULES FOR WORKPIECE WITH FLOW RATE OF 180ML/HR

If CUTTING SPEED is	And FEED is	And DOC is	Then MRR is	And Rt is	And Ra is	And Rq is	And Rz is
M	M	H	H	H	H	H	H
L	M	M	L	VL	VL	VL	VL
H	L	L	VL	H	H	H	VH
L	M	L	VL	L	VL	VL	VL
M	M	M	L	L	L	L	L
L	H	H	M	H	H	H	H
M	L	L	VL	H	H	H	H
M	H	L	L	H	H	M	M
H	H	L	M	VH	VH	VH	H
M	L	M	L	M	L	L	L

H	H	M	H	L	L	L	L
L	M	H	M	H	H	H	H
M	M	L	VL	M	M	M	M
L	H	L	VL	VL	VL	VL	VL
H	H	H	VH	L	M	M	M
H	M	L	L	H	H	H	H
L	L	L	VL	M	M	L	M
M	L	H	M	H	H	H	H
L	L	M	L	VL	VL	VL	VL
H	M	H	H	L	L	L	L
M	H	H	H	H	H	H	H
M	H	M	M	VH	L	L	L
L	L	H	M	L	VH	VH	VH
L	L	M	L	L	L	L	L
H	L	H	M	VL	L	L	L
H	M	M	M	VL	VL	VL	VL
L	H	M	L	H	VL	VL	VL

The above table 5.25 represents the rules used for training the fuzzy logic system. These rules are made using theoretical knowledge from literatures based upon the output values that came from the input values. For an example, for the first line we can write the rule as If CUTTING SPEED is M and FEED is M and DOC is H then MRR is H and Rt is H and Ra is H and Rq is H and Rz is H.

Here L is low , M is medium , H is high , VL is very low , VH is very high.

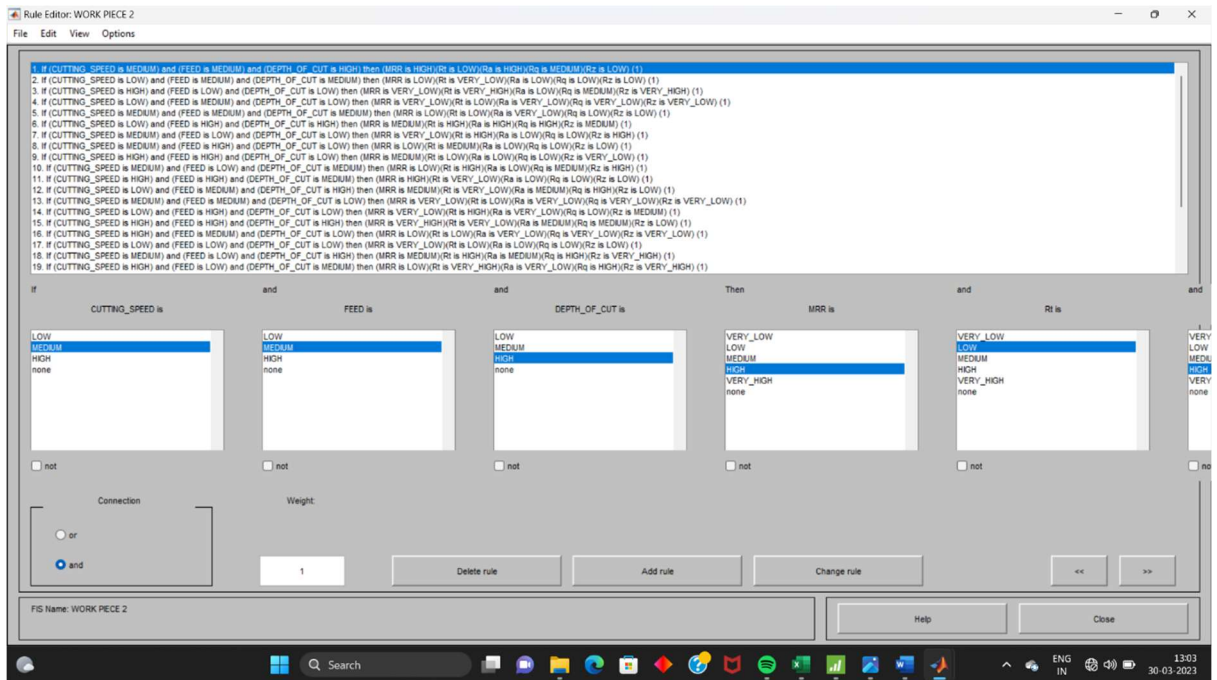


Fig 5.27 Rule editor for the work piece with flowrate of 90ml/hr

The above figure 5.27 discusses about the rules that are given by using theoretical knowledge which are gained by literatures and journals based upon cutting speed , feed and depth of cut. The above are the rules for workpiece 1 ,where its flowrate is 90ml/hr.

Table 5.26 RULES FOR WORKPIECE WITH FLOW RATE OF 90ML/HR

If CUTTING SPEED is	And FEED is	And DOC is	Then MRR is	And Rt is	And Ra is	And Rq is	And Rz is
M	M	H	M	M	H	H	L
L	M	M	L	M	M	L	VL
H	L	L	H	L	L	VL	VH
L	M	L	L	M	L	VL	L
M	M	M	M	M	M	L	L
L	H	H	L	H	H	M	H
M	L	L	M	L	L	VL	H
M	H	L	M	H	L	L	M
H	H	L	H	H	L	M	L
M	L	M	M	L	M	L	H

H	H	M	H	H	M	H	VL
L	M	H	L	M	H	M	VL
M	M	L	M	M	L	VL	L
L	H	L	L	H	L	VL	H
H	H	H	H	H	H	VH	VL
H	M	L	H	M	L	L	L
L	L	L	L	L	L	VL	L
M	L	H	M	L	H	M	H
L	L	M	L	L	M	L	VH
H	M	H	H	M	H	H	L
M	H	H	M	H	H	H	L
M	H	M	M	H	M	M	M
L	L	H	L	L	H	M	L
L	L	M	L	L	M	L	L
H	L	H	H	L	H	M	VH
H	M	M	H	M	M	M	L
L	H	M	L	H	M	L	H

The above table 5.26 represents the rules used for training the fuzzy logic system. These rules are made using theoretical knowledge from literatures based upon the output values that came from the input values. For an example, for the first line we can write the rule as If CUTTING SPEED is M and FEED is M and DOC is H then MRR is M and Rt is M and Ra is H and Rq is L L and Rz is L.

Here L is low , M is medium , H is high , VL is very low , VH is very high.

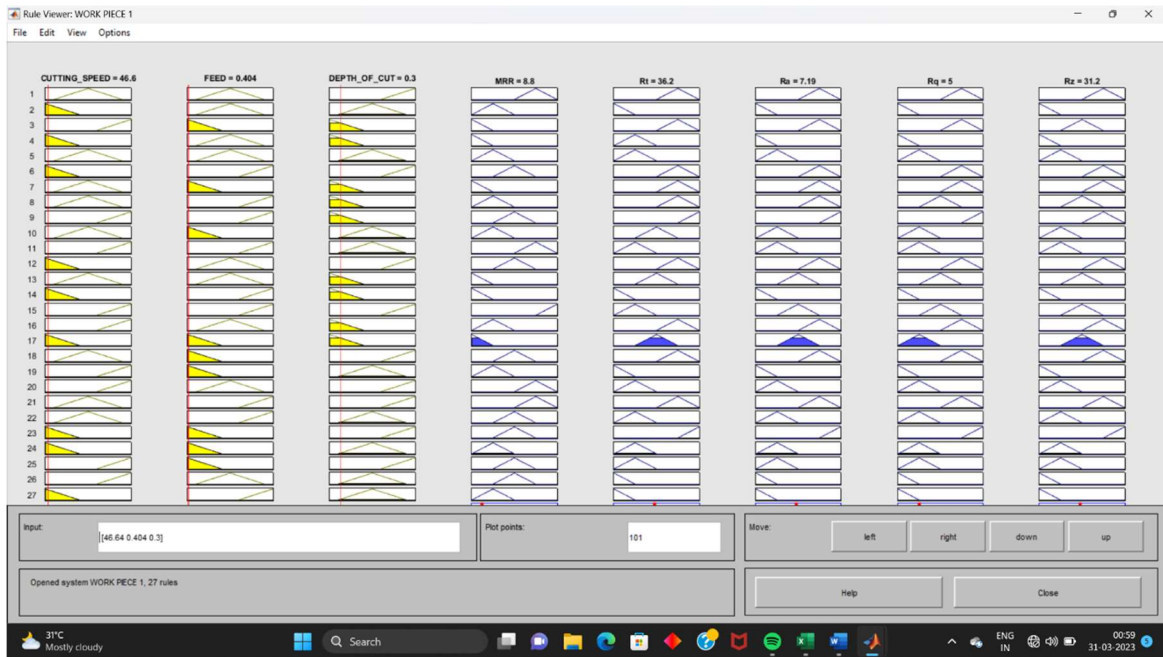


Fig 5.28 Rule viewer for the work piece with flowrate of 180ml/hr

The above figure 5.28 dicusses about the values which are AI generated using the rules given before as in the table.... This table is for workpiece 1 with flow rate of 180ml/hr. Here in the input if we give our input parameter then on the top our output parameters values will be displayed which are AI generated values

Table 5.27 Output values after fuzzy logic optimization for work piece with flow rate of 180ml/hr

Cutting speed (m/min)	Feed (mm)	DoC (mm)	MRR (m3/min)	Rt (µm)	Ra (µm)	Rq (µm)	Rz (µm)
46.74	0.404	0.3	8.8	36.2	7.19	5	27.12
46.74	0.596	0.6	17.3	14.5	2.07	2.32	9.52
46.74	0.808	0.9	32	49	10.2	12.4	44
74.38	0.404	0.6	17.3	37.5	4.25	5	18.8
74.38	0.596	0.9	45.9	48	9.98	10.21	43
74.38	0.808	0.3	18.8	48	9.98	8.62	31.2
100.51	0.404	0.9	32	23.7	4.24	4.99	18.7
100.51	0.596	0.3	18.8	49	10.2	12.4	44
100.51	0.808	0.6	49.7	23.7	4.25	5	18.8

The above table 5.27 represents the input parameters and the output parameters that are generated from fuzzy logic system . The above values are generated based upon the range that we gave in the membership functions and the rules we gave in the rule editor. Based upon our training the above output values are generated through AI of fuzzy logic system. The above values are generated for workpiece with flowrate of 180ml/hr.

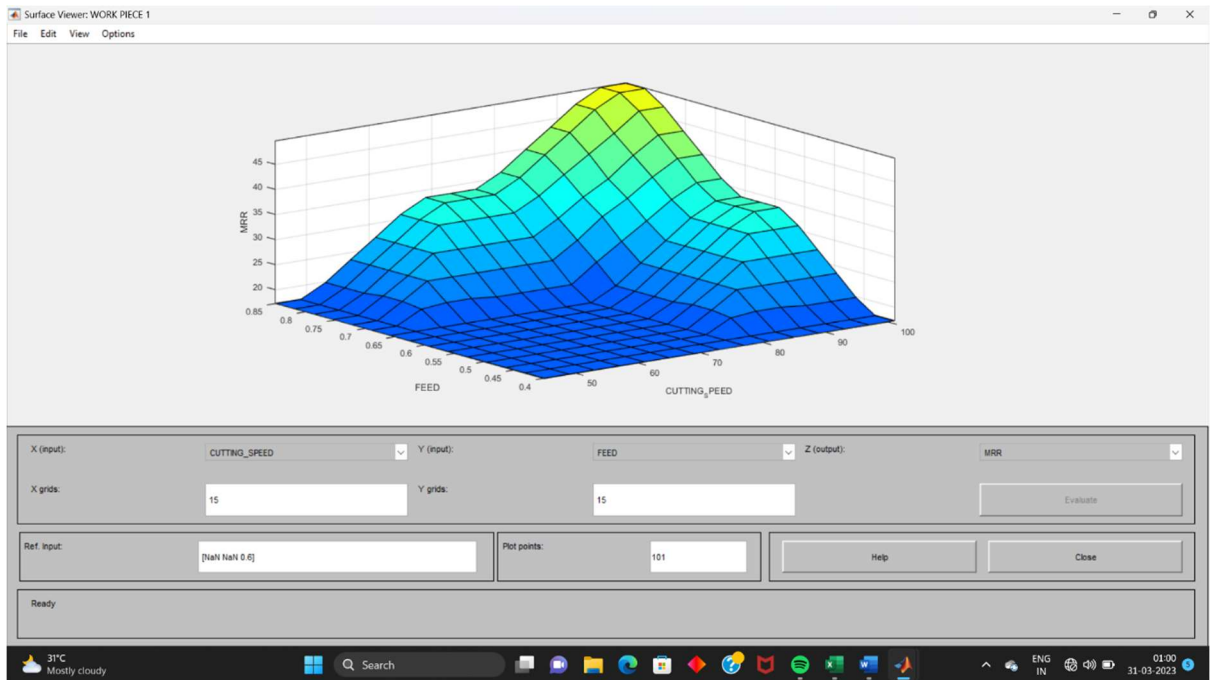


Fig 5.29 Surface viewer for the work piece with flowrate of 180ml/hr

The above figure 5.29 deals with surface that is created by the range given in the membership system and the rules that are given in the fuzzy system where the x axis is represented by cutting speed , y axis is represented by feed and the z axis is represented by MRR. The above surface diagram is for workpiece with flow rate 180ml/hr. This figure says that if the cutting speed increases then the Material Removal Rate increases . Even if the Feed increases while machining the Material removal rate increases. Here we can say that the cutting speed and the feed parameters are effecting the material removal rate.

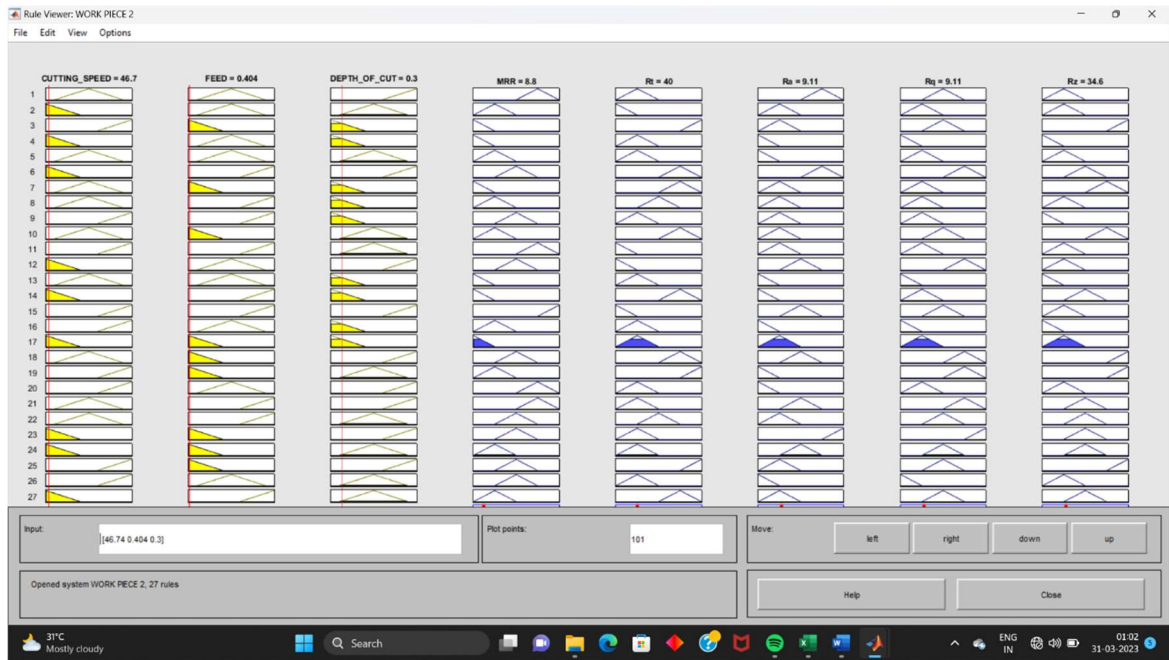


Fig 5.30 Rule viewer for the work piece with flowrate of 90ml/hr

The above figure 5.30 dicusses about the values which are AI generated using the rules given before as in the table 5.28. This table is for workpiece 1 with flow rate of 90ml/hr. Here in the input if we give our input parameter then on the top our output parameters values will be displayed which are AI generated values

Table 5.28 Output values after fuzzy logic optimization for work piece with flow rate of 90 ml/hr

Cutting speed (m/min)	Feed (mm)	DoC (mm)	MRR (m3/min)	Rt (µm)	Ra (µm)	Rq (µm)	Rz (µm)
46.74	0.404	0.3	8.8	40	9.11	9.11	34.6
46.74	0.596	0.6	17.3	33.3	8.75	8.75	33.8
46.74	0.808	0.9	32	60	15.4	15.9	42.5
74.38	0.404	0.6	17.3	60	8.75	12.5	50.12
74.38	0.596	0.9	45.9	40	15.6	12.1	33.8
74.38	0.808	0.3	18.8	50	8.75	9.11	34.6
100.51	0.404	0.9	32	66.5	8.74	12.9	57
100.51	0.596	0.3	18.8	40	6.3	6.3	29.2
100.51	0.808	0.6	49.7	33.4	8.75	8.75	33.8

The above table 5.26 represents the input parameters and the output parameters that are generated from fuzzy logic system . The above values are generated based upon the range that we gave in the membership functions and the rules we gave in the rule editor. Based upon our training the above output values are generated through AI of fuzzy logic system. The above values are generated for workpiece with flowrate of 90ml/hr.

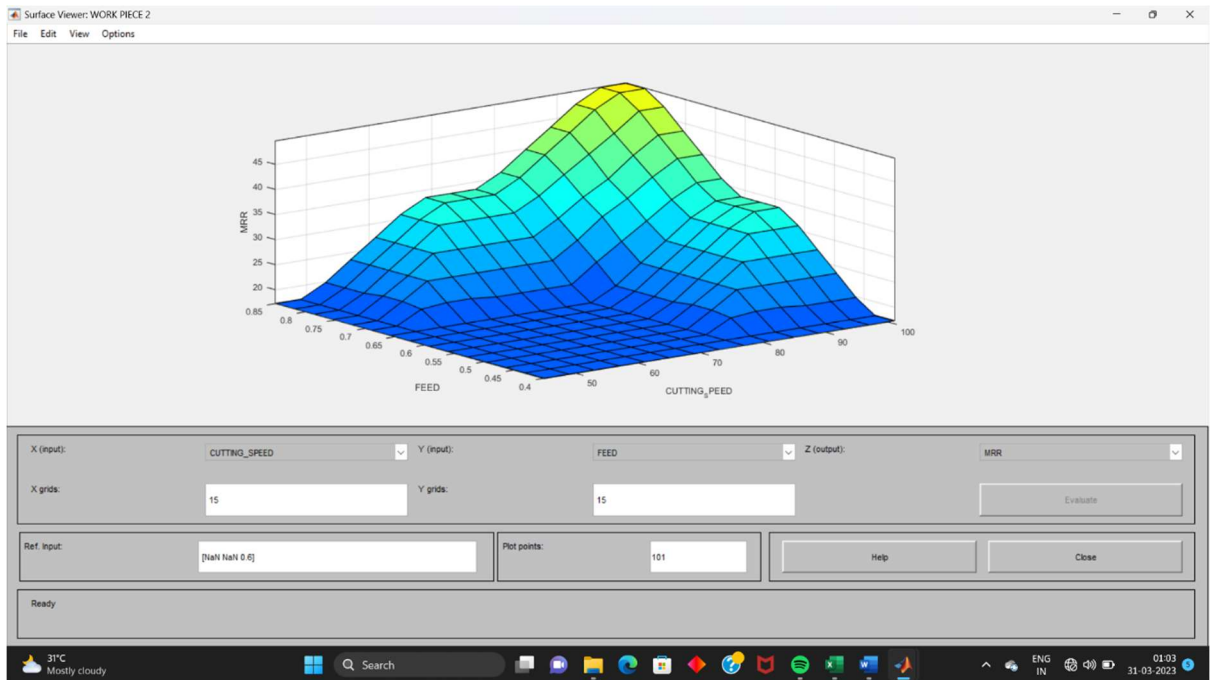


Fig 5.31 surface viewer for the work piece with flowrate of 90ml/hr

The above figure 5.29 deals with surface that is created by the range given in the membership system and the rules that are given in the fuzzy system where the x axis is represented by cutting speed , y axis is represented by feed and the z axis is represented by MRR. The above surface diagram is for workpiece with flow rate 90ml/hr. This figure says that if the cutting speed increases then the Material Removal Rate increases . Even if the Feed increases while machining the Material removal rate increases. Here we can say that the cutting speed and the feed parameters are effecting the material removal rate.

COMPARISON BETWEEN EXPERIMENTAL VALUES VS REGRESSION EQUATION GENERATED VALUES FOR WORK PIECE WITH FLOWRATE OF 180ML/HR

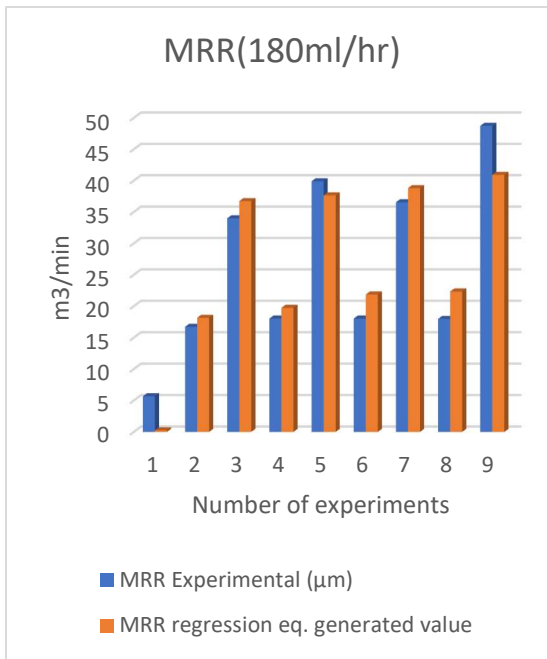


Fig 5.32 MRR Experimental(180ml/hr) Vs MRR Regression equation value

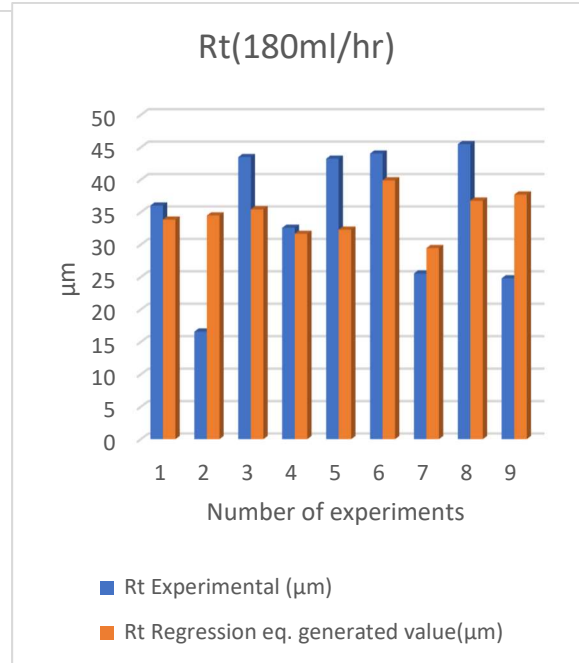


Fig 5.33 Rt Experimental(180ml/hr) Vs Rt Regression equation value

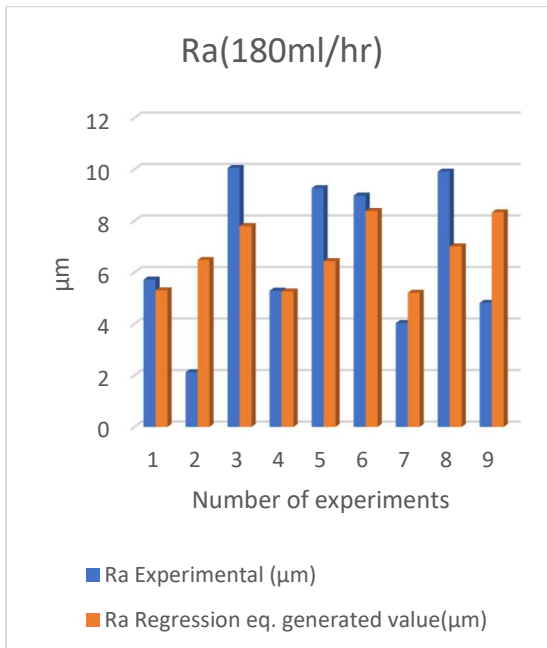


Fig 5.34 Ra Experimental(180ml/hr) Vs Ra Regression equation value

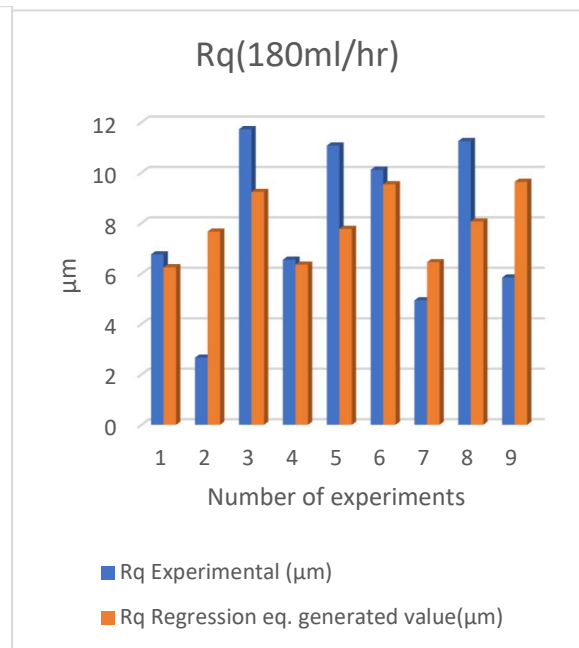


Fig 5.35 Rq Experimental(180ml/hr) Vs Rq Regression equation value

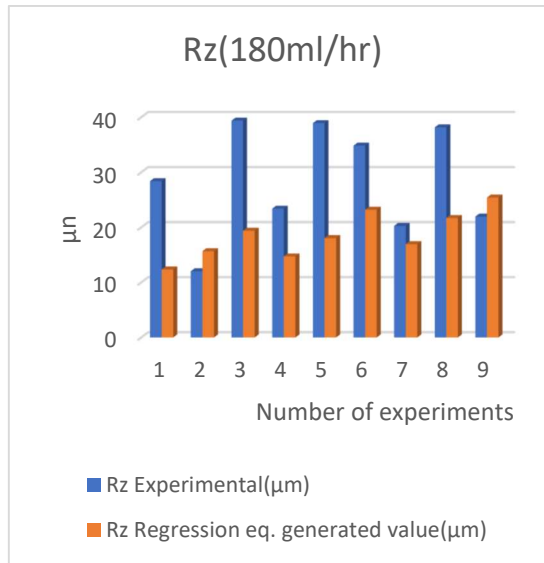


Fig 5.36 Rz Experimental(180ml/hr) Vs Rz Regression equation value

The above figure 5.32, 5.33, 5.34, 5.35, 5.36 represents the difference between the MRR, Rt, Ra, Rq, Rz experimental values and MRR, Rt, Ra, Rq, Rz regression equation generated values that came from equation of the work piece with flowrate of 180ml/hr. Here we can observe the Rz experimental values are showing more difference when compared to the Rz regression equation generated values. Here we can observe the regression equation generated values are not up the values of experimental values.

COMPARISON BETWEEN EXPERIMENTAL VALUES VS REGRESSION EQUATION GENERATED VALUES FOR WORK PIECE WITH FLOWRATE OF 90ML/HR

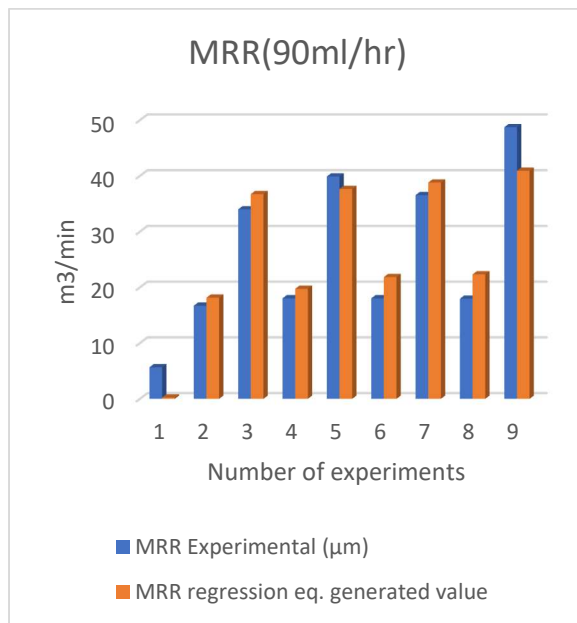


Fig 5.37 MRR Experimental(90ml/hr) Vs MRR Regression equation value

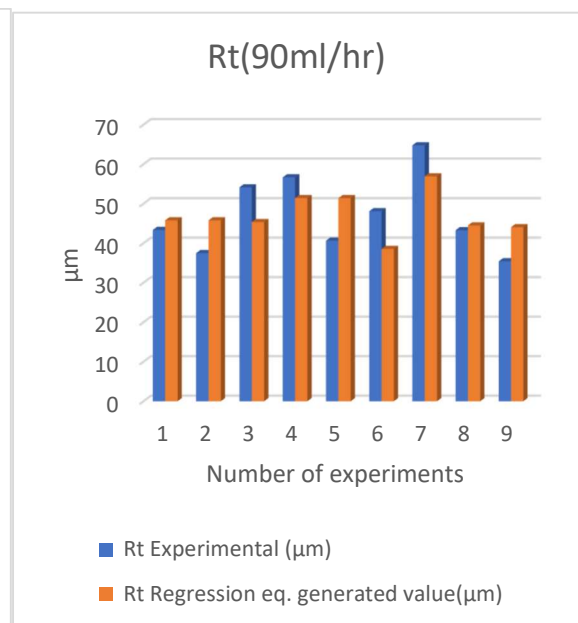


Fig 5.38 Rt Experimental(90ml/hr) Vs Rt Regression equation value

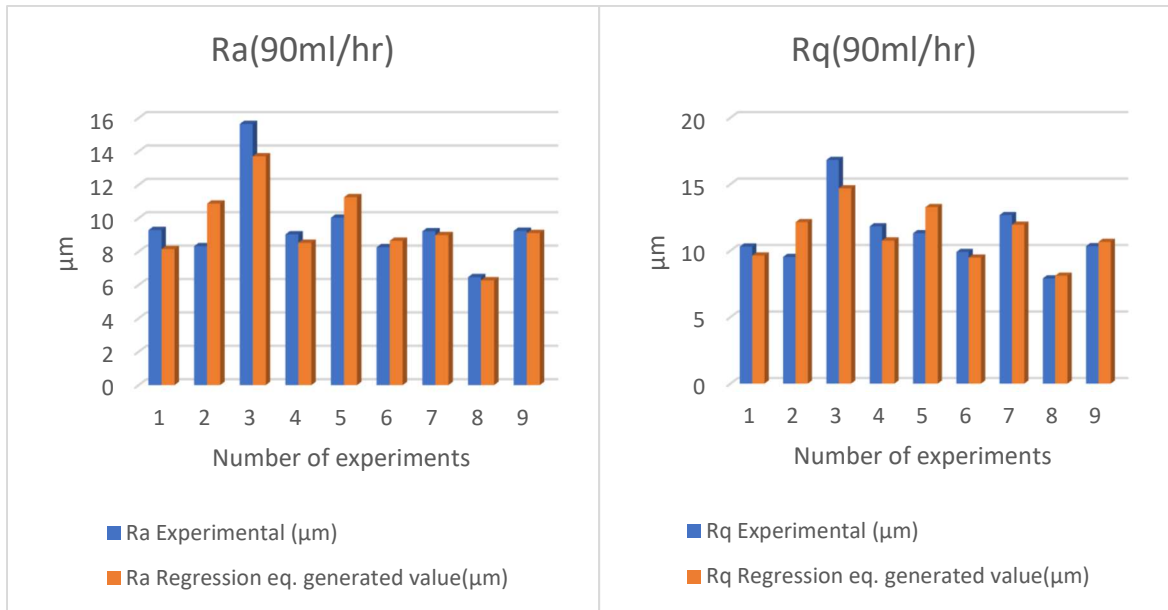


Fig 5.39 Ra Experimental(90ml/hr) Vs Ra Regression equation value

Fig 5.40 Rq Experimental(90ml/hr) Vs Rq Regression equation value

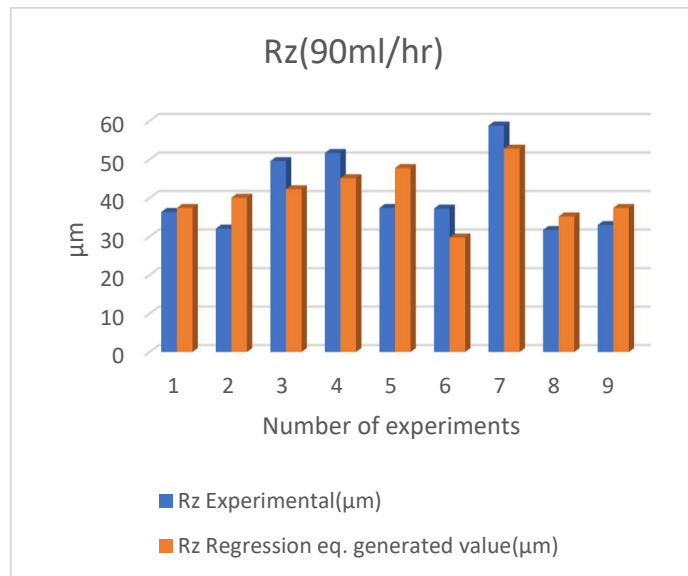
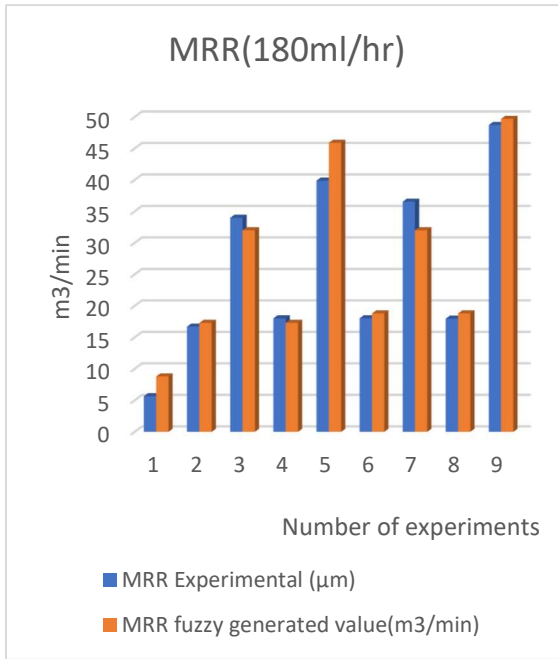


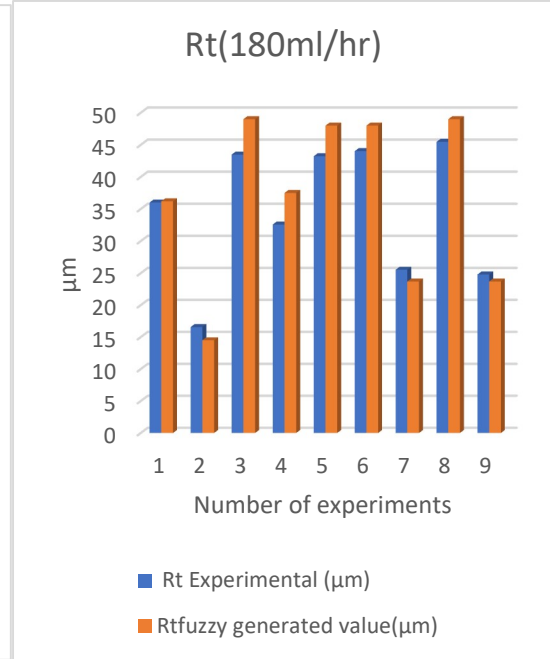
Fig 5.41 Rz Experimental(90ml/hr) Vs Rz Regression equation value

The above figure 3.37, 3.38, 3.39, 3.40, 3.41 represents the difference between the MRR, Rt, Ra, Rq, Rz experimental values and MRR, Rt, Ra, Rq, Rz regression equation generated values that came from equation of the work piece with flowrate of 90ml/hr. Here we can observe the experimental values and the regression equation generated values are nearer to each other.

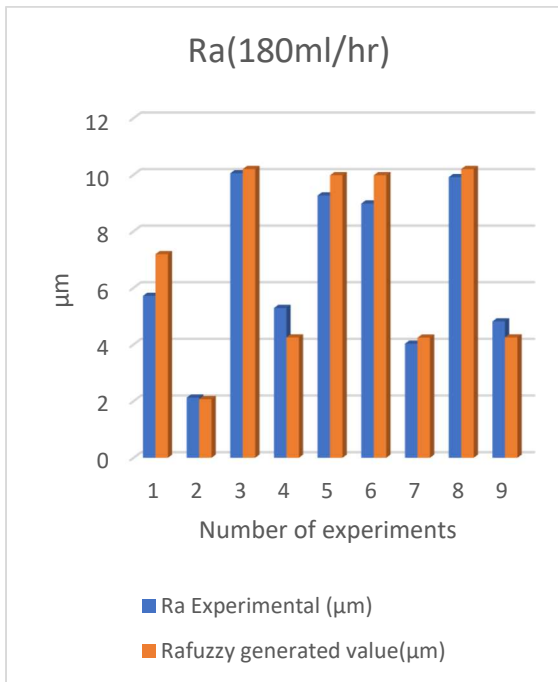
COMPARISON BETWEEN EXPERIMENTAL VALUES VS FUZZY LOGIC VALUES FOR WORK PIECE WITH FLOWRATE OF 180ML/HR



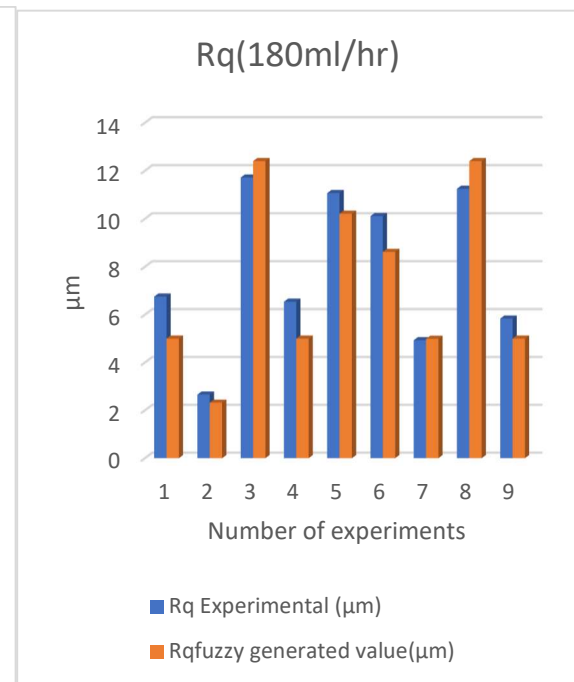
**Fig 5.42 MRR Experimental(180ml/hr)
Vs MRR Fuzzy generated value**



**Fig 5.43 Rt Experimental(180ml/hr)
Vs Rt Fuzzy generated value**



**Fig 5.44 Ra Experimental (180ml/hr)
Vs Ra Fuzzy generated value**



**Fig 5.45 Rq Experimental(180ml/hr)
Vs Rq Fuzzy generated value**

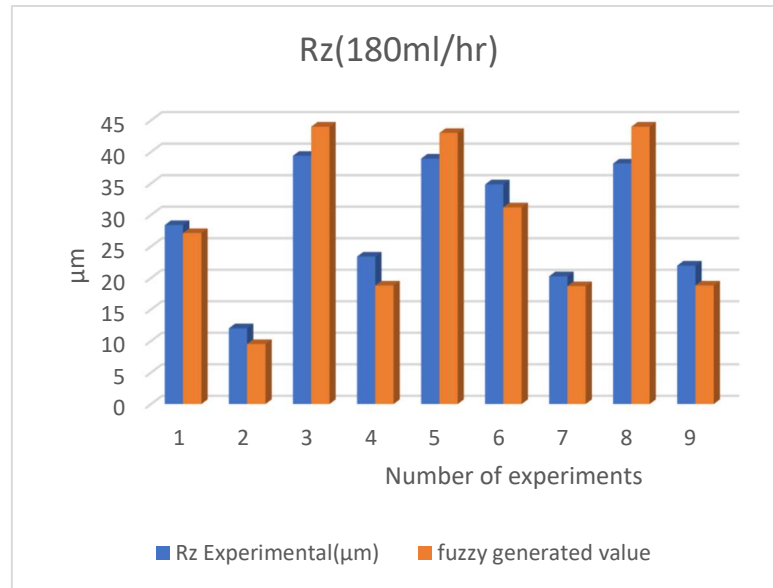


Fig 5.46 Rz Experimental(180ml/hr) Vs Rz Fuzzy generated value

Here from above figure 5.42- 5.46 represents the difference between the MRR, Rt, Ra, Rq, Rz experimental values and MRR, Rt, Ra, Rq, Rz values that are from fuzzy logic values for work piece with flowrate of 180ml/hr. From the above figure we can observe that the experimental values and fuzzy logic values are very much nearer to each other.

COMPARISON BETWEEN EXPERIMENTAL VALUES VS FUZZY LOGIC VALUES FOR WORK PIECE WITH FLOWRATE OF 90ML/HR

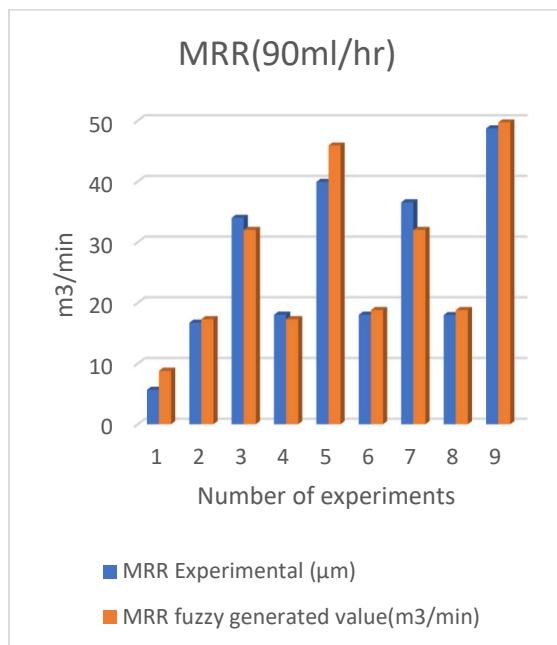


Fig 5.47 MRR Experimental(90ml/hr) Vs MRR Fuzzy generated value

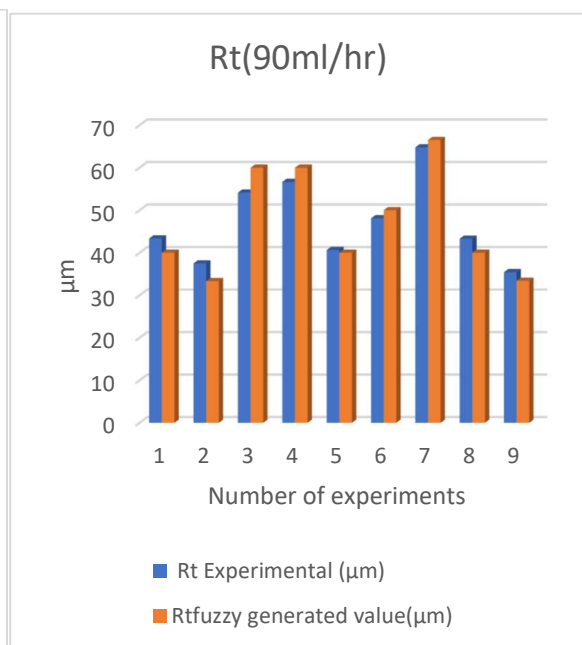


Fig 5.48 Rt Experimental(90ml/hr) Vs Rt Fuzzy generated value

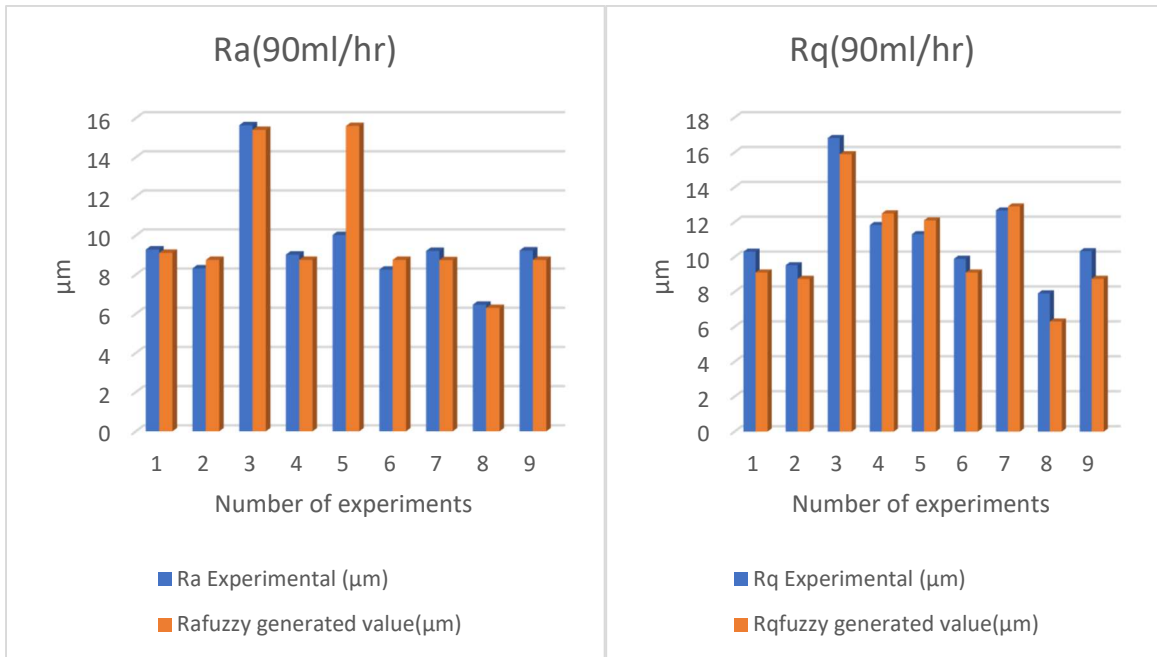


Fig 5.49 Ra Experimental (90ml/hr) Vs Ra Fuzzy generated value

Fig 5.50 Rq Experimental(90ml/hr) Vs Rq Fuzzy generated value

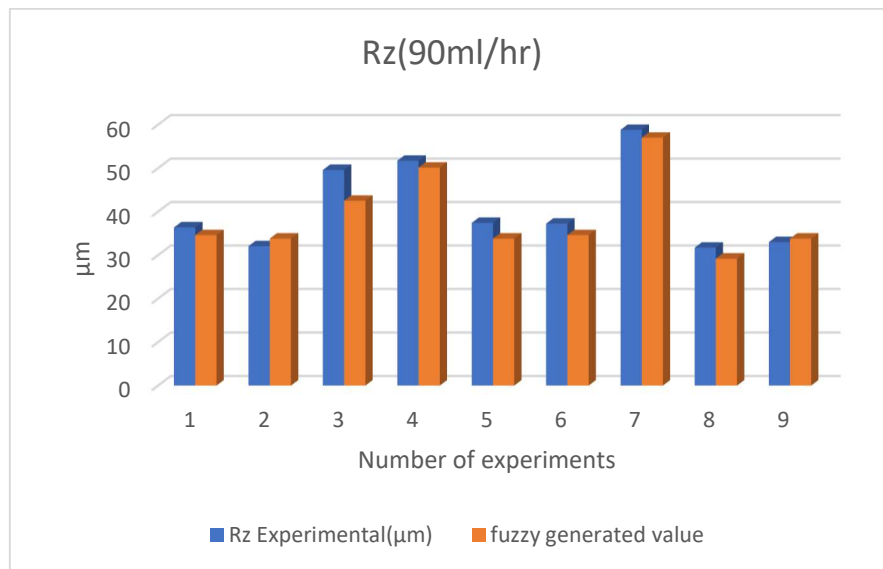


Fig 5.51 Rz Experimental(90ml/hr) Vs Rz Fuzzy generated value

Here the above figure 5.47- 5.51 represents the difference between the MRR, Rt, Ra, Rq, Rz experimental values and MRR, Rt, Ra, Rq, Rz values that are from fuzzy logic values for work piece with flowrate of 90ml/hr. From the above figure we can observe that the experimental values and fuzzy logic values are very much nearer to each other.

COMPARISON BETWEEN REGRESSION EQUATION GENERATED VALUES VS FUZZY LOGIC VALUES FOR WORK PIECE WITH FLOWRATE OF 180ML/HR

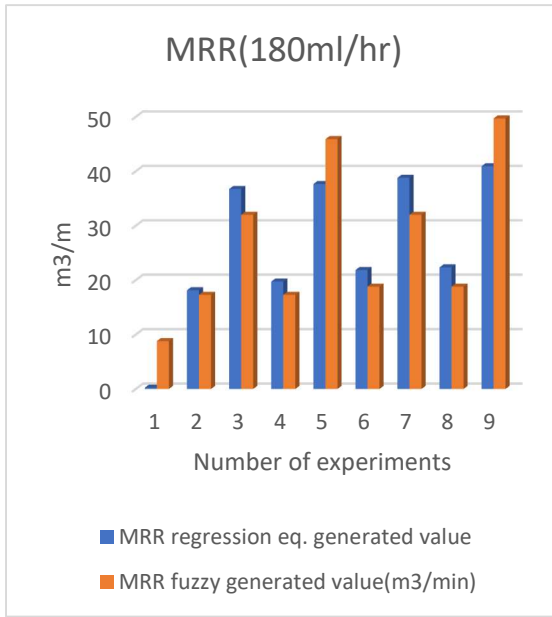


Fig 5.52 MRR Regression equation value (180ml/hr) Vs MRR Fuzzy generated value

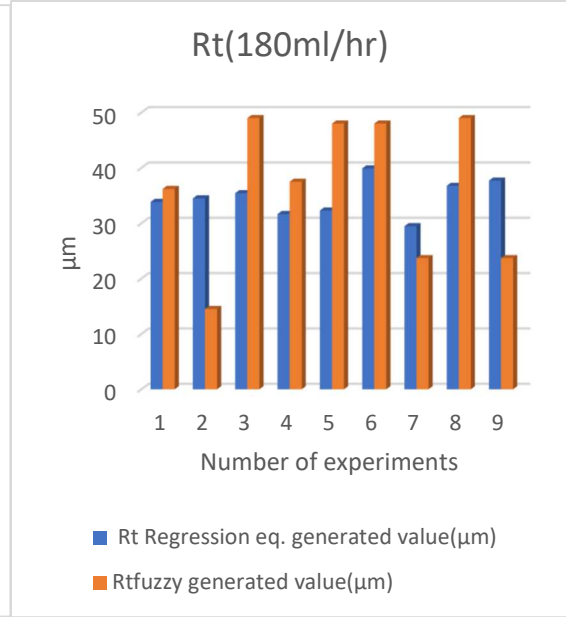


Fig 5.53 Rt Regression equation value (180ml/hr) Vs Rt Fuzzy generated value

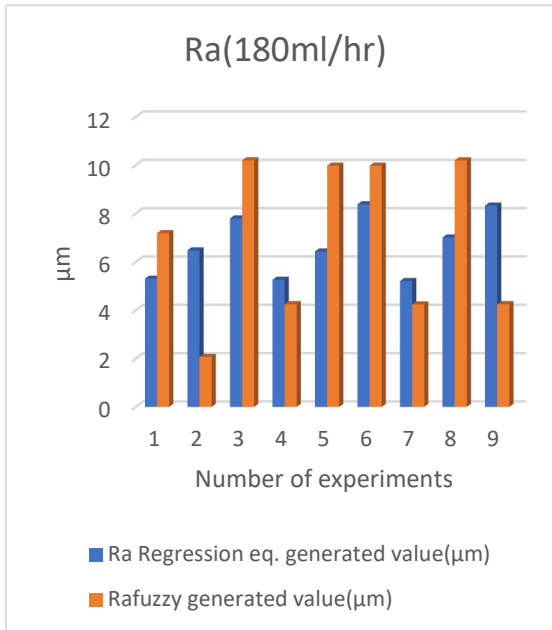


Fig 5.54 Ra Regression equation value (180ml/hr) Vs Ra Fuzzy generated value

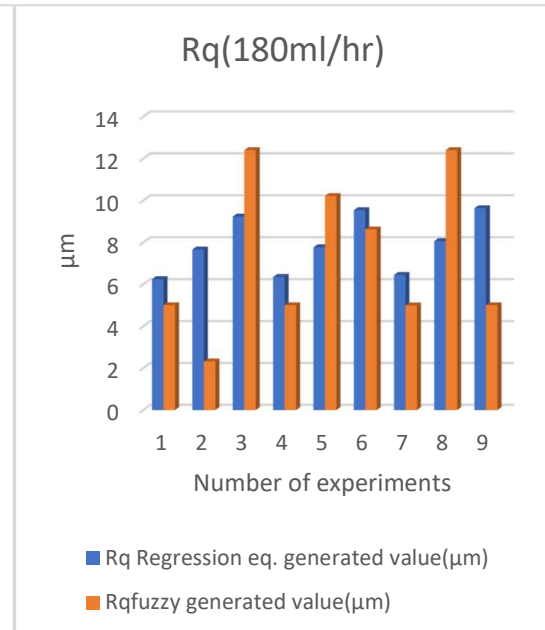


Fig 5.55 Rq Regression equation value (180ml/hr) Vs Rq Fuzzy generated value

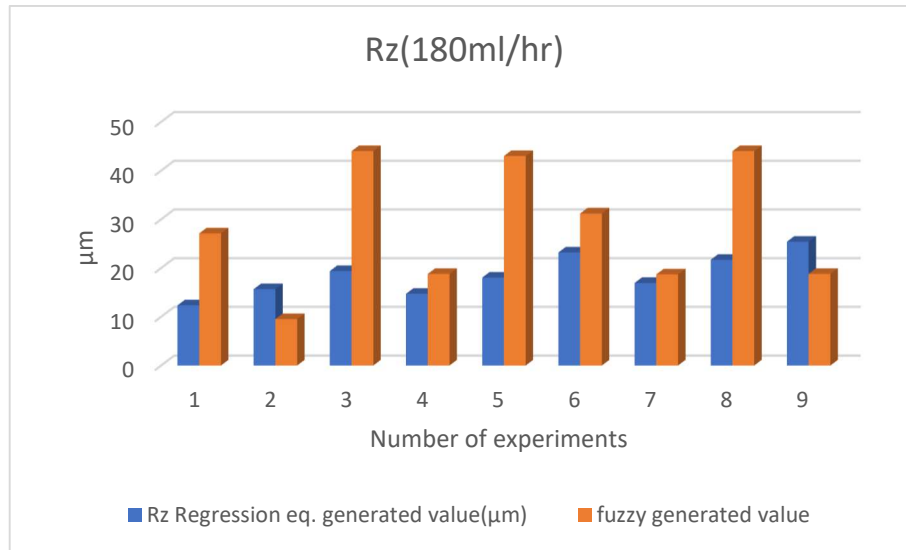


Fig 5.56 Rz Regression equation value (180ml/hr) Vs Rz Fuzzy generated value

Here the above figure 5.52- 5.56 represents the difference between the MRR, Rt, Ra, Rq, Rz regression equation generated values and MRR, Rt, Ra, Rq, Rz values that are from fuzzy logic values for work piece with flowrate of 180ml/hr.

COMPARISON BETWEEN REGRESSION EQUATION GENERATED VALUES VS FUZZY LOGIC VALUES FOR WORK PIECE WITH FLOWRATE OF 90ML/HR

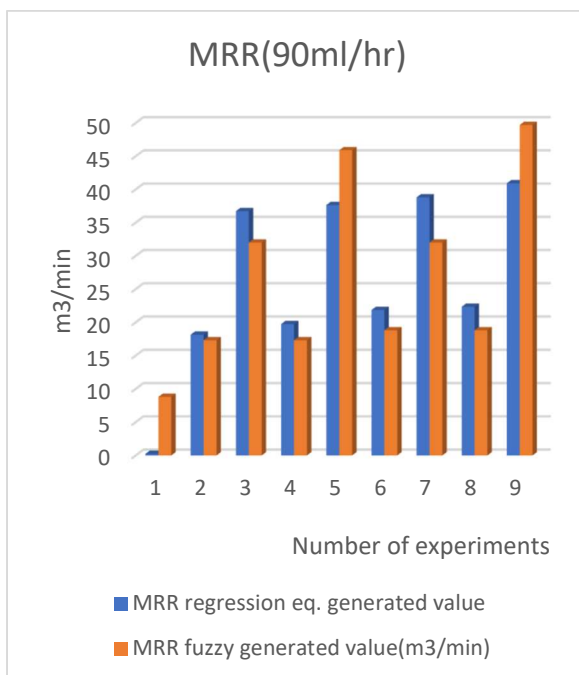


Fig 5.57 MRR Regression equation value (90ml/hr) Vs MRR Fuzzy generated value

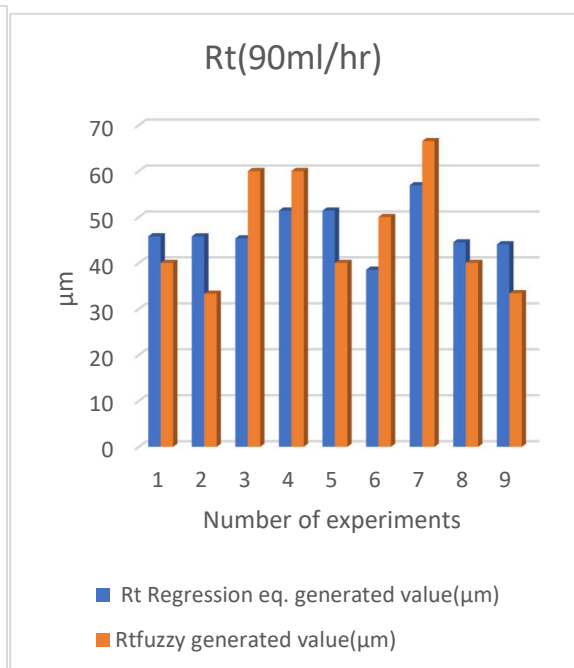


Fig 5.58 Rt Regression equation value (90ml/hr) Vs Rt Fuzzy generated value

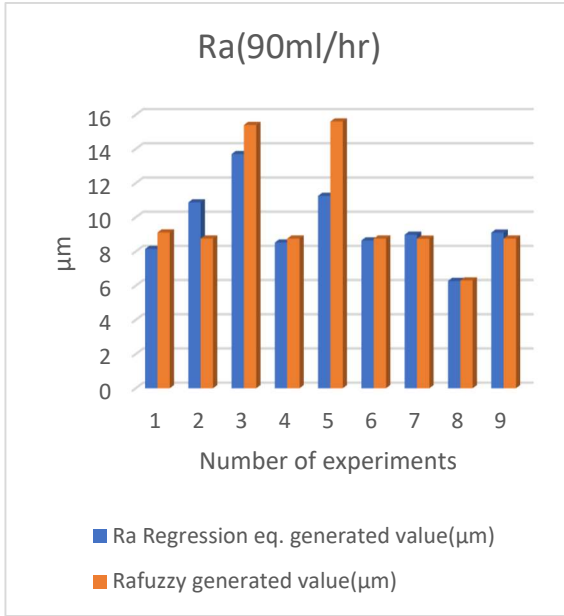


Fig 5.59 Ra Regression equation value (90ml/hr) Vs Ra Fuzzy generated value

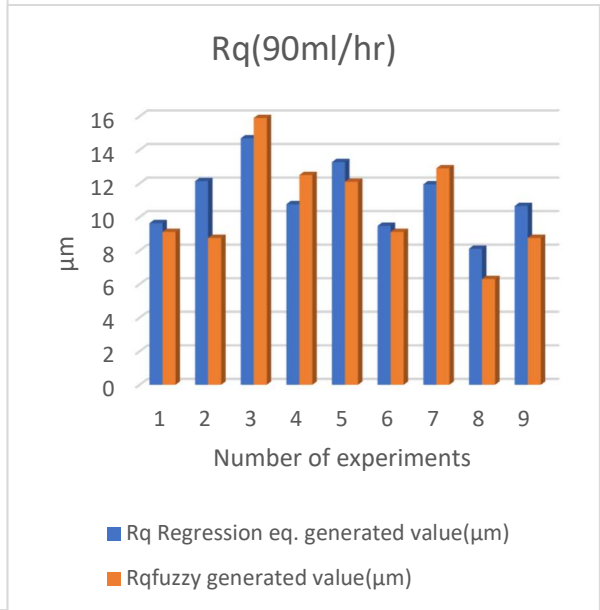


Fig 5.60 Rq Regression equation value (90ml/hr) Vs Rq Fuzzy generated value

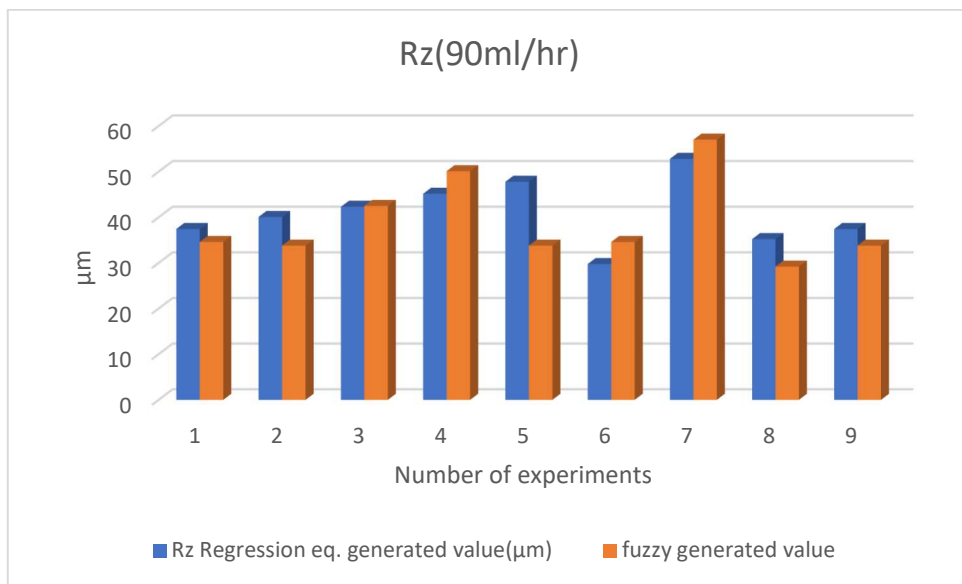


Fig 5.61 Rz Regression equation value (90ml/hr) Vs Rz Fuzzy generated value

Here the above figure 5.57-5.61 represents the difference between the MRR, Rt, Ra, Rq, Rz regression equation generated values and MRR, Rt, Ra, Rq, Rz values that are from fuzzy logic values for work piece with flowrate of 90ml/hr.

Here we can see that the above figures are obtained by taking our nine number of experiments on X axis and Material Removal Rate, Rt, Ra, Rq, Rz values on Y axis. From most of the figures we can observe that Regression equation generated values are nearer to most of the experimental values. But for some of the experiments the values are showing

more variation. But when compared with the experimental values and fuzzy logic values they are almost same i.e., they are very nearer to each other.

By seeing above figures we can state the fuzzy logic generated values are very much accurate to the experimental values. So, that we can state that AI generated values are much more accurate when compared to the Regression equation generated values. Because when we compare experimental values and regression equation generated values vs experimental values and fuzzy logic AI generated values. The values of fuzzy logic generated values are much more near and accurate to the experiment values i.e., the AI generated values are much more near when compared to the statistical values which are generated from the from regression equations.

From the above figures we can state that the surface roughness values with high flowrate are minimum and the surface roughness values with low flow rate are maximum. These figures also states that the comparison between experimental values which are noted from surface roughness tester and statistical values which are generated from the regression equation which are generated from response surface optimization.

CHAPTER 6

CONCLUSION

6.1 Conclusion

An essential part of data analysis and modelling is comparing statistical values produced by fuzzy logic with experimental values. When discussing surface roughness testing, experimental values are those that are obtained directly using a surface roughness metre, while statistical values are those that are obtained by using a fuzzy logic model to forecast the data that has been measured.

When the data is very confusing and changeable and precise numerical values are not accessible, fuzzy logic can be especially helpful. Operator experience, ambient conditions, and other variables that could alter surface roughness are just a few examples of the many input variables that fuzzy logic can take into consideration yet are difficult to accurately define or measure. The experimental results and the statistical values derived by fuzzy logic may be compared using statistical techniques including correlation analysis, mean square error, and coefficient of determination. These techniques make it easier to measure the degree of agreement between experimental and statistical results and assess the fuzzy logic model's precision. The fuzzy logic model is a viable model for forecasting surface roughness under diverse situations if the statistical values it generates are in good agreement with the experimental data. The model may need to be improved or more data need to be gathered if there is a significant difference between experimental and statistical results.

Statistical techniques are used to verify the model and direct additional testing, and they may be used to evaluate the precision of the fuzzy logic model and the anticipated values. Regression analysis and fuzzy logic are both effective methods for modelling and data analysis. Regression analysis is a statistical tool for determining correlations between variables, whereas fuzzy logic is a reasoning technique that works with ambiguous or inaccurate information. The quality and amount of the data utilised, the difficulty of the problem, and the algorithms and models employed are only a few of the variables that affect how accurately the results acquired using either technique.

In general, the current research intends to improve the machining process parameters for effective and sustainable machining of materials under MQL circumstances using vegetable oil (sesame oil) as the cutting fluid. The study examines how several output characteristics, including MRR, Ra, Rq, Rz, and Rt, are impacted by flow rate, speed, feed rate, and depth of cut. For each flow rate, nine experimental runs are designed using the Taguchi L9 orthogonal array, and analysis of variance is performed to determine the primary cutting process parameters for the surface roughness profiles under MQL circumstances.

So, we conclude that :

- The study's findings demonstrate that reducing surface roughness values by increasing cutting fluid flow rate also results in an increase in MRR. When compared to the response surface optimisation approach, the usage of fuzzy logic optimisation produced results that were more exact and precise.
- In general, optimising the cutting process's parameters using fuzzy logic optimisation and vegetable oil (sesame oil) as the cutting fluid can greatly increase the cutting operations' sustainability, accuracy, and productivity while minimising the negative effects of using toxic cutting fluids on the environment and human health.
- A confirmation experiment has been performed. Flowrate with 180ml/hr have better surface finish. The chosen range's optimum feasible combination of cutting speed, feed rate, and cut depth is 100.512 m/min, 0.404 mm, and 0.9 mm. For these the output parameters i.e MRR, Rt, Ra, Rq, Rz are 36.532 m³/min , 27.684 μm , 5.201 μm , 5.099 μm and 15.201 μm respectively.

6.2 Future Scope

Statistical techniques like correlation analysis, mean square error, and coefficient of determination can be used to compare experimental results with statistical results produced by fuzzy logic. These techniques make it easier to measure the degree of agreement between experimental and statistical results and assess the fuzzy logic model's precision.

The fuzzy logic model is a viable model for forecasting surface roughness under diverse situations if the statistical values it generates are in good agreement with the experimental data. The model may need to be improved or more data need to be gathered if there is a significant difference between experimental and statistical results.

To assist verify the model and direct more tests, statistical approaches may be used to assess the precision of the fuzzy logic model and the anticipated values.

CHAPTER 7

REFERENCE

- [1] Harshit B. Kulkarni, Mahantesh M. Nadakatti, Sachin C. Kulkarni, Raviraj M. Kulkarni
Investigations on effect of Nano fluid based minimum quantity lubrication technique for surface milling of Al7075-T6 aerospace alloy.
<https://doi.org/10.1016/j.matpr.2019.10.127>
- [2] Jinyang Xu, Min Ji, Ming Chen & Fei Ren
Investigation of minimum quantity lubrication effects in drilling CFRP/Ti6Al4V stacks.
<https://doi.org/10.1080/10426914.2019.1661431>
- [3] E A Rahim and H Sasahara
Investigation of tool wear and surface integrity on MQL machining of Ti-6AL-4V using biodegradable oil
<https://doi.org/10.1177/0954405411402554>
- [4] E. A. Rahim, M. R. Ibrahim, A. A. Rahim, S. Aziz, Z. Mohid
Experimental Investigation of Minimum Quantity Lubrication (MQL) as a Sustainable Cooling Technique
<https://doi.org/10.1016/j.procir.2014.07.029>
- [5] O. Pereira, A. Rodríguez, A.I. Fernández-Abia, J. Barreiro, L.N. López de Lacalle
Cryogenic and minimum quantity lubrication for an eco-efficiency turning of AISI 304
<https://doi.org/10.1016/j.jclepro.2016.08.030>
- [6] Anuj Kumar Sharma, Arun Kumar Tiwari, Amit Rai Dixit
Effects of Minimum Quantity Lubrication (MQL) in machining processes using conventional and nanofluid based cutting fluids: A comprehensive review
<https://doi.org/10.1016/j.jclepro.2016.03.146>
- [7] E. Budak, E. Ozturk
Dynamics and stability of parallel turning operations
<http://dx.doi.org/10.1016/j.cirp.2011.03.028>
- [8] Yousef Shokoohi, Ehsan Khosrojerdi, B.h. Rassolian Shiadhi
Machining and ecological effects of a new developed cutting fluid in combination with different cooling techniques on turning operation
<https://doi.org/10.1016/j.jclepro.2015.01.055>
- [9] Alakesh Manna, Sandeep Salodkar
Optimization of machining conditions for effective turning of E0300 alloy steel

<https://doi.org/10.1016/j.jmatprotec.2007.09.052>

[10] Gilberto Miller Devós Ganga, Luiz Cesar Ribeiro Carpinetti

A fuzzy logic approach to supply chain performance management

<https://doi.org/10.1016/j.ijpe.2011.06.011>

[11] H.D. Cheng, Huijuan Xu

A novel fuzzy logic approach to contrast enhancement

[https://doi.org/10.1016/S0031-3203\(99\)00096-5](https://doi.org/10.1016/S0031-3203(99)00096-5)

[12] Giovanni, Maria,

Response surface methodology and product optimization

<https://agris.fao.org/agris-search/search.do?recordID=US201302537557>

[13] Marcos Almeida Bezerra, Ricardo Erthal Santelli, Eliane Padua Oliveira, Leonardo Silveira Villar, Luciane Amélia Escaleira

Response surface methodology (RSM) as a tool for optimization in analytical chemistry

<https://doi.org/10.1016/j.talanta.2008.05.019>

[14] SHYAM NARAYAN PANDEY, SHAHNAWAZ ALAM

An Experimental Investigation of Electrode Wear Rate (EWR) on EDM of SS-202 using Different Electrodes

<http://ijsetr.com/uploads/126435IJSETR4590-434.pdf>

[15] Ishwer Shivakoti, Golam Kibria, Premendra Mani Pradhan, Bal Bahadur Pradhan, Ashis Sharma

ANFIS based prediction and parametric analysis during turning operation of stainless steel 202

<https://doi.org/10.1080/10426914.2018.1512134>

[16] Gurudatt Ghadi, Dr. Shivakumar S

Analysis of TIG Welding Process Parameters for Stainless Steel (SS202)

<https://dx.doi.org/10.22161/ijaers/3.10.13>

[17] G Vignesh, C Sathiya Narayanan1, C Pandivelan, K Shanmugapriya, Bhavishya Naik Tejavath, Lavuri Tirupathi

Forming, fracture and corrosion behaviour of stainless steel 202 sheet formed by single point incremental forming process

<https://iopscience.iop.org/article/10.1088/2053-1591/ab5606/meta>

[18] B.K. Sato, J.C. Lopes, A.E. Diniz, A.R. Rodrigues, H.J. de Mello, L.E.A. Sanchez, P.R. Aguiar, E.C. Bianchi

Toward sustainable grinding using minimum quantity lubrication technique with diluted oil and simultaneous wheel cleaning

<https://doi.org/10.1016/j.triboint.2020.106276>

- [19] Leonardo Roberto da Silva, Eduardo Carlos Bianchi, Ronaldo Yoshinobu Fuisse, Rodrigo Eduardo Catai, Thiago Valle França, Paulo Roberto Aguiar
Analysis of surface integrity for minimum quantity lubricant (MQL) in grinding
<https://doi.org/10.1016/j.ijmachtools.2006.03.015>
- [20] José C. Lopes, Carlos E. H. Ventura, Rafael L. Rodriguez, Anthony G. Talon, Roberta S. Volpato, Bruno K. Sato, Hamilton J. de Mello, Paulo R. de Aguiar, Eduardo C. Bianchi
Application of minimum quantity lubrication with addition of water in the grinding of alumina
<https://doi.org/10.1007/s00170-018-2085-8>
- [21] M.J. Hadad, T. Tawakoli, M.H. Sadeghi, B. Sadeghi
Temperature and energy partition in minimum quantity lubrication-MQL grinding process
<https://doi.org/10.1016/j.ijmachtools.2011.11.010>
- [22] YAN Lutao, YUAN Songmei, LIU Qiang
Influence of Minimum Quantity Lubrication Parameters on Tool Wear and Surface Roughness in Milling of Forged Steel
<https://doi.org/10.3901/CJME.2012.03.419>
- [23] W.L.R. Fernando, N. Sarmilan, K.C. Wickramasinghe, H.M.C.M. Herath, G.I.P. Perera
Experimental investigation of Minimum Quantity Lubrication (MQL) of coconut oil based Metal Working Fluid
<https://doi.org/10.1016/j.matpr.2019.06.079>
- [24] Y.S. Liao, H.M. Lin
Mechanism of minimum quantity lubrication in high-speed milling of hardened steel
<https://doi.org/10.1016/j.ijmachtools.2007.01.007>
- [25] C.P. Khunt, M.A. Makhesana, K.M. Patel, B.K. Mawandiya
Performance assessment of vegetable oil-based minimum quantity lubrication (MQL) in drilling
<https://doi.org/10.1016/j.matpr.2020.09.741>
- [26] M. Puvanesan, M.M. Rahman, M.S. Najiha and K. Kadirgama
Experimental Investigation of Minimum Quantity Lubrication on Tool Wear in Aluminum Alloy 6061-T6 using Different Cutting Tools
<https://doi.org/10.15282/ijame.9.2013.5.0127>
- [27] Ibrahim N. Tansel
Simulation of turning operations
[https://doi.org/10.1016/0890-6955\(90\)90005-4](https://doi.org/10.1016/0890-6955(90)90005-4)

- [28] V.T.G. Naves, M.B. Da Silva, F.J. Da Silva
 Evaluation of the effect of application of cutting fluid at high pressure on tool wear during turning operation of AISI 316 austenitic stainless steel
<https://doi.org/10.1016/j.wear.2013.03.016>
- [29] A. Noorul Haq, T. Tamizharasan
 Investigation of the effects of cooling in hard turning operations
<https://doi.org/10.1007/s00170-005-0128-4>
- [30] Eviatar Tron, Michael Margaliot
 Mathematical modeling of observed natural behavior: a fuzzy logic approach
<https://doi.org/10.1016/j.fss.2003.09.005>
- [31] M. R. H. Mohd Adnan, Arezoo Sarkheyli, Azlan Mohd Zain, Habibollah Haron
 Fuzzy logic for modeling machining process: a review
<https://doi.org/10.1007/s10462-012-9381-8>
- [32] K Hashmi, I.D Graham, B Mills
 Data selection for turning carbon steel using a fuzzy logic approach
[https://doi.org/10.1016/S0924-0136\(02\)01011-7](https://doi.org/10.1016/S0924-0136(02)01011-7)
- [33] Sungchul Jee, Yoram Koren
 Adaptive fuzzy logic controller for feed drives of a CNC machine tool
[https://doi.org/10.1016/S0957-4158\(03\)00031-X](https://doi.org/10.1016/S0957-4158(03)00031-X)
- [34] U. Natarajan & PR. Periyanan & S. H. Yang
 Multiple-response optimization for micro-endmilling process using response surface methodology
<https://www.proquest.com/openview/16a5b17a2cea1591b0379e21f2c61eaa/1?pq-origsite=gscholar&cbl=2044010>
- [35] Rashmi Lmalghan, Karthik Rao M C, ArunKumar S, Shrikantha S. Rao, Mervin A. Herbert
 Machining Parameters Optimization of AA6061 Using Response Surface Methodology and Particle Swarm Optimization
<https://doi.org/10.1007/s12541-018-0083-2>
- [36] Khalid H. Hashmi, Ghulam Zakria, Muhammad Baqar Raza & Shahid Khalil
 Optimization of process parameters for high speed machining of Ti-6Al-4V using response surface methodology
<https://doi.org/10.1007/s00170-015-8057-3>
- [37] S. R. Chauhan & Kali Dass
 Optimization of Machining Parameters in Turning of Titanium (Grade-5) Alloy Using Response Surface Methodology

<https://doi.org/10.1080/10426914.2011.593236>

[38] Shruti Sood, Prithu Mishra, Mayank Pandit & Pradeep Khanna

Prediction and Optimization of Weld Bead Geometry of MIG Welded Stainless Steel 202 Plates

https://doi.org/10.1007/978-981-16-2794-1_64

[39] M.A. Chowdhury, D.M. Nuruzzaman

Influence of Gas Flow Rate on the Deposition Rate on Stainless Steel 202 Substrates

<http://www.tribology.fink.rs/journals/2012/2012-4/6.pdf>