

**Optimization of Forces and Surface Roughness During
Turning of EN31 Steel**

DISSERTATION

Submitted in partial fulfilment of the requirement of the Degree of

**MASTER OF TECHNOLOGY
IN
PRODUCTION ENGINEERING**



SUBMITTED BY

ANKITA

(2K14/PIE/02)

UNDER THE GUIDANCE OF

Dr. (Prof.) REETA WATTAL

Department of Mechanical, Production & Industrial and

Automobile Engineering

Delhi Technological University, Delhi

2016

DECLARATION

I, **Ankita**, hereby declare that the project work, which is being presented in this dissertation entitled “**Optimization of Forces and Surface Roughness During Turning of EN31 Steel**” in the partial fulfilment for the award of degree of Masters of Technology in Production Engineering, is an authentic work carried out by me at Delhi Technological University under the guidance of **Dr. (Prof.) Reeta Wattal**, Department of Mechanical, Production & Industrial and Automobile Engineering Department

I have not submitted the work in this dissertation in part or full to any other university for the award of any other degree or diploma

Ankita

(2K14/PIE/02)

CERTIFICATE

This is to certify that the report entitled “**Optimization of Forces and Surface Roughness During Turning of EN31 Steel**” submitted by **Ankita (Roll No. - 2K14/PIE/02)** in the partial fulfilment for the award of degree of Masters of Technology in Production Engineering from Delhi Technological University, is a record of bonafide project work carried out by her under my supervision and guidance.

To the best of my knowledge the result contained in this thesis have not been submitted in part or full to any other university for the award of any other degree or diploma.

Dr. Reeta Wattal

Professor

Department of Mechanical, Production & Industrial and Automobile Engineering

Delhi Technological University

ACKNOWLEDGEMENT

I would like to express my sincere gratitude to my respected guide Dr. (Prof.) Reeta Watal, Department of Mechanical, Production & Industrial and Automobile Engineering, Delhi Technological University for her confidence shown in me and in giving me an opportunity to work, learn and explore under her able guidance.

The pragmatic and invaluable advice of my guide kept me going through the critical phases of my project. I am indebted to her for the insightful and encouraging words that have been the driving force of my project. She provided me with a lot of information and ideas regarding the project.

I am grateful to Prof. R.S. Mishra, Head, Department of Mechanical, Production & Industrial and Automobile Engineering for providing facilities to carry out the investigations.

I wish to express my warm and sincere thanks to Mr. Sunil Kumar, Sr. Mechanic, Metal Cutting Lab and Mr. Manjeet Singh, Sr. Mechanic, Project Shop for their support.

Ankita

(2K14/PIE/02)

Production Engineering

Delhi Technological University

ABSTRACT

Machining is one of the most common and important manufacturing process in the industry. The investigation of the machining process and development of models in order to optimize cutting force, feed force, thrust force and surface roughness is important when it comes to the cost of manufacturing and the quality of finished products. Effect of input parameters: Spindle Speed, Feed and Depth of Cut is determined by correlating these parameters with cutting force, feed force, thrust force and surface roughness.

The main objective of this research was to study the effect of spindle speed, feed and depth of cut on cutting force, feed force, thrust force, surface roughness and tool wear during turning of EN 31 Steel using uncoated and coated titanium based cemented carbide insert. EN-31 Steel is high carbon low alloy steel giving good ductility & shock resisting properties combined with wear resistance. It is also known as bearing steel as it is used for production of bearings. The design matrix was prepared on the basis of 3 factors, 3 level Box-Behnken Design. Response Surface Methodology was used for the development of mathematical models correlating spindle speed, feed and depth of cut with cutting force, feed force, thrust force and surface roughness. Modelling of tool wear could not be done because of the limited readings as no tool wear was observed while machining with coated insert whereas a maximum tool wear of 0.05 mm was observed while machining with uncoated insert. The developed models were checked for adequacy using ANOVA. All the calculations were carried out using Minitab 17. Main and interaction effects were plotted and results were interpreted. The developed models can be suitably used for predicting the response parameters by selecting appropriate input parameters.

Optimization was carried out using Response Optimizer Technique which performs joint optimization as well as using Genetic Algorithm Multi Objective Optimization. For the latter, the models developed using RSM were utilized as the fitness function and optimization was performed yielding a Pareto front.

When the regression models are not fitting the data well, then only modelling using Artificial Neural Network is attempted [20]. Therefore ANN models for cutting force, feed force, thrust force and surface roughness were also developed. The results indicate that the ANN model results are satisfactory.

A comparative study of Experimental results, RSM model results and ANN model results was done and it was concluded that ANN model has an edge over RSM model values in case of cutting force, feed force and thrust force. But in case of surface roughness, RSM has less absolute mean percentage error in comparison to ANN model values.

Keywords: Box-Behnken design, Response Surface Methodology, ANOVA, Response Optimizer technique, Genetic Algorithm, Artificial Neural Network

TABLE OF CONTENTS

Topic	Page No.
Declaration	i
Certificate	i
Acknowledgement	ii
Abstract	iii
Table of Contents	v
List of Figures	ix
List of Tables	xi
List of Symbols	xii
Abbreviations	xii
Chapter 1	
Introduction	
1.1 Manufacturing	1
1.1.1 Broad classification of Engineering Manufacturing Processes	2
1.2. Machining	3
1.2.1 Orthogonal Cutting and Oblique Cutting	3
1.2.2 Turning	3
Chapter 2	
Literature Review and Problem Formulation	
2.1 Review of Literature	5
2.2 Conclusion	12
2.3 Statement of the Problem	12
2.4 Plan of Investigation	12
Chapter 3	
Theory and Experimentation	
3.1. Machining	13
3.1.1 Requirements in Machining	13

3.2. Machine Tool	14
3.2.1 Basic functions of Machine Tools	14
3.3 Parameters in Metal Cutting	14
3.4 Work Material: EN 31 Steel	15
3.5 Cutting Tool Materials	16
3.5.1 Needs and Chronological Development of Cutting Tool Materials	16
3.5.2 Characteristics and Applications of the Primary Cutting Tool Materials	17
3.5.3. Selection of the Cutting Tool	21
3.5.4 Cutting Tool Grade	22
3.6 Response Surface Methodology	22
3.6.1 Experimental Designs for Fitting Response Surfaces	23
3.6.2. Designs for Fitting the First Order Model	24
3.6.3. Designs for Fitting the Second Order Model	24
3.6.4. The Box-Behnken Design	25
3.7. Genetic Algorithm	26
3.7.1 Working of Genetic Algorithm	27
3.7.2 Genetic Algorithm Terminology	28
3.8. Artificial Neural Network	30
3.8.1 Elements of ANN	31
3.8.2. Neural Network Design Steps	32
3.8.3. Artificial Neural Network algorithm	33
3.9. Experimentation	34
3.9.1. Identification of the important machining parameters and the responses	34
3.9.2 Deciding the working range of the input parameters	35
3.9.3 Developing the design matrix	36
3.9.4. Conducting the experiments as per the design matrix	37
3.9.5. Recording the responses	39
Chapter 4	
Development of Mathematical Models	
4.1. Development of Mathematical Models	41
4.1.1 Evaluation of the Coefficient of the Model	41

4.2. Model Adequacy Checking	43
4.2.1 Response: Cutting Force	43
4.2.2 Response: Feed Force	44
4.2.3 Response: Thrust Force	45
4.2.4 Response: Surface Roughness	46
4.3 Testing the models	47

Chapter 5

Results and Discussion

5.1. Main Effect of Input Parameters on the Responses	49
5.1.1 Direct Effect of Spindle Speed, Feed and Depth of Cut on Cutting Force	49
5.1.2 Direct Effect of Spindle Speed, Feed and Depth of Cut on Feed Force	50
5.1.3 Direct Effect of Spindle Speed, Feed and Depth of Cut on Thrust Force	51
5.1.4 Direct Effect of Spindle Speed, Feed and Depth of Cut on Surface Roughness	52
5.2. Interaction Effect of Input Parameters on the Responses	53
5.2.1. Interaction Plot for Cutting Force	53
5.2.2. Interaction Plot for Feed Force	54
5.2.3. Interaction Plot for Thrust Force	55
5.2.4. Interaction Plot for Surface Roughness	56
5.3. Contour Plots	57
5.3.1. Contour Plots for Cutting Force	57
5.3.2. Contour Plots for Feed Force	58
5.3.3. Contour Plots for Thrust Force	59
5.3.4. Contour Plots for Surface Roughness	59

Chapter 6

Optimization of Machining Parameters

6.1. Optimization Using Response Optimizer Technique	61
6.1.1 What are individual desirability and composite desirability?	61
6.1.2. Optimization Plot	62
6.1.3. Steps to be followed in response optimization technique	62

6.2. Optimization using Genetic Algorithm	65
6.2.1 Multiobjective optimization	65
6.2.2 Genetic Algorithm Options	66
6.2.3. Steps to be followed in optimization using Genetic Algorithm	66
6.2.4. Formulation of objective function	66
6.2.5 Writing a M-File	67
6.2.6. Using the Genetic Algorithm	68
6.2.7. Setting the various options in Genetic Algorithm	69
6.2.8. Optimized result	70
Chapter 7	
Modelling Using Artificial Neural Network	
7.1. Basic approach using Artificial Neural Network to mathematically model the present study	73
7.2. Computational work done while training a neural network	75
7.3. Results and discussions	
7.3.1 Comparison of Experimental, RSM and ANN model results for Cutting Force	78
7.3.2 Comparison of Experimental, RSM and ANN model results for Feed Force	79
7.3.3 Comparison of Experimental, RSM and ANN model results for Thrust Force	80
7.3.4 Comparison of Experimental, RSM and ANN model results for Surface Roughness	81
Chapter 8	
Conclusion and Future Scope	
8.1. Conclusion	82
8.2. Future Scope	84
References	85

List of Figures

Figure 1.1 Value addition by manufacturing	1
Figure 1.2 Principle of Turning	4
Figure 3.1 Requirements for Machining	13
Figure 3.2 Chronological development of cutting tool materials	17
Figure 3.3 Flowchart for tool selection	21
Figure 3.4 Diversity in genetic algorithm	29
Figure 3.5 Working of a Neural Network	30
Figure 3.6 Linear Activation Function	31
Figure 3.7 Sigmoid Activation Function	32
Figure 3.8 Working of a NN back propagation algorithm	33
Figure 3.9 The lathe machine along with the dynamometer used for Experimentation	37
Figure 3.10 Test samples	38
Figure 3.11 Tool holder along with the coated insert	38
Figure 5.1 Main Effects Plot for Cutting Force	49
Figure 5.2 Main Effects Plot for Feed Force	50
Figure 5.3 Main Effects Plot for Thrust Force	51
Figure 5.4 Main Effects Plot for Surface Roughness	52
Figure 5.5 Interaction Plot for Cutting Force	53
Figure 5.6 Interaction Plot for Feed Force	54
Figure 5.7 Interaction Plot for Thrust Force	55
Figure 5.8 Interaction Plot for Surface Roughness	56
Figure 5.9 Contour Plots for Cutting Force	58
Figure 5.10 Contour Plots for Feed Force	58
Figure 5.11 Contour Plots for Thrust Force	59
Figure 5.12 Contour Plots for Surface Roughness	60
Figure 6.1 Optimization Plot	64
Figure 6.2 Set of Noninferior Solutions	65
Figure 6.3 GA optimal result window for 1 to 7 Pareto front	70
Figure 6.4 GA optimal result window for 8 to 14 Pareto front	71
Figure 6.5 GA optimal result window for 15 to 18 Pareto front	71

Figure 6.6 Different plots for the optimized results	72
Figure 7.1 Schematic representation of an Artificial Neural Network	73
Figure 7.2. Sequence of steps in signal processing	74
Figure 7.3 Back propagation Neural Network used for predicting the responses	75
Figure 7.4 MSE versus number of Epochs	76
Figure 7.5 Regression plot for network architecture 3-7-4	77

List of Tables

Table 3.1 Chemical Composition of EN 31 Steel	15
Table 3.2 Broad classification of carbide tools	19
Table 3.2 Difference between Classical Algorithm and Genetic Algorithm	26
Table 3.3 Recommendations for Sandvik's CCMT 09 T3 08	35
Table 3.4 Machining parameters with their limits	35
Table 3.5 Design Matrix	36
Table 3.6 Recording of Responses (With CT5015)	39
Table 3.6 Recording of Responses (With GC1525)	40
Table 4.1 Estimated values of the coefficient of the model	42
Table 4.2 ANOVA for Cutting Force	43
Table 4.3 ANOVA for Feed Force	44
Table 4.4 ANOVA for Thrust Force	45
Table 4.5 ANOVA for Surface Roughness	46
Table 4.6 Testing of mathematical models	47
Table 6.1 Response Optimization	63
Table 7.1 Performance of different network architectures	76
Table 7.2 Comparison of Experimental, RSM and ANN model results for Cutting Force	78
Table 7.3 Comparison of Experimental, RSM and ANN model results for Feed Force	79
Table 7.4 Comparison of Experimental, RSM and ANN model results for Thrust Force	80
Table 7.5 Comparison of Experimental, RSM and ANN model results for Surface Roughness	81

List of Symbols

Symbol	Represents	Units
N	Spindle Speed	rpm
f	Feed	mm/rev
d	Depth of Cut	mm
CF	Cutting Force	N
FF	Feed Force	N
TF	Thrust Force	N
R _a	Surface Roughness	μm

Abbreviations

RSM	Response Surface Methodology
ANOVA	Analysis of Variance
GA	Genetic Algorithm
ANN	Artificial Neural Network

Chapter 1

INTRODUCTION

1.1 Manufacturing

Production or manufacturing can be simply defined as a value addition process through which raw materials having low utility and value due to their inadequate material properties and poor or irregular size, shape and finish are converted into high utility and valued products with definite dimensions, forms and finish imparting some functional ability. A typical example of manufacturing is schematically shown in Fig. 1.1[1].

In Fig. 1.1, it can be seen that a lump of mild steel having irregular shape, dimensions and surface, which had almost no use and value, was converted into a useful and valuable product like bolt by a manufacturing process which imparted suitable features, dimensional accuracy and surface finish, required for fulfilling some functional requirements.

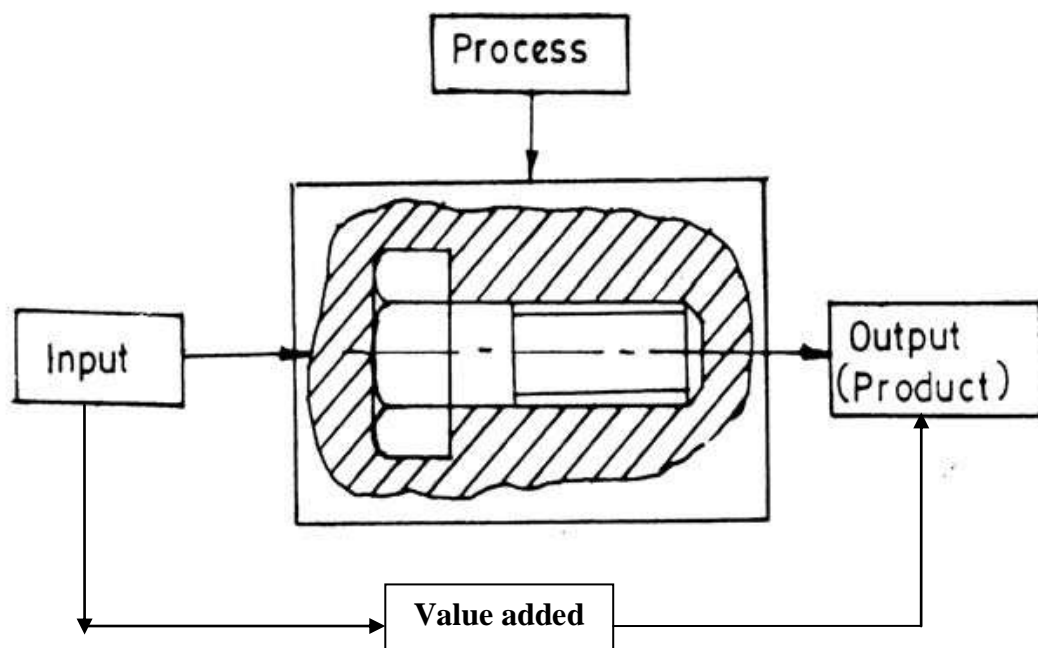


Fig. 1.1 Value addition by manufacturing [1]

1.1.1 Broad classification of Engineering Manufacturing Processes

Because of the development of large number of processes till now and the number is still increasing exponentially with the growing demands and rapid progress in science and technology, it is extremely difficult to tell the exact number of various manufacturing processes existing and are being practiced presently . However, all such manufacturing processes can be broadly classified in four major groups as follows [1]:

(a) Shaping or forming

Manufacturing a solid product of definite size and shape from a given material taken in three possible states:

- In solid state – e.g., forging rolling, extrusion, drawing etc.
- In liquid or semi-liquid state – e.g., casting, injection moulding etc.
- In powder form – e.g., powder metallurgical process.

(b) Joining process

Welding, brazing, soldering etc.

(c) Removal process

Machining (Traditional or Non-traditional), Grinding etc.

(d) Regenerative manufacturing

Production of solid products in layer by layer from raw materials in different form:

- liquid – e.g., stereo lithography
- powder – e.g., selective sintering
- sheet – e.g., LOM (laminated object manufacturing)
- wire – e.g., FDM. (Fused Deposition Modelling)

Out of the aforesaid groups, Regenerative Manufacturing is the latest one which is generally accomplished very rapidly and quite accurately using CAD and CAM for Rapid Prototyping and Tooling.

1.2 Machining

Most of the engineering components such as gears, bearings, clutches, tools, screws and nuts etc. require dimensional and form accuracy and good surface finish for serving their purposes. Preforming like casting, forging etc. generally cannot provide the desired accuracy and finish. These preformed parts, called blanks, require semi-finishing and finishing which is done by machining and grinding.

Machining is an essential process of finishing by which jobs are produced to the desired dimensions and surface finish by gradually removing the excess material from the preformed blank in the form of chips with the help of cutting tool moved past the work surface.

Machining to high accuracy and finish essentially enables a product to

- fulfil its functional requirements
- improve its performance
- prolong its service

1.2.1 Orthogonal Cutting and Oblique Cutting

In orthogonal cutting, the cutting edge of the tool is perpendicular to the direction of cutting velocity. This is necessary condition but not sufficient. The cutting edge is wider than the width of the workpiece and extends beyond the workpiece on either side. Also the width of the workpiece is much greater than the depth of cut. The chip generated flows on the rake face of the tool with chip velocity perpendicular to the cutting edge. The cutting forces act along two directions only.

On the other hand, when the relative velocity of the work and the tool is not perpendicular to the cutting edge, all the work and chip material particles do not move in parallel planes, and thus a two dimensional representation of the operation is not possible. Such a machining is termed as oblique machining.

1.2.2 Turning

This is a very basic operation and produces a cylindrical surface. The machine tool used for this type of operation is lathe. The workpiece is in the form of a cylindrical bar rotated about the axis of symmetry. The tool is provided with a feed motion parallel to the work axis. Here the machining operation is continuous. This operation results in a reduced work diameter and a new cylindrical surface. When the tool is fed in a radial direction along the face, a flat surface is produced and the length of workpiece gets reduced [2].

The basic principle of turning is typically illustrated in Fig. 1.2.

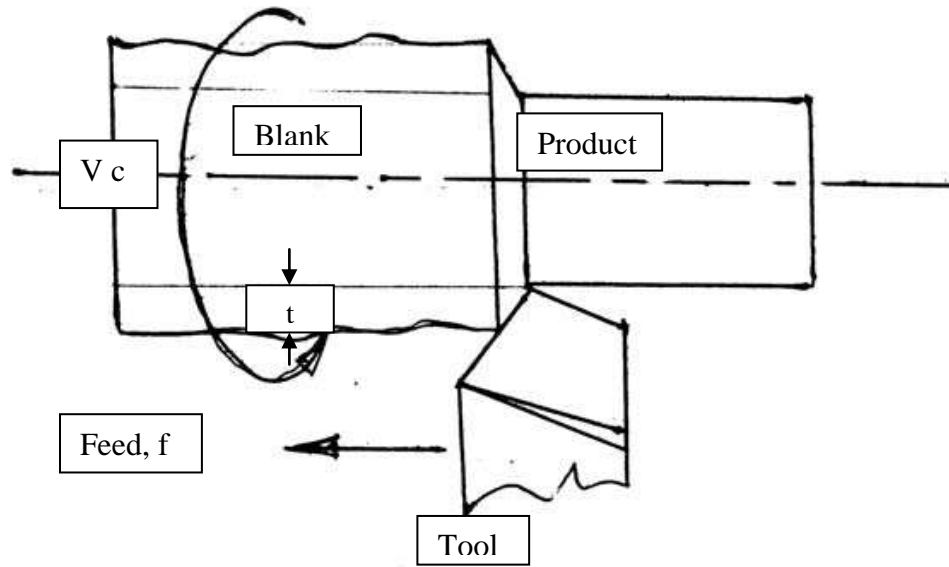


Fig. 1.2 Principle of Turning

Chapter 2

LITERATURE REVIEW AND PROBLEM FORMULATION

2.1 Review of Literature

Turning is one of the most basic machining operations applied to every other material for obtaining the desired shape, size and surface characteristics. The following literature reveals that modelling and optimization have always been an area of interest for the researchers. It is because of the fact that resources are limited and therefore to obtain a balance between cost and surface quality, it is imperative to perform optimization so that the machining can result in economy as well as to provide a good candidate in terms of surface quality for the successive operations.

B C Routara et al [3] presented a second order model for Centre Line Average Roughness (R_a), Root Mean Square Surface Roughness (R_q) and Mean Line Peak Spacing (R_{sm}) during CNC turning of EN-8 steel using coated carbide tool. The methodology adopted was RSM. They used five level rotatable CCD for designing their experiment. They also attempted to optimize the response parameters using the GA technique and found that the technique gave satisfactory results. They concluded that for good surface quality, the feed rate should be kept low and the spindle speed should be kept high.

J. Gerald Anto Arulraj et al [4] proposed that in addition to cutting speed, feed and depth of cut there are some performance parameters such as cutting forces, cutting temperature etc. which also affects surface roughness. Therefore they attempted to model the relationship using the ANN technique. Firstly they developed an ANN model with the consideration of cutting parameters only and secondly they incorporated cutting temperature along with the cutting parameters for modelling surface roughness during hard turning of H-13 Tool Steel. They concluded that fusion model of cutting temperature along with the cutting parameters for predicting surface roughness was superior.

Sajeev A et al [5] attempted to develop ANN model as well as multiple linear and non linear regression models for predicting surface roughness during turning of AISI 4140 steel. The tool chosen was CVD coated carbide tool. The input parameters chosen by them were cutting speed, feed rate and depth of cut. They carried out the experimentation while varying one of the parameters and keeping the other two as constant. For the development of ANN model, they worked with different number of hidden layers with different number of neurons in each one of them before arriving at the optimal model. RMSE was chosen as the criterion for selection of the optimal model. They concluded their study with the founding of close agreement between the experimental and modelled values.

S. Hari Krishna et al [6] proposed the development of modelling of surface roughness using ANN and ANFIS during turning of aluminium alloy, AA 6351 on CNC lathe. The input parameters chosen by them were cutting speed, feed rate and depth of cut. They chose MSE (training error) for arriving at the optimal network performance. They found ANN model suitable for predicting surface roughness as the experimental and modelled values were in close agreement. They also attempted to model surface roughness using ANFIS tool and found that ANFIS had better prediction results when compared with ANN.

Prakash Rao C.R. et al [7] developed a metal matrix composite in which Al6061 was the matrix material and the reinforcement was flyash which was varied between 0% and 15% in step of 5%. They performed Brinell Hardness test on the test specimens and found that hardness increases with increase in the flyash content and density test revealed that it decreases with increase in flyash content. They performed machining of the test pieces using K10 grade carbide and Poly Crystalline Diamond (PCD) inserts and recorded the surface roughness values. The cutting parameters chosen were cutting speed and feed with constant depth of cut. The percentage of filler material was also one of the input parameters. The variation in surface roughness for both the inserts showed that it decreases with increase in cutting speed and increases with increase in feed. The results revealed that surface roughness values were low while machining composites having 10% flyash and measured high when same was performed with 15% flyash. A comparison between the two inserts showed that PCD inserts were better as surface roughness values were lower while machining with them for all combinations.

D. Sai Chaitanya Kishore et al [8] worked upon to identify the effects of cutting parameters and percentage reinforcement on cutting force, surface roughness and flank wear during turning of In-situ Al6061-TiC metal matrix composite. After the preparation of the composite, they performed SEM and EDX tests to identify the presence of TiC. Then Vickers micro hardness test was done and the results revealed that hardness was increased as the percentage of TiC increased. The second part of their experiment dealt with turning which was done on 0, 2 wt % and 4 wt% of TiC reinforcement. L25 Taguchi design was selected for designing the experiments. The recorded values of cutting force, surface roughness and tool wear were analyzed using the means which showed that increase in TiC increases flank wear and surface roughness and decreases cutting force. The results showed that cutting speed had inverse effect on cutting force and surface roughness and proportionate effect on flank wear. Whereas both feed rate and depth of cut had proportionate effect on all the three response parameters.

Uday A. Dabade et al [9] performed experimentation for identifying the optimum process parameters in order to improve the surface integrity on metal matrix composites in which Al was the matrix material and varying percentage of SiC taken as reinforcement. They identified that it is difficult to machine the composites not only because of excessive tool wear but also fracturing of reinforcement. Therefore they attempted to analyze surface integrity and to identify the optimum process parameters. The input parameters taken were cutting speed, feed rate, depth of cut and cutting tool geometry. They identified that in order to study surface integrity they had to consider cutting force, feed force, radial force, surface roughness, micro-hardness and residual stresses as response variables. Therefore they used multi objective optimization using grey relational analysis. Taguchi method was adopted for designing the experiments. The results indicated that the variation in size of reinforcement had a more pronounced effect on surface roughness as compared to variation in volume fraction. The variation in reinforcement size also had a proportionate effect on the depth of altered material zone (AMZ) as revealed by the micro-hardness variation.

A Mahamani [10] performed two phase experimentation. Firstly they prepared in-situ metal composites in which AA2219 was selected as the matrix material and TiB_2 and ZrB_2 were taken as the reinforcement. Then they performed Energy Dispersive X ray spectroscopy (EDAX) spectra of AA2219- 6 % TiB_2/ZrB_2 to identify the presence of various elements. Microstructure study was also taken into consideration.

Secondly machining analysis was done to study the effect of cutting speed, feed rate and depth of cut on cutting force and surface roughness and to identify the optimized parameters. Taguchi based L27 orthogonal layout was used for designing and conducting the experiments. The response graphs revealed that feed rate was the most influential factor for both cutting force and surface roughness. Cutting speed had an inverse effect on cutting force. Depth of cut had direct effect on cutting force but the percentage contribution of depth of cut was the least.

M. Subramanian et al [11] attempted to optimize the machining parameters for minimizing cutting force using the RSM and genetic algorithm technique. A five level CCD was used for designing and conducting the experiments. The input parameters were cutting speed, cutting feed rate and axial depth of cut. The work piece material chosen was Aluminium (Al 7075-T6) and the tool was a shoulder mill with two carbide insert. Second order mathematical model was developed to relate the cutting force with input parameters. ANOVA was done for model adequacy checking. The developed model along with the GA was utilized to obtain the optimized settings. Their results revealed that cutting speed was the most influential factor followed by cutting feed rate and the axial depth of cut. The results also showed that cutting speed had an inverse effect on cutting force whereas the other two had a direct effect.

I. G. Euan et al [12] attempted to develop a model for static and dynamic cutting force and vibrations. The workpiece material chosen was Inconel718 and the tool chosen was indexable milling tool with round ceramic inserts. To identify the effects of parameters on cutting force an analytical model was developed. Then they performed experiments in order to compute cutting force coefficients, which were required for calculating cutting force. Then, they validated the cutting force model with experiments. Then they performed the implementation of the models in a Matlab GUI. The results from the developed models were combined with GUI and simulation of static and dynamic cutting force was done. For vibration analysis the time domain model was used to identify the stability limits.

Harsh Y Valera et al [13] performed an experimental study to identify the effects of cutting speed, feed rate and depth of cut on power consumption and surface roughness during turning of EN-31 alloy steel. The tool chosen was a coated tool whose substrate was made up with TiN and a coating of Al_2O_3 and TiCN was done on it.

The results revealed that cutting speed had an inverse effect on surface roughness and a direct effect on power consumption. Whereas both feed rate and depth of cut had a direct effect on surface roughness and power consumption. Their future scope of work suggested that in order to optimise the responses, design of experiments could be done and accordingly the experiments could be performed and the analysis of results could be done.

Gaurav Bartarya et al [14] carried out the experiments as per the full factorial design for studying the effects of cutting speed, feed and depth of cut on forces and surface roughness. They performed finish hard turning on AISI52100 steel using uncoated CBN tool. They developed second order mathematical models to identify the relationship between the input and the output parameters. They found from the ANOVA that the force models and the surface roughness model were adequate. They found that the percentage error between the predicted and experimental values was under the limits for forces but the same was very high for surface roughness. They attributed this effect to the material inhomogeneity and variation in hardness. They found that the depth of cut was the most influential factor followed by feed for all the forces whereas cutting speed was the least significant factor for the axial and radial force and insignificant for the tangential force. They found that percentage error in model prediction of surface roughness was high; therefore they concluded that the model was insignificant. They concluded their study by identifying the ranges of input parameters for efficient machining. According to them, cutting speed should vary from low to moderate with depth of cut to be in the moderate region while for all the feed values within the selected range.

Ravinder Tonk et al [15] attempted to develop mathematical model for thrust force and feed force and optimize the response parameters during turning of EN31 steel. Cutting speed, feed, depth of cut, cutting tool and cutting fluid were taken as the input parameters. Taguchi design was adopted for designing the experiments. They concluded for thrust force, feed rate was the most influential factor followed by depth of cut, cutting tool, spindle speed and lastly cutting fluid. Whereas for feed force, they found that depth of cut was the most influential factor followed by cutting fluid, feed rate, spindle speed and lastly cutting tool.

Varaprasad.Bh et al [16] attempted to develop second order mathematical model for predicting tool flank wear in terms of cutting speed, feed and depth of cut during hard turning of AISI D3 steel with a mixed ceramic insert based on alumina with the incorporation of TiC. A three level RSM based Central Composite Design (CCD) was adopted for designing and conducting the experiments. They performed ANOVA for model adequacy checking. They plotted main and interaction plots, surface plots and contour plots. They concluded their study by identifying that the depth of cut was the most influential factor whereas speed and feed had a little effect on tool wear variation.

V.Sivaraman et al [17] attempted to study the variation in cutting force while varying cutting speed, feed and depth of cut during turning of multiphase (ferrite-bainite-martensite) microalloyed steel with uncoated P type tungsten carbide insert. Taguchi design was adopted for designing the experiments. They performed ANOVA for identifying the significant contribution of machining parameters. They plotted the main effects and the contour plots and analyzed them to state that feed and depth of cut had a more pronounced effect on cutting force in comparison to cutting speed. They also identified the optimal machining parameters from the plots.

Dr. G. Harinath Gowd et al [18] performed an experimental study to relate tool wear and material removal rate with spindle speed, feed rate & DOC during CNC turning of AISI S2 tool steel grade using carbide insert. They set all the input parameters at three levels and conducted the experiment as per the design matrix. They plotted main effects and interaction effects and analyzed the plots to state that all the three parameters had a proportionate effect on both MRR and tool wear. They concluded their study with the presentation of optimization of parameters with the formulation of multi objective optimization problem.

Doriana M. D' Addona et al [19] attempted to find the optimal machining parameters during machining of a cast steel blank by means of the HSS tool on a NC lathe. They adopted genetic algorithm as an optimization technique. Their objective was to minimize the production time. They developed the objective function in terms of tool idle time, tool set up time, tool change time, tool life, volume of the material removed and the MRR. Then they set up the constraints which were both technological and material based and performed optimization using the Matlab's GA toolbox.

They concluded their study by stating the advantages of GA like it could be used for multi objective optimization, secondly it provides fast solution. They also predicted the future scope of work in the sense that GA could be compared with other optimization techniques.

S.S.K. Deepak [20] proposed a comparative study of different optimization techniques. He made a comparison amongst fuzzy logic, genetic algorithm, scatter search technique, taguchi technique, geometric programming and artificial neural network. In his comparison he defined the advantages, drawbacks and the application areas of each technique. He concluded his study by stating that the proposed research could provide a helping hand for industries for determining the optimal cutting parameters and consequently improving the process quality and simultaneously minimizing the costs.

C.J.Rao et al [21] attempted to determine the optimal process parameters for predicting tool life, cutting force and surface finish. They chose aluminium as the work material and tungsten carbide as cutting tool and performed turning on a CNC machine. The input parameters taken were cutting speed, feed and depth of cut. They conducted the experiments by varying one of the parameters and keeping other two as constants and MRR, tool life, power consumption and cutting forces were recorded. Then they plotted the graphs of tool life versus MRR, cutting force and surface finish and concluded that there was a gradual decrease in tool life as MRR, Cutting speed and cutting force increased.

Mithilesh Kumar Dikshit et al [22] attempted to study the influence of cutting parameters during ball-end milling of Al2014-T6 under dry condition. The input parameters taken were cutting speed, feed per tooth, axial depth of cut and radial depth of cut and the response parameters were tangential, radial and axial forces. A face centred rotary CCD was adopted for designing the experiments. They performed ANOVA and found that the quadratic model was adequate for predicting the forces. The results revealed that the axial depth of cut was the most influential factor for all the three responses whereas radial depth of cut had a more pronounced effect for axial and radial cutting forces when compared to feed per tooth.

2.2 Conclusion

Literature review reveals that good amount of literature is available for the development of regression model of cutting forces and surface roughness but the areas of feed force, thrust force and tool wear were found to gain less importance from research point of view. Secondly for optimization, mostly researchers had used RSM or Taguchi technique. On the contrary, GA optimization technique had been hardly used for optimization of the aforesaid parameters during turning of EN-31 Steel.

Lastly comparison of ANN model with the regression model was found to be an area of attraction for the researchers but most of the times it is only surface roughness which was modelled and the integrated approach of taking all the output parameters simultaneously and modelling them had been attempted rarely for EN 31 steel. Therefore the present research attempted to address these issues.

2.3 Statement of the Problem

“Modelling and Optimization of Cutting Force, feed force, thrust force and Surface Roughness during Turning of EN-31 Steel”

2.4 Plan of Investigation

1. Identifying the important input machining parameters and the output responses to be studied during the research.
2. Setting the working range of the input parameters on the basis of selected cutting tool's parameters' range.
3. Designing the experiments and generating the design matrix.
4. Conducting the experiments as per the design matrix and recording the responses.
5. Development of regression models.
6. Checking the model adequacy using ANOVA.
7. Drawing conclusions and representing them graphically.
8. Performing optimization using response optimizer feature of Minitab as well as using Genetic Algorithm and drawing a comparison between them.
9. Develop a model using Artificial Neural Network technique for predicting the responses and making a comparison between the results obtained with Artificial Neural Network and regression model.

Chapter 3

THEORY AND EXPERIMENTATION

3.1 Machining

Machining can be defined as an essential process of finishing by which jobs are produced to the desired dimension and surface finish by gradual removal of excess material from the preformed blank in the form of chips with the help of cutting tools moved past the work surface. Machining comes under the category of removal process.

- Machining aims to:
1. Fulfil its functional requirements.
 2. Improve its performance.
 3. Prolong its service.

3.1.1 Requirements in Machining

The essential basic requirements for machining are schematically represented in the following figure:

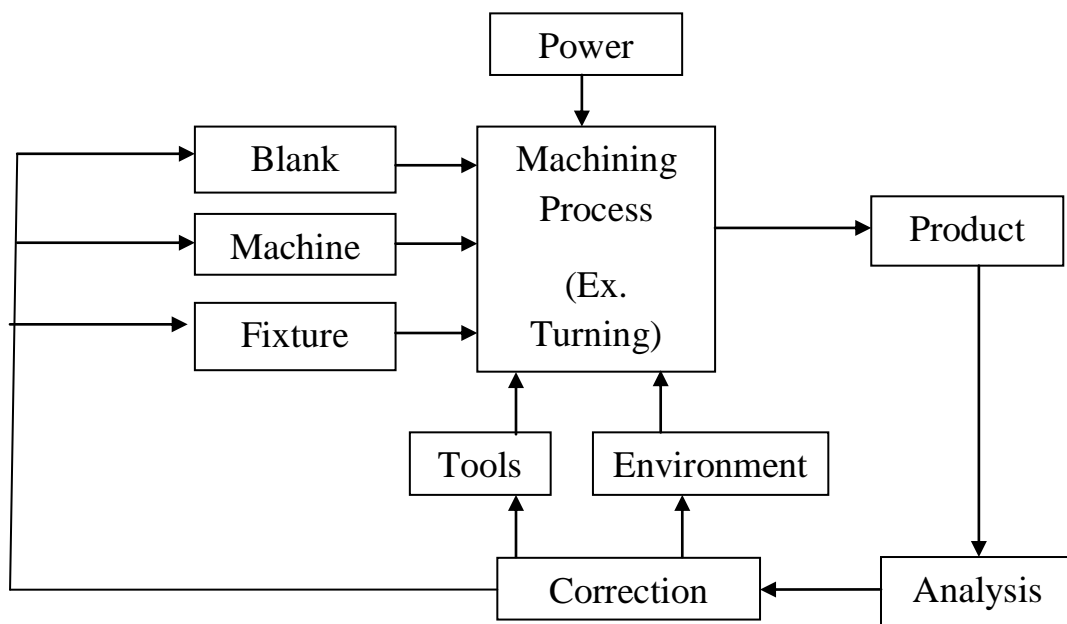


Fig 3.1 Requirements for Machining [1]

Both the blank and the cutting tool are properly mounted (in fixtures) and moved in a powerful device called machine tool which enables gradual removal of layer of material from the work surface which ultimately results in its desired dimensions and surface finish. Additionally the environment in the figure refers to cutting fluid which is generally used to ease machining by primarily cooling and secondary lubrication. After the product is manufactured, it is analysed and if it is not meeting the specifications, then accordingly corrections can be done either in blank, machine, fixture, tool or environment.

3.2 Machine Tool

A machine tool can be defined as a non-portable power operated and reasonably valued device or system of devices in which energy is expended in order to produce jobs of desired size, shape and surface finish by removing excess material from the preformed blanks in the form of chips with the help of cutting tools moved past the work surface [1].

3.2.1 Basic functions of Machine Tools

Machine Tools basically produce geometrical surfaces such as flat, cylindrical or any contour on the preformed blanks by machining work with the help of cutting tools.

The physical functions of a Machine Tool in machining are:

- To firmly hold the blank and the tool.
- To transmit motions to the tool and the blank.
- To provide power to the tool-work pair for machining.
- To control machining parameters, i.e., speed, feed and depth of cut.

3.3 Parameters in Metal Cutting

The following are the parameters which affect the machining operation on a machine tool [15]:

1. Cutting parameters
 - a. Cutting Speed
 - b. Feed
 - c. Depth of cut

2. Cutting tool parameters
 - a. Tool geometry
 - b. Grade of the tool
3. Work material Parameters
 - a. Geometry
 - b. Chemical composition
4. Environmental parameters
 - a. Dry machining
 - b. Wet machining

For this study, the parameters which were varied amongst them include cutting speed, feed, and depth of cut. Another set of readings were also performed using a different tool grade. Besides that, the tool geometry, workpiece geometry and its chemical composition remained same and the machining was performed under dry conditions.

3.4 Work Material: EN 31 Steel

- EN-31 Steel is high carbon low alloy steel giving good ductility & shock resisting properties along with wear resistance.
- It is also known as bearing steel as it is used for production of bearings.

Spectro Analysis of the work material was done and the chemical composition is as follows:

Table 3.1 Chemical Composition of EN 31 Steel

C %	Si %	Mn %	Cr %	S %	P %
1.01	0.2453	0.4673	1.1073	0.0247	0.0281

The analysis says that the material complies with EN 31 specification. Test method used was ASTM E 415-15 and Protocol used was ASTM E-1507-2007.

3.5 Cutting Tool Materials

Cutting tool is a device which is used for the removal of unwanted material from a given workpiece in the form of chips. Cutting tool is the essential and fundamental requirement for carrying out the metal removing process.

3.5.1 Needs and Chronological Development of Cutting Tool Materials

With the progress of the industrial world it has become imperative to continuously develop and improve upon the cutting tool materials and its geometry [24];

- In order to meet the growing demands for high productivity, quality and economy of machining.
- For micro and even nano machining.
- For precision and ultra-precision machining.
- To enable effective and efficient machining of the exotic materials which are coming up with the advancements in science and technology.

The capability and overall performance of the cutting tools depend upon,

- Material of the cutting tool
- Geometry of the cutting tool
- Proper selection and use of those tools
- The machining conditions and the environments under which machining is done

Out of which the tool material plays the most vital role. Productivity has been raised from a MRR of 8 to 70 while turning MS as the tool material progressed from HSS operating at a speed of 25 m/min in the year 1910 to high performance ceramics operating at a speed of 750 m/min in the year 2000 respectively. In between HSS and high performance ceramics, came carbides (brazed), operating at a speed of 60m/min, 80m/min and then coated carbide operating at a speed of 250 m/min and correspondingly MRR showed an increase from 10 to 35 respectively.

The chronological development of cutting tool materials is briefly indicated in Fig. 3.3.

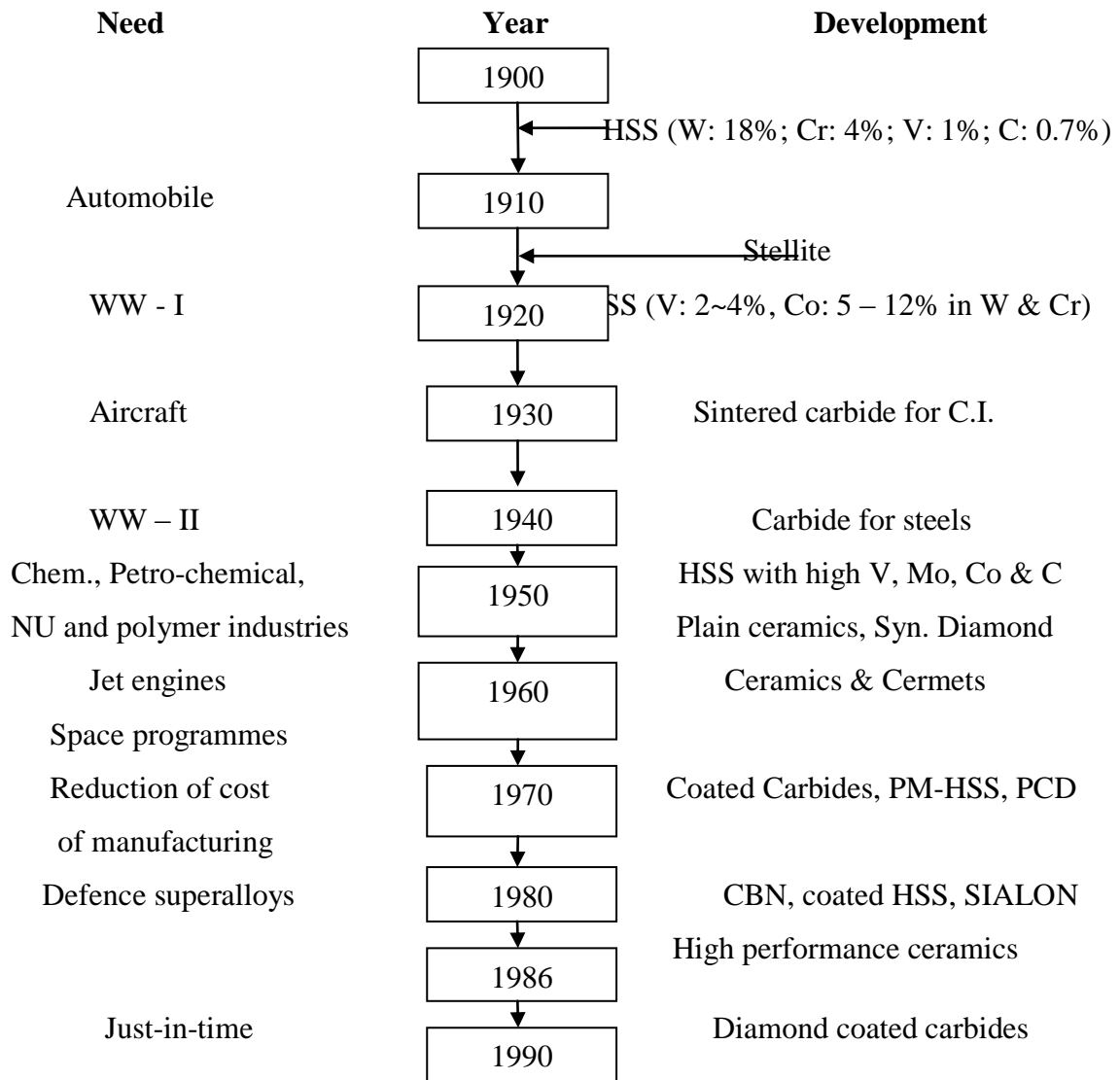


Fig. 3.2 Chronological development of cutting tool materials.

3.5.2 Characteristics and Applications of the Primary Cutting Tool Materials [24]

(a) High Speed Steel (HSS)

In around 1905, advent of HSS was a break through at that time in the history of cutting tool materials but it was later replaced by many other tool materials such as cemented carbides and ceramics which could machine much faster than the HSS tools.

The basic composition of HSS is 18% W, 4% Cr, 1% V, 0.7% C and rest Fe. Such HSS tool could turn mild steel jobs at speed only upto 20 ~ 30 m/min (which was quite substantial in those days).

The addition of large amount of Co and V, microstructure refinement and the presence of coating increased strength and wear resistance and therefore productivity and life of the HSS tools were remarkably enhanced.

(b) Stellite

Stellite is a cast alloy of Co (40 to 50%), Cr (27 to 32%), W (14 to 19%) and C (2%). It is quite tough and more heat and wear resistive than the basic HSS (18 – 4 – 1) But its poor grindability and the arrival of cemented carbides made them obsolete.

(c) Sintered Tungsten carbides

The advent of sintered carbides made another breakthrough in the history of cutting tool materials.

- **Straight or single carbide**

The straight carbide tools also known as single carbide tools or inserts were produced by powder metallurgy by mixing, compacting and sintering 90 to 95% WC powder with cobalt. The hot, hard and wear resistant WC grains are held by the binder Co which provides the necessary strength and toughness. These are suitable for machining grey cast iron, brass, bronze etc. which produce short discontinuous chips and at cutting velocities which is two to three times of HSS tools.

- **Composite carbides**

The above mentioned carbide is not suitable for machining steels because of rapid wear, particularly crater wear, by diffusion of Co and carbon from the tool to the chip under the influence of high stress and temperature. Therefore for machining steels successfully, another type called composite carbide was developed by adding 8 to 20% of gamma phase to WC and Co mix. The gamma phase is a mix of TiC, TiN, TaC, NiC etc. which are more diffusion resistant as compared to WC because of their more stability and less wettability by steel.

- **Mixed carbides**

Titanium carbide (TiC) has not only more stability but it is also much harder than WC. Therefore for machining ferritic steels which causes intensive diffusion and adhesion wear, a large quantity (5 to 25%) of TiC is added with WC and Co to produce another grade called Mixed carbide. But such an increase in content of TiC reduces the toughness of the tools. Therefore, for finishing with light cut but high speed, the harder grades containing upto 25% TiC are used and for heavy roughing work at lower speeds lesser amount (5 to 10%) of TiC is suitable.

- **Gradation of cemented carbides and their applications**

The standards developed by ISO for grouping of carbide tools and their application ranges are given in Table 3.3.2.

Table 3.2 Broad classification of carbide tools

ISO Code	Colour Code	Application
P		For machining long chip forming common materials like plain carbon and low alloy steels
M		For machining long or short chip forming ferrous materials like Stainless steel
K		For machining short chipping, ferrous and non-ferrous material and non-metals like Cast Iron, Brass etc.

P-group is suitably used for machining long chipping ferrous metals i.e. plain carbon and low alloy steels.

M-group is suitable for machining more difficult-to machine materials like strain hardening austenitic steel and manganese steel etc.

K-group is suitable for machining short chip producing ferrous and nonferrous metals and also some non metals.

(d) Plain ceramics

The high compressive strength, chemical stability and hot hardness of the ceramics led to powder metallurgical production of indexable ceramic tool inserts since 1950. Alumina (Al_2O_3) is preferred to silicon nitride (Si_3N_4) for higher hardness and chemical stability. Si_3N_4 is tougher but it is difficult to process. Because of their brittle nature, they have limited applications.

Basically three types of ceramic tool bits are available in the market;

- **Plain alumina with traces of additives** – these are white or pink sintered inserts which are cold pressed and are used mainly for machining cast iron and similar materials at speeds of 200 to 250 m/min
- **Alumina; with or without additives** – these are hot pressed, black in colour, hard and strong – used for machining steels and cast iron at speeds of 150 to 250 m/min
- **Carbide ceramic ($\text{Al}_2\text{O}_3 + 30\% \text{TiC}$) cold or hot pressed, black colour, quite strong and enough tough** – used for machining hard cast irons and plain and alloy steels at speeds of 150 to 200 m/min.

The plain ceramics outperformed the then existing tool materials in some application areas like high speed machining of softer steels mainly for higher hot hardness.

However, the use of these brittle plain ceramic tools until their strength and toughness could be substantially improved since 1970, gradually decreased for being restricted to

- Uninterrupted machining of soft cast irons and steels only
- Relatively high cutting velocity but only in a narrow range (200 ~ 300 m/min)
- Requiring very rigid machine tools

The then ceramics became almost obsolete because of the advent of coated carbide which was capable of machining cast iron and steels at high velocity.

3.5.3. Selection of the Cutting Tool

The following sequence of steps was utilized for selecting the insert which was Sandvik made [23].

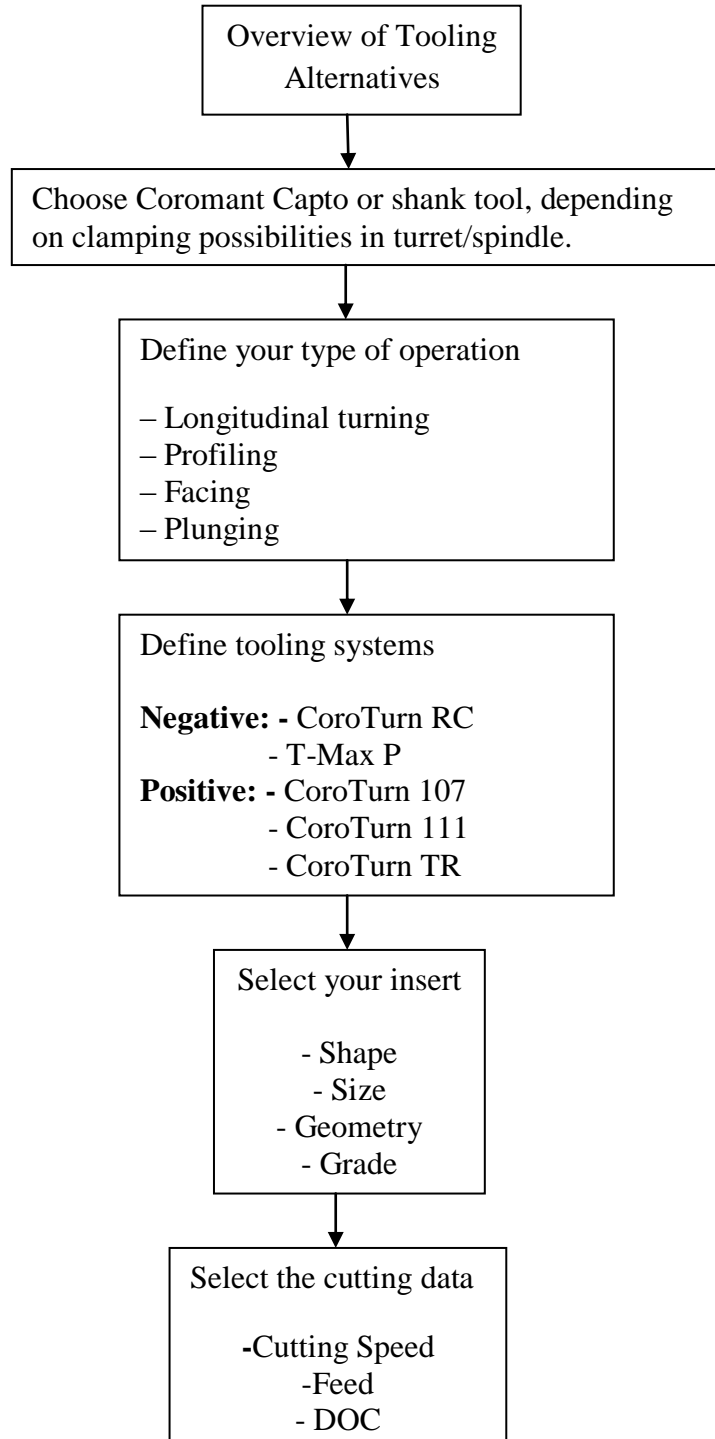


Fig. 3.3 Flowchart for tool selection

After following these steps, CCMT 09 T3 08 was chosen with grade CT5015 and GC1525.

3.5.4 Cutting Tool Grades

- **CT5015**

It is uncoated titanium based cemented carbide, more frequently known as a cermet. The use of titanium instead of tungsten improves the chemical stability and makes CT5015 ideal for machining of smearing materials. CT5015 is a hard wear resistant grade with good resistance to plastic deformation [23]. A pure cobalt binder adds toughness and security to the substrate. A sharp cutting edge will be maintained throughout the tool life is ensured by keeping the tool uncoated which ultimately results in good surface finish and low cutting forces. It is a finishing grade for high quality surfaces at both high and low cutting speeds.

- **GC1525**

It is a PVD coated cermet used for finishing and semi-finishing. The substrate is of the same kind as CT5015 but tougher. The PVD coating of TiCN-TiN of thickness 3 μm adds wear resistance and resistance to plastic deformation. This coating is chosen because of its superior compatibility with the substrate, minimizing the risk of flaking. GC1525 is Sandvik's toughest available cermet for high process security and good surface finish [23].

3.6 Response Surface Methodology

Response Surface Methodology, or RSM, is a collection of mathematical and statistical techniques that are useful for the modelling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize the response [25].

In most RSM problems, the form of the relationship between the response and independent variables is unknown. Thus, the first step in RSM is to find a suitable approximation for the true functional relationship between response and the set of independent variables. Usually, a low order polynomial in some region of the independent variables is employed. If the response is well modelled by the linear function of independent variables, then the approximating function is the first order model

$$y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_kx_k + \varepsilon$$

If there is curvature in the system, then a polynomial of higher degree must be used, such as the second order model

$$y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{i < j} \beta_{ij} x_i x_j + \varepsilon$$

Almost all RSM problems use one or both of these models. Of course, it is unlikely that a polynomial model will be a reasonable approximation of the true functional relationship over the entire space of independent variables, but for a relatively small region they usually work quite well.

The method of least squares is used to estimate the parameters in the approximating polynomials. The response surface analysis is then performed using the fitted surface. If the fitted surface is an adequate approximation of the true response function, then analysis of the fitted surface will be approximately equivalent to analysis of the actual system. The model parameters can be estimated most effectively if proper experimental designs are used to collect the data.

Designs for fitting response surfaces are called response surface designs.

3.6.1 Experimental Designs for Fitting Response Surfaces

Fitting and analyzing response surfaces is greatly facilitated by the proper choice of an experimental design.

When selecting a response surface design, some of the features of a desirable design are as follows [25]:

1. Provides a reasonable distribution of data points (and hence information) throughout the region of interest.
2. Allows model adequacy, including lack of fit to be investigated.
3. Allows experiments to be performed in blocks.
4. Allows designs of higher order to be built up sequentially.
5. Provides an internal estimate of error.
6. Provides precise estimates of the model coefficients.
7. Provides a good profile of the prediction variance throughout the experimental region.

8. Provides reasonable robustness against outliers or missing values.
9. Does not require a large number of runs.
10. Does not require too many levels of the independent variables.
11. Ensures simplicity of calculations of the model parameters.

3.6.2. Designs for Fitting the First Order Model

Suppose we wish to fit the first-order model in k variables

$$y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \varepsilon$$

There is a unique class of designs that minimize the variance of the regression coefficients (β_i). These are the orthogonal first order designs. The class of first order orthogonal designs includes the 2^k factorial and fractions of the 2^k series in which main effects are not aliased with each other. In using these designs, we assume that the low and high levels of the k factors are coded to the usual ± 1 levels.

The 2^k design does not afford an estimate of the experimental error unless some runs are replicated. A common method of including replication in the 2^k design is to augment the design with several observations at the center. The addition of center points to the 2^k design does not influence the (β_i) for all $i \geq 1$, but the estimate of β_0 becomes the grand average of all observations. Furthermore, the addition of center points does not alter the orthogonality property of the design.

3.6.3. Designs for Fitting the Second Order Model

The central composite design or CCD is the most popular class of designs used for fitting the second order models. Generally, the CCD consists of a 2^k factorial (or fractional factorial) with n_F runs, $2k$ axial or star runs, and n_c center runs.

The practical deployment of a CCD often arises through sequential experimentation, i.e., firstly factorial runs are conducted to fit a first order model. If the model exhibits lack of fit, then the axial runs are added to allow the quadratic terms to be incorporated into the model. The CCD is a very efficient design for fitting the second-order model. There are two parameters in the design that must be specified: the distance α of the axial runs from the design center and the number of center points n_c . The choice of these two parameters is based on rotatability and the spherical CCD.

Rotatability

Rotatability is a desirable property because the experimenter does not have any prior information about the location of the optimum. Therefore, a design that provides equal precision of estimation in all directions would be preferred. Such a design will assure the experimenter that no matter what direction is taken to search for the optimum, the response value can be estimated with equal precision.

A CCD is made rotatable by the choice of α . The value of α for rotatability depends on the number of points in the factorial portion of the design; in fact, $\alpha = (n_F)^{1/4}$ yields a rotatable CCD where n_F is the number of points used in the factorial portion of the design.

Spherical CCD

A central composite design is said to be spherical if all factorial and axial points are at same distance from the center of the design. In fact, for a spherical region of interest, the best choice of α from the prediction variance viewpoint for the CCD is to set $\alpha = \sqrt{k}$. This design, called a spherical CCD, puts all the factorial and axial design points on the surface of a sphere of radius \sqrt{k} .

3.6.4. The Box-Behnken Design

Box and Behnken (1960) have proposed some three-level designs for fitting response surfaces. These designs are formed by combining 2^k factorials with incomplete block designs. The resulting designs are usually very efficient in terms of the required runs, or they are either rotatable or nearly rotatable.

Box-Behnken designs are used when performing non-sequential experiments. That is, we are only planning to perform the experiment once. These designs allow efficient estimation of the first and second-order coefficients. Because Box-Behnken designs have fewer design points, they are less expensive to run than central composite designs with the same number of factors [26].

The Box-Behnken design is a spherical design with all points lying on a sphere of radius $\sqrt{2}$. Also, the Box-Behnken design does not contain any points on the vertices of the cubic region created by the upper and lower limits for each variable. This could be advantageous when the points on the corners of the cube represent factor-level combinations that are prohibitively expensive or impossible to test because of physical process constraints.

3.7. Genetic Algorithm

The genetic algorithm is a method to solve both constrained and unconstrained optimization problems. It is based on Darwin's theory of natural selection, the process that drives biological evolution. At each step, the genetic algorithm randomly selects individuals from the current population which will act as parents and uses them for the production of the children for the next generation. The genetic algorithm works by repeatedly modifying a population of individual solutions. Over successive generations, the population "evolves" toward an optimal solution. The optimization problems which are not well suited for standard optimization algorithms, including problems in which the objective function is discontinuous, nondifferentiable, stochastic, or highly nonlinear can be solved by applying the Genetic Algorithm. The genetic algorithm can also address mixed integer programming problems, where some components are restricted to be integer-valued [27].

To create the next generation from the current population, Genetic Algorithm utilizes the following three main rules:

- **Selection** rules select the individuals, called parents which contribute to the population at the next generation.
- **Crossover** rules which combine two parents to form children for the next generation.
- **Mutation** rules apply random changes to individual parents to form children.

Table 3.2 Difference between Classical Algorithm and Genetic Algorithm

Classical Algorithm	Genetic Algorithm
It generates a single point at each iteration. The sequence of points approaches an optimal solution.	Generates a population of points at each iteration. The best point in the population approaches an optimal solution.
Selects the next point in the sequence by a deterministic computation.	Selects the next population by computation which uses random number generators.

3.7.1 Working of Genetic Algorithm

The following outline summarizes the working of genetic algorithm:

1. The algorithm begins by creation of a random initial population.
2. Then a sequence of new populations is created by the algorithm. At each step, the genetic algorithm randomly selects individuals from the current population which will act as parents and uses them for the production of the children for the next generation.

In order to create the new population, the algorithm performs the following steps:

- a. Each member of the current population is given a score by computing its fitness value.
 - b. In order to convert them into a more usable range of values, scaling of the raw fitness scores is done.
 - c. On the basis of their fitness, members are selected, known as parents.
 - d. Some of the individuals in the current population are passed to the next population as such even after having lower fitness. Such individuals are known as elite.
 - e. Produces children from the parents. Children are produced either by mutation or crossover.
 - f. The next generation is formed by replacing the current population with the children.
3. The algorithm stops when one of the stopping criteria is met

The genetic algorithm uses the following conditions to determine when to stop:

- **Generations** --- the algorithm stops when the number of generations reaches the value of Generations.
- **Time limit** --- the algorithm stops after running for an amount of time in seconds equal to Time limit.
- **Fitness limit** --- the algorithm stops when the value of the fitness function for the best point in the current population is less than or equal to Fitness limit.
- **Stall generations** --- the algorithm stops when the average relative change in the fitness function value over Stall generations is less than Function tolerance.
- **Stall time limit** --- the algorithm stops if there is no improvement in the objective function during an interval of time in seconds equal to stall time limit.

- **Stall test** --- the stall condition is either average change or geometric weighted. For geometric weighted, the weighting function is $1/2^n$, where n is the number of generations prior to the current. Both stall conditions apply to the relative change in the fitness function over Stall generations.
- **Function Tolerance** ---the algorithm runs until the average relative change in the fitness function value over Stall generations is less than Function tolerance.
- **Nonlinear constraint tolerance** --- the nonlinear constraint tolerance is not used as stopping criterion. It is used to determine the feasibility with respect to nonlinear constraints. Also, a point is feasible with respect to linear constraints when the constraint violation is below the square root of nonlinear constraint tolerance.

The algorithm stops as soon as any one of these conditions is met.

3.7.2 Genetic Algorithm Terminology

Fitness Functions

The fitness function is the function that we want to optimize. This is known as the objective function for standard optimization algorithms. The toolbox software tries to find the minimum of the fitness function.

We write the fitness function as a M file in MATLAB's editor window, and pass it as a function handle input argument to the main genetic algorithm function.

Individuals

An individual is any point to which we can apply the fitness function. The score is the value of the fitness function for an individual.

An individual is sometimes referred to as a genome and the vector entries of an individual as genes.

Populations and Generations

A population is an array of individuals. For example, if the population size is 100 and the number of variables in the fitness function is 3, then we can represent the population by a 100-by-3 matrix. The same individual can appear more than once in the population.

A series of computations on the current population is performed by the genetic algorithm at each step in order to produce a new population. Each successive population is called a new generation.

Diversity

Diversity refers to the average distance between individuals in a population. If the average distance is large, then population has high diversity; otherwise it has low diversity. In the following figure, the population on the left has high diversity, while the population on the right has low diversity.

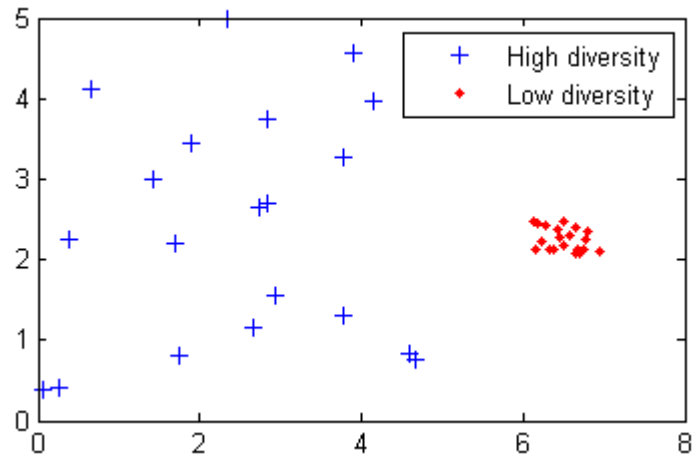


Fig. 3.4 Diversity in genetic algorithm

Diversity is essential to the genetic algorithm because it enables the algorithm to search a larger region of the space.

Fitness Values and Best Fitness Values

The value of the fitness function for a individual is its fitness value. Because the toolbox software finds the minimum of the fitness function, therefore the best fitness value for a population is the smallest fitness value for any individual in the population.

Parents and Children

To create the next generation, the genetic algorithm selects certain individuals in the current population, called parents, and uses them for the creation of individuals in the next generation, called children. Typically, the algorithm is more likely to select parents that have better fitness values.

3.8. Artificial Neural Network

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements [28].

Typically, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. The figure below illustrates such a situation. Here, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically, many such input/target pairs are needed to train a network.

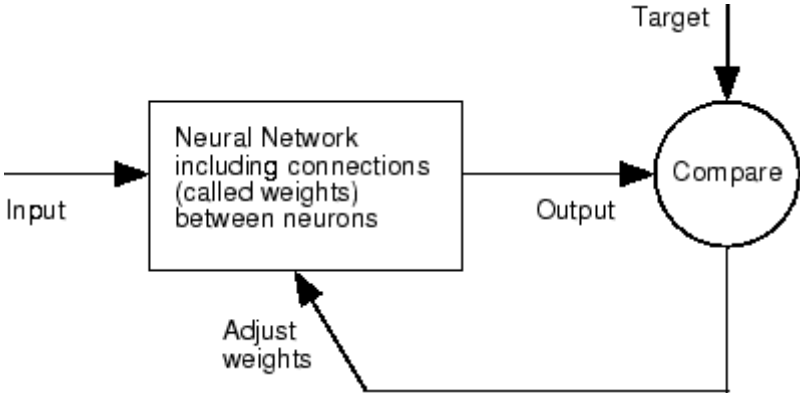


Fig. 3.5 Working of a Neural Network

Neural networks have been trained to perform complex functions in various fields, including pattern recognition, identification, classification, speech, vision, and control systems.

Neural networks can also be trained to solve problems that are difficult for conventional computers or human beings. The toolbox emphasizes the use of neural network paradigms that build up to or are themselves used in engineering, financial, and other practical applications.

3.8.1 Elements of ANN

Inputs

The inputs refer to the single attribute of the system that we are designing.

Weights

Weight is used to express the relative strength of the input. Inhibitory connections are reflected by negative weight values whereas the positive values represent excitatory connections. The bias is also similar to that of a weight except that it has a constant input of 1.

Summation Function

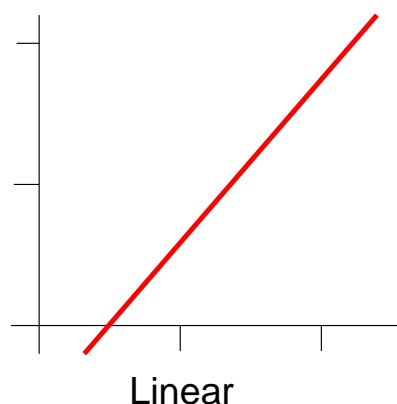
This function is used in order to find out the weighted average of all the input elements to each neuron.

Transfer/Activation Function

The transfer or activation function is used for the production of the desired output in accordance to the value of the weights and the inputs. It can be seen as a function which brings the output of the network within certain limits.

Types of Activation Functions

- Linear Activation function



$$y = \sum_{n=1}^N w_n x_n$$

Fig. 3.6 Linear Activation Function

Here the output is the scaled sum of inputs.

- Sigmoid Activation function

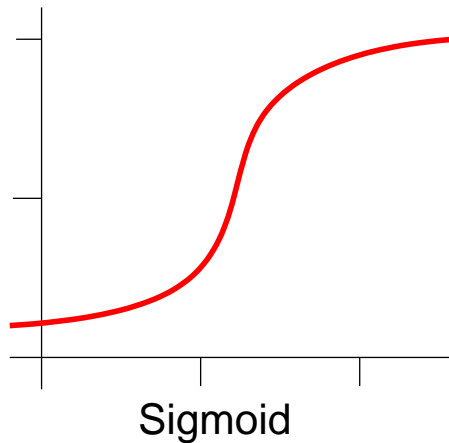


Fig. 3.7 Sigmoid Activation Function

A log-sigmoid function or simply sigmoid is given by the relationship:

$$\sigma(t) = \frac{1}{1 + e^{-\beta t}}$$

where β is a slope parameter. The sigmoid has the property of being similar to the step function, but the addition of region of uncertainty.

Output

One output signal is allowed for each processing element. Generally, the output is equivalent to the result of transfer function but some network topologies modify the transfer result for the incorporation of competition amongst neighbouring processing elements.

3.8.2. Neural Network Design Steps

The four major application areas of neural network are function fitting, pattern recognition, clustering and time series analysis.

The work flow for any of these problems has seven primary steps

1. Collect data
2. Create the network
3. Configure the network

4. Initialize the weights and biases
5. Train the network
6. Validate the network
7. Use the network

3.8.3. Artificial Neural Network algorithm

- Back propagation neural network

The back propagation algorithm is used in layered feed-forward ANNs. The word forward here refers to that the artificial neurons are organized in layers, and send their signals forward, and the back propagation refers to that the errors are propagated backwards.

The network receives inputs via neurons in the input layer whereas the output of the network is given by the neurons on an output layer. In between the input and output layer, there may be one or more hidden neurons. This algorithm utilizes supervised learning, which means that we provide the algorithm with the inputs and the targets and the algorithm tries to reduce the error between the outputs and targets till ANN learns the training data. The training begins with allocation of random weights, and the goal is to adjust them so that the error will be the minimal difference between the outputs and the targets.

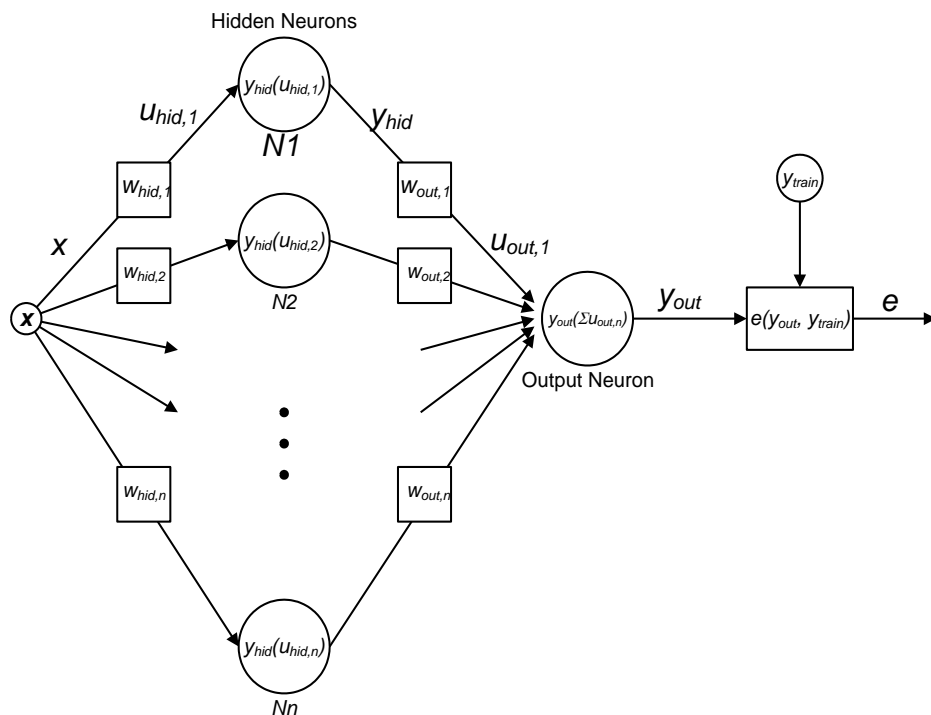


Fig. 3.8 Working of a NN back propagation algorithm

3.9. Experimentation

The main aim of this project was to find out the effect of machining parameters on cutting force, feed force, thrust force, surface roughness and tool wear and to develop mathematical models in order to describe the relationship between the input and response parameters.

After that optimization is attempted using the response optimizer technique of Minitab and also with Genetic Algorithm optimization technique.

After that ANN modelling was done and the results were compared with the RSM model results.

To achieve the aforesaid objectives, following is the sequence of steps which were carried out:

1. Identifying the important input machining parameters and the output responses to be studied during the research.
2. Setting the working range of the input parameters on the basis of selected cutting tool's parameters' range.
3. Designing the experiments and generating the design matrix.
4. Conducting the experiments as per the design matrix and recording the responses.
5. Development of regression models.
6. Checking the model adequacy using ANOVA.
7. Drawing conclusions and representing them graphically.
8. Performing optimization using response optimizer feature of Minitab as well as using GA and drawing a comparison between them.
9. Develop a model using ANN technique for predicting the responses and making a comparison between the results obtained with ANN and regression model.

3.9.1. Identification of the important machining parameters and the responses

Based on the literature survey, it has been identified that cutting speed, feed and depth of cut are the most influential factors during machining and have a significant effect on cutting force, feed force, thrust force, surface roughness and tool wear.

Although tool geometry also has a significant effect on the above mentioned response parameters but since here we are taking tool wear as a response parameter therefore it was not possible to take tool geometry as an input parameter.

3.9.2 Deciding the working range of the input parameters

The working range of input parameters is based upon the tool-work combination, rigidity of the machine, machining conditions etc.

The selected insert was **Sandvik's CCMT 09 T3 08- PM** and the recommended values of feed and depth of cut were identified from the catalogue as follows:

Table 3.3 Recommendations for Sandvik's CCMT 09 T3 08

Recommended feed (mm/rev)		Recommended DOC(mm)	
Minimum	Maximum	Minimum	Maximum
0.1	0.3	0.5	3

The cutting speed is identified by using the tool (grade)-work combination. For that, first of all Brinell hardness test of the work material was conducted and the hardness came out to be 241.189 HB. Using this hardness value and the tool grade, the range of the cutting speed was fixed.

Using the recommendations, trial runs were conducted and finally the ranges of the input parameters were set as follows:

Table 3.4 Machining parameters with their limits

Sl. No.	Parameters	Units	Notation	-1	0	+1
1.	Spindle speed	rpm	N	480	700*	910
2.	Feed	mm/rev	f	0.10	0.19	0.28
3.	Depth of cut	mm	d	0.5	0.8	1.1

*Although the 0 level for spindle speed came out to be 695 rpm but due to the non availability of this speed, the nearest speed of 700 rpm was taken (% error of 0.714).

$$\text{Since } V = \frac{\pi DN}{1000}$$

Where V is cutting speed in m/min

D is diameter of workpiece in mm (=32 mm)

and N is spindle speed in rpm

Therefore we have taken spindle speed instead of cutting speed since cutting speed is directly proportional to spindle speed as the diameter of workpiece remains constant.

3.9.3 Developing the design matrix

The design matrix is based upon RSM second order design. Since from the literature review, we know that the second order model is found to be adequate for fitting a model for forces and surface roughness, therefore it is better to opt Box-Behnken design instead of opting CCD.

Since CCD is mainly used when we need to follow sequential experimentation, i.e. firstly carry out 2 level factorial runs, fit the first order model, if not found adequate, add the axial runs to the previous design and again fit a second order model.

But since we know that second order model is adequate, therefore we had used Box-Behnken design. Box-Behnken designs are used when performing non-sequential experiments. That is, we are only planning to perform the experiment once. These designs allow efficient estimation of the first- and second-order coefficients. Because Box-Behnken designs have fewer design points, they are less expensive to run than central composite designs with the same number of factors.

Table 3.5 Design Matrix

Std. order	Run order	N	f	d
1	1	-1	-1	0
6	2	+1	0	-1
5	3	-1	0	-1
13	4	0	0	0
8	5	+1	0	+1
15	6	0	0	0
12	7	0	+1	+1
7	8	-1	0	+1
14	9	0	0	0
11	10	0	-1	+1
9	11	0	-1	-1
4	12	+1	+1	0
3	13	-1	+1	0
10	14	0	+1	-1
2	15	+1	-1	0

3.9.4. Conducting the experiments as per the design matrix

The experiments were conducted at the project shop of Delhi Technological University with the following experimental set-up:

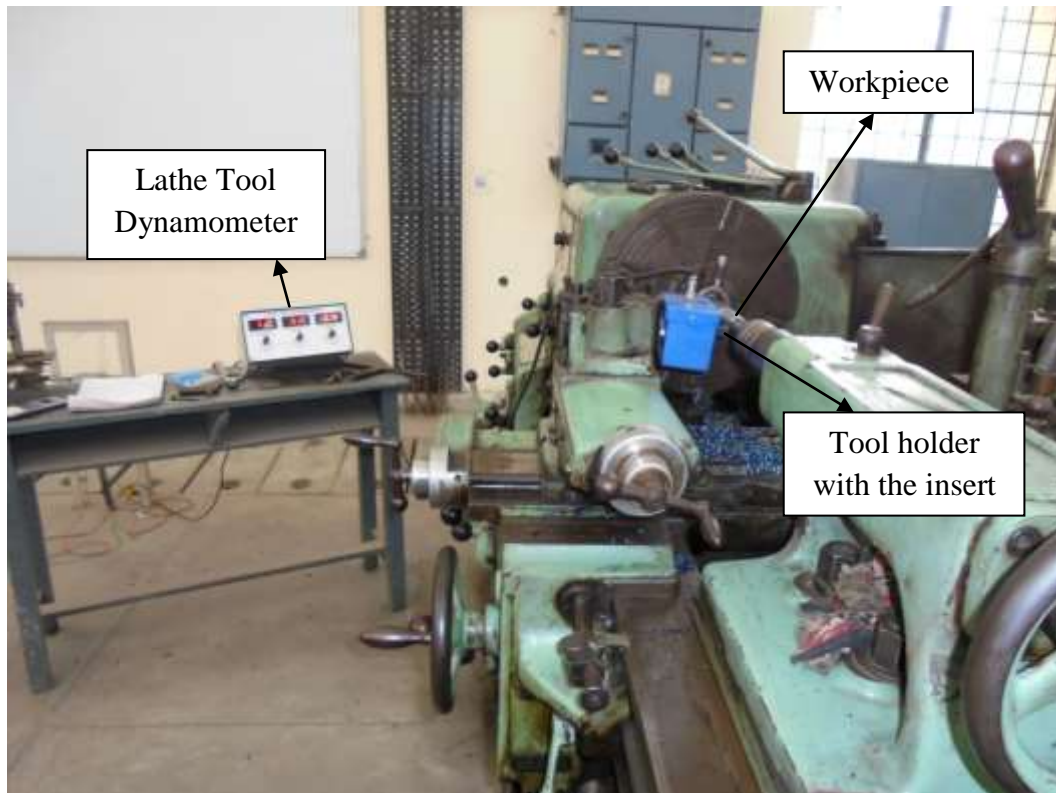


Fig. 3.9 The lathe machine along with the dynamometer used for experimentation

The base metal used: EN 31 Steel

For conducting the experimentation, test specimens were prepared for which firstly centering was done. Then a thin layer of material was removed in order to get a clean surface. Diameter of the rod was 32 mm and machining was done for a length of 100 mm. As the experiments were conducted firstly with uncoated carbide insert and then with coated one, therefore in total 30 test pieces were required.

Fig. 3.10 shows the test samples



Fig. 3.10 Test samples

Tool: The insert used was titanium based cemented carbide whose geometry is CCMT 09 T3 08, made was Sandvik's and the grade was CT5015 (uncoated) and GC1525 (coated).

Tool holder: SCLCR 12 12 D09 WIDAX



Fig. 3.11 Tool holder along with the coated insert

3.9.5. Recording the responses

The experiments were conducted as per the design matrix. Turning was done and the forces in three dimensions were measured during turning using the lathe tool dynamometer. After turning was done, both the workpiece and tool were taken out in order to measure surface roughness and tool wear respectively. Surface Roughness was measured with Taylor/Hobson Precision Surtronic 3+ Portable Surface Roughness Tester. Tool wear was measured with the Tool maker's microscope.

The table below shows the responses when turning was done with the uncoated carbide grade:

Table 3.6 Recording of Responses (With CT5015)

Std. Order	Run Order	N	f	d	CF(N)	FF(N)	TF(N)	R _a (μm)	Tool Wear(mm)
1	1	480	0.10	0.8	284.49	137.34	9.81	2.64	-----
6	2	910	0.19	0.5	255.06	98.10	29.43	2.32	-----
5	3	480	0.19	0.5	255.06	88.29	19.62	3.72	-----
13	4	700	0.19	0.8	382.59	176.58	19.62	2.60	-----
8	5	910	0.19	1.1	461.07	206.01	39.24	2.68	-----
15	6	700	0.19	0.8	441.45	206.01	0.00	2.48	0.0254
12	7	700	0.28	1.1	745.56	304.11	0.00	3.06	0.0254
7	8	480	0.19	1.1	559.17	255.06	0.00	3.23	0.0254
14	9	700	0.19	0.8	372.78	137.34	0.00	2.14	0.0508
11	10	700	0.10	1.1	333.54	176.58	0.00	1.38	0.0508
9	11	700	0.10	0.5	166.77	78.48	29.43	1.36	Tool
4	12	910	0.28	0.8					Chipped
3	13	480	0.28	0.8					away
10	14	700	0.28	0.5					
2	15	910	0.10	0.8					

At the end of 11th reading, the uncoated tool after showing a maximum tool wear of 0.0508 mm chipped away completely; therefore the responses were recorded using the coated tool grade.

Table 3.6 Recording of Responses (With GC1525)

Std. Order	Run Order	N	f	d	CF(N)	FF(N)	TF(N)	R_a(μm)	Tool Wear(mm)
1	1	480	0.10	0.8	225.63	107.91	0.00	2.85	-----
6	2	910	0.19	0.5	274.68	117.72	0.00	1.90	-----
5	3	480	0.19	0.5	274.68	98.10	0.00	3.79	-----
13	4	700	0.19	0.8	333.54	147.15	29.43	2.12	-----
8	5	910	0.19	1.1	519.93	196.20	0.00	1.90	-----
15	6	700	0.19	0.8	382.59	156.96	19.62	2.0	-----
12	7	700	0.28	1.1	510.12	166.77	49.05	3.92	-----
7	8	480	0.19	1.1	598.41	215.82	9.81	2.69	-----
14	9	700	0.19	0.8	353.16	166.77	88.29	1.84	-----
11	10	700	0.10	1.1	362.97	186.39	88.29	1.49	-----
9	11	700	0.10	0.5	215.82	107.91	58.06	3.35	-----
4	12	910	0.28	0.8	519.93	206.01	0.00	1.38	-----
3	13	480	0.28	0.8	598.41	196.20	19.62	4.47	-----
10	14	700	0.28	0.5	343.35	107.91	68.67	3.02	-----
2	15	910	0.10	0.8	264.87	166.77	68.67	1.27	-----

Where N = Spindle Speed

f = Feed

d = Depth of cut

CF = Cutting Force

FF = Feed Force

TF = Thrust Force

R_a = Surface Roughness

Chapter 4

DEVELOPMENT OF MATHEMATICAL MODELS

Mathematical models can be seen as the basis for establishing the interrelationship between the input parameters (spindle speed, feed and depth of cut) and the response parameters (cutting force, feed force, thrust force, surface roughness and tool wear). These mathematical models can be fed into the computer along with the input parameters to predict the aforesaid response parameters. The experimental data was utilized for developing the second order model and analysis of the developed models was performed using ANOVA and response graphs. All the calculations were carried out using Minitab 17.

4.1. Development of Mathematical Models

The response function representing any of the response can be expressed as:

$$Y = f(N, f, d)$$

Where,

Y = Cutting Force/Feed Force/Thrust Force/Surface Roughness/Tool Wear

N = Spindle Speed

f = Feed

d = Depth of Cut

A second order relationship is selected for representing the relation between the input parameters and the responses which is as follows:

$$Y = b_0 + b_1N + b_2f + b_3d + b_{11}N^2 + b_{22}f^2 + b_{33}d^2 + b_{12}Nf + b_{13}Nd + b_{23}fd$$

Where b_0 is a constant and $b_1, b_2, b_3, b_{11}, b_{22}, b_{33}, b_{12}, b_{13}, b_{23}$ are co-efficient of the model.

4.1.1 Evaluation of the Coefficient of the Model

- Sign of each coefficient indicates the direction of the relationship.
- Coefficients represent the mean change in the response for one unit of change in the predictor while holding other predictors in the model constant.

The values of these coefficients were determined using the regression analysis. The calculations were carried out using Minitab 17 and the values are listed in table 4.1.

Table 4.1 Estimated values of the coefficient of the model

Sl. No.	Coefficient	Cutting Force	Feed Force	Thrust Force	Surface Roughness
1	b ₀	87	-170	-561	14.45
2	b ₁	- 1.08	-0.124	1.582	- 0.00532
3	b ₂	2513	810	108	- 22.2
4	b ₃	408	521	114	- 17.90
5	b ₁₁	0.001125	0.000296	- 0.000944	0.000001
6	b ₂₂	- 807	-151	2473	54.4
7	b ₃₃	91	-150	5	5.75
8	b ₁₂	-1.57	- 0.656	- 1.137	- 0.01945
9	b ₁₃	-0.316	- 0.155	-0.038	0.00427
10	b ₂₃	182	- 182	- 454	25.56

The responses were expressed as a non-linear function (second order model) of the input machining parameters as follows:

$$\text{Cutting Force (N)} = 87 - 1.08 (N) + 2513 (f) + 408 (d) + 0.001125 (N^2) - 807 (f^2) + 91 (d^2) - 1.57 (Nf) - 0.316 (Nd) + 182 (fd)$$

$$\text{Feed Force (N)} = -170 - 0.124 (N) + 810 (f) + 521 (d) + 0.000296 (N^2) - 151 (f^2) - 150 (d^2) - 0.656 (Nf) - 0.155 (Nd) - 182 (fd)$$

$$\text{Thrust Force (N)} = -561 + 1.582 (N) + 108 (f) + 114 (d) - 0.000944 (N^2) + 2473 (f^2) + 5 (d^2) - 1.137 (Nf) - 0.038 (Nd) - 454 (fd)$$

$$\text{Surface Roughness } (\mu\text{m}) = 14.45 - 0.00532 (N) - 22.2(f) - 17.90 (d) + 0.000001 (N^2) + 54.4 (f^2) + 5.75 (d^2) - 0.01945 (Nf) + 0.00427 (Nd) + 25.56 (fd)$$

4.2. Model Adequacy Checking

For checking whether the developed models are adequate or not, the Analysis of Variance (ANOVA) technique is utilized. Analysis of variance (ANOVA) is similar to regression in that it is used to investigate and model the relationship between a response variable and one or more predictor variables. However, analysis of variance differs from regression in two ways: the predictor variables tend to be categorical. In effect, analysis of variance extends the two-sample t-test for testing the equality of two population means to a more general null hypothesis of comparing the equality of more than two means, versus them not all being equal. According to this technique:

1. The F-ratio of the lack of fit of the developed model is calculated and is compared against the corresponding standard tabulated value for a specific confidence level.
2. If the calculated value of F-ratio exceeds the standard tabulated value, then with the corresponding confidence, we can say that the model is adequate. In this analysis, we have taken confidence interval to be 95%.

4.2.1 Response: Cutting Force

Table 4.2 ANOVA for Cutting Force

Source	DF	Adj SS	Adj MS	F value	p value
Model	9	217064	24118	4.87	0.048
N	1	1732	1732	0.35	0.580
f	1	102430	102430	20.68	0.006
d	1	97831	97831	19.75	0.007
N ²	1	9973	9973	2.01	0.215
f ²	1	158	158	0.03	0.865
d ²	1	247	247	0.05	0.832
Nf	1	3709	3709	0.75	0.426
Nd	1	1658	1658	0.33	0.588
fd	1	96	96	0.02	0.895
Error	5	24771	4954		
Lack of fit	3	23552	7851	12.88	0.073(not Significant)
Pure Error	2	1219	609		
Total	14	241835			

The model F value of 4.87 is an implication of the significance of the model, since the corresponding standard tabulated value is 4.77($F_{0.05, 9, 5}$) and $4.87 > 4.77$ which implies that the model is adequate. The adequacy can also be checked using p value. The cut off level chosen is 0.05 and since the model p value is 0.048(< 0.05), therefore the model is adequate.

The “Lack of Fit F value” is 12.88 and the corresponding standard tabulated value is 19.16 ($F_{0.05, 3, 2}$) and since $12.88 < 19.16$, therefore the lack of fit is insignificant. Non significant lack of fit is required as we want the model to adequately fit the data. We can also see that the Lack of Fit p value is 0.073(> 0.05) which means that the lack of fit is insignificant.

The R-squared value for the model came out to be 89.76% and the R-squared (adj) was 71.32%. Since the R-squared value came out to be 89.76%, this implies that besides spindle speed, feed and depth of cut, there are other factors also which affects the cutting force such as tool geometry, machining conditions (wet/dry) etc.

4.2.2 Response: Feed Force

Table 4.3 ANOVA for Feed Force

Source	DF	Adj SS	Adj MS	F value	p value
Model	9	18550.9	2061.2	2.67	0.146
N	1	589.4	589.4	0.76	0.423
f	1	1487.2	1487.2	1.92	0.224
d	1	13979.8	13979.8	18.08	0.008
N ²	1	691.7	691.7	0.89	0.388
f ²	1	5.6	5.6	0.01	0.936
d ²	1	671.8	671.8	0.87	0.394
Nf	1	644.0	644.0	0.83	0.403
Nd	1	398.4	398.4	0.52	0.505
fd	1	96.2	96.2	0.12	0.739
Error	5	3865.7	773.1		
Lack of fit	3	3673.2	1224.4	12.72	0.074(not Significant)
Pure Error	2	192.5	96.2		
Total	14	22416.6			

The “Lack of Fit F value” is 12.72 and the corresponding standard tabulated value is 19.16 ($F_{0.05, 3, 2}$) and since $12.72 < 19.16$, therefore the lack of fit is insignificant. Non significant lack of fit is required as we want the model to adequately fit the data. We can also see that the Lack of Fit p value is 0.074 (> 0.05) which means that the lack of fit is insignificant.

The R-squared value for the model came out to be 82.76% and the R-squared (adj) was 51.71%. Since the R-squared value came out to be 82.76%, this implies that besides spindle speed, feed and depth of cut, there are other factors also which affects the cutting force such as tool geometry, machining conditions (wet/dry) etc.

4.2.3 Response: Thrust Force

Table 4.4 ANOVA for Thrust Force

Source	DF	Adj SS	Adj MS	F value	p value
Model	9	12686.2	1409.57	2.17	0.204
N	1	192.5	192.5	0.30	0.610
f	1	730.0	730.0	1.12	0.338
d	1	49.2	49.2	0.08	0.794
N^2	1	7024.3	7024.3	10.80	0.022
f^2	1	1481.2	1481.2	2.28	0.192
d^2	1	0.6	0.6	0.00	0.977
Nf	1	1938.2	1938.2	2.98	0.145
Nd	1	24.1	24.1	0.04	0.855
fd	1	601.5	601.5	0.93	0.380
Error	5	3250.5	650.11		
Lack of fit	3	491.8	163.92	0.12	0.941(not Significant)
Pure Error	2	2758.8	1397.38		
Total	14	15936.7			

The “Lack of Fit F value” is 0.12 and the corresponding standard tabulated value is 19.16 ($F_{0.05, 3, 2}$) and since $0.12 < 19.16$, therefore the lack of fit is insignificant. Non significant lack of fit is required as we want the model to adequately fit the data. We can also see that the Lack of Fit p value is 0.941 (> 0.05) which means that the lack of fit is insignificant.

The R-squared value for the model came out to be 79.60% and the R-squared (adj) was 42.89%. Since the R-squared value came out to be 79.60%, this implies that besides spindle speed, feed and depth of cut, there are other factors also which affects the cutting force such as tool geometry, machining conditions (wet/dry) etc.

4.2.4 Response: Surface Roughness

Table 4.5 ANOVA for Surface Roughness

Source	DF	Adj SS	Adj MS	F value	p value
Model	9	13.4777	1.49752	13.45	0.005
N	1	6.7528	6.7528	60.66	0.001
f	1	1.8668	1.8668	16.77	0.009
d	1	0.5436	0.5436	4.88	0.078
N^2	1	0.0072	0.0072	0.06	0.810
f^2	1	0.7162	0.7162	6.43	0.052
d^2	1	0.9904	0.9904	8.90	0.031
Nf	1	0.5666	0.5666	5.09	0.074
Nd	1	0.3033	0.3033	2.72	0.160
fd	1	1.9044	1.9044	17.11	0.009
Error	5	0.5566	0.11132		
Lack of fit	3	0.5172	0.17239	8.74	0.104(not Significant)
Pure Error	2	0.0395	0.01973		
Total	14	14.0343			

The model F value of 13.45 is an implication of the significance of the model, since the corresponding standard tabulated value is 4.77($F_{0.05, 9, 5}$) and $13.45 > 4.77$ which implies that the model is adequate. The adequacy can also be checked using p value. The cut off level chosen is 0.05 and since the model p value is 0.005(< 0.05), therefore the model is adequate.

The “Lack of Fit F value” is 8.74 and the corresponding standard tabulated value is 19.16 ($F_{0.05, 3, 2}$) and since $8.74 < 19.16$, therefore the lack of fit is insignificant. Non significant lack of fit is required as we want the model to adequately fit the data. We can also see that the Lack of Fit p value is 0.104(> 0.05) which means that the lack of fit is insignificant.

The R-squared value for the model came out to be 96.03% and the R-squared (adj) was 88.89%. Since the R-squared value came out to be 96.03%, this implies that besides spindle speed, feed and depth of cut, there are other factors also which affects the cutting force such as tool geometry, machining conditions (wet/dry) etc.

4.3 Testing the models

The developed models were tested for their predictive ability. Five test cases were selected at random from the design matrix and the values of the responses as obtained from the experiment were compared with the corresponding values obtained from the mathematical models.

Table 4.6 Testing of mathematical models

Run No.	N (rpm)	f (mm/rev)	d (mm)		CF (N)	FF (N)	TF (N)	R _a (μm)
3	480	0.19	0.5	Actual	274.68	98.10	0.00	3.79
				Predicted	300.685	96.589	-7.385	4.0247
				% error	-9.46	1.54	-----	-6.19
5	910	0.19	1.1	Actual	519.93	196.20	0.00	1.90
				Predicted	492.453	197.37	7.3866	1.6658
				% error	5.28	-0.5963	-----	12.32
7	700	0.28	1.1	Actual	510.12	166.77	49.05	3.92
				Predicted	585.577	192.258	46.3131	3.85508
				% error	-14.79	-15.28	5.57	1.656

12	910	0.28	0.8	Actual	519.93	206.01	0.00	1.38
				Predicted	470.216	178.756	-3.6508	1.68055
				% error	9.56	13.22	----	-21.77
15	910	0.10	0.8	Actual	264.87	166.77	68.67	1.27
				Predicted	304.774	176.857	59.3726	1.46695
				% error	-15.06	-6.04	13.53	-15.50

Chapter 5

RESULTS AND DISCUSSION

The mathematical models developed previously can be used for the prediction of cutting force, feed force, thrust force and surface roughness for the range of input parameters used in the experimentation. On the basis of these developed models, main and the interaction effects, response graphs and the contour plots were plotted as shown in Figs.

5.1. Main Effect of Input Parameters on the Responses

Used in conjunction with an analysis of variance and design of experiments to examine differences among level means for one or more factors. A main effect is present when different levels of a factor affect the response differently. A main effects plot the response mean for each factor level connected by a line.

5.1.1 Direct Effect of Spindle Speed, Feed and Depth of Cut on Cutting Force

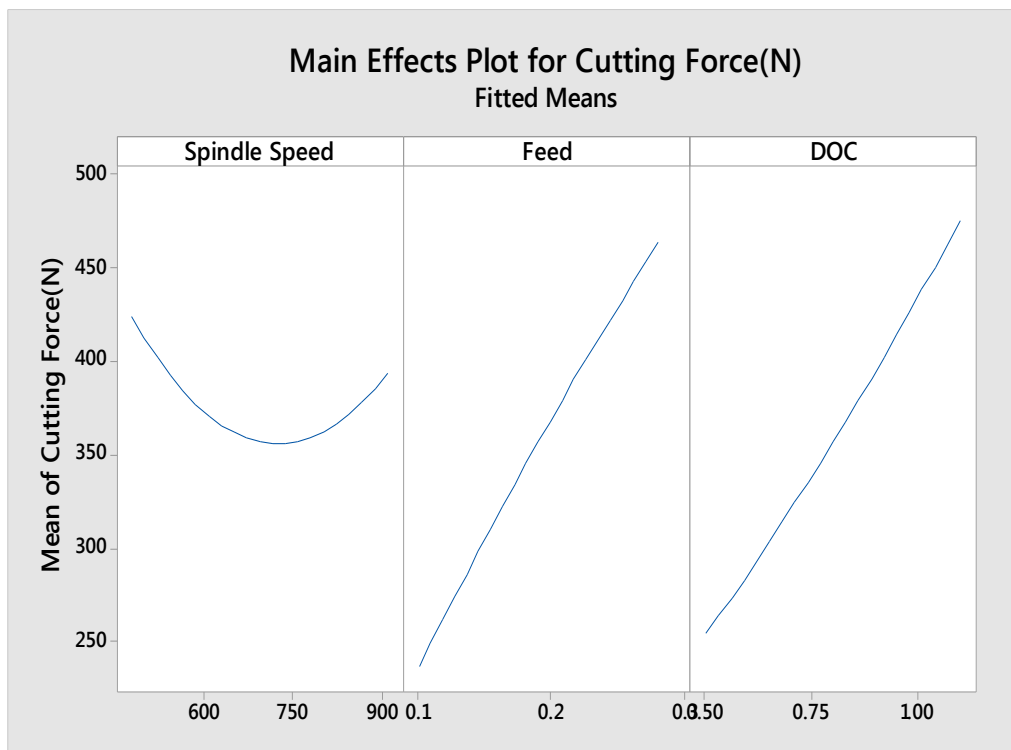


Fig. 5.1 Main Effects Plot for Cutting Force

From Fig. 5.1. it can be seen that as the spindle speed increases from 480 to 700 rpm, there is a decrease in the cutting force from 424 to 357 N which can be attributed to the fact that as the speed increases, temperature increases and the material gets soften and hence the cutting force requirement decreases.

But as the speed increased from 700 to 910 rpm, there is an increase in the cutting force requirement from 357 to 394 N which may be due to wear of the tool because as the machining continues, sharp cutting edge of the tool is lost which results in an increase in the cutting force requirement.

As the feed increases from 0.1 to 0.28 mm/rev, cutting force increases significantly from 250 to 492 N. This is due to the fact that as the feed rate increases, the friction between the tool and the work increases which ultimately results in an increase in the cutting force.

As the depth of cut increases from 0.5 to 1.1 mm, the cutting force increases linearly from 277 to 497 N. This increase is justified by the fact that as the depth of cut increases, it results in an increase in the contact area between the tool and the work which results in an increase in the cutting force.

5.1.2 Direct Effect of Spindle Speed, Feed and Depth of Cut on Feed Force

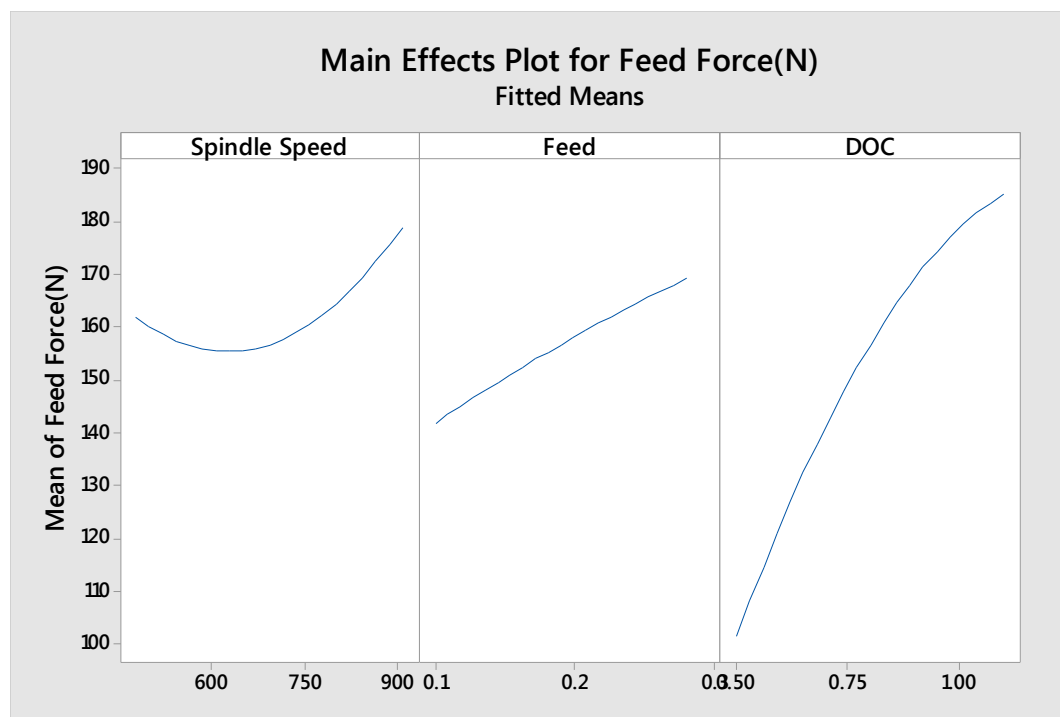


Fig. 5.2 Main Effects Plot for Feed Force

From Fig. 5.2. it can be seen that as the spindle speed increases from 480 to 700 rpm, there is a very slight decrease in feed force from 154 to 148 N and as the speed increases from 700 to 910 rpm, the feed force increases from 148 to 171 N which may be attributed to the fact that as feed velocity, $V_f = fN$ and since f is constant so as N increases, V_f increases and hence the friction between the tool and the work increases and hence feed force increases.

As the feed increases from 0.1 to 0.28 mm/rev, there is an increase in the feed force from 142 to 169 N which may be attributed to the reason stated above.

As the depth of cut increases from 0.5 to 1.1 mm, there is a continuous and very significant increase in the feed force from 100 to 191 N, which may be attributed to the fact that as depth of cut increases, the contact area between the tool and work increases, which results in an increase in the feed force.

5.1.3 Direct Effect of Spindle Speed, Feed and Depth of Cut on Thrust Force

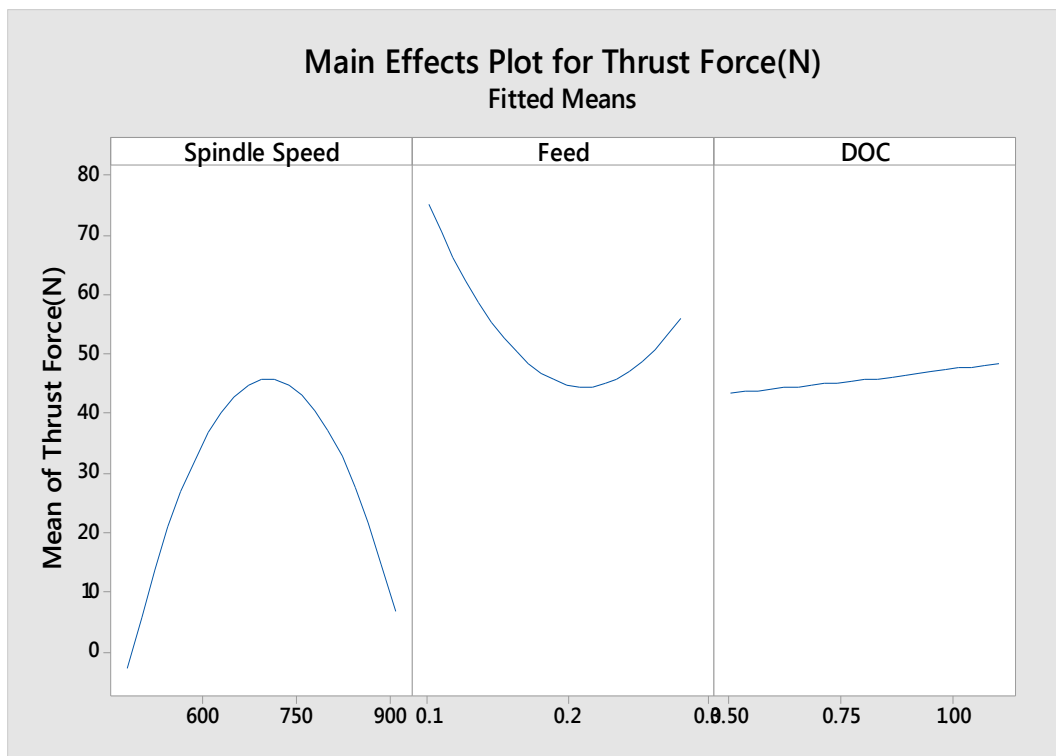


Fig. 5.3 Main Effects Plot for Thrust Force

From Fig. 5.3., it can be seen that as the spindle speed increases from 480 to 700 rpm, there is an increase in the thrust force from 0 to 45 N and as spindle speed increases from 700 to 910 rpm, the thrust force shows a decrease from 45 to 5 N, because when the spindle speed is less, the holding force requirements are more and vice versa. Here it can be seen that the maximum thrust force requirements are at around 700 rpm.

As the feed increases from 0.1 to 0.19 mm/rev, it can be seen that the thrust force requirements decreases 74 to 43 N and as it increases from 0.19 to 0.28, there is an increase in the thrust force from 43 to 55 N.

The depth of cut has almost a negligible effect on the thrust force.

5.1.4 Direct Effect of Spindle Speed, Feed and Depth of Cut on Surface Roughness

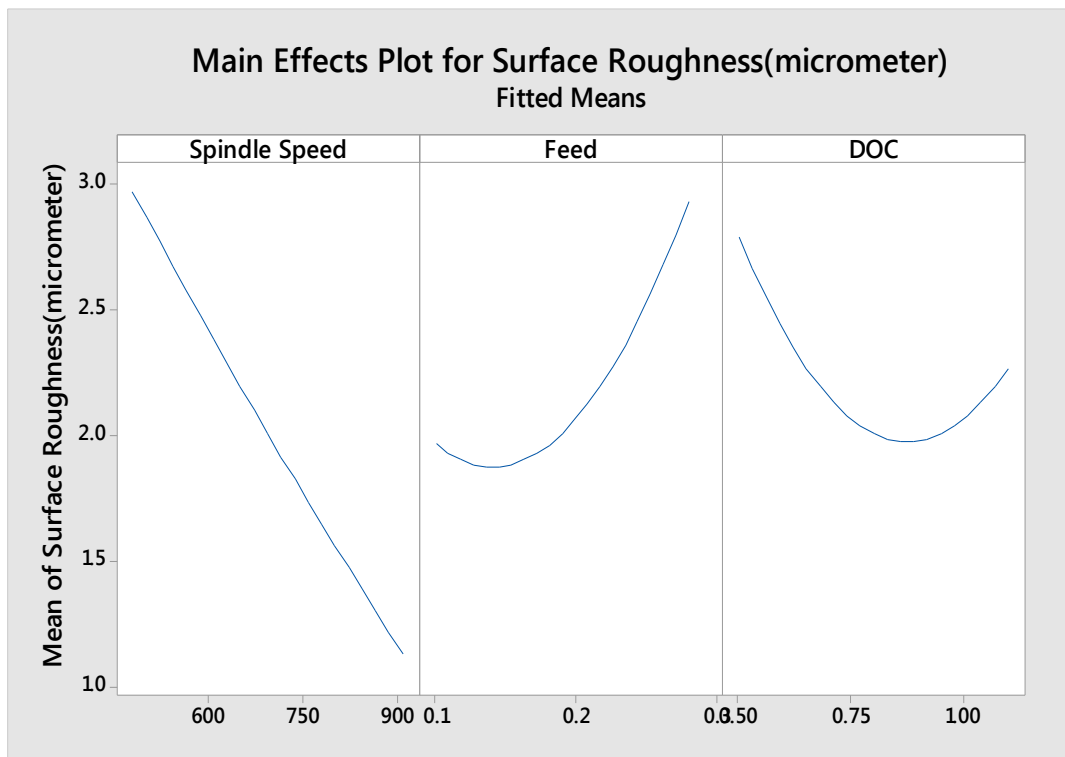


Fig. 5.4 Main Effects Plot for Surface Roughness

From Fig. 5.4., it can be seen that as the spindle speed increases from 480 to 910 rpm, there is a continuous decrease in the values of surface roughness from 3 to 1.1 μm which may be attributed to the fact that as spindle speed increases, built-up-edge formation decreases. Although as speed increases, temperature increases which is a favourable condition for built-up-edge formation but due to such a high speed, it does not get the time to form the bond and hence no built-up-edge formation and therefore we get good surface finish.

As the feed increases from 0.1 to 0.28 mm/rev, surface roughness increases from 2 to 2.9 μm because mathematically also $R_a \propto f^2$ as the tool nose radius is kept constant. Higher feed means higher BUE and hence poor surface finish.

As the depth of cut increases from 0.5 to 0.8 mm, there is a decrease in the value of surface roughness from 2.8 to 2 μm but as it increases from 0.8 to 1.1 mm, surface roughness shows an increase from 2 to 2.25 μm . This may be due to the fact that as depth of cut is increased from 0.8 to 1.1 mm, it results in higher BUE formation and hence poor surface finish.

5.2. Interaction Effect of Input Parameters on the Responses

In a case when the effect of one factor depends on the level of the other factor, we can use an interaction plot to visualize possible interactions.

5.2.1. Interaction Plot for Cutting Force

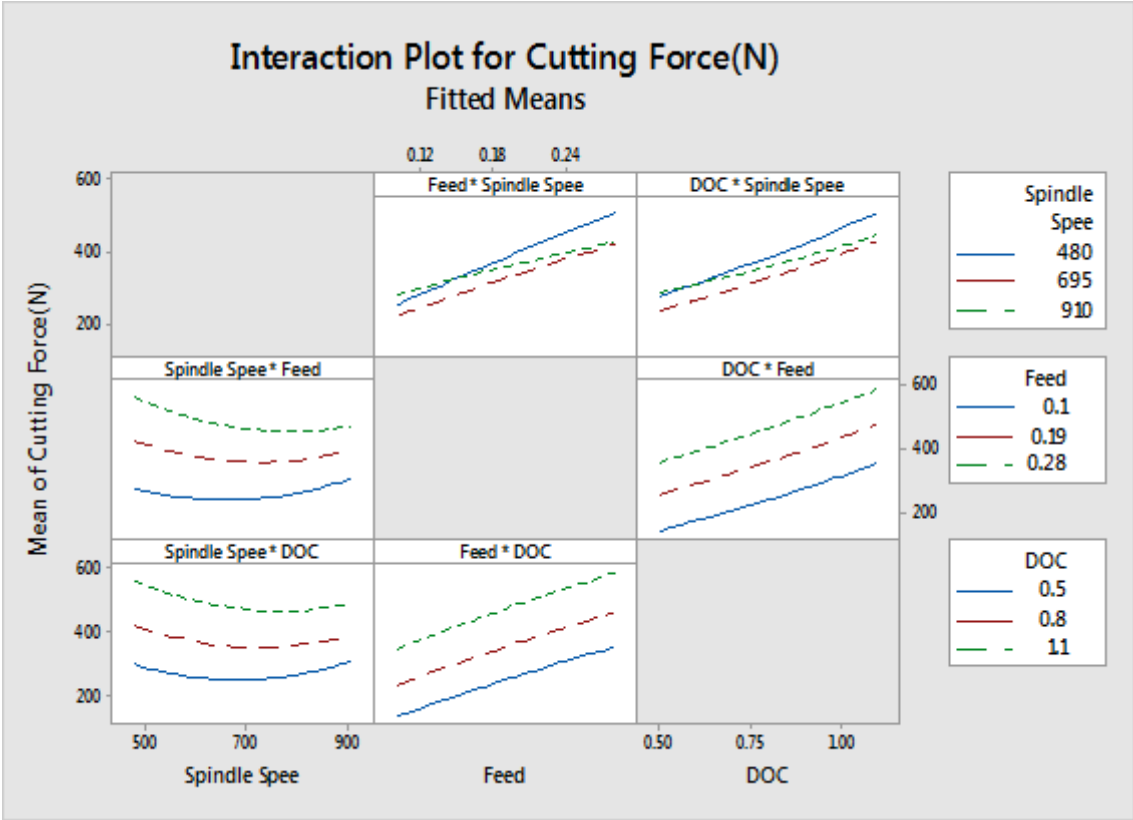


Fig. 5.5 Interaction Plot for Cutting Force

In interaction plots, we have to look for the lines which are not parallel. If the lines are parallel, then it is an indication of no interaction.

In Fig. 5.5, we can see that for any value of the spindle speed, as the depth of cut increases, cutting force increases. But the lines for all levels of depth of cut are parallel which implies that depth of cut has no interaction effect with spindle speed. Also, for any value of the spindle speed, as the feed increases, cutting force increases. But here also, lines for all levels of feed are parallel which implies that feed has no interaction effect with spindle speed.

The figure also says that spindle speed levels have an interactive effect on the feed as we can see that the lines are intersecting. Here we can see that for any feed value, the change in the level of spindle speed does not have much influence on the cutting force requirements. The depth of cut levels does not show any interactive effect with the feed. We can see that for any value of the feed, as the depth of cut increases, cutting force requirement increases.

The figure also reveals that spindle speed levels have an interactive effect on the depth of cut as the lines are intersecting. Here we can see that for any depth of cut value, the change in the level of spindle speed does not have much influence on the cutting force requirements. The feed level does not have any interactive effect on the depth of cut as the lines are parallel. Here, at any level of depth of cut, the cutting force requirement increases as the feed increases.

5.2.2. Interaction Plot for Feed Force

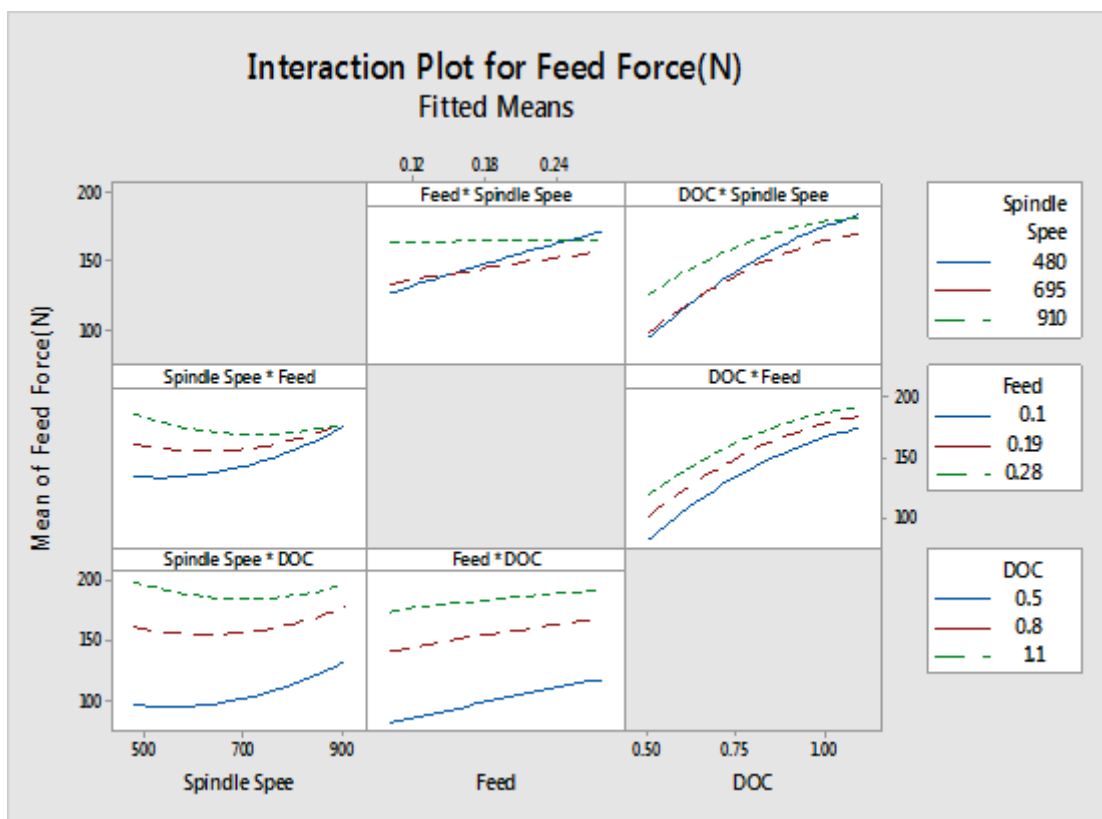


Fig. 5.6 Interaction Plot for Feed Force

From Fig. 5.6., it can be seen that the levels of depth of cut does not have any interaction with the effect of spindle speed as the lines are parallel. We can see that for any level of spindle speed, the feed force requirement increases as the depth of cut increases. We can see that the feed levels have an interactive effect on the spindle speed as the spindle speed approaches to higher value. At lower spindle speeds, the feed levels has no interaction with the effect of spindle speed but the lines approaches to intersection as spindle speed is increased.

The spindle speed levels have a significant interaction effect with the effects of feed on feed force as the lines are intersecting with each other. The level of depth of cut does not have any interactive effect on the feed effect on feed force as the lines are parallel. Here we can see that, for any level of feed, as the depth of cut increases, cutting force requirements increases.

The figure also reveals that the levels of spindle speed have a significant interaction on the effect of depth of cut on feed force as the lines are intersecting. But the feed levels do not show any interaction effect on the effect of depth of cut on feed force as the lines are parallel.

5.2.3. Interaction Plot for Thrust Force

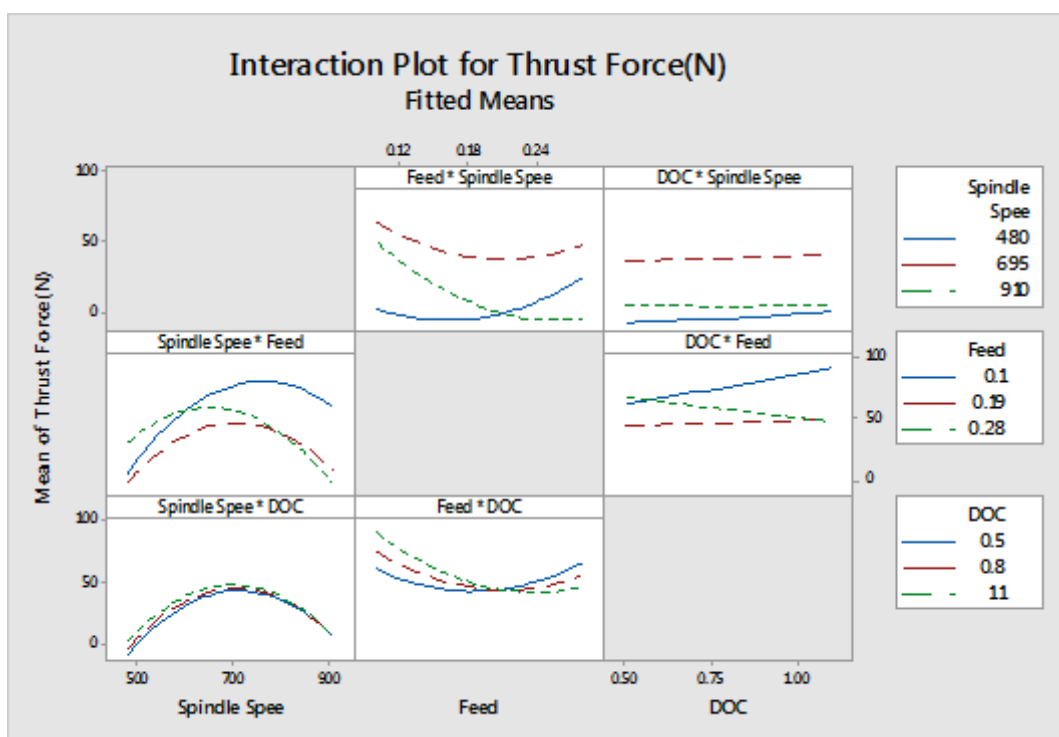


Fig. 5.7 Interaction Plot for Thrust Force

From Fig. 5.7., we can see that the depth of cut has significant interaction with the effect of spindle speed on thrust force as the lines are intersecting with each other. We can see that as the spindle speed goes from 700 to 910 rpm, the level of depth of cut has no meaning as almost all the lines are coinciding with each other. The feed levels also have an interaction effect on the spindle speed effect on thrust force as the lines are intersecting with each other. We can see that as the spindle speed increases, firstly the thrust force increases and then decreases for any feed levels but the effect is more pronounced for the -1 level of feed.

The spindle speed levels have a significant interaction effect with the effects of feed on thrust force as the lines are intersecting with each other. The levels of depth of cut also have interactive effect with the feed effect on thrust force as the lines are not parallel.

The figure also reveals that the levels of spindle speed do not have interaction on the effect of depth of cut on thrust force as the lines are parallel. But the feed levels show slight interaction effect on the effect of depth of cut on thrust force as the lines are intersecting. We can see that as the depth of cut does not have a much effect on thrust force but at the -1 level of feed, the depth of cut has a significant effect on thrust force.

5.2.4. Interaction Plot for Surface Roughness

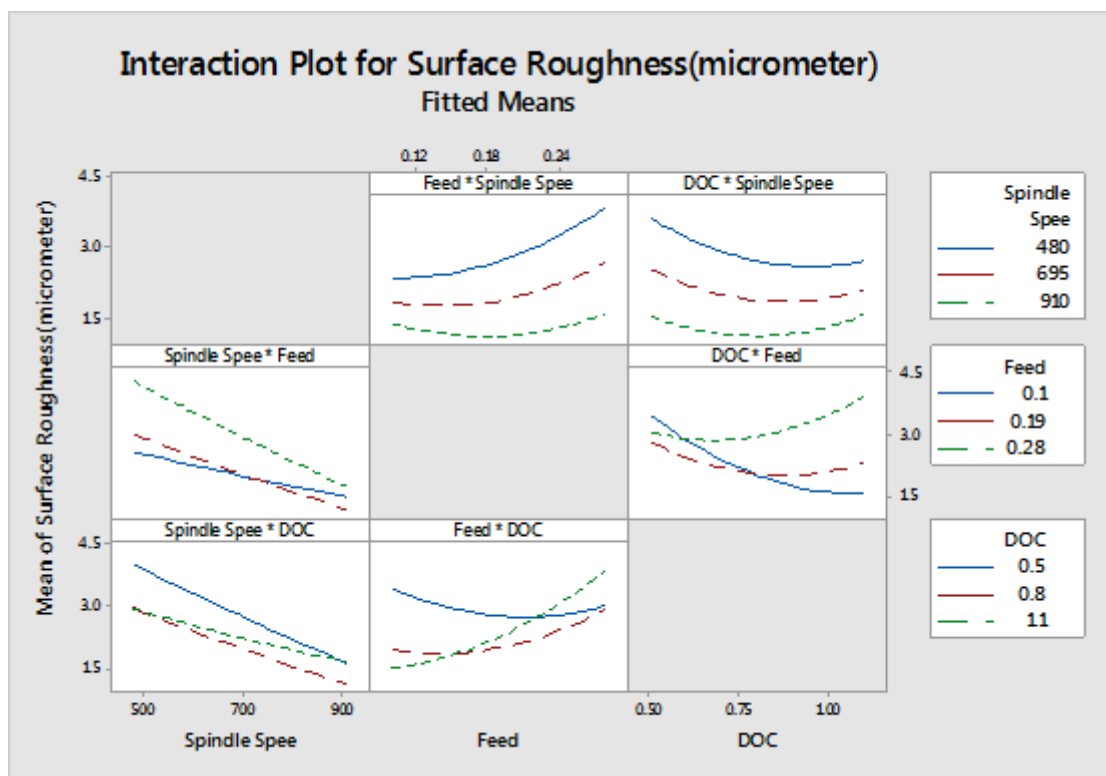


Fig. 5.8 Interaction Plot for Surface Roughness

From Fig. 5.8., we can see that the depth of cut has interaction with the effect of spindle speed on surface roughness as the lines are intersecting with each other but the convergence of lines is at extreme points i.e., when the spindle level is 480 rpm, then the depth of cut at +1 and 0 level are showing an interaction and when it is set at 910 rpm, then the depth of cut at +1 and -1 level are showing an interaction. The feed levels also have an interaction effect on the spindle speed effect on surface roughness as the lines are intersecting with each other but here only the feed levels of -1 and zero is showing an interaction when the spindle speed is set at 700 rpm.

The spindle speed levels do not have any interaction effect with the effects of feed on surface roughness as the lines are parallel. The levels of depth of cut have interactive effect with the feed effect on surface roughness as the lines are not parallel.

The figure also reveals that the levels of spindle speed do not have interaction on the effect of depth of cut on surface roughness as the lines are parallel. But the feed levels show interaction effect on the effect of depth of cut on surface roughness as the lines are intersecting.

5.3. Contour Plots

Contour plots show how response variables relate to two continuous variables while holding the rest of the variables in a model at certain settings. In a contour plot, the fitted response model is viewed as a two-dimensional surface where all points that have the same fitted value are connected to produce contour lines of constants. Contour plots are useful for establishing operating conditions that produce desirable response values.

5.3.1. Contour Plots for Cutting Force

From Fig. 5.9., we can see that the lowest values of cutting force (<200 N) if we keep the feed levels between 0.10 and 0.15 mm/rev. The depth of cut should be kept between 0.1 to 0.7 mm. For spindle speed, if it set at 480 rpm, then the feed and depth of cut should be kept at the lowest level, if kept at 700 rpm, then feed should be kept at 0.15 mm/rev and depth of cut at 0.6 mm and if kept at 910 rpm, then again the feed and depth of cut should be kept at the lowest level.

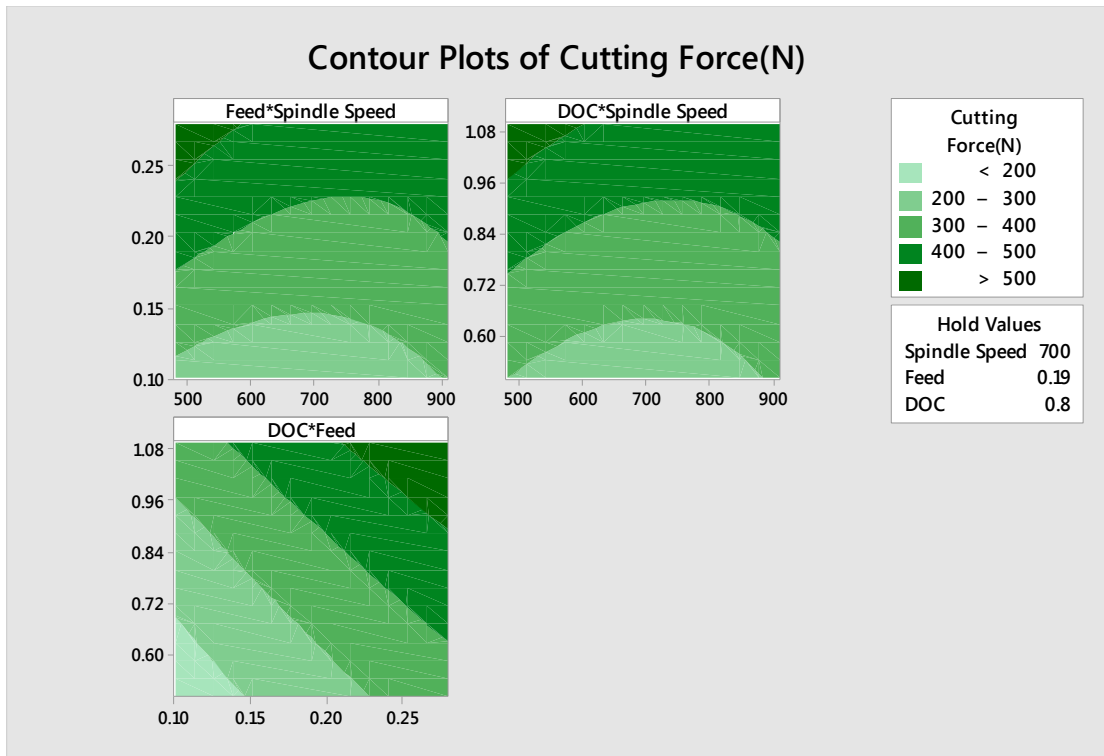


Fig. 5.9 Contour Plots for Cutting Force

5.3.2. Contour Plots for Feed Force

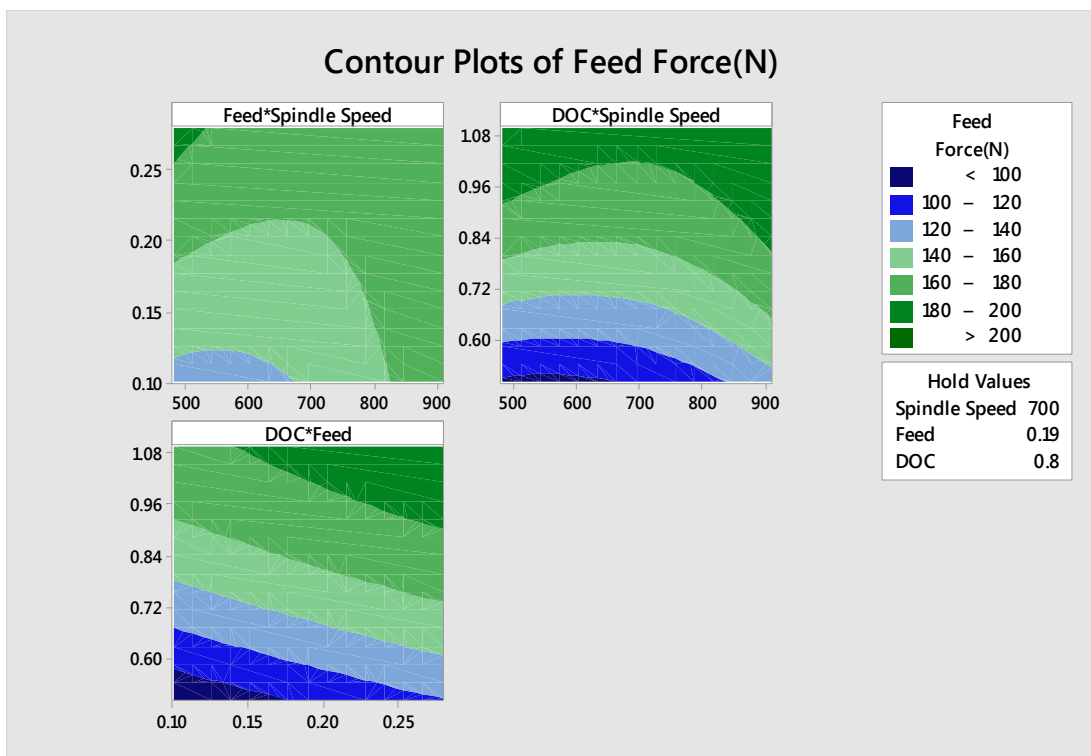


Fig. 5.10 Contour Plots for Feed Force

From Fig. 5.10., we can see that the lowest value of feed force (<100 N) occurs when feed is kept between 0.10 and 0.19 mm/rev, depth of cut between 0.1 to 0.5 mm and the spindle speed to be kept at the lowest level.

5.3.3. Contour Plots for Thrust Force

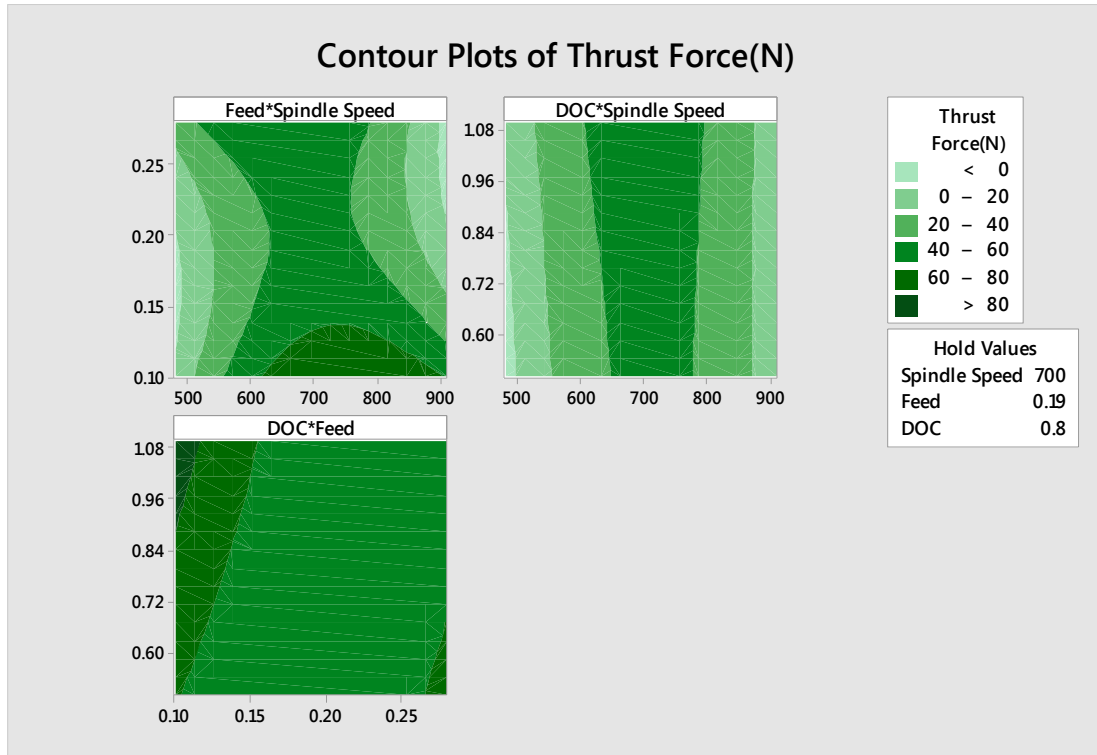


Fig. 5.11 Contour Plots for Thrust Force

From Fig. 5.11., we can see that the lowest values of thrust force occurs when the feed levels are set at 0.10 to 0.20 mm/rev, depth of cut to be set between 0.1 to 0.84 mm and the spindle speed to be kept at the lowest level, i.e., at 480 rpm.

5.3.4. Contour Plots for Surface Roughness

From fig. 5.12., we can see that the lowest values of surface roughness occurs at the highest spindle speed, i.e., at 910 rpm, the feed levels should be kept low and the depth of cut should be kept at almost 0.8 mm.

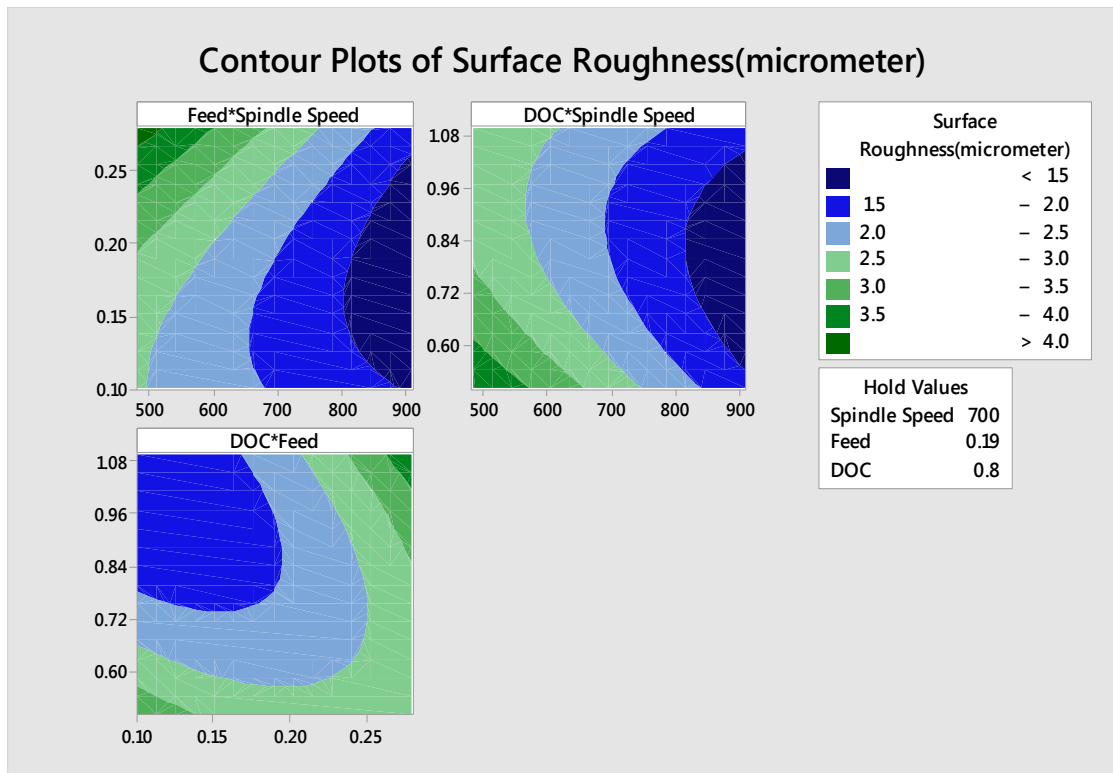


Fig. 5.12 Contour Plots for Surface Roughness

Chapter 6

OPTIMIZATION OF MACHINING PARAMETERS

6.1. Optimization Using Response Optimizer Technique

Response optimization technique is used to help in identifying the combination of input variable settings that jointly optimize a single response or a set of responses. Joint optimization must satisfy the requirements for all the responses in the set, which is measured by the composite desirability [26].

Firstly, we must fit a model before using response optimizer. In the present case, we want optimization of multiple responses, therefore we fitted model for each response separately.

In Minitab, we can use the Response Optimizer to search for optimal responses on the basis of requirements that we define for each response.

- Minimize the response
- Target the response
- Maximize the response

6.1.1 Individual desirability and composite desirability

Individual and composite desirability assess how well a combination of variables satisfies the goals that we have defined for the responses. Individual desirability (d) evaluates how the settings optimize a single response whereas composite desirability (D) evaluates how the input settings optimizes a set of responses overall.

Desirability has a range of zero to one. One is a representation of the ideal case; zero is an indication that one or more responses are outside their acceptable limits.

Minitab's Response Optimizer calculates individual desirability using a desirability function (also known as utility transfer function). We have to select a weight (from 0.1 to 10) to determine how much we are emphasizing on obtaining the target value. The weight determines how the desirability is distributed on the interval between the upper (or lower) bound and the target.

It determines the shape of the desirability function that is used for translating the response scale to the zero to one desirability scale in order to determine the individual desirability of a response. We can consider a weight of one as a neutral setting.

Composite desirability can be defined as the weighted geometric mean of the individual desirabilities for the responses. Minitab determines the optimal settings for the variables by maximizing the composite desirability.

6.1.2. Optimization Plot

An optimization plot is a tool of Minitab's Response Optimizer which shows how different experimental settings affect the predicted responses for factorial, response surface and mixture designs [26].

Minitab calculates an optimal solution and draws a plot. The optimal solution serves as the starting point for the plot. This optimization plot allows us to interactively change the input variable settings to perform sensitivity analysis and possibly improve upon the initial solution. For factorial and response surface designs, we can adjust the factor levels. We might want to change these settings of variables on the optimization plot for many reasons, including:

- To search for those variable settings which can provide a high composite desirability.
- To explore the sensitivity of response variables as the design variables change.
- To calculate the predicted responses for a variable setting of interest.
- To explore variable settings in the neighbourhood of a local solution.

6.1.3. Steps in response optimization technique

1. Decide whether we have to minimize, maximize or target the response variables.
2. Next, we have to set the importance for each response. If every response is equally important, then set the importance level for each response to be one.
3. If our goal is minimization, the lower values will be disabled and the target becomes the lowermost values and the upper values will be set at the uppermost values of the responses.

4. The last is to set a weight for each response. A weight of one implies that we want our response to be between the set target value and the upper value of the response.

Table 6.1 Response Optimization

Response Parameters	Importance	Goal	Lower	Target	Upper	Weight
Cutting Force	1	Minimum		215.82	598.41	1
Feed Force	1	Minimum		98.10	215.82	1
Thrust Force	1	Minimum		0.00	88.29	1
Surface Roughness	1	Minimum		1.27	4.47	1
Solution						
Spindle Speed (rpm)	Feed(mm/rev)	Depth of Cut (mm)	CF(N)	FF(N)	TF(N)	R _a (μm)
910	0.2	0.5	320.53	134.35	5.43	1.57
Solution						
Composite Desirability	0.808100					
Multiple Response Prediction						
Variable setting						
Spindle Speed	910					
Feed	0.2					
Depth of Cut	0.5					

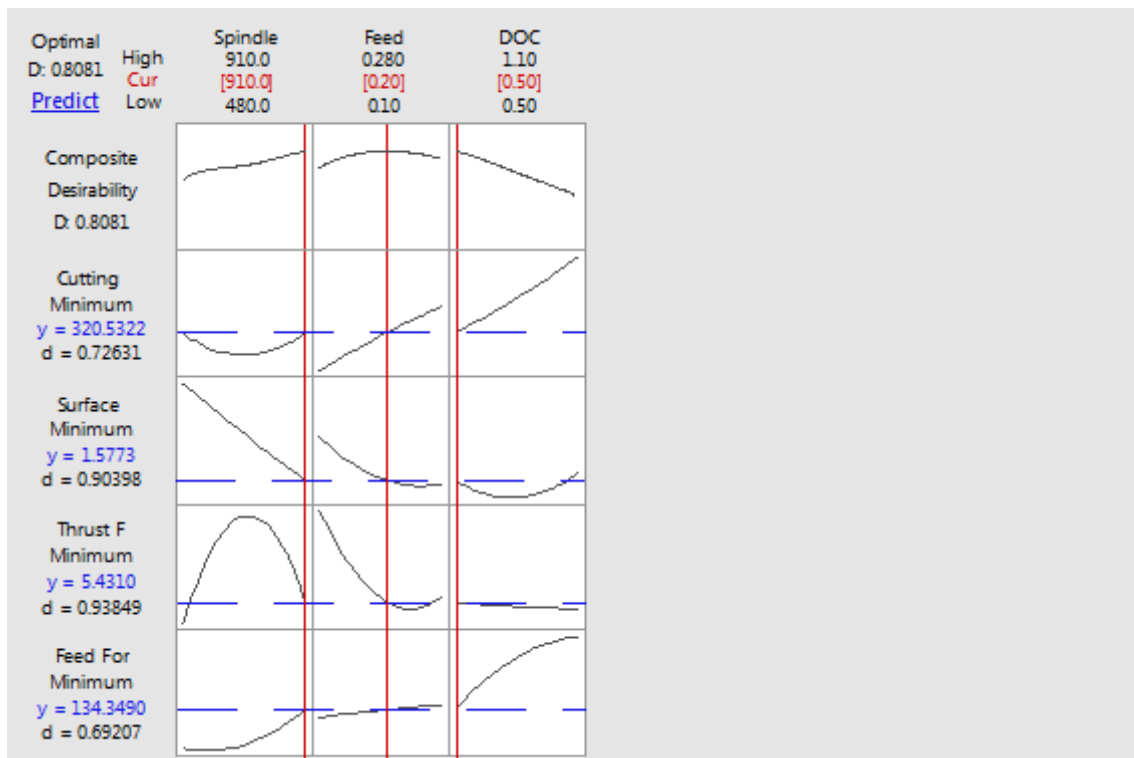


Fig. 6.1 Optimization Plot

From fig. 6.1., it can be seen that the composite desirability is 0.8081. Individual desirabilities for cutting force, feed force, thrust force and surface roughness are 0.72631, 0.69207, 0.93849 and 0.90398 respectively. This implies that the setting of spindle speed at 910 rpm, feed at 0.2 mm/rev and depth of cut at 0.5 mm is the most suited for the minimization of thrust force followed by surface roughness, cutting force and lastly feed force.

6.2. Optimization using Genetic Algorithm

Optimization using Genetic Algorithm (GA) is performed using Matlab’s Global Optimization Toolbox. Global Optimization Toolbox provides methods that search for global solutions to problems that contain multiple maxima or minima. It includes genetic algorithm, global search, multistart, pattern search and simulated annealing solvers [27].

6.2.1 Multiobjective optimization

We might need formulating problems which have more than one objective, since a single objective with several constraints may not represent the problem adequately. Multiobjective optimization is concerned with the minimization of a vector of objectives which can be subjected to a number of constraints or bounds. Multiobjective optimization is concerned with the generation and selection of noninferior solution points. Non inferior solution points can be defined as the one in which an improvement in one objective requires a degradation in other objective.

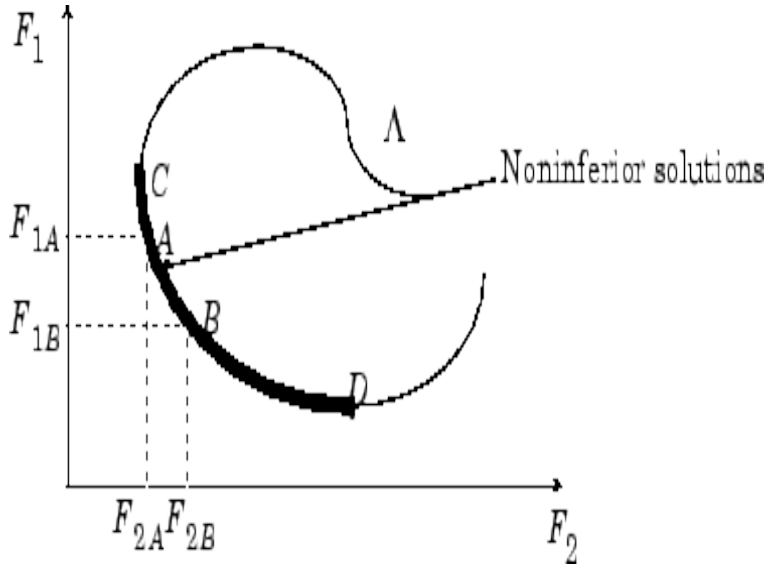


Fig. 6.2 Set of Noninferior Solutions

Non inferior solutions are also called Pareto Optima. A general goal in multiobjective optimization is constructing the Pareto Optima.

6.2.2 Genetic Algorithm Options

There are two ways in which we can use the multiobjective function; one is using the Genetic Algorithm Tool and the other is calling the function gamultiobj at the command line. We have used Genetic Algorithm Tool in the present case and it launches as we write optimtool ('gamultiobj') at the command line.

6.2.3. Steps in optimization using Genetic Algorithm

1. Formulation of objective function, which is known as fitness function in case of Genetic Algorithm.
2. Formulation of constraint functions.
3. To write an M-file in Matlab's Editor Window.
4. To open the GA tool by writing optimtool ('gamultiobj') at the command line.
5. Set the option values to default.
6. Start the optimization process and plot the results.
7. Analysing the GA results.

6.2.4. Formulation of objective function

The objective function, known as fitness function in GA is minimization of cutting force, feed force, thrust force and surface roughness. These responses are related to spindle speed, feed and depth of cut by response surface methodology, and are given by the developed regression models as follow [3]:

Objective Function

$$\text{Min CF (N)} = 87 - 1.08 (N) + 2513 (f) + 408 (d) + 0.001125 (N^2) - 807 (f^2) + 91 (d^2) - 1.57 (Nf) - 0.316 (Nd) + 182 (fd)$$

$$\text{Min FF (N)} = -170 - 0.124 (N) + 810 (f) + 521 (d) + 0.000296 (N^2) - 151 (f^2) - 150 (d^2) - 0.656 (Nf) - 0.155 (Nd) - 182 (fd)$$

$$\text{Min TF (N)} = -561 + 1.582 (N) + 108 (f) + 114 (d) - 0.000944 (N^2) + 2473 (f^2) + 5 (d^2) - 1.137 (Nf) - 0.038 (Nd) - 454 (fd)$$

$$\text{Min } R_a (\mu\text{m}) = 14.45 - 0.00532 (N) - 22.2(f) - 17.90 (d) + 0.000001 (N^2) + 54.4 (f^2) + 5.75 (d^2) - 0.01945 (Nf) + 0.00427 (Nd) + 25.56 (fd)$$

Constraint Functions

$$N \geq 480$$

$$N \leq 910$$

$$f \geq 0.10$$

$$f \leq 0.28$$

$$d \geq 0.5$$

$$d \leq 1.1$$

6.2.5 Writing a M-File

All the functions in the Genetic Algorithm Toolbox are MATLAB M-files which consists of MATLAB statements that implements specialized optimization algorithms. For using this toolbox, firstly an M-file has to be written which computes the function to be optimized. The M-file should accept a row vector, whose length is equal to the number of independent variables in the objective function, and return a scalar.

The objective of present study is to minimize all the response parameters, therefore the M-file which computes this function must accept a row vector whose length is 3, which corresponds to the variables x_1 (spindle speed), x_2 (feed), x_3 (depth of cut), and must return a scalar equal to the function value at x . The following steps are to be followed while writing an M-file:

1. In the MATLAB file menu, select New.
2. Select M-file. This opens a new M-file in the editor.
3. In the M-file, write the following:

```
function f = my_multi(x)
```

$$f(1) = 87 - 1.08*x(1) + 2513*x(2) + 408*x(3) + 0.001125*x(1)^2 - 807*x(2)^2 + 91*x(3)^2 - 1.57*x(1)*x(2) - 0.3168*x(1)*x(3) + 182*x(2)*x(3)$$

$$f(2) = 14.45 - 0.00532*x(1) - 22.2*x(2) - 17.90*x(3) + 0.000001*x(1)^2 + 54.4 * x(2)^2 + 5.75* x(3)^2 - 0.01945*x(1)*x(2) + 0.00427*x(1)*x(3) + 25.56*x(2)*x(3)$$

$$f(3) = -561 + 1.582*x(1) + 108*x(2) + 114*x(3) - 0.000944*x(1)^2 + 2473* x(2)^2 + 5* x(3)^2 - 1.137*x(1)*x(2) - 0.038*x(1)*x(3) - 454*x(2)*x(3)$$

$$f(4) = -170 - 0.124*x(1) + 810*x(2) + 521*x(3) + 0.000296*x(1)^2 - 151* x(2)^2 - 150* x(3)^2 - 0.656*x(1)*x(2) - 0.155*x(1)*x(3) - 182*x(2)*x(3)$$

where f(1) is cutting force

f(2) is surface roughness

f(3) is thrust force

f(4) is surface roughness

4. Save this M-file in a directory on the MATLAB path.

6.2.6. Using the Genetic Algorithm

There are two ways of using Genetic Algorithm:

1. Using the GA tool, a graphical interface to the genetic algorithm.
2. Calling the genetic algorithm function, ga at the command line.

Using the GA Toolbox

In the present case, optimization was performed by utilizing the GA tool which enables us to use genetic algorithm without working at the command line. For launching this tool, enter at the command window:

```
optimtool ('gamultiobj')
```

For using this tool, following information is also required:

1. **Fitness function** – The fitness function refers to the objective function which is to be minimized. Enter the fitness function as @my_multi, where my_multi.m is a M-file which will compute the objective function. The @ sign creates a function handle to my_multi.

2. **Number of Variables** – The number of variables refers to the length of input vector to the fitness function, i.e. my_multi.

6.2.7. Setting the various options in Genetic Algorithm

All the options in genetic algorithm were set at their default values which are as follows:

1. Population

Population type: Double Vector

Population size: Use default: 50 for 5 or fewer variables; otherwise 200

Creation Function: Constraint dependent

Initial population: Use default: []

Initial scores: Use default: []

Initial range: Use default: [-10; 10]

2. Fitness scaling

Scaling function: Rank

3. Selection

Selection function: Stochastic uniform

4. Reproduction

Elite count: Use default: 0.05*Population size

Crossover fraction: Use default: 0.8

5. Mutation

Mutation function: Constraint dependent

6. Crossover

Crossover function: Constraint dependent

7. Migration

Direction: Forward

Fraction: Use default: 0.2

Interval: Use default: 20

8. Stopping criteria

Generations: Use default: 100*number of variables

Time limit: Use default: Inf

Fitness limit: Use default: -Inf

Stall generations: Use default: 50

Stall time limit: Use default: Inf

Stall test: average change

Function tolerance: Use default: 1e-6

Constraint tolerance: Use default: 1e-3

9. Plot functions

Plot interval: 1

Check in the plots that we want

6.2.8. Optimized result

The start button was clicked and the results were displayed in the status and results pane.

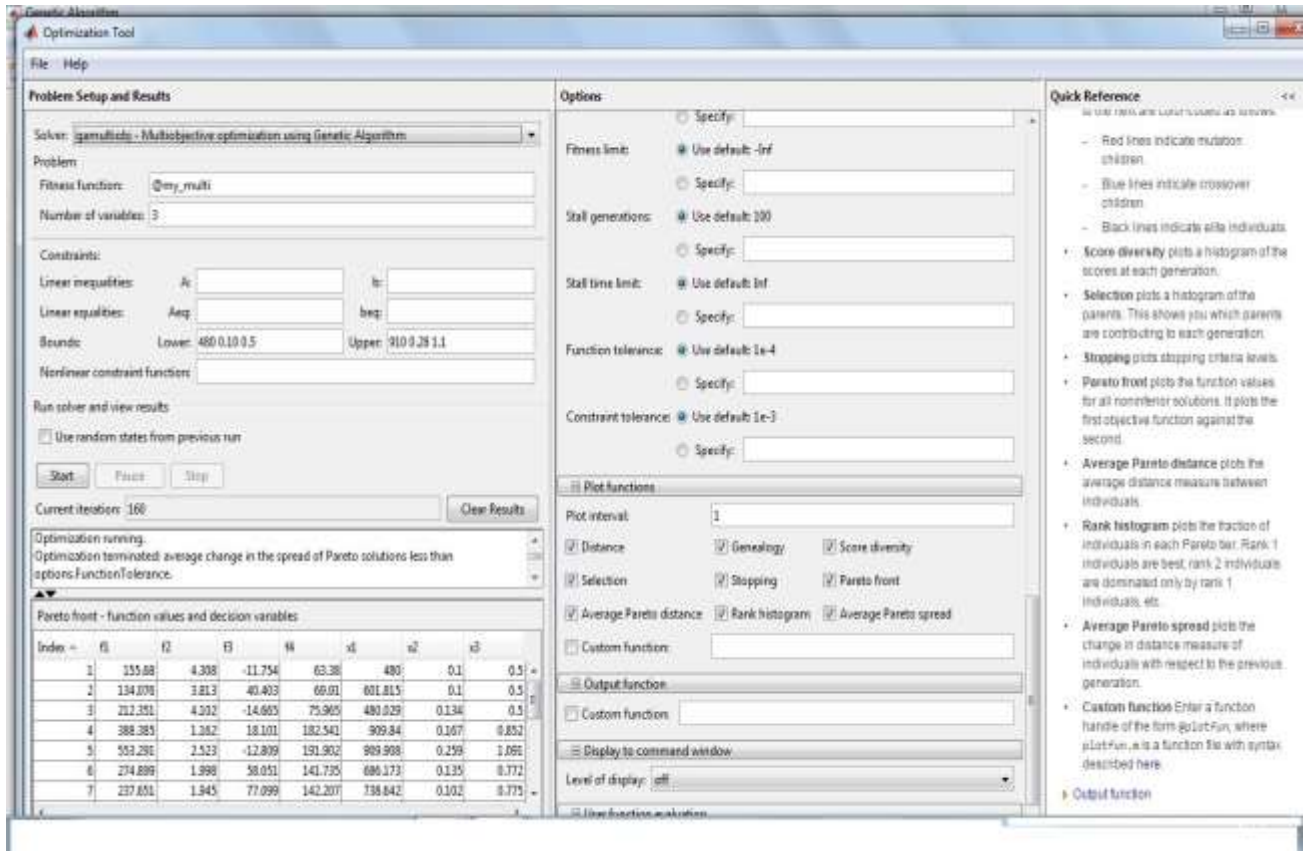


Fig. 6.3. GA optimal result window for 1 to 7 Pareto front

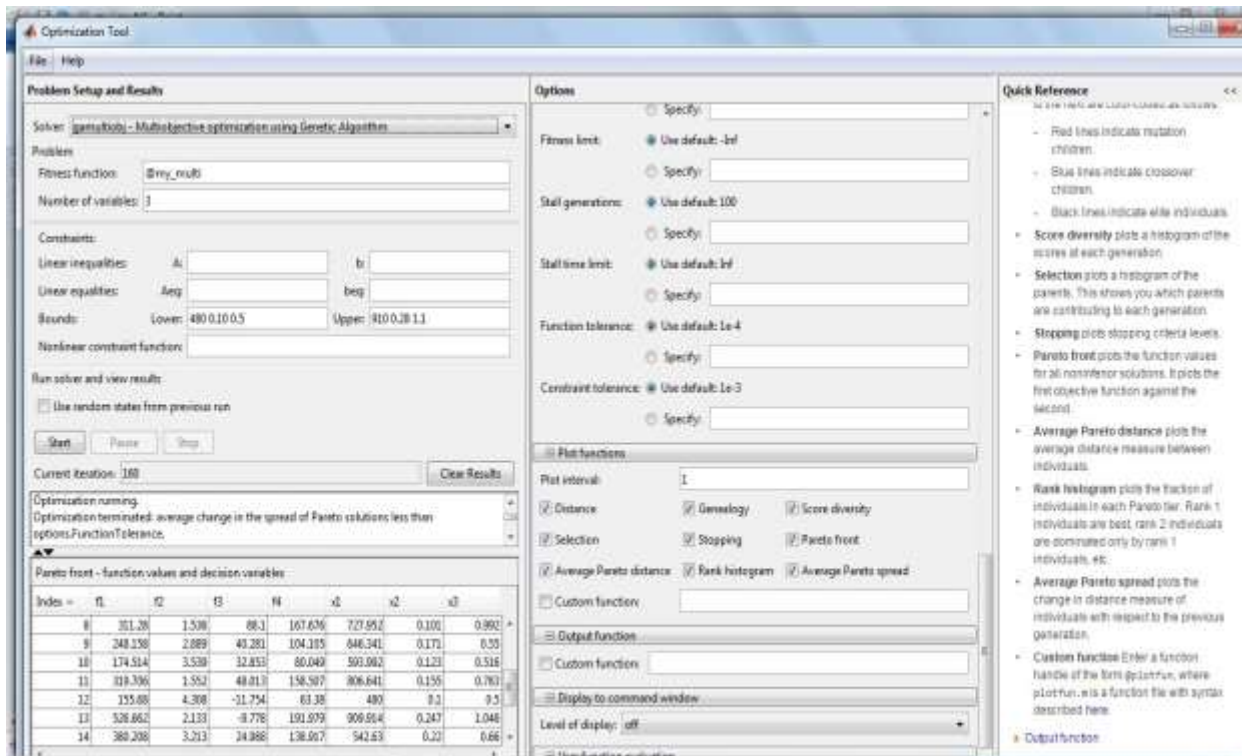


Fig. 6.4. GA optimal result window for 8 to 14 Pareto front

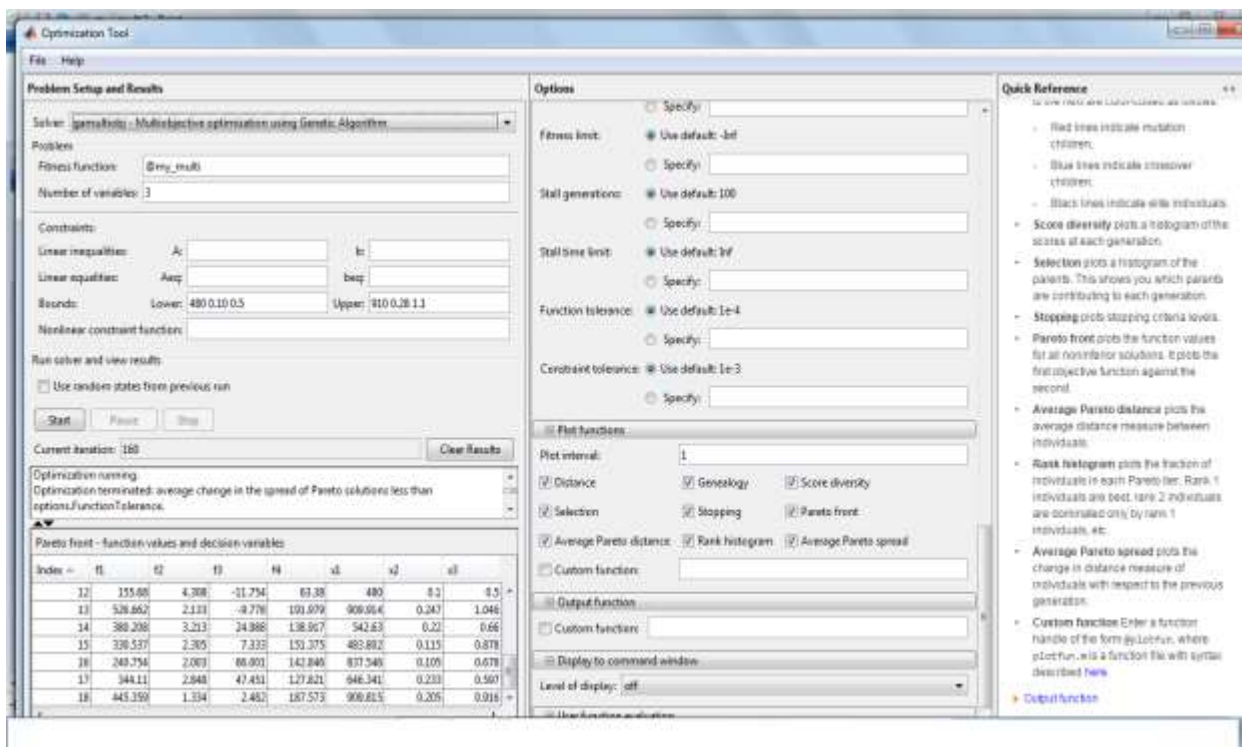


Fig. 6.5 GA optimal result window for 15 to 18 Pareto front

The above figures give us the values of decision variables and the corresponding function values which refer to the Pareto Front. All these eighteen values in the Pareto Front are the optimized results. It depends on the designer which value to choose.

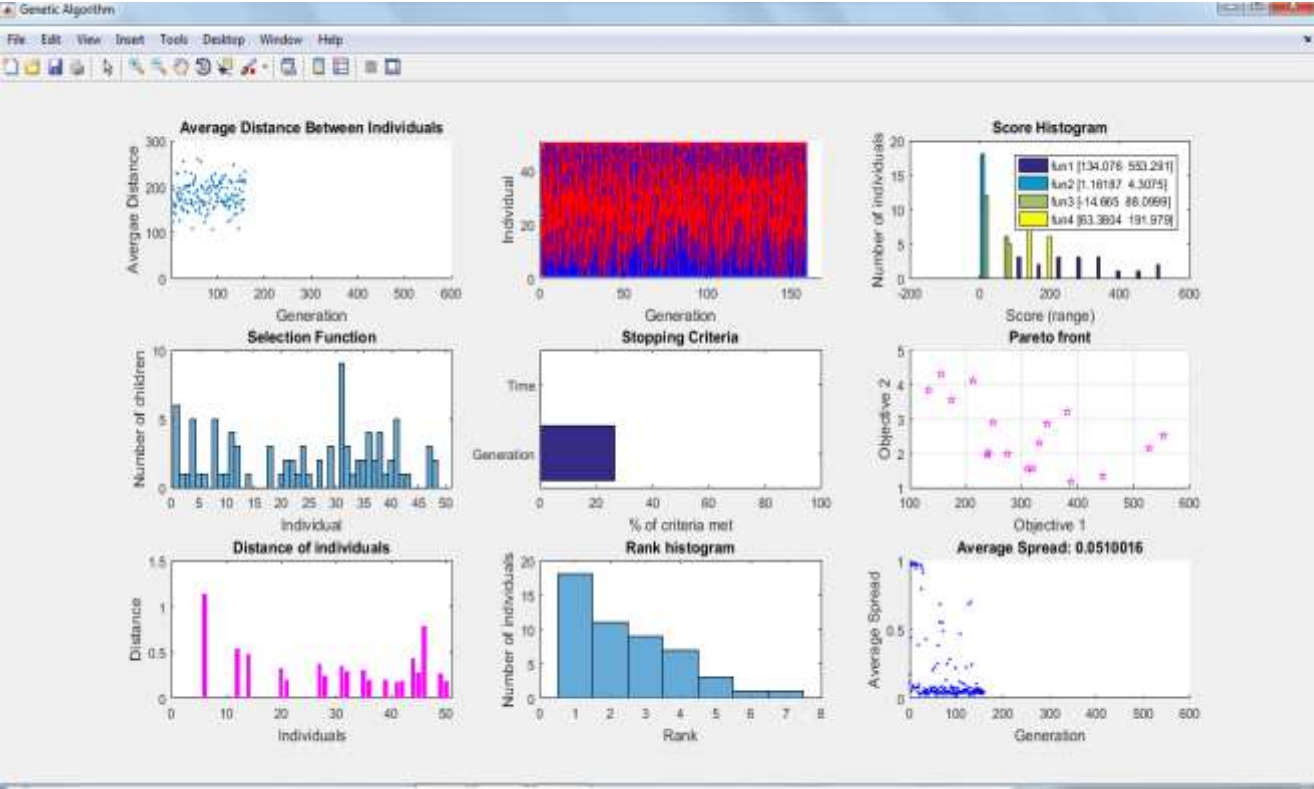


Fig. 6.6 Different plots for the optimized results

Chapter 7

MODELLING USING ARTIFICIAL NEURAL NETWORK

7.1. Basic approach using Artificial Neural Network to mathematically model the present study

Artificial Neural Network has always been an area of interest for the researchers in order to develop mathematical models. This is a cost effective technique in manufacturing and machine tool design approaches. When the regression models are not fitting the data well, then only modelling using ANN is attempted [20].

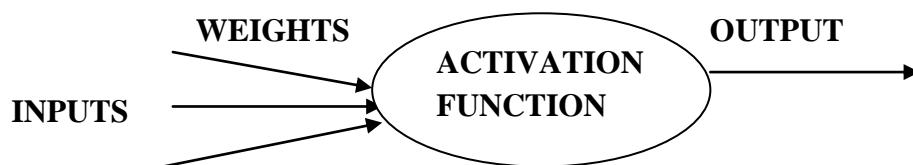
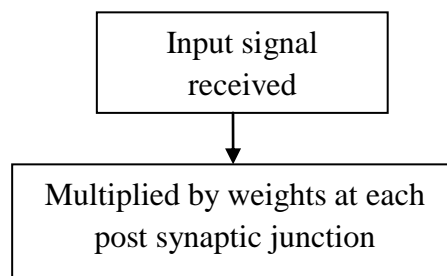


Fig. 7.1 Schematic representation of an Artificial Neural Network

For using the network, inputs, outputs and hidden neurons must be present. The inputs refer to the machining parameters; outputs refer to the response parameters and hidden neurons play an internal role in the network. There has to be a connection amongst input, hidden and the output neurons. As shown in fig. 7.1., the activation function receives a number of inputs (the inputs may be from original data or from the output of other neurons), then processes them for the generation of output for that particular neurone.

For the present modelling, the activation function is a sigmoid function and the output function is a linear function, which is same for all the neurons. For the processing of input signals and the generation of output, the following steps are to be followed:



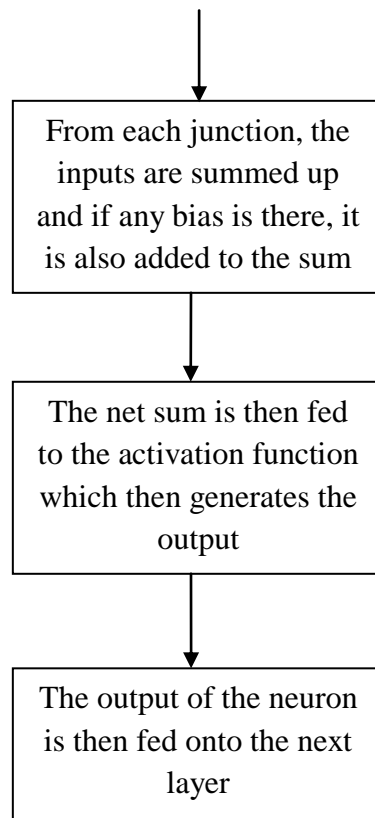


Fig. 7.2. Sequence of steps in signal processing

The back propagation algorithm is used in layered feed forward ANNs. The term layered refers that the neurons are organized in layers; feed forward refers that the neuron signals are fed forward and back propagation implies that the errors are propagated backwards. This algorithm utilizes supervised learning, which means that we provide the algorithm with the inputs and the targets and the algorithm tries to reduce the error between the outputs and targets till ANN learns the training data. The training begins with allocation of random weights, and the goal is to adjust them so that the error will be the minimal difference between the outputs and the targets.

The back propagation algorithm progresses through a number of iterations which are referred as epochs. At each epoch, the training data is submitted to the network and the output and the corresponding error is calculated. This error is utilized for the weights adjustment and this how the process is repeated till the outputs come within a desired level of accuracy.

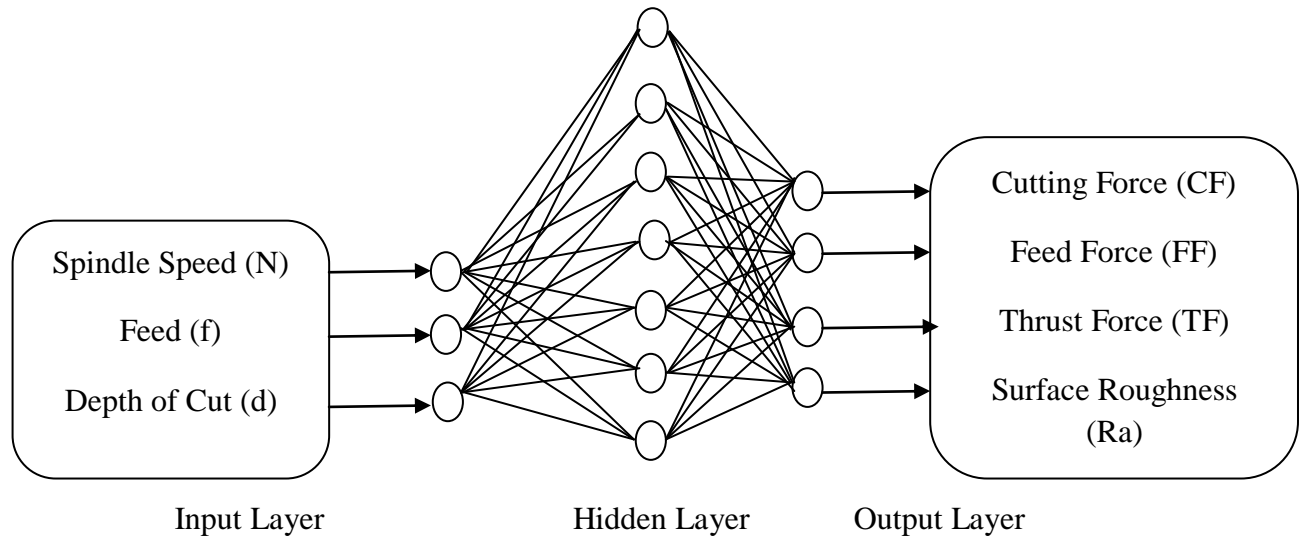


Fig. 7.3. Back propagation Neural Network used for predicting the responses

The network shown in the above figure is used in the present research for mathematical modelling. As stated before, three input parameters, namely spindle speed, feed and depth of cut were considered and their effect on four responses was studied, namely cutting force, feed force, thrust force and surface roughness. Therefore in the present case, three and four neurons were taken for the input and output layer respectively. The input layer is not a neural layer in the true sense of the word; it is mainly used for the introduction of the input parameters. The performance of any neural network is dependent on the number of hidden layers and the number of hidden neurons in them. Therefore, sufficiently large number of trials was conducted before deciding onto the number of hidden layers and hidden neurons.

7.2. Computational work done while training a neural network

Bayesian Regularization (trainbr) was taken as the training algorithm as it was the suggested algorithm if the data sets are small. The data division was done on random basis. Performance of the network was determined by the measure of Mean Square Error (MSE). Lower values of MSE are desired; zero means no error. A lot of networks were trained before deciding onto the optimal number of hidden layers and the number of hidden neurons in them. Firstly, trial was done with the 2 neurons in the hidden layer and then progressively the number of neurons and the number of hidden layers were increased. A large number of hidden neurons may result in overfitting; therefore it is necessary to keep a check on number of hidden neurons.

The performance of some of the network architectures is shown in table 7.1.

Table 7.1 Performance of different network architectures

Sl. no.	Network Architecture	Mean Square Error	Epochs made before attaining the desired goal
1.	3-5-4	0.353	278
2.	3-6-4	0.0696	206
3.	3-7-4	0.00974	115
5.	3-3-4-4	1.05	110
6.	3-4-4-4	0.0193	98
7.	3-5-5-4	0.0290	308
8.	3-4-5-4	0.0351	191
9.	3-4-5-4	0.0183	271

For the present study, the network architecture selected was 3-7-4 (3 neurons in the input layer, 7 neurons in the hidden layer and 4 neurons in the output layer). The selection of this architecture was based on its performance as the mean square error for this network was the lowest amongst all the architectures. The network was trained and simulated to get the outputs and then were compared with the set target values to determine the predictive ability of the ANN model.

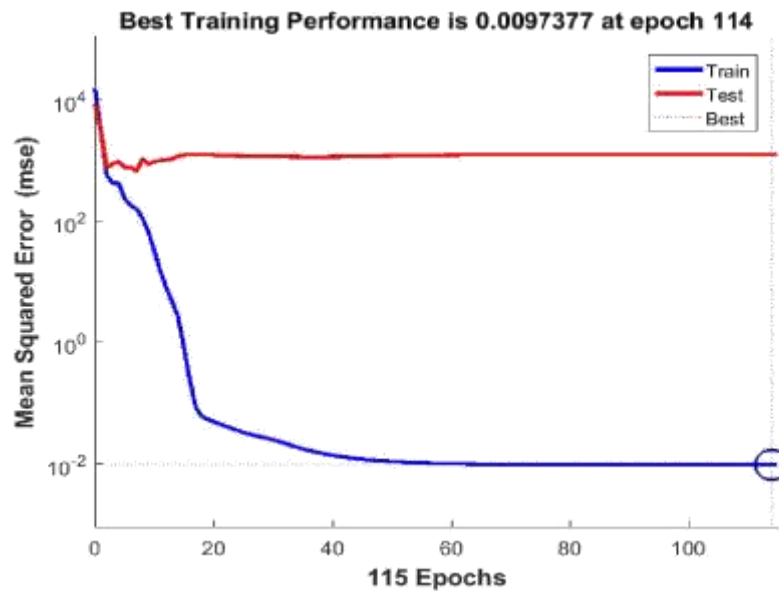


Fig. 7.4 MSE versus number of Epochs

From Fig. 7.4., it can be seen that the best training performance is reached at epoch 114. As the network gets trained, the blue line which is a representation of training error decreases continuously and finally reaches to a minimum. As the training error decreases, it coincides with the best MSE line. The red line which is a representation of testing error is quite high almost 10^3 which may be attributed to the fact that the number of data given for testing the network was low.

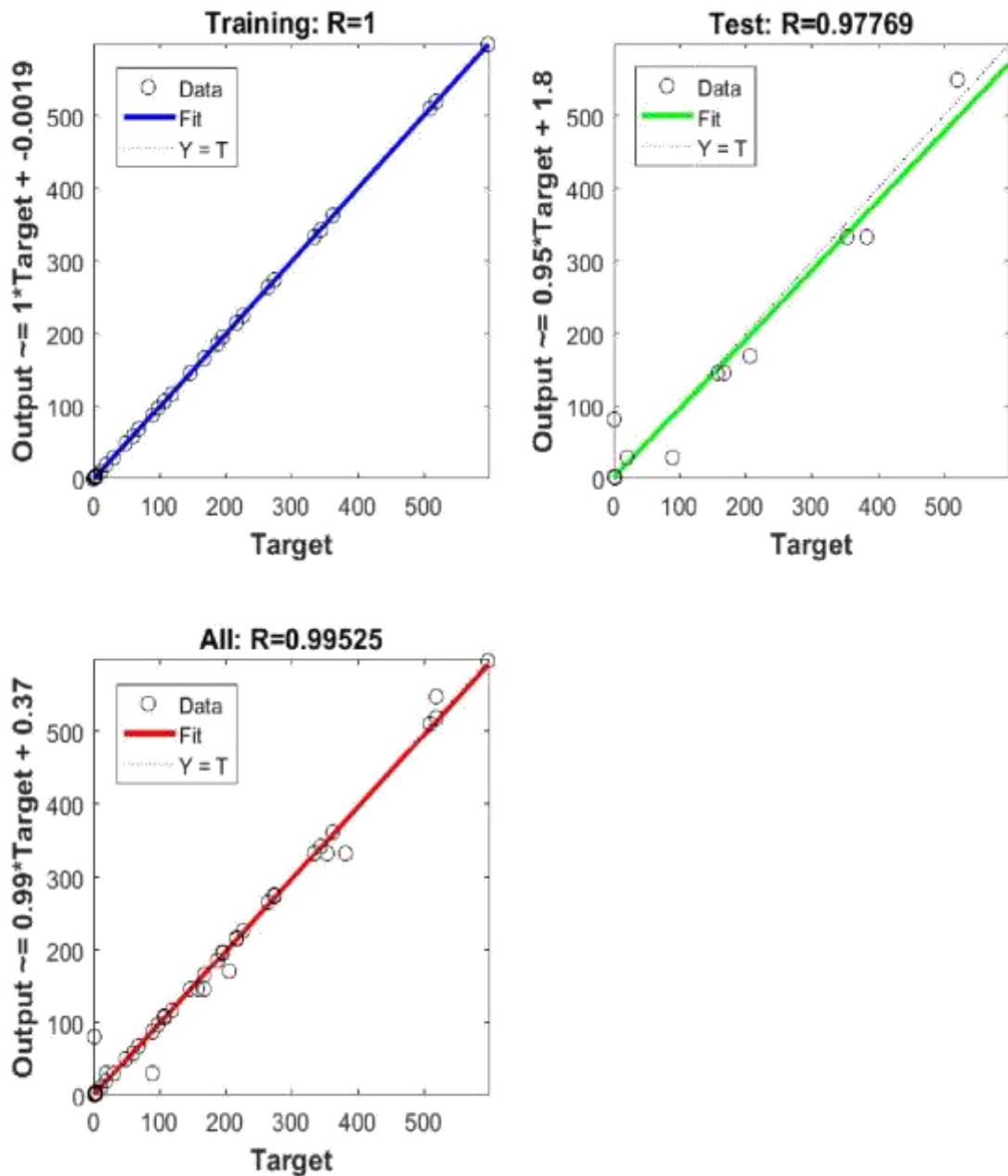


Fig. 7.5 Regression plot for network architecture 3-7-4

The performance of the network can also be judged using the regression plots. R which is known of coefficient of determination, if equals to one represents that a perfect linear relationship exists between the outputs and the targets and if zero, this implies that there is no relationship between the outputs and the targets.

7.3. Results and discussions

7.3.1 Comparison of Experimental, RSM and ANN model results for Cutting Force

Table 7.2 Comparison of Experimental, RSM and ANN model results for Cutting Force

Sl.no.	Experimental Value	RSM Output	% error in RSM prediction	ANN Output	% error in ANN prediction
1	225.63	273.308	-21.13	225.63	-0.00178
2	274.68	311.967	-13.57	274.68	-0.000382
3	274.68	300.685	-9.46	274.67	0.001019
4	333.54	356.43	-6.86	333.53	0.000387
5	519.93	492.453	5.28	519.92	0.000347
6	382.59	356.43	6.83	333.53	12.82
7	510.12	585.557	-14.78	510.12	-0.000451
8	598.41	562.595	5.985	598.41	0.0000823
9	353.16	356.43	-0.925	333.53	5.55
10	362.97	351.19	3.245	362.96	0.000093
11	215.82	140.83	34.74	215.81	0.000668
12	519.93	470.216	9.56	548.69	-5.53
13	598.41	662.33	-10.68	598.40	0.000107
14	343.35	356.53	-3.83	343.34	0.0000597
15	264.87	304.77	-15.06	264.87	-0.000445

Absolute mean % error for RSM prediction = 10.79

Absolute mean % error for ANN prediction = 1.59

7.3.2 Comparison of Experimental, RSM and ANN model results for Feed Force

Table 7.3 Comparison of Experimental, RSM and ANN model results for Feed Force

Sl.no.	Experimental Value	RSM Output	% error in RSM prediction	ANN Output	% error in ANN prediction
1	107.91	134.31	-24.46	107.92	-0.012
2	117.72	133.71	-13.58	117.71	0.00152
3	98.10	96.58	1.54	98.09	0.00645
4	147.15	156.96	-6.67	147.41	0.00641
5	196.20	197.37	-0.59	196.20	-0.00237
6	156.96	156.96	0	147.14	6.25
7	166.77	192.25	-15.27	166.76	0.000449
8	215.82	200.16	7.25	215.82	-0.00097
9	166.77	156.96	5.88	147.14	11.77
10	186.39	174.04	6.62	186.38	0.000687
11	107.91	81.46	24.51	107.90	0.00296
12	206.01	178.75	13.23	170.20	17.38
13	196.20	185.98	5.20	196.91	0.00337
14	107.91	117.89	-9.24	107.92	-0.00993
15	166.77	176.85	-6.044	166.76	0.000809

Absolute mean % error for RSM prediction = 8.99

Absolute mean % error for ANN prediction = 2.36

7.3.3 Comparison of Experimental, RSM and ANN model results for Thrust Force

Table 7.4 Comparison of Experimental, RSM and ANN model results for Thrust Force

Sl.no.	Experimental Value	RSM Output	% error in RSM prediction	ANN Output	% error in ANN prediction
1	0	4.71	-----	0.00735	-----
2	0	7.32	-----	0.00736	-----
3	0	-7.38	-----	0.001058	-----
4	29.43	45.78	-55.55	29.43	-0.015
5	0	7.38	-----	0.0043	-----
6	19.62	45.78	-133.33	29.43	-50.022
7	49.05	46.31	5.58	49.05	-0.00283
8	9.81	2.48	74.71	9.81	-0.0239
9	88.29	45.78	48.14	29.43	66.66
10	88.29	90.96	-3.02	88.27	0.014
11	58.06	62.03	-6.83	58.85	0.00756
12	0	-3.65	-----	81.65	-----
13	19.62	30.28	-54.33	19.62	-0.00234
14	68.67	66.50	3.16	68.66	0.0132
15	68.67	59.37	13.54	68.66	0.00197

Absolute mean % error for RSM prediction = 39.82

Absolute mean % error for ANN prediction = 11.67

7.3.4 Comparison of Experimental, RSM and ANN model results for Surface Roughness

Table 7.5 Comparison of Experimental, RSM and ANN model results for Surface Roughness

Sl.no.	Experimental Value	RSM Output	% error in RSM prediction	ANN Output	% error in ANN prediction
1	2.85	2.55	10.52	3.06	-7.51
2	1.90	1.63	14.21	1.79	5.68
3	3.79	4.02	-6.06	3.78	0.021
4	2.12	1.98	6.60	1.94	8.19
5	1.90	1.66	12.63	2.11	-11.4
6	2.0	1.98	1.00	1.94	2.68
7	3.92	3.85	1.78	3.65	6.79
8	2.69	2.95	-9.66	2.68	0.039
9	1.84	1.98	-7.60	1.94	-5.77
10	1.49	1.54	-3.35	1.6	-8.46
11	3.35	3.43	-2.38	3.00	10.24
12	1.38	1.68	-21.73	2.87	-108.105
13	4.47	4.28	4.25	4.32	3.132
14	3.02	3.01	0.33	3.33	-10.38
15	1.27	1.46	-14.96	1.36	-7.56

Absolute mean % error for RSM prediction = 7.80

Absolute mean % error for ANN prediction = 13.06

Chapter 8

CONCLUSION AND FUTURE SCOPE

8.1. Conclusion

The following conclusion can be drawn from the present research work:

1. A three level box-behnken design can be suitably employed for studying the effects of spindle speed, feed and depth of cut on cutting force, feed force, thrust force and surface roughness.
2. The experimental results indicate that the use of uncoated tool grade was not suitable for studying the aforesaid effects within the selected range of input parameters.
3. Tool wear was not encountered while machining with coated tool grade within the selected range of input parameters.
4. Mathematical models using RSM technique were developed for cutting force, feed force, thrust force and surface roughness and then tested for adequacy using ANOVA.
5. As the spindle speed increases from 480 to 700 rpm, cutting force decreases from 424 to 357 N but as spindle speed increased from 700 to 910 rpm, cutting force increases from 357 to 394 N. As the feed increases from 0.10 to 0.28 mm/rev, there is an increase in cutting force from 250 to 492 N. With the increase in depth of cut from 0.5 to 1.1 mm, cutting force increases from 277 to 497 N.
6. As the spindle speed increases from 480 to 700 rpm, feed force decreases from 154 to 148 N but as spindle speed increased from 700 to 910 rpm, feed force increases from 148 to 171 N. As the feed increases from 0.10 to 0.28 mm/rev, there is an increase in feed force from 142 to 169 N. With the increase in depth of cut from 0.5 to 1.1 mm, feed force increases from 100 to 191 N.
7. As the spindle speed increases from 480 to 700 rpm, thrust force increases from 0 to 45 N but as spindle speed increased from 700 to 910 rpm, thrust force decreases from 45 to 5 N. As the feed increases from 0.10 to 0.19 mm/rev, there is a decrease in thrust force from 74 to 43 N and as the feed increases from 0.19 to 0.28 mm/rev, thrust force increases from 43 to 55 N. The depth of cut has a negligible effect on thrust force.

8. As the spindle speed increases from 480 to 910 rpm, surface roughness decreases from 3 to 1.1 μm . As the feed increases from 0.10 to 0.28 mm/rev, there is an increase in surface roughness from 2.0 to 2.9 μm . With the increase in depth of cut from 0.5 to 0.8 mm, surface roughness decreases from 2.8 to 2 μm and as depth of cut increases from 0.8 to 1.1 mm, surface roughness increases from 2 to 2.25 μm .
9. The response optimizer technique sets the spindle speed, feed and depth of cut at 910 rpm, 0.2 mm/rev and 0.5 mm respectively as the optimal parameters whereas using GA gives a Pareto front amongst which any of them can be taken depending on the choice of designer.
10. For ANN modelling, 3-7-4 was the selected network architecture and the network was trained and the MSE for the corresponding architecture came out to be 0.00974.
11. A comparison between the predictive ability of ANN and RSM models reveals that ANN model has an edge over RSM model values in case of cutting force, feed force and thrust force. But in case of surface roughness, RSM has less absolute mean percentage error in comparison to ANN model values.

8.2. Future Scope

Every study has a scope for further improvement. Following are the areas which can be still explored in the context of present research:

1. The present study includes spindle speed, feed and depth of cut as the input parameters which can be extended to tool geometry, wet machining versus dry machining.
2. The response parameters can be further elaborated by including MRR, Power consumption etc.
3. Other optimization techniques such as scatter search technique, fuzzy logic and taguchi technique can also be attempted and results can be compared.

REFERENCES

- [1] Module 1, Classification of Metal Removal Processes and Machine Tools, Lesson 1 Introduction to manufacturing and machining, Version 2 ME, IIT Kharagpur.
- [2] Amitabha Ghosh, Asok Kumar Mallik, “Manufacturing Science”, Second Edition, East West Press Private Ltd.
- [3] B C Routara, A.K. Sahoo, A.K. Parida, P.C.Padhi 2012. Response Surface Methodology and Genetic Algorithm Used to Optimize the Cutting Conditions for Surface Roughness Parameter in CNC Turning, ICMOC 2012, Procedia Engineering, Vol. 38, pp.1893 – 1904.
- [4] J. Gerald Anto Arulraj, K. Leo Dev Wins, Anil Raj 2014. Artificial Neural Network Assisted Sensor Fusion Model for Surface Roughness During Hard Turning of H13 Steel With Minimal Cutting Fluid Application. International Conference on AMME 2014, Procedia Materials Science, Vol. 5, pp. 2338 – 2346.
- [5] Sajeev A, Benphil C Mathew, Chindhu C Kaippallil 2013. Development of an Artificial Neural Network Surface Roughness Prediction Model in Turning of AISI 4140 Steel Using Coated Carbide Tool. Proceedings of International Conference on Energy and Environment 2013, Volume 2, Special Issue 1, pp. 633-639, ISSN (Online) : 2319 – 8753, ISSN (Print) : 2347 – 6710
- [6] S. Hari Krishna, K.Satyanarayana, K. Bapi Raju 2011. Surface Roughness Prediction Model Using ANN & ANFIS. International Journal of Advanced Engineering Research and Studies 2011, Volume 1, Issue 1, pp. 102-113, E-ISSN2249 – 8974
- [7] Prakash Rao C.R., Bhagyashekar M.S, Narendravishwanath 2014. Effect of Machining Parameters on the Surface Roughness while Turning Particulate Composites. 12th GCMM 2014, Procedia Engineering, Vol. 97, pp. 421 – 431.
- [8] D. Sai Chaitanya Kishore, K. Prahlada Rao, A. Mahamani 2014. Investigation of cutting force, surface roughness and flank wear in turning of In-situ Al6061-TiC metal matrix composite. 3rd ICMPC 2014, Procedia Materials Science, Vol. 6, pp. 1040 – 1050.
- [9] Uday A. Dabade 2013. Multi-objective Process Optimization to Improve Surface Integrity on Turned Surface of Al/SiCp Metal Matrix Composites Using Grey Relational Analysis. Forty Sixth CIRP Conference on Manufacturing Systems 2013, Procedia CIRP, Vol. 7, pp. 299 – 304.

- [10] A Mahamani 2014. Influence of Process Parameters on Cutting Force and Surface Roughness During Turning of AA2219-TiB₂/ZrB₂ In-situ Metal Matrix Composites. 3rd ICMPC 2014, Procedia Materials Science, Vol. 6, pp. 1178 – 1186.
- [11] M.Subramanian, M.Sakthivel, K.Sooryaprakash, R.Sudhakaran 2013. Optimization of Cutting Parameters for Cutting Force in Shoulder Milling of Al7075-T6 Using Response Surface Methodology and Genetic Algorithm. IConDM 2013, Procedia Engineering, Vol. 64, pp. 690 – 700.
- [12] I. G. Euan, E. Ozturk, N. D. Sims 2013. Modeling Static and Dynamic Cutting Forces and Vibrations for Inserted Ceramic Milling Tools. 14th CIRP Conference on Modeling of Machining Operations (CIRP CMMO), Procedia CIRP, Vol. 8, pp. 564 – 569.
- [13] Harsh Y Valera, Sanket N Bhavsar 2014. Experimental Investigation of Surface Roughness and Power Consumption in Turning Operation of EN 31 Alloy Steel. 2nd ICIAME 2014, Procedia Technology, Vol. 14, pp. 528 – 534.
- [14] Gaurav Bartarya, S.K.Choudhury 2012. Effect of cutting parameters on cutting force and surface roughness during finish hard turning AISI52100 grade steel. 5th CIRP Conference on High Performance Cutting 2012, Procedia CIRP, Vol. 1, pp. 651 – 656.
- [15] Ravinder Tonk, Jasbir Singh Ratol 2012. Investigation of the Effects of the Parametric Variations in Turning Process of En31 Alloy. International Journal on Emerging Technologies, Vol. 3, Issue 1, pp. 160-164, ISSN No. (Print): 0975-8364, ISSN No. (Online): 2249-3255
- [16] Varaprasad.Bh, Srinivasa Rao.Ch, P.V. Vinay 2014. Effect of Machining Parameters on Tool Wear in Hard Turning of AISI D3 Steel. 12th GCMM 2014, Procedia Engineering, Vol. 97, pp. 338 – 345.
- [17] V.Sivaraman, S.Sankaran, L.Vijayaraghavan 2012. The Effect of Cutting Parameters on Cutting Force During Turning Multiphase Microalloyed Steel. 3rd CIRP Conference on Process Machine Interactions, Procedia CIRP, Vol. 4, pp. 157 – 160.
- [18] Dr. G. Harinath Gowd, S. Sharmas Vali, V. Ajay, G. Guru Mahesh 2014. Experimental Investigations and Effects of Cutting Variables on MRR & Tool Wear for AISI S2 Tool Steel. International Conference on AMME, 2014, Procedia Materials Science, Vol. 5, pp. 1398 – 1407.

- [19] Doriana M. D' Addona , Roberto Teti 2013. Genetic algorithm-based optimization of cutting parameters in turning processes. Forty Sixth CIRP Conference on Manufacturing Systems 2013, Procedia CIRP, Vol. 7, pp. 323 – 328.
- [20] S.S.K. Deepak Sept. 2012. Applications of Different Optimization Methods for Metal Cutting Operation – A Review. Research Journal of Engineering Sciences, Vol. 1, Issue 3, pp. 52-58, ISSN 2278 – 9472.
- [21] C.J.Rao, D.Sreemulu, Arun Tom Mathew 2014. Analysis of Tool Life during Turning Operation by Determining Optimal Process Parameters. 12th GCMM 2014, Procedia Engineering, Vol. 97, pp. 241 – 250.
- [22] Mithilesh Kumar Dikshit, Asit Baran Puri, Atanu Maity 2014. Experimental Study of Cutting Forces in Ball End Milling of Al2014-T6 Using Response Surface Methodology. 3rd ICMPC 2014,Procedia Materials Science, Vol. 6, pp. 612 – 622.
- [23] Turning Tools, General Turning Manual of Sandvik Coromant 2012.
- [24] Module 3, Machinability, Lesson 15, Cutting Tool Materials of Common Use, Version 2 ME, IIT Kharagpur.
- [25] Montgomery D.C., “Design and Analysis of Experiments”, Fifth Edition, Wiley India private Ltd.
- [26] support.minitab.com/en-us/minitab/17.
- [27] <http://www.mathsworks.com/> Global Optimization Toolbox Documentation.
- [28] <http://www.mathsworks.com/> Neural Network Toolbox Documentation.