

Multi-Objective Optimization of the Surface Roughness Parameters and MRR in Turning Operation Using Utility Concept and Grey-Based Taguchi Method

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Abstract - In highly competitive manufacturing industries nowadays every manufacturing industry aims at producing a large number of products within relatively lesser time, but it is felt that reduction in manufacturing time may causes server quality loss. In order to embrace these two conflicting criteria it is necessary to check quality level of the item either on-line or off-line. In on-line quality control controller and related equipments are provided with the job under operation and continuously the quality is being monitored. In off-line quality control the method is either to check the quality of few products from a batch or lot (acceptance sampling) or to evaluate the best process environment capable of producing desired quality product. This invites optimization problem which seeks identification of the best process condition or parametric combination for the said manufacturing process. If the problem is related to a single quality attribute then it is called single objective (or response) optimization. If more than one attribute comes into consideration it is very difficult to select the optimal setting which can achieve all quality requirements simultaneously.

This study investigated the multi-optimization of the turning process on AISI1045 steel material with CNMG cutting tool for an optimal parametric combination to yield the minimum surfaces roughness with the maximum MRR using a combination of a Grey relational analysis (GRA), Utility concept and the Taguchi method. In view of the fact, that traditional Taguchi method contact solves a multi-objective optimization problem: To overcome this limitations Grey relation theory and Utility concept has been coupled with Taguchi method. Nine experimental runs based on an Orthogonal array of the Taguchi method were performed to drive objective functions to be optimized within the experimental domain the signification of the factors on the overall quality characteristics of the cutting process was also evaluated quantitatively using the Analysis of Variance ANOVA method. Optimal results verified through additional experiments.

Key Words: optimization, turning operation, surface roughness, Mrr, grey-based, taguchi method

1. INTRODUCTION (Size 11, Times New roman)

Today's manufacturing industries are very much concerned about the quality of their products. They are focused on producing high quality products in time at minimum cost. Surface finish is one of the crucial performance parameters that have to be controlled within suitable limits for a particular process. Therefore, prediction or monitoring of the surface roughness of machined components has been an important area of research. Cutting parameters such as speed, feed and depth of cut strongly influence the surface roughness of the machined component. The estimation of the surface roughness and MRR by dynamic simulation of the system is very difficult because determination of the machine tool parameters is not easy and parameters including damping and stiffness change in the course of time. The structure of surface roughness is very complicated and the calculation of its values through analytical formula is very difficult. Today, approximate solutions are totally inadequate for precision manufacturing. At the present time it is approximately known which machining method can give what surface quality. Moreover, it is possible to obtain a desirable surface roughness value using conventional methods but this approach is time consuming because of repetitive and empirical processes. In the past, empirical models and the relationship between surface roughness and cutting parameters for the turning operation were developed. Surface characteristic on a microscopic scale is vitally important with regard to load bearing capacity, lubrication, wear, fatigue and corrosive resistance, friction, heat and electrical conductivity and visual appearance of the mechanical parts. Surface metallurgy, the second ingredient in surface integrity, is concerned with the host of effects a process has below the visible surface. The subsurface characteristics occur in various layers or zones. The sub surface altered material zones can be as simple as a stresses condition different from that in

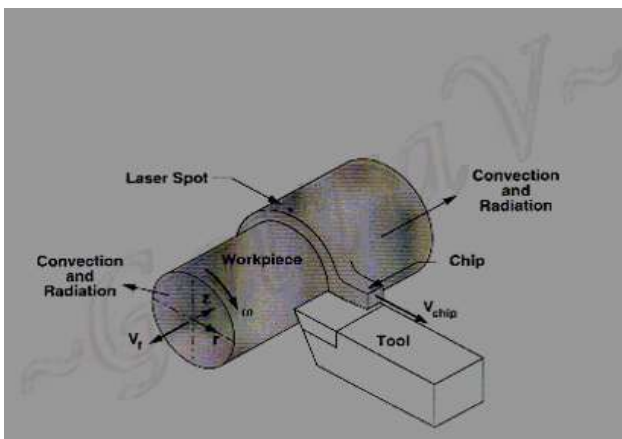
the body of the material or as complex as a grain structure change interlaced with intergranular attack. Changes can be caused by chemical, thermal, or mechanical energy and effect and both the physical and the mechanical properties of the material.

2. INTRODUCTION TO TURNING

Turning is the removal of metal from the outer diameter of a rotating cylindrical work piece. Turning is used to reduce the diameter of the work piece, usually to a specified dimension, and to produce a smooth finish on the metal. Often the work piece will be turned so that adjacent sections have different diameters.

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.



ADJUSTABLE CUTTING FACTORS IN TURNING

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

SPEED

Speed always refers to the spindle and the work piece. When it is stated in revolutions per minute (rpm) it tells their rotating speed. But the important feature for a particular turning operation is the surface speed, or the

speed at which the work piece material is moving past the cutting tool. It is simply the product of the rotating speed times the circumference of the work piece before the cut is started. It is expressed in meter per minute (m/min), and it refers only to the work piece.

$$N = (1000 \cdot v) / (\pi \cdot d)$$

Where, N= Speed in rpm

V= Cutting speed in mm/min

D= Diameter of the work piece in mm

FEED

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

The feed rate determines the rate of advancement of the cutting tool. The tool can be moved in three directions with respect to the axis of the work. Hence there are three types of feeds. Those are:

1. **Longitudinal feed:** The movement of the tool parallel to the axis of work is called longitudinal feed. This is used in turning ,drilling operations
2. **Cross feed:** The movement of the tool perpendicular to the axis of the work is called Cross feed such as in facing operation.
3. **Angular feed:** The movement of the tool at angular direction to the work axis is called angular feed such as in taper turning operation.

For example, in turning operation on a lathe it is equal to advancement of the tool corresponding to each revolution of the work. However, it is computed and mentioned in different machine tools and different operations. Units are expressed in “mm/min” or “mm/rev”.

The cutting speed and feed of a cutting tool is largely influenced by the following factors.

1. Material being machined
2. Material of the cutting tool
3. Geometry of the cutting tool
4. Required degree of surface finish.
5. Rigidity of the machine tool being used.

DEPTH OF CUT

Depth of cut is practically self explanatory. It is the thickness of the layer being removed (in a single pass) from the work piece or the distance from the uncut surface of the work to the cut surface, expressed in mm. It is important to note, though, that the diameter of the work piece is reduced by two times the depth of cut because this layer is being removed from both sides of the work. It is the depth or distance perpendicular to axis of the work (in case of turning), by which the tool penetrates into the work.

This is expressed in “mm”

$$\text{Depth of cut in turning} = (d_1 - d_2)/2$$

Where d_1 = Diameter of work piece before machining.

d_2 = Diameter of work piece after machining.

1 TYPES OF CUTTING

There are two types of metal cutting processes done with a single point cutting tool.

1. Orthogonal or two dimensional cutting
2. Oblique cutting or three dimensional cutting.

1. Orthogonal: Orthogonal cutting takes place when the cutting face of the tool is 90 degrees to the line of action or path of tool.

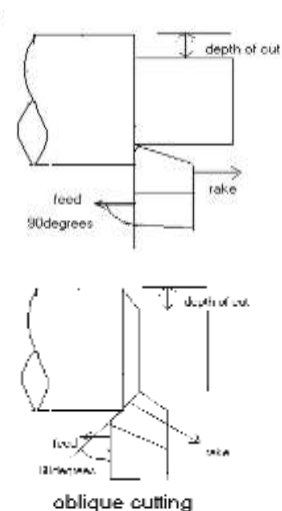


Figure 1.2 Orthogonal cutting

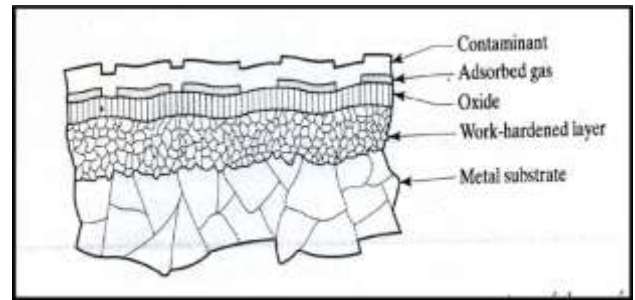


Figure 1.3 Oblique cutting

2. Oblique Cutting: Oblique cutting takes place when cutting face is inclined at an angle less than 90 degrees to the path of the tool.

SURFACE STRUCTURE AND PROPERTIES

Surface roughness is an important measure of product quality since it greatly influences the performance of mechanical parts as well as production cost. Surface roughness has an impact on the mechanical properties like fatigue behavior, corrosion resistance, creep life, etc. It also affects other functional attributes of parts like friction, wear, light reflection, heat transmission, lubrication, electrical conductivity, etc. Before surface roughness, it is also necessary to discuss about surface structure and properties, as they are closely related.

Schematic of a cross-section of the surface structure of metals

Upon close examination of the surface of a piece of metal, it can be found that it generally consists of several layers (Figure 1.16). The characteristics of these layers are briefly outlined here:

1. The bulk metal, also known as the metal substrate, has a structure that depends on the composition and processing history of the metal.
2. Above this bulk metal, there is a layer that usually has been plastically deformed and work-hardened to a greater extent during the manufacturing process. The depth and properties of the work-hardened layer (the Surface Structure) depend on such factors as the processing method used and how much frictional sliding the surface undergoes. The use of sharp tools and the selection of appropriate processing parameters result in surfaces with little or no disturbance. For example, if the surface is produced by machining using a dull and worn tool, or which takes place under poor cutting conditions, or if the surface is ground with a dull grinding wheel, the surface structure layer will be relatively thick. Also, non-

uniform surface deformation or severe temperature gradients during manufacturing operations usually cause residual stresses in the work-hardened layer.

3. Unless the metal is processed and kept in an inert (oxygen-free) environment, or is a noble metal such as gold or platinum, an oxide layer forms over the work-hardened layer.

4. Under normal environmental conditions, surface oxide layers are generally covered with absorbed layers of gas and moisture. Finally, the outermost surface of the metal may be covered with contaminants such as dirt, dust, grease, lubricant residues, cleaning-compound residues, and pollutants from the environment.

Various surface roughness parameters and their formulae

Parameter	Description	Formula
Ra, Raa, Ryni	Arithmetic average of absolute values	$R_a = \frac{1}{n} \sum_{i=1}^n Y_i $
Rq, RRMS	Root mean squared	$R_q = \sqrt{\frac{1}{n} \sum_{i=1}^n Y_i^2}$
RzJIS	Japanese Industrial Standard for Rz, based on the five highest peaks and lowest valleys over the entire sampling length.	$R_{zJIS} = \frac{1}{n} \sum_{i=5}^5 R_{pi} - R_{vi}$

MEASUREMENT OF SURFACE ROUGHNESS

Inspection and assessment of surface roughness of machined work pieces can be carried out by means of different measurement techniques. These methods can be ranked into the following classes:

1. Direct measurement methods
2. Comparison based techniques
3. Non-contact methods

4. On-process measurement

Optimization

The term of “optimization” refers to the process of searching for the optimum solution from a set of candidates to the problem of interest based on certain performance criteria, which has found broad applications in manufacturing, engineering, finance and logistics etc. Generally speaking, all problems to be optimized should be able to be formulated as a system with its status controlled by one or more input variables and its performance specified by a well-defined objective function. The goal of optimization is to find the best value for each variable in order to achieve satisfactory performance. In practice, it could mean to accomplish a predefined task in the most efficient way or the highest quality or to produce maximum yields given limited resources.

LITERATURE REVIEW

INTRODUCTION

Surface roughness and dimensional accuracy have been important factors to predict machining performances of any machining operation. The terms surface finish and surface roughness are used very widely in industry and are generally used to quality the smoothness of a surface finish. Turning is used in variety of manufacturing industries including the aerospace and automotive sectors, where quality is an important factor in the prediction of slots, pockets, precision molds and dies. Numerous amount of research work has been carried out in this area. Several researchers have tried to optimize the machining parameters in turning to obtain an optimum surface roughness value and thus a literature review is carried out to know how the process parameters are optimized.

LITERATURE SURVEY

Youssef.A [1], Investigated on comparison of three different experimental designs aimed at studying the effects of cutting parameters variation on surface finish. The results revealed that the effect obtained by analyzing both the factorial (16trails) and taguchi (16 trails) design were comparable to those obtained by the full factorial design (288 trails) only the most important effects on surface roughness, feed rate(f) and tool nose radius (r) were reveled using these screening designs.

Marc Thomas, Yves Beauchamp[2], Investigated on cutting parameter effects of surface roughness in a lathe dry boring operation the results revealed that using short tool length always provide good surface roughness and that only slight improvement on surface roughness can

achieved by properly controlling the cutting parameters and for the type of boring bar used the results also revealed that using a long tool length may set excessive vibrations that could be effectively controlled by the use of a damped boring bar.

N.R.Dhar, S.Paul [3], mentioned the importance of surface roughness and metal removal rate for any machining operation. AISI4140 steel were taken as material for machining and it was machined on conventional lathe experiments was conducted by considering speed, feed rate and depth of cut as process variables under cryogenic cooling conditions finally they concluded that by the combination of high speed, low depth of cut and feed rate that the better surface finish can be obtained.

Kassab and Khoshnaw [4] examined the correlation between surface roughness and cutting tool vibration for turning operation. The process parameters were cutting speed, depth of cut, feed rate and tool overhanging. The experiments were carried out on lathe using dry turning (no cutting fluid) operation of medium carbon steel with different level of aforesaid process parameters. Dry turning was helpful for good correlation between surface roughness and cutting tool vibration because of clean environment. The authors developed good correlation between the cutting tool vibration and surface roughness for controlling the surface finish of the work pieces during mass production. The study concluded that the surface roughness of work piece was observed to be affected more by cutting tool acceleration; acceleration increased with overhang of cutting tool. Surface roughness was found to be increased with increase in feed rate.

Mahmoud and Abdelkarim [5] studied on turning operation using High-Speed Steel (HSS) cutting tool with 450° approach angles. This tool showed that it could perform cutting operation at higher speed and longer tool life than traditional tool with 900° approach angle. The study finally determined optimal cutting speed for high production rate and minimum cost, tool like, production time and operation costs.

S.Thamizhamanii, S.Saparudin [6] mainly focused on the analysis of optimum cutting condition to get lowest surface roughness in turning on SCM 440 alloy steel by Taguchi method. Experiment was designed using Taguchi L18 Orthogonal array experiments were conducted. The results were analyzed use of Analysis of variance (ANOVA) method. The cutting speed has a lesser role on surface roughness from the test.



Raviraj Shetty, S.S.Rao [7] investigated on surface roughness under dry, oil, water emulsion and steam lubricated conditions, under all the above conditions the surface roughness and MRR were predicted and these values were analyzed or optimized by Taguchi method. And results were analyzed with Analysis of Variance (ANOVA) method (MINITAB15).

Ozel et al. [8] carried out finish turning of AISI D2 steels (60 HRC) using ceramic wiper (multi-radii) design inserts for surface finish and tool flank wear investigation. For prediction of surface roughness and tool flank wear multiple linear regression models and neural network models were developed. Neural network based predictions of surface roughness and tool flank wear were carried out, compared with a non-training experimental data and the results thereof showed that the proposed neural network models were efficient to predict tool wear and surface roughness patterns for a range of cutting conditions. The study concluded that best tool life was obtained in lowest feed rate and lowest cutting speed combination.

Wang and Lan [9] used Orthogonal Array of Taguchi method coupled with grey relational analysis considering four parameters viz. speed, cutting depth, feed rate, tool nose run off etc. for optimizing three responses: surface roughness, tool wear and material removal rate in precision turning on an ECOCA-3807 CNC Lathe. The MINITAB software was explored to analyze the mean effect of Signal-to-Noise (S/N) ratio to achieve the multi-objective features. This study not only proposed an optimization approaches using Orthogonal Array and grey relational analysis but also contributed a satisfactory technique for improving the multiple machining performances in precision CNC turning with profound insight.

Reddy et al. [10] adopted multiple regression model and artificial neural network to deal with surface roughness

prediction model for machining of aluminium alloys by CNC turning. For judging the efficiency and ability of the model in surface roughness prediction the authors used the percentage deviation and average percentage deviation. The study of experimental results showed that the artificial neural network was efficient as compared to multiple regression models for the prediction of surface roughness.

EXPERIMENTATION

The scope and objectives of the present work have already been mentioned in the forgoing chapter. Accordingly the present study has been done through the following plan of experiment.

- 1) Checking and preparing the Centre Lathe ready for performing the machining operation.
- 2) Cutting AISI 1045 bars by power saw and performing initial turning operation in Lathe to get desired dimension of the work pieces.
- 3) Calculating diameter of each specimen by the high precision digital vernier caliper before machining.
- 4) Performing straight turning operation on specimens in various cutting environments involving various combinations of process control parameters like: spindle speed, feed, depth of cut and tool nose radius.
- 5) Calculating diameter of each specimen by the high precision digital vernier caliper after machining.
- 6) The time taken for machining operation was calculated by digital stop watch.
- 7) Measuring surface roughness and surface profile with the help of a portable stylus-type profilometer, *Talysurf* (Taylor Hobson, Surtronic 3+, and UK).

MACHINE TOOL

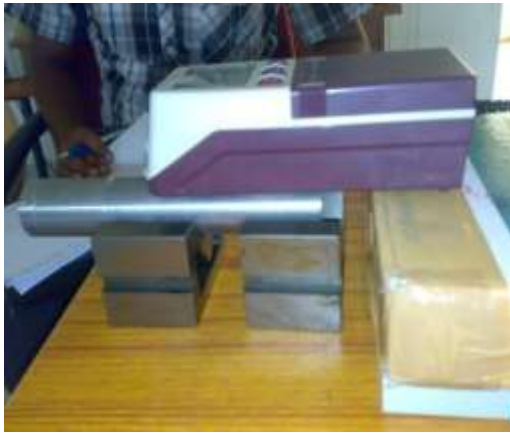
A GEDDE WELIER PRESSION LATHE MACHINE was used for conducting experiments which is shown in fig 5.1. Specifications of the GEDDE WELIER LZ350 machine are shown

Specifications of the GEDDE WELIE LZ350 machine

Make	GEDDE WEILER
Model	LZ350
Cutting speed rang	25-2500 rpm
Height of the center	190mm
Distance bet. Center	1250mm
Swing over bed	300mm
Main motor power	7.5 H.P
Type of check	Four jaw check

SURFACE ROUGHNESS TESTER:

Roughness measurement has been done using a portable stylus-type profilometer, *Talysurf* (Taylor Hobson, Surtronic 3+, and UK) shown in Figure the *Talysurf* instrument (Surtronic 3+) is a portable, self-contained instrument for the measurement of surface texture. The parameter evaluations are microprocessor based. The measurement results are displayed on an LCD screen and can be output to an optional printer or another computer for further evaluation. The instrument is powered by non-rechargeable alkaline battery (9V). It is equipped with a diamond stylus having a tip radius 5 μm . The measuring stroke always starts from the extreme outward position. At the end of the measurement the pickup returns to the position ready for the next measurement. The selection of cut-off length determines the traverse length. Usually as a default, the traverse length is five times the cut-off length though the magnification factor can be changed. The profilometer has been set to a cut-off length of 0.8 mm, filter 2CR, traverse Speed 1 mm/sec and 4 mm traverse length. Roughness measurements, in the transverse direction, on the work pieces have been repeated four times and average of four measurements of surface roughness parameter values has been recorded. The measured profile has been digitized and processed through the dedicated advanced surface finish analysis software *Talysurf* for evaluation of the roughness parameters. Surface roughness measurement with the help of stylus has been shown



specifications of roughness tester

Make	MTTUTOYO
Model	SJ 201
Detection method	Different inductor
Measuring range	350 μ m(-200 μ m to
Stylus material	Diamond
Tip radius	2 μ m to 5 μ m
Measuring force	4mN
Radius of skid curvature	40mm
Drive range	21mm
Roughness parameter	R _a = 0.1 μ m to 100 μ m
Tracing length	3 mm

DESIGN OF EXPERIMENT

The DOE process is divided into three phases which encompass all experimentation approaches. The major steps to complete an effective experiment are listed in the following.

A. The planning phase

1. State the problem or area of concern.
2. State the objective of the experiment.
3. Select the quality characteristic and measurement system.
4. Select the factor that may influence the selected quality characteristic.
5. Select the level of factor.
6. Select the appropriate orthogonal array (OA).
7. Select the interaction that may influence the selected quality characteristic or go back to step 4(iterative steps).
8. Assign factors to OA and locate interaction.

B. The conduction phase

9. Conduct experiments based on OA

C. The analysis phase

10. Analyze and interpret the results of the experiments.
11. Conduct confirmation experiment.

DESIGN OF EXPERIMENT FOR TURNING

The following section describes the design of experiment process for turning of AISI1045 steel.

Factors	Level 1	Level 2	Level 3
Cutting speed (rpm)	250	350	400
Feed (mm/rev)	0.034	0.051	0.069
Depth of cut (mm)	0.2	0.6	1
Tool nose radius(mm)	0.4	0.8	0.4

Selection of appropriate Orthogonal Array (OA)

The selection of which OA to use predominantly depends on the following items in order of priority:

1. The number of factors.
2. The number of levels for the factors of interest.
3. The described experimental resolution or cost limitations.

The most commonly used types of OAs are

For two-level experiments: L4 L8 L12 L16 L32

For three-level experiment: L9 L18 L27

The number in the array designation indicates the number of trails (different possible test combinations) in the array. Once the appropriate OA has been selected, the factors can be assigned to various columns of the array. In the present work process parameters like cutting speed, feed, depth of cut and tool nose radius, iteration between process parameters also considered, so L9 is appropriate. The table shows the L9 orthogonal array for the selected factors.

L9 Orthogonal Array (OA)

Exp. No	Run ord	A	B	C	D	Speed (mm/r)	Feed (mm/r)	Depth of cut (mm)	Tool nos
1	3	1	1	1	1	250	0.034	0.2	0.4
2	2	1	2	2	2	350	0.051	0.6	0.4
3	1	1	3	3	3	400	0.069	1	0.4
4	4	2	1	2	3	350	0.034	1	0.8
5	6	2	2	3	1	400	0.051	0.2	0.8
6	5	2	3	1	2	250	0.069	0.6	0.8
7	8	3	1	3	2	400	0.034	0.6	0.4
8	7	3	2	1	3	250	0.051	1	0.4
9	9	3	3	2	1	350	0.069	0.2	0.4

INTRODUCTION TO TAGUCHI METHOD

Every experimenter has to plan and conduct experiments to obtain enough and relevant data so that they can infer the science behind the observed phenomenon. He can do so by

(1) trial-and-error approach:

Performing a series of experiments each of which gives some understanding. This requires making measurements after every experiment so that analysis of observed data will allow him to decide what to do next - "Which parameters should be varied and by how much". Many a times such series does not progress much as negative results may discourage or will not allow a selection of parameters which ought to be changed in the next experiment. Therefore, such experimentation usually ends well before the number of experiments reaches a double digit! The data is insufficient to draw any significant conclusions and the main problem (of understanding the science) still remains unsolved.

(2) Design of experiments:

A well planned set of experiments, in which all parameters of interest are varied over a specified range, is a much

better approach to obtain systematic data. Mathematically speaking, such a complete set of experiments ought to give desired results. Usually the number of experiments and resources (materials and time) required are prohibitively large. Often the experimenter decides to perform a subset of the complete set of experiments to save on time and money! However, it does not easily lend itself to understanding of science behind the phenomenon. The analysis is not very easy (though it may be easy for the mathematician/statistician) and thus effects of various parameters on the observed data are not readily apparent. In many cases, particularly those in which some optimization is required, the method does not point to the BEST settings of parameters. A classic example illustrating the drawback of design of experiments is found in the planning of a world cup event, say football. While all matches are well arranged with respect to the different teams and different venues on different dates and yet the planning does not care about the result of any match (win or lose)!!!! Obviously, such a strategy is not desirable for conducting scientific experiments (except for coordinating various institutions, committees, people, equipment, materials etc.).

(3) Taguchi method:

Taguchi Method is developed by Dr. Genichi Taguchi, a Japanese quality management consultant. The method explores the concept of quadratic quality loss function (Figure 3.1) and uses a statistical measure of performance called Signal-to-Noise (S/N) ratio. The S/N ratio takes both the mean and the variability into account. The S/N ratio is the ratio of the mean (Signal) to the standard deviation (Noise). The ratio depends on the quality characteristics of the product/process to be optimized. The standard S/N ratios generally used are as follows: - Nominal is Best (NB), Lower the Better (LB) and Higher the Better (HB), (Equations 10 to 12). The optimal setting is the parameter combination, which has the highest S/N ratio.

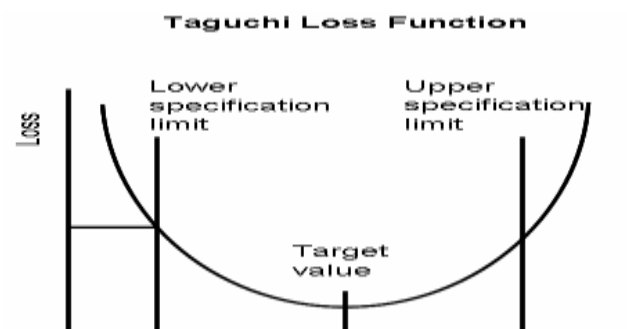


Figure 7.1: Taguchi's quadratic loss function

Taguchi Method treats optimization problem in two categories:

(a) Static problems:

Generally, a process to be optimized has several control factors which directly decide the target or desired value of the output. The optimization then involves determining the best control factor levels so that the output is at the target value. Such a problem is called as a "STATIC PROBLEM". This is best explained using a P-Diagram which is shown below ("P" stands for Process or Product). Noise is shown to be present in the process but should have no effect on the output! This is the primary aim of the Taguchi experiments - to minimize variations in output even though noise is present in the process. The process is then said to have become ROBUST.

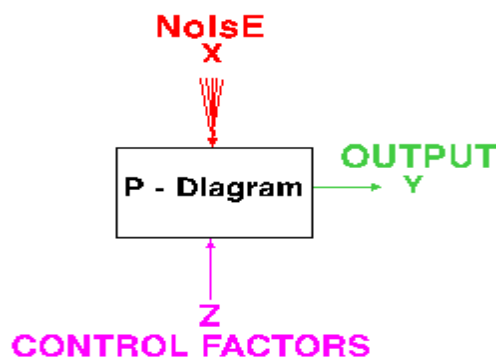


Diagram for static problems

Static problem (Batch process optimization).

There are 3 signal-to-noise ratios of common interest for optimization of static problems.

1. Taguchi's S/N Ratio for (NB) Nominal-the-best

(Quality characteristic is usually a nominal output, say Diameter)

$$\eta = 10 \ln_{10} \frac{1}{n} \sum_{i=1}^n \frac{\mu^2}{\sigma^2}$$

This is usually the chosen S/N ratio for all undesirable characteristics like "Defects" etc. for which the ideal value is zero. Also, when an ideal value is finite and its maximum or minimum value is defined (like maximum purity is 100% or maximum Tc is 92K or minimum time for making a telephone connection is 1 sec) then the difference between measured data and ideal value is expected to be as small as possible. The generic form of S/N ratio then becomes,

2. Taguchi's S/N Ratio for (LB) Lower-the-better

(Quality characteristics is usually a nominal output, say Defects)

$$\eta = -10 \ln_{10} \frac{1}{n} \sum_{i=1}^n y_i^2$$

This case has been converted to SMALLER-THE-BETTER by taking the reciprocals of measured data and then taking the S/N ratio as in the smaller-the-better case.

3. Taguchi's S/N Ratio for (HB) Higher-the-better

(Quality characteristics is usually a nominal output, say Current)

$$\eta = -10 \ln_{10} \frac{1}{n} \sum_{i=1}^n \frac{1}{y_i^2}$$

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

Examples are:

- (1) Most parts in mechanical fitting have dimensions which are nominal-the-best type.
- (2) Ratios of chemicals or mixers are nominally the best type.

E.g. Aqua regains 1:3 of HNO₃: HCL. Ratio of sulphur, kNO₃ and carbon in gun powder.

- (3) Thickness should be uniform in deposition/growth/plating/etching.

(b) Dynamics problems:

If the product to be optimized has a signal input that directly decides the output, the optimization involves determining the best control factor levels so that the "input signal / output" ratio is closest to the desired relationship. Such a problem is called as a "DYNAMIC PROBLEM". This is best explained by a P-Diagram which is shown below. Again, the primary aim of the Taguchi experiments - to minimize variations in output even though noise is present in the process- is achieved by getting improved linearity in the input/output relationship.

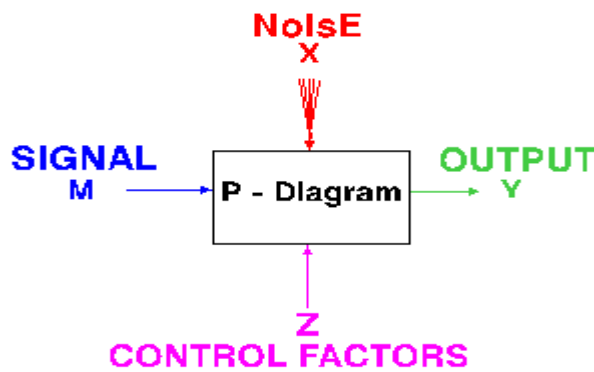


Fig 7.3 Diagram for dynamic problems

In dynamic problems, we come across many applications where the output is supposed to follow input signal in a predetermined manner. Generally, a linear relationship between "inputs" "output" is desirable.

For example: Accelerator pedals in cars, volume control in audio amplifiers, and Document copier (with magnification or reduction) various types of moldings etc.

There are 2 characteristics of common interest in "follow-the-leader" or Transformations" type of applications,

- Slope of the I/O characteristics and
- Linearity of the I/O characteristics (minimum deviation from the best-fit straight line). The Signal-to-Noise ratio for these 2 characteristics has been defined.

PROCEDURE ADAPTED FOR OPTIMIZATION

The proposed optimization methodology combines Principal Component Analysis (PCA), utility concept and Taguchi method based on selected Taguchi's Orthogonal Array (OA) Design of Experiment (DOE). The detailed methodology is described below. Assuming, the number of experimental runs in Taguchi's OA design is m , and the number of quality characteristics is n . The experimental results can be expressed by the following series: $X_1, X_2, X_3, \dots, X_i, \dots, X_m$

Here,

$$X_1 = \{X_1(1), X_1(2) \dots \dots \dots X_1(k) \dots \dots \dots X_1(n)\}$$

.

.

$$X_i = \{X_i(1), X_i(2) \dots \dots \dots X_i(k) \dots \dots \dots X_i(n)\}$$

.

$$X_m = \{X_m(1), X_m(2) \dots \dots \dots X_m(k) \dots \dots \dots X_m(n)\}$$

Here, X_i represents the i^{th} experimental results and is called the comparative sequence. Let, X_0 are the reference sequence:

Let,

$$X_0 =$$

$$\{X_0(1), X_0(2) \dots \dots \dots X_0(k) \dots \dots \dots X_0(n)\}$$

The value of the elements in the reference sequence means the optimal value (ideal or desired value) of the corresponding quality characteristic. X_0 and X_0 both includes n elements and $X_0(k)$ and $X_i(k)$ represent the numeric value of k^{th} element in the reference sequence and the comparative sequence, respectively, $k=1, 2, \dots, n$. The following illustrates the proposed parameter optimization procedures in detail.

Step 1: Normalization of the responses (quality characteristics)

When the range of the series is too large or the optimal value of a quality characteristic is too enormous, it will cause the influence of some factors to be ignored. The original experimental data must be normalized to eliminate such effect. There are three different types of data normalization according to whether we require the LB (Lower-the-Better), the HB (Higher-the-Better) and NB (Nominal-the-Best). The normalization is taken by the following equations.

$$(a) \quad \text{LB (Lower-the-Better)} \\ X_i^*(k) = \frac{\min X_i(k)}{X_i(k)} \quad \text{-----} \quad (1)$$

$$(b) \quad \text{HB (Higher-the-Better)} \\ X_i^*(k) = \frac{X_i(k)}{\min X_i(k)} \quad \text{-----} \quad (2)$$

$$(c) \quad \text{NB (Nominal-the-Best)} \\ X_i^*(k) = \frac{\min\{X_i(k), X_{ob}(k)\}}{\max\{X_i(k), X_{ob}(k)\}} \quad \text{-----} \quad (3)$$

$$i = 1, 2, \dots, m;$$

Here,

$$k = 1, 2, \dots, n.$$

$X_i^*(k)$ is the normalized data of the k^{th} element in the i^{th} sequence.

$X_{ob}(k)$ is the desired value of the k^{th} quality characteristic. After data normalization, the value of $X_i^*(k)$ will be

between 0 and 1. The series X_i^* , $i = 1, 2, 3, \dots, m$ can be viewed as the comparative sequence used in the present case.

Step 2: Checking for correlation between two quality characteristics

$$Q_i = \{X_0^*(i), X_1^*(i), X_2^*(i) \dots \dots \dots X_m^*(i)\} \quad \text{---} \quad (4)$$

Let

Where $i = 1, 2, \dots, n$.

It is the normalized series of the i th quality characteristic. The correlation coefficient between two quality characteristics is calculated by the following equation:

$$\rho_{ik} = \frac{\text{Cov}(Q_j, Q_k)}{\sigma_{Q_j} \sigma_{Q_k}} \quad \text{-----} \quad (5)$$

Here $j = 1, 2, 3, \dots, n$.

$k = 1, 2, 3, \dots, n$.

$j \neq k$.

Here, ρ_{ik} is the correlation coefficient between quality characteristic j and quality characteristic k ; $\text{Cov}(Q_j, Q_k)$ is the covariance of quality characteristic j and quality characteristic k ; σ_{Q_j} and σ_{Q_k} are the standard deviation of quality characteristic j and quality characteristic k , respectively.

The correlation is checked by testing the following hypothesis:

$$\begin{cases} H_0: \rho_{jk} = 0 & (\text{There is no correlation}) \\ H_1: \rho_{jk} \neq 0 & (\text{There is correlation}) \end{cases} \quad \text{-----} \quad (6)$$

Step 3: Calculation of the principal component score

(a) Calculate the Eigenvalue λ_k and the corresponding eigenvector β_k ($k = 1, 2, \dots, n$) from the correlation matrix formed by all quality characteristics.

(b) Calculate the principal component scores of the normalized reference sequence and comparative sequences using the equation shown below:

$$Y_i(k) = \sum_{j=1}^n X_i^*(j) \beta_{kj}, \quad i = 0, 1, 2, 3, \dots, m; \quad k = 1, 2, \dots, n. \quad \text{-----} \quad (7)$$

Here, $Y_i(k)$ is the principal component score of the k th element in the i th series. $X_i^*(j)$ is the normalized value of the j th element in the i th sequence, and β_{kj} is the j th element of eigenvector β_k .

Step 4: Adaptation of utility theory: Calculation of overall utility index

According to the utility theory, if X_i is the measure of effectiveness of an attribute (or quality characteristics) i and there are n attributes evaluating the outcome space, then the joint utility function can be expressed as:

$$U(X_1, X_2, \dots, X_n) = f(U_1(X_1), U_2(X_2), \dots, U_n(X_n))$$

Here $U_i(X_i)$ is the utility of the i th attribute.

The overall utility function is the sum of individual utilities if the attributes are independent, and is given as follows:

$$U(X_1, X_2, \dots, X_n) = \sum_{i=1}^n U_i(X_i)$$

The attributes may be assigned weights depending upon the relative importance or priorities of the characteristics. The overall utility function after assigning weights to the attributes can be expressed as:

$$U(X_1, X_2, \dots, X_n) = \sum_{i=1}^n W_i U_i(X_i)$$

Here W_i is the weight assigned to the attribute i . The sum of the weights for all the attributes must be equal to 1.

A preference scale for each quality characteristic is constructed for determining its utility value. Two arbitrary numerical values (preference number) 0 and 9 are assigned to the just acceptable and the best value of the quality characteristic respectively. The preference number P_i can be expressed on a logarithmic scale as follows:

$$P_i = A \cdot \log \left[\frac{X_i}{X_i^1} \right] \dots \dots \dots 8$$

Here X_i is the value of any quality characteristic or attribute i , X_i^1 is just acceptable value of quality characteristic or attribute i and A is a constant. The value A can be found by the condition that if $X_i = X^*$ (where X^* is the optimal or best value), then $P_i = 9$. Therefore,

Surface Roughness Ra in μm	Surface Roughness Rq in μm	Surface Roughness Rz in μm	MRR in (mm^3/min)	Time Taken in sec
3.613	4.5	22.8	129.41	268
5.43	6.78	33.79	446.336	124
6.98	8.74	43.86	1422.42	8505
4.94	6.01	27.49	635.63	187
4.14	5.16	26.13	296.858	112
4.69	5.86	29.3	550.098	132.5
4.3	5.49	27.8	466.392	170
5.68	7.11	35.5	735.176	180.5
4.69	5.85	29.13	339.988	93.5

$$A = \frac{9}{\log \frac{x_i}{x_1}} \dots \dots \dots$$

....9

The overall utility can be expressed as follows:

$$U = \sum_{i=1}^n W_i P_i$$

Subject to the condition: $\sum_{i=1}^n W_i = 1$.
.....10

Among various quality characteristics types, viz. Lower-the-Better, Higher-the-Better, and Nominal-the-Best suggested by Taguchi, the utility function would be Higher-the- Better type. Therefore, if the quality function is maximized, the quality characteristics considered for its evaluation will automatically be optimized (maximized or minimized as the case may be).

In the proposed approach based on quality loss (of principal components) utility values are calculated. Utility values of individual principal components are accumulated to calculate overall utility index. Overall utility index serves as the single objective function for optimization

DATA COLLECTION AND ANALYSIS

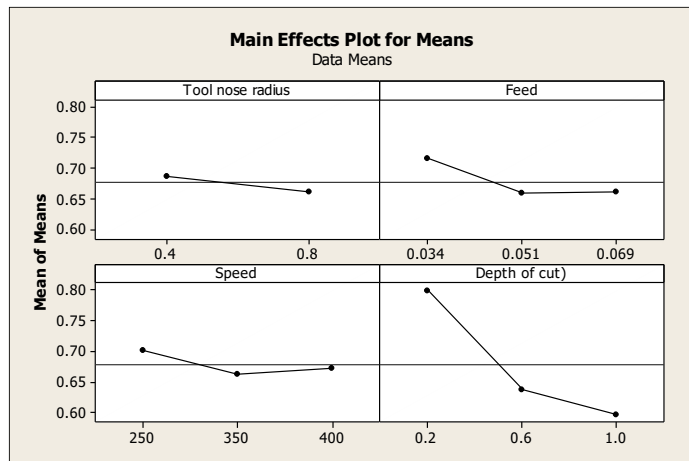
Principal components in all L9 OA experimental observations

SI NO	ψ_1	ψ_2	ψ_3
Ideal Sequence	1.562	1.595	0.097
1	1.7847	0.9562	0.0241
2	0.8424	0.989	0.365
3	0.4644	1.175	0.4653
4	1.0571	0.7929	0.5355
5	1.208	1.1839	0.4444
6	1.0131	0.9825	0.5193
7	1.1574	0.883	0.5114
8	0.8472	0.7511	0.4376
9	0.9909	1.2705	0.4264

Calculation of overall grey relational grade

SI NO	$\Gamma_{0,i}$	S/N Ratio
1	0.9012	-0.9035
2	0.6446	-3.8141
3	0.6173	-4.1900
4	0.5995	-4.4442
5	0.7553	-2.4376
6	0.6265	-4.0615
7	0.6428	-3.8384
8	0.5739	-4.8232
9	0.7406	-2.6083

GRAPHS



ANOVA Table for surface roughness R_a

Source	DOF	Seq SS	Adj MS	F-test	P-Value	%of contribution
A	2	0.3727	6.1864	0.61	0.671	4.72682
B	2	2.1419	1.0709	3.51	0.353	27.1649
C	2	4.528	2.2564	7.4	0.252	57.4269
D	1	0.5523	0.5523	1.81	0.407	7.00462
Error	1	0.3051	0.3051			
Total	8	7.8848				100%

ANOVA Table for surface roughness R_q

source	DOF	Seq SS	Adj MS	F-test	P-Value	% of contribution
A	2	0.6242	0.3121	0.76	0.63	5.051797
B	2	3.4517	1.7258	4.2	0.326	27.93542
C	2	6.7887	3.3944	8.26	0.239	54.94254
D	1	1.0804	1.0804	0.263	0.352	8.74393
Error	1	0.4108	0.4108			
Total	8	12.356				100%

RESULTS AND ANALYSIS

GREY RELATION ANALYSIS AND UTILITY CONCEPT

Experimental data (Table 8.1.1&8.2.1) have been normalized using Equations (1) and (2). For surface roughness (Lower-the-Better) LB; and for material removal rate (MRR) (Higher-the-Better) HB criteria have been selected. The normalized data are shown in Table(8.1.2&8.2.2)After normalization, a check has been made to verify whether the responses are correlated or not. Table (8.1.3&8.2.3)indicates the correlation coefficient among the responses. The coefficient of correlation, between two responses, has been calculated using Equation (5). It has been observed that, all responses are correlated to each other. In order to eliminate response correlations, Principal Component Analysis (PCA) has been applied to derive three independent quality indexes (called principal components), using Equation (7). The analysis of correlation matrix is shown in Table (8.1.4.&8.2.4) The independent quality indexes are denoted as principal components ψ_1 (1st PC) to ψ_3 (3rd PC). Table (8.1.5&8.2.5) represents the values of four independent principal components in all experimental runs.

Table(8.1.6&8.2.6) for all principal components have been evaluated using Equations (8), (9) and (10). Utility index values and Grey relational coefficients of all three principal components have been calculated using Equation (11). These have been furnished in Table (8.1.7.&8.2.7) The overall utility index and grey relational grade has been calculated using Equation (12), shown in Table (8.1.8.&8.2.8) Thus, the multi-criteria optimization problem has been transformed into a single objective optimization problem using the combination of Taguchi approach and grey relational analyses. Higher is the value of grey relational grade, the corresponding factor combination is said to be close to the optimal. The S/N ratio plot for the overall utility index and grey relational grade is represented graphically in Figure (8.1.1&8.2.1) The S/N ratio for overall utility index and grey relational grade has been calculated using HB (higher-the-better) criterion (Equation 13).

$$SN(\text{higher the better}) = -10 \log \left[\frac{1}{t} \sum_{i=1}^t \frac{1}{y_i} \right]$$

Here t is the number of measurements, and y_i the measured i^{th} characteristic value i.e. i^{th} quality indicator. With the help of the Figure 8.1.1&8.2.1 optimal parametric

combination has been determined. The optimal factor setting becomes $A_1 B_1 C_1 D_1$.

ANOVA ANALYSIS

The ANOVA analysis was carried at 95% confidence level. The analysis of variance was carried out for determining the influence of process parameters on the response variables.

ANOVA Table for surface roughness R_a

source	DOF	Seq SS	Adj MS	F-test	P-Value	% of contribution
A	2	0.3727	6.1864	0.61	0.671	4.72682
B	2	2.1419	1.0709	3.51	0.353	27.1649
C	2	4.528	2.2564	7.4	0.252	57.4269
D	1	0.5523	0.5523	1.81	0.407	7.00462
Error	1	0.3051	0.3051			
Total	8	7.8848				100%

From the above table 10.3 factors A (Cutting Speed), B (Feed rate) and C (Depth of cut), and D (tool nose radius) has significant effect on the output parameters. The depth of cut has high influence (57.47%) on surface roughness R_a and feed has (27.16%) of influence on surface quality character R_a . the cutting speed were found to be the second- and third-ranking factors respectively.

CONCLUSIONS

1. Baldonado, M., Chang, C.-C.K., Gravano, L., Paepcke, A.: The Stanford Digital Library Metadata Architecture. Int. J. Digit. Libr. In this study, the Utility concept and Grey-based Taguchi method was applied for the multiple performance characteristics of turning operations. Utility concept and grey relational analysis of the material-removal rate and the surface roughness obtained from the Taguchi method reduced from the multiple performance

characteristics to a single performance characteristic which is called the utility index grade and grey relational grade. Therefore, the optimization of the complicated multiple performance characteristics of the processes can be greatly simplified using the extended Taguchi method. It is also shown that the performance characteristics of the turning operations, such as the material removal rate, the cutting time and the surface roughness are greatly enhanced by using this method. The aforesaid extended Taguchi method can be applied for continuous quality improvement of the product/process and off-line quality control.

According to this analysis, the most effective parameters with respect to the material-removal rate and the surface roughness are the feed rate, depth of cut, cutting speed and tool nose radius. The percentage contribution indicates the relative power of a factor to reduce the variation. For a factor with a high percentage contribution, there is a great influence on the performance. The percent contributions of the cutting parameters on the material-removal rate and the surface roughness are shown in table (10.3&10.4.) From the table 10.3 factors A (Cutting Speed), B (Feed rate) and C (Depth of cut), and D (tool nose radius) has significant effect on the output parameters. The depth of cut has high influence (57.47%) on surface roughness R_a and feed has (27.16%) of influence on surface quality character R_a . the cutting speed were found to be the second- and third-ranking factors respectively. From the table 10.4 factors A (Cutting Speed), B (Feed rate) and C (Depth of cut), and D (tool nose radius) has significant effect on the output parameters. The depth of cut has high influence (54.94%) on surface roughness R_a and feed has (27.93%) of influence on surface quality character R_q . the cutting speed were found to be the second- and third-ranking factors respectively.

In this study, the Utility concept and Grey-based Taguchi method was applied for the multiple performance characteristics of turning operations. Utility concept and grey relational analysis of the material-removal rate and the surface roughness obtained from the Taguchi method reduced from the multiple performance characteristics to a single performance characteristic which is called the utility index grade and grey relational grade. Therefore, the optimization of the complicated multiple performance characteristics of the processes can be greatly simplified using the extended Taguchi method. It is also shown that the performance characteristics of the turning operations, such as the material removal rate, the cutting time and the surface roughness are greatly enhanced by using this method. The aforesaid extended Taguchi method can be

applied for continuous quality improvement of the product/process and off-line quality control.

According to this analysis, the most effective parameters with respect to the material-removal rate and the surface roughness are the feed rate, depth of cut, cutting speed and tool nose radius. The percentage contribution indicates the relative power of a factor to reduce the variation. For a factor with a high percentage contribution, there is a great influence on the performance. The percent contributions of the cutting parameters on the material-removal rate and the surface roughness are shown in table (10.3&10.4.) From the table 10.3 factors A (Cutting Speed), B (Feed rate) and C (Depth of cut), and D (tool nose radius) has significant effect on the output parameters. The depth of cut has high influence (57.47%) on surface roughness R_a and feed has (27.16%) of influence on surface quality character R_a . the cutting speed were found to be the second- and third-ranking factors respectively. From the table 10.4 factors A (Cutting Speed), B (Feed rate) and C (Depth of cut), and D (tool nose radius) has significant effect on the output parameters. The depth of cut has high influence (54.94%) on surface roughness R_a and feed has (27.93%) of influence on surface quality character R_q . the cutting speed were found to be the second- and third-ranking factors respectively.

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