Modelling and Analysis of Surface Roughness for Bearing Metal Turning

M.Tech Major Project II

Submitted in partial fulfillment for the award of the Degree of Master of Technology in Production Engineering

By

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2K14/PIE/21

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DECLARATION

I hereby declare the work which is being presented in this dissertation, entitled **"Modelling and Analysis of Surface Roughness for Bearing Metal Turning"** towards the partial fulfillment of the requirements for the award of degree of Masters of Technology, from Delhi Technological University is an authentic record of my own work carried under the supervision of **Dr. RANGANATH M. SINGARI,** Associate Professor and **Dr. Vipin,** Professor, Department of Production and Industrial Engineering, Delhi Technological University, Delhi.

The matter embodied in this dissertation has not been submitted by me for award of any other degree.

ACHINTYA

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CERTIFICATE

This is to certify that the thesis entitled, **"Modelling and Analysis of Surface Roughness for Bearing Metal Turning"** submitted by Achintya, Roll No.- 2K14/PIE/21 in partial fulfillment of the requirements for the award of Master of Technology Degree in Production engineering at the Delhi Technological University is an authentic work carried out by him under our supervision and guidance.

To the best of our knowledge, the matter embodied in the thesis has not been submitted to any other University/ Institute for the award of any degree or diploma.

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Generally individuals set aims, but more often than not their conquest are by efforts of not just one but many determined people. This complete project could be accomplished because of the contribution of a number of people. We take it as a privilege to appreciate and acknowledge the efforts of all those who have, directly or indirectly helped me in achieving my aim.

I take a great pride in expressing my unfeigned appreciation and gratitude to my guide **Dr. RANGANATH M. SINGARI,** Associate Professor and **DR. VIPIN,** Professor, Department of Mechanical, Production and Industrial Engineering, for their invaluable inspiration, guidance and continuous encouragement through this project work.

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ABSTRACT

Surface roughness of a machined product can affect several of the product's functional attributes such as surface friction between mating parts, wear, heat transmission, ability of distributing and holding a lubricant, coating and resisting fatigue. In this study modelling and analysis of surface roughness of bearing material are done. Aluminium bronze is used as a bearing material because of its availability and common use in journal bearing, where surface roughness may play a major role in its functionality. Both external turning and internal (boring) turning are performed on CNC lathe using cutting speed, feed rate and depth of cut as the process parameters. The values for process parameters of external turning and internal are similar. Design of experiments (DOE) is used to obtain the optimum surface roughness. Response surface methodology (RSM) and artificial neural network (ANN) are implemented to model the surface roughness of external turning and internal turning. Regression models are developed for external turning and internal turning by using full block central composite design and analysis of experimental results are done by using analysis of variance (ANOVA). Predicted values of surface roughness of external turning and internal turnings are compared with experimental values, which show high accuracy.

Keywords: - Surface Roughness, Modelling, RSM, ANN, DOE, ANOVA, External Turning, Internal Turning.

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ABBREVIATIONS

DOE	Design of Experiment
ANOVA	Analysis of Variance
ANN	Artificial Neural Netwok
CNC	Computer Numerical Control
AA	Aluminium Alloy

NOTATIONS

Ra	average surface roughness
Rae	average surface roughness for external turning
Rai	average surface roughness for internal turning
s	cutting speed
f	feed rate
d, doc	depth of cut

CHAPTER 1

INTRODUCTION

1.1 MOTIVATION AND OBJECTIVES

The ever increasing demand for low cost, better quality metal cutting related products in terms of tolerance and surface finish has driven the metal cutting industry to continuously improve the quality of the metal cutting processes. The quality of surface roughness is an important requirement in the machining operations. Minimizing the surface roughness has become one of the main objectives of the latest researches in this industry. Surface roughness of a machined product can affect several of the product's functional attributes such as surface friction between mating parts, wear, light reflection, heat transmission, ability of distributing and holding a lubricant, coating and resisting fatigue. Among the various metal cutting processes, turning is one of the most fundamental metal removal operations for finishing. Surface roughness is one of the major quality attributes of a machined product especially in components like cams, bearings, crankshaft holes in engine blocks etc. Roughness of a machined product is determined by various factors which can be controllable, like cutting parameters, or non-controllable. Therefore, in order to obtain a better surface finish, the proper setting of cutting parameters is crucial before the process should take place. Hence, there is a need to optimize the process parameters in an efficient way to achieve the desired output characteristics by using experimental methods and statistical models.

In modern machining industries, most of the machining operations are performed on CNC machines. Our project, thus, aims to optimize the CNC turning parameters to obtain better surface finish (minimum surface roughness). On the basis of literature review, it was noticed that very few researchers had done their experimental work on Aluminium Bronze, which is commonly used for bearing material. Thus, we decided to perform our experimentation on this material.

The input parameters we took were speed, feed and depth of cut while the output parameter was surface roughness. The input values were decided on the basis of previous experience and literature review. Modelling and analysis were done using RSM and artificial neural network. Both internal and external turning of workpieces were performed on the CNC machine and then their surface roughness were measured separate using Talysurf Instrument. The analysis was done to determine the most significant parameter affecting the surface roughness of turned workpieces. Finally, the result obtained was compared to those obtained by other researchers.

1.2 STATEMENT OF THE PROJECT WORK

The work involves optimization of process parameters in the turning of Aluminium bronze on CNC Lathe by using RSM and artificial neural network. The effect of main process parameters i.e. cutting speed, feed rate and depth of cut have been analysed using this approach.

1.3 ORGANIZATION OF THE REPORT

Initially a thorough literature review was conducted. The topic and material was finalized. The dimensions of the work piece were finalized according to the bearing material commonly used. Thirty one pieces of the material were procured from a reliable source of the desired dimensions at market price. In the meanwhile CNC code was prepared for boring of the work piece. Now the experimentation work on the workpiece is being carried out.

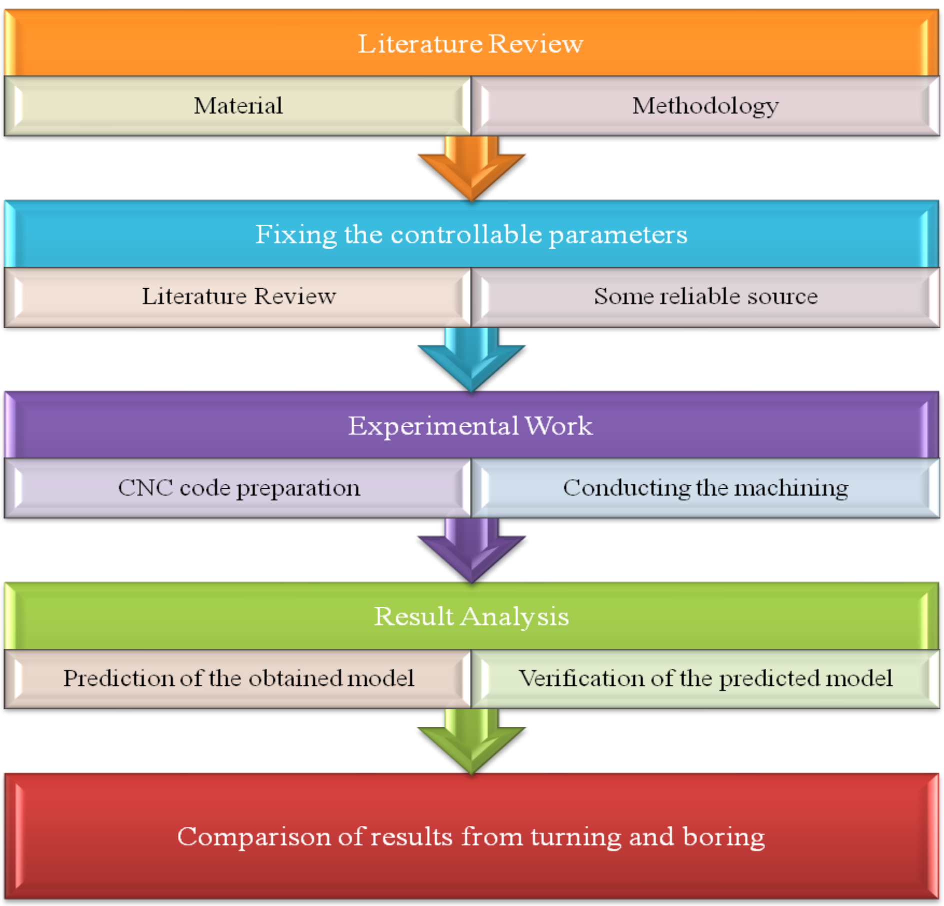


Figure 1.1: Methodology for conducting the work

CHAPTER 2
THEORETICAL BACKGROUND

2.1. BEARINGS

A bearing is a machine element used to support and guide a rotating, oscillating, or sliding shaft, pivot or wheel. Whenever a shaft rotates, it needs a bearing for smooth, effective operation. A bearing allows one part to bear another.

Functions:-

- To guide moving part
- To support a load

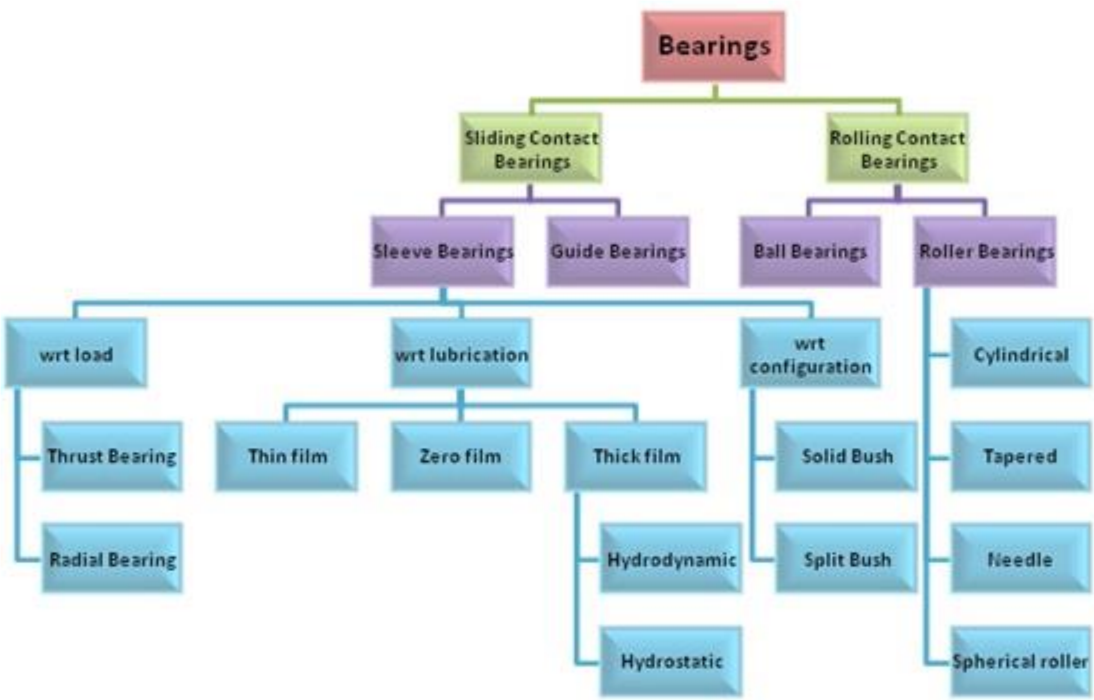


Fig. 2.1: Classification chart of bearing

2.2.JOURNAL BEARINGS

A journal bearing or a plain bearing is a sliding contact bearing working on hydrodynamic lubrication and which supports the load in radial direction. The portion of the shaft inside the bearing is called journal and hence the name journal bearing.

2.3.ALUMINIUM BRONZE BEARING

The material that was chosen for our experimentation purpose is Aluminium Bronze of IS-305 AB2 grade. It is sand casted. The selection was done based on the cost of the material and the applications of the material. It is one of the strongest and most complex of the copper-based bearing alloys. It shows the less corrosion against the atmospheric condition and sea water and also has low oxidation at elevated temperature and less reactive alloy. When exposed to atmospheric oxygen a thin layer of alumina has formed which acts as a barrier to corrosion. Such type of material has good properties like tensile strength of 640 MPa, proof stress of 13 MPa and 13% elongation on gauge length.

2.3.1. Composition

Table 2.1: Chemical Composition of Aluminium

Components	% by weight
Aluminium (Al)	8.8 to 10.0 %
Iron (Fe)	4.0 to 5.5 %
Manganese (Mn)	1.5 %
Nickel (Ni)	4.0 to 5.5 %

Zinc (Zn), max.	0.50 %
Tin(Sn), max.	0.10 %
Lead(Pb), max.	0.05 %
Silicon(Si), max	0.10 %
Magnesium (Mg)	0.05 %
Copper	Remainder

2.4.BORING

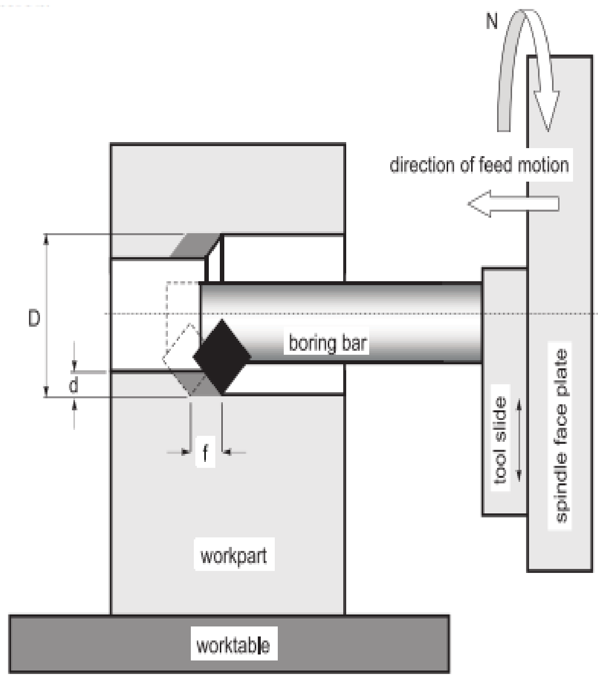


Figure 2.2: A schematic diagram of boring[42]

Boring is a single point cutting operation Used to produce an accurate internal cylindrical surface by enlarging a previously drilled hole in a workpiece. The workpiece moves parallel to the axis of rotation of the cutting tool.In horizontal boring, an existing hole is enlarged by advancing one or more rotating single point cutters horizontally into a stationary workpiece. As the boring bar is advanced horizontally into the workpiece, material is removed in the form of chips. The workpiece may also be fed into the cutter. The bored hole is always concentric with the axis of rotation of cutting tool.

2.5. TURNING

Turning is a machining process in which a single point cutting tool rotates around a workpiece to make it cylindrical in shape and of desired dimension i.e. diameter. The tool is fed linearly in the direction parallel to the axis of rotation of the workpiece by giving specified depth of cut in the direction perpendicular to the axis of rotation. The primary motion of cutting in turning is the rotation of the workpiece, and the secondary motion of cutting is the feed motion.

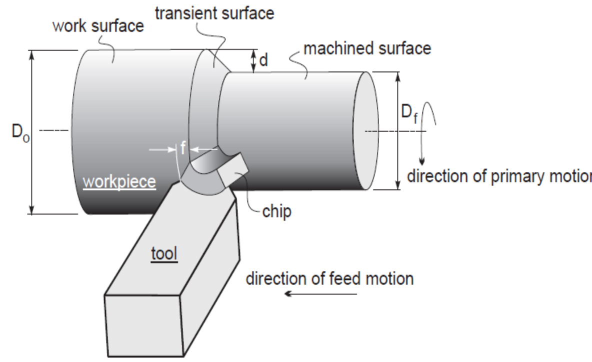


Figure 2.3: A schematic diagram of turning[43]

2.6. SURFACE ROUGHNESS

Surface roughness is defined as the deviation from the nominal surface of the 3rd up to 6th order. 1st and 2nd order deviations refer to form i.e. circularity, flatness, etc. and to waviness, respectively, and are mainly caused by machine tool errors, deformation of the workpiece, inaccurate setups and clamping, vibration and workpiece material in

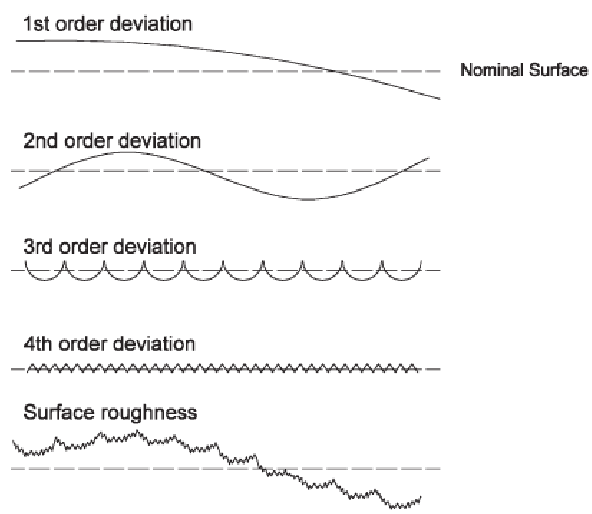


Figure 2.4: Surface form deviations[44]

homogeneities. 3rd and 4th order deviations refer to periodic grooves, and cracks and decays, which are connected to the shape and condition of the cutting edges, chip formation and process kinematics. 5th and 6th order deviations refer to workpiece material structure, which is connected to physical and chemical mechanisms acting on a grain and lattice scale (oxidation, residual stress, diffusion, slip, etc.). Different order deviations are shown in fig 2.4. The surface finish expected from different manufacturing processes is shown in fig.2.5.

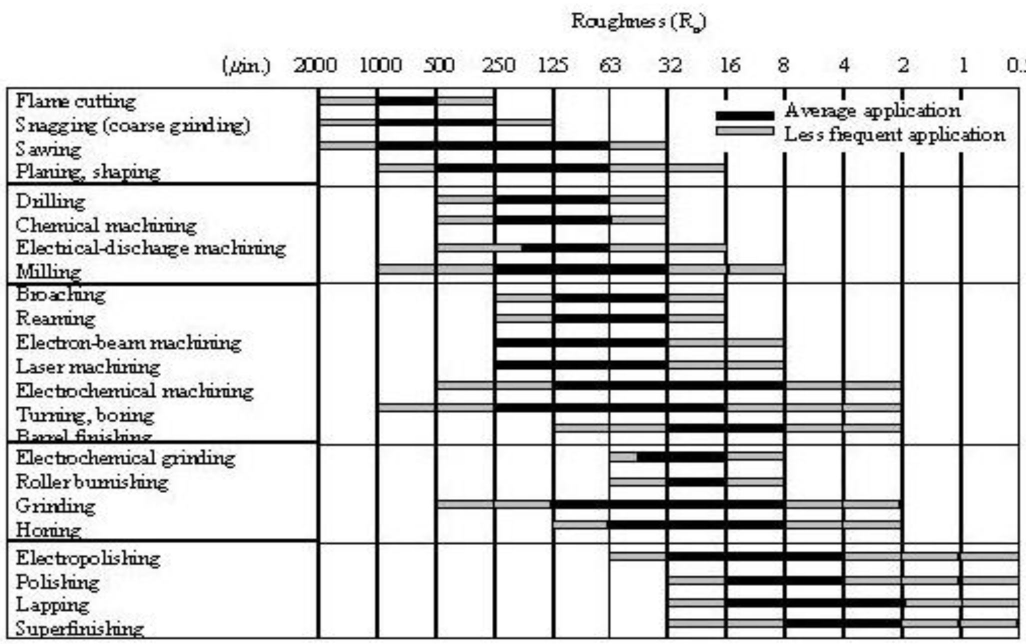


Figure 2.5: Surface finish expected from different manufacturing processes [45]

2.6.1. Methods for predicting surface roughness

Surface roughness is a key factor in determining the friction that comes in to play while operating a machine and hence the power loss. A problem consisting of controllable factors can be easily analysed, modeled and solved. However surface roughness has both controllable and uncontrollable factors. The factors have been shown as a fish bone diagram[44]. It is therefore difficult to accurately predict surface roughness. However we can predict surface roughness with the desired accuracy through various mathematical models that have been developed by researchers in the past. Correct analysis of controllable parameters gives results within the desired accuracy. Cutting speed, depth of cut and feed are the most commonly used parameters for this analysis. Some of the techniques that have been used by researchers and are shown in the fig.2.7**.**

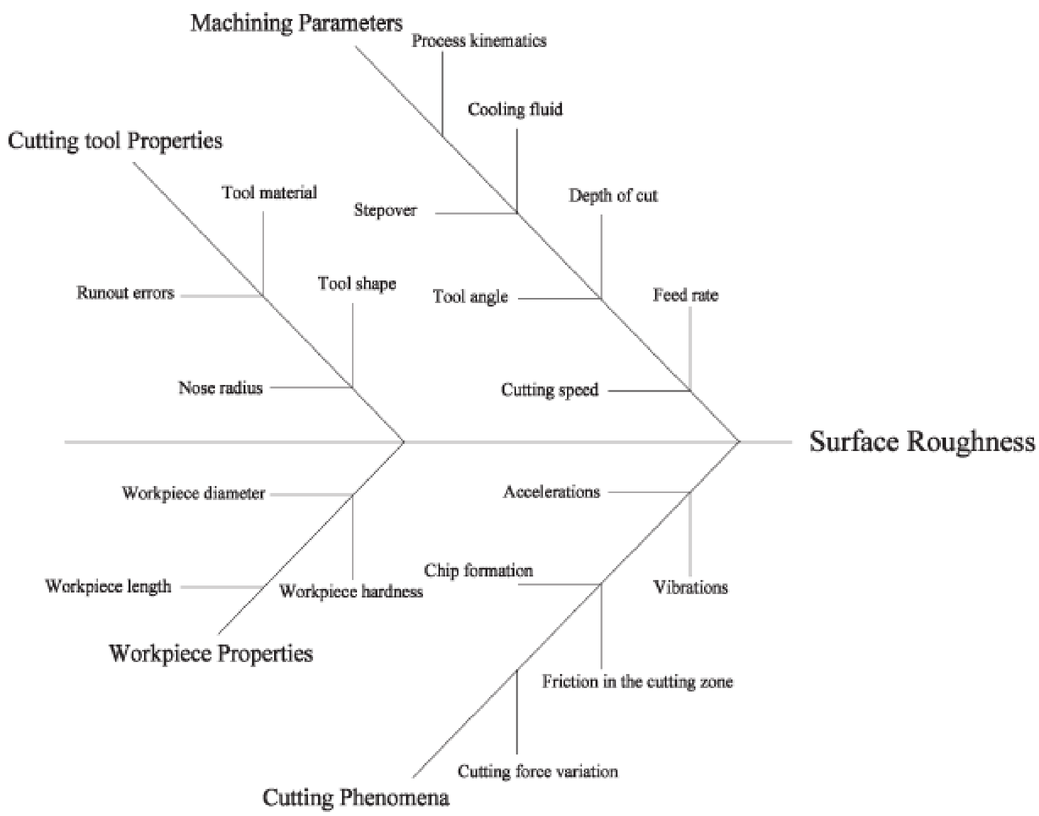


Figure 2.6: Factors affecting surface roughness[44]

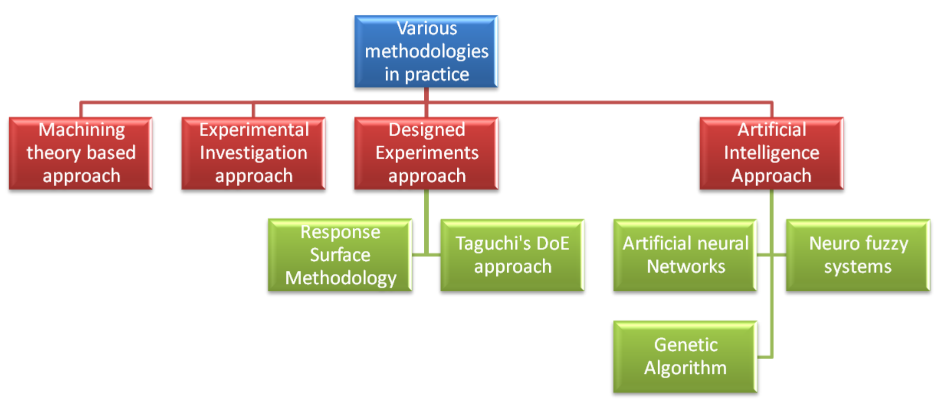


Figure 2.7: Various methodologies used for predictive modeling of surface roughness[44]

CHAPTER 3

LITERATURE REVIEW

1. Ranganath M S et al [1] have investigated the surface roughness and cutting force on conventional dry turning of aluminium(6061). Design of experiment (DOE) were done by using Taguchi and followed by ANOVA to find minimum Ra. Speed had the most influence on Ra followed by feed rate then depth of cut.
2. Ranganath M S, Vipin and Sanchay Gupta[2] predicted surface roughness in CNC turning of aluminium 6061 using taguchi and ANOVA for the effect of tool geometry. Process factors were rake angle, nose radius, cutting speed, feed rate and depth of cut. Feed rate had most influence followed by rake angle.
3. Yuanyuan Li et al[3] did study of aluminum bronze adhesion on tools during turning. M2 high-speed steel (HSS) tool and YW1 cemented carbide tool were used to turn a high strength wear resisting aluminum bronze. Workpiece adhesion was found on both the rake and flank of all samples. Adhesion was more severe and more uneven on the HSS tool than on the cemented carbide tool.
4. Puneet Saini et al.[4] investigated machining parameters for surface roughness in high speed CNC turning of EN-24 alloy steel using Response Surface Methodology. The main purpose of this research was to study effect of carbide inserts on EN-24 Alloy Steel surface by using parameters spindle speed, feed rate and depth of cut. 17 sets of experiments were performed. In this work empirical models were developed for surface roughness by considering spindle speed, feed

rate and depth of cut as main controlling factors using response surface methodology. The optimum value of the surface roughness (Ra) comes out to be 0.48 μm. It was also concluded that feed rate was the most significant factor affecting surface roughness followed by depth of cut. As Cutting speed was less significant factor affecting Ra.

5. Ranganath M S et al.[5] monitored Ra in CNC using RSM and Taguchi. RSM as well as Taguchi's techniques revealed that Feed is the most significant factor in minimizing surface roughness followed by speed and depth of cut. RSM technique predicted results better than the Taguchi's technique.
6. Chen lu[6] studied the prediction of surface quality in machining process. He reviewed the methodologies and practice that are being employed for the prediction of surface profile and roughness, each approach with its advantages and disadvantages is summarized. Finally, the author's present work prediction of surface profile using RBF neural network and future trend were also introduced.
7. Ranganath, Vipin and Harshit[7] did work on Ra prediction model for CNC turning of EN-8 steel using RSM with uncoated carbide inserts. The model was developed in the form of multiple regression equations depend on parameters like surface roughness, with cutting speed, feed rate and depth of cut. The box behnken design was used to plan the experiment. The second order model was found suitable. A good agreement between the predicted and experimental Ra was observed within reasonable limit.

8. John kechagias et al.[8] did research in a parameter design in turning of copper alloy using Taguchi design. Independent variables were cutting speed, feed rate, doc and nose radius of tool. An orthogonal matrix experiment (L_9) was conducted. An additive model was applied on the experimental results and a verification experiment, using the best combination of parameters, was carried out in order to compare the actual and the predicted values.
9. Vishal Sardana et al.[9] did analysis of roughness during CNC Turning using Taguchi and RSM. L27 Orthogonal array has been employed for analysis. The results revealed that feed is the most significant factor in minimizing the surface roughness followed by depth of cut and then speed. RSM is a better tool for optimization. It can better predict the effect of parameters on response.
10. W. Chmura and Z. Gronostajski[10] did research in bearing composite made from aluminium and aluminium bronze chips. Diffusion bonding process of aluminium and aluminium bronze chips leads to creation of the phases typical for Cu–Al equilibrium diagram. Because during the hot extrusion the diffusion bonding is very slow, after extrusion heat treatment must be applied.
11. Ilhan Asiltürk and Mehmet Çunkas[11] did Modeling and prediction of surface roughness in turning operations using artificial neural network and multiple regression method. Surface roughness is measured in turning at different parameters such as speed, feed, and depth of cut. Full factorial experimental design is applied to increase the confidence limit and reliability of the experimental data. Artificial neural networks (ANN) and multiple regression

approaches were used to model the surface roughness of AISI 1040 steel. Both based models were compared using statistical methods. It is clearly seen that the suggested models are capable of prediction of the surface roughness. The ANN model estimates the surface roughness with high accuracy compared to the multiple regression model.

12. Gabriel Medrado Assis Acayaba et al.[12] predicted surface roughness in low speed turning of AISI316 austenitic stainless steel. Turning stainless steel at low cutting speeds may result in a rougher surface due to built-up edge formation; whereas speed increases the surface roughness improves, due to the low contact time between the chip and the tool to allow bonding to occur. Experimental data are used to develop prediction models using Multiple Linear Regression and ANN methodologies. Results show that the neural network outperforms the linear model by a fair margin (1400%).
13. A. Torres et al.[13] did work in surface roughness analysis on the dry turning of an Al-Cu alloy. Parameters were doc, feed, cutting speed and tool radius. The experimental results shown that for dry turning operations and for the amplitude parameters, the most significant factor was the interaction effect between the depth of cut and the feed rate. In addition, for facing operations, the feed rate turned out to be the most statistically influential factor of all the surface roughness parameters.
14. Richárd Horváth et al.[14]analysed surface roughness of aluminium alloys fine turned. United phenomenological models and multi-performance optimization.

The tests were performed with the design of experiments methodology. In order to estimate the Ra and Rz surface roughness parameters widely used in the industry reduced united phenomenological models were built from the measurement results utilizing edge materials, and work piece materials as qualitative members. After multi-performance optimization an optimum point with desirability functions was defined so as to maximize productivity and minimize surface roughness.

15. Abbas Razavykia[15] evaluated cutting force and surface roughness in the dry turning of Al–Mg2Si in-situ metal matrix composite inoculated with bismuth using DOE approach. The experimental trials were designed using the multi-level factorial design (DOE) and their results were analyzed using Analysis of Variance (ANOVA). The statistical observation revealed that the main effect of cutting speed, feed rate and modifier element influenced the cutting force and surface roughness. Built-up-edge (BUE) formation was observed at every combinations of cutting speed and feed rate which affected the surface quality negatively. Our results showed that the Bi is a promising element to improve the machinability of Al–Mg2Si composite.

16. Ashvin J. Makadia and J.I. Nanavati[16] did research in Optimisation of machining parameters for turning operations based on response surface methodology for AISI 410 steel. Response surface contours were constructed for determining the optimum conditions for a required surface roughness. The surface roughness was found to increase with the increase in the feed and it decreased with increase in

the tool nose radius. The verification experiment is carried out to check the validity of the developed model that predicted surface roughness within 6% error.

17. Ravinder Kumar and Santram Chauhan[17] studied surface roughness measurement for turning of Al 7075/10/SiCp and Al 7075 hybrid composites by using RSM and ANN. It is apparent from the analysis that feed rate has significant contribution for both materials than speed and approach angle.
18. Ranganath M. S. et al.[18] did research in parametric analysis of surface roughness studies in turning using artificial neural network. The turning process parameter optimization is highly constrained and nonlinear. Many researchers have used ANN model for the data obtained through experiments to predict the surface roughness. It was concluded that ANN was reliable and accurate for solving the cutting parameter optimization.
19. Ranganath M. S and Vipin[19] did experimental investigation and parametric analysis of surface roughness in CNC turning using DOE. Experiments were carried out with the help of factorial method of design of experiment approach to study the impact of turning parameters on the roughness. A mathematical model was formulated to predict the effect of machining parameters on surface roughness. Model was validated with the experimental data and the reported data of other researchers. Further parametric investigations were carried out to predict the effect of various parameters on the surface research.
20. V V K Lakshmi et al.[20] did research in modelling and optimization of process parameters during end milling of hardened steel. The response surface

methodology (RSM) has been utilized for the postulation of a second order quadratic model in terms of cutting speed, depth of cut and feed.. The ANOVA technique was used to verify the adequacy of the model at 95% confidence interval. From the model it was found that feed and speed plays the most significant role on surface finish. The roughness tends to decrease with decreasing feed and increasing cutting speed.

21. Sener Karabulut[21] did work in Optimization of surface roughness and cutting force during AA7039/Al2O3 metal matrix composites milling using neural networks and Taguchi method. Taguchi design of experiment method using L_{18} 2^1*3^2 with a mixed orthogonal array. The effects of the cutting parameters on surface roughness and cutting force were determined by using ANOVA. The analysis results showed that material structure was the most effective factor on surface roughness and feed rate was the dominant factor affecting cutting force. ANN and regression analysis were used to predict surface roughness and cutting force. ANN was able to predict the surface roughness and cutting force with a mean squared error equal to 2.25% and 6.66% respectively.

22. Ilhan Asiltürk et al.[22] did research on optimisation of parameters affecting surface roughness of Co28Cr6Mo medical material during CNC lathe machining by using the Taguchi and RSM methods. Cutting parameters were spindle rotational speed, feed rate, depth of cut and tool tip radius. In order to determine critical states of the cutting parameters ANOVA was applied. The validity of the developed models necessary for estimation of the surface roughness values (Ra,

Rz), was approximately 92%. It was found that for Ra 38% of the most effective parameters is on the tool tip radius, followed by 33% on the feed rate whereas for Rz tool tip radius occupied 43% with the feed being at 33% rate.

23. Girish Kant et al.[23] did work on predictive modelling and optimization of machining parameters to minimize surface roughness using artificial neural network coupled with genetic algorithm. A real machining experiment had been referred in this study to check the capability of the proposed model for prediction and optimization of surface roughness. The analysis of this study proves that the proposed approach is capable of determining the optimum machining parameter.
24. Shengguan Qu et al.[24] studied the Effects of cutting parameters on dry cutting of aluminum bronze alloy. High-strength wear resisting aluminum bronze alloy is a difficult to machine material. Dry cutting tests were conducted on high-strength wear-resisting aluminum bronze alloy with YW1 cemented carbide tool and YBC251 coated cemented carbide tool. Machining performance of the YBC251 coated cemented carbide tool was better than that of YW1 cemented carbide tool. Among all the cutting parameters, it was found that feed rate had a stronger effect on tool life and surface roughness followed by cutting speed and cutting depth.
25. Ranganath M S et al.[25] had reviewed the optimization of process parameters in turning operation using response surface methodology. DOE were conducted for the analysis on the influence of the turning parameters such as cutting speed, feed and doc on the surface roughness.

26. J. Paulo Davim et al.[26] investigated the effect of cutting conditions on surface roughness in turning of free machining steel by ANN models. The ANN model of surface roughness parameters (Ra and Rt) is developed with the cutting conditions such as cutting speed, feed rate and depth of cut. The analysis revealed that cutting speed and feed rate had significant effects in reducing the surface roughness, while the depth of cut had the least effect.
27. Gerardo Beruvides et al.[27] did research on Surface roughness modeling and optimization of tungsten–copper alloys in micro-milling processes. the optimization process is carried out by considering two contradictory objectives: unit machining time and surface roughness. In the first case (point 1), machine time is of greater importance, and in the second case (point 2), importance is attached to surface roughness.
28. Dadapeer.B et al.[28] analysed the Forces & Surface Roughness on Hardened Steel With Uncoated Ceramic Insert Using Taguchi Technique. The effect of the selected process parameters on the Feed force (FX), Tangential force (FY) and Surface roughness (Ra) had been done by using Taguchi's DOE approach. The percent contributions of parameters in the ANOVA table for Feed force (F_x) for the depth of cut (87.99%) has a major contribution than that of feed rate (2.82 %) and the cutting speed (4.45%).
29. Ulas Çayda¸s and Sami Ekici[29] did research on Support vector machines models for surface roughness prediction in CNC turning of AISI 304 austenitic stainless steel. Turning parameters of cutting speed, feed rate and depth of cut were

considered as model variables. A three-level full factorial design of experiments method was used to collect surface roughness values. A feed forward neural network based on back propagation algorithm was a multilayered architecture made up of 15 hidden neurons placed between input and output layers. The prediction results showed that the all used SVMs results were better than ANN with high correlations between the prediction and experimentally measured values.

30. Naveen narayanan et al.[30] predicted surface roughness using ANN in turning. The study concluded that the model for surface roughness can be improved by modifying the number of layers and nodes in the hidden layers of the ANN network structure, mainly for predicting value of the surface roughness performance measure.
31. Chintan Kayastha and Jaivesh Gandhi[31] did work on optimization of process parameter in turning of copper by combination of Taguchi and Principal Component Analysis Method. The aim was to investigate the effects of process parameters on surface finish and material removal rate to obtain the optimal set of process parameters with good finishing surface and desirable in turning process with minimum machining cost.
32. D. Philip Selvaraj et al.[32] did work on Optimization of surface roughness, cutting force and tool wear of nitrogen alloyed duplex stainless steel in a dry turning process using Taguchi method. The cutting parameters were optimized using signal to noise ratio and the analysis of variance. The results revealed that the feed

rate had more significance on surface roughness and cutting force. The cutting speed was identified as the more significant parameter influencing the tool wear.

33. Behnam Davoodi and Behzad Eskandari[33] did research on Tool wear mechanisms and multi-response optimization of tool life and volume of material removed in turning of N-155 iron–nickel-base superalloy using RSM. The relationships between machining parameters and output variables were modeled by using RSM. Analysis of variance was performed to check the suitability of the mathematical model and its respective variables. The results showed a good agreement between the measured tool life and volume of material removed and predicted values obtained by developed models.
34. Fabrício José Pontes et al.[34] did Optimization of Radial Basis Function neural network employed for prediction of surface roughness in hard turning process using Taguchi's orthogonal arrays. ANN models obtained proved capable to predict surface roughness in accurate, precise and affordable way. The work concludes that the design of experiments (DOE) methodology constitutes a better approach to the design of RBF networks for roughness prediction than the most common trial and error approach.
35. Anupam Agrawal et al.[35] predicted surface roughness during hard turning of AISI 4340 steel(69 HRC). The machining outcome was used as an input to develop various regression models to predict the average machined surface roughness. The performance of these models was compared to ascertain how feed, depth of cut, and spindle speed affect surface roughness and finally to obtain a

mathematical equation correlating these variables. It was concluded that the random forest regression model is a superior choice over multiple regression models for prediction of surface roughness).

36. Varaprasad Bh et al.[36] studied the effect of machining parameters on tool wear in hard turning of AISI D3 steel. The combined effects of cutting speed, feed rate and depth of cut were investigated using contour plots and surface plots. RSM based Central Composite Design was applied as an experimental design. The adequacy of the developed models is checked using Analysis of Variance.
37. Nexhat Qehaja et al.[37] did study on effect of machining parameters and machining time on surface roughness in dry turning process. A model of surface roughness was developed based on the RSM to investigate the feed rate, tool geometry, nose radius, and machining time, affecting the roughness of surface produced in dry turning process. The experiment had been designed and carried out on the basis of a three level factorial design. Obtained results were validating the effectiveness of regression analysis in modeling of surface roughness in dry turning process.
38. R.Suresh and S. Basavarajappa[38] did work on the effect of process parameters on tool wear and surface roughness during turning of hardened steel with coated ceramic tool. A central composite design of RSM was employed. It was observed that cutting speed possessed most dominating effect over tool wear then feed rate and depth of cut. Feed rate had most influence on surface roughness followed by depth of cut and speed.

39. A. Del Prete et al.[39] did study on Super-Nickel orthogonal turning operations optimization. This paperwork was focused about the generation of an automated optimization procedure, for turning processes of nickel superalloys, under certain process conditions. For the automated optimization procedure the RSM had been used to detect the influence of the process variables on its performances.
40. Hemant Jain et al[40] did work on optimisation and evaluation of machining parameters for turning operation of Inconel-625. The main objective of this investigation was to obtain an optimal setting of process parameters in turning for maximizing the material removal rate of the manufactured component, the MRR has been investigated by the analysis while machining practically used component. The data for calculating material removal rate in all the test conditions were observed and recorded. The results from confirmation runs indicated that the determined optimal combination of machining parameters improved the performance of the machining process.

CHAPTER 4

EXPERIMENTAL WORK

4.1 DESIGN OF EXPERIMENT

The process parameters selected for the experiment are spindle speed(rpm), feed (mm/rev) and depth of cut(mm). The output parameter that is under consideration is surface roughness (µm).Based on literature review, previous experience and information from the Copper. Development Association [41], were selected for the different input parameters.

Table 4.1 : Process parameters with their values at three levels

Code	Parameters	Level 1	Level 2	Level 3
A	**Speed (RPM)**	1900	2100	2300
B	**Feed (mm/rev)**	0.05	0.10	0.15
C	**Depth of cut (mm)**	0.12	0.18	0.24

4.2.WORKPIECE MATERIAL

Thirty workpieces of Aluminium Bronze were procured from Jai Bharat Metal Industries with the following dimensions and have been used for the experiment**.**

Table 4.2: Workpiece Dimensions

Outside Diameter	40 mm
Inner Diameter	20 mm
Length	50 mm

Figure 4.1: A set of workpieces

4.3.CUTTING TOOL MATERIAL

The cutting tool material is a tungsten carbide insert boring tool designated as CCMT 09T304 TN2000 manufactured by WIDIA, Germany. The designation is explained below.

Table 4.3: Tool Designation

C	Shape (Rhomboid 80^{O})
C	Clearance Angle (7^{O})
M	Tolerance class
T	Insert features
09	Finishing
T	Chamfered
3	Insert Thickness
04	Nose Radius
T	Turning

N	Non Ferrous
20	General Purpose
00	Version

4.4.CNC LATHE

- CNC Turning: LMW LL20TL3 (Lakshmi Machine Works Limited)
- Available in “Metal Cutting” Lab

Table 4.4: Machine Specifications

Title	Description	Unit	LL20T L3
Capacity	Swing over bed	mm	510
	Chuck dia. max.	mm	200
	Max turning diameter	mm	320
	Max. turning length	mm	310
	Admit between centers	Mm	420
Spindle	Spindle nose	Type	A2 – 6
	Hole through spindle	Mm	61
	Spindle speed	Rpm	3500
	Spindle motor power(cont./15min)	kW	7.5/11
Feed system	Cross travel X-axis	Mm	185
	Longitudinal travel Z-axis	Mm	370
	Rapid traverse rate X/Z-axes	m/min	30 / 30
Turret	No. of stations	Nos.	8
	Tool shank size	Mm	25×25
Turret	Maximum boring bar dia.	Mm	40
	Turret indexing	Type	Hydraulic
Tailstock	Quill dia.	Mm	75
	Quill stroke	Mm	100

	Quill taper	-	MT-4
CNC system	Controller	-	Fanuc
Machine size	Front x Side	Mm	2065 X 1925
	Machine weight (Approx.)	Kg	3500

Figure 4.2: CNC Lathe in the metal cutting shop

4.5.Talysurf

- Used for Surface Roughness Measurement.
- Consists of a diamond-tipped stylus that traces the roughness profile of the workpiece.
- Can be used independently or connected with computer to get a detailed analysis.
- Available in “Metrology lab”.

Figure 4.3: Talysurf in the Metrology Lab

Figure 4.4: Talysurf measuring the internal surface roughness

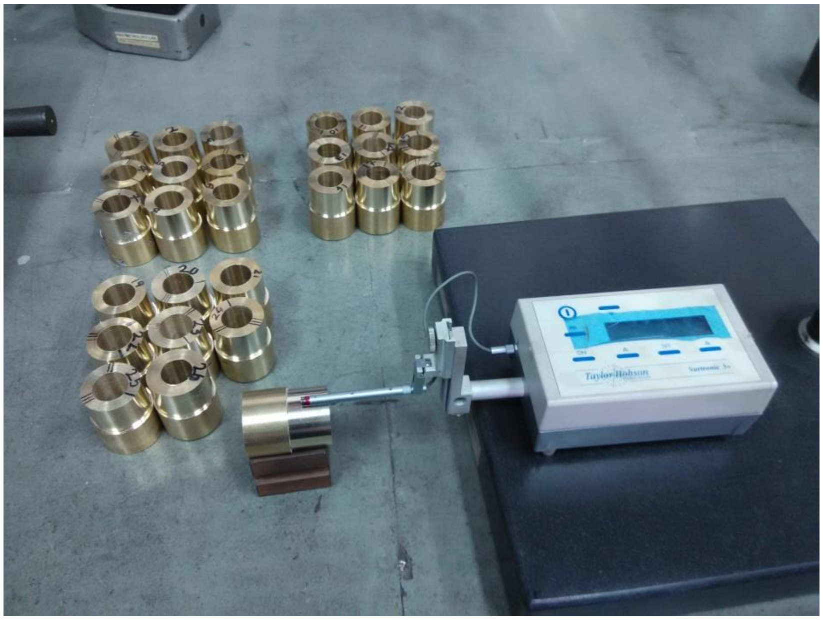


Figure 4.5: Talysurf measuring the external surface roughness

4.6.CNC CODES

The CNC Code is used for internal turning. The workpiece is machined to 21mm for internal turning and 37 mm for external turning, these are the nearest bearing specification. The G99 canned cycle is used for boring the workpiece.

For boring

Speed 1900 rpm feed 0.05 mm/rev

depth of cut 0.12 mm

```
O0071;
T0101;
G21 X0.0 Z0.0;
TY0202;
G00 Z10.0;
G00 X10.0;
G99 M03 S1900 F0.05;
G01 Z5.0;
G01 X19.5;
G90 X20.24 Z-55.0;
/ X20.48;
/ X20.60;
/ X20.84;
/ X21.08;
M05;
M30;
%
```

For external turning

Speed 1900 rpm feed 0.05 mm/rev

depth of cut 0.24 mm

```
O0071;
T0701;
G21 X0.0 Z0.0;
TY0707;
G00 Z10.0;
G00 X40.0;
G99 M03 S1900 F0.05;
G01 Z5.0;
G90 X39.52 Z-25.0;
/ X39.04;
/ X38.56;
/ X38.08;
/ X37.60;
/ X37.12;
M05;
M30;
%
```

For boring

Speed 2100 rpm feed 0.10 mm/rev

depth of cut 0.18 mm

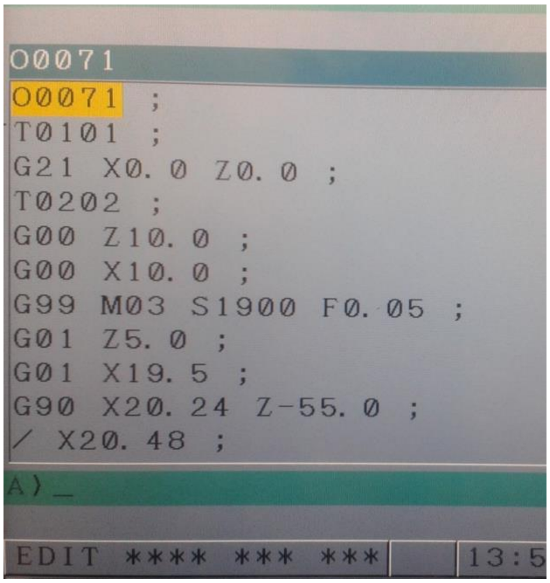
```
O0071;
T0101;
G21 X0.0 Z0.0;
TY0202;
G00 Z10.0;
G00 X10.0;
G99 M03 S1900 F0.05;
G01 Z5.0;
G01 X19.5;
G90 X20.24 Z-55.0;
/ X20.60;
/ X20.96;
/ X21.32;
M05;
M30;
```

For external turning

Speed 2300 rpm feed 0.15 mm/rev

depth of cut 0.24 mm

```
O0071;
T0701;
G21 X0.0 Z0.0;
TY0707;
G00 Z10.0;
G00 X40.0;
G99 M03 S2300 F0.15;
G01 Z5.0;
G90 X39.52 Z-25.0;
/ X39.04;
/ X38.56;
/ X38.08;
/ X37.60;
/ X37.12;
M05;
M30;
%
```



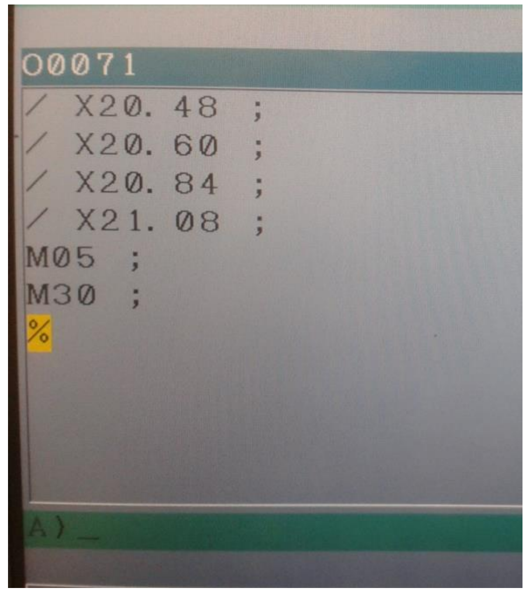


Figure 4.6: CNC Code used for boring

4.7.EXPERIMENTS

27 experiments were done according to the design table and surface roughnesses were measured by using talysurf and these values are shown in the given table. Table 4.5 and Table 4.6 show the design parameter and the output value for external turning and internal turning respectively. The parameters such as cutting speed, feed rate and depth of cut are taken as the input parameters for turning and these values are denoted as, “s, f and doc” respectively. Here the output is surface roughness and three values for surface roughness are measured at three different locations of each workpiece and

are denoted as Ra_1, Ra_2 and Ra_3. Average value of the three Ra is considered and denoted as Rae and Rai for external turning and internal turning respectively.

Table 4.5: Design table and roughness value for external turning

Exp. No.	A	B	C	S	f	doc	Ra_1	Ra_2	Ra_3	Rae
1	1	1	1	1900	0.05	0.12	0.4	0.36	0.36	0.373333
2	1	1	2	1900	0.05	0.18	0.42	0.38	0.58	0.46
3	1	1	3	1900	0.05	0.24	0.44	0.48	0.5	0.473333
4	1	2	1	1900	0.1	0.12	0.82	0.88	0.84	0.846667
5	1	2	2	1900	0.1	0.18	0.84	0.92	0.86	0.873333
6	1	2	3	1900	0.1	0.24	0.82	0.82	0.8	0.813333
7	1	3	1	1900	0.15	0.12	0.8	0.74	0.82	0.786667
8	1	3	2	1900	0.15	0.18	0.72	0.84	0.7	0.753333
9	1	3	3	1900	0.15	0.24	0.8	0.82	0.86	0.826667
10	1	1	1	2100	0.05	0.12	0.38	0.36	0.36	0.366667
11	1	1	2	2100	0.05	0.18	0.38	0.4	0.4	0.393333
12	1	1	3	2100	0.05	0.25	0.44	0.48	0.46	0.46
13	1	2	1	2100	0.1	0.12	0.96	0.9	0.92	0.926667
14	1	2	2	2100	0.1	0.18	0.86	0.86	0.88	0.866667
15	2	2	3	2100	0.1	0.24	1	0.94	0.92	0.953333
16	2	3	1	2100	0.15	0.12	0.7	0.76	0.82	0.76
17	2	3	2	2100	0.15	0.18	0.78	0.72	0.74	0.746667
18	2	3	3	2100	0.15	0.24	0.86	0.84	0.84	0.846667
19	3	1	1	2300	0.05	0.12	0.44	0.4	0.4	0.413333
20	3	1	2	2300	0.05	0.18	0.5	0.42	0.48	0.466667
21	3	1	3	2300	0.05	0.24	0.44	0.44	0.44	0.44
22	3	2	1	2300	0.1	0.12	0.74	0.82	0.82	0.793333
23	3	2	2	2300	0.1	0.18	0.86	0.9	0.94	0.9
24	3	2	3	2300	0.1	0.24	0.96	0.9	0.96	0.94
25	3	3	1	2300	0.15	0.12	0.86	0.78	0.78	0.806667
26	3	3	2	2300	0.15	0.18	0.88	0.74	0.82	0.813333
27	3	3	3	2300	0.15	0.24	0.92	1.04	0.94	0.966667

Table 4.6: Design table and roughness value for internal turning(boring)

Exp. No.	A	B	C	S	F	doc	Ra_1	Ra_2	Ra_3	Rai
1	1	1	1	1900	0.05	0.12	2.96	2.32	2.76	2.68
2	1	1	2	1900	0.05	0.18	0.96	0.96	0.96	0.96
3	1	1	3	1900	0.05	0.24	2.94	2.38	2.5	2.606667
4	1	2	1	1900	0.1	0.12	5.3	6.7	5.78	5.926667
5	1	2	2	1900	0.1	0.18	1.6	1.6	1.58	1.593333
6	1	2	3	1900	0.1	0.24	1.02	0.94	0.86	0.94
7	1	3	1	1900	0.15	0.12	1.4	1.04	1.02	1.153333
8	1	3	2	1900	0.15	0.18	2.04	2.24	2.16	2.146667
9	1	3	3	1900	0.15	0.24	1.14	1.2	1.02	1.12
10	1	1	1	2100	0.05	0.12	3.98	3.46	4.04	3.826667
11	1	1	2	2100	0.05	0.18	1.96	2	1.98	1.98
12	1	1	3	2100	0.05	0.25	2.66	2.22	2.18	2.353333
13	1	2	1	2100	0.1	0.12	0.88	1.14	0.8	0.94
14	1	2	2	2100	0.1	0.18	3.7	3.56	3.68	3.646667
15	2	2	3	2100	0.1	0.24	2.76	2.52	3.08	2.786667
16	2	3	1	2100	0.15	0.12	2.12	2.02	2.12	2.086667
17	2	3	2	2100	0.15	0.18	2.92	3.84	2.24	3
18	2	3	3	2100	0.15	0.24	0.78	0.72	0.76	0.753333
19	3	1	1	2300	0.05	0.12	4.04	3.26	4.3	3.866667
20	3	1	2	2300	0.05	0.18	2.12	1.84	2	1.986667
21	3	1	3	2300	0.05	0.24	0.84	0.86	0.9	0.866667
22	3	2	1	2300	0.1	0.12	5.32	4.28	5.04	4.88
23	3	2	2	2300	0.1	0.18	5.14	5.38	4.84	5.12
24	3	2	3	2300	0.1	0.24	1.18	1.44	1.22	1.28
25	3	3	1	2300	0.15	0.12	7.44	7.52	7.5	7.486667
26	3	3	2	2300	0.15	0.18	1.06	1.1	1.16	1.106667
27	3	3	3	2300	0.15	0.24	1.1	1.14	1.1	1.113333

CHAPTER 5

RESULTS AND DISCUSSIONS

5.1. RSM TECHNIQUE

The results obtained from the machining trials performed as per the design table shown in Table 5.3. These results were input into the Minitab 17 Software for further analysis. An ANOVA table is used to summarize the tests performed. Table 5.4 and table 5.9 show the Analysis of Variance (ANOVA) for external turning and internal turning respectively. The Model F values of 189.20 and 10.80 for Rae and Rai indicate the models are significant. There is 0.0% chance that an F-value this large could occur due to noise in case of Rae and that of 0.0% in case of Rai. Significance of Model is desirable as it indicates that the terms in the model have a significant effect on the response. Some of the model terms were found to be significant. From the ANOVA table 5.4 P values for s, f, d are less than 0.05 prove that these are the significant parameters for roughness. From ANOVA table 5.9 s and d are found to be significant factor due to P values are less than 0.05. Also equation 1 and equation 2 show the regression equations for external and internal turning respectively.

Table 5.1: Central Composite Design

Factors	3	Replicates	1
Base runs	20	Total runs	20
Base blocks	1	Total blocks	1

Table 5.2: Two-level factorial: Full factorial

Cube points	8
Center points in cube	6
Axial points	6
Center points in axial	0
A	1

Table 5.3: Design Table (randomized)

Run	**Blk**	**A**	**B**	**C**	**s**	**f**	**d**
1	1	0	0	0	2100	0.1	0.18
2	1	0	0	0	2100	0.1	0.18
3	1	0	0	0	2100	0.1	0.18
4	1	0	0	1	2100	0.1	0.24
5	1	-1	0	0	1900	0.1	0.18
6	1	1	0	0	2300	0.1	0.18
7	1	1	-1	-1	2300	0.05	0.12
8	1	1	1	-1	2300	0.15	0.12
9	1	-1	1	-1	1900	0.15	0.12
10	1	-1	-1	-1	1900	0.05	0.12
11	1	-1	1	1	1900	0.15	0.24
12	1	1	1	1	2300	0.15	0.24
13	1	0	-1	0	2100	0.05	0.18
14	1	0	0	0	2100	0.1	0.18
15	1	1	-1	1	2300	0.05	0.24
16	1	0	1	0	2100	0.15	0.18
17	1	0	0	-1	2100	0.1	0.12
18	1	-1	-1	1	1900	0.05	0.24
19	1	0	0	0	2100	0.1	0.18
20	1	0	0	0	2100	0.1	0.18

5.1.1. Response Surface Regression: Rae versus S, f, d

Table 5.4: Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	9	0.759122	0.084347	189.20	0.000
Linear	3	0.395640	0.131880	295.82	0.000
S	1	0.004840	0.004840	10.86	0.008
f	1	0.376360	0.376360	844.20	0.000
d	1	0.014440	0.014440	32.39	0.000
Square	3	0.360682	0.120227	269.68	0.000
S*S	1	0.000057	0.000057	0.13	0.729
f*f	1	0.240057	0.240057	538.46	0.000
d*d	1	0.005457	0.005457	12.24	0.006
2-Way Interaction	3	0.002800	0.000933	2.09	0.165
S*f	1	0.001800	0.001800	4.04	0.072
S*d	1	0.000200	0.000200	0.45	0.518
f*d	1	0.000800	0.000800	1.79	0.210
Error	10	0.004458	0.000446		
Lack-of-Fit	5	0.004458	0.000892	*	*
Pure Error	5	0.000000	0.000000		
Total	19	0.763580			

Table 5.5: Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.0211144	99.42%	98.89%	92.11%

Table 5.6: Coded Coefficients

Term	**Effect**	**Coef**	**SE Coef**	**T-Value**	**P-Value**	**VIF**
Constant		0.85418	0.00726	117.68	0.000	
S	0.04400	0.02200	0.00668	3.29	0.008	1.00
F	0.38800	0.19400	0.00668	29.06	0.000	1.00
D	0.07600	0.03800	0.00668	5.69	0.000	1.00
S*S	0.0091	0.0045	0.0127	0.36	0.729	1.82
f*f	-0.5909	-0.2955	0.0127	-23.20	0.000	1.82
d*d	0.0891	0.0445	0.0127	3.50	0.006	1.82
S*f	0.03000	0.01500	0.00747	2.01	0.072	1.00
S*d	0.01000	0.00500	0.00747	0.67	0.518	1.00
f*d	0.02000	0.01000	0.00747	1.34	0.210	1.00

5.1.2. Regression Equation in Uncoded Units for Rae

$$Rae = 0.37 - 0.00059S + 23.77f - 5.03d + 0.0000001S*S - 118.18f*f + 12.37d*d$$

$$+ 0.001500\,S*f + 0.000417S*d + 3.33\,f*d \quad \text{.....(1)}$$

Table 5.7: Fits and Diagnostics for Unusual Observations

Obs	**Rae**	**Fit**	**Resid**	**Std Resid**	
10	0.3600	0.3838	-0.0238	-2.48	R
12	0.9200	0.8918	0.0282	2.93	R
16	0.7200	0.7527	-0.0327	-2.17	R

R Large residual

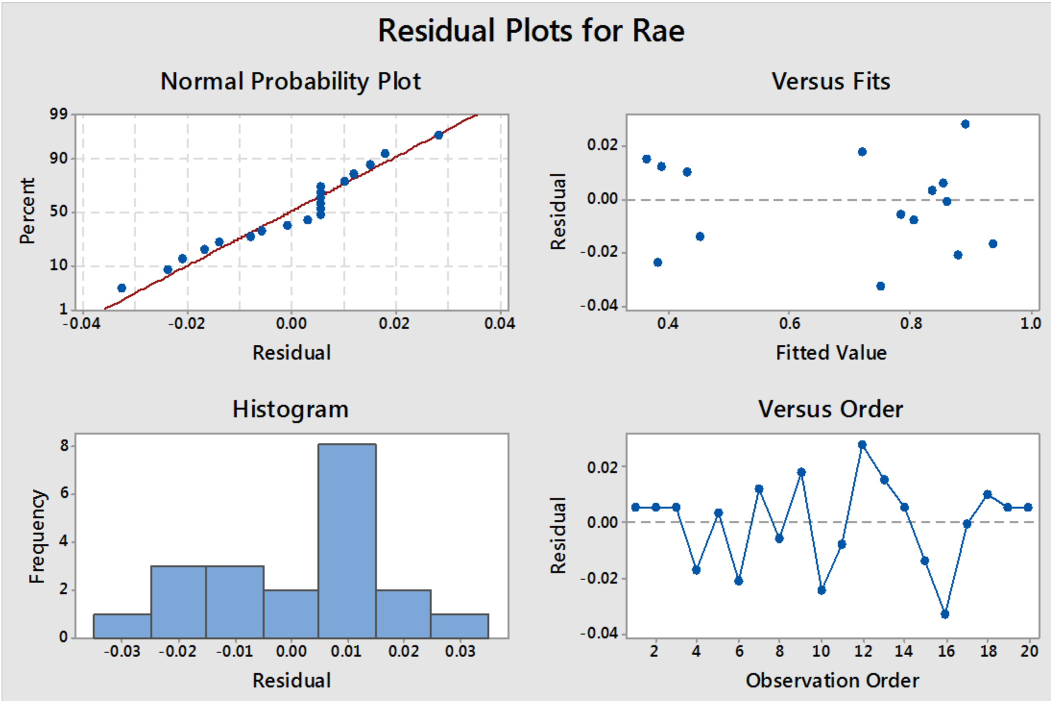


Figure 5.1: Residual Plots for Rae

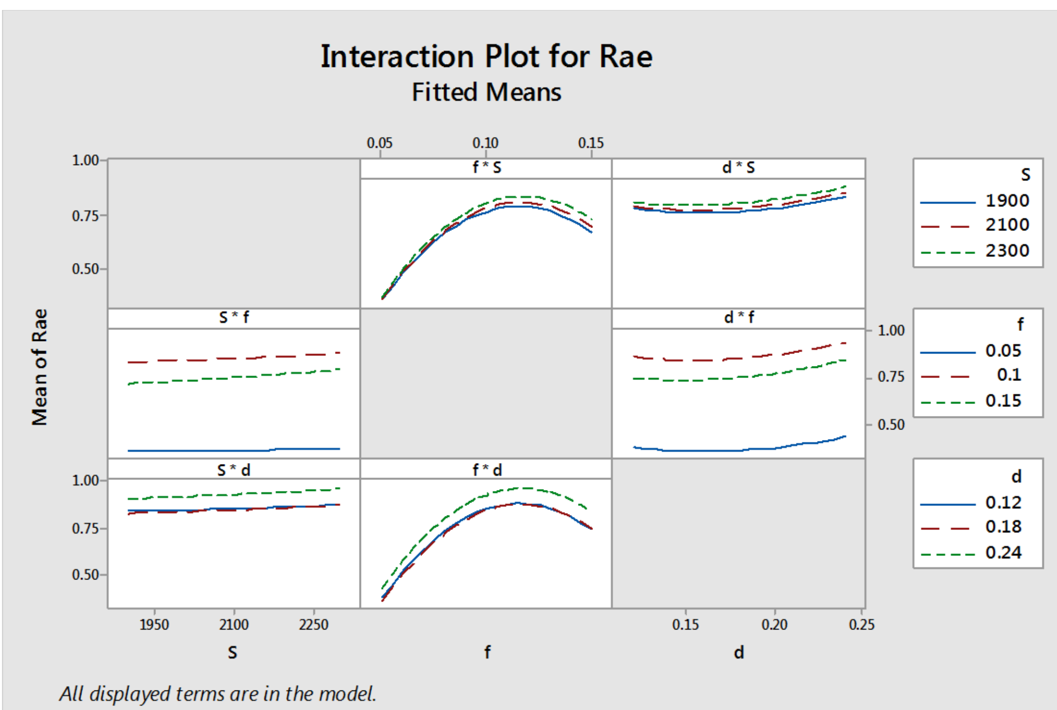


Figure 5.2: Interaction Plot for Rae

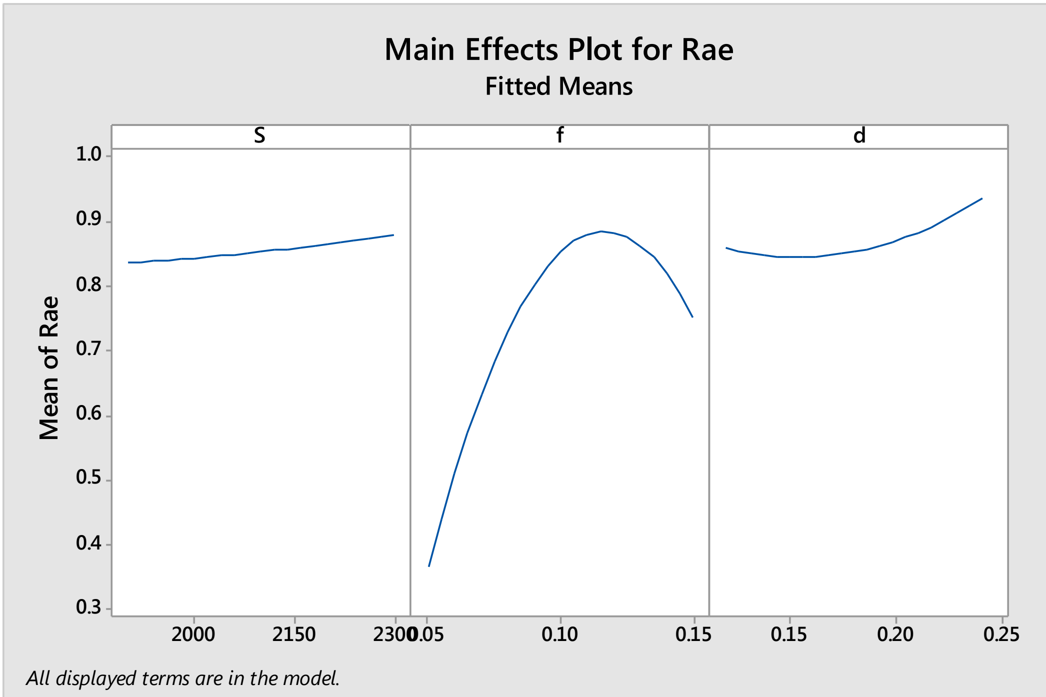


Figure 5.3: Main Effects Plot for Rae

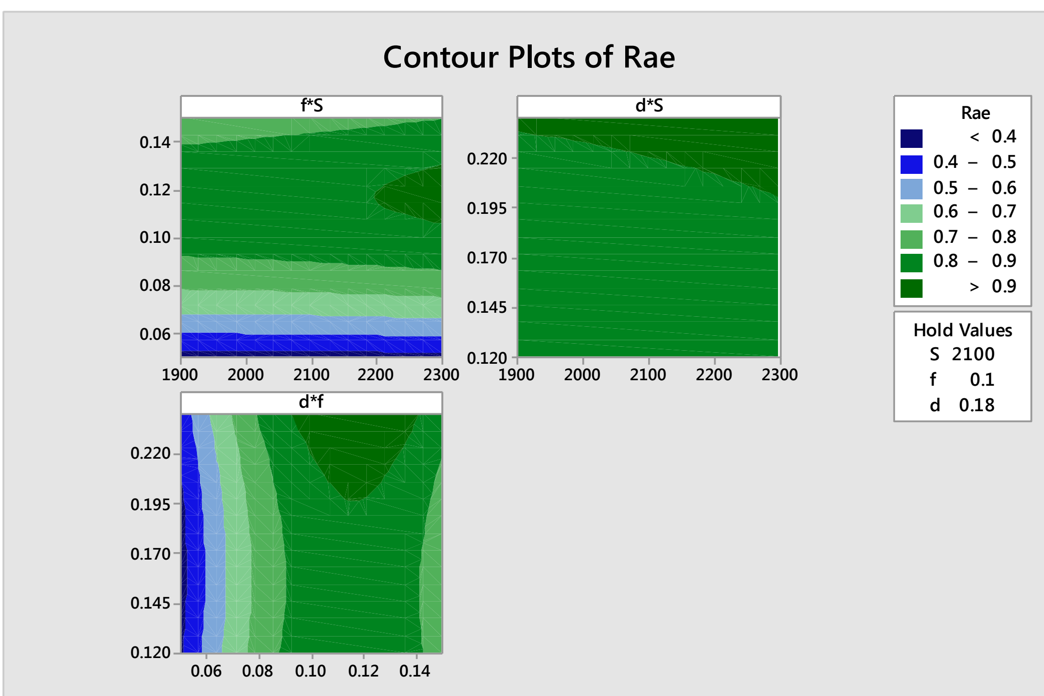


Figure 5.4: Contour Plots of Rae

Table 5.8: Comparison table for Rae

Run	Rae	pr Rae	Error	% error
1	0.866667	0.795154	0.071513	8.251497
2	0.866667	0.795154	0.071513	8.251497
3	0.866667	0.795154	0.071513	8.251497
4	0.953333	0.8776	0.075733	7.944024
5	0.873333	0.788142	0.085191	9.754698
6	0.9	0.810166	0.089834	9.981556
7	0.413333	0.31715	0.096183	23.2701
8	0.806667	0.71551	0.091157	11.30045
9	0.786667	0.673494	0.113173	14.38639
10	0.373333	0.335134	0.038199	10.23188
11	0.826667	0.759294	0.067373	8.149956
12	0.966667	0.821326	0.145341	15.03527
13	0.393333	0.305534	0.087799	22.3218
14	0.866667	0.795154	0.071513	8.251497
15	0.44	0.383006	0.056994	12.95318
16	0.746667	0.693874	0.052793	7.070488
17	0.926667	0.801772	0.124895	13.47787
18	0.473333	0.380974	0.092359	19.51248
19	0.866667	0.795154	0.071513	8.251497
20	0.866667	0.795154	0.071513	8.251497
			Avg. value	11.74496

Table 5.8 shows the comparison table for surface roughness values of experiment and predicted values after modeling. It also shows the error values between two and most of errors are in between 8% to 12% while average value of error is around 11%. So the overall accuracy of the model is 88.25%.

5.1.3. Response Surface Regression: Rai versus S, f, d

Table 5.9: Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	9	41.6199	4.62443	10.80	0.000
Linear	3	18.3017	6.10056	14.24	0.001
S	1	8.3906	8.39056	19.59	0.001
F	1	0.4244	0.42436	0.99	0.343
D	1	9.4868	9.48676	22.15	0.001
Square	3	5.3128	1.77095	4.13	0.038
S*S	1	0.0192	0.01924	0.04	0.836
f*f	1	2.8969	2.89691	6.76	0.026
d*d	1	0.0205	0.02051	0.05	0.831
2-Way Interaction	3	18.0054	6.00178	14.01	0.001
S*f	1	6.3012	6.30125	14.71	0.003
S*d	1	9.7241	9.72405	22.70	0.001
f*d	1	1.9801	1.98005	4.62	0.057
Error	10	4.2837	0.42837		
Lack-of-Fit	5	4.2837	0.85673	*	*
Pure Error	5	0.0000	0.00000		
Total	19	45.9035			

Table 5.10: Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.654496	90.67%	82.27%	0.00%

Table 5.11: Coded Coefficients

Term	Effect	Coef	SE Coef	T-Value	P-Value	VIF
Constant		3.387	0.225	15.05	0.000	
S	1.832	0.916	0.207	4.43	0.001	1.00
f	0.412	0.206	0.207	1.00	0.343	1.00
d	-1.948	-0.974	0.207	-4.71	0.001	1.00
S*S	0.167	0.084	0.395	0.21	0.836	1.82
f*f	-2.053	-1.026	0.395	-2.60	0.026	1.82
d*d	-0.173	-0.086	0.395	-0.22	0.831	1.82
S*f	1.775	0.887	0.231	3.84	0.003	1.00
S*d	-2.205	-1.103	0.231	-4.76	0.001	1.00
f*d	-0.995	-0.498	0.231	-2.15	0.057	1.00

5.1.4. Regression Equation in Uncoded Units

$$Rai = -18.5 + 0.0035\,S - 70.3\,f + 201.9\,d + 0.000002\,S*S - 411\,f*f - 24\,d*d + 0.0888\,S*f - 0.0919\,S*d - 165.8\,f*d \quad \ldots\ldots(2)$$

Table 5.12: Fits and Diagnostics for Unusual Observations

Obs	Rai	Fit	Resid	Std Resid	
5	1.580	2.554	-0.974	-2.09	R
10	2.320	1.497	0.823	2.77	R
11	1.020	0.391	0.629	2.11	R
12	1.100	1.793	-0.693	-2.33	R

R Large residual

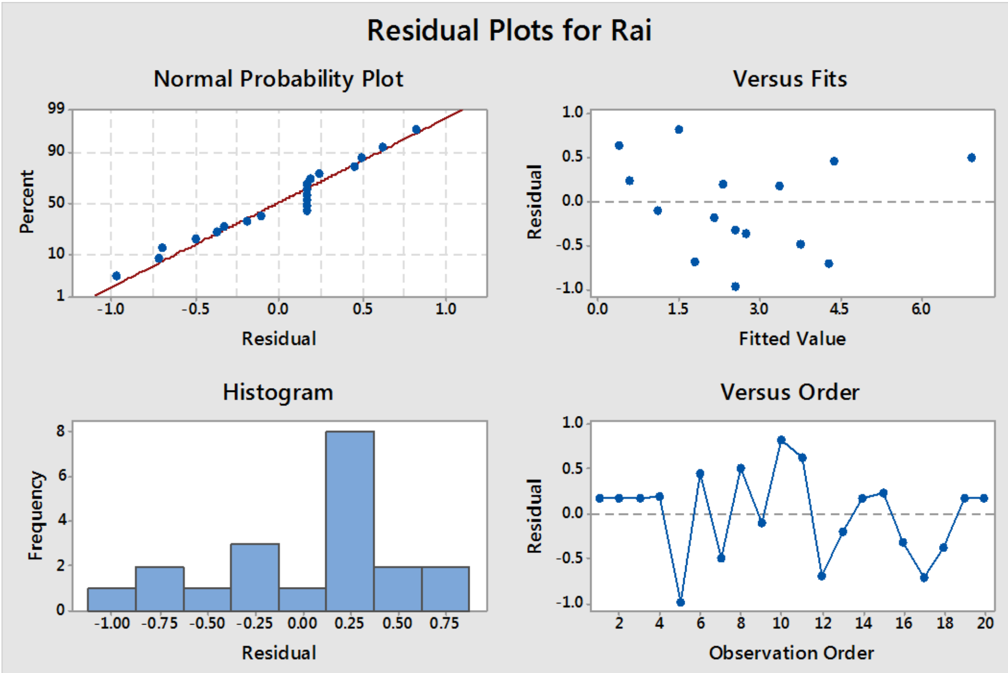


Figure 5.5: Residual Plots for Rai

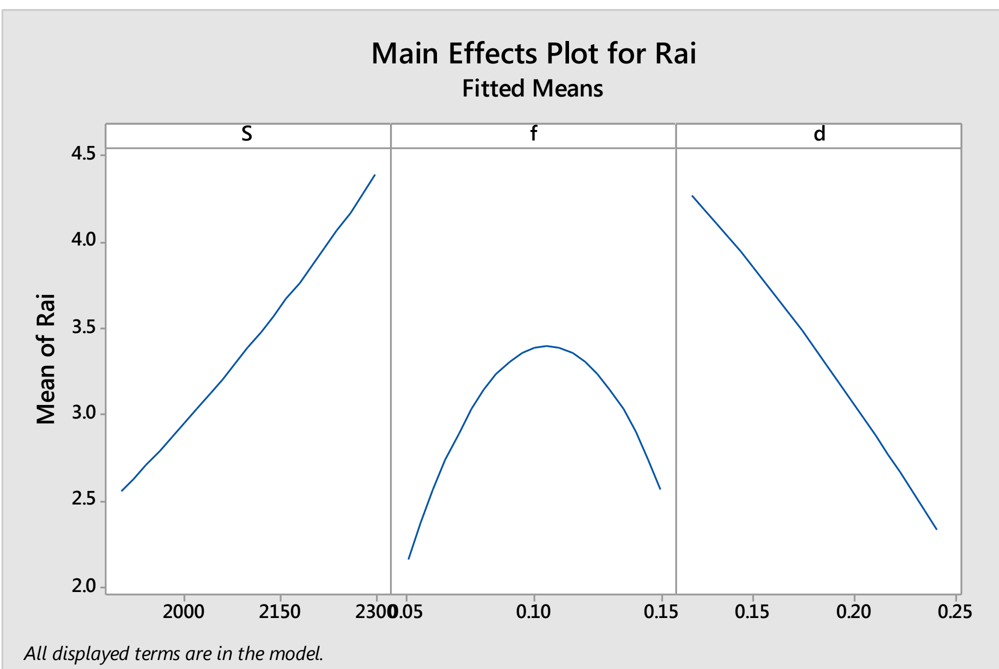


Figure 5.6: Main Effects Plot for Rai

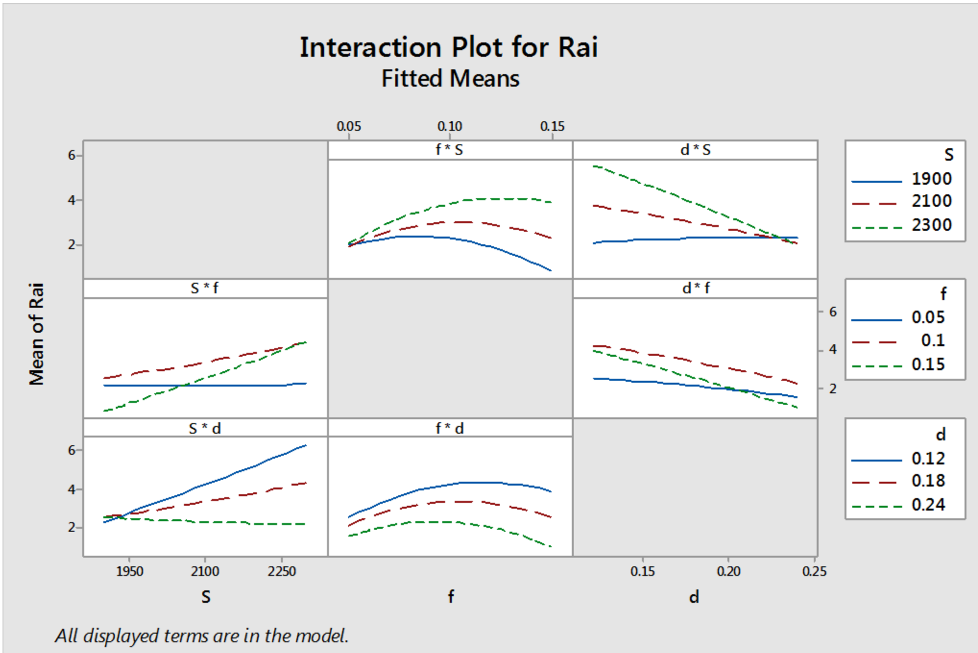


Figure 5.7: Interaction Plot for Rai

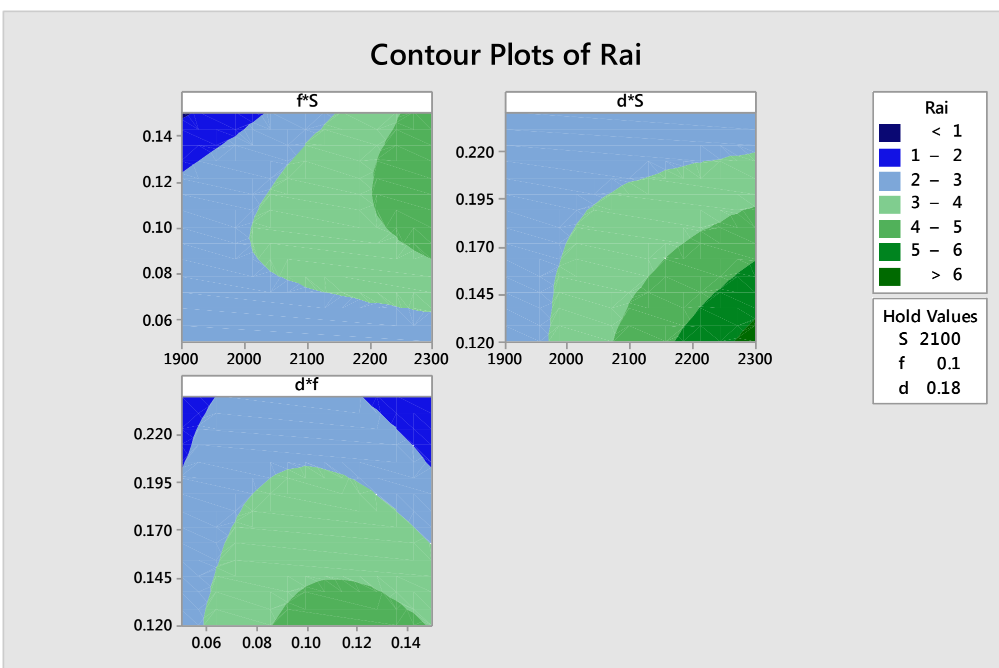


Figure 5.8: Contour Plots of Rai

Table 5.13: Comparison table for Rai

Run	Rai	pr Rai	error	% error
1	3.646667	3.0198	0.626867	17.19014
2	3.646667	3.0198	0.626867	17.19014
3	3.646667	3.0198	0.626867	17.19014
4	2.786667	1.9548	0.831867	29.85168
5	1.593333	2.2522	-0.65887	-41.3515
6	5.12	3.9474	1.1726	22.90234
7	3.866667	3.3227	0.543967	14.06811
8	7.486667	6.5071	0.979567	13.08415
9	1.153333	0.8303	0.323033	28.00865
10	2.68	1.1979	1.4821	55.30224
11	1.12	0.0839	1.0361	92.50893
12	1.113333	1.3495	-0.23617	-21.2126
13	1.98	1.7855	0.1945	9.823232
14	3.646667	3.0198	0.626867	17.19014
15	0.866667	0.1547	0.711967	82.15001
16	3	2.1991	0.8009	26.69667
17	0.94	3.912	-2.972	-316.17
18	2.606667	2.4411	0.165567	6.351674
19	3.646667	3.0198	0.626867	17.19014
20	3.646667	3.0198	0.626867	17.19014
			Avg. value	5.257709

Table 5.13 shows the comparison table for surface roughness values of experiment and predicted values after modeling of internal turning. It also shows the error values between two. A lot of abnormality has been shown in case of boring may be due to entrapment of chips in the hole of workpiece during turning. This may affect the surface roughness of the turned workpiece and can be avoided by using coolant. But average value of error is around 5% and overall accuracy of the model is 94.74%.

5.2. DATA ANALYSIS USING ARTIFICIAL NEURAL NETWORK

For surface roughness analysis, data from two experiments have been used here. Data is taken from the surface roughness value for external turning and internal turning.

Table 5.14: Data

S	f	d	Rae	Rai
1900	0.05	0.12	0.373333	2.68
1900	0.05	0.18	0.46	0.96
1900	0.05	0.24	0.473333	2.606667
1900	0.1	0.12	0.846667	5.926667
1900	0.1	0.18	0.873333	1.593333
1900	0.1	0.24	0.813333	0.94
1900	0.15	0.12	0.786667	1.153333
1900	0.15	0.18	0.753333	2.146667
1900	0.15	0.24	0.826667	1.12
2100	0.05	0.12	0.366667	3.826667
2100	0.05	0.18	0.393333	1.98
2100	0.05	0.25	0.46	2.353333
2100	0.1	0.12	0.926667	0.94
2100	0.1	0.18	0.866667	3.646667
2100	0.1	0.24	0.953333	2.786667
2100	0.15	0.12	0.76	2.086667
2100	0.15	0.18	0.746667	3
2100	0.15	0.24	0.846667	0.753333
2300	0.05	0.12	0.413333	3.866667
2300	0.05	0.18	0.466667	1.986667
2300	0.05	0.24	0.44	0.866667
2300	0.1	0.12	0.793333	4.88
2300	0.1	0.18	0.9	5.12
2300	0.1	0.24	0.94	1.28
2300	0.15	0.12	0.806667	7.486667
2300	0.15	0.18	0.813333	1.106667
2300	0.15	0.24	0.966667	1.113333

5.2.1. Analysis using NN fitting tool

In neural network fitting tool cutting speed, feed rateand depth of cut are taken as input and surface roughness values are taken as output. For data 1 Rae is taken as a target 1 and Rai is taken as a target 2. The following observations are obtained by running NN fitting tool in MATLAB. Network type is feedforwardbackpropagation. Training function is Levenberg Marquardt. Number of hidden layer is 1 and number of neuron is 10. Transfer function is LOGSID(logsigmoid).

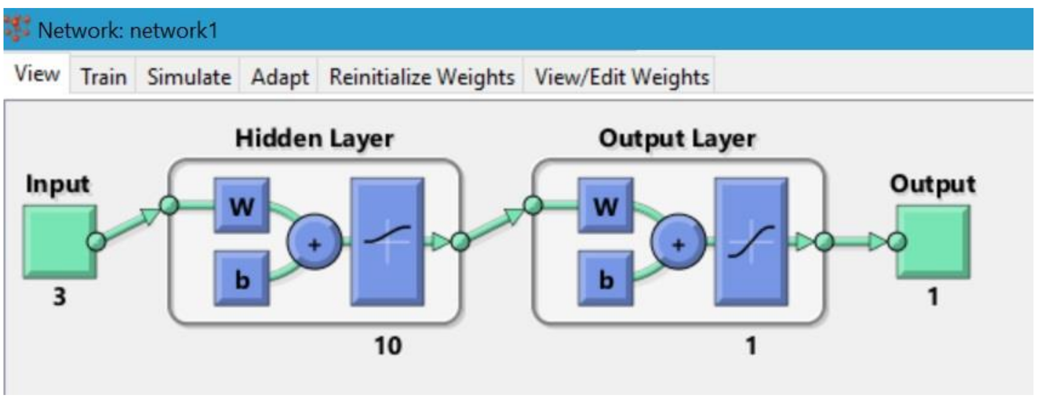


Figure 5.9: Network architecture for target 1

Table 5.15: Data 1 NN fitting tool result

Sl. No.	s	F	d	Rae	tar1	error 1	% error1
1	1900	0.05	0.12	0.373333	0.373268	6.53E-05	1.75E-02
2	1900	0.05	0.18	0.46	0.45993	6.98E-05	1.52E-02
3	1900	0.05	0.24	0.473333	0.483658	-0.01033	-2.18E+00
4	1900	0.1	0.12	0.846667	0.964319	-0.11765	-1.39E+01
5	1900	0.1	0.18	0.873333	0.873171	0.000162	1.85E-02
6	1900	0.1	0.24	0.813333	0.813367	-3.40E-05	-4.19E-03
7	1900	0.15	0.12	0.786667	0.786802	-0.00013	-1.71E-02
8	1900	0.15	0.18	0.753333	0.75332	1.31E-05	1.74E-03
9	1900	0.15	0.24	0.826667	0.835768	-0.0091	-1.10E+00
10	2100	0.05	0.12	0.366667	0.369799	-0.00313	-8.54E-01
11	2100	0.05	0.18	0.393333	0.393179	0.000154	3.90E-02
12	2100	0.05	0.24	0.46	0.459796	0.000204	4.43E-02
13	2100	0.1	0.12	0.926667	0.926654	1.31E-05	1.42E-03
14	2100	0.1	0.18	0.866667	0.866815	-0.00015	-1.71E-02
15	2100	0.1	0.24	0.953333	0.955653	-0.00232	-2.43E-01
16	2100	0.15	0.12	0.76	0.759891	0.000109	1.43E-02
17	2100	0.15	0.18	0.746667	0.863647	-0.11698	-1.57E+01
18	2100	0.15	0.24	0.846667	0.846631	3.59E-05	4.24E-03
19	2300	0.05	0.12	0.413333	0.413337	-3.79E-06	-9.16E-04
20	2300	0.05	0.18	0.466667	0.466732	-6.54E-05	-1.40E-02
21	2300	0.05	0.24	0.44	0.452867	-0.01287	-2.92E+00
22	2300	0.1	0.12	0.793333	0.793362	-2.88E-05	-3.63E-03
23	2300	0.1	0.18	0.9	0.900003	-3.21E-06	-3.56E-04
24	2300	0.1	0.24	0.94	0.94017	-0.00017	-1.81E-02
25	2300	0.15	0.12	0.806667	0.47925	0.327417	4.06E+01
26	2300	0.15	0.18	0.813333	0.837747	-0.02441	-3.00E+00
27	2300	0.15	0.24	0.966667	0.961538	0.005129	5.31E-01
						Avg. % error	4.93E-02

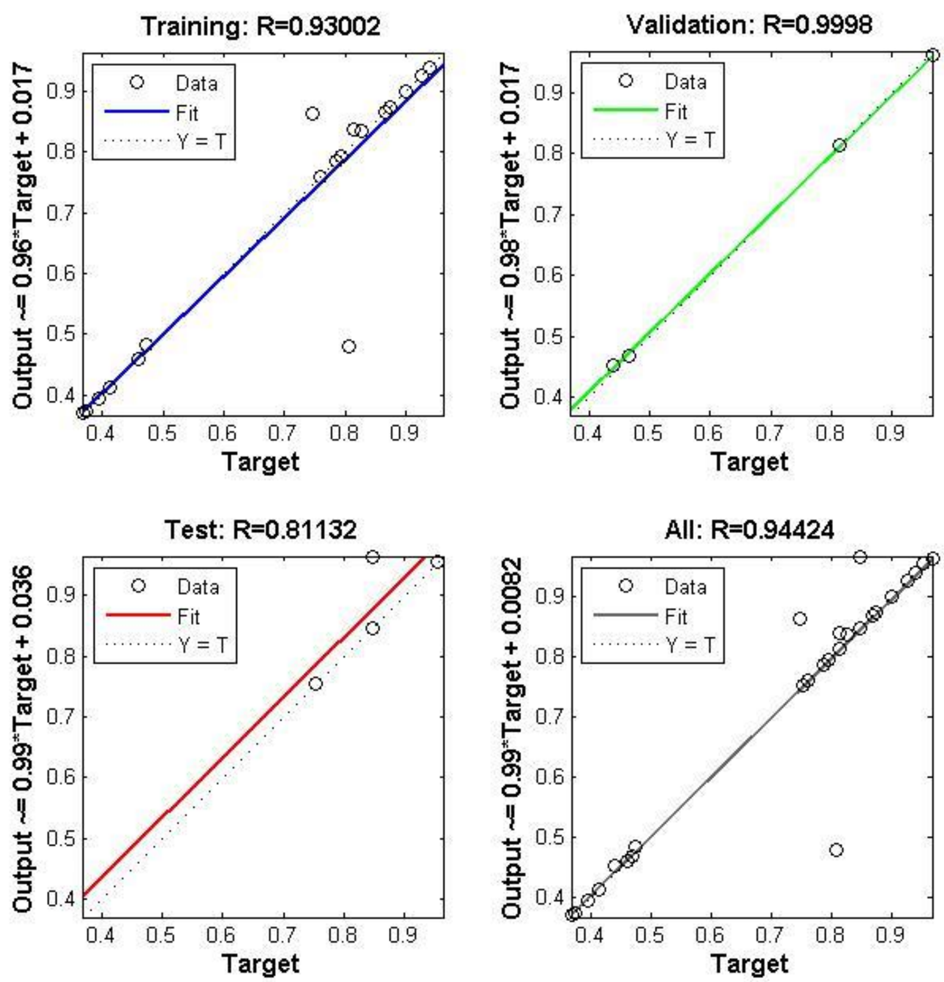


Figure 5.10: Regression plot for target 1

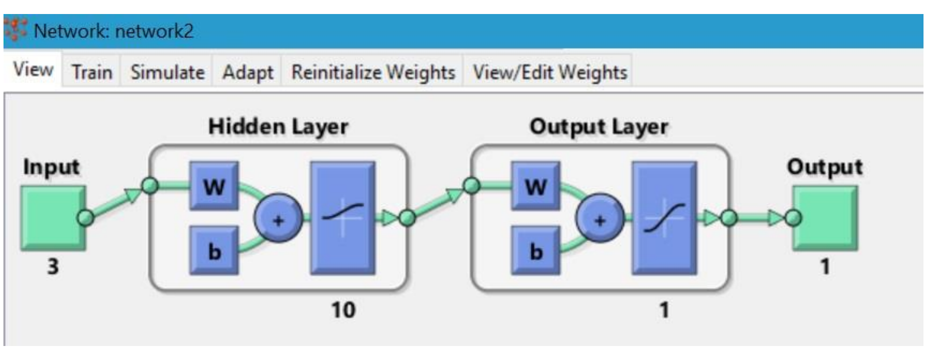


Figure 5.11: Network architecture for target 2

Table 5.16: Data 2 NN fitting tool result

Sl. No.	s	f	d	Rai	tar2	error2	% error2
1	1900	0.05	0.12	2.68	2.681578	-0.00158	-0.05886
2	1900	0.05	0.18	0.96	0.75334	0.20666	21.52707
3	1900	0.05	0.24	2.606667	2.737211	-0.13054	-5.00807
4	1900	0.1	0.12	5.926667	5.917978	0.008689	0.146607
5	1900	0.1	0.18	1.593333	0.753362	0.839971	52.71783
6	1900	0.1	0.24	0.94	2.1559	-1.2159	-129.351
7	1900	0.15	0.12	1.153333	0.754845	0.398488	34.551
8	1900	0.15	0.18	2.146667	2.133155	0.013512	0.629433
9	1900	0.15	0.24	1.12	1.919696	-0.7997	-71.4014
10	2100	0.05	0.12	3.826667	3.832605	-0.00594	-0.15517
11	2100	0.05	0.18	1.98	0.753335	1.226665	61.95275
12	2100	0.05	0.24	2.353333	0.755872	1.597461	67.88081
13	2100	0.1	0.12	0.94	0.947791	-0.00779	-0.82888
14	2100	0.1	0.18	3.646667	3.66723	-0.02056	-0.56389
15	2100	0.1	0.24	2.786667	1.998328	0.788339	28.28969
16	2100	0.15	0.12	2.086667	2.25659	-0.16992	-8.1433
17	2100	0.15	0.18	3	2.119054	0.880946	29.36488
18	2100	0.15	0.24	0.753333	1.723858	-0.97052	-128.831
19	2300	0.05	0.12	3.866667	3.894584	-0.02792	-0.72199
20	2300	0.05	0.18	1.986667	2.034565	-0.0479	-2.41097
21	2300	0.05	0.24	0.866667	0.753349	0.113318	13.07514
22	2300	0.1	0.12	4.88	7.486662	-2.60666	-53.4152
23	2300	0.1	0.18	5.12	5.121589	-0.00159	-0.03103
24	2300	0.1	0.24	1.28	1.098552	0.181448	14.17566
25	2300	0.15	0.12	7.486667	7.42707	0.059597	0.796046
26	2300	0.15	0.18	1.106667	1.165605	-0.05894	-5.32571
27	2300	0.15	0.24	1.113333	1.052145	0.061188	5.495944
						Avg. %error	-2.80161

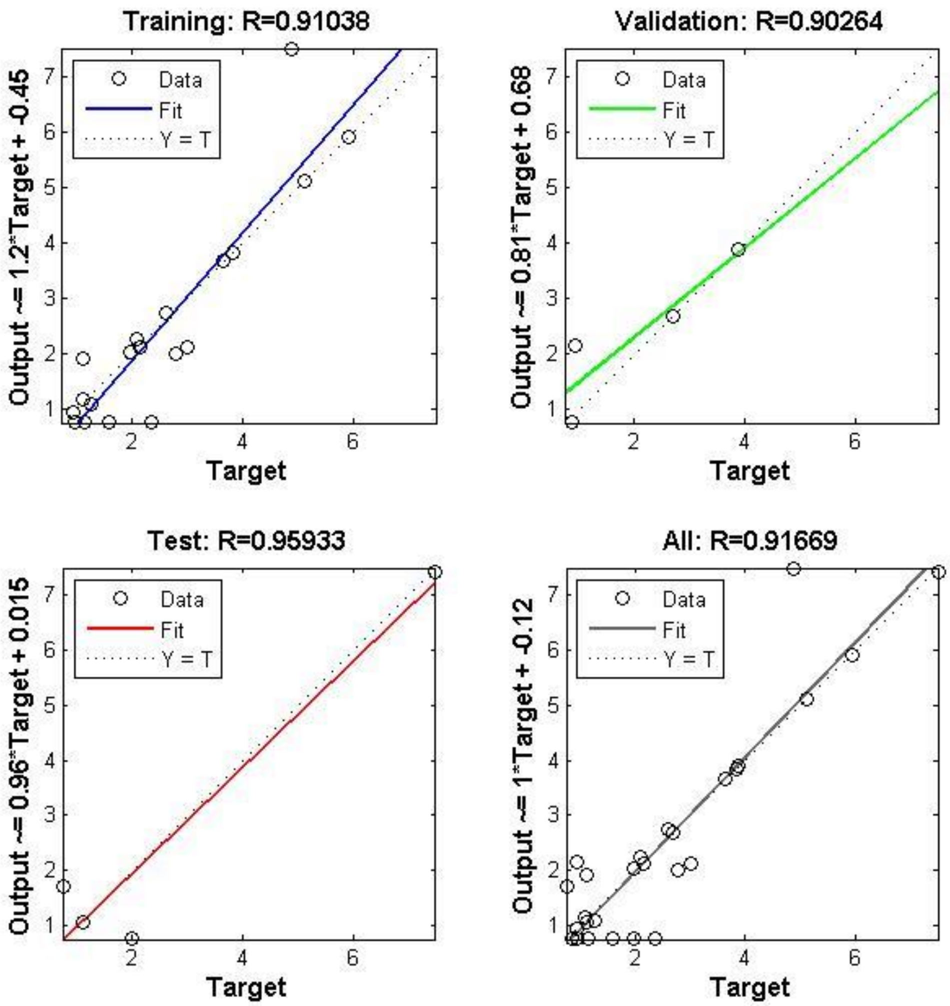


Figure 5.12: Regression plot for target 2

5.3. COMPARISON OF RSM AND ANN MODEL

Fig. 5.13 and fig. 5.14 show the comparison of surface roughness error values of ANN and RSM model for external and internal turning respectively. From fig. 5.13 it has been observed that most of the error values for ANN model are around 10^{-1} % to 10^{-4}.% which are shown in table 5.15. The error values for RSM model are around 7% to 20% for external turning. From fig. 5.14 it has been observed that mix behavior of error values for ANN model, which are shown in table 5.16. RSM model also shows mix behavior of errors for internal turning.

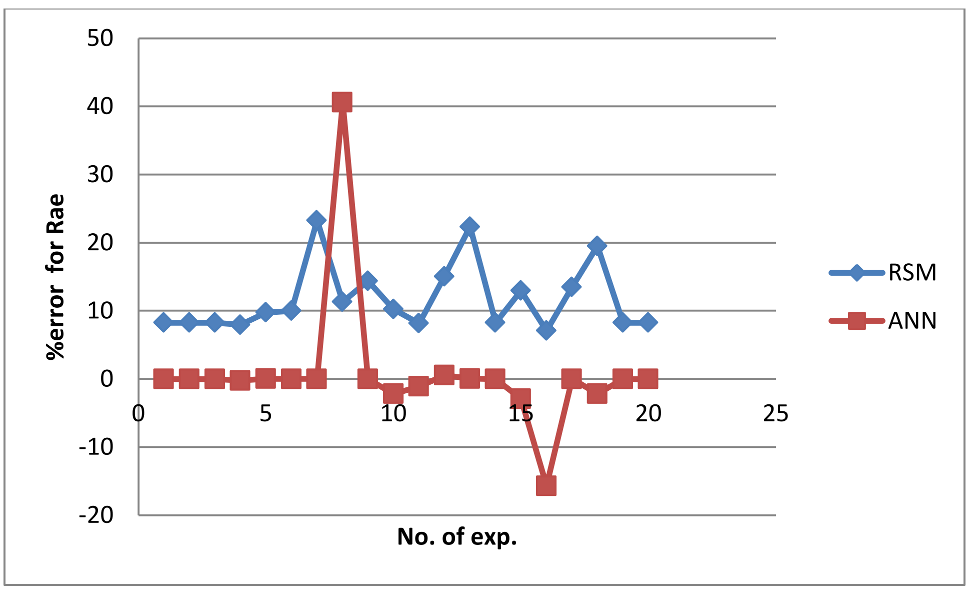


Figure 5.13: Comparison of ANN and RSM for external turning

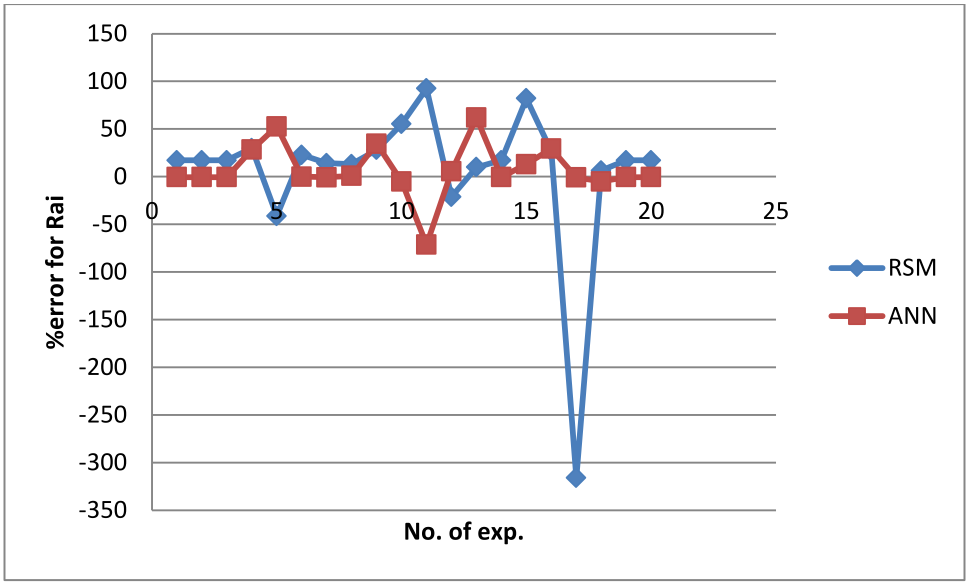


Figure 5.14: Comparison of ANN and RSM for internal turning

Fig. 5.15 shows the comparison of surface roughness values of RSM and ANN model with the experimental values for external turning. It has been observed that ANN values and experimental values are quite similar while there is deviation in RSM model. Fig. 5.16 shows the comparison of surface roughness values of RSM and ANN model with the experimental values for internal turning. There are deviations in both RSM and ANN model with the experimental values in case of internal turning. ANN models are more accurate than RSM models in case of both external turning as well as internal turning.

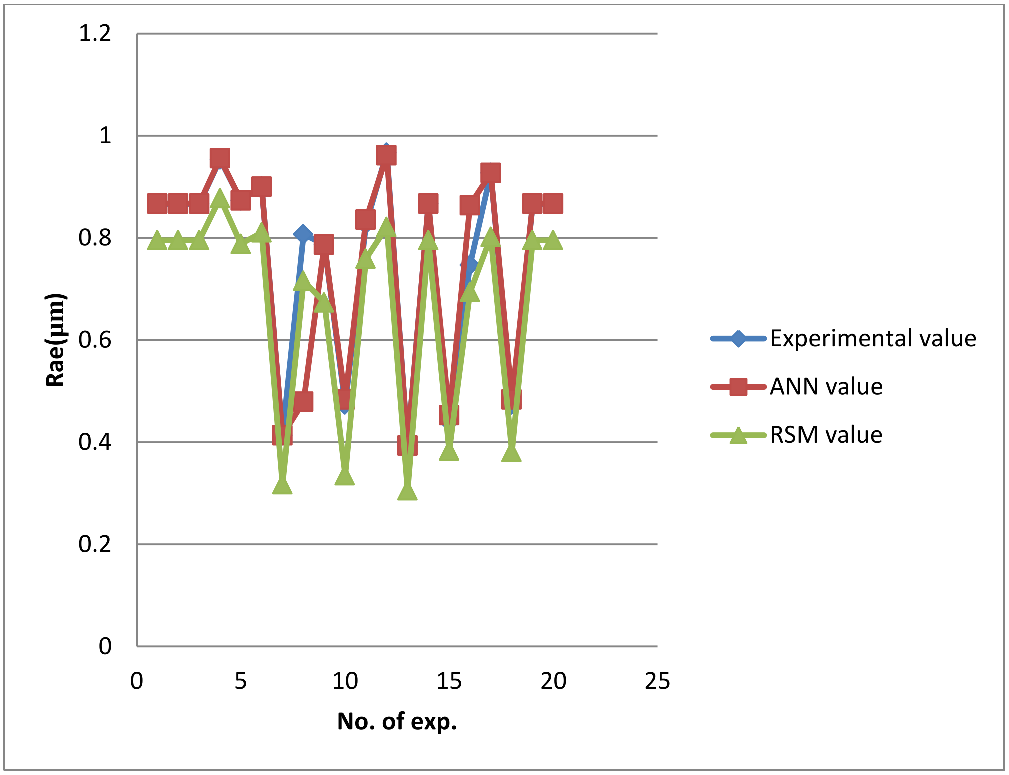


Figure 5.15: Comparison of Ra value for external turning

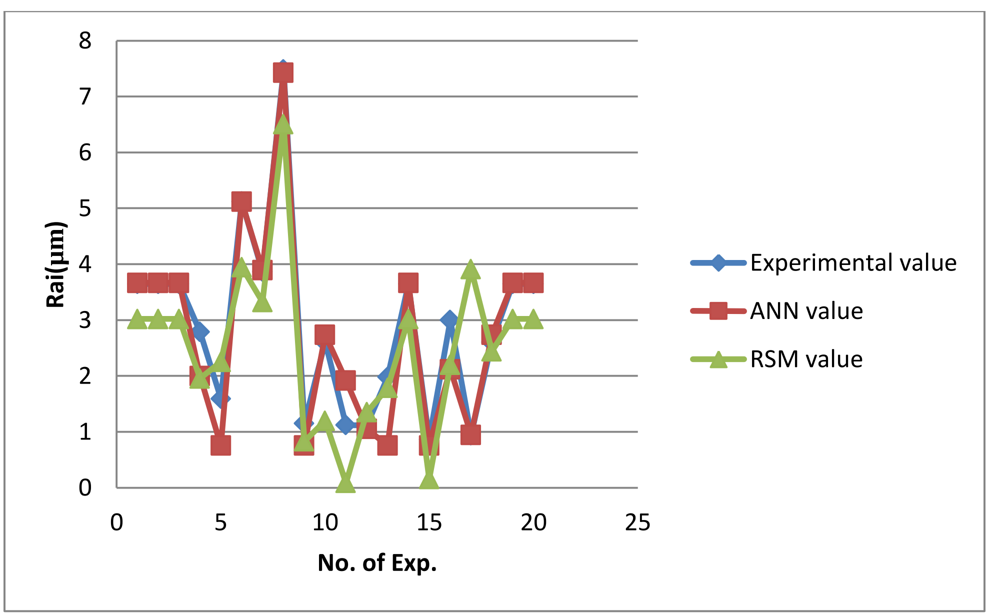


Figure 5.16: Comparison of Ra value for external turning

CHAPTER 6

CONCLUSIONS

The following conclusions can be drawn based on the analysis conducted by employing Response Surface Methodology and Artificial Neural Network to determine the optimal level of process parameters for better surface finish.

- Quadric equations are developed for the surface roughness of external turning and internal turning (boring).
- Feed rate is the most significant factor for surface roughness in case of external turning followed by depth of cut and then speed by using ANOVA and F-test.
- Minimum surface roughness value comes by combining the 1900 rpm as speed, 0.05 mm as feed and 0.12 mm as depth of cut in case of external turning.
- In case of boring ANOVA and F-test reveals depth of cut as the most significant factor followed by feed and speed.
- Minimum surface roughness value comes by combining the 1900 rpm as speed, 0.05 mm as feed and 0.24 mm as depth of cut in case of internal turning.
- ANN model shows 99.95% and 97.20% accuracy between the predicted and experimental values of surface roughness in case of both external turning and internal turning respectively.
- From comparison graphs it is concluded that ANN model is more accurate than RSM model in case of external turning as well as internal turning both.

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