Vol. 2 Issue 1, Jan.2012, pp. 086-101

EXPERIMENTAL INVESTIGATIONS, OPTIMIZATION OF PROCESS PARAMETERS AND MATHEMATICAL MODELING IN TURNING OF TITANIUM ALLOY UNDER DIFFERENT LUBRICANT CONDITIONS

M. Venkata Ramana[1] A. Venkata Vishnu[1] G. Krishna Mohan Rao[2] D. Hanumantha Rao[3]

[1]Department of Mechanical Engineering, VNR Vignana Jyothi Institute of Engineering & Technology, Hyderabad, India.
[2]Department of Mechanical Engineering, JNTUH College of Engineering, Hyderabad, India
[3]Department of Mechanical Engineering, MVSR Engineering College, Hyderabad, India

ABSTRACT

In any metal cutting operation, a lot of heat is generated due to plastic deformation of work material, friction at the tool–chip and tool - work piece. The heat generated in dry machining adversely affects the quality of the products produced. Thus, effective control of heat generated in the cutting zone is essential to ensure good surface quality of the work piece in machining. Cutting fluids have been the conventional choice to deal with this problem. Cutting fluids are introduced in the machining zone to improve the tribological characteristics of machining processes and to dissipate the heat generated. The advantages of cutting fluids, however, have been questioned lately due to the negative effects on product cost, environment and human health. Later on Minimum quantity lubrication (MQL) has been tried as a possible alternative to the use of flooded coolants. Minimum Quantity Lubrication machining refers to the use of a small amount of cutting fluid, typically in order of 300 ml/hr or less, which are about three to four orders of magnitudes lower than that used in flooded lubricating conditions.

This paper deals with the experimental investigations and optimization of process parameters for surface roughness in turning of Ti-6Al-4V alloy under dry, flooded and Minimum Quantity Lubrication (MQL) conditions using Taguchi's robust design methodology and development of prediction models for surface roughness using multiple regression analysis.

The results have been compared among dry, flooded and MQL conditions and it reveals that MQL shows better performance and improvement in reduction of surface roughness compared to dry and flooded lubricant conditions. From Analysis of Mean (ANOM), it is observed that MQL is suitable at higher depth of cut compared to dry and flooded lubricant conditions. It is observed from ANOM that, under MQL condition uncoated tool shows better performance compared to the CVD and PVD coated tools, whereas CVD coated tool shows better performance for dry and flooded lubricant conditions compared to uncoated and PVD coated tools. It is also observed from the ANOVA that, feed rate has major contribution in optimizing the surface roughness.

Mathematical Models are developed to predict the Surface Roughness under dry, flooded and MQL lubricant conditions for three different tools using multiple regression analysis. These models show good agreement with experimental results.

1.0 INTRODUCTION

In any metal cutting process, inherently generates high temperature in cutting zone. Such high temperature causes dimensional inaccuracies and premature failure of cutting tools. Hence, it is generally considered that the heat produced during the machining process is critical in terms of work piece quality. Thus, effective control of heat generated in the cutting zone is essential to ensure good work piece surface quality in machining.

1.1 MACHINING OF TITANIUM ALLOYS:

The Titanium alloy (Ti-6Al-4V), which is a grade-5 titanium alloy. Ti-6Al-4V is an Alpha-Beta alloy grade Titanium Alloy [1]. The composition of Ti-6Al-4V is shown in Table 1.

TABLE 1: composition of Ti-6Al-4V

C	Fe	N_2	O_2	Al	V	H_2	Ti
<0.08%	<0.25%	<0.05%	<0.2%	5.5 -6.7%	3.5 -4.5%	<0.0125%	Balance

Higher difficulties are expected when machining Titanium alloys due to its mechanical properties especially the hardness and the tensile stress at high temperatures, differences of structure with a variable quantity of the alpha phase, morphology of the transformed beta phase, very low thermal conductivity, relatively low modulus of elasticity and high chemical reactivity.

Ti6Al4V is the most widely used in variety of weight reduction applications such as aerospace and jet engine components; auto- motive and marine equipment; medical applications such as implants, bone joint replacements and surgical instruments; marine applications; chemical industry; turbine blades, etc [1]. The advantages of alloys of Ti-6Al-4V are less weight, high tensile strength, bio-compatibility, low thermal and electrical conductivity, corrosion resistance, etc. The physical and mechanical properties of Ti-6Al-4V is shown in Table 2.

TABLE 2: Physical and mechanical properties of Ti-6Al-4V

Property	**Typical value**
Density g/cm^3 (lb/ cu in)	4.42 (0.159)
Melting Range °C±15°C (°F)	1649 (3000)
Specific Heat J/kg.°C (BTU/lb/°F)	560 (0.134)
Volume Electrical Resistivity ohm.cm (ohm. in)	170 (67)
Thermal Conductivity W/m.K (BTU/ft.h.°F)	7.2 (67)
Mean Co-Efficient of Thermal Expansion 0-300°C/°C (0-572°F /°F)	9.2x10^{-6} (5.1)
Tensile Strength MPa (ksi)	1000 (145)
0.2% Proof Stress MPa (ksi)	910 (132)
Elongation Over 2 Inches %	18
Elastic Modulus GPa (Msi)	114 (17)
Hardness Rockwell C	36
Charpy, V-Notch Impact J (ft.lbf)	24 (18)

1.2. INTRODUCTION TO CUTTING FLUIDS:

Cutting fluids are introduced in the machining zone to improve the tribological characteristics of machining processes, to dissipate the heat generated, improving tool life, reducing work piece thermal deformation, improving surface roughness and flushing away chips from the cutting zone. Practically all cutting fluids presently in use are categorized into straight oils, soluble oils (servo cut oils), semi synthetic fluids and synthetic fluids [1,5].

Synthetic oil contains no petroleum or mineral oil base, instead it contains formulated from alkaline inorganic and organic compounds or synthetic hydrocarbons along with additives for corrosion inhibition. They are generally used in a diluted form (usual concentration = 3 to 10%). Synthetic fluids provide the best cooling performance among all cutting fluids. There are various types of synthetic oil, which are full synthetic, semi-synthetic and high performance synthetics. Fully synthetic motor oils contain non-conventional, high performance fluids. The semi-synthetic oil contains blends. These blends are low percentage of non-conventional, high performance fluids combined with conventional base oil. High performance synthetics are some of the most technological advanced engine oils. These oils differ from others in their use of more advance additives. Synthetics break down at a slower rate by resisting oxidation and their low tendency to form deposits. This allows for better lubrication during machining. The advantages of these coolants are excellent microbial control and resistance to rancidity; relatively nontoxic; transparent; nonflammable/nonsmoking; good corrosion control; superior cooling qualities; reduced misting/foaming; easily separated from work piece/chips; good settling/cleaning properties; easy maintenance; long service life; used for a wide range of machining applications. The disadvantages of these coolants are reduced lubrication; may cause misting, may form residues; easily contaminated by other machine fluids. The advantages of flooded/conventional use of cutting fluids, however, questioned lately due to the negative effects such as employee health and environmental pollution and cost. In the recent years a lot of research has been carried out to avoid the use of cutting fluids in machining. Because of them some alternatives has been sought to minimize or even avoid the use of cutting fluid in machining operations in which, one of the alternative is Minimum quantity lubrication (MQL).

1.2.1. Minimum Quantity Lubrication: Minimum Quantity Lubrication machining refers to the use of a small amount of cutting fluid, typically in order of 300 ml/hr or less, which are about three to four orders of magnitudes lower than that used in flooded lubricating conditions [2,4]. The Minimum Quantity Lubrication is supplies mixtures of compressed air and cutting fluid through spray gun. Furthermore, MQL provides environment friendliness, maintaining neat, clean and dry working area, avoiding inconvenience and health hazards due to heat, smoke, fumes, gases, etc. and preventing pollution of the surroundings and improves the machinability characteristics.

1.3. SURFACE ROUGHNESS

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 received serious attention for many years and it is a key process to assess the quality of a particular product. Surface roughness has an impact on the mechanical properties like fatigue behavior, corrosion resistance, creep life, etc. It also affects other functional attributes of parts like friction, wear, light reflection, heat transmission, lubrication, electrical conductivity, etc. Surface roughness of turned components has greater influence on the quality of the product.

1.3.1. FACTORS AFFECTING THE SURFACE ROUGHNESS

Whenever one machined surfaces come in contact with another, the quality of the mating parts plays an important role in the performance and wear of the mating parts. The number of factors affects the surface roughness are: machining variables which includes - cutting speed, feed and depth of cut; tool geometry which includes - nose radius, rake angle, cutting edge angle and cutting edge; work piece-tool material combination and their properties; quality and type of the machine tool used; auxiliary tooling and lubricant/cutting fluid used; vibrations among the work piece, machine tool and cutting tool [3, 12]. Different methods are used to find out surface roughness, which are R_a R_z, R_q, and R_{sk}, but most commonly used is R_a. The average surface roughness R_a is calculated as follows.

$$R_a = \frac{1}{L}\int_0^L |z(x)|dx$$

Where, L is evaluation length, z is height and x is distance along measurement.

2.0 LITERATURE SURVEY

E.O. Ezugwu and Z.M. Wang [1] have reviewed the main problems associated with the machining of titanium as well as tool wear and the mechanisms responsible for tool failure. It was found that the straight tungsten carbide (WC/Co) cutting tools continue to maintain their superiority machining titanium alloys. This paper also reviewed special machining methods, such as rotary cutting, the use of ledge tools, MQL, etc. N.R. Dhar et al [2] has investigated the role of MQL on cutting temperature, chip formation and product quality in turning AISI-1040 steel by uncoated carbide insert and the results are compared dry flooded and MQL machining. The experimental results indicate that such MQL enables substantial reduction in the cutting temperature, dimensional inaccuracy depending upon the levels of the cutting velocity and feed rate. V.N. Gaitonde et al [3] has carried out the work to determine the optimum amount of MQL and the most appropriate cutting speed and feed rate during turning of brass using K10 carbide tool. The experiments were planned as per Taguchi's L9 orthogonal array. The analysis of means (ANOM) and analysis of variance (ANOVA) on multi-response signal-to-noise (S/N) ratio were employed for determining the optimal parameter levels and identifying the level of importance of the process parameters on surface roughness and specific cutting force. M.M.A. Khan et al [4] has compared the effects of dry, wet and MQL in terms of chip–tool interface temperature, chip formation mode, tool wear and surface roughness. MQL machining was performed much superior compared to the dry and wet machining due to substantial reduction in cutting zone temperature enabling favorable chip formation and chip–tool interaction and it was also seen from the results that the substantial reduction in tool wears resulted in enhanced the tool life and surface finish. Vishal S. Sharma et al [5] has reviewed the techniques of MQL, Pressure Coolant (HPC), Cryogenic Cooling, Compressed Air Cooling and use of Solid Lubricants/Coolants. These techniques have resulted in reduction in friction and heat at the cutting zone, hence improved productivity of the process. E.A. Rahim et al [6] have studied the potency of MQL palm oil (MQLPO) as a lubricant in the high speed drilling of Ti–6Al–4V. For the comparison, MQL synthetic ester (MQLSE), air blow and flood conditions were selected. Uniform flank wear, micro-chipping, thermal cracking and flaking were the dominant tool failure modes. It was found that MQLSE and MQLPO gave comparable performance with the flood conditions. In addition, MQLPO outperformed MQLSE on the cutting forces, temperature, power and specific cutting energy. This shows that palm oil can be used as a viable alternative to synthetic ester for MQL lubricant. M.Venkata Ramana et al [7] have worked on performance evaluation and optimization of process parameter in turning of Ti6Al4V alloy with different coolant conditions on surface roughness using uncoated carbide tool. The results have been compared among dry, flooded with Servo cut oil and water and flooded with Synthetic oil coolant conditions. From the experimental investigations, the cutting performance on Ti6Al4V alloy with synthetic oil is found to be better when compared to dry and servo cut oil and water in reducing surface roughness. The results from ANOVA shows that while machining Ti6Al4V alloy, the Synthetic oil is more effective under high cutting speed, high depth of cut and low feed rate compared to dry and servo cut oil and water conditions. Francisco Mata et al [8] applied the response surface methodology to predict the cutting forces in turning operations using TiN-coated cutting tools under dry conditions where the machining parameters are cutting speed ranges, feed rate, and depth of cut. For this study, the experiments have been conducted using full factorial design in the design of experiments (DOEs) on CNC turning machine. Based on statistical analysis, multiple quadratic regression model for cutting forces was derived with satisfactory R^2-squared correlation. This model proved to be highly preferment for predicting cutting forces.

A through study of literature suggests that the machining of titanium alloy is very difficult compared to other alloy materials. Very few works have been done in the optimization of process parameters in turning process of Ti-6Al-4V alloy with different controlled parameters such as cutting speed, feed rate and depth of cut etc. However very few works have carried out on machining of titanium alloys under different lubricant conditions such as dry, wet and Minimum Quantity Lubricant (MQL).

3.0 METHODOLOGY

In this work, Taguchi robust design methodology is used to obtain the optimum conditions for surface roughness in turning of titanium Ti-6Al-4V alloy under dry, wet and MQL conditions. Statistical software Minitab is used along with Taguchi method to obtain results for analysis of variance (ANOVA). Hence, the results obtained from the Taguchi robust design method is compared with the Minitab software results. Prediction models using multiple regression analysis are developed to predict the surface roughness using Minitab software.

3.1 TAGUCHI'S ROBUST DESIGN METHODOLOGY

The scientific approach to quality improvement is becoming more widespread in industrial practice. Designing high quality products and processes at low cost is an economical and technical challenge to the engineer. Robust design is an engineering methodology for improving productivity during design and development so that high quality products and performance can be produced at low cost. The main idea of Robust design method is to choose the levels of design factors to make product or process performance intensive to uncontrollable variations such as manufacturing variations, deterioration and environmental variations. Dr. Genichi Taguchi has popularized the robust design method which employs experimental design techniques to help identify the improved factor levels. Taguchi's approach has been successfully applied by engineers in many leading Japanese and American companies for improving performance and competitiveness of their key products.

The robust design method uses a mathematical tool called Orthogonal Array(O.A) to study large number decision variables with a small number of experiments. It also uses a measure of quality called Signal-to-Noise (S/N) ratio, to predict the quality [9]. The principle of robust design methodology is to minimize the variation without eliminating the causes and maximizing S/N ratio. This is achieved by optimizing the product and process designs to make the performance insensitive to the various causes of variations.

3.2 REGRESSION ANALYSIS:

In statistics, regression analysis includes any techniques for modeling and analyzing several variables, when the focus is on the relationship between a dependent variable and one or more independent variables. More specifically, regression analysis helps in understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed. Regression analysis is widely used for prediction and forecasting, where its use has substantial overlap with the field of machine learning. Regression analysis is also used to understand which among the independent variables are related to the dependent variable, and to explore the forms of these relationships [10].

Regression analysis is two types. They are

3.2.1 SIMPLE LINEAR REGRESSION ANALYSIS: A regression model that involves only one regressor variable is called a simple linear regression model. The general form of linear regression is: $Y = a + bX + u$. Where, Y= Variable to be predict; X= Variable used to predict Y; a = the intercept; b = the slope; u= the regression residual.

3.2.2MULTIPLE REGRESSION ANALYSIS: A regression model that involves more than one regressor variable is called multiple regression models. The general form of multiple regression is: $Y = a + b_1X_1 {}^{+} b_2X_2 + B_3X_3 + B_4X_4 \ldots + B_tX_t + u$. Where, Y= Variable to be predict; X_1, X_2…….X_t = Variables used to predict Y; a= the intercept; b= the slope; u= the regression residual.

In this work, developing a prediction model for surface roughness using multiple regression analysis, four factors are considered viz. cutting speed, feed rate, depth of cut and type of tool material. The first three variables are Quantitative and the left fourth parameter is Qualitative. So in order to include the effect of type of tool material on Surface roughness, it must assign a set of levels to the Qualitative variable. This is done with the help of Indicator variables (also known as Dummy variables). As there are three levels for Qualitative tool material (type of tool material=3), two indicator variables are to be considered, each taking 0 and 1. It's a particular combination of the two indicator variables X_1 and X_2 represents type of carbide tool material.

In general, a Qualitative variable with 'n' levels is represented by 'n-1' indicator variables, each taking on the values 0 and 1. Table 3 shows levels of the Qualitative variables and type of tool material by the set of indicator variables. Now apart from the three quantitative variables, two indicator variables with each combination 0 or 1 represent the tool type [10].

TABLE 3: Specification of qualitative variables

Carbide tool material	Indicator variables	
	X_1	X_2
Uncoated	0	1
CVD coated	1	0
PVD coated	0	0

Further in the regression analysis it has been assumed initially that there is no interaction effect among type of tool material with any of these factors i.e. cutting speed, feed rate and depth of cut. The first order model is assumed as:

Surface roughness=$\beta_0 + \beta_A$cutting speed + β_B feed rate + β_C depth of cut + $\beta_1 X_1 + \beta_2 X_2 + \epsilon$ -----------(1)

Where β_A, β_B, β_C are estimates of the cutting speed, feed rate and depth of cut respectively. In addition, β_1, β_2 estimates of the tool materials, X_1, X_2 are the indicator variables of tool materials, β_0 is the constant and ϵ is the error.

The equation 5.1 is modified as:

$\hat{Y} = \beta_0 + \beta_A (Vc) + \beta_B (F) + \beta_C (D) + \beta_1 X_1 + \beta_2 X_2 + \epsilon$ --(2)

Where $\hat{Y}$= Surface roughness, Vc = cutting speed, F=feed rate, D= depth of cut respectively.

To these regression model higher order terms can be added to predict more accurately by adding interactions among process parameters. The regression equation for higher order terms is modified as follows:

Surface roughness= $\beta_0 + \beta_A$ cutting speed + β_B feed rate + β_C depth of cut + β_A x β_B (cutting speed x feed rate)+β_Bxβ_C(feed rate x depth of cut)+β_C x β_A(depth of cut x cutting speed)+β_1 X_1+β_2 X_2+ ϵ---(3)

The objective of the multiple regression analysis is to develop a prediction models for the surface roughness based on the factors cutting speed, feed rate, depth of cut and different carbide tool material under different lubricant conditions. The experiments include four controllable factors whose levels are represented in Table 5. A total of 18 values are considered to develop prediction models for surface roughness.

3.3 MINITAB SOFTWARE:

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. This software is used for Data and File Management- spreadsheet for better data analysis; Analysis of Variance; Regression Analysis; Power and Sample Size; Tables and Graphs; Multivariate Analysis - includes factor analysis; cluster analysis; correspondence analysis; etc., Nonparametric tests including sing test, runs test, friedman test, etc., Time Series and Forecasting tools that help show trends in data as well as predicting future values [11]. In this work, the Minitab software is used for obtaining ANOVA and to develop prediction mathematical models using multiple regression analysis.

4.0 EXPERIMENAL DETAILS:

The aim of this work is to find out the set of optimum values for the control factors in order to reduce surface roughness under Dry, Flooded and Minimum Quantity Lubrication (MQL) conditions using Taguchi's robust design methodology. The Minitab software is used to generate the linear model for ANOVA. The experiments are carried out on a GEDEEWEILER LZ350 lathe is shown in Fig.1

Figure 1: A typical lathe LZ350

4.1. WORK PIECE MATERIAL

The work piece material used is Ti-6Al-4V alloy of 120mm long and 50mm diameter in the form of bar. The machined work piece material is shown in Fig. 2.

Figure 2: Work-piece Titanium-Ti-6Al-4V

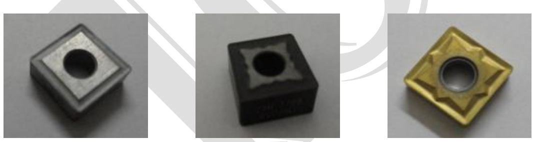
4.2. CUTTING TOOLS

The different types of carbide tools used are in this work is made by SECO with same tool specifications. Three different types of carbide tools used are:

4.2.1 UNCOATED GRADE 883: The uncoated carbide made of tungsten carbide micro grain abrasives is shown in Fig. 3(a). It has high hardness and good toughness and is principally intended for roughing of super alloys. It is specified with SNMG120408-MR4 883

4.2.1. CVD COATED TM 4000: This tool has excellent wear resistance and the superior edge toughness made the first choice in stainless steel applications is shown in Fig. 3(b). It is coated with Ti(C,N) +Al_2O_3. It is designated with DURATOMIC, the term DURATOMIC is derived as DURABLE + ATOMIC = DURATOMIC. The basic structure is Aluminum Oxide represents a very good starting point for machining steel, but the coatings enhance overall ductility significantly. This cumulative result improves mechanical and thermal properties together far beyond the capabilities of any existing grade. This grade provides simplicity and ease of use; reduced tool compensations; increased productivity; improved part quality and machining confidence. It is specified with SNMG120408-MR7 TM4000.

4.2.3. PVD COATED TS 2000: This tool is made of tungsten carbide hard micro grain abrasives are shown in Fig. 3(c). It is new grade of heat resistant alloys coated with (Ti,Al)N + TiN. It is intended for finishing of super alloys. It is machines faster, works harder and last longer. It is specified with SNMG120408-MR3 TS2000.



(a) Uncoated (b) CVD coated (c) PVD coated
Figure 3: Carbide tools

4.3. TOOL HOLDER

The tool holder used for machining is PSBNR16-4R174.3-2525-12 specification and is made by sandvik coromant.

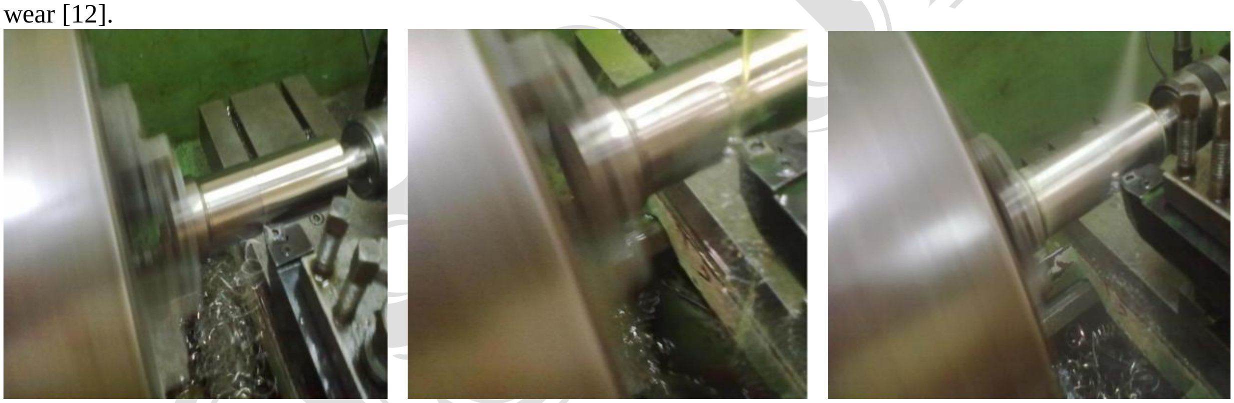
4.4. SURFACE ROUGHNESS TESTER

Surface roughness (Ra) is measured using a portable stylus-type profilometer designated by TR 200 surface roughness tester as shown in Figure 4[12]. It is portable, self-contained instrument for the measurement of surface texture. It is equipped with a diamond stylus having a tip radius 5 µm.

Figure 4: Photographic view of TR 200 surface roughness tester

4.5. CUTTING FLUID/ LUBRICANT

The experiments are conducted under dry, flooded and MQL conditions. Fig 5(a) shows photographic view of dry machining in which cutting fluid is used not used. Fig 5(b) shows photographic view of flooded machining. The cutting fluid used in flooded machining is GANDHAR synthetic water soluble coolant contains 1:20 volumetric concentration is flushed at cutting zone at rate of 3 liters / min. Fig 5(c) shows photographic view of MQL machining. The Minimum Quantity Lubrication setup is shown in Fig. 6. It consists of air compressor, spray gun with fine nozzle and Cutting fluid chamber [2.4]. Air compressor is connected to spray gun and cutting fluid chamber with hose pipe. The cutting fluid used is same as flooded machining. Cutting fluid is supplied to spray gun at the rate of 300 ml/hr, which is mixed with compressed air (3bar) in the mixing chamber of spray gun. Then the mixture of air and cutting fluid (mist) is supplied and impinge with high pressure and velocity at the cutting zone by spray gun nozzle [2,4]. The mist reaches as close to the chip–tool and the work–tool interfaces as possible. The MQL spray is concentrated on rake and flank surface along the cutting edges, to protect the flank faces, minimize the friction, increase the cooling, lubricity abilities and reduce the tool wear [12].



(a) Dry machining (b) Flooded machining (c) MQL machining

Figure 5 Photographic view of turning under dry machining

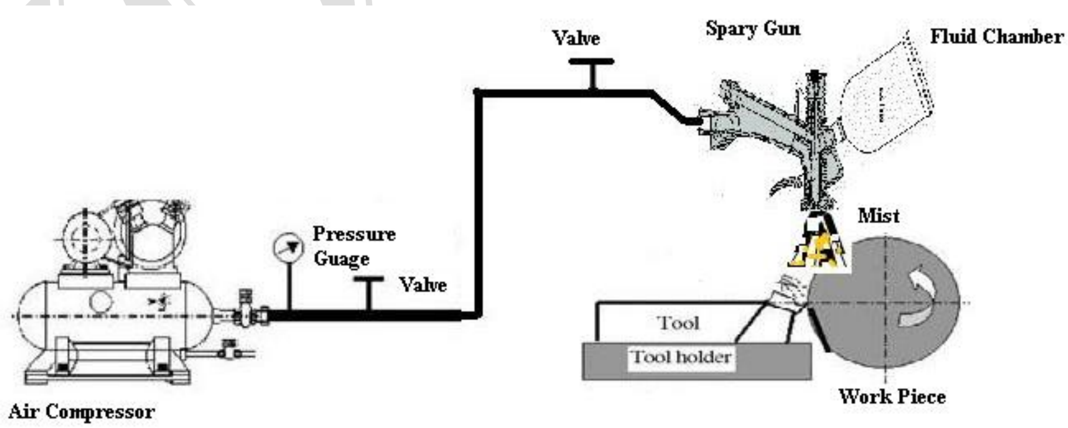


Fig.6. Layout of Minimum Quantity Lubrication setup

4.6. SELECTION OF CONTROL FACTORS, LEVELS AND ORTHOGONAL ARRAY:

A total of four process parameters with three levels have been chosen as the control factors such that the levels are sufficiently covers wide range. The four control factors selected are cutting speed (A), feed rate (B), depth of cut (C) and type of carbide tool material (D). The control factors and their levels are shown in Table 3.

TABLE 3: Control factors and levels

Factors/ Levels	Speed (A) (m/min)	Feed (B) (mm/rev)	Depth of cut(C) (mm)	Type of tool(D)
1	63	0.206	0.6	Uncoated
2	79	0.274	1	CVD coated
3	99	0.343	1.6	PVD coated

Selection of particular orthogonal array from the standard O.A. depends on the number of factors, levels of each factor and the total degrees of freedom. Based on these factors, the required minimum number of experiments to be conducted are nine, the nearest O.A. fulfilling this condition is L_9 (3^4) is shown in Table 4. It can accommodate a maximum four number of control factors each at three levels with 9 numbers of experiments. In L_9 (3^4) O.A., 9 represents number of experiments, 3 represents number of levels and 4 represents number of factors [9]. The factor assigned for L_9 (3^4) O.A. is shown in Table 4.

TABLE 4: Standard $L_9\,(3^4)$ Orthogonal Array.

Experiment Number	Column				Column			
	1	2	3	4	Cutting speed (A) (m/min)	Feed rate (B)(mm/Rev)	Depth of cut (C) (mm)	Type of tool (D)
1	1	1	1	1	63	0.206	0.6	Uncoated
2	1	2	2	2	63	0.274	1.0	CVD coated
3	1	3	3	3	63	0.343	1.6	PVD coated
4	2	1	2	3	79	0.206	1.0	PVD coated
5	2	2	3	1	79	0.274	1.6	Uncoated
6	2	3	1	2	79	0.343	0.6	CVD coated
7	3	1	3	2	99	0.206	1.6	CVD coated
8	3	2	1	3	99	0.274	0.6	PVD coated
9	3	3	2	1	99	0.343	1.0	Uncoated

4.7. EXPERIMENTAL PROCEDURE:

The specimens have turned on lathe according experimental design as shown in Table 4 for dry, flooded and MQL conditions. Each experiment is conducted for two trails. Then surface roughness is measured precisely with the help of a TR 200 surface roughness tester. The surface roughness is measured on the work pieces have been repeated for four times (i.e. at every 90^0 of the specimen). The average of these four measurements has recorded. The average values of the two trails are taken into consideration for optimization of process parameters. The average surface roughness and S/N ratio of the experiments for dry, flooded and MQL conditions is shown in Table 5. Optimization of surface roughness and influence of process parameters is carried out using Taguchi method, ANOVA and Minitab software [3,11]. Prediction mathematical models are developed to predict surface roughness using multiple regression analysis is carried out on Minitab software.

Table 5: Data summary of surface roughness and S/N ratio

Experiment Number	Average surface roughness(Ra)	S/N RATIO (dB)	Average surface roughness(Ra)	S/N RATIO (dB)	Average surface roughness(Ra)	S/N RATIO (dB)
	Dry machining		Flooded Machining		MQL Machining	
1	2.095	-6.43	2.17	-6.73	2.01	-6.07
2	3.46	-10.78	3.61	-11.15	3.14	-9.93
3	5.49	-14.79	5.25	-14.40	4.90	-13.80

4	2.33	-7.34	2.33	-7.34	2.17	-6.73
5	4.63	-13.31	4.29	-12.64	3.63	-11.19
6	4.81	-13.64	4.90	-13.80	4.79	-13.60
7	2.27	-7.12	2.24	-7.013	2.47	-7.87
8	3.82	-11.64	3.46	-10.78	3.71	-11.38
9	5.61	-14.98	5.32	-14.51	4.63	-13.31

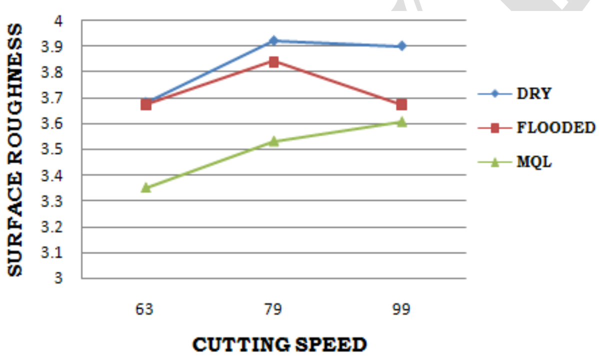
5.0 EXPERIMENTAL RESULTS AND DISCUSSIONS:

In the present work, the performance characteristics namely surface roughness is to be minimized; hence smaller the better type quality characteristic has been selected for the response.

$$\eta = -10\log_{10}\left[\left(\frac{1}{n}\right)\sum_{i=1}^{n} y_i^2\right] \quad \text{------(4)}$$

5.1 EFFECT OF CUTTING PARAMETERS ON SURFACE ROUGHNESS

From Figure 7, it is observed that, the surface roughness is low for MQL compared to dry and flooded conditions. It is also observed that, the surface roughness increases as the cutting speed increases from low to moderate speeds for dry, flooded and MQL conditions, but from moderate to high cutting speeds, the surface roughness decreases for dry and flooded conditions, where as the surface roughness is continuously increases for MQL conditions. This can be explained by the reason that, surface roughness increases due to temperature, stress and wear at tool tip increases. In comparison of MQL with dry and flooded lubricant conditions, the cutting fluid supplied at high pressure and velocity, which penetrates minute particles into tool-chip and tool-workpiece surfaces, causes reduction in friction leads to less surface roughness. In MQL condition, it provides both cooling and lubrication effectively and cooling occurs convective as well as evaporative heat transfer, hence less surface roughness is observed in MQL [3]. In flooded condition effective penetration of the cutting fluid into tool-chip and tool- work surface is not possible and also heat transfer takes place only with convective heat transfer. Hence, high surface roughness is observed in flooded compared to MQL condition, whereas in dry machining, no cutting fluid is supplied, which results into high friction, high tool wear and low heat transfer leads to high surface roughness. The increasing and decreasing pattern of surface roughness in dry and flooded conditions is observed. The main reason for this pattern is due to effect of other factors like interaction between feed and depth of cut.



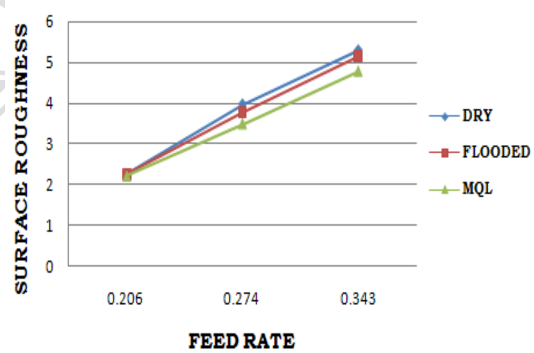
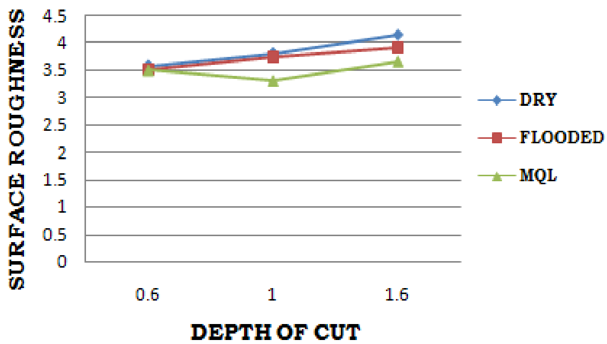


Fig.7 Variation of surface roughness with cutting speed Fig. 8 Variation of surface roughness with feed rate

Figure 8 shows the variation between feed rate and surface roughness under different lubricant conditions. As feed rate increases, the surface roughness is also increases for dry, flooded and MQL conditions. It is observed from the Fig. 8 that, MQL shows reduction in surface roughness compared to dry and flooded condition under different feed rates [2,4]. As the feed rate increases, the surface roughness also increases due to the time available is less to carryout the heat from the cutting zone, high amount material removal rate and accumulation of chip between tool-workpiece zone

Figure 9 shows the variation between depth of cut and surface roughness under different lubricant conditions. It is observed from the Fig. 9 that, MQL shows reduction in surface roughness compared to dry and flooded condition under different depth of cut. As depth of cut increases, the surface roughness increases for dry, flooded and MQL conditions. This can be explained as more area in contact takes place between tool and workpieces, this result in high friction and tool wear leads to high surface roughness.



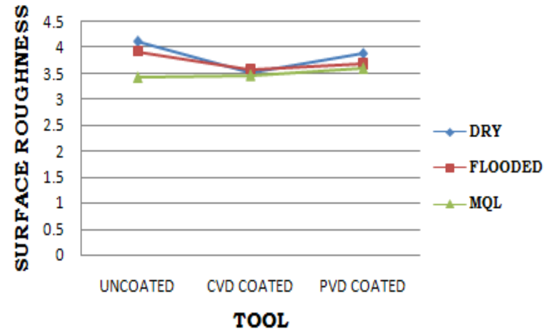


Fig. 9: Variation of surface roughness with depth of cut Fig. 10 Variation of surface roughness with tool of material

It is observed form Figure 10 that, uncoated carbide tool shows better performance compared to CVD and PVD coated tool material in reduction of surface roughness. The reason for this is due to reaction between coated elements and titanium at high temperature forms carbide compounds. These compounds show greater wear due to its brittleness. It is seen form Figure 10, that the surface roughness is also low for MQL compare to dry and flooded conditions for each tool materials.
Finally, it is concluded that MQL condition show better performance in reduction of surface roughness compared to dry and flooded lubricant condition. Hence it is recommended that MQL can be implemented in order to improve surface finish, reduction in quantity of lubricant, cost and environmental pollution.

5.2. OPTIMIZATION OF CUTTING PARAMETERS:
Taguchi's robust design methodology has been successfully implemented to identify the optimum process parameters in order to reduce the surface roughness during machining of Ti-6Al-4V alloy under dry, flooded and MQL conditions is shown in Table 6 [9]. It is observed from Table 6 that, MQL is effective under higher depth of cut compared to dry and flooded conditions. It is also indicated from the Table 6 that, uncoated tool is superior in performance for MQL compared to CVD and PVD coated tools due to formation carbide compounds and high tool wear, where as CVD coated tool shows good performance for dry and flooded conditions due to its toughness and wear resistance.

TABLE: 6. Optimum parameters for surface roughness

Cutting conditions/ Factors	MQL	Flooded	Dry
Cutting speed (m/min)	63	63	63
Feed rate (mm/rev)	0.206	0.206	0.206
Depth of cut (mm)	1	0.6	0.6
Type of tool	Uncoated	CVD coated	CVD coated

5.3. INFLUENCE OF PROCESS PARAMETERS:
Analysis of Variance is performed to find out influence and performance of each process parameter during machining.

5.3.1: Dry machining:
As seen from Table 7, feed rate has major contribution of 92.58% in optimizing the performance characteristics followed by type of tool, depth of cut and cutting speed to minimize the surface roughness under dry machining. Further, it is also observed that ANOVA has results in 0.22 % of error contribution [11].

TABLE: 7 Summary of ANOVA in dry machining on surface roughness

FACTOR	S.S	D.O.F	M.S.S	F-RATIO	SS^1	ρ %
Speed	0.211986	2	0.105993	12.01	0.1943412	0.63%
Feed	28.46937	2	14.234685	1613.47	28.45172	92.65%
Doc	0.93507	2	0.467535	52.99	0.9174252	2.98%
Tool	1.092222	2	0.546111	61.90	1.074577	3.49%
Error	0.079402	9	0.0088224		0.147428	0.22%
S_t	30.708648	17				100%
Mean	264.73005	1				
St	295.5181	18				

The S/N ratios of optimum condition are used to develop predictive or additive model to predict the S/N ratio of the optimum condition using equation 4.

$$\eta_{predicted} = Y + (\overline{A1} - Y) + (\overline{B1} - Y) + (\overline{C1} - Y) + (\overline{D2} - Y) \qquad \text{----------} (4)$$

Where Y is average S/N ratio; A1, B1, C1 and D2 are optimum parameter in dry machining. The predicted S/N ratio is -5.38 dB. Conducting a verification experiment is essential and final step of the robust design methodology. The predicted results must be conformed to the verification test. Hence, the verification experiment is conducted with the optimum conditions as shown in Table 6 and its S/N ratio is (η_{expt}) -5.62dB. It is found that the S/N ratio of the verification test is within the limits of the predicted value at 95% confidence level and the objective is fulfilled. These suggested optimum conditions can be adopted.

The ANOVA is also carried out using Minitab software and their results are shown in Table 8.

TABLE 8: ANOVA using MINITAB for dry condition

General Linear Model: Ra VALUES versus SPEED, FEED, ...

```
Factor         Type   Levels  Values
SPEED          fixed       3  63, 79, 99
FEED           fixed       3  0.206, 0.274, 0.343
DEPTH OF CUT   fixed       3  0.6, 1.0, 1.6
TYPE OF TOOL   fixed       3  CVD coated, PVD coated, Uncoated


Analysis of Variance for Ra VALUES, using Adjusted SS for Tests

Source         DF   Seq SS   Adj SS   Adj MS        F      P
SPEED           2   0.2132   0.2132   0.1066    12.29  0.003
FEED            2  28.4694  28.4694  14.2347  1641.42  0.000
DEPTH OF CUT    2   0.9351   0.9351   0.4675    53.91  0.000
TYPE OF TOOL    2   1.0922   1.0922   0.5461    62.97  0.000
Error           9   0.0781   0.0781   0.0087
Total          17  30.7880


S = 0.0931248   R-Sq = 99.75%   R-Sq(adj) = 99.52%
```

Where DF-Degrees of Freedom, SS-Sum of Squares, F-F-ratio, P-Predicted value (If the predicted value of a factor is <0.05 then the factor is said to be significant). This analysis is carried out at a significance level of 5% and confidence level of 95%.

From Table 8, it is evident that R^2 is 99.75% and P valves are less than 0.05, hence factors are significant to 95% level of confidence [11]. Compare the Table 7 with Table 8, it is observed that the values obtained through Taguchi robust design methodology and Minitab software is the same.

5.3.2: Flooded machining:

As seen from Table 9, feed rate has major contribution of 95.91% in optimizing the performance characteristics followed by depth of cut, type of tool and cutting speed to minimize the surface roughness under flooded machining[9]. Further, it is also observed that ANOVA has results in 0.41% of error contribution [11].

TABLE: 9 Summary of ANOVA in flooded machining on surface roughness

FACTOR	S.S	D.O.F (D_f)	M.S.S (M_{SS})	F-RATIO (DATA)	SS^1	ρ %
Speed	0.108933	2	0.054467	8.3651	0.095911	0.36%
Feed	25.4332	2	12.7166	1953.06	25.42018	95.91%
Doc	0.525733	2	0.262867	40.372	0.512711	1.93%
Tool	0.376133	2	0.188067	28.883	0.363111	1.37%
Error	0.0586	9	0.006511		0.110689	0.41%
S_t	26.5026	17				100%
Mean	250.4322	1				
St	276.9348	18				

The predicted S/N ratio is calculated using eq. (4) for A1, B1, C1 and D2 parameter level combination is -6.10 dB and verification experiment is conducted with the optimum conditions as shown in Table 6 and its S/N ratio is (η_{expt}) -6.30dB. It is found that the S/N ratio of the verification test is within the limits of the predicted value at 95% confidence level and the objective is fulfilled. These suggested optimum conditions can be adopted [10,11].

The ANOVA is also carried out using Minitab software and their results are shown in Table 10.

TABLE 10: ANOVA Using MINITAB for flooded condition

```
General Linear Model: Ra VALUES versus SPEED, FEED, ...

Factor        Type   Levels  Values
SPEED         fixed       3  63, 79, 99
FEED          fixed       3  0.206, 0.274, 0.343
DEPTH OF CUT  fixed       3  0.6, 1.0, 1.6
TYPE OF TOOL  fixed       3  CVD coated, PVD coated, Uncoated


Analysis of Variance for Ra VALUES, using Adjusted SS for Tests

Source        DF   Seq SS   Adj SS   Adj MS        F      P
SPEED          2   0.1089   0.1089   0.0545     8.37  0.009
FEED           2  25.4332  25.4332  12.7166  1953.06  0.000
DEPTH OF CUT   2   0.5257   0.5257   0.2629    40.37  0.000
TYPE OF TOOL   2   0.3761   0.3761   0.1881    28.88  0.000
Error          9   0.0586   0.0586   0.0065
Total         17  26.5026


S = 0.0806915   R-Sq = 99.78%   R-Sq(adj) = 99.58%
```

From Table 10, it is evident that R^2 is 99.78% and Compare the Table 9 with Table 10, it is observed that the values obtained through Taguchi robust design methodology and Minitab software is the same.

5.3.3. Minimum Quantity Lubrication (MQL) machining

As seen from Table 11, feed rate has major contribution of 96.28% in optimizing the performance characteristics followed by depth of cut, cutting speed and type of tool to minimize the surface roughness under MQL machining [9]. Further, it is also observed that ANOVA has results in 0.58% of error contribution.

TABLE 11: Summary of ANOVA in MQL machining on surface roughness

FACTOR	S.S	D.O.F (D_f)	M.S.S (M_{SS})	F-RATIO (DATA)	SS^1	ρ %
Speed	0.2061	2	0.10305	14.75	0.192133	0.94%
Feed	19.5841	2	9.79205	1402.20	19.57013	96.28%
Doc	0.3787	2	0.18935	27.11	0.364733	1.79%
Tool	0.0931	2	0.04655	6.666	0.079133	0.38%
Error	0.06285	9	0.006983		0.118717	0.58%
S_t	20.32485	17				100%
Mean	219.8705	1				
St	240.1953	18				

The predicted S/N ratio is calculated using eq. (4) for A1, B1, C2 and D1 parameter level combination is -5.74 dB and verification experiment is conducted with the optimum conditions as shown in Table 6 and its S/N ratio is (η_{expt}) -5.48 dB. It is found that the S/N ratio of the verification test is within the limits of the predicted value at 95% confidence level and the objective is fulfilled. These suggested optimum conditions can be adopted [10].

The ANOVA is also carried out using Minitab software and their results are shown in Table 12.

From Table 12 it is evident that R^2 is 99.69%. Compare the Table 11 with Table 12, it is observed that the values obtained through Taguchi robust design methodology and Minitab software is the same.

Table 13 shows the comparison of results by robust design methodology. The surface roughness improvement between starting condition and optimum condition for dry, flooded and MQL conditions are shown in Table 13. It is observed that slight improvement is shown i.e. the optimum condition values are lower than the starting condition values [12].

TABLE 12: ANOVA using MINITAB for MQL condition

```
General Linear Model: Ra VALUES versus SPEED, FEED, ...

Factor        Type   Levels  Values
SPEED         fixed       3  63, 79, 99
FEED          fixed       3  0.206, 0.274, 0.343
DEPTH OF CUT  fixed       3  0.6, 1.0, 1.6
TYPE OF TOOL  fixed       3  CVD coated, PVD coated, Uncoated


Analysis of Variance for Ra VALUES, using Adjusted SS for Tests

Source        DF   Seq SS   Adj SS  Adj MS        F      P
SPEED          2   0.2061   0.2061  0.1031    14.76  0.001
FEED           2  19.5841  19.5841  9.7920  1402.20  0.000
DEPTH OF CUT   2   0.3787   0.3787  0.1893    27.11  0.000
TYPE OF TOOL   2   0.0931   0.0931  0.0465     6.67  0.017
Error          9   0.0629   0.0629  0.0070
Total         17  20.3248


S = 0.0835663   R-Sq = 99.69%   R-Sq(adj) = 99.42%
```

TABLE: 13: Comparison results of robust design method for surface roughness

Measurement	Starting condition	Optimum condition	Improvement
Surface roughness for dry condition	2.095	1.91	0.185
S/N Ratio (Dry condition)	-6.43	-5.62	0.81
Surface Roughness for flooded Condition	2.17	2.065	0.105
S/N Ratio (Flooded condition)	-6.73	-6.30	0.43
Surface roughness for MQL condition	2.01	1.88	0.13
S/N Ratio (MQL condition)	-6.07	-5.48	0.59

5.4 REGRESSION ANALYSIS:

Multiple regression analysis [10] has been successfully implemented to develop multiple regression prediction models using the predictors viz. cutting speed, feed rate, depth of cut and three of carbide tool materials for three lubricant Conditions such as dry, flooded and MQL. Minitab software has been used for the analysis of the experimental work. The Minitab software utilizes the specified data to develop predictive models for surface roughness under dry, flooded and MQL conditions.

5.4.1. Dry condition

After Regression analysis under dry machining, the final second order regression model is given by:

$\hat{Y}$ = - 8.78 + 0.0501 Vc + 28.2 F + 7.18 D + 0.0053 Vc x F - 9.12 F x D - 0.0513 D x Vc - 0.194 X_1 + 0.592 X_2

Where, $\hat{Y}$ = surface roughness; Vc = cutting speed; F=feed rate; D= depth of cut; and X_1, X_2 are the indicator variables of tool materials respectively. The specifications of the indicator variables are shown in the Table 3. By considering the values of the indicator variables the equations are obtained for three carbide tool materials i.e. Uncoated, CVD coated and PVD coated.

Regression model for uncoated carbide tool is:

$\hat{Y}$ = - 8.188 + 0.0501 Vc + 28.2 F + 7.18 D + 0.0053 (Vc x F) - 9.12 (F x D) - 0.0513 (D x Vc).

Regression model for CVD coated carbide tool is:

$\hat{Y}$ = - 8.974 + 0.0501 Vc + 28.2 F + 7.18 D + 0.0053 (Vc x F) - 9.12 (F x D) - 0.0513 (D x Vc).

Regression model for PVD coated carbide tool is:

$\hat{Y}$ = - 8.78 + 0.0501 Vc + 28.2 F + 7.18 D + 0.0053 (Vc x F) - 9.12 (F x D) - 0.0513 (D x Vc).

5.4.2 Flooded condition

After Regression analysis under flooded machining, the final second order regression model is given by:

$\hat{Y}$=- 3.47 - 0.0230 Vc + 20.0 F + 5.27 D + 0.134 Vc x F - 10.4 F x D - 0.0229 D x Vc - 0.239 X_1 + 0.221 X_2

Regression model for uncoated carbide tool is:

$\hat{Y}$=- 3.249 - 0.0230 Vc + 20.0 F + 5.27 D + 0.134 (Vc x F) - 10.4 (F x D) - 0.0229 (D x Vc)

Regression model for CVD coated carbide tool is:

$\hat{Y}$=- 3.709 - 0.0230 Vc + 20.0 F + 5.27 D + 0.134 (Vc x F) - 10.4 (F x D) - 0.0229 (D x Vc)

Regression model for PVD coated carbide tool is:

$\hat{Y}$=- 3.47 - 0.0230 Vc + 20.0 F + 5.27 D + 0.134 (Vc x F) - 10.4 (F x D) - 0.0229 (D x Vc).

5.4.3 Minimum Quantity Lubrication (MQL) condition

After Regression analysis under MQL machining, the final regression model is given by:

$\hat{Y}$ = - 2.11 + 0.0046 Vc + 23.0 F - 0.90 D - 4.20 F x D - 0.0016 D x V + 1.07 D x D - 0.263 X_1 - 0.177 X_2

Regression model for uncoated carbide tool is:

$\hat{Y}$ = - 2.287 + 0.0046 Vc + 23.0 F - 0.90 D - 4.20 (F x D) - 0.0016 (D x V) + 1.07 (D x D).

Regression model for CVD coated carbide tool is:

$\hat{Y}$ = - 2.373 + 0.0046 Vc + 23.0 F - 0.90 D - 4.20 (F x D) - 0.0016 (D x V) + 1.07 (D x D).

Regression model for PVD coated carbide tool is:

$\hat{Y}$ = - 2.11 + 0.0046 Vc + 23.0 F - 0.90 D - 4.20 (F x D) - 0.0016 (D x V) + 1.07 (D x D).

Table 14 Regression Table

i. Dry machining

Predictor	Coef	SE Coef	T	P
Constant	-8.781	2.008	-4.37	0.002
Vc	0.05009	0.02569	1.95	0.083
F	28.233	7.354	3.84	0.004
D	7.183	1.213	5.92	0.000
V*F	0.00525	0.08210	0.06	0.950
F*D	-9.120	2.942	-3.10	0.013
D*V	-0.05128	0.01117	-4.59	0.001
X1	-0.1940	0.1634	-1.19	0.265
X2	0.5925	0.1436	4.13	0.003

S = 0.0931248 R-Sq = 99.7% R-Sq(adj) = 99.5%

ii. Flooded Machining

Predictor	Coef	SE Coef	T	P
Constant	-3.471	1.740	-1.99	0.077
Vc	-0.02298	0.02226	-1.03	0.329
F	19.975	6.372	3.14	0.012
D	5.270	1.051	5.02	0.001
V*F	0.13428	0.07114	1.89	0.092
F*D	-10.392	2.549	-4.08	0.003
D*V	-0.022945	0.009681	-2.37	0.042
X1	-0.2392	0.1416	-1.69	0.125
X2	0.2211	0.1245	1.78	0.109

S = 0.0806915 R-Sq = 99.8% R-Sq(adj) = 99.6%

iii. MQL Machining

Predictor	Coef	SE Coef	T	P
Constant	-2.1081	0.9353	-2.25	0.051
Vc	0.00457	0.01108	0.41	0.690
F	23.022	2.919	7.89	0.000
D	-0.897	1.153	-0.78	0.456
F*D	-4.204	2.640	-1.59	0.146
D*V	-0.00164	0.01003	-0.16	0.874
D*D	1.0667	0.1753	6.09	0.000
X1	-0.2627	0.1465	-1.79	0.106
X2	-0.17680	0.09443	-1.87	0.094

S = 0.0835663 R-Sq = 99.7% R-Sq(adj) = 99.4%

Table 15 Analysis of variance

i. Dry machining

Source	DF	SS	MS	F	P
Regression	8	30.7100	3.8388	442.65	0.000
Residual Error	9	0.0780	0.0087		
Total	17	30.7881			

ii. Flooded Machining

Source	DF	SS	MS	F	P
Regression	8	26.4440	3.3055	507.67	0.000
Residual Error	9	0.0586	0.0065		
Total	17	26.5026			

iii. MQL Machining

Source	DF	SS	MS	F	P
Regression	8	20.2620	2.5327	362.68	0.000
Residual Error	9	0.0628	0.0070		
Total	17	20.3248			

In regression Table14 and Analysis of variance Table 15, the P value (0.000) for regression is <0.05 indicating that at least one of the terms in the model have a significant effect on the mean response of surface roughness[10]. From regression Table 14 the P values of predictors such as cutting speed(V), feed rate(F), depth of cut(D) and type of tool material(X1,X2) and interactions are < 0.05 i.e. these factors are significantly related to surface roughness in a linear fashion. From the regression Table 14 - i, ii and iii, the R-Sq (adj) 99.5%, R-Sq (adj) 99.6% and R-Sq (adj) 99.4% value indicates that variation in observed response is well explained by predictors for dry, flooded and MQL conditions respectively.

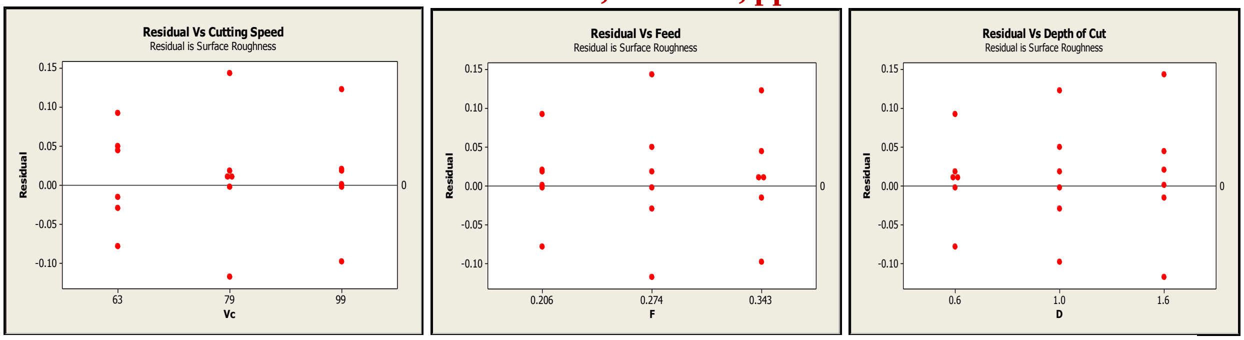
5.4.4. Validation of regression model

The validation of regression model has been carried out by Residual plots.

Residual plots:

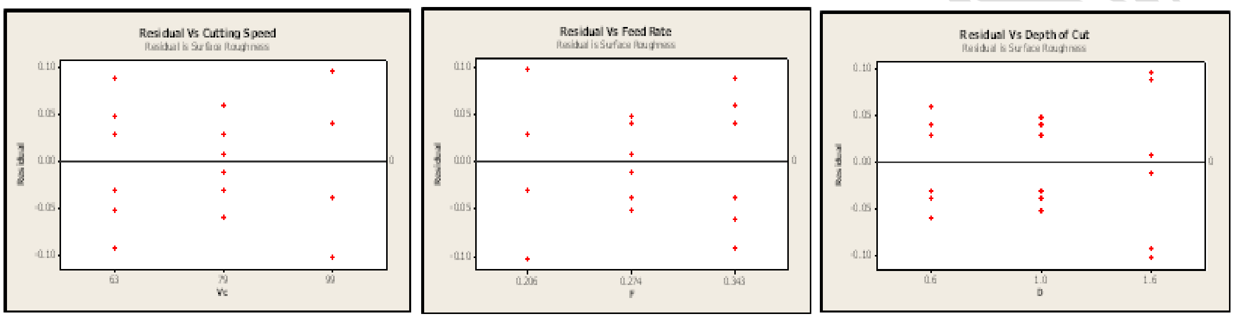
Residual is the difference between actual value (Y_i) and fitted value ($\hat{Y}_i$)**.** Residual plots are used to investigate the adequacy of the fit of a regression model in regression and ANOVA. In multiple regression analysis, if a residual plot of factors shows symmetry in the points, there is no need to add higher order terms of the variables for those factors [12]. If there is asymmetry in points then there is a need to add higher order terms of the variables for factors. Residuals are plotted for each individual factor at each level.

The residual plots “residuals vs cutting speed”, “residuals vs feed” and “residuals vs depth of cut” for dry, flooded and MQL condition are shown in Figure 11,12 and 13. In this final analysis from these plots not showed any asymmetry in the points. These residual plots are scattered randomly about zero i.e. the variables are influencing the surface roughness in a systematic way and it indicates that there is no need to add higher order terms of variables.



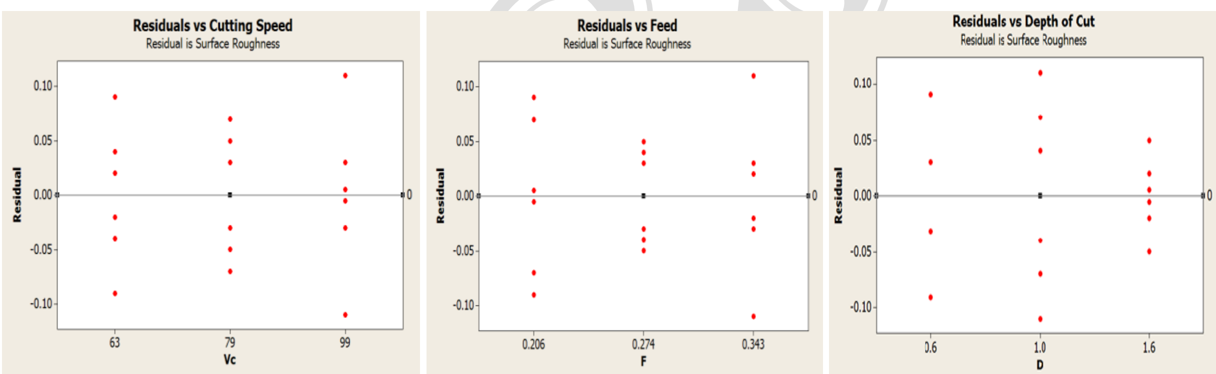
a)Residuals vs cutting speed b) Residuals vs feed rate c) Residuals vs depth of cut

Figure 11: Residual plots for dry machining



a) Residuals vs cutting speed b) Residuals vs feed rate c) Residuals vs depth of cut

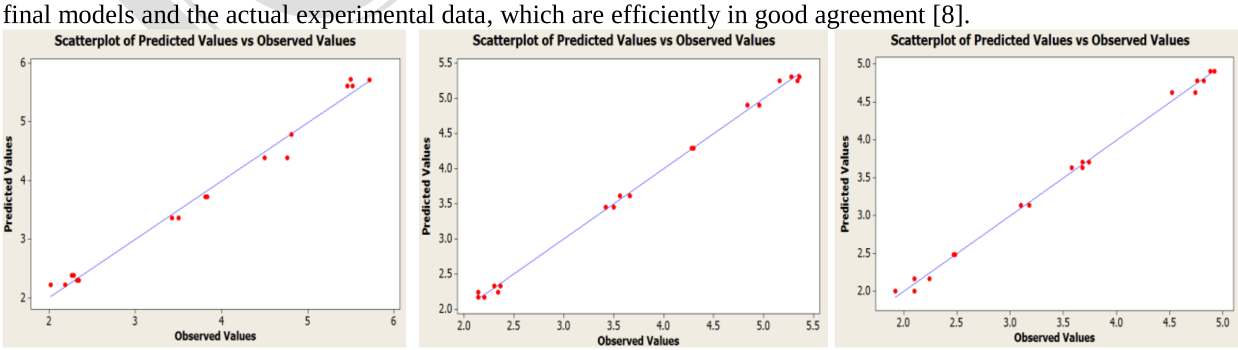
Figure 12: Residual plots for flooded machining



a) Residuals vs cutting speed b) Residuals vs feed rate c) Residuals vs depth of cut

Figure 13: Residual plots for MQL machining

Figure 14 shows the predicted values of different lubricant conditions such as dry, flooded and MQL obtained from the final models and the actual experimental data, which are efficiently in good agreement [8].



i. Dry machining ii. Flooded Machining iii. MQL Machining

Figure: 14: Predicted Versus Actual Values Plot

6.0 CONCLUSIONS:

The objectives of this work are to investigate effect cutting fluid and optimization of process parameters in order to reduce surface roughness under dry, flooded and Minimum Quantity Lubrication lubricant conditions using Taguchi's robust design methodology and to develop the prediction models for surface roughness in turning of Ti-6Al-4V alloy using multiple regression analysis. Based on the results of these experimental investigations, the following conclusions can be drawn:

- The cutting performance of Minimum Quantity Lubrication condition showed better results compared to dry and flooded conditions in reduction of surface roughness.
- Using Analysis of Variance (ANOVA) the individual factor effects are found out and concluded that the effect of feed rate is more on the surface roughness for all lubrication conditions compared to other factors.
- The analysis of conformation experiments has shown that Taguchi robust design methodology can successfully verify the optimum cutting parameters. The values obtained from ANOVA using robust design methodology are compared with the ANOVA from Minitab software. Hence, for all the cases i.e. Dry, Flooded and MQL conditions the values obtained are same in both Taguchi robust design methodology and Minitab.
- The Multiple Regression Analysis method is used to develop the surface roughness prediction models using the predictors such as cutting speed, feed, depth of cut and type of tool material for all lubricant conditions. Three different multiple regression models are developed for three tool materials such as uncoated, CVD coated and PVD coated under dry, flooded and MQL conditions. These models show good agreement with experimental results.

7.0 REFERENCES

[1] E.O. Ezugwu and Z.M. Wang "Titanium alloys and their machinability- a review", Journal of Materials Processing Technology Vol.68, 1997 pp: 262-274.

[2] N.R. Dhar, M.W. Islam, S. Islam and M.A.H. Mithu "The influence of minimum quantity of lubrication (MQL) on cutting temperature, chip and dimensional accuracy in turning AISI-1040 steel", Journal of Materials Processing Technology Vol.171, 2006 pp: 93–99.

[3] V.N. Gaitonde, S.R. Karnik and J. Paulo Davim "Selection of optimal MQL and cutting conditions for enhancing machinability in turning of brass", Journal Of Materials Processing Technology Vol.204, 2008 pp: 459–464.

[4] M.M.A. Khan, M.A.H. Mithu and N.R. Dhar "Effects of minimum quantity lubrication on turning AISI 9310 alloy steel using vegetable oil-based cutting fluid", Journal of Materials Processing Technology Vol. 209, 2009 pp:5573–5583.

[5] Vishal S.Sharma, Manu Dogra and N.M.Suri "Cooling techniques for improved productivity in turning", International Journal of Machine Tools & Manufacture Vol.49, 2009 pp: 435–453.

[6] E.A. Rahim and H.Sasahara "A study of the effect of palm oil as MQL lubricant on high speed drilling of titanium alloys", Tribology International Vol. 44, 2011 pp: 309–317.

[7] M. Venkata Ramana, K.Srinivasulu, G.Krishna Mohan Rao and D. Hanumantha Rao, 2011, "Performance Evaluation and Selection of Optimal Cutting Conditions in Turning of Ti-6Al-4V Alloy under Different Cooling Conditions", International Journal of Innovative Technology & Creative Engineering, 1(5), pp 10-21.

[8] Francisco Mata, Elena Beamud, Issam Hanafi, Abdellatif Khamlichi, Abdallah Jabbouri and Mohammed Bezzazi "Multiple Regression Prediction Model for Cutting Forces in Turning Carbon-Reinforced PEEK CF30" Advances in Materials Science and Engineering Vol. 2010, Article ID 824098, 7 pages.

[9] Phillip J. Ross "Taguchi Techniques for Quality Engineering", Tata McGraw Hill, Second Edition, 2005.

[10] Douglas C. Montogomery, Elizabeth A. Peck and G.Geoffrey Vining "Introduction to Linear Regression Analysis" Arizona State University, 2001.

[11] Minitab Statistical Software Features - Minitab." Software for Statistics, Process Improvement, Six Sigma, Quality - Minitab. N.p., n.d. Web. 11 Apr. 2011.

[12] Kodandaram K., Srinivasa Raju S .V.S.S., Chandrasheker J., Nagendra A, "Prediction of Surface Roughness in Turning Process Using Taguchi Design of Experiments and Developing Regression Model", 3rd Intl & 24th AIMTDR conference, Dec..2010, pp 379-384.