Department of Mechanical & Chemical Engineering (MCE)

ISLAMIC UNIVERSITY OF TECHNOLOGY (IUT)

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PREDICTION AND OPTIMIZATION OF SURFACE ROUGHNESS BY DESIRABILITY ANALYSIS

BY

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بسم الله الرحمن الرحيم

Department of Mechanical & Chemical Engineering (MCE)

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October, 2012

DECLERATION OF CANDIDATES

This is to certify that this thesis or any part thereof has not been submitted anywhere else for the award of any degree or any publication

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ABSTRACT

This project deals with the prediction and optimization of surface roughness by desirability approach. There are some machining parameters that have significant effects on the surface of a metal and cause surface roughness. Now a days, it is a big concern to reduce the surface roughness for various machining operation by changing the value of machining parameters like feed rate, cutting speed etc. Here, in this project there were observations of rough surface at different feed and cutting speed. However, a CNC drilling machine can have different operation along with drilling. Obviously, there is roughness in the machined surface of a drilled hole. In this project there an effort has been made to develop a mathematical model of a CNC drilling machine for reducing surface roughness as much as possible. For getting the optimum values of machining parameters, "Desirability approach" and "ANOVA" were applied. Also there was an application of image processing to evaluate the circularity as it varies widely with the change of machining parameters. However, there is a successful prediction of surface roughness and the optimum cutting condition is found out. And this investigation to reduce roughness by producing a mathematical model for a CNC drilling machine is proved to be very much accurate by experimental validation which might be reference for further investigation on surface roughness for another operating conditions .

TABLE OF CONTENTS

Page No.

CHAPTER 1: INTRODUCTION

CHAPTER 2: LITERATURE RIVIEW

CHAPTER 3: EXPERIMENTAL SETUP

CHAPTER 4: RESULTS AND DISCUSSION

LIST OF FIGURES

CHAPTER 1

CHAPTER 3

CHAPTER 4

LIST OF TABLES

CHAPTER 1

INTRODUCTION

Computer Numerical Control (CNC) Drilling is commonly implemented for mass production. The drilling machine, however, is often a multi-function machining center that also mills and sometimes turns. The largest time sink for CNC drilling is with tool changes, so for speed, variation of hole diameters should be minimized. The appropriate drill is brought into position through movement of the turret, so that bits do not need to be removed and replaced. The holes drilled using the CNC drilling machines are accurate and variations in circularity and surface roughness are to be found prominent. This is because it is easy to vary the feed and speed of the drilling operation.

1.1 DIFFERENT TYPES OF DRILLING MACHINES

1.1.1 Upright Sensitive Drilling Machine

The upright sensitive drill press (Figure 1.1) is a light-duty type of drilling machine that normally incorporates a belt drive spindle head. This machine is generally used for moderate-to-light duty work. The upright sensitive drill press gets its name due to the fact that the machine can only be hand fed. Hand feeding the tool into the work piece allows the operator to "feel" the cutting action of the tool. The sensitive drill press is manufactured in a floor style or a bench style.

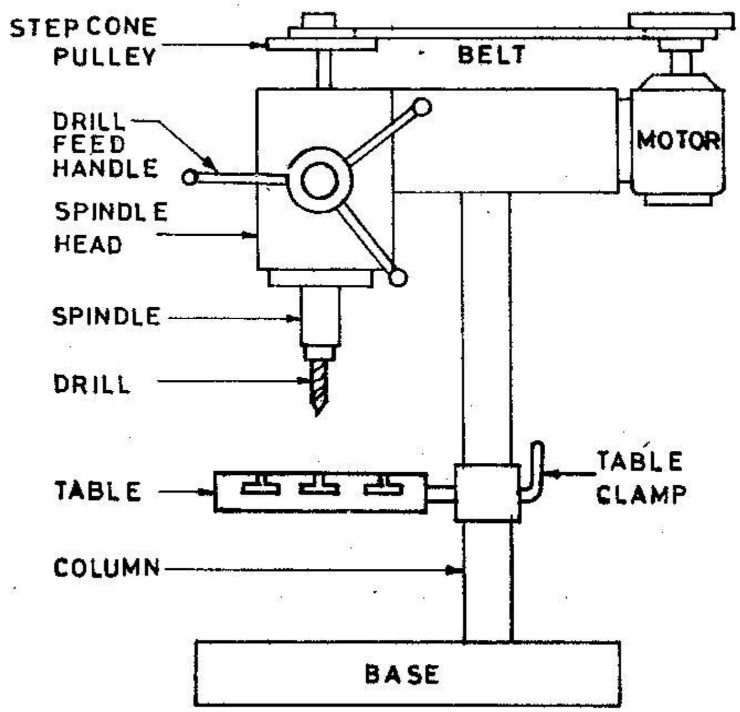


Figure 1.1: Upright sensitive drilling machine

1.1.2 Upright Drilling Machine

The upright drill press (Figure 1.2) is a heavy duty type of drilling machine normally incorporating a geared drive spindle head. This type of drilling machine is used on large hole-producing operations that typically involve larger or heavier parts. The upright drill press allows the operator to hand feed or power feed the tool into the work piece. The power feed mechanism automatically advances the tool into the work piece. Some types of upright drill presses are also manufactured with automatic table-raising mechanisms.

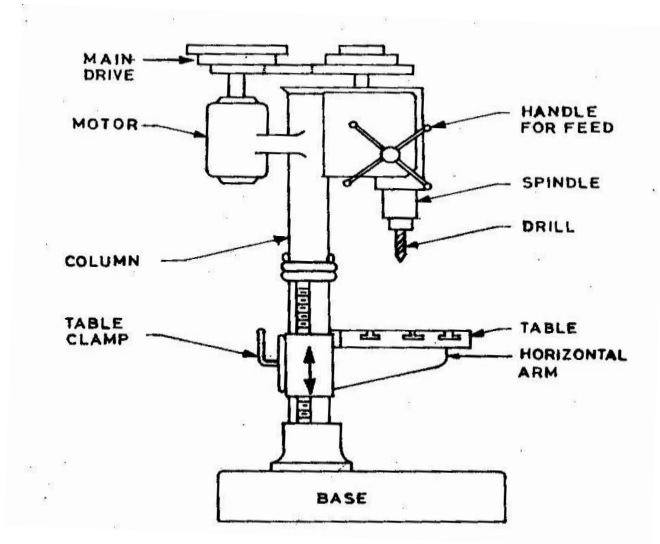


Figure 1.2: Upright drilling machine

1.1.3 Vertical Drilling Machines

The cutting piece is arranged vertically on the mill and drops down to cut into the material. The vertical milling machine tool, regardless of subcategory, refers to a milling tool in which the cutting piece is vertically arranged. In addition to making holes, drills are often used to push screws into wood, metal, plastic, rock, or composites. The hand drill and push drill are both manually operated drilling machines that have been largely replaced by power drills. A hand drill works by turning a crank that rotates gears, which cause the chuck to turn.

Figure 1.3: Vertical drilling machine

1.1.4 Horizontal Drilling Machines

A drill press is quite limited in its abilities because it creates only vertical holes. Horizontal boring machines offer many more drilling options. The horizontal boring machine primarily is a large drilling motor attached to casters that helps it to move from right to left horizontally at the operator's command. While a horizontal milling machine is still commonplace in most large manufacturing centers, vertical machines utilizing computer numerical control (CNC) are becoming more common all the time. A milling machine is a piece of manufacturing equipment. The horizontal milling machine came into use during the early 1800s, and the basic design of a common modern machine is nearly the same as this original model.

Figure 1.4: Horizontal drilling machine

1.1.5 Radial Drilling Machine

- It the largest and most versatile used for drilling medium to large and heavy work pieces.
- Radial drilling machine belong to power feed type.
- The column and radial drilling machine supports the radial arm, drill head and motor. Fig.3 shows the line sketch of radial drilling machine.

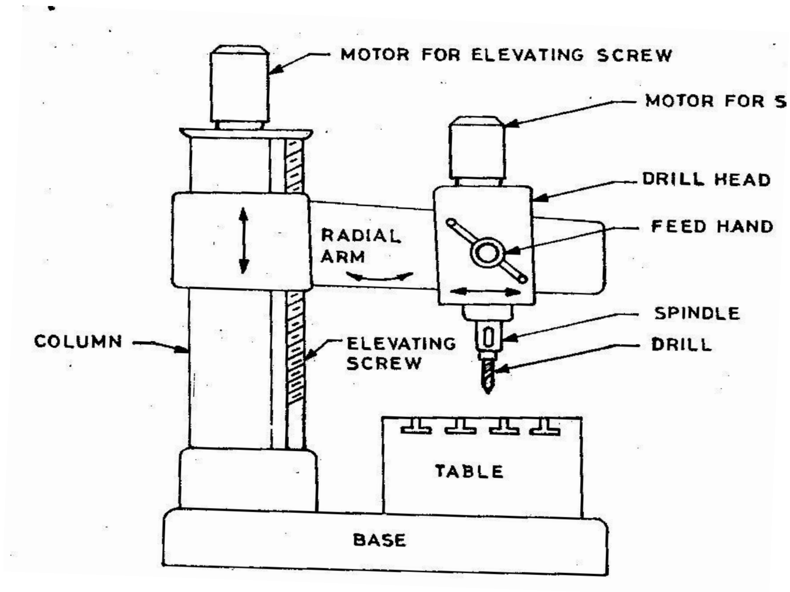


Figure 1.5: Radial Drilling Machine

- The radial arm slides up and down on the column with the help of elevating screw provided on the side of the column, which is driven by a motor.
- The drill head is mounted on the radial arm and moves on the guide ways provided the radial arm can also be swiveled around the column.
- The drill head is equipped with a separate motor to drive the spindle, which carries the drill bit. A drill head may be moved on the arm manually or by power.
- Feed can be either manual or automatic with reversal mechanism.

1.1.6 CNC Drilling Machines

Drills are often used to push screws into wood, metal, plastic, rock, or composites. The hand drill and push drill are both manually operated drilling machines that have been largely replaced by power drills. A hand drill works by turning a crank that rotates gears, which cause the chuck to turn. Here automatic speed and feed variation makes the operation reliable and easy.

1.2 WORKING PRINCIPLE OF CNC DRILLING MACHINE:

A CNC drilling machine uses holding device to hold the drill, and then control the rotational speed of the drill, the depth (Z-axis) of the drilling into the workpiece and its width. The work piece is usually clamped on the table that can move on the surface (X and Y-axis). Because drills have different length, therefore some CNC drilling machines use a program to compensate for the depth of the drilling. Some CNC machines have an automatic drill change system.

1.3 COMPONENTS OF DRILLING MACHINE

Spindle

The spindle holds the drill or cutting tools and revolves in a fixed position in a sleeve.

Sleeve

The sleeve or quill assembly does not revolve but may slide in its bearing in a direction parallel to its axis. When the sleeve carrying the spindle with a cutting tool is lowered, the cutting tool is fed into the work: and when it’s moved upward, the cutting tool is withdrawn from the work. Feed pressure applied to the sleeve by hand or power causes the revolving drill to cut its way into the work a fraction of an mm per revolution.

Column

The column is cylindrical in shape and built rugged and solid. The column supports the head and the sleeve or quill assembly.

Head

The head of the drilling machine is composed of the sleeve, a spindle, an electric motor and feed mechanism. The head is bolted to the column.

Worktable

The worktable is supported on an arm mounted to the column. The worktable can be adjusted vertically to accommodate different heights of work or it can be swung completely out of the way. It may be tilted up to 90 degree in either direction, to allow long pieces to be end or angle drilled.

Base

The base of the drilling machine supports the entire machine and when bolted to the floor, provides for vibration-free operation and best machining accuracy. The top of the base is similar to the worktable and may be equipped with t- slot for mounting work too larger for the table.

Hand Feed

The hand- feed drilling machines are the simplest and most common type of drilling machines in use today. These are light duty machine that are operated by the operator, using a feed handled, so that the operator is able to “feel” the action of the cutting tool as it cuts through the work piece. These drilling machines can be bench or floor mounted.

Power feed

The power feed drilling machine are usually larger and heavier than the hand feed ones they are equipped with the ability to feed the cutting tool in to the work automatically, at preset depth of cut per revolution of the spindle these machines are used in maintenance for medium duty work or the work that uses large drills that require power feed larger work pieces are usually clamped directly to the table or base using t –bolts and clamps by a small work places are held in a vise. A depth –stop mechanism is located on the head, near the spindle, to aid in drilling to a precise depth.

1.4 DRILL MATERIALS

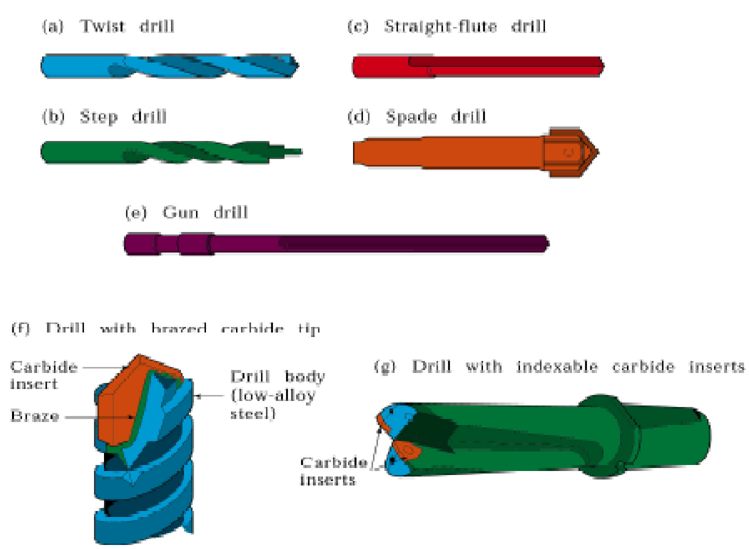
The two most common types are

1. HSS drill- Low cost
2. Carbide- tipped drills- high production and in CNC machines

<u>Other types are-</u>

Solid Carbide drill, Tin coated drills, carbide coated masonry drills, parabolic drills, split point drill. Fig.4 shows various types of drills

Figure 1.6: Various types of Drill bits



Drill fixed to the spindle

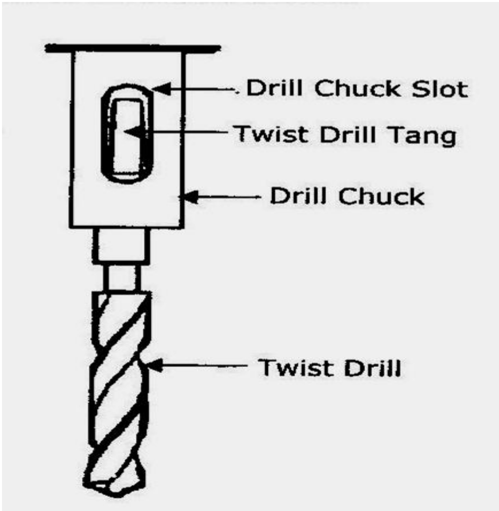


Figure 1.7: Drill fixed to a spindle

1.5 TOOL NOMENCLATURE

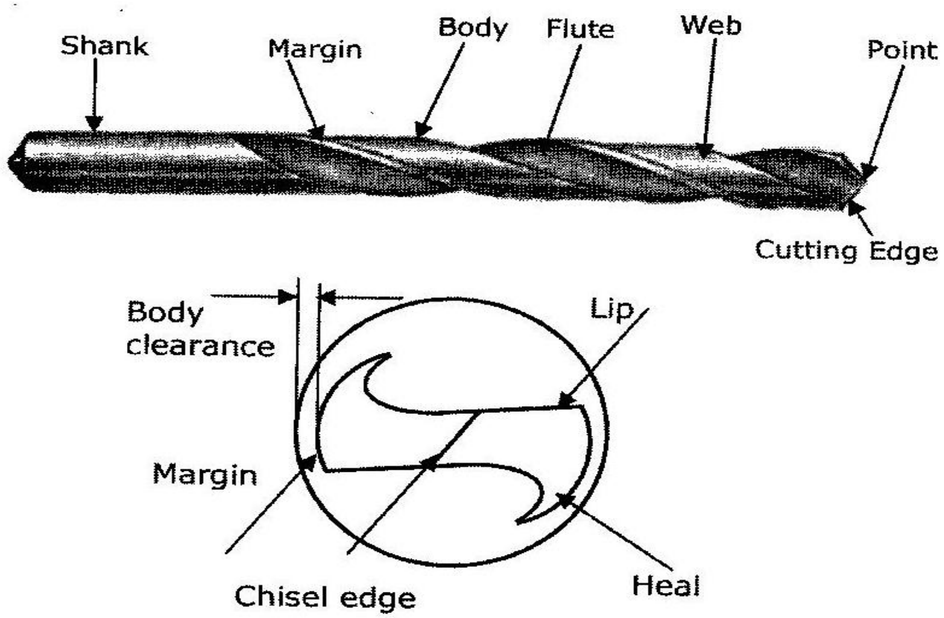


Figure 1.8: Nomenclature of twist drill

1.6 TOOL HOLDING DEVICES

Fig.1.9 shows the different work holding and drill drift device. The different methods used for holding drill in a drill spindle are

- By directly fitting in the spindle hole.
- By using drill sleeve
- By using drill socket
- By using drill chuck

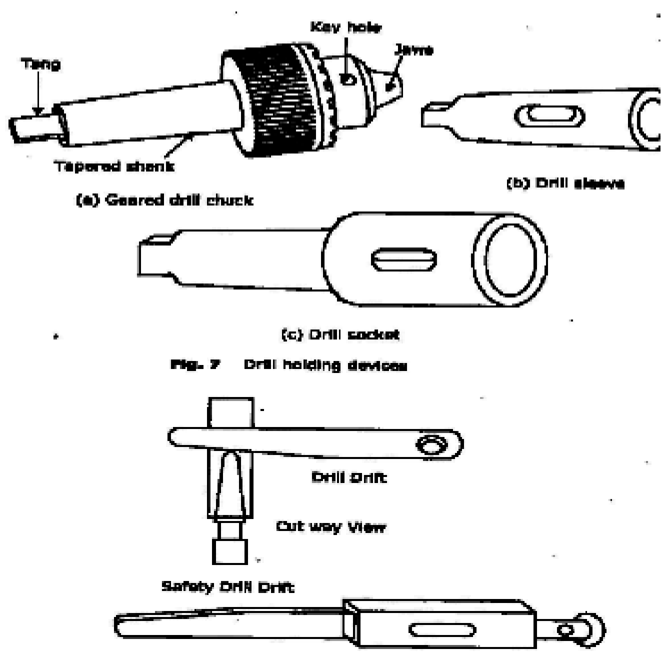


Figure 1.9: Drill holding devices and drill drift

1.7 WHY THIS RESEARCH:

CNC Drilling is an expensive and accurate machining process which is used to machine hard materials, drill holes, and for obtaining results for surface finish. Hence optimizing its process parameters to obtain minimum surface roughness will lead to greater accuracy of the job. Design of experiment's RSM approach can easily predict and optimize EDM process by developing a suitable mathematical model for surface roughness with minimum number of experiments. This mathematical model will aid researchers to better understand the effect of different process parameters on surface roughness generated and professionals to achieve better quality control.

1.8 THE MERITS OF CNC MACHINE

There are many advantages of a CNC machine:

(i) The computer can design the best tool path, spinning and cutting speeds of tools according to the information of the product. This can help decrease the cost and time.

(ii) CNC machines usually have automatic changing tools function.

(iii) CNC machines can control precisely the tools movement in any axis, so it can cut some complicated work piece efficiently.

(iv) With the use of various input devices and the memories of computer, a CNC machine can download and modify program efficiently, so the production procedures can be made quickly.

(v) In operating the CNC machine, manual adjustment is not needed. Therefore, the CNC machine can run at a high speed, and it requires less skillful workers to reduce the labor cost.

(vi) CNC machine uses various designs to produce feedback, and so it can keep its high reliability and quality, this can help decrease the number of disqualified product and the cost of inspection.

1.9 DIFFERNET TYPES OF DRILLING OPERATIONS:

Operations that can be performed in a drilling machine are

- Drilling
- Reaming
- Boring
- Counter boring
- Countersinking
- Tapping

Drilling:

It is an operation by which holes are produced in solid metal by means of revolving tool called ‘Drill’. Fig.1.10 shows the various operations on drilling machine.

Reaming:

Reaming is accurate way of sizing and finishing the pre-existing hole. Multi tooth cutting tool. Accuracy of ±0.005mm can be achieved

Boring:

Boring is a process of enlarging an existing hole by a single point cutting tool. Boring operation is often preferred because we can correct hole size, or alignment and can produce smooth finish. Boring tool is held in the boring bar which has the shank. Accuracy of ±0.005mm can be achieved.

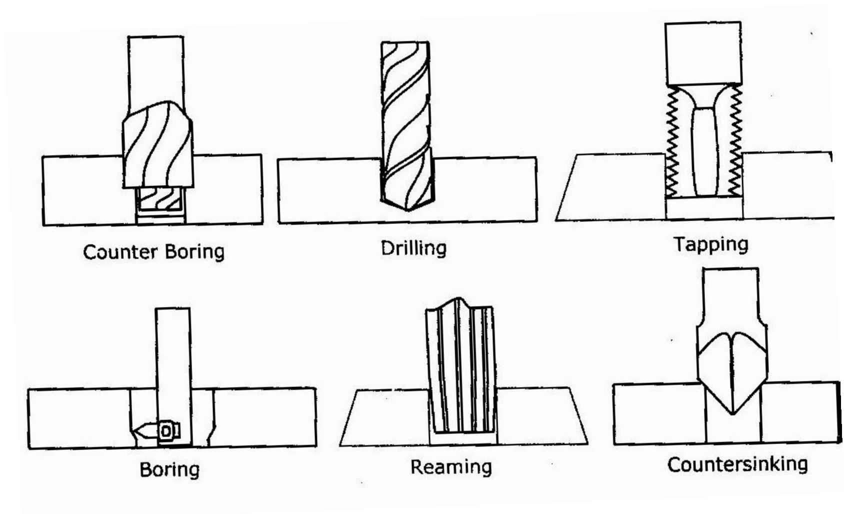


Figure 1.10: Various operations on drilling machine

Counter Bore :

This operation uses a pilot to guide the cutting action to accommodate the heads of bolts. Fig. 1.10 illustrates the counter boring, countersunk and spot facing processes.

Countersink:

Special angled cone shaped enlargement at the end of the hole to accommodate the screws. Cone angles of 60°, 82°, 90°, 100°, 110°, 120°

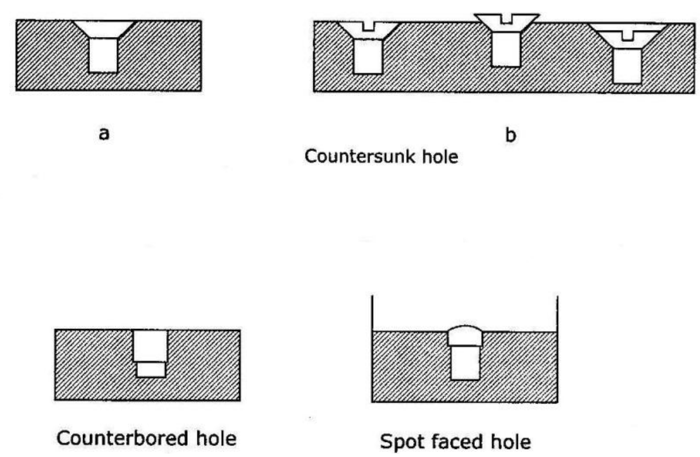


Figure 1.11: Counter boring, countersunk and spot facing

Tapping:

Tapping is the process by which internal threads are formed. It is performed either by hand or by machine. Minor diameter of the thread is drilled and then tapping is done. Fig.1.12 show the tapping processes.

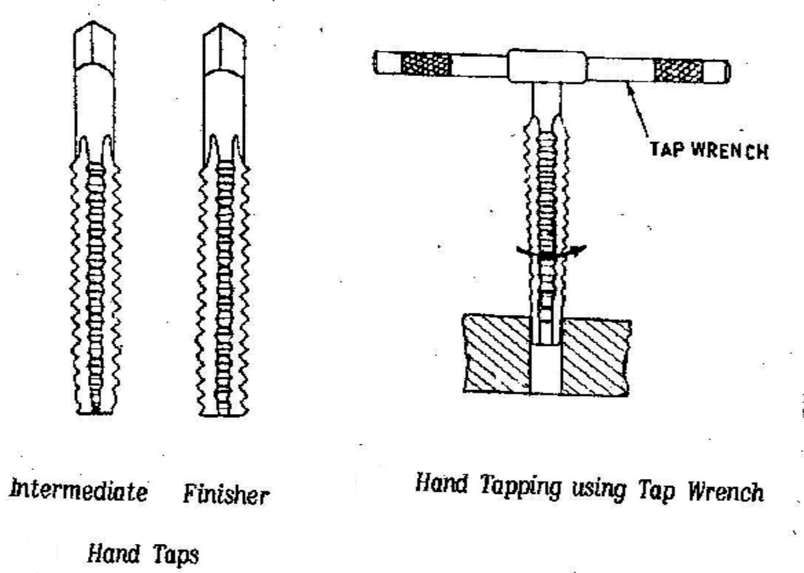


Figure 1.12: Hand taps and tapping process using tap wrench

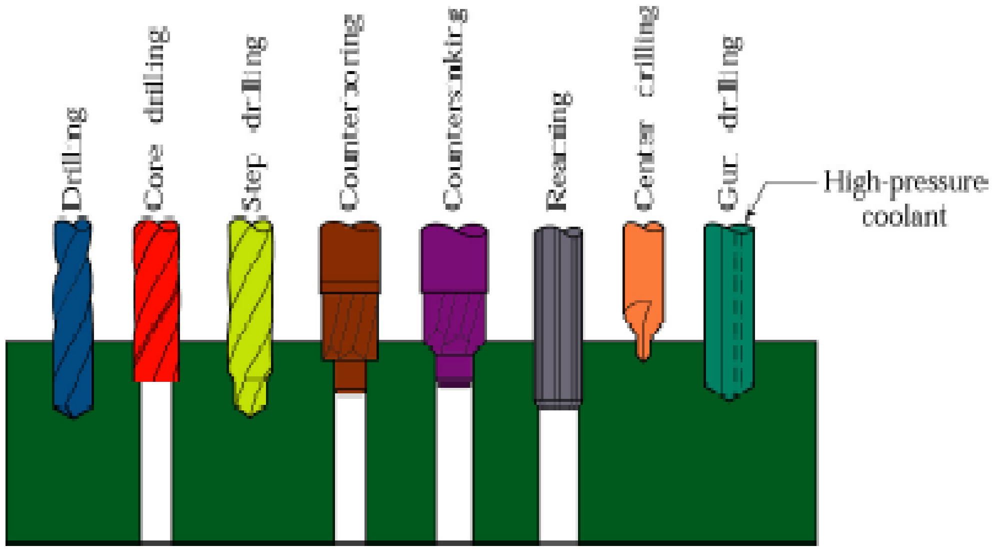


Figure 1.13: Various operations performed on drilling machine

1.10 OBJECTIVE OF THE STUDY:

The main objective of this study is to develop a mathematical model of CNC drilling machine. Another objective is to optimize a formula for the roughness of surface of drilled holes . These holes are drilled in different cutting conditions like at different speed and feed, controlled by a CNC drilling machine, to simulate a formula from different values of surface roughness.

1.11 SIGNIFICANCE AND BENEFITS OF THE RESEARCH

In an industrial point of view, the research will have benefits. Obviously, surface roughness is a phenomena, responsible for good quality of materials. So by comparing surface roughness and some machining parameters, the effects of those parameters on surface roughness can be predicted. Surface roughness can be minimized within the operational domain of the machine and machine parameters. Mathematical model developed can be a reference for researchers studying surface roughness produced in CNC drilling machine. The research approach can be applied for another research dealing with machine parameters.

1.12 THESIS ORGANIZATION:

In the next chapters details of the following is discussed elaborately----

1. Literature review: In this section relevant publications are discussed briefly in order to get the idea of the trend of is going on around in this research discipline.

2. Experiomental Set up: In this section all the methods and procedures which are related to this study is discussed in details

3. Result and Discussion: In this section of the thesis the outcome of the study are illustrated with their adequate significance

4. Conclusion and recommendation for further study: This section deals with the concluding outcomes of the research and recommends the further scope of research in this field

5 Bibliography: Reference of all the research work and publications are mentioned in this chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

A significant amount of research has been done on the optimization of surface roughness by drilling machines. Among them, some of the prominent researches and their results, which are related to this research, are briefly discussed below. This discussion is in no way complete as there is a large volume of research literature in the field.

2.2 DISCUSSION OF RELEVANT RESEARCH

Yogendra Tyagi et al [1] has expermented the drilling of mild steel with the help of CNC drilling machining operation with tool as high speed steel by applying taguchi method. They appied L9 orthogonal array and analysis of variance(ANOVA) to study the performance characteristics of machining parameter (spindle speed, feed, depth) keeping in consideration of good surface finish and high material removal rate(MRR). The results they obtained by taguchi method and signal-to-noise ratio match closely with ANOVA. They also found out that the feed is most effective factor for MRR. And spindle speed is the most effective factor for surface roughness.

J.Pradeep Kumar et al. [2] utilized taguchi method to investigate the effects of drilling parameters such as cutting speed (5, 6.5, 8 m/min), feed (0.15, 0.20, 0.25mm/rev) and drill tool diameter (10, 12, 15mm) on surface roughness, tool wear by weight, material removal rate and hole diameter error in drilling of OHNS material using HSS spiral drill. They used orthogonal arrays of taguchi, the Signal–to- Noise (S/N) ratio, the analysis of variance (ANOVA), and regression analysis to analyze the effect of drilling parameters on the quality of drilled holes. They devolped linear regression equations to establish a relation between the selected drilling parameters with the quality characteristics of the drilled holes. They compared the theoretical values with the experimental data and found it to be close.

Upinder Kumar Yadav et al. [3] investigated the effect and optimization of machining parameters (cutting speed, feed rate and depth of cut) on surface roughness. An L'27 orthogonal array, analysis of variance (ANOVA) and the signal-to-noise (S/N) ratio are used in this study. Three levels of machining parameters are used and experiments are done on CNC lathe. The optimum value of surface roughness(Ra) was found 0.89 and also concluded that feed rate is the most effective factor affecting surface roughness followed by depth of cut. Cutting speed is the least significant factor affecting surface roughness.

Ferit Ficici et al.[4] investigated the optimum cutting parameters when drilling an AISI 304 stainless steel using modified HSS drill tools. In this paper the Taguchi technique and analysis of variance (ANOVA) are applied for minimization of surface roughness (Ra) influenced by drilling cutting parameters. The optimum drilling cutting parameter combination was obtained by using the analysis of signal-to-noise ratio. They concluded that modification of drill and feed rate were the most influential factors on the surface roughness (Ra). The best results of the surface roughness (Ra) were obtained at higher cutting speeds and lower feed rates. They used multiple linear regression to correlate between the cutting parameters and the surface roughness . They came to the conclusion that that Taguchi parameter design can successfully verify the optimum test.

Yogendra Tyagi et al. [5] reported the drilling of mild steel with the help of CNC drilling machine operation with Tool use high speed steel by applying Taguchi methodology. The Taguchi method is applied to formulate the experimental layout to ascertain the Element of impact each optimum process parameters for CNC drilling machining with drilling operation of mild steel. A L9 array, taguchi method and analysis of variance (ANOVA) are used to formulate the procedure tried on the change of parameter layout. They found out that surface roughness and material removal rate are directly related to productivity. The selected machining parameters (i.e., spindle speed, depth of cut and feed rate) for drilling machine operations was investigated in order to minimize the surface roughness and to maximize the material removal rate.

Tolga Bozdana et al. [6] investigated EDM drilling of Ø2 mm holes on Inconel 718 using brass electrode. The mathematical modeling of process has been done using response surface methodology(RSM). The results show that the developed model can achieve reliable prediction of experimental results within acceptable accuracy.

B. Sidda Reddy et al. [7] investigated on the study of minimization of surface roughness by integrating design of experiment method, Response surface methodology (RSM) and genetic algorithm. They did the experiment using Taguchi’s L50 orthogonal array in the design of experiments (DOE) by considering the machining parameters such as Nose radius (R), Cutting speed (V), feed (f), axial depth of cut (d) and radial depth of cut(rd). They developed a predictive response surface model for surface roughness is using RSM. To find the optimum machining parameter values. , the response surface (RS) model is interfaced with the genetic algorithm (GA) .

Noordin et al [8] studied the application of response surface methodology in describing the performance of coated carbide tools when turning AISI1045 steel. The factors investigated were cutting speed, feed and side cutting edge angle. The response variables were surface finish and tangential force. ANOVA revealed that feed is the most significant factor influencing the response variables investigated.

Tadeusz Zaborowski et al. [9] attempted to find optimum formation of chips in drilling materials with specific properties. Engineering manufacturing is one of the key factors of dynamic development of an industry. Present state of machining technology and prospective trends prove machining core position in engineering manufacturing. They experimented to find out the optimum formation of chips during drilling operation.

M. N. Islam et al.[10] presented experimental and analytical results to investigate into the dimensional accuracy and surface finish of drilled holes using different canned cycles. Several factors influence the accuracy of drilled holes. The most obvious ones are the cutting conditions (cutting speed and feed rate) and cutting configurations (tool material, diameter, and geometry). However, in CNC drilling operations, choosing to use canned cycles may have significant effect on drilled hole quality. A traditional analysis, the Pareto ANOVA, and the Taguchi S/N ratio are employed to determine the effects of the three major input parameters (cutting speed, feed rate, and canned cycle) on three key accuracy characteristics of drilled holes (diameter error, circularity, and surface roughness), as well as to obtain an optimal combination of the input parameters. The results indicate that the canned cycle has a profound effect on drilled hole quality, and, in general, canned cycle spot drilling produces the best results.

Dong-Woo Kim et al.[11] attempted to minimize the thrust forces in the step-feed micro drilling process by application of the DOE (Design of Experiment) method, taking into account the drilling thrust, three cutting parameters, feedrate, step-feed, and cutting speed, are optimized based on the DOE method. They used an orthogonal array L27(313) and ANOVA (Analysis of Variance) for experimental studies. Micro drilled holes are utilized in many of today's fabrication processes. Precision production processes in industries are trending toward the use of smaller holes with higher aspect ratios, and higher speed operation for micro deep hole drilling. However, undesirable characteristics related to micro drilling such as small signal-to-noise ratios, wandering drill motion, high aspect ratio, and excessive cutting forces can be observed when cutting depth increases. The results obtained by them show that the sequence of factors affecting drilling thrusts corresponds to feed rate, step-feed, and spindle rpm. They also identified a combination of optimal drilling conditions. In this experiment they came to a conclusion that the federate is the most important factor for micro drilling thrust minimization.

R. H. Hardin and N. J. A. Sloane [12] developed an algorithm by combining a modified version of Hooke and Jeeves' pattern search with exact or Monte Carlo moment calculations. With the help of this algorithm it is possible to find I -, D- and A-optimal (or nearly optimal) designs for a wide range of response-surface problems. The algorithm routinely handles problems involving the minimization of functions of 1000 variables, and so for example can construct designs for a full quadratic response-surface depending on 12 continuous process variables. The algorithm handles continuous or discrete variables, linear equality or inequality constraints, and a response surface that is any low degree polynomial. The design may be required to include a specified set of points, so a sequence of designs can be obtained, each optimal given that the earlier runs have been made. The modeling region need not coincide with the measurement region. The algorithm has been implemented in a program called “gusset”, which has been used to compute extensive tables of designs. Many of these are more efficient than the best designs previously known.

L. B. Abhang and M. Hameedullah [13] in their research paper studied the Power consumption in turning EN-31 steel (a material that is most extensively used in automotive industry) with tungsten carbide tool under different cutting conditions. They planned the experimental runs ac-cording to 24+8 added centre point factorial design of experiments, replicated thrice. They analyzed the data collected statistically using Analysis of Variance technique (ANOVA) and developed first order and second order power consumption prediction models by using response surface methodology (RSM). They concluded that second-order model is more accurate than the first-order model and fit well with the experimental data. The model can be used in the automotive industries for deciding the cutting parameters for minimum power consumption and hence maximum productivity.

L. B. Abhang and M. Hameedullah in their another research work made an experimental investigation on turning of EN-31 steel with tungsten carbide tool at different conditions of cutting speed, feed rate, depth of cut and tool nose radius. They measured the cutting forces and calculated the power consumption. They also developed the first order and second order power prediction models with respect to various combinations of design variables (cutting speed, feed rate, depth of cut and tool nose radius) by response surface methodology with the factorial design of experiments and analysis of variance (ANOVA) applied to the uncoded data

Suresh et al. [14] have developed a surface roughness prediction model for turning mild steel using a response surface methodology. Surface roughness prediction model has also been optimized by using genetic algorithms.

Surface roughness prediction models for dry and wet turning of EN-31 steel with tungsten carbide tool have been developed and reported by Abhang and Hameedullah [15]. Second degree model were found to be more significant than the first degree model. The interaction effects of response parameters were also found to be significant.

Anirban Bhattacharya et al. [16] have investigated the effect of cutting parameters on surface finish and power consumption during high speed machining of AISI irons steel using Taguchi design and ANOVA. In this study, combined technique of orthogonal array and analysis of variance was employed to investigate the contribution and effect of cutting speed, feed rate and depth of cut (only three factors) on three surface roughness parameters and power consumption were studied at different metal cutting conditions. The results showed a significant effect of cutting speed on surface roughness and power consumption, while the other parameters have not substantially affected the response.

Sood et al. [17] studied the specific energy where the power of machining is one of the parameter affecting the specific energy.

C.C. Tsao et al.[18] presented a prediction and evaluation of delamination factor in use of twist drill, candle stick drill and saw drill. The approach is based on Taguchi's method and the analysis of variance (ANOVA). They conducted experiments to study the delamination factor under various cutting conditions. They found the results such that the feed rate and the drill diameter are the two most significant factors contributing to overall performamce. A correlation between feed rate, spindle speed and drill diameter was obtained by multi-variable linear regression and compared with the experimental results.

There have been plenty of recent applications of Taguchi tech-niques to materials processing for process optimization. Statistical methods and Taguchi's technique were used for investigating machinability and optimizing power consumption [19].

Lin [20] has formulated the experimental results of surface roughness and cutting

forces by regression analysis, and modeled the effects of them in his study using S5SC steel. Similar investigations have been re-ported by Risbood [21].

B. C. Routara et al. [22] presented a desirability function approach in this paper in order to find out an optimal combination of machining parameters for multiple performance characteristics of the surface roughness parameters in CNC turning operation on mild steel. Experiments have been conducted using depth of cut, spindle speed and feed rate as cutting parameters for evaluating the roughness parameters such as centre line average (Ra), root mean square (Rq) and mean line peak spacing (RSM). They used an orthogonal array (L9) using the Taguchi design to carry out the experiments on AISI 1040 mild steel bar. They calculated the individual desirability values of each roughness parameters. The signal-to-noise ratio is employed to investigate the optimal combination of cutting parameters to yield maximum overall desirability.

Enrique Del Castillo et al. [23] modified desirability functions that are everywhere differential so that more efficient gradient based optimization methods can be used. Desirability functions have been extensively used to simultaneously optimize several responses. In this study, the proposed functions have extra flexibility of allowing the analyst to assign different priorities among the responses. They applied this method to a wire bonding process that occurs in semiconductor manufacturing.

CHAPTER 3

EXPERIMENTAL SETUP

3.1 INTRODUCTION

The main idea of the research is to develop a mathematical model to study the effects of different process parameters on surface roughness of the drilled hole by using CNC drilling machine. In this research, three process parameters are used for the development of an optimization model to obtain minimal surface roughness for mild steel. The most dominant parameter which effects surface roughness most is also determined.

3.2 EXPERIMENTAL PROCEDURE

For design of experiments, response surface methodology is used. CNC drilling will be done on material specimens accordingly. The drilled holes, thus obtained, will be analyzed in order to measure the surface roughness produced. For the experiment, CNC Drilling Machine in the IUT machining laboratory will be utilized. The advantage of this machine is that it has a built in computer terminal and software. Thus, the outputs of the model can be programmed using this software and input into the machine. The surface roughness and the circularity of the drilled holes will then be measured using digital image processing technique developed by the Patwari et al.

3.4 OBJECTIVES OF THE PROJECT

1) To develop a mathematical model in order to predict the surface roughness for different cutting conditions.

2) To optimize the model for minimum surface roughness.

3) To investigate the effect of feed on circularity of the holes.

3.4 RESEARCH METHODOLOGY:

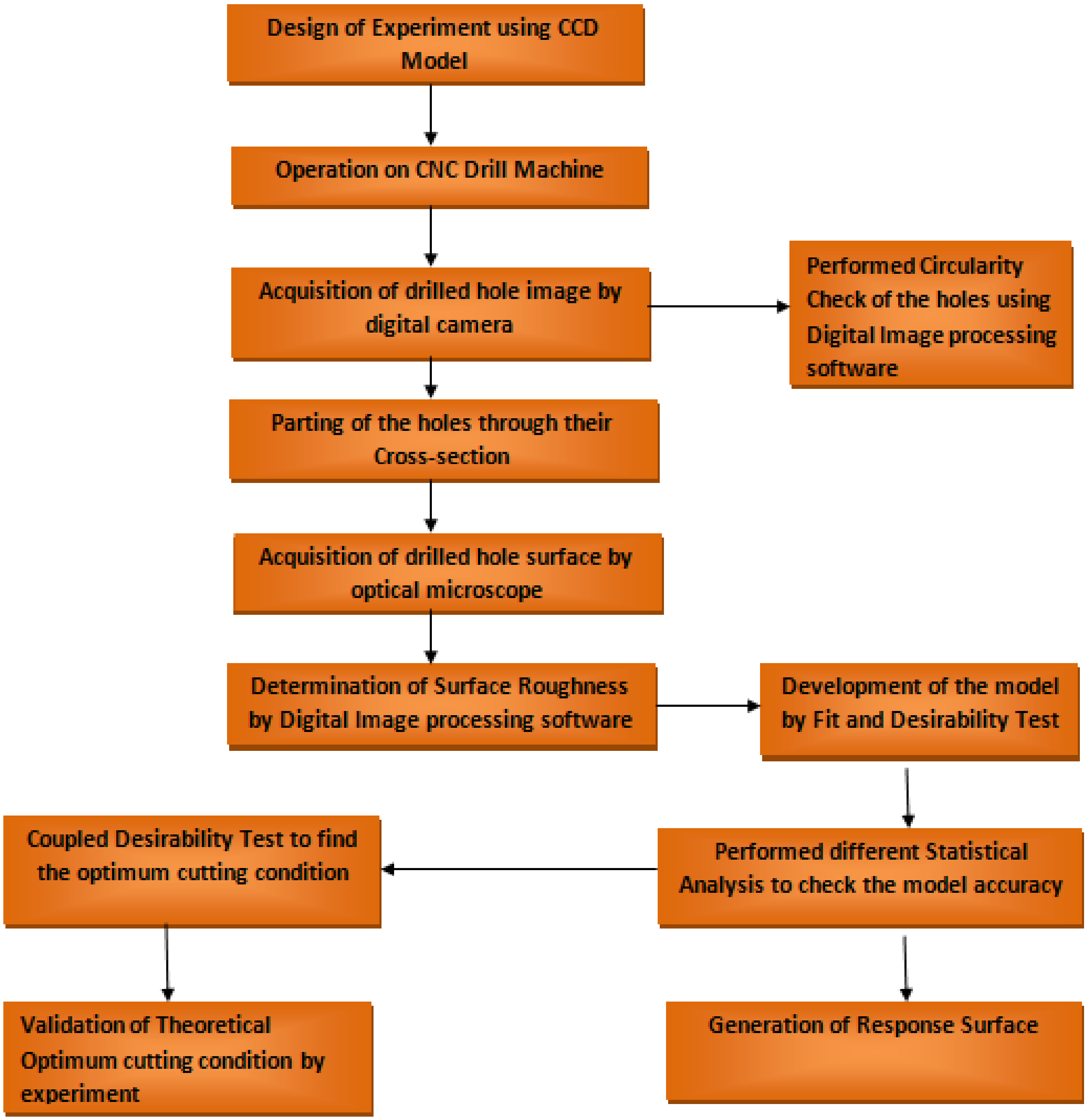


Figure 3.1: Flow Chart Of The Experiment

3.5 EXPERIMENTAL DESIGN

The number of process parameters considered has an effect on the number of experiments required. Therefore, it is important to have a well-designed experiment to minimize the number of experiments which often are carried out randomly. A good design will also cancel the likelihood of using biased independent variables.

Response surface methodology (RSM), a popular statistical tool of Design of Experiment (DOE), is used which is easy to develop and apply. It is a statistical approximation and thus can be used even when little is known about the concerned process and parameters. It uses a sequence of designed experiments in order to obtain an optimal response. There are different methods of RSM. In this research, the rotatable Central Composite Design (CCD) approach of RSM is used. The design is done on the basis of two factors with five levels of coding.

3.5.1 Response Surface Methodology

The Response Surface Methodology (RSM) is a collection of mathematical and statistical techniques useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response (Montgomery 2005). It can be expressed as

$$y = f(x_1, x_2) + e$$

The variables x1 and x2 are independent variables where the response y depends on them. The dependent variable y is a function of x1, x2, and the experimental error term, denoted as e. The error term e represents any measurement error on the response, as well as other type of variations not counted in f. It is a statistical error that is assumed to distribute normally with zero mean and variance s 2. In most RSM problems, the true response function f is unknown. In order to develop a proper approximation for f, the experimenter usually starts with a low-order polynomial in some small region. If the response can be defined by a linear function of independent variables, then the approximating function is a first-order model. A first-order model with 2 independent variables can be expressed as

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$$

If there is a curvature in the response surface, then a higher degree polynomial should be used. The approximating function with 2 variables is called a **second-order model**

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x_{11}^2 + \beta_{22} x_{22}^2 + \beta_{12} x_1 x_2 + \varepsilon$$

In general all *RSM* problems use either one or the mixture of the both of these models. In each model, the levels of each factor are independent of the levels of other factors. In order to get the most efficient result in the approximation of polynomials the proper experimental design must be used to collect data. Once the data are collected, the *Method of Least Square* is used to estimate the parameters in the polynomials. The response surface analysis is performed by using the fitted surface. The **response surface designs** are types of designs for fitting response surface. Therefore, the objective of studying *RSM* can be accomplish by

(1) Understanding the topography of the response surface (local maximum, local minimum, ridge lines), and

(2) Finding the region where the optimal response occurs. The goal is to move rapidly and efficiently along a path to get to a maximum or a minimum response so that the response is optimized.

3.5.2 Orthogonal First-Order Design

The experimenter needs to design a model to be efficient. For that reason, I have to take estimation of variances into consideration. The *orthogonal first-order designs* minimize the variance of the regression coefficients $\hat{b}\ j$. A first-order design is orthogonal if the off-diagonal elements of the (**X´X**) matrix are all zero (Montgomery 2005). Consequently, the cross-products of the columns of the ***X*** matrix sum to zero, the inverse matrix of (**X´X**) can be obtained easily, and all of the regression coefficients are uncorrelated. When the columns of the ***X*** matrix are mutually orthogonal then the levels of the corresponding variables are linearly independent.

A first-order model uses low-order polynomial terms to describe some part of the response surface. This model is appropriate for describing a flat surface with or without tilted surfaces. Usually a first-order model fits the data by least squares. Once the estimated equation is obtained, an experimenter can examine the normal plot, the main effects, the contour plot, and ANOVA statistics (*F*-test, *t*-test, *R2*, the adjusted *R2*, and lack of fit) to determine adequacy of the fitted model. Lack of fit of the first-order model happens when the response surface is not a plane. If there is a significant lack of fit of the first-order model, then a more highly structured model, such as second-order model, may be studied in order to locate the optimum.

3.5.3 Second Order Model

There are many designs available for fitting a second-order model. The most popular one is the *central composite design* (CCD). This design was introduced by Box and Wilson. It consists of factorial point s (from a 2*q* design and 2*q-k fractional factorial design*), central points, and axial points. When a first-order model shows an evidence of *lack of fit*, axial points can be added to the quadratic terms with more center points to develop CCD.

When Second order Model is suitable

When the first-order model shows a significant lack of fit, then an experimenter can use a second-order model to describe the response surface. There are many designs available to conduct a second-order design. The central composite design is one of the most popular ones. An experimenter can start with 2q factorial point, and then add center and axial points to get central composite design. Adding the axial points will allow quadratic terms to be included into the model. Second-order model describes quadratic surfaces, and this kind of surface can take many shapes. Therefore, response surface can represent maximum, minimum, ridge or saddle point. Contour plot is a helpful visualization of the surface when the factors are no more than three. When there are more than three design variables, it is almost impossible to visualize the surface. For that reason, in order to locate the optimum value, one can find the stationary point. Once the stationary point is located, either an experimenter can draw a conclusion about the result or continue in further studying of the surface.

Now we demonstrate the design of experiments by using response surface methodology:

3.6 DESIGN OF EXPERIMENT (DOE):

For developing an appropriate model the first job is to make a well design of experiment which depends on the number of process parameters to be considered.

3.6.1 Full factorial design

To construct an approximation model that can capture interactions between N design variables, a full factorial approach (Montgomery, 1997) may be necessary to investigate all possible combinations. A factorial experiment is an experimental strategy in which design variables are varied together, instead of one at a time. The lower and upper bounds of each of N design variables in the optimization problem needs to be defined. The allowable range is then discretized at different levels. If each of the variables is defined at only the lower and upper bounds (two levels), the experimental design is called 2N full factorial. Similarly, if the midpoints are included, the design is called 3N full factorial and shown in Figure3.2.

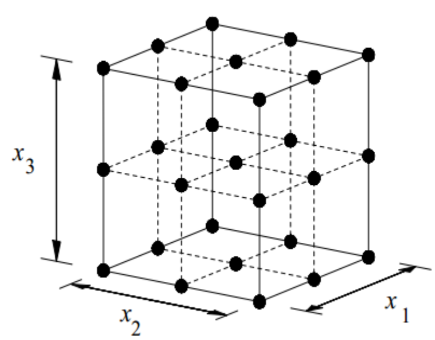


Figure 3.2: Design points in a full factorial design

Factorial designs can be used for fitting second-order models. A second-order model can significantly improve the optimization process when a first-order model suffers lack of fit due to interaction between variables and surface curvature. If the number of design variables becomes large, a fraction of a full factorial design can be used at the cost of estimating only a few combinations between variables. This is called fractional factorial design and is usually used for screening important design variables. For a 3N factorial design, a $(1/3)^p$ fraction can be constructed, resulting in $3^{(N-p)}$ points. For example, for p=1 in a 3^3 design, the result is a one-third fraction, often called $3^{(3-1)}$ design.

3.6.2 D-optimal designs

The D-optimality criterion enables a more efficient construction of a quadratic model (Myers and Montgomery, 1995). The objective is to select P design points from a larger set of candidate points.

Equation can be expressed in matrix notation as:

$$Y = X^* B + e$$

where Y is a vector of observations, e is a vector of errors, X is the matrix of the values of the design variables at plan points and B is the vector of tuning parameters. B can be estimated using the least-squares method as:

$$B = ((X^T * X)^{-1}) X^T Y$$

The D-optimality criterion states that the best set of points in the experiment maximizes the determinant $| X^T X |$. "D" stands for the determinant of the $X^T X$ matrix associated with the model. From a statistical point of view, a D-optimal design leads to response surface models for which the maximum variance of the predicted responses is minimized. This means that the points of the experiment will minimize the error in the estimated coefficients of the response model. The advantages of this method are the possibility to use irregular shapes and the possibility to include extra design points. Generally, D-optimality is one of the most used criteria in computer-generated design of experiments.

3.6.3 Taguchi's contribution to experimental design

Taguchi's methods (Montgomery, 1997) study the parameter space based on the fractional factorial arrays from DOE, called orthogonal arrays. Taguchi argues that it is not necessary to consider the interaction between two design variables explicitly, so he developed a system of tabulated designs which reduce the number of experiments as compared to a full factorial design. An advantage is the ability to handle discrete variables. A disadvantage is that Taguchi ignores parameter interactions.

3.6.4 2-K Design :

If two level factorial considered for investigating the response of the parameters on the process then it is a 2-k first order design. In this design the number of experiments is 2^k, where k is the number of process parameters whose effect should be investigated and optimized. This type of design is very much simple and are not suitable for high precession works. For acquiring more information about the process a 3-k design should be employed.

Center Points in a *2q* Design

In addition to the orthogonal design, the standard first-order design is a 2*q* factorial with a center point. These designs consist of factorial points *nf* and the center points *nc*. The center points are observations collected at the center points xi = 0 (i = 1,2,…, q). The replicated points at the center points can be used to calculate the pure 25 error. Also, the contrast between the mean of the center points and the mean of the factorial points provides a test for the *lack of fit* in a 2*q* design. The lack of fit of a first order model occurs when the model does not adequately represent the mean response as a function of the factor level (Angela 1999). The Figure 3.3 illustrates the graphical viewof a central composite design for q = 2 factors.

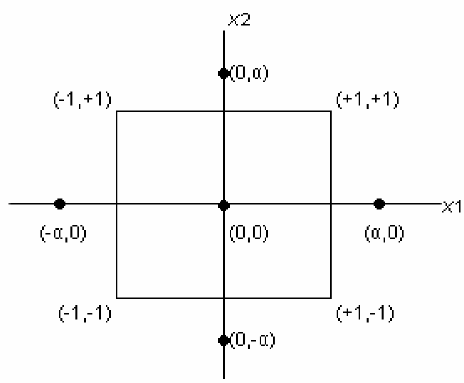


Figure 3.3: 2-level factorial design

3.6.5 3-K Design:

If three level factorial is considered for investigating the response of the parameters on the process then it is a 3-k first order design. In this design the number of experiments is 3^k, where k is the number of process parameters whose effect should be investigated and optimized.

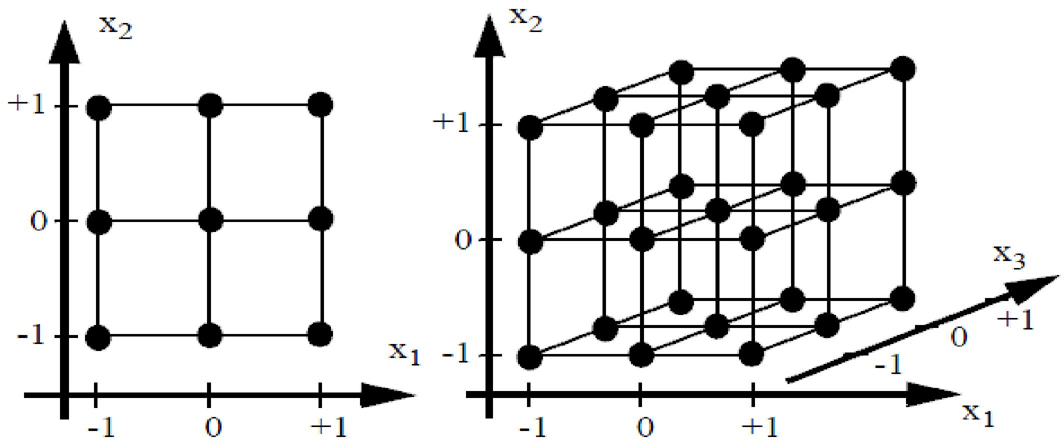


Figure 3.4: 3-level Factorial

The number of experiments to be conducted for different number of k value is given below:

Variables	2	3	4	5
Tests	9	27	81	243

3.6.6 Central Composite Design(CCD):

Central composite design is a modification which is obtained from the base 2-k design with some additional axial and central points in order to furnish the total experiment with more flexibility and thus increasing the probability of moving toward the actual value of response parameters as close as possible.

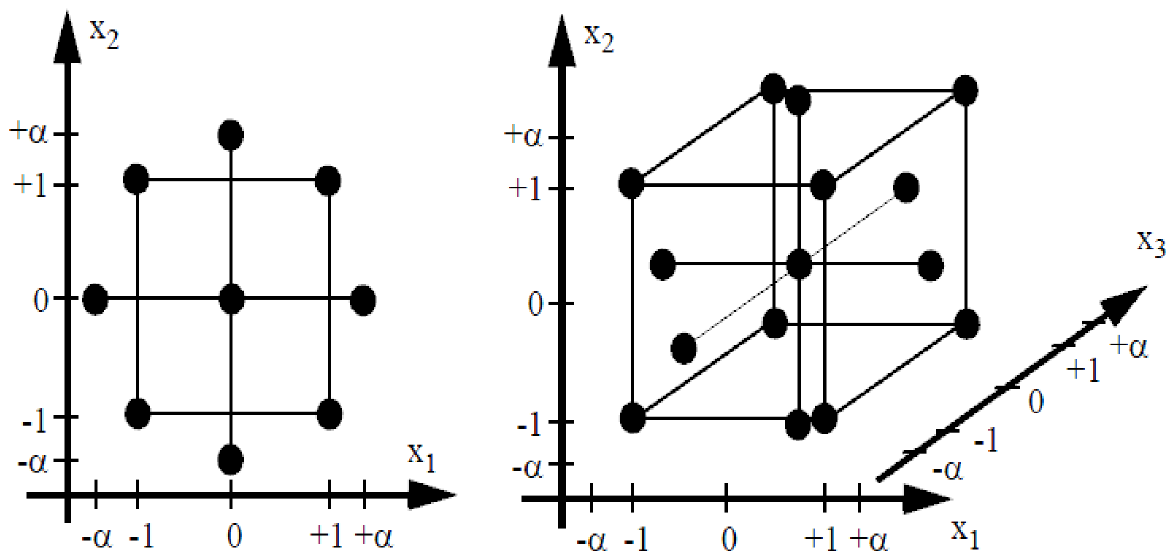


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Figure 3.5: CCD model design

In order to simplify the calculation, it is appropriate to use *coded variables* for describing independent variables in the (-1, 1) interval. The independent variables are rescaled therefore 0 is in the middle of the center of the design, and ±1 are the distance from the center with direction.

The level of coding for this experiment with three level of factorial design and two process parameter for CNC drilling(feed rate and R.P.M) is given below:

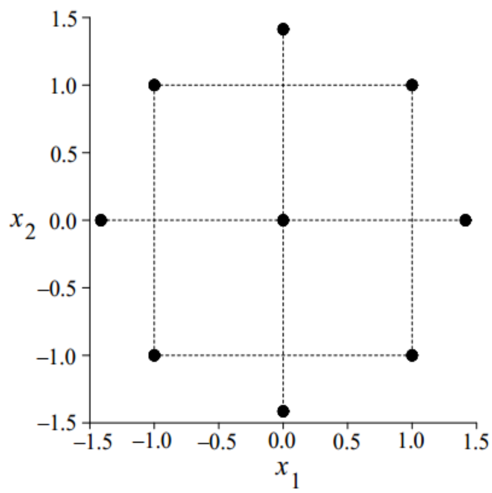


Figure 3.6: CCD model used in experiment

3.7 OVERVIEW OF A CNC DRILLING MACHINE

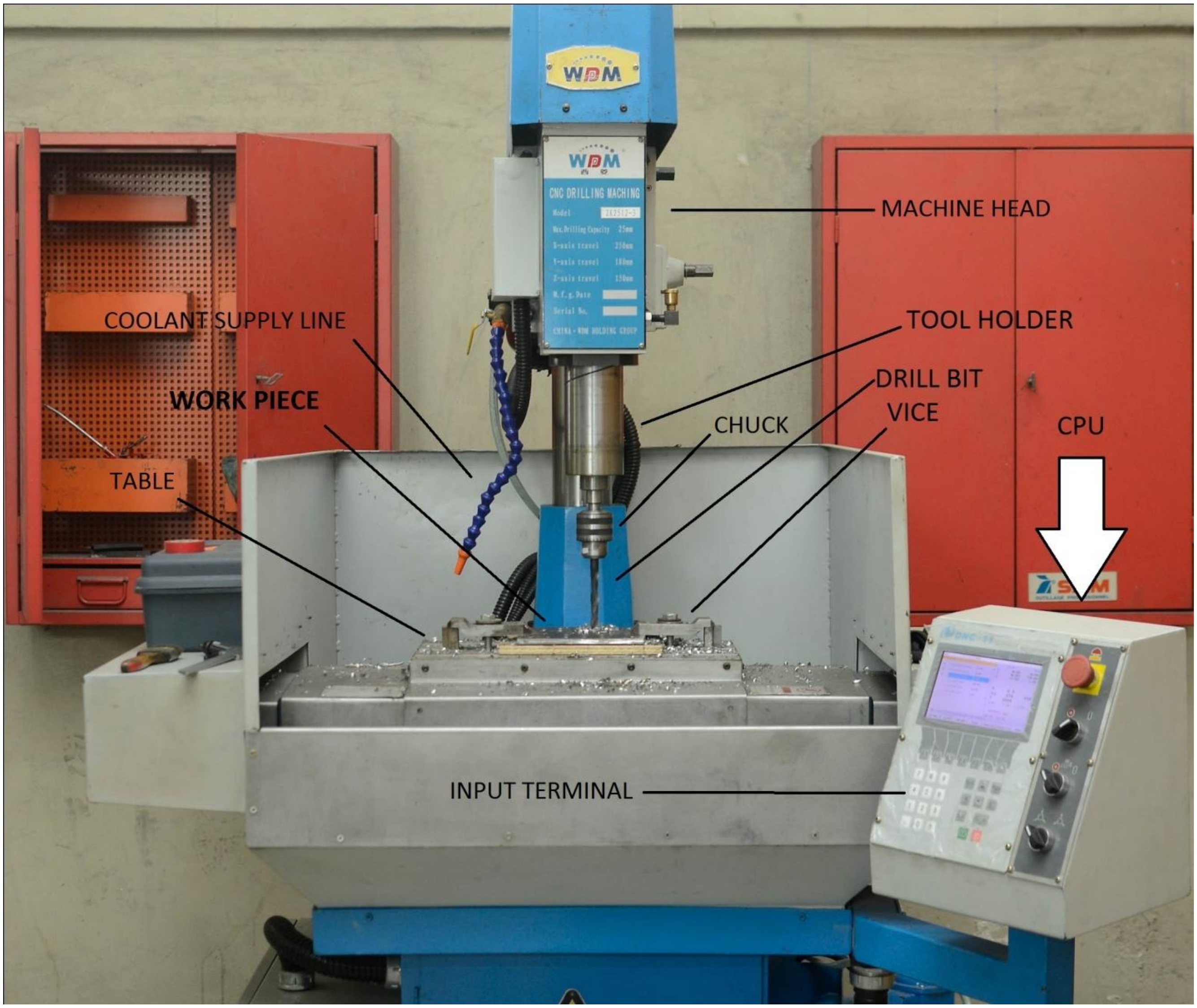


Figure 3.7: CNC Drilling Machine

Specification Of The CNC Drill Machine:

Model No: ZK2512-3

Maximum Drill Capacity: 25 mm

X-Axis Travel: 250mm

Y-Axis Travel: 180mm

Z-Axis Travel: 150mm

The CNC was manufactured by China WDM Holding Group.

3.8 WORK PIECE SPECIFICATION:

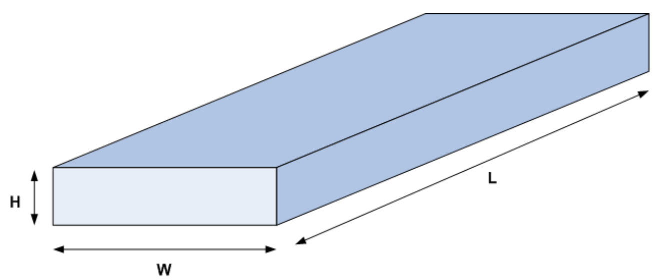


Figure 3.8: Schematics of the work piece specimen

The dimensions of the specimen are given below:

Length: 18 cm

Width: 18 cm

Height: 5 mm

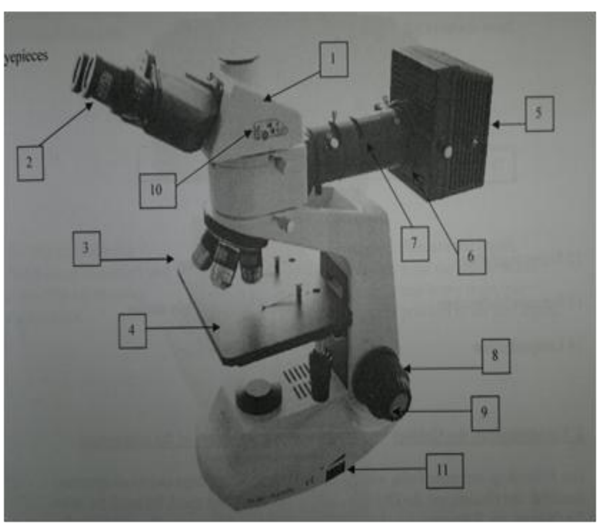
3.9 DRILLING OPERATION:

The work piece is clamped by using necessary blocks and vice and then drill holes are made according to the specified design. During the drilling process time was also measured by a stopwatch.

Figure 3.9: Drilling Operation

3.10 OPTICAL MICROSCOPE:

The model of the microscope used for the DIP technique is Metallurgical Microscope MMB2300. Figure 3.10 and table 3.1 give more details of the microscope.



1. Eyepiece head with photo/video connection
2. Eyepieces
3. Objective
4. Stage with clips
5. Illumination
6. Diaphragm
7. Colour filters
8. Coarse adjustment knob
9. Fine adjustment knob
10. Change between eyepiece head and photo/video connection
11. On/off and brightness control

Figure: 3.10 Photograph and details of the optical microscope

Plano eyepieces	**10X**
Lenses	Plan achromatic 4X,10X,40X
Magnification	40 to 400
Filter	Blue
Power supply	90 to 240 VAC
Fuse	3.15 A
Illumination	Built in lamp 6V 30W, bright-field condenser
Stage moving range	132 x 140 mm
Photo-/video-mounting	Photo-adapter with eyepiece Video-adapter with eyepiece
Weight	10kg net, 15kg cross

Table: 3.1 Detail specification of the microscope

Optical microscope is used to take the image of surface of the drilled hole. Image processing software is used to capture the microscopic view and the image taken and saved in the laptop for further analysis. The microscope along with the laptop used during the experiment is shown below

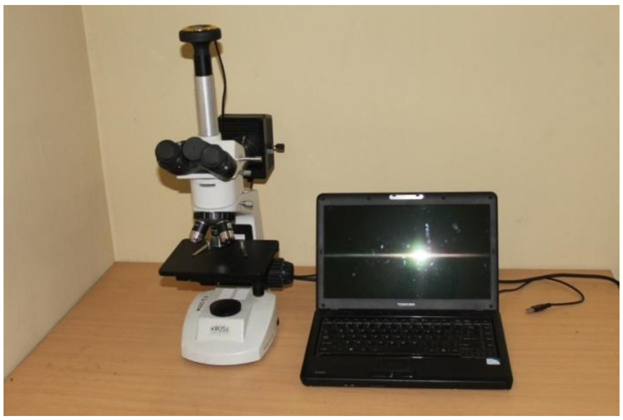


Fig 3.11: Optical microscope connected with laptop for taking image.

3.11 CODED FACTOR FOR THE EXPERIMENT:

Level of coding	Lowest $-\sqrt{2}$	Low -1	Centre 0	High +1	Highest $+\sqrt{2}$
A/ RPM	225	280.0	475	805	1000
B/Feed, mm/min	5	6	8.75	12.75	15

Table 3.2: Coding Identification

Here the highest and lowest R.P.M is taken as 1000 and 225 respectively and for the feed the highest and lowest values are 15 and 5 respectively as stated in the following table

Process Variables	Upper Limit	Lower Limit
Spindle Speed (N) r.p.m	225	1000
Feed (f) mm/min	5	15

The experimental design is according to the following table:

Order	Type	Facctor 1-1	Factor 2-2	Surface Roughness, um
1	Factorial	-1.00	-1.00	
2	Factoial	1.00	-1.00	
3	Factoial	-1.00	1.00	
4	Factoial	1.00	1.00	
5	Centre	0.00	0.00	
6	Axial	-1.41	0.00	
7	Axial	1.41	0.00	
8	Axial	0.00	-1.41	
9	Axial	0.00	1.41	
10	Centre	0.00	0.00	

Table 3.3: Surface Roughness Results (to be obtained) and Machining Parameters in Coded Factors

3.12 EXPERIMENTAL SETUP:

For this experiment we took a new drill bit of radial diameter 12.5 mm or half inch. By using this drill bit we conducted all the set of experiments listed above and we then we cut the drilled holes by a power lathe so that its drilled surface can be analyzed by image processing technique developed by patwari et al. in order to find out the surface roughness value of the drilled surface. But before doing that the hole pictures are taken to determine the circularity of the holes against the variation of feed rate by using the image processing algorithm of MatLab image processing toolbox.

Figure 3.12: Experimental Setup

3.17 ALGORITHM USED FOR PIPE CIRCULARITY

For performing the circularity check test we applied digital image processing technique which involves the application of the computer logic and algorithm to analyze the images. For this purpose we employed the MATLAB R2008a image processing toolbox which can efficiently analysis the acquired images represented by n by m 2-D matrix form. The flow chart of the process sequence for circularity measurement is in figure1.

Figure 2 shows the conversion and analysis sequence of the image. The acquired RGB image is resized keeping its aspect ratios intact to standardize the comparison and then grey scale and binary conversions are performed as the pre-processing steps. A linear filter is applied to omit pixels within certain range. Then morphological operation is performed in order to reduce the noise and unnecessary pixels and thus acquire a uniform valued set of pixels which is necessary for labeling the image. The software then calculated the roundness factor (known as CM factor). The formula for calculating the roundness factor is

CM= 4*pi*area/perimeter^2 ……………………………… (1)

The roundness factor is 1 for a perfect circular shape and it is always less than 1 for non circular shape.

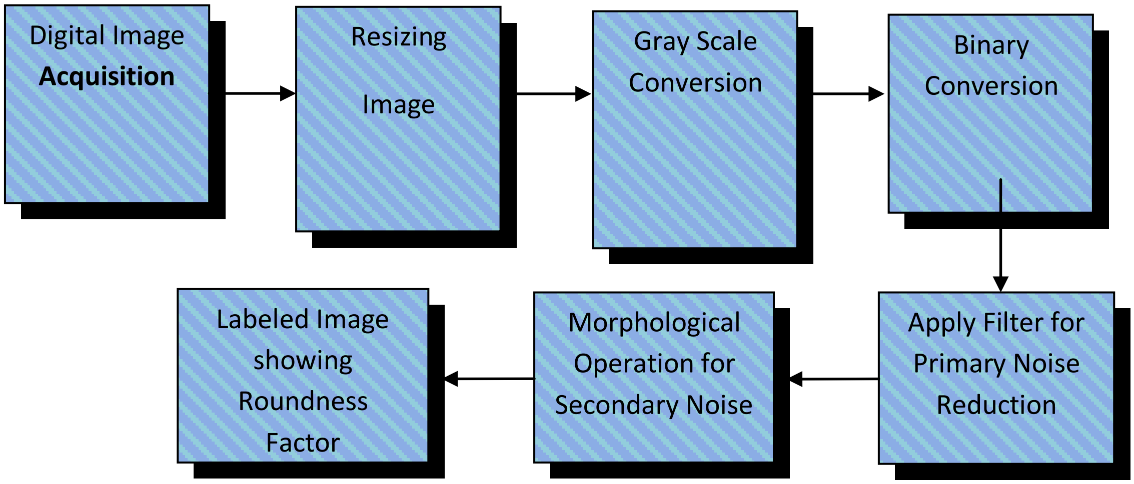


Figure 3.13: Flow chart depicting the process sequence for circularity measurement

The pictures of the holes as taken by a DSLR camera are supplied below:

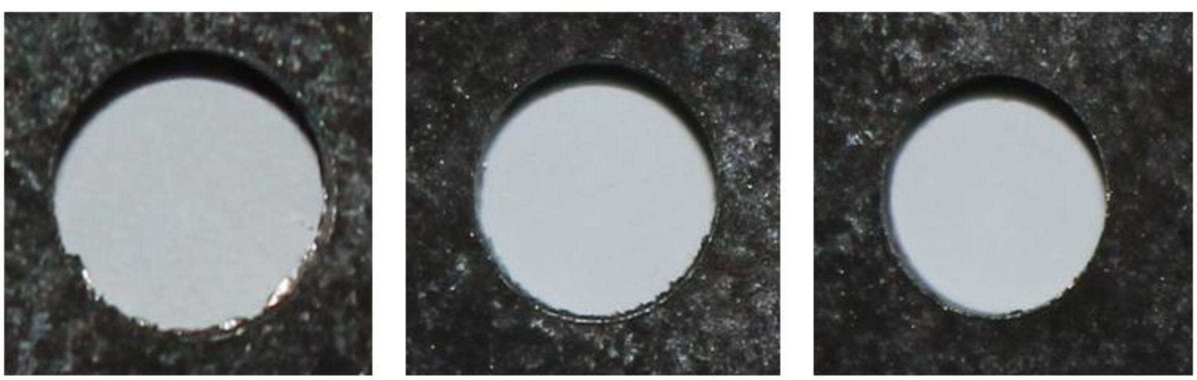


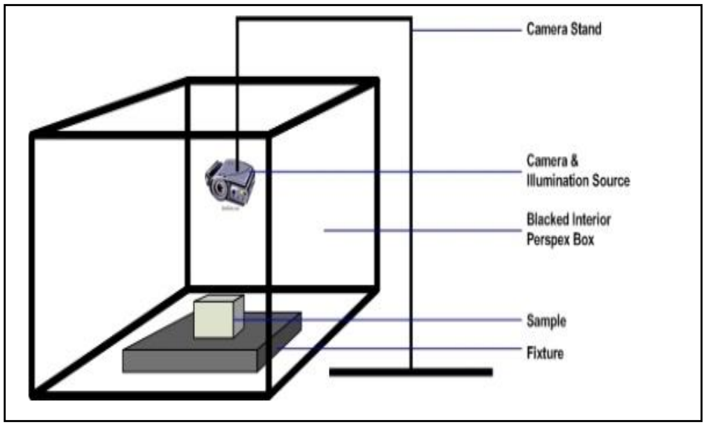
Figure 3.14: Images of the holes for circularity test

3.14 ALGORITHM USED FOR DETERMINING SURFACE ROUGHNESS:

The surface roughness is calculated using digital image processing developed by Patwari et al.

Image processing is done in the following sequence:

1. After acquiring the RGB images of the holes it was converted into resized gray scale image
2. Extracting the grey scale intensities of peaks & valleys.
3. Intensity values were used to determine R_a by comparing with labeled matrix
4. 2-D contour plot of surface profile is generated
5. The 3-D contour of surface roughness is then plotted.



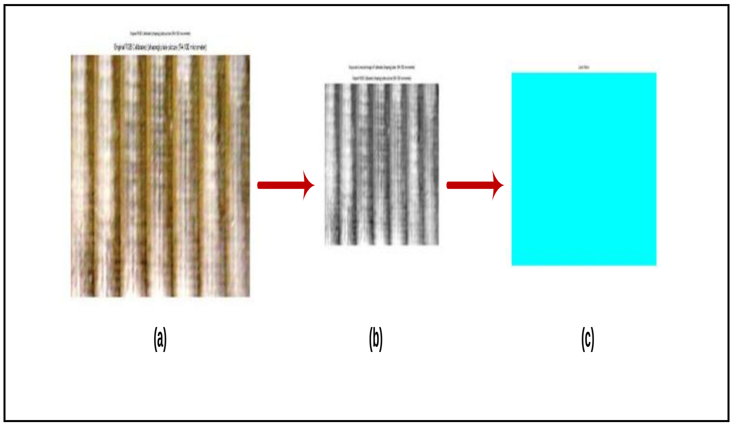


Figure 3.15: Standardized setup for image

Figure 3.16: Sequence in conversion of image

Flow diagram of method used:

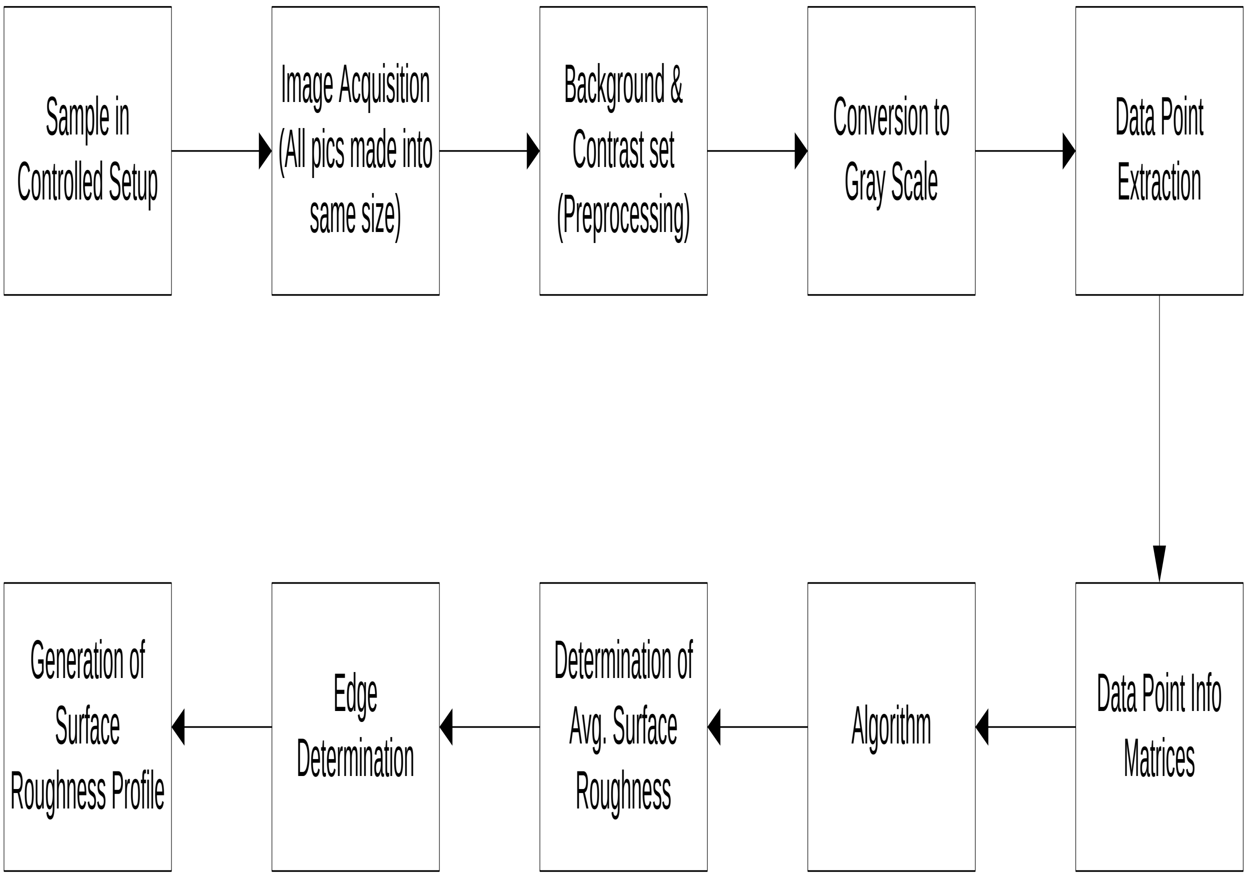


Figure 3.17: Flow diagram of the digital image processing

Sequential Steps of the process:

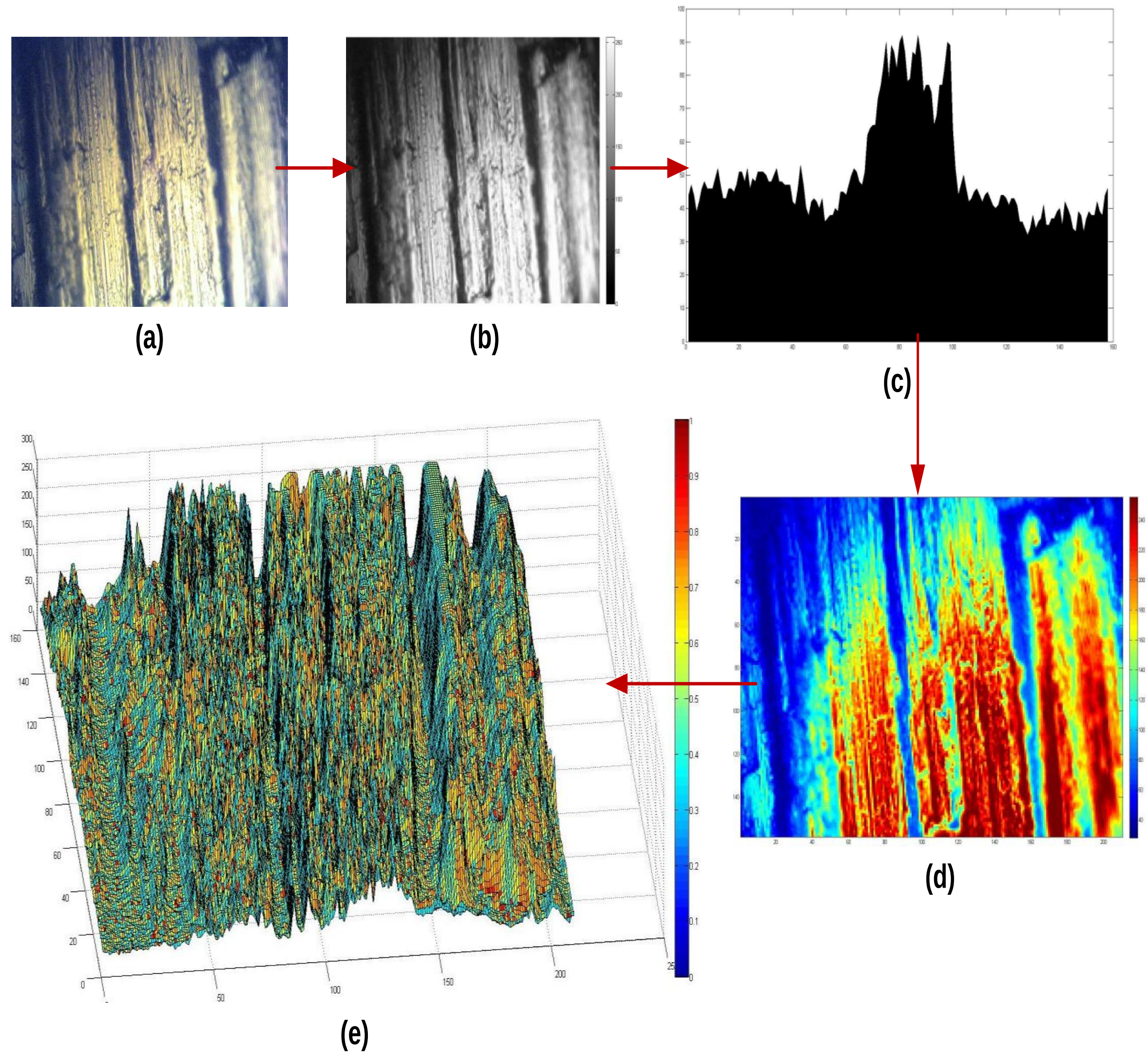


Figure: 3.18: DIP results (work-piece surface roughness) (a) 10x zoom RGB microphotograph, (b) grayscale, (c) profile plot, (d) 2-D colored contour plot, (e) 3-D colored contour plot [27]

The pictures of the drilled surface taken by the optical microscope are supplied below:

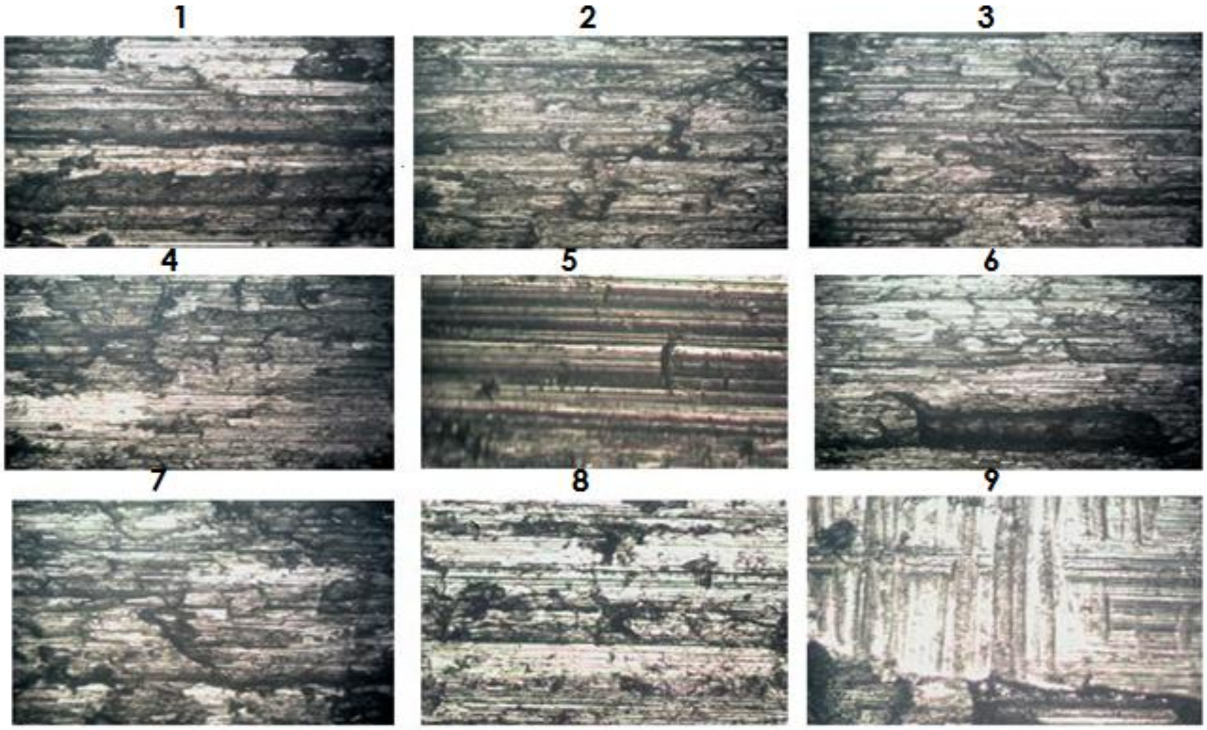


Figure 3.19: Microscopic view of the drilled hole surface

Then after the surface roughness value is determined we put the value in the table.

Now we run several statistical tests like F test, lack of fit test and ANOVA in order to find out the appropriate model of the process and therefore we see that a quadratic model is suggested by the statistical tests performed. Then by the application of RSM method the value of the process parameters for minimum response variable (surface roughness in this case) is determined which is further verified by another experiment in combination desirability approach.

3.15 DESIRABILITY FUNCTION:

Desirability function approach is powerful tools for solving the multiple performance characteristics optimization problems, where all the objectives are attain a definite goal simultaneously. The basic idea of this approach is to convert a multiple performance characteristics optimization problem into a single response optimization problem with the objective function of overall desirability. Then the overall desirability function is optimized. The general approach is to first convert each response yi, into an individual desirability function di , that may vary over the range $0 \le di \le 1$, where if the response yi meets the goal or target value, then di = 1, and if the response falls beyond the acceptable limit, then di = 0. The next step is to select the parameter combination that will maximize overall desirability D. For each response Yi(x), a desirability function di(Yi) assigns numbers between 0 and 1 to the possible values of Yi, with di(Yi) = 0 representing a completely undesirable value of Yi and di(Yi) = 1 representing a completely desirable or ideal response value. The individual desirability are then combined using the geometric mean, which gives the overall desirability D:

D= (d1(y1)*d2(y2)*d3(y3)*……….*dk(yk))^(1/k)

Where k is the total number of responses. If any response is totally undesirable then (di(yi)=0) then the overall desirability is zero(D=0)

Let Li, Ui and Ti be the lower, upper, and target values, respectively, that are desired for response Yi, with Li . Now Xi quality characteristic and Yi(X) is the response value of Xi

There are three different types of approaches for determining the desirability function which are illustrated below:

Nominal the best: (NTB)

$$d_i(\hat{Y}_i) = \begin{cases} 0 & \text{if } \hat{Y}_i(x) < L_i \\ \left(\frac{\hat{Y}_i(x)-L_i}{T_i-L_i}\right)^s & \text{if } L_i \le \hat{Y}_i(x) \le T_i \\ \left(\frac{\hat{Y}_i(x)-U_i}{T_i-U_i}\right)^t & \text{if } T_i \le \hat{Y}_i(x) \le U_i \\ 0 & \text{if } \hat{Y}_i(x) > U_i \end{cases}$$

Smaller the better(STB):

$$d_i(\hat{Y}_i) = \begin{cases} 1.0 & \text{if } \hat{Y}_i(x) < T_i \\ \left(\frac{\hat{Y}_i(x)-U_i}{T_i-U_i}\right)^s & \text{if } T_i \le \hat{Y}_i(x) \le U_i \\ 0 & \text{if } \hat{Y}_i(x) > U_i \end{cases}$$

Large the better (LTB):

$$d_i(\hat{Y}_i) = \begin{cases} 0 & \text{if } \hat{Y}_i(x) < L_i \\ \left(\frac{\hat{Y}_i(x)-L_i}{T_i-L_i}\right)^s & \text{if } L_i \le \hat{Y}_i(x) \le T_i \\ 1.0 & \text{if } \hat{Y}_i(x) > T_i \end{cases}$$

3.16 ANOVA

In statistics, analysis of variance (ANOVA) is a collection of statistical models, and their associated procedures, in which the observed variance in a particular variable is partitioned into components attributable to different sources of variation. In its simplest form, ANOVA provides a statistical test of whether or not the means of several groups are all equal, and therefore generalizes t-test to more than two groups. Doing multiple two-sample t-tests would result in an increased chance of committing a Type 1 error. For this reason, ANOVAs are useful in comparing two, three, or more means. The Analysis Of Variance, popularly known as the ANOVA, can be used in cases where there are more than two groups. When we have only two samples we can use the t-test to compare the means of the samples but it might become unreliable in case of more than two samples. If we only compare two means, then the t-test (independent samples) will give the same results as the ANOVA. It is used to compare the means of more than two samples. This can be understood better with the help of an example. The likely range of variation of the averages if our location-effect hypothesis is wrong, and the null hypothesis is correct, is given by the standard deviation of the estimated means: σ /N½ where σ is the standard deviation of the size of all the leaves and N (10 in our example) is the number of leaves in a group. Thus if we treat the collection of the 7 group means as data and find the standard deviation of those means and it is "significantly" larger than the above, we have evidence that the null hypothesis is not correct and instead location has an effect. This is to say that if some (or several) group's average leaf-size is "unusually" large or small, it is unlikely to be just "chance". The comparison between the actual variation of the group averages and that

expected from the above formula is expressed in terms of the F ratio:

F=(found variation of the group averages)/(expected variation of the group averages) Thus if the null hypothesis is correct we expect F to be about 1, whereas "large" F indicates a location effect.

3.16.1 Why Not Multiple T-Tests?

As mentioned above, the t-test can only be used to test differences between two means. When there are more than two means, it is possible to compare each mean with each other mean using many t-tests. But conducting such multiple t-tests can lead to severe complications and in such circumstances we use ANOVA. Thus, this technique is used whenever an alternative procedure is needed for testing hypotheses concerning means when there are several populations.

3.16.2 One Way And Two Way Anova

Now some questions may arise as to what are the means we are talking about and why variances are analyzed in order to derive conclusions about means. The whole procedure can be made clear with the help of an experiment. Let us study the effect of fertilizers on yield of wheat. We apply five fertilizers, each of different quality, on five plots of land each of wheat. The yield from each plot of land is recorded and the difference in yield among the plots is observed. Here, fertilizer is a factor and the different qualities of fertilizers are called levels. This is a case of one-way or one-factor ANOVA since there is only one factor, fertilizer. We may also be interested to study the effect of fertility of the plots of land. In such a case we would have two factors, fertilizer and fertility. This would be a case of two-way or two-factor ANOVA. Similarly, a third factor may be incorporated to have a case of three-way or three-factor ANOVA.

3.16.3 Chance Cause And Assignable Cause

In the above experiment the yields obtained from the plots may be different and we may be tempted to conclude that the differences exist due to the differences in quality of the fertilizers. But this difference may also be the result of certain other factors which are attributed to chance and which are beyond human control. This factor is termed as "error". Thus, the differences or variations that exist within a plot of land may be attributed to error. Thus, estimates of the amount of variation due to assignable causes (or variance between the samples) as well as due to chance causes (or variance within the samples) are obtained separately and compared using an F-test and conclusions are drawn using the value of F.

3.16.4 Assumptions

There are four basic assumptions used in ANOVA:

- the expected values of the errors are zero
- the variances of all errors are equal to each other
- the errors are independent
- they are normally distributed

Assumptions to use two-way ANOVA

As with other parametric tests, we make the following assumptions when using two-way ANOVA:

1) The populations from which the samples are obtained must be normally distributed.
2) Sampling is done correctly. Observations for within and between groups must be independent.
3) The variances among populations must be equal (homogeneity).
4) Data are interval or nominal.

3.16.5 Design-of-experiments terms

(Condensed from the NIST Engineering Statistics handbook: Section 5.7. A Glossary of DOE Terminology.)

Analysis of variance (ANOVA)

A mathematical process for separating the variability of a group of observations into assignable causes and setting up various significance tests.

Balanced design

An experimental design where all cells (i.e. treatment combinations) have the same number of observations.

Blocking

A schedule for conducting treatment combinations in an experimental study such that any effects on the
experimental results due to a known change in raw materials, operators, machines, etc., become concentrated in the levels of the blocking variable. The reason for blocking is to isolate a systematic effect
and prevent it from obscuring the main effects. Blocking is achieved by restricting randomization.

Design

A set of experimental runs which allows the fit of a particular model and the estimate of effects.

DOE

Design of experiments. An approach to problem solving involving collection of data that will support valid, defensible, and supportable conclusions.

Effect

How changing the settings of a factor changes the response. The effect of a single factor is also called a main effect.

Error

Unexplained variation in a collection of observations. DOE's typically require understanding of both

random error and lack of fit error.

Experimental unit

The entity to which a specific treatment combination is applied.

Factors

Process inputs an investigator manipulates to cause a change in the output.

Fixed effect

An effect associated with an input variable that has a limited number of levels or in which only a limited number of levels are of interest to the experimenter.

Lack-of-fit error

Error that occurs when the analysis omits one or more important terms or factors from the process model. Including replication in a DOE allows separation of experimental error into its components: lack of fit and random (pure) error.

Model

Mathematical relationship which relates changes in a given response to changes in one or more factors.

Random effect

An effect associated with input variables chosen at random from a population having a large or infinite number of possible values.

Random error

Error that occurs due to natural variation in the process. Random error is typically assumed to be normally distributed with zero mean and a constant variance. Random error is also called experimental error.

Randomization

A schedule for allocating treatment material and for conducting treatment combinations in a DOE such that the conditions in one run neither depend on the conditions of the previous run nor predict the
conditions in the subsequent runs.

Replication

Performing the same treatment combination more than once. Including replication allows an estimate of the random error independent of any lack of fit error.

Responses

The output(s) of a process. Sometimes called dependent variable(s).

Treatment

A treatment is a specific combination of factor levels whose effect is to be compared with other treatments.

Variance components

Partitioning of the overall variation into assignable components.

3.16.6 Classes of models

There are three classes of models used in the analysis of variance, and these are outlined here.

Fixed-effects models (Model 1)

Main article: Fixed effects model

The fixed-effects model of analysis of variance applies to situations in which the experimenter applies one or more treatments to the subjects of the experiment to see if the response variable values change. This allows the experimenter to estimate the ranges of response variable values that the treatment would generate in the population as a whole.

Random-effects models (Model 2)

Main article: Random effects model

Random effects models are used when the treatments are not fixed. This occurs when the various factor levels are sampled from a larger population. Because the levels themselves are random variables, some assumptions and the method of contrasting the treatments (a multi-variable generalization of simple differences) differ from the fixed-effects model.

Mixed-effects models (Model 3)

Main article: Mixed model

A mixed-effects model contains experimental factors of both fixed and random-effects types, with appropriately different interpretations and analysis for the two types.

Example: Teaching experiments could be performed by a university department to find a good introductory textbook, with each text considered a treatment. The fixed-effects model would compare a list of candidate texts. The random-effects model would determine whether important differences exist among a list of randomly selected texts. The mixed-effects model would compare the (fixed) incumbent texts to randomly selected alternatives.

3.16.7 Characteristics of ANOVA

ANOVA is used in the analysis of comparative experiments, those in which only the difference in outcomes is of interest. The statistical significance of the experiment is determined by a ratio of two variances. This ratio is independent of several possible alterations to the experimental observations: Adding a constant to all observations does not alter significance. Multiplying all observations by a constant does not alter significance. So ANOVA statistical significance results are independent of constant bias and scaling errors as well as the units used in expressing observations. In the era of mechanical calculation it was common to subtract a constant from all observations (when equivalent to dropping leading digits) to simplify data entry. This is an example of data coding.

3.16.8 Logic of ANOVA

The calculations of ANOVA can be characterized as computing a number of means and variances, dividing two variances and comparing the ratio to a handbook value to determine statistical significance. Calculating a treatment effect is then trivial, "the effect of any treatment is estimated by taking the difference between the mean of the observations which receive the treatment and the general mean.

Partitioning of the sum of squares

Main article: Partition of sums of squares

The fundamental technique is a partitioning of the total sum of squares *SS* into components related to the effects used in the model. For example, the model for a simplified ANOVA with one type of treatment at different levels.

The number of degrees of freedom *DF* can be partitioned in a similar way: one of these components (that for error) specifies a chi-squared distribution which describes the associated sum of squares, while the same is true for "treatments" if there is no treatment effect. See also Lack-of-fit sum of squares.

3.16.9 The F-test

The F-test is used for comparisons of the components of the total deviation. For example, in one-way, or single-factor ANOVA, statistical significance is tested for by comparing the F test statistic where *MS* is mean square, = number of treatments and n_T = total number of cases to the F-distribution with $I-1$, $n_T - I$ degrees of freedom. Using the F-distribution is a natural candidate because the test statistic is the ratio of two scaled sums of squares each of which follows a scaled chi-squared distribution. The expected value of F is $1 + n\sigma^2_{\text{Treatment}}/\sigma^2_{\text{Error}}$ (where n is the treatment sample size) which is 1 for no treatment effect. As values of F increase above 1 the evidence is increasingly inconsistent with the null hypothesis. Two apparent experimental methods of increasing F are increasing the sample size and reducing the error variance by tight experimental controls. The textbook method of concluding the hypothesis test is to compare the observed value of F with the critical value of F determined from tables. The critical value of F is a function of the numerator degrees of freedom, the denominator degrees of freedom and the significance level (α). If F ≥ F_{Critical} (Numerator DF, Denominator DF, α) then reject the null hypothesis.

CHAPTER 4

Results and Discussion

4.1 INTRODUCTION:

After the successful completion of the experimentation part of the research, the results are tabulated and the experimental data are used for further analysis which include the circularity check, surface roughness determination, application of statistical tests for fitting an appropriate model. These tests are Model summary test, lack of fit test, ANOVA test. Desirability function approach is coupled with the developed model in order to find out the optimum cutting condition for which the surface roughness will be minimum.

4.2 RESULT

After taking all the surface pictures by the optical microscope with a 10x10 magnification we used the pictures for further analysis by our image processing software in order to determine the surface roughness (Ra) value. The Ra value for each drilling condition is determined, which is given below:

Order	Type	Factor A-A	Factor B-B	Surface Roughness, um
1	Factorial	-1.00	-1.00	0.96
2	Factorial	1.00	-1.00	0.89
3	Factorial	-1.00	1.00	0.91
4	Factorial	1.00	1.00	0.86
5	Centre	0.00	0.00	0.78
6	Axial	-1.41	0.00	0.99
7	Axial	1.41	0.00	0.90
8	Axial	0.00	-1.41	0.86
9	Axial	0.00	1.41	0.93
10	Centre	0.00	0.00	0.80

Table 4.1: Experimental value of surface roughness

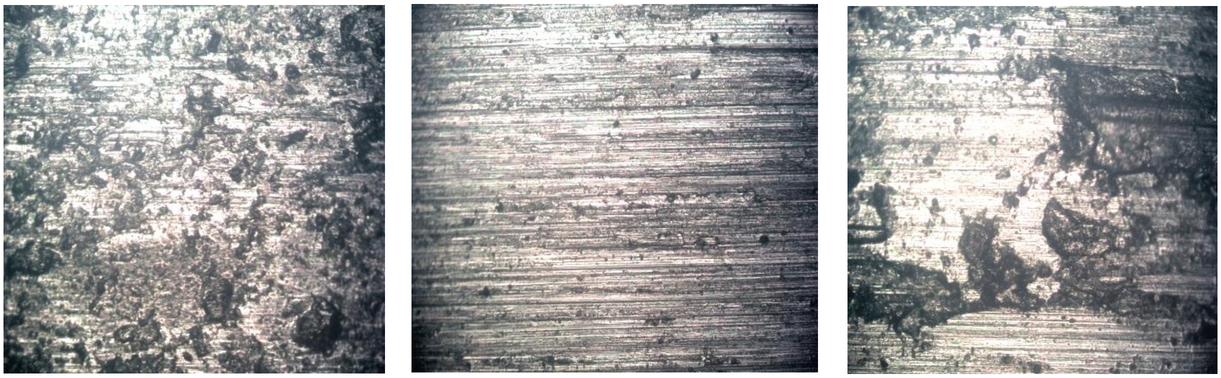
Now the Ra value are noted down against the actual cutting condition (feed rate & R.P.M),rather than the coded factors; with their associated time needed for each operation:

Serial	**Cutting Speed, rpm**	**Feed Rate, mm/min**	**Time, sec**	**Surface Roughness, um**
1	280	6	02:13:84	0.96
2	805	6	02:09:29	0.89
3	280	12.75	00:51:29	0.91
4	805	12.75	01:02:14	0.86
5	475	8.75	01:32:30	0.78
6	225	8.75	01:40:18	0.99
7	1000	8.75	01:36:08	0.90
8	475	5	03:00:00	0.86
9	475	15	00:52:01	0.93
10	475	8.75	01:30:00	0.80

Table 4.2: Experimental details with surface roughness and time required

4.2.1 Variation of feed:

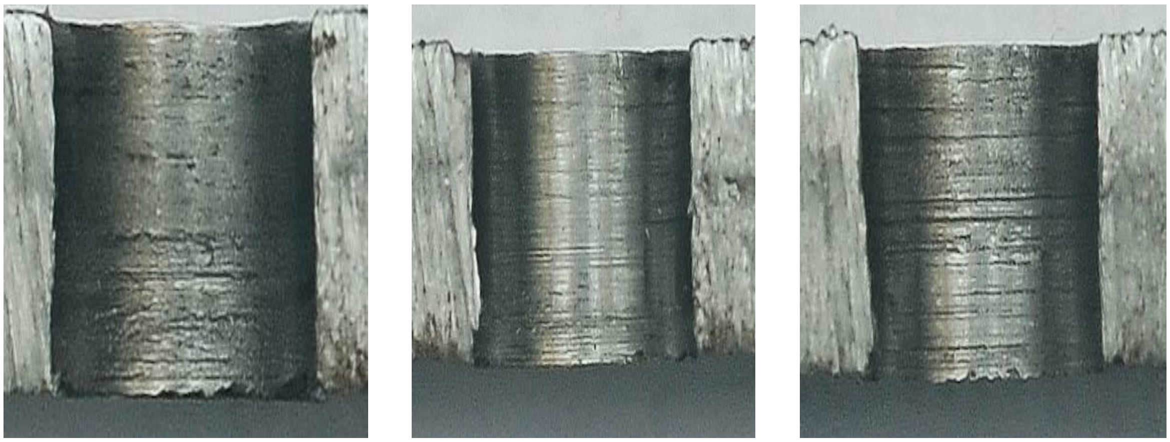
For the operation number 8,9 and 10 where the cutting speed is all the same(475 r.p.m) and the feed rate is varying considerably we made a comparison among these three condition. These are the drilled surface for these three condition:



5 mm/min 8.75mm/min 15mm/min

Figure 4.1: Effect of feed on drilled hole surface(microscopic)

Here are the cut section of drilled surface which shows the variation of increasing feed rate:



5 mm/min 8.75mm/min 15mm/min

Figure 4.2: Effect of feed on drilled hole surface

From the above pictures the effect of feed rate is very clear. We see as the feed is increased the surface roughness value tend to have a higher value. But always there is certain range of feed rate within which the surface roughness will be the minimum. That will be the optimum feed rate for the specific drill machine and for the range of cutting condition considered.

4.2.2 Circularity Check:

We also checked the circularity of the 3 holes at different feed rate in order to investigate the effect of changing the feed on the circularity of drilled holes. The different steps in determining the circularity matrix (CM factor) are illustrated below:

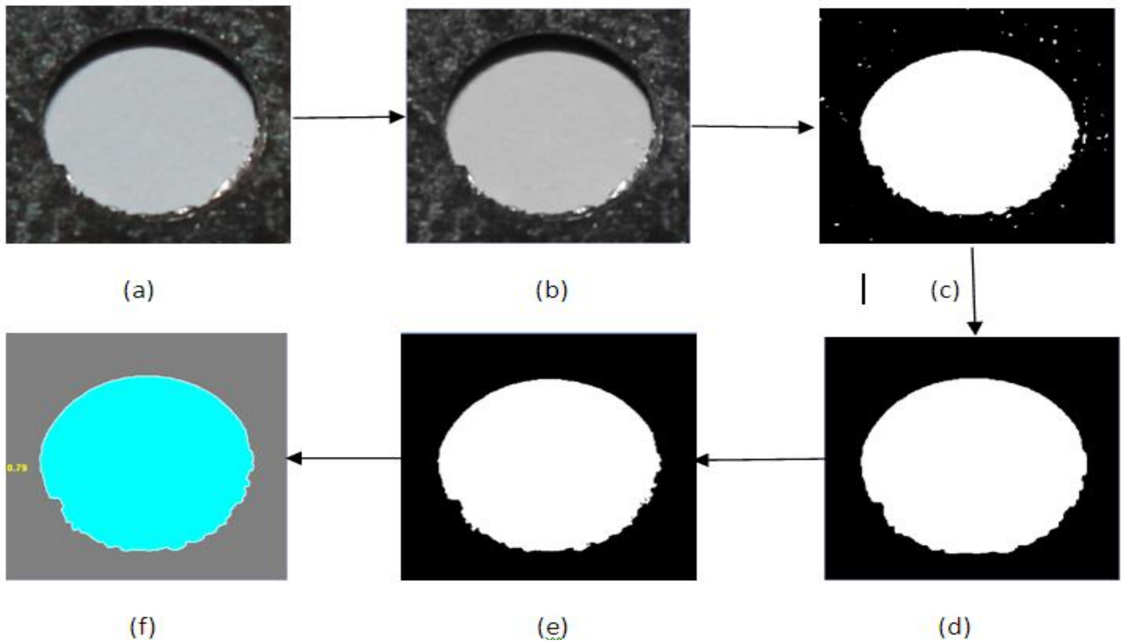
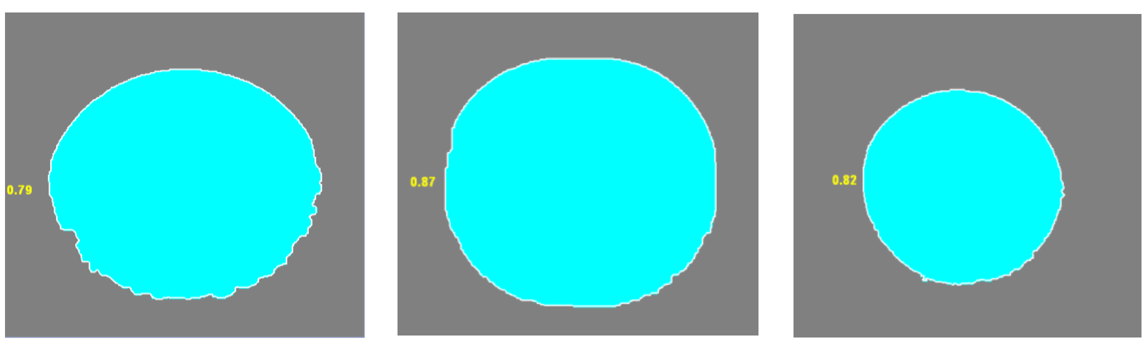


Figure 4.3: Sequence of image processing in circularity check

Here is a comparative presentation of the CM factors of drilled holes at different feed rate:



f =5mm/min f =8.75mm/min f =15mm/min

Figure 4.4: Effect of changing feed rate on CM factor at the same speed(475 r. p. m)

Thus we can see that at lower feed the CM factor is less indicating the poor quality of the drilled hole and for higher feed the CM factor is closer to the acceptable limit (0.9-1.0) for perfect circularity. But at a feed of 8.75mm/mim in between the two, it is almost close to the acceptable limit indicating the best quality of the drill hole.Thus in this case also we see that the quality of the drill hole is good in terms of circularity of the drilled hole; for the centre design run of the CCD considered in this research which indicate that the optimum value or range is nearer to this cutting condition.

Sequential Model Sum of Squares

Source	Sum of Squares	DF	Mean Square	F Value	Prob>F	Comment
Mean	0.23	1	0.23			
Block	5.934E-003	1	5.934E-003			
Linear	9.323E-003	2	4.662E-003	0.69	0.5279	
2FI	9.216E-005	1	9.216E-005	0.012	0.9158	
Quadratic	0.048	2	0.024	21.05	0.0037	Suggested
Cubic	4.930E-003	2	2.465E-003	9.54	0.0501	Aliased
Residual	7.751E-004	3	2.584E-004			
Total	**0.30**	**12**	**0.025**			

Table 4.3: Sequential Model Sum of Squares

Sequential Model Sum of Squares Select the highest order polynomial where the additional terms are significant and the model is not aliased. From the above table the quadratic model is suggested.Lack of fit test is also performed in order to investigate further which model fits the experimental data best.

Lack of Fit Tests

Source	Sum of Squares	DF	Mean Square	F Value	Prob>F	Comment
Linear	0.053	6	8.849E-003	24.01	0.0405	
2FI	0.053	5	0.011	28.76	0.0339	
Quadratic	4.968E-003	3	1.656E-003	4.49	0.1874	Suggested
Cubic	3.792E-005	1	3.792E-005	0.10	0.7788	Aliased
Pure Error	7.372E-004	2	3.686E-004			

Table 4.4: Lack of Fit Tests

Lack of Fit Tests Want the selected model to have insignificant lack-of-fit.

Model Summary Statistics

Source	Std. Dev.	R-squared	Adjusted R-squared	Predicted R-squared	PRESS	Comment
Linear	0.082	0.1476	-0.0655	-0.7919	0.11	
2FI	0.088	0.1491	-0.2156	-2.0118	0.19	
Quadratic	0.034	0.9097	0.8193	0.0074	0.063	Suggested
Cubic	0.016	0.9877	0.9591	0.8357	0.010	Aliased

Table 4.5: Model Summary Statistics

From the Model Summary Test again Quadratic model is suggested and cubic model is found to be aliased

ANOVA for Response Surface Quadratic Model

Analysis of variance table [Partial sum of squares]

Source	Sum of squares	DF	Mean Square	F-value	Prob > F	Comment
Block	5.934E-003	1	5.934E-003	10.07	0.0121	significant
Model	0.057	5	0.011	*8.11*	*0.0359*	
A	9.258E-003	1	*9.258E-003*	*0.057*	*0.8202*	
B	6.548E-005	1	*6.548E-005*	*35.32*	*0.0019*	
A^2	0.040	1	*0.040*	*15.14*	*0.0115*	
B^2	0.017	1	*0.017*	*0.081*	*0.7877*	
AB	9.216E-005	1	*9.216E-005*			
Residual	5.705E-003	5	1.141E-003			
Lack of Fit	4.968E-003	3	*1.656E-003*	*4.49*	*0.1874*	not significant
Pure Error	7.372E-004	2	*3.686E-004*			
Core total	0.069	11				

Table 4.6: ANOVA for Response Surface Quadratic Model

The Model F-value of 10.07 implies the model is significant. There is only a 1.21% chance that a "Model F-Value" this large could occur due to noise. Values of "Prob > F" less than 0.0500 indicate model terms are significant. In this case A, A^2, B^2 are significant model terms. Values greater than 0.1000 indicate the model terms are not significant. If there are many insignificant model terms (not counting those required to support hierarchy), model reduction may improve your model. The "Lack of Fit F-value" of 4.49 implies the Lack of Fit is not significant relative to the pure error. There is a 18.74% chance that a "Lack of Fit F-value" this large could occur due to noise. Non-significant lack of fit is good -- we want the model to fit.

Non-significant lack of fit is good -- we want the model to fit.

Std. Dev	**0.034**	**R-Squared**	**0.9097**
Mean	-0.14	Adj R-Squared	0.8193
C.V.	-24.48	Pred R-Squared	0.0074
PRESS	0.063	Adeq Precision	8.692

Final Equation of The model in Terms of Actual Factors:

$$\mathrm{Ln(surface\ roughness)} = -0.22587-(0.034018*A)+(2.86094E-003*B)+(0.080784*A^2)+(0.052881*B^2)+(4.79990E-003*A*B)$$

Diagnostics Case Statistics:

Standard Order	Actual Value	Predicted Value	Student Residual	cook's Leverage	Outlier Residu al	Run Distance	t
1 2	-0.041	-0.064	0.023	0.716	1.261	0.573	1.366
2 5	-0.12	-0.14	0.025	0.716	1.368	0.674	1.547
3 6	-0.094	-0.067	-0.027	0.716	-1.494	0.804	-1.797
4 4	-0.15	-0.13	-0.025	0.716	-1.387	0.693	-1.582
5 1	-0.25	-0.23	-0.015	0.273	-0.531	0.015	-0.489
6 3	-0.24	-0.23	0.0025	0.273	-0.089	0.000	-0.080
7 7	-0.21	-0.23	0.022	0.273	0.779	0.032	0.743
8 9	6.421E-003	8.918E-003	0.0025	0.716	0.139	0.007	0.124
9 8	-0.11		0.00022	0.716	-0.012	0.000	-0.011
10 11	-0.15	-0.12	0.034	0.716	-1.885	1.280	-3.136
11	-0.073	-0.11	0.036	0.716	2.012	1.457	4.120 *

12							
12	-0.22	-0.22	0.0045	0.455	-0.182	0.004	-0.164
10							

Table 4.7: Diagnostics Case Statistics

4.2.3 Graphical Representation:

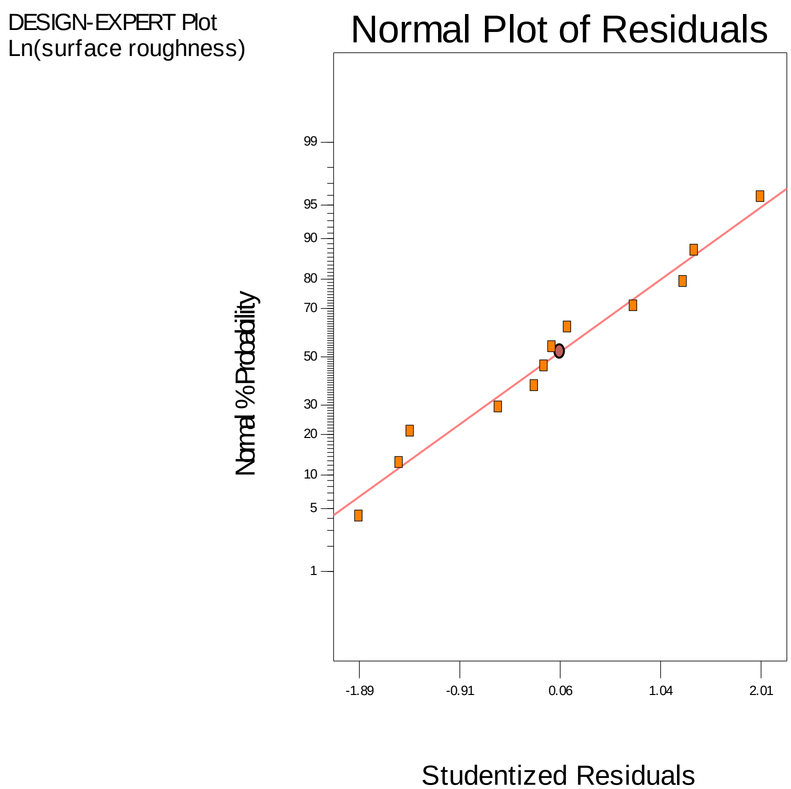


Figure 4.5: Normal % Probability Vs Studentized Residuals curve

The above figure shows the variation of Normal % Probability against Studentized Residuals

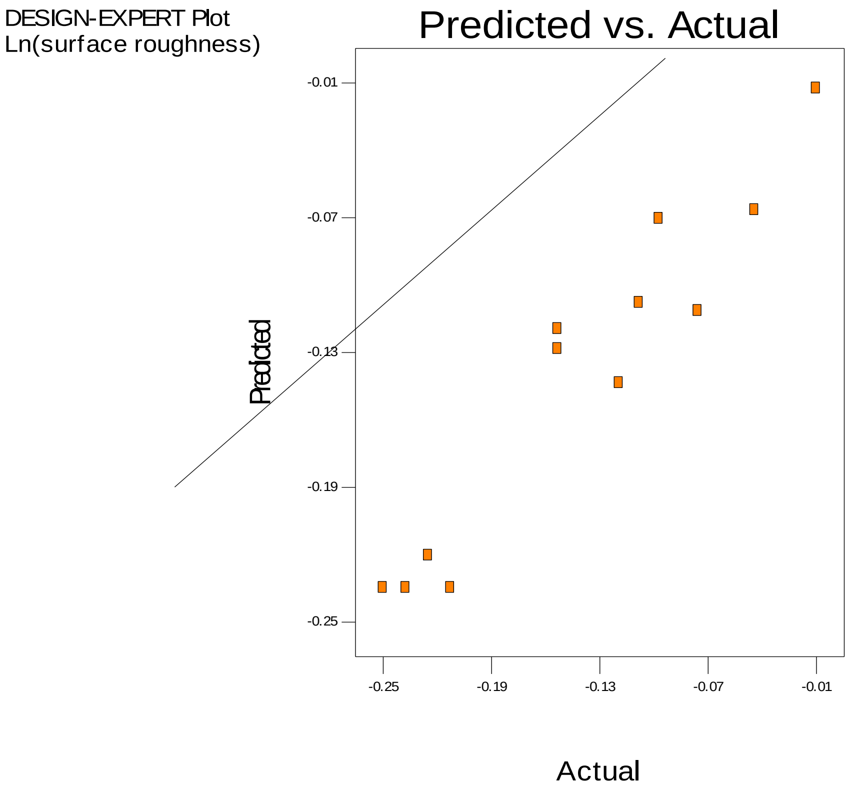


Figure 4.6: Predicted Vs. Actual Surface Roughness curve

In figure the predicted (natural logarithmic) values of surface roughness are plotted against the actual natural logarithmic values of surface roughness. The model shows uniform deviation from the actual values. Thus a quadratic second order model is suggested and proves to be more accurate in predicting the surface roughness values.

4.2.4 Response Surface of the Experimental Process:

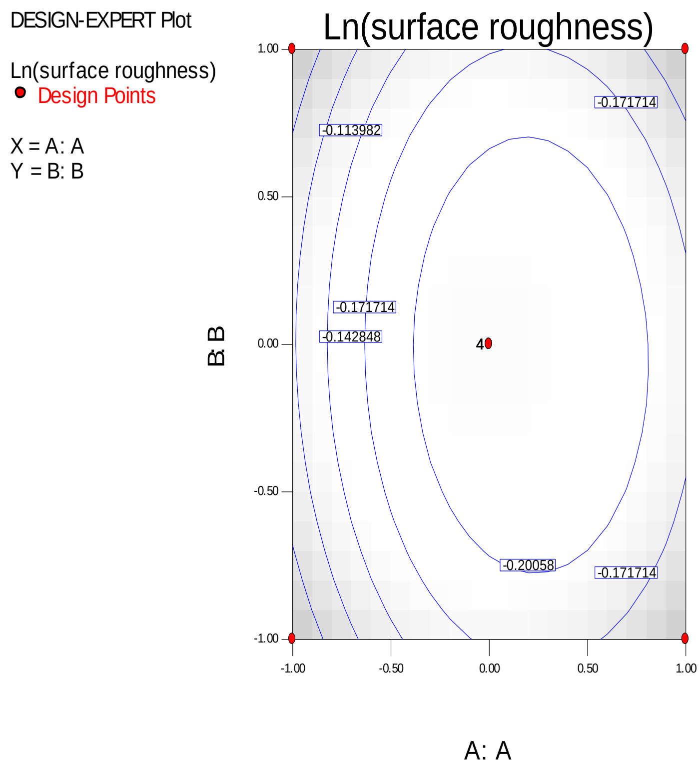


Figure 4.7: 2-D response surface

Figure shows the two dimensional response surface of surface roughness. It shows the effect of both the cutting speed and feed rate on the surface roughness of the drilled hole surface. The response surface shows that the minimum value of surface roughness is obtained for the increase in cutting speed and decrease in feed rate within our chosen experimental limit of process parameters.

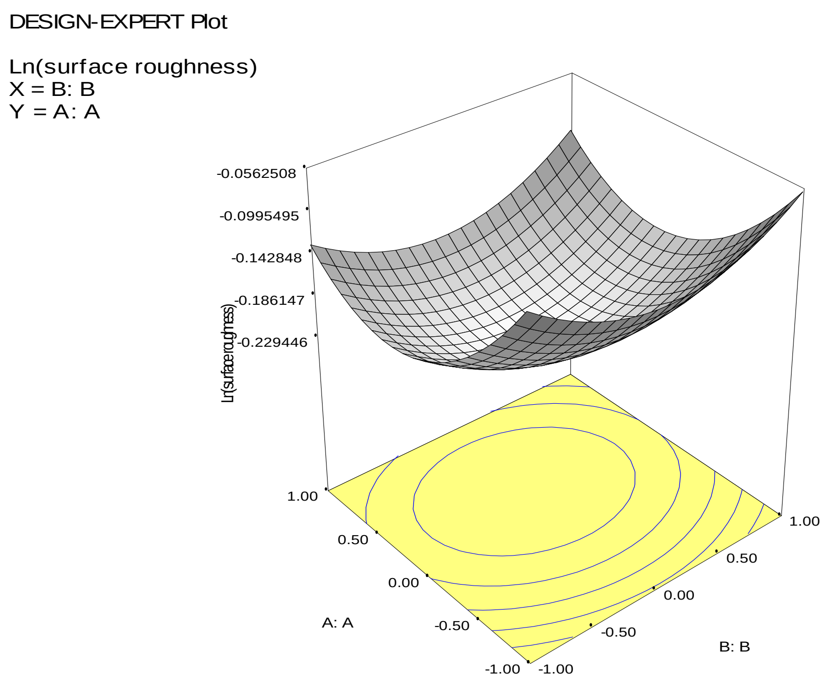


Figure 4.8: 3-D response surface

Figure is the representation of three dimensional response surface. It shows the effect of both the cutting speed and feed rate on the surface roughness of mild steel for CNC drilling. This 3D view shows the effects of the parameters more clearly.

4.2.5 Result of Desirability Test:

We used desirability function approach in order to find out the probability of the minimum surface roughness within the range predicted by response surface method (RSM). If the desirability value is greater than 0.9 then we accept the values of process parameters to be the optimum for giving minimum surface roughness. Following table shows the parameters and results of desirability function-

Name	Goal	Lower Limit	Upper Limit	Lower Weight	Upper Weight	Importance
A	**is in range**	**-1.414**	**1.414**	1	1	3
B	**is in range**	**-1.414**	**1.414**	1	1	3
Ln(surface roughness)	**minimize**	**-0.248461**	**-0.00642057**	**1**	**1**	**3**

Solutions

Number	**A**	**B**	**Ln(surface roughness)**	**Desirability**	
1	0.21	-0.04	-0.230	0.922	Selected

Now we put the value of 'A' and 'B' in equation no. ( ) to obtain the optimum value of cutting speed and feed rate

$$A = \frac{\ln V - \ln A_0}{\ln A_1 - \ln A_o}$$;where Ao=475 and A1=805

V= 530.6462341

And,

$$B = \frac{\ln a - \ln B_0}{\ln B_1 - \ln B_o}$$;where Bo=8.75 and B1=12.75

a= 8.61922

Thus we see that the optimum value of cutting speed is **530 rpm** and feed rate is **8.62 mm/min**. The following figure illustrates the response sureface for desirability analysis.

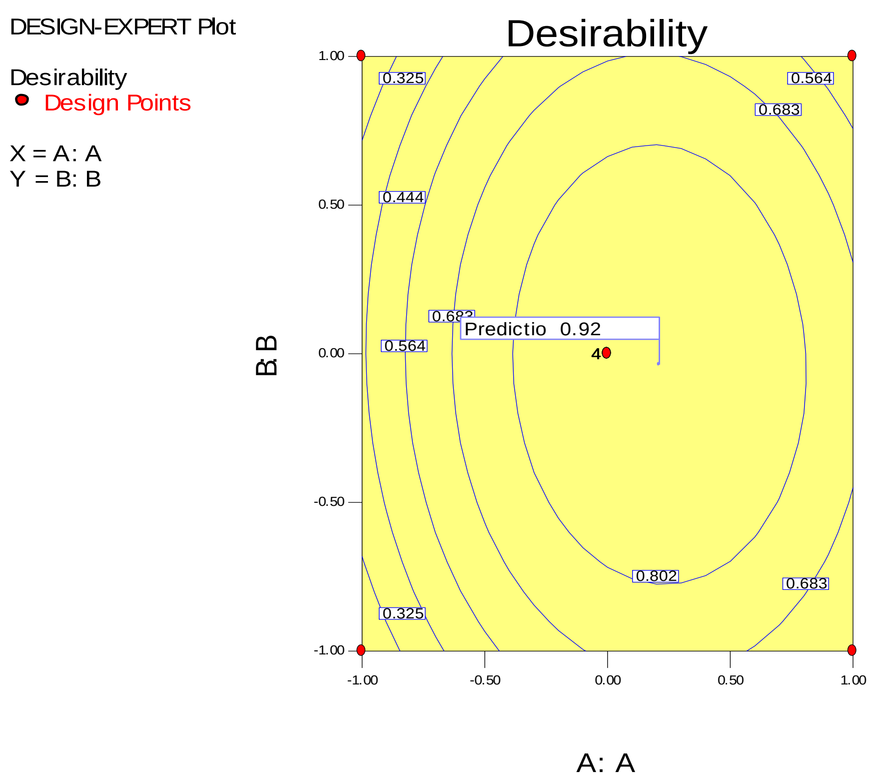


Figure 4.9: Response Surface of the Desirability function

Figure shows the graphic view of the points lying on the desirable optimum area for which optimum cutting condition for minimum surface roughness can be obtained.Here, the desirability of the probability that the minimum point lie on the desirable area is shown to be 0.92 which is greater than 0.9 and thus is accepted.

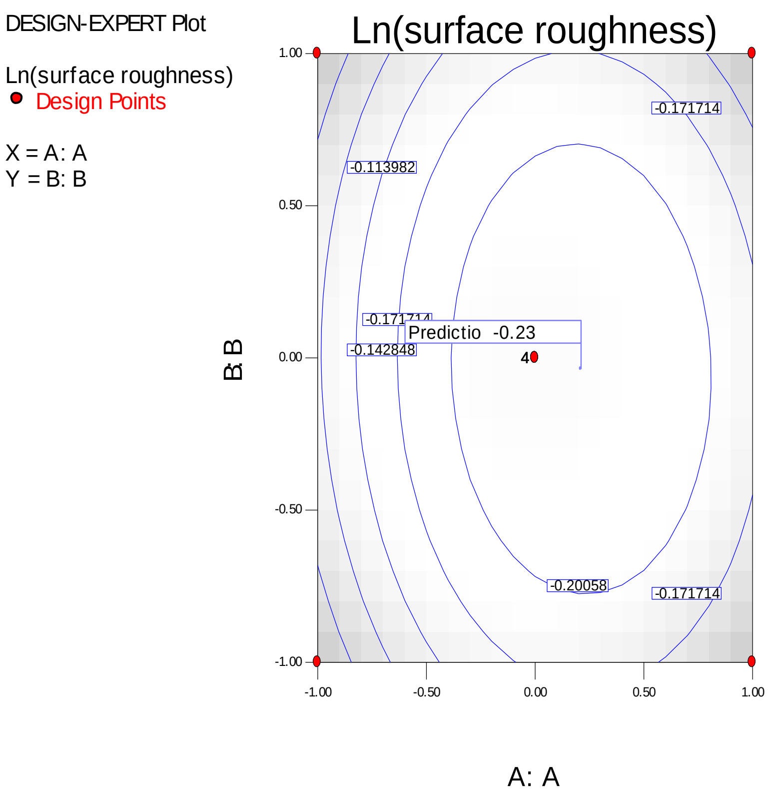


Figure 4.11: Response surface showing the minimum point for surface roughness

The above figure shows the response surface in which the desired point for minimum surface roughness is identified and marked. The natural logarithmic value of the minimum surface roughness is -0.23 which gives the minimum surface roughness value to be 0.79 um

4.3 Experimental validation

For experimental validation of the voptimum condition another drill is made and in the sane procedure the surface roughness value is determined and it is seen that the surface roughness value is same as the system minimum value which is **0.79 um**

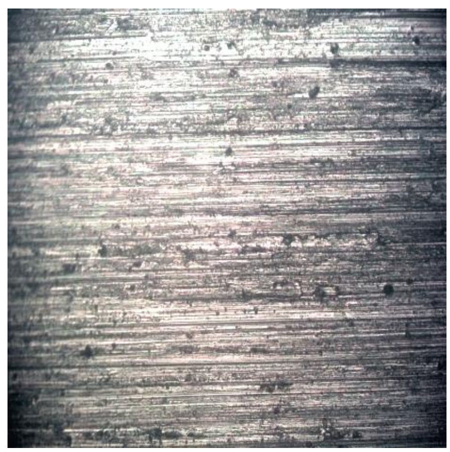


Figure: Drill hole for vbalidation of optimization model

CHAPTER 5

CONCLUSIONS AND RECOMMENDATION FOR FURTHER STUDY

5.1 CONCLUSION

1. After the successful completion of this research work we developed an algorithm which is able to measure the circularity matrix and thus the quality of drilled hole. We see that the process parameter feed rate has notable effect on the circularity of drill hole

2. The drill hole become more perfectly circular at a optimum feed rate for a certain cutting speed and the CM factor shows deviation from the acceptable range at a higher or lower feed rate. The circularity matrix is nearer to the value for perfect circle when the feed rate is higher than the optimum one. But the circularity matrix becomes lower (indicating poor circularity), at a lower value of feed rate compared to the optimum feed rate for that speed.

3. We developed a mathematical model for prediction and optimization of surface roughness of mild steel for drilling in CNC drill machine. We coupled the developed model with desirability function approach in order to find out the optimum cutting condition within the range we considered.

4. The model showed that it is more sensitive to change of feed. The change of feed rate has a significant effect on the model. As the feed rate increases the surface roughness also increases and vice versa. But there is always a optimum feed rate for a certain cutting speed when the surface roughness value will be minimum

5. The cutting speed has also effect on surface roughness. As the speed increases the surface roughness is less and as the speed decreases the surface roughness increases remarkably.

5.2 RECOMMENDATION FOR FURTHER STUDY

- In this research we studied only the effect of cutting speed and feed rate on CNC drilling. Other process parameters such as drill bit diameter can also be studied in order to investigate which parameter has the major effect on the quality parameters like circularity of drill hole, surface roughness and finish etc.
- In this study we used only mild steel. Other materials can also be used in to carry the study in order to investigate which material has the best machinability factors in terms of quality of the product.
- Tool wear is every important parameter which needs to be optimized for minimum wear. Now a days many industries are trying to find out the optimum process parameters for minimum cost of production. In some of the industries they use very highly expensive cutting tool for running their operations. That's why tool wear is a big concern for them. So, tool wear optimization can be studied as a challenging job.

CHAPTER 6

BIBLIOGRAPHY

[1] Yogendra Tyagi, Vedansh Chaturvedi and Jyoti Vimal (2012), "*Parametric Optimization of Drilling Machining Process using Taguchi Design and ANOVA Approach*", International Journal of Emerging Technology and Advanced Engineering , ISSN 2250-2459, Volume 2, Issue 7.

[2] J.Pradeep Kumar and, P.Packiaraj , "*Effect Of Drilling Parameters On Surface Roughness, Tool Wear, Material Removal Rate And Hole Diameter Error In Drilling Of Ohn*s", International Journal of Advanced Engineering Research and Studies E-ISSN2249–8974.

[3] Upinder Kumar Yadav, Deepak Narang and Pankaj Sharma Attri (2012), "*Experimental Investigation And Optimization Of Machining Parameters For Surface Roughness In CNC Turning By Taguchi Method*", International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com Vol. 2, Issue4.

[4] Ferit Ficici, Sakip Koksal and M.Cemil Karacadag (2012), "*Optimization of Cutting Parameters for Surface Roughness of Stainless Steel in Drilling Process*",
International Journal of Science and Advanced Technology (ISSN 2221-8386) Volume 2 No 3.

[5] Yogendra Tyagi, Vedansh Chaturvedi and Jyoti Vimal, "*Parametric optimization of CNC Drilling machine for mild steel using Taguchi design and Single to Noise ratio Analysis*", International Journal of Engineering Science and Technology (IJEST).

[6] Tolga Bozdana, Oguzhan Yilmaz, M. Ali Okka and I. Huseyin Filiz, "*Mathematical modeling of EDM hole drilling using response surface methodology*".

[7] B. Sidda Reddy1, J. Suresh Kumar and K. Vijaya Kumar Reddy(2011), "*Optimization of surface roughness in CNC end milling using response surface methodology and genetic algorithm*", International Journal of Engineering, Science and Technology Vol. 3, No. 8, pp. 102-109.

[8] Noordin M.Y., Venkatesh V.C., Sharif S., Elting S.(2004), "*Abdullah A. Application of response surface methodology in describing the performance of coated carbide tools when turning AISI 1045 steel*", Journal of Materials Processing Technology, 145: 46-58.

[9] Tadeusz Zaborowski and.Vladimir Serebryakov(2010), " *Evaluation Surface Roughness On Product From Stainless Steels At Cutting*", ACTA Technica Corviniensis.

[10] M. N. Islam, N. H. Rafi, and P. Charoon(2009), "*An Investigation into Effect of Canned Cycles on Drilled Hole Quality*", Proceedings of the World Congress on Engineering 2009 Vol I WCE 2009.

[11] Dong-Woo Kim , Myeong-Woo Cho , Tae-Il Seo and Eung-Sug Lee (2008), "*Application of Design of Experiment Method for Thrust Force Minimization in Step-feed Micro Drilling*", *Sensors* 2008, *8*, 211-221, ISSN 1424-8220.

[12] R. H. Hardin And N. J. A. Sloane, "*A New Approach to the Construction of Optimal Designs*'.

[13] L. B. Abhang and M. Hameedullah (2010), "*Power Prediction Model for Turning EN-31 Steel Using Response Surface Methodology*", Journal of Engineering Science and Technology Review 3 (1) 116-122.

[14] Suresh P. V. S, Rao P. V, Deshmukh S. G.(2002), "*A genetic algorithm approach for optimization of surface roughness prediction model*", International Journal of Machine Tool and Manufacture, 42, 675-680.

[15] L. B. Abhang and M. Hameedullah.(2009), "*Development of a prediction model for surface roughness in finish turning of alloy steel*", Int. Con. PSG. College Coimbatore, Narosa Publishing Housing New Delhi, India, 138-1404.

[16] Anirban Bhattacharya, Santanu Das, P. Majumdar and Ajay Batish(2009), "*Estimation of the effect of cutting parameters on surface finish and power consumption during high speed machining of AISI 1045 steel using Taguchi design and ANOVA*", Prod. Eng. Res. Devel.3, 31-40.

[17] Sood R., C. Guo and S. Malkin(2000), "*Turning of hardened steels*", Journal of Manufacturing Processes, 2(3):187-193.

[18] C.C. Tsao and H. Hocheng (2003), "*Taguchi analysis of delamination associated with various drill bits in drilling of composite material*", International Journal of Machine Tools & Manufacture 44 (2004) 1085–1090.

[19] Aman A., Hari S., Pradeep Kumar, Manmohan S.(2007), " *Optimizing power consumption for CNC turned parts using response surface methodology and Taguchi technique- a comparative analysis*", Journal of Materials Processing Technology, 200: 373-384, (2007).

[20] Sood R., C. Guo and S. Malkin, "*Turning of hardened steels. Journal of Manufacturing Processes*", 2(3):187-193.

[21] Risbood K. A., Dixit U. S. and Sahasrabudhe A. D(2003), "*Prediction of surface roughness and dimensional deviation by measuring cutting forces and vibration in turning process. Journal of Materials Processing Technology*", 132: 203-14..

[22] B. C. Routara, A. Bandyopadhyay and P. Sahoo(2007), "*Use Of Desirability Function Approach For Optimization Of Multiple Performance Characteristics Of The Surface Roughness Parameters In Cnc Turning*", International Conference on Mechanical Engineering 2007 ICME07-AM-16.

[23] Enrique Del Castillo, Douglas C. Montgomery and Daniel R. McCarville, "*Modified desirability functions for multiple response optimization*".

[24] Anayet U. Patwari, M.N. Mahmood, M.D. Arif(2012), "*Improvement of Machinability of Mild Steel during turning operation by Magnetic Cutting*", International Journal on Advanced Science Engineering Information Technology, Vol. 2 No. 3

[25] Patwari, A. U., Arif, M. D. and Mahmood, M.N.(2012), "An innovative application of Digital Image Processing to Analyze Tool wear in Turning Operation", *Submitted to INRIT 2012*, Thailand.

[26] Anayet U. Patwari, Arif M.D., Chowdhury N.A., and Chowdhury Md. S. I., "*3-D contour generation and determination of surface roughness and determination of surface roughness of shaped and horizontally milled plates using digital image processing,"* International Journal of Engineering, Annals of Faculty of Engineering, Hunedoara, Romania.

[27] Arif M.D., Patwari A.U., Chowdhury N.A.(2010), *"Surface roughness characterization using digital image processing technique."* Proceedings of the 13th Annual Paper Meet, Mechanical Engineering Department, Institute of Engineers, Bangladesh.

[28] NIST Engineering Statistics handbook: Section 5.7. A Glossary of DOE Terminology.

[27] Wikipedia

[28] A Thesis by Nuran Bradley," *The Response Surface Methodology",*

[29] Matlab 2008 working manual

APPENDIX

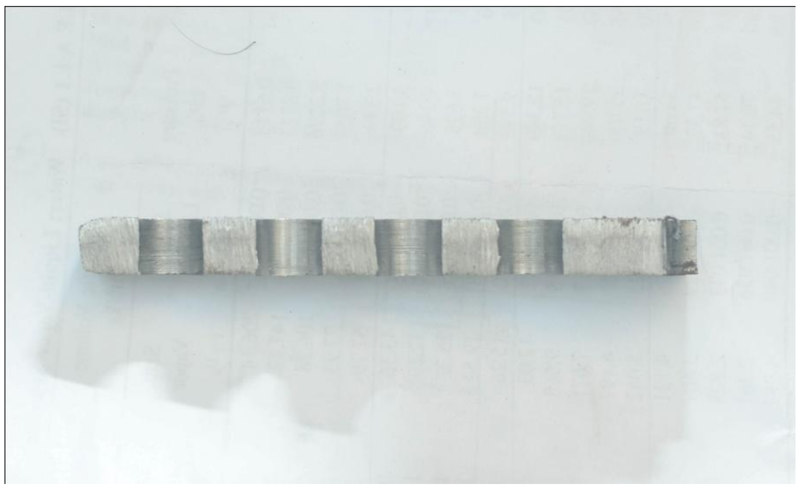


Figure: Cross section of the drill holes

Figure: Drill Operation in the CNC drill machine