Candidate Declaration

I hereby certify that the work, which is being presented in the thesis, entitled **Optimization of cutting parameters in machining of UD-GFRP with PCD tool using NSGA II**, in partial fulfillment of the requirements for the award of the degree of **Master of Engineering** in Information Security submitted in Computer Science and Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out during the period **July 2014** to **July 2016** under the supervision of **Dr. Prashant Singh Rana**. I have also cited the reference about the text(s)/figure(s)/table(s) from where they have been taken.

The matter presented in this thesis has not been submitted elsewhere for the award of any other degree or diploma from any institution.

Date: 15/06/2016

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This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

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Optimization of cutting parameters in machining of UD-GFRP with PCD tool using NSGA II

Thesis submitted in partial fulfillment of the requirements for the award of the degree of

Master of Engineering

in

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.........dedicated to all young generation researchers

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Manish Kumar

Abstract

Fiber glass reinforced plastic was developed in 21^{st} century. GFRP has drastically change the engineering materials and used in various fields like aircrafts, marines and many more, but their machining is quite different from conventional metals. For make any engineering material useable its machining plays a vital role. Since GFRP materials are different in nature its machining is also quite different and to get a perfect finished material all the cutting parameters should be selected carefully as bad parameter prediction leads to poor quality of finished material.

Machining (cutting) parameters are essential to attain good quality in the cutting (machining) process. The current research focuses on the process of optimized machining parameters in machining of unidirectional glass fiber reinforced plastic (UD-GFRP) composites. The machining parameters selected for experimental work, were accomplished using Taguchis L_{18} orthogonal array technique. The parameters selected are rake angle of tool, nose radius of tool, rate of tool feed, speed of cutting, environment used for cutting (dry, wet and cooled) and depth of cut. Since all the parameters can not be used for optimization as only significant parameters need to be optimized. Selection of significant parameters ia also a tedious job for the researcher. This also make the optimization slower if insignificant parameters are selected along with significant ones.

Hence out of these six parameters only the significant one are selected to optimize and literature surveys shows that significant parameters vary with the objective-function were selected. Here we selected two objectives, first is to increase the rate of material removal by the tool and second is to decrease the roughness of the targeted surface. So based on these objectives three parameters are selected as significant i.e. rate of feed the tool, speed of cutting and depth of cut. Since here we have two objectives so optimization algorithm with one objective may not serve our purpose, hence we need an optimization algorithm with more then one objective. Hence the Non-dominated Sorting Genetic Algorithm II (NSGA II) is suitable to fulfill our requirements.

Keywords: UD-GFRP Composites, NSGA II, Roughness of targeted surface(SR), Rate of material removal(MRR).

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List of Abbreviations

ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
BLAST	Basic Local Alignment Search Tool
CASM	Contact Assisted Structure Modeling
CR	Crossover rate in NSGA II
CS	Cutting Speed
DC	Depth of Cut
DE	Differential Evolution
EA	Evolutionary Algorithm
ED	Euclidean Distance
F	Scaling Factor in DE
FM	Template free modeling
FR	Feed Rate
GA	Genetic Algorithm
HB	Higher the Better
LB	Lower the Better
LM	Linear Model
LPP	Linear Programming Problem
MR	Mutation Rate in NSGA II
MRR	Material Removal Rate
NB	Normal the Best
NI	Nature Inspired
NLP	Nonlinear Programming Problem
NP	Population Size
NSGA	Non dominated Sorting Genetic Algorithm
PSO	Particle Swarm Optimization
RMSD	Root Mean Square Devation
RMSE	Root Mean Square Error
SM	Structure Modeling
SSR	Sum of Square Regression
SR	Surface Roughness of targeted surface
SVM	Support Vector Machine
TBM	Template Based Modeling
UD-GFRP	Unidirectional Glass Fiber Reinforced Plastic

Chapter 1

Introduction

This chapter gives a brief introduction of the work done and gives an outline about the optimization of tuning parameters for UD-GFRP. The chapter ends with a brief summary of the chapters included in this thesis.

The work presented in this thesis mainly focuses on the optimization of cutting parameters for unidirectional glass fiber reinforced plastic (UD-GFRP) with poly crystalline diamond (PCD) tool using non dominated sorting genetic algorithm II (NSGA II). The aim is to optimize the cutting parameters i.e. rate of tool feed, speed of cutting and depth of cut in order to get less roughness of the targated surface and high rate of material removal. In similar work, a performance study of taguchi,s L_{18} orthogonal array approach is done. Optimization of process parameters is done using a commonly known method called Taguchi's method. The method was initially aimed to improve the quality of products through the concepts of statistics and engineering and forms the basis of Orthogonal Array (OA) experiments, which results in very-lower variance regarding the experiment. This leads process parameters to be optimal. Orthogonal Array (OA) consists of well-defined experiments having few experimental runs and Taguchis signal-to-noise ratios (S/N), which is the logarithmic functions of expected output, act as a target function for optimization. This process is helpful in analysis of data and result predictions. The S/N includes mean and the variability and is defined as the ratio of the mean (Signal) and the standard deviation (Noise). The ratio rely on the quality features of the problem to be optimized. Generally the S/N ratios are considered best in normal case(NB), however higher and lower values are considered better(LB and HB). Highest S/N ratio provides best set of optimal parameters.

Since Taguchi method is used to optimize single objective at a time and we have to optimize the two objectives i.e. lower roughness of targeted surface and higher rate of material removal at the same time which can not be done by taguchi method. Hence we go for evolutionary algorithm to get fast and optimized results but single objective evolutionary algorithm are not fit for our desired work so we go for multi objective optimization using evolutionary algorithm. We select Non Dominated Sorting Genetic Algorithm II (NSGA II) for optimization. NSGA II is a fast multi objective optimization algorithm whic produce a set of feasible solutions and best among them is selected and presented in output as pareto optimal front.

The major contribution of this thesis is to provide the production engineer a set of optimized values from which he can select the desired values according to his needs of lower or higher roughness of targeted surface and rate of material removal respectively. Also the optimized values reduce the machining time and efforts of the machining team to get the desired results.

The above briefly highlighted topics are described in the respective sections or chapters.

1.1 Organization of Thesis

This thesis is structured into 6 chapters. A brief review of each chapter is provided below:

- **Chapter 1**: This chapter includes the basic optimization problem that is being tackled in this thesis. It provide a briefing of the topic that is what is being accomplished by this thesis. This section also provide a brief summary about all the chapters and act as a guide for the reader as reader can know briefly about each chapter and directly move to the chapter which interest him.
- **Chapter 2**: This chapter describe the literature review of the problem. In this basic of optimization, different types of optimization problems (single objective and multi objective) and different approaches to solve these problems is presented. After this evolutionary algorithms are discussed with NSGA II explained as example algorithm.
- **Chapter 3**: This chapter focuses on the problem that is being tackled by the thesis. It includes the research motivation, key research area to be focused. This chapter talks about the gaps introduced through the research and also the objectives formulated to carry out this research in a systematic way.
- **Chapter 4**: This chapter describe the process of optimization of cutting parameters in machining of UD-GFRP using NSGA II. This chapter talks about the procedure adopted to solve the problem tackled by the thesis. It presents the Taguchi's method to get the experimental results, selection of important three parameters out of six parameters to be optimized, formulation of two objectives (lower roughness of targeted surface and higher rate of material removal) as mathematical formula and

application of NSGA II to those objectives so that optimized set of result can be obtained.

- **Chapter 5**: This chapter study the relative comparison of the experimental results and optimized results produced by NSGA II. This chapter shows a set of 40 optimized parameter values out of 100 optimized values produced by NSGA II. It also represent a pareto optimal set comparing the effect of two objectives relatively on each other (Figure 5.1).
- **Chapter 6**: In this chapter the principal findings and key contributions of the thesis are provided along with the possible directions for future research work.

Chapter 2

Literature Review

The chapter briefly reviewed the optimization process, types of optimization, Evolutionary algorithms and NSGA II.

2.1 Optimization

Optimization is the method to get a set of optimal points within the search space which makes the value of fitness function to be high or low depending upon the objective to be achieved and specification of problem. The process of getting the best collection of optimized values to satisfy an objective defined under constraints and presented as mathematical formulas is called Global optimization. Global optimization problems comes in the class of NP-Complete so there exist not even a single algorithm which can solve these problems in polynomial time[1].

Rest of the chapter is organized as follows: Section 2.2 describes brief overview of types of optimization. Section 2.3 provides the single objective problem and corresponding algorithms to solve them . In section 2.4 the multi objective optimization and corresponding algorithms are discussed. At the last, section 2.5 concludes the chapter.

2.2 Types of Optimization

Optimization problems are generally divided into two sections viz. continuous optimization and discrete optimization.

2.2.1 Continuous Optimization

In this type of optimization every variable is permitted to have values form subintervals of ($-\infty$, ∞) i.e. real number line and these values are equally spaced. Global optimization algorithms requires to get that value of selected variables which minimize the fitness function regarding all the allowed values. The continuous optimization is further classified into two parts viz. (1.) unconstrained optimization and (2.) constrained optimization. With unconstrained optimization there is no other condition specified to be fulfill and any relation can exist between decision variables for eg. non linear least squares, non linear equations etc. In constraint optimization a constraint condition should be fulfilled by any decision variable, if it is not fulfilled then this variable can not be selected. It includes the problems of quadratic, linear and network programming etc.

2.2.2 Discrete Optimization

This optimization makes the variables to take selected points from the interval (-∞, ∞) and these required not to be equally spaced. Comparing with continuous problems, discrete problems are tough to solve . Two general techniques are taken into account to handle discrete optimization problems and are described as (1.) Integer programming which is selected for problems where the solution is feasible only if some of variables are integer only. (2.) Stochastic programming which also be implemented for continuous optimization also. In some real life problems the data can not be determined due to a number of limits. These kind of problems are perfectly handled by stochastic optimization [2].

2.3 Single Objective optimization and Algorithms

A lot of real world problems can be formulated as optimization problems with only one objective under limited resources form the challenge for the given problem. In a multi solution condition it is difficult to find global optimal solution using the conventional methods. Optimization as a key research topic can devise several approaches to solve these problems. Section 2.3.1 provides insight on single objective optimization problem and section 2.3.2 shows several approaches to solve these problems.

2.3.1 Optimization Problems

This section provides insight on common concepts of optimization in which section 2.3.1.1 discuss the basic idea about optimization and section 2.3.1.2 discuss the principle of single objective optimization.

2.3.1.1 Introduction and Overview

Optimization as a key area in research is the process of getting best solution to the requested problem. Many real world problems can be formulated as optimization problem having global minima that is covered by local minima. For example
- In financial investment analysis finding the best return over investment.
- In distribution system to find the best shortest route to travel between two points with an aim to minimize the transit time.
- In CPU scheduling minimize the processor idle time while planning the execution of the processes.

For these types of problems, all feasible solution can be sorted or ranked regarding their objective values. Thus goal of such optimization is well explained and is to find the best ranked solution within the complete set of feasible solution[3].

2.3.1.2 Single Objective Optimization

A single objective optimization problem can be formulated to find the distinct optimal solution of a function known as objective or fitness function. Thus optimization needs to find a vector of decision parameters that optimize the given objective function (f(x)) of a problem.

For a minimization case: f(α) $\geqslant$ f(x)

For a maximization case: f(α) $\leqslant$ f(x)

where X=[x_1,x_2,x_3,......,x_n] is the vector of n dimension decision variables of function f and α=[α_1,α_2,α_3,.......,α_n] is the vector of decision variable such that objective function f is optimized. The final purpose of global optimization us to find vector of decision variables (α) such that the function is optimized [3].

2.3.2 Single-Objective Optimization Algorithms

In support of the discussion about optimization problem in section 2.3.1, this section describes the review and analysis of different kind of algorithms developed to solve these problems. Classical techniques are presented in section 2.3.2.1 and population based stochastic search methods are discussed in section 2.3.2.2.

2.3.2.1 Classical Techniques

Classical optimization techniques are many including linear programming, non linear programming, and dynamic programming for solving optimization problems. Heuristic technique is another optimization problem solving approach used by researchers.

A heuristic expressed as rule of thumb which provides a good solution for a difficult problem. The heuristic mainly ignore whether the solution is practically the best solution. This approach is mainly applied when there is no proper method exist to find the optimal solution or the method is not practically achievable using the present computing resources.

This approach involves having some information about the problem being solved to design specific rules for solving the problem. Such need restrict the usage of general heuristic approach as it requires certain pre knowledge about target problem. Metaheuristic are thus become useful as they are generalization of heuristic approach which are used to solve general for good solution. A metaheuristic is defined as good if it directs the process of searching in perfect direction. This reduces the time for repeated search in search process of good solution.

Local or neighborhood search is the simplest technique used for metaheuristic. A neighborhood approach initialize with a randomly generated initial solution and then goes on generating the neighborhood solutions. If a better solution is found then it replaced with original solution and process is iterated. Such approach is similar to hill climbing process and generally covers local optimal solution. Several types of local search techniques have been proposed including the Tabu search and gradient approach [4].

2.3.2.2 Population based stochastic search approach

Classic heuristic based approach is a very simple concept of problem solving. The rule based procedure fails most of the heuristic approach to solve some general problems. Heuristic approach solves only specific problems with specific characteristics and cannot be used to solve all problems related to optimization. Hence population based stochastic search method is designed to solve all types of problems with a little change in the algorithmic procedure.

In previous literature, a number of population based stochastic search methods are developed for optimization problems. Mainly GA algorithm, DE algorithm, PSO algorithm and ACO algorithm are the popular known optimization algorithm [4].

Genetics is considered as one of the biological process that is attracting the researchers towards itself. As it is originated from nature its optimization power is making it the basic of all optimization algorithms. Genetic algorithm which uses the process of gene evolution has always a high priority for developing most of the computation algorithms.

2.4 Multi-objective Optimization and Optimization Algorithms

This section discusses multi-objective optimization. The difference between single objective optimization and multi objective optimization lies in the fact that the definition of optimum has to be re-stated. Algorithms used to solve multi-objective optimization produce a set of solution in accordance with the multiple objectives of the problem.

Section 2.4.1 defines the multi-objective optimization problem and the corresponding multi-objective algorithms are discussed in section 2.4.2.

2.4.1 Optimization Problems

This section enlighten the general concepts of optimization with basic idea is discussed in section 2.4.1.1. The principle behind multi-objective optimization is given in section 2.4.1.2 and section 2.4.1.3 discuss the fundamental concepts of multi-objective optimization.

2.4.1.1 Introduction and review

Real world problems requires satisfaction of more then one objective at a time. In science, engineering, finance and many other domains problems are having more then one aims to satisfy. For example:
- In financial investment we have to balance risk and return simultaneously.
- In traveling problem a route is to be selected with short traveling time and minimize the relative cost.
- In scheduling the minimization of idle time and maximization of output is required.

These problems requires concurrent optimization of more then one objective. Moreover it is impossible to find an optimal solution which satisfy every objective of a problem at same time. A solution can be optimal to one objective but at the same time may not be optimal for another.

2.4.1.2 Multi-Objective Optimization

For a multi-objective optimization more then one objective needs to be satisfied at the same time. A multi-objective optimization problem thus needs to find the vector of decision variables that optimize all the objective functions:

$$Minimize/Maximize f'(x) \tag{2.1}$$

f'(x) = f_1(x),f_2(x),f_3(x),........,f_n(x)
where x = [x_1,x_2,x_3,........,x_n] is the n-dimensional decision vector representing the variables of objective function f.

In multi-objective optimization it is almost impossible to find a single optimum solution to satisfy every objective as these objectives most of the time related to each other. Thus mostly a set of solutions is found instead of single solution to satisfy the requirements of different objectives [5].

2.4.1.3 Concept of Multi-Objective Optimization

a. Concept of Pareto Dominance

It is not necessary that multi-objective optimization provides a solution that is better then other solutions for objective function i.e. value of objective function can not be used for comparison. The comparison is done by using concept of pareto dominance i.e. two solutions are compared on the basis that which solution dominates the other solutions.

Pareto dominance requires comparison of pair of solutions (s and t) with respect to following conditions
(1.) In all objectives, t is worse than s

$$g_i(s) \geqslant g_i(t) \quad \forall_i = 1, 2, ..., n \tag{2.2}$$

(2.) s is strictly better than t in some sense

$$g_i(s) > g_i(t) \quad \exists_i \in [1, n] \tag{2.3}$$

If both the conditions met then s is dominating over t and if any of the condition is violated neither solution is dominating. Figure 2.1 shows different types of solutions. In the above figure black dot shows a feasible solution. Region 1 shows the solution

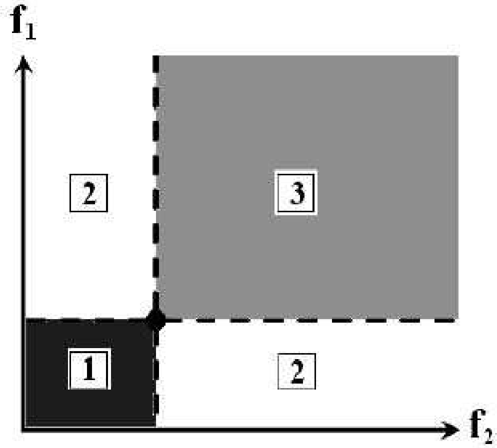

Figure 2.1: Relationship of solutions in the objective space

which dominated the solution under observation, region 3 shows the solution which are dominated by observed solution and region 2 contains the solutions that are indifferent with observed solution.

b. Pareto Optimality

Pareto optimality is the optimality criteria for multi-objective optimization and is summarized as the best solution that can be obtained without degrading atleast one objective using the criteria of pareto dominance. All solutions in the solution set are compared in

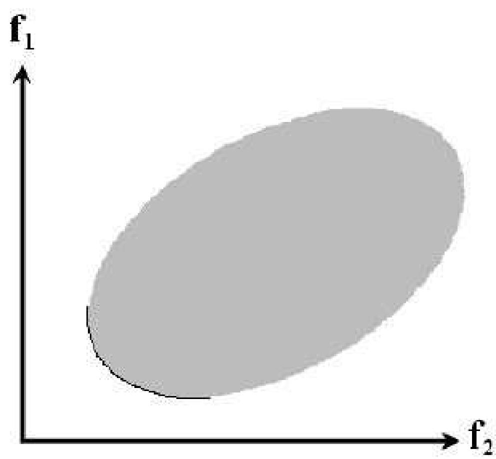

Figure 2.2: An objective space with pareto optimality

pairs to get the dominating solutions. Non dominated solutions are those which dominate others but not dominated by others. No improvement an be possible to these solutions without sacrificing the optimality of any objective function. Hence thry are the pareto optimal solution set. Figure 2.2 shows an idea of pareto optimality in which shaded region provides entire solution set and a black line at left bottom part provides the pareto optimal solution set [6].

2.4.2 Multi Objective Optimization Algorithm

This section discuss the classic concept of solving multi-objective optimization in section 2.4.2.1. Evolutionary algorithms are presented in section 2.4.2.2 and NSGA II is discussed in section 2.4.2.3.

2.4.2.1 Classical approach

Multi-objective optimization problems were solved using the two classical approaches. First one is the aggregate approach which aggregate all the objectives to form a single objective function. Second is the constraint approach which redefines the multi-objective problem to optimize one of the objective function and put constraint on residual objectives. This approach also convert the problem into single objective problem.

a. Aggregate Approach

This approach merge all the objective functions with weighted addition of each of the objectives with user defined weights.

$$Minimize H(s) = \sum_{j=0}^{n} w_j h_j(x) \tag{2.4}$$

where w is the defined weight of objectives.
The weights are selected on basis of the relative importance of objectives. Hence single objective optimization techniques can be used to solve the problem. When this aggregated objective is optimized it is possible to get a particular solution for pre-defined weights. This is one of the simplest and widely used classical approach but suffers a difficulty to assign weights to some objectives.

b. Constraint Method

This method use the procedure to optimize one of the objective and put constraints on the residue objectives. It reduce the problem into single objective optimization as:

$$Minimize\ \ g_z(x) \quad subject\ \ to\ \ g_i(x) \leqslant \jmath_i, \quad i = [1, 2, ..., n] \& i \neq z \tag{2.5}$$

where $\jmath$ is the upper bound of objectives and converted into constraints.
This method results in only a single solution instead of a set of solutions. The right

selection of objective function for constraint method is difficult to be accurate. Another difficulty is the choice of the value of $\jmath$. Too high a value results in poor solution, but too low a value leads to no solution found by the method [7].

2.4.2.2 Evolutionary approach

In classical approach the multi-objective problem is solved by converting it into single objective problem. However practically merging of objective does not give the desired result as objectives are mainly inseparable. In this situation evolutionary algorithms can serve our purpose as they work with all objectives and produce a group of solution which is highly uniform distributed and near to pareto optimal set.

a. Fundamentals of evolutionary algorithms

Evolutionary algorithm are best to solve multi-objective problems due to their property to produce many solutions in just one run. Solutions to multi-objective problem requires a set of solution from the feasible search space and population based process of evolutionary algorithm is suited to these problems. The first advantage over classical method is the supported search in the search space that decrease the redundance between solutions and less number of iterations are needed. Second advantage is that evolutionary algorithm find similar solution rapidly using crossover and mutation and evaluate them quickly. Hence these algorithm needs very less computational resources in getting full set of solutions.

Because of less need of computation, ease of implementation and less knowledge requirement evolutionary algorithms are more suitable for multi-objective optimization problems.

b. Working of evolutionary algorithm

Algorithm 2.1 shows the steps to be followed by evolutionary algorithm to solve a multi-objective problem. Now the algorithm starts by first generating the initial population using the preset parameters. Then a loop consisting of several steps including fitness evaluation, generation of new solutions with selection and variation i.e. selecting the solution according to their fitness value and application of crossover and mutation operations is executed for some number of iterations and terminated by reaching to stopping criteria on predefined number of iterations.

Algorithm 2.1 A simple evolutionary algorithm

Set the initial control attributes i.e. CR, MR, Population size and number of generations;
Generate the initial population;
while stopping condition(s) not met **do**
  for each chromosome $y_j(H) \in POP(H)$ **do**
    (i) Calculate the fitness, $Fitness(y_j(H))$;
    (ii) Create the start vector, $v_j(H)$ by using the mutation operator;
    (iii) Create a new individual, $y'_j(H)$, through the crossover operation;
    if $Fitness(y'_j(H))$ is greater than $Fitness(y_j(H))$ **then**
      Insert $y'_j(H)$ into $POP(H++)$;
    else
      Insert $y_j(H)$ to $POP(H++)$;
    end if
  end for
end while
Return the solution having the best fitness value in output;

2.4.2.3 Non dominated Sorting Genetic Algorithm II

NSGA II is a fast and elitist multi-objective optimization algorithm. It is a very famous algorithm among research community to solve multi-objective optimization problems due to its simplicity of operations and fast computation. The main features of NSGA II are:
- A procedure for non dominated sorting‘where solutions are sorted regarding the non dominance level.
- Elitism is implemented by storing all non dominated solutions hence increasing convergence among solutions.
- A satisfactory self directing phenomena is used using crowding distance to get diversity among solutions.
- Constraints are applied by re-define the dominance by no penalty function is used.

A simple NSGA II is presented in algorithm 2.2.

2.5 Conclusion

In this chapter a literature review of the thesis is presented in which we discussed about optimization, different types of optimization i.e. single and multi-objective optimization. Different approaches to solve single and multi objective optimization problems were discussed. Then Evolutionary approach to solve optimization problems and how to develop a multi objective optimization algorithm by evolutionary approach were being discussed

Algorithm 2.2 A non dominated sorting genetic algorithm II (NSGA II)

Set the Population size, number of generations, Crossover rate and Mutation rate;
Population ← InitializePopulation(Population size, no of generations);
Fitness ← EvaluateFitness(Population);
NonDominatedSort(Population);
Parent ← SelectParentsByRank(Population, Population size);
NewGeneration ← GAOperations(Selected, Crossover rate, Mutation rate);
while stopping condition(s) not met **do**
  for each chromosome in NewGeneration **do**
    (i) fitness ← EvaluateFitness(NewGeneration);
    (ii) Vector ← Merge(Population, NewGeneration);
    (iii) Vector ← NonDominatedSort(Vector);
    if fitness(chromosome) is better than Fitness(Parent) **then**
      Add chromosome to ($Vector_{size}$+1);
    else
      Add Parent to ($Vector_{size}$+1);
    end if
  end for
end while
Return the solution with the best fitness as result;

and at the last a famous non dominated sorting genetic algorithm (NSGA II) is presented. Next chapter introduces the problem that is being solved by this thesis and how NSGA II is implemented to solve the problem.

Chapter 3

Description of the problem

Machining is one of the critical process in mechanical manufacturing industry. The machining process is required to change the geometry of the raw product so that it can be used for our purpose. Machining process includes a number of parameters to be taken into account during the process. These parameters are the critical section or the driver of the whole process. If we are able to get a good set of parameters then the finishing of the material will also be remarkable and at the same time bad selection of parameter values can ruin the whole machining process. Hence an optimized set of parameters is necessary to accomplish a better machining process [8].

Optimization of cutting parameters is the main and the tough work [9] in which many aspects are necessary viz. machining awareness, tool life relating equations, an effective optimization criteria and knowledge of various optimization techniques. Normally the selection of right machining parameters is necessary but relies heavily on the parameters table provided by tool builder for various materials. Hence optimization of machining parameter is necessary where economy and quality of tool play a vital role.

3.1 Problem Statement

The purpose of this thesis is to optimize the cutting parameters in machining of Uni-directional glass reinforced plastic (UD-GFRP) with a Poly crystalline diamond (PCD) tool using non dominated sorting genetic algorithm (NSGA II).

1. Analyze the Taguchi's method of optimization.
2. Selecting the important parameters to optimize.
3. Development of optimization criteria for different objectives.
4. Optimize the objectives using NSGA II.

3.2 Research Direction

This section describes the motivation to carry out this research and the key research areas selected for this research.

3.2.1 Research Motivation

Optimization is defined as the process to find the alternative(s) which is best among available solutions which a given function can achieve in its domain, to get required results. For example, in civil engineering, one is interested to get best possible mixture ratio of the material to make a good structure of building. These type of problems are aiming to get desirable response can be scientifically resolved through modeling and optimization. Modeling refers to convert the original problem into mathematical structure and to do the model must be designed in such a way that it includes all key characteristics of the original system. The created models are mainly written as procedures, called objective functions, in single or more options which corresponds to adoptable parameters of the system. Complex systems use the models having complex multi-dimensional functions in most of the optimization problems and therefore, they cannot be easily communicated. To solve these kind of optimization problems mathematically, algorithmic procedures which takes all the pros of recent computer technologies can be implemented. Thus, time constraint, computation accuracy and efforts of implementation become main points of the optimization of numerical problems. In most of such problems, the objective function is noisy, discontinuous and with lack of analytical representation. Under these restrictions, the relevancy and adequacy of classical and deterministic optimization approaches are doubtful. The primary drawbacks with deterministic algorithms are their non robustness i.e. can be implemented for restricted types of problems and too slow towards solution or erstwhile not able to solve problems of real world. To avoid these drawbacks, it is a great requirement to produce fast, effective and accurate algorithms which can solve real world optimizations problems.

Optimization of UD-GFRP cutting parameters have two major objectives: (1) lower the roughness of the targeted surface and (2) higher the rate of material removal. In this chapter, the multi objective optimization algorithm named non dominated sorting genetic algorithm II (NSGA-II) is used to optimize these objectives. Three parameters viz rate of tool feed, speed of cutting and depth of cut are selected for optimization and the resulting solution set is presented as pareto optimal front between the defined objectives.

3.2.2 Key Research Area

The key research emphasis on the optimization of cutting parameters of Unidirectional glass reinforced plastic (UD-GFRP) composite with poly crystalline diamond (PCD) tool using non dominated sorting genetic algorithm II (NSGA II) with two objectives viz. lower the roughness of targeted surface and increase the rate of material removal. Following are the key research areas:

1. Premature convergence is the problem inherited by almost every NI algorithm. Any algorithm inspired by evolutionary criteria is termed to be an economic algorithm if it is quick to convergence and capable to search the larger area of the search space. It can also be said like that, if an evolutionary algorithm is not able to have a proper balance between exploration and exploitation with respect to the search space, then that algorithm is termed as an inefficient one.

2. Furthermore, Lothar et al. [10] show that a proper equivalence between exploitation and exploration regarding the search space is not established by GA. Some studies also proved that a notable drawback with GA is stagnation i.e. GA may be one-time do not head in the direction of global optima however the population has not coincide to the local optima or any other spot.

3. Optimized cutting parameters have been one of the main hurdle in machining process. The prediction of optimal parameters are generally treated as optimization problem. However in some cases it is impossible to predict the parameters due to their large dimension.

4. The prediction of optimized parameters is a key research area in the field of mechanical and civil engineering. The availability of optimized parameters according to the need of production engineer makes their work easy and fast. Hence the proposed approach can be very useful.

5. Impact of having better optimized parameters can help in reduction of machining time, resource wastage, increase the chances of better cutting of the composite and many more.

3.3 Research Gaps and Objectives

3.3.1 Research Gaps

1. All parameters are not important and optimization can not be applied without knowing specific parameters [11].
2. Optimization principle, different types of optimization and optimization algorithms need to be studied.
3. Evolutionary methods of optimization need to be studied for NSGA II understanding and implementation.
4. Unavailability of tool to optimize cutting parameters with two objectives i.e. lower roughness of targeted surface and higher rate of material removal .
5. konak et al. [12] show that no proper trade-off regarding exploitation and exploration of the search space is established by NSGA II.
6. Some studies also stated that selection of objectives in optimization of cutting parameters is very crucial and as well as hard to perform as selection of important parameters is a time consuming process [13].

3.3.2 Research Objectives

The following research objectives are formulated:

1. To get experimental results that are to be optimized.
2. To investigate the performance of Taguchi's method in optimization of objectives.
3. To select the main parameters for optimization process.
4. To formulate the objectives used by NSGA II for optimization.
5. To get the optimized parameters as output from NSGA II.
6. To investigate the performance of NSGA II algorithm by comparing the values with experimental results.
7. To provide the process engineers a set of optimized values so that the parameter values according to engineer's need can be selected by them.

Chapter 4

Optimization of cutting parameters for machining of UD-GFRP

Machining (cutting) parameters are essential to attain good quality in the cutting (machining) process. The current research focuses on the process of optimized machining parameters in machining of unidirectional glass fiber reinforced plastic (UD-GFRP) composites. The machining parameters selected for experimental work, were accomplished using Taguchis L_{18} orthogonal array technique. The parameters selected are rake angle of tool, nose radius of tool, rate of tool feed, speed of cutting, environment used for cutting (dry, wet and cooled) and depth of cut. Out of these six parameters only the significant one are selected to optimize and literature surveys shows that significant parameters vary with the objective-function were selected. Here we selected two objectives, first is to increase the rate of material removal by the tool and second is to decrease the roughness of the targeted surface. So based on these objectives three parameters are selected as significant i.e. rate of feed the tool, speed of cutting and depth of cut. Since here we have two objectives so optimization algorithm with one objective may not serve our purpose, hence we need an optimization algorithm with more then one objective. Hence the Non-dominated Sorting Genetic Algorithm II (NSGA II) is suitable to fulfill our requirements.

4.1 Introduction

Variety of structures such as robots, aircraft and machines widely used fiber reinforced plastic (FRP) composite material. The salient feature of the process of manufacture is machining. Literature shows notable distinction between the traditional metals and their alloy's machining process and that of composite materials as FRPs are inhomogeneous and anisotropic. Machining attributes of composites differ from metals as described below:

1. Machining of FRP can be done within a restricted bounds of temperature
2. The less thermal conductivity leads to production of heat in the operating area at the

time of machining operation, as very small dissipation by the materials.
3. The variation in the coefficient of linear expansion between the matrix and the fiber leads to residual stresses and makes it tough to get high dimensional accuracy.

A lot of research work and experiments were performed on the machining of GFRP composites. Ferreira et al. [14] surveyed the capability of different tool materials like Cubic Boron Nitride (CBN), cemented carbide, ceramic and diamond during turning but results proved that only diamond tools perform well in finish turning. Wunsch and Spur et al. [15] observed the turning of glass fiber reinforced (GFR) polyester and epoxy and noted an increase in surface roughness with increasing feed rate but no dependency regarding cutting velocity. Takeyama and Lijima et al. [16] explained the chip development process with regard to fiber familiarization. Up to present maximum investigations on machining of GFRP have focused on the system of tool wear and surface roughness [17] but for reasonable machining of GFRP, optimized cutting parameters should be obtained to get good surface finish with less tool wear. Hussain et al. [18] proposed a model to forecast surface roughness for machining of GFRP tubes using carbide tool through fuzzy model. Cutting speed, depth of cut, feed rate and work piece were the four parameters used to decrease the surface roughness.

The cutting parameters should be optimized to achieve high MRR and low SR. This thought motivates us to find out the optimal cutting parameters for machining of UD-GFRP. We have proposed an organized and sophisticated approach to solve this parameter optimization problem. The algorithm had taken into account rate of tool feed, depth of cut and speed of cutting to decrease the roughness of targeted surface as well as increase the rate of material removal.

Underlying proposed approach is to design experiments using Taguchi's orthogonal array approach with preselected machining state. The machining parameters rate of tool feed, nose radius of cutting tool, speed of cutting, environment used for cutting (dry, wet and cool), rake angle of cutting tool and depth of cut are optimized with multiple feedback features as SR and MRR and models are proposed for average SR and MRR. The proposed models are used for optimization and optimized parameters are obtained which can provide higher MRR and lower average SR. The NSGA II is selected for this process of optimization of the cutting parameters in machining of UD-GFRP.

This chapter is organized as follow: Section 4.2 discusses the experimental procedure opted to get real time values of the cutting parameters. NSGA II is concisely demonstrated in Section 4.3. Parameter optimization using NSGA II is explained in Section 4.4.

4.2 Experimental Process

4.2.1 Material Used

Sardana et al. [19] used unidirectional reinforced plastic (UD-GRFP) composite rods which are pultrusion processed. Pultrusion process is a potential way to produce strong lightweight composite materials. The pultrusion denotes the process of passing the material through the machinery. Fibers are drawn from spools using a device with coating of a resin. The length of rod used is 840 mm and diameter is 42 mm. The fiber and resin used is E-glass and epoxy respectively. Figure 4.1 shows the composite rod part used for experimentation and the material properties are given in Table 4.1.

Table 4.1: Properties of UD-GFRP material.

SN	Property	Value	Dimension
1	Compression Strength	600	(N/mm^2)
2	Density	1.95-2.1	gm/cc
3	Electrical Strength(Radial)	3.5	KV/mm
4	Epoxy Resin composition (by weight)	25+5 or 25-5	%
5	Glass composition (by weight)	75+5 or 75-5	%
6	Martens Heat Distortion Temperature	210	Centigrade
7	Modulus of elasticity	320	(N/mm^2)
8	Reinforcement, unidirectional	E-Glass Roving	—
9	Shear Strength	255	(N/mm^2)
10	Tensile Strength	650	(N/mm^2)
11	Thermal Conductivity	0.30	Kcal/Mhc
12	Water absorption	0.07	%
13	Weight of rod used	2.300	Kgs
14	Working Temperature Class	Class 'F' (155)	Centigrade

Figure 4.1: UD-GFRP composite rod specimens

4.2.2 Taguchi Approach

Dr. Taguchi of Japan has developed a method based on orthogonal array experiments which provides much less variance for the experiments with optimal set of control factors. Orthogonal array gives a least set of experiments and Dr. Taguchi's signal to noise ratios (S/N) serve as objective function for optimization. Taguchi's method categorize S/N ratios as follows: the nominal the best, the smaller the better, the larger the better.

In this paper removal rate of material is taken larger the better and roughness of the targeted surface is taken smaller the better. The respective loss functions are defined as shown in equation 4.1 and equation 4.2.
Smaller the better:

$$S/N_{SR} = -10Log_{10}\left(\frac{\sum_{i=1}^{M} x_i^2}{M}\right) \tag{4.1}$$

Larger the better:

$$S/N_{MRR} = -10Log_{10}\left(\frac{\sum_{i=1}^{M} \frac{1}{x_i^2}}{M}\right) \tag{4.2}$$

where M is the aggregate number of records and x_i is the value of i^{th} record.

4.2.3 Control Parameters

Table 4.2 shows the control parameters used by Taguchi's method for optimization.

Table 4.2: Control Parameters

SN	**Parameter**	**Unit**
1	Nose Radius of cutting tool	mm
2	Rake Angle of cutting tool	Degrees
3	Rate of tool feed	mm/rev.
4	Speed of cutting	m/min.
5	Environment used for cutting	–
6	Depth of Cut	mm

4.2.4 Objective Metrics

In machining, the common basis selected for evaluating machinability are Roughness of targeted surface (SR) and Rate of material removal (MRR). This is observed that the two related to each other through the worth of machining process and they can be significantly serve as the base of comparison.

In the current paper Average Roughness of targeted surface (S_a) and Rate of material removal (MRR) are selected as objective metrics as described below:

1. **Average Surface Roughness:** Surface roughness is serving as a major particular in machining of composites. The average surface roughness (S_a) is selected for present study, which is largely used in industry. The surface roughness was measured at number of times and averaged Palanikumar et al. [20]. The roughness of surface was measured using an instrument as shown in Figure 4.2.

Figure 4.2: Tokyo Seimitsu Surfcom 130A type instrument for Surface Roughness Testing.

2. **Rate of material removal:** Rate of material removal (MRR) is also a major particular in deciding the machining operation. A larger MRR is required in such operations. MRR is given as following:

$$MRR = \frac{\frac{\pi}{4}D^2L - \frac{\pi}{4}d^2L}{t_c} \tag{4.3}$$

where D=Diameter's initial value (mm), d=Diameter's final (mm), L=length (mm), t_c=L/f_rS is the machining time, S=Speed of spindle (rpm), f_r=feed rate (m/revolution).

where D=Dry, W=Wet and C=Cooled.

A plan of 18 experiments is made with nose radius of cutting tool, rake angle of cutting tool, rate of tool feed, speed of cutting, environment used for cutting (dry,wet,cooled) and depth of cut are treated as parameters using Taguchi's orthogonal array approach. The experimental results are shown above in table 4.3. Based on these results, the mathematical models were prepared with only the required parameters [19]. Taguchi's

Table 4.3: Experimental Results.

Sr. No.	**Nose Radius of cutting tool** (mm)	**Rake Angle of cutting tool** (degrees)	**Rate of tool feed** (mm/rev)	**Speed of cutting** (m/min)	**Environment for cutting**	**Depth of cut** (mm)	**Average Roughness of targeted surface** $(R_a)(\mu$m)	**Rate of material removal** $(mm^3$/sec)
1	0.4	-6	0.05	55.42	D	0.2	1.397	8.6
2	0.4	-6	**0.1**	**110.84**	W	**0.8**	**1.453**	**144.99**
3	0.4	-6	**0.2**	**159.66**	C	**1.4**	**3.076**	**340.61**
4	0.4	0	0.05	55.42	W	0.8	1.366	36.24
5	0.4	0	0.1	110.84	C	1.4	1.53	249.91
6	0.4	0	0.2	159.66	D	0.2	2.4	105.93
7	0.4	+6	0.05	110.84	D	1.4	1.513	124.99
8	0.4	+6	0.1	159.66	W	0.2	1.636	52.97
9	0.4	+6	0.2	55.42	C	0.8	2.263	144.99
10	0.8	-6	0.05	159.66	C	0.8	1.547	104.4
11	0.8	-6	0.1	55.42	D	1.4	1.606	125.00
12	0.8	-6	0.2	110.84	W	0.2	1.966	73.57
13	0.8	0	0.05	110.84	C	0.2	1.597	18.39
14	0.8	0	0.1	159.66	D	0.8	1.63	208.85
15	0.8	0	0.2	55.42	W	1.4	2.237	250.08
16	0.8	+6	0.05	159.66	W	1.4	1.940	180.01
17	0.8	+6	0.1	55.42	C	0.2	1.486	18.38
18	0.8	+6	0.2	110.84	D	0.8	1.973	275.85

optimization technique is applied separately on roughness of targeted surface and rate of material removal with same parameters and results are observed. So for comparison we need a multiple objective optimization technique to be applied in the mathematical models developed using the experimental data.

In this work rate of tool feed, speed of cutting and depth of cut have been used to figure up the machining of UD-GFRP. The computation of cutting parameters may not be computed by means of one(single) objective function that required to be optimized. So, the classical optimization technique is not appropriate for computing optimum values of cutting parameters. An alternative modern approach for parameter estimation is soft computing. Non-dominated sorting genetic algorithm II (NSGA II) is being utilized for this objective, details of which are given in Section-4.3.

4.3 Non-dominated sorting genetic algorithm II (NSGA II)

Non-dominated sorting genetic algorithm II (NSGA II) [21] observe a supplementary set of solutions using a race (population) for feasible solutions, denoted as chromosomes. Chromosomes are described by a Y-dimensional vector $[x_{j1}, x_{j2}, ..., x_{jY}]$ where j=1, 2,..., NC is the race size (number of chromosomes). Each decision variable x_{jz} for z=1, 2, ..., Y in j^{th} chromosome represents z^{th} threshold value. The initial race is computed randomly and corresponding fitness function readings are taken using equation 4.4 and equation 4.5. Before applying the genetic algorithm operations i.e. "selection, crossover and mutation" to generate a new solution, supposed race is ordered using NSGA II sorting method i.e. "non-dominated sorting technique and crowding distance". The sorting approach appoint a value to every solution with $O(BNP^2)$ computational complexity, where B represent total count of fitness functions. Crowding distance measure the affinity of a solution(individual) respective to its nearby solutions i.e. the closeness of solutions. It is computed using the average of distances from its on hand neighbors along same front in each aspect. Assignment of parents from the population is carried out using binary-tournament selection method which depends on two factors, crowding distance and rank. Now from this sorted population, new children(solutions) are generated using GA operators i.e. "crossover and mutation". This procedure is reiterated till the termination condition is satisfied which is specified by number of generations. In this work, binary-tournament [22], single-point crossover [23], and single-point mutation operator [23] are operated for NSGA II implementation.

Algorithm 4.1 : Non-dominated sorting genetic algorithm II (NSGA II).

Intake: Size of race (NC) and allowed iterations.
Turnout: A group of perfect solutions defined as optimal pareto front

1. The race NP of dimension NC is initialized randomly.
2. Calculate the fitness function readings through equation 4.4 and equation 4.5.
3. Arrange the race through defined operations i.e. "non-dominated sorting technique and crowding distance."
4. Pick the individuals through the selection method i.e. "binary-tournament".
5. Apply GA operations i.e. "crossover and mutation" on the elected parents.
6. Perform the choice between the individuals and their new generation.
7. Replace incompatible solutions(individual) with the compatible ones to maintain a constant population size.
8. Repeat the steps 2−7 until termination condition is achieved.

4.4 Parameter Optimization for machining of UD-GFRP using NSGA II

There are several parameters used by PCD tool in machining of UD-GFRP. The literature reveals that there are total six parameters that affect the cutting process of UD-GFRP. These parameters are described in Table 4.2.Out of these six parameters only significant parameters are selected. The selected parameters are Rate of tool feed, Speed of cutting and Depth of Cut. There are two objectives for machining of UD-GFRP. First is to maximize the Rate of material removal (MRR(p)) and second is to minimize the Roughness of targeted surface (SR(p)) for a provided group of parameters. The two fitness functions are described as:

$$FitnessFunction1 = minimum(SR(p)) \tag{4.4}$$

$$FitnessFunction2 = maximum(MRR(p)) \tag{4.5}$$

The parameters set is represented as $\mathbf{P} = (p_1, p_2, p_3)$ where, $p_1 \rightarrow$ Rate of tool Feed, $p_2 \rightarrow$ Speed of cutting, p_3, $\rightarrow$ Depth of Cut. The thorough steps for predicting these parameters are provided in Algorithm 4.1. This algorithm provides a set of best solutions known as pareto-optimal front shown in Figure 5.1. Initial generated random sample of the population is given as:

p_1	p_2	p_3
0.05	75.00	0.45

The next chapter provides the results and discussion of the result.

Chapter 5

Result and discussion

This chapter discuses about environment setup, NSGA II implementation, its parameter setting and results.

5.0.1 Environment setup

NSGA II is programmed in Octave 4.0.0. Details about machine configuration and softwares used are provided in the Table 5.1.

Table 5.1: Environment used for simulation.

Category	**Model/Configuration**
Chipset	Intel® Z87
Processor	Intel® Core™ i7-M370, 3.2 GHz
Video Card	NVIDIA GEFORCE 840
RAM	1 x 8 GB DDR4
Hard Disk (Storage)	Dell 1 x 1 TB
Operating system	Linux (Ubuntu 14.04 LTS)
NSGA II Implementation	Octave 4.0.0

5.0.2 Parameter Setting for NSGA II

Table 5.2: Parameters and their values used by NSGA II.

Parameter	**Setting**
NSGA II Implementation	Octave 4.0.0 (GNU GPL Licensed)
GA Operations	Single point Crossover and Single point Mutation
Selection Method	Binary Tournament
Crossover Rate (CR)	0.8
Mutation Rate	0.02
Race (Population) Size	100
Maximum allowed Iterations (Generations)	200

5.0.3 Results and Illustration

In this current work NSGA II is being used to optimize the machining parameters using the defined objectives. The hundred generations were computed to get the perfect optimized solution. The non-dominated solution set obtained as pareto optimal front is shown in figure 3.

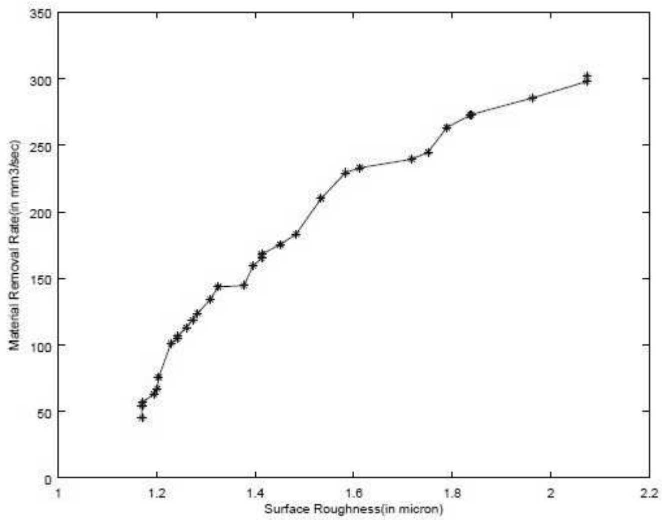

Figure 5.1: Pareto Optimal graph using NSGA II for the defined objectives.

The figure 5.1 shows the pareto optimal front heading to concluding set of values. Out of 100 observations a set of 40 observations is represented as table 5.3. Since no solution in the presented set of non-dominated solutions is better than any of the remaining solutions, each one of them is superior solution. If the production engineer is desired to have better roughness of targeted surface or a greater rate of material removal, a relevant sequence of values might be chosen form table 5.3.

From the experimental values presented in table 4.3 the parameter of trial no 3 resulted ia an R_a of 3.076 μm and MRR of 340 mm^3/sec. After optimization of parameters with NSGA II, it can be seen that the R_a has been reduced to 1.287 μm and for the nearly equal MRR has been increases to 345.11 mm^3/sec (refer to table 5.3, serial no 25). Similarly, the improvement can be seen in other observations also (trial 2 of table 4.3 and trial 10 of table 5.3).

Table 5.3: Optimized machining parameters using the NSGA II.

Sr. No.	**Rate of tool feed** mm/rev	**Speed of cutting** m/min	**Depth of Cut** mm	**Roughness of targeted surface** μm	**Rate of material removal** mm^3/sec
1	0.05	75.00	0.45	1.168	45.00
2	0.06	76.30	0.49	1.170	45.18
3	0.07	85.55	0.52	1.171	56.88
4	0.06	76.28	0.49	1.170	45.18
5	0.09	77.70	0.47	1.189	60.15
6	0.09	76.36	0.47	1.194	63.15
7	0.08	92.55	0.46	1.199	64.12
8	0.10	96.20	0.68	1.272	118.70
9	0.08	88.50	0.81	1.242	104.45
10	**0.10**	**108.86**	**0.80**	**1.410**	**165.08**
11	0.09	88.65	0.78	1.192	63.00
12	0.08	93.12	0.75	1.190	62.58
13	0.11	104.12	0.85	1.186	60.12
14	0.10	96.12	0.68	1.270	118.65
15	0.08	88.98	0.82	1.241	104.45
16	0.12	96.12	0.68	1.271	115.51
17	0.11	83.21	1.09	1.413	165.12
18	0.11	83.22	1.10	1.412	164.95
19	0.13	100.50	0.87	1.480	182.11
20	0.12	98.21	0.75	1.284	186.01
21	0.11	100.50	1.32	1.580	225.61
22	0.12	103.35	1.08	1.483	215.13
23	0.15	104.11	1.15	1.762	260.54
24	0.18	125.14	1.08	2.078	295.12
25	**0.20**	**159.56**	**1.4**	**1.287**	**345.11**
26	0.19	116.14	1.05	2.139	300.75
27	0.16	147.11	1.16	2.184	314.45
28	0.15	104.15	1.17	1.784	265.11
29	0.18	125.34	1.05	2.044	270.1
30	0.11	112.04	0.95	1.324	197.10
31	0.16	148.05	1.15	2.185	315.10
32	0.19	117.20	1.07	2.135	301.54
33	0.12	138.12	1.30	1.852	275.01
34	0.14	154.15	1.31	2.195	320.14
35	0.13	101.23	0.86	1.458	184.12
36	0.09	120.95	0.98	1.452	175.45
37	0.10	107.45	0.81	1.412	166.01
38	0.11	83.14	1.10	1.414	168.12
39	0.15	104.10	1.81	1.789	262.80
40	0.19	117.25	1.05	2.184	315.21

Chapter 6

Conclusions and Future Works

This chapter includes the final outcome of the work carried out by this thesis and also suggests some directions through which the present work should be further investigated. Section 6.1 takes out the final outcomes reached through the research process performed by this thesis and in section 6.2 directions related to the future extension of the research work and how to achieve these objectives are made.

6.1 Conclusion

This thesis results as a trial to find solution to the problem of optimization of cutting parameters in machining of UD-GFRP using NSGA II algorithm and approaches of machine learning. Several phases are designed to achieve main contribution of this thesis and are presented as shown:

1. The important parameters of machining process are selected (Chapter 2).
2. Taguchi's method is explored and experimental values are collected. (Section 4.2.2).
3. The two objectives are formulated (Chapter 4) and used by NSGA II for optimization.
4. A comparative performance study is carried out between the experimental parameter values and predicted parameter values (Chapter 5).
5. A pareto optimal set is presented as a graph to compare the two objectives relatively (Figure 5.1).

6.2 Scope for future work

Research is a repeated and always going on process. The aim of the research presented in the thesis is to perform optimization of cutting parameters in machining of UD-GFRP using NSGA II algorithm along with machine optimization approaches. It is evident that a lot of directions exists in which the presented work could be taken for expansion. A bit of the opinions in the direction of the future work are:

1. Efficient modification can be done in the parallel implementation of the proposed NSGA II algorithm that may improves its performance. A parallel processed algorithms can be implemented for a distributed and shared-memory architecture.

2. The research can be used to develop a tool (Web based or windows based) so that production engineers can get their desired parameter values according to their needs.

3. The optimization of cutting parameters is done using three parameters such as Rate of tool feed, speed of cutting and depth of cut. More parameters need to be explored for more accurate prediction.

4. In this thesis, only NSGA II evolutionary optimization algorithm is used. New multi-objective evolutionary algorithms are feasible and need some sort of exploration for the sake of accuracy and fast forseights.

References

[1] A. Törn, M. M. Ali, and S. Viitanen, "Stochastic global optimization: Problem classes and solution techniques," *Journal of Global Optimization*, vol. 14, no. 4, pp. 437–447, 1999.

[2] Y. Ermoliev, *Numerical techniques for stochastic optimization.* Springer-Verlag New York, Inc., 1988.

[3] Z. Michalewicz and M. Schoenauer, "Evolutionary algorithms for constrained parameter optimization problems," *Evolutionary computation*, vol. 4, no. 1, pp. 1–32, 1996.

[4] A. Lisnianski and G. Levitin, "Assessment, optimization and applications," 2003.

[5] K. Miettinen, F. Ruiz, and A. P. Wierzbicki, "Introduction to multiobjective optimization: interactive approaches," in *Multiobjective Optimization.* Springer, 2008, pp. 27–57.

[6] Y. Censor, "Pareto optimality in multiobjective problems," *Applied Mathematics and Optimization*, vol. 4, no. 1, pp. 41–59, 1977.

[7] R. T. Marler and J. S. Arora, "Survey of multi-objective optimization methods for engineering," *Structural and multidisciplinary optimization*, vol. 26, no. 6, pp. 369–395, 2004.

[8] H. Tönshoff, J. Wulfsberg, H. Kals, W. König, and C. Van Luttervelt, "Developments and trends in monitoring and control of machining processes," *CIRP Annals-Manufacturing Technology*, vol. 37, no. 2, pp. 611–622, 1988.

[9] R. Q. Sardinas, M. R. Santana, and E. A. Brindis, "Genetic algorithm-based multi-objective optimization of cutting parameters in turning processes," *Engineering Applications of Artificial Intelligence*, vol. 19, no. 2, pp. 127–133, 2006.

[10] E. Zitzler and L. Thiele, "Multiobjective optimization using evolutionary algorithmsa comparative case study," in *Parallel problem solving from naturePPSN V.* Springer, 1998, pp. 292–301.

[11] J. J. Grefenstette, "Optimization of control parameters for genetic algorithms," *Systems, Man and Cybernetics, IEEE Transactions on*, vol. 16, no. 1, pp. 122–128, 1986.

[12] A. Konak, D. W. Coit, and A. E. Smith, "Multi-objective optimization using genetic algorithms: A tutorial," *Reliability Engineering & System Safety*, vol. 91, no. 9, pp. 992–1007, 2006.

[13] M. Chua, M. Rahman, Y. Wong, and H. Loh, "Determination of optimal cutting conditions using design of experiments and optimization techniques," *International Journal of Machine Tools and Manufacture*, vol. 33, no. 2, pp. 297–305, 1993.

[14] J. Ferreira, N. Coppini, and F. L. Neto, "Characteristics of carbon–carbon composite turning," *Journal of Materials Processing Technology*, vol. 109, no. 1, pp. 65–71, 2001.

[15] G. Spur and U. Wunsch, "Turning of fiber-reinforced plastics," *Manuf Rev*, vol. 1(2), pp. 24–129, 1988.

[16] H. Takeyama and N. Iijima, "Machinability of glassfiber reinforced plastics and application of ultrasonic machining," *CIRP Annals-Manufacturing Technology*, vol. 37, no. 1, pp. 93–96, 1988.

[17] S.-O. An, E.-S. Lee, and S.-L. Noh, "A study on the cutting characteristics of glass fiber reinforced plastics with respect to tool materials and geometries," *Journal of Materials Processing Technology*, vol. 68, no. 1, pp. 60–67, 1997.

[18] S. Hussain, V. Pandurangadu, K. Palanikumar, and V. Bharathi, "A predictive model for surface roughness in turning glass fiber reinforced plastics by carbide tool (k-20) using soft computing," *Jordan Journal of Mechanical and Industrial Engineering*, vol. 5, no. 5, pp. 433–438, 2011.

[19] S. Kumar, M. Gupta, P. Satsangi, and H. Sardana, "Modeling and analysis for surface roughness and material removal rate in machining of ud-gfrp using pcd tool," *International Journal of Engineering, Science and Technology*, vol. 3, no. 8, pp. 248–270, 2011.

[20] K. Palanikumar and R. Karthikeyan, "Assessment of factors influencing surface roughness on the machining of al/sic particulate composites," *Materials & design*, vol. 28, no. 5, pp. 1584–1591, 2007.

[21] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: Nsga-ii," *Evolutionary Computation, IEEE Transactions on*, vol. 6, no. 2, pp. 182–197, 2002.

[22] B. L. Miller and D. E. Goldberg, "Genetic algorithms, selection schemes, and the varying effects of noise," *Evolutionary Computation*, vol. 4, no. 2, pp. 113–131, 1996.

[23] S.-Y. Shin, I.-H. Lee, D. Kim, and B.-T. Zhang, "Multiobjective evolutionary optimization of DNA sequences for reliable DNA computing," *IEEE Tran. on Evol. Comp.*, vol. 9, no. 2, pp. 143–158, 2005.

[24] N. Srinivas and K. Deb, "Muiltiobjective optimization using nondominated sorting in genetic algorithms," *Evolutionary computation*, vol. 2, no. 3, pp. 221–248, 1994.

[25] S. Kukkonen and K. Deb, "A fast and effective method for pruning of non-dominated solutions in many-objective problems," in *Parallel Problem Solving from Nature-PPSN IX*. Springer, 2006, pp. 553–562.

Appendix

A.1 Dominated Sorting

The dominated sorting technique [24] used by NSGA II is shown below:

`fast-non-dominated-sort`(P)

for each $p \in P$
  $S_p = \emptyset$
  $n_p = 0$
  for each $q \in P$
    if $(p \prec q)$ then — If p dominates q
      $S_p = S_p \cup \{q\}$ — Add q to the set of solutions dominated by p
    else if $(q \prec p)$ then
      $n_p = n_p + 1$ — Increment the domination counter of p
  if $n_p = 0$ then — p belongs to the first front
    $p_{\text{rank}} = 1$
    $\mathcal{F}_1 = \mathcal{F}_1 \cup \{p\}$
$i = 1$ — Initialize the front counter
while $\mathcal{F}_i \neq \emptyset$
  $Q = \emptyset$ — Used to store the members of the next front
  for each $p \in \mathcal{F}_i$
    for each $q \in S_p$
      $n_q = n_q - 1$
      if $n_q = 0$ then — q belongs to the next front
        $q_{\text{rank}} = i + 1$
        $Q = Q \cup \{q\}$
  $i = i + 1$
  $\mathcal{F}_i = Q$

A.2 Crowding Distance

The density of solutions surrounding a particular solution is calculated by finding the average distance of two solutions on both sides of particular solution i along all objectives. This is known as crowding distance [25]. Figure 6.1 shows the crowding distance of i^{th} solution in its front is the average side length of the cuboid (shown by box in figure).

The crowding distance is calculated using following steps:

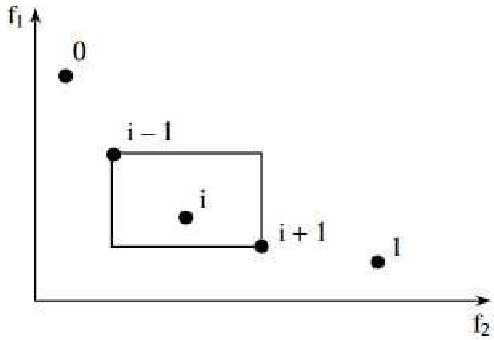

Figure 6.1: Calculation of crowding distance

Step 1: The number of solutions in Front F_r is called as v. For each solution in the set, first assign crowding distance as 0.

Step 2: For each objective function f_m, m =1, 2,..., M, sort the set in worse order of f_m or, find the sorted indices vector, F_m = sort (f_m, >).

Step 3: For m = 1, 2,..., M, assign a large distance to the boundary solutions, 1 is the first solution in the front and l is the last solution in the front, or $d_{F_1^m} = d_{F_l^m} = \infty$, and for all other solutions j = 2 to (l – 1), assign:

$$d_{F_v^m} = d_{F_{v-1}^m} + \frac{f_m^{(F_{v+1}^m)} - f_m^{(F_{v-1}^m)}}{f_m^{max} - f_m^{min}}$$

A.3 Variation of the two objective functions with remaining three parameters

This thesis mainly shows the variation of the two objectives with each other i.e. Surface Roughness with Material Removal Rate. Here is a demonstration of variation of the two objectives with respect to remaining parameters.

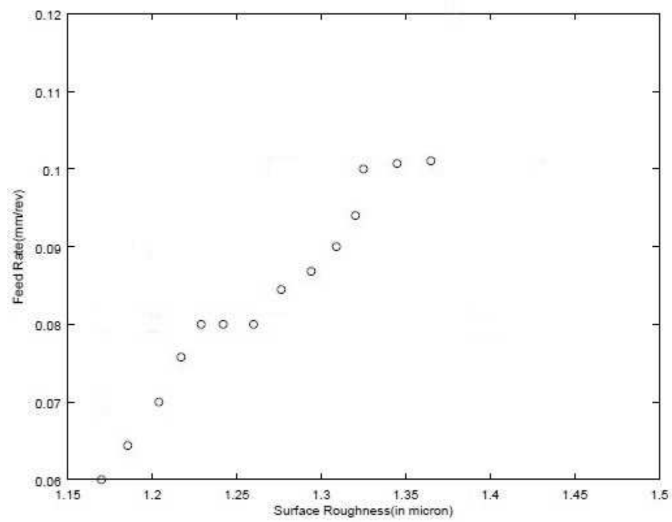

Figure 6.2: Variation of Surface Roughness with Feed Rate

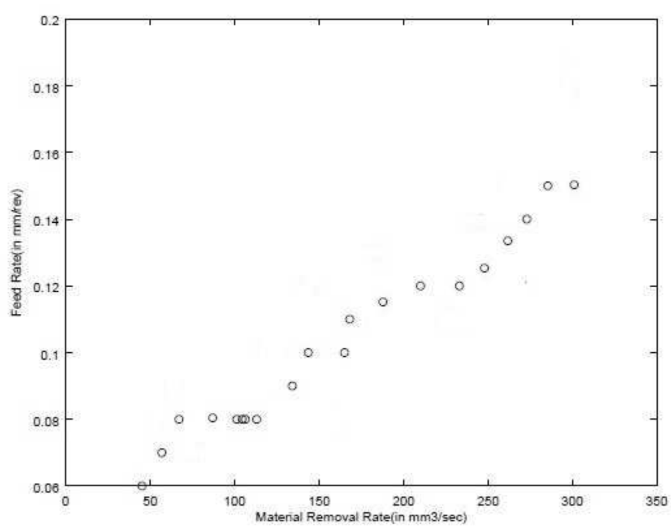

Figure 6.3: Variation of Material Removal Rate with Feed Rate

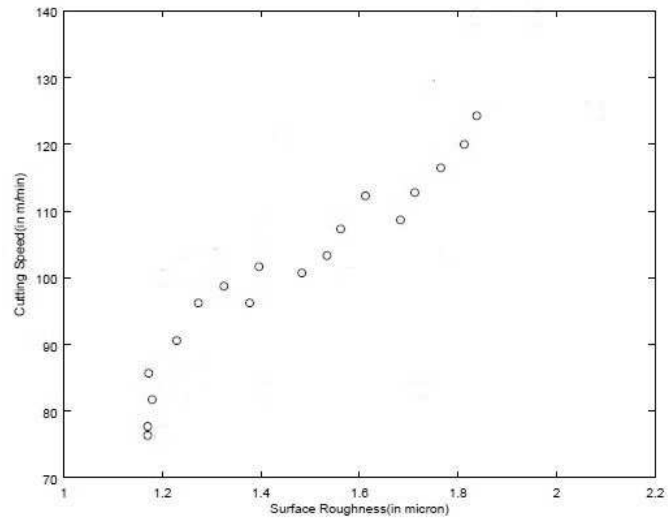

Figure 6.4: Variation of Surface Roughness with Cutting Speed

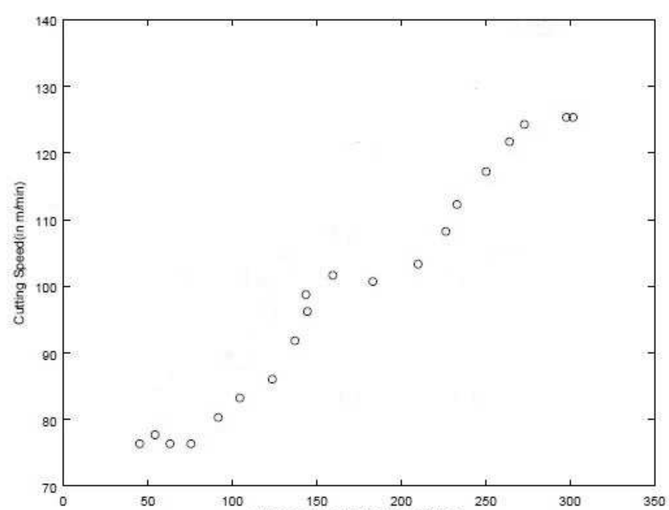

Figure 6.5: Variation of Material Removal Rate with Cutting Speed

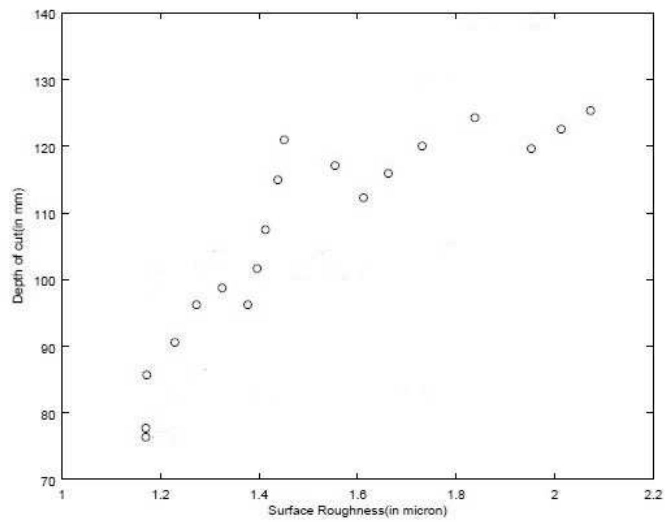

Figure 6.6: Variation of Surface Roughness with Depth of Cut

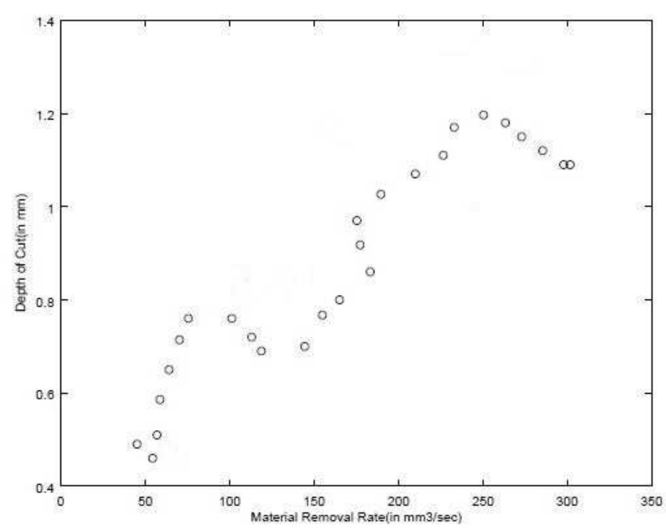

Figure 6.7: Variation of Material Removal Rate with Depth of Cut

Supplement Information

S.1 Video Presentation Link

The video of the current work is available as supplement at https://youtu.be/T3rFReFi1U8

S.2 Publication Status

- **Communicated**

  M. Kumar, P. Rana, "Optimization of cutting parameters in machining of UD-GFRP with PCD Tool using NSGA-II" in 6th International Conference on Soft Computing for Problem Solving SocProS 2016 going to be held at Thapar University Patiala.