MULTIOBJECTIVE OPTIMAL POWER FLOW

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

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CERTIFICATE

I hereby certify that work which is being presented in the Thesis entitled **"Multi-objective optimal power flow"**, in partial fulfillment of the requirement 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 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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It is certified that the above statement made by the student is correct to the best of our knowledge and belief.

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ABSTRACT

The optimization is one of the challenging problems in power system. The optimization sometimes is mainly restricted to the minimization of the operating cost. However, the operation of power plants, mostly thermal units, results into various types of emissions like SOx, NOx and COx etc. The environmental concern dictates the minimization of the emissions by the thermal plant. Individually, if one objective is optimized, other is compromised. The objectives like minimization of cost, losses and emission may be conflicting and thus the decision has to be based on robust multi-objective optimization.

The Optimal power flow (OPF) is used widely for the decision making by various power system operators. The OPF can provide the solution (decision variables) by optimizing various objectives namely generation cost, transmission losses etc. The objectives may be conflicting and the robust multi-objective formulation will help the decision making process. The optimal power flow using genetic algorithm has been considered for both single objective optimization and for multi-objective optimization. Different objectives considered are minimization of generation cost, minimization of transmission losses and minimization of emission. The multi-objective optimization problem is formulated for simultaneous minimization of fuel cost and losses, losses and emission and finally fuel cost and emission to obtain a Pareto optimal front. The optimization is carried out using Elitist Non Dominating sorting Genetic Algorithm for standard IEEE-30 bus system.

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CHAPTER 1
INTRODUCTION

1.1 OVERVIEW

Optimal Power Flow (OPF) was first discussed by Carpentier in 1962 [1]. In the past two decades, OPF problem has received much attention, because of its ability to solve for the optimal solution that takes account of the security of the system. OPF is important software in Energy Management Systems (EMS).OPF is a nonlinear, non-convex, large-scale, static optimization problem with both continuous and discrete control variables [2]. Even in the absence of discrete control variables, the OPF problem is non-convex due to the existence of the nonlinear (AC) power flow equality constraints.

To guide the decision making of the power system operator, the OPF solution should not be sensitive to selected starting points. Complexity of OPF problem must be reduced. OPF programs must be user friendly. Therefore, there is a need for more robust and faster OPF algorithm. OPF can be used periodically to determine the optimal settings of the control variables to minimize the generation cost, minimization of losses in the transmission system. For a secure operation of the power system, it is also important to maintain required level of security margin.

When an optimization problem involves more than one objective function, the task of finding one or more optimum solutions is known as multi-objective optimization [3]. Since classical search and optimization algorithms use a point by point approach, the outcome of using a classical approach is a single optimized solution.

Evolutionary Algorithms (EA) such as Genetic Algorithms (GA) have been used for optimization problems that are too complex to be solved using deterministic techniques such as linear programming or gradient (Jacobian) methods. Because of their universality, ease of implementation, and fitness for parallel computing, EAs have been preferred than gradient methods [4]. However, most real world problems involve simultaneous optimization of several often mutually concurrent objectives. Some have treated the weighted sum of objectives to obtain the solution. For multi-objective optimization the preference based approach requires multiple runs as many times as the number of desired optimal solutions. Multi-objective EAs are able to find optimal trade-offs in order to get a set of solutions that are optimal in an overall sense. However, multi-objective EAs inherit all of the favorable properties from their single objective relatives.

1.2 LITERATURE REVIEW

The OPF optimizes a power system operating objective function such as operating cost of thermal resources, transmission losses etc. while satisfying a set of system operating constraints, including constraints dictated by the electric network. In its most general formulation, the OPF is a non-linear, non-convex, large scale, static optimization problem with both continuous and discrete control variables.

The increasing demand for an optimal power flow (OPF) tool for assessing state and recommended control actions for off-line and on-line studies has been on the increase since the first OPF paper was presented in the 60's. The lack of uniformity in usage and definition has also been a source of challenge to developer/users in OPF. OPF has enjoyed the renewed interest in a variety of formulations, including the use of advanced optimized techniques such as, Genetic Algorithms, simulated annealing method etc. and has been used for analysis of vertically integrated and deregulated systems.

The literature on OPF is vast and [9] presented the major contributions in this area, where a review of literature is done on Optimal Power Flow up to 1993. Dommel and Tinney [19] has given a practical method for solving the power flow program with control variables such as real and reactive power and transformer ratios automatically adjusted to minimize instantaneous costs or losses. The solution is feasible with respect to constraints on control variables and dependent variables such as load voltages, reactive sources, and tie line power angles. The method is based on power flow solution by Newton’s method, a gradient adjustment algorithm for obtaining the minimum and penalty functions to account for dependent constraints.

The paper [10] extended the problem formulation and solution scheme by incorporating exact outage contingency constraints into the method, to give an optimal steady state secure system operating point. The controllable system quantities in the base-case problem (e.g. generated MW, controlled voltage magnitudes, transformer taps) are optimized within their limits according to some definite objective, so that no limit violations on other quantities(e.g. generator MVAR and current loading, transmission circuit loadings, load bus voltage magnitudes, angular displacement) occur in either the base-case or contingency-case system operating conditions.

Mathematical programming approaches, such as non linear programming (NLP) [10-13], quadratic programming (QP) [14,15], and linear programming (LP) [16-18], have been used for the solution of the OPF problem.OPF problems based on mathematical programming approaches are used daily to solve very large OPF problems. Many different mathematical techniques have been employed for its solution namely Lambda iteration method, Gradient method, Newton's method, and Interior point method [33]. However, they are not guaranteed to converge to the global optimum of the general non-convex OPF problem. Recent attempts to overcome the limitations of the mathematical programming approaches include the application of simulated annealing type methods [20,21] and genetic algorithms[5,23].

Evolutionary Algorithms (EA) such as Genetic Algorithms (GA) have become the method of choice for optimization problems that are too complex to be solved using deterministic techniques such as linear programming or gradient (Jacobian) methods. EAs often take less time [4] to find the optimal solution than gradient methods. GAs has been successfully applied for solution of OPF problem as single objective optimization approaches [2], [5], and [6]. Ref. [2] presents an Enhanced Genetic Algorithm (EGA) for solution of OPF. Particle Swarm Optimization (PSO) is also used to solve OPF [7] with different objectives that reflect fuel cost minimization and Voltage profile improvement. But the problem used the weighted sum of the objectives. Ref. [8] presents a multi-objective Strength Pareto Evolutionary Algorithm (SPEA) for Optimal VAR dispatch problem considering simultaneous optimization of system transmission loss and bus voltage deviations.

In paper [22], a simple genetic algorithm (SGA) for the OPF solution. The control variables modeled are generated active power outputs and voltages, shunt devices, and transformer taps. Branch flow, reactive generation and voltage magnitude constraints are treated as quadratic penalty terms in the GA fitness function (FF).

In paper [23], presented a GA to solve the optimal power dispatch problem for a multimode auction market. The GA maximizes the total participant's welfare, subject to network flow and transport limitation constraints.

The paper presented by Bakirtzis *et.al*.[26] presents an enhanced genetic algorithm (EGA) for the solution of the optimal power flow (OPF) with both continuous and discrete control variables. The continuous control variables modeled are unit active power outputs and generator-bus voltage magnitudes, while the discrete ones are transformer tap settings and switchable shunt devices. A number of functional operating constraints, such as branch flow limits, and load bus voltage magnitude limits, and generator reactive capabilities, are included as penalties in the GA fitness function (FF). Advanced and problem specific operators are introduced in order to enhance the algorithm's efficiency and accuracy.

Optimization is a procedure of finding and comparing feasible solutions until no better solution can be found. When an optimization problem involves more than one objective function, the task of finding one or more optimum solutions is known as multi-objective optimization [24].Since classical search and optimization algorithms use a point by point approach, the outcome of using a classical approach is a single optimized solution. The paper [26] has presented multi-objective optimization problem of three objectives namely generation costs, transmission loss and voltage stability index in which the OPF problem is formulated as simultaneous minimization of system generation cost and transmission loss, generation cost and voltage stability index, system transmission loss and voltage stability index and fuel cost, loss and voltage stability index. Enhanced Genetic Algorithm with Decoupled Quadratic Load flow [27] solution is used to solve OPF. Strength Pareto Evolutionary Algorithm (SPEA) [24] with strong-dominated solutions is used to form the Pareto optimal set.

1.3 OBJECTIVE OF THE WORK

The objective of the present work is to obtain the optimal generation levels satisfying power flow for single and multi-objective optimization by considering different objectives like fuel cost, transmission losses and emission and their different combinations.

The optimization is to be carried out using the genetic algorithms for both single objective optimization and multi-objective optimization.

1.4 ORGANIZATION OF THE THESIS

The work carried out has been summarized in four Chapters. The Chapter 1 highlights the brief introduction, summary of work carried out by various researchers, and the outline of the thesis is also given in this chapter. The Chapter 2 explains the optimal power flow using GA in MATLAB environment to minimize different objective functions namely the operating cost, transmission losses and emission individually. The Chapter 3 describes the Multi-objective optimization of above objectives using GA in MATLAB by which operating cost and transmission losses are minimized simultaneously to obtain a Pareto optimal front. The conclusions and the scope of further work are detailed in Chapter 4.

CHAPTER 2

SINGLE OBJECTIVE OPTIMAL POWER FLOW USING GENETIC ALGORITHM

2.1 OPTIMAL POWER FLOW

Optimal power flow (OPF) has been widely used in power system operation and planning. The Optimal power flow module is an intelligent load flow that employs techniques to automatically adjust the power system control settings while simultaneously solving the load flows and optimizing operating conditions with specific constraints. Optimal power flow (OPF) is a static nonlinear programming problem which optimizes a certain objective function while satisfying a set of physical and operational constraints imposed by equipment limitations and security requirements. In general, OPF problem is a large dimension nonlinear and highly constrained optimization problem. [28-31]. So the objective is to minimize the fuel cost and keep the power outputs of generators, bus voltages, shunt capacitors/reactors and transformers tap setting in their secure limits The OPF has been usually considered as the minimization of an objective function representing the generation cost and/or the transmission loss. The constraints involved are the physical laws governing the power generation-transmission systems and the operating limitations of the equipment.

Before beginning the creation of an OPF, it is useful to consider the goals that the OPF will need to accomplish. The primary goal of a generic OPF is to minimize the costs of meeting the load demand for a power system while maintaining the security of the system. The costs associated with the power systems may depend on the situation but in general they can be attributed to the cost of generating power (megawatts) of each generator. From the viewpoint of an OPF, the maintenance of system security requires keeping each device in the power system within its desired operation range at steady state. This will include maximum and minimum output for generators, maximum MVA flows on transmission lines and transformers, as well as keeping the system bus voltages within the specified ranges. It should be noted that the OPF only addresses steady state operation of the power system [32].

The standard OPF problem can be written in the following form :

$$\text{Min. } F(x) \tag{2.1}$$

Subject to: $$h(x) = 0 \tag{2.2}$$

and $$g(x) \geq 0 \tag{2.3}$$

where,

$F(x)$ is the objective function,

$h(x)$ is the equality constraints and

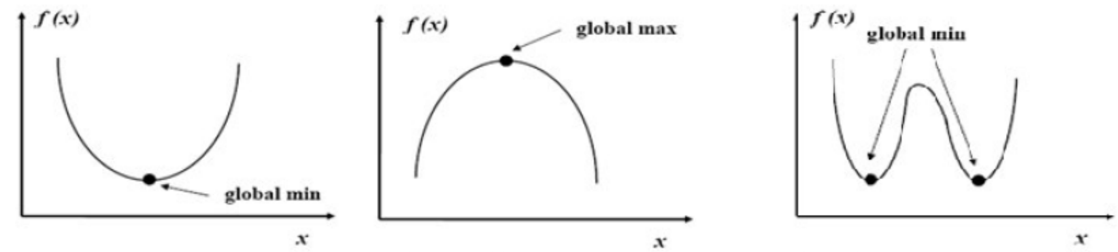
$g(x)$ is the inequality constraints.

And x is the vector of control variables, the control variable can be generated active and reactive power, generation bus voltage magnitudes, transformer taps etc. However it is the active power generation for problems under consideration.

The essence of the optimal power flow problem resides in reducing the objective function and simultaneous satisfying the load flow equations (equality constraints) without violating the inequality constraints [29,35]. Optimization is one of the challenging problems in power system. The goal of optimization is to minimize or maximize a specific objective function subject to the operational constraints of the power system. The objective can be the minimization of losses or cost of operation or emission losses, maximization efficiency or reliability etc.

The above formulation coincides with the single objective optimization. For single objective optimization, 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 Fig 2.1 (a) and 2.1 (b) respectively. If the problem is non convex or non concave, there may exist more than one globally optimal solution as shown in Fig 2.1 (c). However each globally optimal solution will have the same objective function value.

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.



(a) Convex objective function (b) concave objective function (c) function with number of global optimal solutions

Fig 2.1: Optimal solution for various formulations

2.2 OPF FORMULATION FOR GENERATION COST MINIMIZATION

2.2.1 OBJECTIVE FUNCTION

The most commonly used objective in the OPF problem formulation is the minimization of total cost of real power generation. The individual costs of each generating unit are assumed to be function, only of active power generation and are represented by quadratic curves of second order. The objective function of entire power system can then be written as the sum of the quadratic cost model at each generator.

$$F(x) = min \sum_{i=1}^{n_g} a_i Pg_i{}^2 + b_i Pg_i + c_i \tag{2.4}$$

Such that : $Pg_i^{min} < Pg_i < Pg_i^{max}$ (2.5)

where, i = 1, 2, 3…………..n_g and

n_g is the number of generators including the slack bus

Pg_i is the generated active power at bus i.

a_i , b_i , c_i are the unit costs curve for i^{th} generator.

2.2.2 EQUALITY CONSTRAINTS

While minimizing the cost function, it is necessary to make sure that the generation still supplies the load demands (P_d) plus losses in transmission lines [36]. Usually the power flow equations are used as equality constraints:

- The power flow equation of the network

$$g(V, \Phi) = 0 \tag{2.6}$$

where,

$$g(V,\Phi) = \begin{Bmatrix} P_i(V,\Phi) - P_i^{net} \\ Q_i(V,\Phi) - Q_i^{net} \\ P_m(V,\Phi) - P_m^{net} \end{Bmatrix} \tag{2.7}$$

where,

P_i and Q_i are calculated real and reactive power for ith PQ bus.

P_i^{net} and Q_i^{net} are specified real and reactive power for ith PQ bus.

P_m and $P_m{}^i$ are calculated and specified real power for mth PV bus.

V and Φ are voltage magnitude and phase angle at various buses.

2.2.3 INEQUALITY CONSTRAINTS

The inequality constraints of the OPF reflect the limits on physical device in the power systems as well as the limits created to ensure system security. The most usual types of inequality constraints are upper bus voltage limits at generations at load buses, lower bus voltage limits at some generators, maximum line loading limits and limits on tap settings. The inequality constraints on problem variables considered include:

- The inequality constraints on reactive power generation Qg_i at each PV bus.

$$Qg_i^{min} \leq Qgi \leq Qg_i^{max} \tag{2.8}$$

Where, Qg_i^{min} and Qg_i^{max} are respectively minimum and maximum value of reactive power at PV bus i.

- The inequality constraint on voltage magnitude V of each PQ bus.

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{2.9}$$

Where, V_i^{min} and V_i^{max} are respectively minimum and maximum voltage at bus i.

- The inequality constraint on phase angle Φ_i of voltage at all buses i.

$$\Phi_i^{min} \leq \Phi_i \leq \Phi_i^{max} \tag{2.10}$$

Where Φ_i^{min} and Φ_i^{max} are respectively minimum and maximum phase angle at bus i.

- MVA flow limit on transmission line

$$MVAij \leq MVAij^{max} \tag{2.11}$$

where $MVAij^{max}$ is the maximum rating of transmission line connecting bus i and j.

2.3 OPF FORMULATION FOR MINIMIZATION OF LOSS

Active and reactive power losses occur in transmission lines depending on the power to be transmitted. The active power loss equation for the k^{th} line between buses I and j can be written as

$$P_{L-k} = G_k(V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)) \tag{2.12}$$

where

G_k; is k^{th} line conductance

B_k; is k^{th} line susceptance

V_i ; is voltage magnitude of i^{th} bus

δ_i ; is phase angle of i^{th} bus

The objective function of entire power system can then be written as the sum of transmission loss model of all the lines of system is

$$F(x) = min \sum_{k=1}^{nl} P_{L-k} \qquad (2.13)$$

where,

nl is the total number of lines

The constraints

These constraints have already been explained in 2.2**.**

$$g(V, \Phi) = 0$$

$$Qg_i^{min} \leq Qgi \leq Qg_i^{max}$$

$$V_i^{min} \leq V_i \leq V_i^{max}$$

$$\Phi_i^{min} \leq \Phi_i \leq \Phi_i^{max}$$

$$MVAij \leq MVAij^{max}$$

2.4 OPF FORMULATION FOR MINIMIZATION OF EMISSION

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 NOx Emission:

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

$$\text{Minimize} \quad F_2 = \sum_{k=0}^{n} (a_{Ni} + b_{Ni} P_{Gi} + c_{Ni} P_{Gi}^2) \quad \text{kg/hr} \qquad (2.14)$$

Minimization of SOx Emission:

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

$$\text{Minimize} \quad \mathrm{F}_3 = \sum_{k=0}^{n} (\mathrm{a}_{\mathrm{Si}} + \mathrm{b}_{\mathrm{Si}} P_{Gi} + c_{Si} P_{Gi}^2) \qquad \text{kg/hr}$$

(2.15)

Minimization of COx Emission:

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

$$\text{Minimize} \quad \mathrm{F}_4 = \sum_{k=0}^{n} (\mathrm{a}_{\mathrm{Ci}} + \mathrm{b}_{\mathrm{Ci}} P_{Gi} + c_{Ci} P_{Gi}^2) \qquad \text{kg/hr}$$

(2.16)

Problem formulation for given objective functions is given as:

Minimization of $F(P_{Gi}) = [\, F_2, F_3 \; or \; F_4 \,]$ (2.17)

Subjected to: $h(P_{Gi}) = 0$ (2.18)

$g(P_{Gi}) \le 0$ (2.19)

where,

F_2 is the total NOx Emission

F_3 is the total SOx Emission

F_4 is the total COx Emission

a_{Ni} , b_{Ni}, c_{Ni} are the NOx Emission Coefficients of i_{th} generator

a_{Si} , b_{Si}, c_{Si} are the SOx Emission Coefficients of i_{th} generator

a_{Ci} , b_{Ci}, c_{Ci} are the COx Emission Coefficients of i_{th} generator

The constraints

These constraints have already been explained in 2.2.

$$g(V, \Phi) = 0$$

$$Qg_i^{min} \leq Qgi \leq Qg_i^{max}$$

$$V_i^{min} \leq V_i \leq V_i^{max}$$

$$\Phi_i^{min} \leq \Phi_i \leq \Phi_i^{max}$$

$$MVAij \leq MVAij^{max}$$

2.5 OPTIMAL POWER FLOW USING GENETIC ALGORITHM

Evolutionary algorithms (EAs) are computer-based problem solving systems which are computational models of evolutionary processes as key elements in their design and implementation. Genetic algorithm is the most popular and widely used of all evolutionary algorithms. It transforms a set (population) of individual mathematical objects (usually fixed length character or binary strings), each with an associated fitness value, into a new population (next generation) using genetic operations similar to the corresponding operations of genetics in nature. GAs seem to perform a global search on the solution space of a given problem domain [9,34,36]. The theoretical aspect of GA is outlined in the further topic.

2.5.1 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. These algorithms encode a potential solution to a special problem on a simple chromosome like data structure and apply recombination operators to these structures so as to preserve critical information.

Genetic Algorithms (GA's), a class of population-based optimization approaches, have been recognized to be well suited for multi-objective optimization. In GA's, multiple individuals can search for multiple solutions in parallel, advantageously producing a family of possible solutions to the problem. The ability to handle complex problems involving features such as discontinuities, multimodality, and disjoint feasible spaces, reinforces the potential effectiveness of GA's in multi-objective search and optimization [39].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 off-springs using crossover operator.

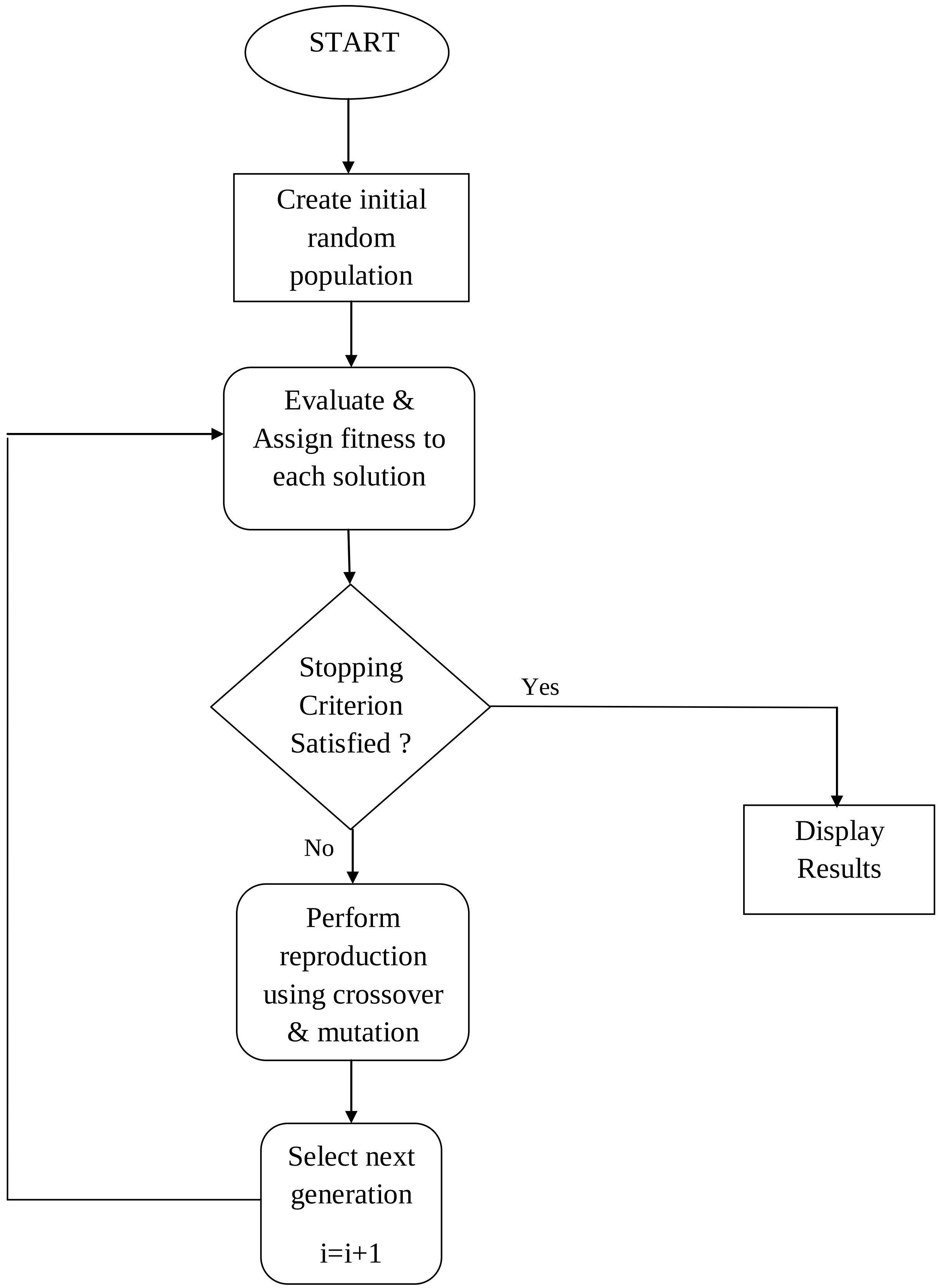


Fig 2.2: Block diagram of Genetic Algorithm

Step 5: Mutation: This operator randomly **s**elects 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.

The block diagram of basic genetic algorithm is shown below in Fig 2.2 which describes the function of genetic algorithm.

2.5.2 OPTIMAL POWER FLOW USING GA IN MATLAB

ga

ga implements the genetic algorithm at the command line to minimize an objective function.

X = ga(fitnessfcn,nvars) finds a local unconstrained minimum, x , to the objective function, fitnessfcn. nvars is the dimension(number of design variables) of fitnessfcn. The objective function, fitnessfcn, accepts a vector x of size 1-by-nvars, and returns a scalar evaluated at x.

GA attempts to solve problems of the form:

min F(x)

subject to: $$A \times x \leq B, \qquad (2.20)$$

$$A_{eq} \times x = B_{eq} \quad \text{(linear constraints)} \qquad (2.21)$$

$$C(x) \leq 0, C\_eq\,(x) = 0 \quad \text{(non linear constraints)} \qquad (2.22)$$

$$LB \leq X \leq UB \qquad (2.23)$$

In general,

X = GA(PROBLEM) finds the minimum for PROBLEM.

PROBLEM is a structure that has the following fields:

Fitnessfcn : < Fitness function >

nvars : < Number of design variables >

Options : < options structure created with GAOPTIMSET >

A_{ineq} : < A matrix for inequality constraints >

B_{ineq} : < B vector for inequality constraints >

A_{eq} : < A matrix for equality constraints >

B_{eq} : < B vector for equality constraints >

LB : < Lower bound on x >

UB : < Upper bound on x >

[X,FVAL] = GA(FITNESSFCN,…..)

returns FVAL, the value of the fitness function FITNESSFCN at the solution X.

[X,FVAL,EXITFLAG] = GA(FITNESSFCN,..…)

returns EXITFLAG which describes the exit condition of GA.

gaoptimset

It creates genetic algorithm options structure.

Syntax : gaoptimset

Options = gaoptimset

Options = gaoptimset('param1', value1, 'param2', value2,……)

Dscription :

Options = gaoptimset ('param1', value1, 'param2', value2,……) creates a structure options and sets the value of 'param1' to value1', 'param2' to value 2, and so on. Any unspecified parameters are set to their default values.

options

The following are the list of options which can be set with gaoptimset.

Generations :	It specifies the maximum number of iterations. Here the no. of generation is taken as 100.
PlotFcns :	It plots the data computed by the algorithm. In algorithm @gaplotbestf and @gaplotbestindiv are used for plotting the best fitness value and best individual(decision bariable) respectively shown in fig
Population Size :	The population size for GA programming is taken 20.
StallGenLimit :	This is the stopping criterion. The algorithm stops if there is no improvement in the objective function for StallGenLimit consecutive generations. StallGenLimit is taken 50 in the programming part.
StallTimeLimit :	The algorithm stops if there is no improvement in the objective function for StallTimeLimit seconds. The value of StallTimeLimit is initialized as Inf. Seconds.

2.3 RESULTS AND DISCUSSIONS

The results have been obtained for the single objective OPF problem based on genetic algorithm. The algorithm has been tested on IEEE 30 bus test system whose data is given in APPENDIX-I. The emission coefficient data is given in APPENDIX-II. The single objective OPF problem is formulated for different objectives individually namely minimization of fuel cost, emissions and transmission loss. The emission loss can be divided as NOx, COx and SOx minimization. The problem is formulated with five control variables i.e. active power at generator buses except the slack bus. The results are compared with the power flow results one by one. And in the last, result for different OPF solutions for different objectives is also shown in Table 2.4. Keeping the above the following cases have been studied:

Case Study 1: Fuel cost minimization.
Case Study 2: Transmission loss minimization.
Case Study 3: COx emission minimization.

Case Study 1: Fuel Cost Minimization

In this case study, developed algorithm has been applied for single objective fuel cost minimization. The simulation results are obtained and are compared with power flow results as given in Table 2.1. Correspondingly, the cost minimization curve is also shown in Fig 2.3. The Fig 2.3 has two parts. Part I shows the graph plotted between Fitness value and No. of Generations in which GA population is shown as dots with best Fitness value and average Fitness value. Part II shows the bar graph plotted between current best individual for decision variables and No. of decision variables.

In this case, the objective was to minimize the total Fuel cost. And it can be easily seen from the given Table 2.1 that the Fuel cost after Load Flow is 875.4477 \$/hr and after applying OPF with GA is 801.9319 \$/hr.

Table 2.1: Comparison of OPF for Fuel cost minimization

Units (in MW)	Solution after Load Flow	Solution after OPF with GA
PG1	260.9980	174.5864
PG2	40.00	49.1225
PG5	0.00	21.0870
PG8	0.00	22.4595
PG11	0.00	12.6812
PG13	0.00	12.7031
Fuel Cost (in $/hr)	875.4477	**801.9319**
Transmission loss(in MW)	17.5985	9.2395
NOx emission(in Kg/hr)	1728.70	1423.20
COx emission(in Kg/hr)	25951.00	19110.00
SOx emission(in Kg/hr)	3107.90	2975.50

In Fig 2.3, Part I shows that when the no. of Generation increases, the curve is approaching to a minimum value of Fitness function i.e. Fuel cost. Part-II shows the value of decision variable as current best individual for last Generation or iteration.

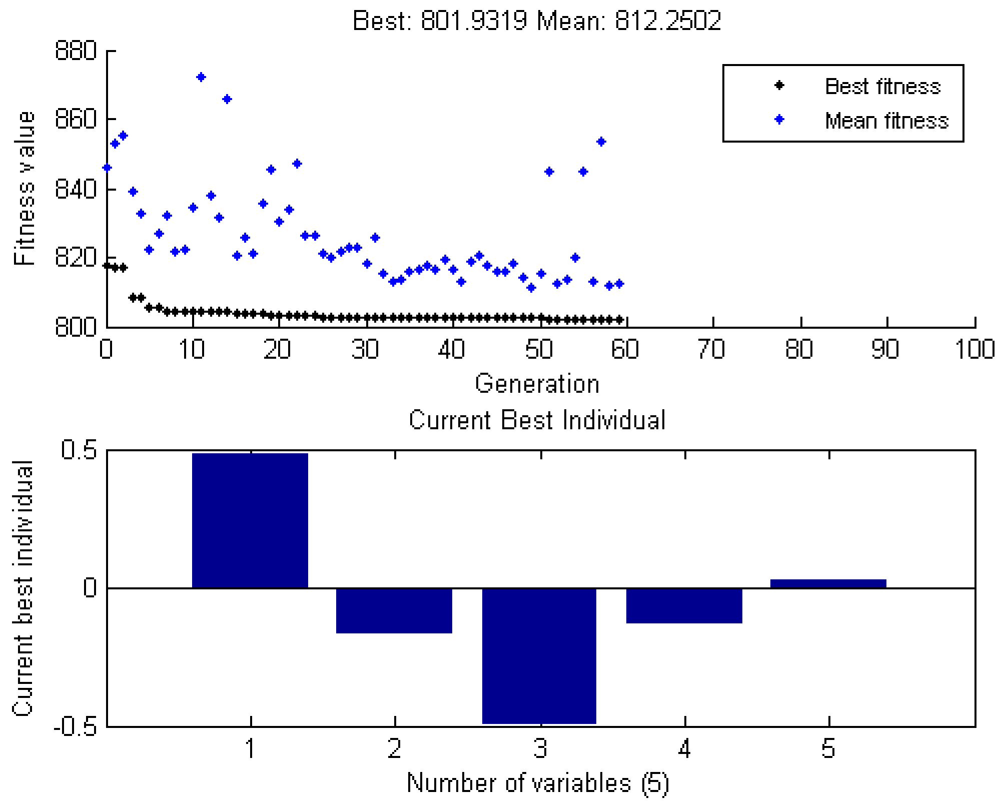


Fig 2.3: Cost minimization curve

Case Study 2: Transmission Loss Minimization

In this case study, developed algorithm has been applied for single objective transmission loss minimization. The simulation results are obtained and are compared with the Power Flow results. The results are given in Table 2.2.

In the present case, our objective was to minimize the Transmission loss. And we can see from the Table 2.2 that the loss after the Power Flow is 17.5985 MW but after the application of OPF with GA the losses are reduced to 3.4973 MW.

Table 2.2: Comparison of OPF for Transmission loss minimization

Units (in MW)	Solution after Load Flow	Solution after OPF with GA
PG1	260.9980	51.8973
PG2	40.00	80.00
PG5	0.00	50.00
PG8	0.00	35.00
PG11	0.00	30.00
PG13	0.00	40.00
Fuel Cost (in $/hr)	875.4477	968.5621
Transmission loss(in MW)	17.5985	**3.4973**
NOx emission(in Kg/hr)	1728.70	1214.70
COx emission(in Kg/hr)	25951.00	15885.00
SOx emission(in Kg/hr)	3107.90	2835.40

Fig 2.4 shows the curve for minimization of Transmission losses. Part-I shows that the GA population curve for the Fitness value approaches to a minimum. The Best and Mean values are also given after the final Generation. Part-II shows the values of decision variables after the last iteration.

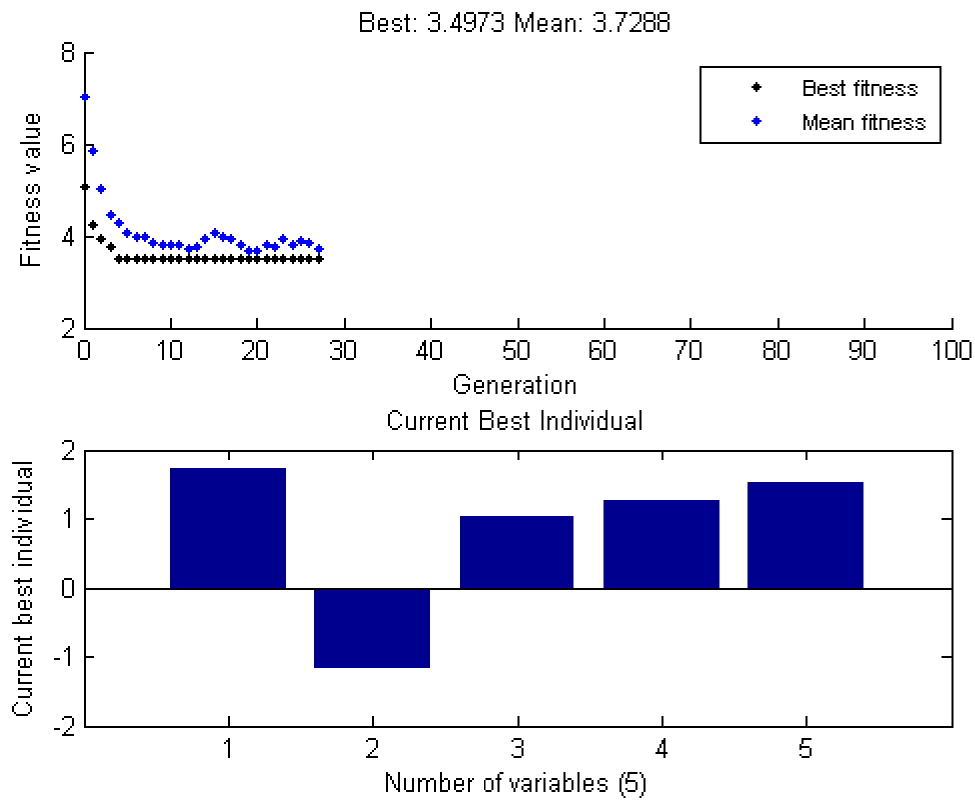


Fig 2.4: Loss minimization curve

Case Study 3: COx Emission Minimization

In this case study, developed algorithm has been applied for single objective COx emission minimization. The simulation results are obtained and compared with Power Flow results. The results are given in Table 2.3 and curve is shown in Fig 2.5.

Table 2.3: Comparison of OPF for COx Emission Minimization

Units (in MW)	Solution after Load Flow	Solution after OPF with GA
PG1	260.9980	103.5515
PG2	40.00	80.00
PG5	0.00	17.7580
PG8	0.00	32.4800
PG11	0.00	15.9458
PG13	0.00	40.00
Fuel Cost (in $/hr)	875.4477	865.2913
Transmission loss(in MW)	17.5985	6.3353
NOx emission(in Kg/hr)	1728.70	1304.70
COx emission(in Kg/hr)	25951.00	**15018.00**
SOx emission(in Kg/hr)	3107.90	2885.90

For the present case, the objective was to minimize the COx emission. After the formulation of problem with Load Flow the COx emission is 25951 Kg/hr as given in the above Table 2.3. But after applying OPF with GA the COx emission is reduced to 15018 Kg/hr.

In Fig 2.5 the reduction of COx emission is shown. Part-I shows the GA population for Best and Mean Fitness value of the Fitness function. And Part-II shows the value of all five decision variable after the final Generation.

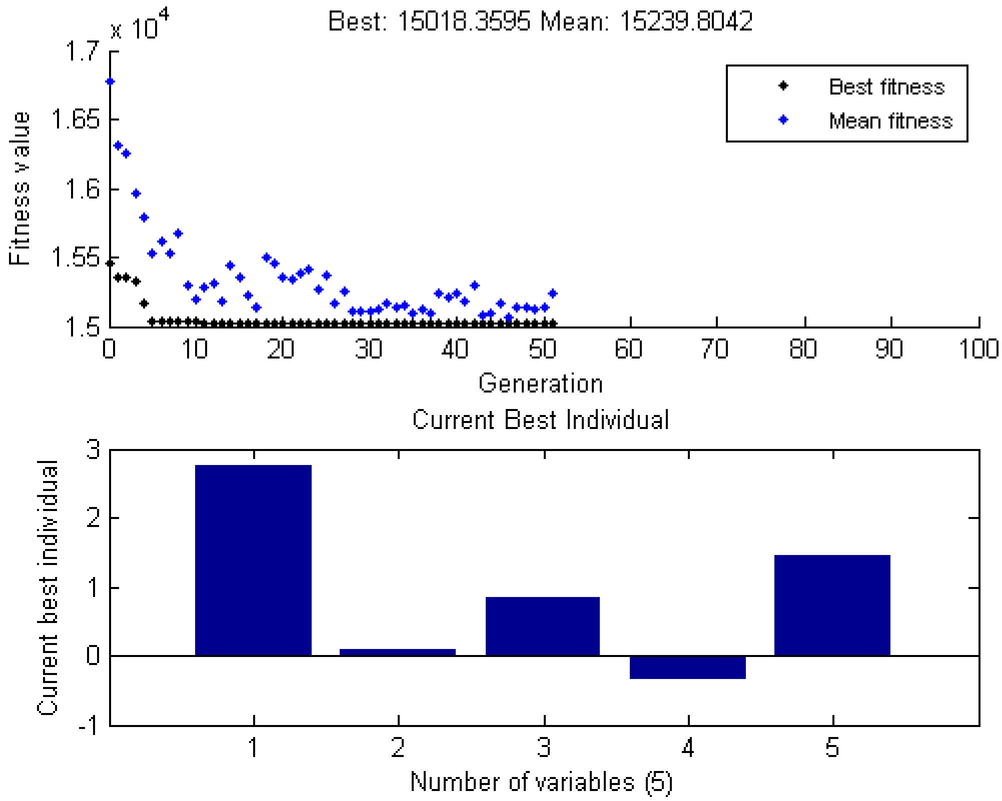


Fig 2.5 : COx minimization curve

Table 2.4 shows the optimal power flow solution for different objectives i.e. solution at minimum Fuel cost, solution at minimum transmission losses, solution at minimum COx emission. The results are compared for active power at all generator buses, Fuel cost, Transmission loss and COx emission.

Table 2.4: Optimal Power Flow Solutions for different objectives

Units	Solution at minimum fuel cost	Solution at minimum transmission loss	Solution at minimum COx emission
PG1	174.5864	51.8973	103.5515
PG2	49.1225	80.00	80.00
PG5	21.0870	50.00	17.7580
PG8	22.4594	35.00	32.480
PG11	12.6812	30.00	15.9458
PG13	12.7031	40.00	40.00
Fuel cost(in $/hr)	**801.9319**	968.5621	865.2913
Transmission loss(in MW)	9.2395	**3.4973**	6.3353
COx emission (in Kg/hr)	19110.00	15885.00	**15018.00**

CHAPTER 3

MULTIOBJECTIVE OPTIMAL POWER FLOW USING GENETIC ALGORITHM

3.1 MULTIOBJECTIVE OPTIMIZATION

The multi-objective problem may be presented as:

Min\Maximization

$$F(x) = [f_1(x), f_2(x) \ldots\ldots\ldots f_k(x)] \tag{3.1}$$

Subjected to

$$g_j(x) \leq 0 \text{ ,} j = 1,2,3 \ldots\ldots j \tag{3.2}$$

$$h_k(x) = 0 \text{ where } k = 1,2,3 \ldots\ldots k \tag{3.3}$$

where, $f_1(x), f_2(x) \ldots\ldots\ldots f_k(x)$ 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 Fig 3.1, can be used for ideal multi-objective optimization. It involves two step defined as:-

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

Step2: Choose one solution using higher level information.

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.

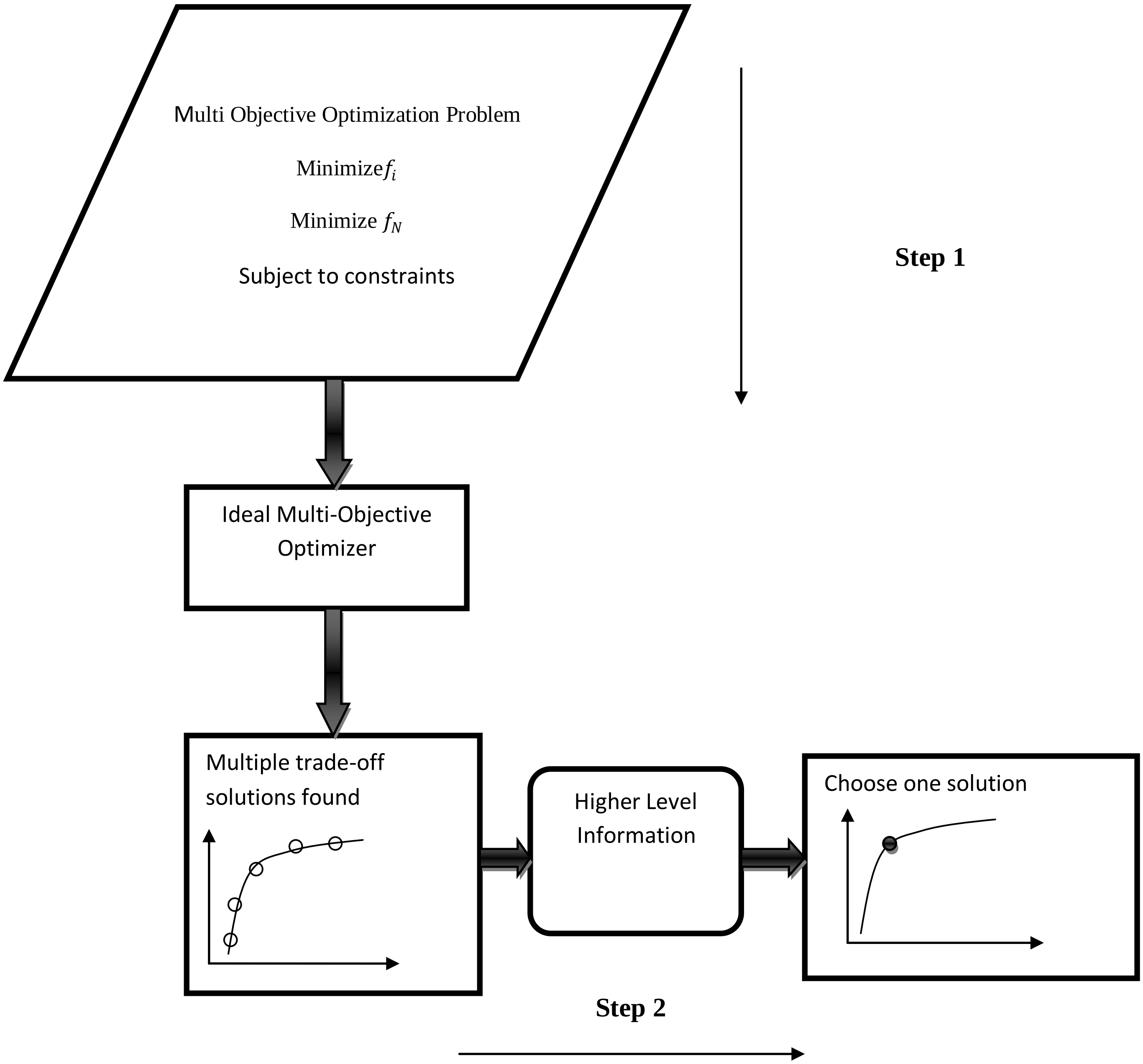


Fig 3.1: Schematic of an ideal multi objective optimization procedure

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, $f_i(x) \leq f_i(y)$ for i=1, …, K

and $f_j(x) < f_j(y)$ 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 tradeoffs.

- 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.

3.1.1 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. $x^{(1)}$ dominates $x^{(2)}$ if $x^{(1)}$ is no worse than $x^{(2)}$ in all objectives and $x^{(1)}$ is strictly better than $x^{(2)}$ in at least one objective. Solution $x^{(1)}$ is said to dominate $x^{(2)}$ or $x^{(1)}$ is said to be non-dominated by $x^{(2)}$ if both above conditions are true [3].

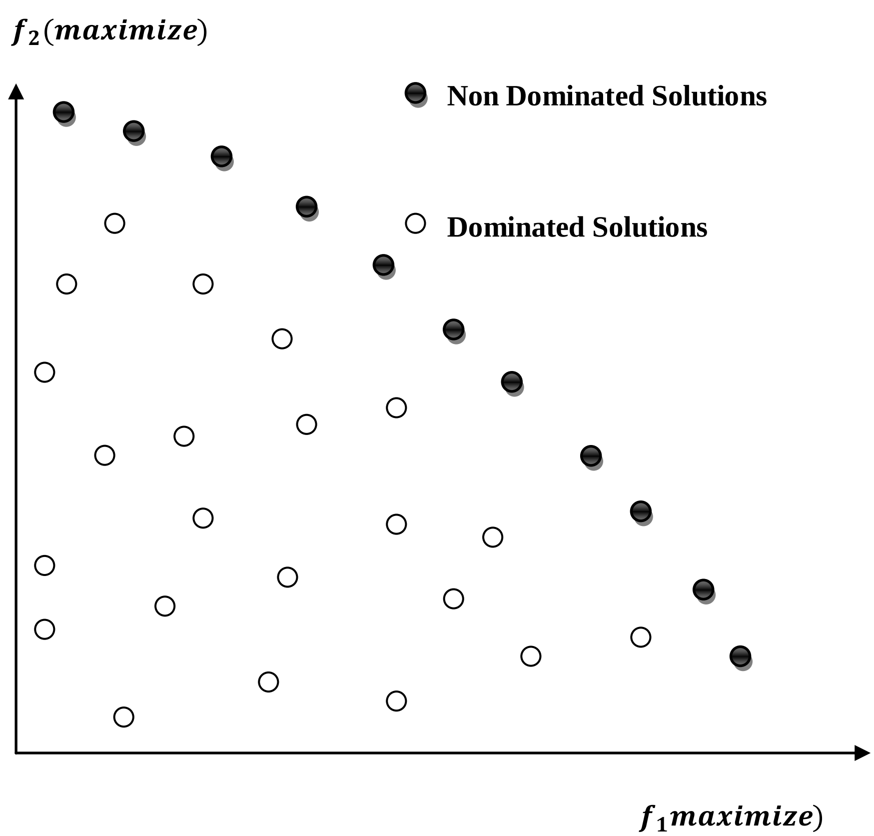


Fig 3.2: All solutions of objective functions

Fig 3.2 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.

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 [26].

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, 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.

3.2 NON DOMINATED SORTING GENETIC ALGORITHM (NSGA II)

The Non-dominated Sorting Genetic Algorithm (NSGA) was proposed by Srinivas and Deb [24], 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 searching 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 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 $\boldsymbol{\sigma_{share}}$. NSGA uses non dominated sorting procedure, which compare each solution in population with every other to find the first non dominated front.

Multi-objective evolutionary algorithms which use non-dominated sorting and sharing (NSGA) have been mainly criticized for their. The main criticism of NSGA approaches have been as follows [25]: -

High computational complexity of non-dominated sorting: The non dominated sorting algorithm in use until 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 $\boldsymbol{\sigma_{share}}$: 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 ($\boldsymbol{\sigma_{share}}$). 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. 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.

3.3 MULTIOBJECTIVE OPF USING NSGA-II IN MATLAB

multiobj

This function determines optimal Pareto fronts from specified criteria, including Pareto fronts that are nonconvex, disconnected, or both.

X = gamultiobj (FITNESSFCN, NVARS, A, b, Aeq, beq, LB, UB, options) finds a Pareto set X with the default optimization parameters replaced by values in the structure options. options can be created with the gaoptimset function.

For multi-objective optimization the variables Fitnessfcn, nvars,etc have similar meanings as explained in 2.5.2 for single-objective optimization. The multi-objective genetic algorithm (GAMULTIOBJ) works on a population using a set of operators that are applied to the population. A population is a set of points in the design space. The initial population is generated randomly by default. The next generation of the population is computed using the non-dominated rank and a distance measure of the individuals in the current generation.

A non-dominated rank is assigned to each individual using the relative fitness. Individual 'p' dominates 'q' ('p' has a lower rank than 'q') if 'p' is strictly better than 'q' in at least one objective and 'p' is no worse than 'q' in all objectives. This is same as saying 'q' is dominated by 'p' or 'p' is non-inferior to 'q'. Two individuals 'p' and 'q' are considered to have equal ranks if neither dominates the other. The distance measure of an individual is used to compare individuals with equal rank. It is a measure of how far an individual is from the other individuals with the same rank.

The multi-objective GA function GAMULTIOBJ uses a controlled elitist genetic algorithm (a variant of NSGA-II). An elitist GA always favors individuals with better fitness value (rank) whereas, a controlled elitist GA also favors individuals that can help increase the diversity of the population even if they have a lower fitness value. It is very important to maintain the diversity of population for convergence to an optimal Pareto front. This is done by controlling the elite members of the population as the algorithm progresses. Two options 'ParetoFraction' and 'DistanceFcn' are used to control the elitism. The Pareto fraction option limits the number of individuals on the Pareto front (elite members) and the distance function helps to maintain diversity on a front by favoring individuals that are relatively far away on the front.

3.4 RESULTS AND DISCUSSIONS

The results have been obtained from the developed algorithm for multi-objective OPF based on Genetic Algorithm which has been discussed in this chapter. The developed algorithm has been tested in IEEE 30 bus system whose data is given in APPENDIX. As discussed above, the multi-objective OPF problem has been formulated with different combinations of objectives namely fuel cost, transmission loss, emission. The emission minimization can be the NOx, SOx and COx minimization. Keeping the above, the following cases have been studied:

Case Study 1: Multi-Objective Fuel Cost & Transmission Loss Minimization
Case Study 2: Multi-Objective Fuel Cost & NOx Emission Minimization
Case Study 3: Multi-Objective Fuel Cost & COx Emission Minimization
Case Study 4: Multi-Objective Fuel Cost & SOx Emission Minimization
Case study 5: Multi-Objective Transmission Loss & COx Emission Minimization

Case Study 1: Multi-Objective Fuel Cost & Transmission Loss Minimization

In this case study, developed algorithm has been applied for multi-objectives namely fuel cost and transmission loss minimization. The simulation results obtained are given in Table 3.1 for six generator buses. Correspondingly the optimal Pareto front is shown in Fig 3.3.

The optimum value of six generator buses, Fuel cost & Transmission Loss is given below in the below Table 3.1. Note that only five control variables i.e. active power at generation buses are taken into consideration except the slack bus.

Table 3.1: Results for Fuel cost and Transmission loss minimization

Units (in MW)	Solution at minimum Fuel cost & minimum Transmission losses
PG1	103.8948
PG2	58.5197
PG5	37.6984
PG8	34.6959
PG11	24.5570
PG13	29.0649
Fuel cost(in $/hr)	856.9422
Transmission losses(in MW)	5.0306

In Fig 3.3 Pareto optimal solution for Fuel cost and Transmission loss minimization is shown. The solution is a set of non-dominated solutions. The figure also contains the best compromise solution which is shown in black colour.

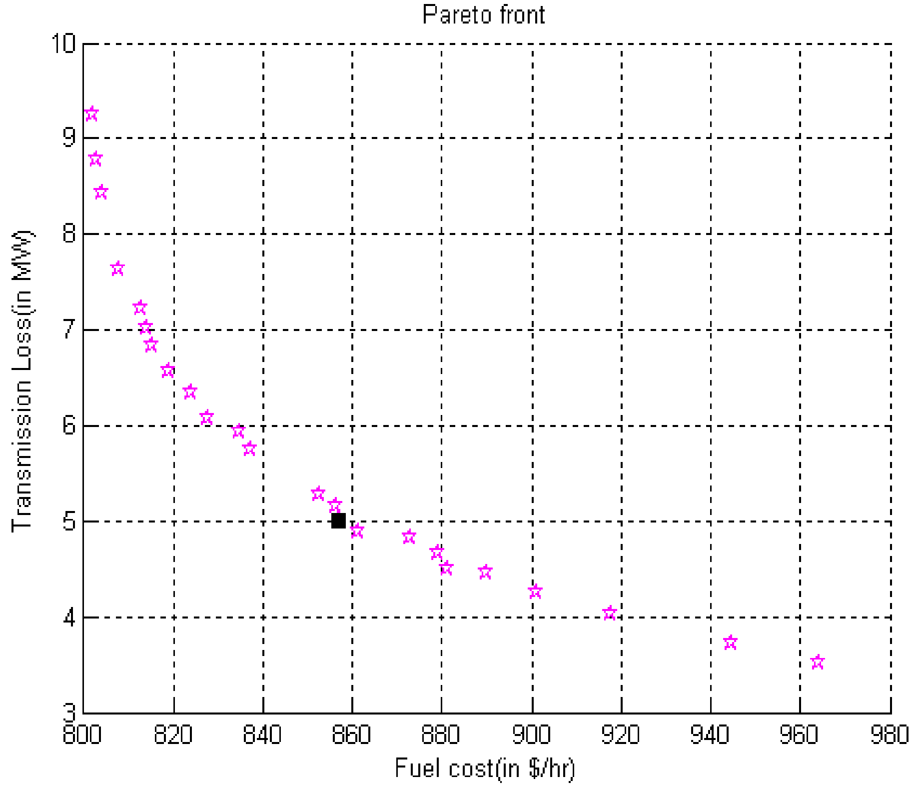


Fig 3.3: Pareto optimal solution for Fuel cost and Transmission loss minimization

Case Study 2: Multi-Objective Fuel Cost & NOx Emission Minimization

The results for minimizing Fuel cost and NOx are summarized in Table 3.2. Correspondingly the Pareto optimal front is shown in Fig 3.4.

Table 3.2: Results for Fuel cost and NOx emission minimization

Units (in MW)	Solution at minimum Fuel cost & minimum NOx emission
PG1	119.4149
PG2	58.9205
PG5	30.3936
PG8	33.8257
PG11	28.2725
PG13	18.430
Fuel cost(in $/hr)	832.30
NOx emission (in Kg/hr)	1286.40

In Fig 3.4, Pareto optimal front for Fuel cost and NOx emission is shown. The front consists of non-dominated values considering both objectives. The figure also contains the best compromise solution which is shown in black colour.

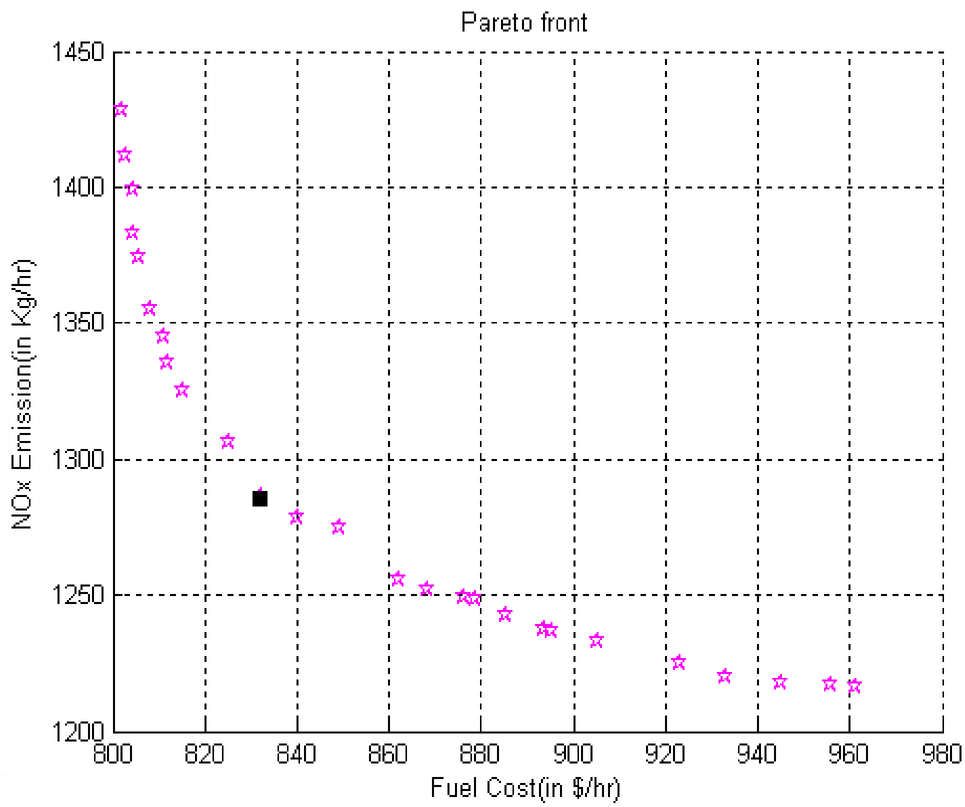


Fig 3.4: Pareto optimal solution for Fuel cost and NOx emission minimization

Case Study 3: Multi-Objective Fuel Cost & COx Emission Minimization

In this case study, developed algorithm has been applied for multi-objectives namely fuel cost and COx emission. The simulation results obtained are given in Table 3.3. Correspondingly, the Pareto optimal front is also shown in Fig 3.5.

Table 3.3: Results for Fuel cost and COx emission minimization

Units (in MW)	Solution at minimum Fuel cost & minimum COx emission
PG1	139.9082
PG2	53.6350
PG5	20.8373
PG8	24.5139
PG11	15.6283
PG13	36.2588
Fuel cost(in $/hr)	825.0
COx emission (in Kg/hr)	15822.0

In Fig 3.5 Pareto optimal front for Fuel cost and COx emission is shown. The optimized values are shown considering both objectives simultaneously. The figure also contains the best compromise solution which is shown in black colour.

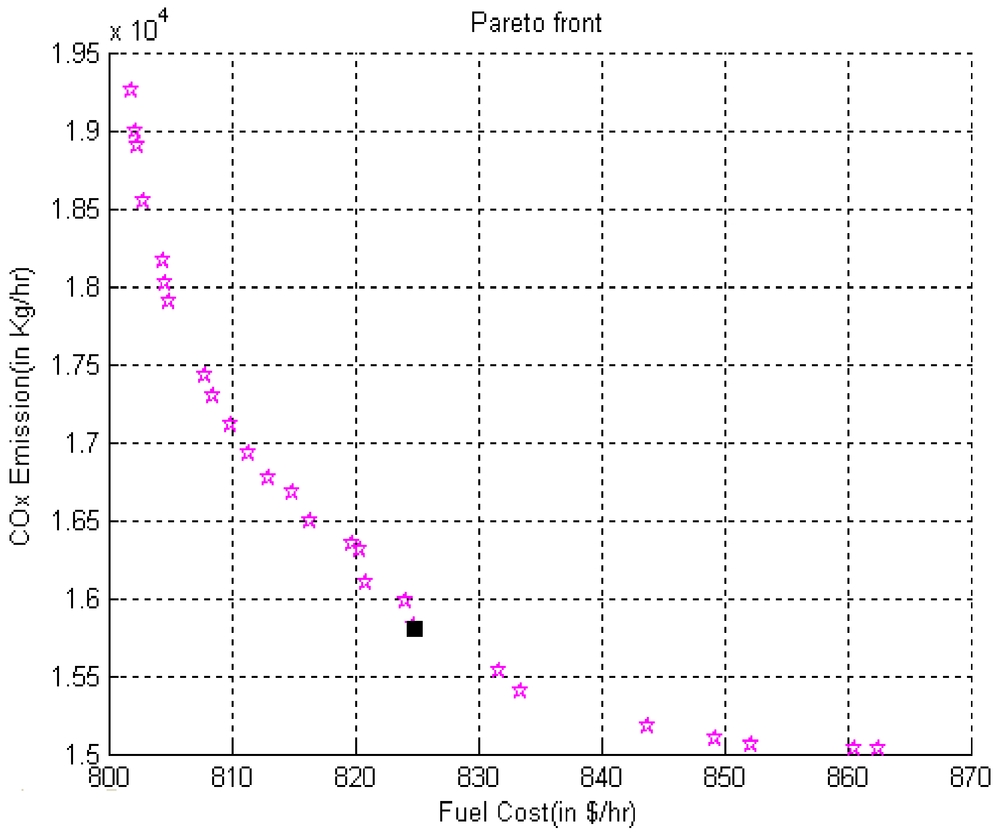


Fig 3.5: Pareto optimal front for Fuel cost and COx emission minimization

Case Study 3: Multi-Objective Fuel Cost & SOx Emission Minimization

The results for minimizing fuel cost and SOx emission are summarized in Table 3.4. Correspondingly, the Pareto optimal front is shown in Fig 3.6.

Table 3.4: Results for Fuel cost and SOx emission minimization

Units (in MW)	Solution at minimum Fuel cost & minimum SOx emission
PG1	102.2809
PG2	72.9394
PG5	25.6633
PG8	34.3935
PG11	24.2676
PG13	29.5023
Fuel cost(in $/hr)	850.80
SOx emission (in Kg/hr)	2886.10

The optimization of Fuel cost and COx emission is done, and the Pareto optimal front is obtained. The optimal front consists of non-dominated values. The figure also contains the best compromise solution which is shown in black colour.

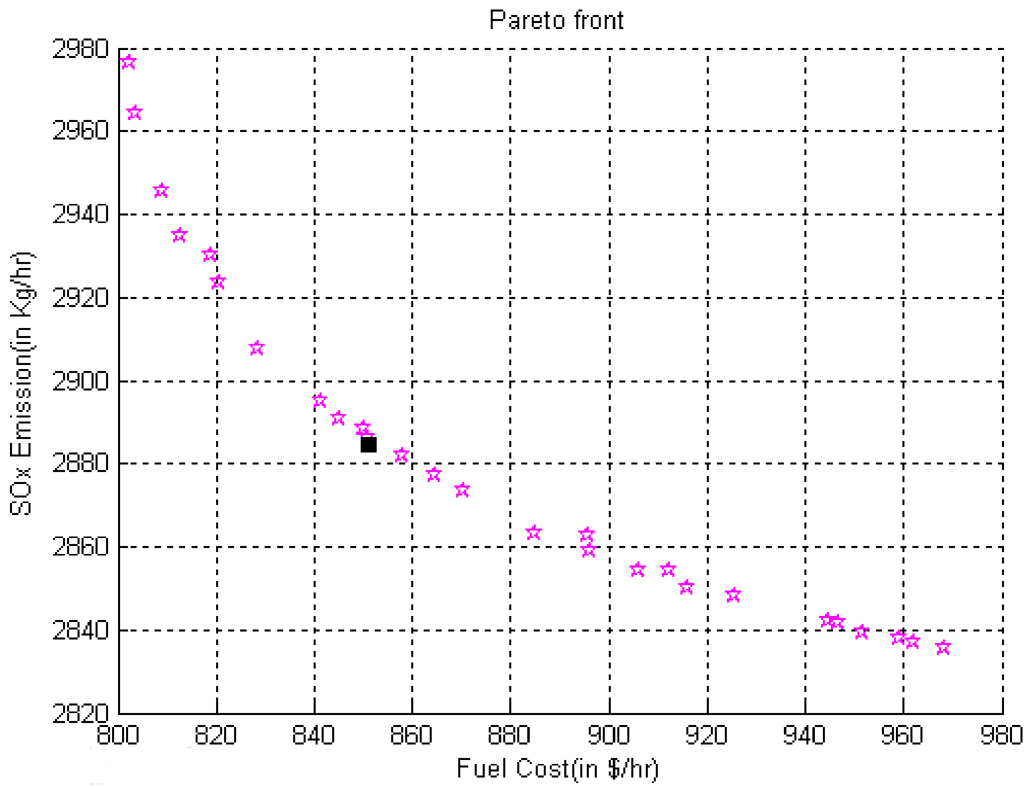


Fig 3.6: Pareto optimal front for Fuel cost and SOx emission minimization

Case study 5: Multi-Objective Transmission Loss & COx Emission Minimization

In this case study, developed algorithm has been applied for multi-objectives namely Transmission Loss and COx emission. The simulation results obtained are given in Table 3.5. Correspondingly, the Pareto optimal front is also shown in Fig 3.7.

Table 3.5: Results for Transmission Loss and COx emission minimization

Units (in MW)	Solution at minimum Transmission Loss & minimum COx emission
PG1	78.3054
PG2	64.9369
PG5	45.6795
PG8	34.1165
PG11	24.5083
PG13	39.9650
Transmission Loss(in MW)	4.1117
COx emission (in Kg/hr)	15357.0

The optimization of Transmission Loss and COx emission is done, and the Pareto optimal front is obtained which is shown in Fig 3.6. The optimal front consists of non-dominated values. The figure also contains the best compromise solution which is shown in black colour.

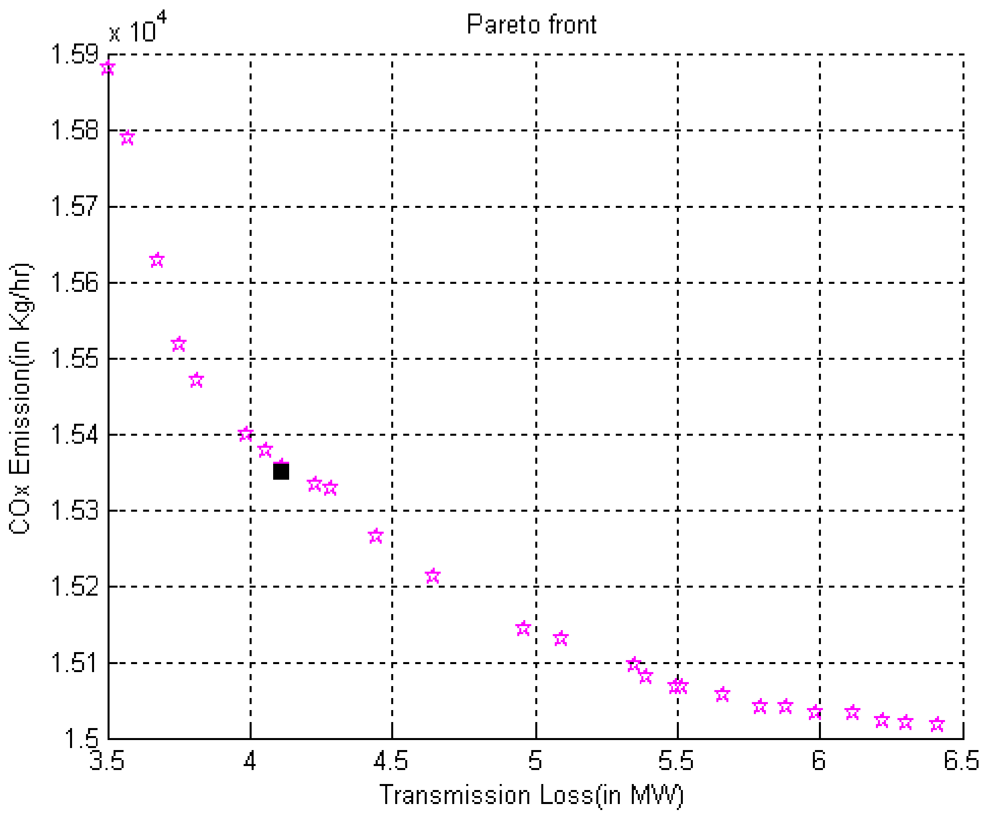


Fig 3.7: Pareto optimal front for Transmission Loss and COx emission minimization

CHAPTER 4

CONCLUSION AND FUTURE SCOPE

4.1 CONCLUSION

The various aspects of single–objective optimal power flow and multi-objective optimal power flow are studied. An efficient and diversified approach using genetic algorithm is identified to solve the above optimization problems.

Several case studies have been employed separately for single & multi-objective optimization problem. Firstly, the results are obtained for single objective OPF for the optimization of Fuel cost, losses, emission which is then compared with the power flow results. And in the last the results are obtained for multi-objective OPF problem i.e. for different combinations of objectives namely fuel cost & transmission losses, fuel cost and COx emission etc. Pareto optimal front for each combination is also obtained. After studied all the cases, it is observed that Pareto optimal fronts for different combinations of objectives are convex.

4.2 FUTURE SCOPE

The scope of work is identified as:

- Extend the multi-objective formulation of power system with FACTS devices
- Extend the problem with discrete control variables namely transformer tap settings, shunt compensators etc.
- Extend the above studies under deregulated environment.

APPENDIX-I

The diagram and the data for IEEE-30 bus test system is given below. This test system consists of six generator buses provide with fuel coefficient. The diagram is shown in Fig A.1 and bus data, load, generator data is given in Table (A.1, A.2)

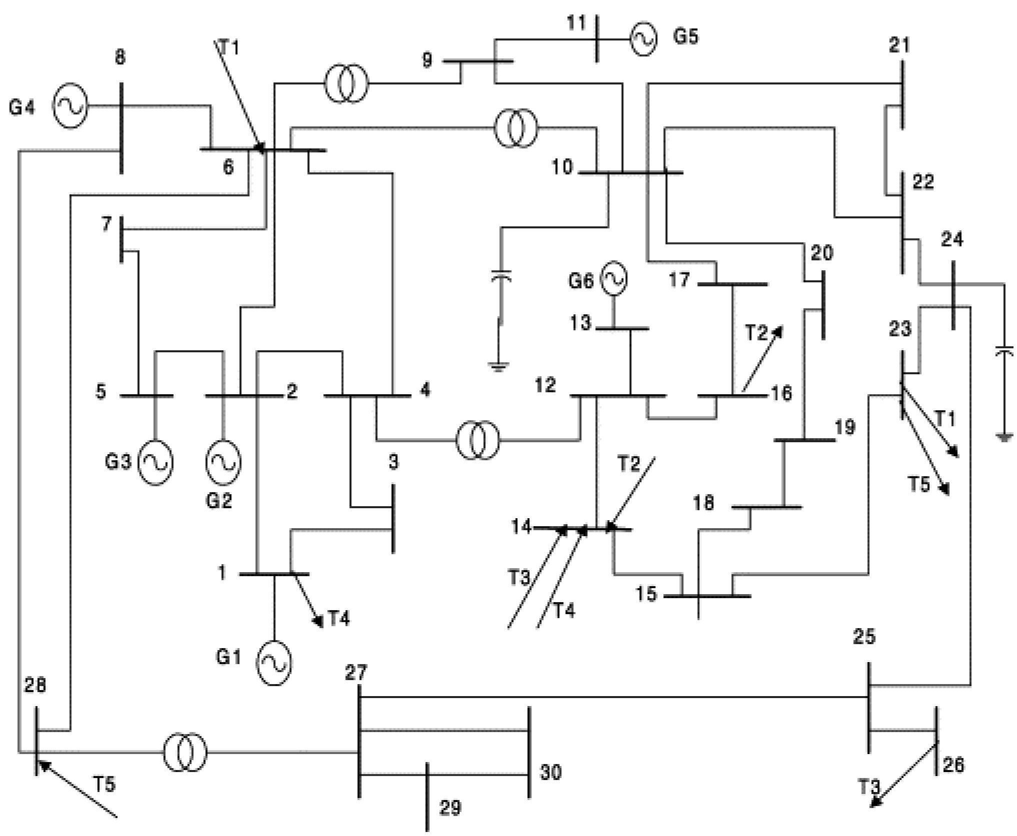


Fig A.1: IEEE 30 bus test system

Table A.1: Bus data

Bus No.	Bus code	Voltage Mag.	Angle Degree	Load MW	Load MVAR	Gen. MW	Gen. MVAR	Gen. Qmin.	Gen. Qmax.	Injected MVAR
1	1	1.06	0.0	0.0	0.0	0.0	0.0	0	0	0
2	2	1.043	0.0	21.70	12.7	40.0	0.0	-40	50	0
3	0	1.0	0.0	2.4	1.2	0.0	0.0	0	0	0
4	0	1.06	0.0	7.6	1.6	0.0	0.0	0	0	0
5	2	1.01	0.0	94.2	19.0	0.0	0.0	-40	40	0
6	0	1.0	0.0	0.0	0.0	0.0	0.0	0	0	0
7	0	1.0	0.0	22.8	10.9	0.0	0.0	0	0	0
8	2	1.01	0.0	30.0	30.0	0.0	0.0	-10	60	0
9	0	1.0	0.0	0.0	0.0	0.0	0.0	0	0	0
10	0	1.0	0.0	5.8	2.0	0.0	0.0	-6	24	19
11	2	1.082	0.0	0.0	0.0	0.0	0.0	0	0	0
12	0	1.0	0	11.2	7.5	0	0	0	0	0
13	0	1.071	0	0	0.0	0	0	-6	24	0
14	0	1	0	6.2	1.6	0	0	0	0	0
15	0	1	0	8.2	2.5	0	0	0	0	0
16	0	1	0	3.5	1.8	0	0	0	0	0
17	0	1	0	9.0	5.8	0	0	0	0	0
18	0	1	0	3.2	0.9	0	0	0	0	0
19	0	1	0	9.5	3.4	0	0	0	0	0
20	0	1	0	2.2	0.7	0	0	0	0	0
21	0	1	0	17.5	11.2	0	0	0	0	0
22	0	1	0	0	0.0	0	0	0	0	0
23	0	1	0	3.2	1.6	0	0	0	0	0
24	0	1	0	8.7	6.7	0	0	0	0	4.3
25	0	1	0	0	0.0	0	0	0	0	0
26	0	1	0	3.5	2.3	0	0	0	0	0
27	0	1	0	0	0.0	0	0	0	0	0
28	0	1	0	0	0.0	0	0	0	0	0
29	0	1	0	2.4	0.9	0	0	0	0	0
30	0	1	0	10.6	1.9	0	0	0	0	0

Table A.2: Generator data

Bus No.	c_i	b_i	a_i	P_{min}	P_{max}
1	0.00375	2	0	50	200
2	0.0175	1.75	0	20	80
5	0.0625	1	0	15	50
8	0.0083	3.25	0	10	35
11	0.025	3	0	10	30
13	0.025	3	0	12	40

APPENDIX-II

The data for a system of six generator test system [22] has been presented. This test system consists of six generator provide with fuel and emission coefficient. But here only the emission coefficient data is considered. The data related to these coefficients given below in Table (A.3 to A.5).

Table A.3: NOx emission coefficient for six generator system

Bus No.	c_i	b_i	a_i	P_{min}	P_{max}
1	0.006323	-0.38128	80.9019	50	200
2	0.006483	-0.79027	28.8249	20	80
5	0.003174	-1.36061	324.1775	15	50
8	0.006732	-2.39928	610.2535	10	35
11	0.003174	-1.36061	324.1775	10	30
13	0.006181	-0.39077	50.1775	12	40

Table A.4: SOx emission coefficient for six generator system

Bus No.	c_i	b_i	a_i	P_{min}	P_{max}
1	0.001206	5.09928	51.3778	50	200
2	0.002320	3.84654	182.2605	20	80
5	0.001248	4.45647	508.5207	15	50
8	0.000813	4.97641	165.3433	10	35
11	0.001248	4.45647	508.5207	10	30
13	0.003578	4.14938	121.2133	12	40

Table A.5: COx emission coefficient for six generator system

Bus No.	c_i	b_i	a_i	P_{min}	P_{max}
1	0.265110	-61.01945	5080.148	50	200
2	0.140053	-29.95221	3824.770	20	80
5	0.105929	-9.552794	1342.851	15	50
8	0.106409	-12.73642	1819.625	10	35
11	0.105929	-9.552794	1342.851	10	30
13	0.403144	-121.9812	11381.070	12	40

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