Multi Objective Optimization of Cutting Parameters in Turning Operation Using Taguchi Method

Thesis submitted in partial fulfillment of the requirements for the Degree of

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In

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By

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Certificate of Approval

This is to certify that the thesis entitled **Multi Objective Optimization of Cutting Parameters in Turning Operation Using Taguchi Method** submitted by **Raja Sutar** has been carried out under my supervision in partial fulfillment of the requirements for the Degree of **Bachelor of Technology** in **Mechanical Engineering** at National Institute of Technology, Rourkela, and this work has not been submitted elsewhere before for any other academic degree/diploma.

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ABSTRACT

This paper refers to parametric optimization of turning process applying Taguchi method in order to improve quality of manufacturing goods, and engineering development of designs for studying variation.SS-304 is used as work-piece for carrying out experiment to optimize material removal rate and surface roughness.

There are three machining parameters i.e. spindle speed, feed rate and depth of cut. Different experiments are done by varying one parameter and keeping other two fixed so that optimized value of each parameter can be obtained. In this project dry turning of S. S. 304 graded steel as a work piece and carbide insert tool (SNMG120408MS, SNMG432MS) is performed. The range of cutting parameters are cutting speed (40, 66 and 92 m/min), feed rate (0.05, 0.1 and 0.15 mm/rev), depth of cut (0.25, 0.5 and 0.75 mm).

Taguchi orthogonal array is designed with three levels of turning parameters with the help of software Minitab version 16. Taguchi method stresses the importance of studying the response variation using the signal to noise (S/N) ratio, resulting in minimization of quality characteristic variation due to uncontrolled parameters. It is predicted that Taguchi method is a good method for optimization of various machining parameters as it reduces number of experiments. The results indicate the optimum values of the input factors and the results are conformed by a confirmatory test.

Keywords**: -** Depth of Cut; Feed; Speed; Spindle Speed; Taguchi Orthogonal Array;

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CHAPTER 1:

INTRODUCTION

1. Introduction

Turning is one of the major machining processes which includes metal cutting as removal of metal chips in order to get finished product of desired shape, size and surface roughness. The engineers have to face challenge in order to get optimal parameters for preferred output using available sources.

Usually selection of machining parameters is very much difficult for desired product. Actually it depends upon experience of the engineers and the table given by machine-tool designer. So the importance of optimization arises in order to satisfy economy and quality of machined part.

The Taguchi's method tells about reduction in variation in order to improve quality by method of offline or online quality control. The offline quality control helps in improving quality of processes, where online quality control helps in maintaining conformance to the original or intended design. The main and fundamental part of Taguchi's design is to ensure that the product perform well even in noise; it helps in making the product long lasting. Taguchi method is applied in a very short period of time without lots of efforts. That is why Taguchi's method is adopted in various industries in order to improve the process quality in manufacturing sectors.

Surface roughness and cutting force are two very important parameters in machining process. Cutting force is necessary for calculation of power machining. Cutting forces influences dimensional accuracy, deformation of work-piece and chip formation.

Components of certain surface roughness are always required in industries as per customer requirement. This can be achieved by optimization process which we are going to discuss about.

1.1. Single Point Cutting Tool

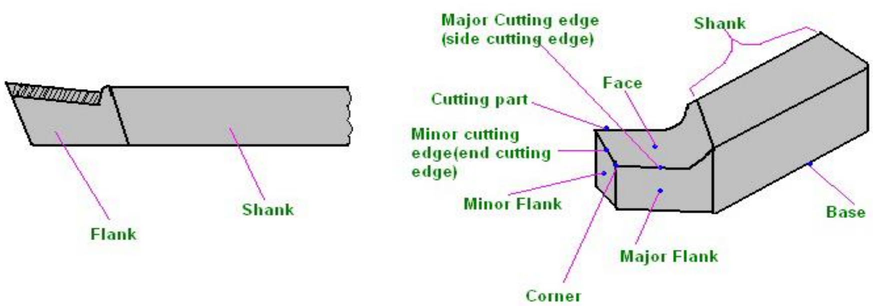


Fig. 1 Nomenclature of a single point cutting tool(refer 40)

Single point cutting tools have one principal cutting edge which is mainly used for cutting. These tools are used for turning, boring, planning etc. used in machines like lathe, boring and shaping machines. Single point cutting tools contain following parts: - shank (this is the main body of the tool), flank (which is adjacent below the cutting edge), face (the surface upon which chip slides), nose radius (it is the point where cutting edge intersects with side cutting edge). The schematic diagram of single point cutting tool is shown in Fig. 1.

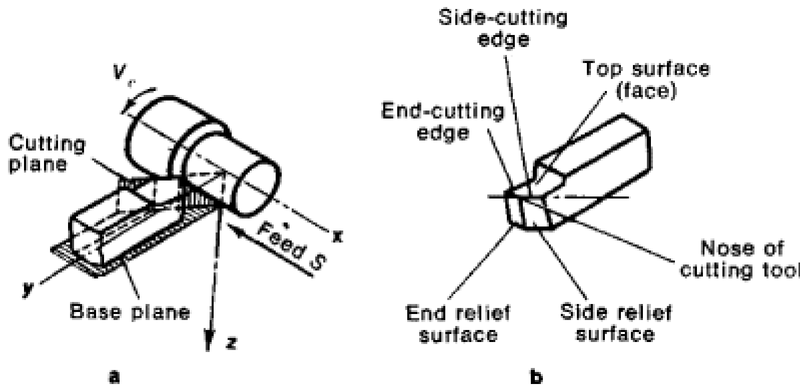


Fig. 2 Diagram of the machining process(refer 37)

The angle between the side relief face of the tool and machining plane is called side relief angle α. The relief angle depends upon rate of feed parameter, if feed increases, then relief angle increases in order to avoid friction between relief surface and cutting edge.

The angle between the top and side relief surface of the tool is known as lip angle β. The angle between the plane perpendicular to the cutting plane and the top surface of the tool is known as side rake angle γ. The mechanism of turning process is shown in Fig. 2.

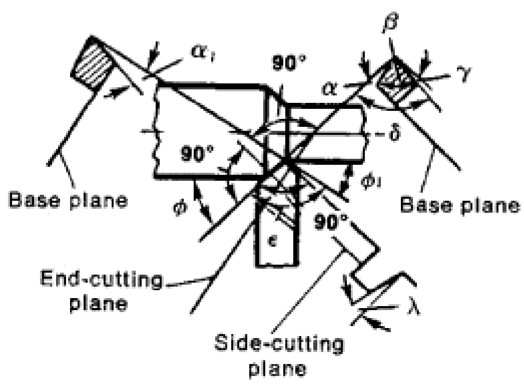


Fig. 3 Cutting angles(refer 37)

Larger rake angles facilitate easier formation of chip in machining, but it decreases cutting force(less power consumption). For hard material, tool with small rake angle is always used. Finally, it can be observed that rake angle depends upon physical and mechanical properties of work-piece material. The cutting angles which are used for machining shown in Fig. 3 with projected point of view.

Turning is the removal of metal from the outer diameter of a rotating cylindrical work piece. Turning is used to reduce the diameter of the work piece, usually to a specified dimension, and to produce a smooth finish on the metal can be defined as the machining of an external surface:

- With the work piece rotating
- With a single-point cutting tool, and
- With the cutting tool feeding parallel to the axis of the work piece and at a
- Distance that will remove the outer surface of the work.

1.2. Cutting factors in turning

The primary factors in any basic turning operation are speed, feed, and depth of cut. Other factors such as kind of material and type of tool have a large influence, of course, but these three are the ones the operator can change by adjusting the controls.

1.2.1. Speed:

Speed refers to the spindle and the work piece. When it is stated in rpm, it tells their rotating speed. But the important feature for a particular turning operation is the surface speed that is the speed at which the work piece material is moving past the cutting tool. It is simply the product of the rotating speed times the circumference of the work piece before the cut is started. It is expressed in meter per minute (m/min), and it refers only to the work piece. Every different diameter on a work piece will have a different cutting speed, even though the rotating speed remains the same.

v = 3.14DN/1000 (m/min)

Here, v is the cutting speed in turning; D is the initial diameter of the work piece in mm.

1.2.2. Feed:

Feed refers to the cutting tool and it is the rate at which the tool advances along its cutting path. In most of power-fed lathes, the feed rate is directly related to the spindle speed and is expressed in mm (of tool advance) per revolution (of the spindle), or mm/rev.

1.2.3. Depth of Cut:

Depth of cut is the thickness of the layer being removed (in a single pass) from the work piece or the distance from the uncut surface of the work to the cut surface, expressed in mm. It is important to note that the diameter of the work piece is reduced by two times the depth of cut because this layer is being removed from both sides of the work piece.

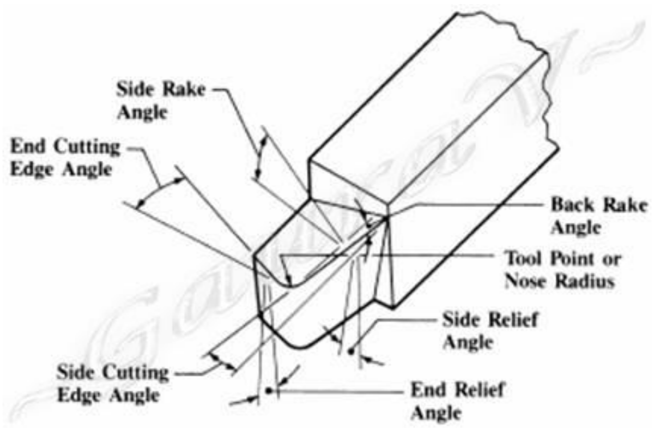
The Taguchi's method tells about reduction in variation in order to improve quality by method of offline or online quality control. The offline quality control helps in improving quality of processes, where online quality control helps in maintaining conformance to the original or intended design. The main and fundamental part of Taguchi's design is to ensure that the product perform well even in noise; it helps in making the product long lasting. Taguchi method is applied in a very short period of time without lots of efforts. That is why Taguchi's method is adopted in various industries in order to improve the process quality in manufacturing sectors.

Taguchi methods provide a cost effective, efficient and systematic way to optimize designs for performance, quality, and cost. This method has been used successfully in designing reliable, high-quality products at low cost in such areas as automotive, aerospace, and consumer.

Cutting forces, surface roughness and tool wear are among the most important technical parameters in machining process. Cutting forces are necessary for evaluation of machine tool components and the tool body. Cutting forces influences the deformation of the work piece machined, its dimensional accuracy, machine stability and chip formation.

1.3. Tool Geometry:

For cutting tools, geometry shown in fig 1.3 depends on the properties of the tool material and the work material. For single point tools, the most important angles are the rake angles and the end and side relief angle.



(Tool geometry shown in fig 1.3)(refer. 40)

1.3.1. Flank:

A flat surface of a single-point tool that is adjacent to the face of the tool. During turning, the side flank faces the direction that the tool is fed into the work piece. At the end flank passes over the newly machined surface.

1.3.2. Face:

The flat surface of a single point tool through which, the work piece rotates during turning operation is called the face of tool. On a typical turning setup, the face of the tool is positioned upwards.

1.3.3. Back rake angle:

If viewed from the side facing the end of the work piece, it is the angle formed by the face of the tool, and a line parallel to the base. A positive back rake angle tilts the tool face back, and a negative angle tilts it forward and up.

1.3.4. Side rake angle:

If viewed behind the tool down the length of the tool holder, it is the angle formed by the face of the tool and the centerline of the work piece. A positive side rake angle tilts the tool face down toward the floor, and a negative angle tilts the face up and toward the work piece.

1.3.5. Side cutting edge angle:

If viewed from above looking down on the cutting tool, it is the angle formed by the side flank of the tool and a line perpendicular to the work piece centerline. A positive side cutting edge angle moves the side flank into the cut, and a negative angle moves the side flank out of the cut.

1.3.6. End cutting edge angle:

If viewed from above looking down on the cutting tool, the angle formed by the end flank of the tool and a line parallel to the work piece centerline is called end cutting edge angle. Increasing the end cutting edge angle tilts the far end of the cutting edge away from the work piece.

1.3.7. Side relief angle:

If viewed behind the tool down the length of the tool holder, the angle formed by the side flank of the tool and a vertical line down to the floor is called side relief angle. Increasing the side relief angle tilts the side flank away from the work piece.

1.3.8. End relief angle:

If viewed from the side facing the end of the work piece, the angle formed by the end flank of the tool and a vertical line down to the floor is named as end relief angle. Increasing the end relief angle tilts the end flank away from the work piece.

1.3.9. Nose radius:

It is the rounded tip on the cutting edge of a single point tool. A sharp point of the cutting tool is created by a zero degree nose radius.

1.3.10. Lead angle:

Lead angle is the common name for the side cutting edge angle. If a tool holder is built with dimensions that shift the angle of an insert, the lead angle takes this change into consideration.

Here, the experts of machining gave their opinions regarding obtained results. A numerous studies have been carried out regarding turning operation and the applied optimization techniques.

Zhou et al. (1995) [1] investigated on tool life criteria in raw turning. A new tool-life criterion depending on a pattern-recognition technique was proposed and neural network and wavelet techniques were used to realize the new criterion. The experimental results showed that this criterion was applicable to tool condition monitoring in a wide range of cutting conditions.

Lin et al. (2001) [2] adopted an abdicative network to construct a prediction model for surface roughness and cutting force. Once the process parameters: cutting speed, feed rate 44 and depth of cut were given; the surface roughness and cutting force could be predicted by this network. Regression analysis was also adopted as second prediction model for surface roughness and cutting force. Comparison was made on the results of both models indicating that adductive network was found more accurate than that by regression analysis.

Feng and Wang (2002) [3] investigated for the prediction of surface roughness in finish turning operation by developing an empirical model through considering working parameters: work piece hardness (material), feed, cutting tool point angle, depth of cut, spindle speed, and cutting time. Data mining techniques, nonlinear regression analysis with logarithmic data transformation were employed for developing the empirical model to predict the surface roughness.

Suresh et al. (2002) [4] focused on machining mild steel by TiN-coated tungsten carbide (CNMG) cutting tools for developing a surface roughness prediction model by using Response Surface Methodology (RSM). Genetic Algorithms (GA) used to optimize the objective function and compared with RSM results. It was observed that GA program provided minimum and maximum values of surface roughness and their respective optimal machining conditions.

Lee and Chen (2003) [5] highlighted on artificial neural networks (OSRR-ANN) using a sensing technique to monitor the effect of vibration produced by the motions of the cutting tool and work piece during the cutting process developed an on-line surface recognition system. The authors employed tri-axial accelerometer for determining the direction of vibration that significantly affected surface roughness then analyzed by using a statistical method and compared prediction accuracy of both the ANN and SMR.

Choudhury and Bartarya (2003) [6] focused on design of experiments and the neural network for prediction of tool wear. The input parameters were cutting speed, feed and depth of cut; flank wear, surface finish and cutting zone temperature were selected as outputs. Empirical relation between different responses and input variables and also through neural network (NN) program helped in predictions for all the three response variables and compared which method was best for the prediction.

Chien and Tsai (2003) [7] developed a model for the prediction of tool flank wear followed by an optimization model for the determination of optimal cutting conditions in machining 17-4PH stainless steel. The back-propagation neural network (BPN) was used to construct the predictive model. The genetic algorithm (GA) was used for model optimization.

Kirby et al. (2004) [8] developed the prediction model for surface roughness in turning operation. The regression model was developed by a single cutting parameter and vibrations along three axes were chosen for in-process surface roughness prediction system. By using multiple regression and Analysis of Variance (ANOVA) a strong linear relationship among the parameters (feed rate and vibration measured in three axes) and the response (surface roughness) was found. The authors demonstrated that spindle speed and depth of cut might not necessarily have to be fixed for an effective surface roughness prediction model.

Őzel and Karpat (2005) [9] studied for prediction of surface roughness and tool flank wear by utilizing the neural network model in comparison with regression model. The data set from measured surface roughness and tool flank wear were employed to train the neural network models. Predictive neural network models were found to be capable of better predictions for surface roughness and tool flank wear within the range in between they were trained.

Luo et al. (2005) [10] carried out theoretical and experimental studies to investigate the intrinsic relationship between tool flank wear and operational conditions in metal cutting processes using carbide cutting inserts. The authors developed the model to predict tool flank wear land width which combined cutting mechanics simulation and an empirical model. The study revealed that cutting speed had more dramatic effect on tool life than feed rate.

Kohli and Dixit (2005) [11] proposed a neural-network-based methodology with the acceleration of the radial vibration of the tool holder as feedback. For the surface roughness prediction in turning process the back-propagation algorithm was used for training the network model. The methodology was validated for dry and wet turning of steel using high speed steel and carbide tool and observed that the proposed methodology was able to make accurate prediction of surface roughness by utilizing small sized training and testing datasets.

Pal and Chakraborty (2005) [12] studied on development of a back propagation neural network model for prediction of surface roughness in turning operation and used mild steel work-pieces with high speed steel as the cutting tool for performing a large number of experiments. The authors used speed, feed, depth of cut and the cutting forces as inputs to the neural network model for prediction of the surface roughness. The work resulted that predicted surface roughness was very close to the experimental value.

Sing and Kumar (2006) [13] studied on optimization of feed force through setting of optimal value of process parameters namely speed, feed and depth of cut in turning of EN24 steel with TiC coated tungsten carbide inserts. The authors used Taguchi’s parameter design approach and concluded that the effect of depth of cut and feed in variation of feed force were affected more as compare to speed.

Ahmed (2006) [14] developed the methodology required for obtaining optimal process parameters for prediction of surface roughness in Al turning. For development of empirical model nonlinear regression analysis with logarithmic data transformation was applied. The developed model showed small errors and satisfactory results. The study concluded that low feed rate was good to produce reduced surface roughness and also the high speed could produce high surface quality within the experimental domain.

Abburi and Dixit (2006) [15] developed a knowledge-based system for the prediction of surface roughness in turning process. Fuzzy set theory and neural networks were utilized for this purpose. The authors developed rule for predicting the surface roughness for given process variables as well as for the prediction of process variables for a given surface roughness.

Zhong et al. (2006) [16] predicted the surface roughness of turned surfaces using networks with seven inputs namely tool insert grade, work piece material, tool nose radius, rake angle, depth of cut, spindle rate, and feed rate.

Kumanan et al. (2006) [17] proposed the methodology for prediction of machining forces using multi-layered perceptron trained by genetic algorithm (GA). The data obtained from experimental results of a turning process were explored to train the proposed artificial neural networks (ANNs) with three inputs to get machining forces as output. The optimal ANN weights were obtained using GA search. This function-replacing hybrid made of GA and ANN was found computationally efficient as well as accurate to predict the machining forces for the input machining conditions.

Mahmoud and Abdelkarim (2006) [18] studied on turning operation using High-Speed Steel (HSS) cutting tool with 450 approach angle. This tool showed that it could perform cutting operation at higher speed and longer tool life than traditional tool with 90 degree approach angle. The study finally determined optimal cutting speed for high production rate and minimum cost, tool like, production time and operation costs.

Doniavi et al. (2007) [19] used response surface methodology (RSM) in order to develop empirical model for the prediction of surface roughness by deciding the optimum cutting condition in turning. The authors showed that the feed rate influenced surface roughness remarkably. With increase in feed rate surface roughness was found to be increased. With increase in cutting speed the surface roughness decreased. The analysis of variance was applied which showed that the influence of feed and speed were more in surface roughness than depth of cut.

Kassab and Khoshnaw (2007) [20] examined the correlation between surface roughness and cutting tool vibration for turning operation. The process parameters were cutting speed, depth of cut, feed rate and tool overhanging. The experiments were carried out on lathe using dry turning (no cutting fluid) operation of medium carbon steel with different level of aforesaid process parameters. Dry turning was helpful for good correlation between surface roughness and cutting tool vibration because of clean environment. The authors developed good correlation between the cutting tool vibration and surface roughness for controlling the surface finish of the work pieces during mass production. The study concluded that the surface roughness of work piece was observed to be affected more by cutting tool acceleration; acceleration increased with overhang of cutting tool. Surface roughness was found to be increased with increase in feed rate.

Al-Ahmari (2007) [21] developed empirical models for tool life, surface roughness and cutting force for turning operation. The process parameters used in the study were speed, feed, depth of cut and nose radius to develop the machinability model. The methods used 48 for developing aforesaid models were Response Surface Methodology (RSM) and neural networks (NN).

Thamizhmanii et al. (2007) [22]applied Taguchi method for finding out the optimal value of surface roughness under optimum cutting condition in turning SCM 440 alloy steel.

The experiment was designed by using Taguchi method and experiments were conducted and results thereof were analyzed with the help of ANOVA (Analysis of Variance) method. The causes of poor surface finish as detected were machine tool vibrations, tool chattering whose effects were ignored for analyses. The authors concluded that the results obtained by this method would be useful to other researches for similar type of study on tool vibrations, cutting forces etc. The work concluded that deppth of cut was the only significant factor which contributed to the surface roughness.

Natarajan et al. (2007) [23] presented the on-line tool wear monitoring technique in turning operation. Spindle speed, feed, depth of cut, cutting force, spindle-motor power and temperature were selected as the input parameters for the monitoring technique. For finding out the extent of tool wear; two methods of Hidden Markov Model (HMM) such as the Bar-graph Method and the Multiple Modeling Methods were used. A decision fusion centre algorithm (DFCA) was used for increasing the reliability of this output which combined the outputs of the individual methods to make a global decision about the wear status of the tool. Finally, all the proposed methods were combined in a DFCA to determine the wear status of the tool during the turning operations.

Ozel et al. (2007) [24] carried out finish turning of AISI D2 steels (60 HRC) using ceramic wiper (multi-radii) design inserts for surface finish and tool flank wear investigation. For prediction of surface roughness and tool flank wear multiple linear regression models and neural network models were developed. Neural network based predictions of surface roughness and tool flank wear were carried out, compared with a non-training experimental data and the results thereof showed that the proposed neural network models were efficient to predict tool wear and surface roughness patterns for a range of cutting conditions. The study concluded that best tool life was obtained in lowest feed rate and lowest cutting speed combination.

Wang and Lan (2008) [25] used Orthogonal Array of Taguchi method coupled with grey relational analysis considering four parameters viz. speed, cutting depth, feed rate, tool nose run off etc. for optimizing three responses: surface roughness, tool wear and material removal rate in precision turning on an ECOCA-3807 CNC Lathe. The MINITAB software was explored to analyze the mean effect of Signal-to-Noise (S/N) ratio to achieve the multi-objective features. This study not only proposed an optimization approaches using Orthogonal Array and grey relational analysis but also contributed a satisfactory technique for improving the multiple machining performances in precision CNC turning with profound insight.

Srikanth and Kamala (2008) [26] evaluated optimal values of cutting parameters by using a Real Coded Genetic Algorithm (RCGA) and explained various issues of RCGA and its advantages over the existing approach of Binary Coded Genetic Algorithm (BCGA). They concluded that RCGA was reliable and accurate for solving the cutting parameter optimization and construct optimization problem with multiple decision variables. These decision variables were cutting speed, feed, depth of cut and nose radius. The authors highlighted that the faster solution can be obtain with RCGA with relatively high rate of success, with selected machining conditions thereby providing overall improvement of the product quality by reduction in production cost, reduction in production time, flexibility in machining parameter selection.

Sahoo et al. (2008) [27] studied for optimization of machining parameters combinations emphasizing on fractal characteristics of surface profile generated in CNC turning operation. The authors used L_{27} Taguchi Orthogonal Array design with machining parameters: speed, feed and depth of cut on three different work piece materials viz. aluminum, mild steel and brass. It was concluded that feed rate was more significant influencing surface finish in all three materials. It was observed that in case of mild steel and aluminum feed showed some influences while in case of brass depth of cut was noticed to impose some influences on surface finish. The factorial interaction was responsible for controlling the fractal dimensions of surface profile produced in CNC turning.

Reddy et al. (2008) [28] adopted multiple regression model and artificial neural network to deal with surface roughness prediction model for machining of aluminium alloys by CNC turning. For judging the efficiency and ability of the model in surface roughness prediction the authors used the percentage deviation and average percentage deviation. The study of experimental results showed that the artificial neural network was efficient as compared to multiple regression models for the prediction of surface roughness.

Wannas (2008) [29] carried out experiments for hard turning of graphitic cast iron for the prediction of status of tool wear by using radial basis function neural network (RBFNN) model. The RBFNN had three inputs: speed, feed and depth of cut and one output: state variable node. The error was less as obtained from neural network model than the regression model.

Lan et al. (2008) [30] considered four cutting parameters: speed, feed, depth of cut, and nose runoff varied in three levels for predicting the surface roughness of CNC turned product.

Thamma (2008) [31] constructed the regression model to find out the optimal combination of process parameters in turning operation for Aluminium 6061 work pieces. The study highlighted that cutting speed, feed rate, and nose radius had a major impact on surface roughness. Smoother surfaces could be produced when machined with a higher cutting speed, smaller feed rate, and smaller nose radius.

Fnides et al. (2008) [32] studied on machining of slide-lathing grade X38CrMoV5-1 steel treated at 50 HRC by a mixed ceramic tool (insert CC650) to reveal the influences of cutting parameters: feed rate, cutting speed, depth of cut and flank wear on cutting forces as well as on surface roughness. The authors found that tangential cutting force was very sensitive to the variation of cutting depth. It was observed that surface roughness was very sensitive to the variation of feed rate and that flank wear had a great influence on the evolution of cutting force components and on the criteria of surface roughness.

Biswas et al. (2008) [33] studied that on-line flank wear directly influenced the power consumption, quality of the surface finish, tool life, productivity etc. The authors developed a Neuro-Fuzzy model for prediction of the tool wear. From the orthogonal machining of aluminium with high-speed steel tool for various rake angles, feed and velocity the experimental data were obtained and input along with other machining parameters ratio between cutting force and tangential forces was collected. These were used to predict the tool wear. The final parameters of the model were obtained by tuning the crude values obtained from mountain clustering method by using back-propagation learning algorithm and finally the present Neuro-Fuzzy system which predicted the flank.

Fu and Hope (2008) [34] established an intelligent tool condition monitoring system by applying a unique fuzzy neural hybrid pattern recognition system. The study concluded that armed with the advanced pattern recognition methodology, the established intelligent tool condition monitoring system had the advantages of being suitable for different machining conditions, robust to noise and tolerant to faults.

Wang et al. (2008) [35] studied on Hybrid Neural Network-based modeling approach integrated with an analytical tool wear model and an artificial neural network that was used to predict CBN tool flank wear in turning of hardened 52100 bearing steel. Experimental results showed that the proposed Hybrid Neural Network excelled the analytical tool wear model approach and the general neural network-based modeling aproach.

1.2. Objective of Work

The objective of work is to observe the cutting parameters in turning and to calculate the optimum value of the parameters in order to optimize the surface roughness and tool wear using Taguchi method. The statistical analysis is to be performed for better machining operation which can be used for quality control of machining parts. This will help to concerned R and D researchers or industrial experts.

CHAPTER 2

CHAPTER 2:

BRIEF DESCRIPTION OF APPARATUS USED

2. Cutting tool specification

The specification of cutting tool used is SNMG 120408MS and the dimensions are as follows.

Table 1: Specification of cutting tool (mm)

Cutting Edge Length	Inscribed Circle or Height	Thickness	Hole Diameter	Corner Radius	Side Clearance
12.7	12.7	4.76	5.16	0.8	0°

2.1. Composition and application of work piece

S.S. 304 is a most widely used austenitic steel popularly known as 18/8 stainless steel. The Fig. 4 shows the experimental set up of turning operation with work piece of S. S. 304 graded steel.

Fig. 4 Experimental set up for machining

2.2. Physical data

Table 2: S. S. 304 steel physical data

Density (lb/cu.in.)	0.285
Specific Gravity	7.9
Specific Heat (Btu/lb/Deg F)	0.12
Electrical Resistivity (microhm-cm)	432
Melting Point (Deg F)	2650
Modulus of Elasticity Tension	28

2.3. Composition

Table 3: Chemical composition of S. S. 304 steel

C	Mn	Si	Cr	Ni	P	S
0.08	2.0	1.0	18-20	8-10.05	0.045	0.03

2.4. Material notes

Essentially non-magnetic, becomes slightly magnetic when cold worked, it has excellent corrosion and forming characteristics and highly ductile. This has corrosion resistance mostly with oxidizing acids and salt spray.

2.5. Applications

This steel is widely used in petrochemical industries, diary, household and pharmaceutical purposes and cryogenic vessels, and as heat exchanger in air conditioning refrigeration factories.

2.6. Talysurf measurements

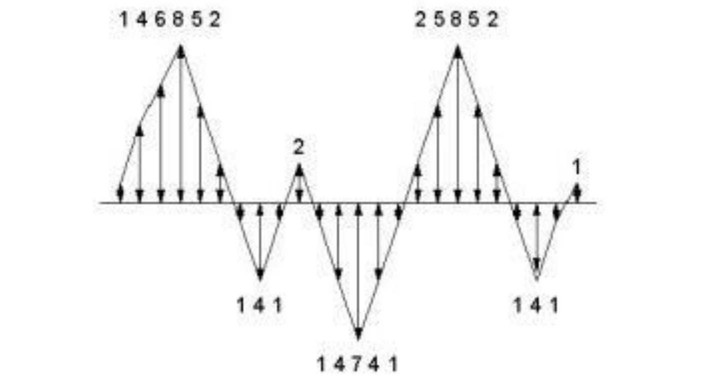
Talysurf (shown in Fig. 5) is a device used for measurement of surface roughness which known as Portable profilometer (Taylor Hobson Surtronic 3+). This is a stylus based instrument which is based on the principle of a probe running across the surface to measure the variation of height as a function of distance.

Fig. 5 Talysurf

In this instrument, a transducer is used which converts the vertical distance into electrical signal. The signal is processed later in order to get the surface roughness value. Some error may arise due to some factors like stylus speed, stylus load, size and shape of the stylus and lateral deflection.

2.7. Centre line average roughness

It refers to arithmetic average or center line average (CLA). It is denoted as Ra. This is calculated as the average distance of the surface from the mean line looking at all the points of the profile.



(reference 37)Fig. 6 Measurement of R_a

The principle regarding measuring surface roughness is described in Fig. 6. Based on this method of the profilomer of Talysurf the surface roughness is measured and recorded as per each run.

2.8. Procedure followed for experimentation

First of all, the work-piece (S.S. 304) is mounted on the head stock of lathe. The other end of material is center-bored using center drill and then fixed with the tail stock respectively. Then, according to the design of experiment (Table 4), different levels of parameters are set to get 9 numbers of run.

The work piece was given initial roughness pass. Then the surface roughness (R_a) value is calculated for each run using Talysurf. And tool wear at each respective cutting edge of the tool is also calculated using Tool maker microscope. Statistical analysis of obtained data carried out using Taguchi optimization technique.

CHAPTER 3

Chapter 3:

Methodology

3.1. Taguchi Method

Taguchi method is one of the powerful tools for optimization technique. This is based on the “Orthogonal Array” experiments which give much optimum setting of control parameters with reduced variance. So after optimization the best result is obtained from the Taguchi method. “Taguchi Orthogonal Array” gives a well-balanced (minimum) set of parameter. The signal-to-noise ratios which are log function of desired output serves as objective function for method of optimization which helps in data analysis and finding the optimal result. The optimization problems which involve selection of best levels of parameters in order to get a desired output are called as “static problem”.

There are three signal-to-noise ratios of common interest for optimization of static problems:-

1) Smaller-The-Better

$$n = -10 \, \text{Log}_{10} \, [\text{mean of sum of squares of measured data}] \tag{1}$$

This is usually the chosen S/N ratio for all undesirable characteristics for which the ideal value is zero. But when the ideal value is zero, then the difference between measured data and ideal value is expected to be as small as possible. The generic form of S/N ratio becomes:-

$$n = -10 \, \text{Log}_{10} \, [\text{mean of sum of squares of \{measured - ideal\}}] \tag{2}$$

2) Larger-The-Better

$$n = -10 \, \text{Log}_{10} \, [\text{mean of sum squares of reciprocal of measured data}] \tag{3}$$

By taking the reciprocals of measured data and taking the value of S/N ratio as in smaller-the-better case, we can convert it to smaller-the-better case.

3) Nominal-The-Best

$$n = 10\ Log_{10}\ (\text{square of mean/ variance}) \qquad (4)$$

This case arises when a specified value is most desired, meaning that neither a smaller nor a larger value is desirable.

CHAPTER 4

Chapter 4:

Experimental Observation & Analysis

According to Taguchi's orthogonal array theory L_9 orthogonal array is adopted for the whole experimentation for turning operation of S. S. 304 graded steel. In L_9 orthogonal array, 9 experimental runs are conducted and the corresponding out puts is evaluated by Taguchi optimization technique. Here, Tool wears and means of surface roughness are measured by above said instruments and these values are taken out put responses in Taguchi optimization method. Table 4 shows the standard structure of L_9 orthogonal array which levels of each parameters are taken as 1, 2 and 3 respectively.

Table 4: Taguchi orthogonal array

Sl. no.	Cutting speed	Feed	Depth of cut
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	3
5	2	2	1
6	2	3	2
7	3	1	2
8	3	2	3
9	3	3	1

Here, the process variables are cutting speed, feed rate and depth of cut. These are the input parameters for the Taguchi optimization. So, nine experiments are carried out as per this orthogonal array and corresponding output data are recorded serially. The surface roughness was measured thrice times at different parts of the surface of work piece and then calculate the mean of those value. The full structure of experimentation is tabulated in Table 5 as per L_9 orthogonal array.

Table 5: Observation table

Run	Speed (V_c)	Feed (f)	Doc (d)	Tool Wear (micron)	S. R. (1)	S. R. (2)	S. R. (3)	Average S. R.
1	40	0.15	0.75	0.810	1.84	1.64	1.76	1.746
2	40	0.1	0.5	1.051	1.36	1.16	1.24	1.253
3	40	0.05	0.25	1.008	1.42	1.44	1.52	1.46
4	66	0.15	0.25	1.127	1.44	1.28	1.3	1.34
5	66	0.1	0.75	0.800	1.98	1.74	1.86	1.86
6	66	0.05	0.5	0.659	1.66	1.58	1.66	1.63
7	92	0.15	0.5	0.928	1.88	1.74	1.84	1.82
8	92	0.1	0.25	1.302	1.52	1.40	1.38	1.43
9	92	0.05	0.75	1.381	3.56	3.28	3.42	3.42

CHAPTER 5

Chapter 5:

Results & Analysis

These above data are analyzed by a power full statistical tool named Minitab software of latest version 16. First of all the input parameters are defined in the software as per their corresponding value and then give the responses data to optimize. Here, the main objective of the problem is to minimize the value of tool wear and surface roughness. So, the criterion of Smaller-The-Better is adopted for the optimization. The analysis of S/N ratio and Means are carried out by the software. Then, ANOVA analysis of each parameter is done after simulation of optimization. And lastly the influences of residuals on parameters are carried out by plotting graphs.

5.1. Taguchi Analysis: Tool Wear versus Speed, Feed, Doc

The following terms cannot be estimated, and were removed.

Speed*Feed

Speed*Doc

Feed*Doc

The interaction terms are not be analyzed by Taguchi.

5.2. Linear Model Analysis: S/N ratios versus Speed, Feed, Doc

Table 6: Estimated Model Coefficients for S/N ratios

Term	Coef.	S.E. Coef.	T	P
Constant	0.15600	0.7928	0.197	0.862
Speed 40	0.28701	1.1212	0.256	0.822
Speed 66	1.35134	1.1212	1.205	0.351
feed 0.05	0.09374	1.1212	0.084	0.941
feed 0.10	-0.41802	1.1212	-0.373	0.745
doc 0.25	-1.28930	1.1212	-1.150	0.369
doc 0.50	1.12376	1.1212	1.002	0.422

S = 2.378   R-Sq = 67.5%   R-Sq (adj) = 0.0%

Table 7: Analysis of Variance for S/N ratios

Source	D.O.F.	Seq. S. S.	Adj. S. S.	Adj. M. S.	F	P	% contribution
Speed	2	13.7781	13.7781	6.8890	1.22	0.0451	39.57
Feed	2	0.8661	0.8661	0.4330	0.08	0.0929	2.49
Doc	2	8.8576	8.8576	4.4288	0.78	0.0561	25.44
Residual Error	2	11.3140	11.3140	5.6570			32.49
Total	8	34.8157					100

5.3. Linear Model Analysis: Means versus Speed, Feed, Doc

Table 8: Estimated Model Coefficients for Means

Term	Coef	SE Coef	T	P
Constant	1.00733	0.08956	11.247	0.008
Speed 40	-0.05100	0.12666	-0.403	0.726
Speed 66	-0.14533	0.12666	-1.147	0.370
feed 0.05	0.00867	0.12666	0.068	0.952
feed 0.10	0.04367	0.12666	0.345	0.763
doc 0.25	0.13833	0.12666	1.092	0.389
doc 0.50	-0.12800	0.12666	-1.011	0.419

S = 0.2687   R-Sq = 68.1%   R-Sq (adj) = 0.0%

Table 9: Analysis of Variance for Means

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Speed	2	0.18681	0.18681	0.093404	1.29	0.436
Feed	2	0.01416	0.01416	0.007081	0.10	0.911
Doc	2	0.10688	0.10688	0.053440	0.74	0.575
Residual Error	2	0.14439	0.14439	0.072194		
Total	8	0.45224				

Table 10: Response Table for Signal to Noise Ratios

Smaller-is-better

Level	Speed	Feed	Doc
1	0.4430	0.2497	-1.1333
2	1.5073	-0.2620	1.2798
3	-1.4824	0.4803	0.3215
Delta	2.9897	0.7423	2.4131
Rank	1	3	2

Table 11: Response Table for Means

Level	Speed	Feed	Doc
1	0.9563	1.0160	1.1457
2	0.8620	1.0510	0.8793
3	1.2037	0.9550	0.9970
Delta	0.3417	0.0960	0.2663
Rank	1	3	2

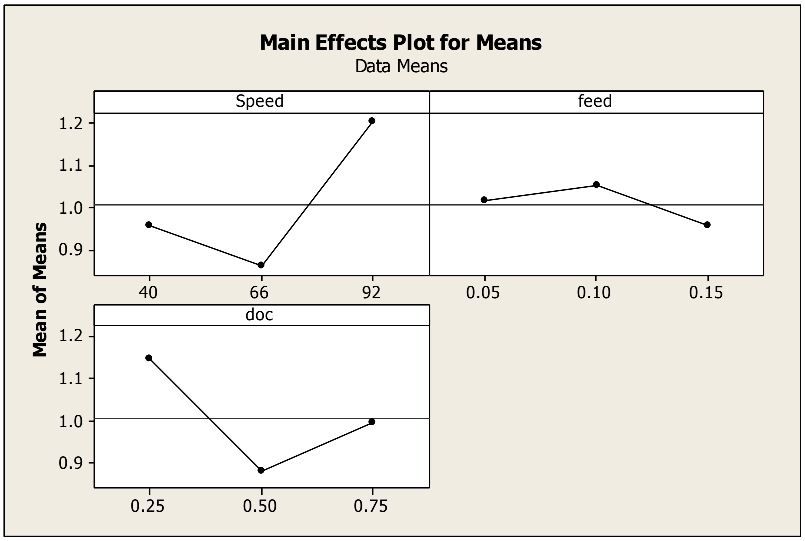


Fig. 7 Main Effects Plot for Means

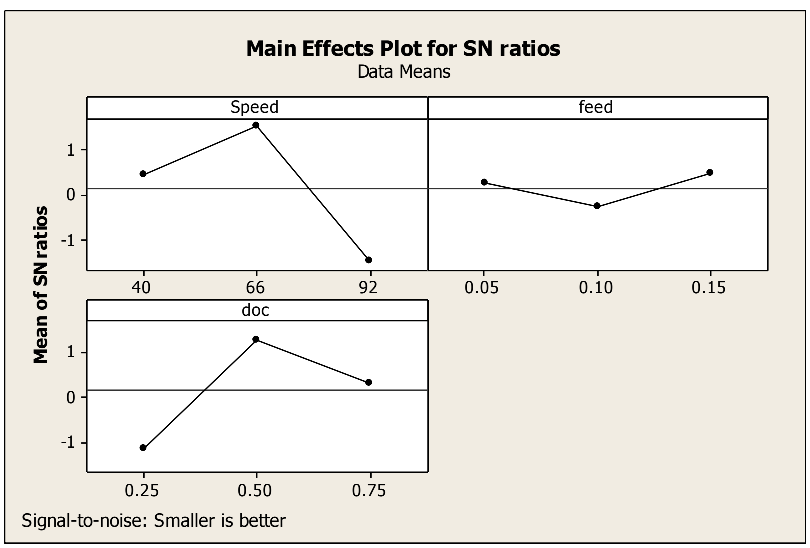


Fig. 8 Main Effects Plot for S/N ratios

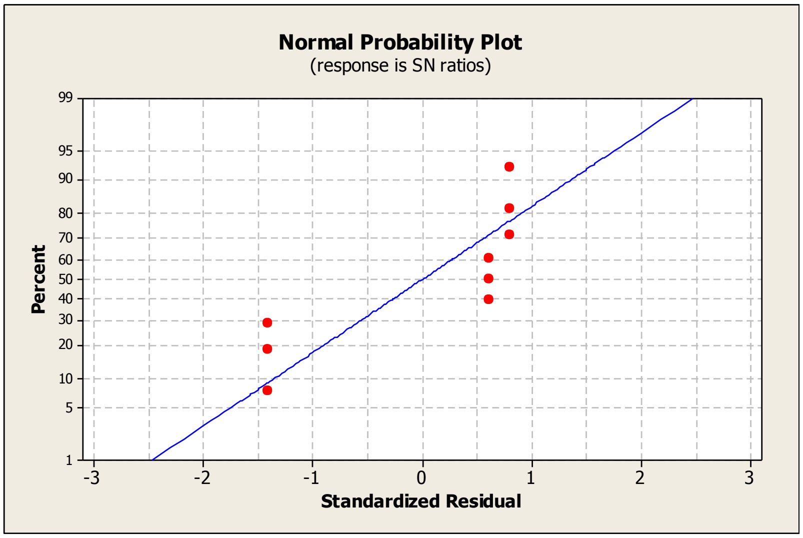


Fig. 9 Normal plot of Residuals for S/N ratios

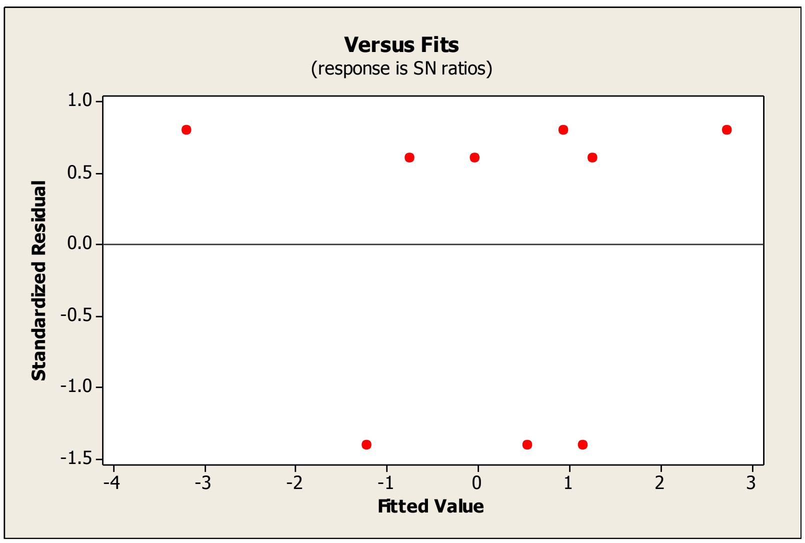


Fig. 10 Residuals vs Fits for S/N ratios

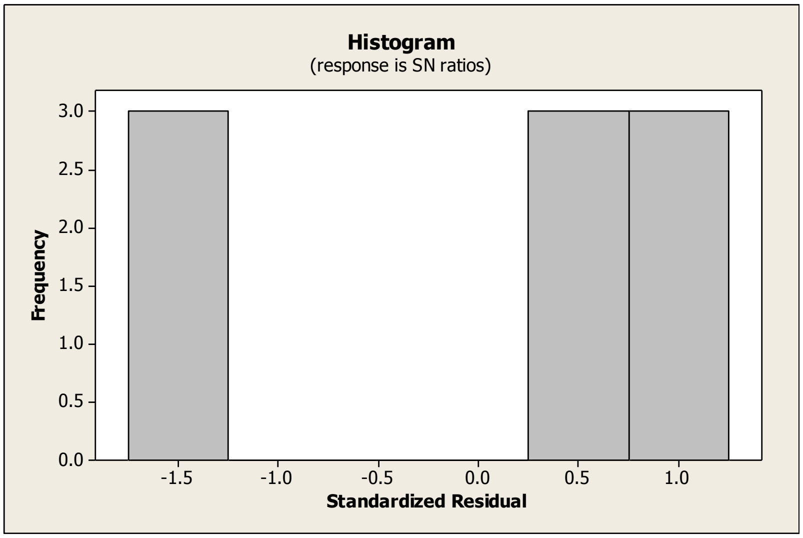


Fig. 11 Residual Histogram for S/N ratios

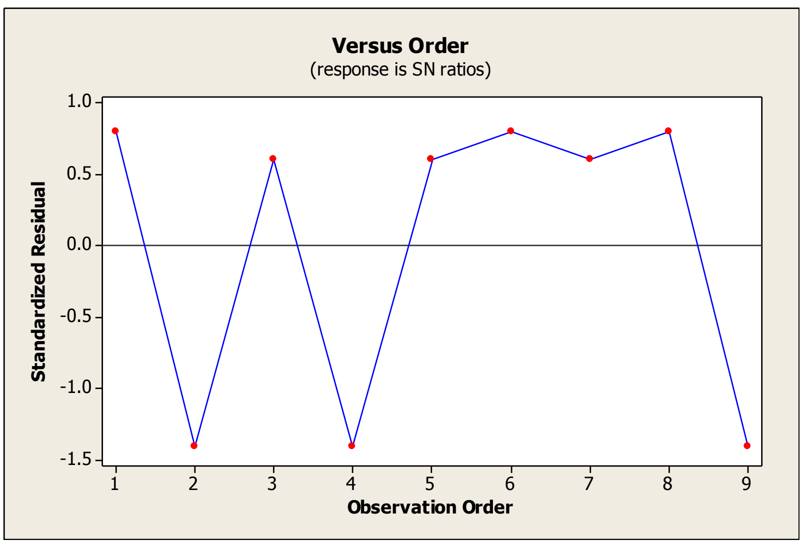


Fig. 12 Residuals vs Order for S/N ratios

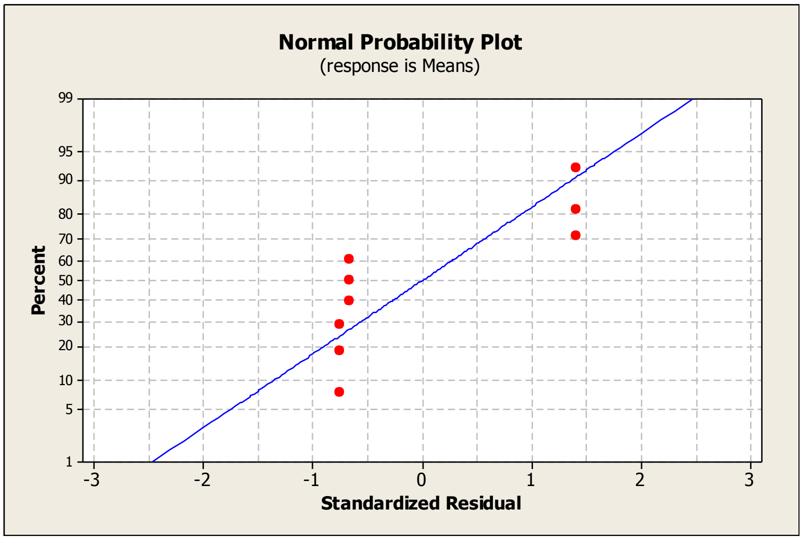


Fig. 13 Normal plot of Residuals for Means

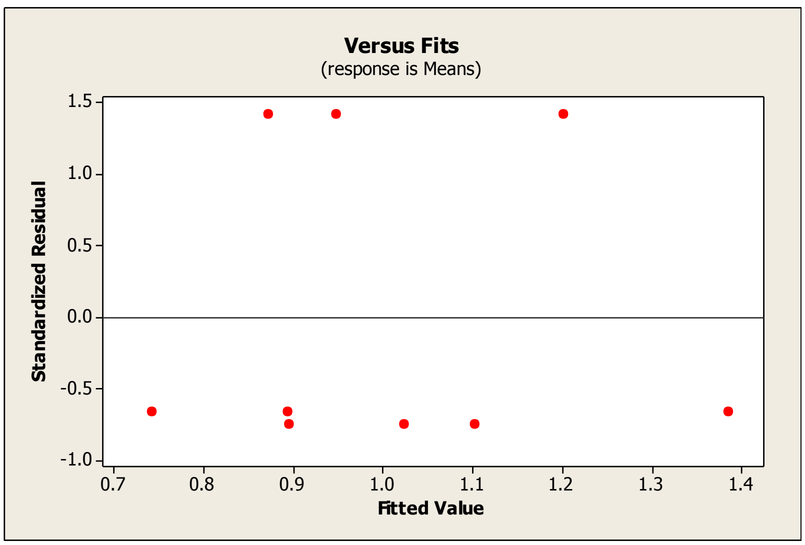


Fig. 14 Residuals vs Fits for Means

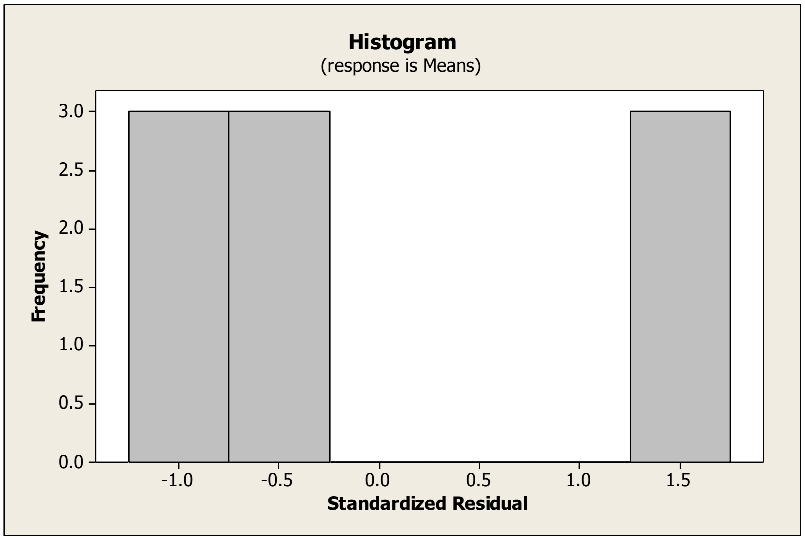


Fig. 15 Residual Histogram for Means

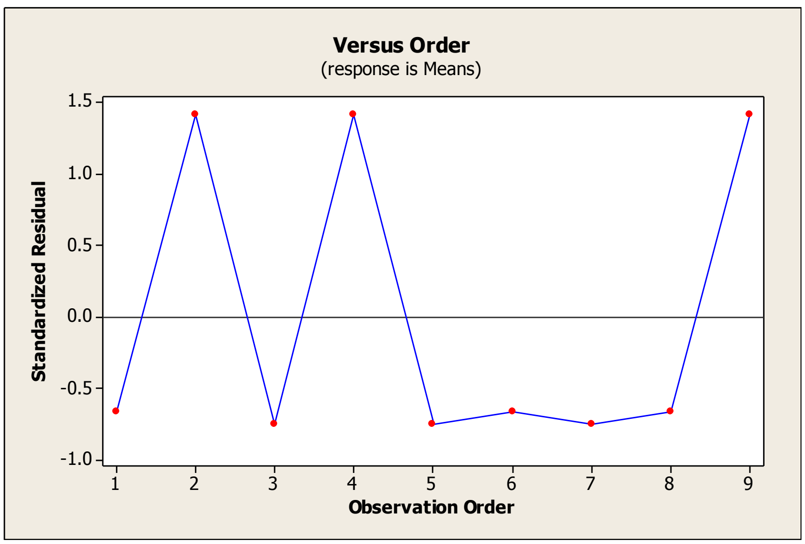


Fig. 16 Residuals vs Order for Means

5.4. Taguchi Analysis: S. R. versus Speed, Feed, Doc

The following terms cannot be estimated, and were removed.

Speed*Feed

Speed*Doc

Feed*Doc

5.5. Linear Model Analysis: S/N ratios versus Speed, Feed, Doc

(table 4.8:-Estimated Model Coefficients for SN ratios)

Term	Coef.	S. E. Coef.	T	P
Constant	-4.5835	0.2885	-15.886	0.004
Speed 40	1.2212	0.4080	2.993	0.096
Speed 66	0.5248	0.4080	1.286	0.327
feed 0.05	-1.4869	0.4080	-3.644	0.068
feed 0.10	1.0982	0.4080	2.691	0.115
doc 0.25	1.6049	0.4080	3.933	0.059
doc 0.50	0.7821	0.4080	1.917	0.195

S = 0.8656 R-Sq = 97.2% R-Sq(adj) = 88.8%

(table 4.9:-Analysis of Variance for S/N ratios)

Source	D. O. F.	Seq. S. S.	Adj. S. S.	Adj. M. S.	F	P	% contribution
Speed	2	14.446	14.446	7.2231	9.64	0.094	27.10
Feed	2	10.704	10.704	5.3521	7.14	0.123	20.08
Doc	2	26.656	26.656	13.3280	17.79	0.053	50.00
Residual Error	2	1.499	1.499	0.7493			2.81
Total	8	53.305					100

5.6. Linear Model Analysis: Means versus Speed, Feed, Doc

(table 4.10:-Estimated Model Coefficients for Means)

Term	Coef	SE Coef	T	P
Constant	1.7732	0.1199	14.784	0.005
Speed 40	-0.2869	0.1696	-1.691	0.233
Speed 66	-0.1632	0.1696	-0.962	0.437
feed 0.05	0.3968	0.1696	2.339	0.144
feed 0.10	-0.2589	0.1696	-1.526	0.266
doc 0.25	-0.3632	0.1696	-2.141	0.166
doc 0.50	-0.2056	0.1696	-1.212	0.349

S = 0.3598 R-Sq = 92.4% R-Sq(adj) = 69.7%

(table 4.11:-Analysis of Variance for Means)

Source	D. O. F.	Seq. S. S.	Adj. S. S.	Adj. M. S.	F	P
Speed	2	0.9346	0.9346	0.4673	3.61	0.217
Feed	2	0.7304	0.7304	0.3652	2.82	0.262
Doc	2	1.4931	1.4931	0.7465	5.77	0.148
Residual Error	2	0.2589	0.2589	0.1295		
Total	8	3.4171				

(table 4.12:-Response Table for Signal to Noise Ratios)

Smaller-is-better

Level	Speed	Feed	Doc
1	-3.362	-6.070	-2.979
2	-4.059	-3.485	-3.801
3	-6.330	-4.195	-6.971
Delta	2.967	2.585	3.992
Rank	2	3	1

(table 4.13:-Response Table for Means)

Level	Speed	Feed	Doc
1	1.486	2.170	1.410
2	1.610	1.514	1.568
3	2.223	1.635	2.342
Delta	0.737	0.656	0.932
Rank	2	3	1

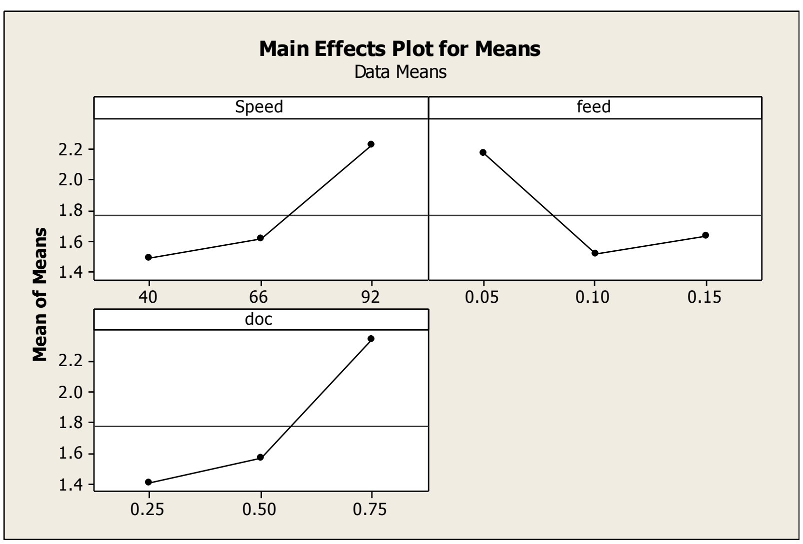


Fig. 17 Main Effects Plot for Means

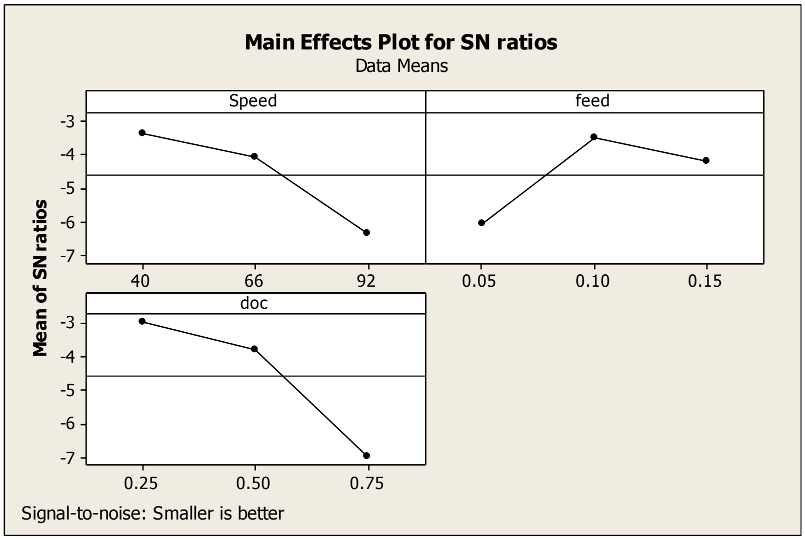


Fig. 18 Main Effects Plot for SN ratios

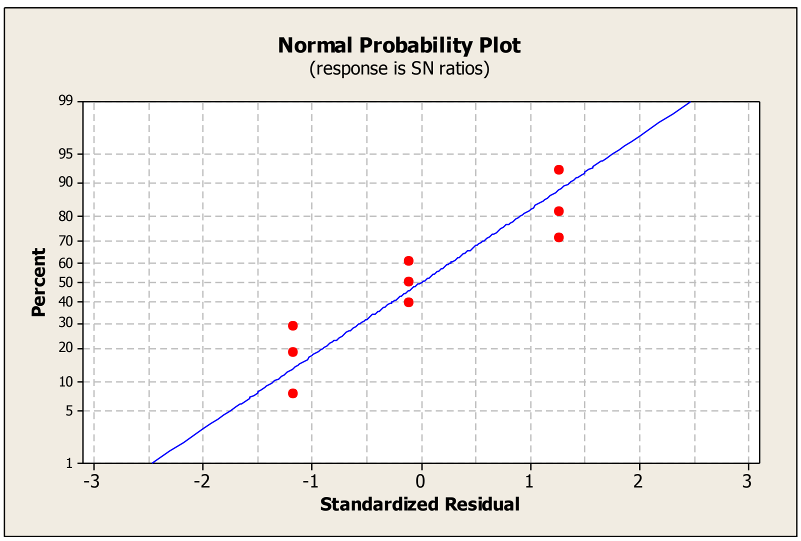


Fig. 19 Normal plot of Residuals for SN ratios

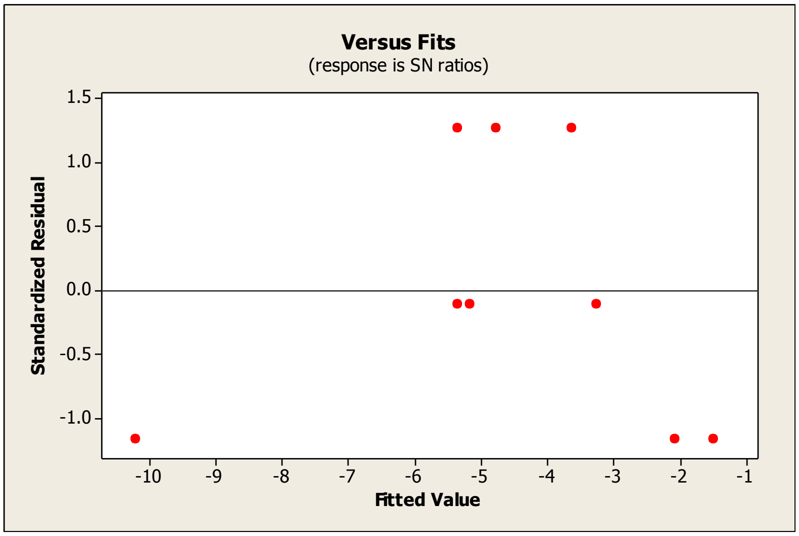


Fig. 20 Residuals vs Fits for SN ratios

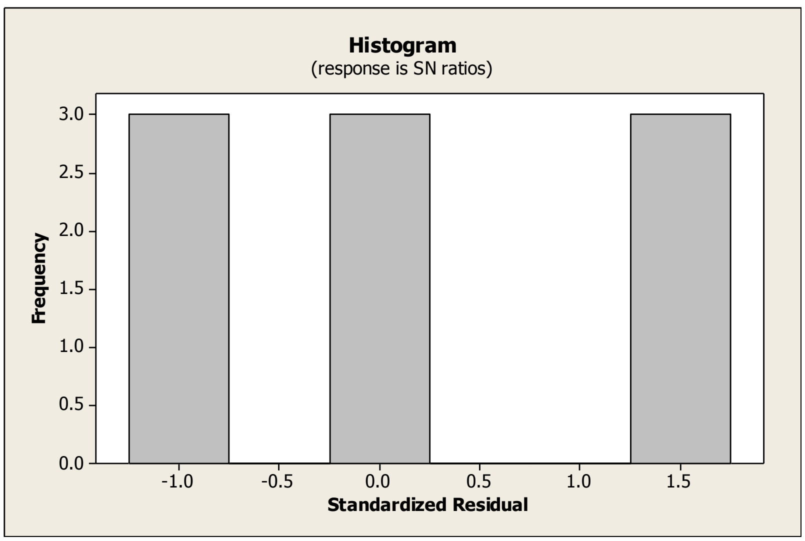


Fig. 21 Residual Histogram for SN ratios

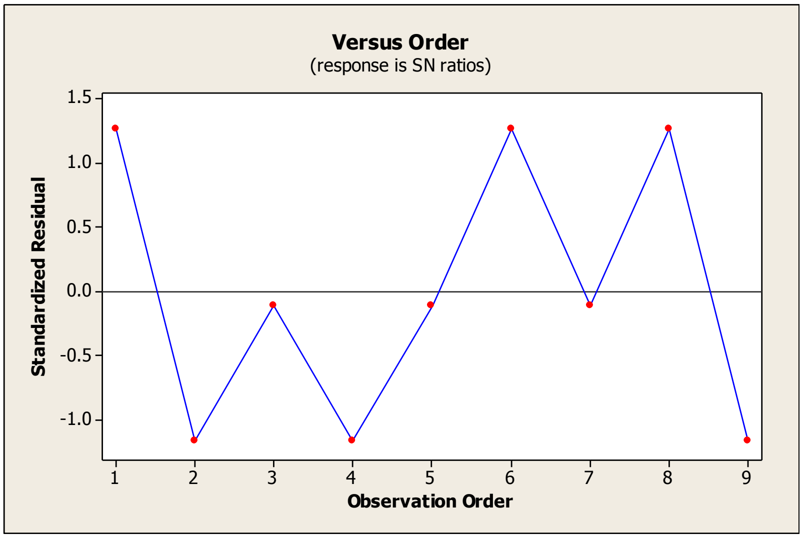


Fig. 22 Residuals vs Order for SN ratios

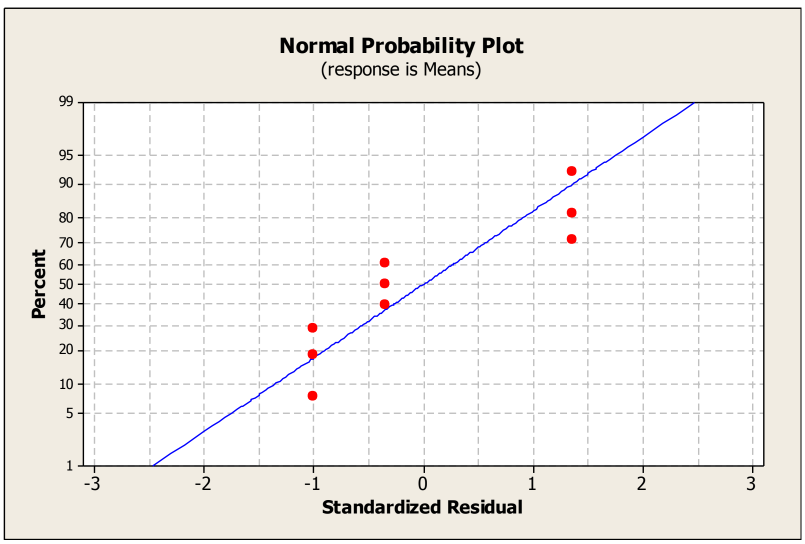


Fig. 23 Normal plot of Residuals for Means

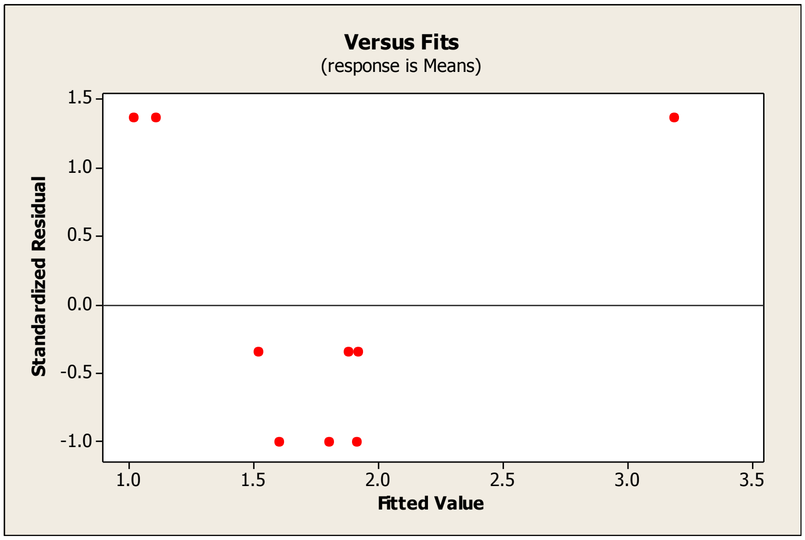


Fig. 24 Residuals vs Fits for Means

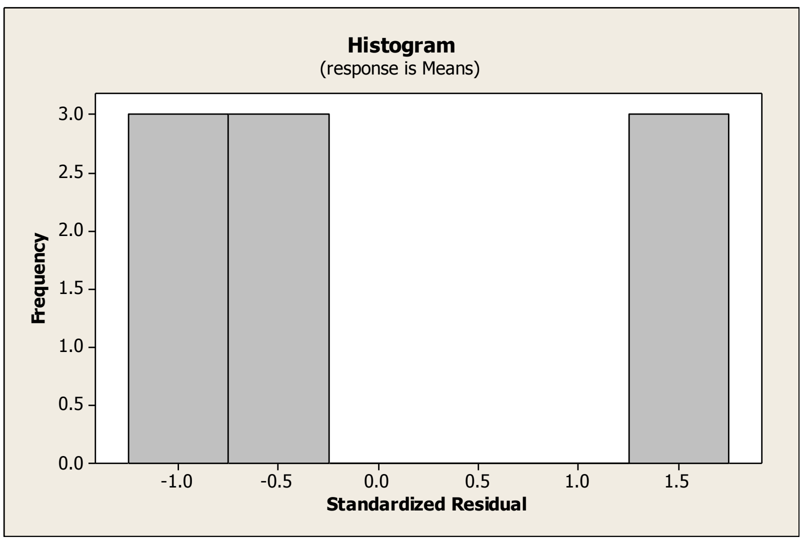


Fig. 25 Residual Histogram for Means

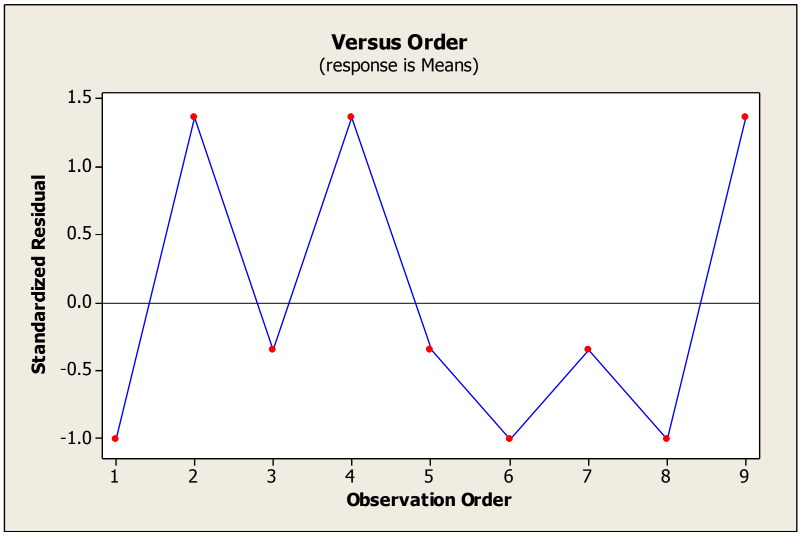


Fig. 26 Residuals vs Order for Means

CHAPTER 6

Chapter 6:

Summery

6. Conclusion

- Conclusion can be derived from the experimentation done using S. S. 304 graded steel and carbide cutting tool.
- A set of levels of parameter is obtained in order to minimize surface roughness as well as tool wear.
- It is found that cutting velocity affects more while calculating tool wear and where depth of cut affects more while experimentation of surface roughness.
- A conformation test is done in order to get optimal setting, it is evidenced that A^2 B^3 C^2 for measuring tool wear and it is found to be 0.659 micron and A^1 B^2 C^1 for surface roughness, it is found to be 1.253 micron.

CHAPTER 7

Chapter 7:

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