CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Machining operations have been the centre of attraction of the manufacturing industry since the revolution of industries. Machining of different materials strive hard either to achieve a minimum cost of production or maximum production rate or an optimum combination of both, along with the better quality in machining. These objectives have gained importance in economic liberalization and globalization. Manufacturing process for a product consists of several phases, such as design, process planning, machining and quality control. Machinability is the measure of ease with which the work material can be machined.

The economics of machining involves in the determination of optimum process parameters like cutting speed, feed and depth of cut in order to optimize an objective function. Minimum cost of production, minimum surface roughness, minimum tool wear, maximum production rate, minimum cutting force, minimum flank wear and maximum tool life are some of the essential objective functions in the machining process. Machinability also involves finishability and obtaining good surface finish. The standard machining process input and output variables are shown in Table 1.1
Table 1.1 Machining Process Variables

<table>
<thead>
<tr>
<th>Machining process input and output variables</th>
</tr>
</thead>
</table>

**Machining process Input parameters:**

1. Machine tool (rigidity, capacity, accuracy, etc.)
2. Cutting tool (material, coating, geometry, nature of engagement with the work material, tool rigidity, etc.)
3. Cutting conditions (speed, feed and depth of cut)
4. Work material properties (hardness, tensile strength, chemical composition, microstructure, method of production, thermal conductivity, ductility, shape and dimensions of the job, work piece rigidity, etc.)
5. Cutting fluid properties and characteristics

**Machining process Output parameters:**

1. Cutting tool life/tool wear/tool wear rate
2. Cutting forces/specific cutting forces
3. Power consumption/specific power consumption
4. Processed surface finish
5. Processed dimensional accuracy
6. Metal removal rate
7. Noise
8. Vibrations
9. Cutting temperature
10. Chip characteristics
Heat resistant super alloys (HRSA) maintain excellent mechanical strength at elevated temperatures, typically between 700°C and 1100°C. HRSA represents the largest group of materials in aerospace industries. HRSA exhibit exceptional properties such as corrosion resistance, creep resistance, and retaining strength and hardness at elevated temperatures. Among HRSA, nickel based alloys are most widely used nowadays for various manufacturing processes. Inconel 718 is one among the most commonly used alloys and find application in aero engine parts, rotor blades, casing rings, and engine parts. Inconel 718 super alloy has been widely applied in high load, high temperature and corrosion resistant environment due to its excellent properties.

Inconel 718 has been widely applied in aerospace industry and nuclear reactor due to its superior high temperature mechanical properties such as resistance to oxidation and corrosion, high tensile stress and rupture stress, etc. But, the combined effects of poor thermal properties, high temperature, strength, tendency to severe work hardening, and high tool-work piece affinity make machining of Inconel 718 very difficult to machine material, Aruncachalam et al (2004). Because of these properties, the material results in high temperature stress, and a thick adhering layer at the tool-work interface during machining. Several studies on the machining of nickel base alloys had disclosed surface integrity and tool wear mechanisms, Arunachalam et al (2004), Jawaid et al (2000), Deng et al (2005). Even though there are several studies on the machining of nickel base alloys by ceramics, carbide tools remained to be the important tool material in machining this kind of material owing to their high toughness and low cost. Owing to the advance of machine tool and control system, high speed machining (HSM) technology is becoming matured in recent years. In HSM, a higher metal removal rate is not the only advantage. It features several other aspects such as lower cutting force, surface quality improvement, etc. The
applications of HSM for aircraft parts are recognized for a longer time. Machining die steels by HSM and successfully applying it to die and mould manufacturing is another appealing example of application of HSM in manufacturing industry. In machining Inconel 718 alloy, it is well known that the tool temperature rises easily due to its poor thermal properties. Micro-welding at tool-tip and chip interface takes place leading to the formation of built-up edge (BUE). The excellent material toughness results in difficulty in chip breaking during the process. In addition, precipitate hardening of secondary phase (Ni3Nb) together with work-hardening during machining makes the cutting condition even worse. All these difficulties lead to high tool wear less material remove rate (MRR) and poor surface finish (Rahman et al 1997, Choudhary and El-baradie 1998). The manufacture of aerospace components involves a variety of machining operations such as turning, facing, milling and drilling. Considerable research has been done on selection and optimization of machining parameters for coated and uncoated carbide cutting tools using wet and dry cutting conditions. However understanding the wear mechanism of turning operations, are very important in the aerospace industry for desired surface roughness and economic manufacturing of the product.

1.2 MACHINABILITY PARAMETERS OF INCONEL 718

Machining parameter and tool geometry are the important parameters that affects the machinability properties. A machinability model may be defined as a functional relationship between the input parameters such as cutting speed, feed, and depth of cut and the output responses of machining process such as cutting force, power consumption, tool wear, tool life etc. In order to develop a mathematical model, it is necessary to conduct the experiments involving the tool material and the work material. The response data are obtained from the experimental work, by keeping cutting speed, feed
and depth of cut as the function of machining process. Uncoated carbide tools are used to machine nickel based alloy Inconel 718 at cutting speed range of 25 – 45m/min, feed rates 0.1 – 0.2 mm/rev and at depth of cut 1 – 1.5 mm for improved productivity. The use of different tool materials such as aluminium oxide base cermets, special coating of carbide, whisker reinforced ceramic, CBN etc., to cut this kind of material had been investigated, Choudhary and El-baradie (1999), Ezugwu et al (1999). Uncoated carbides are most widely used as cutting tool material to machine inconel 718 due to its economic considerations.

During machining, tools are subjected to rubbing process, which creates friction between the cutting tool and work piece material. This results in progressive material loss in the cutting tool. Tool wear is a change of shape of tool from its original position resulting from gradual loss of tool material. The consequences of tool wear are poor surface finish, increase in vibration of the machine tool, increase in cutting force, lowering the productivity and quality. Tool wear can be categorized into several types as crater wear, notch wear, chipping, plastic deformations, ultimate failure and flank wear based on tool wear phenomenon. Flank wear determines the tool life. Wear on the relief side is the flank wear and it occurs due to abrasive wear of the cutting tool against the machined surface. Surface finish is a very important aspect for designing mechanical elements and also presented as a quality indicator of manufacturing processes, Puertas and Luis (2003).

Any machining process does not allow achieving the theoretical surface roughness due to defects appearing on machined surfaces due to rapid tool wear and imbalances in the process. This requires to measure surface quality of manufactured parts with accuracy. Aslan et al (2007) and Hascalik et al (2007) quoted in their research an optimum selection of process condition is extremely important as this one determine surface quality and
flank wear phenomena of the manufactured parts. In turning operations an improper selection of cutting parameters will cause undesired surface roughness and high tooling cost. Minimization of wear is the predominant factor which improves the surface finish of the product, Benghersallah et al (2008). Numerous investigations have been conducted to determine the effect of parameters such as feed rate, tool nose radius, cutting speed and depth of cut on surface roughness in hard turning operation, Jawaid et al (2000) and Davim (2001). The surface finish is better when the feed rate is low and in this phenomenon there is no significant influence of cutting speed on surface roughness, Natarajan et al (2006).

Design of experiments is a powerful tool for modelling and analysis of process variables over some specific variable which is an unknown function of these process variables. Taguchi methods has been widely utilized in engineering analysis and consists of plan of experiments with the objective of acquiring data in a controlled way, in order to obtain information about the behaviour of a given process, Mustafa et al (2009). Hence, design of experiments by Taguchi’s method on cutting parameters was adopted to study the responses, Yang and Tang (1998).

Response surface methodology (RSM) is a collection of mathematical and statistical techniques which are useful for modeling and analyzing engineering problems and developing, improving, and optimizing processes. It also has important applications in the design, development, and formulation of new products, as well as in the improvement of existing product designs, and it is an effective tool for constructing optimization models, Myers and Montgomery (1997). RSM consists of the experimental strategy for exploring the space of the process or input factors, empirical statistical modeling to develop an appropriate approximating relationship between the yield and the process variables, and optimization methods for
finding the levels or values of the process variables that produce desirable values of the response outputs. Response surface method designs also help in quantifying the relationships between one or more measured responses and the vital input factors. The first step of RSM is to define the limits of the experimental domain to be explored. These limits are made as wide as possible to obtain a clear response from the model, Pradhan and Biswas (2008). The next step is the planning to accomplish the experiments by means of RSM using a Box–Behnken design. In many engineering fields, there is a relationship between an output variable of interest (y) and a set of controllable variables \((x_1, x_2, \ldots, x_n)\). The relationship between the machining parameters and the responses is given as:

\[
    y = f(x_1, x_2, x_3, \ldots, x_n) + \varepsilon 
\]  

Where \(\varepsilon\) represents the noise or error observed in the response \((y)\). If we denote the expected response to be

\[
    E(y) = f(x_1, x_2, x_3, \ldots, x_n) = \eta, 
\]  

then the surface represented by

\[
    \eta = f(x_1, x_2, x_3, \ldots, x_n) \tag{1.3} 
\]

is called a response surface.

The variables \(x_1, x_2, x_3, \ldots, x_n\) are called natural variables because they are expressed in natural units of measurement. In most RSM problems, the form of the relationship between the independent variables and the response is unknown; it is approximated. Thus, the first step in RSM is to find an appropriate approximation for the true functional relationship between response and the set of independent variables.
Traditional experimental design methods are very complicated and difficult to use. Additionally, these methods require a large number of experiments when the number of process parameters increases, Rosa et al (2009). In order to minimize the number of tests required, Taguchi experimental design method, a powerful tool for designing high-quality system, was developed by Taguchi. This method uses a special design of orthogonal arrays to study the entire parameter space with small number of experiments only. Taguchi recommends analyzing the mean response for each run in the inner array, and he also suggests analyzing variation using an appropriately chosen signal-to-noise ratio (S/N). These S/N ratios are derived from the quadratic loss function, and three of them are considered to be standard and widely applicable; Lower is the best; medium is better; larger is better, Mohan et al (2007). Regardless of category of the performance characteristics, the lower S/N ratio corresponds to a better performance. The statistical analysis of the data was performed by analysis of variance (ANOVA) to study the contribution of the factor and interactions and to explore the effects of each process on the observed value, Montgomery (2008), Yang and Tang (1998).

1.3 MATHEMATICAL MODELLING AND ANALYSIS

Mathematical model is a representation in mathematical terms of the behavior of real devices and objects. Nonlinear regression models are another important and useful family of regression analysis. Non linear regression finds a nonlinear model of the relationship between the dependent and a set of independent variables. Linear regressions are restricted to eliminate linear models, whereas non linear regression can estimate models with arbitrary relationships between independent and dependent variables. The proposed mathematical responses are presented in the following form.
\[ Y_i = C \times v^p \times f^q \times a^r \] (1.4)

Where C is the indication of constant, v is the cutting speed, f is the feed, a is the depth of cut and p, q, r are estimated coefficients of regression models. Statistical simulation software estimates the parameters in nonlinear models using the Levenberg – Marquardt nonlinear least-square algorithm. The empirical relationships between the independent variable (cutting speed, feed and depth of cut) and dependent variable for all the six objective functions namely, minimization of cutting force, power consumption, surface roughness, flank wear and maximization of tool life and material removal rate are developed.

1.4 MULTI OBJECTIVE OPTIMIZATION

Many researchers optimize the machining parameters as a single objective like minimizing the machining cost or maximizing material removal rate or tool life, Chua et al (1991), Chien and Tsai (2003), Asokan et al (2003), Cus and Balic (2003), and Amiolemhen and Ibhadode (2004). The Multi-Objective Evolutionary Algorithms (MOEA) provides a set of compromised solutions called Pareto optimal solution since no single solution can optimize all the objectives. NSGA-II is the improved population-based search and optimization techniques. These techniques are widely used by the researchers in engineering design application, Saravanan et al (2009). Similarly, multi objective optimizations based on posterior techniques were used to obtain the optimal parameters in turning processes for two objective functions, Quiza Sardinas et al (2006). Selecting the best personnel among many alternatives is a multi criteria decision making (MCDM) problems, Metin (2010). It is often a difficult task for the decision-makers to accurately assess weighting information as the number of performance criteria increase.
Three separate steps are utilized in MCDM models to obtain the ranking of alternatives; (1) Determine the relevant criteria and alternatives; (2) Attach numerical measures to the relative importance of the criteria and to the impacts of the alternatives on these criteria; (3) Process the numerical values to determine a ranking score of each alternative. TOPSIS is more efficient in dealing with the tangible attributes and the number of alternatives to be assessed, Venkata Rao (2006).

One of the major problems in industries is to cut down the manufacturing cost without sacrificing the quality of the components. As a consequence of this, modern sophisticated machine tools need optimization procedure for the selection of operating parameters such as cutting speed, feed rate, and depth of cut. The problem of selection of optimal machining parameters in turning has been analyzed with varying degree of generality by many investigators. Calculus method was used by Armarego and Russel (1966) to solve this optimization problem. Ermer (1971) and Petropoulos (1973) suggested geometric programming as an optimization technique to find the optimum machining conditions in turning. Moreover, the similar problem had been solved by using several other methods, namely, penalty function approach, dynamic programming, sequential unconstrained minimization technique, mathematical programming and sequential quadratic programming.

The main drawback of the traditional method lies in the fact that there is a chance of the solutions for getting trapped into local minima. To overcome this problem, evolutionary techniques are presently gaining significant attentions from researchers, Storn and Price (1997), Mayer et al(2005), Coello et al (2007), Abbas and Sarker (2002). These algorithms are mostly applied due to their effectiveness and robustness in searching for global solutions. Vijayakumar et al (2003), Baskar et al (2005), and
Saravanan et al (2005) attempted various non-traditional optimization techniques to optimize the machining parameters in turning operations. Vijayakumar et al (2003) worked in multi-pass turning operation to optimize the cutting parameters using ant colony system. Natarajan et al (2006) and Felix Prasad et al (2007) suggested the particle swarm optimization method and genetic algorithm for the prediction of tool life and cutting parameters optimization. As non-dominated sorting genetic algorithm (NSGA-II) is the improved population-based search and optimization techniques, these are widely used by the researchers in engineering design application. NSGA is one of the multi-objective evolutionary algorithms, proposed by Srinivas and Deb (1994). This algorithm was subjected to the criticism due to the following shortcomings, such as, high computational complexity of non-dominated sorting, lack of elitism, which otherwise helps to prevent the loss of good solutions once they are found, need for specifying the sharing parameter which is used to insure diversity in a population to get a wide variety of equivalent solutions. Deb et al (2002) proposed NSGA-II, which alleviates all the above three difficulties. Essentially, NSGA-II differs from the non-dominated sorting genetic algorithm (NSGA) implementation in a number of ways. First, NSGA-II uses an elite-preserving mechanism, thereby assuring preservation of previously found good solutions. Second, NSGA-II uses a fast non-dominated sorting procedure. Third, NSGA-II does not require any tunable parameter, thereby making the algorithm independent of the user.

1.5 MULTI CRITERIA DECISION MAKING (MCDM)

Multi-criteria decision making has been one of the fastest growing areas during the last decades depending on the changing’s in the manufacturing sector. Decision makers need a decision aid to decide between the alternatives and mainly excel less preferable alternatives fast. With the help of computers the decision making methods have found great acceptance
in all areas of the decision making processes. Since multi criteria decision making (MCDM) has found acceptance in areas of operation research and management science, the discipline has created several methodologies. Especially in the last years, where computer usage has increased significantly, the application of MCDM methods has considerably become easier for the users to the decision makers as the application of most of the methods are corresponded with complex mathematics. In discrete alternative multi criteria decision problems, the primary concern for the decision aid is the following:

(1) Choosing the most preferred alternative to the decision maker (DM),

(2) Ranking alternatives in order of importance for selection problems, or

(3) Screening alternatives for the final decision.

The general concepts of domination structures and non-dominated solutions play an important role in describing the decision problems and the decision maker’s revealed preferences described above. So far, various approaches have been developed as the decision aid. That is, for many such problems, the decision maker wants to solve a multiple criteria decision making (MCDM) problem, Jahanshahloo et al (2006). In MCDM problems, there does not necessarily the solution will exist that optimizes all objectives functions, and then the concept which is called Pareto optimal solution is introduced. Usually, there exist a number of Pareto optimal solutions, which are considered as candidates of final decision making solution. It is an issue how decision makers decide one from the set of Pareto optimal solutions as the final solution. A MCDM problem can be concisely expressed in matrix format as
\[
\begin{array}{c|cccc}
 & C_1 & C_2 & \ldots & C_n \\
\hline
A_1 & x_{11} & x_{12} & \ldots & x_{1n} \\
A_2 & x_{21} & x_{22} & \ldots & x_{2n} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
A_m & x_{m1} & x_{m2} & \ldots & x_{mn} \\
\end{array}
\]

\[W = [w_1, w_2, w_3, \ldots, w_n], \quad (1.5)\]

Where \(A_1, A_2, \ldots, A_m\) are possible alternatives among which decision makers have to choose, \(C_1, C_2, \ldots, C_n\) are criteria with which alternative performance are measured, \(x_{ij}\) is the rating of alternative \(A_i\) with respect to criterion \(C_j\), \(w_j\) is the weight of criterion \(C\).

The main steps of multiple criteria decision making are the following:

(a) Establishing system evaluation criteria that relate system capabilities to goals;

(b) Developing alternative systems for attaining the goals (generating alternatives);

(c) Evaluating alternatives in terms of criteria (the values of the criterion functions);

(d) Applying a normative multi criteria analysis method;

(e) Accepting one alternative as “optimal” (preferred);
(f) If the final solution is not accepted, gather new information and go into the next iteration of multi criteria optimization.

Steps (a) and (e) are performed at the upper level, where decision makers have the central role, and the other steps are mostly engineering tasks. For step (d), a decision maker should express his/her preferences in terms of the relative importance of criteria, and one approach is to introduce criteria weights. These weights in MCDM do not have a clear economic significance, but their use provides the opportunity to model the actual aspects of decision making (the preference structure). Technique for order performance by similarity to ideal solution (TOPSIS), one of known classical MCDM method, was first developed by Hwang and Yoon (1981) for solving a MCDM problem. TOPSIS, known as one of the most classical MCDM methods, is based on the idea, that the chosen alternative should have the shortest distance from the positive ideal solution and on the other side the farthest distance of the negative ideal solution.

1.6 OBJECTIVE OF THIS RESEARCH

The objective of this research focuses on multi criteria decision making in machinability evaluation of Inconel 718 using uncoated carbide cutting tools. The responses considered in this work are cutting forces, surface roughness, tool life, tool wear, power consumption and material removal rate against the machining parameters cutting speed, feed and depth of cut. The objectives of this research include;

1. Multi objective optimization using Non-dominated Sorting Genetic Algorithm (NSGA-II) of six objective functions namely minimization of surface roughness, tool wear, power consumption, cutting forces and maximization of tool life and material removal rate for machinability of Inconel 718.
2. To select an optimal solution using Multi Criteria Decision Making (MCDM) techniques such as TOPSIS and AHP methods for the machinability assessment of Inconel 718 from the set of non-dominated solutions obtained from NSGA-II.

This research ranks the set of non-dominated solutions obtained from the non-dominated sorting genetic algorithm NSGA-II and the first rank sequence of machining parameters are identified as the most significant machining parameters. This research is useful in determining the reliable machinability assessment model for the work material Inconel 718. An optimum machining conditions Inconel 718 is generated, which would be useful to researchers, tool engineers and process planners.

1.7 ORGANIZATION OF THESIS

Chapter 2 entitled “Literature Review” discusses the several literature reviews carried out during the complete course of this research work. This chapter highlights the limitations of the earlier research works and discussions on the recent developments in Inconel 718. The several literature reviews on Mathematical modeling, Optimization processes such as Taguchi Technique, Response surface methodology, Genetic algorithm based multi-objective Optimization, Multi criteria decision making techniques etc., used in selection of machining parameters of Inconel 718 are discussed in detail.

Chapter 3 entitled “Experimental methodology” elaborates the details of the work material, cutting tool, experimental set up carried out in this research. The experimental conditions and results for machinability assessment of turning of inconel 718 are discussed.

Chapter 4 entitled “Mathematical Modeling and Optimization Processes” presents the various mathematical models developed using non-
linear regression analysis used in this work. Several optimization techniques such as Taguchi technique, Response Surface Methodology, Single Objective Optimization, Multi Objective Optimization using Non-dominated Sorting Genetic Algorithm (NSGA-II), Multi Criteria Decision Making (MCDM) methods such as Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Analytical Hierarchy Process (AHP) are discussed. A Multi criteria decision making method describes the selection of best machining parameter from the non-dominated solution pool obtained by the NSGA-II optimization process. The optimal solutions obtained are then ranked by the MCDM techniques.

Chapter 5 entitled “Results and Discussion” discusses the results of several optimization processes used for the machinability assessment of turning of Inconel 718. In this work, Taguchi technique and Response surface methodology is used for machinability evaluation of surface roughness and flank wear while turning Inconel 718. Also Genetic algorithm based multi objective optimization is used for optimizing the objective functions such as minimization of cutting force, power consumption, tool wear, surface roughness and maximization of tool life and material removal rate. The results obtained through NSGA-II are then ranked using the MCDM techniques and the first ranked cutting parameters are selected as the best optimum solution for turning of Inconel 718.

Chapter 6 entitled “Summary and Conclusion” presents the contribution, limitations and future scope of this research work.