ABATRACT

An optimization technique for turning process based on the Taguchi method with multiple performance characteristics is proposed in this thesis. The three cutting parameters taken into account are , cutting speed (N), feed rate (f) and depth of cut (d), are being optimized by considering multiple performance characteristics and also including surface roughness and material removed. A robust design and quality optimization tool, the Taguchi methodology is applied to find the optimal cutting parameters for cutting BS970En32 steel. The steps involved in Taguchi method are, determining the control factors, selection of appropriate orthogonal array, then implementing experiment, and lastly analysing and examining result by execution through ANNOVA analysis and then confirming the experiment for planning of future application. A considerable improvement in the surface roughness and material removed has been found in results on the basis of Taguchi method. Further, the Taguchi quality loss function has also been used for multi-objective optimization and finally the results are compared with single-objective optimization.

Chapter 1

Introduction

Manufacturing involves converting raw material into finished good that got values in the market. The improved qualities of product and the economics of the manufacturing operation are very important consideration to produce product having the functional and aesthetic appeal. Although all the above processes are used for obtaining the desired work-piece shape, size & finish. The selection of a particular process depends on several factors, which includes the shape & size of a finished component; precision required the volume of production, cost of material and its availability. The commonly used method for obtaining the desired shape, size & finish is machining, which involves removal of excess material in the form of chips. Machining is one of the most versatile manufacturing processes. Popularity of turning for machining application is increasing particularly due to the introduction of High Speed Machining (HSM) made possible due to improvement in the design and operation of turning machines and tools. Most frequently, turning entails the generation of round parts having different diameters. However, its application for contour milling is growing with the availability of CNC milling machines. With the introduction of high speed machining (HSM), the scope of application of turning is continuously expanding. The variable that influences the economics of machining operation are numerous; some of the important ones are machine tool capacity, work piece material and tool geometry, cutting parameters affects the production rate, have an impact on cutting conditions, which is reflected on surface roughness, surface texture and dimensional deviations of the product quality and unit cost of component. The economic selection of cutting conditions require knowledge of technical and cost data, which are not easily available in many cases. Surface roughness is a measure of the technological quality of a product and a factor that greatly influences manufacturing cost. It describes the geometry of the machined surface and combined with the surface texture, which is process dependent, can play an important role to optimize the operational characteristics of the process.

There are several methods of optimization of cutting parameters in metal cutting processes which will be discussed later. Each method has its advantages and disadvantages. Despite of Taguchi Method has some disadvantages but many researchers uses this method such as turning, milling, drilling etc.

Biggest advantage of Taguchi method is that by conducting few numbers of experiments it gives near optimal solution.

Chapter 2

Literature Review

As applying Taguchi parameter design requires the identification of factors affecting targeted quality characteristics, relevant literature must be reviewed to screen the most important among a number of factors or conditions affecting surface roughness of turned surface.

2.1 Critical study of associated research papers

[1] C.Y. Nian, W. H. Yang and Y.S. Tarng worked on Optimization of turning operations with multiple performance characteristics. In this study, the optimization of turning operations based on the Taguchi method with multiple performance characteristics is proposed . The orthogonal array, multi-response signal-to-noise ratio, and analysis of variance are employed to study the performance characteristics in turning operations. Three cutting parameters namely, cutting speed, feed rate, and depth of cut, are optimized with considerations of multiple performance characteristics including tool life, cutting force, and surface finish. Experimental results are provided to illustrate the effectiveness of this approach.

[2] M. Nalbant, H. Go kkaya, G. Sur applied Taguchi method in the optimization of cutting parameters for surface roughness in turning. In this study, the Taguchi method is used to find the optimal cutting parameters for surface roughness in turning. The orthogonal array, the signal-to-noise ratio, and analysis of variance are employed to study the performance characteristics in turning operations of AISI 1030 steel bars using TiN coated tools. Three cutting parameters namely, insert radius, feed rate, and depth of cut, are optimized with considerations of surface roughness. Experimental results are provided to illustrate the effectiveness of this approach.

[3] Ersan Aslan, Necip Camuşcu and Burak Birgören Design optimization of cutting parameters when turning hardened AISI 4140 steel (63 HRC) with Al_2O_3 + TiCN mixed ceramic tool. Due to their high hardness and wear resistance, Al_2O_3-based ceramics are one of the most suitable cutting tool materials for machining hardened steels. However, their high degree of brittleness usually leads to inconsistent results and sudden catastrophic failures. This necessitates a process optimization when machining hardened steels with Al_2O_3 based ceramic cutting tools. The present paper outlines an experimental study to achieve this by employing Taguchi techniques. Combined effects of three cutting parameters, namely cutting speed, feed rate and depth of cut on two performance measures, flank wear (VB) and surface roughness (R_a), were investigated employing an orthogonal array and the analysis of variance (ANOVA). Optimal cutting parameters for each performance measure were obtained; also the relationship between the parameters and the performance measures were determined using multiple linear regression.

[4] Chorng-Jyh Tzeng, Yu-Hsin Lin, Yung-Kuang Yang and Ming-Chang Jeng optimize turning operations with multiple performance characteristics using the Taguchi method and Grey relational analysis. This study investigated the optimization of CNC turning operation parameters for SKD11 (JIS) using the Grey relational analysis method. Nine experimental runs based on an orthogonal array of Taguchi method were performed. The surface properties of roughness average and roughness maximum as well as the roundness were selected as the quality targets. An optimal parameter combination of the turning operation was obtained via Grey relational analysis. By analyzing the Grey relational grade matrix, the degree of influence for each controllable factors onto individual quality targets can be found. The depth of cut was identified to be the most influence on the roughness average and the cutting speed is the most influential factor to the roughness maximum and the roundness. Additionally, the analysis of variance (ANOVA) is also applied to identify the most significant factor; the depth of cut is the most significant controlled factors for the turning operations according to the weighted sum grade of the roughness average, roughness maximum and roundness.

[5] J. Paulo Davim **given** A note on the determination of optimal cutting conditions for surface finish obtained in turning using design of experiments. This paper presents a study of the influence of cutting conditions on the surface finish obtained by turning. A plan of experiments, based on the techniques of Taguchi was designed and executed on controlled machining with cutting conditions prefixed in workpieces. Afterwards, the roughness was evaluated on workpieces using two different profilometers. The objective was to establish a correlation between cutting velocity, feed and depth of cut with the roughness evaluating parameters R_a and R_t, following the international norms. These correlations were obtained by multiple linear regression. Finally, confirmation tests were performed to make a comparison between the results predicted from the mentioned correlations and the theoretical results.

[6] Aman Aggarwal' Hari Singh, Pradeep Kumar and Manmohan Singh worked on optimization of multiple quality characteristics for CNC turning under cryogenic cutting environment using desirability function. This paper optimizes multiple characteristics (tool life, cutting force, surface roughness and power consumption) in CNC turning of AISI P-20 tool steel using liquid nitrogen as a coolant. Four controllable factors of the turning process viz. cutting speed, feed, depth of cut and nose radius, were studied. Face centred central composite design was used for experimentation. Response surface methodology was used for modelling the responses. Desirability function was used for single and multiple response optimization.

[7] P. Matooria, S. Sulaiman and M.M.H.M. Ahmad done an experimental study for optimization of electrical discharge turning (EDT) process. This study presents the application of the Taguchi robust design methods to optimize the precision and accuracy of the electrical discharge machining process (EDM) for machining of precise cylindrical forms on hard and difficult-to-machine materials. The present study has been carried out on the influence of six design factors: intensity supplied by the generator of the EDM machine (I), pulse-on time (t_i), voltage (V), pulse-off time (t_o), servo (V_G), and rotational speed (C) which are the most relevant parameters to be controlled by the EDM process machinists, over

material removal rate (MRR) as an indicator of the efficiency and cost-effectiveness of the process. The study of behaviour of the mentioned response has done by means of the technique called design of experiments (DOE). In this case, an L_{18} ($2^1 \times 3^7$) Taguchi standard orthogonal array was chosen due to the number of factors and their levels in the study.

[8] Hasan Oktem' Tuncay Erzurumlu and Ibrahim Uzman applied Taguchi optimization technique in determining plastic injection molding process parameters for a thin-shell part. This paper deals with the application of Taguchi optimization technique to reduce warpage problem related to the shrinkage variation depended on process parameters during production of thin-shell plastic components for or those part. For this purpose, a number of MoldFlow analyses are carried out by utilizing the combination of process parameters based on three-level of L_{27} and L_9 Taguchi orthogonal design. The signal-to-noise (S/N) and the analysis of variance (ANOVA) are used to find the optimum levels and to indicate the impact of the process parameters on warpage and shrinkage. The results show that warpage and shrinkage are improved by about 2.17% and 0.7%. A verification test is also performed to prove the effectiveness of Taguchi technique after the optimum levels of process parameters are determined. It can be clearly inferred from this conclusion that Taguchi optimization is sufficient to solve the warpage problem with shrinkage for thin-shell plastic components of or those part

[9] M. Kaladhar1, K. V. Subbaiah, Ch. Srinivasa Rao and K. Narayana Rao. They worked on application of Taguchi approach and Utility Concept in solving the Multi-objective problem when turning AISI 202 Austenitic Stainless Steel. The traditional Taguchi method is widely used for optimizing the process parameters of a single response problem. Optimization of a single response results the non-optimum values for remaining. But, the performance of the manufactured products is often evaluated by several quality characteristics/responses. Under such circumstances, multi-characteristics response optimization may be the solution to optimize multi-responses simultaneously. In the present work, a multi-characteristics response optimization model based on Taguchi and Utility concept is used to optimize process parameters, such as speed, feed, depth of cut, and nose radius on multiple performance characteristics, namely, surface roughness (Ra) and material removal rate (MRR) during turning of AISI 202 austenitic stainless steel using a CVD coated cemented carbide tool. Taguchi's L8 orthogonal array (OA) is selected for experimental planning. The experimental result analysis showed that the combination of higher levels of cutting speed, depth of cut, and nose radius and lower level of feed is essential to achieve simultaneous maximization of material removal rate and minimization of surface roughness. The ANOVA and F-tests are used to analyze the results. Further, the confirmation tests are conducted and the results are found to be within the confidence interval.

[10] Bharat Chandra, Saumaya Darshan Mohanty, Ashish Badyopadhaya optimized in CNC end milling of UNS C34000 medium leaded brass with multiple surface roughness characteristics. The present study highlights a multi-objective optimization problem by applying utility concept coupled with Taguchi method through a case study in CNC end milling of UNS C34000 medium leaded brass. The study aimed at evaluatingthe best process

environment which could simultaneously satisfy multiple requirements of surface quality. In view of the fact, the traditional Taguchi method cannot solve a multi-objective optimization problem; to overcome this limitation, utility theory has been coupled with Taguchi method. Depending on Taguchi's Lower-the- Better (LB) response criteria; individual surface quality characteristics has been transformed into corresponding utility values. Individual utility values have been aggregated finally to compute overall utility degree which serves as representative objective function for optimizing using Taguchi method. Utility theory has been adopted to convert a multi-response optimization problem into a single response optimization problem; in which overall utility degree serves as the representative single objective function for optimization. The study of combined utility theory and Taguchi method for predicting optimal setting. Based on Taguchi's Signal-to-Noise ratio (S/N), analysis has been made on the overall utility degree and optimal process environment has been selected finally which corresponds to highest S/N Ratio. Optimal result has been verified through confirmatory test. The case study indicates application feasibility of the aforesaid methodology proposed for multi response optimization and off-line control of multiple surface quality characteristics in CNC end milling.

[11] Sanjit Moshat, Saurav Datta, Asish Bandyopadhyay and Pradip Kumar Pal worked on Optimization of CNC end milling process parameters using PCA-based Taguchi method. In order to build up a bridge between quality and productivity, the present study highlights optimization of CNC end milling process parameters to provide good surface finish as well as high material removal rate (MRR). The surface finish and material removal rate have been identified as quality attributes and are assumed to be directly related to productivity. An attempt has been made to optimize aforesaid quality attributes in a manner that these multi-criterions could be fulfilled simultaneously up to the expected level. This invites a multi-objective optimization problem which has been solved by PCA based Taguchi method. To meet the basic assumption of Taguchi method; in the present work, individual response correlations have been eliminated first by means of Principal Component Analysis (PCA). Correlated responses have been transformed into uncorrelated or independent quality indices called principal components. The principal component, imposing highest accountability proportion, has been treated as single objective function for optimization (multi-response performance index). Finally Taguchi method has been adapted to solve this optimization problem. The aforesaid methodology has been found fruitful in the cases where simultaneous optimization of huge number of responses is required.

[12] Julie Z. Zhang, Joseph C. Chenb, E. Daniel Kirby. They worked on surface roughness optimization in an end-milling operation using the Taguchi design method. This study presents a study of the Taguchi design application to optimize surface quality in a CNC face milling operation. Maintaining good surface quality usually involves additional manufacturing cost or loss of productivity. The Taguchi design is an efficient and effective experimental method in which a response variable can be optimized, given various control and noise factors, using fewer resources than a factorial design. This study included feed rate, spindle speed and depth of cut as control factors, and the noise factors were the operating chamber temperature and the usage of different tool inserts in the same specification, which

introduced tool condition and dimensional variability. An orthogonal array of L9 (34) was used; ANOVA analyses were carried out to identify the significant factors affecting surface roughness, and the optimal cutting combination was determined by seeking the best surface roughness (response) and signal-to-noise ratio. Finally, confirmation tests verified that the Taguchi design was successful in optimizing milling parameters for surface roughness.

Chapter 3

A review of optimization techniques in metal cutting process

3.1.1 Introduction

Technology of metal has grown substantially over time owing to the contribution from may branches of engineering with a common goal of achieving higher machining process efficiency. Selection of optimal machining condition(s) is a key factor in achieving this condition. In metal cutting operation, the manufacturer seeks to set the process - related controllable variable(s) at their optimal operating conditions with minimum effect of uncontrollable or noise variables on the levels and variability in the output(s). To design and implement an effective process control for metal cutting operation by parameter optimization, a manufacturer seeks to balance between quality and cost at each stage of operation resulting in improved delivery and reduced warranty or field failure of a product under consideration. Out of many types of machining machining operations, boring, turning, milling, broaching, grinding, honing and lapping are the key value-adding metal cutting process required to produce assembly components and final products. Process parameters optimization in these machining operations is required to produce assembly components and final products. Process parameter optimization in these machining operation is required to be undertaken in two stages :

(i) modelling of input-output and in process parameter relationship, and
(ii) determination of optimal or near-optimal cutting conditions.

Modelling of input-output and in-process parameter relationship is considered as an abstract representation of a process linking causes and effects or transforming process inputs into outputs. The resulting model provides the basic mathematical input required for formulation of the process objective function. An optimization technique provides optimal or near-optimal solution(s) to the overall optimization problem formulated, and subsequently implemented in actual metal cutting process.

The first necessary step for process parameter optimization in any metal cutting process is to understand the principles governing the cutting processes by developing an explicit mathematical model, which may be of two types : mechanistic and empirical. The functional relationship between input-output and in-process parameters as determined analytically for a cutting process is called mechanistic models. However, as there is a lack of adequate and acceptable mechanistic models for metal cutting processes. The list of applications of modelling techniques of process input-output and in-process parameter relationship based on statistical regression, artificial neural network, and fuzzy set theory is endless. Although these types of modelling techniques may be working satisfactorily in different situations, there are constraints, assumptions and shortcomings, limiting the use of a specific technique. The usefulness, applications, and limitations of these techniques are explained below.

3.1.2 Statistical regression technique

Regression is a conceptually simple technique for investigating functional relationship between output and input decision variables of a cutting process and may be useful for cutting process data description, parameter estimation, and control. Several applications of regression equation-based modelling in metal cutting process are reported in literature. Although statistical regression may work well for modelling, this technique may not describe precisely the underlying non-linear complex relationship between the decision variables and responses. A prior assumption regarding functional relationship(s) [such as linear, quadratic, higher-order-polynomial, and exponential] between output(s) and input decision variable(s), is a pre-requisite for regression equation-based modelling. Prediction of output(s) for an unknown set of input(s) based on regression technique is valid only over the region of the repressors variable(s) contained in the observed cutting process data. It is only an aid to confirm cause-effect relationship, and does not imply a cause and effect relationship. Moreover, error components of regression equation need to be mutually independent, normally distributed, and having constant variance.

3.1.3 Artificial neural network (ANN)-based modelling

ANN may handle complex input-output and in process parameter relationship of machining control problems. The learning ability of nonlinear relationship in a cutting operation without going deep into the mathematical complexity, or prior assumption on the functional form of the relationship between input(s), in process parameter(s) and output(s) (such as linear, quadratic, higher order polynomial, and exponential) makes ANN an attractive choice for many researchers to model cutting processes. Being a multi-variable, dynamic, non-linear estimator, it solves problems by self-learning and self organization. The intelligence of an ANN emerges from the collective behaviour of so called ‘artificial neuron’, and derives the process knowledge from input and output data set. Several applications of ANN-based input-output relationship modelling for metal cutting processes are reported in the literature.

There are certain assumptions, constraints, and limitations inherent in these approaches, which may be worth mentioning, ANN techniques are attempted only when regression techniques fail to provide an adequate model. Some of the drawbacks of ANN techniques are :

(i) Model parameters may be un-interpretable for non-linear relationship.
(ii) It is dependent on voluminous data set, as sparse data relative to number of input and output variables may result in over fitting or terminate training before network error reaches optimal or near-optimal point.
(iii) Identification of influential observations, outliers, and significance of various predictors may not be possible by this technique.

There is always an uncertainty in finite convergence of algorithms used in ANN-based modelling technique, and generally convergence criteria are set based on prior experience gained from earlier applications. No universal rules exist regarding choice of a particular ANN technique for any typical metal cutting process problem.

3.1.4 Fuzzy set theory-based modelling

The fuzzy set also play an important role in input-output and in –process parameter relationship modelling. The theory on fuzzy set admits the existence of a type of uncertainty (or indecision) in process decision variables due to vagueness (referred to as 'fuzzy uncertainty') rather than due to randomness alone, and many decisions in process control are in fuzzy environment. Fuzzy set theory-based modelling technique is generally preferred when subjective knowledge or opinion(s) of process expert(s) play a key role in defining objective function and decision variables. Several applications of fuzzy set theory-based modelling of metal cutting processes are reported in the literature. Fuzzy set theory-based techniques suffer from a few shortcomings, such as rules developed based on process expert(s) knowledge, and their prior experiences and opinion(s) are not easily amenable to dynamic changes of underlying cutting process. It also does not provide any means of utilising analytical models of metal cutting processes.

3.2 Determination of optimal or near-optimal cutting condition(s)

With time, complexity in metal cutting process dynamics has increased and as a consequence, problems related to determination of optimal or near-optimal cutting condition(s) are faced with discrete and continuous parameter spaces with multi-model, differentiable as well as non-differentiable objective function or response(s). Search for optimal or acceptable near-optimal solution(s) by a suitable optimization technique based on input-output and in process parameter relationship or objective function formulated from model(s) with or without constraint(s), is a critical and difficult task for researchers and practitioners. A large number of techniques has been developed by researchers to solve these types of parameter optimization problems, and may be classified as conventional and non-conventional optimization techniques.

Conventional techniques attempt to provide a local optimal solution, non-conventional techniques based on extrinsic model or objective function developed, is only an approximation, and attempt to provide near-optimal cutting condition(s). Conventional techniques may be broadly classified into two categories. In the first category, experimental techniques that include statistical design of experiment, such as Taguchi method, and response surface design methodology (RSM) are referred to. In the second category, iterative mathematical search techniques, such as linear programming (LP), non-linear programming (NLP), and dynamic programming (DP) algorithms are included. Non-conventional meta-heuristic search-based techniques, which are based on genetic algorithm (GA), tabu search

(TS), and simulated annealing (SA). A critical appraisal of each of these techniques is given below.

3.3 Conventional optimization techniques

3.3.1 Taguchi method

Taguchi's contribution to qualify engineering has been far ranging. The concept of Taguchi's robust design is based on designing a product or process in such a way so as to make its performance less sensitive to variation due to uncontrolled or noise variables which are not economical to control. Taguchi method is usually appreciated for its distribution-free and orthogonal array design and it provides a considerable reduction of time and resource needed to determine important factors affecting operations with simultaneous improvement of quality and cost of manufacturing.

The Taguchi method over the years has been criticized by a number of researchers.

The following criticism are worth mentioning :

(i) The orthogonal array design suggested by Taguchi are limited in numbers, and may fail to adequately deal with many important interaction effects within the domain of the design proposed.

(ii) Taguchi proposes a short term, one-time improvement technique to reduce the number and cost of experimentations, which may eventually lead to sub-optimal solutions.

(iii) Taguchi's method refers to optimization without intrinsic empirical or mechanistic modelling during experimentation. This type of technique closes the possibility for greater in-depth knowledge of the process.

(iv) Alternative methods, claimed to be efficient for simultaneous optimization of multiple responses [such as data transformation and using dual-response surface technique] are available in the literature where basic goals of Taguchi method are achieved by simultaneous optimization of mean and standard deviation without the use of controversial S/N ratio.

(v) Universal method for multiple objective optimization problem is purely based on judgemental and subjective process knowledge.

3.3.2 Response surface design methodology (RSM)

The RSM is a dynamic and foremost important tool of design of experiment (DOE) wherein the relationship between response(s) of a process with its input decision variables is mapped to achieve the objective of maximization or minimization of the response properties. It is a set of statistical DOE techniques, intrinsic regression modelling, and optimization methods useful for any field of engineering. The first necessary step in RSM is to map response(s), Y as a function of independent decision variables (X1, Xn). If the model is adequate, hill climbing or descending technique for maximization or minimization problem is attempted and the same mapping technique is repeated. In the vicinity of optimal point, a second order regression model is generally found adequate. Maximum, minimum, or a saddle point is identified by stationary point approach and canonical analysis of the second order model developed, and 'ridge analysis' is attempted if it is a saddle point. Many researchers and practitioners use RSM in metal cutting process parameters optimization problems.

Although RSM works well in many different process optimization problems, there are few limitations inherent in this approach. Researchers emphasize on the application of mathematical iterative search algorithm, and heuristic or meta-heuristic search techniques, in preference to RSM, specific to highly nonlinear, multi-modal, objective function. They also highlight that these types of problems are extremely difficult to solve by RSM, and problem complexity increases further by the presence of multiple objectives. RSM works well when the number of responses is maximum three, it generally gives indefinite saddle function in quadratic response surface model with more than three responses. RSM techniques are based on series of experimentation, and may not be feasible or cost effective for manufacturer in many manufacturing situations. Moreover, objective or response function needs to be continuously differentiable for determination of optimal cutting condition, which may not be the case in many complex physical process.

3.3.3 Iterative mathematical search technique

Linear, non-linear, and dynamic programming techniques (Hillier & Liebermann, 1999) may be described in terms of their structures, computational procedures, and important decision problems formulated as minimization or maximization of a mathematical function of several variables having a number of constraints. In this approaches, there is no need to construct an actual physical model of the metal cutting process under consideration, which is mostly replaced by an empirical model describing the actual process.

As metal cutting process problem are mostly complex and non-linear in nature, LP technique does not provide an adequate answer, or may not be appropriate for many such problems.

Multi- modal functions and consideration of multiple nonlinear response functions justify the use of NLP solution techniques in this case. In any NLP cutting process optimization problem formulation, either the objective function(s) or at least one of the constraints is non-linear in nature, and a particular combination of cutting conditions is optimal, if and only if, all of Kuhn-Tucker conditions with other convexity assumptions on response function are satisfied.

Determination of optimal cutting process parameter settings is a key factor to achieve machine or process efficiency and a number of mathematical programming techniques has been proposed and effectively used to achieve this objective. Many researchers used the application of dynamic programming (DP) approach for attaining optimal machine parameter setting when tool changes occur only between passes in cutting operation.

Although LP, NLP, and DP work well in many situations, a few shortcomings of these techniques may be worth mentioning :

(i) Mathematical iterative search techniques focus on certain specific aspects of machining (such as cutting force, temperature, and tool wear) and may not handle the overall cutting process, complexities due to large number of interdependent variables and their stochastic relationships.

(ii) The multi-modal, multi-objective response function need to be continuously differentiable to attain optimal set point by NLP and DP techniques, which may be a restrictive assumption in real life problems. Moreover, heuristic and meta-heuristic techniques may provide an alternative near-optimal cutting condition(s), which are cost effective and reasonably acceptable for implementation by manufacturers rather than searching for exact optimal cutting condition(s) based onLP, NLP or DP techniques.

3.4 Non-conventional techniques

3.4.1 Heuristic search technique

Heuristic, generally providing simple means of indicating which among several alternative solutions seems to be the most effective one in order to achieve some goal, consist of a rule or a set of rules seeking acceptable solution(s) at a reasonable computational cost. Heuristic-based search techniques may be very useful for cases where conventional optimization techniques are not suitable, such as problems with high-dimensional search space with many local optima. Researchers and practitioners prefer alternative cost effective near-optimal (or approximate) solution(s) than exact optimal, as it may be extremely difficult to find exact optimal point in higher dimension, and multimodal search space. In this context, the so-called 'evolutionary algorithm' has been extensively used in different types of combinatorial process optimization problems for near-optimal solution(s).

3.4.2 Metaheuristic search technique

Although heuristic search may offer near-optimal solution(s), they are mainly problem-specific. Researchers suggest several alternatives to problem specific heuristics, also called generalized iterative master strategy or 'metaheuristic', which guide and modify other heuristics to produce solutions that are normally generated in a quest for local optimality. As has been reported in the literature, three types of metaheuristic-based search algorithms viz. genetic algorithm (GA), simulated annealing (SA), and tabu search (TS) are applied in the domain of cutting process parameter optimization. These techniques are derivative-free, and are not based on functional form of its search direction. Each of these techniques is explained below along with their application and limitation.

3.5.1 Genetic algorithm (GA)

The working of GA (Holland, 1975; Godberg, 2002; Deb, 2002) generally preferred for large and complex cutting process parameter optimization problems, is based on three basic operators, viz. reproduction, crossover, and mutation, in order to offer a population of solutions. The algorithm creates new population from an initial random population (obtained from different feasible combination of process decision variables) by reproduction, crossover, and mutation in an iterative process. The selection, crossover and mutation on initial population create a new generation, which is evaluated with pre-defined termination criteria. The procedure continues by considering current population as initial population till the termination criteria are reached. GA is very appealing for single and multi-objective optimization problems and some of its advantages are as follows :

(i) As it is not based on gradient-based information, it does not require the continuity or convexity of the design space.
(ii) It can explore large search space and its search direction or transition rule is probabilistic, not deterministic, in nature, and hence, the chance of avoiding local optimality is more.
(iii) It works with a population of solution points rather than a single solution point as in conventional techniques, and provides multiple near-optimal solutions.
(iv) It has the ability to solve convex and multi-modal function, multiple objectives and non-linear response function problems, and it may be applied to both discrete and continuous objective functions.

Several application of GA based technique in metal cutting process parameter optimization problems have been reported in the literature.

Although GA-based optimization technique works well in many situations, a few shortcomings of this technique may be worth mentioning :

(i) Convergence of the GA is not always assured.
(ii) No universal rule exists for appropriate choice of algorithm parameters, such as population size, number of generations to be evaluated, crossover probability, mutation probability, and string length.
(iii) GA may require a significant execution time to attain near-optimal solutions, and convergence speed of the algorithm may be slow. Moreover the repeatability of results obtained by GA with same initial decision variable setting conditions is not guaranteed.

3.5.2 Tabu search (TS)

A local search algorithm-based technique, called 'Tabu Search' (TS), developed by Glover derives its attractiveness due to its greater flexibility and ease of implementation in combinatorial optimization problems. TS algorithm starts with initial feasible solution point from random feasible combination of process decision variables, and moves stepwise towards an improved solution point. A sample of decision vector is generated, and the best vector within the sample is determined based on a heuristic approach. A move is made from current decision vector to a best decision vector not in tabu list, which provides improved objective function value in a single step by simple modifications of current decision vector.

A tabu list contains a certain number of last decision vectors visited. The best decision vector replaces the oldest vector in the tabu list, and the survival vectors in the list are given a tabu status, which reduces risk of cycling of same decision vector (i.e., modification in current decision vector, which would bring back previously visited vector). In the subsequent iteration, uses of tabu active vectors in the neighbourhood of current decision vector space. Tabu active status of a decision vector is overridden only on certain aspiration level criteria, such as acceptance of the modification on current vector that improves objective function value.

TS- based technique has been successfully applied to provide near-optimal and acceptable solution in many combinatorial process optimization problems.

Although TS may be considered to be a good alternative to GA or SA to solve complex combinatorial optimization problems within a reasonable amount of computational time, there are certain constraints and assumptions inherent in this technique. The convergence of TS algorithm for multi-modal objective function in a finite number of steps is not guaranteed like other metaheuristic. The choice of tabu list size always influences end solution of the problem, as a list of small size may result in wasteful revisit of same cutting condition vectors, and a list of long size may lead to significantly longer computational time to verify tabu status of a candidate cutting condition vector. Selection of aspiration level criteria also plays a key role in randomization of search to unexplored feasible regions.

3.5.3 Simulated annealing

SA technique based on the concept of modelling and simulation of a thermodynamic system may be used to solve many combinatorial process optimization problems. This technique starts with selection of an initial random process decision vector, and moves to new neighbourhood decision vector that improves objective function value. SA technique may accept inferior decision vector based on certain probabilistic measure to avoid local optimal in a multimodal response function. The probability that there is a move to an inferior decision vector (or the decision vector which provides degraded objective function value) decreases as the value of a 'temperature parameter' defined in the algorithm, decreases, which is analogous with slow cooling in an annealing process to attain perfect crystalline state. SA procedure of stochastic search algorithm gradually changes to a traditional gradient descent search method as the temperature parameter value drops.

A number of different versions and applications of SA algorithm-based technique in metal cutting process problems is reported in the literature.

SA technique may be used to solve continuous or discrete state space cutting process optimization problems. The stochastic nature of the algorithm and guided probabilistic moves are two of its key aspects in case of a multi-modal response function. Although SA is appreciated for its simplicity and effectiveness, the convergence of the algorithm may be strongly affected by the parameters of cooling schedule, and no universally acceptable levels of control parameters in cooling schedule exist for different types of cutting process parameter optimization problem. Moreover, the repeatability of the near-optimal solution obtained by SA with same initial cutting conditions is not guaranteed.

Although, each modelling or optimization technique, with its variants, as mentioned have its versatility, no single guideline or clear-cut criterion exists to chose the best one and judge the performance of different alternative techniques in any metal cutting process optimization problem.

CHAPTER 4

Introduction to Taguchi Method

4.1 A Historical Perspective

When Japan began its reconstruction efforts after World War II. It faced acute shortage of good quality raw material, high quality manufacturing equipments and skilled engineers. The challenge was to produce high quality products and continue to improve the quality under those circumstances. The task of developing a methodology to meet the challenge was assigned to Dr. Genichi Taguchi, who at that time was a manager in charge of developing certain telecommunications products at Electrical Communications Laboratories (ECL) of Nippon Telephone and Telegraph Company (NTT). Through his research in the 1950s and early 1960s, Dr.Taguchi developed the foundations of Robust design and validated its basic philosophies by applying them in the development of many products. In recognitions of this contribution, Dr. Taguchi received Deming Award in 1962, which is one of the highest recognitions in the field of quality.

4.2 Taguchi Method in Quality Engineering

The term quality engineering encompasses a broad range of engineering and operational activities whose aim is to ensure that a product's quality characteristics are at their nominal or target values. It could be argued that the areas of quality engineering and TQM overlap to significant degree, since implementation of good quality engineering is strongly dependent on management support and direction. The field of quality engineering owes much to G.Taguchi, who has had an important influence on its development, especially in design area-both product design and process design.

Taguchi Methods

1. Off-line and On-line control
2. Robust Design
3. Loss function

Off-line and On-line quality control

Taguchi believes that the quality system must be distributed throughout the organization. The quality system is divided into two basic functions:

4.3 Off-line quality control

This function is concerned with issues, both product and process design. It is applicable prior to the production and shipment of the product. It consists of two stsges:

1. Product design
2. Process design

The ***product design*** stage is concerned with the development of new product or a new model of an existing product according to customer needs and economically feasible.

The ***process design*** concerned with specifying the processes and equipment, setting work standards, documenting procedures and developing clear and workable specifications for manufacturing. A three step approach is applicable to both of these design stages is outlined :

1. System design
2. Parameter design
3. Tolerance design

System design

In the product design stage, system design refers to the final product configuration and features, including starting materials, components and subassemblies. For example, in the design of new car, system design includes the size of car, its styling, engine size and power and other features that target it for a certain market segment. In process design, it means selecting the most appropriate manufacturing methods.

Parameter design

It concerned with determining optimal parameter setting for the product or process. In parameter design, the nominal values of product or process parameters are specified. Example of parameters in product design includes the dimensions of components in an assembly. In process design it may be speed or feed in machining operation. It is the parameter design stage that a robust design is achieved.

Tolerance design

The tolerance design phase attempts to achieve a balance setting wide tolerances to facilitate a manufacture and minimizing tolerances to optimize product performance.

4.4 On-line quality control

This is concerned with production operation and relations with customer after shipment. In production, Taguchi classifies three approaches to quality control:

1. **Process diagnosis and adjustment :** In this approach, the process is measured periodically and adjustments are made to move parameters of interest towards nominal values.

2. **Process prediction and correction:** This refers to the measurements of process parameters at periodic intervals so that trends can be projected. If projections indicate deviations from the target values, corrective process adjustments are made.
3. **Process measurement and action:** It involves inspection of all units to detect deficiencies that rework or scrapped. Since the approach occurs after the unit is alredy made, it is less desirable than the other two forms of control.

4.5 Robust Design

The objective of parameter design in Taguchi's off/on-line quality control is to set specifications on product and process parameters to create a design that resist failure or reduced performance in the face variation. Taguchi calls the variations noise factors. ***A noise factor*** is a source of variation that is impossible or difficult to control and that affects the functional characteristics of the product. Three types of noise factors can be distinguished :

1. **Unit-to-unit noise factors:** These are inherent random variations in the process and product caused by variability in raw materials, machinery, and human participation. They are associated with the production process that is in statistical control.
2. **Internal noise factor:** These sources of variation are internal to the product or process. They include: (1) time dependent factors, such as wear of mechanical components, spoilage of raw materials, and fatigue of metal parts and (2) operational errors, such as improper settings on the product or machine tools.
3. **External noise factor:** An external noise factor is a source of variation that is external to product or process, such as outside temperature, humidity, raw materials supply, and input voltage, internal and external factors constitute what we have previously called assignable variations. Taguchi distinguishes between internal and external noise factors because external noise factors are generally more difficult to control.

A Robust Design is one which the function and performance of the product or process are relatively insensitive to variation in any of these noise factors. In product design robustness means that product can maintain consistent performance with minimal disturbance due to variation in uncontrollable factors in its operating environment. In process design, robustness means that the process continue to produce good product with minimal effect from uncontrollable variations in the operating environment.

4.6 The Taguchi Loss Function

The Taguchi loss function is a useful concept. Taguchi defines quality as" the loss a product costs society from the time product released for shipment ". Loss includes costs to operate, failure to function, maintenance and repair costs, customer dissatisfaction, injuries caused by poor design, and similar costs. defective products that are detected, repaired, reworked, or scrapped before shipment are not considered part of this loss. Loss occurs when a product's functional characteristics differs from its nominal or target value. When the dimension of the component deviates from its nominal value, the component's function is adversely affected. No matter how small the deviation, there is some loss in function. The loss increases at an accelerating rate as the deviation grows, according to Taguchi.

If we let y = the quality characteristics of interest and

m = its normal value. (Target value for y)

The loss function will be a U-shaped curved as shown in figure. Taguchi uses a quadratic equation to describe this curve.

$$L(y) = k(y-m)^2$$

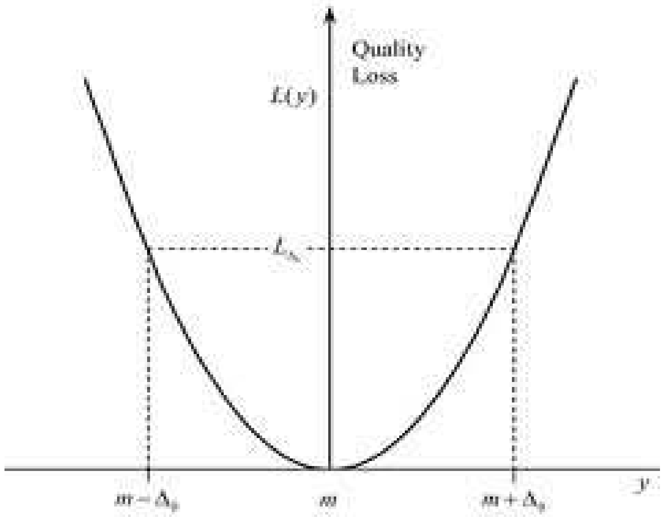


Fig. No. 1 Quality Loss Function

where, L(y) = loss function

k = Constant of proportionality (quality loss coefficient)

The loss function increases slowly when we near *m* ; but we go farther from, the loss increases more rapidly.

It is important to determine the constant *k* so that quality loss equation can beat approximate the actual loss within region of interest. A convenient way to determine *k* is to determine first the functional limits for the value of y.

Let $m \pm \Delta_\circ$ be the functional limits. Suppose the loss at $y = \pm \Delta_\circ$ is $A_\circ$.

Then, $k = A_\circ / \Delta_\circ^2$

$A_\circ$ is the cost of repair or replacement of the product.

CHAPTER 5

Taguchi Methodology for single objective optimization

Every experiment has to plan and conduct experiments to obtain enough and relevant data so that he 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 instruments 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-Experiment

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 (material 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 effect 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 co-ordinating various institutions, committees, people, equipment, materials etc.).

(3)Taguchi Method

Dr. Taguchi of Nippon Telephones and Telegraph Company, Japan has developed a method based on “Orthogonal Array” experiments which gives much reduced “variance” for the experiment with “optimum settings” of control parameters to obtain BEST results is achieved in the Taguchi Method. “Orthogonal Arrays” (OA) provide a set of well balanced (minimum) experiments and Dr. Taguchi’s Signal-to-Noise ratios (S/N), which are log functions of desired output, serve as objective functions for optimization, help in data analysis and prediction of optimum results.

5.1 Orthogonal Array (OA)

The classical experiment design methods are to complex, time consuming and not easy to use. A large number of experiments have to be carried out when number of process parameter are more. To solve this problem Taguchi method uses a special design of orthogonal array to study the entire parameter space with minimum number of experiments. In present study three parameters namely cutting speed, feed rate, and depth of cut are identified and the range of parameter for the present investigation determined from ASME’s machining hand book. Each parameter is investigated at three levels to study the non linearity effect of process parameters. In the Taguchi method, the main parameters which influence on process results are located in different rows of a designed orthogonal array (OA). Selection of the OA is based on the calculation of the total degree of freedom of all the factors, and the number of rows of an OA selected should be greater than or equal to the total degree of freedom of a process. Orthogonal arrays are a special matrix in which entries are at various levels of input parameters, and each row represents individual treatment condition. In orthogonal array, for any pair of column all combinations for each factor level occur, and they occur an equal number of times (this is called the balancing property). With such an arrangement, one can conduct completely randomized experiments. To select an appropriate orthogonal array for the experiments, the total degrees of freedom need to be computed. The degrees of freedom are defined as the number of comparisons between design parameters that need to be made to determine which level is better and specifically how much better it is. For example, a three level-level design parameter counts for two degree of freedom. The degrees of freedom associated with the interaction between the two designs parameters are given by the product of the degrees of freedom for the two design parameters. In the present study, the interaction between the cutting parameter is neglected. Therefore, there are six degrees of freedom owing to there being three cutting parameters in the turning operation. Once the required degrees of freedom are known, the next step is to select an appropriate orthogonal array to fit the specific task. Basically, the degrees of freedom for the orthogonal array should be greater than or at least equal to those for the design parameters.

Mathematically, the dof can be computed as :

DOF = [(number of levels – 1) for each control factor + (number of levels for A – 1) x (number of levels for B – 1) for each interaction + 1]

Where, A and B are the interacting control factors.

Three levels were specified for each of the factors as indicated in Table 1 The orthogonal array chosen was L_{27}, which has 27 rows corresponding to the number of parameter combinations (26 degrees of freedom), with 13 columns at three levels. The first column was assigned to the cutting speed, the second column to the feed rate, the fifth column to the axial depth of cut, and the remaining columns to the interactions.

Table No. 1 Experimental layout using an L27 orthogonal array

Test no.	**Column no.**												
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2	2	2	2	2	2
3	1	1	1	1	3	3	3	3	3	3	3	3	3
4	1	2	2	2	1	1	1	2	2	2	3	3	3
5	1	2	2	2	2	2	2	3	3	3	1	1	1
6	1	2	2	2	3	3	3	1	1	1	2	2	2
7	1	3	3	3	1	1	1	3	3	3	2	2	2
8	1	3	3	3	2	2	2	1	1	1	3	3	3
9	1	3	3	3	3	3	3	2	2	2	1	1	1
10	2	1	2	3	1	2	3	1	2	3	1	2	3
11	2	1	2	3	2	3	1	2	3	1	2	3	1
12	2	1	2	3	3	1	2	3	1	2	3	1	2
13	2	2	3	1	1	2	3	2	3	1	3	1	2
14	2	2	3	1	2	3	1	3	1	2	1	2	3
15	2	2	3	1	3	1	2	1	2	3	2	3	1
16	2	3	1	2	1	2	3	3	1	2	2	3	1
17	2	3	1	2	2	3	1	1	2	3	3	1	2
18	2	3	1	2	3	1	2	2	3	1	1	2	3
19	3	1	3	2	1	3	2	1	3	2	1	3	2
20	3	1	3	2	2	1	3	2	1	3	2	1	3
21	3	1	3	2	3	2	1	3	2	1	3	2	1
22	3	2	1	3	1	3	2	2	1	3	3	2	1
23	3	2	1	3	2	1	3	3	2	1	1	3	2
24	3	2	1	3	3	2	1	1	3	2	2	1	3
25	3	3	2	1	1	3	2	3	2	1	2	1	3
26	3	3	2	1	2	1	3	1	3	2	3	2	1
27	3	3	2	1	3	2	1	2	1	3	1	3	2

Taguchi Method treats optimization problems in two categories:

5.2 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 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.*

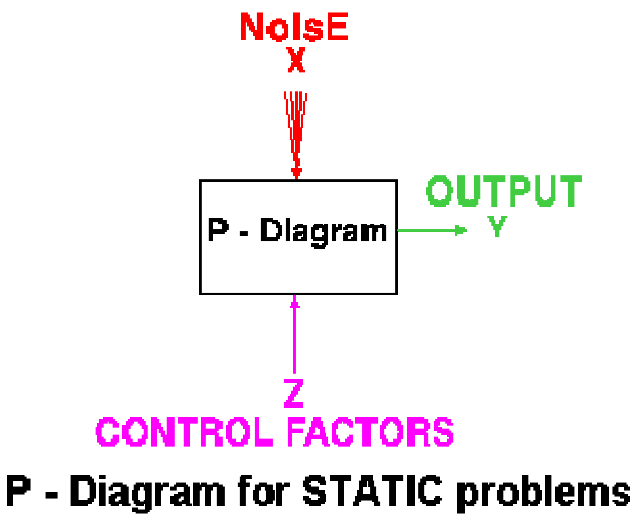


Fig. No. 2

5.3 Dynamic problem

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.

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.

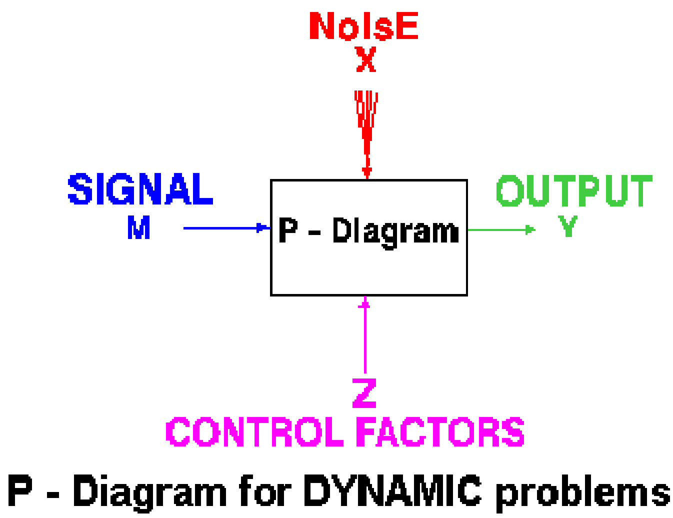


Fig No. 3

Static Problem *(Batch process optimization)*

There are 3 Signal-to-noise ratios of common interest for optimization of Static Problems :

(I)Smaller-The-Better

n = -10 Log_{10} [mean of square of measured data]

This is usually the chosen S/N ratio for all undesirable characteristic 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 T_c 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,

n = -10 Log_{10} [mean of sum of squares of (measured – ideal)]

(II) Larger-The-Better

n = -10 log_{10} [mean of sum squares of reciprocal of measured data]

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

(III)Nominal-The-Best

n = -10 log_{10} (Square of means/variance)

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 fittings have dimensions which are nominal-the-best type.
2) Ratios of chemicals or mixtures are nominally the best type.
   Ratio of sulphur, KNO_3 and carbon in gun powder
3) Thickness should be uniform in deposition / growth / plating / etching..

Dynamic Problem *(Technology Development)*

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 “input” “output” is desirable.

For example : Accelerator paddle in cars,

Volume control in audio amplifiers,

Document copier (with magnification or reduction)

Various types of modelling etc.

Taguchi method is a scientifically disciplined mechanism for evaluating and implementing improvements in products, processes, materials, equipment, and facilities. These improvements are aimed at improving the desired characteristics and simultaneously reducing the number of defects by studying the key variables controlling the process and optimizing the procedures or design to yield the best results.

The method is applicable over a wide range of engineering fields that include processes that manufacture raw materials, sub systems, products for professional and consumer markets. In fact, the method can be applied to any engineering fabrication, computer-aided-design, banking and services sectors etc. Taguchi method is useful for ‘tuning’ a given process for ‘best’ results.

Taguchi proposed a standard procedure for applying his method for optimizing any process

5.4 Steps in Taguchi Design procedure

1. Planning experiment

(a) Determine the control factors, noise factors and quality response of the product or process.

(b) Determine the levels of each factor.

(c) Select an appropriate orthogonal array (OA) table.

The selection of the most appropriate OA depends on the number of factors and interactions, and the number of levels for the factors.

(d) Transform the data from the experiments into proper S/N ratio.

2. Implementing experiment

3. Analyzing and examining result

(a) Execute an ANNOVA analysis to determine the significant parameters.

(b) Conduct a main effect plot analysis to determine the optimal level of the control factors.

(c) Execute a factor contribution rate analysis.

(d) Confirm experiment and plan future application.

5.5 Analysis of the S/N ratio

In general, the signal-to-noise (S/N) ratio (ή, dB) represents quality characteristics for the observed data in the TM, S/N ratio is a quality index, and in quality engineering, this concept was adapted by Dr. Genichi Taguchi to evaluate the quality of manufacturing processes.

Taguchi suggests the transformation of the repetition output data in a trail into a consolidated single value called the S/N ratio. Here, the 'signal' represents the desirable value and the 'noise' represents the undesirable value and signal to noise ratio expresses the scatter around the desired value. The larger the ratio, the smaller will be the scatter. Depending upon the objective function of the quality characteristic there can be various types of S/N ratios.

The S/N ratio (ή) is mathematically represented as :

$$\acute{\eta} = -10 \log_{10} (MSD)$$

where MSD = mean square deviation from the desired value and commonly known as quality loss function. The MSD is different type of problems. Here, smaller surface finish and higher MRR is desired i.e., the surface finish is smaller-the=better (SB) type and MRR is larger-the-better (LB) type. The quality loss function for these two types is computed in the following :

For SB-type,

$$\text{MSD} = \left[\frac{1}{n} \sum_{i=1}^{n} y_i^2 \right]$$

For LB-type,

$$\text{MSD} = \left[\frac{1}{n} \sum_{i=1}^{n} \frac{1}{y_i^2} \right]$$

Where y_i are the observed data (or quality characteristics) at the i^{th} trial, and n is the number of trials at the same level. The aim is always kept to maximise the S/N ratio whatever may be the nature of quality characteristics.

The average value of all S/N ratios when a parameter is at same distinct level is used to describe the effect of a parameter or factor on quality characteristics at that level. A parameter level corresponding to the maximum average S/N ratio is called the optimum level for that parameter. The predicted value of S/N ratio ($\acute{\eta}_{0\,pt}$) at optimum levels is calculated by using the following formula :

$$\eta_{opt} = \eta_m + \sum_{i=1}^{k}(\eta_i^- - \eta_m)$$

Where η_m is the total mean S/N ratio of all experimental runs,

k is the no. of control factors, and

η_i^- is the mean S/N ratio at optimal level.

5.6 Analysis of Variance

The purpose of the analysis of variance (ANNOVA) is to investigate which design parameters significantly affect the quality characteristic. This is to accomplished by separating the total variability of the S/N ratios, which is measured by the sum of the squared deviations from the total mean S/N ratio, into contributions by each of the design parameters and the error. First, the total sum of squared deviations SS_T from the total mean ratio $\acute{\eta}_m$ can be calculated as :

$$SS_T = \sum_{I=1}^{n}(\eta_i - \eta_m)^2$$

Where n is the number of experiments in the orthogonal array

$\acute{\eta}_i$ is the mean S/N ratio for the i^{th} experiment.

The total sum of spared deviations SS_T is decomposed into two sources : the sum of squared deviations SS_d due to each design parameter and the sum of squared error SS_e.

The sum of squares from the tested parameter SS_d can be calculated as :

$$SS_d = \sum_{j=1}^{t} \frac{(s\eta_i)^2}{t} - \frac{1}{n} [\sum_{i=1}^{n} \eta_i]^2$$

Where d represents one of the tested parameters,

J is the level number of this parameter d,

T is the repetition of each level of the parameter d, and

$s\eta_i$ is the sum of the response S/N ratio involving this parameter d and level j

The sum of square from error parameters, SS_e is

$$SS_e = SS_T - SS_A - SS_B - SS_C$$

The total degree of freedom is D_T = n-1

The degree of freedom of the tested parameter, D_d = t-1. The variance of the parameter tested is $V_d = SS_d/D_d$. Statistically, there is a tool called an F test named after Fisher to see which design parameters have a significant effect on the quality characteristic. The F-value for each design parameter is simply the ratio of the mean deviations to the mean squared error $(F_{d=} V_d/V_e)$. Usually, when F > 4, it means that the change of the design parameter has a significant effect on the quality characteristic.

CHAPTER 6

Taguchi's methodology for Multi-objective optimization

6.1 Taguchi's Parameter Design (PD) with Multiple Quality Characteristics - An Overview

Much of the discussion about the methods of Taguchi's PD has been focused on the optimization of a single quality characteristic. In the optimization process of multiple quality characteristics, the objective is to determine the best factor settings which will simultaneously optimize all the quality characteristics of interest to the experimenter. Byrne and Taguchi illustrate an example of the optimization of two quality characteristics: the force required to insert the tube into the connector : and the pull-off force. It was required that the pull-off force be as high as possible, and the insertion force be as low as possible for the case of manufacturing. An informal argument was used to arrive at a compromise solution. Under such circumstances, we often need a powerful methodology to resolve the compromise. It is important to note that engineering judgement, together with past experience, will often bring some uncertainty in the decision making process. The statistical validity and robustness of the results cannot be assured using the above procedure.

Derringer and Suich made use of modified desirability functions which measure the designer's requirements over a range of the values of the selected quality characteristics. They have used the approach for the development of a tyre tread compound, which involves four responses (abrasion index, modulus, elongation at break, and hardness) and three independent variables or factors. This method increases the complexity of the computational process and it therefore cannot be easily understood by engineers with limited statistical skills.

6.2 Proposed Methodology for Optimization of Multiple Characteristic in Taguchi's PD Experiment :

The following issues must be considered when optimizing multiple quality characteristics in Taguchi's PD experiments. The units of each quality characteristic will possibly be different and therefore the loss associated with each characteristic cannot be added directly. Different quality characteristics have different relative weights and therefore a certain relative weight may be assigned to each characteristic prior to optimization. If the experiment involves target-the-best quality characteristics (e.g. length, thickness, diameter, time, force, pressure, and viscosity), the adjustment factor(s) will then be used for tuning the mean performance onto the target value. Having considered the above issues, the following steps can be taken into account. It is important to note that these steps will serve only as a guide to engineers with limited skills in multiple response process optimization using Taguchi's PD experiments.

Step 1) Identification of the Factors for the experiment

The selection of factors or process variables is crucial to the success of any optimization problem. In a Taguchi's PD experiment, the factors can be classified into control, noise, and signal factors. Some of the possible ways to identify the factors include the use of brainstorming and historical data. A typical brainstorming session includes people from manufacturing, design, quality, and shop-floor. It is also good practice to use brainstorming in conjunction with cause-and-effect analysis. The cause-and-effect analysis will provide a better picture of the problem and the possible causes which influence the problem. Having identified the factors for the experiments, it is important to define the level of each factor.

Step 2) Selection of Quality Characteristics or Responses for the Experiment

It is important that there must be a correlation between the quality characteristic(s) chosen for a certain experiment and the factors selected for experimentation. The selection of appropriate quality characteristic(s) requires a sound engineering knowledge of the process under investigation. To select a good response, it is advisable to start with the engineering or economic goal. Having determined the goal, identify the basic mechanism and physical laws affecting it, then chose the appropriate quality characteristic to increase the understanding of these mechanisms and laws. Quality characteristics for Taguchi's PD experiments can be divided into two main categories :

1. Static quality characteristics.
2. Dynamic quality characteristics.

Static quality characteristics are further classified into smaller-the-better (STB), large-the-better (LTB), nominal-the-best (NTB) and classified attributes (CA). A process is said to exhibit dynamic quality characteristic when the state of a particular factor has a direct impact on the quality characteristic. Such a factor is called a tuning or adjustment factor.

The advantage of using such characteristics is that the experimenters may gain a better understanding for many processes has proved to be a complex procedure.

Step 3) Computation of Normalised Quality Loss for each Quality Characteristic

Quality loss is the associated with a product owing to the deviation in the functional performance of the product from its target. In this paper, only three static quality characteristics (STB, LTB, and NTB) are considered as these are the most commonly used in industry. The Eq. for the quality loss functions of these quality characteristics is available in most Taguchi textbooks. Let L_{ij} be the quality loss for the j^{th} quality characteristic has different units of measurement, it is important to normalise the quality loss. The normalised quality loss can be computed using :

$$L'_{ij} = L_{ij} \;/\; L_{I^*}$$

Where, L'_{ij} = normalised quality loss for j^{th} quality characteristic at the i^{th} trial condition

L_{I^*} = maximum quality loss for the i^{th} quality characteristic among all the experimental runs.

The L'_{ij} varies from a minimum of zero to a maximum of 1.

Step 4) Computation of Total Normalised Quality Loss

For computing the total normalised quality loss (L_j) corresponding to each trial condition, we must assign a weighting factor for each quality characteristic considered in the optimization process. If w_i represents the weighting factor for the j^{th} quality characteristic, p is the number of quality characteristics and L'_{ij} is the loss function associated with the j^{th} quality characteristic at the i^{th} trial condition, then L_j can be computed using :

$$L_j = \sum_{i=1}^{p} w_i L'_{ij}$$

Step 5) Computation of multiple Signal-to-noise ratio (MSNR) (η_j^e)

After the total normalised quality loss (L_j) corresponding to each trial condition has been calculated, the next step is to compute the multiple signal-to-noise ratio ($\boldsymbol{\eta_j^e}$) at each design point. This is given by :

$$\eta_j^e = -10 \log_{10} (L_j)$$

Step 6) Determination of Significant Factor/Interaction effects and optimal setting

In Taguchi's PD experiment with multiple quality characteristics, the optimal condition for processes with STB and LTB quality characteristics is obtained by selecting the factor levels with the highest multiple signal-to-noise ratio (η). However, for NTB quality characteristics, we must identify the factor(s) which influences only the mean quality characteristics but has no effect on the η (also called adjustment factor). In other words, for NTB quality characteristics, a multiple signal-to-noise ratio analysis may have to be performed first, followed by an analysis of the mean quality characteristic. The idea is to reduce variability in the functional performance of product and then bring the mean characteristic onto its target value. In order to identify the significant factors or interaction effects, the use of analysis of variance (ANNOVA) is recommended. ANNOVA is a powerful tool to subdivide the total variability into useful components of variability. In the case of a multiple quality characteristic optimization problem, we must separate the total variability of the multiple signal-to-noise ratios into the contributions made by each of the factors (or process parameters) and the error term.

Step 7) Perform the Confirmation Trial of Experiment

The purpose of a confirmation trial or experiment is to verify that the optimal factor setting actually yield an improvement. It is important to note that the multiple signal-to-noise ratio value for the confirmation experiment cannot be estimated by Eq. (3). It is advisable to compare signal-to-noise ratio values (predicted and observed) separately. If the predicted signal-to-noise ratio, we can conclude that the interactions among the factors were not important for the study. On the other hand, if the predicted and observed signal-to-noise ratios do not match, it is then an indication of the presence of interactions and therefore further experiments may be required to verify this.

Chapter 7

Experimental setup and cutting conditions

Experimentation was conducted on a lathe machine (HMT HD 22) fitted with high spindle which can rotate up to 2500 RPM. Wet condition is recommended for the experimental work. A carbide tool is used for the experimental work. The experiments were conducted on workpiece material (970En32) of British Standard (BS), of diameter 40 mm and length 600 mm. the schematic diagram of the experimental set-up is shown in fig. No. 4

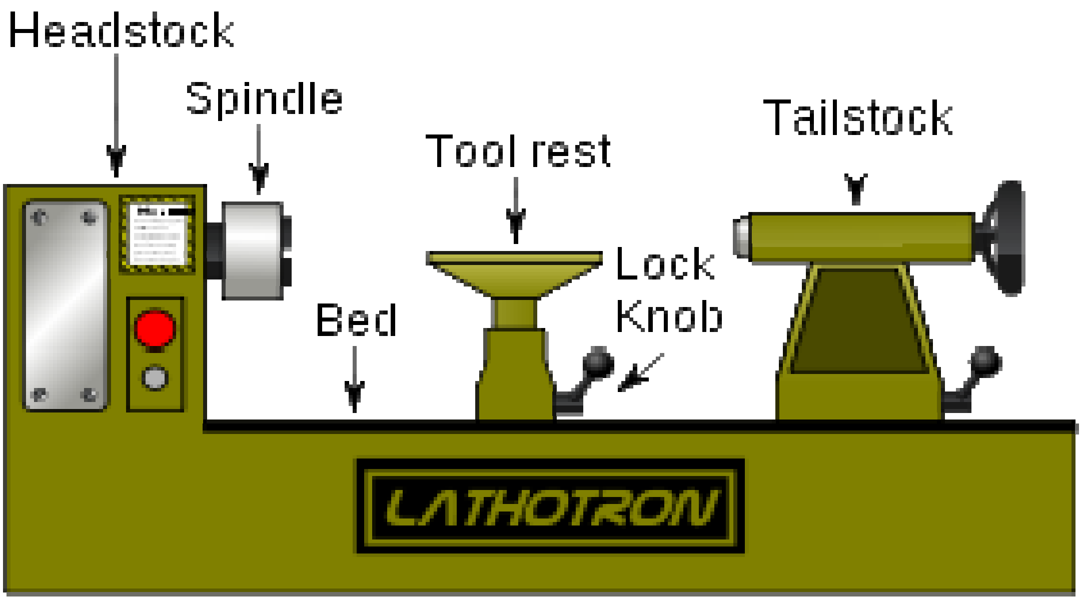


Fig. No. 4

7.1 Selection of Levels for Process Variables

The process parameters and their levels have been decided on the basis of experiments conducted previously, by different researchers and machining hand-book. The limitations imposed by the machine are also considered during the parameter and level-selection

The surface roughness was measured using surface roughness tester (Taylor Hobson, Precision, Softronic 3+). The chemical composition of work material in percentage by weight is shown in table.

Table 2 Chemical composition of work material

C	0.15 - 0.25
Mg	0.70
Mn	0.01 – 0.015
Si	0.05 – 0.35
S	0.06
P	0.06

The three controllable parameters and their levels are given in table 3

Table No. 3 Factors and level used in experiment

Process parameters	Parameter designation	Levels		
		1	2	3
Speed (RPM)	A	147	247	320
Feed (mm/min)	B	0.32	0.38	0.48
Depth pf cut (mm)	C	0.2	0.4	0.6

7.2 Tabulation work of single objective optimization for surface roughness

Table No.- 4 Measured parameter for different cutting condition

Speed (rpm)	Feed (mm/min)	Depth of cut (mm)	Surface roughness, (µm)	Material removed, (gm)
147	.32	.6	3.4	10.75
147	.32	.4	3.02	7.49
147	.32	.2	2.64	4.02
147	.38	.6	2.18	16.77
147	.38	.4	2.72	7.42
147	.38	.2	2.42	5.08
147	.48	.6	3.24	16.63
147	.48	.4	3.26	10.04
147	.48	.2	3.10	4.91
247	.32	.6	6.0	14.87
247	.32	.4	4.18	10.13
247	.32	.2	4.46	5.34
247	.38	.6	3.62	14.99
247	.38	.4	3.60	10.33
247	.38	.2	3.36	6.90
247	.48	.6	3.08	15.79
247	.48	.4	3.02	10.26
247	.48	.2	3.12	6.43
320	.32	.6	4.86	14.99
320	.32	.4	5.56	9.36
320	.32	.2	3.96	5.13
320	.38	.6	2.78	16.4
320	.38	.4	2.52	10.41
320	.38	.2	2.82	5.52
320	.48	.6	2.62	20.8
320	.48	.4	2.46	13.9
320	.48	.2	2.52	6.43

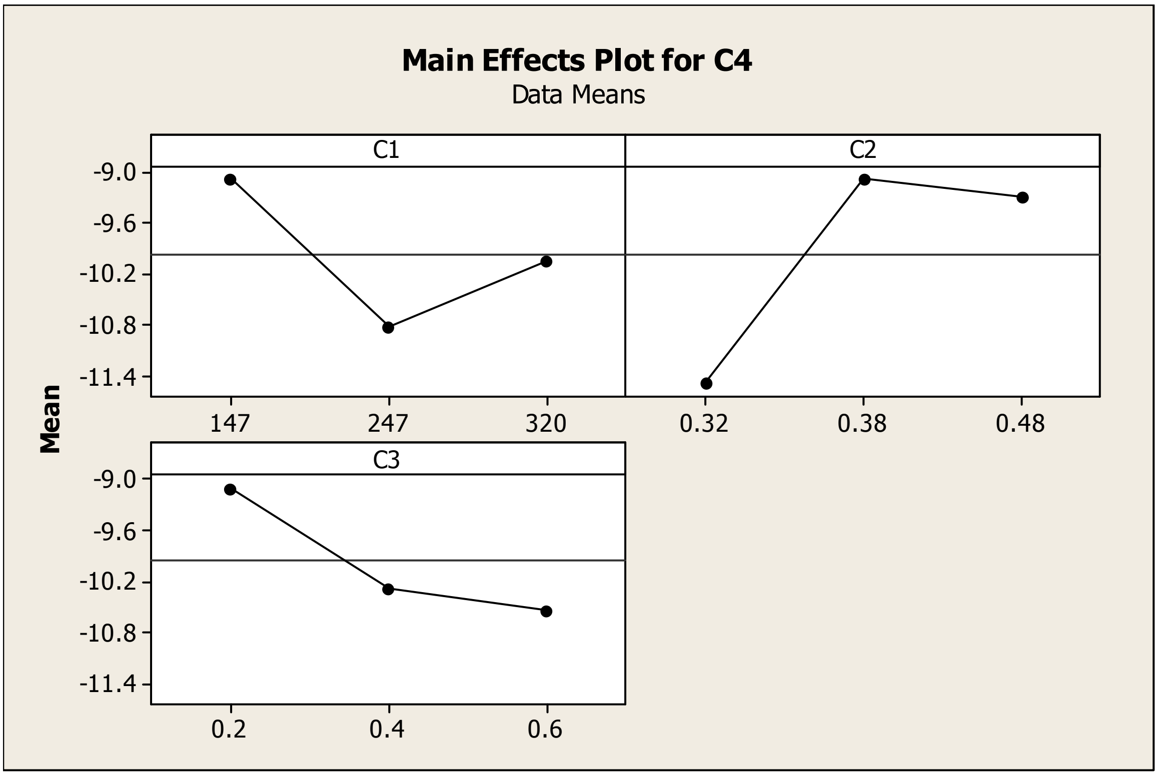
Table 5 shows the experimental results for the surface roughness and Material Removed (MR) and their corresponding S/N (signal to noise) ratio.

Parameters			Calculated S/N ratio (dB)	
Speed (rpm)	Feed (mm/min)	Depth of cut (mm)	Surface roughness, (µm)	Material removal,(gm)
147	.32	.6	-10.629	20.628
147	.32	.4	-9.600	17.489
147	.32	.2	-8.432	12.084
147	.38	.6	-6.769	20.644
147	.38	.4	-8.691	17.408
147	.38	.2	-7.676	14.117
147	.48	.6	-10.210	24.417
147	.48	.4	-10.264	20.034
147	.48	.2	-9.827	13.821
247	.32	.6	-15.563	23.446
247	.32	.4	-12.42	20.112
247	.32	.2	-6.493	14.550
247	.38	.6	-11.174	23.516
247	.38	.4	-11.126	20.282
247	.38	.2	-10.526	16.776
247	.48	.6	-9.771	23.967
247	.48	.4	-9.600	20.222
247	.48	.2	-9.883	16.164
320	.32	.6	-13.730	23.516
320	.32	.4	-14.901	19.425
320	.32	.2	-11.953	14.202
320	.38	.6	-8.880	24.296
320	.38	.4	-8.028	20.349
320	.38	.2	-9.004	14.838
320	.48	.6	-8.366	26.361
320	.48	.4	-7.818	22.860
320	.48	.2	-8.028	16.164

Table 6 Response table of average S/N for Surface Roughness

Symbol	Factors	Mean S/N ratios (dB)		
		Level 1	Level 2	Level 3
A	Cutting Speed (RPM)	-9.122*	-10.728	-10.078
B	Feed (mm/min)	-11.524	-9.097*	-9.307
C	Depth of cut (mm)	-9.091*	-10.272	-10.565

*optimum level



C1 – Speed (RPM)

C2 – Feed rate (mm/min)

C3 – Depth of cut (mm)

C4 – Surface roughness (µm)

From Table 6 and Factor response plot it clear that the optimum parameters are

Cutting speed (RPM) at level 1 = 147 RPM

Feed (mm/min) at level 2 = 0.4 mm/min

Depth of cut (mm) at level = 0.2 mm

The optimum S/N ratio at optimum parameter level can calculate as :

$$\eta_{opt} = \eta_m + \sum_{i=1}^{k}(\bar{\eta_i} - \eta_m)$$

η_{opt} = -9.976 + (-9.122+9.976) + (-9.097+9.976) + (-9.091+9.976)

= -7.358

Table No. 7 Analysis of Variance of Surface roughness

Symbol	DOF	Factors	Seq SS	Seq SS	Adj MS.	F	P	Contribution (%)
A	2	Speed	3.9771	3.9771	1.9885	4.71	0.21	25.03
B	2	Feed	10.4281	10.4281	5.2141	12.35	0.000	65.63
C	2	Depth of cut	0.6393	0.6393	0.3197	0.76	0.482	4.02
Error	20		8.4428	8.4428	0.4221			5.31
Total	26		23.4873		7.9444			100.0

It has been observed from the analysis of variance of surface roughness that the effect of feed rate is more significant compared to speed and depth of cut.

Table 8 Result of confirmation experiment for Surface roughness

Initial parameter setting		Optimal turning	
		Prediction	Experiment
Level	$A_1B_1C_1$	$A_1B_2C_1$	$A_1B_2C_1$
Surface roughness (µm)	2.64	2.332	2.420
S/N ratio (dB)	-8.432	-7.358	-7.676

Improvement in S/N ratio 0.756

7.3 Tabulation work of single objective optimization for Material Removal

Table 9 Response Table of Average S/N for Material Removal

Symbol	Factors	Mean S/N ratios (dB)		
		Level 1	Level 2	Level 3
A	Cutting Speed (RPM)	17.849	19.892	20.226*
B	Feed (mm/min)	18.383	19.136	20.445*
C	Depth of cut (mm)	14.746	19.797	23.421*

*optimum level

From Table 9 and factor response plot it is clear that the optimum parameter are

Cutting speed (RPM) at level 3 = 320 RPM

Feed rate (mm/min) at level 3 = 0.48 mm/min

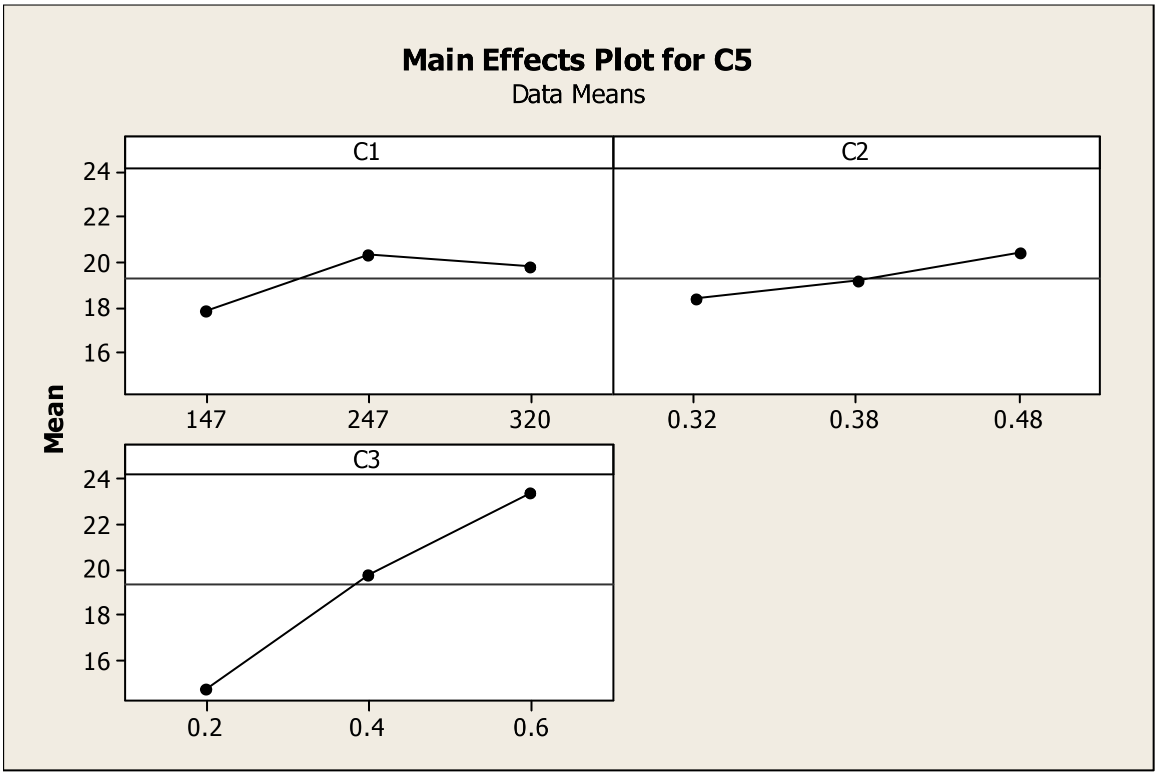
Depth of cut (mm) at level 3 = 0.6 mm

The optimum S/N ratio at optimum parameter level can calculated as :

$$\eta_{opt} = \eta_m + \sum_{i=1}^{k}(\eta_i^{-} - \eta_m)$$

η_m = 19.321 + (20.226-19.321) + (20.445-19.321) + (23.421-19.321)

= 25.45



C1 – Speed (RPM)

C2 – Feed rate (mm/min)

C3 – Depth of cut (mm)

C4 – Material removed (gm)

Table No. 10 Analysis of Variance of Material Removal

Symbol	DOF	Factors	Seq SS	Adj SS	Adj MS	F	P	Contribution (%)
A	2	Speed (RPM)	38.929	38.929	19.465	9.96	0.001	7.96
B	2	Feed (mm/min)	32.175	32.175	16.088	8.23	0.002	6.57
C	2	Depth of cut (mm)	414.015	414.015	207.008	105.91	0.000	84.66
Error	20		30.091	39.091	1.955			0.799
Total	26		524.211		244.516			100.0

It has been observed from the analysis of variance of Material Removal that the effect of velocity and feed rate is not significant in comparison to depth of cut

Table 11 Result of confirmation experiment for Material Removal

Initial parameter setting		Optimal turning cutting parameter	
		Prediction	Experiment
Level	$A_1B_1C_1$	$A_3B_3C_3$	$A_3B_3C_3$
Material removed (gm)	4.02	18.72	20.8
S/N ratio	12.084	25.45	26.361

Improvement in S/N ratio 14.277

7.4 Tabulation work of Multi-objective-optimization

Table 12 Quality loss values for Surface roughness and Material Removal

Quality Loss Values (dB)		
S.No.	Surface roughness	Material Removal
1	11.5600	0.0086
2	9.1204	0.0178
3	6.9696	0.0618
4	4.7524	0.0086
5	7.3984	0.0181
6	5.8564	0.0387
7	10.4976	0.0036
8	10.6276	0.0099
9	9.6100	0.0414
10	36.0000	0.0045
11	17.4724	0.0097
12	19.8916	0.0350
13	13.1044	0.0044
14	12.9600	0.0093
15	11.2896	0.0210
16	9.4864	0.0040
17	9.1204	0.0094
18	9.7344	0.0241
19	23.6196	0.0044
20	30.9136	0.0114
21	15.6816	0.0379
22	7.7284	0.0037
23	6.3504	0.0092
24	7.9524	0.0328
25	6.8644	0.0023
26	6.0516	0.0051
27	6.3504	0.0241

For smaller-The-Better

Quality Loss = (MSD)

For Larger-The-Better

Quality Loss = (1/MSD)

Table 13 Normalised quality loss values for surface roughness and Material Removed

Normalised Quality Loss		
S.No	Surface Roughness	Material Removal
1	0.3211	0.1391
2	0.2533	0.2880
3	0.1936	1.0000
4	0.1320	0.1391
5	0.2055	0.2928
6	0.1626	0.6262
7	0.2916	0.0582
8	0.2952	0.1601
9	0.2669	0.6699
10	1.0000	0.0728
11	0.4853	0.1569
12	0.5525	0.5663
13	0.3640	0.0711
14	0.3600	0.1504
15	0.3136	0.3398
16	0.2635	0.0647
17	0.2533	0.1521
18	0.2704	0.3899
19	0.6561	0.0711
20	0.8587	0.1844
21	0.4356	0.6132
22	0.2146	0.0598
23	0.1764	0.1488
24	0.2209	0.5307
25	0.1906	0.0372
26	0.1681	0.0825
27	0.1764	0.3899

Table 14 Total Normalised Quality Loss (TNQL)AND Multiple S/N ratio (MSNR)

When $W_1 = 0.5$ $W_2 = 0.5$

S.No.	TNQL	MSNR
1	0.2301	6.3808
2	0.2706	5.6767
3	0.5968	2.2417
4	0.1355	8.6806
5	0.2491	6.0362
6	0.3944	4.0406
7	0.1749	7.5721
8	0.2276	6.4282
9	0.4684	3.2938
10	0.5364	2.7051
11	0.3211	4.9335
12	0.5594	2.5227
13	0.3995	3.9848
14	0.2552	5.9311
15	0.3267	4.8585
16	0.1641	7.8489
17	0.2027	6.9314
18	0.3301	4.8135
19	0.3636	4.3937
20	0.5215	2.8274
21	0.5244	2.8033
22	0.1372	8.6264
23	0.1626	7.8887
24	0.3758	4.2504
25	0.1139	9.4347
26	0.1253	9.0204
27	0.2831	5.4806

Mean MSNR = 5.5409

Table 15 Multiple S/N response table (average factor effect at different levels)

Symbols	Factors	Mean S/N ratios (dB)		
		Level 1	Level 2	Level 3
A	Cutting speed (RPM)	5.934*	4.935	5.835
B	Feed (mm/min)	4.149	6.173*	3.731
C	Depth of cut (mm)	3.166	5.8102	7.649*

*optimum level

Now, the optimum parameters are

Cutting speed (RPM) at level 1 = 147 RPM

Feed (mm/min) at level 2 = 0.38 mm/min

Depth of cut (mm) at level 3 = 0.6 mm

The optimum S/N ratio at optimum parameter level can calculated as :

$$\eta_{opt} = \eta_m + \sum_{i=1}^{k}(\bar{\eta_i} - \eta_m)$$

η_{opt} = 5.5409 + (5.934-5.5409) + (6.173-5.5409) + (7.649-5.5409)

= 8.6742

Table 16 Results of ANNOVA in Multi-objective optimization

Symbol	DOF	Seq. SS	Adj SS	Adj MS	F	P	Contribution (%)
A	2	13.149	11.335	5.667	1.44	0.259	19.01
B	2	30.562	30.793	15.396	3.92	0.037	51.66
C	2	9.624	9.624	4.812	1.23	0.314	16.14
Error	20	78.470	78.470	3.924			13.16
Total	26	131.805		29.799			100.0

In multi-objective optimization, the effect of feed is more significant than speed and depth of cut.

Table 17 Result of confirmation experiment in multi-objective optimization

Initial parameter setting		Optimal turning cutting parameter cutting	
		Prediction	Experiment
Level	$A_1B_1C_1$	$A_1B_2C_3$	$A_1B_2C_3$
Surface roughness (µm)	2.64	---	2.18
Material removed (gm)	4.02	---	16.77
Multiple S/N ratio (dB)	2.2417	8.6742	8.6806

Improvement of S/N ratio = 6.4389

Table 18 Comparison of results from single for single-objective and multiple-objective optimization

Responses	Single quality optimization		Multi quality optimization	
	Surface roughness (SR)	Material removal (MR)	SR &MR	Loss in quality (Loss in %)
Level	$A_1B_2C_1$	$A_3B_3C_3$	$A_1B_2C_3$	
Surface roughness (µm)	2.42	--	2.18	9.9
Material removed (gm)	--	20.8	16.77	19.37

CHAPTER 8

Results and discussion

8.1 Single objective optimization results

The calculated S/N ratio (η values) corresponding to each experimental run is given in Table 4. The average factor effect of parameters at each level for responses surface roughness and material removed are shown in Table 6 and Table 8 respectively. Also, the graphical representations of factors effect for surface roughness and material removed are shown in Fig. 5 and 6 respectively. The maximum average S/N ratio for minimum surface roughness is obtained at level 1 (147 RPM) of speed, level 2 (0.38 mm/min) of feed, and level 1 (0.2 mm) of depth of cut i.e., the optimum parameter setting for minimum surface roughness is $A_1B_2C_1$. Also, the maximum average S/N ratio for maximum material removed is obtained at level 3 (320 RPM) of speed, level 3 (0.48 mm/min) of feed and level 3 (0.6 mm) of depth of cut. i.e., the optimum parameter setting for maximum material removed is $A_3B_3C_3$. The results of ANNOVA for surface roughness and material removed are given in Table 7 and Table 9 respectively. The contribution of factors in decreasing order for the surface roughness is feed, speed and depth of cut and for material removed is depth of cut, speed and feed. The S/N ratio and corresponding surface roughness and material removed values for initial parameter setting, by prediction, and by confirmation experiments are given in Table 8 and Table 10 respectively. The predicted value and the results of verification experiments are in good agreement i.e., the quality characteristics surface roughness and material removed have been considerably improved using TM. The improvement in S/N ratio at optimum parameter setting for surface roughness is 0.756 Db and for material removed is 14.277 Db.

8.2 Multi-objective optimization results

The quality loss values for the surface roughness and material removed against different experimental runs have been calculated from observed quality values (Table 1) and are shown in Table 11. The computed normalised quality loss for surface roughness and material removed are given in Table 12. The equal weights (w1 = w2= 0.5) for surface roughness and material removed have been assumed because material removal using turning operation is equally important to that of minimizing the surface roughness. The total normalised quality loss (TNQL) and multiple S/N ratio in each experimental run have been calculated summarised in Table 13. The average factor effect has been shown in Table 14. The optimum parameter setting corresponding maximum average η^e values for minimum surface roughness and maximum material removed is $A_1B_2C_3$. i.e., speed at 147 RPM, feed at 0.38 mm/min and depth of cut at 0.6 mm. The ANNOVA given in Table 15 shows the contribution of different factors in decreasing order: feed, speed and depth of cut. The predicted value of MSNR from confirmation test is shown in Table 16. The improvement in multiple S/N ratios at the optimum level is found to be 6.4389 db as compared with initial parameter setting. The value of surface roughness (µm) and material removed (gm) at this optimum level are 2.18 and 16.77 against the initial setting of 2.64 and 4.02, respectively. The results of multiple quality optimization and single quality optimization using Taguchi methodology has been compared in Table 17. The results shows that the surface roughness in multi-objective optimization is decreased by 9.9 % as compared to surface roughness in single-objective optimization, while material removed is decreased by 19.37 % in multi-optimization. It means the chance of quality loss is always there in shifting from single quality optimization to multiple qualities optimization. Therefore, a careful selection of weighting factor is required in order to minimize the loss in quality.

Chapter 9

Conclusions

In this study, the optimal condition for turning was selected by varying parameters through the Taguchi parameter design method. With L27 orthogonal array, a total of 27 experimental runs, covering three main factors each at three levels indicated that the Taguchi parameter design was an efficient way of determining the optimal cutting parameters for surface finish and Material Removed. For single optimization of surface roughness, the experimental results indicate that in this study the effects of feed rate was more significant than spindle speed and depth of cut. For material removed, the effect of depth of cut was more significant than speed and feed. The surface finish and material removed achievement of the confirmation runs under the optimal cutting parameters indicated that of the parameter settings used in this study, those identified as optimal through Taguchi parameter design were able to produce the best surface roughness and material removed in this turning operation. This was accomplished with 27 experimental runs, given the number of control factors, suggesting that Taguchi parameter design is an efficient and effective method for optimizing surface roughness and material removed in a turning operation.

While doing multi optimization that is simultaneous optimization of surface roughness and material removed the effect of feed was more significant than speed and depth of cut. In simultaneous optimization consideration of weighting factors plays an important role because final optimum parameter are comes based on selection of weighting factors. Selection of weighting factors is based on once wish that is how much weightage he/she wants to give each quality characteristic.

The loss which occurred while doing simultaneous optimization of surface roughness and material removed can be improved by taking L32 or L50 orthogonal array.

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