Effect of Process Parameters in Turning 20MnCr5 using Taguchi's Technique

A dissertation submitted in partial fulfilment of
the requirements for the award of the degree of

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By
GAURAV GAUR
Roll No.3133531

Under the Guidance of

Prof. HARI SINGH

DEPARTMENT OF MECHANICAL ENGINEERING
NATIONAL INSTITUTE OF TECHNOLOGY
(Institute of National Importance)
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CANDIDATE`S DECLARATION

Gaurav Gaur, a student of M.Tech. (Industrial and Production Engineering) of echanical Engineering Department at National Institute of Technology, urukshetra, hereby declare that I own full responsibility for the information, esults, conclusion etc provided in this dissertation entitled "Effect of Process arameters in Turning 20MnCr5 using Taguchi's Technique" being submitted to ational Institute Of Technology, Kurukshetra, for the award of M.Tech (Industrial nd Production Engineering) degree. I have completely taken care in cknowledging the contribution of others in the academic work. I further declare at in case of violation of intellectual property right or copyrights found at any tage, myself as the candidate will be solely responsible for the same.

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Date- 10 JULY 2015

GAURAV GAUR
Roll No - 3133531

Place: Kurukshetra

M.Tech. (Industrial and Production Engineering)

CERTIFICATE

This is to certify that this dissertation report entitled **"Effect of Process Parameters in Turning 20MnCr5 using Taguchi's Technique"** being submitted by Mr. Gaurav Gaur in partial fulfilment of the requirements for the award of Degree of Master of Technology in Industrial and Production Engineering to National Institute Of Technology, Kurukshetra, Haryana, India, is a record of student's own work carried out under my supervision and guidance.

To the best of my knowledge, this dissertation report has not been submitted in part or full elsewhere in any other University or Institution for the award of any degree. It is further understood that by this certificate the undersigned does not endorse or approve the opinion expressed and conclusion drawn therein but approves the dissertation report only for the purpose for which it is submitted.

10.07.201

Prof. Hari Singh
Department Of Mechanical Engineering
National Institute Of Technology, Kurukshetra

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GAURAV GAUR

Roll No - 3133531

Place: Kurukshetra

M.Tech (Industrial and Production Engineering)

ABSTRACT

In this work, the Taguchi method is used to optimize the Material Removal Rate and Surface Roughness in Turning Operation of 20MnCr5 alloy steel using Tungsten Carbide inserts. Three process parameters namely, cutting speed, feed rate, and depth of cut, have been selected for investigation. Experiments were conducted on the basis of Taguchi's L9 orthogonal array and MINITAB 17 software was used to obtain the design matrix and then carry out analysis.The Signal to noise ratio (SNR) is applied to optimize the effects of the selected process parameters on MRR, surface roughness. Feed rate has maximum influence on MRR followed by depth of cut and speed. Depth of cut , speed and feed rate affect the surface finish in decreasing order. The optimal levels of process parameters for simultaneous optimization of MRR and Surface roughness have been identified. Optimal results were verified through confirmation experiments.

CONTENTS

TOPICS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

CNC	Computer Numerical Control
DOE	Design of Experiments
LB	Larger the Batter
MRR	Material Removal Rate
OA	Orthogonal Array
RPM	Revolution per minute
SB	Smaller the Batter
S/N	Signal to Noise ratio
TQM	Total Quality Management
GRA	Grey Relational Analysis

LIST OF SYMBOLS

S. No.	Symbol	Description
1.	N	Spindle Speed
2.	f	Feed Rate
3.	d	Depth of cut
4.	R_a	Arithmetic average of roughness
5.	Wt.	Weight
6.	F	Frequency value
7.	η	S/N ratio
8.	n	Total number of replication
9.	y_i	Simulation result for the response
10.	V	Cutting speed
11.	D	Diameter of work piece before turning
12.	W_i	Initial weight of work piece
13.	W_f	Final weight of work piece
14.	t	Machining time

CHAPTER 1

INTRODUCTION

1.1 Turning Operation

The term turning, in the general sense, refers to the generation of any cylindrical surface with a single point cutting tool [1]. More specifically, it is often applied just to the generation of external cylindrical surfaces oriented primarily parallel to the work piece axis. Turning is performed on lathe machine in which the tool is stationary and the part is rotated. The turning operation is shown in figure 1.1.

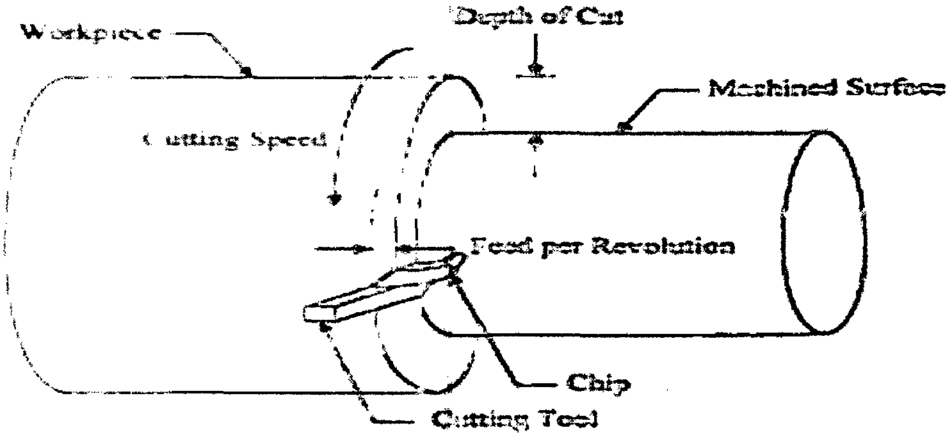


Figure 1.1: Turning operation

1.1.1: Cutting parameters for turning

There are several turning process parameters affecting the performance. Cutting speed, feed rate and depth of cut are normally called cutting parameters in machining. An optimized setting of these parameters is usually sufficient to solve many industrial problems.

- **Cutting feed (f)** – The cutting feed is defined as the distance advanced by the cutting tool during one revolution of the spindle and is normally expressed in mm per revolution.

- **Spindle speed (N)-** The rotational speed of the spindle and the work piece in revolutions per minute (RPM) is known as spindle speed. The spindle speed is equal to the cutting speed divided by the circumference of the work piece where the cut is being made. In order to maintain a constant cutting speed, the spindle speed must vary based on the diameter of the cut. Mathematically, it is given by the following equation.

$$N = 1000\, v / (\pi D)$$

Where,
N = Spindle speed in rpm
v = Cutting speed in m/min
D = Diameter of the work piece in mm

- **Depth of cut:** Depth of cut is the distance that the tool advances along the radius of the work piece in a turning operation. A large depth of cut will require a low feed rate; otherwise it will result in a high load on the tool and reduce tool life. It is normally stated in mm.

1.2 Work Material

20MnCr5 alloy steel is very resistant to corrosion and is used for this purpose in industry. It is used in parts of gas turbine engines that are subject to high temperature and require high strength, excellent high temperature creep resistance, fatigue life, and oxidation and corrosion resistance. Because of its unique properties, it is widely used in making of small gears, shafts, crankshafts, connecting rods, cam shafts, boxes, piston bolts, spindles, etc.
The high strength to weight ratio and outstanding wearing resistance inherent in 20MnCr5 alloy steel have led to a wide and diversified range of successful applications which demand high level of reliable performance in different mechanical parts. Designing with 20MnCr5 alloy steel taking all factors into account has resulted in reliable, economic and more durable components, which in many situations have substantially exceeded performance and service life expectations.

The Chemical composition, Mechanical and physical properties of 20MnCr5 alloy steel are reported in Tables 1.1, 1.2, and 1.3 respectively.

Table 1.1: Chemical composition of 20MnCr5 alloy steel

ELEMENT	WEIGHT (%)
Carbon	0.17-0.20
Silicon	Max 0 .4
Manganese	1.1-1.4
Phosphorus	Max 0.025
Sulphur	Max 0.035
Chromium	1.0-1.3

Table 1.2: Mechanical properties of 20MnCr5 alloy steel

MECHANICAL PROPERTIES	VALUE	UNIT
Young's modulus	200000	MPa
Tensile strength	1158	MPa
Elongation	8-25	%
Fatigue	275	MPa
Yield strength	1034	MPa

Table 1.3: Physical properties of 20MnCr5 alloy steel

PHYSICAL PROPERTIES	VALUE	UNIT
Modulus of elasticity	210	KN/mm^2
Thermal Expansion	10	mm/k
Thermal conductivity	25	W/m-k
Specific heat	460	J/Kg-k
Melting temperature	1450-1510	°C
Density	7700	Kg/m^3
Resistivity	.55	$Ohm\text{-}mm^2/m$

1.3 Motivation for the present work

20MnCr5 alloy steel has a wide variety of applications such as plating steel components, parts of gas turbine engines that are subject to high temperatures, used in making of small gear, shafts, crankshafts, connecting rods, cam shafts, boxes, piston bolts, spindles, and other mechanical controlling parts, etc. The material 20MnCr5 alloy steel is difficult to machine. There are a number of parameters like cutting speed, feed and depth of cut, etc. which must be given consideration during the machining of 20MnCr5 alloy steel. So it becomes necessary to find out the ways by which 20MnCr5 alloy steel can be machined easily and economically. Therefore the present work is focused on finding the optimal parameters combination of spindle speed, feed and depth of cut for higher Material removal rate (MRR) and lower surface roughness.

CHAPTER-II

LITERATURE REVIEW AND FORMULATION OF PROBLEM

2.1 Literature Review

A number of researchers have focused their work on the study of effects of various process parameters during turning operation. The work is summarized in this section.

Meng, Arseculasince and Mathew (2000) [2] calculate the optimum cutting conditions for turning operation using a machining theory. The method uses a variable flow stress machining theory to predict cutting forces and stresses which are then used to check process constraints such as machine power, tool plastic deformation and built-up edge formation. The result indicates that the method is capable of selecting the appropriate cutting conditions.
Huang and chen (2001) [3] set up a multiple regression model that was capable of predicting the in-process surface roughness of a turned work piece. The model used machining parameters, such as feed rate, spindle speed and depth of cut, as predictors. Vibration information collected with an accelerometer was applied as another predictor. The predictor variables, such as feed rate, vibration amplitude average, spindle speed and depth of cut, had strong linear correlation with the surface roughness. Venugopal et al. (2003) [4] used Tib_2 –coated carbide inserts to machine titanium alloy under dry as well as cryogenic cooling conditions. The cutting forces, surface quality, surface roughness and tool wear were investigated. Tib_2 as a coating material on carbide insert was found unsuitable for machining titanium alloys. However, the extent of tool wear under cryogenic cooling was less compared to dry machining.

Noordin et al. (2004) [5] applied the response surface methodology in describing the performance of coated carbide tools when turning AISI 1045 steel. Cutting tests were performed with constant depth of cut and under dry cutting conditions. The factors investigated were cutting speed, feed and the side cutting edge angle of the cutting edge. The main cutting force and surface roughness as the response variables were investigated. The feed was the most significant factor that influenced the surface roughness and the tangential force. However, there are other factors that provide secondary contribution to the performance indicators.

Petropoulos, Ntziantzias and Anghel (2005) [7] developed a predictive model of cutting force in turning of St37 steel with a Tin coated carbide tool using Taguchi and Response surface techniques. The model was formulated in terms of the cutting conditions namely feed, cutting speed and depth of cut. Taguchi method was used for the plan of experiments and the analysis is performed using response surface methodology. The result shows that the highest influence on cutting forces is exerted by the depth of cut and the feed of varying order of contribution for every force component, while the cutting speed has a less significant negative effect.

Kirby (2006) [8] used the Taguchi's parameter design approach for optimizing surface roughness generated by a CNC turning operation. A standard orthogonal array was utilized for determining the optimum turning parameters with an applied noise factor. Control factors include spindle speed, feed rate and depth of cut and the noise factor is slightly damaged jaws. The noise factor is included to increase the robustness and applicability. Feed rate had the highest effect, spindle speed had a moderate effect and depth of cut had an insignificant effect on surface roughness.

Thamizhmanii and Hasan (2006) [9] carried out the analysis of roughness, forces and wear in turning cast iron. The tests were conducted by varying cutting speed and feed at a constant depth of cut. The surface roughness decreases at higher cutting speed and feed rate. There is no formation of built-up-edge that usually occurs during machining cast iron at lower cutting speed.

Ahmari (2007) [10] developed the empirical models for tool life, surface roughness and cutting force for turning operations. Process parameters viz. cutting speed, feed rate, depth of cut and tool nose radius, were used as inputs to the developed machinability models. Response surface methodology and neural networks were used for analysis of the experimental data. The developed machinability models can be utilized to formulate an optimization model for the machining economic problem to determine the optimal values of process parameters for the selected material.

Thamizhmanii, Saparudin and Hasan (2007) [11] analyzed the optimum cutting conditions to get lowest surface roughness in turning SCM 440 alloy steel by Taguchi method. The cutting speed, feed rate and depth of cut were used as the input process parameters. The depth of cut had significant role to play in producing lower surface roughness followed by feed. The results showed that the cutting speed had lesser effect on the surface roughness.

Awan and Hadi (2008) [12] studied and analyzed the surface quality in turning operation of Aluminium and Copper. An empirical model was developed for surface roughness (RA) prediction in turning using Al (6061T) and Cu (ASME B152 annealed). The impact of cutting speed, feed, depth of cut, tool geometry and work piece material was studied on surface roughness. The results produced using Regression Analysis (RA) give a good prediction of surface roughness when compared with actual surface roughness.

Burhanuddin et al. (2008) [13] investigated the significant factors that affect the tool life, wear progression and wear mode mechanism of the CBN cutting tool when turning Ti-6A1-4V. The effects of cutting variables viz. cutting speed, feed rate and depth of cut, were investigated by the application of partial factorial design method. The machining tests were carried out under dry cutting condition. The cutting speeds selected were 180 and 280 m min^{-1}. The feed rates were 0.05 and 0.25 mm rev^{-1}. The study revealed that cutting speed and feed significantly affect the tool life. The detailed study using SEM revealed that the wear occurred on both flank and rake faces of the cutting edge. The wear mechanisms such as rubbing, abrasion, adhesion, diffusion-dissolution and fracture were observed.

Kuo, Yang and Huang (2008) [14] proposed the grey- based Taguchi method to solve multi-response simulation optimization problems. Following the procedure of the Taguchi method, GRA was used to transform a multi-response problem into a single-response problem. A practical case study illustrates that the difference in performance between the proposed method and other methods identified in the literature was not significant. However, the results of this study illustrate the GRA procedure is simple and straight forward in calculations and optimization; it is therefore a very suitable method for solving multi-response simulation problems. In addition, the proposed method can easily be extended to problems that have more than two responses, even though the case study in this article has only two responses. The proposed method presents a new option for solving multi-response simulation optimization problems.

Panda and Mohapatra (2008) [15] used the Grey based Taguchi method for the optimization of multi response drilling process. Surface roughness of drilled holes and drill flank wear were combined into a single response characteristic. Experiments were conducted on a radial drilling machine with five input parameters. It is concluded that drill diameter is the most significant factor and feed rate the least significant one in influencing the combined responses.

Singh (2008) [16] obtained an optimal setting of turning process parameters viz. cutting speed, feed and depth of cut, which may result in optimizing tool life of TiC coated carbide inserts while turning En24 steel (0.4% C). The effects of the selected process parameters on the tool life and the subsequent optimal settings of the parameters had been accomplished using Taguchi's design of experiments approach. The result indicated that the selected process parameters significantly affect the mean and variance of the tool life of the carbide inserts. The percent contributions of parameters as quantified in the S/N pooled ANOVA envisage that the relative power of feed (8.78%) in controlling variation and mean tool life is significantly smaller than that of the cutting speed (34.89%) and depth of cut (25.80%).

Kahraman (2009) [18] utilized regression modelling in turning of AISI 4140 steel using Response Surface Methodology (RSM) with rotatable Central Composite Design (CCD). A quadratic model was developed for the prediction and analysis of the relationship between the cutting parameters and surface roughness. The statistical analysis showed that cutting speed and feed rate have the significant effect on surface roughness.

Aruna, Dhanalakshmi and Mohan (2010) [19] carried out the finish turning of Inconel 718 using ceramic tools under high pressure coolant supply. The approach was based on Taguchi's method and the analysis of variance

(ANOVA). A series of experiments were conducted by varying the process parameters and their effects on surface finish and tool wear were measured. It was found that the surface roughness was well below the rejection criteria. The experimental results indicated that the cutting speed was the most significant factor to the overall performance. In addition, SEM analysis is performance of ceramic tools under varying process parameters. The performance of ceramic tool is better at low cutting speeds.

Datta and Mahapatra (2010) [20] applied utility theory combined with Principal Component Analysis (PCA) and Taguchi's robust design for simultaneous optimization of correlated multiple surface quality characteristics of mild steel machined product prepared by straight turning operation. The study aimed at evaluating the most favourable process environment followed by an optimal parameter combination for achieving high surface quality.

Galanis and Manolakos (2010) [21] developed a surface roughness model for turning of femoral heads from AISI 316L stainless steel. The model was developed in terms of cutting speed, feed rate and depth of cut, using response surface methodology. Machining tests were carried out with TiN-Al_2O_3-TiC-coated carbide cutting tools under various conditions.

Kirby (2010) [22] optimized the turning process towards an ideal surface roughness target through Taguchi's parameter design approach. The purpose of the study was to create an optimization scheme that allows the system to meet the quality requirement without sacrificing productivity.
Sijo and Biju (2010) [23] used the Taguchi method for optimization of cutting parameters namely, cutting velocity, feed rate, depth of cut, nose radius of tool and hardness of the material, in turning operation. The results of analysis showed that feed rate, cutting velocity and nose radius have more significant contribution in affecting the surface roughness while depth of cut and hardness of material have less significant contribution on the surface roughness.

Suhail, Ismail, Wong and Jail (2010) [25] optimized the cutting parameters in turning process using Taguchi method. Cutting speed, feed rate and depth of cut were used as the machining parameters to analyze their effect on surface roughness and work piece surface temperature. The orthogonal array, signal to noise ratio and analysis of variance were employed to study the performance characteristics in turning operations. The feed rate had the strongest influence on surface roughness followed by cutting speed and depth of cut in that order. On the other hand, the depth of cut had the strongest influence on work piece surface temperature followed by feed rate and cutting speed.

Kaladhar, Subbaiah and Rao (2011) [27] used a multi-characteristics response optimization model based on Taguchi and Utility concept to optimize process parameters, such as speed, feed, depth of cut and nose radius on multiple performance characteristics, namely, surface roughness (Ra) and material removal rate (MRR) during turning of AISI 202 austenitic stainless steel using a CVD coated cemented carbide tool. The experimental result analysis showed that the combination of higher levels of cutting speed, depth of cut and nose radius and lower level of feed is essential to achieve simultaneous maximization of material removal rate and minimization of surface roughness. The ANOVA and F-tests were used to analyze the results.

Kazancoglu et al. (2011) [28] investigated the multi-response optimization of the turning process for an optimal parametric combination to yield the minimum cutting forces and surface roughness with the maximum Material-Removal rate (MRR) using a combination of a Grey Relational Analysis (GRA) and the Taguchi method. The study showed that a proper selection of the cutting parameters produces a high material-removal rate coupled with a better surface finish and a lower cutting force.

Pawade and Joshi (2011) [29] applied Taguchi grey relational analysis to experimental result in order to optimize the high-speed turning of Inconel 718 with consideration to multiple performance measures. Grey relational theory was adopted to determine the best process parameters that give lower magnitude of cutting forces as well as surface roughness. The feed rate showed strongest correlation to cutting forces and surface roughness.

2.2 Formulation of problem

Literature depicts that a considerable amount of work has been carried out by previous investigators for optimization on a large number of materials. Apart from optimizing a single response, multi objective optimization problems have also been solved using Taguchi method followed by Grey Relation theory. But there is no reported study on the machining of 20MnCr5 using Taguchi Method. Owing to its vast industrial applications, the present work material has been selected and Taguchi's approach based on design of experiments has been applied to achieve optimization of MRR and Surface Roughness.

CHAPTER-III

DESIGN OF EXPERIMENTS

3.1 Design of Experiments

Experiments can have a wide variety of objectives. In some experiments, the objective is to find the most important variables affecting quality characteristics. The plan for conducting such experiments is called the Design of experiments (DOE). The objective of the designed experiments is to understand the impact of specific changes to the inputs of a process, and then to maximize, minimize or normalize the outcome by manipulating the input.

The variable under investigation is a factor and each variation of the factor is called a level. Multiple runs are made at different levels of each input and the resulting observations are recorded. An analysis of the inputs as well as the results will determine the level of input needed to arrive at the optimum result.

Design of experiments has become one of the most popular and efficient tool to explore various operating conditions of a process with goal of reducing cost and improving quality. DOE allows to quickly narrowing the gap through scientific and statistical planning, design, data analysis, modeling and confirmation. DOE consists of purposeful changes of the input factors of a process in order to observe the corresponding changes in the output.

3.2 Types of Design of Experiments

The following are the most common DOE types:

- One factor Designs
- Factorial Designs
- Taguchi Orthogonal Arrays
- Response Surface method Designs
- Mixture Designs

3.2.1 One Factor Designs

These are the designs where only one factor is under investigation and the objective is to determine whether the response is significantly different at different factor levels. The factor can be qualitative or quantitative. In the case of qualitative factor (e.g. different suppliers, different materials, etc.), no predictions can be performed outside the tested levels and only the effect of the factor on the response can be determined. On the other hand, data from tests where the factor is quantitative (e.g. temperature, voltage, load, etc.) can be used for the effect investigation and prediction, provided that sufficient data is available.

3.2.2 Factorial Designs

Factorial designs allow for the simultaneous study of the effects that several factors may have on a process. When performing an experiment, varying the levels of the factors simultaneously rather than one at a time is efficient in term of time and cost and also allows for the study of interactions between the factors. Without the use of factorial experiments, important interactions may remain undetected.

The factorial designs are further divided into various types of designs. These are as follows:

i. **Screening Designs**

   In many process development and manufacturing applications, the number of potential input variables are large. Screening is used to reduce the number of input variables by identifying the key input variables or process conditions that affect product quality. This reduction allows focusing process improvement efforts on the few important variables. Screening may also suggest the best or optimal setting for these factors and indicate whether or not curvature exists in the responses. Optimization experiments can then be done to determine the best setting and to define the nature of the curvature.

ii. **Full factorial design**

In a full factorial experiment, responses are measured at all combinations of the experimental factor levels. The combinations of factor levels represent the conditions at which responses will be measured. Each experimental condition is called a run and the response measurement an observation. The entire set of runs is the design. For example, a two-level full factorial design with 6 factors requires 64 runs and a design with 9 factors requires 512 runs.

iii. **Two-level full factorial design**

In a two-level full factorial design, each experimental factor has only two levels. The experimental runs include all combinations of these factor levels. Although two-level factorial designs are unable to explore fully a wide region in the factor space, these provide useful information for relatively few runs per factor.

iv. **Fractional factorial designs**

In a full factorial experiment, responses are measured at all combinations of the factor levels, which may result in a prohibitive number of runs. To minimize time and cost, designs that exclude some of the factor level combination are used. Factorial designs in which one or more level combinations are excluded are called fractional design.

3.2.3 Taguchi's Orthogonal Arrays

Orthogonal Arrays represent a versatile class of combinational arrangements useful for conducting experiments to determine the optimum mix of a number of factors in a product to maximize the yield, and in the construction of a variety of designs for agricultural, medical and other experiments.

Taguchi's orthogonal arrays are highly fractional designs, used to estimate main effects using only a few experimental runs. These designs are not only two-level factorial experiments, but also can investigate main effects when factors have more than two levels. Designs are also available to investigate main effects for certain mixed level experiments where the factors included do not have the same number of levels.

3.2.4 Response Surface Designs

Response surface methods are used to examine the relationship between one or more response variables and a set of quantitative experimental variables or factors. These methods are often employed after identifying a vital few controllable factors and to find the factor settings that optimize the response. Designs of this type are usually chosen when there is any suspect curvature in the response surface. Many response surface applications are sequential in nature in that they require more than one stage of experimentation and analysis. It directly gives the empirical relation between process parameters and the objective function.

3.2.5 Mixture Designs

Mixture experiments are a special class of response surface experiments in which the product under investigation is made up of several components or ingredients. Designs for these experiments are useful because many product design and development activities in industrial situations involve formulation or mixtures. In these situations, the response is a function of the proportions of the different ingredients in the mixture.

3.3 Selected Design of Experiments

Taguchi's orthogonal array is selected for the experimentation which reduces the number of runs considerably as compared to other available designs of experiments.

3.4 Taguchi method

The Taguchi method is the most commonly used method in optimization of design parameters. This method is basically used for improving the quality of products with the use of statistical and engineering concepts [32]. The method which is based on orthogonal array provides a significantly reduced variance for the experiment, resulting in the optimum setting of the process parameters. Orthogonal array provides a set of well-balanced experiments, with less number of experiment runs. This technique is used for the data analysis and in the prediction of the optimal results.

3.5 Taguchi's Philosophy

Taguchi's philosophy has far reaching consequences on product/process quality improvement; yet it is based upon on three very simple and fundamental concepts.

I. Quality should be designed into a product and not inspected into it. No amount of inspection can put quality back into the product.
II. Quality is best achieved by minimizing the deviation from a target. The product should be so designed that it is immune to uncontrollable environmental factors.
III. The cost of quality should be measured as a function of deviation from the standard and the losses should be measured system wide.

3.6 Steps applied in Taguchi method

Taguchi proposed a standard procedure for applying his method for optimizing any process. The steps suggested by Taguchi are [7, 8, and 11]:

- **Determination of the quality characteristic to be optimized**

The first step in the Taguchi method is to determine the quality characteristic to be optimized. The quality characteristic is a parameter whose variation has a critical effect on product quality. It is the output or the response variable to be observed.

- **Identification of the noise factors and test conditions**

  The next step is to identify the noise factors that can have a negative impact on system performance and quality. Noise factors are those parameters which are either uncontrollable or are too expensive to control. Noise factors include variations in environmental operating conditions, deterioration of components with usage and variation in response between products of same design with the same input.

- **Identification of the control parameters and their alternative levels**

  The third step is to identify the control parameters considered to have significant effects on the quality characteristic. Control (test) parameters are those design factors that can be set and maintained. The number of levels, with associated test values, for each test parameter defines the experimental region.

- **Designing the matrix experiment and defining the data analysis procedure**

  The next step is to design the matrix experiment and define the data analysis procedure. First, the appropriate orthogonal arrays for the noise and control parameters to fit a specific study are selected. Taguchi provides many standard orthogonal arrays and corresponding linear graphs for this purpose. After selecting the appropriate orthogonal arrays, a procedure to simulate the variation in the quality characteristic due to the noise factors needs to be defined.

- **Conduct the matrix experiment**

  The next step is to conduct the matrix experiment and record the results. The Taguchi method can be used in any situation where there is a controllable process. The controllable process can be an actual hardware experiment, system of mathematical equations, or computer model that can adequately model the response of many product and processes.

- **Analysis of data and determination of the optimum levels for control factors**

After the experiments have been conducted, the optimal test parameter configuration within the experiment design must be determined. To analyze the result, the Taguchi method uses a statistical measure of performance called signal to noise (S/N) ratio.

- **Prediction of performance at optimum levels**

Using the Taguchi method for parameter design, the optimum setting is predicted from the graphs of S/N ratio and means. In the final step, an experimental confirmation run is done using predicted optimum levels for the control parameters being studied.

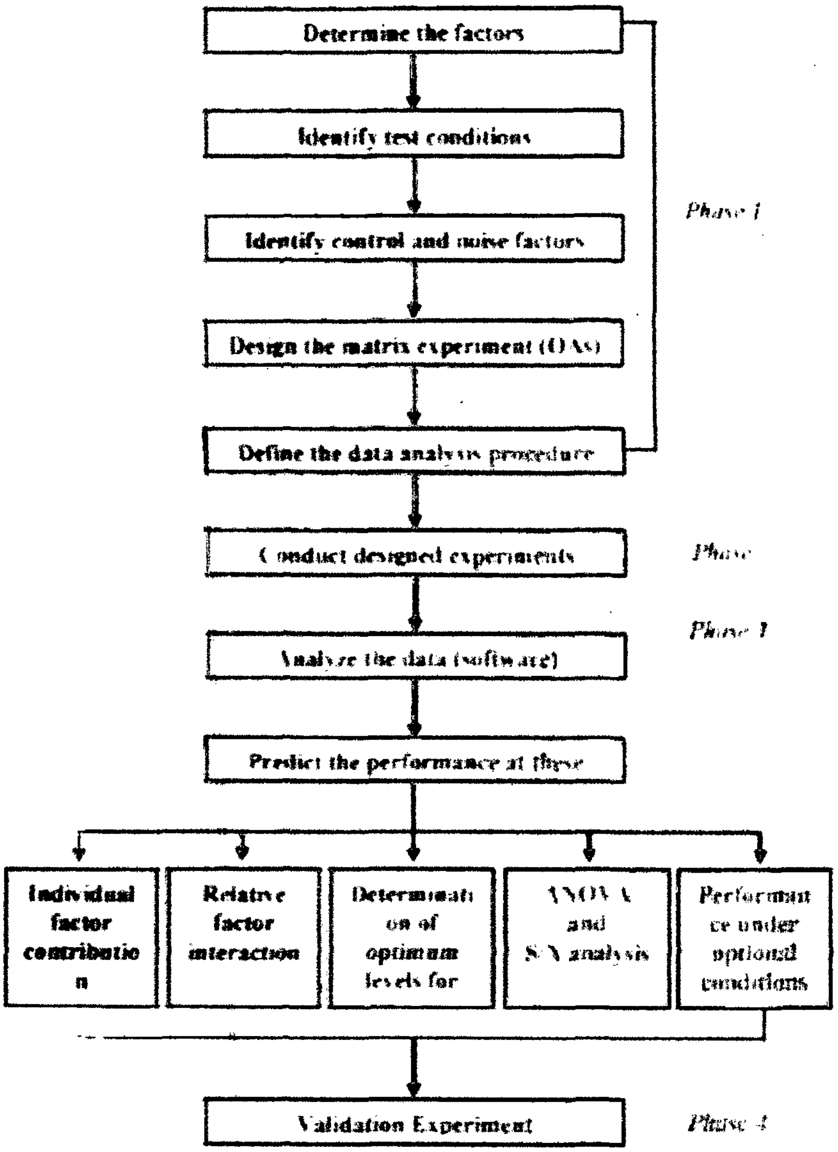


Figure 3.1: Steps applied in Taguchi method

3.7 Analysis of Variance

ANOVA is a statistical analysis tool that separates the total variability found within a data set into two components: random and systematic factors. The random factors do not have any statistical influence on the given data set, while the systematic factors do. The ANOVA test is used to determine the impact of independent variables on the dependent variable in a regression analysis [17 and 23].

The ANOVA test is the initial step in identifying factors that are influencing a given data set. After the ANOVA test is performed, the analyst is able to perform further analysis on the systematic factors that are statistically contributing to the data set's variability. Depending upon the type of analysis, it is important to determine:

a) Which factors have a significant effect on the response, and
b) How much of the variability in the response variable is attributable to each factor.

3.8 Signal-To-Noise Ratio Calculations

The Taguchi method aims to find an optimal combination of parameters that have the smallest variance in performance. The Signal-to-noise ratio (S/N ratio, η) is an effective way to find significant parameters by evaluating minimum variance. In Taguchi designs, a measure of robustness is used to identify control factors that reduce variability in a product or process by minimizing the effects of uncontrollable factors (noise factors). Control factors are those design and process parameters that can be controlled. Noise factors cannot be controlled during production or product use, but can be controlled during experimentation. In a Taguchi designed experiment, noise factors are manipulated to force variability to occur and optimal control factor settings are identified that make the process or product robust, or resistant to variation from the noise factors. Higher values of the signal-to-noise ratio (S/N) identify control factor settings that minimize the effects of the noise factors.

The signal-to-noise ratio measures how the response varies relative to the nominal or target value under different noise conditions. One can choose from different signal-to-noise ratios, depending on the goal of the experiment.

A higher S/N ratio means better performance for combinational parameters. Let 'η' be the S/N ratio for the response and let 'Y_i' be the simulation result for the response, n is the total number of replications. The definition of the S/N ratio is given in Equations 3.1 and 3.2.

$$\eta = -10 \, \mathrm{Log}_{10} \left(1/n \;\; \Sigma \, 1/Y_i^2\right) \qquad [3.1]$$

$$\eta = -10 \, \mathrm{Log}_{10} \left(1/n \;\; \Sigma \, Y_i^2\right) \qquad [3.2]$$

The equation 3.1 is used for the 'larger -the- better' responses and equation 3.2 is used for the 'smaller-the-better' responses.

CHAPTER-IV

EXPERIMENTAL SET UP & EXPERIMENTATION

4.1 Lathe Machine

Lathe is one of the most versatile and widely used machine tools. It is commonly known as the mother of all other machine tools. The main function of a lathe is to remove metal from a job to give it the required shape and size. The job is securely and rigidly held in the chuck and then turned against a single point cutting tool which will remove metal from the job in the form of chips. Besides the turning operation lathe can be used to carry out other operation also such as drilling, reaming, boring, taper turning, knurling, thread cutting etc.

For the present work the centre lathe machine shown in figure 4.1 is used. Its specifications are given in table 4.1.

Table 4.1: Specifications of the Lathe

Main Specifications:	
Max. Swing dia. Over bed	410 mm
Max. Swing dia. Over carriage	235 mm
Max. Swing dia. In gap piece	640 mm
Max. Length of work piece	1500 mm
Bed Width	300 mm
Max. Weight of work piece between centers	300 Kg

Specification of Components:

Headstock:

Max. Dia. of spindle bore	48 mm
Steps of spindle speeds	12 steps
Range of spindle speeds	32-2000 rpm

Feed Box:

Longitudinal Feed	0.06-0.82 mm
cross slide Feed	0.017-0.242 mm
Metric Threads	0.5-14 mm
Whitworth Threads	2-56 T.P.I
Module Threads	0.5-14 mm

Cross slide and Top slide:

Travel of Cross slide	200 mm
Travel of Top slide	125 mm

Tailstock:

Travel of Tailstock sleeve	150 mm
Dia. of Tailstock sleeve	63 mm

Motor:

Power of Main Motor	4.5 kW
Power of coolant pump	0.09 kW

Longitudinal lead screw:

Dia. and Pitch	36mm * 6mm

Overall Dimensions and weight of machine:

Overall dimensions	2750*1020*1210 mm
Gross weight	1593 kg

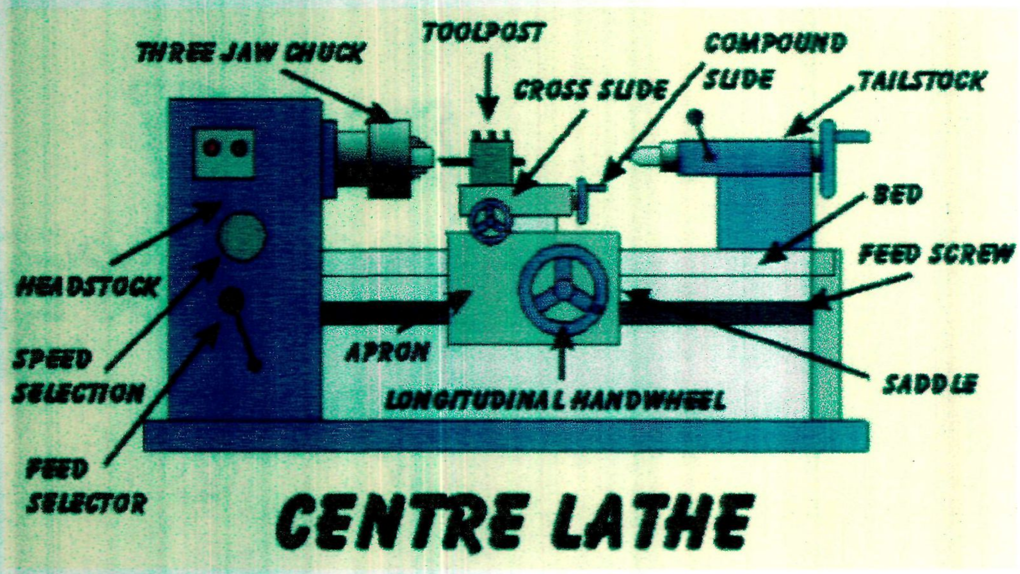


Figure 4.1: Centre Lathe Machine

4.2 Work piece

Manganese-Chromium steel (20MnCr5 steel alloy) bar having 35 mm diameter and 290 mm length was turned using tungsten carbide inserts. The work piece before and after turning is shown in figures 4.2 and 4.3 respectively.

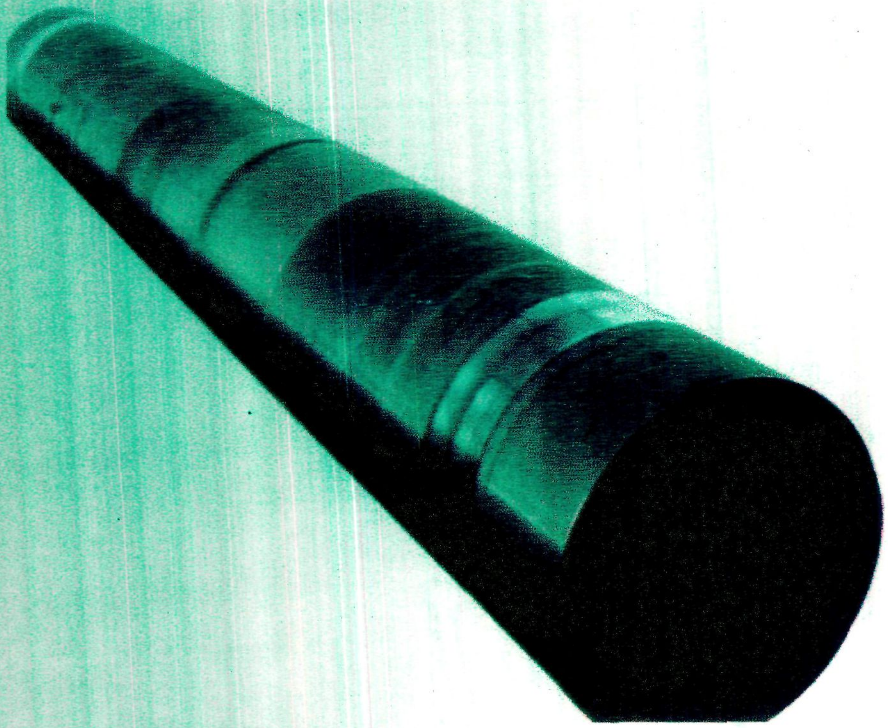


Figure 4.2: Work piece before Turning

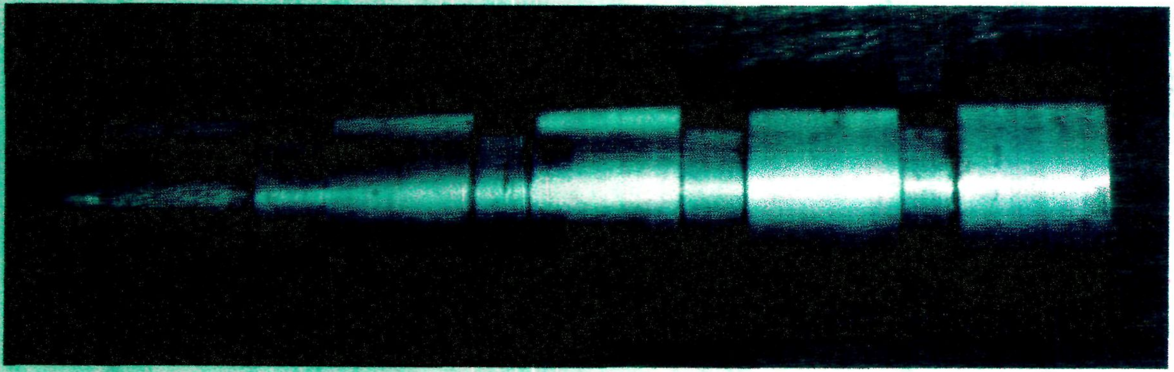


Figure 4.3: Work piece after Turning

4.3 Roughness Measurement

Roughness is measured using a portable stylus-type roughness tester, Surftest SJ-201P (Mitutoyo, Japan) shown in figure 4.4. The measurement results are displayed digitally and graphically on the touch panel. The instrument is portable and self-contained for the measurement of surface texture. It is equipped with a diamond stylus having a tip of radius 5 µm. The measuring stroke always starts from the extreme outward position. At the end of the measurement the pickup returns to the position ready for the next measurement.

The instrument is capable of evaluating surface texture in three parameters i.e. Arithmetic average value (R_a), Root mean square value (R_a) and Average distance between the highest peak and lowest valley (R_a). Based upon the literature review, Average surface roughness (R_a) is utilized for analysis purpose. Roughness measurements, in the transverse direction to the cut, on the work pieces have been repeated four times and average surface roughness values have been recorded.

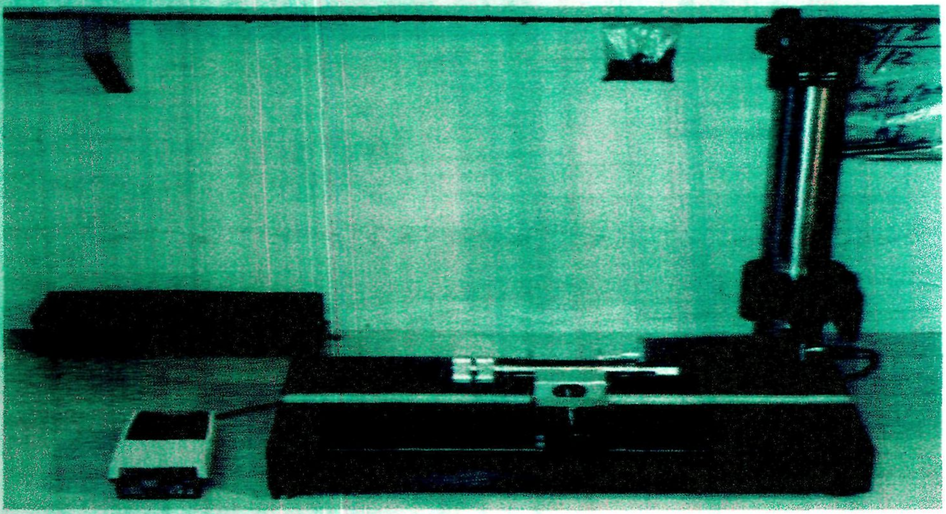


Figure 4.4: Surftest SJ-201P (Mitutoyo, Japan)

4.4 Material Removal Rate Measurement

Material Removal Rate (MRR) is calculated from the difference of weight of work piece before and after experiment by using the relation:

$$MRR = \frac{W_i - W_f}{t} \quad g/s$$

Where, W_i is the initial weight of work piece in g; W_f is the final weight of work piece in g; t is the machining time in seconds.

The weight of the work piece is measured on a high precision digital balance meter made by Sansui (Vibra-AJ3200E), having a least count of 10 mg.

MRR (t) represents Theoretical Material Removal Rate in mm^3/min [31]

MRR (t) = f * d * v * 1000 mm^3/min

Here 'f' denotes feed in mm/rev, 'd' denotes depth of cut in mm and 'v' denotes cutting speed in m/min

To calculate Machining time (t) (theoretical) following formula is used [31]

$t = \frac{L}{f \times N}$ **in min;** L = Distance travelled by the tool in the direction of feed in single cut; F = Feed in mm/rev; N = speed in rpm

4.5 Preliminary Study

This study is undertaken to ascertain the working ranges of the process parameters. Based on the literature review and some pilot trials, Control factors namely Speed, Feed and Depth of cut, have been selected with their three levels as given in Table 4.2.

Table 4.2: Control factors with their symbols and different levels

Symbol	Control factors	Unit	Level 1	Level 2	Level 3
N	Speed	rpm	420	550	715
F	Feed	mm/rev	0.04	0.06	0.08
D	Depth of cut	mm	0.5	0.7	0.9

4.6 Experimentation Plan

The three selected parameters each at three levels have six degrees of freedom. The nearest possible three level orthogonal array is Taguchi's L_9 OA. The experimental design consists of 9 different combinations of spindle speed, longitudinal feed rate and depth of cut. Using the MINITAB 17 software the Orthogonal Array Design has been generated. The experimental design is given in Table 4.3.

Table 4.3: Design of Experiments (Taguchi L_9 Orthogonal Array)

S.NO.	CONTROL FACTOR LEVELS		
	Speed (rpm)	**Feed (mm/rev)**	**Depth of cut (mm)**
1	420	0.04	0.5
2	420	0.06	0.7
3	420	0.08	0.9
4	550	0.04	0.7
5	550	0.06	0.9
6	550	0.08	0.5
7	715	0.04	0.9
8	715	0.06	0.5
9	715	0.08	0.7

4.7 Experimental data

The experimentation was accomplished as per the experimental design. Material removal rate (MRR) and surface roughness values are reported in Table 4.4.

Table 4.4: Experimental data of Material Removal Rate (MRR) and Surface Roughness

S. NO.	CONTROL FACTOR LEVELS			MACHINING TIME (min)	MATERIAL REMOVAL RATE(mm^3/min)	SURFACE ROUGHNESS (µm)
	Speed (rpm)	Feed (mm/rev)	Depth of cut (mm)			
1	420	0.04	0.5	1.2845	910.2	2.782
2	420	0.06	0.7	0.9918	1889.4	2.834
3	420	0.08	0.9	0.7100	3210.6	3.667
4	550	0.04	0.7	0.7668	1630.2	1.964
5	550	0.06	0.9	0.5365	3116.4	3.712
6	550	0.08	0.5	0.4011	2301.6	1.476
7	715	0.04	0.9	0.8000	2676.6	3.190
8	715	0.06	0.5	0.5266	2217	2.418
9	715	0.08	0.7	0.4203	4113.6	3.785

CHAPTER-V

RESULTS AND DISCUSSION

5.1 Data Analysis

The process of data analysis has been divided in the following two cases:

1. Optimization of Material Removal Rate (MRR) using the Taguchi method.
2. Optimization of Surface Roughness using the Taguchi method

5.2 CASE-I: Optimization of Material Removal Rate using Taguchi Method

The observed data for material removal rate (MRR) as given in Table 4.4 has been analyzed using the Taguchi optimization method with the help of MINTAB 17 software. The Signal-to-Noise ratio has been calculated based on Taguchi's Larger-the-Better approach as it aims to maximize the MRR by using the following relation 5.1:

$$\eta = -10 \operatorname{Log}_{10} (1/n \ \Sigma \ 1/Y_i^2) \qquad [5.1]$$

Where

η - S/N ratio for the response;

Y_i – Individual MRR measurements;

n - Total number of replications.

The statistical analysis is done using MINITAB (version17) software and the Response tables for means and signal to noise ratios of MRR are given in Tables 5.1 & 5.2 respectively.

Table 5.1: Response Table for Means of MRR

Level	Speed (rpm)	Feed (mm/rev)	Depth of cut(mm)
1	2003	1739	1810
2	2349	2408	2544
3	3002	3209	3001
Delta	999	1470	1192
Rank	3	1	2

Table 5.2: Response Table for Signal to Noise ratio of MRR

Level	Speed (rpm)	Feed (mm/rev)	Depth of cut (mm)
1	64.95	63.99	64.45
2	67.12	67.44	67.35
3	69.25	69.89	69.52
DELTA	4.30	5.89	5.07
RANK	3	1	2

It is revealed clearly from the response tables that feed rate is the most influencing parameter in affecting MRR followed closely by depth of cut and speed.

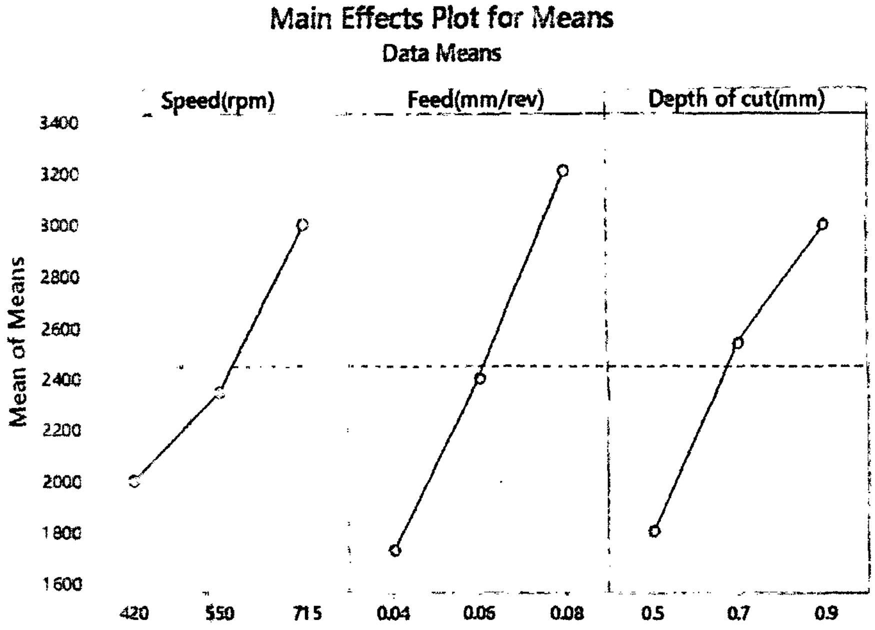


Figure 5.1: Main Effects plot for Means of MRR

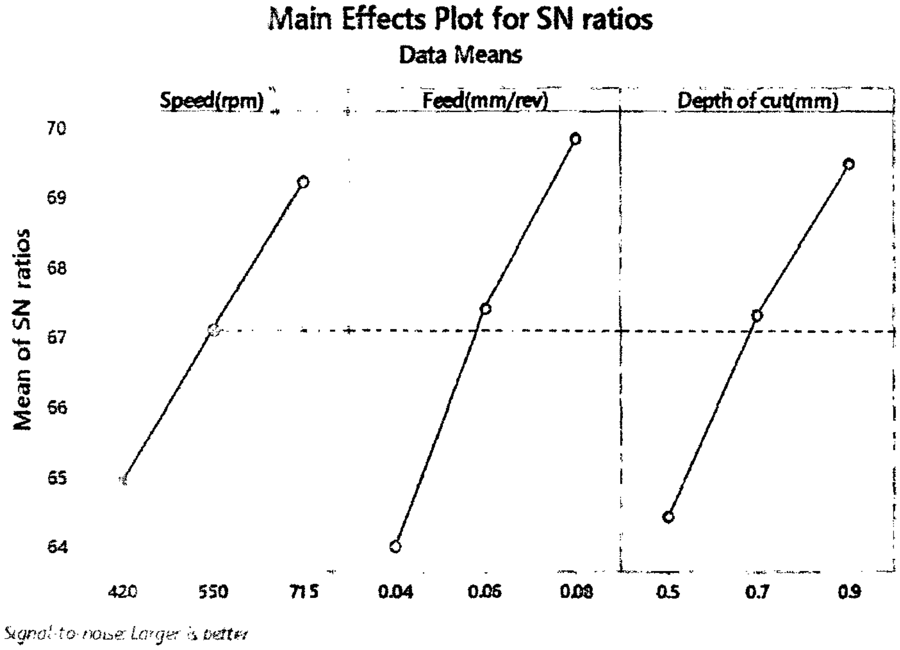


Figure 5.2: Main Effects plot for Signal to Noise ratio of MRR

5.2.1 Determination of optimum conditions

The quality characteristic, MRR, is Larger-the-Better type. The highest points in both the main effects plots shown in figures 5.1 and 5.2 correspond to the optimal levels of the selected parameters. The graphs clearly depict that the third level of each process parameter is optimal. Therefore, the optimum combination is spindle speed (N) = 715 rpm, depth of cut (d) = 0.7 mm and feed rate (f) = .08 mm/rev.

5.2.2 Predictive Equation and Verification

The predicted value of MRR at the optimum levels is calculated by using the relation [28]:

$$\hat{\gamma} = \gamma_m + \sum_{i=0}^{n} (\overline{\gamma i} - \gamma_m) \qquad [5.2]$$

Where, $\hat{\gamma}$ is the predicted response value, γ_m is the total mean of quality characteristics, $\overline{\gamma}i$ is the mean of characteristics at the optimal level of each process parameter, and 'n' is the number of the main design parameters that affect the quality characteristics. Applying this relation predicted value of MRR at the optimum conditions is obtained as:

$$\hat{\gamma}\ (\mathbf{MRR}) = 2451 + [(3002-2451) + (3209-2451) +(3001-2451)]$$

$$= 4310\ \mathrm{mm}^3/\mathrm{min}$$

The robustness of this parameter optimization is verified experimentally. This requires the confirmation run at the predicted optimum conditions. The error in the predicted and experimental value is less than 5 %; it thus confirms excellent reproducibility of the results. The results show that the optimal parameter setting ($N_3\ d_3\ f_3$) gives higher material removal rate.

5.3 CASE-II: Optimization of Surface Roughness using Taguchi Method

The observed data for Surface Roughness (R_a) as given in Table 4.4 has been analyzed using the Taguchi optimization method with the help of MINTAB 17 software. The Signal-to-Noise ratio has been calculated based on Taguchi's Smaller-the-Better approach as it aims to minimize the Surface Roughness by using the following relation 5.3:

$$\eta = -10 \, \mathrm{Log}_{10} \left(1/n \; \Sigma \, Y_i^2\right) \qquad [5.3]$$

Where

η - S/N ratio for the response;

Y_i – Individual Surface Roughness measurements;

n - Total number of replications.

The statistical analysis is done using MINITAB (version17) software and the Response tables for means and signal to noise ratios of Surface Roughness are given in Table 5.3 & Table 5.4 respectively.

The Table 5.3 and Table 5.4 i.e. the Response tables for means and signal to noise ratio's of Surface Roughness respectively, from which it can be observed that the prime parameter on which the Surface Roughness depends is depth of cut and then it depends on speed and finally on feed.

Table 5.3: Response Table for Means of Surface Roughness

Level	Speed(rpm)	Feed(mm/rev)	Depth of cut(mm)
1	3.094	2.645	2.135
2	2.384	2.898	2.528
3	2.708	2.643	3.523
Delta	0.710	0.255	1388
Rank	2	3	1

Table 5.4: Response Table for Signal to Noise ratio of Surface Roughness

Level	Speed (rpm)	Feed (mm/rev)	Depth of cut (mm)
1	-9.740	-8.275	-6.646
2	-6.879	-9.370	-7.936
3	-8.880	-7.855	-10.918
Delta	2.862	1.515	4.272
Rank	2	3	1

Figure 5.3: Main Effects plots for Means of Surface Roughness

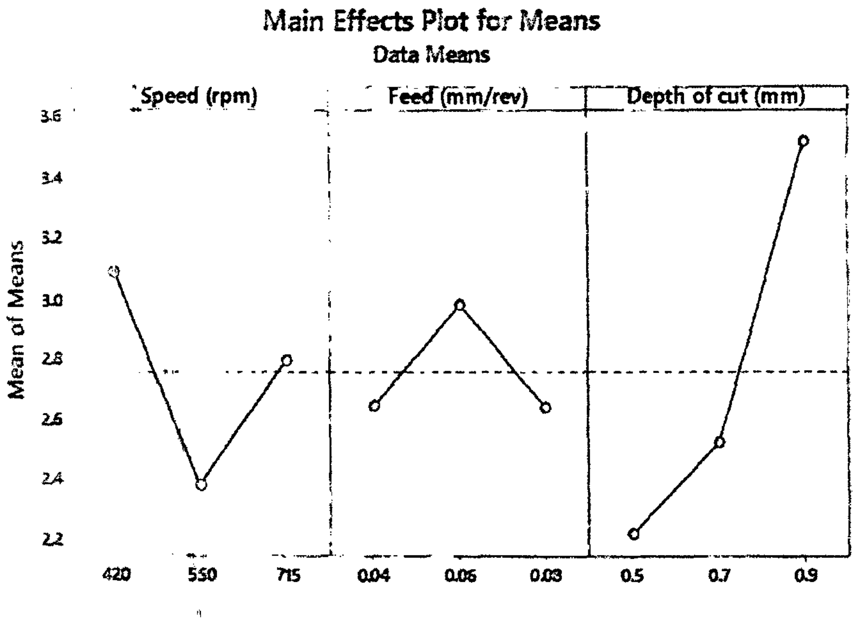
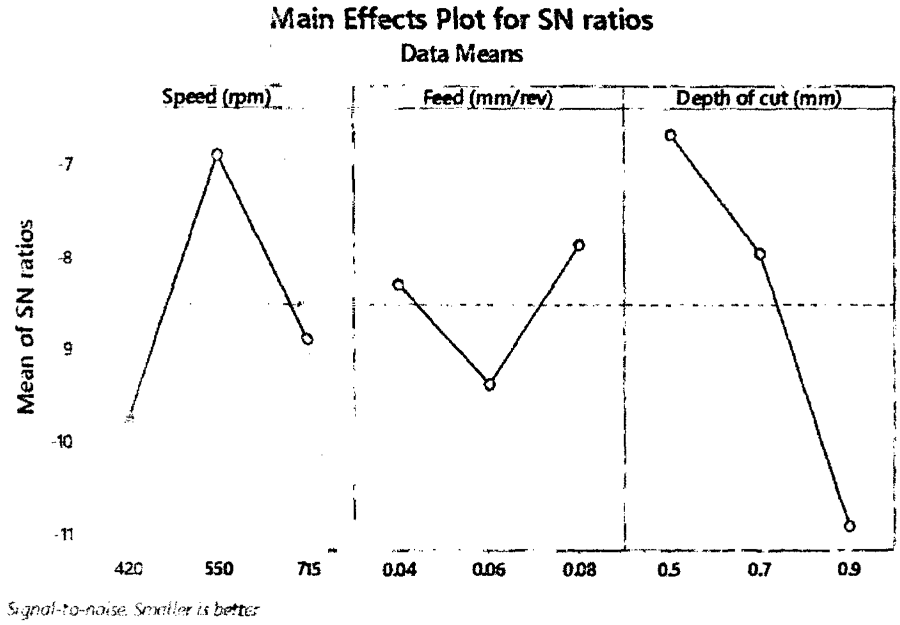


Figure 5.4: Main Effects plots for Signal to Noise ratio of Surface Roughness



5.3.1 Determination of optimum conditions

Both the main effects plots for means and S/N ratio are used to derive the optimum conditions. Since surface roughness is smaller-the-better type of response, the lowest points on main effects plot for means and highest points on main effects plot for signal to noise ratio correspond to the optimal setting of the process parameters. The graphs of figures 5.3 and 5.4 are used to determine the optimum process parameters combination. Therefore the optimum combination is spindle speed (N) = 550 rpm, depth of cut (d) = 0.5 mm and feed rate (f) = .08 mm/rev.

5.3.2 Predictive Equation and Verification

The predicted value of Surface Roughness at the optimum levels is calculated by using the relation [28]:

$$\hat{\gamma} = \gamma_m + \sum_{i=0}^{n} (\bar{\gamma}i - \gamma_m) \qquad [5.4]$$

Where, $\hat{\gamma}$ is the predicted response value, γ_m is the total mean of quality characteristics, $\bar{\gamma}$i is the mean of characteristics at the optimal level of each process parameter, and 'n' is the number of the main design parameters that affect the quality characteristics. Applying this relation predicted value of Surface roughness at the optimum conditions is obtained as:

$$\hat{\gamma}\ \textbf{(MRR)} = 2.869 + [(2.384-2.869) + (2.643-2.869) + (2.135-2.869)]$$

$$= 1.422\ \mu m$$

The robustness of this parameter optimization is verified experimentally. This requires the confirmation run at the predicted optimum conditions. The error in the predicted and experimental value is less than 5 %, which confirms excellent reproducibility of the results. The results show that best finish is achieved corresponding to second level of speed, first level of depth of cut and third level of feed rate.

CHAPTER-VI

CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

The present work shows the use of Taguchi method to find out optimal machining parameters. Machining Parameters namely spindle speed (N), Feed rate (f), depth of cut (d) are optimized to meet the objectives. The following conclusions are drawn from the study:

a) From the optimization of MRR, it was observed that optimum value of MRR is 4113.6 mm^3/min obtained at spindle speed (N) = 715 rpm, depth of cut (d) = 0.7 mm and feed rate (f) = .08 mm/rev.
b) Results of the optimization of Surface Roughness indicate that optimum value of Surface Roughness is 1.476 μm at spindle speed (N) = 550 rpm, depth of cut (d) = 0.5 mm and feed rate (f) = .08 mm/rev., whereas at these levels the MRR is 2301.6 mm^3/min only.
c) Feed rate has maximum influence on MRR followed by depth of cut and speed.
d) Depth of cut , speed and feed rate affect the surface finish in decreasing order.

6.2 Futuristic Research Direction

The further research can be carried out:

I. To study the effects of cutting fluids and tool geometry on the Surface roughness and MRR.
II. Optimization of MRR and Surface Roughness in Turning Process using Taguchi Method and Grey Relational Analysis.

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LIST OF PUBLICATIONS

Gaurav Gaur and Hari Singh, "Application of Taguchi Method in the Optimization of the Cutting Forces in Turning Operation of 20MnCr5 Alloy Steel", **Journal of Material Science and Mechanical Engineering (Print ISSN: 2393-9095; Online ISSN: 2393-9109), Vol. 2, No. 9, April-June 2015, pp. 58-61.**

Gaurav Gaur and Hari Singh, "Parametric Optimization of MRR and Surface Roughness on 20MnCr5 using Taguchi Method in Turning Process", 5th National Conference on Recent Advances in Manufacturing (RAM-2015), SVNIT Surat, 16-17 May 2015, pp. 17-20.