OPTIMIZATION OF MATERIAL REMOVAL RATE AND SURFACE ROUGHNESS OF ALUMINIUM METAL MATRIX COMPOSITE REINFORCED WITH MoS_2 IN DRILLING PROCESS

A thesis submitted in partial fulfillment of the requirements for the award of the Degree of

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IN
MECHANICAL ENGINEERING

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CERTIFICATE

This is to certify that the Project Report entitled **"OPTIMIZATION OF MATERIAL REMOVAL RATE AND SURFACE ROUGHNESS OF ALUMINIUM METAL MATRIX COMPOSITE REINFORCED WITH MoS_2 IN DRILLING PROCESS"** has been carried out by P. Chandini (314126520112), N. Yaswanth (314126520106), K. Suresh (314126520073), P. Anil SaiKiran (314126520126), R. Venkataramana (314126520130) under the guidance of M. Raja Roy, in the partial fulfilment of requirements of Degree of Bachelor of Mechanical Engineering of Andhra University, Visakhapatnam.

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ABSTRACT

The main objective of this work is to evaluate the material removal rate (MRR) and surface roughness (Ra) of MoS2 reinforced aluminium (6061) metal matrix composite material fabricated by stir casting in drilling process using Taguchi-Topsis method. The process output is affected by large number of input variables. Therefore a suitable selection of input variables for the drilling process relies heavily on operators technology & experience because of their numerous and diverse range.

In the present work, Taguchi design is considered with three process parameters: speed, feed and diameter each to be varied in four different levels. Data related to material removal rate and surface roughness have been measured for each experimental run. The optimum values for each parameter were calculated by using TOPSIS method.

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1 INTRODUCTION

1.1 Composite Materials

Composite is a combination of two or more chemically distinct and insoluble phases. Constituent materials or phases must have significantly different properties for it to combine them: thus metals and plastics are not considered as composites although they have a lot of fillers and impurities. The properties and performance of composites are far superior to those of the constituents. Composites consist of one or more discontinuous phases (reinforcement) embedded in a continuous phase (matrix).

1.1.1 Classification

Based on the type of matrix material

- Polymer Matrix Composites (PMCs)
- Metal Matrix Composites (MMCs)
- Ceramic Matrix Composites (CMCs)
- Carbon/Carbon Composites (C/Cs)

Based on the geometry of reinforcement

- Particulate reinforced Composites
- Whisker/Flakes reinforced composites
- Fiber reinforced composites

1.2 Aluminium Composites

Aluminium metal matrix composites (AMMC) are the composites in which aluminium is used as the matrix and several reinforced materials are embedded into the matrix. Some of the reinforced materials are silicon carbide, graphite, fly ash, particulate alumina, red mud, cow dung, rice husk etc. AMMC are in demand due to their properties like low density, high specific strength, high damping capacity, high thermal conductivity, high specific modulus, and high abrasion and wear resistance, low density, good mechanical properties, low thermal coefficient of expansion, better corrosion resistance , high strength to weight ratio and high temperature resistance etc. Aluminium metal matrix composite provides lesser wear resistance when compared to steel and hence it is widely used as a matrix metal.

1.2.1 Properties

- High Specific Strength
- Versatile light weight and highly durable
- Wear resistance and strength equal to cast iron
- Good surface finish

1.2.2 Chemical Composition of Aluminium 6061

The alloy composition of 6061 is:

- Silicon minimum 0.4%, maximum 0.8% by weight
- Iron no minimum, maximum 0.7%
- Copper minimum 0.15%, maximum 0.4%
- Manganese no minimum, maximum 0.15%
- Magnesium minimum 0.8%, maximum 1.2%
- Chromium minimum 0.04%, maximum 0.35%
- Zinc no minimum, maximum 0.25%
- Titanium no minimum, maximum 0.15%
- Other elements no more than 0.05% each, 0.15% total
- Remainder aluminum (95.85–98.56%)

1.2.3 Advantages of AMC

The major advantages of AMC's are as follows:

- Greater strength
- Improved stiffness
- Reduced density (weight)
- Improved high temperature properties

• Controlled thermal expansion coefficient

• Thermal/heat management

• Enhanced and tailored electrical performance

• Improved abrasion and wear resistance

• Control of mass (especially in reciprocating applications)

• Improved damping capabilities.

1.2.4 Methods to prepare Aluminium Matrix Composite

Primary processes for manufacturing of AMCs at industrial scale can be classified into two main groups.

(1) Solid state processes

Powder blending followed by consolidation (PM processing), diffusion bonding and vapour deposition techniques come under solid state processing..

(2) Liquid state processes

Liquid state processes include stir casting or compo casting, infiltration, spray casting and in situ (reactive) processing

1.2.5 Stir Casting

Stir casting technique is simple and the most commercial method of production of metal matrix composites. In preparing metal matrix composites by the stir casting method, there are several factors that need to be considered, including:

1. Difficulty in uniform distribution of the reinforcement material.

2. Wettability between the two main substances.

3. Porosity in the cast metal matrix composites, and

4. Chemical reactions between the reinforcement material and the matrix alloy.

In conventional stir casting method, reinforced particulate is mixed into the aluminium melt by mechanical stirring. Mechanical stirring is the most important element of this process. After the mechanical mixing, the molten metal is directly transferred to a shaped mould prior to complete solidification. The essential thing is to create the good wetting between particulate reinforcement and aluminium melt. The distribution of the reinforcement in the final solid depends on the wetting condition of the reinforcement with the melt, relative density, rate of solidification etc. Distribution of reinforcement depends on the geometry of the stirrer, melt temperature and the position of the stirrer in the melt. Figure 1 shows a schematic diagram of stir casting process.

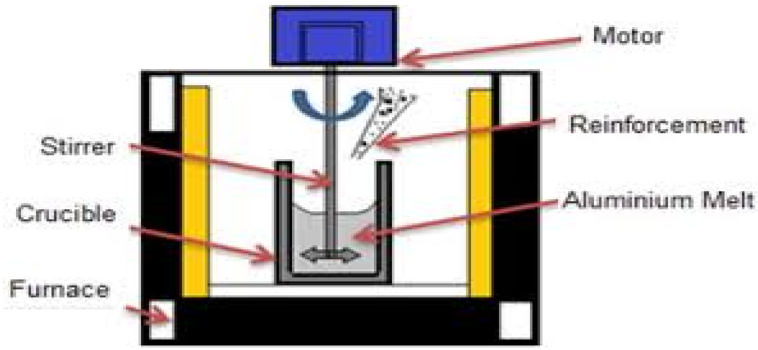


Fig 1.1 Stir Casting

1.2.6 Applications

- Aerospace
- Defence
- Automotive
- Thermal management areas
- Sports and recreation

1.3 Drilling

1.3.1 History

Bow drill (strap - drills) are the first machine drills, as they convert a back and forth motion to a rotary motion, and they can be traced back to around 10,000 years ago. It was discovered that tying a cord around a stick, and then attaching the ends of the string to the ends of a stick (a bow), allowed a user to drill quicker and more efficiently. Mainly used to create fire, bow-drills were also used in ancient woodwork, stonework and dentistry. Archaeologists discovered a Neolithic grave yard in Mehrgath, Pakistan dating from the time of the Harappans, around 7,500–

9,000 years ago, containing 9 adult bodies with a total of 11 teeth that had been drilled. There are hieroglyphs depicting Egyptian carpenters and bead makers in a tomb at Thebes using bow-drills. The earliest evidence of these tools being used in Egypt dates back to around 2500 BCE. The usage of bow-drills was widely spread through Europe, Africa, Asia and North America, during ancient times and is still used today. Over the years many slight variations of bow and strap drills have developed for the various uses of either boring through materials or lighting fires.

1.3.2 Principle

The rotating edge of the drill exerts a large force on the work piece and the hole is generated. The removal of metal in a drilling operation is by shearing and extrusion.

1.3.3 Drilling machine

The drilling machine or drill press is one of the most common and useful machine employed in industry for producing forming and finishing holes in a work piece. The unit essentially consists of:

1. A spindle which turns the tool (called drill) which can be advanced in the work piece either automatically or by hand.

2. A work table which holds the work piece rigidly in position.

A **drill** (known in many countries as a **drill machine**) is a tool fitted with a cutting tool attachment or driving tool attachment, usually a drill bit or driver bit, used for boring holes in various materials or fastening various materials together. The attachment is gripped by a chuck at one end of the drill and rotated while pressed against the target material. The tip, and sometimes edges, of the cutting tool does the work of cutting into the target material. This may be slicing off thin shavings (twist drills and auger bits), grinding off small particles (oil drilling), crushing and removing pieces of the work piece.

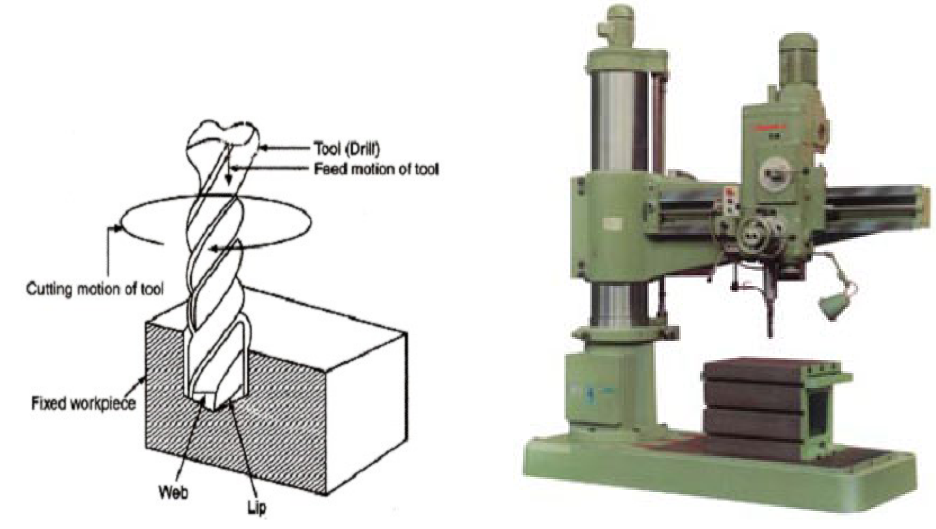


Fig 1.2 Working Principle of Sensitive Drill Machine/Drill Press

1.3.4 Drill bit:

Drill bits are cutting tools used to remove material to create holes, almost always of circular cross-section. Drill bits come in many sizes and shapes and can create different kinds of holes in many different materials. In order to create holes drill bits are usually attached to a drill, which powers them to cut through the work piece, typically by rotation. The drill will grasp the upper end of a bit called the shank in the chuck.

Drill bits come in standard sizes, described in the drill bit sizes article. A comprehensive drill bit and tap size chart lists metric and imperial sized drill bits alongside the required screw tap sizes. There are also certain specialized drill bits that can create holes with a non-circular cross-section.

While the term drill may refer to either a drilling machine or a drill bit for use in a drilling machine, in this article, for clarity, drill bit or *bit* is used throughout to refer to a bit for use in a drilling machine, and drill refers always to a drilling machine.

1.3.5 Classification

Types of Drilling Machines: A wide variety of drilling machines are available ranging from the simple portable to highly complex automatic and numerically controlled machines are as follows:

1. Portable drilling machine: It is a small light weight, compact and self contained unit that can drill holes up to 12.5 mm diameter. The machine is driven by a small electric motor operating at high speed. The machine is capable of drilling holes in the work pieces in any position.

2. Sensitive drill machine/press: This is a light weight, high speed machine designed for drilling small holes in light jobs. Generally the machine has the capacity to rotate drills of 1.5 to 15.5mm at high speed of 20,000 rev/min.

1.3.6 Major components

The main operating parts of a sensitive machine/drill press are base, column, table, and drill Head.

1. Base: The base is a heavy casting that supports the machine structure; it provides rigid mounting for the column and stability for the machine. The base is usually provided with holes and slots which help to Bolt the base to a table or bench and allow the work-holding device or the work piece to be fastened to the base.

2. Column: The column is a vertical post that Column holds the worktable and the head containing the driving mechanism. The column may be of round or box section.

3. Table: The table, either rectangular or round. Drill machine/press in shape supports the work piece and is carried by the vertical column. The surface of the table is 90-degree to the column and it can be raised, lowered and swivelled around it. The table can be clamp/hold the required the work piece. Slots are provided in most tables to allow the jigs, fixtures or large work pieces to be securely fixed directly to the table.

4. Drilling Head: The drilling head, mounted close to the top of the column, houses the driving arrangement and variable speed pulleys. These units transmit rotary motion at different speeds to the drill spindle. The hand feed lever is used to control the vertical movement of the spindle sleeve and the cutting tool.

Fig 1.3 Drilling machine components

1.3.7 Cutting parameters

Conventional metal-cutting processes involve metal reduction by single point, multiple point, or abrasive tools. The word "conventional" is used to distinguish these traditional machining processes from non-traditional or unconventional machining processes which are more involved with chemical, electrical, or thermal energy. Conventional metal-cutting is the outwardly simple process of removing metal on a work piece in order to get a desired shape by relative movement of the work piece and tool, either by rotating the work piece (as in a lathe) or by rotating the tool (as in a drilling machine). But behind this simple process lie numerous parameters that play their roles, from a small to a big way, in deciding many things in the act of metal-cutting, including the speed of doing the job, the quality and accuracy of the finish, the life of the tool, the cost of production, and so on.

Some parameters involved in the metal-cutting process are in fact closely related with some other parameters in the metal-cutting process; playing with one will have an influencing effect on another. Thus, even after several years of experience, process planning engineers may find difficulty in confidently declaring themselves as experts in metal-cutting!

In this series of articles, we shall first list the major conventional metal-cutting parameters and learn a few basic things about them. In subsequent articles, we shall delve deeper into how they contribute their roles in relation with others in the conventional metal removal process.

1) Material machinability:

The machinability of a material decides how easy or difficult it is to cut. The material's hardness is one factor that has a strong influence on the machinabilty. Though a general statement like "a soft material is easier to cut than a harder material" is true to a large extent, it is not as simple as that. The ductility of a material also plays a huge role.

2) Cutting Tool Material:

In metal-cutting, High Speed steel and Carbide are two major tool materials widely used. Ceramic tools and CBN (Cubic Boron Nitride) are the other tool materials used for machining very tough and hard materials. A tool's hardness, strength, wear resistance, and thermal stability are the characteristics that decide how fast the tool can cut efficiently on a job.

3) Cutting speed and spindle speed:

Cutting speed is the relative speed at which the tool passes through the work material and removes metal. It is normally expressed in meters per minute (or feet per inch in British units). It has to do with the speed of rotation of the work piece or the tool, as the case may be. The higher the cutting speed, the better the productivity. For every work material and tool material combo, there is always an ideal cutting speed available, and the tool manufacturers generally give the guidelines for it.

Spindle speed is expressed in RPM (revolutions per minute). It is derived based on the cutting speed and the work diameter cut (in case of turning/ boring) or tool diameter (in case of drilling/ milling etc). If V is the cutting speed and D is the diameter of cutting, then Spindle speed N = $V / (Pi \times D)$

4) Depth of cut:

It indicates how much the tool digs into the component (in mm) to remove material in the current pass.

5) Feed rate:

The relative speed at which the tool is linearly traversed over the work piece to remove the material. In case of rotating tools with multiple cutting teeth (like a milling cutter), the feed rate is first reckoned in terms of "feed per tooth," expressed in millimetres (mm/tooth). At the next stage, it is "feed per revolution" (mm/rev).

In case of lathe operations, it is feed per revolution that states how much a tool advances in one revolution of work piece. In case of milling, feed per revolution is nothing but feed per tooth multiplied by the number of teeth in the cutter.

To actually calculate the time taken for cutting a job, it is "feed per minute" (in mm/min) that is useful. Feed per minute is nothing but feed per revolution multiplied by RPM of the spindle.

6) Tool geometry:

For the tool to effectively dig into the component to remove material most efficiently without rubbing, the cutting tool tip is normally ground to different angles (known as rake angle, clearance angles, relief angle, approach angle, etc). The role played by these angles in tool geometry is a vast subject in itself.

7) Coolant:

To take away the heat produced in cutting and also to act as a lubricant in cutting to reduce tool wear, coolants are used in metal-cutting. Coolants can range from cutting oils, water-soluble oils, oil-water spray, and so on.

8) Machine/ Spindle Power:

In the metal-cutting machine, adequate power should be available to provide the drives to the spindles and also to provide feed movement to the tool to remove the material. The power required for cutting is based on the metal removal rate – the rate of metal removed in a given time, generally expressed in cubic centimetres per minute, which depends on work material, tool material, the cutting speed, depth of cut, and feed rate.

9) Rigidity of machine:

The rigidity of the machine is based on the design and construction of the machine, the age and extent of usage of the machine, the types of bearings used, the type of construction of slide ways, and the type of drive provided to the slides. All play a role in the machining of components and getting the desired accuracy, finish, and speed of production.

1.3.8 Tool dynamometer

A **machine-tool dynamometer** is a multi-component dynamometer that is used to measure forces during the use of the machine tool. Empirical calculations of these forces can be cross-checked and verified experimentally using these machine tool dynamometers.

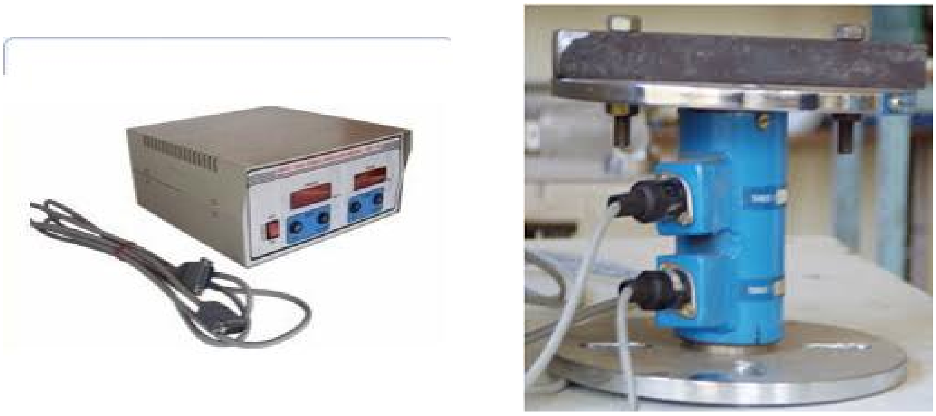


Fig 1.4 Drill tool dynamometer

With advances in technology, machine-tool dynamometers are increasingly used for the accurate measurement of forces and for optimizing the machining process. These multi-component forces are measured as an individual component force in each co-ordinate, depending on the coordinate system used. The forces during machining are dependent on depth of cut, feed rate, cutting speed, tool material and geometry, material of the work piece and other factors such as use of lubrication/cooling during machining.

1.3.9 Coolant:

A coolant is a substance, typically liquid or gas, that is used to reduce or regulate the temperature of a system. An ideal coolant has high thermal capacity, low viscosity, is low-cost, non-toxic, chemically inert, and neither causes nor promotes corrosion of the cooling system. Some applications also require the coolant to be an electrical insulator.

1.3.10 Drilling with coolant

There are many benefits of drilling with coolant. Directing the coolant through the tool to the cutting edge improves lubricity and reduces the temperature at the point of contact. Reduced heat build-up and improved lubricity lead to lower wear and tear on the drill that improves the tool life and reduces the cost per hole. Depending on the application, the introduction of through the tool coolant may enable the operator to increase feeds and speeds as well as reducing or eliminating the retract cycle (pecking) which contributes to a lower cost per hole. Hole finishes are improved due to the flushing of the chips away from the drill/work piece interface which reduces the scarring of the work piece by previously cut chips.

Coolant fed drills should be used for production drilling of holes greater than three tool diameters deep. They offer high penetration rates, reduced cycle times and straighter/rounder holes with better finishes often eliminating secondary finishing operations such as reaming or boring. Coolants fed drills typically have longer flutes to facilitate deep-hole drilling. They perform well in a wider range of materials then a non-coolant fed drill.

1.4 Material removal rate

The material removal rate, MRR, can be defined as the volume of material removed divided by the machining time. Another way to define MRR is to imagine an "instantaneous" material removal rate as the rate at which the cross-section area of material being removed moves through the work piece. The usefulness of this view can be seen in answering the following question. Since the depth of cut is changing the material removal rate changes continuously during the process. In some cases this may be important. For example, if cutting forces and the resulting work piece and tool deflections are of interest. The changing amount of material being removed along the tapered shaft means the cutting force and so the deflections will change during the process.

The material removal rate (MRR) in drilling is the volume of material removed by the drill per unit time. For a drill with a diameter D, the cross-sectional area of the drilled hole is $\Pi d^2 /4$. The velocity of the drill perpendicular to the work piece, if is the product of the feed fr and the rotational speed N where $N = V / \pi D$. Thus,

$$MRR = (\pi D^2 / 4)\ (f)\ mm^3 /min$$

Conversion of feed rate fr (mm/rev) to feed rate f (mm/min) f = N fr (mm/min)

1.5 Surface roughness

Surface roughness often shortened to **roughness**, is a component of surface texture. It is quantified by the deviations in the direction of the normal vector of a real surface from its ideal form. If these deviations are large, the surface is rough; if they are small, the surface is smooth. In surface metrology, roughness is typically considered to be the high-frequency, short-wavelength component of a measured surface. However, in practice it is often necessary to know both the amplitude and frequency to ensure that a surface is fit for a purpose in manufacturing. Although a high roughness value is often undesirable, it can be difficult and expensive to control. For example, it is difficult and expensive to control surface roughness of fused deposition modelling (FDM) manufactured parts. Decreasing the roughness of a surface usually increases its manufacturing cost. This often results in a trade-off between the manufacturing cost of a component and its performance in application.

Roughness can be measured by manual comparison against a "surface roughness comparator" (a sample of known surface roughness), but more generally a surface profile measurement is made with a profilometer.

1.5.1 Profile roughness parameters

Each of the roughness parameters are calculated using a formula for describing the surface. Standard references that describe each in detail are Surfaces and their Measurement.

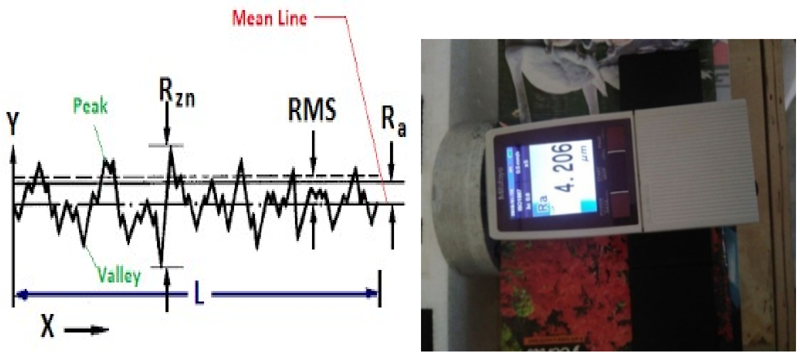


Fig 1.5 surface roughness profile and instrument

The profile roughness parameters are included in BS EN ISO 4287:2000 British standards, identical with the ISO 4287:1997 standard. The standard is based on the ″M″ (mean line) system.

There are many different roughness parameters in use, but **R_a** is by far the most common, though this is often for historical reasons and not for particular merit, as the early roughness meters could only measure **R_a**. Other common parameters include **R_z, R_q**and **R_{sk}** and Some parameters are used only in certain industries or within certain countries. For example, **R_k** the family of parameters is used mainly for cylinder bore linings, and the *Motif parameters* are used primarily in the French automotive industry. The MOTIF method provides a graphical evaluation of a surface profile without filtering waviness from roughness. A *motif* consists of the portion of a profile between two peaks and the final combinations of these motifs eliminate ″insignificant″ peaks and retains ″significant″ ones. Please note that R_a is a dimensional unit that can be micrometer or micro inch.

Since these parameters reduce all of the information in a profile to a single number, great care must be taken in applying and interpreting them. Small changes in how the raw profile data is filtered, how the mean line is calculated, and the physics of the measurement can greatly affect the calculated parameter. With modern digital equipment, the scan can be evaluated to make sure there are no obvious glitches that skew the values.

Because it may not be obvious to many users what each of the measurements really mean, a simulation tool allows a user to adjust key parameters, visualizing how surfaces which are obviously different to the human eye are differentiated by the measurements. For example, **R_a** fails to distinguish between two surfaces where one is composed of peaks on an otherwise smooth surface and the other is composed of troughs of the same amplitude. Such tools can be found in app format.

By convention every 2D roughness parameter is a capital R followed by additional characters in the subscript. The subscript identifies the formula that was used, and the R means that the formula was applied to a 2D roughness profile. Different capital letters imply that the formula was applied to a different profile. For example, Ra is the arithmetic average of the roughness profile, Pa is the arithmetic average of the unfiltered raw profile, and **S_a** is the arithmetic average of the 3D roughness.

Each of the formulas listed in the tables assume that the roughness profile has been filtered from the raw profile data and the mean line has been calculated. The roughness profile contains **n**th ordered, equally spaced points along the trace, and $\mathbf{y}_i$ is the vertical distance from the mean line to the **i**th data point. Height is assumed to be in the up direction, away from the bulk material.

1.5.2 Amplitude parameters

Amplitude parameters characterize the surface based on the vertical deviations of the roughness profile from the mean line. Many of them are closely related to the parameters found in statistics for characterizing population samples. For example, $\mathbf{R_a}$ is the arithmetic average value of filtered roughness profile determined from deviations about the centre line within the evaluation length and R_t is the range of the collected roughness data points.

The arithmetic average roughness $\mathbf{R_a}$ is the most widely used one-dimensional roughness parameter.

1.6 TAGUCHI APPROACH

Taguchi approach of an experiment. Therefore a method of calculating the Signal-To-Noise ratio we had gone for quality characteristic. They are

- Smaller-The-Better
- Larger-The-Better,
- Nominal-The-Best.

Basically, experimental design methods were developed originally Fisher. However, classical experimental design methods are too complex and not easy to use. Furthermore, a large number of experiments have to be carried out when the number of the process parameters increases, to solve this problem, the Taguchi method uses a special design of orthogonal arrays to study the entire parameter space with a small number of experiments only. The experimental results are then transformed into a signal – to – noise (S/N) ratio to measure the quality characteristics deviating from the desired values. Usually, there are three categories of quality characteristics in the analysis of the S/N ratio, i.e., the – lower – better, the – higher – better, and the – nominal – better. The S/N ratio for each level of process parameter is compared based on the S/N analysis. Regardless of the category of the quality characteristic, a greater S/N ratio corresponds to better quality characteristics. Therefore, the optimal level of the process parameters is the level with the greatest S/N ratio. Furthermore, a statistically significant with the S/N and ANOVA analyses, the optimal combination of the process parameters can be predicted. Finally, a confirmation experiment is conducted to verify the optimal process parameters obtained from the parameter design. There are 3 Signal-to-Noise ratios of common interest for optimization of Static Problems. The formulae for signal to noise ratio are designed so that an experimenter can always select the largest factor level setting to optimize the quality characteristic

The Smaller-The-Better: The Signal-To-Noise ratio for the Smaller-The-Better is: S/N = -10 *log (mean square of the response)

$S/N= -10 \log_{10} (\sum y_i^2/n)$ .... (1)

Larger-The-Better: The Signal-To-Noise ratio for the bigger-the-better is:

S/N = -10*log (mean square of the inverse of the response)

$S/N=-10\log_{10} (1/n\sum 1/y_i^2)$. .... (2)

Where n= number of measurements in trial/row, in this case n=1, 2…, 9 and Yi is the i^{th} measured value in a run/row. i =1, 2…, 27.

Nominal-the-Best: The S/N equation for the Nominal-The-Best is:

S/N = 10 * log (the square of the mean divided by the variance)

$S/N=10 \log_{10} (y^2/s^2)$. .... (3)

1.7 Proposed Methodology

1.7.1 TOPSIS

The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method was firstly proposed by (Hwang and Yoon, 1981) for assessing the alternatives before the multiple-attribute decision making. TOPSIS is implemented to measure the extent of closeness to the ideal solution. The basic concept of this method is that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from negative ideal (anti-ideal) solution. Positive ideal solution is the composition of the best performance values demonstrated (in the decision matrix) by any alternative for each attribute. The negative-ideal solution is the composition of the worst performance values. The steps involved for calculating the TOPSIS values are as follows:

Step 1: Development of decision Matrix: The row of this matrix is allocated to alternative and each column to one attribute. The matrix can be expressed as the following:

$$\mathbf{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ . \\ A_i \\ . \\ A_m \end{array} \begin{array}{c} \begin{array}{ccccc} X_1 & X_2 & . & X_j & X_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & . & x_{1j} & x_{1n} \\ x_{21} & x_{22} & . & x_{2j} & x_{2n} \\ . & . & . & . & . \\ x_{i1} & x_{i2} & . & x_{ij} & . \\ . & . & . & . & . \\ x_{m1} & x_{m2} & . & x_{mj} & x_{mn} \end{bmatrix} \end{array}$$

where , A_i represents the possible alternatives , i=1,2,3,.... , m; X_j denotes the attributes relating to alternative performances , j=1,2....,n and x_{ij} is the performance of A_i with respect to the attribute X_j.

Step 2: Obtain the normalized decision matrix r_{ij}. This can be represented as :

$$\mathbf{r_{ij}} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad \text{..} \quad \mathbf{(5)}$$

where ,r_{ij} represents the normalized performance of A_i with respect to X_j.

Step 3: Assume the weight of each attribute is $\{W_j || j=1,2,...,n\}$,the weighted normalized decision matrix $V=[v_{ij}]$ can be found as :

$$V = w_j \, r_{ij} \quad \text{----------------------------------} \quad \mathbf{(6)}$$

Where:

$\sum_{j=1}^{n} w_j = 1$

Step 4: develop the ideal (best) and negative ideal (worst) solutions in this step. The ideal and negative ideal solution can be expressed as:

$A^{+}=\{(\max v_{ij}|j\in J),(\min v_{ij}|j\in J^{'}|\ i=1,1,....,m)\}$ -------------------- (7)

$=\{v_1^{+},v_2^{+},....,v_j^{+},......,v_n^{+}\}$

$A^{-}=\{(\min v_{ij}|j\in J),(\min v_{ij}|j\in J^{'}|\ i=1,2,....,m)\}$ ------------------------ (8)

$=\{v_1^{-},v_2^{-},...,v_j^{-},....,v_n^{-}\}$

Where

$J=\{j=1,2,...,n|j\}$: associated with the beneficial attributes.

$J^{'}=\{j= 1,2,....,n|j\}$: associated with the beneficial attributes.

Step 5: Determine the distance measures .the separation of the each alternative from the ideal one is given by n-dimensional Euclidean distance from the following equations:

$S_i^{+}=\sqrt{\sum_{j=1}^{n}(v_{ij}\ \ v_j^{+})^2}$, i=1,2,....,m ------------------- (9)

$S_i^{-}=\sqrt{\sum_{j=1}^{n}(v_{ij-}\ v_j^{-})^2}$, i=1,2,...., ---------------- (10)

Step 6: The proximity of a particular alternative to the ideal solution is expressed in this step as follows:

$C_i^{+}=\frac{S_i^{-}}{S_i^{-}+S_i^{+}}$ ---------------- (11)

Step 7 :A set of alternatives is made in descending order according to the preference value indicating the most preferred and least preferred feasible solutions.

$$(S/N)_{PREDICTED} =(S/N)_{total\ mean} + (Speed – (S/N)_{total}) +(Feed – (S/N)_{total}) + (Diameter – (S/N)_{total}).$$

CHAPTER 2
LITERATURE REVIEW

2.1 Aluminium alloy metal matrix composite

Rama rao et al [1] examined that aluminium alloy-boron carbide composites were fabricated by liquid metallurgy techniques with different particulate weight fraction (2.5, 5 and 7.5%). Phase identification was carried out on boron carbide by x-ray diffraction studies microstructure analysis was done with SEM a composites were characterized by hardness and compression tests. The results shows increase the amount of the boron carbide. The density of the composites decreased where as the hardness is increased. Compressive strength of the composites was increased with increase in the weight percentage of the boron carbide in the composites.

Balasivanandhaprabu et al [2] investigated that better stir process and stir time. The high silicon content aluminium alloy –silicon carbide MMC material, with 10% SiC by using a variance stirring speeds and stirring times. The microstructure of the produced composite was examined by optical microscope and scanning electron microscope. The results with respected to that stirring speed and stirring time influenced the microstructure and the hardness of the composite. Also they investigate that at lower stirring speed with lower stirring time, the particle group was more. Increase in stirring time and speed result in better distribution of particles. The mechanical test results also revealed that stirring speed and stirring time have their effect on the hardness of the composite. The uniform hardness valued was achieved at 600 rpm with 10min stirring, but above this stirring speed the properties degraded again. This study is to establish the trend between processing parameters such as stirring speed and stirring time with microstructure and hardness of composite.

Karunamoorthy et al [3] analyzed that 2D microstructure-based FEA models were developed to study the mechanical behaviour of MMC. The model has taken into account the randomness and clustering effects. The particle clustering effects on stress-strain response and the failure behaviour were studied from the model. The optimization of properties was carried out from analysis of microstructure of MMC since the properties depend on particles arrangement in microstructure. In order to model the microstructure for finite element analysis (FEA), the micro-structures image converted into vector form from the raster than it conversion push to IGES step and mesh in FEA model in ANSYS 7. The failure such as particle interface de-cohesion and fracture the predicted for particle clustered and non-clustered micro structures. They analyzed that failure mechanisms and effects of particles arrangement.

Sozhamanna et al [4] analyzed that the methodology of microstructure based elastic-plastic finite element analysis of PRMMC. This model is used to predict the failure of two dimensional microstructure models under tensile loading conditions. Hence analyses were carried out on the microstructure of random and clustered particles to determine its effect on strength and failure mechanisms. The FEA models were generated in ANSYS using SEM images. The percentage of major failures and stress-strain responses were predicted numerically for each microstructure. Here the mixture material Al alloy, SiC.

P. K. Rohatgi et al [5] analyzed that A356-fly ash cenosphere composites can be synthesized using gas pressure infiltration technique over a wide range of reinforcement volume fraction from 20 to 65%. The densities of Al356-fly ash cenosphere composites, made under various experimental conditions, are in the range of 1250-2180 kg/m3 corresponding to the volume fraction of cenosphere in the range 20-65%. The density of composites increased for the same cenosphere volume fraction with increasing size of particles, applied pressure and melt temperature. This appears to be related to a decrease in voids present near particles by and enhancement of the melt flowing a bed of cenosphere. The compressive strength Plateau stress and modulus of the composites increased with the composite density.

N. Radhia et al [6]Investigated that tribological behaviour of aluminium alloy reinforced with alumina and graphite this are fabricated by stir casting process. The wear and frictional properties of the hybrid metal matrix composites was studied by performing dry sliding wear test using a pin – on- test wear test. Experiments were conducted based on the plan of experiments generated through taguchi's technique. Al27 orthogonal array was selected for analysis of the data. Investigation to find the influence of wear rate sliding speed applied load sliding distance, as well as the coefficient of friction. The results show that sliding distance has the highest influence followed by load and sliding speed. Finally confirmation test were carried out to verify the experimental results and scanning electrons microscopic studies were done on the wear surfaces. The incorporation of graphite as primary reinforcement increases the wear resistance of composites by forming a protective layer between pin counter face and the inclusion of alumina as a secondary reinforcement also has a significant effect on the wear behaviour. The regression equation generated for the present model was used to predict the wear rate and coefficient of friction of HMMC for intermediate conditions with reasonable accuracy.

C. S. Ramesh et al [7] Experimented that Al6061 matrix composite reinforced with nickel coated silicon nitride particles were fabricated by liquid metallurgy. Microstructure and tribological properties of both matrix alloy and developed composites have been evaluated. wear tests and dry sliding friction were carried out using pin on disk type machine over a load range of 20-100N and sliding velocities is 0.31-1.57m/s. Results revealed that, coated of nickel in silicon nitride partially are uniformly distributed throughout the matrix alloy. Al6061-Ni-p-si3N4 composite explore lower wear rate and coefficient of friction compared to matrix alloy. The coefficient of friction decreased with increased in load up to 80N. Further increase in the load, also increases coefficient of friction and sliding velocity.

Mahendra Boopathi et al [8] reported that the Development of hybrid metal matrix composites has become an important area of research interest in materials science. In view of this, the present study was studied based on evaluating the physical properties of aluminium 2024 in the presence of fly ash, silicon carbide and its combinations. Stir casting method was used for the fabrication of aluminium MMC. Structural characterization was carried out on MMC by x-ray diffraction studies and optical microscopy was used for the micro structural studies. The mechanical behaviours of MMC like density, elongation, hardness, yield strength and tensile test were ascertained by performing carefully designed laboratory experiments that replicate as nearly as possible the service conditions. In the presence of fly ash and silicon carbide [sic (5%) + fly ash (10%) and fly ash (10%) +sic (10%)] with aluminium, the result show that the decreasing the density with increasing harness and tensile strength was also observed but elongation of the hybrid MMC in comparison with unreinforced aluminium was decreased. The hybrid metal matrix composites significantly differed in all of the properties measured. Aluminium in the presence of sic (10%)-fly ash (10%) was the hardest instead of aluminium –sic and aluminium-fly ash composites.

J. Bienias et al [9] Experimented that microstructure characteristics of aluminium matrix Ak12 composites containing of fly ash particles, obtained by gravity and squeeze costing techniques, pitting corrosion behaviour and corrosion kinetics are presented and discussed. It was found that one in the comparison with squeeze casting, gravity casting technology is advantageous for obtaining higher structural homogeneity with minimum possible porosity levels, good interfacial bonding and quite a uniform distribution of reinforcement, second one the fly ash particles lead to an enhanced potting corrosion of the Ak12/9% flyash (75-100 μm fraction) composite in comparison with unreinforced matrix (Ak12 alloy), and third one the presence of nobler second phase of fly ash particles, cast defects like pores, and higher silicon content formed as a result of reaction between aluminium and silica in Ak12 alloy and aluminium fly ash composite determine the pitting corrosion behaviour and the properties of oxide film forming on the corroding surface.

H.C. Anilkumar et al [10] investigated that mechanical properties of fly ash reinforced aluminium alloy (Al 6061) composites fabricated by stir casting. They are three sets of composites with fly ash particle sizes of 75-100, 45-50 and 425 μm were used. Each set had three types of composite samples with the reinforcement weight fractions of 10 15 and 20%. The mechanical properties studied were the compressive strength, tensile strength, ductility and hardness. Unreinforced Al6061 samples also tested the mechanical properties. It was found that the compressive strength, tensile strength and hardness of the aluminium alloy composites decreased with the increase in particle size of reinforced fly ash. Increase in the weight fractions of the fly ash particles the ultimate tensile strength, compressive strength, hardness and decreases the ductility of the composite. The SEM of the samples indicated uniform distribution of the fly ash particles in the matrix without any voids.

2.2 Al6061 Reinforced with Molybdenum Disulphide (MoS_2)

M. Geeta Rani et al [11] The investigation is done on the characterization of Al 6061 base metal matrix composite (MMC) reinforced with Molybdenum disulphide (MoS2) samples are reported in this paper. Aluminium MMC prepared with MoS_2 powder of particle size of less than 2μm, with weight ratios of 1, 2, 3, 4, 5 & 5.5 %. These composites were prepared by using stir casting technique. A series of tests were conducted to evaluate mechanical properties such as tensile strength, yield strength, impact strength and hardness for the specimen. The results were compared with base alloy. The results are revealing that the hardness and tensile strength increased with increase in wt. % of reinforcement particles in the matrix up to 4% and the hardness and tensile strength decreased for 5 % , 5.5% addition of reinforcement in the matrix. Investigations show that the MMC with 4% of MoS_2 have better mechanical properties i.e. hardness and tensile strength yield strength.

Shreyas Pawar et al [12] Studied based on the individual aluminium alloy and combined effect of reinforcements on aluminium alloy discussed. For preparation of composites Al6061 taken as base metal and varying weight percentage of Molybdenum disulphide (MoS_2). The composite of Al6061 and MoS_2 is prepared by stir casting technique. A series of mechanical tests are conducted on fabricated composite specimen and compare the result of different percentage composition with the base alloy. Optical microscope is used for microstructure studies and grain size measurement. Mechanical and tribology properties like stiffness, tensile strength and hardness improved due to composite fabrication. Due to this aluminium metal matrix composite with reinforcement increase application in aerospace, underwater, high temperature application and automobile.

Mitesh Kumar [13] explained about the development of Al 6063 base hybrid metal matrix composite reinforced with 10 weight percentage of Aluminium Oxide (Al_2O_3), and varying weight percentage of Molybdenum disulphide (i.e. 3%, 5%, 7% & 9%). The composite was prepared by using stir casting technique. The density of Al 6063/ MoS_2/ Al_2O_3 were increasing when reinforcement of MoS_2 increases from 3% to 9%. The Ultimate Tensile Strength decreasing due to the additions of 3% to 9% of MoS_2 and also reinforced with alumina (Al_2O_3) into the base matrix. It was seen that while the Al 6063 alloys shows the pre- dominantly ductile fracture (base matrix). The composite specimens (with a MoS_2 addition) show an increase in the mixed mode (ductile and brittle regions). Investigation also predicts that hardness increases due to varying addition of MoS_2. Micrographs of the composite specimen are taken for the study of particular or overall behaviour of the material.

R. Ranjith kumar et al [14] investigated on the optimization of dry sliding performances on the aluminum hybrid metal matrix composites using Taguchi method.The parameters selected for this experimental study are applied load, sliding velocity and sliding distance. Using a pin-on-disk apparatus, dry sliding wear testis performed. The experiments were carried out using Taguchi technique with an L27 orthogonal array. The validity of the developed model is checked by applying Analysis of variance (ANOVA) technique. The results reveal that with increasing applied load, sliding distance and sliding velocity the wear rate was also increasing. The molybdenum disulphide composite showed less wear in comparison to the MoS2free composite.

2.3 Manufacturing of AMMC's using Stir Casting Process

Kandpal et al [15] made a composite using aluminium 6063 as a matrix component and alumina (aluminium oxide, Al_2O_3) as a reinforcement using stir casting technique. The results confirmed that stir formed Al alloy 6063 with Al_2O_3 reinforced composites is clearly superior to base Al alloy 6063 in the comparison of tensile strength, Impact strength as well as Hardness. Dispersion of Al_2O_3 particles in aluminum matrix improves the hardness of the matrix material. It is found that elongation tends to decrease with increasing particles weight percentage, which confirms that alumina addition increases brittleness. Aluminum matrix composites have been successfully fabricated by stir casting technique with fairly uniform distribution of Al2O3 particles. It appears from this study that UTS and Yield strength trend starts increases with increase in weight percentage of Al2O3 in the matrix.

Pargunde et al [16] In this study a modest attempt would be made to develop Aluminium based silicon carbide particulate MMCs with an objective to develop a conventional low cost method of producing MMCs and to obtain homogenous dispersion of ceramic material. To achieve these objectives two step-mixing method of stir casting technique has been proposed and subsequent property analysis has been made. Aluminium (98.41%) and SiC(320-grit) has been chosen as matrix and reinforcement material respectively. Experiments are planned for conducting varying weight fraction of SiC (in the steps of 5%) while keeping all other parameters constant. The results would be evaluated by Tests-Hardness, Impact (including micro-structure) for this 'development method'. The trend of hardness and impact strength with increase in weight percentage of SiC would be observed and recommendation made for the potential applications accordingly.

The major advantages of this technology are elimination of porosity and shrinkage, 100% casting yield, attainment of greater part details, good surface finish, good dimensional accuracy, high strength to weight ratio, improved wear resistance, higher corrosion resistance, higher hardness, resistance to high temperature, improved fatigue and better creep strength.

Khalid Almadhoni et al [17] The low density, environment resistance and adequate mechanical and physical properties of aluminium metal matrix composites (AMMC's) make them one of the most interesting material alternatives for the manufacture of lightweight parts for many types of modern engineering equipments. Fabrication of aluminum and it's alloys based casting composite materials via stir casting is one of the prominent and economical technique for development and processing of metal matrix composites materials. The major challenges of this technique are to achieve sufficient wetting of particles by liquid metal, to get ahomogeneous dispersion of ceramic particles and to reduce porosity in the cast metal matrix composite.This article is just a review of stir casting for production of aluminum metal matrix composites, various process parameters of stir casting process, such as stirrer design, stirrer speed, stirring temperature, stirring time (holding time), preheat temperature of reinforcement, preheated temperature of mould, reinforcement feed rate, wet ability-promoting agent and pouring of melt, and difficulties encountered in successful fabrication of AMMC's via stir casting technique.

2.4 Optimization of Cutting Parameters in Drilling Process

Anurag Tewari [18] Drilling is one of the most widely used machining processes for various purposes. Now-a-days it is frequently used in aircraft, aerospace and automotive and dies or mold industries. Drilling is material removal process within the work piece via a rotating drill bits in circular form and creation of holes take place with longitudinal force. Lot of researcher has been already scramble to find out most efficient parameter for low surface roughness and high material removal rate. This paper reviews the various literatures on the optimization of cutting parameters in drilling process such as spindle speed, drill diameter, drill point angle, feed rate on the performance parameters material removal rate, surface roughness and thrust force during drilling process.

N. S. Kurzekar et al [19] used a material 304 stainless steel for study the performance of input parameters on Surface roughness in drilling. Modified HSS drill with 10 mm diameter used as tool for experimental investigations. They used Taguchi method to solve the optimization of surface roughness. The optimal results of the surface roughness were obtained at and higher drilling speeds and lower feed rate by using 0.5 μm drill. They concluded that modification of feed and drill bit were the most important factors on the surface roughness.

J. P. Kumar et al [20] worked to investigate the influence of drilling parameters on material removal rate, tool wear, surface roughness and hole diameter error in drilling of OHNS material. HSS spiral drill bit used as tool for experimental investigation. MINITAB 13 software was used to analyze the effect. On material 18 number of experimental trials has been conducted. From this study it is found that feed and speed are the most critical factor that effects the output response characteristics.

A. Cicek et al [21] used AISI 316 austenitic stainless as a material to investigated the effect of deep cryogenic and cutting parameters on surface roughness in drilling. Cutting parameters such as cutting tools, cutting speeds and feed rate was taken. M35 twist drill bit were used as tool for doing the experiment. L8 orthogonal array was used and multiple regression analysis was performed to find out predictive equation of surface roughness.

A. M. Raj et al [22] investigates the drilling of Al/SiC/ Graphite hybrid composite material (Al6061) with input parameter such as spindle speed, drill diameter, feed rate and type of drill and surface roughness as performance parameter. They used Response surface methodology (RSM) to solve the optimization of surface roughness. It was found that minimum surface roughness could be achieved at lower feed rate, higher spindle speed and low or moderate drill diameter.

E. Kilickap, M. Huseyinoglu, A.Yardimeden [23]focuses study on the influence of input parameters- feed rate, cutting speed and cutting environment on the surface roughness obtained in drilling of AISI 1045. It was found that minimum surface roughness is obtained at lower cutting speeds, while feed rate increased it deteriorates. Surface roughness was much better for the MQL condition than for the dry drilling and under dry drilling it increases.

J.Pradeep Kumar et al [24] The aim of this work is to utilize 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. Orthogonal arrays of taguchi, the Signal–to- Noise (S/N) ratio, the analysis of variance (ANOVA), and regression analysis are employed to analyze the effect of drilling parameters on the quality of drilled holes. A series of experiments based on L18 orthogonal array are conducted using DECKEL MAHO-DMC 835V machining centre.The experimental results are collected and analyzed using commercial software package MINITAB 13. Linear regression equations are developed with an objective to establish a correlation between the selected drilling parameters with the quality characteristics of the drilled holes. The predicted values are compared with experimental data and are found to be in good agreement.

2.5 Multi Objective Optimization of drilling parameters using Taguchi Method

Hartaj Singh [25] explained about the Taguchi method, which is used to find the best process parameters and Improved quality results. Taguchi technique investigates the variation in experiments, and generally approach of system, parameter and acceptance aim have been significant in improving man-made quality world wide.The highest possible performance is obtained by determining the optimum combination of design factors. The present work focused by using L9 Orthogonal Array (OA) on the processing steps to get the optimal values with the help of main effects graph, and Analysis of variance (ANOVA) was employed to investigate the characteristics and experimental results are provided the effectiveness of this approach. This technology has met the current needs of industry owing to its shorter design cycles and improved the design of quality.

K. Lipin et al [26] reported about a multi-objective optimization of drilling parameters using Taguchi method. The quality and productivity aspects are equally important in the analysis of drilling parameters. Taguchi methods are widely used for design of experiments and analysis of experimental data for optimization of processing conditions. The research contributions are classified into methodology for investigation and analysis, input processing conditions and response variables. It was observed that the optimal speed for a machine tool is influenced by several processing parameters such as hardness, composition, stiffness of work/tool and tool life. Furthermore, it is evident that surfaces finish necessary and power available significantly controls the feed. The roughness of drilled surfaces depends severely on the input conditions, material of the work piece or tool and condition of the machine tool. The grey relational analysis is the most accurate and effective tool for analysis of data for a CNC drilling process. This study has indicated that Taguchi method followed by grey relational analysis is the most efficient combination for the following: design of experiments, analysis of experimental data and for the subsequent multi-objective optimization in drilling process.

Srinivas Athreya [27] reported about the application of Taguchi method for optimization of process parameters in improving the surface roughness of Lathe facing operation.Taguchi Method is a statistical approach to optimize the process parameters and improve the quality of components that are manufactured. The objective of this study is to illustrate the procedure adopted in using Taguchi Method to a lathe facing operation. The orthogonal array, signal-to-noise ratio, and the analysis of variance are employed to study the performance characteristics on facing operation. In this analysis, three factors namely speed; feed and depth of cut were considered. Accordingly, a suitable orthogonal array was selected and experiments were conducted. After conducting the experiments the surface roughness was measured and Signal to Noise ratio was calculated. With the help of graphs, optimum parameter values were obtained and the confirmation experiments were carried out. These results were compared with the results of full factorial method.

Ajay Singh Verma et al [28] explained about the effect of process parametersof Al 6063 is reinforced with fly ash particles produced by using stir casting process using taguchi. The weight percentage of Fly ash particles in Al 6063 varies from 3wt% to 9wt%.Fatigue strength and Vickers hardness of fabricated samples was observed by Vickers hardness testing machine and tensile testing machine. From the results it was conclude that the hardness of composite increases and decreasingthe fatigue strength with increasing percentage of Fly Ash .The maximum hardness value found with 9% wt of fly ash at 7200 C with 400rpm stirring speed

Ramesh Rudrapati et al [29] reported about the multi-objective in Transverse cut Cylindrical Grinding using Taguchi and to study the effects of grinding parameters on surface roughness (Ra and Rq) in traverse cut cylindrical grinding process, while grinding of stainless steel. Experiments have been conducted as per L9 orthogonal array of Taguchi method. Grey based Taguchi method has been used to optimize the grinding parameters to minimize surface roughness parameters Ra and Rq simultaneously. The analysis of signal to noise ratio has been applied to investigate the effects of grinding parameters and optimize them. From the results of this study, longitudinal feed is identified as the most influential grinding parameter on surface roughness. The optimization methodology used in the present study of cylindrical grinding process is very useful to determine the optimum grinding parameters for minimum surface roughness.

2.6 TOPSIS method

Tian-Syung Lan [30] Studied about the Taguchi optimization of multi-objective CNC machining using TOPSIS. Surface roughness, tool wear and material removal rate are major intentions in modern computer numerical controlled machining industry. The L9 (3^4) orthogonal array of taguchi experiment is selected for optimizing the multi-objective machining. Through the examination of surface roughness (Ra), tool wear ratio and the calculation of material removal rate (MRR). The machining objectives are then received by using technique for order preference of similarity to ideal solution (TOPSIS), the multiple objectives can additionally be integrated and introduced as the S/N(signal to noise) ratio into the Taguchi experiment. The mean effects for S/N ratios are moreover analyzed by MINITAB to achieve the multi-objective turning parameters. Through the confirmation results, it is shown that the three objectives from our optimum parameters are greatly advanced and compared to those from benchmark parameters. Parametric Optimization is a hard solving matter because of the interactions between parameters. This study not only proposes a novel parametric optimization technique using technique for order performance by similarity to ideal solution (TOPSIS), but also contributes solution for multiple CNC turning objectives with profound insight.

Mahdi Sabaghi et al [31] explained about the application of DOE-TOPSIS technique in decision-making problems. Decision-making problems are not fixed, and by the time some modifications to the initial problem may be required. TOPSIS technique has been commonly used to solve decision making problems. This technique is based on the comparison between all the alternatives included in the problem. Thus, if one alternative is removed or added, depending on the situation, the whole process for TOPSIS should be re-done, which is laborious and time-consuming. The integration of design of experiment (DOE) and TOPSIS allows easily determine the score for each alternative independently, without any comparison. This gives more degree of freedom to the users, even though the accuracy is compromised. In this work both techniques were applied to a simple case-study. Results showed that using a polynomial regression model with 84.53% reliability, the rankings from DOE-TOPSIS and normal TOPSIS are the same. This proposed technique can be highly useful in large scale decision-making problems as often found in aeronautic and automotive industries.

Rajesh Kumar Bhuyan et al [32] investigated about an approach for optimization the process parameters during electrical discharge machining (EDM) process of Al-SiC 24% metal matrix composite. The process parameters are peak current, pulse on time and flushing pressure for each experiment on the responses like material removal rate (MRR), tool wear rate (TWR) and surface roughness (Ra). Box-Behnken Central composite design method is used for designing a three factor to construct a statistical model for accurate prediction of responses. In order to optimize the multiple responses problem Technique for order preference by similarity to an ideal solution (TOPSIS) methodology is used to get a single numerical index. The Analysis of Variance (ANOVA) technique is carried out to check the significance of the models and study the effect of process parameters. The second -order mathematical equitation is developed by using Response surface methodology (RSM) to get the predicted result. Finally conformity test is conducted to perform the desirable approach of present work.

Gadakh et al[33] Studied about the application of techniques for order preference by similarity to ideal solution (TOPSIS) method is applied for solving multiple criteria (objective) optimization problem in wire electrical discharge machining (WEDM) process. Three examples are included to illustrate the approach. In all the cases, it is found that, the results obtained using the TOPSIS method almost match with those derived by the past researchers which prove the applicability of this method while solving various complex decision-making problems in present day manufacturing environment.

2.7 Coolant used in Drilling of Aluminium metal matrix composite

Stuart Barnes et al [34] investigated the effect of the coolant application method on the performance of the drilling operations on an aluminium / Sic metal matrix composites using Ti-N coated carbide tools and reported that the application of through – tool coolant produced a significant improvement in the drilling performance. They also suggested that the results obtained with conventional coolant were similar to those obtained when drilling dry.

CHAPTER 3

DESIGN OF EXPERIMENTS

3.1 Design of experiments (DOE) overview

In industry, designed experiments can be used to systematically investigate the process or product variables that influence product quality. After identifying the process conditions and product components that influence product quality, direct improvement efforts enhance a product's manufacturability, reliability, quality, and field performance. As the resources are limited, it is very important to get the most information from each experiment performed. Well designed experiments can produce significantly more information and often require fewer runs than haphazard or unplanned experiments. A well-designed experiment identifies he effects that are important. If there is an interaction between two or more input variables, they should be included in design rather than doing a "one factor at a time" experiment. An interaction occurs when the effect of one input variable is influenced by the level of another input variable.

Design experiments are often carried out in four phases: planning, screening (also called process characterization), optimization, and verification

3.1.1 Planning

Careful planning helps in avoiding the problems that can occur during the execution of experimental plan. For example, personnel, equipment, availability, funding, and the mechanical aspects of system may affect the ability to complete the experiment. The preparation required before beginning experimentation depends on the problem. Here are some steps need to go through:

- **Define the problem.** Developing a good problem statement helps in studying the right variables.
- **Define the objective.** A well defined objective will ensure that the experiment answers the right questions and yields practical, usable information. At this step, define the goals of the experiment.

- **Develop an experimental plan that will provide meaningful information.** Review relevant background information, such as theoretical principals, and knowledge gained through observation or previous experimentation
- **Make sure the process and measurement systems are in control.** Ideally, both the process and measurements should be in statistical control as measured by a functioning statistical process control (SPC) system. Minitab provides numerous tools to evaluate process control and analyse your measurement system.

3.1.2 Screening

In many process and manufacturing applications, potentially influential variables are numerous. Screening reduces the number of variables by identifying the key variables that affect product quality. This reduction allows focusing process improvement efforts on the really important variables. Screening suggests the "best" optimal settings for these factors.

The following methods are used for screening

- Two level full and fractional designs are used extensively in industry.
- Plackett-Burman designs have low resolution, but they are useful in screening experimentation and robustness testing.
- General full factorial designs (designs with more than two levels) may also be useful for small screening experiments

3.1.3 Optimization

After identifying the vital variables by screening, there is no need to determine the best or optimal values for these experimental factors. Optimal factor values depend on the process objective.

The optimization methods available in Minitab include general full factorial designs (designs with more than two levels), response surface designs, mixture designs, and Taguchi designs.

- Factorial designs overview describes methods for designing and analysing general full factorial designs

- Response surface designs overview describes methods for designing and analysing central composite and Box-Behnken designs.
- Mixture designs overview describes methods for designing and analysing simplex centroid, simplex lattice, and extreme vertices designs. Mixture designs are a special class of response surface designs where the proportions of components (factors), rather than their magnitude, are important.
- Response optimization describes methods for optimizing multiple responses. Minitab provides numerical optimization, an interactive graph, and an overlaid control plot to help to determine the "best" settings to simultaneously optimize multiple responses.Taguchi designs overview describes methods for analysing Taguchi designs. Taguchi designs may also be called orthogonal array designs, robust designs, or inner-outer array designs. These designs are used for creating products that are robust to conditions in their expected operating environment.

3.1.4 Verification

Verification involves performing a follow-up experiment at the predicted "best" processing conditions to confirm the optimization results.

3.2 Advantages & Disadvantages of DOE

DOE became a more widely used modelling technique supersiding its predecessor one-factor-at-time(OFAT) technique. One of the main advantages of DOE is that it shows the relationship between parameters and responses. In other words, DOE shows the interaction between variables which in turn allows us to focus on controlling important parameters to obtain the best responses. DOE also can provide us with the most optimal setting of parametric values to find the best possible output characteristics. Besides from that, the mathematical model generated can be used as a prediction model which can predict the possible output response based on the input values. Another main reason DOE is used because it saves time and cost in terms of experimentation.

DOE function in such manner that the number of runs is determined before the actual experimentation is done. This way, time and cost can be saved as we do not have to repeat unnecessary experiment runs. Most usually, experiments will have error occurring. Some of them might be predictable while some errors are just out of control. DOE allows us to handle these errors while still continuing with the analysis. DOE is excellent when it comes to prediction linear behaviour. However, when it comes to nonlinear behaviour, DOE does not give best results.

3.3 To Create a Taguchi Design

Step 1: Stat > DOE > Taguchi > Create Taguchi Design

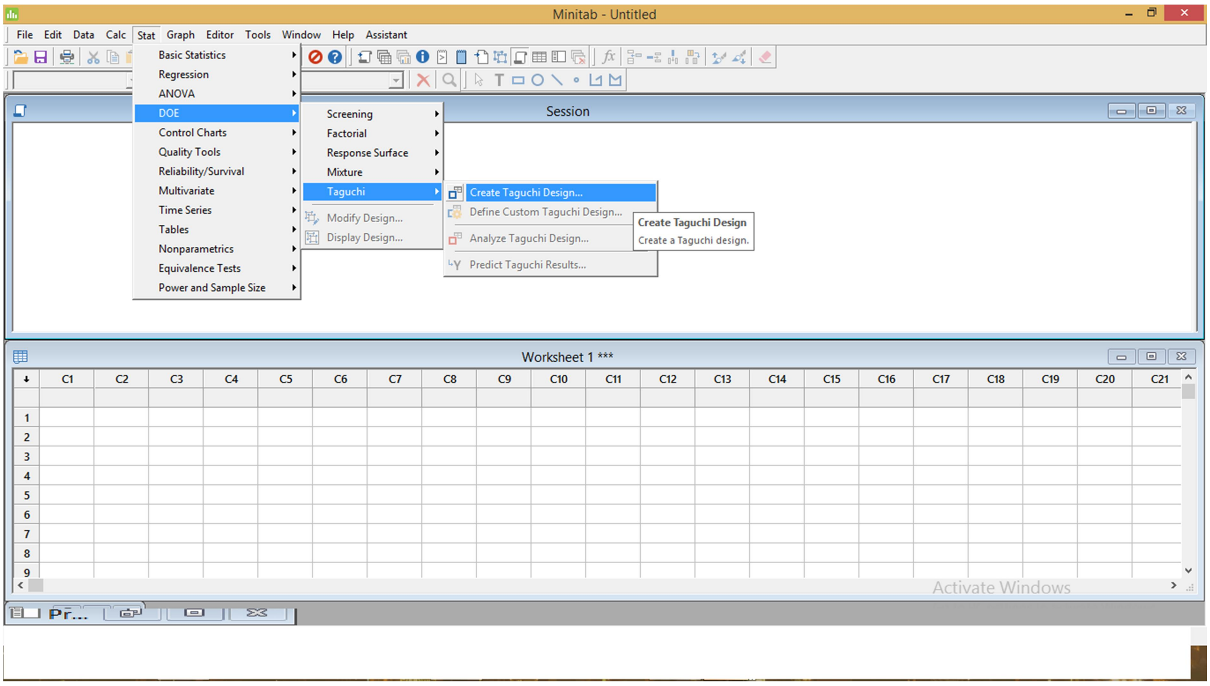
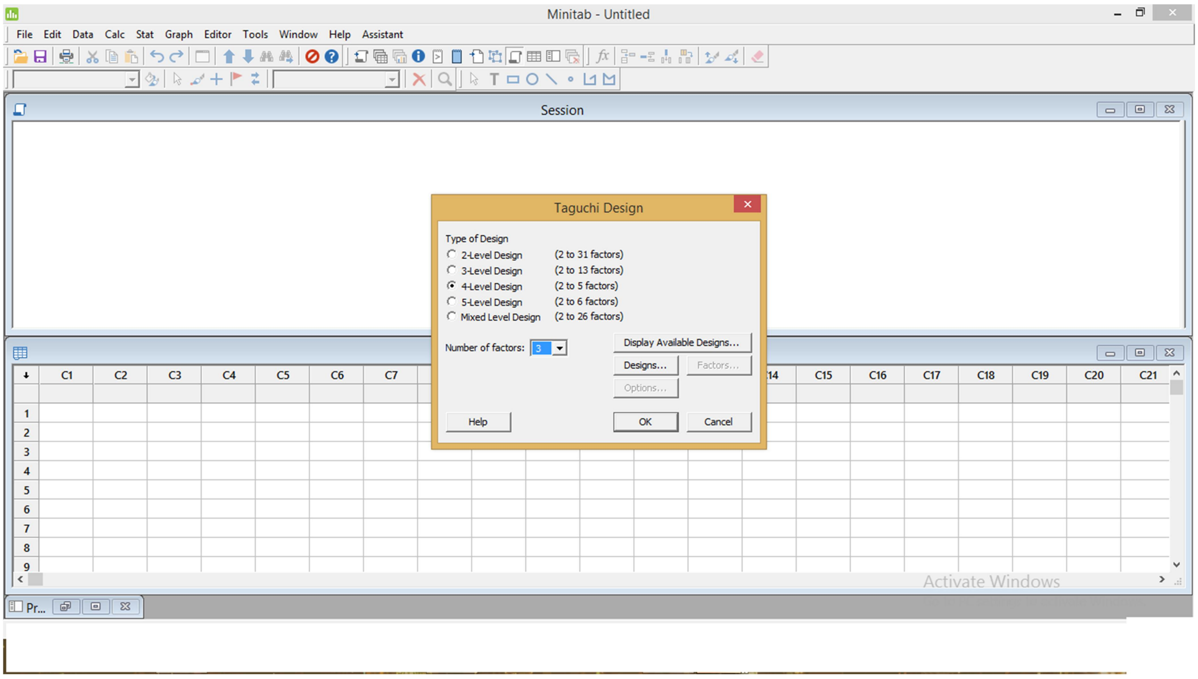


Fig 3.1: Taguchi design

Step 2: choose 4 level design (2to 5 factors).

Step 3: choose number of factors as 3; shown in fig



Step 4: Stat > DOE > Taguchi > Create Taguchi Design > Display AvailableDesigns

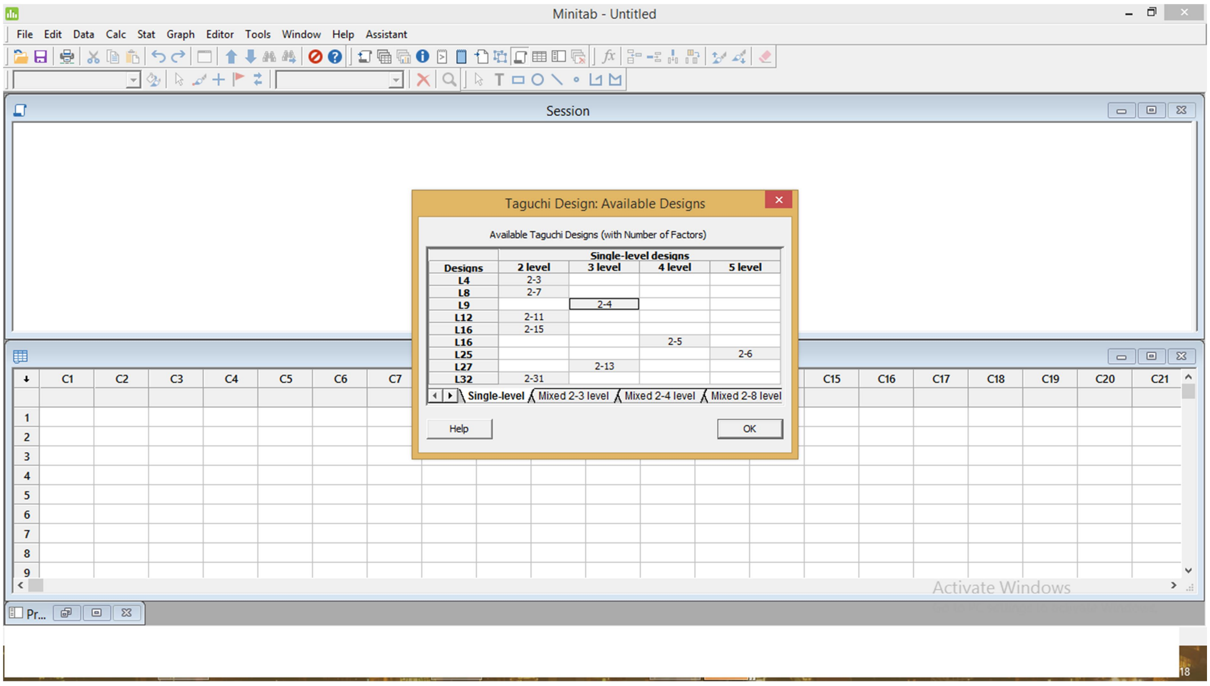


Fig 3.2: Creation of Taguchi design

Step 5: Stat > DOE > Taguchi > Create Taguchi Design > **Factors**

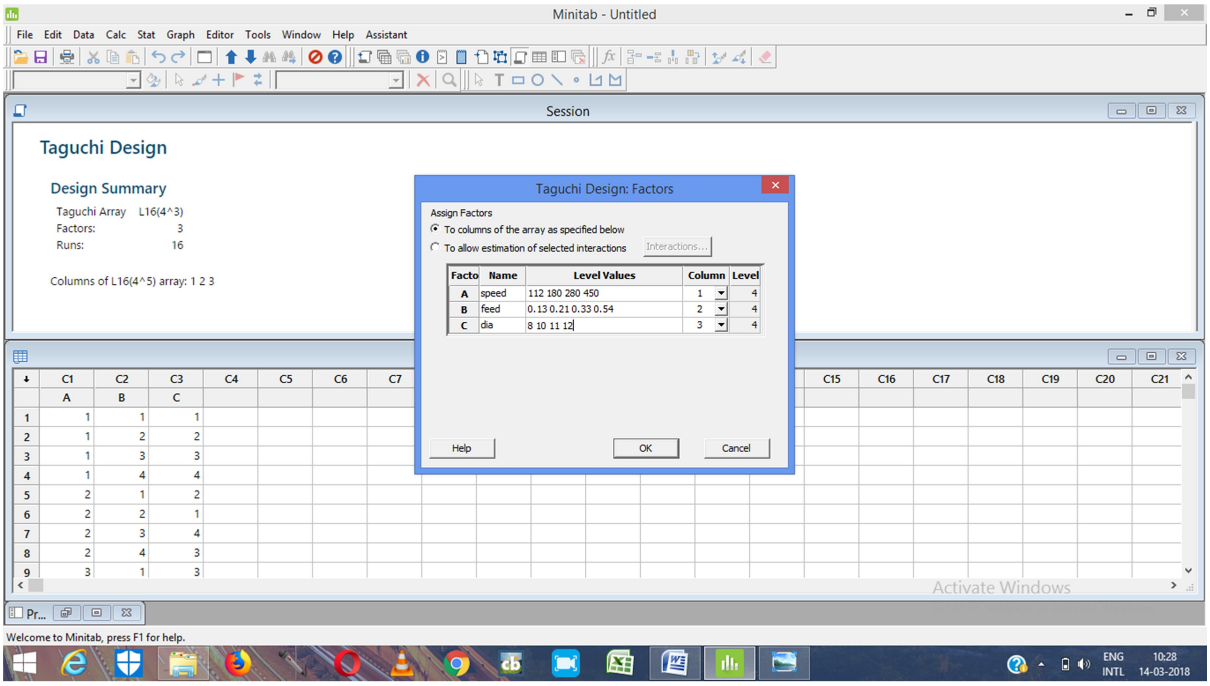
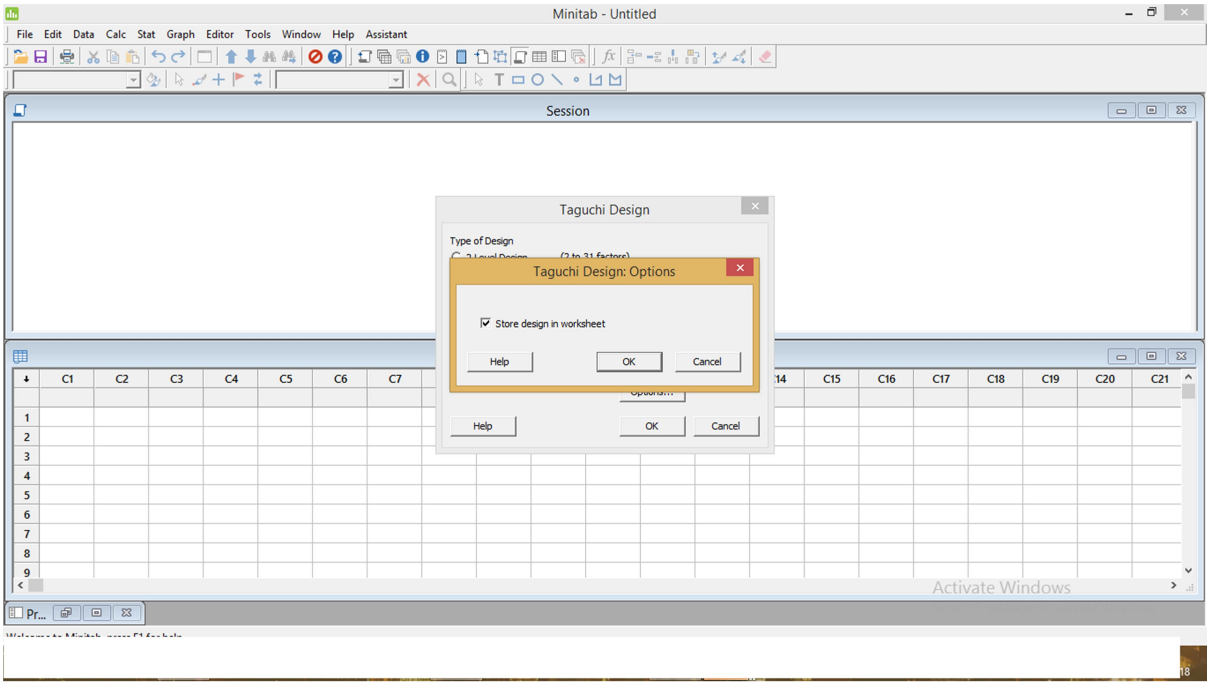
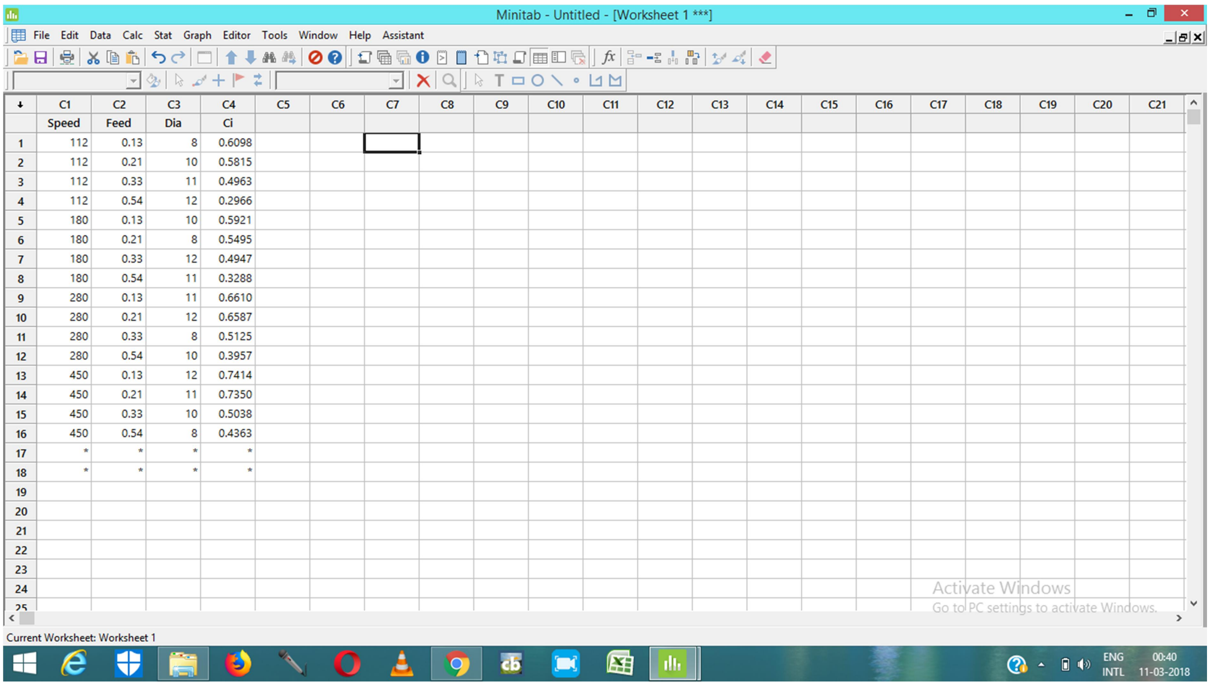


Fig 3.3: dialog box for entering parameters

Step 6: Stat > DOE > Taguchi > Create Taguchi Design > **Options**



Step 7: Stat > DOE > Taguchi > Create Taguchi Design >**Ok**



	C1 Speed	C2 Feed	C3 Dia	C4 Ci
1	112	0.13	8	0.6098
2	112	0.21	10	0.5815
3	112	0.33	11	0.4963
4	112	0.54	12	0.2966
5	180	0.13	10	0.5921
6	180	0.21	8	0.5495
7	180	0.33	12	0.4947
8	180	0.54	11	0.3288
9	280	0.13	11	0.6610
10	280	0.21	12	0.6587
11	280	0.33	8	0.5125
12	280	0.54	10	0.3957
13	450	0.13	12	0.7414
14	450	0.21	11	0.7350
15	450	0.33	10	0.5038
16	450	0.54	8	0.4363

Fig 3.4: Taguchi design in MINITAB.

Design of Experiments in coded form:

S.NO	Speed (rpm)	Feed(mm/rev)	DRILL DIA (mm)
1	1	1	1
2	1	2	2
3	1	3	3
4	1	4	4
5	2	1	2
6	2	2	1
7	2	3	4
8	2	4	3
9	3	1	3
10	3	2	4
11	3	3	1
12	3	4	2
13	4	1	4
14	4	2	3
15	4	3	2
16	4	4	1

Table 3.1 Design of Experiments in coded form

Design of Experiments in Un-coded form:

S.NO	SPEED (rpm)	FEED (mm/rev)	DRILL DIA (mm)
1	112	0.13	8
2	112	0.21	10
3	112	0.33	11
4	112	0.54	12
5	180	0.13	10
6	180	0.21	8
7	180	0.33	12
8	180	0.54	11
9	280	0.13	11
10	280	0.21	12
11	280	0.33	8
12	280	0.54	10
13	450	0.13	12
14	450	0.21	11
15	450	0.33	10
16	450	0.54	8

Table 3.2 Design of Experiments in Un-coded form.

EXPERIMENTAL SETUP AND MACHINING

The project was done in 3 stages:

- Design of experiments was done using Taguchi design method
- Cutting forces was measured by machining the work piece on Radial Drilling machine for calculating the material removal rate.
- Analysis of results was done using MINITAB 17 trial version.

Selection of process variables:

- A total of 3 process variables and 4 levels are selected for experimental procedure.
- The deciding process variables are
    1. Speed
    2. Feed
    3. Diameter

3.4 Selection of Levels

- Since it is a four level design by observing the parameters taken in various projects the level of factors are designed as follows

FACTORS	LEVEL 1	LEVEL 2	LEVEL 3	LEVEL 4
Speed	112	180	280	450
Feed	0.13	0.21	0.33	0.54
Diameter	8	10	11	12

Table 3.3 Selection of process variables

3.5 Design of Experiments

- Design of experiments was done using Taguchi design.
- Design of experiments (D.O.E) or experimental design is the design of any information gathering exercises where variation is present, whether under the full control of the experimenter or not.

3.6 Machining

Definition: Drilling is material removal process within the work piece via a rotating drill bits in a circular form and creation of holes take place with longitudinal force. A drill bit cuts a blind hole or a through hole with diameter equal to that of the tool when it enters the work piece axially.

Fig 3.5 Radial Drilling Machine

3.6.1 Machining of work piece

The machining of work piece on drilling is done using following procedure

- Selection of material.
- Clamping the work piece on lathe.
- Performed facing and turning operations.

3.6.2 Selection of Material

By studying the various projects, alumimium is selected for machining operation. The composition of aluminium (6061 series) is:

- Al- 98.9-98.5
- Si- 0.20-0.5
- Cu- 0.20
- Mn- 0.05
- Mg- 0.45
- Zn- 0.05

3.7 Measurement of Surface Roughness

Surface roughness of the work piece is measured using surface roughness tester.It displays the reading when placed on the work piece .It measures surface roughness in the order of microns. SJ210 surface roughness tester shown in figure 3.6

Fig 3.6 Surface Roughness Tester

3.8 Material removal rate:

The material removal rate of the work piece is calculated by using the formula.

$$\text{MRR}=\frac{1}{4}\pi.\text{d}^2.\text{f}.\text{N}\ (\text{mm}^3/\text{min})$$

Where:

d = diameter of drill bit in mm,

f = feed in mm/rev,

N = spindle speed in rev/min

3.9 Preparing the specimen:

Aluminium is purchased in the form of a plate and the reinforced material i.e., Molybdenum Disulphide (MoS_2) is purchased in the form powder. The composite material is prepared by using stir casting process and obtained the disc with dimensions 115 mm×35mm. On the Radial Drilling Machine 32 holes of different diameters were drilled. These 32 holes are used for the present work and they are shown in fig 3.7

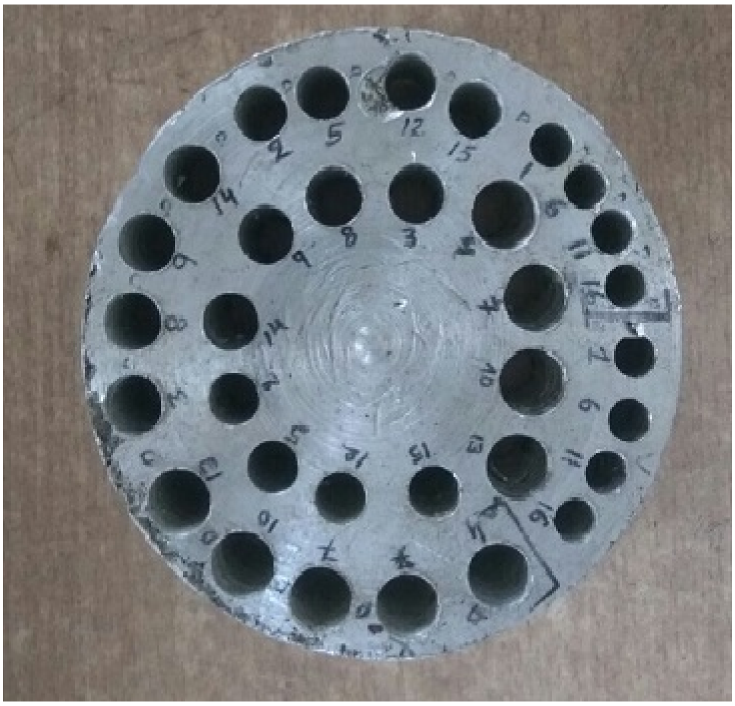


Fig 3.7 Holes obtained from Drilling machine

3.10 List of experimental surface roughness and MRR values

The surface roughness values are measured and calculated MRR are tabulated as follows:

DRY CONDITION:

S.NO	SPEED (rpm)	FEED (mm/rev)	DRILL DIA (mm)	TORQUE (kgm)	THRUST FORCE (kgf)	MRR (mm^3/min $MRR = \frac{\pi}{4}.d^2.f.N$	Ra
1	112	0.13	8	7	9	731.87	0.5281
2	112	0.21	10	14	17	1847.26	1.1025
3	112	0.33	11	20	29	3512.43	2.475
4	112	0.54	12	36	41	6840.14	6.075
5	180	0.13	10	20	11	1837.84	0.4225
6	180	0.21	8	16	22	1900.04	1.3781
7	180	0.33	12	34	29	6718	2.2688
8	180	0.54	11	41	44	9237.25	6.6273
9	280	0.13	11	8	15	3459.22	0.3841
10	280	0.21	12	20	23	6650.14	0.9188
11	280	0.33	8	22	21	4644.54	3.4031
12	280	0.54	10	40	39	11875.25	7.29
13	450	0.13	12	14	14	6616.21	0.3521
14	450	0.21	11	18	22	8980.66	1.0023
15	450	0.33	10	49	28	11663.19	2.7225
16	450	0.54	8	28	31	12214.54	9.1125

Table 3.4 Experimental values of surface roughness and MRR

3.11 List of experimental surface roughness and MRR values

The surface roughness values are measured and calculated MRR are tabulated as follows:

WET CONDITION:

S.NO	SPEED (rpm)	FEED (mm/rev)	DRILL DIA (mm)	TORQUE (kgm)	THRUST FORCE (kgf)	MRR (mm^3/min $MRR = \frac{\pi}{4}.d^2.f.N$	Ra
1	112	0.13	8	14	9	731.87	0.5281
2	112	0.21	10	13	15	1847.26	1.1025
3	112	0.33	11	21	23	3512.43	2.475
4	112	0.54	12	20	34	6840.14	6.075
5	180	0.13	10	9	10	1837.84	0.4225
6	180	0.21	8	9	12	1900.04	1.3781
7	180	0.33	12	18	22	6718	2.2688
8	180	0.54	11	20	43	9237.25	6.6273
9	280	0.13	11	24	13	3459.22	0.3841
10	280	0.21	12	26	15	6650.14	0.9188
11	280	0.33	8	25	18	4644.54	3.4031
12	280	0.54	10	21	36	11875.25	7.29
13	450	0.13	12	10	10	6616.21	0.3521
14	450	0.21	11	20	19	8980.66	1.0023
15	450	0.33	10	13	22	11663.19	2.7225
16	450	0.54	8	43	18	12214.54	9.1125

Table 3.5 Experimental values of surface roughness and MRR

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Methodology

Select the four levels of speed, feed, drill diameter values for experimental analysis. By using MINITAB software, create the Taguchi design of 16 runs. Perform drilling operations under dry and wet conditions in the order of matrix given by Taguchi design. Surface roughness is to be measured by using tally surface roughness tester and torque, thrust forces are measured by tool dynamometer. MRR is calculated using MRR drilling equation.

TOPSIS

The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method was firstly proposed by (Hwang and Yoon, 1981) for assessing the alternatives before the multiple-attribute decision making. TOPSIS is implemented to measure the extent of closeness to the ideal solution. The basic concept of this method is that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from negative ideal (anti-ideal) solution. Positive ideal solution is the composition of the best performance values demonstrated (in the decision matrix) by any alternative for each attribute. The negative-ideal solution is the composition of the worst performance values. The steps involved for calculating the TOPSIS values are as follows:

Step 1: Development of decision Matrix: The row of this matrix is allocated to alternative and each column to one attribute. The matrix can be expressed as the following:

$$
\mathbf{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ \cdot \\ A_i \\ \cdot \\ A_m \end{array}
\begin{array}{c}
\begin{array}{ccccc} X_1 & X_2 & . & X_j & X_n \end{array} \\
\begin{bmatrix}
x_{11} & x_{12} & \cdot & x_{1j} & x_{1n} \\
x_{21} & x_{22} & \cdot & x_{2j} & x_{2n} \\
\cdot & \cdot & \cdot & \cdot & \cdot \\
x_{i1} & x_{i2} & \cdot & x_{ij} & \cdot \\
\cdot & \cdot & \cdot & \cdot & \cdot \\
x_{m1} & x_{m2} & \cdot & x_{mj} & x_{mn}
\end{bmatrix}
\end{array}
$$

where , A_i represents the possible alternatives , i=1,2,3,.... , m; X_j denotes the attributes relating to alternative performances , j=1,2....,n and $x_{ij}$is the performance of A_i with respect to the attribute X_j.

Step 2: Obtain the normalized decision matrix r_{ij}. This can be represented as :

$$\mathbf{r_{ij}} = \frac{\boldsymbol{x_{ij}}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \text{...} \mathbf{(5)}$$

where ,r_{ij} represents the normalized performance of A_i with respect to X_j.

Step 3: Assume the weight of each attribute is $\{W_j || j=1,2,...,n\}$,the weighted normalized decision matrix $V=[v_{ij}]$ can be found as :

$$V= w_j r_{ij} \quad \text{.....................................} \quad \mathbf{(6)}$$

Where:

$\sum_{j=1}^{n} w_j = 1$

Step 4: develop the ideal (best) and negative ideal (worst) solutions in this step. The ideal and negative ideal solution can be expressed as:

$$A^{+}=\{(\max v_{ij}|j\in J),(\min v_{ij}|j\in J'|\ i=1,1,....,m)\} \quad \text{....................} \quad (7)$$

$$=\{v_1^{+},v_2^{+},....,v_j^{+},......,v_n^{+}\}$$

$A^{-}=\{(\min v_{ij}|j\in J),(\min v_{ij}|j\in J^{'}|\ i=1,2,....,m)\}$ .... (8)

$=\{v_1^{-},v_2^{-},...,v_j^{-},....,v_n^{-}\}$

Where

$J=\{j=1,2,...,n|j\}$: associated with the beneficial attributes.

$J^{'}=\{j= 1,2,....,n|j\}$: associated with the beneficial attributes.

Step 5: Determine the distance measures .the separation of the each alternative from the ideal one is given by n-dimensional Euclidean distance from the following equations:

$$S_i^{+}=\sqrt{\sum_{j=1}^{n}(v_{ij-}\ v_j^{+})^2},\ i=1,2,....,m \qquad (9)$$

$$S_i^{-}=\sqrt{\sum_{j=1}^{n}(v_{ij-}\ v_j^{-})^2},\quad i=1,2,...., \qquad (10)$$

Step 6: The proximity of a particular alternative to the ideal solution is expressed in this step as follows:

$$C_i^{+}=\frac{S_i^{-}}{S_i^{-}+S_i^{+}} \qquad (11)$$

Step 7 :A set of alternatives is made in descending order according to the preference value indicating the most preferred and least preferred feasible solutions.

$$(S/N)_{PREDICTED} =(S/N)_{total\ mean\ +}\ (Speed - (S/N)_{total}) +(Feed - (S/N)_{total}) +$$

$$(Diameter - (S/N)_{total}).$$

4.2 Different terms used in TOPSIS method

Alternatives: A_1, A_2, $A_{3,}$..................,A_m are possible alternatives that decision makers have to choose from.

Criteria: $C_1, C_2, C_3, \ldots\ldots\ldots C_n$ are the criteria for which the alternative performance is measured.

$\mathbf{X_{ij}}$**:** It is value of i- alternative with respect to j- criterion.

$\mathbf{r_{ij}}$**:** It represents the normalized performance of A_i with respect to X_j.

$\mathbf{W_j}$**:** It is the weight of each attribute.

$\mathbf{V_{ij}}$**:** It is the weighted normalised decision matrix.

$\mathbf{S_i^+}$ **:** Positive Ideal Solution.

$\mathbf{S_i^-}$ **:** Negative Ideal Solution.

$\mathbf{C_i}$ **:** The proximity of a particular alternative to the ideal solution.

4.3 DRY RESULTS:

S.NO	SPEED (rpm)	FEED (mm/rev)	DRILL DIA (mm)	TORQUE (kgm)	THRUST FORCE (kgf)	MRR (mm^3/min) $MRR = \frac{\pi}{4}.d^2.f.N$	Ra (µm)	C_i	S/N Ci
1	112	0.13	8	7	9	731.87	7.784	0.4721	-6.51931999
2	112	0.21	10	14	17	1847.26	1.152	0.585	-4.65688268
3	112	0.33	11	20	29	3512.43	3.353	0.4839	-6.30488756
4	112	0.54	12	36	41	6840.14	5.805	0.3288	-9.66136382
5	180	0.13	10	20	11	1837.84	0.18	0.5976	-4.47178822
6	180	0.21	8	16	22	1900.04	4.206	0.4802	-6.37155689
7	180	0.33	12	34	29	6718	7.579	0.3477	-9.17590619
8	180	0.54	11	41	44	9237.25	0.157	0.5147	-5.76891663
9	280	0.13	11	8	15	3459.22	0.779	0.6561	-3.66059924
10	280	0.21	12	20	23	6650.14	0.923	0.6628	-3.57235001
11	280	0.33	8	22	21	4644.54	0.058	0.6258	-4.07128882
12	280	0.54	10	40	39	11875.25	5.799	0.4441	-7.05038454
13	450	0.13	12	14	14	6616.21	1.384	0.7221	-2.8280531
14	450	0.21	11	18	22	8980.66	6.646	0.5358	-5.41994581
15	450	0.33	10	49	28	11663.19	7.02	0.4213	-7.50817082
16	450	0.54	8	28	31	12214.54	7.185	0.4956	-6.09737405

Table 4.1 table for C_i and S/N C_i value

				Xij			
S.NO	**SPEED (rpm)**	**FEED (mm/rev)**	**DRILL DIA (mm)**	**TORQUE (kgm)**	**THRUST FORCE (kgf)**	**MRR (mm^3/min)** $MRR = \frac{\pi}{4}.d^2.f.N$	**Ra**
1	112	0.13	8	7	9	731.87	7.784
2	112	0.21	10	14	17	1847.26	1.152
3	112	0.33	11	20	29	3512.43	3.353
4	112	0.54	12	36	41	6840.14	5.805
5	180	0.13	10	20	11	1837.84	0.18
6	180	0.21	8	16	22	1900.04	4.206
7	180	0.33	12	34	29	6718	7.579
8	180	0.54	11	41	44	9237.25	0.157
9	280	0.13	11	8	15	3459.22	0.779
10	280	0.21	12	20	23	6650.14	0.923
11	280	0.33	8	22	21	4644.54	0.058
12	280	0.54	10	40	39	11875.25	5.799
13	450	0.13	12	14	14	6616.21	1.384
14	450	0.21	11	18	22	8980.66	6.646
15	450	0.33	10	49	28	11663.19	7.02
16	450	0.54	8	28	31	12214.54	7.185

Table 4.2 Table for X_{ij} values

squares X_{ij}^2				**Normalised** $r_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{n} X_{ij}^2}}$			
49.00	81.00	535633.70	60.5907	0.0648	0.0842	0.0254	0.4079
196.00	289.00	3412369.51	1.3271	0.1295	0.1591	0.0642	0.0604
400.00	841.00	12337164.50	11.2426	0.1850	0.2714	0.1220	0.1757
1296.00	1681.00	46787515.22	33.6980	0.3330	0.3837	0.2376	0.3042
400.00	121.00	3377655.87	0.0324	0.1850	0.1030	0.0638	0.0094
256.00	484.00	3610152.00	17.6904	0.1480	0.2059	0.0660	0.2204
1156.00	841.00	45131524.00	57.4412	0.3145	0.2714	0.2333	0.3972
1681.00	1936.00	85326787.56	0.0246	0.3793	0.4118	0.3208	0.0082
64.00	225.00	11966203.01	0.6068	0.0740	0.1404	0.1201	0.0408
400.00	529.00	44224362.02	0.8519	0.1850	0.2153	0.2310	0.0484
484.00	441.00	21571751.81	0.0034	0.2035	0.1966	0.1613	0.0030
1600.00	1521.00	141021562.56	33.6284	0.3700	0.3650	0.4125	0.3039
196.00	196.00	43774234.76	1.9155	0.1295	0.1310	0.2298	0.0725
324.00	484.00	80652254.04	44.1693	0.1665	0.2059	0.3119	0.3483
2401.00	784.00	136030000.98	49.2804	0.4533	0.2621	0.4051	0.3679
784.00	961.00	149194987.41	51.6242	0.2590	0.2902	0.4242	0.3765
11687.00	11415.00	828954158.95	364.1271	0.25	0.25	0.25	0.25

Table 4.3 Table for squares and Normalized values

Weighted Normalized	$V_j = W_j \times r_{ij}$		
0.0162	0.0211	0.0064	0.1020
0.0324	0.0398	0.0160	0.0151
0.0463	0.0679	0.0305	0.0439
0.0833	0.0959	0.0594	0.0761
0.0463	0.0257	0.0160	0.0024
0.0370	0.0515	0.0165	0.0551
0.0786	0.0679	0.0583	0.0993
0.0948	0.1030	0.0802	0.0021
0.0185	0.0351	0.0300	0.0102
0.0463	0.0538	0.0577	0.0121
0.0509	0.0491	0.0403	0.0008
0.0925	0.0913	0.1031	0.0760
0.0324	0.0328	0.0574	0.0181
0.0416	0.0515	0.0780	0.0871
0.1133	0.0655	0.1013	0.0920
0.0648	0.0725	0.1061	0.0941

Table 4.4 Table for Weighted Normalized values

Positive Matrix	V_j^+		
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008

Table 4.5 Table for V_j^+ values

S_iPlus $S_i^+ = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^+)^2}$	Negative Matrix V_j^-				S_i Minus $S_i^- = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^-)^2}$
0.142079898	0.1133	0.1030	0.0064	0.0993	0.127074606
0.094453746	0.1133	0.1030	0.0064	0.0993	0.133140149
0.103280815	0.1133	0.1030	0.0064	0.0993	0.096838884
0.133981242	0.1133	0.1030	0.0064	0.0993	0.065622703
0.095113577	0.1133	0.1030	0.0064	0.0993	0.141240723
0.111054451	0.1133	0.1030	0.0064	0.0993	0.102613336
0.134445579	0.1133	0.1030	0.0064	0.0993	0.071672315
0.11644432	0.1133	0.1030	0.0064	0.0993	0.123497759
0.077918084	0.1133	0.1030	0.0064	0.0993	0.148633766
0.066631958	0.1133	0.1030	0.0064	0.0993	0.130985225
0.079449786	0.1133	0.1030	0.0064	0.0993	0.132884514
0.128130375	0.1133	0.1030	0.0064	0.0993	0.102353347
0.055351026	0.1133	0.1030	0.0064	0.0993	0.143794198
0.099048061	0.1133	0.1030	0.0064	0.0993	0.114319036
0.1405436	0.1133	0.1030	0.0064	0.0993	0.102296998
0.117161802	0.1133	0.1030	0.0064	0.0993	0.115115036

Table 4.6 Table for S_i^+, V_j^+, and S_i^- values

$C_i = \frac{S_i^-}{S_i^+ + S_i^-}$
0.4721
0.585
0.4839
0.3288
0.5976
0.4802
0.3477
0.5147
0.6561
0.6628
0.6258
0.4441
0.7221
0.5358
0.4213
0.4956

Table 4.7: table for C_i values

4.3.1 GRAPHS: (dry condition)

Main effects plot of S/N ratio:

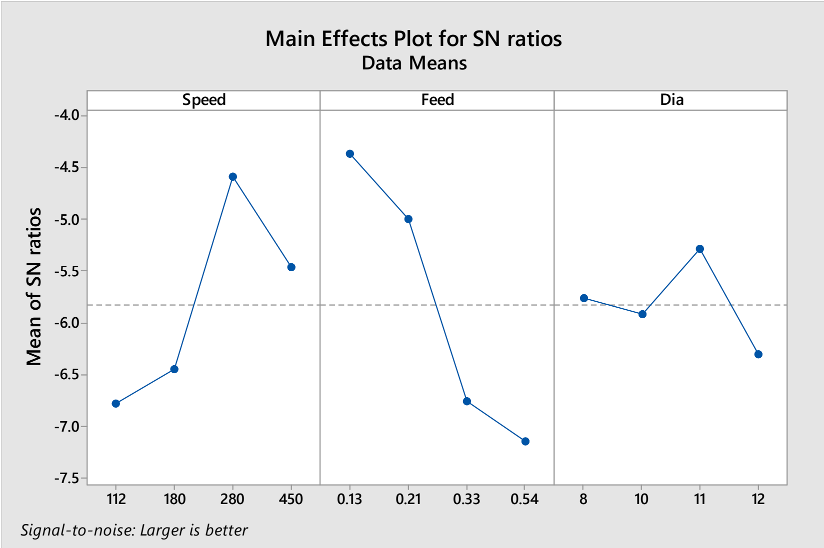


Fig 4.1 Main effects plot of S/N ratio

Main effects plots show how each factor affects the response characteristic (S/N ratio, means, slopes, standard deviations). A main effect exists when different levels of a factor affect the characteristic differently. For a factor with four levels, you may discover that one level increases the mean compared to the other level. This difference is a main effect.

Normal Probability Plot:

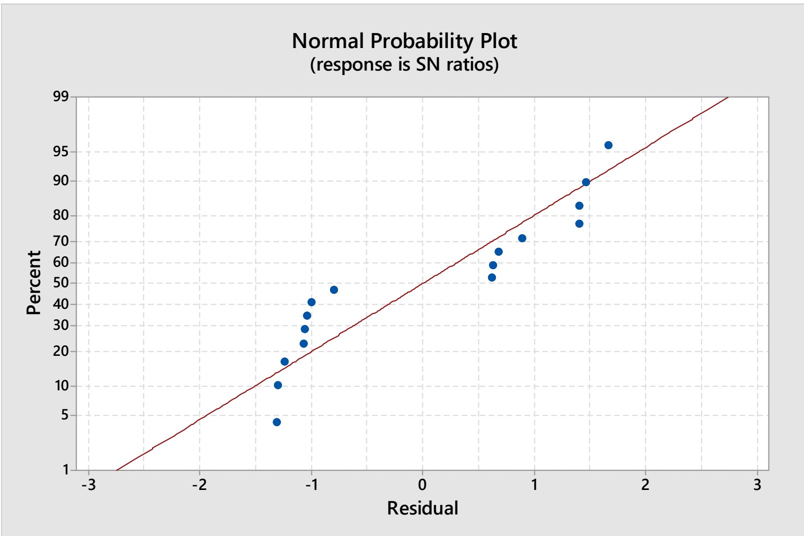


Fig 4.2 Normal Probability Plot

The graph is plotted in between the residuals Vs their expected values when the distribution is normal. The residuals from the analysis should be normally distributed. In practice, for balance or nearly balanced designs or for data with large number of observations, moderate departures from normality do not seriously affect the results. The normal probability plot of the residuals should roughly follow a straight line.

Residuals Vs Fits:

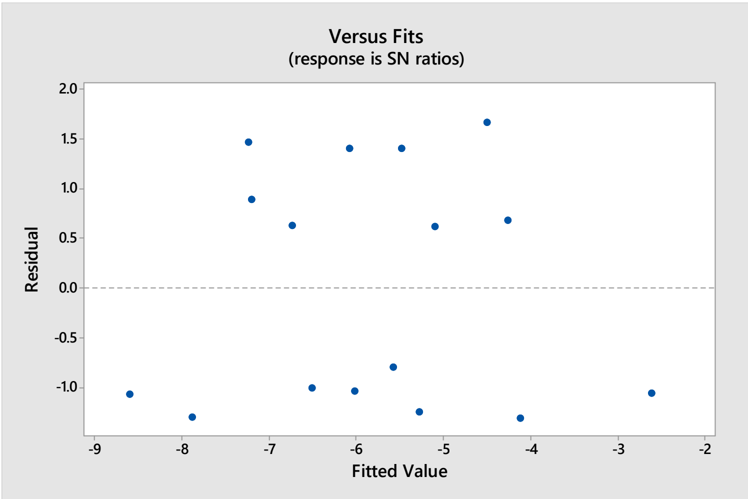


Fig 4.3 Residuals Vs Fits

The graph is plotted between the residuals Vs fitted values. The residuals should be scattered randomly about zero.

4.4 WET RESULTS:

Wet condition coolant: BPCL

S.NO	SPEED (rpm)	FEED (mm/rev)	DRILL DIA (mm)	TORQUE (kgm)	THRUST FORCE (kgf)	MRR (mm^3/min) $MRR = \frac{\pi}{4}.d^2.f.N$	Ra (µm)	C_i	S/N Ci
1	112	0.13	8	14	9	731.87	2.705	0.516	-5.737756299
2	112	0.21	10	13	15	1847.26	2.014	0.5389	-5.369083095
3	112	0.33	11	21	23	3512.43	5.065	0.353437196	-9.033754947
4	112	0.54	12	20	34	6840.14	1.444	0.514718825	-5.768598955
5	180	0.13	10	9	10	1837.84	6.908	0.446177614	-7.00984446
6	180	0.21	8	9	12	1900.04	1.523	0.587102332	-4.65723885
7	180	0.33	12	18	22	6718	3.064	0.536734201	-5.404814602
8	180	0.54	11	20	43	9237.25	2.38	0.483939658	-6.304175728
9	280	0.13	11	24	13	3459.22	3.132	0.469032237	-6.575946133
10	280	0.21	12	26	15	6650.14	9.141	0.372102058	-8.586758553
11	280	0.33	8	25	18	4644.54	0.14	0.565992995	-4.943778872
12	280	0.54	10	21	36	11875.25	5.245	0.467973801	-6.595569189
13	450	0.13	12	10	10	6616.21	2.765	0.66728252	-3.513805032
14	450	0.21	11	20	19	8980.66	2.771	0.605538682	-4.357162178
15	450	0.33	10	13	22	11663.19	1.363	0.742304405	-2.588359244
16	450	0.54	8	43	18	12214.54	0.12	0.561602126	-5.011425139

Table 4.8 Table for C_i and S/N C_i values

				Xij			
S.NO	**SPEED (rpm)**	**FEED (mm/rev)**	**DRILL DIA (mm)**	**TORQUE (kgm)**	**THRUST FORCE (kgf)**	**MRR (mm^3/min)** $MRR = \frac{\pi}{4}.d^2.f.N$	**Ra**
1	112	0.13	8	14	9	731.87	2.705
2	112	0.21	10	13	15	1847.26	2.014
3	112	0.33	11	21	23	3512.43	5.065
4	112	0.54	12	20	34	6840.14	1.444
5	180	0.13	10	9	10	1837.84	6.908
6	180	0.21	8	9	12	1900.04	1.523
7	180	0.33	12	18	22	6718	3.064
8	180	0.54	11	20	43	9237.25	2.38
9	280	0.13	11	24	13	3459.22	3.132
10	280	0.21	12	26	15	6650.14	9.141
11	280	0.33	8	25	18	4644.54	0.14
12	280	0.54	10	21	36	11875.25	5.245
13	450	0.13	12	10	10	6616.21	2.765
14	450	0.21	11	20	19	8980.66	2.771
15	450	0.33	10	13	22	11663.19	1.363
16	450	0.54	8	43	18	12214.54	0.12

Table 4.9 Table for X_{ij} values

squares X_{ij}^2				**Normalised** $r_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{n} X_{ij}^2}}$			
196.00	81.00	535633.70	7.3170	0.1682	0.1016	0.0254	0.1738
169.00	225.00	3412369.51	4.0562	0.1562	0.1693	0.0642	0.1294
441.00	529.00	12337164.50	25.6542	0.2523	0.2596	0.1220	0.3254
400.00	1156.00	46787515.22	2.0851	0.2403	0.3837	0.2376	0.0928
81.00	100.00	3377655.87	47.7205	0.1081	0.1129	0.0638	0.4438
81.00	144.00	3610152.00	2.3195	0.1081	0.1354	0.0660	0.0978
324.00	484.00	45131524.00	9.3881	0.2163	0.2483	0.2333	0.1968
400.00	1849.00	85326787.56	5.6644	0.2403	0.4853	0.3208	0.1529
576.00	169.00	11966203.01	9.8094	0.2883	0.1467	0.1201	0.2012
676.00	225.00	44224362.02	83.5579	0.3124	0.1693	0.2310	0.5872
625.00	324.00	21571751.81	0.0196	0.3004	0.2031	0.1613	0.0090
441.00	1296.00	141021562.56	27.5100	0.2523	0.4063	0.4125	0.3370
100.00	100.00	43774234.76	7.6452	0.1201	0.1129	0.2298	0.1776
400.00	361.00	80652254.04	7.6784	0.2403	0.2144	0.3119	0.1780
169.00	484.00	136030000.98	1.8578	0.1562	0.2483	0.4051	0.0876
1849.00	324.00	149194987.41	0.0144	0.5166	0.2031	0.4242	0.0077
6928.00	7851.00	828954158.95	242.2978	0.25	0.25	0.25	0.25

Table 4.10 Table for squares and normalized values

Weighted Normalized	$V_j = W_j \times r_{ij}$		
0.0420	0.0254	0.0064	0.0434
0.0390	0.0423	0.0160	0.0323
0.0631	0.0649	0.0305	0.0813
0.0601	0.0959	0.0594	0.0232
0.0270	0.0282	0.0160	0.1109
0.0270	0.0339	0.0165	0.0245
0.0541	0.0621	0.0583	0.0492
0.0601	0.1213	0.0802	0.0382
0.0721	0.0367	0.0300	0.0503
0.0781	0.0423	0.0577	0.1468
0.0751	0.0508	0.0403	0.0022
0.0631	0.1016	0.1031	0.0842
0.0300	0.0282	0.0574	0.0444
0.0601	0.0536	0.0780	0.0445
0.0390	0.0621	0.1013	0.0219
0.1292	0.0508	0.1061	0.0019

Table 4.11 Table for Weighted Normalized values

Positive Matrix	V_j^+		
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008
0.0162	0.0211	0.1061	0.0008

Table 4.12 Table for V_j^+ values

S_iPlus $S_i^+ = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^+)^2}$	Negative Matrix V_j^-				S_i Minus $S_i^- = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^-)^2}$
0.111582735	0.1133	0.1030	0.0064	0.0993	0.119222282
0.10037902	0.1133	0.1030	0.0064	0.0993	0.117337734
0.127764488	0.1133	0.1030	0.0064	0.0993	0.069841201
0.101056325	0.1133	0.1030	0.0064	0.0993	0.107186505
0.142928199	0.1133	0.1030	0.0064	0.0993	0.11514768
0.094151148	0.1133	0.1030	0.0064	0.0993	0.133874233
0.0879886	0.1133	0.1030	0.0064	0.0993	0.101942537
0.118535431	0.1133	0.1030	0.0064	0.0993	0.111157536
0.107714976	0.1133	0.1030	0.0064	0.0993	0.095150402
0.167181748	0.1133	0.1030	0.0064	0.0993	0.099074496
0.093144281	0.1133	0.1030	0.0064	0.0993	0.121470414
0.125133004	0.1133	0.1030	0.0064	0.0993	0.110067827
0.067164948	0.1133	0.1030	0.0064	0.0993	0.134702858
0.075413839	0.1133	0.1030	0.0064	0.0993	0.115767997
0.051711092	0.1133	0.1030	0.0064	0.0993	0.148956258
0.116817074	0.1133	0.1030	0.0064	0.0993	0.149646522

Table 4.13 Table for S_i^+, V_j^+, and S_i^- values

$C_i = \frac{S_i^-}{S_i^+ + S_i^-}$
0.516549785
0.538946735
0.353437196
0.514718825
0.446177614
0.587102332
0.536734201
0.483939658
0.469032237
0.372102058
0.565992995
0.467973801
0.66728252
0.605538682
0.742304405
0.561602126

Table 4.14 Table for C_i values

4.4.1 GRAPHS: (wet condition)

Main effects plot of S/N ratio:

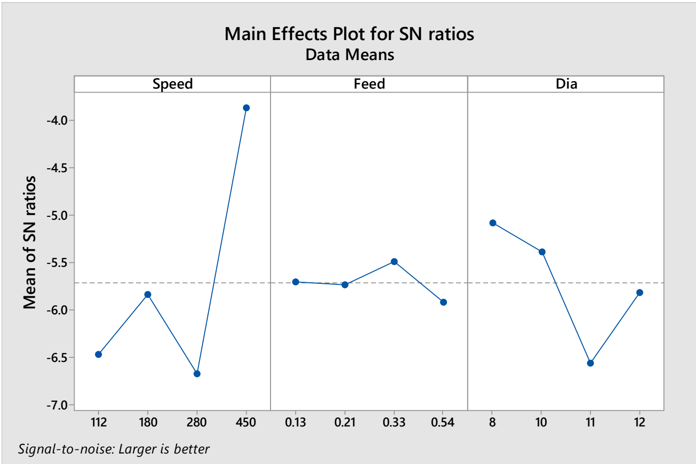


Fig 4.4 Main effects plot of S/N ratio

Main effects plots show how each factor affects the response characteristic (S/N ratio, means, slopes, standard deviations). A main effect exists when different levels of a factor affect the characteristic differently. For a factor with four levels, you may discover that one level increases the mean compared to the other level. This difference is a main effect.

Normal probability plot:

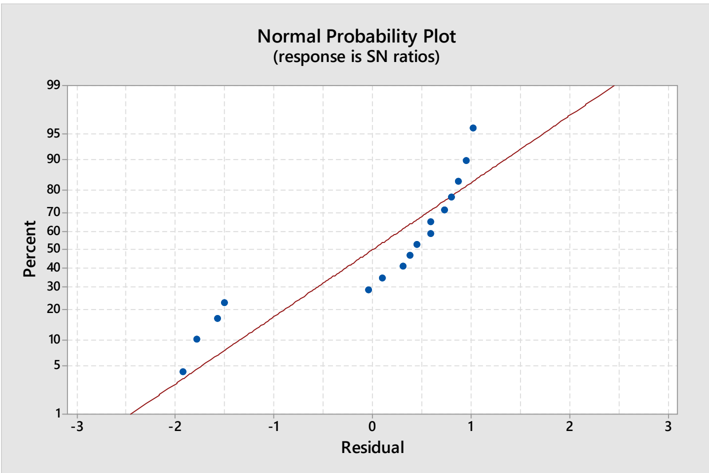


Fig 4.5 Normal Probability Plot

The graph is plotted in between the residuals Vs their expected values when the distribution is normal. The residuals from the analysis should be normally distributed. In practice, for balance or nearly balanced designs or for data with large number of observations, moderate departures from normality do not seriously affect the results. The normal probability plot of the residuals should roughly follow a straight line.

Residuals Vs Fits:

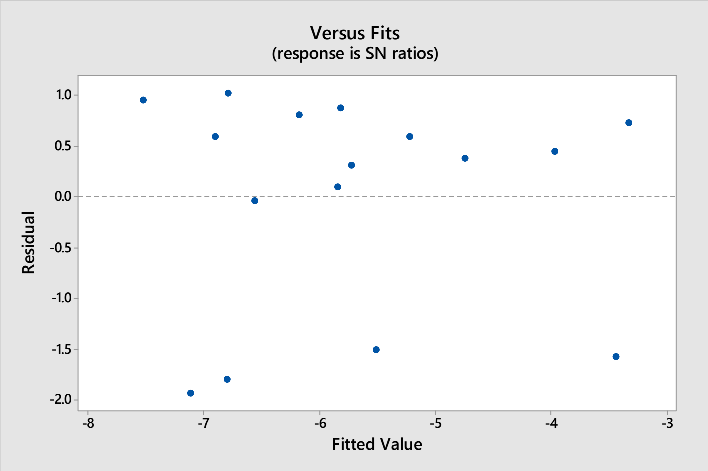


Fig 4.6 Residual Vs Fits

The graph is plotted between the residuals Vs fitted values. The residuals should be scattered randomly about zero.

CHAPTER 5

CONCLUSIONS:

- Multi response optimization of torque, thrust, MRR and R_a has been done using TOPSIS
- During the Drilling operation as given below
  Speed: 280 rpm
  Feed: 0.13mm^3/rev
  Diameter of drill: 11 mm
- Confirmation test was done at the optimum parameters and closeness (c_i) value obtained after multi response optimization was
  Experimental C_i =-3.66
- Predicted C_i value has been obtained as
  Predicted C_i=-2.60
  Experimental and predicted values are good in agreement.
- Multi response optimizing has been carried out in the wet condition by taking BPCL oil as coolant.
- Experimental and predicted values obtained after multi response optimality of torque, thrust, MRR and R_a are -3.46, -3.01171 respectively.
  Experimental and predicted values are good in agreement during the wet condition.

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