MUTLI OBJECTIVE OPTIMIZATION OF POWER DISPATCH PROBLEM USING NSGA-II

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CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, **"Multi Objective Optimization of Power Dispatch Problem using NSGA-II"**, in partial fulfillment of the requirements for the award of degree of Master of Engineering in ***Power Systems & Electric Drives*** submitted in Electrical & Instrumentation Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of Dr. Sanjay K. Jain, Assistant Professor, EIED.

The matter presented in this thesis has not been submitted for the award of any other degree of this or any other university

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ABSTRACT

The optimization of power dispatch is a general term that can be used for the optimization of various objective(s) for thermal units, the economic dispatch, generation scheduling or real power dispatch are interchangeable and can be attempted to find the generation level by minimizing fuel cost. The environmental dispatch is the problem of obtaining the generation by minimizing the emission due to thermal units. The reactive power dispatch is attempted by minimizing the losses incurred in the transmission network. Such optimization must be carried out to obtain the solution subjected to equality constraint by power balance equation these problems when attempted separately are bound to give different results and may be conflicting. This situation is similar to most of the practical decision making or optimization.

The multi objective optimization of power dispatch problems has been attempted by considering various combinations of objective functions corresponding to real power, emission and reactive power dispatch, the emission dispatch is represented as minimization of SO_X, NO_X and CO_X emissions.

An algorithm to attempt such multi objective optimization has been formulated using non dominated sorting genetic algorithm (NSGA-II). The results obtained for NSGA-II are indicating optimal pareto. A program is also developed to obtain best compromise solutions. The performance has been studied for various combinations of objectives for systems employing three generators and six generators.

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CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

The optimization still important for finding an optimal solution. An optimization process consists of three basic components: an objective function, variables, and constraints. The optimization process finds the value of the variables that minimize or maximize the objective function while satisfying the constraints. The problem relies on many variables and therefore various combinations of values of the variables have to be explored to obtain the optimism of the objective function [3]. Sometimes many confliction criteria such as cost, capacity performance and reliability are to be considered simultaneously. It is very difficult to decide which selection is most suitable for the criteria because the criteria may conflict with each other. This is also called a multi-objective optimization problem (MOOP).

The power dispatch problem is a nonlinear programming problem and is used to determine optimal outputs of generators in a power system with objective to minimize the total production cost while the system is operating within its constraints limit. The Power dispatch problem can be divides into two parts, which known as real and reactive power dispatch problem.

The real power dispatch problem aims to minimize the total cost of real power generation from thermal power plants at various stations while satisfying the loads and losses in power transmission system [1]. The objective is to distribute the total demand and total loss among units connected while simultaneously minimizing generation costs and satisfying power balance equation and other constraints.

Along with real power dispatch, reactive power dispatch is also importance in power system. Reactive power dispatch influence the power system stability and power quality. The objective of Reactive power dispatch is to minimizing the real power loss in the power system transmission line while satisfying various constraints.

The operation of thermal power plants depends on combustion of fossil fuels which produces NO_X, SO_X and CO_X emissions. These emissions have given rise to environmental concerns. Even the Clean air act [2] persuades the utilities to change their practices to meet the environmental emission norms. Thus, it becomes important to perform the emission dispatch or include the emission constraints into the real or reactive power dispatch.

A minimum emission dispatch is performed in much the same way as real power dispatch with the end goal being to reduce emissions like NO_X, SO_X and CO_X emissions instead of costs. The fuel cost objective function is replaced by an emissions objective function. The constraints are the same but the optimal solution will produce the lowest total emissions as opposed to the lowest total cost.

The solution of real power dispatch, reactive power dispatch or minimum emission problems, when attempted in isolation will be different and may be conflicting with each other therefore it requires that more than one objective be considered simultaneously for optimization.

1.2 SINGLE OBJECTIVE OPTIMIZATION

A single objective optimization problem is a problem in which one seeks the best (lowest or highest) value of a well defined objective [4].

Min\Maximization $f(x)$

Subjected to $g_j(x) \leq 0$ where $j = 1,2,3\ldots\ldots.j$

$h_k(x) = 0$ where $k = 1,2,3\ldots\ldots k$

where $x = (x_1, x_2 \ldots\ldots\ldots\ldots x_n)$ is a vector of n design decision variable. $g_j(x)$, $h_k(x)$ are inequality and equality constraints, j is the index for inequality constraints and k is the index for equality constraints, j and k are the number of inequality and equality constraints. If the problem is convex for a minimization objective function or concave for a maximization objective function, there will exist only one optimal solution to the problem as shown in figure 1.1 (a) and 1.1 (b) respectively. If the problem is non convex or non concave, there may exist more than one globally optimal solution as shown in figure 1.1 (c). However each globally optimal solution will have the same objective function value.

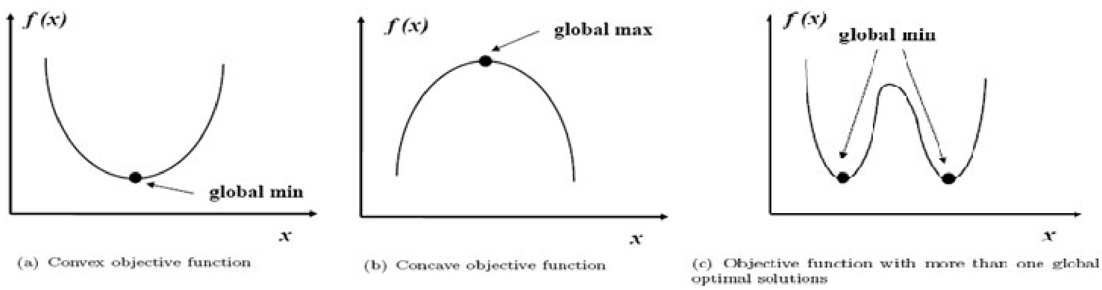


FIGURE 1-1: Various type of optimal solution

While single objective optimization provides a powerful tool to explore the trade space of a given optimization problem, most problems in nature have several objectives to be satisfied. These problems are classified as multi-objective or multi-criteria problems [5].

1.3 MULTI-OBJECTIVE OPTIMIZATION

The multi-objective problem may be presented as:

Min\Maximization $F(x) = [f_1(x), f_2(x) \ldots\ldots\ldots\ldots f_k(x)]$

Subjected to $g_j(x) \leq 0$ where $j = 1,2,3\ldots\ldots\ldots J$

$h_k(x) = 0$ where $k = 1,2,3\ldots\ldots\ldots K$

where $f_1(x), f_2(x) \ldots\ldots\ldots\ldots f_k(x)$ are the objective functions. The objective function can be of minimization or maximization type. In multi-objective optimization, ideally the effort must be made in finding the set of trade –off optimal solution by considering all objective to be important. After a set of such trade off solution are found a user can then use higher level qualitative consideration to make a single choice. The procedure, as shown in figure 1.2, can be used for ideal multi-objective optimization. It involves two step defined as:-

Step 1: Find the multiple trade off optimal solutions with a wide range of value of objective.

Step2: Choose one solution using higher level information.

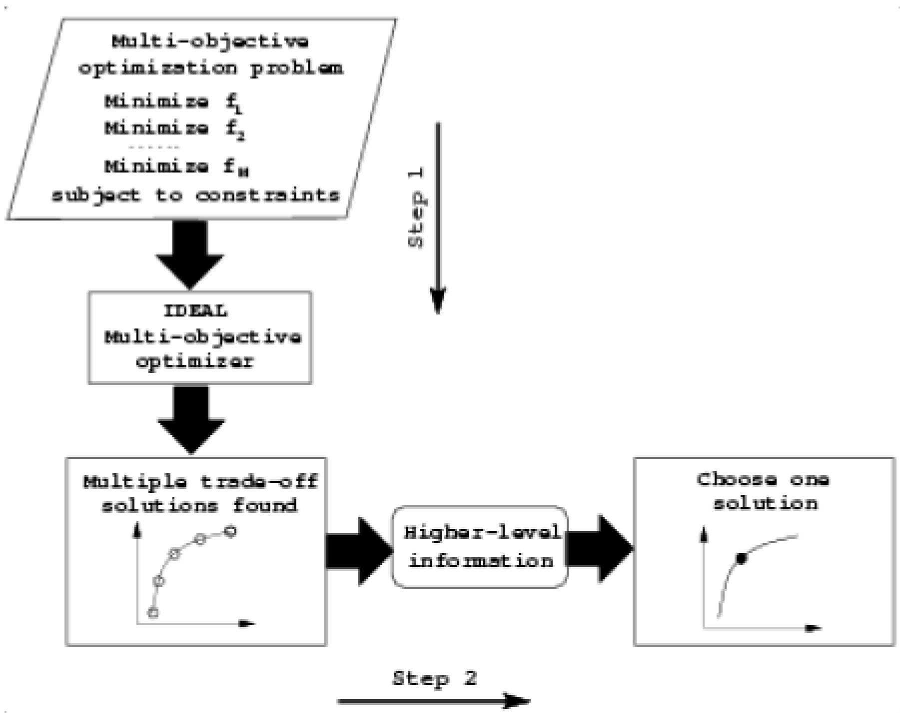


FIGURE 1-2: Ideal Multi objective optimization procedure

A perfect multi-objective solution that simultaneously optimizes each objective function is almost impossible. A reasonable solution to a multi-objective problem is to investigate a set of solutions, each of which satisfies the objectives at an acceptable level without being dominated by any other solution. If all objective functions are for minimization, a feasible solution **x** is said to dominate another feasible solution **y** (**x>y**), if and only if, $f_i(\mathbf{x}) \leq f_i(\mathbf{y})$ for $i=1, \ldots, K$ and $f_j(\mathbf{x}) < f_j(\mathbf{y})$ for least one objective function j. A solution is said to be *Pareto optimal* if it is not dominated by any other solution in the solution space. A Pareto optimal solution cannot be improved with respect to any objective without worsening at least one other objective. The set of all feasible non-dominated solutions in **X** is referred to as the *Pareto optimal set,* and for a given Pareto optimal set, the corresponding objective function values in the objective space is called the *Pareto front*. For many problems, the number of Pareto optimal solutions is enormous (maybe infinite). The ultimate goal of a multi-objective optimization algorithm is to identify solutions in the Pareto optimal set. However, identifying the entire Pareto optimal set, for many multi-objective problems, is practically impossible due to its size. In addition, for many problems, especially for combinatorial optimization problems, proof of solution optimality is computationally infeasible. Therefore, a practical approach to multi-objective optimization is to investigate a set of solutions (*the best-known Pareto set*) that represent the Pareto optimal set as much as possible. With these concerns in mind, a multi-objective optimization approach should achieve the following three conflicting goals:

- The best-known Pareto front should be as close possible as to the true Pareto front. Ideally, the best-known Pareto set should be a subset of the Pareto optimal set.
- Solutions in the best-known Pareto set should be uniformly distributed and diverse over of the Pareto front in order to provide the decision maker a true picture of trade-offs.
- In addition, the best-known Pareto front should capture the whole spectrum of the Pareto front. This requires investigating solutions at the extreme ends of the objective function space.

1.4 CONCEPT OF DOMINATION AND PARETO OPTIMALITY

Multi Objective optimization uses a concept of domination by comparing between two solutions. If a feasible solution is not dominated by any other feasible solutions of the multi-objective optimization problem, a solution is said to be a non-dominated solution. The following procedure can be adopted to find a set of non dominated solutions. $\mathbf{x}^{(1)}$ dominates $\mathbf{x}^{(2)}$ if $\mathbf{x}^{(1)}$ is no worse than $\mathbf{x}^{(2)}$ in all objectives and $\mathbf{x}^{(1)}$ is strictly better than $\mathbf{x}^{(2)}$ in at least one objective. Solution $\mathbf{x}^{(1)}$ is said to dominate $\mathbf{x}^{(2)}$ or $\mathbf{x}^{(1)}$ is said to be non-dominated by $\mathbf{x}^{(2)}$ if both above conditions are true [5].

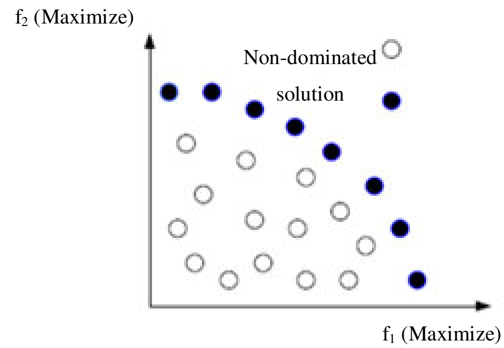


FIGURE 1-3: All solutions of objective functions

Figure 1-3 shows a set of solutions to two objective functions where $f_1(x)$ and $f_2(x)$ are maximized. The set of solutions are consists of dominated solutions and non-dominated solutions. The non-dominated solutions are the black circle and the dominated solutions are clear circle. The set of non-dominated solution is referred as pareto optimal front.

Pareto optimal points are also known as efficient, non-dominated or non-inferior points that are in the relationship of trade-off solutions. Figure 1-4 shows different Pareto optimal solutions sets for different combinations of objective functions.

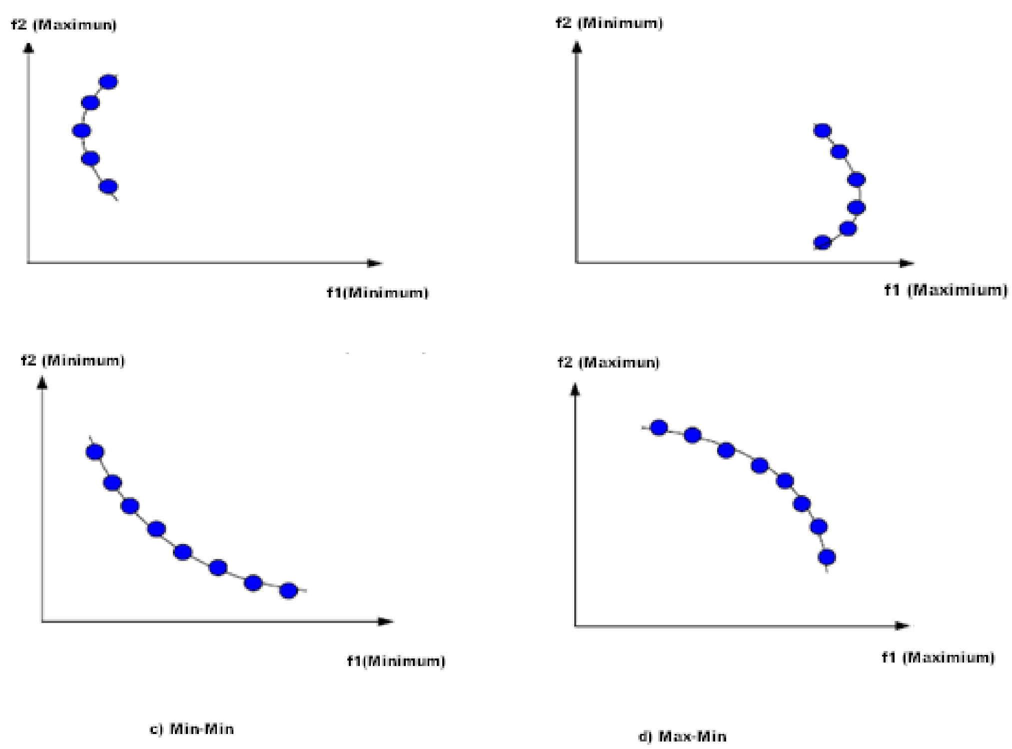


FIGURE 1-4: Nature of Pareto optimal front for different type objective functions

1.5 LITERATURE REVIEW

In power system, the operating cost can be minimized via economic load dispatch i.e. how the real power output of each controlled generating unit in an area is selected to meet a given load and to minimize the total operating costs in the area [1]. The economic load dispatch of an electric power system attempts to determine a generation schedule which will not violate unit operating limits and is capable of minimizing the total generation cost. In the conventional economic dispatch the emission are not considered. Emission control has received increasing attention owing to increased concern over environmental pollution caused by thermal generating units and the enforcement of environmental regulations in recent years. Many approaches [22-69] have been carried out to minimize fuel cost and emission. These studies include use of classical method [23-37], Goal programming techniques [22], Linear programming techniques [17], Neural network [5], fuzzy approach [29, 31] and Evolutionary Algorithms [51-54, 64-68]. A majority of evolution algorithm based studies have been carried out using Genetic algorithms [55, 64- 65].

The literature of the economic dispatch problem and its solution methods are surveyed in [6] and [7]. Recently, a global optimization technique known as genetic algorithm which is a kind of the probabilistic heuristic algorithm has been studied to solve the power optimization problems. Sheble, *et al.* [8-9] used GA to solve the economic dispatch problem and presented the results for three units. Bakirtzis *et al* [10] have proposed a simple genetic algorithm solution to the economic dispatch problem. The operation cost obtained from GA was slightly higher than the optimum cost. Chang and Chen [11] have presented a genetic algorithm for solving economic dispatch problem. The proposed method can take into account network losses, ramp rate and valve point zone.

A fuzzy logic controlled genetic algorithm has been applied to environmental – economic dispatch by Song *et al.* [12] Song and Chou [13] have proposed a hybrid GA that is combination strategy involving local search algorithms and genetic algorithm. The validity of a fuzzy logic controlled genetic algorithm [12] and a hybrid GA [13] is illustrated for economic dispatch problem with a six unit system.

Power utilities seek to provide reliable supply of electrical energy at a reasonable cost while operating to meet the environment limits and constraints. Combustion of fossil fuels produces NOx, SOx and COx emissions. Possible means of meeting these environmental constraints include burning higher quality fuel, replacing older plants with new efficient cleaner plants, considering emission-free alternate forms of energy, upgrading existing plants. In many jurisdictions, provisions are made for utilities to trade unused portions of their emission allowances [14]. Thus, the emission levels can be reduced through economic/environmental dispatching of thermal generating units. A summary of economic/environmental dispatching algorithms using conventional optimization methods has been presented [19].

In recent years, the consideration of emission in economic dispatch has received much attention [2, 15]. In [15-16] the problem has been reduced to a single objective problem by treating the emission as a constraint with a permissible limit. Alternatively, minimizing the emission has been handled as another objective in addition to usual cost objective. A linear programming based optimization procedures in which the objectives are considered one at a time was presented in [17]. The multi objective environmental and economic dispatch (EED) problem was converted to a single objective problem by linear combination of different objectives as a weighted sum [18-19]. The important aspect of this weighted sum method is that a set of non-inferior (or Pareto-optimal) solutions can be obtained by varying the weights. This requires multiple runs as many times as the number of desired Pareto-optimal solutions. Goal programming method was also proposed for multi objective EED problem [20]. In this method, a target or a goal to be achieved for each objective is assigned and the objective function will then try to minimize the distance from the targets to the objectives. This method requires a priori knowledge about the shape of the problem search space.

Several algorithms have been introduced in the past decade for the multi objective power dispatch (MPD) problem. Gent and Lamont [21] proposed minimizing the total emission dispatch. Nanda *et al.* [22-23] introduced the goal programming technique and the Gauss-Seidel iterative method for the economic-emission dispatch. Numerous investigators [24-27] presented algorithms capable of solving the optimization problem for a power system. Several models have been used to represent emission levels. Zahavi and Eisenberg [18] used a second order polynomial, while Kermanshahi, *et al.* [20] used the sum of a quadratic and an exponential term. Gent and Lamont [21] used a combination of a straight line and an exponential term.

The recent direction is to handle both objectives simultaneously as competing objectives instead of simplifying the multi objective problem to a single objective problem, A fuzzy multi objective optimization technique for EED problem was proposed [29]. However, the solutions produced are sub-optimal and the algorithm does not provide a systematic framework for directing the search towards Pareto-optimal front. An evolutionary algorithm based approach evaluating the economic impacts of environmental dispatching and fuel switching was presented in [30]. The important aspect of this approach is that it produces several alternatives along the Pareto-optimal front. A fuzzy satisfaction-maximizing decision approach was successfully applied to solve the bi objective EED problem regarding minimization of both fuel cost and environmental impact of NO_X emissions [31].

Along with real power dispatching reactive power dispatching also keep its importance to provide the optimal power flow in the power systems. Reactive power dispatching is done by minimizing the real power loss across the transmission network. The reactive power dispatching has been done using various classical optimization techniques [32-35], the fuzzy logic approach has been used for handling the reactive power problem in [36-37]. Rehman *et al.* [38] have studied reactive power dispatch for fuzzy loads. Heuristic approach was used to get the solution of reactive power problem in [39-40]. Genetic algorithm [41-44] has been used as an optimizing technique for solving reactive power problem. Evolutionary programming, Evolutionary strategies [45-49] was applied for reactive power problem. Particle Swarm optimization [50] has been used as an optimization technique to deal with reactive power problem. Differential Evolution and the hybrid evolutionary approaches [51-52] are recent trends to handle reactive power optimization problem. For providing the optimal power flow, both real and reactive power dispatching has been done simultaneously.

Over the last ten years, there has been an increasing interest in applying evolutionary algorithms to multi objective optimization problems. The most contemporary multi objective evolutionary algorithms (MOEAs) are designed to return a set of promising solutions, from which a solution can be picked by a human expert. These methods include Genetic Algorithm approach, Particle Swarm Optimization and Simulated annealing methods.

Most MOEAs use *Pareto domination* to guide the search. A solution is said to dominate another solution, if is no worse than in all objectives and better than in at least one objective. A solution is said to be *non dominated* if it is not dominated by any other solution. Ideally, a MOEA returns the *Pareto optimal* set, the solutions not dominated by any other solution in the search space. If the Pareto optimal set is infinite or very large, the algorithm returns a set of non dominated solutions covering the Pareto set as well as possible. Examples of this work include Zitzler and Thiele's strength Pareto evolutionary algorithm (SPEA) [54], and Deb *et al.*'s non dominated sorting genetic algorithm II (NSGA-II) [55].

Even though contemporary MOEAs work with several objectives simultaneously, they still transform all of the objectives into one fitness measure. This is necessary, since ultimately what makes an EA work is the selection of highly fit individuals over less fit individuals. This transformation is usually made in an explicit way, e.g., by assigning each solution a measure of its non dominatedness (e.g. SPEA [54], NSGA-II [55]) but it can also be done implicitly. The transformation of multiple objectives into a single fitness measure is usually a costly matter in terms of processing time. Most Pareto-based fitness assignment schemes require that each solution is compared with a large number of other solutions.

1.6 AUTHOR'S CONTRIBUTION

The multi objective optimization of power dispatch problem has been carried out considering the combination of real power dispatch, emission dispatch and reactive power dispatch. The objective functions for these are minimization of fuel cost, emission and transmission losses. The problem of multi objective optimization has been solved using non-dominated sorting genetic algorithm NSGA-II. Having obtained the set of non-dominated solution using NSGA-II, the optimal solution calculated using best compromise techniques.

1.7 ORGANIZATION OF THESIS

The work carried out has been summarized in five chapters. The Chapter 1 highlights the brief introduction, summary of work carried out by various researchers. Author's contribution and the outline of the thesis also discussed in this chapter. The Chapter 2 briefly describes NSGA-II method for the optimization of Multi Objective problem. The Chapter 3 explains the various types of power dispatch problem and their formulation using NSGA-II. The Chapter 4 details the results pertaining to various cases and the comparison of results obtained for various solutions. The conclusions and the scope of further work are detailed in Chapter 5.

CHAPTER 2

MULTI OBJECTIVE OPTIMIZATION USING GENETIC ALGORITHM

2.1 BASIC GENETIC ALGORITHM

The basic algorithm by which GAs operate is reasonably well established. GA is inspired by the evolutionary theory explaining the origin of species. In nature, weak and unfit species within their environment are faced with extinction by natural selection. The strong ones have greater opportunity to pass their genes to future generations via reproduction. In the long run, species carrying the correct combination in their genes become dominant in their population. Sometimes, during the slow process of evolution, random changes may occur in genes. If these changes provide additional advantages in the challenge for survival, new species evolve from the old ones. Unsuccessful changes are eliminated by natural selection.

In GA terminology, a solution vector $\mathbf{x} \in \mathbf{X}$ is called an individual or a *chromosome*. Chromosomes are made of discrete units called *genes*. Each gene controls one or more features of the chromosome. In the original implementation of GA, genes are assumed to be binary numbers. In later implementations, more varied gene types have been introduced. Normally, a chromosome corresponds to a unique solution $\mathbf{x}$ in the solution space. This requires a mapping mechanism between the solution space and the chromosomes. This mapping is called an encoding. In fact, GA works on the *encoding* of a problem, not on the problem itself.

GA operates with a collection of chromosomes, called a *population*. The population is normally randomly initialized. As the search evolves, the population includes fitter and fitter solutions, and eventually it converges, meaning that it is dominated by a single solution. For convergence to the global optimum where chromosomes are binary vectors GA use two operators to generate new solutions from existing ones: *crossover* and *mutation*. The crossover operator is the most important operator of GA. In crossover, generally two chromosomes, called *parents*, are combined together to form new chromosomes, called *offspring*. The parents are selected among existing chromosomes in the population with reference towards fitness so that offspring is expected to inherit good genes which make the parents fitter. By iteratively applying the crossover operator, genes of good chromosomes are expected to appear more frequently in the population, eventually leading to convergence to an overall good solution. The mutation operator introduces random changes into characteristics of chromosomes. Mutation is generally applied at the gene level. In typical GA implementations, the mutation rate is very small, typically less than 1%. However the mutation plays a critical role in GA. As discussed earlier, crossover leads the population to converge by making the chromosomes in the population alike. Mutation reintroduces genetic diversity back into the population and assists the search escape from local optima. Reproduction involves selection of chromosomes for the next generation. In the most general case, the fitness of an individual determines the probability of its survival for the next generation. There are different selection procedures in GA depending on how the fitness values are used. Proportional selection, ranking, and tournament selection are the most popular selection procedures. The procedure for genetic algorithm is given as below:

Step 1: **Initialization:** Randomly generate the initial population of size N and set i = 0.

Step 2: **Fitness Assignment:** Evaluate the fitness value for each population based on its objective function value.

Step 3: If the stopping criterion is satisfied, terminate the search and display the result else, go to Step 4.

Step 4: **Crossover**: To generate the offspring using crossover, randomly select two parents solution from the initial population and then generate the two offsprings using crossover operator.

Step 5: **Mutation:** This operator randomly selects one parent solution from the initial population and applies the mutation operator to generate a single offspring.

Step 6: **Selection:** Select *N* solutions from generated population and the old population, based on their fitness. Set generation i = i+1. Go to step 2.

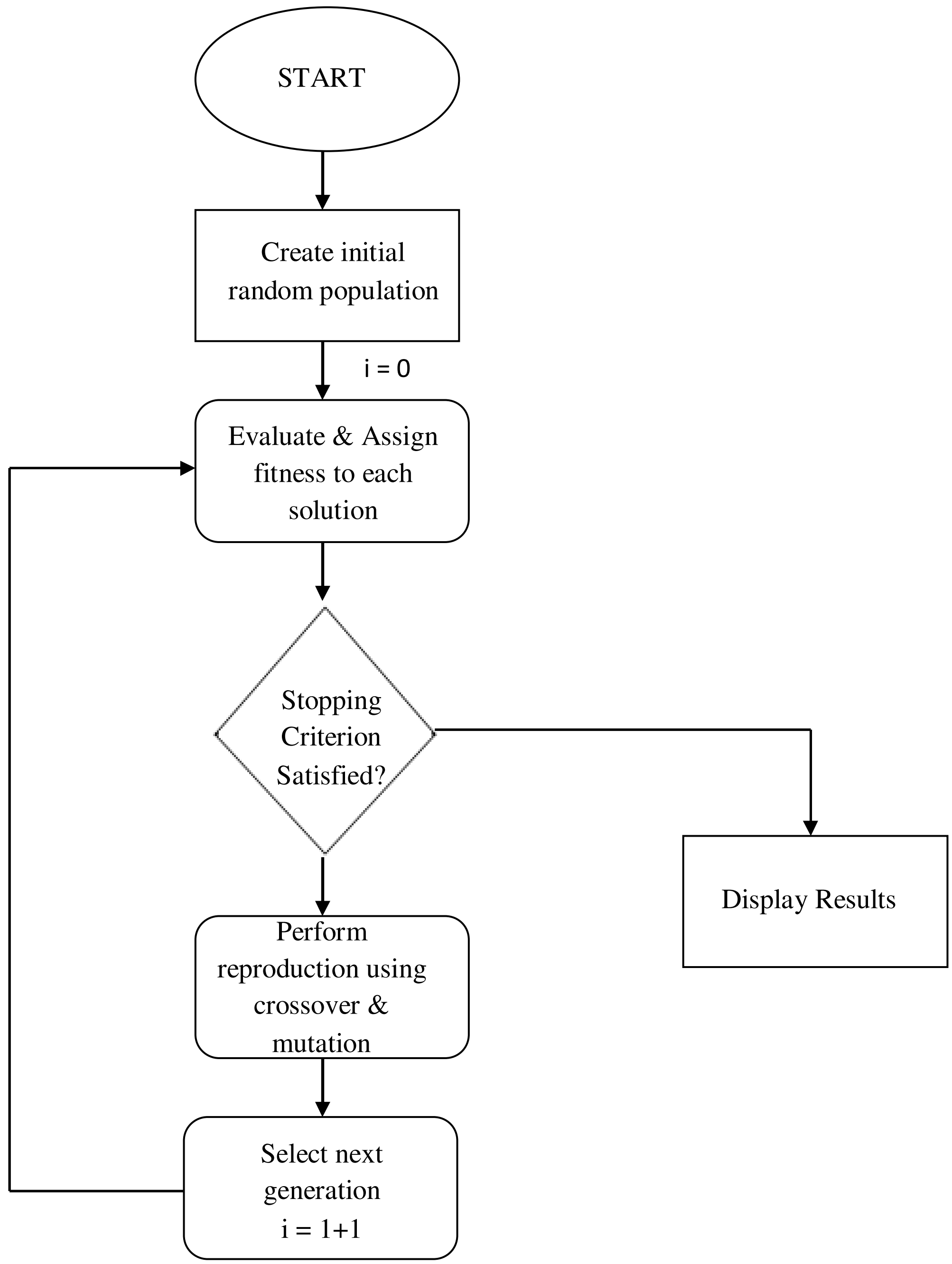


FIGURE 2-1: Block Diagram of Genetic Algorithm

2.2 MULTI OBJECTIVE OPTIMZATION USING GENETIC ALGORITHM

Being a population based approach, GA are well suited to solve multi-objective optimization problems. A generic single-objective GA can be easily modified to find a set of multiple non-dominated solutions in a single run. The ability of GA to simultaneously search different regions of a solution space makes it possible to find a diverse set of solutions for difficult problems with non-convex, discontinuous, and multi-modal solutions spaces. The crossover operator of GA may exploit structures of good solutions with respect to different objectives to create new non-dominated solutions in unexplored parts of the Pareto front. In addition, most multi-objective GA do not require the user to prioritize, scale, or weight objectives. Therefore, GA has been the most popular heuristic approach to multi-objective design and optimization problems. Jones et al. [60] reported that 90% of the approaches to multi-objective optimization aimed to approximate the true Pareto front for the underlying problem. A majority of these used a meta-heuristic technique, and 70% of all meta-heuristics approaches were based on evolutionary approaches. Manly there are four approaches for multi objective optimization in genetic algorithm [56-58]: plain aggregating approaches, population-based non-Pareto approaches, Niched induction approaches, and Pareto-based approaches.

Plain aggregating approaches apply a weighted aggregating method to convert the multi-objective optimization problem into a single objective problem, and then use the single function genetic algorithm to get solutions. Aggregation methods combine multiple objectives into a higher scalar function that are used for fitness calculation. An aggregation approaches have the advantage of producing one single solution. On the contrary, defining the goal function in this way requires profound domain knowledge that is often not available. Popular aggregation methods are the weighted-sum approach, target vector optimization, and the method of goal attainment.

Population-based non-Pareto approaches able to evolve multiple non-dominated solutions then the population is monitored for non-dominated solutions concurrently in a single simulation run by changing the selection criterion during the reproduction phase. The search is guided in several directions at the same time then they cannot make direct use the concept of Pareto dominance or Pareto optimality. A vector evaluated genetic algorithm (VEGA) [61] is a kind of population-based non-Pareto approaches.

Niching approach are suggested to keep GA from convergence to the single point on the front and a niching mechanism such as a fitness sharing that allows GA to maintain individuals along the non-dominated frontier. The use of fitness sharing was proposed to prevent the genetic drift and to promote the sampling of the Pareto set [61].

An idea of using *Pareto-based fitness assignment* is to use the non-dominated ranking and selection to move a population to the Pareto front in MOOP. The basic idea is to find a set of individuals that are the non-dominated solutions to the rest of population. These individuals are assigned the highest rank and eliminated from further contention. Another set of Pareto non-dominated individuals are determined from the remaining individuals and are assigned the next highest rank. This process continues until the individuals are suitably ranked. The examples of Pareto-based are NSAG-II [55]

There are many formulations or variants of multi objective genetic algorithm like Multi-objective Genetic Algorithm (MOGA), Niched Pareto Genetic Algorithm, Non-dominated Sorting Genetic Algorithm [63], Strength Pareto Evolutionary Algorithm (SPEA) and Fast Non-dominated Sorting Genetic Algorithm (NSGA-II). The NSGA-II has been used which is the advanced version of NSGA. Therefore NSGA-II described after reviewing NSGA in the following section:

2.2.1 NON-DOMINATED SORTING GENETIC ALGORITHM (NSGA)

The Non-dominated Sorting Genetic Algorithm (NSGA) was proposed by Srinivas and Deb [63], and is based on several layers of classifications of the individuals. Before selection is performed, the population is ranked on the basis of non-domination: all non-dominated individuals are classified into one category (with a dummy fitness value, which is proportional to the population size, to provide an equal reproductive potential for these individuals). To maintain the diversity of the population, these classified individuals are shared with their dummy fitness values. Then this group of classified individuals is ignored and another layer of non-dominated individuals is considered. The process continues until all individuals in the population are classified. A stochastic remainder proportionate selection was used for this approach. Since individuals in the first front have the maximum fitness value, they always get more copies than the rest of the population. This allows to search for non-dominated regions, and results in quick convergence of the population toward such regions. Sharing by its part helps to distribute it over this region. The efficiency of NSGA lies in the way in which multiple objectives are reduced to a dummy fitness function using a non-dominated sorting procedure. With this approach, any number of objectives can be solved and both maximization and minimization problems can be handled.

The main strength of this technique is that can handle any number of objectives and that does sharing in the parameter value space instead of the objective value space, which ensures a better distribution of individuals, and allows multiple equivalent solutions exist. Its main weakness is that it is more inefficient (both computationally and in terms of quality of the Pareto fronts produced) than MOGA, and more sensitive to the value of the sharing factor σ_{share}. NSGA uses non dominated sorting procedure, which compare each solution in population with every other to find the first non dominated front.

2.2.2 NON-DOMINATED SORTING GENETIC ALGORITHM-II (NSGA-II)

Multi-objective evolutionary algorithms which use non-dominated sorting and sharing (NSGA) have been mainly criticized for their. The main criticism of NSGA approach have been as follows [55]: -

High computational complexity of non-dominated sorting: The non-dominated sorting algorithm in use uptil now is $O(mN^3)$ which in case of large population sizes is very expensive, especially since the population needs to be sorted in every generation.

Lack of elitism: Recent results show clearly that elitism can speed up the performance of the GA significantly; also it helps to prevent the loss of good solutions once they have been found.

Need for specifying the sharing parameter σ_{share}: Traditional mechanisms of insuring diversity in a population so as to get a wide variety of equivalent solutions have relied heavily on the concept of sharing. The main problem with sharing is that it requires the specification of a sharing parameter (σ_{share}). Though there has been some work on dynamic sizing of the sharing parameter, a parameter less diversity preservation mechanism is desirable.

However as mentioned earlier there have been a number of criticisms of the NSGA. In this section, we modify the NSGA approach in order to alleviate all the above difficulties. We begin by presenting a number of different modules that form part of NSGA-II.

The Solutions are competing based on their crowding distances, no niching parameter is required here, as needed in the MOEA, NSGA's & NPGAs. In the absence of the crowding comparison operator, this algorithm also exhibits a convergence proof to the Pareto-optimal solution set, but the population size would grow with the generation counter. The elitism mechanism does not allow an already found Pareto-optimal solution to be deleted. However when the crowded comparison is used to restrict the population size, the algorithm loses its convergence properly.

2.3 DESCRIPTION OF NSGA-II

Two distinct entities are calculated in the NSGA-II to validate the quality of a given solution [5, 64]. The first is a domination-count where the numbers of solutions that dominate a given solution are tracked. The second keeps track of how many sets of solutions a given solution dominates. In the process, all the solutions in the first non-dominated front will have their domination count set to zero. The next step is to select each solution in which the non-domination count is set to zero and visit all other solutions in the solution set and reduce the domination count by one. In doing so, if the domination count of any other solution becomes zero, this solution is grouped in a separate list. This list is flagged as the second non- dominated front. This process is then continued with each member of the second list until the next non-dominated front is identified. The process is continued until all fronts are identified. Based on the non-domination count given to a solution, a non-domination level will be assigned. Those solutions that have higher non-domination levels are flagged as non-optimal and will never be visited again.

One of the key requirements of a successful solution method is ensuring that a good representative sample from all possible solutions is chosen. Introduction of a density estimation process and a crowded-comparison operator has helped NSGA- II to address the above need.

The crowding-distance computation requires sorting of a given population according to each objective function value in ascending order of magnitude. Once this is done, the two boundary solutions with the largest and smallest objective value are assigned distance values of infinity. All other solutions lying in between these two solutions are then assigned a distance value calculated by the absolute normalized distance between each pair of adjacent solutions. After each population member is assigned a crowding-distance value, a crowded-comparison operator is used to compare each solution with the others. This operator considers two attributes associated with every solution which is the non-domination rank and the crowding-distance. Every solution is rated with others based on the non-domination rank. Solutions with lower ranks are deemed better in this attribute. Once solutions that belong to the best front are chosen based on the non-domination rank, the solution that is located in a lesser-crowded region is considered better and forms the basis of the NSGA-II algorithm.

In this approach, the sharing function approach is replaced with a crowded comparison. Initially, an offspring population Q_t is created from the parent population P_t at the t_{th} generation. After, a combined population R_t is formed.

$$\boldsymbol{R_t = P_t \cup Q_t}$$

R_t is sorted into different no domination levels Fj as shown in the NSGA approach. So, we can write :

$$\boldsymbol{R_t = P_t \bigcup_{j=1}^{r} F_j}$$

The main objective of NSGA-II is to find multiple Pareto-optimal solutions in one single simulation run. Since NSGA-II work with a population of solutions [55, 66], a simple multi objective genetic algorithm (MOGA) can be extended to maintain a diverse set of solution. To enhance the convergence properties of multi objective elitist operator is use, it helps to keep the best solution of the current population and does not allow its to deteriorate in next generation. So in this thesis, NSGA-II is used which is known as Elitist Non-dominated Sorting algorithm, main advantage of using these techniques are given below:

- It uses non dominated sorting techniques to provide the solution as close to the pareto-optimal solution as possible
- It uses crowding distance techniques to provide diversity in solution.
- It also uses elitist techniques to preserve the best solution of current population in next generation.

2.4 PROCEDURE FOR NSGA-II

- Initialize the population Pt.
- Create the offspring population Qt from the current population Pt.
- Combine the two populations Qt and Pt to form Rt.
  Rt = Pt U Qt
- Find the all non-dominated fronts Fi of Rt.
- Initiate the new population Pt+1 = /0 and the counter of front for inclusion i = 1.
- While Pt+1 + Fi $\leq$ Npop, do:
  Pt+1$\leftarrow$Pt+1$\cup$Fi, i $\leftarrow$ i+ 1
- Sort the last front Fi using the crowding distance in descending order and choose the first (Npop – Pt+1) elements of Fi.
- Use selection, crossover and mutation operators to create the new offspring population Qt+1 size Nobj.

2.4.1 INITIALIZATION

Initialize the population Pt using equality and inequality constraints. Where power balance constraint is taken as equality constraints and generator capacity constraints is taken as inequality constraints. After initialization it creates offspring population Qt from the current population Pt and then combine the two populations to form Rt. Where Rt is define as:

$$Rt = PtUQt$$

2.4.2 NON-DOMINATED SORTING

After the initialization, the population is sorted on the based on non-domination,

for each ($p\epsilon$P)	
for each ($q\epsilon$P)	
if (p $\prec$ q) then	if p dominates q then
$S_p = S_p$U {q}	add q in the set S_p
else if (q $\prec$ p) then	if p dominated by q
$n_p = n_p + 1$	increment the dominated counter of P i.e n_p
end	
end	
if (n_p= = 0) then	no solution dominate p
$F_1 = F_1$U {p}	then p belong to first front i = 1 initialize the front counter to 1
end	
end	
While ($F_i \neq \emptyset$)	
$Q = \emptyset$	
for each ($p\epsilon F_i$)	for each p in front F_i
for each ($q\epsilon S_p$)	for each q in set Sp
$n_q = n_q - 1$	decrement the domonation count n_q by 1
If ($n_q = 0$) then	if n_q is zero

Q = Q U {q}	add the q in set Q
end	
end	
end	
i = i+1	increment the Front by 1
$F_i = Q$	Set Q is next front
end	

2.4.3 CROWDING DISTANCE

To provide the diversity in population, it is required to calculate crowding distance. Following algorithm is used for calculate the crowding distance of each point in set I:

$l = \|I\|$	l is the number of soluitons in I for each i
set $I[i]_{distance} = 0$	initialize the distance to zero for each individual i in set I
end	
for each objective m	
I = sort(I,m)	sort using each objective value m
$I[1]_{distance} = I[l]_{distance} = \infty$	Assign infinite distance to boundary value for all other point
end	
for (I = 2 to (l-1))	
$I[i]_{distance} = I[i]_{distance} + \frac{I(k+1).m - I(k-1).m}{f_m^{max} - f_m^{min}}$	
end	

I(k).m is the value of the mth objective function of the kth individual in I

2.4.4 SELECTION

Once the individuals are sorted based on non-domination and with crowding distance assigned, the selection is carried out using a *crowded-comparison-operator* *($>_n$)* and best solution is selected. It assumes that every solution i has two attribute:

1. A Non-domination rank (r_i) in population
2. A local Crowding distance ($I[i]_{distance}$)

$i >_n j$	Solution i is better than j
if ($r_i < r_j$)	if rank of ith solution is better than jth
or	
if ($r_i = r_j$)	if they have same rank
and	
($I[i]_{distance} > I[j]_{distance}$)	but the crowding distance of ith solution is better than jth

2.4.5 SIMULATED BINARY CROSSOVER

For the real coded Genetic Algorithm Simulated Binary crossover (SBX) is used [65]. As the name suggest, SBX operator simulates the working principle of the single point crossover operator on binary strings. In this crossover operator the common interval schemata between parents are preserved in offspring. The procedure of computing the offspring $x_i^{(1,t+1)}$, $x_i^{(2,t+1)}$ from the parent solutions $x_i^{(1,t)}, x_i^{(2,t)}$ is described as follows as follows. A spread factor β_i as given in eq. (1) is defined as the ratio of the absolute difference in offspring values to that of the parents:

$$\beta_i = \left| \frac{x_i^{(1,t+1)} - x_i^{(2,t+1)}}{x_i^{(1,t)} - x_i^{(2,t)}} \right| \qquad (1)$$

First, a random number u between 0 and 1 is created. Thereafter, from a specified probability distribution function as given in eq. (2), the ordinate β_{qi} is found so that the area under the probability curve from 0 to β_{qi} is equal to the chosen random number u_i.

$$P(\beta_i) = \begin{cases} 0.5\,(\eta_c + 1)\beta_i^{\eta_c}, & if\ \beta_i \leq 0 \\ 0.5\,(\eta_c + 1)\dfrac{1}{\beta_i^{\eta_c+2}}, & if\ \beta_i > 0 \end{cases} \qquad (2)$$

Figure 2-2 shows the above probability distribution with η_c = 2 and 5 for creating children solutions from two parent solutions ($x_i^{(1,t)} = 2.0$, $x_i^{(2,t)} = 5.0$) and the real space. In the above expressions, the distribution index η_c is any nonnegative real number. A large value of η_c gives a higher probability for creating near parent solutions and a small value of η_c allows distant solutions to be selected as children solutions. Using eq. (3), β_{qi} is calculated by equating the area under the probability curve equal to u_i as follows:

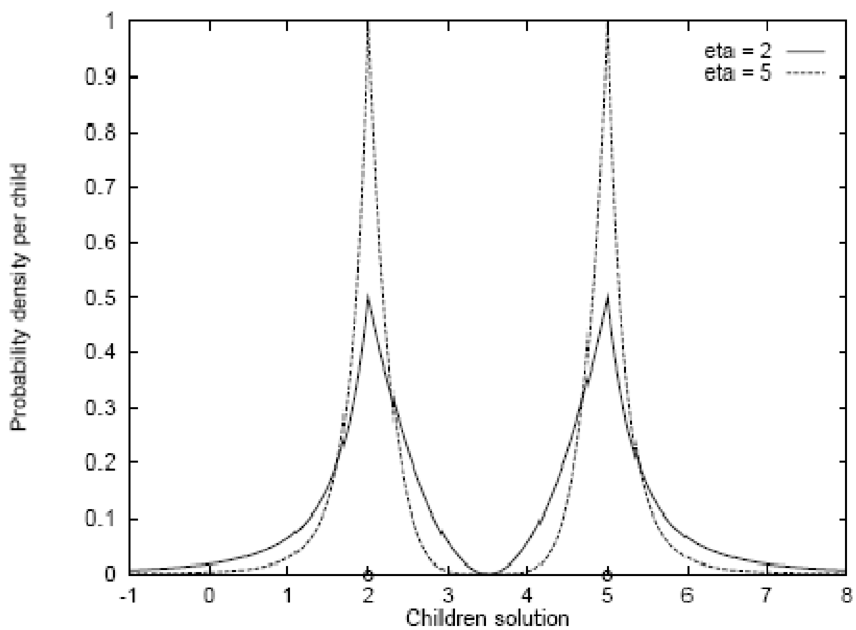


FIGURE 2-2: Probability distribution function for creating children solutions

$$\beta_{qi} = \begin{cases} (2u_i)^{\frac{1}{(\eta_c+1)}}, & if\ u_i \leq 0 \\ \dfrac{1}{[2\,(1-u_i)]^{\frac{1}{(\eta_c+1)}}}, & if\ u_i > 0 \end{cases} \qquad (3)$$

After obtaining βqi from the above probability distribution, the children solutions are calculated as follows.

$$c_{1.k} = \frac{1}{2}\,[(1-\beta_k)p_{1,k} + (1+\beta_k)p_{2,k}] \tag{4}$$

$$c_{2.k} = \frac{1}{2}\,[(1+\beta_k)p_{1,k} + (1-\beta_k)p_{2,k}] \tag{5}$$

where $c_{i.k}$ as given in eq (4) and (5) is the *ith* child with *kth* component, $p_{i.k}$ is the selected parent and β_k (≥ 0) is a sample from a random number generated having the density

Simulated Binary Crossover (SBX) Procedure

Npop = |pop|	Npop is the total number of population for each k
r(1,k) = random(1,Npop)	where r(1,k) and r(2,k) are the randomly genrated
r(2,k) = random(1,Npop)	number between(1to Npop)
p(1,k) = pop(r(1,k))	where p(1,k) and p(2,k) are the randomly selected
p(2,k) = pop(r(2,k))	parent solutions
u_k = random(0,1)	choose any random number between 0 to1
if (u_k>0.5)	
$\beta_k = (2u_k)^{\frac{1}{(\eta_c+1)}}$	η_c is the crossover distribution index β_k is the spread factor
else	
$\beta_k = \frac{1}{[2\,(1-u_i)]^{\frac{1}{(\eta_c+1)}}}$	
end	
$c_{1.k} = \frac{1}{2}\,[(1-\beta_k)p_{1,k} + (1+\beta_k)p_{2,k}]$	
	Where $c_{1.k}$ and $c_{2.k}$ are the offspring populations
$c_{2.k} = \frac{1}{2}\,[(1+\beta_k)p_{1,k} + (1-\beta_k)p_{2,k}]$	
Qt = Qt U $c_{1.k}$	Add both offspring in the set Qt
Qt = Qt U $c_{2.k}$	
end	

2.4.6 POLYNOMIAL MUTATION

The role of mutation operator in GA is to restore lost or unexpected genetic material into a population to prevent the premature convergence at sub-optimal solutions; it ensures that the probability of reaching any point in the search space is never zero. The polynomial mutation operators are described as follows.

$$c_k = p_k + (p_k^u - p_k^l)\delta_k \tag{6}$$

where c_k as given in eq. (6) is the child and p_k is the parent with p_k^u being the upper bound on the parent component, p_k^l is the lower bound and δ_k is small variation which is calculated from a polynomial distribution by using

$$\delta_k = (2r_k)^{\frac{1}{(\eta+1)}} - 1 \qquad \text{if } r_k < 0.5 \tag{7}$$

$$\delta_k = 1 - [(2(1 - r_k)]^{\frac{1}{(\eta+1)}} - 1 \qquad \text{if } r_k \geq 0.5 \tag{8}$$

r_k is an uniformly sampled random number between (0; 1) and m is mutation distribution index.

Polynomial Mutation Procedure

for each k

r(k) = random(1,Npop) where r(k) is the randomly generated number between (1to Npop)

p(k) = pop(r(1,k)) where p(k) is randomly selected parent solutions

u_k = random(0,1) choose any random number between 0 to1

if (u_k < 0.5)

$\delta_k = (2r_k)^{\frac{1}{(\eta+1)}} - 1$ η is the mutation distribution index

else

$\delta_k = 1 - [(2(1 - r_k)]^{\frac{1}{(\eta+1)}}$

end

$c_k = p(k) + (p_k^u - p_k^l)\delta k$

Qt = Qt U c_k

end

2.5 BEST COMPROMISE SOLUTION

Optimization of the above-formulated objective functions using NSGA-II yields set of Pareto optimal solutions [66], in which one objective cannot be improved without sacrificing other objectives. For practical applications, however, is selected one solution, which is satisfying the different goals to some extent. Such a solution is called best compromise solution. The algorithm for best compromise solution is given below:

for each (k ϵ M)	M is the number of objective function
for each (i ϵ Nobj)	Nobj is the number of non-dominate solution
if ($F_i^k > F_{max}^k$)	F_i^k is the fitness value of ith solution of kth objective and
$u_i^k = 1$	F_{max}^k is the maximum fitness value of kth objective function

else if ($F_{min}^k \le F_i^k \le F_{max}^k$)

$$u_i^k = \frac{F_{max}^k - F_i^k}{F_{max}^k - F_{min}^k}$$

else

$u_i^k = 0$

end

end

end

for each (i ϵ Nobj)

$$\beta_i = \frac{\sum_{k=1}^{M} u_i^k}{\sum_{i=1}^{Nobj} \sum_{k=1}^{M} u_i^k}$$

end

where β_i is the normalize membership function.

The β_i provides the fuzzy cardinal priority ranking of the non-dominated solution. Solution attaining the maximum membership β_i in fuzzy set can be considered as best compromise solution.

CHAPTER 3

POWER DISPATCH OPTIMIZATION AND FORMULATION USING NSGA-II

3.1 INTRODUCTION

To operate power systems in an efficient and reliable way, several techniques have been developed to schedule power plants and determine their production level. Power dispatch is one of these techniques which adjusts some control variables and allocated the power throughout the system resulting in an optimal operation. Power dispatch has two approaches: Real power dispatch problem and the Reactive power dispatch problem. Real power dispatch problem seeks to optimize the system operation by allocating the real power among the power system while reducing production costs. The reactive power dispatch minimizes the system losses improving the system efficiency and utilization of resources.

The conventional real power dispatch problem of power generation involves allocation of power generation to different thermal units to minimize the operating cost subjected to various equality and inequality constraints of the power system [68]. This makes the real power dispatch problem non-linear constrained optimization problem. However, as a result of public awareness of environmental protection, diverse emission compliance strategies have emerged. These strategies include emission dispatching or trading, fuel switching and/or blend, installation of emission reduction equipment in the existing thermal plants, and retirement of old fuel-burning equipment or generating unit and replacement with cleaner and efficient one. Among these strategies, unit dispatch considering emission and cost minimization have received widespread attention due to its effective short-term results and smaller capital outlay. In addition, the power system reactive power optimization directly influences the power system stability and power quality and achieves the objective of minimizing the total system real power loss in the transmission network. Thus, the power dispatch problem considering system loss can reasonably improve real and reactive power dispatch simultaneously. So, the power dispatch problem considering economic, environment and system loss can be handled as a multi-objective optimization problem with non-commensurable and contradictory objectives. This chapter reviews the formulation of real power, reactive power and emission dispatch problems and their combination leading to multi objective optimization problems. The NSGA-II algorithm for the multi objective power dispatch optimization is also briefed.

3.2 REAL POWER DISPATCH PROBLEM

The basic purpose of the real power dispatch function is to schedule the outputs of thermal generating units so as to meet the system load at least cost [70]. The improvement in the economic dispatch function has the potential of cost savings. The factors influencing power generation at minimum cost are operating efficiencies of generators, fuel cost, and transmission losses. The most efficient generator in the system does not guarantee minimum cost as it may be located in an area where fuel cost is high. Also, if the plant is located far from the load center, transmission losses may be considerably higher and hence the plant may be overly uneconomical. Hence, the problem is to determine the generation of different plants such that the total operating cost is minimum. In analyzing the problems associated with the controlled operation of power systems, there are many possible parameters of interest. Fundamental to economic operation problem is the fuel cost characteristics of thermal power generation unit. The fuel cost depends on the number of hours the plant is in operation it also depends upon the number of units of electrical energy generated i.e. the operating cost is directly related to units generated. The fuel cost of the system can be regarded as on essential criterion for economic feasibility.

PROBLEM FORMULATION

The fuel cost curve is assumed to be approximated by a quadratic function of generator real power output as where, P_{Gi} is the real power output of an i_{th} generator; N is the total number of generators; a_i, b_i, c_i, fuel cost curve coefficients of an i_{th} generator, respectively. The Fuel cost objective is represent by following expression given below, *Minimization of Fuel Cost:*

$$\text{Minimize } F_1 = \sum_{i=1}^{Ng} C_i = \sum_{i=1}^{Ng} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \quad (\$/h) \qquad (1)$$

Subjected to: $h(P_{Gi}) = 0$ $\quad$ i= 1,2,3……Ng

$g(P_{Gi}) \leq 0$

where:

Ng is the total number of generator

P_{Gi} is the real power output of i_{th} genrator

C_i is the Fuel cost of i_{th} genrator

F_1 is the total Fuel cost

a_i, b_i, c_i are the Fuel Cost Coefficients of i_{th} genrator

$h(P_{Gi})$ is the power balance constraints

$g(P_{Gi})$ is the generation capacity constraints

3.3 EMISSION DISPATCH PROBLEM

In fossil-fuel based power plant are burn fossil fuels such as coal, natural gas or petroleum (oil) to produce electricity. Fossil-fuel power plants are designed on a large scale for continuous operation. In many countries, such plants provide most of the electrical energy used. A fossil fuel power plant always has some kind of rotating machinery to convert the heat energy of combustion into mechanical energy, which then operates an electrical generator. The prime mover may be a steam turbine, a gas turbine or in small isolated plants, a reciprocating internal combustion engine. Some thermal plants have the intermediate step of using the heat from combustion to produce steam, reducing overall efficiency of electricity production. The flue gas from combustion of the fossil fuels is discharged to the air; this contains carbon dioxide and water vapour, as well as other substances such as nitrogen, nitrogen oxides, sulfur oxides, and (in the case of coal-fired plants) fly ash and mercury. Fossil fueled power stations are major emitters of greenhouse gases (GHG) which according to the consensus of scientific organizations are a major contributor to the global warming observed over the last 100 years. Brown coal emits 3 times as much GHG as natural gas, black coal emits twice as much. Efforts exist to use carbon capture and storage of emissions but these are not expected to be available on a commercial scale and economically viable basis by 2020, if at all.

The world's power demands are expected to rise 60% by 2030. The International Energy Agency (IEA) estimates that fossil fuels will account for 85% of the energy market by 2030. World organizations and international agencies like the IEA are concerned about the environmental impact of burning fossil fuels, and coal in particular. The combustion of coal contributes the most to acid rain and air pollution, and has been connected with global warming, due to the chemical composition of coal and the difficulties of removing the impurities from this solid fuel prior to its combustion. Acid rain is caused by the emission of nitrogen oxides and sulfur dioxide into the air. When they react with the atmosphere, they create acidic compounds (such as sulfurous acid, nitric acid, and sulfuric acid) that fall as rain, hence the term acid rain. In Europe and the U.S.A., stricter emission laws and decline in heavy industries have reduced the environmental hazards associated with this problem, leading to lower emissions after their peak in 1960s.

Electricity generation using carbon based fuels is responsible for a large fraction of carbon dioxide (CO_2) emissions worldwide. Coal combustion in thermal power stations result in greater amounts of carbon dioxide emissions per unit of electricity generated while natural and gas produces the least for fossil fuels. Carbon dioxide is produced and released to the atmospheres from both natural sources such as volcanoes, biological breakdown and respiration by living things. Carbon dioxide is absorbed and converted during photosynthesis by plants and dissolved into water, such as the oceans. Increasing concentrations of CO_2 assist plant growth and are radiactive forcing. Increased concentration of carbon dioxide in the atmosphere assist climate change including global warming; concern over the rate of climate change has led to targets to stabilize or reduce carbon dioxide and other greenhouse gas (GHG) emissions by between 25 and 40% by 2020. Fossil fueled, especially coal-fired, plants make reductions difficult. Emissions may be reduced through more efficient and higher combustion temperature and through more efficient production of electricity within the cycle. Carbon capture and storage (CCS) of emissions from coal fired power stations is another alternative but the technology is still being developed and will increase the cost of fossil fuel based production of electricity. CCS may not be economically viable, unless the price of emitting CO_2 to the atmosphere rises. Emissions of sulphur dioxide and nitrogen oxides are the main cause of acid deposition leading to changes in soil and water quality and damage to forests, crops and other vegetation, and to adverse effects on aquatic ecosystems in rivers and lakes. Acidification also damages buildings and cultural monuments and potentially has links to human respiratory diseases. Other health impacts can arise if acidification affects groundwater used for public water supply.

Concerning environmental emission is important issue in the operation of modern power plants [2]. Operating at absolute minimum cost can no longer be the only criterion for dispatching electric power due to increasing concern of the environmental consideration. The generation of electricity from fossil fuel releases several contaminants, such as Sulphur oxides, Nitrogen oxides and Carbon dioxide, into the atmosphere. The characteristics of emissions of different pollutants are different and are usually highly nonlinear. This increases the complexity of the emission problem. The harmful ecological effects by the emission of particulate and gaseous pollutants from fossil fuel power plants can be reduced by proper load allocation among the various generating units of the plants.

PROBLEM FORMULATION

For this dispatch problem, problem formulation is same as that of real power dispatch problem, but in this dispatch problem we are using emission coefficients in place of fuel coefficients and dispatching done by allocation of power generation across various generation units. The problem formulations for various emissions are given below:

Minimization of NO_X*Emission:*

The NO_X emission objective is represented by the expression given below,

$$\text{Minimize } F_2 = \sum_{i=1}^{Ng} (a_{Ni} + b_{Ni}P_{Gi} + c_{Ni}P_{Gi}^2) \quad (\$/h) \tag{2}$$

Minimization of SO_X Emission:

The SO_X emission objective is represented by the expression given below,

$$\text{Minimize } F_3 = \sum_{i=1}^{Ng} (a_{Si} + b_{Si}P_{Gi} + c_{Si}P_{Gi}^2) \quad (\$/h) \tag{3}$$

Minimization of CO_X Emission:

The CO_X emission objective is represented by the expression given below,

$$\text{Minimize } F_4 = \sum_{i=1}^{Ng} (a_{Ci} + b_{Ci}P_{Gi} + c_{Ci}P_{Gi}^2) \quad (\$/h) \tag{4}$$

Problem formulation for given objective functions is given as:

Minimization $F(P_{Gi}) = [F_2, F_3 \text{ or } F_4]$ i= 1,2,3……Ng

Subjected to: $h(P_{Gi}) = 0$

$g(P_{Gi}) \le 0$

where

F_2 *is the total* NO_X *Emission*

F_3 is the total SO_X Emission

F_4 is the total CO_X Emission

a_{Ni}, b_{Ni}, c_{Ni} are the NO_X Emission Coefficients of i_{th} genrator

a_{Si}, b_{Si}, c_{Si} are the SO_X Emission Coefficients of i_{th} genrator

a_{Ci}, b_{Ci}, c_{Ci} are the CO_X Emission Coefficients of i_{th} genrator

3.4 REACTIVE POWER DISPATCH PROBLEM

Reactive power dispatch (RPD) is treated as an optimization problem that reduces grid congestion by minimizing the active power losses. The RPD requires solving the power flow problem and for this reason is usually known as optimal reactive power dispatch problem or as an optimal power flow problem. Reactive power dispatch reduces the power system losses and provides better system voltage control, resulting in an improved voltage profile, system security power transfer capability and overall system operation. Reactive power dispatch provide by optimize the various objective function but in this thesis, only transmission losses has considered for provide the reactive power dispatch in the power systems. For minimize the transmission losses real power output of generator units has considered as decision variable. The problem formulation for reactive power dispatch is given below.

PROBLEM FORMULATION

The objective function of reactive power dispatch problem is to minimize the active or real power loss, subjected to various equality and inequality constraints. Problem formulation for reactive power dispatch problem is given below:

$$\text{Minimize } F_5 = P_{Loss} \tag{5}$$

Subjected to: $h(P_{Gi}) = 0$ i= 1, 2, 3……Ng

$g(P_{Gi}) \leq 0$

F_5 is the total Real power loss

P_{Loss} is the total power loss given as below

$$P_{Loss} = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} P_{Gi} B_{ij} P_{Gj} \tag{6}$$

Power balance and Generation capacity constraints are define as below:

1) *Power balance constraints:* The total power generation must cover the total demand P_D and the real power loss in the transmission lines P_{LOSS}. Hence,

$$\sum_{i=1}^{Ng} P_{Gi} - P_D - P_{Loss} = 0 \qquad (7)$$

2) Generation capacity constraints: For stable operation, the generator outputs and bus voltage magnitudes are restricted by lower and upper limits as follows:

$$P_{Gimin} \leq P_{Gi} \leq P_{Gimax} \quad i = 1,2,3 \ldots..Ng \qquad (8)$$

3.5 MULTI OBJECTIVE REAL POWER - EMISSION DISPATCH

The real power and emission dispatch problem is to minimize various objective functions like fuel cost and emission [68, 69], while satisfying several equality and in equality constraints.

Minimization of Fuel Cost and NO_X Emission:

Minimize F_1, F_2

Subjected to: $h(P_{Gi}) = 0$ i= 1,2,3……Ng

$g(P_{Gi}) \leq 0$

Minimization of Fuel Cost and SO_X Emission:

Minimize F_1, F_3

Subjected to: $h(P_{Gi}) = 0$ i= 1,2,3……Ng

$g(P_{Gi}) \leq 0$

Minimization of Fuel Cost and CO_X Emission:

Minimize F_1, F_4

Subjected to: $h(P_{Gi}) = 0$ i= 1,2,3……Ng

$g(P_{Gi}) \leq 0$

Minimization of Fuel Cost, NO_X and SO_X Emission:

Minimize F_1, F_2, F_3

Subjected to: $h(P_{Gi}) = 0$ i= 1,2,3……Ng

$g(P_{Gi}) \leq 0$

Minimization of Fuel Cost, NO_X and CO_X Emission:

Minimize F_1, F_2, F_4

Subjected to: $h(P_{Gi}) = 0$ i= 1,2,3……Ng

$g(P_{Gi}) \leq 0$

Where F_1 is the fuel cost, F_2 is the NO_X emission, F_3 is the SO_X and F_4 is the CO_X emission as given in eq. (1), eq. (2), eq. (3) and eq. (4) respectively.

3.6 MULTI OBJECTIVE REAL - REACTIVE POWER DISPATCH

The optimal operation of power system network has been determined based on economic factors by using real power dispatching. However, recent concerns about power quality and system security have forced power systems planners and operators to incorporate other criteria such as minimization of transmission losses. Generally, power losses in the transmission of electrical energy cause a significant loss of profits due to increased generation capacity requirements. Reactive power dispatch is one of application functions of modern energy management systems, used to minimized total transmission losses. So for provide the optimal operation of power system we use both real and reactive power dispatching. In addition to real and reactive power dispatching, emission dispatching also be done, which provides the additional advantage of optimal operation as well as minimize the harmful ecological effect. The problem formulation for multi objective real-reactive power dispatch has been given below:

Minimization of Fuel Cost and Power loss

Minimize F_1, F_5

Subjected to: $h(P_{Gi}) = 0$ i= 1,2,3……Ng

$g(P_{Gi}) \leq 0$

Minimization of $Fuel\ Cost, NO_X\ Emission\ and\ Power\ loss$

Minimize F_1, F_2, F_5

Subjected to: $h(P_{Gi}) = 0$ i= 1,2,3……Ng

$g(P_{Gi}) \leq 0$

Minimization of $Fuel\ Cost, SO_X\ Emission\ and\ Power\ loss$

Minimize F_1, F_3, F_5

Subjected to: $h(P_{Gi}) = 0$ i= 1,2,3……Ng

$g(P_{Gi}) \leq 0$

Minimization of $Fuel\ Cost, CO_X\ Emission\ and\ Power\ loss$

Minimize F_1, F_4, F_5

Subjected to: $h(P_{Gi}) = 0$ i= 1,2,3……Ng

$g(P_{Gi}) \leq 0$

Where F_1 is the fuel cost, F_2 is the NO_X emission, F_3 is the SO_X emission, F_4 is the CO_X emission and F_5 is the $Power\ loss$ as given in eq. (1), eq. (2), eq. (3), eq. (4) and eq. (5) respectively.

3.7 NSGA-II APPLICATION FOR MULTIOBJECTIVE POWER DISPATCH OPTIMIZATION

In previous section, different types of power dispatch problems have been considered. These problems are solved by using the NSGA-II algorithm. The detailed illustration of NSGA-II application for multi objective real power and emission dispatch problem is presented in this section for three generators data given in APPENDIX – I. This illustration is only a sample case, however, the effectiveness of the algorithm to carry out various multi objective optimization studies has been presented in Chapter-4.

3.7.1 INITIALIZATION

Initialize the population Pt. The stringlength of population is equal to number of decision variables. The generation capacity constraint has taken as inequality constraints and the power balance equation has taken as equality constraints. According to these constraints initialize all decision variables in the population and calculate the value of each objective function.

As an example, initial population of 10 is illustrated. Fuel cost and emission objective functions which have been calculated for each population. The data initialized by NSGA-II during intialization is shown in Table 3-1.

Table 3-1: Initialization of population using NSGA-II

S.no	P1	P2	P3	Fuel cost ($/hr)	Emission (ton/hr)
1.	371.68	296.46	183.51	8231.29	.11029
2.	411.67	381.30	057.16	8220.82	.10611
3.	579.63	180.32	087.51	8277.56	.09789
4.	566.77	189.54	100.71	8348.87	.09721
5.	378.50	356.99	107.64	8134.05	.10057
6.	387.34	317.49	141.11	8159.69	.10079
7.	486.82	270.35	094.84	8238.13	.09562
8.	543.72	136.30	178.45	8398.83	.11004
9.	571.18	216.78	067.57	8335.91	.09916
10.	566.61	153.65	127.63	8285.77	.09933

3.7.2 NON-DOMINATED SORTING

In this section, the entire population has been sorted according to its non-dominated level. Each solution assigned a fitness value according to its non-dominated level, where level one is considered to be the best level. The solution at the level one did not dominate by any of other solution. Whereas solutions at other level dominated by least one solution. Perform the non-dominated sorting to the initial population and identify the different rank to each population: rank1, rank2, rank3....etc.

As given below in Table 3-2, N.no is the numbers of the solutions which dominate the respective solution. Across solution one and two the N.no are zero which means that these solutions have not been dominated by any of other solution. Rank provides the value of non-dominated rank across each solution. All the solutions have sorted according to its non-dominated rank.

Table 3-2: Non-dominated sorting of the initial population

S.no	P1	P2	P3	Fuel Cost ($/hr)	Emission (ton/hr)	N.no	Rank
1.	378.50	356.99	107.64	8134.05	.10057	0	1
2.	486.82	270.35	094.84	8238.13	.09562	0	1
3.	579.63	180.32	087.51	8277.56	.09789	1	2
4.	566.77	189.54	100.71	8348.87	.09721	1	2
5.	387.34	317.49	141.11	8159.69	.10079	1	2
6.	411.67	381.30	057.16	8220.82	.10611	2	3
7.	571.18	216.78	067.57	8335.91	.09916	2	3
8.	566.61	153.65	127.63	8285.77	.09933	2	3
9.	371.68	296.46	183.51	8231.29	.11029	3	4
10.	543.72	136.30	178.45	8398.83	.11004	8	4

3.7.3 CROWDING DISTANCE

Once the non-dominated sorting is done, the crowding distance is assigned to each solution. The individuals in the population are selected on the basis of rank and crowding distance. Crowding distance is assigned front wise and comparing the crowding distance between two individuals in different front is meaningless. The procedure for calculating crowding distance has given in section 2.3.4.

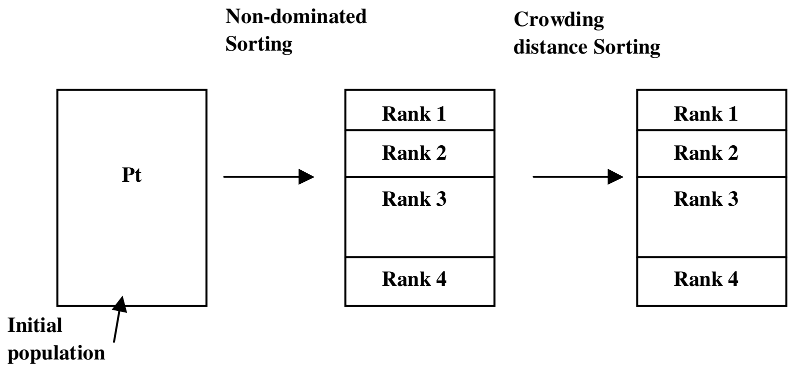


FIGURE 3-1: Non-dominated and Crowding distance sorting

A table is given below, where Cd provides the value of crowding distance across each solution.

Table 3-3: Population with its crowding distance value

S.no	P1	P2	P3	Fuel Cost ($/hr)	Emission (ton/hr)	N.no	Rank	Cd
1.	378.50	356.99	107.64	8134.05	.10057	0	1	inf
2.	486.82	270.35	094.84	8238.13	.09562	0	1	inf
3.	579.63	180.32	087.51	8277.56	.09789	1	2	2
4.	566.77	189.54	100.71	8348.87	.09721	1	2	inf
5.	387.34	317.49	141.11	8159.69	.10079	1	2	inf
6.	411.67	381.30	057.16	8220.82	.10611	2	3	inf
7.	571.18	216.78	067.57	8335.91	.09916	2	3	inf
8.	566.61	153.65	127.63	8285.77	.09933	2	3	2
9.	371.68	296.46	183.51	8231.29	.11029	3	4	inf
10.	543.72	136.30	178.45	8398.83	.11004	8	4	inf

3.7.4 TOURNAMENT SELECTION

Once the individuals are sorted based on non-domination and with crowding distance assigned, the selection is carried out two solutions are randomly picked from the population and best solution is selected form these two. These selection is carried out using a crowded – comparison operator (as given in section 2.3.5). Tournament Select the any two individual solution from the population randomly and compare the both solution with each other according to its non dominated rank. The solution with better rank is selected as winner otherwise if both have the same rank then the solution which located in lesser crowding region is preferred. Copy of winner placed in the mating pool. As solution 2 has higher non-dominated rank as compared to solution 7, so solution 2 will be copy to mating pool. This procedure will remain continues until it satisfy the desire condition (like tournament size).

2.	486.82	270.35	094.84	8238.13	.09562	0	1	inf
7.	571.18	216.78	067.57	8335.91	.09916	2	3	inf

As given in Table 3-3 given below, which provide the data selected by the tournament selection from the intial population.

Table 3.4: Data Selected by the Tournament Selection

S.no	**P1**	**P2**	**P3**	**Fuel Cost ($/hr)**	**Emission (ton/hr)**	**N.no**	**Rank**	**Cd**
1.	486.82	270.35	094.84	8238.13	.09562	0	1	inf
2.	378.50	356.99	107.64	8134.05	.10057	0	1	inf
3.	411.67	381.30	057.16	8220.82	.10611	2	3	inf
4.	566.77	189.54	100.71	8348.87	.09721	1	2	inf
5.	378.50	356.99	107.64	8134.05	.10057	0	1	inf

3.7.5 CROSSOVER & MUTATION

Apply the crossover and mutation rate to each individual in the mating pool and select the parent (s). For two parents perform the crossover and generate the offspring similarly one parents perform the mutation and generate the offsprings. These offsprings will place in the offspring population Qt.

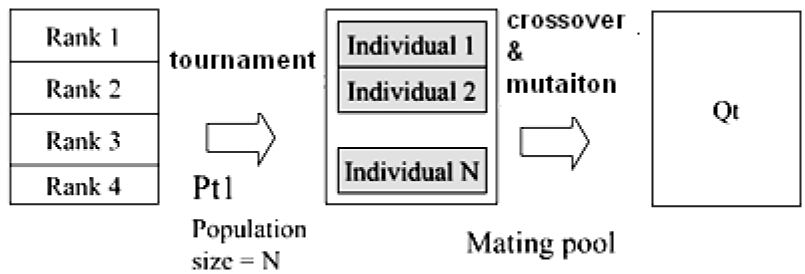


FIGURE 3-2: Crossover and Mutation operation

During Crossover operation, two offsprings generate from two parent solution

Parent 1 -	378.50	356.99	107.64	8134.05	.10057
Parent 2 -	411.67	381.30	057.16	8220.82	.10611
Offspring 1 -	380.19	354.12	108.80	8133.36	.100345
Offspring 2 -	409.97	384.16	055.99	8221.90	.106612

During Mutation operation, one offspring generates from one parent solution

Parent -	385.51	352.23	108.84	8164.76	.10023
Offspring -	387.46	346.73	115.07	8188.29	.10012

3.7.6 RECOMBINATION

The offspring population Qt is combined with the current generation population Pt and selection is performed to set the individual of the next generation Rt. Since all the previous and current best individuals are added in the population elitist is ensured. Population is now sorted based on non-domination.

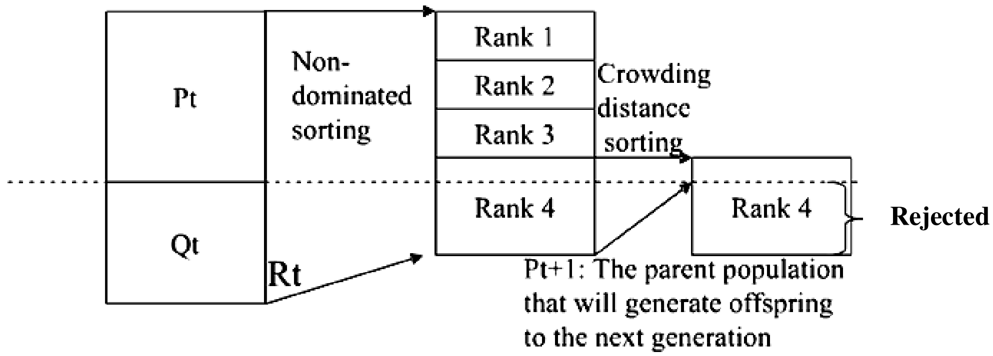


FIGURE 3-3: Recombination Operation

The new generation is filled by each front subsequently until the population size exceeds the current population size. If by adding all the individuals in Rt the populations exceeds N then individuals in Rt are selected based on their crowding distance in the descending order until the population size is N and other individual above N has been rejected. Hence the process repeats to generate the subsequent generations. Results after recombination are given below:

Table 3-5: Regenerated population after the Recombination Operation

S.no	P1	P2	P3	Fuel Cost ($/hr)	Emission (ton/hr)	Rank	Cd
1.	375.98	356.31	109.30	8119.75	.10056	1	inf
2.	375.98	356.31	109.30	8119.75	.10056	1	0
3.	380.19	354.12	108.80	8133.36	.10034	1	0.0018950
4.	380.50	357.78	104.25	8129.00	.10051	1	0.0001828
5.	375.98	356.31	109.30	8119.75	.10056	1	0
6.	375.98	356.31	109.30	8119.75	.10056	1	0
7.	375.98	356.31	109.30	8119.75	.10056	1	0
8.	486.22	266.06	097.37	8216.87	.95362	1	inf
9.	375.98	356.31	109.30	8119.75	.10056	1	inf
10.	374.57	359.81	110.15	8146.89	.10102	2	inf

3.8 NSGA-II ALGORITHM

STEP 1: A random initial population is generated of size N. This step is repeated N times where N is the size of the population.

STEP 2: The population produced above is sorted using fast non-dominated sorting for producing fronts. This process is repeated till the whole population is divided into fronts.

STEP 3: Initially crowded distance assignment is done for each solution of a front and then the front is included in the parent population. For the crowded distance computation the population is sorted according to each objective value .The boundary solutions are assigned infinite distance values all other intermediate solutions are assigned a distance value equal to the absolute differences in the function values of two adjacent solutions.

STEP 4: Crossover and mutation is applied to the parent population generated above to produce child population. To create new offspring, simulated binary crossover (SBX) operator and polynomial mutation operator are used.

STEP 5: The parent and child population are combined together to produce a population of size 2N. This step is performed for elitism, the elitism select the best N value according to its objective function or the fitness value.

STEP 6: Stopping criteria is checked if achieved the Pareto optimal front is printed else go to step 2

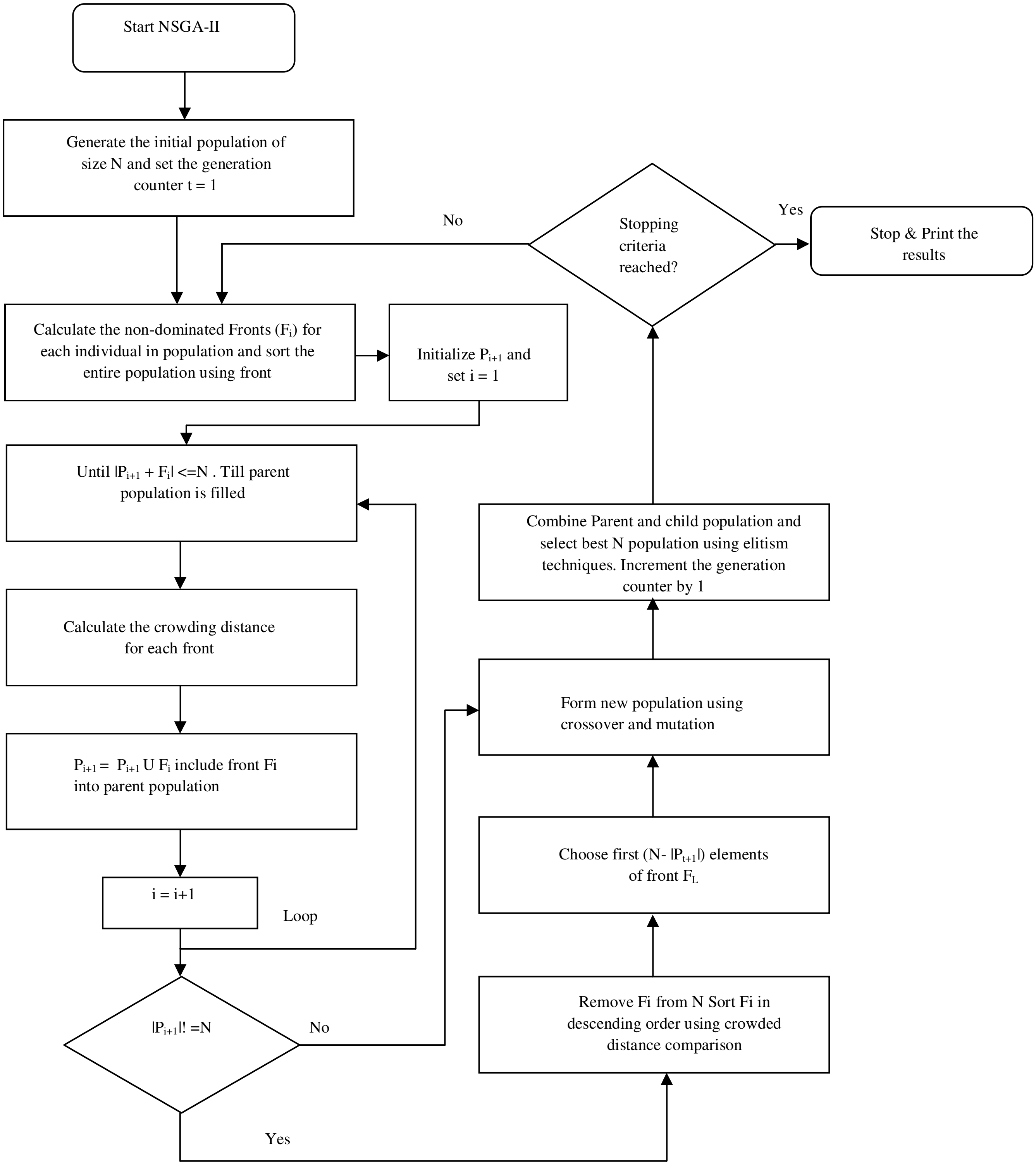


FIGURE 3-4: Flow chart of NSGA-II

CHAPTER 4

RESULTS AND DISCUSSION

The results have been obtained from the developed algorithm for multi-objective power dispatch based on NSGA-II, which has been discussed in Chapter-3. The developed algorithm has been tested on three and six generators test systems whose data are given in APPENDEX - I and II respectively. As explained in Chapter-3, multi-objective power dispatch problem has been formed with the combinations of real power dispatch, emission dispatch and reactive power dispatch which are formulated with objective of minimizing fuel cost, emissions and Power loss respectively. Further, the emission minimization can be the NO_X, SO_X and CO_X minimization. Keeping the above, the following cases have been studied –

Case Study 1: Multi-objective Fuel Cost and NO_X Emission
Case Study 2: Multi-objective Fuel Cost and SO_X Emission
Case Study 3: Multi-objective Fuel Cost and CO_X Emission
Case Study 4: Multi-objective Fuel Cost and Power loss
Case Study 5: Multi-objective Fuel Cost, NO_X and SO_X Emission
Case Study 6: Multi-objective Fuel Cost, NO_X and CO_X Emission
Case Study 7: Multi-objective Fuel Cost, NO_X and Power loss
Case Study 8: Multi-objective Fuel Cost, SO_X and Power loss
Case Study 9: Multi-objective Fuel Cost, CO_X and Power loss

These cases are studied with and without losses. The simulation has been carried out on system having 1.8 GHz Pentium 4 processor with 256 MB of RAM in MATLAB 7.5.0 environment. Maximum Generation are taken as 1000 for two objectives and 30000 for three objectives optimization. For the studies, the following parameters are used

- Population size = 100
- Crossover probability = 0.9
- Mutation probability = 0.1
- Distribution index for crossover = 20
- Distribution index for mutation = 20

4.1 Case Study 1: Multi-objective Fuel Cost and NO_X Emission

In this case study, developed algorithm has been applied for multi-objective real (fuel cost) and emission dispatch (NO_X). The simulation results obtained are given in Table 4-1 and Table 4-2 for a system of three generators and six generators respectively. Correspondingly the optimal-pareto fronts are also shown in Figure 4-1 and Figure 4-2 respectively.

A. Three generator system

The results for minimizing fuel cost and NO_X after neglecting losses and considering them are summarized in Table 4-1 (a) and Table 4-1 (b). Correspondingly the pareto optimal fronts and best compromise solutions are shown in Figure 4-1 (a) and Figure 4-1 (b) respectively.

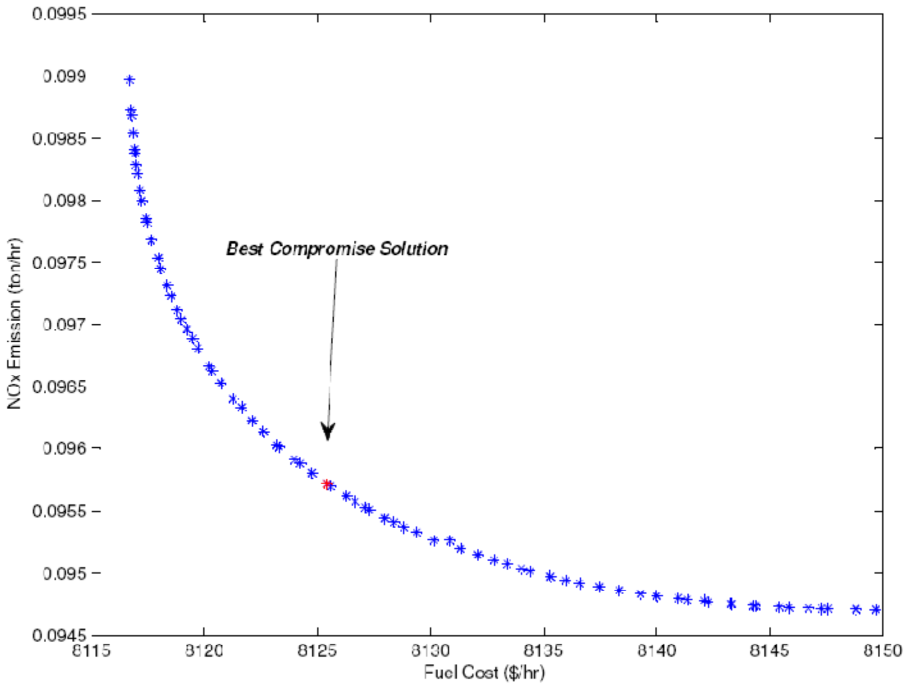
TABLE 4-1: Result for Fuel Cost and NO_X minimization for three generators

(a) Neglecting Power loss

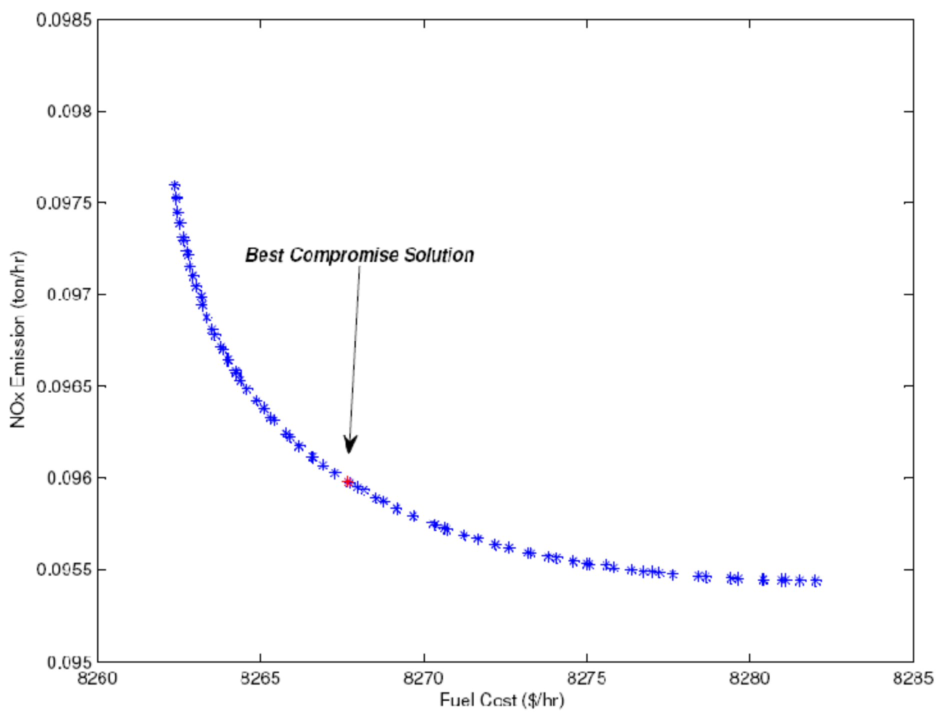
Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum NO_X Emission	Best Compromise Solution
PG1	390.7035	493.1729	443.5063
PG2	332.4453	243.9747	289.4805
PG3	118.3512	104.3527	108.5142
Fuel Cost (in $/hr)	**8116.6883**	8149.6939	**8125.4197**
NO_X Emission (in ton/hr)	0.0989	**0.0947**	**0.0957**

(b) Considering Power loss

Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum NO_X Emission	Best Compromise Solution
PG1	436.8263	502.5137	467.2490
PG2	293.6469	248.0226	277.7231
PG3	126.2713	105.2828	111.3576
Fuel Cost (in $/hr)	**8262.3675**	8282.0182	**8267.6804**
NO_X Emission (in ton/hr)	0.0976	**0.0954**	**0.0960**



(a) Neglecting Power loss



(b) Considering Power loss

FIGURE 4-1: Pareto Optimal Solution for Fuel Cost and NO_X Emission minimization for three generators

B. Six generator system

The results for minimizing fuel cost and NO_X after neglecting losses and considering them are summarized in Table 4-2 (a) and Table 4-2 (b). Correspondingly the pareto optimal fronts and best compromise solutions are shown in Figure 4-2 (a) and Figure 4-2 (b) respectively.

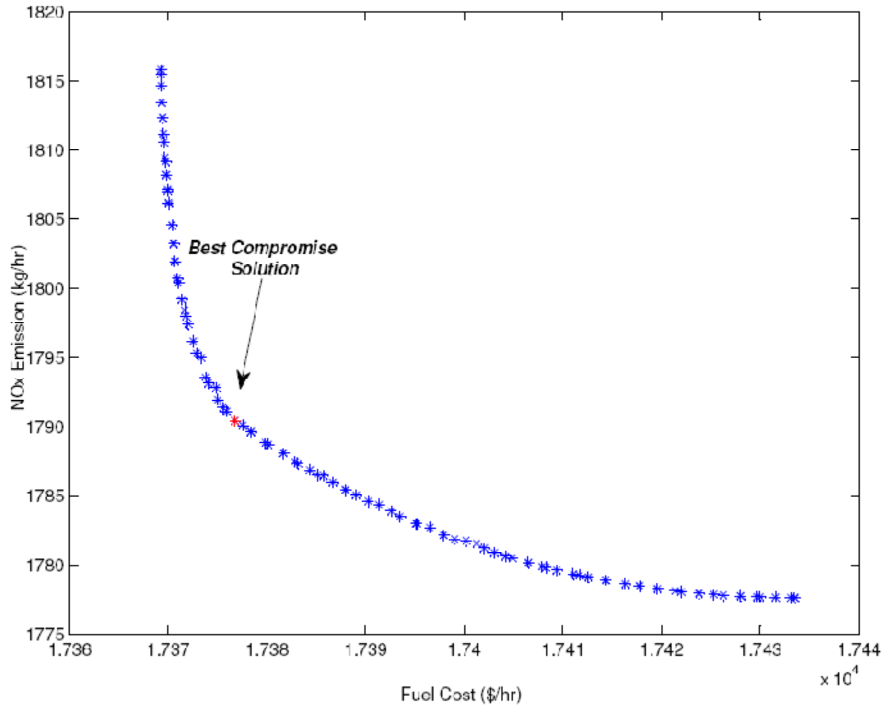
TABLE 4-2: Result for Fuel Cost and NO_X minimization for six generators

(a) Neglecting Power loss

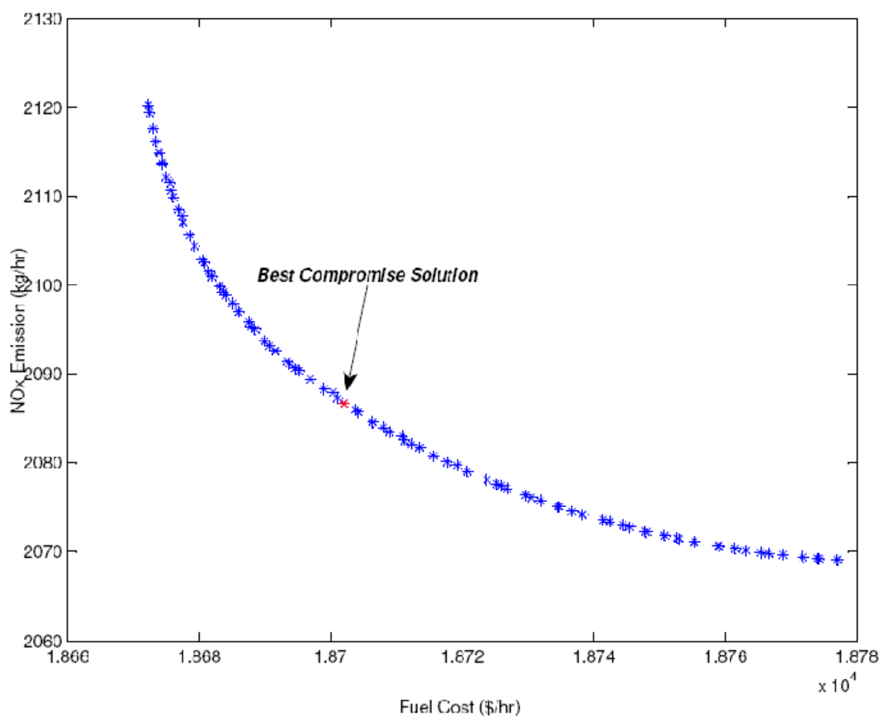
Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum NOx Emission	Best Compromise Solution
PG1	212.3122	164.4289	168.8502
PG2	230.0000	191.3549	229.9111
PG3	433.4326	480.7228	456.7734
PG4	264.9999	264.97727	264.9916
PG5	438.7919	480.5149	461.4776
PG6	202.4636	200.00122	200.0000
Fuel Cost (in $/hr)	**17369.2768**	17433.5163	**17376.7571**
NOx Emission (in kg/hr)	1815.8092	**1777.6319**	**1790.4117**

(b) Considering Power loss

Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum NOx Emission	Best Compromise Solution
PG1	249.9831	218.5747	245.4132
PG2	229.9999	229.9998	229.9999
PG3	499.9733	499.9974	499.9812
PG4	265.0000	264.9999	265.0000
PG5	417.5482	499.9921	455.73396
PG6	217.3949	217.3949	227.1909
Fuel Cost (in $/hr)	**18672.2656**	18777.1574	**18702.1238**
NOx Emission (in kg/hr)	2120.2842	**2069.1294**	**2086.6595**



(a) Neglecting Power loss



(b) Considering Power loss

FIGURE 4-2: Pareto Optimal Solution for Fuel Cost and NO_X Emission minimization for six generators

4.2 Case Study 2: Multi-objective Fuel Cost and SO_X Emission

In this case study, developed algorithm has been applied for multi-objective real (fuel cost) and emission dispatch (SO_X). The simulation results obtained are given in Table 4-3 and Table 4-4 for a system of three generators and six generators respectively. Correspondingly the optimal-pareto fronts are also shown in Figure 4-3 and Figure 4-4 respectively.

A. Three generator system

The results for minimizing fuel cost and SO_X after neglecting losses and considering them are summarized in Table 4-3 (a) and Table 4-3 (b). Correspondingly the pareto optimal fronts and best compromise solutions are shown in Figure 4-3 (a) and Figure 4-3 (b) respectively.

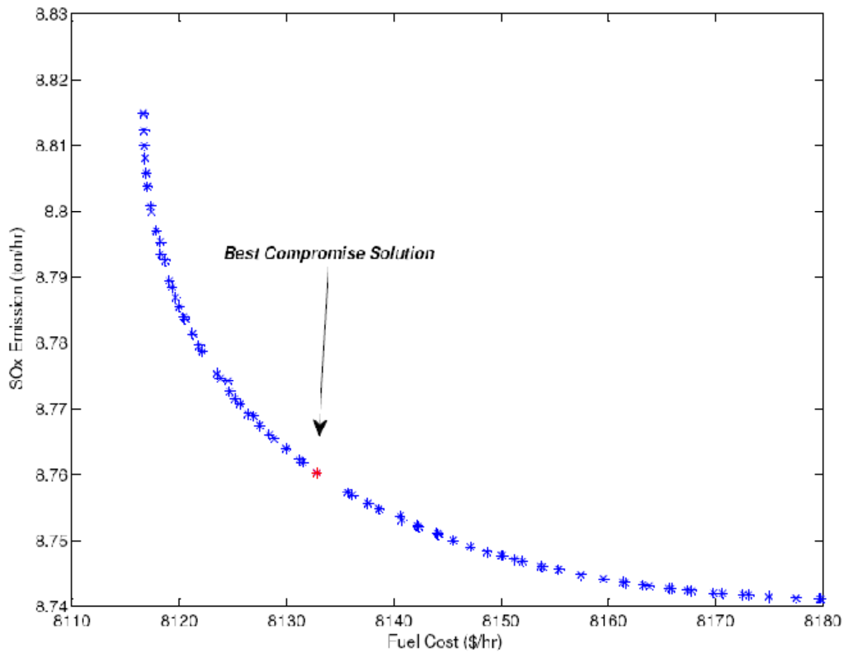
TABLE 4-3: Result for Fuel Cost and SO_X minimization for three generators

(a) Neglecting Power loss

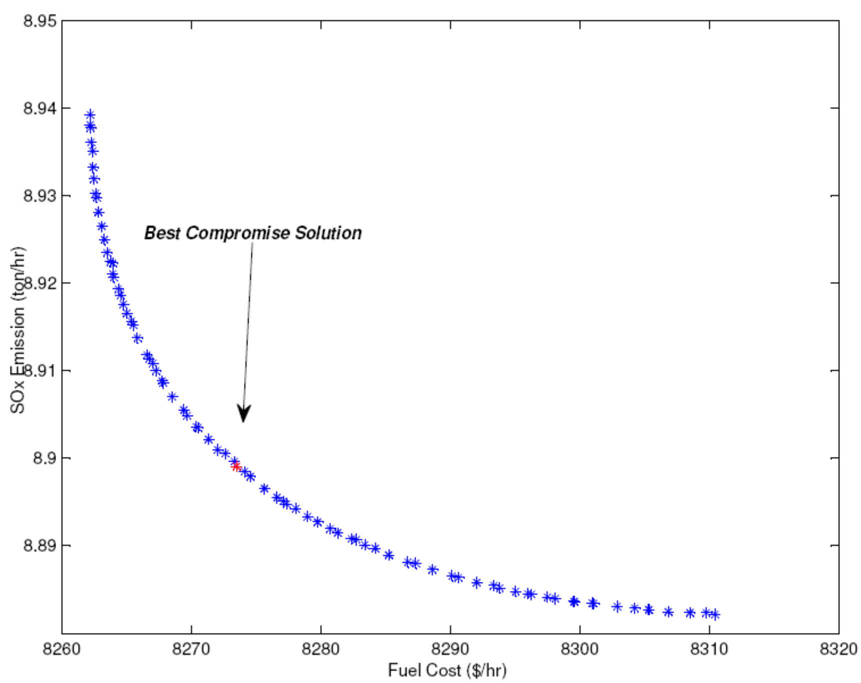
Units (in MW)	**Solution at minimum Fuel Cost**	**Solution at minimum SO_X Emission**	**Best Compromise Solution**
PG1	389.4647	535.5313	463.2578
PG2	331.6088	229.9482	279.9481
PG3	121.4265	76.0207	98.6314
Fuel Cost (in \$/hr)	**8116.6522**	8179.7937	**8132.8215**
SO_X Emission (in ton/hr)	8.8149	**8.74115**	**8.7602**

(b) Considering Power loss

Units (in MW)	**Solution at minimum Fuel Cost**	**Solution at minimum SO_X Emission**	**Best Compromise Solution**
PG1	431.1564	543.2157	484.7521
PG2	296.3973	220.2321	261.1049
PG3	129.2810	92.1467	110.1379
Fuel Cost (in \$/hr)	**8262.2086**	8310.4408	**8273.4855**
SO_X Emission (in ton/hr)	8.9392	**8.8821**	**8.8991**



(a) Neglecting Power loss



(b) Considering Power loss

FIGURE 4-3: Pareto Optimal Solution for Fuel Cost and SO_X Emission minimization for three generators

B. Six generator system

The results for minimizing fuel cost and SO_X after neglecting losses and considering them are summarized in Table 4-4 (a) and Table 4-4 (b). Correspondingly the pareto optimal fronts and best compromise solutions are shown in Figure 4-4 (a) and Figure 4-4 (b) respectively.

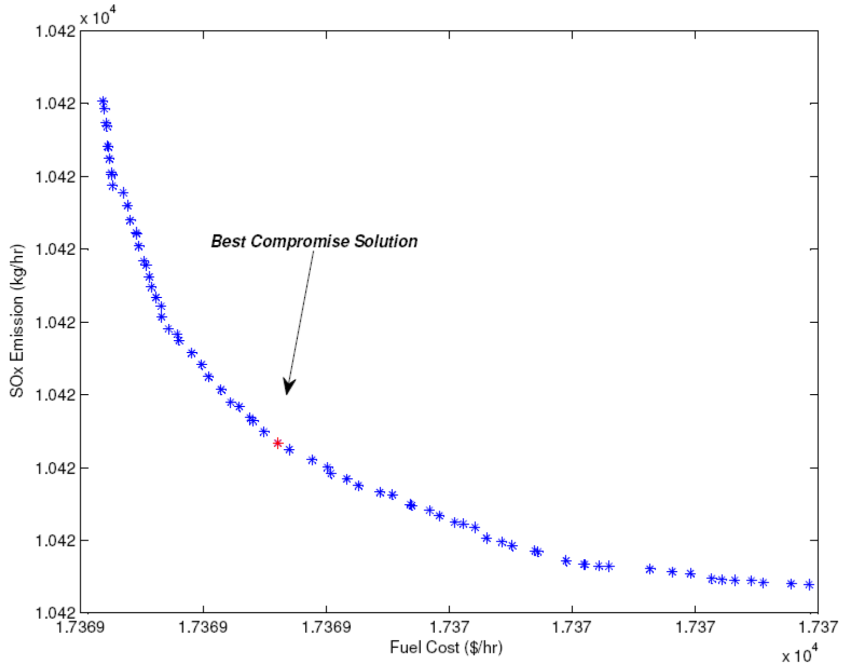
TABLE 4-4: Result for Fuel Cost and SO_X minimization for six generators

(a) Neglecting Power loss

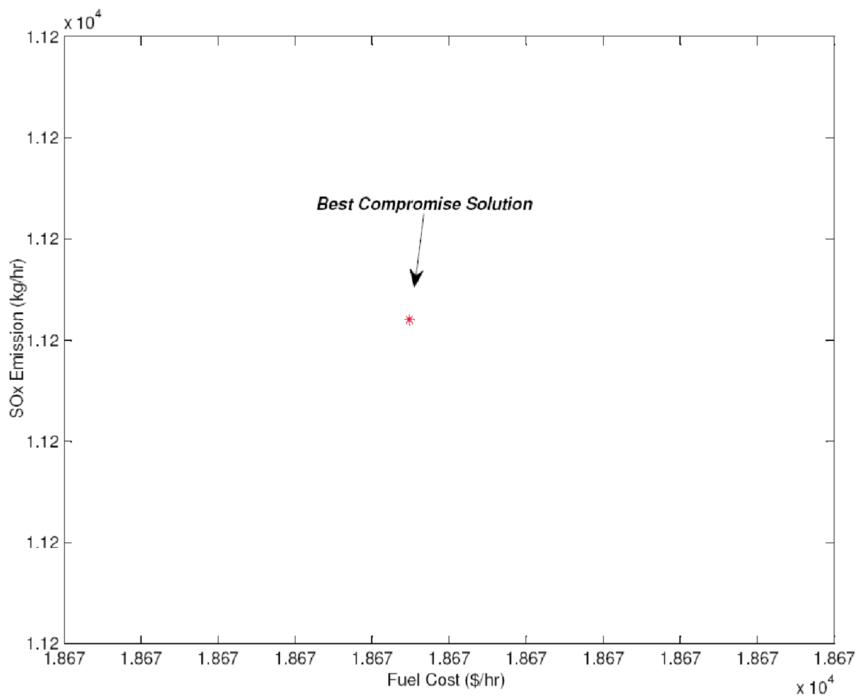
Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum SO_X Emission	Best Compromise Solution
PG1	216.6226	203.6428	210.6618
PG2	230.0000	230.0000	230.0000
PG3	432.2694	440.5593	436.6352
PG4	264.9999	264.9851	264.9999
PG5	438.0878	441.9856	439.9999
PG6	200.0201	200.8272	200.0000
Fuel Cost (in $/hr)	**17369.2186**	17369.7926	**17369.3609**
SO_X Emission (in ton/hr)	10419.9015	**10419.5698**	**10419.6667**

(b) Considering Power loss

Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum SO_X Emission	Best Compromise Solution
P_{G1}	250.0000	250.0000	250.0000
P_{G2}	230.0000	230.0000	230.0000
P_{G3}	500.0000	500.0000	500.0000
P_{G4}	265.0000	265.0000	265.0000
P_{G5}	404.9990	404.9990	404.9990
P_{G6}	267.3419	267.3419	267.3419
Fuel Cost (in $/hr)	**18670.3564**	18670.3564	**18670.3564**
SO_X Emission (in kg/hr)	11200.4422	**11200.4422**	**11200.4422**



(a) Neglecting Power loss



(b) Considering Power loss

FIGURE 4-4: Pareto Optimal Solution for Fuel Cost and SO_X Emission minimization for six generators

4.3 Case Study 3: Multi-objective Fuel Cost and CO_X Emission

In this case study, developed algorithm has been applied for multi-objective real (fuel cost) and emission dispatch (CO_X). The simulation results after neglecting losses and considering them are summarized in Table 4-5 (a) and Table 4-5 (b) for a system of six generators. Correspondingly, the pareto optimal fronts and best compromise solutions are shown in Figure 4-5 (a) and Figure 4-5 (b) respectively.

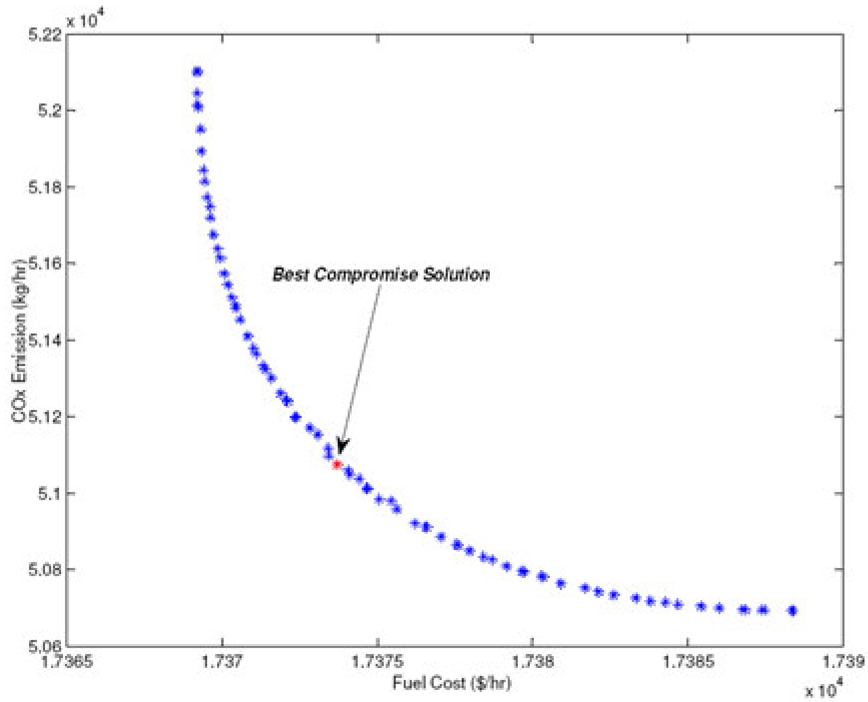
TABLE 4-5: Result for Fuel Cost and CO_X minimization for six generators

(a) Neglecting Power loss

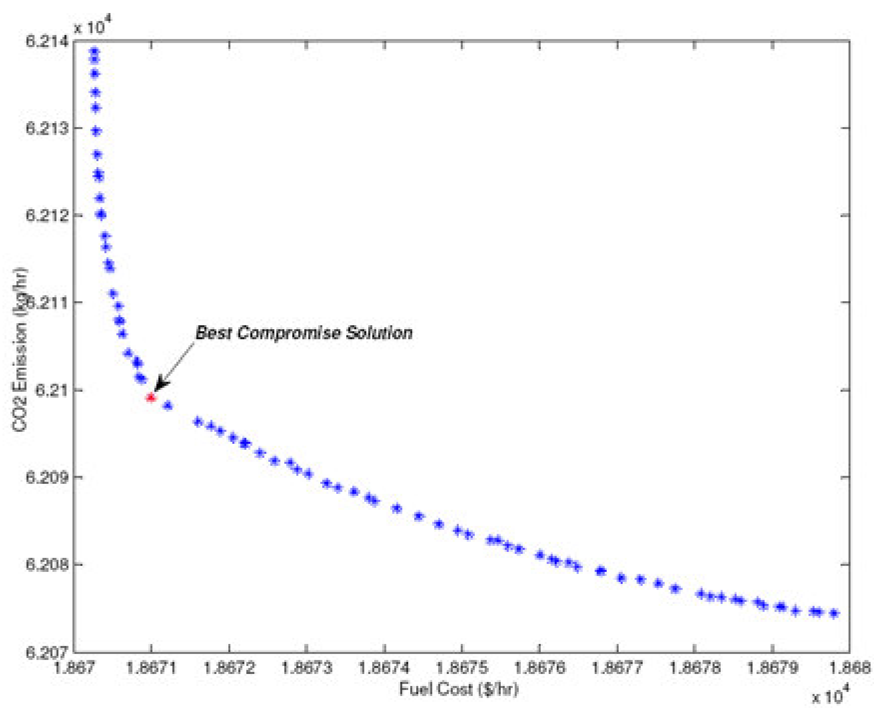
Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum CO_X Emission	Best Compromise Solution
PG1	218.1451	249.9915	238.6483
PG2	229.9986	229.9825	229.9982
PG3	432.4348	396.3755	414.0802
PG4	264.9967	264.9984	264.9984
PG5	435.9067	396.9096	415.2898
PG6	200.5179	243.7425	264.9981
Fuel Cost (in $/hr)	**17369.2113**	17388.3781	**17373.7155**
CO_X Emission (in kg/hr)	52104.7728	**50693.2627**	**51074.6863**

(b) Considering Power loss

Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum CO_X Emission	Best Compromise Solution
PG1	250.0000	249.9976	249.9949
PG2	230.0000	229.9993	229.9997
PG3	500.0000	492.4018	499.9540
PG4	265.0000	265.0000	265.0000
PG5	404.7746	419.3589	412.2104
PG6	267.5369	262.3882	260.8661
Fuel Cost (in $/hr)	**18670.2672**	18679.8004	**18670.9988**
CO_X Emission (in ton/hr)	62138.8053	**62074.4455**	**62099.1718**



(a) Neglecting Power loss



(b) Considering Power loss

FIGURE 4-5: Pareto Optimal Solution for Fuel Cost and CO_X Emission minimization for six generators

4.4 Case Study 4: Multi-objective Fuel Cost and Power loss

In this case study, developed algorithm has been applied for multi-objective real (fuel cost) and Power loss. The simulation results obtained are given in Table 4-6 and Table 4-7 for a system of three generators and six generators respectively. Correspondingly the optimal-pareto fronts are also shown in Figure 4-6 and Figure 4-7 respectively.

TABLE 4-6: Result for Fuel Cost and Power loss minimization for three generators

Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum P_{LOSS}	Best Compromise Solution
PG1	439.7367	538.7817	487.0120
PG2	286.9134	180.9558	231.4834
PG3	129.9333	135.4821	137.0562
Fuel Cost (in $/hr)	**8262.6692**	8321.8726	**8280.5892**
P_{LOSS} (in MW)	15.2357	**13.8582**	**14.1921**

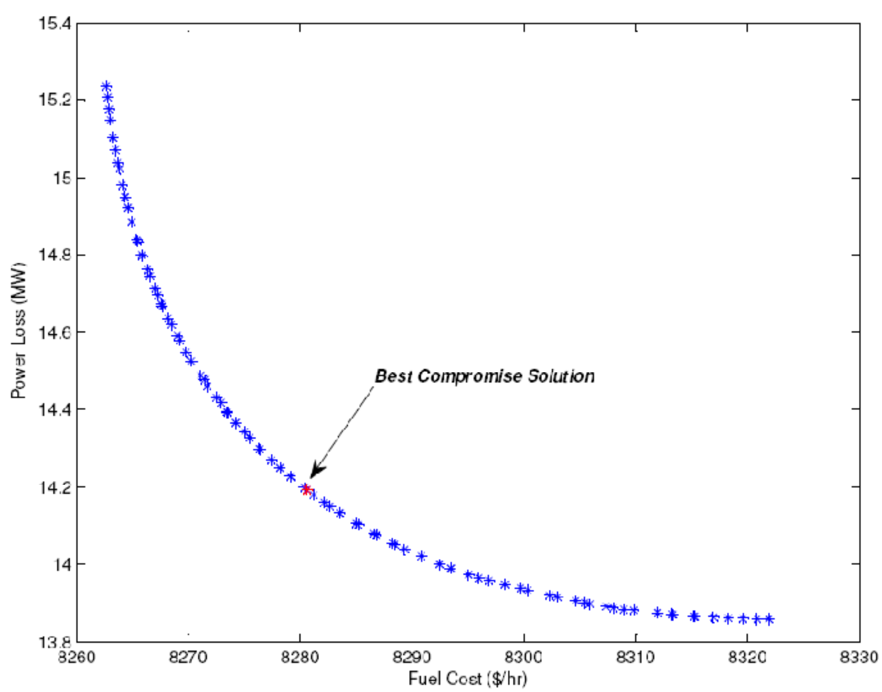


FIGURE 4-6: Pareto Optimal Solution for Fuel Cost and Power loss minimization for three generators

TABLE 4-7: Result for Fuel Cost and Power loss minimization for six generators

Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum P_{LOSS}	Best Compromise Solution
PG1	249.9999	249.9999	249.9999
PG2	229.9999	229.9999	229.9994
PG3	499.9975	499.9955	499.9955
PG4	265.0000	264.9994	264.9913
PG5	398.3935	310.8040	353.3878
PG6	273.3524	356.9829	315.4273
Fuel Cost (in $/hr)	**18670.7321**	18778.4066	**18701.7493**
P_{LOSS} (in MW)	136.1025	**132.1024**	**133.1192**

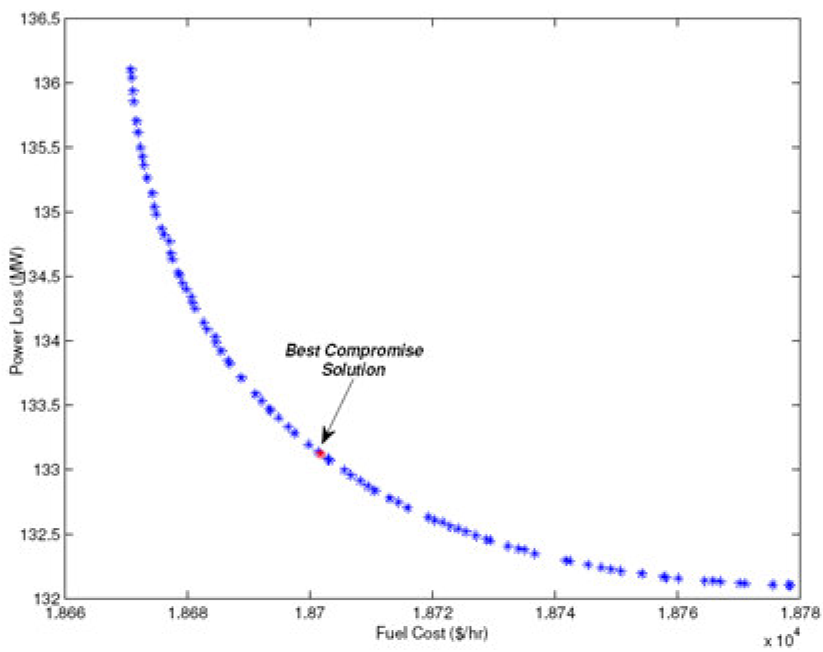


FIGURE 4-7: Pareto Optimal Solution for Fuel Cost and Power loss minimization for six generators

4.5 Case Study 5: Multi-objective Fuel Cost, NO_X and SO_X Emission

In this case study, developed algorithm has been applied for multi-objective fuel cost NO_X and SO_X emission. The simulation results obtained are given in Table 4-8 and Table 4-9 for a system of three generators and six generators respectively.

Correspondingly the optimal-pareto fronts are also shown in Figure 4-8 and Figure 4-9 respectively.

A. Three generator system

The results for minimizing fuel cost, NO_X and SO_X emission after neglecting losses and considering them are summarized in Table 4-8 (a) and Table 4-8 (b). Correspondingly the pareto optimal fronts and best compromise solutions are shown in Figure 4-8 (a) and Figure 4-8 (b) respectively.

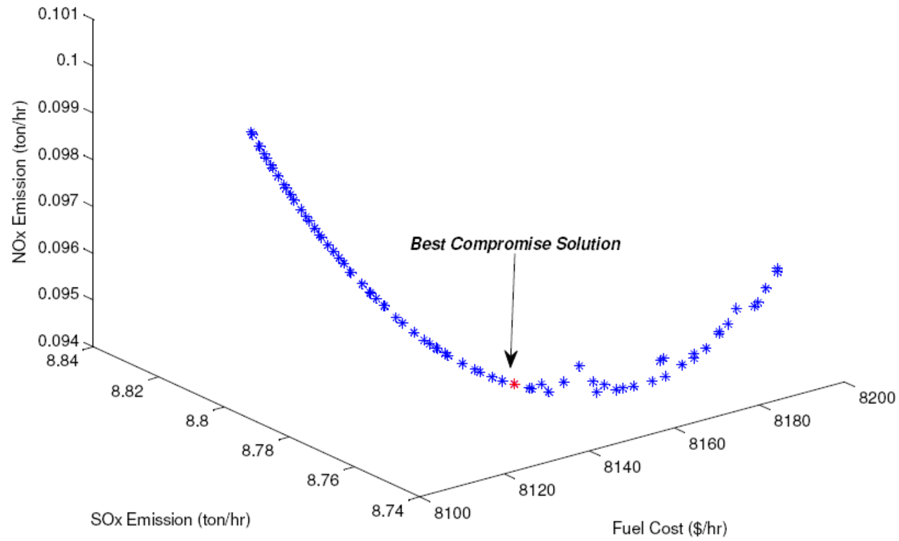
TABLE 4-8: Result for Fuel Cost, NO_X and SO_X minimization for three generators

(a) Neglecting Power loss

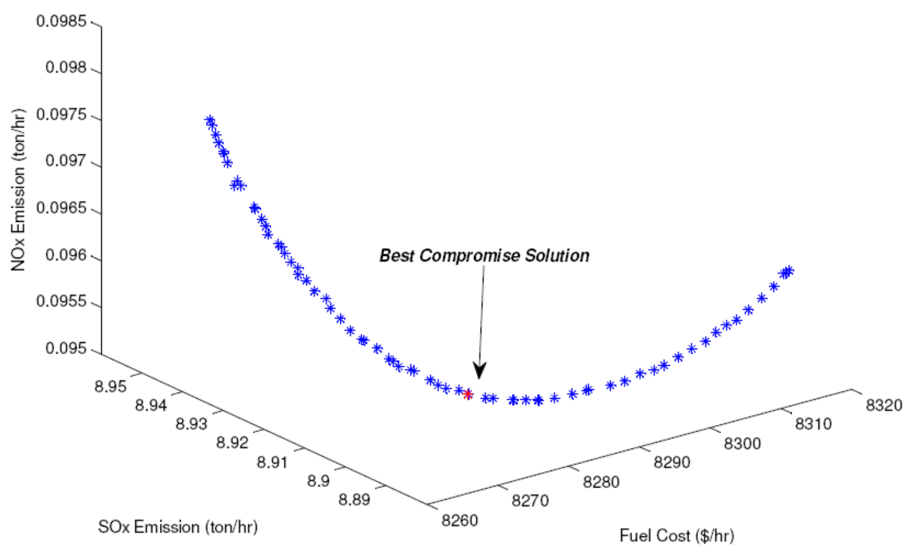
Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum NOx Emission	Solution at minimum SO_X Emission	Best Compromise Solution
PG1	390.0505	492.7933	541.4681	469.5129
PG2	330.7669	244.2445	224.2281	268.7573
PG3	120.6825	104.4623	75.8038	103.2299
Fuel Cost (in $/hr)	**8116.6513**	8149.4593	8184.9701	**8135.8518**
NOx Emission (in ton/hr)	0.0990	**0.0947**	0.0967	**0.0949**
SO_X Emission (in ton/hr)	8.8134	8.7501	**8.7410**	**8.7576**

(b) Considering Power loss

Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum NOx Emission	Solution at minimum SO_X Emission	Best Compromise Solution
PG1	433.2368	502.6335	545.4116	489.2307
PG2	294.7041	247.9057	219.9337	258.2171
PG3	128.8177	105.2562	90.2676	108.5026
Fuel Cost (in $/hr)	**8262.2368**	8282.0612	8312.3405	**8275.4337**
NOx Emission (in ton/hr)	0.0979	**0.0954**	0.0964	**0.0955**
SO_X Emission (in ton/hr)	8.9372	8.8909	**8.8820**	**8.8968**



(a) Neglecting Power loss



(b) Considering Power loss

FIGURE 4-8: Pareto Optimal Solution for Fuel Cost, NO_X and SO_X Emission minimization for three generators

B. Six generator system

The results for minimizing fuel cost, NO_X and SO_X emission after neglecting losses and considering them are summarized in Table 4-9 (a) and Table 4-9 (b). Correspondingly the pareto optimal fronts and best compromise solutions are shown in Figure 4-9 (a) and Figure 4-9 (b) respectively.

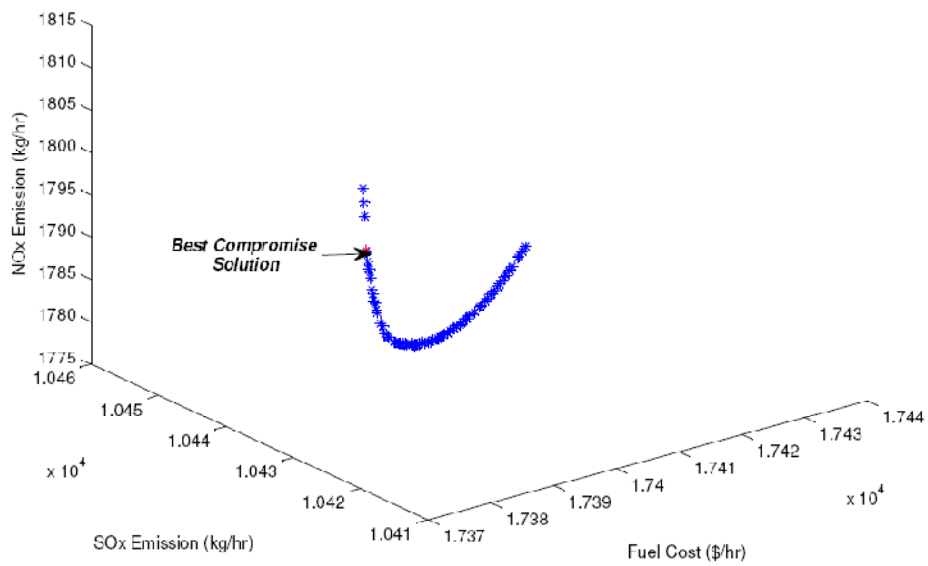
TABLE 4-9: Result for Fuel Cost, NO_X and SO_X minimization for six generators

(a) Neglecting Power loss

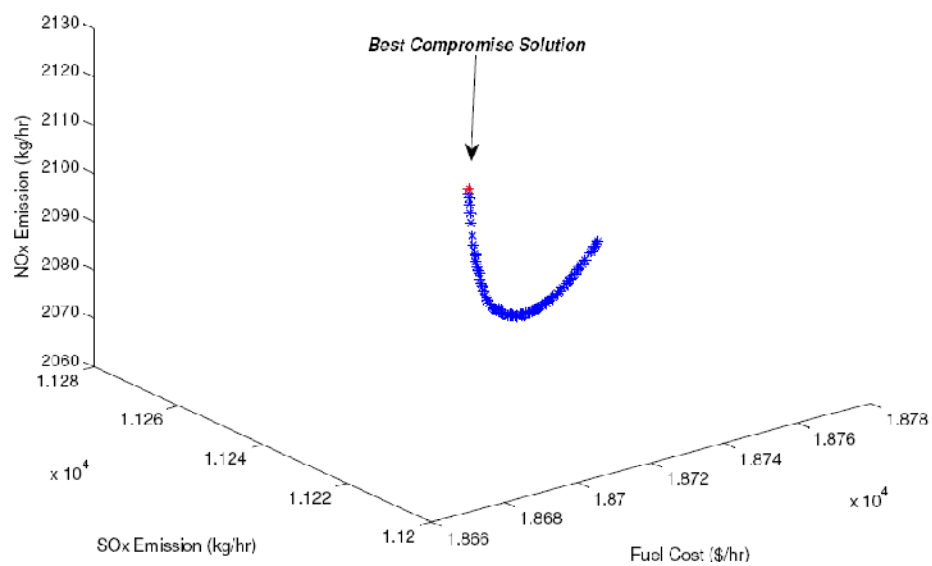
Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum NOx Emission	Solution at minimum SO_X Emission	Best Compromise Solution
PG1	214.8062	163.8169	206.6958	164.5926
PG2	229.9999	191.5229	229.9948	229.9309
PG3	434.6419	480.939	438.8242	460.8014
PG4	264.9928	264.9980	264.9979	264.9826
PG5	437.5591	480.7230	441.1372	461.6944
PG6	200.0000	200.0000	200.3503	200.0000
Fuel Cost (in $/hr)	**17369.2394**	17433.4891	17369.5787	**17378.0800**
NOx Emission (in ton/hr)	1816.3543	**1777.6188**	1809.5714	**1789.6822**
SO_X Emission (in ton/hr)	10419.8057	10454.9135	**10419.5946**	**10422.4643**

(b) Considering Power loss

Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum NOx Emission	Solution at minimum SO_X Emission	Best Compromise Solution
PG1	249.9999	218.8448	249.9999	249.9999
PG2	229.9279	229.9965	229.9279	229.9279
PG3	499.9999	499.9999	499.9999	499.9999
PG4	264.9999	264.9997	264.9999	264.9999
PG5	412.7281	499.9990	412.7281	412.7281
PG6	260.4196	262.6843	260.4196	260.4196
Fuel Cost (in $/hr)	**18671.1923**	18777.0002	18671.1923	**18671.1923**
NOx Emission (in ton/hr)	2126.2873	**2069.1225**	2126.2873	**2126.2873**
SO_X Emission (in ton/hr)	11200.8526	11262.1760	**11200.8526**	**11200.8526**



(a) Neglecting Power loss



(b) Considering Power loss

FIGURE 4-9: Pareto Optimal Solution for Fuel Cost, NO_X and SO_X Emission minimization for six generators

4.6 Case Study 6: Multi-objective Fuel Cost, NO_X and CO_X Emission

In this case study, developed algorithm has been applied for multi-objective fuel cost NO_X and CO_X emission. after neglecting losses and considering them are summarized in Table 4-10 (a) and Table 4-10 (b). Correspondingly the pareto optimal fronts and best compromise solutions are shown in Figure 4-10 (a) and Figure 4-10 (b) respectively.

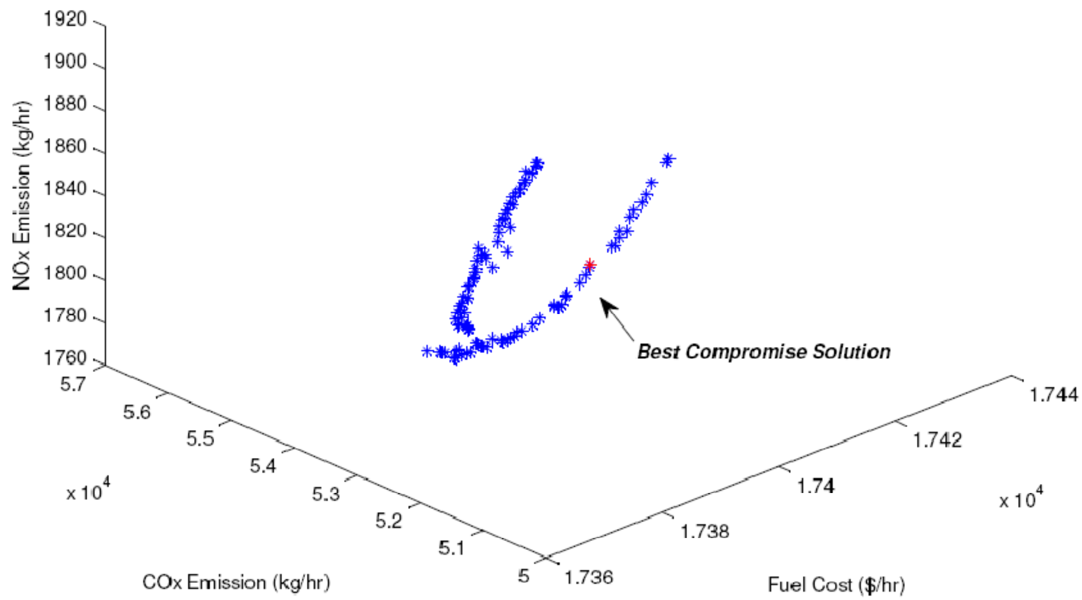
TABLE 4-10: Result for Fuel Cost, NO_X and CO_X minimization for six generators

(a) Neglecting Power loss

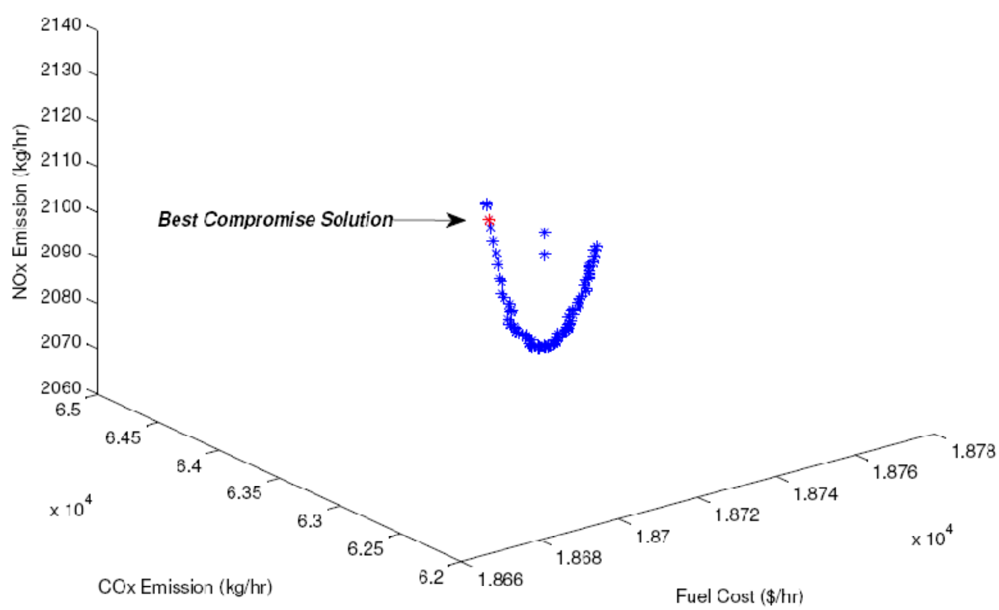
Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum NOx Emission	Solution at minimum CO_X Emission	Best Compromise Solution
PG1	217.2032	164.0247	250.0000	234.3847
PG2	230.0000	191.5446	229.9995	229.9939
PG3	432.4094	480.5429	396.0744	409.7739
PG4	264.9990	265.0000	265.8076	264.9999
PG5	436.3419	480.8877	397.1595	411.9733
PG6	201.0507	200.0000	244.03382	230.8766
Fuel Cost ($/hr)	**17369.2053**	17433.3589	17388.5559	**17377.4710**
NOx (kg/hr)	1819.3582	**1777.6177**	1908.4342	**1867.6659**
CO_X (kg/hr)	52108.7306	56916.7063	**50692.6632**	**50912.5448**

b) Considering Power loss

Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum NOx Emission	Solution at minimum CO_X Emission	Best Compromise Solution
PG1	249.9998	219.2286	250.0000	250.0000
PG2	229.9999	229.9927	229.9927	229.9998
PG3	499.9999	499.9998	489.7413	499.9999
PG4	264.9999	264.9953	264.9999	264.9990
PG5	404.4512	500.0000	422.8435	408.8986
PG6	266.0168	216.7131	262.0677	263.8065
Fuel Cost ($/hr)	**18670.3100**	18776.7723	18683.3646	**18670.4965**
NOx (kg/hr)	2134.6900	**2069.1249**	2125.9161	**2131.31153**
CO_X (kg/hr)	62125.2833	64682.7723	**62072.2342**	**62110.3781**



(a) Neglecting Power loss



(b) Considering Power loss

FIGURE 4-10: Pareto Optimal Solution for Fuel Cost, NO_X and CO_X Emission minimization for six generators

4.7 Case Study 7: Multi-objective Fuel Cost, NO_X and Power loss Emission

In this case study, developed algorithm has been applied for multi-objective fuel cost NO_X and Power loss. The simulation results obtained are given in Table 4-11 and Table 4-12 for a system of three generators and six generators respectively. Correspondingly the optimal-pareto fronts are also shown in Figure 4-11 and Figure 4-12 respectively.

TABLE 4-11: Result for Fuel Cost, NO_X and Power loss minimization for three generators

Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum NOx Emission	Solution at minimum P_{LOSS}	Best Compromise Solution
PG1	430.6027	502.7639	540.0945	491.7951
PG2	297.1101	247.7444	180.1275	258.6267
PG3	129.1406	105.2845	134.9974	105.5453
Fuel Cost (in $/hr)	**8262.1996**	8282.1321	8322.9046	**8276.7952**
NOx Emission (in ton/hr)	0.0981	**0.0954**	0.0987	**0.0955**
P_{LOSS} (in MW)	15.5085	14.4373	**13.8581**	**14.6125**

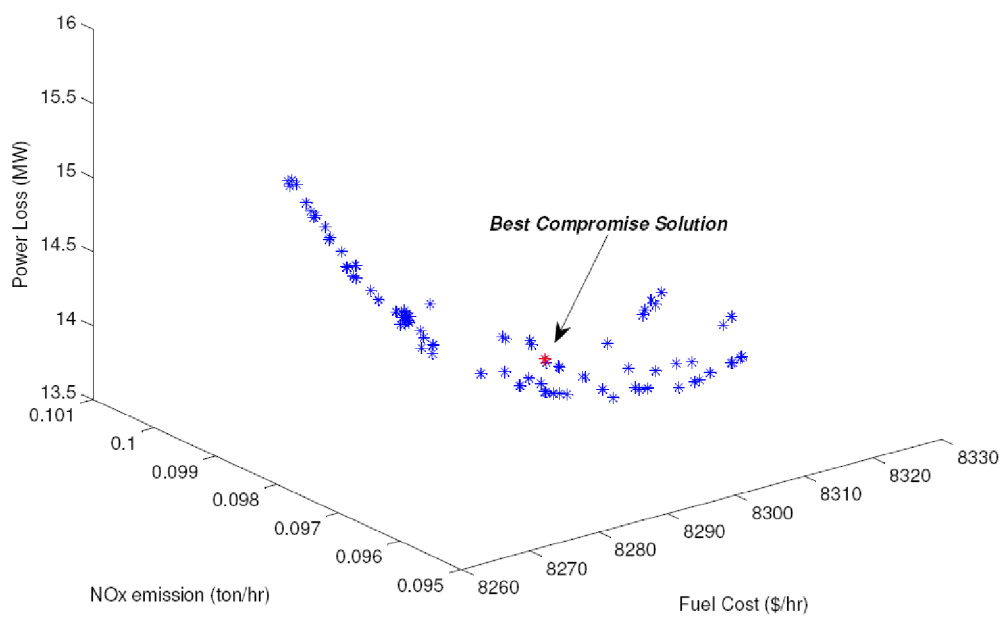


FIGURE 4-11: Pareto Optimal Solution for Fuel Cost, NO_X and Power loss minimization for three generators

TABLE 4-12: Result for Fuel Cost, NO_X and Power loss minimization for six generators

Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum NOx Emission	Solution at minimum P_{LOSS}	Best Compromise Solution
PG1	250.0000	219.4133	249.9999	247.8314
PG2	229.9989	229.99222	229.9998	229.9894
PG3	499.9998	499.9985	500.0000	500.0000
PG4	264.9913	264.9999	265.0000	264.9995
PG5	404.7714	500.0000	308.4882	420.5229
PG6	267.5504	216.5155	359.2902	255.6399
Fuel Cost (in $/hr)	**18670.2838**	18776.6565	18783.9636	**18675.05341**
NOx Emission (in kg/hr)	2137.0967	**2069.1194**	2369.7359	**2117.0534**
P_{LOSS} (in MW)	136.6785	150.4252	**132.0993**	**138.3643**

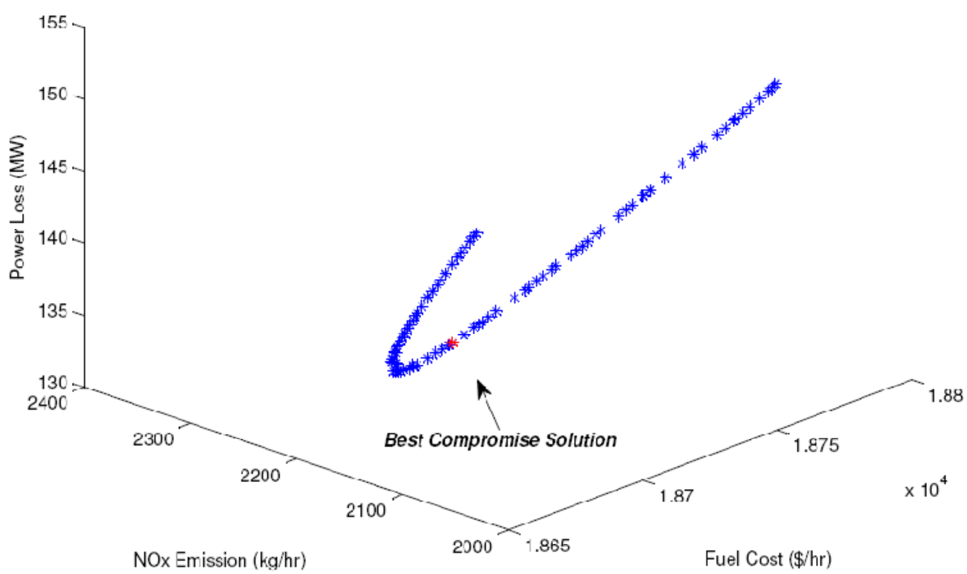


FIGURE 4-12: Pareto Optimal Solution for Fuel Cost, NO_X and Power loss minimization for six generators

4.8 Case Study 8: Multi-objective Fuel Cost, SO_X and Power loss Emission

In this case study, developed algorithm has been applied for multi-objective fuel cost SO_X and Power loss. The simulation results obtained are given in Table 4-13 and Table 4-14 for a system of three generators and six generators respectively.

Correspondingly the optimal-pareto fronts are also shown in Figure 4-13 and Figure 4-14 respectively.

TABLE 4-13: Result for Fuel Cost, SO_X and Power loss minimization for three generators

Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum SO_X Emission	Solution at minimum P_{LOSS}	Best Compromise Solution
PG1	431.2516	544.9633	539.9789	494.9699
PG2	296.6623	218.9258	180.4375	244.1846
PG3	128.9258	92.1110	134.8031	116.5484
Fuel Cost (in \$/hr)	**8262.2026**	8311.9383	8322.6425	**8278.7314**
SO_X Emission (in ton/hr)	8.9323	**8.8772**	8.8938	**8.8889**
P_{LOSS} (in MW)	15.4947	14.2248	**13.8581**	**14.3462**

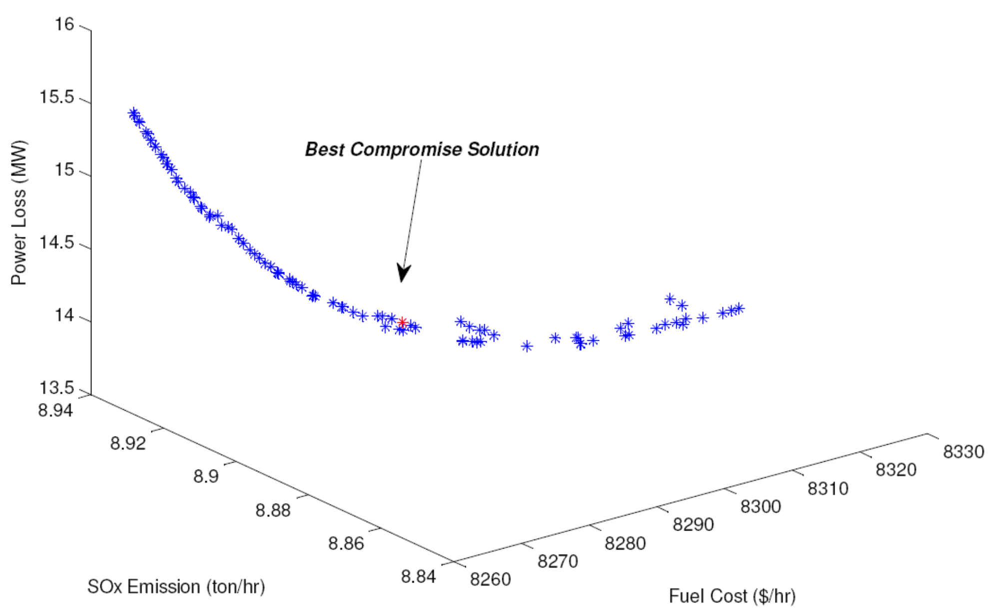


FIGURE 4-13: Pareto Optimal Solution for Fuel Cost, SO_X and Power loss minimization for three generators

TABLE 4-14: Result for Fuel Cost, SO_X and Power loss minimization for six generators

Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum SO_X Emission	Solution at minimum P_{LOSS}	Best Compromise Solution
PG1	250.0000	250.0000	249.9998	250.0000
PG2	229.9999	229.9999	229.9998	229.9999
PG3	499.9999	499.9999	499.9993	499.9999
PG4	264.9999	264.9999	264.9999	264.9999
PG5	404.3382	404.3382	309.0691	404.3382
PG6	267.9333	267.9333	358.7103	267.9333
Fuel Cost (in $/hr)	**18670.2678**	18670.2678	18782.5538	**18670.2678**
SO_X Emission (in ton/hr)	11200.3967	**11200.3967**	11268.7621	**11200.3967**
P_{LOSS} (in MW)	136.6378	136.6378	**132.0995**	**136.6378**

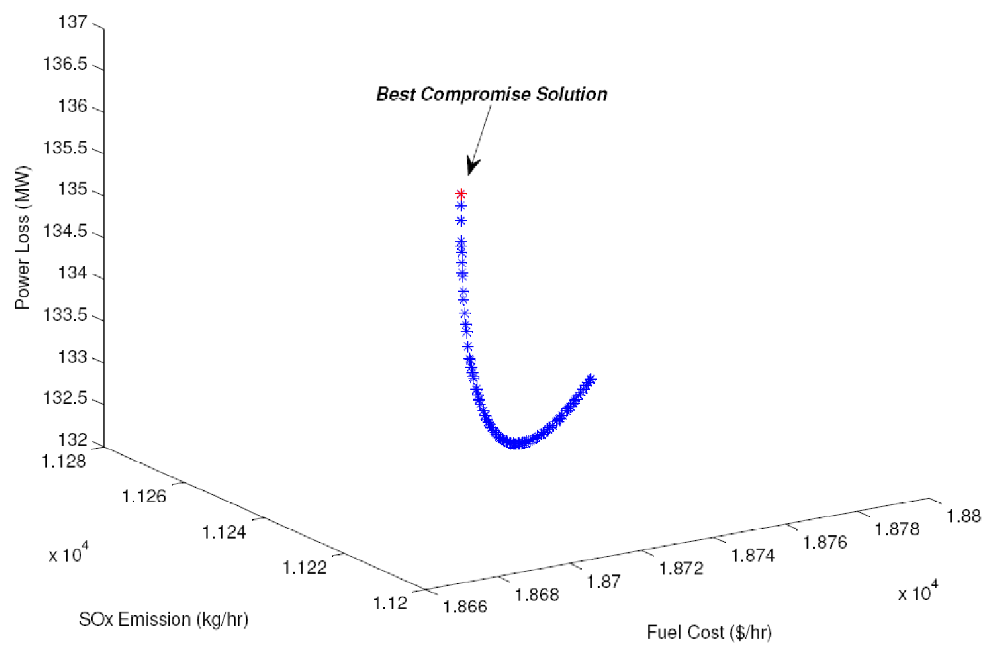


FIGURE 4-14: Pareto Optimal Solution for Fuel Cost, SO_X and Power loss minimization for six generators

4.9 Case Study 9: Multi-objective Fuel Cost, CO_X and Power loss Emission

In this case study, developed algorithm has been applied for multi-objective fuel cost CO_X and Power loss. The simulation results obtained are given in Table 4-15 for a system of six generators respectively. Correspondingly the optimal-pareto fronts are also shown in Figure 4-15.

TABLE 4-15: Result for Fuel Cost, CO_X and Power loss minimization for six generators

Units (in MW)	Solution at minimum Fuel Cost	Solution at minimum CO_X Emission	Solution at minimum P_{LOSS}	Best Compromise Solution
PG1	249.9991	250.0000	249.9990	250.0000
PG2	229.9995	229.9999	229.9998	229.9999
PG3	500.0000	500.0000	499.9999	500.0000
PG4	264.9985	265.0000	265.0000	265.0000
PG5	404.4898	366.0737	343.7837	366.0737
PG6	267.7984	303.3524	324.6217	303.3524
Fuel Cost (in $/hr)	**18670.2709**	18687.8727	18714.7983	**18687.8727**
CO_X Emission (in kg/hr)	62141.5074	**62012.1704**	67766.0141	**67766.0141**
P_{LOSS} (in MW)	136.6519	138.9478	**132.0993**	**136.8667**

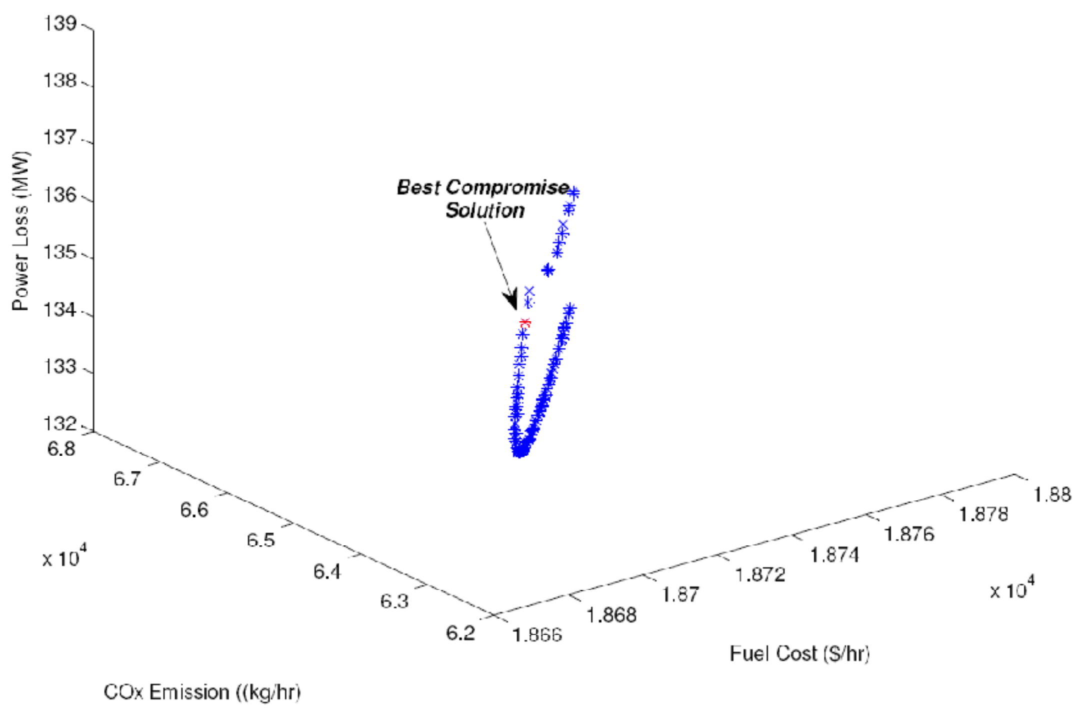


FIGURE 4-15: Pareto Optimal Solution for Fuel Cost, CO_X and Power loss minimization for six generators

4-10 COMPARISION OF BEST COMPROMISE SOLUTIONS

The comparison of different best compromise solutions resulted for different cases has been presented for both three and six generators systems in Tables 4-16 and Table 4-17 respectively. These results are for the cases involving losses and are obtained from previous results.

Mostly, the operating cost for respective generation system is not changing significantly in both the systems. For six bus, the generating units PG1, PG2, PG3 and PG4 are attaining the respective maximum limit or it can be said that the loss coefficients are such that the operation of these generating units are forced to respective maximum level. This is analogous to the low value of penalty factors for these generators. These results are shaded in Table 4-17.

Table 4-16: Comparison of best compromise solutions for three generators for cases involving losses

Units	Case 1	Case 2	Case 4	Case 5	Case 7	Case 8
PG1	467.2490	484.7521	487.0120	489.2307	491.7951	494.9699
PG2	277.7231	261.1049	231.4834	258.2171	258.6267	244.1846
PG3	111.3576	110.1379	137.0562	108.5026	105.5453	116.5484
Fuel cost	**8267.6804**	**8273.4855**	**8280.5892**	**8275.4337**	**8276.7952**	**8278.7314**

Table 4-17: Comparison of best compromise solutions for six generators for cases involving losses

Units	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9
PG1	245.4132	250.0000	249.9949	249.9999	249.9999	250.0000	247.8314	250.0000	250.0000
PG2	229.9999	230.0000	229.9997	229.9994	229.9279	229.9998	229.9894	229.9999	229.9999
PG3	499.9812	500.0000	499.9540	499.9955	499.9999	499.9999	500.0000	499.9999	500.0000
PG4	265.0000	265.0000	265.0000	264.9913	264.9999	264.9990	264.9995	264.9999	265.0000
PG5	455.7339	404.9990	412.2104	353.3878	412.7281	408.8986	420.5229	404.3382	366.0737
PG6	227.1909	267.3419	260.8661	315.4273	260.4196	263.8065	255.6399	267.9333	303.3524
Fuel Cost	**18702.12**	**18670.35**	**18670.99**	**18701.74**	**18671.19**	**18670.49**	**18675.053**	**18670.26**	**18687.87**

The best compromise solutions without considering losses are compared and the results are presented in Table 4-18 and Table 4-19 for three generators and six generator systems. Although there is a noticeable change in generation pattern, there is no significant change is fuel cost for different cases for given system. For six generator system, the PG2 and PG4 are attaining to respective maximum limiting values.

Table 4-18: Comparison of best compromise solutions for three generators for cases without considering losses

Units	Case 1	Case 2	Case 5
PG1	443.5063	463.2578	469.5129
PG2	289.4805	279.9481	268.7573
PG3	108.5142	98.6314	103.2299
Fuel cost	**8125.4197**	**8132.8215**	**8135.8518**

Table 4-19: Comparison of best compromise solutions for six generators for cases without considering losses

Units	Case 1	Case 2	Case 3	Case 5	Case 6
PG1	168.8502	210.6618	238.6483	164.5926	234.3847
PG2	229.9111	230.0000	229.9982	229.9309	229.9939
PG3	456.7734	436.6352	414.0802	460.8014	409.7739
PG4	264.9916	264.9999	264.9984	264.9826	264.9999
PG5	461.4776	439.9999	415.2898	461.6944	411.9733
PG6	200.0000	200.0000	264.9981	200.0000	230.8766
Fuel Cost	**17376.7571**	**17369.3609**	**17373.7155**	**17378.0800**	**17377.4710**

CHAPTER 5

CONCLUSIONS AND SCOPE FOR FUTURE WORK

5.1 CONCLUSIONS

The multi objective power dispatch problem has been solved using an algorithm based on non-dominated sorting genetic algorithm-II (NSGA-II). Various combinations of real power, reactive power and emission-dispatch have been solved for systems having three generators and six generators.

Initially the multi objective problem has been solved for two objectives and then the problem has been solved for three objectives. The pareto-optimal front with good diversity has been obtained in all considered cases with the exception of fuel cost and SO_X emission for six generators with loss, where only a point is obtained. The following conclusions are drawn from the study.

- The developed algorithm is capable to handle different competing objectives.
- The number of iteration needed to obtain result for three objectives function is more compared to number of iteration for two objectives.
- The operating cost for various cases while neglecting losses and considering them are coming out to be in close range whereas there is a significant change in generation patters.
- The operation of six generators system is resulting into PG1, PG2, PG3 and PG4 attaining values at respective limits.

5.2 SCOPE FOR FUTURE WORK

The scope of work after studying Power Dispatch using NSGA-II is identified as:

- ➢ Extend the problem for large number of units i.e., 30 or 90 or even higher units.
- ➢ Extend the problem of multi-objective optimization to Optimal Power Flow with or without FACTS devices.

APPENDEX-I

The data for a system of three generators test system [70, 66] has been presented. This test system consists of three generators, provide with fuel and emission coefficient. In test system losses are taken in the form of B-coefficient. The load demand is given as 850MW for this system. The data related to these coefficients are given below in Table (A-1 to A-4)

TABLE A-1: Fuel Cost Coefficients for three generators system

Units	c_i	b_i	a_i	P_{min}	P_{max}
1	0.001562	7.92	561	150	600
2	0.001940	7.85	310	100	400
3	0.004820	7.97	78	50	200

TABLE A-2: NO_X Emission Coefficients for three generators system

Units	c_{Ni}	b_{Ni}	a_{Ni}
1	$1.4721848e^{-7}$	$-9.4868099e^{-5}$	0.04373254
2	$3.0207577e^{-7}$	$-9.7252878e^{-5}$	0.055821713
3	$1.9338531e^{-6}$	$-9.5373734e^{-4}$	0.027731524

TABLE A-3: SO_X Emission Coefficients for three generators system

Units	c_{Si}	b_{Si}	a_{Si}
1	$1.6103e^{-6}$	0.00816466	0.5783298
2	$2.1999e^{-6}$	0.00891174	0.3515338
3	$5.4658e^{-6}$	0.00903782	0.0884504

TABLE A-4: B - Coefficients for three generators system

0.000030	0.000000	0.000000
0.000010	0.000090	0.000000
0.000000	0.000000	0.000120

APPENDIX - II

The data for a system of three generators test system [71] has been presented. This test system consists of six generators provide with fuel and emission coefficient. In test system losses are taken in the form of B-coefficient. The load demand is given as 1800 MW for this system. The data related to these coefficients are given below in Table (A-5 to A-9)

TABLE A-5: Fuel Cost Coefficients for six generators system

Units	c_i	b_i	a_i	P_{min}	P_{max}
1	0.002035	8.43205	85.6348	100	250
2	0.003866	6.41031	303.7780	50	230
3	0.002182	7.42890	847.1484	200	500
4	0.001345	8.31540	274.2241	85	265
5	0.002162	7.42289	847.1484	200	500
6	0.005963	6.91559	202.0258	200	490

TABLE A-6: NO_X Emission Coefficients for six generators system

Units	c_{Ni}	b_{Ni}	a_{Ni}
1	0.006323	-0.38128	80.9019
2	0.006483	-0.79027	28.8249
3	0.003174	-1.36061	324.1775
4	0.006732	-2.39928	610.2535
5	0.003174	-1.36061	324.1775
6	0.006181	-0.39077	50.3808

TABLE A-7: CO_X Emission Coefficients for six generators system

Units	c_{Ci}	b_{Ci}	a_{Ci}
1	0.265110	-61.01945	5080.148
2	0.140053	-29.95221	3824.770
3	0.105929	-9.552794	1342.851
4	0.106409	-12.73642	1819.625
5	0.105929	-9.552794	1342.851
6	0.403144	-121.9812	11381.070

TABLE A-8: SO_X Emission Coefficients for six generators system

Units	c_{Si}	b_{Si}	a_{Si}
1	0.001206	5.09928	51.3778
2	0.002320	3.84654	182.2605
3	0.001284	4.45647	508.5207
4	0.000813	4.97641	165.3433
5	0.001284	4.45647	508.5207
6	0.003578	4.14938	121.2133

TABLE A-9: B- Coefficients for six generators system

0.000200	0.000010	0.000015	0.000005	0.000000	-0.000030
0.000010	0.000300	-0.000020	0.000001	0.000012	0.000010
0.000015	-0.000020	0.000100	-0.000010	0.000010	0.000008
0.000005	0.000001	-0.000010	0.000150	0.000006	0.000050
0.000000	0.000012	0.000010	0.000006	0.000250	0.000020
-0.000030	0.000010	0.000008	0.000050	0.000020	0.000210

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