Multiple Response Optimization of machining parameters on turning of AA 6063 T6 aluminium alloy using Taguchi L_9 orthogonal array coupled with Grey Relational Analysis.

A project report submitted in partial fulfilment of the requirement for

the award of the degree of

BACHELOR OF TECHNOLOGY

IN

MECHANICAL ENGINEERING

BY

SANAPALA SRI RAM (318126520L11)

TANGETI BHASKARARAO (318126520L02)

BODDU ESWAR VENKAT SAI (317126520005)

KARI SURAJ KUMAR (317126520026)

DUVVI VEERA VENKATA PAVAN KUMAR (317126520018)

Under the esteemed guidance of

Mr. D S Sai RAVI KIRAN

Assistant professor

PRAGNANAM BRAHMA

ANITS

DEPARTMENT OF MECHANICAL ENGINEERING

ANIL NEERUKONDA INSTITUTE OF TECHNOLOGY & SCIENCES (A)

(Affiliated to Andhra University, Accredited By NBA and NAAC with 'A' Grade)

SANGIVALASA, VISAKHAPATNAM (District) – 531162

ANIL NEERUKONDA INSTITUTE OF TECHNOLOGY & SCIENCES
[Autonomous, Accredited by NBA, NACC, Affiliated to Andhra University]
Sangivalasa - 531 162, Bheemunipatnam Mandal, Visakhapatnam [District]

PRAGNANAM BRAHMA
ANITS

CERTIFICATE

This is to certify that the project report entitled **"Multiple Response Optimization Of Machining Parameters On Turning Of AA 6063 T6 Aluminium Alloy using Taguchi L_9 Orthogonal Array Coupled With Grey Relational Analysis"** has been carried out by **SANAPALA SRI RAM (318126520L11), TANGETI BHASKARARAO (318126520L02), BODDU ESWAR VENKAT SAI (317126520005), KARI SURAJ KUMAR (317126520026), DUVVI VEERA VENKATA PAVAN KUMAR (317126520018)** of 4/4 Mechanical Engineering, ANIL NEERUKONDA INSTITUTE OF TECHNOLOGY AND SCIENCES, Visakhapatnam during the year 2020-2021, under my guidance in partial fulfillment of the requirements of Degree in Bachelor of Mechanical Engineering.

PROJECT GUIDE

D.S.S. [signature]

(MR.D.S.S.RAVI KIRAN)
Assistant Professor
Mechanical Engineering Department
ANITS, Visakhapatnam.

Approved By
HEAD OF THE DEPARTMENT

(Dr. B. Naga Raju)
Head of the Department
Mechanical Engineering Department
ANITS, Visakhapatnam.

PROFESSOR & HEAD
Department of Mechanical Engineering
ANIL NEERUKONDA INSTITUTE OF TECHNOLOGY & SCIENCE
Sangivalasa-531 162 VISAKHAPATNAM Dist A P

ACKNOWLDGEMENTS

We express immensely our deep sense of gratitude to **Mr. D. S. Sai Ravi Kiran,** Assistant Professor, Department of Mechanical Engineering, Anil Neerukonda Institute of Technology & Sciences, Sangivalasa, Bheemunipatnam Mandal, Visakhapatnam district for his valuable guidance and encouragement at every stage of the work made it a successful fulfillment.

We were very thankful to **Dr. B. Nagaraju**, Professor &Head of the Mechanical Engineering Department, Anil Neerukonda Institute of Technology & Sciences for their valuable suggestions.

We express our sincere thanks to the members of non-teaching staff of Mechanical Engineering for their kind co-operation and support to carry on work.

Last but not the least, we like to convey our thanks to all who have contributed either directly or indirectly for the completion of our work.

SANAPALA SRI RAM (318126520L11)

TANGETI BHASKARARAO (318126520L02)

BODDU ESWAR VENKAT SAI (317126520005)

KARI SURAJ KUMAR (317126520026)

DUVVI VEERA VENKATA PAVAN KUMAR (317126520018)

ABSTRACT

The current work presents a novel approach for the optimization of machining parameters on turning of AA 6063 T6 aluminium alloy with multiple responses established on Taguchi L_9 orthogonal array coupled with grey relational analysis. Experimental assessments are accomplished on AA 6063 T6 aluminium alloy. Turning trials are conceded out by means of an uncoated carbide insert under dry cutting conditions. In this exertion turning parameters such as cutting speed, feed rate, and depth of cut are optimized bearing in mind the multiple responses such as surface roughness (Ra) and material removal rate (MRR). A grey relational grade (GRG) is determined from the grey analysis. Optimum levels of parameters have been acknowledged based on the values of grey relational grade and then the noteworthy contribution of parameters is determined by ANOVA. To authenticate the test result, a confirmation test is executed. Experimental conclusions have substantiated that the responses in turning process can be enhanced efficiently through this approach.

CONTENTS

Chapter-3

Surface Roughness

Chapter-4

Design of Experiments

Chapter-5

Experimental Setup

Chapter 6

Results and Discussions

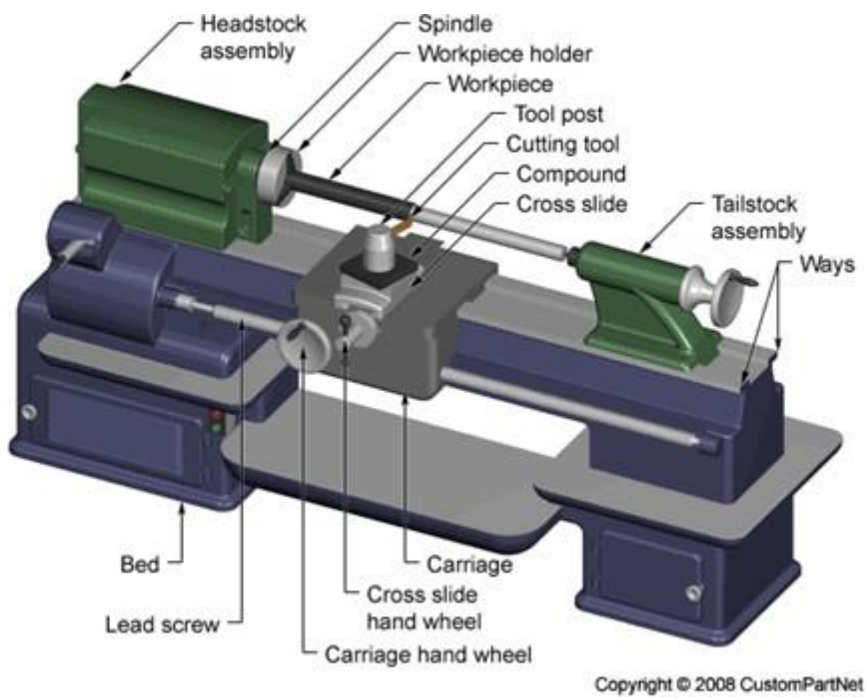
CHAPTER 1
INTRODUCTION

Turning is a form of machining, a material removal process, which is used to create rotational parts by cutting away unwanted material. The turning process requires a turning machine or lathe, workpiece, fixture, and cutting tool. The workpiece is a piece of pre-shaped material that is secured to the fixture, which itself is attached to the turning machine, and allowed to rotate at high speeds. The cutter is typically a single-point cutting tool that is also secured in the machine, although some operations make use of multi-point tools. The cutting tool feeds into the rotating workpiece and cuts away material in the form of small chips to create the desired shape.

Turning is used to produce rotational, typically axisymmetric, parts that have many features, such as holes, grooves, threads, tapers, various diameter steps, and even contoured surfaces. Parts that are fabricated completely through turning often include components that are used in limited quantities, perhaps for prototypes, such as custom-designed shafts and fasteners. Turning is also commonly used as a secondary process to add or refine features on parts that were manufactured using a different process. Due to the high tolerances and surface finishes that turning can offer, it is ideal for adding precision rotational features to a part whose basic shape has already been formed.

1.1.1 Equipment:

Turning machines, typically referred to as lathes, can be found in a variety of sizes and designs. While most lathes are horizontal turning machines, vertical machines are sometimes used, typically for large diameter workpieces. Turning machines can also be classified by the type of control that is offered. A manual lathe requires the operator to control the motion of the cutting tool during the turning operation. Turning machines are also able to be computer-controlled, in which case they are referred to as a computer numerical control (CNC) lathe. CNC lathes rotate the workpiece and move the cutting tool based on commands that are pre-programmed and offer very high precision. In this variety of turning machines, the main components that enable the workpiece to be rotated and the cutting tool to be fed into the workpiece remain the same. These components include the following:



Manual lathe

- ***Bed***

The bed of the turning machine is simply a large base that sits on the ground or a table and supports the other components of the machine.

- ***Headstock assembly***

The headstock assembly is the front section of the machine that is attached to the bed. This assembly contains the motor and drive system which powers the spindle. The spindle supports and rotates the workpiece, which is secured in a workpiece holder or fixtures, such as a chuck or collet.

- ***Tailstock assembly***

The tailstock assembly is the rear section of the machine that is attached to the bed. The purpose of this assembly is to support the other end of the workpiece and allow it to rotate, as it's driven by the spindle. For some turning operations, the workpiece is not supported by the tailstock so that material can be removed from the end.

- ***Carriage***

The carriage is a platform that slides alongside the workpiece, allowing the cutting tool to cut away material as it moves. The carriage rests on tracks that lay on the bed, called "ways", and is advanced by a lead screw powered by a motor or handwheel.

- ***Cross slide***

The cross slide is attached to the top of the carriage and allows the tool to move towards or away from the workpiece, changing the depth of the cut. As with the carriage, the cross slide is powered by a motor or handwheel.

- ***Compound***

The compound is attached on top of the cross slide and supports the cutting tool. The cutting tool is secured in a tool post which is fixed to the compound. The compound can rotate to alter the angle of the cutting tool relative to the workpiece.

- ***Turret***

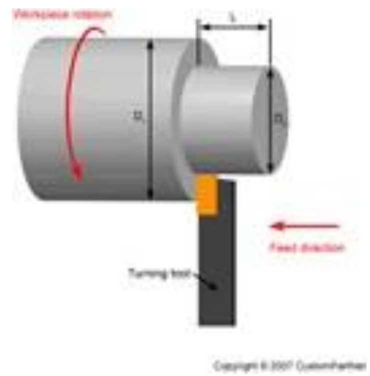
Some machines include a turret, which can hold multiple cutting tools and rotates the required tool into position to cut the workpiece. The turret also moves along the workpiece, feeding the cutting tool into the material. While most cutting tools are stationary in the turret, live tooling can also be used. Live tooling refers to powered tools, such as mills, drills, reamers, and taps, which rotate and cut the workpiece.

1.1.2 Operations:

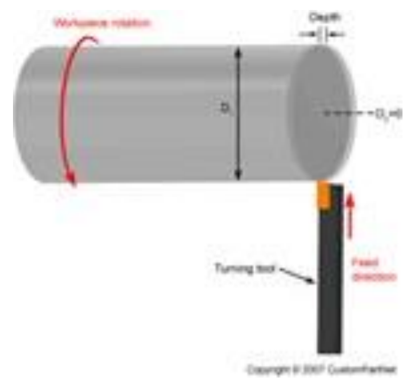
During the process cycle, a variety of operations may be performed on the workpiece to yield the desired part shape. These operations may be classified as external or internal. External operations modify the outer diameter of the workpiece, while internal operations modify the inner diameter. The following operations are each defined by the type of cutter used and the path of that cutter to remove material from the workpiece.

- **External operations**

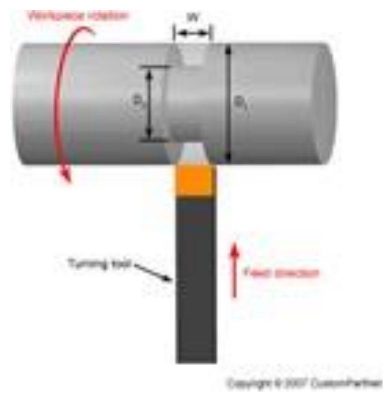
  - ***Turning*** - A single-point turning tool moves axially, along the side of the workpiece, removing material to form different features, including steps, tapers, chamfers, and contours. These features are typically machined at a small radial depth of cut and multiple passes are made until the end diameter is reached.



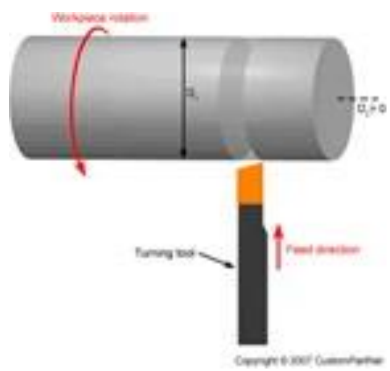
  - ***Facing*** - A single-point turning tool moves radially, along the end of the workpiece, removing a thin layer of material to provide a smooth flat surface. The depth of the face, typically very small, maybe machined in a single pass or may be reached by machining at a smaller axial depth of cut and making multiple passes.



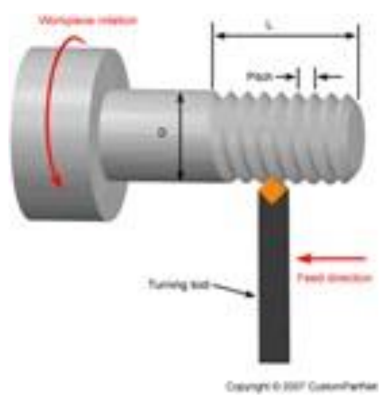
- ***Grooving*** - A single-point turning tool moves radially, into the side of the workpiece, cutting a groove equal in width to the cutting tool. Multiple cuts can be made to form grooves larger than the tool width and special form tools can be used to create grooves of varying geometries.



- ***Cut-off (parting)***- Similar to the grooving, a single-point cut-off tool moves radially, into the side of the workpiece, and continues until the center or inner diameter of the workpiece is reached, thus parting or cutting off a section of the workpiece.

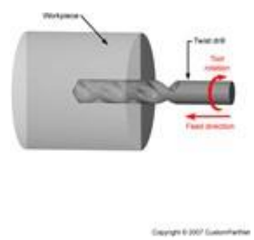


- ***Thread cutting*** - A single-point threading tool, typically with a 60-degree pointed nose, moves axially, along the side of the workpiece, cutting threads into the outer surface. The threads can be cut to a specified length and pitch and may require multiple passes to be formed.

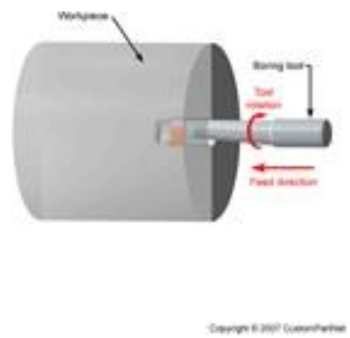


• Internal operations

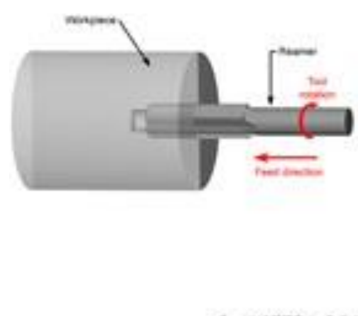
- ***Drilling*** - A drill enters the workpiece axially through the end and cuts a hole with a diameter equal to that of the tool.



- ***Boring*** - A boring tool enters the workpiece axially and cuts along an internal surface to form different features, such as steps, tapers, chamfers, and contours. The boring tool is a single-point cutting tool, which can be set to cut the desired diameter by using an adjustable boring head. Boring is commonly performed after drilling a hole to enlarge the diameter or obtain more precise dimensions.

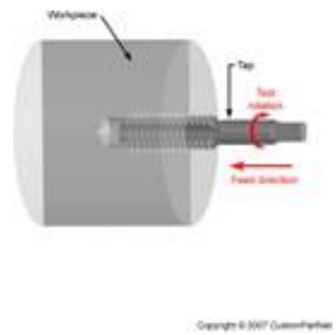


- ***Reaming*** - A reamer enters the workpiece axially through the end and enlarges an existing hole to the diameter of the tool. Reaming removes a minimal amount of material and is often performed



after drilling to obtain both a more accurate diameter and a smoother internal finish.

- ***Tapping*** - A tap enters the workpiece axially through the end and cuts internal threads into an existing hole. The existing hole is typically drilled by the required tap drill size that will accommodate the desired tap.



1.1.3 Cutting Tools for Lathe:

The classes of cutting tool materials currently in use for machining operation are high-speed tool steel, cobalt-base alloys, cemented carbides, ceramic, polycrystalline cubic boron nitride and polycrystalline diamond. Different machining applications require 6 different cutting tool materials. The Ideal cutting tool material should have all of the following characteristics:

- Harder than the work it is cutting
- High temperature stability
- Resists wear and thermal shock
- Impact resistant
- Chemically inert to the work material and cutting fluid

To effectively select tools for machining, a machinist or engineer must have specific information about:

- The starting and finished part shape
- The work piece hardness
- The material's tensile strength
- The material's abrasiveness
- The type of chip generated
- The work holding setup
- The power and speed capacity of the machine tool

Some common cutting tool materials are described below:

Carbon steels: Carbon steels have been used since the 1880s for cutting tools. However, carbon steels start to soften at a temperature of about 180o C. This limitation means that such tools are rarely used for metal cutting operations. Plain carbon steel tools, containing about 0.9% carbon and about 1% manganese, hardened to about 62 Rc, are widely used for woodworking and they can be used in a router to machine aluminium sheet up to about 3mm thick.

High speed steels (HSS): HSS tools are so named because they were developed to cut at higher speeds. Developed around 1900 HSS are the most highly alloyed tool steels. The tungsten (T series) was developed first and typically contains 12 - 18% tungsten, plus about 4% chromium and 1 - 5% vanadium. Most grades contain about 0.5% molybdenum and most grades contain 4 - 12% cobalt. It was soon discovered that molybdenum (smaller proportions) could be substituted for most of the tungsten resulting in a more economical formulation which had better abrasion resistance than the T series and undergoes less distortion during heat treatment. Consequently about 95% of all HSS tools are made from M series grades. These contain 5 - 10% molybdenum, 1.5 - 10% tungsten, 1 - 4% vanadium, 4% Chromium and many grades contain 5 - 10% cobalt. HSS tools are tough and suitable for interrupted cutting and are used to manufacture tools of complex shape such as drills, reamers, taps, dies and gear cutters. Tools may also be coated to improve wear resistance. HSS accounts for the largest tonnage of tool materials currently used. Typical cutting speeds: 10 - 60 m/min.

Cast Cobalt alloys: Introduced in early 1900s these alloys have compositions of about 40 - 55% cobalt, 30% chromium and 10 - 20% tungsten and are not heat treatable. Maximum hardness values of 55 - 64 Rc. They have good wear resistance but are not as tough as HSS but can be used at somewhat higher speeds than HSS. Now only in limited use. Carbides: Also known as cemented carbides or sintered carbides were introduced in the 1930s and have high hardness over a wide range of temperatures, high thermal conductivity, high Young's modulus making them effective tool and die materials for a range of applications. The two groups used for machining are tungsten carbide and titanium carbide; both types may be coated or uncoated. Tungsten carbide particles (1 to 5 micrometer) are bonded together in a cobalt matrix using powder metallurgy. The powder is pressed and sintered to the required insert shape. Titanium and niobium carbides may also be included to impart special properties. A wide range of grades are available for different applications. Sintered carbide tips are the dominant type of material used in metal cutting. The proportion of cobalt (the usual matrix material) present has a significant effect on the properties of carbide tools. 3 - 6% matrix of cobalt gives greater 8 hardness while 6 - 15% matrix of cobalt gives a greater toughness while decreasing the hardness, wear resistance and strength. Tungsten carbide tools are commonly used for machining steels, cast irons and abrasive non-ferrous materials. Titanium carbide has a higher wear resistance than tungsten but is not as tough. With a nickel-molybdenum alloy as the matrix, TiC is suitable for machining at higher speeds than those which can be used for tungsten carbide. Typical cutting speeds are: 30 - 150 m/min or 100 - 250 when coated.

Coatings: Coatings are frequently applied to carbide tool tips to improve tool life or to enable higher cutting speeds. Coated tips typically have lives 10 times greater than uncoated tips. Common coating materials include titanium nitride, titanium carbide and aluminium oxide, usually 2 - 15 micro-m thick. Often several different layers may be applied, one on top of another, depending upon the intended application of the tip. The techniques used for applying coatings include chemical vapour deposition (CVD) plasma assisted CVD and physical vapour deposition (PVD). Diamond coatings are also in use and being further developed.

Ceramics:

Alumina:

Introduced in the early 1950s, two classes are used for cutting tools: fine grained high purity aluminium oxide (Al_2O_3) and silicon nitride (Si_3N_4) are pressed into insert tip shapes and sintered at high temperatures. Additions of titanium carbide and zirconium oxide (ZrO_2) may be made to improve properties. But while ZrO_2 improves the fracture toughness, it reduces the hardness and thermal conductivity. Silicon carbide (SiC) 9 whiskers may be added to give better toughness and improved thermal shock resistance. The tips have high abrasion resistance and hot hardness and their superior chemical stability compared to HSS and carbides means they are less likely to adhere to the metals during cutting and consequently have a lower tendency to form a built-up edge. Their main weakness is low toughness and negative rake angles are often used to avoid chipping due to their low tensile strengths. Stiff machine tools and work set ups should be used when machining with ceramic tips as otherwise vibration is likely to lead to premature failure of the tip. Typical cutting speeds: 150-650 m/min.

Silicon Nitride: In the 1970s a tool material based on silicon nitride was developed, these may also contain aluminium oxide, yttrium oxide and titanium carbide. SiN has an affinity for iron and is not suitable for machining steels. A specific type is 'Sialon', containing the elements: silicon, aluminium, oxygen and nitrogen. This has higher thermal shock resistance than silicon nitride and is recommended for machining cast irons and nickel based super alloys at intermediate cutting speeds.

Cubic Boron Nitride (CBN): Introduced in the early 1960s, this is the second hardest material available after diamond. cBN tools may be used either in the form of small solid tips or or as a 0.5 to 1 mm thick layer of of polycrystalline boron nitride sintered onto a carbide substrate under pressure. In the latter case the carbide provides shock resistance and the cBN layer provides very high wear resistance and cutting edge strength. Cubic boron nitride is the standard choice for machining alloy and tool steels with a hardness of 50 Rc or higher. Typical cutting speeds: 30 - 310 m/min.

Diamond: The hardest known substance is diamond. Although single crystal diamond has been used as a tool, they are brittle and need to be mounted at the correct crystal orientation to obtain optimal tool life. Single crystal diamond tools have been mainly replaced by 10 polycrystalline diamond (PCD). This consists of very small synthetic crystals fused by a high temperature high pressure process to a thickness of between 0.5 and 1mm and bonded to a carbide substrate. The result is similar to cBN tools. The random orientation of the diamond crystals prevents the propagation of cracks, improving toughness. Because of its reactivity, PCD is not suitable for machining plain carbon steels or nickel, titanium and cobalt based alloys. PCD is most suited to light uninterrupted finishing cuts at almost any speed and is mainly used for very high-speed machining of aluminium - silicon alloys, composites and other non - metallic materials. Typical cutting speeds: 200 - 2000 m/min.

To improve the toughness of tools, developments are being carried out with whisker reinforcement, such as silicon nitride reinforced with silicon carbide whiskers.

As rates of metal removal have increased, so has the need for heat resistant cutting tools. The result has been a progression from high-speed steels to carbide, and on to ceramics and other super hard materials.

High-speed steels cut four times faster than the carbon steels they replaced. There are over 30 grades of high-speed steel, in three main categories: tungsten, molybdenum, and molybdenum-cobalt based grades.

In industry today, carbide tools have replaced high-speed steels in most applications. These carbide and coated carbide tools cut about 3 to 5 times faster than high-speed steels. Cemented carbide is a powder metal product consisting of fine carbide particles cemented together with a binder of cobalt. The major categories of hard carbide include tungsten carbide, titanium carbide, tantalum carbide, and niobium carbide.

Ceramic cutting tools are harder and more heat-resistant than carbides, but more brittle. They are well suited for machining cast iron, hard steels, and the super alloys. Two types of ceramic cutting tools are available: the alumina-based and the silicon nitride-based ceramics. The alumina-based ceramics are used for high speed semi- and final-finishing of ferrous and some non-ferrous materials. The silicon nitride-based ceramics are generally used for rougher and heavier machining of cast iron and the super alloys.

1.1.4 Cutting parameters:

In turning, the speed and motion of the cutting tool are specified through several parameters. These parameters are selected for each operation based upon the workpiece material, tool material, tool size, and more.

- ***Cutting feed*** - The distance that the cutting tool or workpiece advances during one revolution of the spindle, measured in inches per revolution (IPR). In some operations, the tool feeds into the workpiece and in others, the workpiece feeds into the tool. For a multi-point tool, the cutting feed is also equal to the feed per tooth, measured in inches per tooth (IPT), multiplied by the number of teeth on the cutting tool.
- ***Cutting speed*** - The speed of the workpiece surface relative to the edge of the cutting tool during a cut, measured in surface feet per minute (SFM).
- ***Spindle speed*** - The rotational speed of the spindle and the workpiece in revolutions per minute (RPM). The spindle speed is equal to the cutting speed divided by the circumference of the workpiece where the cut is being made. To maintain a constant cutting speed, the spindle speed must vary based on the diameter of the cut. If the spindle speed is held constant, then the cutting speed will vary.
- ***Feed rate*** - The speed of the cutting tool's movement relative to the workpiece as the tool cuts. The feed rate is measured in inches per minute (IPM) and is the product of the cutting feed (IPR) and the spindle speed (RPM).

- ***Axial depth of cut*** - The depth of the tool along the axis of the workpiece as it cuts, as in a facing operation. A large axial depth of cut will require a low feed rate, or else it will result in a high load on the tool and reduce the tool life. Therefore, a feature is typically machined in several passes as the tool moves to the specified axial depth of cut for each pass.

- ***Radial depth of cut*** - The depth of the tool along the radius of the workpiece as it cuts, as in a turning or boring operation. A large radial depth of cut will require a low feed rate, or else it will result in a high load on the tool and reduce the tool life. Therefore, a feature is often machined in several steps as the tool moves over at the radial depth of cut.

1.2 Surface Finish Definitions:

Surface Deviations:

Any departure from the nominal surface in the form of waviness, roughness, flaws, lay and profile.

Waviness:

Surface irregularities which deviate from the mean surface in the form of waves they may be caused by vibrations in the machine or work. These are generally widely spaced. The peak to valley distance in inches or millimetres.

Waviness Width:

The distance between successive waviness peaks or valleys in inches or millimetres.

Roughness:

Relatively finely spaced irregularities superimposed on the waviness pattern and caused by the cutting tool or the abrasive grain action and the machine feed. These irregularities are much narrower than the waviness pattern.

Roughness height:

The deviation measured normal to the centre line in micro inches or micrometres.

Roughness width:

The distance between successive roughness peaks parallel to the normal surface in inches or millimetres.

Roughness width cut-off:

The greatest spacing of repetitive surface irregularities to be included in

the measurement of the roughness height. It must always greater than

the roughness width.

Flaws:

Irregularities such as scratches, holes, cracks, ridges that do not follow a

regular pattern as in the case of waviness and roughness.

Lay:

The direction of the predominant surface pattern caused by the

machining process.

Profile:

The counter of specified section through a surface.

1.3 Factors affecting the surface finish:

The following effecting surface roughness are

- Vibrations
- Material of the work piece
- Hardness of the work piece
- Type of machining

- Rigidity of the system consisting of machine took, fixture, cutting tool and work.

1.4 Introduction to Minitab:

Minitab is a statistics package. It was developed at the Pennsylvania state University by researchers Barbara F. Ryan, Thomas A. Ryan Jr., and Brian L. Joiner in 1972. Minitab began as a light version of OMINITAB, statistical analysis program by NIST. It can be used for learning about statistics as well as statistical research. Statistical analysis computer application has the advantage of being accurate, reliable and general faster than computing statistics and drawing graphs by hand. Minitab is relatively easy to use once you know a few fundamentals. Minitab is distributed by Minitab Inc., a privately owned company headquartered in state college, Pennsylvania with subsidiaries Coventry, England (Minitab limited), Paris, France (Minitab SARL) and Sydney, Australia (Minitab Pty.)

Today, Minitab is often used in conjunction with the implementation of six sigma, CMMI and other statistics-based process improvement methods. Minitab 17, the latest version of the software, is available in 7 languages: English, French, German, Japanese, Korean, Simplified Chinese and Spanish.

Minitab is statistical analysis software. It can be used for learning about statistics as well as statistical research. Statistical analysis computer applications have the advantage of being accurate, reliable, and generally faster than computing statistics and drawing graphs by hand. Minitab is relatively easy to use once you know a few fundamentals.

Minitab Inc. produces two other products that complement Minitab 17: Quality trainer, a learning package that teaches statistical tools and concepts in the context of quality improvement that integrates with Minitab 17 to simultaneously develop the user's statistical knowledge and ability to use the Minitab software and Quality companion 3, an integrated tool for managing six sigma and Lean manufacturing projects that allows Minitab data to be combined with management and governance tools and documents.

Minitab has two main types of files, projects and worksheets. Worksheets are files that are made up of data; think of a spreadsheet containing variables of data. Projects are made up of the commands, graphs, and worksheets. Every time you save a Minitab project you will be saving graphs, worksheets and commands. However each one of the elements can be saved individually for use in other documents or Minitab projects. Likewise, you can print projects and its elements.

1.4.1 Minitab project and Worksheets:

Minitab has two main types of files, projects and worksheets. Worksheets are files that are made up of data; think of a spreadsheet containing variables of data. Projects are made up of commands, worksheets and commands. Every time you save a Minitab project, you will be saving graphs, worksheets and commands. However each one of the elements can be saved individually for use in other documents or Minitab projects. Likewise you can print projects and its elements.

The Menu bar: You can open menus and choose commands. Here you can find the built - in routines.

The Toolbar: Shortcuts to some Minitab commands.

1.4.2 Two windows in Minitab

1. Session window:

The area that displays the statistical results of your data analysis and can also be used to enter commands.

2. Worksheet window:

A grid of rows and columns used to enter and manipulate the data. Note: This area looks like a spreadsheet but will not automatically update the columns when entries are changed.

Other windows include,

Graph Window: When you generate graphs, each graph is opened in its own window.

Report Window: Version 17 has the report manager that helps you organize your results in a report.

Other Windows: History and project manager are other windows. See Minitab help for more information on these if needed.

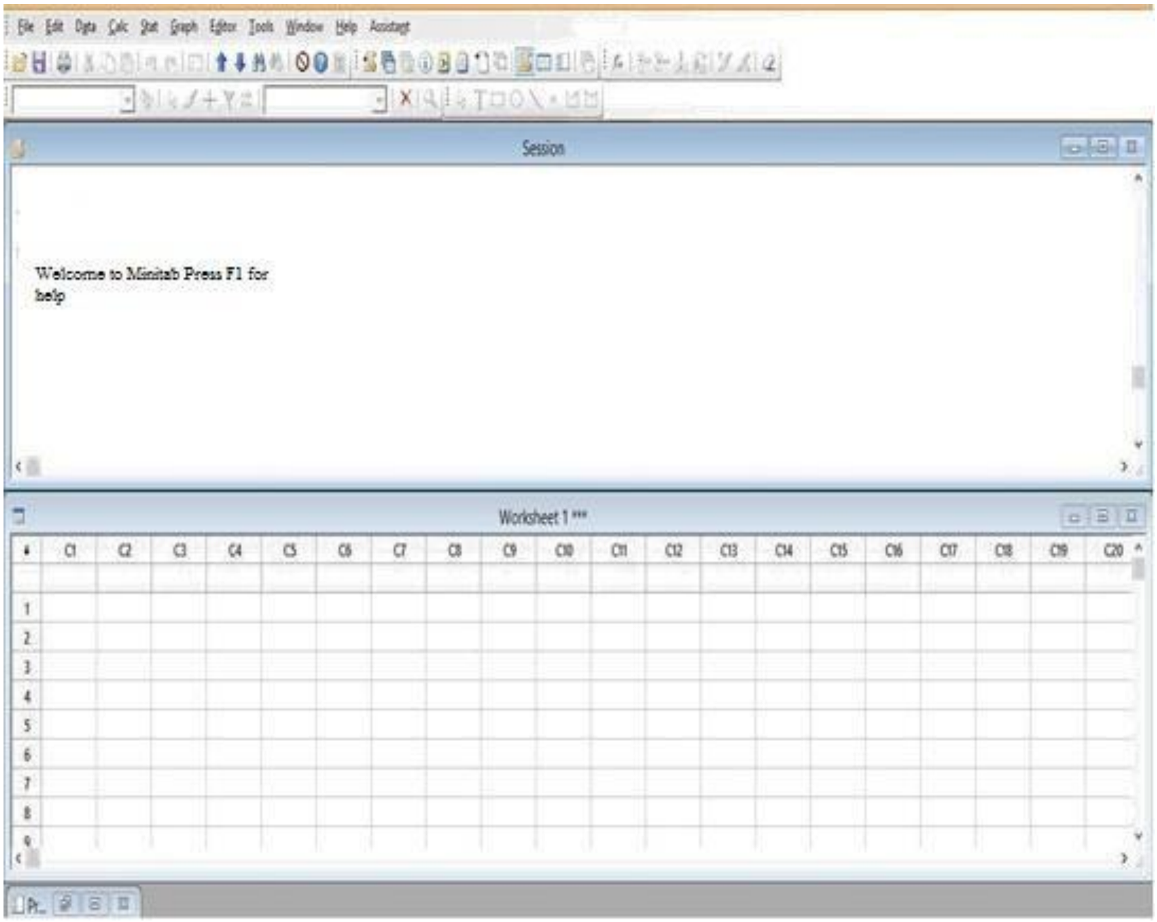


Fig 1.11 Minitab worksheet

CHAPTER 2

LITERATURE REVIEW

Zhou et al. [1] investigated on tool life criteria in raw turning. A new tool-life criterion depending on a pattern-recognition technique was proposed and neural network and wavelet techniques were used to realize the new criterion. The experimental results showed that this criterion was applicable to tool condition monitoring in a wide range of cutting conditions.

Lin et al. [2] adopted an abdicative network to construct a prediction model for surface roughness and cutting force. Once the process parameters: cutting speed, feed rate 44 and depth of cut were given; the surface roughness and cutting force could be predicted by this network. Regression analysis was also adopted as second prediction model for surface roughness and cutting force. Comparison was made on the results of both models indicating that adductive network was

Suresh et al. [3] focused on machining mild steel by TiN-coated tungsten carbide (CNMG) cutting tools for developing a surface roughness prediction model by using Response Surface Methodology (RSM). Genetic Algorithms (GA) used to optimize the objective function and compared with RSM results. It was observed that GA program provided minimum and maximum values of surface roughness and their respective optimal machining conditions.

Lee and Chen [4] highlighted on artificial neural networks (OSRR-ANN) using a sensing technique to monitor the effect of vibration produced by the motions of the cutting tool and work piece during the cutting process developed an on-line surface recognition system. The authors employed tri-axial accelerometer for determining the direction of vibration that significantly affected surface roughness then analyzed by using a statistical method and compared prediction accuracy of both the ANN and SMR.

Choudhury and Bartarya [5] focused on design of experiments and the neural network for prediction of tool wear. The input parameters were cutting speed, feed and depth of cut; flank wear, surface finish and cutting zone temperature were selected as outputs. Empirical relation between different responses and input variables and also through neural network (NN) program helped in predictions for all the three response variables and compared which method was best for the prediction.

Chien and Tsai [6] developed a model for the prediction of tool flank wear followed by an optimization model for the determination of optimal cutting conditions in 45 machining 17-4PH stainless steel. The back-propagation neural network (BPN) was used to construct the predictive model. The genetic algorithm (GA) was used for model optimization.

Őzel and Karpat [7] studied for prediction of surface roughness and tool flank wear by utilizing the neural network model in comparison with regression model. The data set from measured surface roughness and tool flank wear were employed to train the neural network models. Predictive neural network models were found to be capable of better predictions for surface roughness and tool flank wear within the range in between they were trained.

Kohli and Dixit [8] proposed a neural-network-based methodology with the acceleration of the radial vibration of the tool holder as feedback. For the surface roughness prediction in turning process the back-propagation algorithm was used for training the network model. The methodology was validated for dry and wet turning of steel using high speed steel and carbide tool and observed that the proposed methodology was able to make accurate prediction of surface roughness by utilizing small sized training and testing datasets.

Ahmed [9] developed the methodology required for obtaining optimal process parameters for prediction of surface roughness in Al turning. For development of empirical model nonlinear regression analysis with logarithmic data transformation was applied. The developed model showed small errors and satisfactory results. The study concluded that low feed rate was good to produce reduced surface roughness and also the high speed could produce high surface quality within the experimental domain.

Abburi and Dixit [10] developed a knowledge-based system for the prediction of surface roughness in turning process. Fuzzy set theory and neural networks were utilized for this purpose. The authors developed rule for predicting the surface roughness for given process variables as well as for the prediction of process variables for a given surface roughness.

Zhong et al. [11] predicted the surface roughness of turned surfaces using networks with seven inputs namely tool insert grade, work piece material, tool nose radius, rake angle, depth of cut, spindle rate, and feed rate.

Kumanan et al. [12] proposed the methodology for prediction of machining forces using multi-layered perceptron trained by genetic algorithm (GA). The data obtained from experimental results of a turning process were explored to train the proposed 47 artificial neural networks (ANNs) with three inputs to get machining forces as output. The optimal ANN weights were obtained using GA search. This function-replacing hybrid made of GA and ANN was found computationally efficient as well as accurate to predict the machining forces for the input machining conditions.

Thamizhmanii et al. [13] applied Taguchi method for finding out the optimal value of surface roughness under optimum cutting condition in turning SCM 440 alloy steel. The experiment was designed by using Taguchi method and experiments were conducted and results thereof were analysed with the help of ANOVA (Analysis of Variance) method. The causes of poor surface finish as detected were machine tool vibrations, tool chattering whose effects were ignored for analyses. The authors concluded that the results obtained by this method would be useful to other researches for similar type of study on tool vibrations, cutting forces etc. The work concluded that depth of cut was the only significant factor which contributed to the surface roughness.

Natarajan et al. [14] presented the on-line tool wear monitoring technique in turning operation. Spindle speed, feed, depth of cut, cutting force, spindle-motor power and temperature were selected as the input parameters for the monitoring technique. For finding out the extent of tool wear; two methods of Hidden Markov Model (HMM) such as the Bar-graph Method and the Multiple Modelling Methods were used. A decision fusion centre algorithm (DFCA) was used for increasing the reliability of this output which combined the outputs of the individual methods to make a global decision about the wear status of the tool. Finally, all the proposed methods were combined in a DFCA to determine the wear status of the tool during the turning operations.

Ozel et al. [15] carried out finish turning of AISI D2 steels (60 HRC) using ceramic wiper (multi-radii) design inserts for surface finish and tool flank wear investigation. For prediction of surface roughness and tool flank wear multiple linear regression models and neural network models were developed. Neural network-based predictions of surface roughness and tool flank wear were carried out, compared with a non-training experimental data and the results thereof showed that the proposed neural network models were efficient to predict tool wear and surface roughness patterns for a range of cutting conditions. The study concluded that best tool life was obtained in lowest feed rate and lowest cutting speed combination.

Wang and Lan [16] used Orthogonal Array of Taguchi method coupled with grey relational analysis considering four parameters viz. speed, cutting depth, feed rate, tool nose run off etc. for optimizing three responses: surface roughness, tool wear and material removal rate in precision turning on an ECOCA-3807 CNC Lathe. The MINITAB software was explored to analyse the mean effect of Signal-to-Noise (S/N) ratio to achieve the multi-objective features. This study not only proposed an optimization approaches using Orthogonal Array and grey relational analysis but also contributed a satisfactory technique for improving the multiple machining performances in precision CNC turning with profound insight.

Sahoo et al. [17] studied for optimization of machining parameters combinations emphasizing on fractal characteristics of surface profile generated in CNC turning operation. The authors used L27 Taguchi Orthogonal Array design with machining parameters: speed, feed and depth of cut on three different work piece materials viz. aluminum, mild steel and brass. It was concluded that feed rate was more significant influencing surface finish in all three materials. It was observed that in case of mild steel and aluminum feed showed some influences while in case of brass depth of cut was noticed to impose some influences on surface finish. The factorial interaction was responsible for controlling the fractal dimensions of surface profile produced in CNC turning.

Reddy et al. [18] adopted multiple regression model and artificial neural network to deal with surface roughness prediction model for machining of aluminium alloys by CNC turning. For judging the efficiency and ability of the model in surface roughness prediction the authors used the percentage deviation and average percentage deviation. 50 The study of experimental results showed that the artificial neural network was efficient as compared to multiple regression models for the prediction of surface roughness.

Wannas [19] carried out experiments for hard turning of graphitic cast iron for the prediction of status of tool wear by using radial basis function neural network (RBFNN) model. The RBFNN had three inputs: speed, feed and depth of cut and one output: state variable node. The error was less as obtained from neural network model than the regression model. Lan et al. (2008) considered four cutting parameters: speed, feed, depth of cut, and nose runoff varied in three levels for predicting the surface roughness of CNC turned product.

Fu and Hope [20] established an intelligent tool condition monitoring system by applying a unique fuzzy neural hybrid pattern recognition system. The study concluded that armed with the advanced pattern recognition methodology, the established intelligent tool condition monitoring system had the advantages of being suitable for different machining conditions, robust to noise and tolerant to faults.

Shetty et al. [21] discussed the use of Taguchi and response surface methodologies for minimizing the surface roughness in turning of discontinuously reinforced aluminum composites (DRACs) having aluminum alloy 6061 as the matrix and containing 15 vol. % of silicon carbide particles of mean diameter 25µm under pressured steam jet approach. The measured results were then collected and analyzed with the help of the commercial software package MINITAB15. The experiments were conducted using Taguchi's experimental design technique. The matrix of test conditions included cutting speeds of 45, 73 and 101 m/min, feed rates of 0.11, 0.18 and 0.25 mm/rev and steam pressure 4, 7, 10 bar while the depth of cut was kept constant at 0.5

mm. The effect of cutting parameters on surface roughness was evaluated and the optimum cutting condition for minimizing the surface roughness was also determined finally. A secondorder model was established between the cutting parameters and surface roughness using response surface methodology. The experimental results revealed that the most significant machining parameter for surface roughness was steam pressure followed by feed. The predicted values and measured values were fairly close, which indicated that the developed model could be effectively used to predict the surface roughness in the machining of DRACs.

CHAPTER 3

SURFACE ROUGHNESS

Surface structure and Properties

Surface roughness is an important measure of product quality since it greatly influences the performance of mechanical parts as well as production cost. Surface roughness has an impact on the mechanical properties like fatigue behaviour, corrosion resistance, creep life, etc. It also affects other functional attributes of parts like friction, wear, light reflection, heat transmission, lubrication, electrical conductivity, etc. Before surface roughness, it is also necessary to discuss about surface structure and properties, as they are closely related.

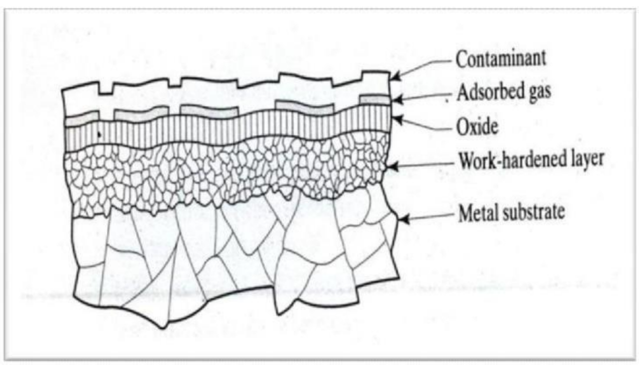


Fig 3.1: Schematic of a Cross section of the surface structure of metals.

Upon close examination of the surface of a piece of metal, it can be found that it generally consists of several layers. The characteristics of these layers are briefly outlined here:

1. The bulk metal, also known as the metal substrate, has a structure that depends on the composition and processing history of the metal.

2. Above this bulk metal, there is a layer that usually has been plastically deformed and work-hardened to a greater extent during the manufacturing process. The depth and properties of the work-hardened layer (the Surface Structure) depend on such factors as the processing method used and how much frictional sliding the surface undergoes.

For example, if the surface is produced by machining using a dull and worn tool, or which takes place under poor cutting conditions, or if the surface is ground with a dull grinding wheel, the surface structure layer will be relatively thick.

3. Unless the metal is processed and kept in an inert (oxygen-free) environment, or is a noble metal such as gold or platinum, an oxide layer forms over the work-hardened layer.

4. Under normal environmental conditions, surface oxide layers are generally covered with absorbed layers of gas and moisture. Finally, the outermost surface of the metal may be covered with contaminants such as dirt, dust, grease, lubricant residues, cleaning-compound residues, and pollutants from the environment.

Thus, surfaces have properties that generally are very difficult from those of the substrate. The oxide on a metal surface is generally much harder than the base metal. Consequently, oxides tend to be brittle and abrasive. This surface characteristic has several important effects on friction, wear, and lubrication in materials processing, and on products.

3.1 Surface Integrity:

Surface integrity is the sum of all the elements that describes all the conditions exiting on or at the surface of a work piece. Surface integrity has two aspects. The first is surface topography which describes the roughness, 'lay' or texture of this outermost layer of the work piece, i.e., its interface with the environment. The second is surface metallurgy which describes the nature of the altered layers below the surface with respect to the base of the matrix material. This term assesses the effect of manufacturing processes on the properties of the work piece material. Figure 1.8 depicts a simulated section showing the various layers between the base material and the environment.

Surface integrity describes not only the topological (geometric) features of surfaces and their physical and chemical properties, but their mechanical and metallurgical properties and characteristics as well. Surface integrity is an important consideration in manufacturing operations because it influences properties, such as fatigue strength, resistance to corrosion, and service life.

3.2 Surface Topography:

Outermost layers of all machined surfaces display a great number of both macro-geometrical and micro-geometrical deviations from the ideal geometrical surface. Surface roughness refers to deviation from the nominal surface of the third up to sixth order. Order of deviation is defined in international standards. First and second-order deviations refer to form, i.e. flatness, circularity, etc. and to waviness, respectively, and are due to machine tool errors, deformation of the work piece, erroneous setups and clamping, vibration and work piece material in homogeneities. Third and fourth-order deviations refer to periodic grooves, and to cracks and dilapidations, which are connected to the shape and condition of the cutting edges, chip formation and process kinematics. Fifth and sixth-order deviations refer to work piece material structure, which is connected to physical-chemical mechanisms acting on a grain and lattice scale (slip, diffusion, oxidation, residual stress, etc.).The principal elements of surfaces are discussed below:

a. Surface: The surface of an object is the boundary which separates that object from another substance. Its shape and extent are usually defined by a drawing or descriptive specifications.

b. Profile: It is the contour of any specified section through a surface.

c. Roughness: It is defined as closely spaced, irregular deviations on a scale smaller than that of waviness. Roughness may be superimposed on waviness. Roughness is expressed in terms of its height, its width, and its distance on the surface along which it is measured.

d. Waviness: It is a recurrent deviation from a flat surface, much like waves on the surface of water. It is measured and described in terms of the space between the two corresponding points on the profile.

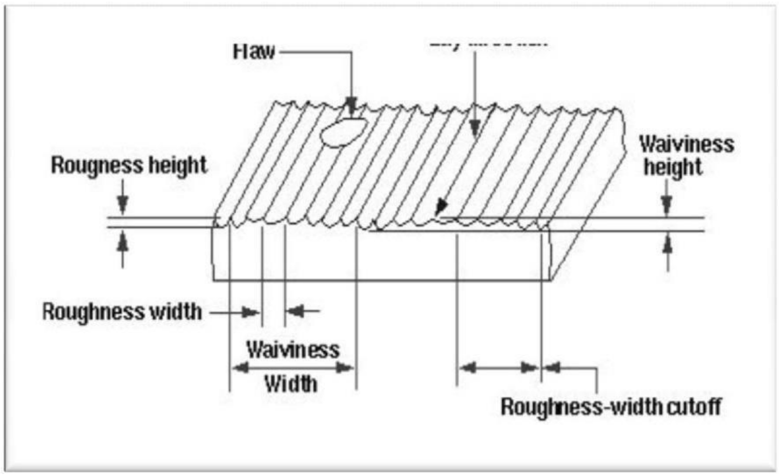


Fig 3.2: Surface characteristics

e. Flaws: Flaws, or defects, are random irregularities, such as scratches, cracks, holes, depressions, seams, tears, or inclusions.

f. Lay: Lay, or directionality, is the direction of the predominant surface pattern and is usually visible to the naked eye.

3.3 Surface Finish in Machining:

The resultant roughness produced by a machining process can be thought of as the combination of two independent quantities:

a. Ideal roughness
b. Natural roughness

a. Ideal roughness:

Ideal surface roughness is a function of feed and geometry of the tool. It represents the best possible finish which can be obtained for a given tool shape and feed. It can be achieved only if the built-up-edge, chatter and inaccuracies in the machine tool movements are eliminated completely.

The surface roughness value is given by, $\mathbf{R_a = R_{max}/4}$

In practice, it is not usually possible to achieve conditions such as those described above, and normally the natural surface roughness forms a large proportion of the actual roughness. One of the main factors contributing to natural roughness is the occurrence of a built-up edge and vibration of the machine tool. Thus, larger the built up edge, the rougher would be the surface produced, and factors tending to reduce chip-tool friction and to eliminate or reduce the built-up edge would give improved surface finish industries or within certain countries. For example, the R_k family of parameters is used mainly for cylinder bore lining.

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.

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, R_a is the arithmetic average of the roughness profile.

3.4 Measurement of Surface Roughness:

Inspection and assessment of surface roughness of machined work pieces can be carried out by means of different measurement technique

These methods can be ranked into the following classes:

1. Direct measurement.
2. Comparison based techniques.
3. Non-contact methods.
4. On-process measurement.

1. Direct measurement methods:

Direct methods assess surface finish by means of stylus type devices. Measurements are obtained using a stylus drawn along the surface to be measured. The stylus motion perpendicular to the surface is registered. This registered profile is then used to calculate the roughness parameters. This method requires interruption of the machine process, and the sharp diamond stylus can make micro-scratches on surfaces.

One example of this is the Brown and Sharpe Surfcom unit.

Basically, this technique uses a stylus that tracks small changes in surface height, and a skid that follows large changes in surface height. The use of the two together reduces the effects of non-flat surfaces on the surface roughness measurement. The relative motion between the skid and the stylus is measured with a magnetic circuit and induction coils.

The actual apparatus uses the apparatus hooked to other instrumentation. The induction coils drive amplifiers conditioning hardware, and other signal. The then amplified signal is used to drive a recorder that shows stylus position, and a digital readout that displays the CLA/R_a value.

The paper chart that is recorded is magnified in height by 100000:1, and in length by 82: 1 to make the scale suitable to the human eye. The datum that the stylus position should be compared to can be one of three,

a. **Skid** - can be used for regular frequency roughness

b. **Shoe** - can be used for irregular frequency roughness

c. **Independent** - can use an optical flat

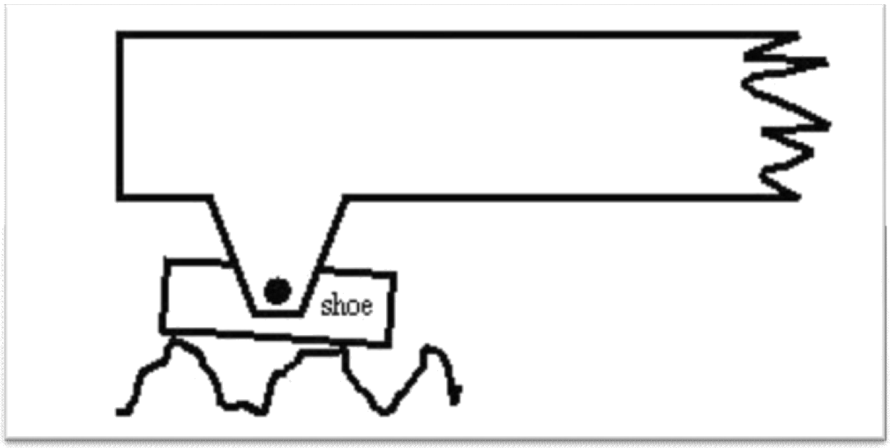


Fig 3.3: Flat shoe – used for surfaces with irregular frequencies.

2. Comparison based techniques:

Comparison techniques use specimens of surface roughness produced by the same process, material and machining parameters as the surface to be compared. Visual and tactile sensors are used to compare a specimen with a surface of known surface finish. Because of the subjective judgment involved, this method is useful for surface roughness R_q>1.6 micron.

3. Non-contact methods:

There have been some works done to attempt to measure surface roughness using noncontact technique. Here is an electronic speckle correlation method given as an example. When coherent light illuminates a rough surface, the diffracted waves from each point of the surface mutually interfere to form a pattern which appears as a grain pattern of bright and dark regions. The spatial statistical properties of this speckle image can be related to the surface characteristics. The degree of correlation of two speckle patterns produced from the same surface by two different illumination beams can be used as a roughness parameter. Monochromatic plane wave with an angle of incidence with respect to the normal to the surface; multi-scattering and shadowing effects are neglected. The photo-sensor of a CCD camera placed in the focal plane of a Fourier lens is used for recording speckle patterns. Assuming Cartesian coordinates x,y,z, a rough surface can be represented by its ordinates Z (x,y) with respect to an arbitrary datum plane having transverse coordinates (x,y,z). then the RMS value of surface roughness can be defined and calculated.

a. **Inductance method:** An inductance pickup is used to measure the distance between the surface and the pickup. This measurement gives a parametric value that may be used to give a comparative roughness. However, this method is limited to measuring magnetic materials.

b. **Ultrasound:** A spherically focused ultrasonic sensor is positioned with a non-normal incidence angle above the surface. The sensor sends out an ultrasonic pulse to the personal computer for analysis and calculation of roughness parameters.

CHAPTER 4

DESIGN OF EXPERIMENTS

DOE (design of experiments) helps you investigate the effects of input variables (factors) on an output variable (response) at the same time. These experiments consist of a series of runs, or tests, in which purposeful changes are made to the input variables. Data are collected at each run. You use DOE to identify the process conditions and product components that affect the quality and then determine the factor settings that optimize results.

Minitab offers five types of designs: screening designs, factorial designs, response surface designs, mixture designs, and Taguchi designs (also called Taguchi robust designs). The steps you follow in Minitab to create, analyze, and visualize a designed experiment are similar for all types. After you perform the experiment and enter the results, Minitab provides several analytical tools and graph tools to help you understand the results. This chapter demonstrates the typical steps to create and analyze a factorial design. You can apply these steps to any design that you create in Minitab.

Minitab DOE commands include the following features:

- Catalogues of designed experiments to help you create a design
- Automatic creation and storage of your design after you specify its properties
- Display and storage diagnostic statistics to help you interpret the results
- Graphs to help you interpret and present the results.

4.1 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 the important effects. If there is an interaction between two or more input variables, they should be included in the 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.

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

4.1.1 Planning:

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

- **Make sure the process and measurement systems are in control:**

Ideally, both the process and the measurements should be in statistical control as measured by a functional statistical process control (SPC) system.

Minitab provides numerous tools to evaluate process control and analyse your measurement system.

4.1.2 Screening:

In many process development 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 often used for screening:

- Two-level full and fractional factorial designs are used extensively in industry.

• Plackett-Burman designs have low resolution, but they are useful in some screening experimentation and robustness testing.

• General full factorial designs (designs with more than two levels) may also be useful for small screening experiments.

4.1.3 Optimization:

After identifying the vital variables by screening, there is a 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 analyzing 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 analyzing simplex centroid, simplex lattice, and extreme vertices designs. Mixture designs are a special class of response surface designs where the proportions of the 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 contour plot to help to determine the "best" settings to simultaneously optimize multiple responses.

• Taguchi Designs Overview describes methods for analyzing 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.

4.1.4 Verification:

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

4.2 Advantages & Disadvantages of DOE:

DOE became a more widely used modelling technique superseding 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 set of parametric values to find the best possible output characteristics. Besides 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 functions in such a manner that the number of experiments or 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 errors occurring. Some of them might be predictable while some errors are just out of control. DOE allows us to handle these errors while continuing with the analysis. DOE is excellent when it comes to predicting linear behaviour. However, when it comes to nonlinear behaviour, DOE does not always give the best results.

CHAPTER – 5

EXPERIMENTAL SETUP

5.1 TAGUCHI DESIGN:

The technique of laying out the conditions of experiments involving multiple factors was first proposed by the Englishman, Sir R. A. Fisher. The method is popularly known as the factorial design of experiments. A full factorial design will identify all possible combinations for a given set of factors. Since most industrial experiments usually involve a significant number of factors, a full factorial design results in a large number of experiments. To reduce the number of experiments to a practical level, only a small set from all the possibilities is selected. The method of selecting a limited number of experiments that produce the most information is known as a partial fraction experiment. Although this method is well known, there are no general guidelines for its application or the analysis of the results obtained by performing the experiments.

Taguchi constructed a special set of general design guidelines for factorial experiments that cover many applications. Taguchi has envisaged a new method of conducting the design of experiments that are based on well-defined guidelines. This method uses a special set of arrays called orthogonal arrays. These standard arrays stipulate the way of conducting the minimal number of experiments which could give the full information of all the factors that affect the performance parameter. The crux of the orthogonal arrays method lies in choosing the level combinations of the input design variables for each experiment.

While there are many standard orthogonal arrays available, each of the arrays is meant for a specific number of independent design variables and levels. For example, if one wants to experiment to understand the influence of 3 different independent variables with each variable having 3 set values (level values), then an L9 orthogonal array might be the right choice. The L9 orthogonal array is meant for understanding the effect of 3 independent factors each having 3-factor level values. This array assumes that there is no interaction between any two factors.

The orthogonal arrays have the following special properties that reduce the number of experiments to be conducted.

I. The vertical column under each independent variable of the above table has a special combination of level settings. All the level settings appear an equal number of times. For L9 array under feed rate, level 1, level 2 and level 3 appear thrice. This is called the balancing property of orthogonal arrays.

II. All the level values of independent variables are used for conducting the experiments.

III. The sequence of level values for conducting the experiments shall not be changed. This means one cannot experiment 1 with variable 1, level 2 setup, and experiment 4 with variable 1, level 1 setup. The reason for this is that the array of each factor column is mutually orthogonal to any other column of level values. The inner product of vectors corresponding to weights is zero.

5.1 Material Specification:

The composition of **AA 6063 T6** is 0.6 wt.% Si, 0.34 wt.% Fe, 0.09 wt.% Cu, 0.09 wt.% Mn, 0.88 wt.% Mg, 0.092 wt.% Cr, 0.095 wt.% Zn, 0.092 wt.% Ti, 97.721 wt.% Al.

This alloy is widely used in the manufacturing of doors, extrusions, window frames, and irrigation tubing. CNC lathe was used for machining. The tool used is an uncoated carbide insert tool.

The specification of the cutting tool is DCGT 11 T3 04. The surface roughness was measured using the Surf order SE 1200, Surface profilometer. The machining was done under dry-cutting conditions.

5.2 Experimental Work:

Taguchi’s L9 orthogonal array was used to design the experiments with three factors and three levels. Experiments were conducted based on Taguchi’s method which is a powerful tool used in the design of experiments. Taguchi advocates the use of orthogonal array designs to assign the factors chosen for the experiment. The advantage of the Taguchi method is that it uses a special design of orthogonal arrays to study the entire parameter space with only a small number of experiments. Compared to the conventional approach of experimentation, this method reduces drastically the number of experiments that are required to model the response functions . The assignment of the levels to the factors and the various parameters used are given in Table(1). The experimental results for L9 orthogonal array are given in Table(2).

Machining Parameters					
S.No	**Factors**	**Symbol**	**Level 1**	**Level 2**	**Level 3**
1	Spindle Speed (rpm)	N	2000	3500	5000
2	Feed Rate (mm/rev)	F	0.05	0.075	0.1
3	Depth of Cut (mm)	D	0.1	0.15	0.2

Table (1)

Design of Experiments					
S. No	**N**	**F**	**d**	**Ra**	**MRR**
1	2000	0.05	0.1	0.380	0.2123
2	2000	0.075	0.15	0.360	0.4302
3	2000	0.1	0.2	0.535	0.6872
4	3500	0.05	0.15	0.388	0.3865
5	3500	0.075	0.2	0.509	0.6872
6	3500	0.1	0.1	0.533	0.5208
7	5000	0.05	0.2	0.459	0.5821
8	5000	0.075	0.1	0.469	0.4899
9	5000	0.1	0.15	0.556	0.8531

Table (2)

CHAPTER 6
RESULTS AND GRAPHS

6.1 Multi-Response Optimization Using GRA:

Taguchi's experimental method is adequate to determine the optimal setting of process parameters for a single response characteristic. In the case of two or more responses, with dissimilar quality characteristics, multi-response optimization using GRA is the preferred method. Grey analysis can also be utilized to determine the similarity between seemingly irregular finite data [ ]. Hence, multi-response optimization of wear parameters in this study is performed using the following steps in GRA.

6.1.1 Grey-Relational Generation

In GRA, when the standard value and reference sequence range are considerably high, the function of the factors is neglected. Additionally, if the goals and directions of factors are disparate, GRA may yield inaccurate results. Hence, data pre-processing is performed to normalize the original reference sequences to a comparable sequence within the range of zero to one [ ]. This approach of pre-processing data by normalization, into a group of sequences, is termed grey relational generation. To pre-process data using GRA, the response of the transformed sequences can be grouped into two quality characteristics, namely, larger-the-better or smaller-the-better.

For smaller-the-better characteristic, the sequence can be normalized using Equation (1):

$$x_i^*(k) = \frac{max y_i(k) - y_i(k)}{max y_i(k) - min y_i(k)} \tag{1}$$

For Higher-the-Better (HB) criterion, the normalized data can be expressed as:

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)}$$

$x_i^*(k)$ denotes the reference sequence after pre-processing for the ith experiment and $y_i(k)$ represents the initial sequence of the mean of the responses.

6.1.2 Computation of Grey Relational Coefficient and Grade

Once the sequence is normalized, the next step is to calculate the deviation sequence of the reference sequence using Equation (2):

$$\Delta_{0i}(k) = |x_0^*(k) - x_i^*(k)| \tag{2}$$

where $\Delta_{0i}(k)$, $x_0^*(k)$ and $x_i^*(k)$ refer to the deviation, reference, and comparability sequences, respectively. The grey relational coefficient (GRC) is then determined using Equation (3):

$$\xi_i(k) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{0i}(k) + \zeta\Delta_{max}} \tag{3}$$

where, $\xi_i(k)$ signifies the GRC of individual response variables computed as a function of Δ_{min} and Δ_{max}, the minimum and maximum deviations of each response variable. The distinguishing or identification coefficient represented by ζ, defined in the range $\zeta \in [\ ]$, is generally set at 0.5 to allocate equal weights to every parameter. As shown in Equation (4), a composite grey relational grade (GRG), is then computed by averaging the GRC of each response variable:

$$\gamma_i = \frac{1}{n}\sum_{i=1}^{n} \xi_i(k) \tag{4}$$

where γ_i represents the value of GRG determined for the ith experiment, n being the aggregate count of performance characteristics.

Experiment Nos	Normalization		Deviation Sequence		Grey Relational Coefficient -GRC		Grey Relational Grade -GRG	Rank Order
	Ra	MRR	Ra	MRR	Ra	MRR		
1	0.89796	0.00000	0.10204	1.00000	0.83051	0.33333	0.58192	4
2	1.00000	0.34004	0.00000	0.65996	1.00000	0.43105	0.71553	1
3	0.10714	0.74110	0.89286	0.25890	0.35897	0.65885	0.50891	7
4	0.85714	0.27185	0.14286	0.72815	0.77778	0.40712	0.59245	3
5	0.23980	0.74110	0.76020	0.25890	0.39676	0.65885	0.52781	5
6	0.11735	0.48143	0.88265	0.51857	0.36162	0.49088	0.42625	9
7	0.49490	0.57709	0.50510	0.42291	0.49746	0.54177	0.51961	6
8	0.44388	0.43321	0.55612	0.56679	0.47343	0.46870	0.47106	8
9	0.00000	1.00000	1.00000	0.00000	0.33333	1.00000	0.66667	2

Table(3)

An order of 1 is allotted to the greatest grey relational grade. Grey relational grades are calculated using Eq. (4) and grey relational order was figured out in the table(3). From table(2), we come to know that the control parameter's setting of 2(experiment 2) had the greatest grey relational grade and this indicates that experiment 2 was the optimal turning factor setting for minimum surface roughness and MRR simultaneously among the chosen nine experiments. The larger better S/N quality characteristics were considered for the grey relational grade since higher multiple performance characteristics are our target. The level of a parameter with the highest S/N ratio gives the optimal level. So the optimal process parameter setting for the multiple performance characteristics was N1f2d2. The main effects plot for mean for GRG is shown in Fig 1. and the main effects plot for S/N ratio for GRG is shown in Fig 2.

6.1.3 S/N Ratios in the Taguchi Method:

The Taguchi method employs orthogonal arrays to reduce variance and optimize process parameters. In the Taguchi method, the signal to noise (S/ N) ratio is used as a performance characteristic to measure process robustness and to evaluate deviation from desired values . The S/ N ratio, a logarithmic function, is computed by assessing the proportion of signal (mean) to the noise (standard deviation). To diminish noise and the effects of uncontrollable factors, higher values of S/ N ratios are preferred . High S/ N ratios indicate the improved quality of the product. There exist three types of S/ N ratios, namely, higher-the-better, nominal-the-best, and smaller-the-better as shown in Equations (5)−(7):

$$\left(\frac{S}{N}\right)_{HTB} = -10 * \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right) \quad \text{-(5)}$$

$$\left(\frac{S}{N}\right)_{NTB} = -10 * \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \quad \text{-(6)}$$

$$\left(\frac{S}{N}\right)_{STB} = -10 * \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \quad \text{-(7)}$$

where n is the number of experiments, y_i represents the response value of the ith experiment in the OA, $\bar{y}^2$ indicates the mean, and s^2 the variance of the observed data.

6.1.4 Analysis of Variance (ANOVA):

ANOVA is conventionally used to investigate whether the experimental design parameters have a significant effect on the responses. The ANOVA table is also widely used to analyze the interactions between factors and the effect of such interactions on the dependent variables [ ]. Generally, the F-test is employed as a measure to evaluate the extent of factors controlling the test results. For a 95% confidence level, if the value of 'Prob > F', commonly known as 'p-value', is less than 0.05, the factors and interactions are considered significant [ ]. Additionally, a large F-value is an indication of a process parameter having a significant effect on the performance characteristic. In ANOVA, the adjusted correlation coefficient,R^2_{adj} , is used to evaluate the validity of the fitted model. R^2_{adj}measures the percentage of variation explained exclusively by those independent factors and interactions which predominantly affect the response variables. Further, to conclude that the created models fit the performed experiments well, it is desired that the values of R^2 and R^2_{adj}should be high and close to each other.

Response Table for Means

Level	N	F	D
1	0.6021	0.5647	0.4931
2	0.5155	0.5715	0.6582
3	0.5524	0.5339	0.5188
Delta	0.0866	0.0375	0.1651
Rank	2	3	1

Table (4)

Average mean = 0.55669

This table provides the order of most influencing factor in determining the multiple performance characteristics or Grey relational Grade.

The Depth of cut is the 1st influencing factor which has highest mean of GRG at Level-2. So the depth of cut has Rank 1 in the above table.

The Spindle speed is the 2nd most influencing factor which has highest mean of GRG at Level-1. So the spindle speed has Rank 2 in the above table.

The Feed rate is the 3rd most influencing factor which has highest mean of GRG at Level-2. So the feed rate has Rank 3 in the above table.

The main effects plot for mean for GRG is shown in Fig 1

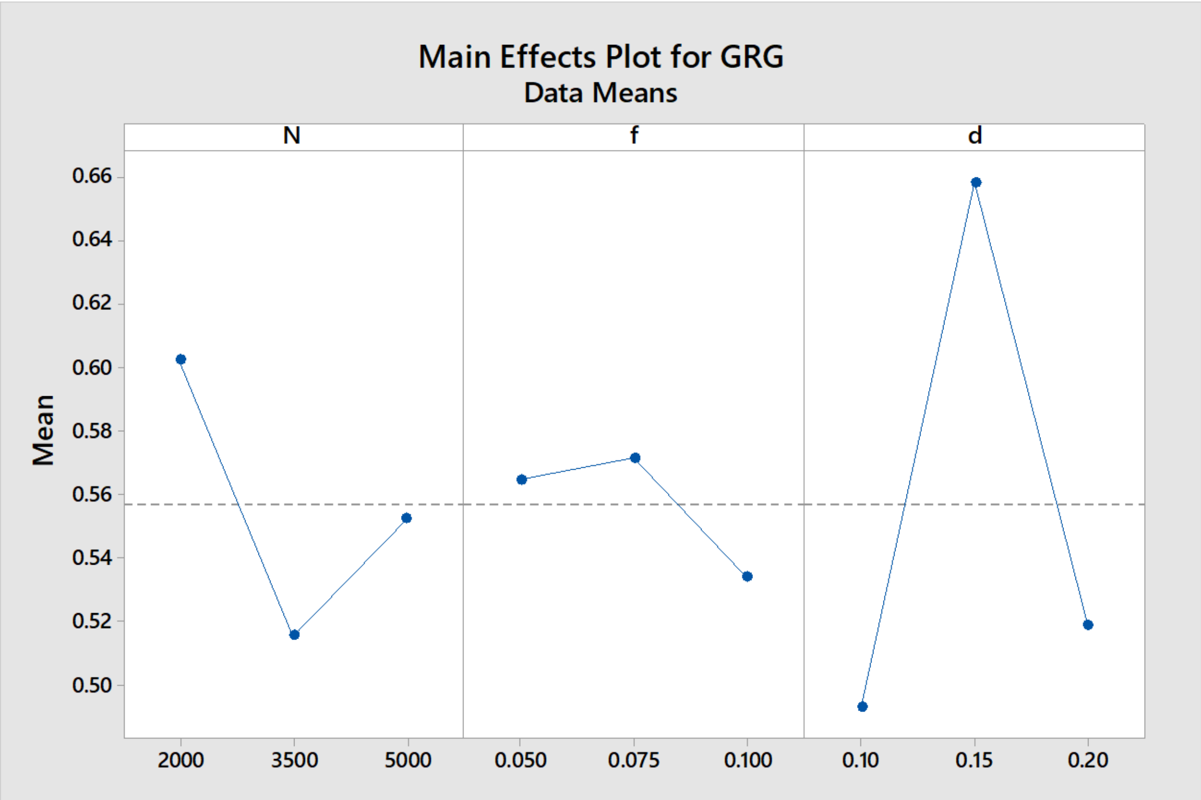


Fig 1.

The main effects plot for GRG for Data Means was created in MiniTab for each value of a categorical variable. A line connects the points for each variable. Look at the line to determine whether a main effect is present for a categorical variable.

Minitab also draws a reference line at the overall mean. Interpret the line that connects the means as follows:

- When the line is horizontal (parallel to the x-axis), there is no main effect present. The response mean is the same across all factor levels.
- When the line is not horizontal, there is a main effect present. The response mean is not the same across all factor levels. The steeper the slope of the line, the greater the magnitude of the main effect.

Response Table for Signal to Noise Ratios:

Larger is better

Level	N	F	D
1	-4.492	-4.979	-6.216
2	-5.835	-4.999	-3.659
3	-5.249	-5.599	-5.701
Delta	1.342	0.620	2.557
Rank	2	3	1

Table (5)

The Response Table for Signal-to-Noise Ratios contains a row for the average signal-to-noise ratio for each factor level, Delta, and Rank. The table contains a column for each factor.

The Response Table for Standard Deviations contains a row for the average signal-to-noise ratio for each factor level, Delta, and Rank. The table contains a column for each factor.

Delta is the difference between the maximum and minimum average response (signal-to-noise ratio or standard deviation) for the factor.

The Rank is the rank of each Delta, where Rank 1 is the largest Delta.

The larger, better S/N quality characteristics was considered for grey relational grade, since higher multiple performance characteristics is our target. The level of a parameter with the highest S/N ratio gives the optimal level.

The main effects plot for S/N ratio for GRG is shown in Fig 2.

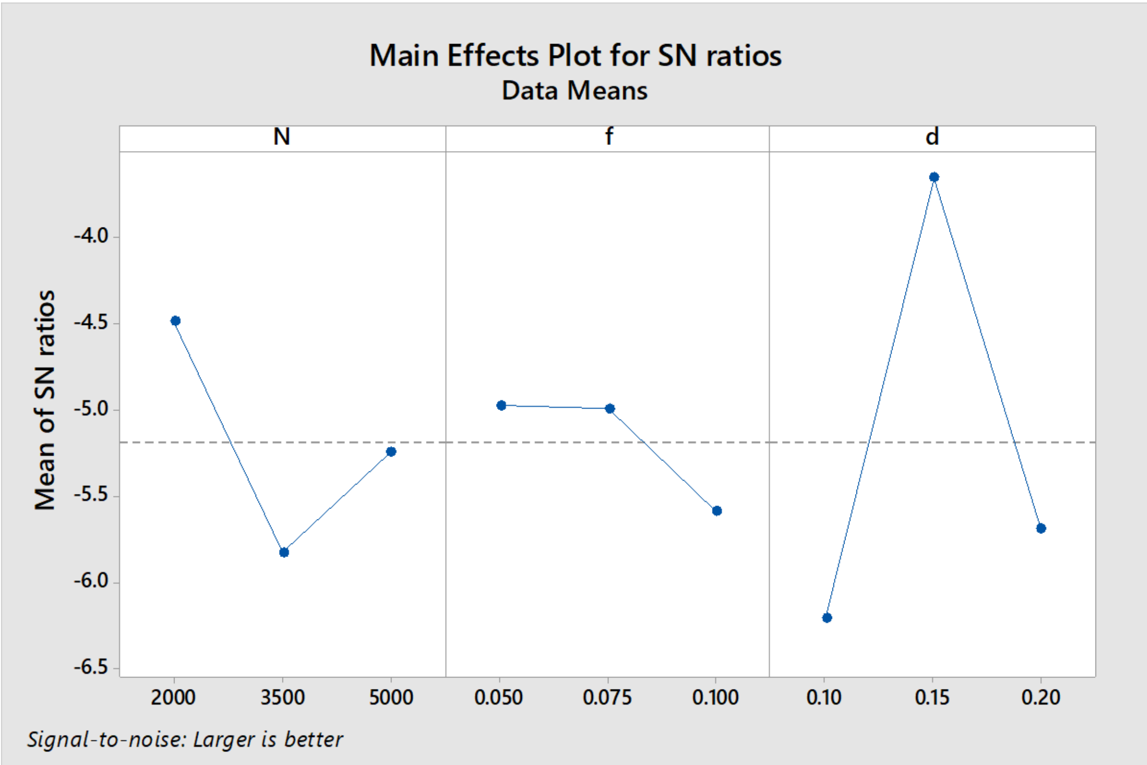


Fig 2.

In these results, the main effects plot for S/N ratio indicates that Depth of Cut has the largest effect on the signal-to-noise ratio. On average, experimental runs with depth of cut at level 2 had much higher signal-to-noise ratios than experimental runs with depth of cut at level 1 & 3. Feed Rate had a small effect or no effect on the signal-to-noise ratio.

6.1.5 Characteristics of ANOVA:

ANOVA is used in the analysis of comparative experiments, those in which only the difference in outcomes is of interest. The statistical significance of the experiment is determined by a ratio of two variances. This ratio is independent of several possible alterations to the experimental observations: Adding a constant to all observations does not alter significance. Multiplying all observations by a constant does not alter significance. So ANOVA statistical significance results are independent of constant bias and scaling errors as wel0l as the units used in expressing observations.

6.2. MATHEMATICAL MODELING

6.2.1. Linear Regression equation:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots\ldots\ldots\ldots + \beta_k X_k$$

6.2.2. Multiple linear regression equation:

Multiple linear regression equation is a second-order polynomial equation of the form –

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_{i^2} + \sum \sum_{i<j} \beta_{ij} x_i x_j + \in$$

Where,

Y is the corresponding response

(1,2, ... , S) are coded levels of S quantitative process variables.

The terms are the second-order regression coefficients.

The second term is attributable to the linear effect.

The third term corresponds to the higher-order effects.

The fourth term includes the interactive effects.

The last term indicates the experimental error.

6.3. TERMS & GRAPHS USED

6.3.1. Regression table

1.Adj SS:

Adj SS. Adjusted sums of squares are measures of variation for different components of the model..... The error sum of squares is the sum of the squared residuals. It quantifies the variation in the data that the predictors do not explain.

2.Adj MS:

Adj MS. Adjusted mean squares measure how much variation a term or a model explains, assuming that all other terms are in the model, regardless of the order they were entered. Unlike the adjusted sums of squares, the adjusted mean squares consider the degrees of freedom.

3.F-values:

The F value in one-way ANOVA is a tool to help you answer the question "Is the variance between the means of two populations significantly different?" The F value in the ANOVA test also determines the P-value; The P-value is the probability of getting a result at least as extreme as the one that was observed, given that the null hypothesis is true.

4. P-values

P-values (P) are used to determine which of the effects in the model are statistically significant.

- If the p-value is less than or equal to α (0.05), conclude that the effect is significant.
- If the p-value is greater than α, conclude that the effect is not significant.

5. Coefficients

Coefficients are used to construct an equation representing the relationship between the response and the factors.

6. R-squared

R and adjusted R represent the proportion of variation in the response that is explained by the model.

- R (R-Sq) describes the amount of variation in the observed responses that is explained 0by the model.
- Predicted R reflects how well the model will predict future data.
- Adjusted R is a modified R that has been adjusted for the number of terms in the model. If we include unnecessary terms, R can be artificially high. Unlike R , adjusted R may get smaller when we add terms to the model.

4. Analysis of variance table

P-values (P) are used in the analysis of variance tables to determine which of the effects in the model are statistically significant. The interaction effects in the model are observed first because a significant interaction will influence the main effects.

5. Estimated coefficients using uncoded units

Minitab displays the coefficients in uncoded units in addition to coded units if the two units differ.

For each term in the model, there is a coefficient. These coefficients are useful to construct an equation representing the relationship between the response and the factors.

Source	DF	Adj SS	Adj MS	F-Value	P-Value	Percentage Contribution(%)
N	2	0.011335	0.005667	1.63	0.0381	16.65
F	2	0.002398	0.001199	0.34	0.0744	3.52
D	2	0.047372	0.023686	6.79	0.0128	69.58
Error	2	0.006972	0.003486			
Total	8	0.068076				

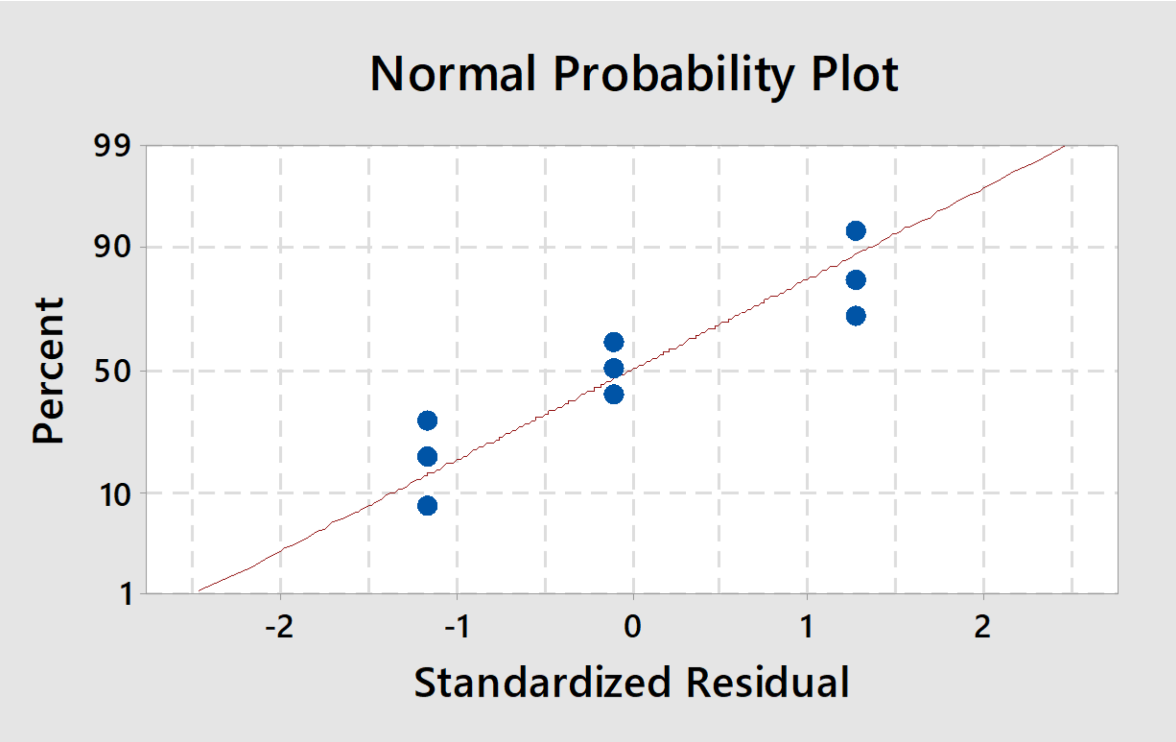
Table (6)

Thus, the finest combination values for maximizing the multiple performance characteristics or grey relational grade (GRG) were spindle speed of 2000 rpm, feed rate of 0.05 mm/rev, and depth of cut of 0.15 mm. The response table for the means of grey relational grade is shown in Table (4). The response table for the S/N ratios of grey relational grade is shown in Table (5).ANOVA output of the multiple performance characteristics is given in Table (6). From the analysis of this table, it could be concluded that depth of cut, spindle speed followed by feed rate, and, are significantly affecting the grey relational grade.

6.3.2. Graphs

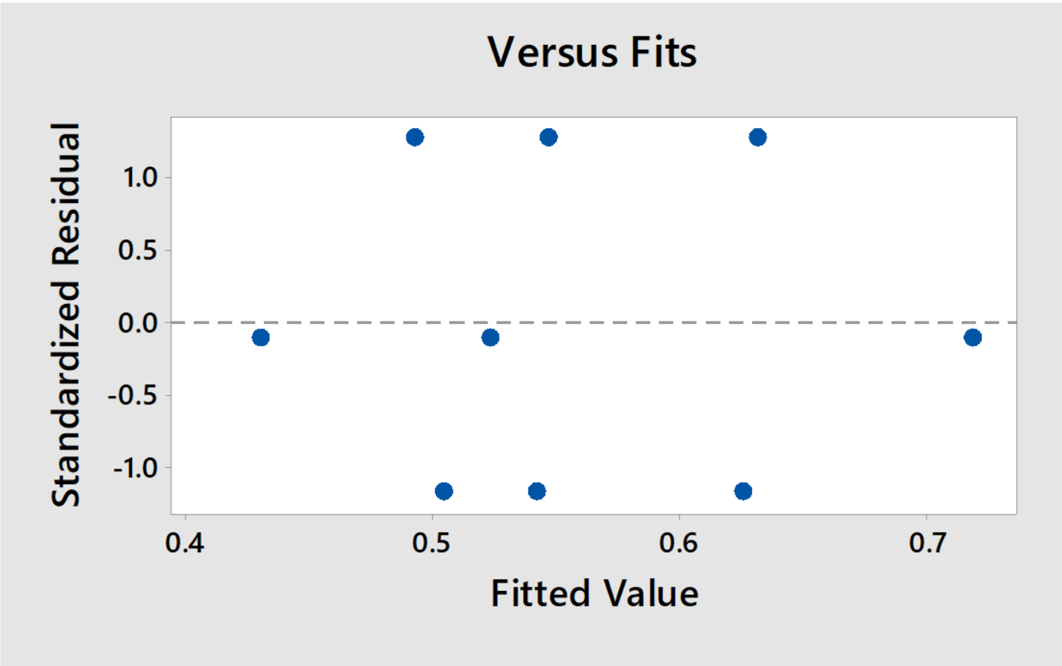
1. Normal Probability Plot

Graph is plotted between the residuals versus their expected values when the distribution is normal. The residuals from the analysis should be normally distributed. In practice, for balanced or nearly balanced designs or data with a 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.



2. Residuals versus fits

Graph is plotted between the residuals versus the fitted values. The residuals should be scattered randomly about zero.



6.4 Results of Confirmation Experiment for GRG :

The purpose of this confirmation experiment is to verify the improvement in the quality characteristics.

After the optimal level has been selected, one could predict the optimum response using the following equation:

$$\gamma_{predicted} = \gamma_m + \sum_{i=1}^{q} \gamma_0 - \gamma_m$$

where γ_m is the total mean S/N ratio, γ_0 is the mean S/N ratio at optimal level, n is the number of main design parameters that affect the quality characteristics.

Based on the Eq. ( ) the grey relational grade (GRG) is predicted for the optimal combination of parameters (N1-f2-d2) and its value is 0.7184. Lastly confirmation test was conducted using the optimum combination of parameters (N1-f2-d2). Table ( ). shows the comparison of predicted multiple performance characteristics (GRG) with the actual one. The grey relational grade for the confirmation experiment is found to be 0.7640.

	Initial Cutting Parameters	Optimal Cutting Parameters	
Level	N1 f1 d1	N1 f2 d2	
		Prediction	Experiment
GRG	0.5819	0.7184	0.7640
S/N Ratio	-5.229	-2.76601	-2.4271

The results of confirmation experiment has done for different level of cutting parameters which are Initial and Optimal Cutting parameters.

The initial cutting parameters are taken as N1f1d1 which is the 1st experiment conditions and Optimal cutting parameters are taken as N1f2d2 which is the optimal process parameter setting for the multiple performance characteristic.

The Prediction value of GRG and S/N ratio are 0.7184 and -2.76601 respectively with the lower spindle speed of 2000 rpm, lower feed rate of 0.05 mm/rev and medium depth of cut of 0.15 mm with the estimated multiple performance characteristics (GRG).

The Experimental value of GRG and S/N ratio are 0.7640 and -2.4271 respectively of parameter setting N1f2d2.

The percentage of error between the predicted and experimental values of the multiple performance characteristics during the confirmation experiments is almost within 5.96%. So, we can say the improvement in quality characteristics has been verified by confirmation experiment.

The improvement in the S/N ratio from the initial cutting parameters to the optimal cutting parameters is calculated by difference of them, i.e., 5.229 - 2.4271 = 2.8019 db for GRG.

6.5 Conclusions

The surface roughness (Ra) and material removal rate (MRR) were measured under different cutting conditions for diverse combinations of machining parameters. The conclusions arrived, at the end of this work are as follows:

1. From this analysis, it is revealed that depth of cut and spindle speeds are prominent factors that affect the turning of aluminium alloy. The depth of cut (p=69.58%) is the most influencing factor in determining the multiple performance characteristics or grey relational grade (GRG) followed by spindle speed (p=16.65%) and feed rate (p=3.52%).
2. The best multiple performance characteristics were obtained with an uncoated carbide insert when turning aluminium alloy with the lower spindle speed of 2000 rpm, lower feed rate of 0.05 mm/rev, and medium depth of cut of 0.15 mm with the estimated multiple performance characteristics (GRG) of 0.7184. The experimental value of GRG for this combination of parameters is 0.7640.
3. The percentage of error between the predicted and experimental values of the multiple performance characteristics during the confirmation experiments is almost within 5.96%.
4. The improvement in the S/N ratio from the initial cutting parameters to the optimal cutting parameters is 2.8019 db. for GRG.
5. The value of multiple performance characteristics obtained from confirmation experiment is within the 95% confidence interval of the predicted optimum condition.

REFERENCES

1. Zhou Q., Hong G. S. and Rahman M., "A New Tool Life Criterion For Tool Condition Monitoring Using a Neural Network", Engineering Application Artificial Intelligence, Volume 8, Number 5, pp. 579-588.

2. Lin W. S., Lee B. Y., Wu C. L., (2001), "Modelling the surface roughness and cutting force for turning", Journal of Materials Processing Technology, Volume 108, pp. 286-293.

3. Suresh P. V. S., Rao P. V. and Deshmukh S. G., (2002), "A genetic algorithmic approach for optimization of surface roughness prediction model", International Journal of Machine Tools and Manufacture, Volume 42, pp. 675–680.

4. Lee S. S. and Chen J. C., (2003), "Online surface roughness recognition system using artificial neural networks system in turning operations" International Journal of Advanced Manufacturing Technology, Volume 22, pp. 498–509.

5. Choudhury S. K. and Bartarya G., (2003), "Role of temperature and surface finish in predicting tool wear using neural network and design of experiments", International Journal of Machine Tools and Manufacture, Volume 43, pp. 747– 753.

6. Chien W.-T. and Tsai C.-S., (2003), "The investigation on the prediction of tool wear and the determination of optimum cutting conditions in machining 17-4PH stainless steel", Journal of Materials Processing Technology, Volume 140, pp. 340–345. 92

7. Özel T. and Karpat Y., (2005), "Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks", International Journal of Machine Tools and Manufacture, Volume 45, pp. 467–479.

8. Kohli A. and Dixit U. S., (2005),"A neural-network-based methodology for the prediction of surface roughness in a turning process", International Journal of Advanced Manufacturing Technology, Volume 25, pp.118–129.

9. Ahmed S. G., (2006), "Development of a Prediction Model for Surface Roughness in Finish Turning of Aluminium", Sudan Engineering Society Journal, Volume 52, Number 45, pp. 1-5. 3.

10. Abburi N. R. and Dixit U. S., (2006), "A knowledge-based system for the prediction of surface roughness in turning process" Robotics and ComputerIntegrated Manufacturing, Volume 22, pp. 363–372.

11. Zhong Z. W., Khoo L. P. and Han S. T., (2006), "Prediction of surface roughness of turned surfaces using neural networks", International Journal of Advance Manufacturing Technology, Volume 28, pp. 688–693.

12. Kumanan S., Saheb S. K. N. and Jesuthanam C. P., (2006), "Prediction of Machining Forces using Neural Networks Trained by a Genetic Algorithm", Institution of Engineers (India) Journal, Volume 87, pp. 11-15.

13. Thamizhmanii S., Saparudin S. and Hasan S., (2007), "Analysis of Surface Roughness by Using Taguchi Method", Achievements in Materials and Manufacturing Engineering, Volume 20, Issue 1-2, pp. 503-505.

14. Natarajan U., Arun P., Periasamy V. M., (2007), "On-line Tool Wear Monitoring in Turning by Hidden Markov Model (HMM)" Institution of Engineers (India) Journal (PR), Volume 87, pp. 31-35.

15. Özel T., Karpat Y., Figueira L. and Davim J. P., (2007), "Modeling of surface finish and tool flank wear in turning of AISI D2 steel with ceramic wiper inserts", Journal of Materials Processing Technology, Volume189, pp.192–198.

16. Wang M. Y. and Lan T. S., (2008), "Parametric Optimization on Multi-Objective Precision Turning Using Grey Relational Analysis". Information Technology Journal, Volume 7, pp.1072-1076.

17. Sahoo P., Barman T. K. and Routara B. C., (2008), "Taguchi based practical dimension modeling and optimization in CNC turning", Advance in Production Engineering and Management, Volume 3, Number 4, pp. 205-217.

18. Reddy B. S., Padmanabhan G. and Reddy K. V. K., (2008), "Surface Roughness Prediction Techniques for CNC turning", Asian Journal of Scientific Research, Volume 1, Number 3, pp. 256-264.

19. Wannas A. A., (2008), "RBFNN Model for Prediction Recognition of Tool Wear in Hard Turning", Journal of Engineering and Applies Science, Volume 3, Number 10, pp. 780-785.

20. Fu P. and Hope A. D., (2008), "A Hybrid Pattern Recognition Architecture for Cutting Tool Condition Monitoring" Technology and Applications, Volume 24, Number 4, pp. 548-558.

21. Shetty R., Pai R., Kamath V. and Rao S. S., (2008), "Study on Surface Roughness Minimization in Turning of DRACs using Surface Roughness Methodology and Taguchi under Pressured Steam Jet Approach", ARPN Journal of Engineering and Applied Sciences, Volume 3, Number 1, pp. 59-67.