"DESIGN AND OPTIMISATION OF PROCESS PARAMETERS DURING TURN-MILLING PROCESS OF TITANIUM ALLOY USING GRA METHOD UNDER WET CONDITION"

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CERTIFICATE

This is to certify that the project report entitled **"DESIGN AND OPTIMISATION OF PROCESS PARAMETERS DURING TURN-MILLING PROCESS OF TITANIUM ALLOY USING TAGUCHI GRA METHOD UNDER WET CONDITION"** has been carried out by N PRASANTH SAI (318126520194), J SURYA DURGA PRASAD (318126520182),M CHANDU (318126520191),K HARSHITH (318126520180), V MADHUSUDHANA RAO (319126520L51) under my guidance, in partial fulfillment of requirements of Degree of Mechanical Engineering of Andhra University, Visakhapatnam.

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ABSTRACT

The machinability rating of an engineering material is the fundamental property of material which decides the increase and decrease of productivity, machining cost and optimization of material selection in design of mechanical parts. Therefore, this work focuses on the study of surface roughness parameter (Ra), tool temperature (T_t) and work temperature (T_w) while performing Turn-milling on the Ti alloy Ti6Al4V which is relatively a low machinability alloy for various combination of machining parameters like feed (f), depth of cut (doc) and spindle speed (N) using Taguchi philosophy with non-coated PVD tool inserts under wet conditions. Surface roughness tester and IR Gun are used to measure the roughness and temperature respectively.

Taguchi design of experiments (DOE) based on Orthogonal Arrays (OA) and Signal-to-noise ratio (S/N ratio) is used for experimental design. Responses thus generated are used to predict performance and significance of machining parameters combinations in turn-milling operation on a CNC lathe using Analysis of Variance (ANOVA). Individual optimality of responses is carried out using S/N ratios of the responses and a multi-response optimization of responses is carried out using Grey Relational Analysis (GRA) for both the conditions of machining and better responses in wet conditions.

Keywords: Design of Experiments, Taguchi, Grey Relational Analysis, Orthogonal Arrays, ANOVA.

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Chapter 1

INTRODUCTION

Introduction

Machinability of a material basically depends on two factors viz. a. Work material factors (like Micro-structure, grain size, hardness, strength and composition) b. Physical properties (like elasticity, conductivity, work hardening). It is a quality characterized by the degree of difficulty in machining a metallic work under consideration. Design of experiments (DOE) is the process of information gathering where variation is present, whether under the full control of the experimenter or not. Taguchi which restricts replication of experimental combinations using the concept of orthogonal array is well suited for DOE. Taguchi's optimization philosophy is the starting point for every manufacturing process/product optimization, but however this method is capable of solving multi-response optimization problems and hence application of methods like Grey relational analysis (GRA) can be integrated with Taguchi method

1.1 Machinability

Machinability is the ease with which a metal can be cut permitting the removal of the material with a satisfactory finish at low cost.[1] Materials with good machinability (free machining materials) require little power to cut, can be cut quickly, easily obtain a good finish, and do not wear the tooling much. The factors that typically improve a material's performance often degrade its machinability. Therefore, to manufacture components economically, engineers are challenged to find ways to improve machinability without harming performance.

Machinability can be difficult to predict because machining has so many variables. Two sets of factors are the condition of work materials and the physical properties of work materials.[2] The condition of the work material includes eight factors: microstructure, grain size, heat treatment, chemical composition, fabrication, hardness, yield strength, and tensile strength. Physical properties are those of the individual material groups, such as the modulus of elasticity, thermal conductivity, thermal expansion, and work hardening. Other important factors are operating conditions, cutting tool material and geometry, and the machining process parameters.

1.2 Machining

Machining is a process in which a material (often metal) is cut to a desired final shape and size by a controlled material-removal process. The processes that have this common theme are collectively called subtractive manufacturing, in contrast to additive manufacturing, which uses controlled addition of material. Subtractive manufacturing utilizes machine tools, while additive manufacturing utilizes 3D printing.

Machining is a part of the manufacture of many metal products, but it can also be used on other materials such as wood, plastic, ceramic, and composite material.[2] A person who specializes in machining is called a machinist. A room, building, or company where machining is done is called a machine shop. Much of modern-day machining is carried out by computer numerical control (CNC), in which computers are used to control the movement and operation of the mills, lathes, and other cutting machines. This increases efficiency, as the CNC machine runs unmanned therefore reducing labour costs for machine shops.

1.4 CNC Milling

Fig 1.1 CNC MILLING MACHINE

CNC milling is a machine process which produces custom-designed parts or components by progressively removing material from the workpiece using rotating multi-point cutting tools and computerized controls. These systems usually have three linear degrees of freedom. They can move freely around the X, Y, and Z axes while the workpiece remains stationary. This limited dimensional operation reduces the speed of operations, making milling more suitable for prototyping and smaller production runs.

1.5 CNC Turning

CNC turning is a manufacturing process that involves holding bars of material in a chuck and rotating them while feeding a tool to the piece to remove material until the desired shape is achieved. As the desired shape is achieved through the removal of material, it is also known as subtraction machining.

Fig 1.2 Turning Machine

All of the work can be completed from one side if the CNC turning center has only one turret, but some turning centres have a main spindle and sub-spindle for even faster operation. With this configuration, the main spindle partially machines the workpiece, which is then moved to the sub-spindle to complete the job on the other side of the part. The speed of CNC turning operations makes it an ideal process for large production runs with short lead times.

1.6 CNC Turn-mill

Turn milling machines can vary from the simpler 3-axis lathes (XZ&C) – where the spindle becomes a separate axis that is controllable angularly for milling operations – to the more advanced 6-axis machines, with the addition of a linear Y-axis, W-axis, and a sundry programmable sub-spindle or counter-spindle. On machines with a secondary spindle, the W-axis is used to position the secondary spindle for machining.

Turn-milling is an advanced processing technology. It has a strong ability of producing complicated curved surfaces or special-shaped parts, wherein both the cutting tool and workpiece are given a rotary motion simultaneously. In the field of aviation manufacturing, instead of using conventional grinding technologies, extensive studies have been conducted to produce difficult-to-cut thin-walled workpieces. In this paper, an overview is given based on existing works on turn-milling technology. Firstly, workpiece types used in the turn-milling were summarized. After this, the turn-milling mechanization and cutting process were studied. The research status of the chip formation, cutting force, chatter stability, and surface quality was analysed respectively based on the turn-milling mechanization and forming process before presenting some suggestions and predictions for future turn-milling research and applications. The results of this review are useful for gaining some insights on key foundations and references on turn-milling for future researchers and research areas.

Fig 1.3 CNC Turn-Mill

1.3 Computer Numerical Control (CNC)

Today's numerical control is produced with the needs of the operator in mind. Programs, machine coordinates, cutting speed, graphics and relevant information is displayed on a colour monitor, with easy-to-use menus.

The control unit displays menus that are designed to give top priority to operability. Characters and commands are input using the keyboard. The system is very easy to use, allowing the operator to quickly become familiar with it, resulting in his/her learning curve being drastically reduced.

Besides executing NC data for positioning movement of the axes, the control amends these movements when using offsets, tapering, scaling, rotation, mirror images, or axis exchange. The control also compensates for any pitch error compensation or backlash error in the axes drives, to ensure high accuracy positioning. The machine has multiple coordinate systems, and jobs can be programmed in absolute or incremental modes saving valuable programming time. For example, multiple jobs can be set-up on the worktable, while storing the separate reference points or locations of these jobs in specific coordinate registers.

1.6.1 Advantages of Turn Milling

1. It reduces clamping times and improves machining accuracy.
2. It reduces the machine footprint and saves processing costs.

   It reduces the product processing procedures and improves processing efficiency.

1.7 Titanium Alloys

Titanium alloys are metals that contain titanium and other chemical elements. Such alloys have very high tensile strength and toughness. They are light in weight, have extraordinary corrosion resistance and ability to withstand extreme temperatures. However, the high cost of raw materials and cost of processing, limits their use to military applications, aircraft, spacecraft and biological implants.

Although "commercially pure" titanium has acceptable mechanical properties and has been used for orthopaedic and dental implants, for most applications' titanium is alloyed with small amounts of aluminium and vanadium, typically 6% and 4% respectively, by weight. This mixture has a solid solubility which varies dramatically with temperature, allowing it to undergo precipitation strengthening. This heat treatment process is carried out after the alloy has been worked into its final shape but before it is put to use, allowing much easier fabrication of a high-strength product.

1.8 Transition Temperature

The crystal structure of titanium at ambient temperature and pressure is a close packed hexagonal a phase with a c/a ratio of 1.587 at about 890°C, titanium undergoes: an allotropic transformation to body-centred cubic ß phase which remains stable to the melting temperature.

Some alloying elements raise the alpha-to-beta transition temperature (i.e., alpha stabilizers) while others lower the transition temperature (i.e., beta stabilizer). Aluminium, gallium, germanium, carbon, oxygen and nitrogen are alpha stabilizers. Molybdenum, vanadium, niobium, manganese, iron, chromium, cobalt, nickel, copper and silicon are beta stabilizers.

1.9 Categories of Ti Alloys

Titanium alloys are generally classified into four main categories:

- Alpha alloys which contain neutral alloying elements (such as tin) and/or alpha stabilizers (such as aluminium or oxygen) only. These are not heat treatable.
- Near-alpha alloys contain a small amount of ductile beta-phase. Besides alpha-phase stabilizers, near-alpha alloys are alloyed with 1-2% of beta phase stabilizers such as molybdenum, silicon or vanadium.
- Alpha and beta alloys, which are metastable and generally include some combination of both alpha and beta stabilizers, and which can be heat treated.
- Beta alloys, which are metastable and which contain sufficient beta stabilizers (such as molybdenum, silicon and vanadium) to allow them to maintain the beta phase when quenched, and which can also be solution treated and aged to improve strength.

1.10 Material Properties

Generally, alpha-phase titanium is the more ductile phase and beta-phase titanium is stronger yet less ductile, Alpha-beta-phase titanium has a mechanical property which is in between both

Titanium dioxide dissolves in the metal at high temperatures. And its formation is very energetic. These two factors mean that all titanium except the most carefully purified has a significant amount of dissolved oxygen, and so may be considered a Ti-O alloy. Oxide precipitates offer some strength (as discussed above), but are not very responsive to heat treatment and can substantially decrease the alloy's toughness.

Many alloys also contain titanium as a minor additive, but since alloys are usually categorized according to which element forms the majority of the material, these are not usually considered to be "titanium alloys" as such. Titanium alone is a strong and light metal. It is stronger than low-carbon steels, but 45% lighter. It is also twice as strong as weak aluminium alloys but only 60% heavier. Titanium is not easily corroded by sea water, and thus is used in propeller shaft, rigging and other parts of boats that are exposed to seawater. Titanium and its alloys are used in airplanes, missiles and rockets where high strength, low weight and resistance to high temperatures are important. Further, since titanium does not react within the human body, it and its alloys are used to create artificial hips, pins for setting bones, and for other biological implants.

1.11 Grades of Titanium

Alloys may be supplied in the following conditions:

- Grades 5, 23, 24, 25, 29, 35, or 36 annealed or aged.
- Grades 9, 18, 28, or 38 cold-worked and stress-relieved or annealed.
- Grades 9, 18, 23, 28, or 29 transformed-beta condition and
- Grades 19, 20, or 21 solution-treated and aged.

1.12 Ti6A14V or Grade 5

Fig 1.4 Work-piece Material (Ti-6Al-4V)

Grade 5, also known as T16A14V, Ti-6A1-4V or Ti 6-4, is the most commonly used alloy. It has a chemical composition of 6% aluminium, 4% vanadium, 0.25% (maximum) iron, 0.2% (maximum) oxygen, and the remainder titanium. It is significantly stronger than commercially pure titanium while having the same stiffness and thermal properties (excluding thermal conductivity, which is about 60% lower in Grade 5 Ti than in CP Ti). Among its many advantages, it is heat treatable. This grade is an excellent combination of strength, corrosion resistance, weld and fabric ability.

This alpha-beta alloy is the workhorse alloy of the titanium industry. The alloy is fully treatable in section sizes up to 15mm and is used up to approximately 400°C (750°F). Since it is the most commonly used alloy over 70% of all alloy grades melted are a sub-grade of Ti6A14V, its uses span many aerospace, airframe and engine components, marine offshore and power generation industries in particular.

1.13 Selection of Cutting Tool

The new thin Physical vapour deposition (PVD) Ti-Al-N coating with excellent adhesion, also on sharp edges, guarantees toughness, even flank wear and outstanding performance in heat resistant super alloys. The physical vapor deposition (PVD) Ti-Al-N coated carbide inserts are used. Standard Kennametal inserts (ADET 090308 SR 42) for Turn mill operation which are mounted on to tool holder (PCLNL 2020 K12 WDAS).

Fig 1.5 Work-piece Inserts

1.14 Applications

While having excellent biocompatibility, Ti6Al4V suffers from poor shear strength and poor surface wear properties in certain loading conditions.

Biocompatibility: Excellent, especially when direct contact with tissue or bone is required. Ti6A14V's poor shear strength makes it undesirable for bone screws or plants. It also has poor surface wear properties and tends to seize when in sliding contact with itself and other metals. Surface treatments such as nitriding and oxidizing can improve the surface wear properties.

1.15 Coolant used for Wet Machining

1.15.1 Neem Oil Extraction

The oil can be obtained through pressing or crushing of the seed kernel both through cold pressing and through a process incorporating temperature controls 40-50 °C. Neem seed oil can be obtained by solvent extraction of the Neem seed, fruit, oil, cake or kernel. A large industry in India extracts this oil remaining in the seed cake using hexane. This solvent extracted oil is of lower quality as compared to the cold pressed oil and is generally used for soap manufacturing. Neem cake is a by-product obtained in the solvent extraction method for Neem oil.

1.15.2 Physical Properties

1. The minimum surface roughness (best surface quality) was obtained using neem seed oil as cutting fluid compared to soluble oil cutting fluid during the turning operation.

2. The least surface roughness was achieved

3. It doesn’t infect respiratory organs

Fig 1.6 Neem Oil

1.15.3 Extraction Procedure

40g, 50g, and 61.4g of Neem seeds, leaves and barks respectively, were every weighed and put into the thimble of the Soxhlet extractor. 300ml of the solvent or ethanol was measured with a measuring cylinder and poured into the still pot of the Soxhlet extractor, the apparatus was then coupled and the condenser unit was connected to an overhead water tank to cool rising solvent vapor. The heat source was a Bunsen burner operating at a temperature of 68°C. At this position, the condensed vapor returned to the thimble as liquid droplets and got in contact with the sample therein. It then broke the sample membranes to release the Neem oil content which accumulated with the solvent at the siphon (or reflux arm) of the Soxhlet extractor. When the solvent in the thimble rose to the point of the siphon top, the entire content of the thimble and siphon was emptied back into the still pot of the Soxhlet extractor. The process was repeated severally for about nine refluxes in three hours after which the extraction process was completed. The temperature was regulated using a thermometer.

1.15.6 Methods of Neem Oil Extraction:

Neem oil is generally extracted from Neem seeds Neem oil is usually light to dark brown depending on the time of harvest as well as growing conditions before harvesting it is bitter and smells like peanuts combined with garlic. Neem oil is generally used in agricultural products, cosmetics, and pharmaceuticals.

Different types of Neem oil extraction technologies are available: -

1)Mechanical Pressing

2)Steam Distillation Extraction

3) Solvent Extraction

4)Super Critical Extraction and

5) Aqueous Extraction.

1.16 IR Thermometer Gun

Fig 1.7 IR GUN

Infrared (IR) thermometers enable you to measure temperature quickly, at a distance, and without touching the object you're measuring. They are so useful, easy, and even fun to use that they have become as common in kitchens as they have on factory floors

The accuracy of readings is more reliable in cases of infrared thermometers as compared to digital thermometers. The readings taken with infrared thermometers are obtained quickly i.e., within 10 seconds. However digital thermometers take much longer a time for recording the temperature.

1.16.1 Specifications

- Temperature range: -4 to 500°F (-20 to 260°C)
- Built-in laser pointer for easy targeting
- Large backlit LCD display
- Fixed 0.95 emissivity covers 90% of surface applications
- Automatic Data Hold when trigger released
- Auto power off

1.17 Two Stage Air Compressor

Fig 1.8 Two-Stage Air-Compressor

In a single stage compressor, the air is compressed once; in a two-stage compressor, the air is compressed twice for double the pressure. By increasing the number of cylinder stages and pressure, these machines work more effectively with a faster recovery time, and can handle more tools at once.

1.18 Surface Roughness Test Rig

Fig 1.9 Surface Roughness Tester

Surface roughness is defined as the irregularities which are inherent in the production process. (e.g., cutting tool or abrasive grit). Roughness It is quantified by the deviations in the direction of the normal vector of a real surface from its ideal form. If these deviations are large, the surface is rough; if they are small, the surface is smooth. The statistical significance of the proposed predictive model has been tested by the analysis of variance (ANOVA) test.

A roughness tester is used to quickly and accurately determine the surface texture or surface roughness of a material. A roughness tester shows the measured roughness depth (Rz) as well as the mean roughness value (Ra) in micrometers or microns (µm).

1.19 Submerged Water Pump

Fig 1.10 Submersible Pump

A submersible water pump has the same function as the standard water pumps of draining water. However, it comes with an added advantage of the ability to be placed even underwater and still function properly. Some pumps work only when fully submerged underwater, while others work even when placed on a dry surface.

- 9W Motor, can lift water up to 1.8 meters
- Voltage: 165-220V/50 HZ, An ISO 9001:2008 Certified Company.
- Power: 19W H-MAX: 1.8 m (5 foot approx.), Power Cord length: 115 cm
- Output: 1100L/H, Output Pipe Size: 1/2 inch
- With Thermal Overheat Protector Inside.

Chapter 2

LITERATURE REVIEW

LITERATURE REVIEW

Won Soo Yeon, SooKwangKim et.al. [1]:

The development of high-speed feed drive systems has been a major issue in the machine tool industry for the past few decades. The resulting reduction in the time needed for tool changes and the rapid travel time can enhance productivity. However, a high-speed feed drive system naturally generates more heat and resultant thermal expansion, which adversely affects the accuracy of machined parts. This paper divides the feed drive system into two parts: the ball screw and the guide way. The thermal behaviour model for each part is developed separately, in order to estimate the position errors of the feed drive system caused by thermal expansion. The modified lumped capacitance method (MLCM) and genius education algorithm (GEA) are used to analyse the linear positioning error of the ball screw. Thermal deformation of the guideway affects straightness and introduces angular errors, as well as affecting linear positioning. The finite element method is used to estimate the thermal behaviour of the guideway. The effectiveness of the proposed models is verified through experiments using a laser interferometer.

Yiqiang wang, Richard c.m yam, Ming. J. Zuo et.al. [2]:

In the design and development of computerized numerical control lathes, an effective reliability allocation method is needed to allocate system level reliability requirements into subsystem and component levels. During the allocation process, many factors have to be considered. Some of these factors can be measured quantitatively while others have to be assessed qualitatively. In this paper, we consider seven criteria for conducting reliability allocation. A comprehensive failure rate allocation method is proposed for conducting the task of reliability allocation. Example data from field studies are used to illustrate the proposed method.

P.C. Tseng, J.L. Ho et.al. [3]:

This study addresses the thermal deformation errors resulting from temperature rise that contribute to 40%–70% of the precision errors in machining at a turning centre, and proposes an economic, accurate, and quick measurement method. It also investigates the thermal error differentials between static idle turning and in the actual cutting environment.

The temperature measurement units are intelligent IC temperature sensors with correction circuits. The A/D card extracts and transforms data and saves data in the computer files, and the displacement sensor measures the displacement deviation online during cutting. The temperatures and the deviation of thermal drifts obtained are used to establish the relationship function using multivariable linear regression and nonlinear exponential regression models, respectively. Finally, this paper compares software compensation methods for the thermal-drift relationship. As proven by experiments, the software compensation method can limit the thermal error of a turning centre to within 5 μm. Moreover, the software compensation for the thermal error relationship using a single variable nonlinear exponential regression model can reduce the error by 40% to 60%

Vivek Joshi, Harish Kumar et.al. [4]:

Computer numeric control (CNC) machines are electro-mechanical devices that use a computer program as an input for performing the desired machining. Various machine tools that can be numerically controlled are mills, grinders and lathe. Conventional machining to impart complex geometries on blank requires a complex jig to control cutting tool motion. But since the CNC tool path is digitally programmed so there is no need for a jig in a CNC machine. In addition to this, CNC offers various advantages over conventional machine-like products that can easily be replicated thousands of times, less labour needed to operate on CNC; CNC software increases production options, more accuracy, etc. In turning, the cutting mainly affects the MRR and surface finish. Increasing struggle for higher production with high quality surface finish has forced the production industry to use quality machining tools. The sundry parameter turning process which affects surface qualities are spindle velocity, cutting depth, feed and cutting velocity. The present work is to review the work done by the researcher in the area of the optimization of CNC lathe turning. Due to its widespread availability and its capability of performing various tasks without altering its setup, the lathe machine was chosen for parameter optimization. As turning operation provides various benefits such as it can be used for machining a large variety of the material, and it is one of the cheapest machining processes that is why turning operation was explicitly chosen.

Christian Holzer, Manfred fretch et.al. [5]:

This paper describes which multiple comparison procedures (MCP’s) for usual ANOVA models with normally distributed data are implemented in the statistical program packages SAS, SPSS, BMDP, and MINITAB. The results, and also deficiencies and difficulties when executing these MCP’s in the four programs are explained, and some recommendations regarding which multiple procedures to use for different problems in practice are given.

G.V.N.D. Satya Surya Kiran, M.R.S.V.Y. Shastry et.al. [6]:

The present work is an attempt to make use of Taguchi optimization technique and Response Surface Methodology to optimize cutting Parameters during high-speed turning of Inconel 718 using cemented carbide tool insert to Minimize cutting forces thereby stresses on the Cutting tool and work piece. The cutting parameters are cutting speed 40m/min, 50m/min, 60m/min, feed 0.05mm/rev, 0.1mm/rev, 0.15mm/rev and depth of cut 0.2mm,0.4mm, 0.6mm are considered for optimization. Cutting forces are taken experimentally and Static analysis is performed on the cutting tool and work piece assembly by applying the forces to determine displacements, stresses and Strains Process used in this project is turning process. Modelling is done in Creo 2.0 and analysis is Done in ANSYS.

Ch. Ratnam, K. Arun Kumar et.al. [7]:

Process monitoring in machining constitutes machine performance and machine condition for performing the desired objective. The optimality and effect of machining parameters on machine performance monitoring in tangential and orthogonal turn-milling processes is been studied. Surface Roughness (Ra) and Surface Hardness (H) has been taken as machine performance responses and Tool Vibrations (VIB) as machine condition monitoring response. Laser Doppler Vibrometer (LDV) is used for online capturing of tool vibrations and is analysed using VibSoft analyser for processing Acousto-optic emissions (AOE). Single cut machining on A-axis of CNC Vertical Milling centre using HSS end mill cutters is adopted. Process parameters like cutter (tool) speed, feed rate and depth of cut with constant rotation of the workpiece on A-axis are chosen while machining Brass material under dry condition. Statistical design of experiments (DOE) based on Taguchi’s Orthogonal

Array (OA) is adopted for experimentation and Signal-to-Noise ratio (SN ratio) of the responses is used for finding optimality of process parameters. The influence and contribution of the process parameters on the responses is being studied with the help of Analysis of Variance (ANOVA).

Chorng-JyhTzengaYu-HsinLinbYung-KuangYang et.al. [8]:

This study investigated the optimization of CNC turning operation parameters for SKD11 (JIS) using the Grey relational analysis method. Nine experimental runs based on an orthogonal array of Taguchi methods were performed. The surface properties of roughness average and roughness maximum as well as the roundness were selected as the quality targets. An optimal parameter combination of the turning operation was obtained via Grey relational analysis. By analysing the Grey relational grade matrix, the degree of influence for each controllable process factor onto individual quality targets can be found. The depth of cut was identified to be the most influential on the roughness average and the cutting speed is the most influential factor to the roughness maximum and the roundness. Additionally, the analysis of variance (ANOVA) is also applied to identify the most significant factor; the depth of cut is the most significant controlled factor for the turning operations according to the weighted sum grade of the roughness average, roughness maximum and roundness.

Nihat Tosun et.al. [9]:

The theory of grey systems is a new technique for performing prediction, relational analysis and decision making in many areas. In this paper, the use of grey relational analysis for optimizing the drilling process parameters for the workpiece surface roughness and the burr height is introduced. Various drilling parameters, such as feed rate, cutting speed, drill and point angles of drill were considered. An orthogonal array was used for the experimental design. Optimal machining parameters were determined by the grey relational grade obtained from the grey relational analysis for multi-performance characteristics (the surface roughness and the burr height). Experimental results have shown that the surface roughness and the burr height in the drilling process can be improved effectively through the new approach.

C.L. Lin et.al. [10]:

This article addresses an approach based on the Taguchi method with grey relational analysis for optimizing turning operations with multiple performance characteristics. A grey relational grade obtained from the grey relational analysis is used to solve the turning operations with multiple performance characteristics. Optimal cutting parameters can then be determined by the Taguchi method using the grey relational grade as the performance index. Tool life, cutting force, and surface roughness are important characteristics in turning. Using these characteristics, the cutting parameters, including cutting speed, feed rate, and depth of cut are optimized in the study. Experimental results have been improved through this approach.

Jiju Antony, Frenie jiju Antony et.al. [11]:

The Taguchi method is a powerful problem-solving technique for improving process performance, yield and productivity. It reduces scrap rates, rework costs and manufacturing costs due to excessive variability in processes. However, its application by industrial engineers in the UK is limited, in part due to the inadequate statistical education of engineers. This paper presents a simple experiment which can be used in the classroom to teach engineers the basics of the technique and illustrates simple analytical and graphical tools which promote rapid understanding of the results of the experiment.

J.A. Ghani, I.A. Choudhary et.al. [12]:

This paper outlines the Taguchi optimization methodology, which is applied to optimize cutting parameters in end milling when machining hardened steel AISI H13 with TiN coated P10 carbide insert tool under semi-finishing and finishing conditions of high-speed cutting. The milling parameters evaluated are cutting speed, feed rate and depth of cut. An orthogonal array, signal-to-noise (S/N) ratio and Pareto analysis of variance (ANOVA) are employed to analyse the effect of these milling parameters.

The analysis of the result shows that the optimal combination for low resultant cutting force and good surface finish is high cutting speed, low feed rate and low depth of cut. Using Taguchi method for design of experiment (DOE), other significant effects such as the interaction among milling parameters are also investigated. The study shows that the

Taguchi method is suitable to solve the stated problem with a minimum number of trials as compared with a full factorial design.

Ravella Sreenivas Rao, C. Ganesh Kumar, R. Shetty Prakasham et.al. [13]:

Success in experiments and/or technology mainly depends on a properly designed process or product. The traditional method of process optimization involves the study of one variable at a time, which requires a number of combinations of experiments that are time, cost and labour intensive. The Taguchi method of design of experiments is a simple statistical tool involving a system of tabulated designs (arrays) that allows a maximum number of main effects to be estimated in an unbiased (orthogonal) fashion with a minimum number of experimental runs. Taguchi principles and concepts have made extensive contributions to industry by bringing focused awareness to robustness, noise and quality. This methodology has been widely applied in many industrial sectors; however, its application in biological sciences has been limited. In the present review, the application and comparison of the Taguchi methodology has been emphasized with specific case studies in the field of biotechnology, particularly in diverse areas like fermentation, food processing, molecular biology, wastewater treatment and bioremediation.

H. YangY.S. Tarng et.al. [14]:

In this study, the Taguchi method, a powerful tool to design optimization for quality, is used to find the optimal cutting parameters for turning operations. An orthogonal array, the signal-to-noise (S/N) ratio, and the analysis of variance (ANOVA) are employed to investigate the cutting characteristics of S45C steel bars using tungsten carbide cutting tools. Through this study, not only can the optimal cutting parameters for turning operations be obtained, but also the main cutting parameters that affect the cutting performance in turning operations can be found. Experimental results are provided to confirm the effectiveness of this approach.

Chapter 3

DESIGN OF EXPERIMENTS

DESIGN OF EXPERIMENTS

This chapter reports the brief introduction to Design of experiments and Taguchi's DOE. It also shows the step-by-step procedure to obtain Taguchi DOE using Minitab 17 software.

3.1 Design of Experiments (DOE) overview.

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

3.1.1 Planning

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

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

- Develop an experimental plan that will provide meaningful information Review relevant background information, such as theoretical 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 functioning statistical process control (SPC) system. Minitab provides numerous
- tools to evaluate process control and analyse your measurement system.

3.1.2 Screening

In many processes' 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 setting for these factors The following methods are often used for screening

- Two-level full and fractional designs are used extensively in industry.
- Plackett-Burman designs have low resolution, but they are useful in some screening experimentation and robustness testing.

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

3.1.3 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, and mixture designs. and Taguchi designs

- Factorial Designs overview describes methods for designing and analysing general full factorial designs.
- Response surface designs overview describes methods for designing and analysing central composite and Box-Behnken designs. Mixture Designs

overview describes methods for designing and 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.

3.1.4 Verification

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

3.2 Merits and Demerits of DOE

DOE becomes 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 order 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 most optimal setting of parametric values to find the best possible output characteristics Besides from that the mathematical model generated can be used as a prediction model which can predict the possible output response based on the input values Another main reason DOE is used because it saves time and cost terms of experimentation

DOE functions in such a manner that the number of experiments or number of rans is determined before the actual experimentation is done. This way, time and cost can be saved as we do not have to respect 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 still continuing with the analysis. DOE is excellent when it comes to predicting linear behaviour. However, when it comes to linear behaviour, DOE does not always give the best results.

3.3 Taguchi Method

Taguchi techniques have been used widely in engineering design. The Taguchi method contains system design, parameter design, and tolerance design procedures to achieve a robust process and result for the best product quality. The main thrust of Taguchi's techniques is the use of parameter design, which is an engineering method for product or process design that focuses on determining the parameter (factor) settings producing the best levels of a quality characteristic (performance measure) with minimum variation. Taguchi designs provide a powerful and efficient method for designing processes that operate consistently and optimally over a variety of conditions to determine the best design, it requires the use of a strategically designed experiment. which exposes the process to various levels of design parameters. Experimental design methods were developed in the early years of the 20th century and have been extensively studied by statisticians since then, but they were not easy to use by practitioners. Taguchi's approach to design of experiments is easy to be adopted and applied for users with limited knowledge of statistics; hence it has gained a wide popularity in the engineering and scientific community. Taguchi specified three situations:

- Larger is the better (for example, agricultural yield).
- Smaller is the better (for example, carbon dioxide emissions); and
- On-target, minimum-variation (for example, a mating part in an assembly),

Taguchi has used Signal-Noise (S/N) ratio as the quality characteristic of choice. S/N ratio is used as a measurable value instead of standard deviation due to the fact that, as the mean decreases, the standard deviation also decreases and vice versa.

3.4 Contributions of Taguchi Method

Taguchi has made a very influential contribution to industrial statistics. Key elements of his quality philosophy include the following:

3.4.1 Taguchi's loss function

It is used to measure financial loss to society resulting from poor quality.

The philosophy of off-line quality control:

Designing products and processes so that they are insensitive ("robust") to parameters outside the design engineer's control; and Innovations in the statistical design of experiments: Atkinson, Donev, and Tobias, notably the use of an outer array for factors that are uncontrollable in real life, but are systematically varied in the experiment. Taguchi proposed a standard 8-step procedure for applying his method for optimizing any process.

3.4.2 Taguchi's Rule for Manufacturing

Taguchi realized that the best opportunity to eliminate variation is during the design of a product and its manufacturing process. Consequently, he developed a strategy for quality engineering that can be used in both contexts. The process has three

stages:

I. System design

II. Parameter design

III. Tolerance design

3.5 Mathematical Modelling

A mathematical model is a description of a system using mathematical concepts and language. The process of developing a mathematical model is termed mathematical modelling. Mathematical models are used in engineering disciplines like computer science and artificial intelligence.

3.5.1 Orthogonal Array

Experiments using OAs significantly reduces the number of experimental configurations to be studied Montgomery, (1991). The effect of many different parameters on the performance characteristic in a process can be examined by using the orthogonal array experimental design proposed by Taguchi. Once the parameters affecting a process that can be controlled have been determined, the levels at which these parameters should be varied must be determined. Determining what levels of a variable to test requires an in-depth understanding of the process, including the minimum, maximum, and current value of the parameter. If the difference between the minimum and maximum value of a parameter is large, the values being tested can be further apart or more values can be tested. If the range of a parameter is small, then less value can be tested or the values tested can be closer together.

3.5.2 Array Selector

The Taguchi method is a powerful tool for designing high quality systems. To increase the experimental efficiency, the L16 mixed orthogonal table in the Taguchi quality design. Ross (1988) is used to determine the significant machining factors. In the experiments, we select six influential machining parameters, such as cutting tools of different materials, surface roughness, depth of cut, cutting speed, feed rate, working temperature and tool temperature each of which has three different levels (high, medium and low levels)

3.6 Factorial Design

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

3.6.1 Full Factorial Designs

In a full factorial experiment, responses are measured at all combinations of the experimental factor levels. The combinations of factor levels represent the conditions at which responses will be measured. Each experimental condition is called a "run" and the response measurement an observation. The entire set of runs is the "design"

3.6.2 Two Level Full Factorial Designs

In a two-level full factorial design, each experimental factor has only two levels. The experimental runs include all combinations of these factor levels. Although two level factorial designs are unable to explore fully a wide region in the factor space, they provide useful information for relatively few runs per factor. Because two-level factorials can indicate major trends, which are used to provide direction for further experimentation.

3.6.3 General full factorial designs

In a general full factorial design, the experimental factors can have any number of levels. For example, Factor A may have two levels, Factor B may have three levels and Factor c may have five levels. The experimental runs include all combinations of these factor levels. General full factorial designs may be used with small screening experiments, or in optimization experiments.

3.7 Fractional factorial designs

In a full factorial experiment, responses are measured at all combinations of the factor levels, which may result in a prohibitive number of runs. For example, a two-level a full factorial design with 6 factors requires 64 runs, a design with 9 factors requires 512 runs.

To minimize time and cost, can use designs that exclude some of the factor level combinations. Factorial designs in which one or more level combinations are excluded are called fractional factorial designs. Minitab generates two-level fractional factorial designs for up to 15 factors.

Fractional designs are useful in factor screening because they reduce down the number of runs to a manageable size. The runs that are performed are a selected subset or fraction of the full factorial design.

3.8 Placket-Burman designs

Placket-Burman designs are a class of resolution III, two-level fractional factorial designs that are often used to study the main effects. In a resolution III design, main effects are aliased with two-way interactions. Minitab generates designs for up to 47 factors. Each design is based on the number of nins, from 12 to 48, and is always a multiple of 4. The number of factors must be less than the number of runs,

3.9 Design of Experiment (DOE's) Planning

I. Design and Communicate the Objective

II. Define the Process

III. Select a Response and Measurement System

IV. Ensure that the Measurement System is Adequate

V. Select Factors to be studied

VI. Select the Experimental Design

VII. Set Factor Levels

VIII. Final Design Consideration

Table 3.1 L16 Orthogonal Array

Run No.	A	B	C
1	1	1	1
2	1	2	2
3	1	3	3
4	1	4	4
5	2	1	2
6	2	2	1
7	2	3	4
8	2	4	3
9	3	1	3
10	3	2	4
11	3	3	1
12	3	4	2
13	4	1	4
14	4	2	3
15	4	3	2
16	4	4	1

CHAPTER 4
EXPERIMENTAL SETUP

EXPERIMENTAL SETUP

The experimental work was done by following Taguchi design of experiments.

4.1 Selection of Process Variables

A total of three process variables and four levels are selected for experimental Procedure.

The deciding process variables are:

- Speed
- Feed
- Depth of cut

4.2 Selection of levels

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

Table 4.1 Process Variables and Levels

Process Factor	Level 1	Level 2	Level 3	Level 4
Speed	510	764	1019	1273
Feed	0.05	0.1	0.15	0.2
DOC	0.25	0.5	0.75	1

4.3 Design of Experiments

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

4.4 Machining

Computer numerical control (CNC) is one in which function and motion of a machine tool are controlled by the means of a prepared program containing coated alphanumeric data. CNC can control the motion of the workpiece or tool, the input parameters such as feed, speed, and the functions such as turning coolant on/off.

4.4.1 Part program

The part program is a detailed set of commands to be followed by the machine tool. Each command specifies a Cartesian coordinate system (x, y and z) or motion (work piece travel or cutting tool travel), machine parameters on/off function. Part program should be well versed with machine tools, machining processes, effect of process variables and limitations of CNC controls. The part programming is written manually or by using computer assisted languages such as APT (automated programming tool).

4.4.2 Positioning

- Absolute positioning

In this mode the desired target position of the tool for a particular move is given relative

to the origin point of the program.

- Incremental positioning:

In this mode, the next target position of the tool is given relative to the current tool position.

4.5 The machining of the workpiece

The machining of the workpiece on CNC turn mill using the following procedure

- Selection of material
- Clamping of the workpiece
- Loading the program into a CNC machine.
- Running the program

4.5.1 Selection of Material

By studying various projects titanium is selected for machining operation. The

Composition of titanium is:

- 6% Aluminium
- 4% Vanadium
- 0.25% Iron
- 0.2 Oxygen

4.6 Experimental Procedure

Taguchi DOE basing on concept of orthogonal array (OA) adopted for designing experiments, considering three process parameters (like Spindle speed (N), feed (f) and depth of cut (doc) with four levels each which generated 16 (L16) experimental combinations as shown in Table.

Table 4.2 Input Parameters and corresponding output Responses

Expt. No.	Speed	Feed	DOC	Surface Roughness	Tool Temp	Work piece Temp
1	510	0.05	0.25	0.59	32	31
2	510	0.1	0.5	0.73	34	33
3	510	0.15	0.75	0.94	37	35
4	510	0.2	1	1.24	38	36
5	764	005	0.25	0.42	34	33
6	764	0.1	0.5	0.85	36	35
7	764	0.15	0.75	0.87	40	39
8	764	0.2	1	0.91	39	37
9	1019	0.05	0.25	0.33	41	38
10	1019	0.1	0.5	0.71	43	41
11	1019	0.15	0.75	0.75	35	34
12	1019	0.2	1	1.19	37	36
13	1273	0.05	0.25	0.28	42	38
14	1273	0.1	0.5	0.34	39	37
15	1273	0.15	0.75	0.38	37	35
16	1273	0.2	1	0.58	35	32

4.7 Grey Relational Analysis (GRA):

GRA is a multi-response optimization technique which generates an optimal process parameter combination for all the responses generated by normalizing the SN ratio, determining the gray relation coefficients based on the deviation of normalized SN ratios and ranking them accordingly to identify the optimal combination as rank 1. The grey system theory proposed by Deng has been proven to be useful for dealing with the problems with poor, insufficient, and uncertain information. The main moto is to convert multiple objectives into an equivalent single objective function, which can finally be optimized. However, these approaches rely on some assumptions.

Execution of the Procedure

Signal-to-Noise ratio: SN Ratio was calculated using equations by considering **smaller-is-better** criterion. Responses like surface roughness and temperatures requires low disturbance as per the corresponding criterion.

Smaller is better: The signal-to-noise (S/N) ratio is calculated for each factor level combination. The formula for the smaller-is-better S/N ratio using base 10 log is:

$$S/N = -10*\log(\Sigma(Y^2)/n)$$

where Y = responses for the given factor level combination and n = number of responses in the factor level combination.

Table 4.3 Signal-Noise Ratio Table

Speed (RPM)	Feed (mm/rev)	DOC (mm)	Tool Temperature (ºC)	Workpiece Temperature (ºC)	Surface Roughness (Ra)	TT SN Ratio	WT SN Ratio	Ra SN Ratio
510	0.05	0.25	32	31	0.59	-30.10	-29.83	4.58
510	0.1	0.5	34	33	0.73	-30.63	-30.37	2.73
510	0.15	0.75	37	35	0.94	-31.36	-30.88	0.54
510	0.2	1	38	36	1.24	-31.60	-31.13	-1.87
764	0.05	0.5	34	33	0.42	-30.63	-30.37	7.54
764	0.1	0.25	36	35	0.85	-31.13	-30.88	1.41
764	0.15	1	40	39	0.87	-32.04	-31.82	1.21
764	0.2	0.75	39	37	0.91	-31.82	-31.36	0.82
1019	0.05	0.75	41	38	0.33	-32.26	-31.60	9.63
1019	0.1	1	43	41	0.71	-32.67	-32.26	2.97
1019	0.15	0.25	35	34	0.75	-30.88	-30.63	2.50
1019	0.2	0.5	37	36	1.19	-31.36	-31.13	-1.51
1273	0.05	1	42	38	0.28	-32.46	-31.60	11.06
1273	0.1	0.75	39	37	0.34	-31.82	-31.36	9.37
1273	0.15	0.5	37	35	0.38	-31.36	-30.88	8.40
1273	0.2	0.25	35	32	0.58	-30.88	-30.10	4.73
					AVERAGE	-31.44	-31.01	4.01
					IDEAL SPEED	-30.92	-30.55	8.3908
					IDEAL FEED	-31.36	-30.85	8.2011
					IDEAL DOC	-30.75	-30.36	5.0892
					Opt. SN RATIO	-30.15	-29.74	13.67
					Opt.VALUE	32.19	30.68	0.21

Procedure of GRA:

Step 1: The SN ratios of experimental data (which has no similarity for comparison) of all the responses is converted to a sequence of comparable data by **normalizing.**

$$\text{For Lower-is-Better (LB): } x_i^*(j) = \frac{[\max(x_i(j)) - x_i(j)]}{[\max(x_i(j)) - \min(x_i(j))]}$$

$$\text{For Higher-is-Better (HB): } x_i^*(j) = \frac{[x_i(j) - \min(x_i(j))]}{[\max(x_i(j)) - \min(x_i(j))]}$$

where $X_i(j)$ is the value of response of i^{th} experiment, $\max(x_i(j))$ and $\min(x_i(j))$ are the smallest and largest values of $X_i(j)$ respectively.

Step 2: The **deviation sequence** $\Delta_{oi}(k)$ of each response, which is defined as the absolute difference between the maximum value taken from the normalized values (reference sequence) and the normalized value (sequence) under study and is given as:

$$\Delta_{oi}(k) = \|X_o(k) - X_i(k)\|$$

Step 3: Then the sequence of comparable data between different responses are to be correlated by giving some due weight age (distinguishable coefficient) which determines **grey relational coefficient** as given in the equation.

$$\gamma_i = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{oi}(k) + \zeta\Delta_{max}}$$

Where Δ_{min} is smallest value of the normalized values, Δ_{max} is maximum value of the normalized values, ζ is distinguishing coefficient and ranges from 0 to 1 and had been assumed as 0.5. According to Deng, larger normalized results correspond to better performance and the best normalized result should be equal to 1. Thus, the grey relational coefficients which express the relationship between the ideal (best) and the actual experimental results are determined.

Table 4.4 GRA Technique Normalisation and Deviation Sequence

	Normalisation			Deviation Sequence		
Expt No.	Surface Roughness	Tool Temperature	W/p Temperature	Ra	T_t	T_w
1	0.677	1.000	1.000	0.323	0.000	0.000
2	0.531	0.818	0.800	0.469	0.182	0.200
3	0.313	0.545	0.600	0.688	0.455	0.400
4	0.000	0.455	0.500	1.000	0.545	0.500
5	0.854	0.818	0.800	0.146	0.182	0.200
6	0.406	0.636	0.600	0.594	0.364	0.400
7	0.385	0.273	0.200	0.615	0.727	0.800
8	0.344	0.364	0.400	0.656	0.636	0.600
9	0.948	0.182	0.300	0.052	0.818	0.700
10	0.552	0.000	0.000	0.448	1.000	1.000
11	0.510	0.727	0.700	0.490	0.273	0.300
12	0.052	0.545	0.500	0.948	0.455	0.500
13	1.000	0.091	0.300	0.000	0.909	0.700
14	0.938	0.364	0.400	0.063	0.636	0.600
15	0.896	0.545	0.600	0.104	0.455	0.400
16	0.688	0.727	0.900	0.313	0.273	0.100

Step 4: Basing on the grey relational coefficients of all the responses which are correlated measure, is graded using Grey Relational Grade as given in the equation. Based on the grey relational grade, the ranking has to be given in descending order. The combination of process parameters which have the highest rank is considered to be optimal.

Table 4.5 Grey Relational Analysis Results

Experiments	Grey relation coefficient			Grey Relational Grade	Rank
	Ra	Tt	Tw	GRG	
1	1.000	1.000	1.000	0.869	1
2	1.000	1.000	1.000	0.655	4
3	1.000	1.000	1.000	0.500	11
4	1.000	1.000	1.000	0.437	14
5	1.000	1.000	1.000	0.741	2
6	1.000	1.000	1.000	0.531	10
7	1.000	1.000	1.000	0.414	15
8	1.000	1.000	1.000	0.442	13
9	1.000	1.000	1.000	0.567	9
10	1.000	1.000	1.000	0.398	16
11	1.000	1.000	1.000	0.592	7
12	1.000	1.000	1.000	0.456	12
13	1.000	1.000	1.000	0.591	8
14	1.000	1.000	1.000	0.594	6
15	1.000	1.000	1.000	0.636	5
16	1.000	1.000	1.000	0.699	3

4.8 Sample calculations of experimental run 1 of surface roughness in wet condition:

The GRA method procedure has been adopted to calculate optimal combination of responses using GRA in both the conditions and is listed in Table.

For Normalization responses based on SN ratios, Lower-is-Better (HB) and using the Eq, we get For Lower-is-Better (LB) during wet machining.

$$x_i^*(j) = \frac{[\max(x_i(j)) - x_i(j)]}{[\max(x_i(j)) - \min(x_i(j))]}$$

= (1.24-0.59)/ (1.24-0.28) = 0.677(Normalization)

= (1.00-0.677) = 0.323(Deviation Sequence)

= (0+(0.5*1))/ (0.323+(0.5*1)) = 0.608(Grey relation coefficient)

= (0.608+1+1)/3 = **0.869**(Grey Relational Grade)

Chapter 5
RESULTS AND DISCUSSIONS

RESULTS AND DISCUSSIONS

5.1 ANOVA-ANALYSIS OF VARIANCE:

Analysis of variance (ANOVA) which is a collection of statistical models based on accepting null hypothesis or not by analyzing the difference between group means of responses or SN ratios and the variation among and between groups. It assumes the null hypothesis to be correct until and unless, the alternate hypothesis is proved to be correct. To accept or reject null hypothesis, the F-statistical values are useful, like if F-statistic > F-critical then reject null hypothesis. It also determines and indicates the contribution of design parameters on the quality characteristic of the response based on F-statistic test with significance level of 95% (i.e. < 0.05 probability). The ANOVA on SN ratios of the responses under wet conditions are tabulated in Table showing the significance and contribution of process parameters on the responses.

$$SS_{Total} = \sum X^2 - \frac{(\sum X)^2}{N} \quad \text{and} \quad DF = N - 1$$

$$SS_{Between} = \frac{(\sum x_1)^2}{n_1} + \frac{(\sum x_2)^2}{n_2} + \cdots + \frac{(\sum x_{AC})^2}{n_{AC}} - \frac{(\sum x)^2}{N}$$

$$SS_{Within} = SS_{Total} - SS_{Between}$$

$$\%Contribution = {}^{MS}/_{MS_{Total}}$$

where “SS” is sum of squares, MS is mean square, “DF” is degree of freedom, N is total observations, n is size of population.

5.2. General Linear Model:

Table 5.1 Tool Temperature (°C) versus Speed (rpm), Feed (mm/rev), DOC (mm)

Source	DF	Adj SS	Adj MS	F-Value	P-Value	Contribution	Remarks
Speed (RPM)	3	31.687	10.562	8.59	0.014	22%	Significant
Feed (mm/rev)	3	1.687	0.5625	0.46	0.722	1%	Not Significant
DOC (mm)	3	103.18	34.395	27.98	0.001	71.68%	Highly Significant
Error	6	7.375	1.2292				
Total	15	143.93					

Table 5.2 Work-Piece Temperature (°c) Versus Speed (rpm), Feed (mm/Rev), Doc (mm)

Source	DF	Adj SS	Adj MS	F-Value	P-Value	Contribution	Remarks
Speed (rpm)	3	25.250	8.4167	12.62	0.005	24%	Significant
Feed (mm/rev)	3	5.250	1.7500	2.36	0.145	5%	Significant
DOC (mm)	3	73.250	24.416	36.63	0.000	68%	Highly significant
Error	6	4.000	0.6667				
Total	15	107.75					

Table 5.3 Surface Roughness Versus Speed (rpm), Feed (mm/Rev), DOC (mm)

Source	DF	Adj SS	Adj MS	F-Value	P-Value	Contribution	Remarks
Speed (RPM)	3	0.5178	0.1726	10.01	0.009	39%	Significant
Feed (mm/rev)	3	0.6733	0.2244	13.02	0.005	50%	Highly Significant
DOC (mm)	3	0.0434	0.0144	0.84	0.520	3%	Not Significant
Error	6	0.1034	0.0172				
Total	15	1.3379					

5.3 Individual Optimisation: -

This is done to know how an optimum response as an individual parameter.The tabulated response values thus generated while machining Ti6Al4V material using Taguchi DOE L16 experiments are taken for determining individual response (T_t, R_a,W_t) using signal-to-noise (S/N) ratios. S/N ratios are calculated using equations,

$$(S/N)_{\text{Smaller-is-better}} = -10*\log(\Sigma(Y^2)/n)$$

$$(S/N)_{\text{Larger-is-better}} = -10*\log(\Sigma(1/Y^2)/n)$$

The calculated S/N ratios are used to determine the individual optimality of the generated responses based on the equations.

$$\eta_{optimum} = \eta_{average} + \sum_{i=1}^{n}(\eta_{ideal} - \eta_{average})$$

$$\text{Response}_{optimum} = \sqrt{10 \pm \frac{\eta_{optimum}}{10}}$$

Where ‘n’ is observation number, η_{opt} is optimum S/N ratio, η_{avg} is average S/N ratio, η_{ideal} is the ideal level of each S/N ratio parameter.

5.3.1 Taguchi Analysis of Tool Temperature (ºC) v/s Speed (rpm), Feed (mm/rev), Depth of cut (mm): -

Table 5.4 Taguchi Analysis of Tool Temperature (ºC) v/s Speed (rpm), Feed (mm/rev), Depth of cut (mm)

S.NO.	Speed (RPM)	Feed (mm/rev)	DOC (mm)	Optimal Design
1	-30.92	-31.36	-30.75	A1-B1-C1
2	-31.4	-31.56	-31	
3	-31.79	-31.41	-31.82	
4	-31.63	-31.42	-32.19	

The average of S/N ratio ($\eta_{average}$) = -31.4382

The S/N ideal speed ($\eta_{ideal\ speed}$) = -30.92

The S/N ideal feed ($\eta_{ideal\ feed}$) = -31.36

The S/N ideal depth of cut ($\eta_{ideal\ doc}$) = -30.75

Temperature-Main Effect Plots:

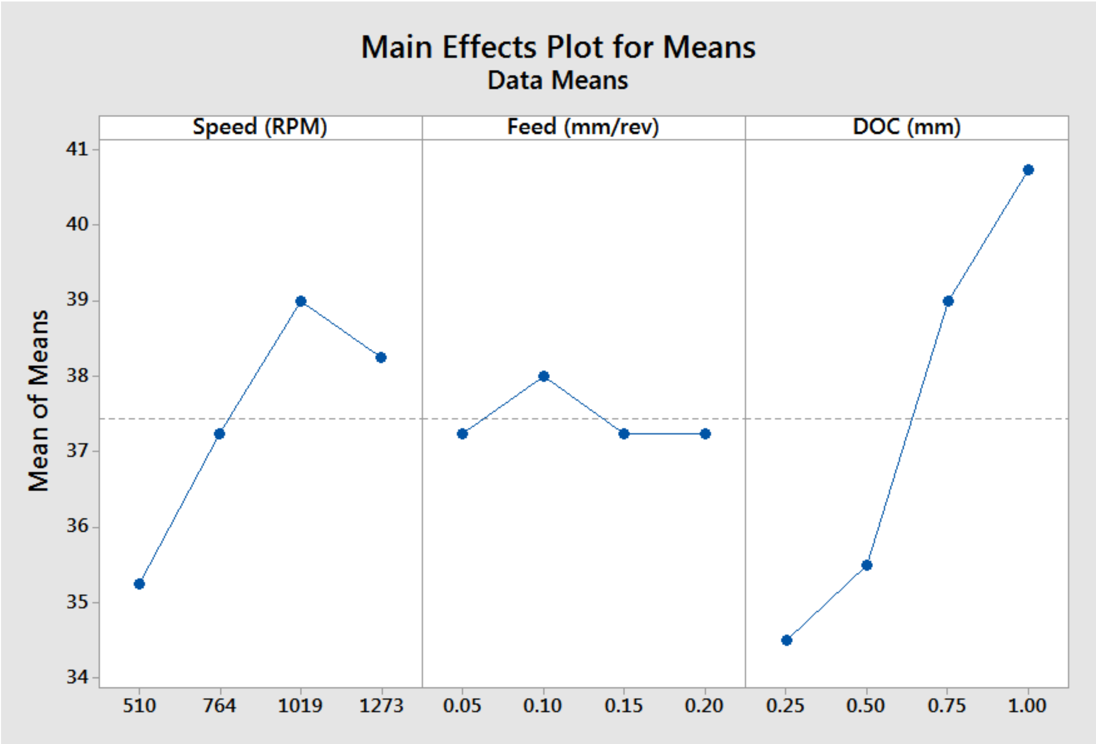

Fig 5.1 Tool Temperatures -Main Effect Plot For Means

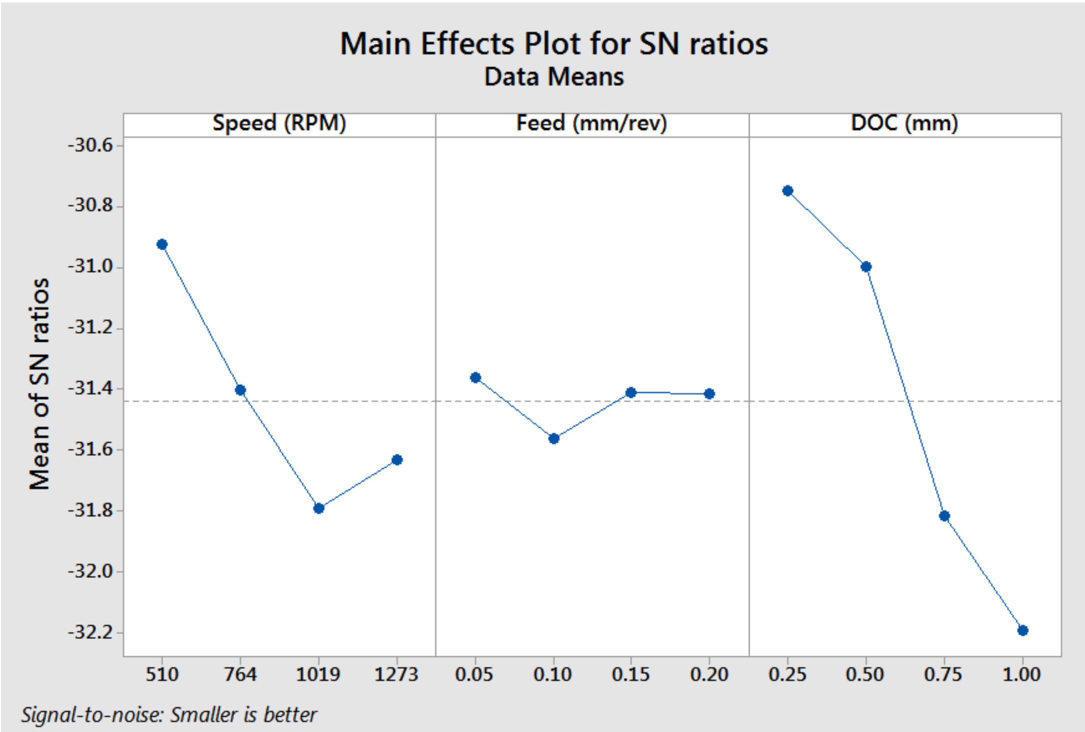

Fig 5.2 Tool Temperatures- Main Effect Plots of SN Ratios

5.3.2 Taguchi Analysis of Work-piece Temperature (ºC) v/s Speed (rpm), Feed (mm/rev), Depth of cut (mm): -

Table 5.5 Taguchi Analysis of Work-piece Temperature (ºC) v/s Speed (rpm), Feed (mm/rev), Depth of cut (mm)

Level	Speed (RPM)	Feed (mm/rev)	DOC (mm)	Optimal Design
1	-30.55	-30.85	-30.36	A1-B1-C1
2	-31.11	-31.22	-30.69	
3	-31.4	-31.05	-31.3	
4	-30.99	-30.93	-31.7	

Work-piece Temperature Main Effect Plots:

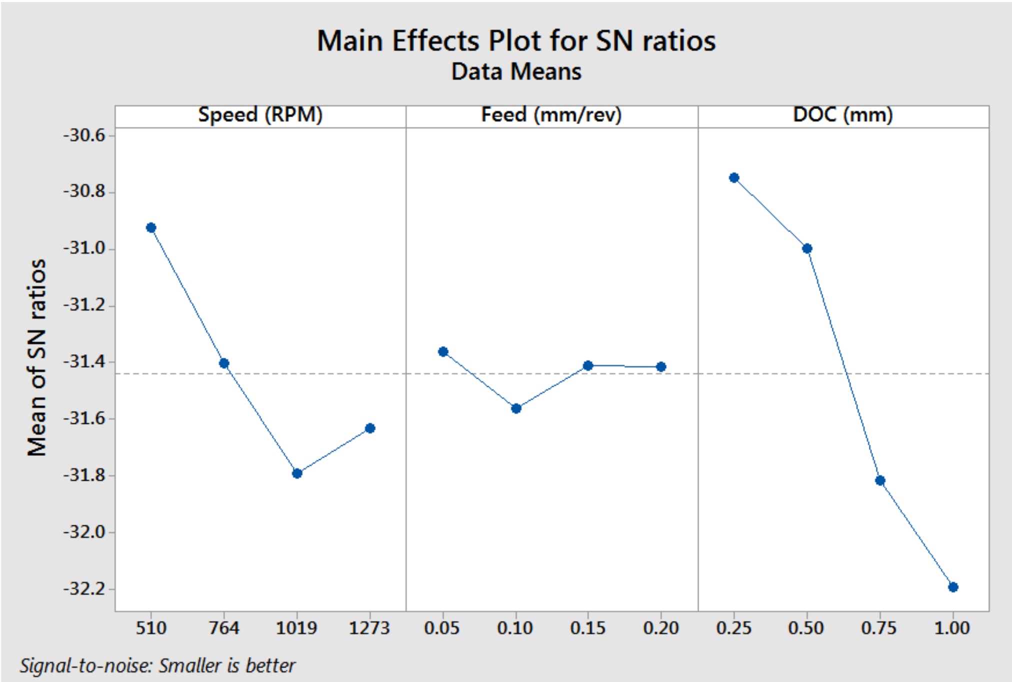

Fig 5.3 W/P Temperature Main Effect Plots-Means

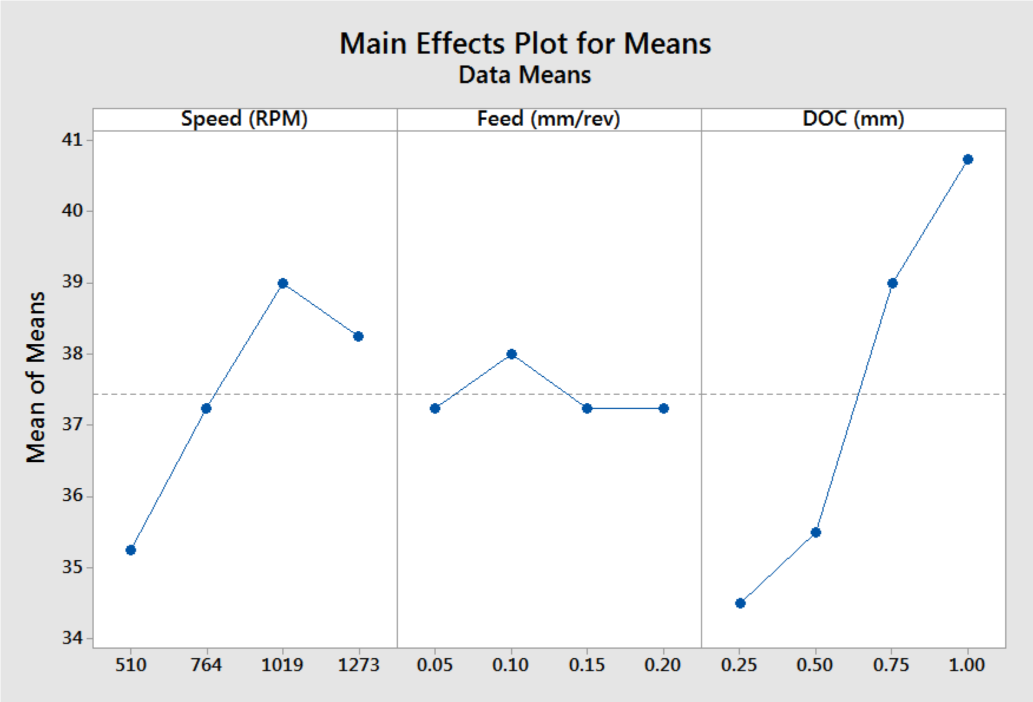

Fig 5.4 W/P Temperature Main Effect Plots- SN Ratios

5.3.3 Taguchi Analysis of Surface Roughness (ºC) v/s Speed (rpm), Feed (mm/rev), Depth of cut (mm): -

Table 5.6 Taguchi Analysis of Surface Roughness (ºC) v/s Speed (rpm), Feed (mm/rev), Depth of cut (mm)

Level	Speed (RPM)	Feed (Mm/Rev)	DOC (Mm)	Optimal Design
1	1.4964	8.2011	3.3062	A4-B1-C3
2	2.7439	4.1226	4.2905	
3	3.3981	3.1625	5.0892	
4	8.3908	0.5428	3.3432	

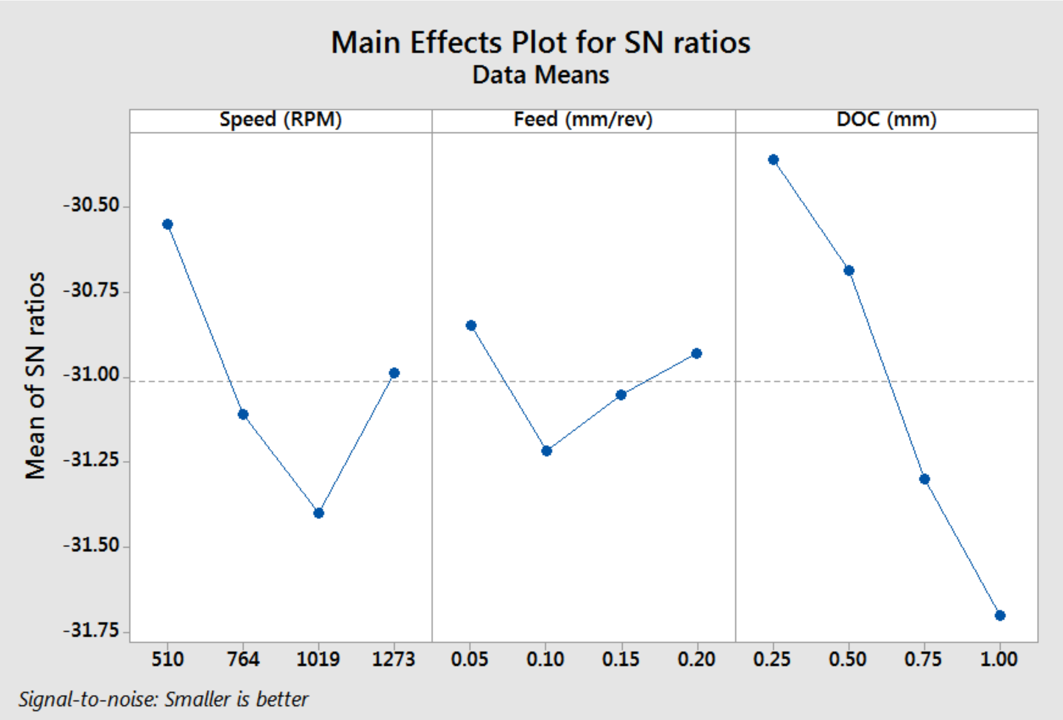

Fig 5.5 Surface Roughness Main Effect Plots- SN Ratios

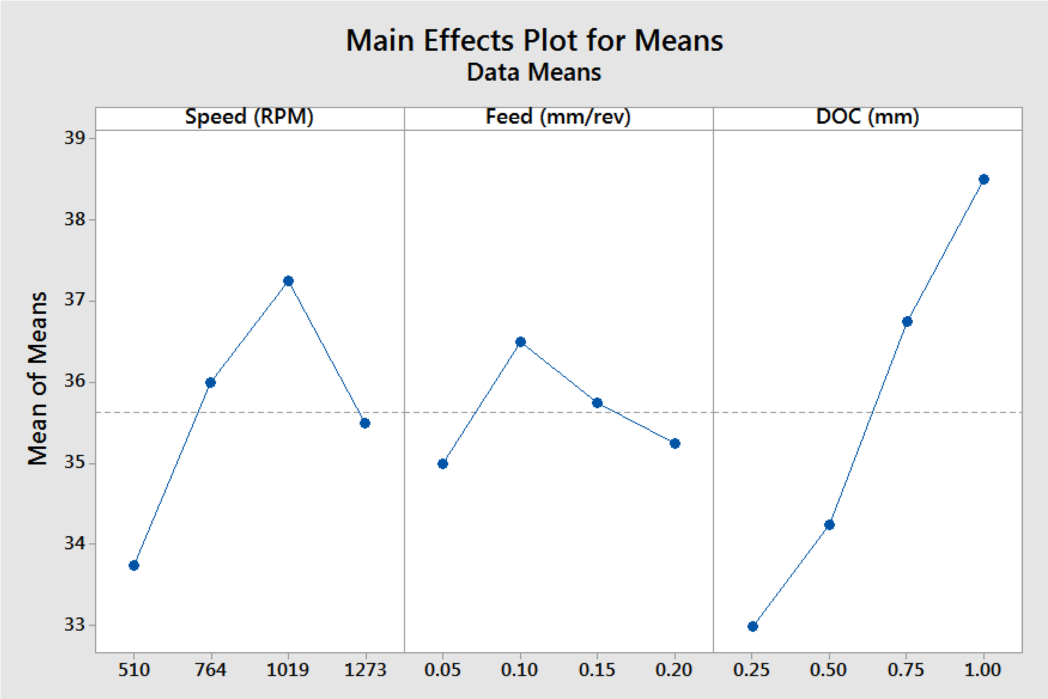

Fig 5.6 Surface Roughness Main Effect Plots-Means

Chapter 6
CONCLUSIONS

CONCLUSIONS

- Turn Milling Operations have been done on Ti alloy work-pieces using PVD tool bit. Based on Taguchi DOE, 16 operations have been performed with different sets of process parameters.

- By using GRA Technique optimum set of process parameters is found whose values of speed, depth of cut and feed respectively are 510 rpm, 0.25mm and 0.05 mm/rev.

ANOVA is carried out now and its results show that:

Table 6.1 Significance

	T_T	T_W	R_a
Speed	Significant with 22%	Significant with 24%	Significant with 39%
Feed	-	Significant with 5%	Highly Significant With 50%
Depth of Cut	Highly Significant with 72%	Highly Significant with 68%	-

- w.r.t Tool Temperature, depth of cut is highly significant, speed is significant and feed has no much impact
- w.r.t Workpiece temperature, depth of cut is highly significant while speed and feed shows significant impact
- w.r.t Surface roughness, feed is a highly significant parameter, speed shows significant effect and depth of cut has not much effect.

Individual Optimal Values and Process Parameters in Machining

Table 6.2 Optimal Values and Process Parameters in Machining

Optimal design			T_T (ºC)	T_W (ºC)	R_a (µm)
T_T	W_T	R_a			
A1-B1-C1	**A1-B1-C1**	**A4-B1-C3**	**32.24**	**30.69**	**0.2073**

Taguchi optimisation process is performed for individual parameters and following results were obtained:

1)At speed 510 rpm, feed rate of 0.05 mm/rev and depth of cut of 0.25 mm we have an optimal tool temperature of 32.24^{O}C.

2) At speed 510 rpm, feed rate of 0.05 mm/rev and depth of cut of 0.25 mm we have an optimal work-piece temperature of 35.52^{O}C.

3) At speed 1273 rpm, feed rate of 0.05 mm/rev and depth of cut of 0.75 mm we have an optimal Surface Roughness of 0.2073µm.

7 REFERENCES

[1] Won Soo Yun; Soo Kwang Kim; Dong Woo Cho. Thermal error analysis for a CNC lathe feed drive system., 39(7), 1087–1101 (1999).

[2] Alptunc Comak and Yusuf Altintas, MECHANICS OF TURN-MILLING OPERATIONS, International Journal of Machine Tools and Manufacture, (2017).

[3] J. Kopač; M. Pogačnik, Theory and practice of achieving quality surface in turn milling., 37(5), 709–715, (1997).

[4] V. Savas, C. Ozay. Analysis of the surface roughness of tangential turn milling for machining with an end milling cutter. Journal of Materials Processing Technology, 186:279-283, (2007).

[5] Christian Holzer; Manfred Precht, Multiple comparison procedures for normally distributed ANOVA models in SAS, SPSS, BMDP, and MINITAB., 13(3), 351–358, (1992).

[6] G.V.N.D. Satya Surya Kiran, M.R.S.V.Y. Shastry, Analysing of Cutting Parameters by Turning Operation for Incole Material Using Mini Tab (2013).

[7] K. Arun Vikram, Ch. Ratnam, K. Sankara Narayana, B. Satish Ben, Indian J. Eng. & Materials Sciences. 22(3), 321-330 (2015).

[8] Yiqiang Wang; Richard C.M. Yam; Ming J. Zuo; Peter Tse. A comprehensive reliability allocation method for design of CNC lathes. 72(3), 247–252, (2001).

[9] P.-J. Arrazola; A. Garay; L.-M. Iriarte; M. Armendia; S. Marya; F. Le Maître Machinability of titanium alloys (Ti6Al4V and Ti555.3)., 209(5), 2223–2230, (2009).

[10] C. L. Lin Use of the Taguchi Method and Grey Relational Analysis to Optimize Turning Operations with Multiple Performance Characteristics, Materials and Manufacturing Processes, 19:2, 209-220, (2004).

[11] Antony, J. and Jiju Antony, "Teaching the Taguchi method to industrial engineers", Work Study, Vol. 50 No. 4, pp. 141-149, (2001).

[12] J. A Ghani; I.A Choudhury; H.H Hassan, Application of Taguchi method in the optimization of end milling parameters., 145(1), 84–92, (2004).

[13] Ravella Sreenivas Rao; C. Ganesh Kumar; R. Shetty Prakasam; Phil J. Hobbs. The Taguchi methodology as a statistical tool for biotechnological applications: A critical appraisal., 3(4), 510–523 (2008).

[14] W.H. Yang; Y.S. Tarng, Design optimization of cutting parameters for turning operations based on the Taguchi method., 84(1-3), 122–129 (1998).

[15] S.K. Choudhury, J.B. Bajpai. Investigation in orthogonal turn-milling towards better surface finish. Journal of Materials Processing Technology, 170:487-493, (2005).

[16] Zhu, L., Jiang, Z., Shi, J. et al. An overview of turn-milling technology. Int J Adv Manuf Techno 81, 493–505 (2015).

[17] Ahilan C, Kumaran S and Sivakumaran N, Advances in Production Engineering and Management. 5 (3) (2010) 171-180. Technol. 84, 122–129 (1998).

[18] T.R. Lin, Experimental design and performance analysis of tin-coated carbide tool in face milling stainless steel, J. Mater. Process. Technol.5654, 1–7 (2002).

[19] K.L. Tsui, Modeling and analysis of dynamic robust design experiments, IEE Trans. 31, 113–1122 (1999).

[20] C. Zhang, H.P. Wang, Robust design of assembly and machining tolerance allocations, IEE Trans. 30, 17–29 (1998).

[21] C.T. Si, L.I. Tong, Multi response robust design by principal component analysis, Total Qual. Manage. 8, 409–416 (1997).

[22] J. Kopac, M. Bahor, M. Sokovic, Optimal machining parameters for achieving the desired surface roughness in fine turning of cold preformed steel workpieces, Int. J. Mach. Tool Manuf. 42, 707–796 (2002).

[23] P.G. Benardos, G.C. Vosniakos, Prediction of surface roughness in cnc face milling using neural networks and Taguchi's design of experiments, Robot. Comput. Integr. Manuf. 18, 343–351 (2002).

[24] M.S. Phadke, Quality Engineering Using Design of Experiments,Quality Control, Robust Design, and the Taguchi Method, Wadsworth & Books, California, (1988).