Optimization of Machining Parameters on Surface Roughness by Taguchi Approach

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Abstract: **The present work Optimization of Machining parameters on Surface Roughness by Taguchi approach has been undertaken keeping into consideration the following problems:**

1) **In today's fast growing manufacturing sector, applications of proper simulation, modeling and optimization strategies in CNC turning process is essential to improve the machining, and the overall productivity.**
2) **High cost of numerically controlled machine tools, compared to their conventional counterparts, has forced us to operate these machines as efficiently as possible in order to obtain the required payback.**
3) **Usually the previous turning experimental study based on spindle speed, feed rate and depth of cut and these cutting parameters are use for optimization of operations. Due to the highly competitive global competition and precision product requirements these important machining parameters optimize for the best process optimization.**
4) **It is not possible to obtain mathematical model for Taguchi model, the investigation of mathematical model is thus very essential. Because mathematical model is powerful tool to predict response for any of input parameters values within the experimental domain, and optimal values can be any of parameters point i.e., parameters are continuous and can take any real value. So, the necessary data required for developing the mathematical model for Taguchi method only possible when Taguchi method is coupled with other optimization technique.**

The problem was to find an optimum set of conditions that were to produce minimum surface roughness.

There are two purposes of this research. The first is to demonstrate a systematic approach of using Taguchi parameter design of process control of individual CNC turning machine. The second is to demonstrate the use of Taguchi parameter design in order to identify the optimum surface roughness and performance with a particular combination of cutting parameters in a CNC turning operation.

Keywords: **CNC Turning, Taguchi method, ANSYS.**

I. INTRODUCTION

Turning is the machining operation that produces cylindrical parts. In its basic form, it 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.

CNC turning process is widely used in industry including the aerospace and automotive sectors because of its versatility and efficiency. In CNC Turning process, the cutting conditions such as spindle speed, depth of cut, feed rate etc., features of cutting tool and work piece materials affects the process efficiency and performance characteristics. Performance evaluation of CNC turning is based on the performance characteristics like cyclic time, power consumption, surface roughness, material removal rate, tool wear, tool life, cutting force, dimensional accuracy and geometrical error. Very few research attempts have been done to estimate the significance of cyclic time, surface roughness, geometrical error and power consumption based on the all important machining parameters. Recent increase in high quality product demand and becomes a priority for the manufacturing industry. Surface quality is important performance to evaluate the productivity of machine tools as well as machined components. Surface roughness is used as the critical quality indicator for the machined surfaces. In today's manufacturing industry, special attention is given to surface quality and power consumption with less machining time. It is necessary to select the most appropriate machining strategies in order to improve cutting efficiency, process at low cost and produce high-quality products. So it needs well suited predictive strategies for process studies. Thus in today's fast growing manufacturing sector, applications of proper simulation, modeling and optimization strategies in metal cutting is essential to minimize machining time and to improve the overall productivity.

Whenever two machined surfaces come in contact with one and the other, the quality of the mating parts plays an important role in the performance and wear of the mating parts. The height, shape, arrangement and direction of these surface irregularities on the work piece depend upon a number of factors such as:

a) Cutting speed.

b) Feed.

c) Depth of cut.

d) Tool wear

e) Material of tool and work piece

f) Tool life, etc.

(a) Cutting speed:

It is found that an increase of cutting speed generally improves surface quality.

(b) Feed:

Experiments show that as feed rate increases surface roughness also increases due to the increase in cutting force and vibration.

(c) Depth of cut:

Increasing the depth of cut increases the cutting resistance and the amplitude of vibrations. As a result, cutting temperature also rises. Therefore, it is expected that surface quality will deteriorate.

(d) Tool wear:

The irregularities of the cutting edge due to wear are reproduced on the machined surface. Apart from that, as tool wear increases, other dynamic phenomena such as excessive vibrations will occur, thus further deteriorating surface quality.

(e) Tool material & Work material:

High strength cutting tool has less chance of failure, hence required for good surface finish. The work material also play important role for selection of finished product quality. High strength material is hard to machine causes low surface finish and vice-versa.

(f) Tool life:

The factor tool life is concerned with tool wear as the tool if easily worn out during machining, corresponding tool life with surface roughness will be degraded.

1.0 TAGUCHI TECHNIQUE:

Genichi Taguchi is a Japanese engineer who has been active in the improvement of Japan's industrial products and processes since the late 1940s. He has developed both the philosophy and methodology for process or product quality improvement that depends heavily on statistical concepts and tools, especially statistically designed experiments. Many Japanese firms have achieved great success by applying his methods. Wu (1982) has reported that thousands of engineers have performed tens of thousands of experiments based on his teachings.

Sullivan reports that Taguchi has received some of Japan's most prestigious awards for quality achievement, including the Deming prize. In 1986, Taguchi received the most prestigious prize from the International Technology Institute – The Willard F. Rockwell Medal for Excellence in Technology. Taguchi's major contribution has involved combining engineering and statistical methods to achieve rapid improvements in cost and quality by optimizing product design and manufacturing processes.

Barker (1990) reported that since 1983, after Taguchi's association with the top companies and institutes in USA (AT & T Bell Laboratories, Xerox, Lawrence Institute of Technology (LIT), Ford Motor Company etc.), his methods have been called a radical approach to quality, experimental design and engineering. Sullivan reported that the term "Taguchi methods" (TM) refers to the parameter design, tolerance design, quality loss function, on-line quality control, design of experiments using orthogonal arrays, and methodology applied to evaluate measuring systems.

Pignatiello (1988) identifies two separate aspects of the Taguchi methods: the strategy of Taguchi and the tactics of Taguchi. Taguchi tactics refer to the collection of specific methods and techniques used by Genichi Taguchi, and Taguchi strategy is the conceptual framework or structure for planning a product or process design experiment.

Benton (1991) reported that Taguchi addresses design and engineering (off-line) as well as manufacturing (on-line) quality. This fundamentally differentiates TM from statistical process control (SPC), which is purely an on-line quality control method.

Taguchi's ideas can be distilled into two fundamental concepts:

(a) Quality losses must be defined as deviations from targets, not conformance to arbitrary specifications (Benton 1991).
(b) Achieving high system-quality levels economically requires quality to be designed into the product. Quality is designed, not manufactured, into the product (Taguchi 1989).

Lin et al. (1990) stated that Taguchi methods represent a new philosophy. Quality is measured by the deviation of a functional characteristic from its target value. Noises (uncontrolled variables) can cause such deviations resulting in loss of quality. Taguchi methods seek to remove the effect of noises.

Taguchi (1989) described that quality engineering encompasses all stages of product/ process development: system design, parameter design, and tolerance design. Byrne & Taguchi (1987), however, pointed out that the key element for achieving high quality and low cost is parameter design. Through parameter design, levels of product and process factors are determined, such that the product's functional characteristics are optimized and the effect of noise factors is minimized. Kackar & Shoemaker (1986) observed that parameter design reduces performance variation by reducing the influence of the sources of variation rather than by controlling them, it is thus a very cost-effective technique for improving engineering design. Chanin et al. (1990) remarked that Japanese companies such as Nippon, Denso, NEC, and Fugitsu have become world economic competitors by using Taguchi's approach which has potential for saving experimental time and cost on product or process development, as well as quality improvement. Kacker & Shoemaker (1986). Ghosh (1990) remarked that Taguchi's ideas are also being used in many others US companies such as Ford and Xerox. There are also many courses on robust parameter design offered by organizations like American Supplier Institute, Rochester Institute of Technology, and the Center for Quality and Productivity Improvement at the University of Wisconsin in Madison.

The American Supplier Institute also has an annual symposium where case studies on the application of the Taguchi Methods are presented.

1.1: Parameter Design by Taguchi Method:

To summarize, the parameter design of the Taguchi method includes the following steps:

1) Identification of the quality characteristics and selection of design parameters to be evaluated.
2) Determination of the number of levels for the design parameters of possible interactions between the design parameters.
3) Selection of appropriate orthogonal array and assignment of the orthogonal array.
4) Analysis of the experimental results using the S/N and ANOVA analyses.
5) Selection of the optimal level of design parameters.
6) Verification of optimal design Parameters through confirmation experiments.

Therefore, three objectives can be achieved through parameter design of the Taguchi method, i.e.

a) Determination of the optimal design of parameters for a process or a contribution of the quality characteristics.
b) Estimation of each design parameter to the contribution of the quality characteristics.
c) Prediction of quality characteristics based on the optimal design parameters. The Taguchi method has been successfully used worldwide by researchers of different field to optimize varieties of problems pertaining to their field.

II. PROBLEM FORMULATION

2.1 OBJECTIVES OF THE PRESENT INVESTIGATION

a. Investigation of the working ranges and levels of the CNC turning parameters using one factor at a time approach.

b. Experimental determination of the effects of the various process parameters viz cutting speed, depth of cut, feed on the performance measures like surface roughness in CNC turning process in this study.

c. Optimization of the performance measures using Taguchi method.

d. Modeling of the performance measures by using Analysis of variance(ANOVA) and regression analysis.

2.2 PROBLEM DESCRIPTION

It was required to work on the round bar of Aluminum alloy (AM40), machined up to diameter (20 mm).The upper and lower deviation was given as 0.8-1.0 mm. As far as surface roughness is concerned, it was instructed to keep the surface roughness well below 2 microns.

The machining process on a CNC lathe is programmed by speed, feed rate and cutting depth, which are frequently determined based on the job shop experiences. However, the machine performance and the product characteristics are not guaranteed to be acceptable. Therefore, the optimum turning conditions have to be accomplished.

With all the viewpoints, this study proposes an optimization approach using orthogonal array and ANOVA, S/N ratios and graphs plotted with the help of MINITAB software to optimize precision CNC turning conditions. The optimum multi-objective cutting parameters can then be achieved through the analysis of factor responses in the Taguchi experiment. This study definitely contributes to the optimum solution by Taguchi technique for precision CNC turning as per the customer specifications in a satisfactory manner.

2.3 PARAMETER IDENTIFICATION:

It is necessary to be well versed with the parameters that affect the CNC operation in general. The input parameters which affect the aforementioned output parameters are numerous such as:

a) Cutting speed
b) Feed rate.
c) Depth of cut.
d) Side cutting edge angle
e) Type of power.
f) Cutting tool material.
g) Working temperature.
h) Operator.
i) Make of the CNC machine.
j) Noise.

In order to identity the process parameters, affecting the selected machining quality characteristic of turned parts, an Ishikawa cause-effect diagram was constructed as shown in figure 1.1.

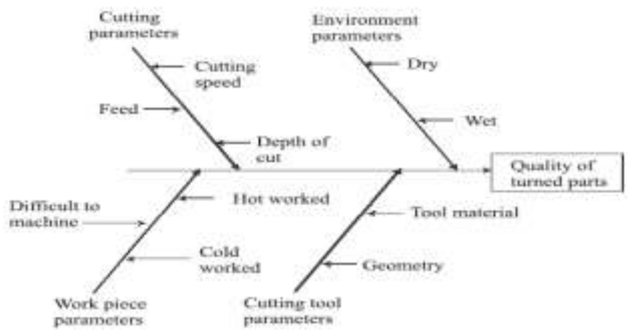


Figure 1.1: Ishikawa cause-effect diagram of a turning process

The identified process parameters are the cutting tool parameters – tool geometry, tool material, Physical and mechanical properties, the cutting parameters – cutting speed, feed rate, Depth of cut, work piece-related parameters – hot-worked, cold-worked, difficult-to-machine, and environment parameters – dry cutting, wet cutting.

2.4 SELECTION OF INPUT PARAMETERS:

The following process parameters were selected for the present work:

Cutting speed – (A),

Feed rate – (B),

Depth of cut – (C),

Tool material – HSS,

Work material –Aluminium Alloy (AM-40),

Environment – Dry cutting.

The selection of parameters of interest was based on some preliminary experiments and earlier studies by the authors [Yang and Tarng, 1998]. The following parameters were kept fixed during the entire experimentation:

a) Work material
b) Cutting tool material
c) Insert geometry
d) Tool holder
e) Cutting conditions

In combination, speed , feed and depth of cut were the primary factors investigated whilst tool nose radius , tool length edge preparation of tools , work piece length and work piece hardness were the secondary factors considered by the renowned investigators of my domain.[Yang and Tarng,1998][Ghani, Choudhary and Hassan, 2004]. Keeping the view of these renowned researchers into consideration, these secondary factors were not considered in the present study.

A mathematical and statistical approach for determining the key influencing factors and their percentage influence on the output parameters has been utilized by the aforementioned researchers.

III. EXPERIMENTAL DESIGN METHODOLOGY

3.1: DESIGN OF EXPERIMENT:

A scientific approach to plan the experiments is a necessity for efficient conduct of experiments. By the statistical design of experiments the process of planning the experiment is carried out, so that appropriate data will be collected and analyzed by statistical methods resulting in valid and objective conclusions. When the problem involves data that are subjected to experimental error, statistical methodology is the only objective approach to analysis. Thus, there are two aspects of an experimental problem: the design of the experiments and the statistical analysis of the data. These two points are closely related since the method of analysis depends directly on the design of experiments employed. The advantages of design of experiments are as follows:

1) Numbers of trials is significantly reduced.
2) Important decision variables which control and improve the performance of the product or the process can be identified.
3) Optimal setting of the parameters can be found out.
4) Qualitative estimation of parameters can be made.
5) Experimental error can be estimated.
6) Inference regarding the effect of parameters on the characteristics of the process can be made.

In the present work, the Taguchi's method has been used to plan the experiments and subsequent analysis of the data collected.

3.2 Taguchi Experimental Design and Analysis

3.2.1 Taguchi's Philosophy:

Taguchi methods are statistical methods developed by Genichi Taguchi to improve the quality of manufactured goods and, now are being used in versatile fields of engineering and non engineering problems including biotechnology, marketing and advertising. Taguchi's principal contributions to statistics are Taguchi loss function; the philosophy of offline quality control and innovations in the design of experiments. Taguchi has developed a methodology for the application of designed experiments, including a practitioner's handbook. This methodology has taken the design of experiments from the exclusive world of the statistician and brought it more fully into the world of manufacturing. His contributions have also made the practitioner work simpler by advocating the use of fewer experimental designs, and providing a clearer understanding of the variation nature and the economic consequences of quality engineering in the world of manufacturing. Taguchi introduces his approach, using experimental design for:

1) Designing products/processes so as to be robust to environmental conditions;
2) Designing and developing products/processes so as to be robust to component variation;
3) Minimizing variation around a target value.

The philosophy of Taguchi is broadly applicable. He proposed that engineering optimization of a process or product should be carried out in a three-step approach, i.e., system design and parameter design.

In system design, the engineer applies scientific and engineering knowledge to produce a basic functional prototype design, this design including the product design stage and the process design stage. In the product design stage, the selection of materials, components, tentative product parameter values, etc., are involved. As to the process design stage, the analysis of processing sequences, the selections of production equipment, tentative process parameter values, etc., are involved. Since system design is an initial functional design, it may be far from optimum in terms of quality and cost.

The objective of the parameter design is to optimize the settings of the process parameter values for improving performance characteristics and to identify the product parameter values under the optimal process parameter values. In addition, it is expected that the optimal process parameter values obtained from the parameter design are insensitive to the variation of environmental conditions and other noise factors.

Fig. 1.2 shows the block diagram of a process or product with signal and noise factors. Therefore, the parameter design is the key step in the Taguchi method to achieving high quality without increasing cost.

Basically, classical parameter design, developed is complex and not easy to use. Especially, a large number of experiments have to be carried out when the number of the process parameters increases. To solve this task, the Taguchi method uses a special design of orthogonal arrays to study the entire parameter space with a small number of experiments only. A loss function is then defined to calculate the deviation between the experimental value and the desired value. Taguchi recommends the use of the loss function to measure the performance characteristic deviating from the desired value. The value of the loss function is further transformed into a signal-to-noise (S/N) ratio η .

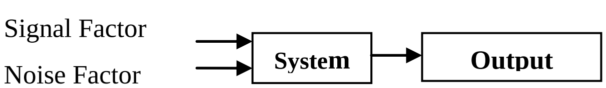


Figure 1.2 : Block diagram of a process/product

3.2.2: TAGUCHI EXPERIMENTAL DESIGN STRATEGY:

Taguchi method can reduce the trial and error type experiments by using a matrix design. An orthogonal array means the design is balanced so that factor levels are weighted equally. Because of this, each factor can be evaluated independently of all the other factors, so the effect of one factor does not influence the estimation of another factor. All interactions are considered for the initial screening DOE to eliminate any confounding of the matrix columns that make interpretation of the results difficult. An interaction is defined as an occurrence where the total effect is greater than the sum of the total effects taken independently. Some of the commonly used orthogonal arrays are shown in Table 3.1. As Table 3.1 shows, there are greater savings in testing for the larger arrays. Also, if we use –1 to replace level 1, 0 to replace level 2, and 1 to replace level 3, then all the dot product of any two columns are 0, which is the mathematical meaning of orthogonal for array columns.

Table 3.1: Standard orthogonal arrays

OA	Factors	Levels	Full Factorial
L4	3	2	8
L8	7	2	128
L9	4	3	81
L12	11	2	2048
L27	13	3	1594323
L64	21	4	$4.4x10^{12}$
L81	40	4	$1.2x10^{19}$

3.2.2.1: Loss Function:

The mathematical expression for the loss of quality of a product or process is determined by the term “Quality Loss Function” as described and formulated by Taguchi. The quality level of a product is defined as the total loss incurred by society due to the failure of the product to deliver the target performance and due to harmful side effects of the products, including its operating cost. Quantifying this loss is difficult because the same product may be used by different customers, for different applications, under different environmental conditions etc. The traditional way to measure the quality is in terms of fraction defective. This commonly used measure of quality is often incomplete and misleading. It implies that the products that meet the specifications (allowable deviation from the target response) are equally good, while those outside the specifications are bad. The fallacy here that the products barely meet the specifications is, from the customer’s point of view, as good or as bad as the products that is barely outside the specifications. In reality the products whose response is exactly on target gives the best performance. As the products response deviates from the target, the quality becomes progressively worse. Quality loss function shown that as we deviates from the targets the cost due to loss of quality of the product increases. Taguchi proposed a loss function equation to determine how much society loses every time the parts produced do not match the specified target.

The loss function determines the financial loss that occurs every time a product characteristics deviates from its target. The loss function is the square of the deviation multiplied by a constant k, with k being ratio of the cost of the defective and the square of the tolerance. The loss function quantifies the deviation from the target and assigns a quantitative value to the deviation.

$$L(y) = k\ (y-m^2) \qquad (3.1)$$

where loss in monetary units is represented by L, characteristic should be set at m value, y is the characteristic actual.

According to Taguchi, the cost of quality in relation with the deviation from the target is not linear because the customer's frustration increases (at a faster rate) as more defects are found on a product, that's why the loss function is quadratic.

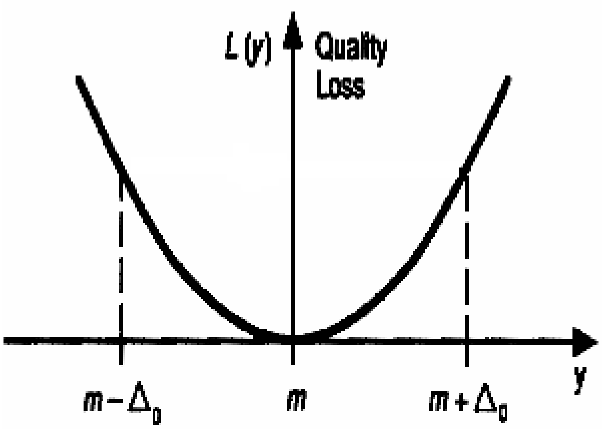
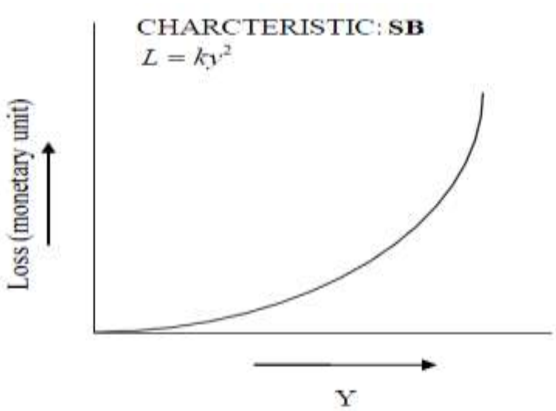


Figure 3.2: The Taguchi loss-function

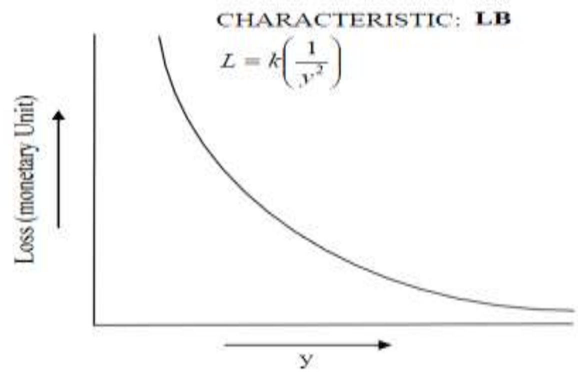
3.2.2.2: Other Loss Functions:

The loss-function can also be applied to product characteristics other than the situation

The loss function is identical to the "nominal-is-best" type of situation when m=0, which is the best value for "smaller is better" characteristic (no negative value). The loss function for a "larger-is-better" type of product characteristic (LB) is also shown in Fig.3.3b, where also m=0.



(a)



(b)

Figure 3.3 (a, b): The Taguchi loss-function for SB and LB characteristics

IV. EXPERIMENTAL SET-UP AND PROCESS PARAMETER SELECTION

4.1: MACHINE TOOL:

In this study, $L_9(3^3)$ orthogonal array of Taguchi experiment is selected for three parameters (speed, feed, depth of cut) with three levels for optimizing the surface roughness in precision turning on an HE-100-CNC-PC CNC (Computerized Numerical Controlled) lathe.

Detail of machine tool is attached in ANNEXURE-I.

Figure 5.1: CNC Lathe

4.2: MATERIALS AND METHODS:

This experimental investigation was carried out in AFSET, Dhauj. Objective of the experiments under reference was to optimize important output parameter namely surface roughness. Taguchi approach of design of experiment (DOE) was adopted in this case and orthogonal array L-9 was used for determining the number of experiments.

The material used in this experimental is the alloy of aluminum (AM-40, Material number ENAW-5083) having excellent corrosion resistance with good weldability and formability in the form of round bar having diameter of 20 mm dimension. It is machined according to Taguchi's L_9

orthogonal array. The chemical composition of flat bar material is given in Table 4.1.

Table 4.1: Chemical composition of Aluminum alloy

Material	Al	Mg	Mn
Al- Alloy	94.8%	4.5%	0.7%

The cutting tool selected for turning operation is made of High speed steel.

4.3: MEASUREMENT OF EXPERIMENTAL PARAMETERS:

4.3.1: SURFACE ROUGHNESS:

Roughness is often a good predictor of the performance of a mechanical component, since irregularities in the surface may form nucleation sites for cracks or corrosion. Roughness is a measure of the texture of a surface. It is quantified by the vertical deviations of a real surface from its ideal form. If these deviations are large, the surface is rough; if small, the surface is smooth. Roughness is typically considered to be the high frequency, short wavelength component of a measured surface. The parameter mostly used for general surface roughness is Ra. It measures average roughness by comparing all the peaks and valleys to the mean line, and then averaging them all over the entire cut-off length. Cut-off length is the length that the stylus is dragged across the surface; a longer cut-off length will give a more average value, and a shorter cut-off length might give a less accurate result over a shorter stretch of surface. The surface roughness measurements were taken by MITUTOYO Surfpak-ez in micron.

For taking the reading of surface roughness first keeping work piece on the plane surface after that stylus of Surfpak-ez is kept on the circumference of the finish part of the work piece, press the start button on the top of the instrument. The stylus had traversed a 4.8mm portion of the job and gives the reading of surface roughness which display on the screen of the pc-monitor.

Reading was taken at the circumference or each work piece hence the readings of surface roughness are obtained for a single work piece. Taking the average of these four readings, this gives the average roughness value of the finished work piece. The same was repeated for each work piece. **S**pecification of surfpak-ez R_a version is attached in ANNEXURE-II.

4.4: SELECTION OF PARAMETERS AND THEIR LEVELS:

Turning operation experiments were carried out on a CNC lathe that provides the power to turn the work piece at a given rotational speed and to feed to the cutting tool at specified rate and depth of cut. Therefore three cutting parameters namely cutting speed, feed and depth of cut need to be optimized.

Therefore, three parameters (i.e. Speed, Feed & Depth of cut) as the input parameters and the surface roughness as the output parameters are taken in the present experimental setup.

After deciding the three parameters for the study, which is done as discussed in the literature review on turning process and the selection of three levels of each parameter has been taken on the bases of past practical experience of the operators.

The feasible space for the cutting parameters was defined by varying the turning speed in the range 1000-1600rpm, feed in the range 0.02-0.04mm/rev. and depth of cut from 0.25 to 0.35mm. Three levels of each cutting parameters were selected as shown in table 4.1. Selected cutting parameters were fed with the help of in-built control panel of the CNC machine itself.

Corresponding Cutting speed in mm/min. is found for work piece is (1046.66,1360.66,1674.66 mm/min.) by V=(3.14x20xN)/60

Table 4.2 : Parameters and their levels

Parameters	Symbols	Units	Level – 1	Level – 2	Level – 3
Speed	A	Cutting speed (mm/min.)	1674.66	1360.66	1046.66
Feed	B	mm/rev.	0.04	0.03	0.02
Depth of Cut	C	Mm	0.35	0.3	0.25

4.5: Experimentation:

The experiments were performed on a CNC machining centre. Following steps were followed in the cutting operation:

1) The work piece was made round shape with the help of conventional lathe machine.
2) The work piece was mounted and clamped on the work table.
3) A reference point on the work piece was set for setting work co-ordinate system (WCS). The programming was done with the reference to the WCS. The reference point was defined by the external edge of the work piece.
4) The program was made for cutting operation of the work piece with limitation of the upper and lower deviation as 0.8-1.0 mm. While performing various experiments, the following precautionary measures were taken:

   a) Each set of experiments was performed at room temperature in a narrow temperature range (32 ± 2^{o} C).
   b) Before taking measurements of surface roughness, the work piece was cleaned with acetone.
   c) All the experiments are conducted by one operator only.

d) Same tool is used for all the experiment.
e) If during an experiment, there is power cut then experiment is repeated again.

V. OBSERVATIONS AND RESULTS

5.1 OBSERVATIONS:

As discussed in section 3.3, three levels of each input parameters Cutting Speed, Feed rate and depth of cut are taken and the experimental layout of three parameters using the L9 orthogonal array is formed as shown in Table 5.1.

Table-5.1 Experimental Layout Using an L-9 Orthogonal Array

Exp. No.	Process Parameter levels		
	A	**B**	*C*
	Cutting Speed (mm/min.)	**Feed rate(mm/rev)**	**Depth of cut (mm)**
1	1674.66	0.04	0.35
2	1674.66	0.03	0.3
3	1674.66	0.02	0.25
4	1360.66	0.04	0.25
5	1360.66	0.03	0.35
6	1360.66	0.02	0.3
7	1046.66	0.04	0.3
8	1046.66	0.03	0.25
9	1046.66	0.02	0.35

Nine experiments are conduced for the above mentioned nine sets of parameters (speed, feed rate & depth of cut) and the average value surface roughness in microns are listed in table 6.2.

Table 6.2: Experimental Results

ExpNo.	**Factor**			**Results**
	Cutting Speed (A) (mm/min.)	Feed (B) (mm/rev)	Depth of Cut (C) (mm)	Surface Roughness (Microns)
1	1674.66	0.04	0.35	2.813
2	1674.66	0.03	0.3	1.210
3	1674.66	0.02	0.25	1.372
4	1360.66	0.04	0.25	1.302
5	1360.66	0.03	0.35	1.385
6	1360.66	0.02	0.3	1.172
7	1046.66	0.04	0.3	2.894
8	1046.66	0.03	0.25	1.240
9	1046.66	0.02	0.35	2.854

5.2: ANALYSIS OF RESULTS:

In the Taguchi method the results of the experiments are analyzed to achieve one or more of the following three objectives:

a) To establish the best or the optimum condition for a product or a process.
b) To estimate the contribution of individual factors.
c) To estimate the response under the optimum conditions.

Studying the main effects of each of the factors identifies the optimum condition. The process involves minor arithmetic manipulation of the numerical result and usually can be done with the help of a simple calculator. The main effects indicate the general trend of the influence of the factors. Knowing the characteristic i.e. whether a higher or lower value produces the preferred result, the levels of the factors, which are expected to produce the best results, can be predicted.

The knowledge of the contribution of individual factors is the key to deciding the nature of the control to be established on a production process. The analysis of variance (ANOVA) is the statistical treatment most commonly applied to the results of the experiment to determine the percent contribution of each factor. Study of the ANOVA table for a given analysis helps to determine which of the factors need control and which do not.

In this study, an L9 orthogonal array with four columns and nine rows was used. Each parameter is assigned to a column, nine parameters combination being available. Therefore only nine parameters are required to study the entire parameter space using the L9 orthogonal array.

5.2.1: ANALYSIS OF THE S/N RATIO:

In the Taguchi method, the term “signal” represents the desirable value (mean) for the output characteristic and the term “noise” represents the undesirable value (S.D.) for the output characteristic. Therefore, the S/N ratio is the ratio of the mean to the S.D.

The relevant graphs for the S/N ratio for all the three process parameters are obtained by using the MINITAB software.

As mentioned earlier, there are three categories of quality characteristics, i.e. the-lower the-better, the-higher-the-better, and the-nominal-the-better. To obtain optimal turning performance, the-lower-the-better quality characteristic for outer diameter of the surface roughness are taken.

5.2.2: ANALYSIS OF VARIANCE (ANOVA):

Analysis of variance is a computational technique to quantitatively estimate the relative contribution, which each controlled parameter makes to the overall measured response and expressing it as a percentage. Thus the information about how significant the effect of each controlled parameter is on the experimental results can be obtained. ANOVA uses S/N ratio responses to investigate which control factors significantly affect the quality characteristic. It is accomplished by separating the total variability of the S/N ratios, which is measured by sum of the squared deviations from the total mean S/N ratio, into contributions by each of the control factors and the errors. In this experimental study ANOVA was used to determine the significant parameters influencing the surface roughness. The factors associated with analysis are shown in Table no.6.7.

5.2.3: CALCULATION FOR THE CONTRIBUTION OF INDIVIDUAL FACTORS:

The calculation has made for the following:

- **a.** A factor that can be pooled
- **b.** The factor with the most influencing the variation of results.

Calculation is shown in **APPENDIX**

Table 5.3: S/N Ratios For Surface Roughness

Exp. No.	Factor			Results	
	Cutting Speed (A) (mm/min.)	Feed (B) (mm/rev)	Depth of Cut (C) (mm)	Surface Roughness (Microns)	S/N Ratio Surface Roughness (db)
1	1674.66	0.04	0.35	2.813	-8.98
2	1674.66	0.03	0.3	1.210	-1.65
3	1674.66	0.02	0.25	1.372	-2.74
4	1360.66	0.04	0.25	1.302	-2.29
5	1360.66	0.03	0.35	1.385	-2.82
6	1360.66	0.02	0.3	1.172	-1.37
7	1046.66	0.04	0.3	2.894	-9.22
8	1046.66	0.03	0.25	1.240	-1.86
9	1046.66	0.02	0.35	2.854	-9.10

TABLE 5.4: Means For Surface Roughness

Exp. No.	Factor			Results	
	Cutting Speed (A)(mm/min.)	Feed (B) (mm/rev)	Depth of Cut (C) (mm)	Surface Roughness (Microns)	Means Surface Roughness (db)
1	1674.66	0.04	0.35	2.813	2.813
2	1674.66	0.03	0.3	1.210	1.210
3	1674.66	0.02	0.25	1.372	1.372
4	1360.66	0.04	0.25	1.302	1.302
5	1360.66	0.03	0.35	1.385	1.385
6	1360.66	0.02	0.3	1.172	1.172
7	1046.66	0.04	0.3	2.894	2.894
8	1046.66	0.03	0.25	1.240	1.240
9	1046.66	0.02	0.35	2.854	2.854

for each parameter at levels 1, 2, and 3 for S/N data, S/N response is computed by MINITAB software. Mathematical formula is also given in APPENDIX. For manual calculation of S/N response table. The delta statistic is the highest minus the lowest average for each factor. MINITAB assigns ranks based on delta values; rank 1 to the highest delta value, rank 2 to the second highest, and so on. The ranks indicate the relative importance of each factor to the response.

Table 5.5: S/N response table for Surface roughness

Level	Cutting Speed (A)	Depth of Cut (B)	Feed (C)
1	-6.736	-4.412	-2.303
2	-2.167	-2.118	-4.088
3	-4.462	-6.835	-6.974
Delta	4.569	4.717	4.671
Rank	3	1	2

From the Table 6.5 it is clearly shown that the parameter B is having highest effect on the process as compared to the other parameters because these having highest max-min value (4.717). It is also shown that maximum value of mean S/N ratio of A is at level 2 (-2.167), B is at level 2 (-2.118), C is at level 1 (-2.303) So the optimal cutting parameters are Cutting speed at level 2 i.e. 1360.66mm/mim, depth of cut at level 2 i.e. 0.3mm, feed at level 1 i.e.0.03 mm/rev.

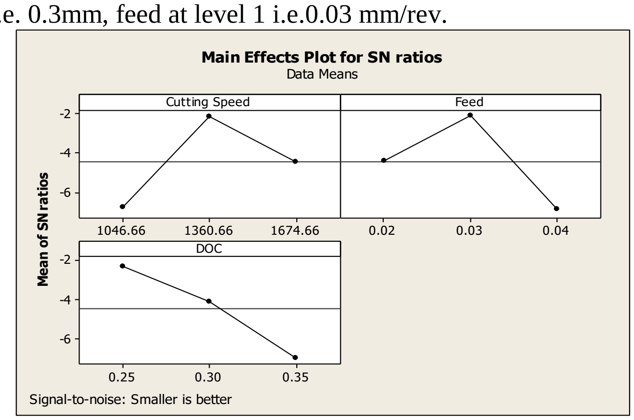


Figure.-5.2a: Main Effects Plot For S/N Ratio

S/N ratio and response effects data plotted are shown in Fig. 5.2a, it can be used to decide the optimal combination of parameters for Surface roughness. Fig. 5.2a shows that the Surface roughness decreases with the increase of depth of cut, and increases with increase in spindle speed and feed up to certain limit.

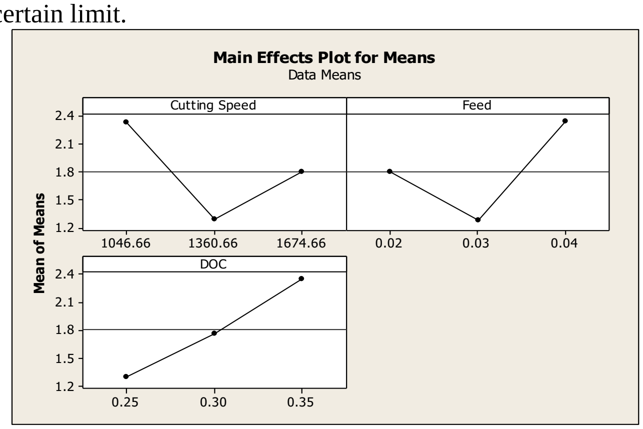


Figure.-5.2b Main Effects Plot For S/N Ratio

5.2.4: CALCULATION FOR RESPONSE UNDER THE OPTIMUM CONDITIONS:

To calculate the response under optimal condition, regression analysis has been done with the help of Mini-tab software .

5.2.4.1: REGRESSION ANALYSIS

The regression equation is

Roughness = - 0.99 - 0.000846 Cutting Speed + 26.9 Feed + 10.5 DOC

=-0.99-.000846*1360.66+26.9*.03+10.5*.30

= 1.81

Table 5.6: Performance Factor of Regression Analysis

S. no.	Predictor	Coefficient	SE Coef.	T	P
1.	CONSTANT	-0.988	2.316	-0.43	0.687
2.	SPEED	-0.0008455	0.0009187	-0.92	0.400
3.	FEED	26.85	28.85	0.93	0.395
4.	D.O.C	10.460	5.770	1.81	0.130

S = 0.706619 R-Sq = 50.0% R-Sq(adj) = 20.0%

Table 5.7: Analysis of Variance

S.No.	Source	DF	SS	MS	F	P
1.	Regression	3	2.4967	0.8322	1.67	0.288
2.	Residual Error	5	2.4966	0.4993	-	-
3.	Total	8	4.9932	-	-	-

Table 5.8: Summary of S/N values and ANOVA results for Surface Roughness

Factor	Degree of Freedom (DOF)	Average S/N Values			Sum of Squares	Percentage of Contribution (%)
		Level 1	Level 2	Level 3		
Cutting speed	2	-6.736	-4.412	-2.303	31.30	31.59
Depth of Cut	2	-2.167	-2.118	-4.088	33.41	33.70
Feed	2	-4.462	-6.835	-6.974	33.30	33.57
Error	0	-	-	-	1.13	1.13
Total	8	-	-	-	177.42	100

In order to study the significance of the process variables towards surface roughness, analysis of variance (ANOVA) was performed. The calculation is written in the APPENDIX. The degrees of importance of each parameter considered, namely, cutting speed, depth of cut, feed is given in Table 6.8. Each three level parameter has 2 degree of freedom (DOF) (Number of level – 1), the total DOF required for three parameters each at three levels is 8[=4x (3-1)]. Table 6.8 showed the summary of S/N values and ANOVA results for roughness. It was found that feed and cutting speed are non significant process parameters. It clearly shows that the cutting speed, feed and depth of cut ratio contribution are varying to each other. In case of surface roughness, dominant parameter followed by depth of cut (B), feed (C) and cutting speed (A), had lower effects. Depth of cut has greatest influence on the surface roughness for turning operation with 33.70% influence followed by feed with 33.59% and cutting speed 31.30%.

5.3: VERIFICATION OF RESULTS:

There are two methods are generally used for validation of Taguchi model's. First is based upon confirmation test. It is used to verify the estimated result with the experimental results and in the second method of validation is based upon the comparison between optimized model output results with an example taken from reference. In this study, first method is used in order to validate the Taguchi model for verification. The objective of the confirmation run was to determine that the selected control parameter values would produce better response than those produced in the first part of the experiment. The optimum conditions are set for the significant parameters (the insignificant parameters are set at economic levels) and a selected number of tests are run under specified conditions. Once the optimal level of the design parameters has been selected, the final step is to predict and verify the improvement of the quality characteristic using the optimal level of design parameters. In this experimental study optimal combination of parameters and their levels obtain by Taguchi technique using MINITAB software coincidently match with one of the experiments.

The results obtained were verified by running a separate experiment and manufacturing around 20 pieces of component Out of these 20 components, randomly selected 3 pieces were selected separately for surface roughness test. The R_A for the component was found out to be **1.76** microns. [Using the Parameter combination A2B2C1].

VI. CONCLUSION AND SCOPE FOR FUTURE WORK

6.1: CONCLUSION:

It is found that the parameter design of the Taguchi method provides a simple, systematic and efficient methodology for the optimization of process parameters. Based on the results obtained in this study, the following can be concluded:

a) The percentage contribution of cutting speed is **31.30 %,** feed rate is **33.70%,** depth of cut is **33.59%** and that of error is **1.13%** for minimum value of surface roughness.

b) The percentage contribution of the Depth of cut is maximum i.e.**33.70 %** for obtaining the minimum value of the surface roughness.
c) The optimum combination of the parameters and their levels for obtaining minimum surface roughness is **A2B2C1.**
d) Out of the above two combinations the surface roughness was found to be the minimum at A2B2C1 with the R_A value of **1.81 microns.**
e) The initial values of surface roughness were obtained by the operator without the application of Taguchi technique was **1.76 microns.**

Thus, it can be safely concluded that the output quality conditions (Surface Roughness) are greatly advanced by the application of Taguchi technique. Hence, one can very well conclude that the project work is successfully completed.

6.2: SCOPE FOR FUTURE WORK:

In this study only 3 process parameters were taken into consideration and the interaction between them were not considered. The percentage influences of the various contributing factors vary as a result of interaction between parameters. Similarly, there would be variations in the results if we consider a greater number of influencing factors like tool and work piece material etc. Cycle time, Power consumption, Geometrical error may also be the parameters that is to be optimized. Some suitable interpolation/extrapolation technique along with GRA could then perhaps be used to solve the problem of optimal parameter determination.

In future, similar study can be conducted in which more than 3 process parameters and the interaction between them can be carried out as an extension to the present project work.

APPENDIX

A: CALCULATION FOR ANALYSIS OF VARIANCE

Analysis of variance is a computational technique to quantitatively estimate the relative contribution, which each controlled parameter makes to the overall measured response and expressing it as a percentage. Thus the information about how significant the effect of each controlled parameter is on the experimental results can be obtained. ANOVA uses S/N ratio responses to calculate.

A1: OVERALL MEAN OF SIGNAL-TO-NOISE RATIO

The overall mean from which all the variation (standard deviation) is calculated is given by,

$$\overline{S/N} = \frac{1}{n}\sum_{i=1}^{n} S/N_i$$

In this experimental study,

$$\overline{S/N}_{STB} = \frac{1}{9}\sum_{i=1}^{9}\left(S/N_{STB}\right)_I$$

$$= -\frac{1}{9}(8.98 + 1.65 + 2.74 + 2.29 + 2.82 + 1.37 + 9.22 + 1.86 + 9.10)$$

$$= -4.44$$

A2: GRAND TOTAL SUM OF SQUARE OF SIGNAL-TO-NOISE RATIO

The grand total sum of squares GTSS is given by,

$$GTSS = \sum_{i=1}^{n}\left(S/N_i\right)^2$$

In this experimental study,

$$GTSS = \sum_{i=1}^{9}\left(S/N_{STB}\right)_i^2 = (-8.98)^2 + (-1.65)^2 + (-2.74)^2 + (-2.29)^2 + (-2.82)^2 + (-1.37)^2 + (-9.22)^2 + (-1.86)^2 + (-9.10)^2$$

$$= 277.22$$

A3: THE SUM OF SQUARES DUE TO OVERALL MEAN OF S/N

The GTSS can be decomposed into two parts, the sum of the squares due to overall mean and the sum of the squares due to variation around overall mean:

$$GTSS = SS_{mean} + SS_{variation}$$

The sum of the squares due to overall mean:

$$SS_{mean} = n \times \overline{(S/N)}^2$$

Where n is the number of total test runs.

In this experimental study,

$$SS_{mean} = 9 \times \left(\overline{S/N_{sTB}}\right)^2 = 9 \times (-4.44)^2 = 177.42$$

A4: THE MEAN SIGNAL-TO-NOISE RATIO

The mathematical formula for the calculation of mean signal-to-noise ratio for parameter A(Cutting Speed) is given by,

$$A_{level1} = \frac{\eta_1 + \eta_2 + \eta_3}{3}$$

$$A_{level2} = \frac{\eta_4 + \eta_5 + \eta_6}{3}$$

$$A_{level3} = \frac{\eta_7 + \eta_8 + \eta_9}{3}$$

The mathematical formula for the calculation of mean signal-to-noise ratio for parameter B (Depth of Cut) is given by,

$$B_{level1} = \frac{\eta_1 + \eta_4 + \eta_7}{3}$$

$$B_{level2} = \frac{\eta_2 + \eta_5 + \eta_8}{3}$$

$$B_{level3} = \frac{\eta_3 + \eta_6 + \eta_9}{3}$$

The mathematical formula for the calculation of mean signal-to-noise ratio for parameter C(Feed) is given by,

$$C_{level1} = \frac{\eta_1 + \eta_6 + \eta_8}{3}$$

$$C_{level2} = \frac{\eta_2 + \eta_4 + \eta_9}{3}$$

$$C_{level3} = \frac{\eta_3 + \eta_5 + \eta_7}{3}$$

A5: THE SUM OF THE SQUARES DUE TO VARIATION AROUND OVERALL MEAN

$SS_{variation}$ is given by

$$SS_{variation} = \sum_{i=1}^{n} \left(S/N_i - \overline{S/N}\right)^2$$

In this experimental study,

$$\sum_{i=1}^{9} = (-8.98 + 4.44)^2 + (-1.65 + 4.44)^2$$
$$+ (-2.74 + 4.44)^2 + (-2.29 + 4.44)^2$$
$$+ (-2.82 + 4.44)^2 + (-1.37 + 4.44)^2$$
$$+ (-9.22 + 4.44)^2 + (-1.86 + 4.44)^2$$
$$+ (-9.10 + 4.44)^2$$
$$= 99.14$$

A6: THE SUM OF SQUARES OF S/N VARIATION INDUCED BY CUTTING PARAMETERS

The $SS_{variation}$ can be further decomposed into the sums of the squares of the variation induced by individual parameter effects around overall mean.

For parameter A, the sum of the squares due to variation around overall mean is:

$$SS_A = n_{A1} \times \left(\overline{S/N}_{A1} - \overline{S/N}\right)^2$$
$$+ n_{A2} \times \left(\overline{S/N}_{A2} - \overline{S/N}\right)^2$$
$$+ n_{A3} \times \left(\overline{S/N}_{A3} - \overline{S/N}\right)^2$$

Where n_{Ai} is number of tests conducted at level i of parameter A and $\overline{S/N}_{Ai}$ is the level average S/N of parameter A at level i

In this experimental study,

$$SS_A = 3 \times (-6.736 + 4.44)^2$$
$$+3 \times (-2.167 + 4.44)^2$$
$$+3 \times (-4.462 + 4.44)^2$$
$$= 31.30$$

Similarly,

$$SS_B = 33.38$$

$$SS_C = 33.30$$

A7: THE PERCENTAGE CONTRIBUTION OF EACH PARAMETER

The percentage contribution of each parameter is found:

Percentage contribution of Parameter $_j$ = ($SS_{parameter\ j}$ / $SS_{variation}$)

In this experimental study,

Parameter A, Cutting Speed: P_A=31.59%

Parameter B, Depth of Cut: $P_{B=}$ 33.70%

Parameter C, Feed: $P_{C=}$33.57%

Percent influence of error term,

= 100 - ($P_A + P_B + P_C$) %

= 1.13%

REFERENCES

[1]. Agapiou, J. S., 1992, 'The optimization of machining operations based on a combined criterion, Part 1: The use of combined objectives in single-pass operations, Part 2: Multi-pass operations'. J. Eng. Ind., Trans. ASME 114: 500–513

[2]. Armarego, E. J. A., Brown, R. H., 1969, 'The machining of metals (Englewood Cliffs, NJ: Prentice Hall) ASME 1952 Research committee on metal cutting data and bibliography'. Manual on cutting of metals with single point tools 2nd edn.

[3]. Barker, T. B., 1990, Engineering quality by design New York: Marcel Dekker.

[4]. Behzad, M. & Chartrand, G. Introduction to the Theory of Graphs. Boston, Allyn and Bacon, Boston,

[5]. Benardos, P.G. & Vosniakos, G.C. 'Prediction of surface roughness in CNC face milling using neural networks and Taguchi's design of experiments, Robotics and computer integrated manufacturing', vol. 18 , 343-354.

[6]. Benton, W. C., 1991, 'Statistical process control and the Taguchi method: A comparative evaluation'. International Journal of Prod. Res., Vol. 29, 1761-1770

[7]. Bhattacharya, A., Faria, R., Inyong, H., 1970, 'Regression analysis for predicting surface finish and its application in the determination of optimum machining conditions'. Trans. Am. Soc. Mech. Eng, .vol. 92, 711

[8]. Brewer, R. C., 1966, 'Parameter Selection Problem in Machining'. Ann. CIRP vol.14, 11-23

[9]. Brewer, R. C. & Rueda, R., 1963, 'a simplified approach to the optimum selection of machining parameters'. Eng. Dig. Vol. 24 (9), 133-150

[10]. Chanin, M. N., Kuei, C.H. & Lin, C., 1990, 'Using Taguchi design, regression analysis and simulation to study maintenance float systems'. Int. J. Prod. Res., vol. 28, 1939-1953
[11]. Chen, M. & Chen, K. Y., 2003, 'Determination of optimum machining conditions using scatter search. New optimization techniques in engineering', 681-697
[12]. Chung, C. T. & Hong, H., 2002, 'Comparison of the tool life of tungsten carbides coated by multilayer TiCN & TiAICN for end mills using the Taguchi method', Journal of Materials Processing Technology vol. 123, 1-4.
[13]. Cirstoiu, C. A., 2005, 'Influence of feed rate on surface roughness in turning processes with different tool inserts'. UPB Scientific Bulletin, Series D: Mechanical Engineering, vol. 67(2), 63-70.
[14]. Danacioglu, N., 1999, 'A Comparison of Construction Methods of Orthogonal Arrays used in Taguchi designs', H.U. Department of Statistics, M.Sc. Thesis.
[15]. Dhavlikar, M.N., Kulkarni, M.S. & Mariappan, V., 2003, 'Combined Taguchi and dual response method for optimization of a centreless grinding operation', Journal of Materials Processing Technology, vol. 132, 90-94.
[16]. Ermer, D. S., Kromordihardjo, S., 1981, 'Optimization of multi-pass turning with constraints'. J. Eng. Ind., vol. 103, 462-468
[17]. Feng, C. X., & Wang, X. F., 2003, 'Surface roughness predictive modeling: neural networks versus regression'. IIE Transactions vol. 35(1), 11-27.
[18]. Feng C. X. & Wang X., 2002, 'Development of Empirical Models for Surface Roughness Prediction in Finish Turning', International Journal of Advanced Manufacturing Technology, Vol. 20, 348-356
[19]. George, P.M., Raghunath, B.K., Manocha, L.M. & Warrier, A. M., 2004, 'EDM machining of carbon-carbon composite - a Taguchi approach', Journal of Materials Processing Technology, vo1. 45, 66-71.
[20]. Ghani, J.A., Chaudhury, I.A. & Hassan H.H., 2004, 'Application of Taguchi method in the optimization of end milling parameters'. Journal of Materials Processing Technology, vol. 145, 84-92
[21]. Ghosh S., 1990, 'Statistical design and analysis of industrial experiments', New York: Marcel Dekker.
[22]. Gilbert, W. W., 1950, 'Economics of machining. In Machining-Theory and practice'. Am. Soc. Met., 476-480
[23]. Gökkayaa, H., & Nalbant, M., 2007, 'The effects of cutting tool geometry and processing parameters on the surface roughness of AISI 1030 steel', Materials & Design, vol. 28(2), 717-721
[24]. Gopalakrishnan, B., Khayyal, F., 1991, 'A Machine parameter selection for turning with constraints: An analytical approach based on geometric programming'. Int. J. Prod. Res., vol. 29, 1897p-1908
[25]. Hinduja, S., Petty, D. J., Tester, M. & Barrow G., 1985, 'Calculation of optimum cutting conditions for turning operations'. Proc. Inst. Mech. Eng. Vol. 199 (B2): 81-92
[26]. Puertas, A. I., & Luis, C.J., 2003, 'Surface Roughness Prediction by Factorial design of Experiments in turning processes', Journal of Material Processing Technology, 390-396.
[27]. Kackar, R. N. & Shoemaker, A. C., 1986, 'Robust design: A cost effective method for improving manufacturing processes', AT & T Tech. J. vol.65, 39-50.
[28]. Kirby E. D., Zhang Z. and Chen J. C., (2004), 'Development of An Accelerometer based surface roughness Prediction System in Turning Operation Using Multiple Regression Techniques', Journal of Industrial Technology, Volume 20, Number 4, pp. 1-8.)
[29]. Kosko B 1997 'Neural network and fuzzy systems – A dynamic approach to machine intelligence' New Delhi: Prentice Hall of India
[30]. Kuo L Y, Yen J Y 2002, 'A genetic algorithm based parameter-tuning algorithm for multi dimensional motion control of a computer numerical control machine tool'. Proc. Inst. Mech. Eng. B216:
[31]. Lalwani, D.I. (2008). 'Experimental investigations of cutting parameters influence on cutting forces and surface roughness in finish hard turning of MDN250 steel'. Journal of Materials Processing Technology, 206(1-3), 167-179.
[32]. Lascoe, O. D., Nelson, C. A., & Porter, H. W. (1973). 'Machine shop operations and setups'. Alsip, IL: American Technical Publishers.
[33]. Lin, J.L., Wang, K.S.. Yan, B.H. and Tarng, Y.S., 'Optimization of the electrical discharge machining process based on the Taguchi method with fuzzy logics', Journal of Materials Processing Technology 102,2000, pp. 48-55.
[34]. Lin, Paul K H, Sullivan L P, Taguchi G 1990 'Using Taguchi methods in quality engineering'. Quality Progress 55–59
[35]. Maxwell, L. M. and Reed, M.B. 'The Theory of Graphs, Networks and Algorithms' Pergamon Press, New York, 1971, pp-164.
[36]. N. H. Rafi & M. N. Islam (2009), 'An Investigation Into Dimensional Accuracy And Surface Finish Achievable In Dry Turning' Machining Science and Technology, Volume 13, Issue 4 October 2009 , pages 571 - 589
[37]. Özel, T., Hsu, T.-K., & Zeren, E. (2005). 'Effects of cutting edge geometry, workpiece hardness, feed rate and cutting speed on surface roughness and forces in finish turning of hardened AISI H13 steel'. International Journal of Advanced Manufacturing Technology, 25(3-4), 262-269.
[38]. Peace, G.S. 'Taguchi Methods: A Hands-On Approach'. Addison-Wesley Publishing Company, Reading M.A. U.S.A. ,1993.
[39]. Petropoulos P G 1973 'Optimal selection of machining rate variable by geometric programming'. Int. J. Prod. Res. 11: 305–314
[40]. Ranjit K Roy., 'Design of experiments using Taguchi approach' John Wiley and Sons, Inc., 2001
[41]. Sundaram R M 1978, 'An application of goal programming technique in metal cutting'. Int. J. Prod. Res. 16: 375–38.
[42]. Taguchi, G. 'System of Experimental Design: Engineering Methods to Optimize
[43]. Quality and Minimize costs, (UNIPUB/ Kraus International Publications-Two Volumes, 1987).
[44]. Taguchi G 1989 Quality engineering in production systems (New York: McGraw-Hill)
[45]. Tarng, Y.S.,Juang, S.C. and Chang, C.H., 'The use of grey-based Taguchi methods to determine submerged arc welding process parameters in hard facing' Journal of Materials Processing Technology, 5624 (2002). pp. 1-6.
[46]. Tong, K.W., Kwong, C.K. and Ip, K.W., 'Optimization of process conditions for the transfer molding of electronic packages' Journal of Materials Processing Technology, 138 , 2003.pp. 361-365.
[47]. Tsai P 1986 'An optimization algorithm and economic analysis for a constrained machining model'. PhD thesis, West Virginia University Optimization of machining techniques 711.
[48]. Vernon, A., & Özel, T. (2003). 'Factors affecting surface roughness in finish hard turning'. Paper presented at the 17th International Conference on Production Research, Blacksburg, Virginia.)
[49]. Walvekar A G, Lambert B K 1970 'An application of geometric programming to machining variable selection'. Int. J. Prod. Res. 8: 3
[50]. Wang X, Jawahir I S 2004 'Web based optimization of milling operations for the selection of cutting conditions using genetic algorithms'. Proc. Inst. Mech. Eng. 218: 212–223
[51]. Wu V 1982 'Off-line quality control: Japanese quality engineering' Dearborn, MI: American Supplier Institute
[52]. X.L. Liu, D.H. Wen, Z.J. Li, Xiao, G. Yan, 'Experimental Study on Hard Turning of Hardened GCr15 steel with PCBN tool' Journal of Material processing Technology, 129,2002").pp-217-221.
[53]. Yang, W.H. and Tarng, Y.S., 'Design optimization of cutting parameters for turning operations based on the Taguchi method', Journal of Materials Processing Technology, 84, 1998.
[54]. Pignatiello J J 1988 'An overview of the strategy and tactics of Taguchi'. Inst. Ind. Eng. Trans. 20: 247–254.