# "Investigation of Effect of Machining Parameters in CNC Milling For Surface Quality and Its Optimization"

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## ABSTRACT

*Prediction of surface roughness and dimensional inaccuracies is an essential prerequisite for any unmanned computer numeric controlled (CNC) machinery. This prediction technique is also important for optimization of machining process. In the present work, it is observed that, using Taguchi approach, the quality of surface finish can be predicted within a reasonable degree of accuracy. Surface roughness is the critical factor which influences the quality of the machined parts.*

*In this research work, an attempt has been made to optimize the cutting conditions to get predicted surface roughness in end milling of mild steel work piece. The experiment was designed using Taguchi method and 16 experimental runs were conducted for various combinations of cutting parameters according to L16' orthogonal array technique. The orthogonal array, signal to noise ratio and analysis of variance (ANOVA) were employed to study the performance characteristics at different conditions. In order to analyze the response of the system, experiments were carried out at various spindle speeds, depth of cut and feed rate. The results obtained by this research will be useful for various industries and researchers working in this field.*

*Feed rate is observed to be main parameters affecting surface roughness. Regression equation is formulated for estimating predicted values of surface roughness. Finally, to illustrate the effectiveness of the regression equation, the rate of error is found between the actual and predicted surface roughness values.*

***Keywords:*** *CNC; Taguchi; Surface roughness; ANOVA; Regression.*

## 1. INTRODUCTION

This is the era of Customized market rather than Custom Market. In this era of customized market the industries are preparing themselves to produce the products according to the need of customers to stay in this competitive market. Specially, Manufacturing sectors are facing a new challenge of customized demand fulfillment rapidly to provide outstanding services to their customers. Due to „Mass Customization" along with the flexibility according to the changing environment of the market the industries are adopting the trend of modern machineries. These modern machineries are fully programmable with high output rates. Computer numeric controlled (CNC) machines are the part of these modern machineries in manufacturing segment. Numerous segments are opting for these CNC Cells like Automobiles, Textiles, Cement, Steel, Heavy Engineering and many more. Industries are using a number of CNC cells like according to applications like CNC- Milling, Boring, Turning, Drilling etc. Out of the above stated machines the milling machines are considered to be more versatile as a large number of machining components requires various milling operation for surface quality. Better operator monitoring should be there while working with these machineries. Although these machines can provide a better surface quality but the present need of market ask for customized surface quality. To achieve this target the major influencing parameters must be identified which affect the value of surface roughness in end milling operation. Although numerous industries and small as well as medium scale enterprises had provided the readily available solution for such problems but those results have their certain limitations. Thus present study focuses on developing such a model by which the operator can set in advance all the machining parameters according to the surface quality. There is no need to set those values to control surface finish while working on the job.

## 1.1 METAL MACHINING

Metal machining is a major concerning area in which a number of researches are going on throughout the world. With the advancement and technical revolution this segment has become the most challenging segment for industrialist and researchers. All the industries are moving towards increasing their production with maximizing their profit which is the need of today's economy. The only solution to this problem is to use automated CNC cells with better controlling over the machining parameters. Along with that better operator monitoring should be there.

In this global manufacturing environment, this is the need of market to produce the best quality product at least cost. it is only possible if the industries fulfill the following criterion like component according to need of customers, less wear, fast delivery, dimensional accuracy, better surface quality, high performance rates and reduced wastage etc. The mechanism behind the formation of surface roughness is very dyn amic, complicated, and process dependent which need continuous operator monitoring else that may lead to defects.

There are various machined parts which may cause unusual behaviour if surface quality is not maintained over those parts like couplings, aircraft fittings, valves, gaskets etc. usually these parts are made up of light in weight material having durability and corrosive resistance. Thus, Aluminium alloy is proven to be right material which matches the above discussed properties and applications. Aluminium Alloy is commonly used alloy in most of the industries dealing in manufacturing of these components.

Instead of all these techniques it is best method to employ statistical techniques for optimizing the cutting parameters to obtain best set of results. We can use robust design methodology for optimizing the results. Numerous statistical methodologies like Correlation Techniques, Pareto Chart method, Analysis of variance (ANOVA), Artificial Nural Network (ANN) technique, Regression method and many more other techniques are most widely used by researchers for obtaining best set of results.

## 1.2 OBJECTIVES

Looking to the need of studies in the field of predictive modeling of surface roughness in the turning operation the following objectives are shortlisted:

1. To study the effect of different machining parameters on surface roughness in CNC Milling process.
2. To perform the experimentation according to "Taguchi Methodology" at different cutting parameters with their varying levels and to collect the respective response results.
3. To identify the degree of correlation between the cutting parameters and surface roughness using "Pareto Chart".
4. To apply the "Analysis of Variance (ANOVA) technique" to obtain best set of cutting parameters.

## 2. LIERATURE REVIEW

### 2.1 CURRENT AND PREVIOUS STUDIES

Current and previous studies are basically reviewed to analyze the gap between conventional technologies and current technologies. By in-depth analysis of these studies it can be easily judged that how the technology is moving ahead and still what is the research gap that can be a step ahead towards future extension of that particular work. Thus, that previous work and literatures provide a path and guidance for future work so that objectives can be planned.

#### 2.1.1 Manufacturing and Machining Technology

The ‘Manufacturing Segment’ is a major sector in global economic market. Manufacturing is a key to development throughout the world. The economic prosperity of a nation is directly linked to the manufacturing capabilities of the nation. Manufacturing indeed has positive impact on GDP growth of the country**.**

Metal cutting technology is a most influencing part of any mechanical manufacturing facility. It is alsoconsidered as the most commonly employed metal shaping process by which whatever type of component we want we can get.

Generally, the term metal cutting is defined as an operation in which a thin layer of metal is removed from a larger body by using a wedge-shaped tool. The term machining can be defined as a metal cutting process in which both the workpiece and the tool are held firm by a power-driven mechanical structure and the material removed from the work piece in form of chips is instigated by the relative motion between tool and work piece. Machining process can be subdivided into following four major types, based upon the mode of material removal**.**

1. Turning.
2. Drilling.
3. Shaping/Planing.
4. Milling.

#### 2.1.2 A Review of Automation in Machine Tool

Researchers involved in manufacturing research and industries are continuously optimizing the manufacturing systems to produce parts or products that are good in quality, delivered on time and lower in cost. This will not only make the company to survive in the today’s competitive world but it will also delight the customer. A manufacturing system is defined as, a complex arrangement of the following four physical elements

- Machine tool
- Tools and tooling
- People
- Material handling equipments

The measureable output of a manufacturing system can be characterized by the following measurable parameters;

1. Productivity
2. Defects rate
3. Unit cost, etc.

The manufacturing system will be highly optimized, effective and cost efficient if incorporation of these four physical elements is good. Machine tool, among above four physical elements, in particular plays a very important role because its function is to add value in term of quality, cost and time in manufacturing. There are improvements going on in technologies in manufacturing to make a machine tool more precise and efficient. Numerical control, NC, refers to the automated machine tool that is operated by coded programmed commands. The first NC machine was built in the late 1940s, and since then, research and new developments have been continuously striving to produce better and smart machines

**2.1.3 Statistical Tools**

Since long, statistical techniques or mathematical techniques had become a choice of researchers. These techniques have been a part of all researches for optimizing the results and identifying the parameter effect relative to each other.

Such techniques may be as follows:

1. Design of experiment (DOE): Full Factorial design,
2. Taguchi Method: Orthogonal Array Technique
3. Analysis of variance (ANOVA)
4. Artificial Neural Network (ANN) Technique
5. Pearson's Correlation Technique
6. Pareto Analysis
7. Work Study methods
8. Regression Technique etc.

For obtaining best set of results and for improving quality of work these techniques may be highly helpful which show the results in accurate manner .These techniques may explore the effect of all parameters affecting the results. As conclusions drawn from the various studies, the Taguchi design methodology is found to be a easily adoptable technique. It uses a set of a strategically designed experiment which can give a best set of result Taguchi methodology uses the orthogonal array technique to choose the minimum and best set of experiments which is also known as fractional design approach. In minimum numbers of experiments all the parameter combinations are involved in Taguchi methodology which is not possible in fractional design approach at all Numerous informative studies related tooptimization of cutting parameters in machining operations have been accomplished by using Taguchi parameter design method with different combinations and levels of cutting speed, feed rate, depth of cut, cutting time, workpiece length, cutting tool material, cutting tool geometry, coolant, and other machining parameters.

Analysis of variance has also been proven a best statistical tool for obtaining significance level and involvement of each variable in affecting response parameter.

Analysis of variance (ANOVA) technique is found to be best technique for obtaining the level of significance among various parameters involved in the study.

In some studies, ANOVA was employed to develop empirical models to analyze response of the system. ANOVA is a best tool for recognizing most significant variables and their interaction effects along with their percentage contribution in affecting the response value.

A number of studies have been accomplished in which Regression technique was used for acquiring predicted results and it has proven to be a good tool for such applications with better approximation and minimum error. Regression is basically applied to only highly correlated data which affect the surface roughness. For that, numerous researchers have used different methods like Pearson's correlation technique, Pareto chart analysis and many more. Thus, from the literature reviewed it has clearly identified that, statistical tools has become first choice of the researchers and scholars to optimize their work and these techniques serve all the intended purpose to fulfil their objectives.

## 3. MATERIALS AND METHODS

### 3.1 Experimental Setup

Present study basically involves the use of 'Milling Operation' as it is most widely adopted method for machining. Thus, for accomplishment of the present work, the experimental setup is needed to select which involves a set of machineries which are used for completion of the work along with the material used for workpiece. The requirements of experimental setup are as follows:

- CNC Milling Machine
- Workpieces
- Surface roughness tester

A brief description of all these components has been presented below.

### 3.1.1 CNC Milling Machine

In accordance with objective of the present work, the machine selected for present experiment is CNC Milling machine. The machine tool selection is a crucial factor which affects the outcome of experimental work. Thus, it should be selected in such a manner that it incorporates the basic needs of the present study like desired range of spindle speed, depth of cut and feed rate etc. In present time the technology of CNC vertical milling machine has been improved significantly to meet the advance requirements in various manufacturing fields, especially in the precision metal cutting industry. This experiment gives the effect of different machining parameters (spindle speed, feed, and depth of cut) on material removal rate in end milling.

Horizontal Milling Centre has some other special features that help in better machining and surface finish. The major technical specifications of the machine are given in Table 3.1. This experiment is performed with dry cutting i.e. without use of coolant.

Table 3.1: Technical Specifications of CNC Machine

| Sr. No. | Specifications | Range |
|---|---|---|
| 1 | Table Size | 1000*530 $mm^2$ |
| 2 | Spindle speed | 0-8000 rpm |
| 3 | Spindle motor power | 4.5-10.5 kW |
| 4 | Maximum tool length | 250 mm |
| 5 | Maximum tool weight | 7 kg. |
| 6 | Controller | Fanuc- Siemens |
| 7 | Number of station on tool changer | 20 |
| 8 | Weight | 5700 kg |
| 9 | Max. travel in X Axis | 820 mm |
| 10 | Max. travel in Y Axis | 510 mm |
| 11 | Max. travel in Z Axis | 510 mm |

Fig 3.1: Layout of CNC Machine

### 3.1.2 Material

For present experimental work, Low Carbon Mild Steel is chosen which is a most widely used alloy in the manufacturing industries for production of numerous components. There are different grades of mild steel alloy used in the industries out of that for present work low carbon grade is chosen having good workability as well as good weldability.

Mechanical properties and chemical composition of Mild steel is as shown in Table 3.2 and Table 3.3 respectively.

The dimensions of the workpieces are as follows:

- Length : 100mm
- Breadth : 30 mm
- Height : 20 mm

### 3.1.3 Surface Roughness Tester

After completion of machining process on the workpieces, their surface roughness is measured for further analysis. There are various surface roughness measurement techniques, by which in-process and post-process measurements can be taken. Usually, the techniques of measuring roughness of machined parts can be classified into two categories:

- ➢ Non-Contact Surface Roughness Measurements Technique
- ➢ Contact Surface Roughness Measurements Technique

The instrument used for present work was Mitutoyo Surftest SJ-201P as shown in Figure 3.3. The measurements were obtained with the help of movement of stylus with diamond tip over the surface. The surftest SJ-201P (mitutoyo) is a shop–floor type surface-roughness measuring instrument, which traces the surface various machine parts and calculates the surface roughness based on roughness standards, and displays the results.


## 3.2 TAGUCHI DESIGN APPROACH

This section presents a detailed description about experimental work and data collection system for the present work as per Taguchi design methodology which is fractional orthogonal array technique. Taguchi method is a statistical method to improve the quality of manufactured goods, and more recently this technique is widely applied to engineering problems. These are the optimization tools by which best set of results can be obtained by conducting minimum number of experiments thus called 'Fractional' design approach. Taguchi method uses a special set of arrays called 'Orthogonal Arrays'. These standard arrays stipulate the way of conducting the minimal number of experiments which could give the full information of all the factors that affect the performance parameter. The bottom of the orthogonal arrays method lies in choosing the level combinations of the input design variables for each experiment.

### 3.2.1Steps for Taguchi Method

The design of an experiment by Taguchi method involves the following steps:

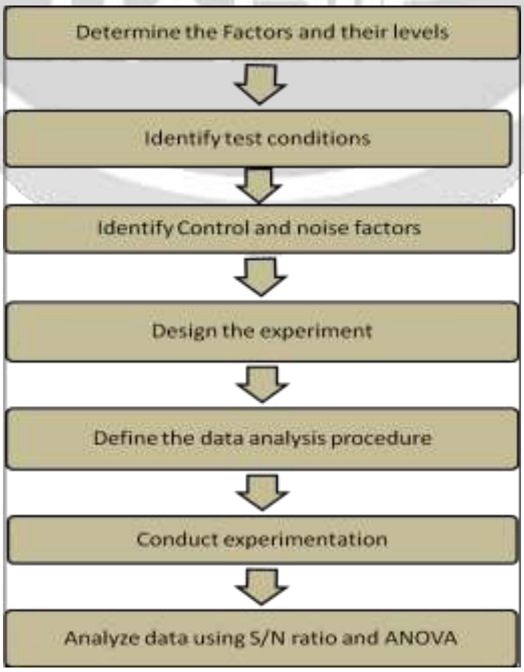
i. Define the process objective
ii. Selection of independent variables
iii. Selection of number of level settings for each independent variable
iv. Selection of orthogonal array
v. Assigning the independent variables to each column
vi. Conducting the experiments
vii. Analyzing the data
viii. Inference

**3.2.2 Experimental Levels and Orthogonal Array Selection**

The effect of various parameters on the performance characteristic in a condensed set of experiments 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 the levels of a variable requires an in-depth understanding of the process, including the minimum, maximum, and current value of the parameter. Also, the cost of conducting experiments must be considered when determining the number of levels of a parameter to be included in the experimental design. Typically, the number of levels for all parameters in the experimental design is chosen to be the same to aid in the selection of the proper orthogonal array.

There is one more approach by which the array can be selected directly by statistical software approach i.e. MiniTab statistical software. This is also a quite easy approach in which just by entering the number of factors and their corresponding number of levels, the software will itself provide us the suitable type of orthogonal arrays for particular study.

For the present work, the experimental levels for the controlled factors are as shown in Table 3.6, where all the three controlled factors i.e. spindle speed (SS), depth of cut (DC) and feed rate (FR) have four levels.



Flow Chart 3.1: Pictorial Depiction of Steps in Taguchi

| Number of Levels | Number of Parameters (P): 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | L4 | L4 | L8 | L8 | L8 | L8 | L12 | L12 | L12 | L12 | L16 | L16 | L16 | L16 | L32 | L32 | L32 | L32 | L32 | L32 | L32 | L32 | L32 | L32 | L32 | L32 | L32 |
| 3 | L9 | L9 | L9 | L18 | L18 | L18 | L18 | L27 | L27 | L27 | L27 | L27 | L36 | L36 | L36 | L36 | L36 | L36 | L36 | L36 | L36 | | | | | | |
| 4 | L'16 | L'16 | L'16 | L'16 | L'32 | L'32 | L'32 | L'32 | L'32 | | | | | | | | | | | | | | | | | | |
| 5 | L25 | L25 | L25 | L25 | L25 | L50 | L50 | L50 | L50 | L50 | L50 | | | | | | | | | | | | | | | | |

Table 3.1: Orthogonal Array Selector

Thus, for the present experimental levels, from the given orthogonal array selector table, L16' orthogonal array was chosen which requires 16 experimental runs to be conducted to test all the factors to analyze the results. The combinations of these cutting parameters for experimentation were obtained by Taguchi design of experiment through MiniTab-17 statistical software as shown in Table 3.1

The experiment will involve following variables:

- Independent variables:

i. Spindle speed(SS)
ii. Depth of cut (DC)
iii. Feed rate (FR)

- Dependent variables:

i. Surface roughness($R_a$)

For conducting the experiment each controlled factor or independent variable will have certain fixed levels as shown in Table 3.3 and this will result in total of 16 runs to be conducted as per L16' orthogonal array in Taguchi methodology.

Table 3.2: Experimental Levels of Cutting Parameters

| Cutting Parameters | Units | No. of Levels | Values For Each Level | | | |
|---|---|---|---|---|---|---|
| | | | Level 1 | Level 2 | Level 3 | Level 3 |
| SS | rpm | 4 | 1500 | 2000 | 2500 | 3000 |
| DC | inches | 4 | 0.01 | 0.02 | 0.03 | 0.04 |
| FR | ipr | 4 | 0.001 | 0.002 | 0.003 | 0.004 |

- **Experimental Process**

For completion of the present study, a randomized schedule of runs was created according L16' orthogonal array experimental setup at various combinations according to Taguchi design of experiments as shown in Table 3.3. The end milling process was performed the ends of workpiece on one side to measure final surface roughness and machining was performed linearly. After completion of all the runs, the surface roughness of all the work pieces was measured using SJ-201P Surface roughness tester.

Table 3.3: Design of Experiment via Taguchi Method

| Spindle Speed (rpm) L-1: 1500 | | | | | L-2: 2000 | | | |
|---|---|---|---|---|---|---|---|---|
| Depth of Cut (inches) | | | | | Depth of Cut (inches) | | | |
| FR (ipr) | L-1 0.01 | L-2 0.02 | L-3 0.03 | L-4 0.04 | L-1 0.01 | L-2 0.02 | L-3 0.03 | L-4 0.04 |
| L-1 0.001 | Run 1 | ----- | ----- | ----- | ----- | Run 5 | ----- | ----- |
| L-2 0.002 | ----- | Run 2 | ----- | ----- | ----- | ----- | Run 6 | ----- |
| L-3 0.003 | ----- | ----- | Run 3 | ----- | ----- | ----- | ----- | Run 7 |
| L-4 0.004 | ----- | ----- | ----- | Run 4 | Run 8 | ----- | ----- | ----- |

| Spindle Speed (rpm) L-3: 2500 | | | | | L-4: 3000 | | | |
|---|---|---|---|---|---|---|---|---|
| Depth of Cut (inches) | | | | | Depth of Cut (inches) | | | |
| FR (ipr) | L-1 0.01 | L-2 0.02 | L-3 0.03 | L-4 0.04 | L-1 0.01 | L-2 0.02 | L-3 0.03 | L-4 0.04 |
| L-1 0.001 | ----- | ----- | Run 9 | ----- | ----- | ----- | ----- | Run 13 |
| L-2 0.002 | ----- | ----- | ----- | Run 10 | Run 14 | ----- | ----- | ----- |
| L-3 0.003 | Run 11 | ----- | ----- | ----- | ----- | Run 15 | ----- | ----- |
| L-4 0.004 | ----- | Run 12 | ----- | ----- | ----- | ----- | Run 16 | ----- |

- **Analysis Methodology**

Once the experimental design is determined and the trials have been carried out, the measured performance characteristic from each trial can be used to analyze the relative effect of the different parameters. To determine the effect of each variable on the output, the signal-to-noise (S/N) ratio needs to be calculated for each experiment conducted. In S/N ratio, the signal is representing the desirable value i.e. mean of the output characteristics while the noise represents the undesirable value i.e. squared deviation of output characteristics.

The following equations are used to calculate S/N ratio [MiniTab-17 Free Trial, 2014]:

1) The smaller is better :

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

2) The larger is better:

$$\eta = -10\log_{10}\left(\left(\sum_{i=1}^{n}\frac{1}{y_i^2}\right)/n\right)$$

(3.3)

3) The nominal is best:

$$\eta = 10\log_{10}\sum_{i=1}^{n}\frac{y_i^2}{s^2}$$

Where:

$\eta$ = Signal to Noise ratio

n = No. of repetitions of the experiment

$y_i$ = Measured value of the quality characteristics

s = Variance

The S/N ratios are expressed on the decibel scale.

## 4. RESULTS AND DISCUSSION

In accordance with the strategy of the present work experimentation, in which a fractional experimental runs using orthogonal array technique were created as discussed below.

### 4.1.1 Experimental Run

In accordance with the experimental data collection setup as shown in Table 3.3. This table involves all the results of surface roughness with respect to the given inputs i.e. spindle speed, feed rate and depth of cut. The task of data collection was performed using the given experimental setup as discussed in previous chapter according to L16’ orthogonal array. After selecting L16’ orthogonal array values, Taguchi analysis was applied for obtaining signal to noise ratio (S/N) which is a major emphasizing values for analysis. For identifying S/N ratio response is taken as roughness value while the factors are chosen as spindle speed, feed rate and depth of cut. Out of three methodology discussed in chapter 3 for Taguchi analysis, smaller is better was employed in present analysis.

### 4.1.2 Analysis of Variance, Rank Value and Main Effect Plots

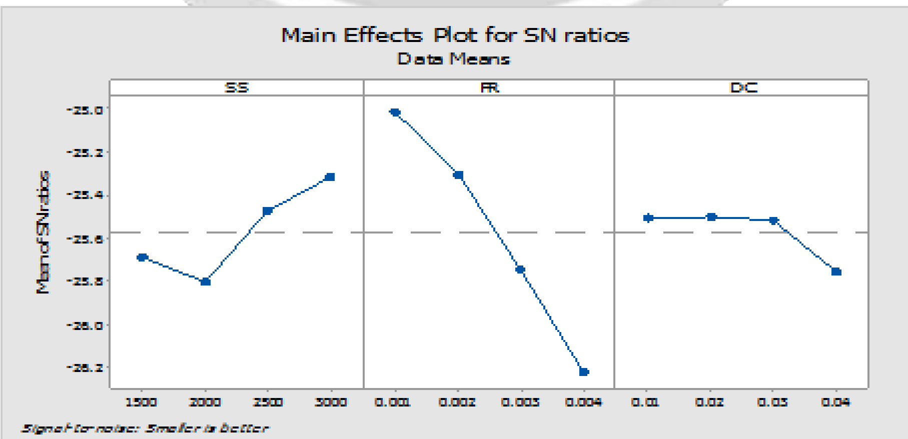
It can be seen by the collected data in that, in end milling operation the surface roughness is affected by all the controlled factors i.e. spindle speed, feed rate and depth of cut. But it is not clearly justified that which factor has significant effect. Hence, Rank table and analysis of variance (ANOVA) table were developed for S/N ratio to explore these observations using MiniTab-17 statistical software.

Therefore, based on S/N ratio and variance analysis tables, the optimal cutting parameters for surface roughness are the Feed rate at level 1, the Spindle speed at level 2 and the Depth of cut at level 3 are shown in Table 4.1.2.

Table 4.1.2: Rank Table for S/N Ratios with Cutting Parameters

| Level | SS | FR | DC |
|---|---|---|---|
| 1 | -25.68 | -25.01 | -25.50 |
| 2 | -25.81 | -25.30 | -25.50 |
| 3 | -25.47 | -25.74 | -25.52 |
| 4 | -25.32 | -26.22 | -25.76 |
| Delta | 0.49 | 1.21 | 0.26 |
| Rank | 2 | 1 | 3 |

It can be analyzed from the main effect plots of S/N Ratio as shown in Graph 4.1.2, that in order to obtain optimized value of surface roughness, the feed rate and depth of cut should be set to their lowest value i.e. 0.001 ipr and 0.01 inch respectively while the spindle speed their highest values i.e. 3000 rpm because for optimization, largest S/N ratio should be employed. Although, Depth of cut has third rank, so it's any level can be chosen because it will not influence the surface roughness.




Graph 4.1: S/N Ratios vs. Cutting Parameters (SS, DC, FR) Plots

## 4.2 Regression Analysis

Regression analysis is performed to formulate predictive equation for most significant data i.e. data having highest correlation coefficient so that it will create more robust model. For that, Pearson's correlation coefficient is measured for each factor with respect to the surface roughness as shown in Table 4.2. The positive correlation is analysed as discussed in the previous chapter and a pie chart is also developed which shows the percentage correlation with surface roughness. Finally, the regression model is created with the help of highly correlated factors to get prediction equation.

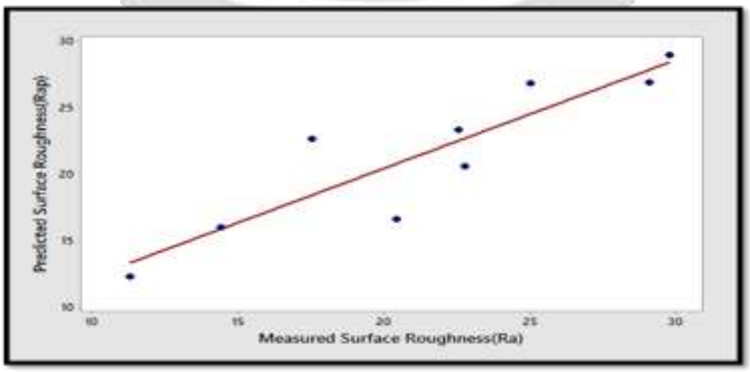
As it can be analyzed from Table 4.2 and that, the feed rate and depth of cut have positive correlation with the surface roughness so these most significant variables can be used in regression analysis to create the predictive equation. Thus, by using these factors the predictive equation was developed through MiniTab-17 statistical software which was found to be:

$$(Ra)_p = 16.331 + 901\ FR + 17.6\ DC$$

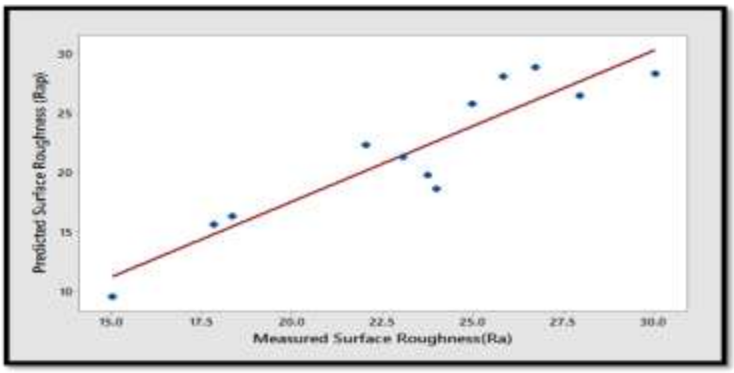
This equation is used to obtain the predicted values of surface roughness using the data of both the experimental and validation run. Initially, the equation was applied for experimental data for each run as shown in to predict the roughness values for given input as used in predictive equation.

Table 4.2: Pearson Correlation of Various Parameters with Surface Roughness

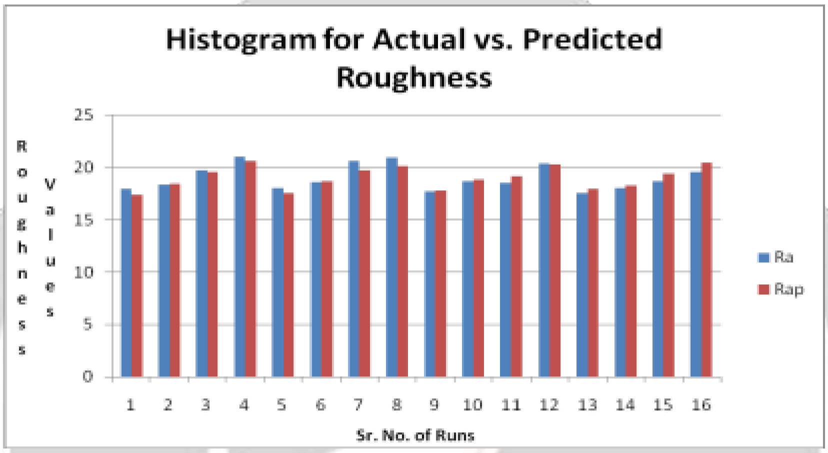
| Sr. No. | Variables | Pearson's Correlation Coefficient |
|---|---|---|
| 1 | SS | -0.312 |
| 2 | DC | 0.876 |
| 3 | FR | 0.176 |



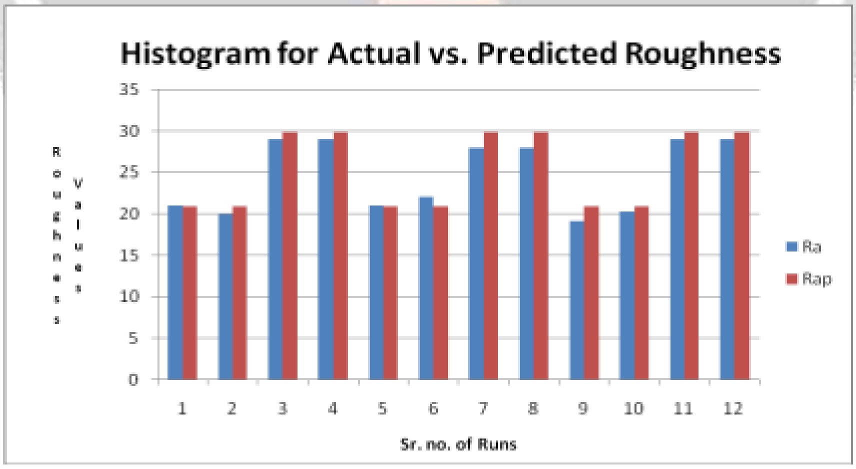

Graph 4.2: Scatter Plot for $Ra_p$ versus Ra for Experimental Run




Graph 4.3: Scatter Plot for $Ra_p$ versus Ra for Validation Run




Flow Chart 4.1: Histogram for $Ra_p$ versus Ra for Experimental Run




Flow Chart 4.2: Histogram for $Ra_p$ versus Ra for Validation Run

## 5. CONCLUSIONS

The present investigation aimed at obtaining controlled Surface roughness during CNC end milling of mild steel work piece with end mill tool. Experiments were accomplished by taking into consideration three factors i.e. spindle speed, depth of cut and feed rate.

The experimentations were performed as per Fractional design approach using L16' orthogonal array technique and furthermore the collected data were analyzed. This analysis was carried out by developing regression model of highly significant arithmetic values obtained by Pearson's correlation approach based on Taguchi design of experiment approach. Main effect plots, histograms, cross relationship curves and various other manual curves were drawn which shows relationship among the collected data.

Finally, the following conclusions may be drawn for fractional design of experiment:

1. It is impossible to achieve surface roughness in controlled manner by 'Trial and Error' method. It needs an in-depth analysis of the parameters affecting it.

2. Surface roughness and cutting parameters (i.e. SS, FR and DC) have highly non-linear relationships among them.

3. Amongst the cutting parameters, surface roughness is strongly affected by feed rate while the depth of cut and spindle speed has least effect on surface roughness.

4. In end milling operation, while predicting the value of surface roughness major emphasis should be given to value of feed rate.

5. Positive effect of cutting tool's temperature was also identified on surface roughness while machining. It shows that to achieve accurate value of required surface roughness, effect of cutting tool's temperature can also be considered.

6. The fractional design approach is proven to be a best choice because it involves only a number of effective possible combinations of parameter values and gives minimum error rate hence shows accuracy of the experimental setup and statistical model and roughness values can be predicted up to close level of accuracy and precision.

7. Validation run performed for fractional design of experiment approach shows the accuracy and effectiveness of the regression model because surface roughness values were predicted to a close degree of accuracy with least error.

8. Cross relationship curves and Histograms drawn for actual vs. predicted surface roughness for both approaches show a close relationship among those roughness values proving effectiveness of 'Regression Model' with least rate of error.

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