An Investigation of Multi-Characteristic Optimisation of Cutting Parameters in Turning Operation- A Theoretical Study

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Abstract— This research is intended to make an extensive literature survey and theoretical study on the multi objective optimization of the spindle speed, feed and depth of cut in orthogonal turning for surface roughness and MRR using Design of Experiments and Taguchi Method.

Keywords — Taguchi method, surface roughness, MRR. Put your keywords here, keywords are separated by comma.

I. INTRODUCTION

Machining is one of the important metal removing processes in manufacturing industries and turning is still considered the most important operation used to shape metal because in turning the condition of operation are most varied. Increasing productivity and reducing manufacturing cost has always been the primary objective of an Industrial and Production Engineer. Turning process is affected by many factors such as cutting parameters, cutting conditions, tool geometries, environmental conditions, rigidity of machine structure, tool and work piece clamping method, etc. It is not possible or very difficult to consider all these factors into account for optimization of the process. Increasing productivity and reducing manufacturing cost with best quality has always been the primary objective. In turning, higher values of cutting parameters provide an opportunity to increase productivity, but it may lead to deterioration of the work piece, its surface quality and tool life. Thus, this calls for the necessity to select the most appropriate machining settings in order to increase productivity, reduce process cost and improve the quality.

It is found that Taguchi Method is the most widely used optimization technique apart from RSM, GA, etc. This research found that most of the experiments done on optimization of process parameters for surface roughness in orthogonal turning showed feed as the most significant factor and for MRR depth of cut and spindle speed are found to be the most significant factors. The utility model developed by Barua, P.B. (1997) for determining optimal setting of process parameters for multi-characteristic response is also studied.

A. Turning Process

Turning is a machining operation for generating external surfaces of revolution. In this operation, the work piece is rotated about its axis and cutting tool is also given a feed motion in a direction normal to the cutting speed. Machining is the primary process used for every industrial work. Turning is the most common and important machining process to cut out extra metal from a rotating cylindrical work piece. Turning can be done either manually in a lathe which requires an operator or by computer numerical control unit in an automated lathe without an operator. On the basis of the use of coolant, turning process can be classified into dry and wet turning. Due to higher tolerance and surface finish, turning is also the most widely used secondary process. It is the process of removing materials from a work piece in the form of chips. It is done with the help of a body having cutting edge known as cutting tool.

B. Surface Roughness

Surface roughness is an evaluation of surface texture. It is quantified by the deviations in the direction of the normal vector of a real surface from its ideal form. If these deviations are large, the surface is rough; if they are small, the surface is smooth.

Surface roughness is an evaluation of surface texture. It is the vertical deviations of the real form from the ideal form [6]. Surface finish is the method of measuring the quality of a product and is an important parameter in machining process. It is one of the prime requirements of customers for machined parts. For this purpose quality of a product and productivity should be high. Roughness plays an important role in determining how a real object will interact with its environment. Rough surfaces usually wear more quickly and have higher friction coefficients than smooth surfaces. 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. On the other hand, roughness may promote Adhesion. To measure
Cutting Quality, Surface Roughness parameter is measured. In many cases, Surface Roughness is an important external customer requirement. Irregularities produced by cutting tool are referred to as Surface Roughness. Characteristic evidence in the form of finely spaced micro irregularities is left by the cutting tool. Each type of cutting tool leaves its own individual pattern which therefore can be identified. This pattern is known as surface finish or surface roughness.

C. Material Removal Rate

Material removal rate is the amount of metal removed per unit time during a metal removing process. MRR is a measurement of how efficient a metal removal process is because MRR influences the productivity of the process. The Metal Removal Rate (MRR) is a key variable effecting part accuracy. As the MRR increases, the chances of decreasing part accuracy increases. In simpler terms, more power is required to remove more metal. Unless the stiffness of the tool is compatible with the higher horsepower, then deflection is likely to occur.

D. Taguchi Philosophy

According to the Taguchi philosophy the improvement in quality is the deviation of a design parameter from the target value and not to conformance to some fixed specified limits. His philosophy can be bullet listed as follows:

- Quality should be designed into a product and not inspected into it.
- Quality is best achieved by reducing the deviation from a target.
- Cost of quality should be measured as a function of deviation from the standard and the losses should be measured system wide.

He believed in building quality by design and not by just inspecting the products. He proposed an off-line quality concept rather than online quality inspection. He emphasized on building a robust design which is resistant to the influence of uncontrolled variable factors. Taguchi suggested a three stage process for quality improvement [9]:

- System design
- Parameter design
- Tolerance design

In system design phase, the factors which are suitable for the selected materials, parts or products are recognized through brainstorming and recent technology. A prototype design is prepared to test and study the factors suitable for the performance of the product. The parameter design phase determines the levels of factors selected for the best performance of the product. The optimum levels are selected to develop a robust design. The robust design is so designed that the performance of the product is insensitive to various sources of variation in the performance of the product. The variation of the output response by the effect of uncontrolled factors is measured by a statistical measure known as Signal to Noise (S/N) ratio. Signal refers to the desired output produced by the controlled factors (i.e., selected factors or parameters) and noise is the effect of variations produced by the uncontrolled external factors. A higher value of S/N ratio indicated that the output response is more insensitive to uncontrolled external variations i.e., the design is more robust to noise. To find out the significance of each controlled factors a statistical analysis of variance (ANOVA) is performed. During the tolerance phase, the output response of the parameter design is adjusted with narrower tolerance ranges of the selected factors for better performance of the product.

II. LITERATURE REVIEW

Many research workers have investigated and demonstrated the effect of various cutting parameters viz. Spindle speed, feed, depth of cut etc. on the surface roughness and the MRR in orthogonal turning. The literature describing the effect of above mentioned variable has been discussed below:

Mohan S., Dharmpal D., et al (2010) [12] have investigated the robust design technique to minimize the variance of the response and orthogonal arrays are an effective simulation aid to evaluate the relative effects of variation in different parameters on the response with the minimum number of experiments. Experiments are designed and conducted based on Taguchi’s L9 Orthogonal array design. This study discusses an investigation into the use of Taguchi Parameter Design for optimizing surface roughness generated by a CNC turning operation. Controlled factors include spindle speed, feed rate and depth of cut in straight turning of bright mild steel bar using HSS tool. After ANOVA was made, it is found that feed rate has got the most significant influence in controlling dimension characteristics.

J.B.Shaiakh, J.S.Sidhu, et al (2014) [14] have determined the influence of lubricant on surface roughness and material removal rate (MRR) by using CNC LATHE Machine with AISI D2 steel as a work material and TiAlN coated carbide tool as a tool material. Different lubricant used on this experiment are Cotton seed oil, Servo cut and soya bean oil and machining parameters are cutting speed, feed rate and depth of cut. Experiments are designed and conducted based on Taguchi’s L9 Orthogonal array design. After the Analysis of Variance was made, it is found that feed rate, Cotton seed oil, Servo cut and soya bean oil has got the greater influence on surface roughness.

turning operation. The parameters used to investigate their effect on output responses are tool nose radius, tool rake angle, feed rate, cutting speed, cutting environment (dry, wet and cooled) and depth of cut. Experiment are designed and conducted based on Taguchi’s L18 orthogonal array design. Principal Component Analysis (PCA) is used to solve such correlated multi-attribute optimization of turning operation. Feed rate is the factor, which has great influence on surface roughness, followed by cutting speed and depth of cut. 

S. A. Rizvi, et al (2015) [16] have analyzed that an effort was made to optimize the cutting parameters to achieve better surface finish and to identify the most effective parameter for cost evolution during turning by using CNC LATHE MACHINE with IS 2062 steel rods (35 mm diameter) as a work material and Chemical Vapor Deposition (CVD) coated carbide inserts as a tool material. In this work, the input parameters are cutting speed, Feed Rate and Depth of cut. Experiment are designed and conducted based on Taguchi’s L27 orthogonal array design. After ANOVA results it is found that insert radius, feed rate and depth of cut have different effects on the surface roughness.

S. Sahu, B.B. Choudhury (2015) [17] have analyzed that the performance of multi-layer TiN coated tool in machining of hardened steel (AISI 4340 steel) as a work material under high speed turning, which has also been compared with that of uncoated tool. In this work, the input parameters are cutting speed, Feed Rate and Depth of cut. Experiment are designed and conducted based on Taguchi’s L16 orthogonal array design. From the Taguchi analysis it has been found that the feed is playing as a main parameter for reducing surface roughness, where as depth of cut is having the least affect or does not have significant effect on the surface roughness. From the experimental investigation it is also observed that coated tools give better results as compared to uncoated tools in turning.

T. Rajasekaran, K. Palanikumar, et al (2013) [19] have determined the influence of cutting parameters for surface roughness on carbon fibre reinforced polyester (CFRP) resin by turning operation with Cubic boron nitride (CBN). In this work, cutting parameters are cutting speed, feed rate and depth of cut in turning by using conventional Lathe (Make NAGMATI, INDIA). Experiment are designed and conducted based on Taguchi’s L9 orthogonal array design. From the Taguchi analysis it has been found that primarily feed rate and secondarily cutting speed has got the greater influence on surface roughness.

Yusuf S., et al (2005) [20] have determined surface roughness model for turning using response surface methodology (RSM) with mild steel as a work material and TiN coated carbide as a tool material. In this work, cutting parameters are cutting speed, feed rate and depth of cut. From the experiment it is found that Feed is the most significant factor on surface roughness. 

Ilhan A., et al (2011) [21] have investigate the effect of cutting speed, feed rate and depth of cut using AISI 4140 (51 HRC) steel as a work material and Al₂O₃ and TiC coated carbide as a tool material. Experiment are designed and conducted based on Taguchi’s L9 orthogonal array design. From the experiment it is found that Feed rate is the most significant factor on surface roughness.

Satyanarayana K., et al (2015) [22] have determined that effect of process parameters on performance characteristics in finish hard turning of MDN350 steel using cemented carbide tool. In this work, cutting parameters are cutting speed, feed rate and depth of cut. Experiment are designed and conducted based on Taguchi’s L9 orthogonal array design. From the experiment it is found that Feed and Cutting speed are the most significant factor on surface roughness and Cutting Force respectively.

Ashvin J. M., et al (2013) [23] have investigated the effect of turning parameters such as cutting speed, feed rate, tool nose radius and depth of cut on surface roughness with AISI 410 steel as a work material and ceramic as a tool material using Response Surface Methodology (RSM). From the experiment it is found that Feed rate is the most significant factor on surface roughness.

Tanveer H. B., Intiaz A. (2014) [24] have experimented an study of cutting parameters of AISI 1040 steel as a work metrial and uncoated carbide as a tool material using Genetic algorithm and Response Surface Methodology. In this work, cooling condition, cutting parameters are cutting speed, feed rate and depth of cut. From the experiment it is found that Feed rate is the most significant factor on surface roughness.

Sayak M., et al (2014) [26] have experimented that to develop the combination of optimum cutting parameters SAE 1020 mild steel as a work material and carbide as a cutting tool using Taguchi technique. In this work, cutting parameters are cutting speed, feed rate and depth of cut. Experiment are designed and conducted based on Taguchi’s L25 orthogonal array design. From the experiment it is found that Depth of Cut has the most significant effect on MRR followed by Feed.

Rahul D., et al (2014) [27] have determined the process parameters of turning operation using Taguchi DOE with EN 24 steel as a work material and Carbide P-30 as a tool material. In this work, cutting parameters are spindle speed, feed rate and depth of cut. Experiment are designed and conducted based on Taguchi’s L9 orthogonal array design. From the experiment it is found that Feed rate is the most significant factor on surface roughness.

Sushil K. S., et al (2014) [28] have experimented that using Taguchi orthogonal array combination of machining parameters of Mild steel 1018 as a work
material and coated carbide as a tool material. In this work, cutting parameters are cutting speed, feed rate and depth of cut. Experiment are designed and conducted based on Taguchi’s L9 Orthogonal array design. From the experiment it is found that Feed rate is the most significant factor on surface roughness.

Karthie S., et al (2015) [30] have investigated to reduce the lead time, increasing productivity and improve the surface roughness of EN 8 steel with tungsten carbide as a tool material using two cutting fluid namely coconut oil and mineral oil. In this work, cutting parameters are cutting speed, feed rate and depth of cut. Experiment are designed and conducted based on Taguchi’s L9 Orthogonal array design. From the experiment by comparing two cutting fluid we conclude that coconut oil have given better surface finish.

Sahoo P. (2011) [31] have presented an experimental study of roughness characteristics of surface profile generated in CNC turning of AISI 1040 mild steel and optimization of machining parameters based on genetic algorithm. Response surface methodology is applied successfully in analyzing the effect of process parameters on different surface roughness parameters. In this work, cutting parameters are spindle speed, feed rate and depth of cut. From the study, it is seen that the surface roughness parameters Ra, Rq and Rsm decrease with increase in depth of cut and spindle speed but increase with increase in feed.

Bala Raju, J., et al (2015) [32] investigated the effect of cutting parameters such as cutting speed, feed and depth of cut in turning mild steel and aluminium using HSS cutting tool. It was carried out to achieve better surface finish and to decrease power requirement by flattening the cutting force in machining. The experiments were carried based on 2k factorial techniques. ANOVA was used to find out the effect of cutting parameters in surface. And multiple regression analysis was used to develop cutting forces required for machining. It was found that feed has significant effect on both surface roughness and cutting force.

Ramyasree K., et al (2015) [33] have experimented to understand the relationships between input parameters i.e. cutting speed, feed and depth of cut and output parameter i.e. surface roughness (Ra) of AISI 1045 in Dry Machining with Cubic Boron Nitride (CBN) cutting tool. Experiment are designed and conducted based on Taguchi’s L9 Orthogonal array design. From the study, it is found that Feed rate is the most influencing factor on surface roughness.

Suresh R.K., et al (2015) [34] made an attempt to optimize the selected turning cutting parameters (cutting speed, feed rate, depth of cut, nose radius of insert edge) to get optimal values of the two chosen response characteristics or objectives (Surface Roughness and Material Removal Rate) and solve the Multi Objective Optimization (MOO) problem. Ant Colony Optimization (ACO), an Evolutionary Algorithm is utilized to find the optimal treatment and the results are compared against those of actual CNC turning. Input to the Algorithm is input parameter bounds, Regression of Material Removal Rate (fitting the MRR obtained by direct formula) and Regression Equation of Surface Roughness obtained by experiment.

Md. Maksudul I., et al (2015) [43] presents an optimization of metal removal rate in turning operation by the effects of machining parameters applying Taguchi & ANOVA (Analysis of Variance) method to improve the quality of manufactured goods & engineering development of designs for studying variations. For investigation ASTM A48 grey cast iron is considered as workpiece and spindle speed, feed rate & depth of cut have been considered as cutting parameters, while a HSS (High Speed Steel) has been used as cutting tool. This research work reveals that spindle speed has the most significant contribution on the metal removal rate among all the three parameters.

Dileep Kumar C., et al (2014) [44] focused on an experimental study to find the effects of cutting parameters on surface finish and optimize them for better surface finish and high Material Removal Rate (MRR) during turning of Ti-6Al-4V. Uncoated WC/Co inserts are used for the machining purpose. A combined Taguchi method and Grey Relational Analysis (GRA) is used for the optimization. Analysis of Variance (ANOVA) is employed to find out contribution of each parameter. Four parameters are chosen as process variables: cutting speed, feed, depth of cut and nose radius each at three levels. The experiment plan is designed using Taguchi’s L9 Orthogonal Array (OA). The results show that feed rate and nose radius are the most important parameters that affect the surface finish. A prediction model is also developed separately for both surface finish and MRR using multiple regression analysis.

Basim A. K., et al (2015) [46] have experimented to develop a predictive model for surface roughness and temperature in turning operation of AISI 1020 mild steel using cemented carbide in a dry condition using the Response Surface Method (RSM). In this work, cutting parameters are cutting speed, feed rate and depth of cut. From the experiment it is found that Feed rate is the most significant factor on surface roughness.

III. DESIGN OF EXPERIMENTS APPROACH AND ANOVA

The technique of defining and investigating all possible conditions in an experiment involving multiple factors is known as “Design of Experiments (DOE)” or sometimes “Factorial Design”. The concept of design of experiments have been used since Fisher’s work in agricultural experimental,
almost half a century ago [9]. Since then, numerous applications of this approach have been found in various fields. At first, experiments were designed using Full Factorial Design, where all possible combinations of factors are considered. In Full Factorial Design, the number of experiments, 

\[ N = L^m \]

where, \( L \) = Number of level for each factor and \( m \) = Number of factors

But, it is seen that in Full Factorial Design as the number of factors and levels increases, number of experiments also increases considerably. Thus, to overcome this and simplify the experiments, Fractional Factorial Experiments Technique is used. In this technique only a fraction of all possible combinations are investigated, thus decreasing the number of experiments and saving a lot of time and money. But it includes rigorous mathematical calculations in both design and analysis of results. Also each experimenter may design different sets of fractional factorial experiments for the same problem that may yield different results. In this point, lies Dr. Genichi Taguchi’s contribution to the discipline and structure of design of experiments. He developed a new technique called Taguchi Method which standardised and simplified the Fractional Factorial Experiments Technique in such a way that two experimenters experimenting on the same problem will always get the same result. Taguchi Method makes use of number of arrays known as Orthogonal Arrays (OA) which are used as templates for design of experiments.

A. Orthogonal Array

Taguchi developed a number of arrays which can be used as a template to design an experiment. Each array is named depending on the number of trial condition, for example Orthogonal Array L9 has nine trial conditions. The rows represent trial condition whereas columns represent factor assignments. In these arrays a level occur same number of time in each column and hence they are called orthogonal arrays. The main advantage of OA is that it greatly reduces number of experiments and hence reduces time and cost of experimentation. The Orthogonal Arrays also ensures unbiased estimation of factorial effects.

B. Signal to Noise Ratio (S/N Ratio)

The concept of S/N ratio is introduced to increase the robustness of the experimental results. He took this concept from electrical engineering where this term used to refer quality of an electrical signal. In Taguchi terminology Signal is the desired effect produced by the factors of an experiment and Noise is the effect of uncontrollable numerous external factors. The ratio of these two factors gives us an idea of robustness or insensitiveness of a trial condition to the noise factors. Raw data obtained from an experiment is converted to S/N ratio using the formula given below:

\[ S/N = -\log_{10}(MSD) \]

The term Mean Squared Deviation (MSD) reflects deviation from the target value. The expression for MSD is different for different quality characteristics.

\[ a) \text{ For smaller the better quality characteristics:} \]

\[ MSD = \frac{(Y_1^2+Y_2^2+...+Y_n^2)/r}{\left(1/Y_1^2+1/Y_2^2+...+1/Y_n^2\right)/r} \]

Where, \( r \) is the number of repetitions, \( Y_1 \) is the response and \( i = 1,2,3,.......,n \)

\[ b) \text{ For nominal the best quality characteristics:} \]

\[ MSD = \frac{\left((Y_1-Y_0)^2+(Y_2-Y_0)^2+...+(Y_n-Y_0)^2\right)/r}{\left(1/Y_1^2+1/Y_2^2+...+1/Y_n^2\right)/r} \]

Where, \( Y_0 \) is the nominal value or target value of response.

\[ c) \text{ For higher the better quality characteristics:} \]

\[ MSD = \frac{1/Y_1^2+1/Y_2^2+...+1/Y_n^2}{1/\left(Y_1^2+Y_2^2+...+Y_n^2\right)} \]

The aim of any experiment is to produce highest possible S/N ratio for the result. A high value of S/N ratio implies that the signal is much higher than the random effects of the noise factors. It converts all types of quality characteristics to Higher the better type.

C. Data Analysis

A number of method have been suggested by Taguchi for analysing the data; observation, ranking, column effects, ANOVA, S/N ANOVA, plot of average response curves (main effect plot) etc. However, the following methods are widely and usually used.

\[ a) \text{ Main Effect Plot} \]

\[ b) \text{ Raw data ANOVA} \]

\[ c) \text{ S/N data ANOVA} \]

D. Main Effect Plot

The graphical representation of effect of each level of a factor is called Main Effect Plot of the factor. To draw a Main Effect Plot, Main effect of each level of factor is found out and plotted in a graph where the output variable lies in the vertical axis and level lies in the horizontal axis.

E. Raw Data ANOVA

In Raw data ANOVA average values of the output of each of the trial is used for the analysis. The important terms of Raw data ANOVA is given below:

Degree of Freedom (f):

It is a measure of the amount of information that can be uniquely determined from a given set of data. In ANOVA there are four types of degree of freedom:
i. **Degree of Freedom (DOF) of a factor (f_a):** For a factor A having L number of levels, DOF is given by:
\[ f_a = L - 1 \]

ii. **Degree of Freedom (DOF) of interaction of factor A and B (f_{AB}):** If \( f_a \) and \( f_b \) is the DOF of factor A and B, then DOF of interaction AB is given as:
\[ F_{AB} = f_a * f_b \]

iii. **Total Degree of Freedom of the experiment (f_T):** For an experiment having n number of trials with r repetitions, DOF is given by:
\[ f_T = n*r - 1 \]

iv. **Error Degree of Freedom (f_e):** For an experiment having m number of factors, DOF of the error is given by:
\[ f_e = f_T - \sum_{k=1}^{m} f_k \]

### Correction Factor (CF):

To isolate the variance caused by a factor from the variance due to error, a correction factor is needed. This amount of variation is deducted from the Sum of Square of a factor and added to Sum of square of error. CF is given by:
\[ CF = T^2/N \]

Where, \( T = \sum_{i=1}^{n} \sum_{j=1}^{m} Y_{ij} \), \( Y_{ij} \) being the value of the output variable of the \( i^{th} \) trial condition and \( j^{th} \) repetition.
\( N = n*r \), total number of data.

### Sum of Square (S):

It is the measure of deviation of experimental data from the mean value of the data. In ANOVA there are four types of Sum of Square:

i. **Sum of square of a factor (S_A):** For a factor having L number of levels, if \( A_1 \) is the summation of the values of the output variables of those trials, which contains factor A at level 1, \( A_2 \) is the summation of the values of the output of those trials, which contain factor A at level 2 and in the same way if \( A_L \) is the summation of the values of the output variable of those trials, which contains factor A at \( L^{th} \) level, then Sum of Square of a factor A is given by:
\[ S_A = [(A_1^2 + A_2^2 + \ldots + A_L^2)/N] - CF \]

ii. **Total Sum of Square (S_T):** Total Sum of the square is computed by:
\[ S_T = \sum_{i=1}^{n} \sum_{j=1}^{m} Y_{ij} - CF \]

iii. **Sum of square of Interaction (S_{AB}):** If interaction of factor A and B is considered, Sum of square of Interaction is computed by:
\[ S_{AB} = S_{AB} - S_A - S_B \]

Where, \( S_{AB} = [(Y_{11}^2 + Y_{12}^2 + \ldots + Y_{1n}^2)/R] - CF \)
\( Y_{11}, Y_{12}, \ldots, Y_{1n} = \) Average output values of the trial condition 1,2,\ldots,n and \( R = \) Number of Replications

iv. **Sum of Square of Error (S_e):** Sum of square of error is given by:
\[ S_e = S_T - S_A - S_B - S_{AB} \]

### Variance or Mean Square (V):

Sum of square of a term does not include degree of freedom of the term in the calculation. As it is known that higher degree of freedom also increases variation or sum of square of a term. To compensate this, sum of square is divided by the degree of freedom of the term to get actual variation per degree of freedom of the term. Mean Square or Variance of a Factor:
\[ V = S_e/f_e \]

**Variance Ratio or F Value (F):**

It is the ratio of variance of a term to the error variance. It is calculated as:
\[ F = V/V_e \]

#### Tabulated F Value or Critical F Value:

It is the value obtained from Standard F table with given confidence level, DOF of the factor and DOF of the error term. The same can be obtained from MS Excel using the formula "=F.INV.RT(X,Y,Z)", where X is the probability of the error, Y is the DOF of the factor and Z is the DF of the error term.

If value of the calculated F value or variance ratio of a factor is found to be greater than tabulated F value, the factor has significant effect on the output variable.

### Pure sum of square (S[]):

When the product of Degree of Freedom of a term and Error variance is subtracted from the sum of square of that term, the resulting term is called pure sum of square. If in an experiment has two factors A and B, having Degree of Freedom \( f_a \) and \( f_b \) then pure sum of square is computed by:
\[ S'_A = S_A - f_a \times V_e \]
\[ S'_B = S_B - f_b \times V_e \]

For calculating pure sum of square of the error term, the subtracted portion of sum of square of the factors is added to the error sum of square.
\[ S'_e = S_e + (f_a + f_b) \times V_e \]

#### Percentage Contribution (P):

The percentage contribution of a factor (suppose A) is obtained by dividing the pure sum of square (\( S'_A \)) of that term by total sum of square (\( S_T \)) and multiplying the result by 100.
\[ P_A = (S'_A/S_T) \times 100 \]

### F. S/N data ANOVA

Here Signal is the desired effect produced by the factors of an experiment and Noise is the effect of uncontrollable numerous external factors. The term S/N ratio measures the sensitivity of the quality characteristic being investigated in a controlled manner, to those external influencing factors (noise factors) not under control. Taguchi applied this concept in his method to get a robust design from the experiments. In S/N data ANOVA the raw data obtained from an experiment is converted to S/N ratio.
The aim of any experiment is to produce highest possible S/N ratio for the result. A high value of S/N ratio implies that the signal is much higher than the random effects of the noise factors.

After converting all raw data to S/N data, ANOVA is performed on the S/N data using the modified equations described below:

Total DOF \((f_{T}) = n - 1\), here \(r = 1\)
\[ CF = \frac{T^2}{N} \]
where, \(T = \sum_{i=1}^{n} Y_i\), \(Y\) being the value of S/N ratio of the \(i^{th}\) trial condition.
\[ N = \text{Total number of data or Trial.} \]

All other expression are same as raw data ANOVA except in place of \(N = nr, \text{total number of data} \), \(n (\text{Number of Trial condition})\) should be used. It should be noted S/N data ANOVA cannot be performed for experiments with single factor.

### G. Pooling

Pooling is a procedure in which the sums of square of ineffective factors (factors with lesser sum of square value or which are found to insignificant) are added to error sum of square. In S/N ratio ANOVA variance of the error term cannot be computed as it has zero DOF. In this case pooling becomes necessary, which adds the DOF of the pooled term to the DOF of the error term. Pooling starts with the factors having smallest main effect and successively includes factors with larger effects, until total pooled DOF equals approximately half of the total DOF. The increased DOF of the error term increases the confidence level of the significant factors.

### H. Factor Classification

When the Raw data ANOVA (identifies control parameters which affect average) and S/N data ANOVA (identifies control parameters which affect variation) are completed, the control parameters (factors) may be put into four classes:

- **Class I**: Parameters which affect both average and variation
- **Class II**: Parameters which affect variation only
- **Class III**: Parameters which affect average only
- **Class IV**: Parameters which affect nothing

The proper levels of Class I and Class II parameters are selected to reduce variation and Class III parameters to adjust the average to the target value. Class IV parameters may be set at the most economical level.

### I. Optimum Level of the Factors

From the Main Effect Plot the optimal level of the factors can be selected easily. If the Main Effect Plot is drawn on the basis of average raw data, then optimal level should be selected depending on the Quality Characteristic used (LB, NB, HB). S/N ratio converts all types of Quality Characteristics in to Higher the Better (HB) type.

If interaction is present, then optimal level of a factor found from Main Effect Plot may not be always optimal. In the case Interaction Effect Plot should be taken into consideration.

### J. Prediction of Mean

After determining of optimum condition, the mean \((\mu)\) at the optimum condition is estimated as:
\[
\mu = T_{avg} + (A_{2avg} - T_{avg}) + (B_{2avg} - T_{avg}) + (C_{2avg} - T_{avg})
\]
where \(T_{avg} = \text{Overall mean of the output variable (Response)}\)
\(A_{2avg}, B_{2avg}, C_{2avg} = \text{Average value of responses at the second level of parameters A ,B & C respectively.}\)

### K. Confidence Interval (C.I.)

It is mandatory to represent the values of statistical parameter as a range within which it is likely to fall, for a given level of confidence. To get the confidence interval is added to the mean and subtracted from the mean value to get the maximum and minimum limit of the range respectively.

Taguchi suggested the following two types of confidence level.

- **Confidence interval for the population (C.I.,pop)**: Around the estimated average of a treatment condition predicted from the experiment.
- **Confidence interval for a sample group (C.I.,ce)**: Around the estimated average of a treatment condition used in a confirmation experiment to verify predictions.

The difference between C.I.,pop and C.I.,ce is that C.I.,pop is for the entire population and C.I.,ce is for only a sample group made under the specified condition (confirmation experiment). The expression for C.I.,pop and C.I.,ce is given as:
\[
\text{C.I.,pop} = \sqrt{F_{0}(1, f_{T}) V_{e} \frac{1}{N_{t}} + \frac{1}{R}}
\]
\[
\text{C.I.,ce} = \sqrt{F_{0}(1, f_{T}) V_{e} \frac{1}{N_{t}} + \frac{1}{R}}
\]

Where,
\[ F_{0}(1, f_{T}) = \text{The F ratio at a confidence Level of (1-}\alpha) \text{ against error DOF 1 and error DOF } f_{T}. \]
\[ V_{e} = \text{Error variance from ANOVA} \]
\[ N_{t} = \text{Total no. of results} \]
\[ R = \text{Sample size of confirmation Experiment} \]

The second equation as \(R \) approaches to infinity, C.I.,ce value approaches to C.I.,pop and as \(R \) approaches 1, the C.I.,ce becomes wider.

### L. Range of Confidence Interval

As mentioned earlier the Confidence Intervals added to mean and subtracted from the mean value to get the maximum and minimum limit of the range respectively.
Range \text{pop} : \mu - C.I.\text{pop} \leq \mu \leq \mu + C.I.\text{pop} \\
Range \text{ce} : \mu - C.I.\text{ce} \leq \mu \leq \mu + C.I.\text{ce}

M. Confirmation Experiment (CE)

Taguchi suggested conducting a Confirmation Experiment setting the factors at their optimum level to confirm the findings. Higher sample size of the CE yields smaller C.I.\text{ce} value and range of the sample group approaches the range of the population (Range \text{pop}).

IV. MULTI-CHARACTERISTIC OPTIMISATION

The Taguchi method for determining the optimal settings of controllable factors (parameters) through off-line experiments focuses on products with a Single quality characteristic. But at times there are situations where there are more than one quality characteristics of interest. A single setting of process parameters may be optimal for one quality characteristic but the same setting may yield detrimental results for other quality characteristics. This calls for the need to obtain a setting of the process parameters so that the product can be produced with optimum or near optimum quality characteristics. A number of techniques have been developed for obtaining the multi-characteristic optimization of product quality such as Grey Relational Analysis, Utility Concept etc. Barua, P.B.(1997) [38] made a case study of products with multiple characteristics such as Al-7% Si casting hardness, surface roughness, volume porosity, tensile strength etc. The loss caused by quality characteristics which are inversely affected by the change in the process parameters are estimated by assigning a weight from experience to each quality characteristic. However, it roughly chooses the most important characteristic in the case of multi-characteristic product and determines the optimal level settings of controllable factors accordingly. Barua, P.B.(1997) [38] presented a model using loss function approach to determine the optimal settings of the process parameters for situations with multiple characteristics. Taguchi also gave a method where the quality characteristics were independently optimized using Taguchi approach and then the results were compared subjectively to select the best levels in terms of the quality characteristics of interest.

A. The Utility Concept

A product can be evaluated on a number of diverse quality characteristics. These evaluations on different characteristics should be combined to give a composite index, so that rational choices can be made. Such a composite index represents the utility of a product. The overall utility of a product measures the usefulness of that product for the evaluator. The utility of a product on a particular characteristic measures the usefulness of that particular characteristic of the product. The overall utility of a product is the sum of utilities of each of the quality characteristics.

Thus, if \( x_i \) is the measure of effectiveness of the attribute (characteristic) \( i \) and there are \( n \) attributes evaluating the outcome space then the joint utility function can be expressed as [38]:

\[
U(X_1, X_2, ..., X_n) = f [U_1(X_1), U_2(X_2), ..., U_n(X_n)]
\]

In linear case, the function becomes:

\[
U(X_1, X_2, ..., X_n) = \sum_{i=1}^{n} W_i U_i(X_i)
\]

Where, \( W_i \) is the weightage assigned to the attribute \( i \) and the sum of the weightages for all attributes is equal to 1.

If the composite measure (the overall utility) is maximized the quality characteristics considered for evaluation of utility will automatically be optimized (maximized or minimized whatsoever the case may be)

B. Determination Of Utility Value

A preference scale for each quality characteristic is constructed to determine the utility value for a number of quality characteristics. Later these scales are weighted to obtain a composite number (overall utility). The weighing is done to satisfy the test of indifference on the various quality characteristics. The preference scale should be a logarithmic one [38]. The minimum acceptable quality level for each quality characteristic is set out at 0 preference number and the best available quality is assigned a preference number of 9. If a log scale is chosen the preference number (Pi) is given by [38], for Higher the Better (HBT) type quality.

\[
P_i = A \log \left( \frac{X_i}{X_i'} \right)
\]

where \( X_i \) = any value of quality characteristic or attribute \( i \) \\
\( X_i' \) = minimum acceptable value of quality characteristic or attribute \( i \) \\
\( A \) = a constant

At optimum value (\( X_i' \)) of attribute \( i \) the \( P_i = 9 \) so, \\
\( A = 9/ \log \left( X_i'/X_i \right) \)

The next step is to assign weights or relative importance to the quality characteristics. This assignment is subjective and based on experience. Moreover, it depends on the end use of the product or it may depend on the customer’s requirements. The weightage should be assigned such that the following condition holds:

\[
\sum_{i=1}^{n} W_i = 1
\]

The overall utility can be calculated as:

\[
U_j = \sum_{i=1}^{n} W_i P_i
\]

Where \( j \) = product index
C. The Algorithm

The step by step procedure of the model developed is as follows [38]:
1. Find optimal values of the selected quality characteristics separately using Taguchi experimental design and analysis.
2. Using these optimal values and bare minimum quality levels for the quality characteristics from the experimental data construct difference scales (preference scales) for each quality characteristic.
3. Assign weightage, \( W_i = 1, 2, \ldots, n \) based on experience and end use of the product such that eq. 8.5 is satisfied.
4. Find utility values for each product against each trial condition of the experiment .
5. Use these values as responses of the trial conditions of the experimental plan (OA) that is earlier used to determine the individual optimal values of the quality characteristics. If trials are repeated, find the S/N ratios (Higher-the-better type).
6. Analyse results using procedure as suggested by Taguchi (Roy 1990)[9].
7. Find the optimal settings of the process parameters for optimum utility (mean and minimum deviation around the mean (optimum S/N ratio) based on the analysis in step 6.
8. Predict the individual characteristic values considering the optimal significant parameters determined in step 7.
9. Conduct confirmation experiment at the optimal setting and compare the predicted optimal values of the quality characteristics with the actual ones.

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V. Conclusions

The whole investigation was done theoretically by extensive literature survey. In study it is found that turning is most widely used manufacturing process and in turning the conditions are most varied. This work revealed that Taguchi method is the most widely used optimising technique. It is found out that turning is affected by various factors but due to the difficulty to optimise all the parameters speed, feed and depth of cut is mainly optimised for various characteristics. As producing high quality product at low cost in less time is mostly desirable in today’s world optimisation of cutting parameters for minimum surface roughness and maximum MRR is very important. In the study it is found that the use of design of experiment technique for designing the experiments will lower the number of trials to be done and hence reduce the total cost. Taguchi method is widely used for designing experiments where some standard templates called Orthogonal Arrays are used. Another method for designing experiments is OFAT where level of only one factor is changed at a time. This method is not capable of studying multiple factors and interaction effects and may also skip the optimum condition. The data from the experiments are analyzed using main effect plot, Raw Data ANOVA and S/N ANOVA. This research found that most of the experiments done on optimization of process parameters for surface roughness in orthogonal turning showed feed as the most significant factor and for MRR depth of cut and speed is found as the most significant factors. The utility model developed by Barua, P.B. (1997) [1] for determining optimal setting of process parameters for multi-characteristic response is also studied and found to be a suitable method for multi characteristic optimization. A proposed methodology for an experimental investigation on the multi characteristic optimization of cutting parameters on surface roughness and MRR in orthogonal turning using AISI 1020 as work material and HSS cutting tool is also made and planned towards the end of this investigation based on the theoretical study made.

ACKNOWLEDGMENT

I hereby wish to give sincere thanks and deep sense of gratitude to my respected teacher and guide Mr. Diganta Kalita, Assistant Professor, Department of Mechanical Engineering, Jorhat Engineering College, Jorhat for his advice, guidance, help and motivation in completing this study. I am indebted to him for allowing me to draw upon his precious and valuable time. Last but not the least I would also like thank the entire Department of Mechanical Engineering, Jorhat Engineering College, my classmates and all those who directly or indirectly helped me in conducting this project.

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