OPTIMAL POWER FLOW USING HYBRID GENETIC ALGORITHM

Submitted in partial fulfillment of the requirement for the reward of degree

MASTER OF ENGINEERING

IN

POWER SYSTEMS AND ELECTRIC DRIVES

THAPAR UNIVERSITY, PATIALA

Submitted By:

Deepanshu Nimal

Roll no.801041007

Under the supervision of

Mr. Parag Nijhawan

Assistant Professor, EIED

JULY 2012

ELECTRICAL AND INSTRUMENTATION ENGINEERING DEPARTMENT

THAPAR UNIVERSITY

PATIALA-147004

CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, "Optimal Power Flow using Hybrid Genetic Algorithm", 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 *Mr. Parag Nijhawan*, Assistant Professor. The matter presented in this thesis has not been submitted for the award of any other degree of this or any other university.

Deepanshu 13/07/12

(Deepanshu Nimal)

Regn. No. 801041007

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

Parag 13/07/2012

(Mr. Parag Nijhawan)

Assistant Professor

Electrical & Instrumentation Engg. Department

Thapar University

Patiala

Countersigned by

S. Ghosh

(Dr. Smarajit Ghosh)

Professor & Head

Electrical & Instrumentation Engg. Department

Thapar University

Patiala

(Dr. S. K. Mohapatra)

Dean (Academic Affairs)

Thapar University

Patiala

ACKNOWLEDGEMENT

First of all, I wish to express my profound gratefulness and appreciation to *Mr. Parag Nijhawan* (Assistant Professor) Department of Electrical And Instrumentation, Thapar University, Patiala, for his patient guidance and support throughout the report. He has been my mentor for help and without whose encouragement the learning would not have been realized.

Last but not least, I would like to add a few words to express my thanks to *Dr.Smarajit Ghosh*, Head of Electrical & Instrumentation Engineering Department, & all the faculty of EIED Department of Thapar University, Patiala, for their valuable and unstinted advice from time to time.

Deepanshu Nimal

(801041007)

ABSTRACT

Optimal Power Flow is incorporated for minimizing the objective function. It may be single objective or multiobjective. In this work, an attempt is made to minimize the fuel cost and to keep the voltages, power outputs of the generator within prescribed limit. An Optimal Power Flow (OPF) is highly constrained and non optimization problem. Any other objective can be used based on utility's interest and needs. Performance & Reliability of OPF algorithms remain important problem in Power System control and planning areas.

Many simplified network models have been incorporated in the past by various researchers for OPF problem such as Linear Programming, Non Linear Programming, Quadratic Programming, Newton Based Techniques, Parametric Methods, Interior Point Methods etc. All these conventional methods have many disadvantages associated with them such as insecure convergence, algorithm complexity etc. So it becomes essential to develop optimization techniques that are efficient to overcome these drawbacks. A wide variety of advanced optimization techniques like Evolutionary Programming, Genetic Algorithm, PSO Algorithm etc are proposed in literature for solving OPF problem. In this thesis, the Simulated Annealing is intermixed with Genetic Algorithm to develop a hybrid algorithm to obtain the solution of OPF Problem. The proposed algorithm is applied to IEEE-30 bus system.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

The Power Plants are not located at the same distance from the load centre and their fuel costs are different. The generation capacity of the power plant is more than total load demand and losses during normal conditions. Therefore there are plenty of options for scheduling generations. In the earlier times, there were state wise individual power system which feed the power requirement of that particular state. So as to improve this old system, the interconnected power system is made. So as to make the power system in interconnected fashion, the generator's real and reactive power should be varied within certain limits for maximum power output at minimum fuel cost. In the interconnected system, both active and reactive powers are dispatch able in electrical network for optimal operation of generation cost. The real and reactive powers of generator are allowed to vary within certain limits for optimal operation of fuel cost. This is called as Optimal Power flow (OPF) problem [1]. OPF have become reliable enough for the practical use and have taken the place of standard power system analysis tool [2].

The OPF is used to optimize the power flow solution of large scale power system. OPF is highly non linear and multimodal optimization problem. The objective functions are optimized while maintaining an acceptable system performance in terms of generator capability limits and the output of the compensating devices. The objective function is also known as cost function, may present economics costs, system security or other objectives. Effective reactive power planning enhances economic operation as well as system security. The OPF is used to achieve the following benefits:

- Minimization of cost
- Reduction in system losses
- To improve system security
- To improve voltage control

Earlier the Optimal Power Flow Problems are calculated with the help of conventional methods like Gauss Seidal Method, Newton Raphson Method, Linear Programming Method, Non-linear Programming Method, Quadratic Programming Method, Interior Point Method etc. These methods have some drawbacks that they sometime do not converge, they depend upon 1^{st} and 2^{nd} derivative of the objective function.

Due to these drawbacks, Artificial Intelligence Methods take over these conventional methods. Some of the Artificial Intelligence Methods are Fuzzy Logic, Genetic Algorithm, Artificial Neural Network etc and heuristic functions such as Hill Climbing, Best Search, A* Algorithm, Simulated Annealing or combination of these.

1.2 SCOPE OF WORK

The Optimal Power Flow is used to minimize the cost of generation. In this thesis, the IEEE-30 bus system data is optimized.

The aim of proposed work is to apply the Hybrid GA optimization technique to solve Single objective OPF problem to reduce the cost. The generation fuel cost can be achieved by using Hybrid GA technique which gave better results as compared to other optimization techniques.

The things those are to be taken care of while going for OPF system

- Load Demands are satisfied
- Transmission system elements are not overloaded

In this thesis, Artificial Intelligence Method and Heuristic Method is used i.e. Genetic Algorithm and Simulated Annealing Methods are used to optimize the Optimal Power Flow problem. Genetic Algorithm is random search method and does not require derivative information. Simulated Annealing is the concept of annealing i.e. Temperature.

1.3 ORGANIZATON OF THESIS

The thesis is divided into seven chapters.

Chapter 1 It gives the overview of the problem of the thesis.

Chapter 2 The Literature review is done on the Optimal Power flow Problem and also contains methods applied to solve Optimal Power Flow Problem.

Chapter 3 It describes the formulation of OPF problem. The Objective of OPF is defined in this chapter.

Chapter 4 It describes about Genetic Algorithm, its applications, its advantages, flow chart and also introduces the concept of Hybrid GA.

Chapter 5 Theory of Simulated Annealing.

Chapter 6 Hybrid GA based OPF.

Chapter 7 Results.

CHAPTER-2

LITERATURE REVIEW

2.1 INTRODUCTION

The literature on Optimal Power Flow [1-2] is very vast. The OPF problem has had a long history in its development. More than twenty five years ago, Carpentier introduced a generalized formulation of the economic dispatch problem including voltage and other operating constraints. This formulation was named as the Optimal Power Flow Problem [3]. The main objective was to minimize the generation cost. OPF programs based on mathematical programming approaches are used daily to solve very large OPF problems. At this stage of research, it was assumed that the system was designed such that the generation is dispatched economically there will be no violations of limits. Dommel and W.F Tinney [4] gave realistic method for solving the power flow programs with control variables such as real power, 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 Raphson Method, a Gradient adjustment algorithm for obtaining the minimum and penalty functions to account for dependent constraints. The conventional techniques are overcomed by artificial intelligent computer based mathematical techniques.

2.2 MATHEMATICAL TECHNIQUES

An optimization problem with one objective function is known as Single Objective Optimization. When an optimization problem involves more than one objective function, the task of finding one or more optimum solutions is known as Multiobjective Optimization [5]. Optimization is a method to find and compare feasible solutions until no better solution other than previous one can be found. The paper [6] has presented multi-objective optimization problem of three objectives i.e. generation costs, transmission losses and voltage stability index in which OPF problem is formulated as altogether minimization of all above objective functions.

There are a lot of conventional optimization techniques which are applied in solving the OPF problems such as Newton-based techniques[7], Linear Programming[8], Non-Linear Programming [9], Quadratic Programming [10], Interior point methods [11], Parametric method [12] Sequential and unconstrained minimization technique [13]. The conventional optimization methods has some disadvantages such as insecure convergence, and may even fail to converge due to in appropriate initial conditions for Newton based method, disadvantages associated with the piecewise quadratic cost approximation. The cause of infeasible of Optimal Power Flow is due to either badly posed or being under heavy operational stress [14]. The generation cost is minimized when both active and reactive powers are dispatchable in the electrical network. If only a reactive power is dispatchable then active power loss minimization is desired [9]. The OPF problem is a highly non linear and a multimodal optimization problem i.e. there exists more than one local optima. Hence local optimization techniques mentioned earlier are not suitable for such a problem and there is no criterion to decide whether a local solution is also the global solution. These are the some problems that are associated with the conventional methods. So as to overcome these problems, artificial intelligence techniques like Fuzzy Logic, Genetic Algorithm etc are used instead of these conventional methods.

Most of the classical optimization techniques apply sensitivity analysis and gradient-based optimization algorithms by linearizing the objective function and the system constraints around an operating point. J.A.Momoh [2] gave an extension in basic Kuhn-Tucker conditions and employing a generalized Quadratic based model for OPF. The widely used method to solve optimal power flow problem is Newton Raphson. K.L.Lo *et al.* [15] have proposed Newton method for load flow. X. Tong *et al.* [16] describe the semi smooth Newton-type algorithms for solving OPF problems. The only form of non linear programming whose objective function is quadratic and constraints are linear is Quadratic Programming. In 1984, Karmarkar proposed a new method i.e. Interior method for solving large-scale linear programming problems very efficiently by using linear programming method. These methods suffers from various drawbacks

- All these methods have some assumption like of continuity and differentiability of objective function which is not true practically
- All these methods cannot be applied with discrete variables which are transformer taps.
- These methods are not providing the optimal solution as they usually gets stuck at a local optimum

- Problems may arise due to handling of inequality constraints that presents the differences of potentially non convexed or even disjoint feasible regions.
- Linear Programming and Non Linear Programming Techniques are not suitable for constraint problems.
- Newton-Raphson Method has a drawback that these are sensitive to the initial conditions and they may even fail to converge due to the inappropriate initial conditions.
- In Interior Point Method, if the step size is not chosen properly, the sub-linear problem may have a solution that is infeasible in the original nonlinear domain.

So as to overcome these problems, Artificial Intelligence techniques are used such as Genetic Algorithm, Fuzzy Logic, Particle Swarm Optimization, Ant Colony Method etc. Genetic Algorithm is proposed by 'Holland' and is efficient search technique based on rules of natural selection. With the development of microprocessors and parallel computers, this algorithm became a new algorithm for a new field of research known as Evolutionary Computation. Genetic Algorithm has capability of parallelism and is used for solving stochastic optimization problems [17]. Holland was first scientist who coined GA technique but later on it was elaborated and improved by many other scientists. The Genetic Algorithm is characterized by the following [18].

1. The GA work with base code of the variables group (Artificial Genetic Strings) and not with the variables in themselves.
2. The GA work with a set of potential solutions (population) instead of trying to improve a single solution.
3. The GA do not use information obtained directly from the object function, of its derivatives, or of any other auxiliary knowledge of the same one.
4. The GA applies probabilistic transition rules not deterministic rules.

Genetic Algorithm is random search technique. It is a part of Artificial Intelligence. The main limitation of GA is that it does not allow finding solution in global optima. Tomoyuki et al. describes the parallel simulated annealing using genetic crossover to avoid the GA to stuck in local optima [19]. To develop a hybrid algorithm, the features of Simulated Annealing has to combine to basic GA framework and arrange the major operation in various stages. Simulated annealing was introduced by 'S. Kirpatrick' in 1983 [20] and is one of the most important algorithms to solve optimization problem. It resembles with the physical evaluation of a solid from a high temperature state to a thermal equilibrium state. Though SA takes some time to cool down to the equilibrium state, it eliminates the dependency of the selection process on a complete pool of candidate solutions required in conventional method at the selection stage. Both SA & GA are randomized guided search methods and are combined to result in hybrid genetic algorithm (HGA). Simulated Annealing helps to find the optimal solution without getting stuck into local optima [21]. Jeon and Kim [22] proposed simulated annealing (SA) for solving combinatorial optimization problem because SA can avoid local minima but an excessive computation time is required. To overcome this major limitation of SA, a modified SA and cost function with penalty factor are used. Carpento and Chicco [23] proposed SA algorithm to perform global optimization but high computation time limits their acceptability for the optimization of real distribution system. Gracia and Lopez [24] proposed and evaluated the reconfiguration problem for minimum loss using SA and a radial load flow. The proposed technique has an ability to avoid becoming trapped at local minimum. The SA algorithm does not require or deduce derivative information it merely needs to be supplied with an objective function for each trial solution it generates.

Carpentier [25] gave introduction as network constrained economic dispatch. Jason Yuryevich and Eliphas Shikongo define the Objective function that represents fuel cost [26-27]. The objective function is to be minimized. Allen J. Wood describes that the network components do not violate the operating limits [28]. Conventional computing converges to mathematical approaches and therefore demands a high degree of precision. This problem is overcomed by soft computing mathematical approaches proposed by S. Rajasekaran [29]. Mandira Chakraborty combines genetic algorithm and simulated annealing for optimization problem [30]. K.P. Wong also gave hybrid theory of combination of genetic algorithm and simulated annealing approach. He proposed that at the early stages, fitter chromosomes are replaced by weak child chromosome in controlled manner [31]. C.A Rao proposed that the initial temperature should be kept high in simulated annealing method. In this paper he defines an equation of Normalized Energy function [32]. T. Yalcinoz divided this equation, further into two parts to obtain the optimal solution [33]. For the calculation of objective function, the cost coefficients are taken from paper [34].

CHAPTER 3

OPTIMAL POWER FLOW

3.1 INTRODUCTION

Its introduction as network constrained economic dispatch by Carpentier [25] and its definition as optimal power flow by Dommel and Tinney [4], the OPF problem has been the subject of intensive research Power Flow means transmitting Power from generating end to distribution end. A power flow may have any number of operating limit violations. When such conditions occur, one may wish to determine if the troubles can be alleviated by appropriate or various corrective actions. The analytical process is known as Optimal Power Flow. In an interconnected power system, the objective is to find the real and reactive power scheduling of each power plant in such a way to minimize the operating cost**.** This means that the generator's real and reactive powers are allowed to vary within certain limits so as to meet a particular load demand with minimum fuel cost**.** The optimal actions Analysis is formulated as an optimization problem with the objective of minimizing load curtailment, MW generation redispatched, and transformer phase angle adjusted. It includes a standard ac power flow solution with local automatic adjustments, power system network linearization, and a linear programming solution to relieve the overload and voltage limit violations. The corrective action algorithm recognizes several types of constraints and controls. Constraints are operating limits imposed on bus voltages, branch flows, power transfers over interfaces, etc. The system troubles in contingency analysis are violations of such constraints. The objective of the corrective action algorithm is to observe all constraints while minimizing the weighted sum of the control movement. The OPF utilizes all control variables to help minimize the costs of the power system operation. It also yields valuable economic information and insight into the power system. The OPF is used to optimize the power flow solution of a large-scale power system. This is done by minimizing selected objective functions while maintaining an acceptable system performance in terms of generator capability limits and the output of the compensating devices.

There are many conventional methods to calculate load flow problems such as Gauss Seidal Method, Newton Raphson Method, Fast De-Coupled Method, Linear Programming Method, Non-Linear Programming Method, Quadratic Programming Method, Interior Point Method etc. All these methods have some drawbacks. The drawback of Gauss Seidal Method is it takes too much iterations and takes too much time to solve Optimal Power Problem. In Newton Raphson Method, main drawback is its convergence characteristics are dependent on initial conditions and sometimes it even fails to converge at initial conditions. Linear Programming Methods are fast and reliable but the problem that is concerned to Linear Programming is that they have some disadvantages associated with the piecewise linear cost approximation. The problem associated with Non-Linear Programming method are algorithms become complex and insecure convergence is there. Quadratic Programming Method has disadvantage with the piecewise quadratic cost approximation. Although Interior Point Methods is computationally efficient but if the step size is not chosen properly, the sub linear problem may have a solution that is infeasible in the original nonlinear domain.

3.2 FEATURES OF OPTIMAL POWER FLOW

The main features of Optimal Power Flow are

- It minimizes the cost function such as operating cost, emission of pollutants while taking equality constraints and inequality constraints into an account.
- Basically it is a combination of Economic Dispatch and Losses.
- While formulating OPF problem Bus real and reactive power balance, generator voltage set points, area MW interchange etc. are equality constraints.
- Transmission line/transformer/interface flow limits, generator MW limits, generator reactive power capability curves, bus voltage magnitudes are inequality constraints.
- Generator MW outputs, transformer taps and phase angles etc. are the available Controls.

3.3 APPLICATIONS OF OPTIMAL POWER FLOW

The main features of Optimal Power Flow are:

- For planning studies, Optimal Power Flow is used to determine the maximum stress that a planned transmission system can withstand.

- To provide a preventive dispatch, the OPF can be set up if the security constraints are incorporated.

- In case of emergency, when some component of the system is overloaded or a bus is experiencing a voltage violation, the Optimal Power Flow can provide a corrective dispatch, which tells the system's operators what kind of adjustments can be performed in order to mitigate the overload or voltage violation problems.

- The calculation of the optimum generation pattern in order to achieve the minimum cost of the generation together while transmission system limitations are not violated.

- The OPF can be calculated by checking optimum settings for generation voltages, transformers taps and switch-able capacitors or static VAr components (called "Voltage-VAR" optimization) periodically.

3.4 TYPES OF BUSES IN POWER SYSTEM

There are three types of buses in Power System:

I. Load Bus (PQ Bus)
II. Generator Bus (PV Bus)
III. Slack Bus (Swing Bus)

There are four variables named as

i. Real Power (P)
ii. Reactive Power (Q)
iii. Voltage Magnitude (V)
iv. Voltage Angle (δ)

Out of these four variables, two variables are known at each bus.

In Load Bus, Real Power and Reactive Power are known i.e. acive and reactive powers are injected into the network and Voltage Magnitude and Voltage Angle are unknown. Voltage Magnitude and Voltage Angle are to be calculated in this.

In Generator Bus, Real Power and Voltage Magnitude are specified. The Reactive Power and Voltage Angle are to be determined. Voltage magnitude is kept constant at a specified value by injection of reactive power. These buses are also known as Regulated Buses/ Voltage Controlled Buses.

In Slack Bus, Voltage Magnitude and Voltage Angle are known and Real Power and Reactive Power are to be determined. This Bus makes up the difference between the scheduled load and generator power that are caused by losses in the network. This Bus is taken as Reference Bus. If slack bus is not specified then the generation bus with usually with a maximum active power P is taken as reference bus.

Table 3.1 Type of Bus and its variables

TYPE OF BUS	**KNOWN VARIABLE**	**UNKNOWN VARIABLE**
Load Bus (PQ Bus)	P,Q	V, δ
Generator Bus (PV Bus)	P,V	Q, δ
Slack Bus (V- δ Bus)	V, δ	P,Q

3.5 GENERAL OPF PROBLEM FORMULATION

The main aim of electric supply utility is provide the Smooth electrical energy to the consumers taking into account that the electrical power is generated with minimum cost. It is only possible when the total demand is shared to all the units. This will lead to cost minimization. The objective function is represented by quadratic curves of second order. The major considerations for the fulfilling the objective of this is

- Minimize the fuel cost

The general definition of optimization problem is given by [26].

Minimize: f(x, u)

Subject to: g(u, x) = 0

h(u, x) ≥ 0

Where,

f: Objective Function

g: Equality Constraints

h:Inequality Constraints

u and x represents a set of controllable and dependent variables respectively.

The optimal power flow problem can be defined by specifying the following five attributes

1. Objective Function
2. The controls
3. The dependent variables
4. The equality constraints
5. Inequality constraints

3.5.1 Objective Function

The main objective function helps to minimize the operating cost. The objective function is the function of the real power generation. The objective function for the OPF reflects the costs associated with generating power in the system. The quadratic cost model for generation of power will be utilized. The Objective Function is the function of real power generation [27].

$$F_i = a_i + b_i(Pg_i) + c_i(Pg_i)^2$$

Where:

Pg_i is the amount of generations in MW at generator i

a_i , b_i , c_i are the cost coefficients

NG is the number of generation including the slack bus.

This objective function will minimize the total system costs, and does not necessarily minimize the costs for a particular area within the power system. It is scalar function of the variable of the problem. So the objective function for the whole power system for cost minimization is

Minimize $$F = \sum_{i=1}^{NG}(a_i + b_i(Pg_i) + c_i(Pg_i)^2)$$

Where,
a_i , b_i , c_i are the cost coefficients

NG is the number of generation including the slack bus.

3.5.2 The Controls

In Optimal Power Flow Problem, the objective function can be minimized directly by adjusting the values of the control variables and satisfy the constraints. The control variables can be given as:

1. Active Power Generation
2. Reactive Power Generation
3. Transformer Tap Ratio
4. Generator Bus Voltage

The Control variables help in making the desired results. For example, the active power generation cost is minimized by controlling the active power generation. The main function of the control variables is to minimize the cost of generation by adjusting them to appropriate values.

3.5.3 The Dependent Variables

These are those variables which are not under control. These include all type of variables that are free to assume value to solve the particular problem. The main dependent variables are the complex bus voltage angle and magnitude.

3.5.4 Equality Constraints

In Optimal Power Flow Problem, the equality constraints reflect the physics of the power system. The objective function can be minimized only when the power system is running under normal condition while the network components are operating within limits [28] i.e. the net power generation should be equals to the sum of total demand and total losses.

This can be achieved by the active and reactive power analysis:

$$P_i = P_{Load} + P_{Loss}$$

$$Q_i = Q_{Load} + Q_{Loss}$$

Where:

P_i & Q_i are the active and reactive power outputs

P_{Load} & Q_{Load} are the active and reactive load power

P_{Loss} & Q_{Loss} are the active and reactive power loss

The Power Flow Equations of the network mainly given by

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

Where,

$$g(V,\delta) = \begin{cases} P_i(V,\delta) - P_i^{net} \\ Q_i(V,\delta) - Q_i^{net} \\ P_m(V,\delta) - P_m^{net} \end{cases}$$

P_i & Q_i are the calculated values of real and reactive power at PQ bus i

P_i^{net} & Q_i^{net} are the specified values of real and reactive power for the PQ buses i

P_m & P_m^{net} are respectively calculated and specified real power for PV bus m.

V & δ are the voltage magnitude and voltage phase angle at different buses

3.5.5 Inequality Constraints

In Optimal Power Flow, the inequality constraints reflect the limits on physical devices in the power system as well as the limits created to ensure system security. The given objective function can be minimized by keeping the network components within the security limits which is now known as Inequality Constraints. There are many types of inequality constraints such as bus voltage limits at generations, maximum line loading limits and limits on tap settings.

- The inequality constraints on real power generation at bus i

$$\mathrm{Pg}_i^{\min} \le \mathrm{Pg}_i \le \mathrm{Pg}_i^{\max}$$

$\mathrm{Pg}_i^{\min}$ & $\mathrm{Pg}_i^{\max}$ are the minimum and maximum values of real power generation at i^{th} bus.

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

$$\mathrm{Qg}_i^{\min} \le \mathrm{Qg}_i \le \mathrm{Qg}_i^{\max}$$

$\mathrm{Qg}_i^{\min}$& $\mathrm{Qg}_i^{\max}$ are the minimum and maximum values of reactive power generation at PV bus.

- The inequality constraints on voltage magnitude V of each PQ bus

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

$V_i^{\min}$& $V_i^{\max}$ are the maximum and minimum values of voltage at bus i

- The inequality constraints on phase angle δ of voltages at all buses i

$$\delta_i^{min} \le \delta_i \le \delta_i^{max}$$

δ_{min} & δ_{max} are the minimum and maximum values of phase angle at bus i

- The inequality constraints on MVA flow limit

$$MVA_{ij} \le MVA_{ij}^{max}$$

MVA_{ij}^{max} = MVA rating of transmission line connecting i^{th} and j^{th} buses

CHAPTER 4

GENETIC ALGORITHM

4.1 INTRODUCTION

Genetic Algorithm was first proposed by John Holland at University of Michigan. The main theme for the research of Genetic Algorithm was robustness. These are theoretically and empirically proven to provide robust search in complex spaces. Genetic Algorithm is random search technique. These are search algorithms based on natural selection and natural genetics. They combine survival of the fittest among string structures with a structured yet randomized information exchange to form a search algorithm with some of the innovative flair of human search. A new set of artificial chromosomes are generated using bits and pieces of fittest of the old. Genetic Algorithm is the branch of Artificial Intelligence. Artificial Intelligence is that part of computer science to make computers to do smart things. It is inspired by Biological Evolution Theory. It has inherited intelligence of a designer by some set of rules. Term Soft Computing was coined by Lotif A. Zadeh of University of California. Soft computing refers to probabilistic reasoning. According to L.A Zadeh, soft computing differs from the convention computing (known as hard computing) in its tolerance to imprecision, uncertainty and partial truth. Conventional computing converges to mathematical approaches and therefore demands a high degree of precision. Whereas the soft computing basically incorporates the traits of biological system and basically consist of Fuzzy Logic (FL), Neural Networks (NN) and Genetic algorithm (GA) [29]. Genetic algorithm keeps on converging to best possible solution at each iteration, that's why Genetic algorithms are often seen as a function optimizer. Genetic algorithms can be applied to a wide range of problems, even where conventional computing (hard computing) fails. In order to solve the problem by genetic algorithm the first step is to create the population (random) of chromosomes. Then these chromosomes are selected in such a way that the chromosome which represents a best solution for the problem will be given more chances than any other.

4.2 HISTORY OF GENETIC ALGORITHM

Computer simulations of evolution started as early as in 1954 with the work of Nils Al Barricelli who was using the computer at the Institute for advanced study in Princeton, New Jersy. His 1954 publication was not widely noticed. Starting in 1957, the Australian quantitative geneticist Alex Fraser published a series of papers on simulation of artificial selection of organisms with multiple loci controlling a measurable trait. From these beginnings, computer simulation of evolution by biologists became more common in the early 1960s, and the methods were described in books by Fraser and Burnell (1970) and Crosby (1973). Fraser's simulations included all of the essential elements of modern genetic algorithms. In addition, Hans Bremermann published a series of papers in the 1960s that also adopted a population of solution to optimization problems, undergoing recombination, mutation and selection. Bremermann's research also included the elements of modern genetic algorithms. Other noteworthy early pioneers include Richard Friedberg, George Friedman and Michael Conrad. Many early papers are reprinted by Fogel (1998). Although Barricelli, in work he reported in 1963, had simulated the evolution of ability to play a simple game, artificial evolution became a widely recognized optimization method as a result of the work of Ingo Rechenberg and Hans-Paul Schwefel in the 1960s and early 1970s - his group was able to solve complex engineering problems through evolution strategies. Another approach was the evolutionary programming technique of Lawrence J. Fogel, which was proposed for generating artificial intelligence. Evolutionary programming originally used finite state machines for predicting environments, and used variation and selection to optimize the predictive logics. Genetic algorithms in particular became popular through the work of John Holland in the early 1970s, and particularly his book Adaptation in Natural and Artificial Systems (1975). His work originated with studies of cellular automata, conducted by Holland and his students at the University of Michigan. There were two goals for developing Genetic Algorithm

- To abstract and rigorously explain the adaptive processes of natural system
- To design artificial systems software that retains the important mechanisms of natural systems.

The research was not focused on optimization and domain specific practical problem but it was based on the concept of adaptation seen in nature. Te gist of Genetic Algorithm is based on natural selection i.e. survival of the fittest. Later on this was modified by many. The GA uses this power of evolution to solve optimization problems. As we are saying that the genetic algorithm is related with the nature, so there is some analogy between them and this can be described as

Table 4.1 Analogy b/w GA and nature

Genetic Algorithm	**Nature**
Optimization problem	Environment
Feasible solution	Individuals living in that environment
A set of feasible solution	Population of organism
Fitness function	Individual degree of adaptation
Operators used for results	Selection, recombination, mutation in nature

Holland introduced a formalized framework for predicting the quality of the next generation, known as Holland's Schema Theorem. Research in GAs remained largely theoretical until the mid-1980s, when the First International Conference on Genetic Algorithms was held in Pittsburgh, Pennsylvania. As academic interest grew, the dramatic increase in desktop computational power allowed for practical application of the new technique. In the late 1980s, General Electric started selling the world's first genetic algorithm product, a mainframe-based toolkit designed for industrial processes. In 1989, Axcelis, Inc. released Evolver, the world's second GA product and the first for desktop computers. The New York Times technology writer John Markoff wrote about Evolver in 1990.

4.3 SOME APPLICATIONS OF GENETIC ALGORITHMS

GA is not only used for solving optimization problems, but there are number of GA applications as mentioned below:

1. Industrial design by parameterization
2. Scheduling problems such as manufacturing, facility scheduling, allocation of resources, etc.
3. System design
4. Time series prediction
5. Data base mining
6. Control system
7. Artificial life system
8. Various medical applications, such as image segmentation and modeling
9. Combinatorial optimization problems like travelling sales man problem, routing, bin packing, graph partitioning and coloring.
10. Trajectory planning of robots
11. Game playing like chase playing, prisoner's dilemma, etc.
12. Resource allocation problem
13. Graph coloring and partitioning, etc

Genetic Algorithms are different from normal optimization and search procedures in four ways

i. GA work with a coding of the parameter set, not the parameters themselves.
ii. GA search from a population of points, not a single point
iii. GA use payoff (objective function) information, not derivatives or other auxiliary knowledge.
iv. GA use probabilistic transition rules, not deterministic rules.

4.4 DEFINITIONS FOR NATURAL TERMS

Chromosome: It is build of DNA. Chromosomes are in human form pairs. Genetic information is stored in chromosomes. There are 23 pairs.

Genes : The chromosome is divided in parts called genes. Genes code for properties.

Allele : The possibilities of the genes for one trait is called Allele.

Locus : Every gene has a unique position on the chromosome is called locus.

4.5 ADVANTAGES OF GENETIC ALGORITHM

Advantages of GA's are given below as discussed in

1. Simple to understand and to implement, and early give a good near solution.
2. It solves problems with multiple solutions.
3. Since the genetic algorithm execution technique is not dependent on the error surface, we can solve multi-dimensional, non-differential, non-continuous and even non-parametrical problems.
4. Is well suited for parallel computers.
5. Optimizes variables with extremely complex cost surfaces (they can jump out of a local minimum).
6. Provides a list of optimum variables, not just a single solution.
7. Can encode the variables so that the optimization is done with the encoded variables i.e. it can solve every optimization problem which can be described with the chromosome encoding.
8. Works with numerically generated data, experimental data or analytical functions. Therefore, works on a wide range of problems. For each problem of optimization in GAs, there are number of possible encodings. These advantages are intriguing and produce stunning results where traditional optimization approaches fail miserably. Due to various advantages as discussed above, GAs are used for a number of different application areas.

In power system, the GAs has been used in following areas:

- Loss reduction using Active Filter
- Power system restoration planning
- Controllers
- Optimal load dispatch
- Voltage stability

4.6 LIMITATIONS OF GENETIC ALGORITHM

In spite of its successful implementation, GA does posses some weaknesses leading to

1. Certain optimization problems (they are called variant problems) cannot be solved by means of genetic algorithms. This occurs due to poorly known fitness functions which generate bad chromosome blocks in spite of the fact that only good chromosome blocks cross-over.
2. There is no absolute assurance that a genetic algorithm will find a global optimum. It happens very often when the populations have a lot of subjects.
3. Genetic algorithm applications in controls which are performed in real time are limited because of random solutions and convergence, in other words this means that the entire population is improving, but this could not be said for an individual within this population. Therefore, it is unreasonable to use genetic algorithms for on-line controls in real systems without testing them first on a simulation model.
4. One well-known problem that can occur with a GA is known as premature convergence. If an individual that is more fit than most of its competitors emerges early on in the course of the run, it may reproduce so abundantly that it drives down the population's diversity too soon, leading the algorithm to converge on the local optimum that that individual represents rather than searching the fitness landscape thoroughly enough to find the global optimum.
5. One type of problem that genetic algorithms have difficulty dealing with are problems with "deceptive" fitness functions, those where the locations of improved points give misleading information about where the global optimum is likely to be found.

4.7 OPERATORS IN GENETIC ALGORITHM

A simple Genetic Algorithm that yields good results in many practical problems is composed of three operators:

1. Reproduction Operator
2. Crossover Operator
3. Mutation Operator

4.7.1 Reproduction Operator

The Reproduction is the straightforward copying of an individual to the next generation, otherwise known as Darwinian or asexual reproduction. Reproduction is a process in which individual strings are copied according to their objective function values. It is also known as Selection operator. It copies strings according to their fitness values. In other words, it copies good solutions for contributing one or more offspring in the next generation and reject the bad solutions in the population. Reproduction is usually first operator applied on a population. That is why this operator is artificial version of natural selection, a Darwinian survival of the fittest among string population. Selection is done by:

- Identifying good solution in population
- Making multiple copies of solution
- Rejecting bad solutions from the population so as to place multiple copies of good solution.

The gist of reproduction operator is to consider average strings from current population and making their multiple copies and replacing bad solutions hence making a new population. There are number of reproduction operators in Genetic algorithm. The various reproduction operators are:

1. Tournament Selection
2. Ranking Selection
3. Roulette Wheel Selection

4.7.1.1 Tournament Selection: In this process of selection, one parent is selected by randomly comparing other individual in the same population and select with the best fitness. To select the second parent the same process is repeated. It is most popular selection method due to its simplicity (Baker 1987).

4.7.1.2 Ranking Selection: In this method the individuals are ordered according to their fitness values (Grefenstette 1986). The individuals of highest fitness are kept on the top and worst on the bottom.

4.7.1.3 Roulette Wheel Selection: The easiest way to implement reproduction operator is Roulette Wheel selection. This is widely used reproduction operator. In roulette wheel selection, the string is selected in mating pool with a probability proportional to its fitness. Thus the ith string in the population is selected with a probability proportional to F .Since the population size is kept constant in a Genetic Algorithm, the sum of the probability of each string being selected from the mating pools must be one. Thus the probability of the ith string is given by

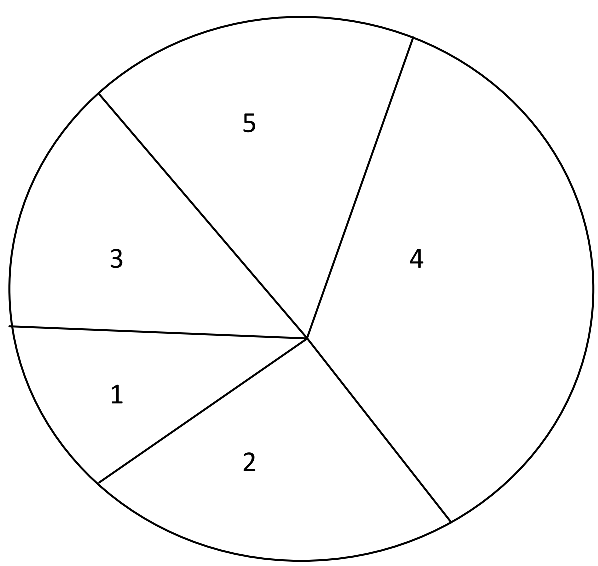
$$P_i = {F_i}\Big/{\sum_{i=1}^{n} F_i}$$

Where,

N=population size

F=fitness

Figure 4.1 Roulette Wheel Diagram



The roulette wheel is spun n times and every time selecting an instance string. The average fitness of the population is calculated as

$$F_i = \sum_{i=1}^{n} F_i$$

Table 4.2 Fitness value for corresponding population

POPULATION	FITNESS VALUE
1	20
2	20.7
3	25
4	40
5	35

Fourth have highest fitness function as compared to other values, so the roulette wheel will select this value.

4.7.2 Crossover

The basic operator for producing new chromosome in the genetic algorithm is crossover. In the crossover operator, information is exchanged among strings of the mating pool to create new strings. In other words, crossover produces new individuals that have some parts of both parent's genetic materials. It consists of taking two individuals A and B and randomly selecting a crossover point in each. The two individuals are then split at these points. The choice of crossover point is not always uniform. It is expected from the crossover operator that good substrings from the parent strings will be combined to form a better child offspring. At the molecular level what occurs is that a pair of Chromosomes bumps into one another, exchange chunks of genetic information and drift apart. This is the recombination operation, which GA generally refers to as crossover because of the way that genetic material crosses over from one chromosome to another. The crossover operation happens in an environment, where the selection of who gets to mate is a function of the fitness of the individuals. How good the individual is at competing in its environment. Some Genetic Algorithms use a simple function of the fitness measure to select individuals (probabilistically) to undergo genetic operations such as crossover or asexual reproduction (the propagation of genetic material unaltered). This is fitness-proportionate selection. Other implementations use a model in which certain randomly selected individuals in a subgroup compete and the fittest is selected. This is called tournament selection and is the forms of selection we see in nature .The two processes that most contribute to evolution are crossover and fitness based selection/reproduction.

There are three forms of crossover:

(1) one point crossover,

(2) multi-point crossover, and

(3) mid-point crossover.

4.7.2.1 One Point Crossover:

Before crossover	1	1101	0	0010
	String 1		String 2	
After Crossover	1	0010	0	1101

4.7.2.2 Multi Point Crossover:

Before crossover

String 1		
1	01	11

String 2		
0	11	10

After crossover

1	11	11

0	01	10

4.7.2.3 Mid-Point Crossover:

Before crossover

String 1	
110	101

String 2	
011	010

After crossover

110	010

011	101

4.7.3 Mutation:

Mutation also plays a role in this process, although how important its role is, depends upon the conditions. It is also known as background operator .It plays dominant role in the evolutionary process. It cannot be stressed too strongly that the genetic Algorithm is not a random search for a solution to a problem for highly fit individual. It consists of randomly selecting a mutation point. The genetic algorithm uses stochastic processes, but the result is distinctly non-random. Genetic Algorithms are used for a number of different applications areas.

An example of this would be multidimensional optimization problems in which the character string of the Chromosome can be used to encode the values for the different parameters being optimized. Mutation is an important operator, as newly created individuals have no new inheritance information, this process results in contraction of the population at one single point, which is wished one. Mutation operator changes 1 to 0 at only one place in the whole string with a small probability and vice versa.

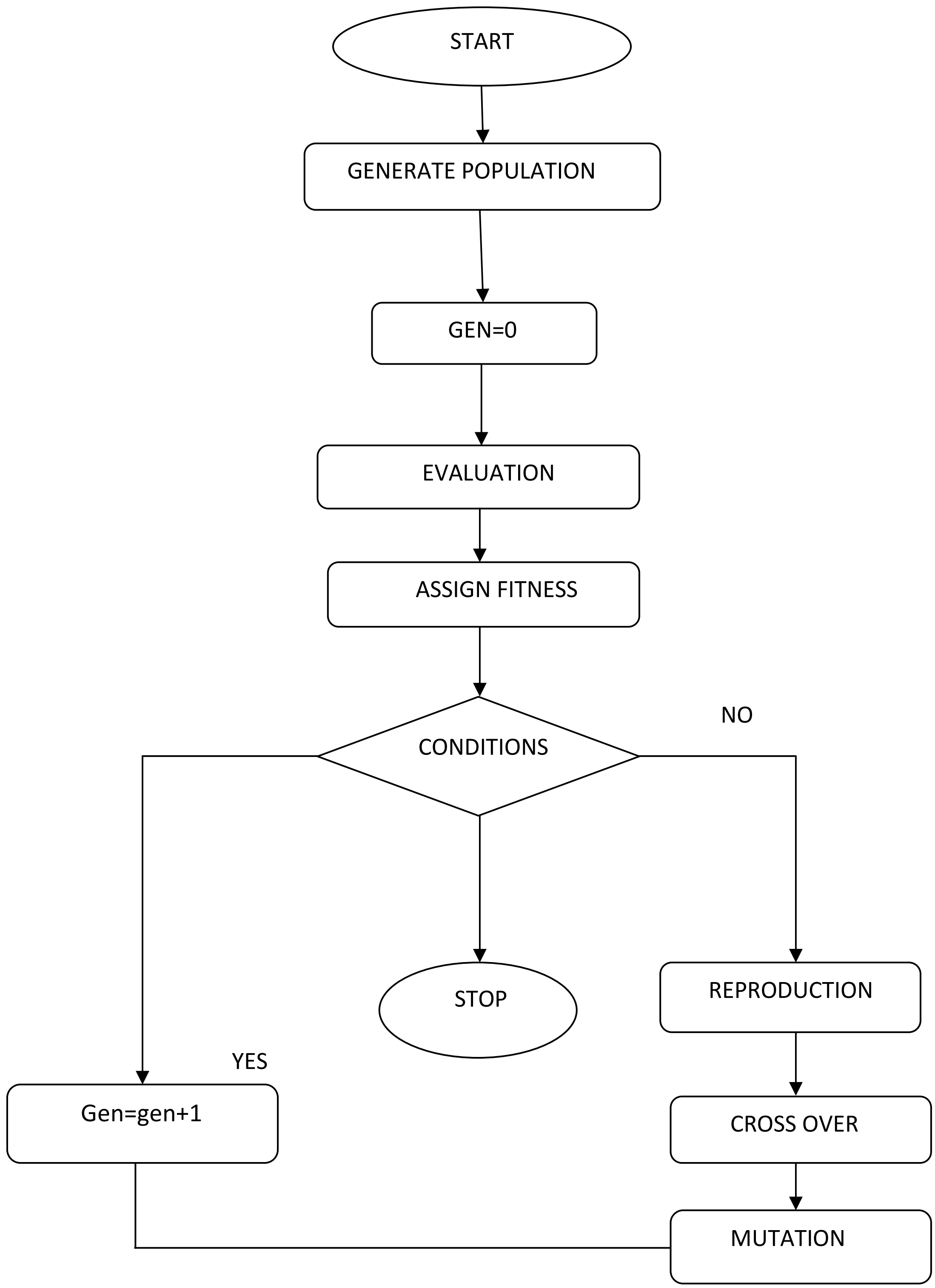
E.g. Child 1 1011**0**0

Let mutation is done at location 5 the new child will be

New child 1011**1**0

4.8 FLOW CHART OF GENETIC ALGORITHM

Figure 4.2 Flowchart of GA



4.9 GA BASED OPTIMAL POWER FLOW

In GA based Optimal Power Flow, Genetic Algorithm is used as a search technique for optimization of power flow in different lines of the power system. The Genetic Algorithm requires the evaluation of the so-called fitness function (FF) to assign a quality value to every solution produced. Movement in a Genetic Algorithm is accomplished using three primary operations: Parent reproduction, crossover and mutation. The details of important operations during solution of GA based Optimal Power Flow are as follows:

1. **Encoding**

Binary coded strings having 1s and 0s are used for building chromosomes through random process. The randomly generated chromosomes represent binary coded values of controllable variables e.g. power generation at all generator (PV) buses other than slack bus, the voltage magnitude at all PV buses, tap settings of variable tap transformers and shunt capacitor/reactor compensations. Load flow using Newton–Raphson method is run for set of control variables values belonging to each chromosome. If load flow converges and slack bus generation obtained from load flow solution is within specified limits then chromosome is included to complete initial population. Otherwise, a new chromosome is generated according to same procedure and checked again.

2. Fitness function evaluation

GAs are usually designed so as to maximize the fitness function (FF), which is a measure of quality of each candidate solution. The objective of the OPF problem is to minimize the total generation cost including power flow constraint for each line and other equality and inequality constraints.

3. GA operators

As a next step in solution finding process, GA operators – Reproduction, Crossover and Mutation are applied in above sequence for each generation. The reproduction operator selects a chromosome string from the previous generation based on the string's fitness and its probability of propagation to the next generation. In the reproduction operator a stochastic remainder selection is used instead of simple Roulette wheel. In simple Roulette wheel selection, there is no guarantee that the best strings would be selected. To overcome this problem the stochastic selection is used in this work. Selection continues until the population of the next generation is filled. The crossover and mutation operators work in conjunction with selection. After crossover and mutation, load flow using Newton-Raphson method is run. If load flow converges and slack bus generation obtained from load flow solution is within specified limits then chromosome is included to valid population.

CHAPTER-5

SIMULATED ANNEALING

5.1 INTRODUCTION

Simulated Annealing is a probabilistic method which was proposed by Kirkpatrick, Gelett and Vecchi in 1983 and Cerny in 1985 for finding the global minimum of a cost function that may possess several local minima. SA has a great ability that it does not trap in local minima when tested in several optimization problems. Like Genetic Algorithm, Simulated Annealing performs random search in complex, multimodal search space for giving a very close optimal solution. The values of number of parameters define the problem state in SA. It works by emulating the physical process whereby a solid is slowly cooled so that when eventually its structure is frozen, this happens at a minimum energy configuration. The main advantage of SA is that it accepts the worst solution with probability without discarding it.

Simulated Annealing is a generic probabilistic meta-heuristic for global optimization problem of applied mathematics, namely locating a good approximation to the global minimum of a given function in a large search space. SA is a search method based on ideas drawn from statistical physics and is an effective technique for solving combination optimization problem [19]. SA is an optimization technique which simulates the physical annealing process of a molten particle starting from a high temperature. With the help of SA, a very near to optimum solution of optimization can be obtained. SA is the process which is related to temperature i.e. sudden heating and cooling. This method is inspired by experimental observations on crystallization. At high temperatures, the atoms are free to move around the sample. As the temperature is reduced, the atoms tend to crystallize into a solid. If the sample is quenched, i.e., cooled very rapidly, then the solid is usually polycrystalline or amorphous in form. If the sample is annealed, i.e., cooled slowly, then the sample stands a better chance of forming a perfect crystal, which is the global minimum energy configuration of the system. The algorithm begins with a randomly generated initial solution [30]. This initial solution is said to be the current solution. A neighbour of this current solution is then generated. If the neighbour is found to be better than the current point, it is unconditionally accepted to be the next current point. On the other hand, if the neighbor is found to be worse, it is not rejected outright, but accepted with a certain probability. To begin with, the probability of accepting a worse point is kept high (thereby reducing the chance of the SA algorithm getting trapped in a local optimum). As the number of iterations increases, this probability is reduced according to a specific distribution. The control parameter is known as the temperature (analogous to that of the physical process). The temperature is started at a very high value and is then brought down according to a schedule known as the cooling / annealing schedule.

5.2 IMPLEMENTATION OF SA

The Optimal Power Flow problem can be realized as Optimization problem using Simulated Annealing by defining the Energy Function, E. With the help of this energy function, optimal solution can be determined, hence converges the solution and minimizes the generation cost. The energy function is given by

$$E = \alpha \frac{\begin{bmatrix} \Delta P_P \\ \Delta Q_P \end{bmatrix}}{T} + \frac{F_i}{\beta}$$

Where,

α & β= weighting factors

T= Annealing temperature

Normalized Energy Function is obtained by using weighting factors. The temperature T divides the equation into two parts so as to obtain the optimal solution [32]. Above equation defines an optimization function in which a minimum of first term solves the load flow problem using the polar formulation of active and reactive powers partial differences and the second term solves the OPF problem mapping the overall generating cost of the system [33].

$$\Delta P_P = P_G - P_c - \sum_{q=1}^{NG} V_p V_q Y_{pq} \cos(\delta_p - \delta_q - \theta_{pq})$$

$$\Delta Q_P = Q_G - Q_c - \sum_{q=1}^{NG} V_p V_q Y_{pq} \sin(\delta_p - \delta_q - \theta_{pq})$$

Where

P_G and Q_G are real and reactive power generation at bus

P_c and Q_c are the real and reactive power demands at bus

V_p and V_q are the voltage magnitude at bus P and Q

Y_{pq} are the admittance magnitude.

δ_p and δ_q are the voltage bus angle at bus P and Q

θ_{pq} is the admittance angle

The factors plays important role in SA are:

1. **Acceptance criteria**

   Like Genetic Algorithm, Simulated Annealing performs random search. The SA has ability to all those solutions that improves the system energy. According to the law of thermodynamics at temperature T, the probability of an increase in energy of magnitude δE is

$$P(\delta E) = \exp \frac{\delta E}{kT}$$

Where,

k is Boltzmann's constant

E is Energy

Kirkpatrick used Metropolis Algorithm to solve some typical problems of OPF. The new energy of the system is calculated by simulation in the Metropolis Algorithm. The system remains in same state if the energy is decreased vice versa if the energy has increased then the new state is accepted by the probability expressed by the above probability expression.

At each temperature, certain number of iterations is carried out and then the temperature is lowered. This process is repeated until the system freezes into a steady state.

2. Cooling Schedule

In cooling schedule, it is assumed that the annealing process is done until the temperature is reduced to minimum value [21]. In Simulated Annealing, the cooling schedule is further divided into Starting Temperature, Temperature Decrement and Final Temperature. These are elaborated as:

- Starting temperature: The starting temperature should be kept high then search can move to almost any neighboring state. If the starting temperature is not kept high then the end solution might be very near to the initial solution. If the starting temperature is high then the search can move to any neighboring state. This converts the search into random search. This random search will carry on till the temperature is cooled down and simulated annealing algorithm is started. During this process we get initial and final temperature.

- Temperature decrement: Now the initial and final temperatures are known. The temperature is reduced until the final temperature is attained. This will be known as Stopping Criterion.

  For the accurate results, the temperature is reduced in such a manner to success the method. According to the Simulated Annealing Theory, the iterations should be as much as to stabilize the system to that temperature. The number of iterations at each temperature may be exponential to the problem size. So as to move away from this problem, either the lesser number of iterations carried out at many temperatures, larger number of iterations at less number of temperatures or a balance between the two.

- Final temperature: This is last and final step. In this step, temperature reaches to final state. Temperature is reduced till it reaches zero. This makes the process to run for longer time especially when geometric cooling schedule is used. It is not essential that temperature reaches to zero because when it approaches to zero value, the probability of accepting worse cases increases. So because of this, the final temperature should be suitably low so that worse moves are not there.

CHAPTER 6

HYBRID GA BASED OPF

6.1 INTRODUCTION

The performance of Genetic Algorithm can be improved by using Hybrid Genetic Algorithm i.e. combining GA with some other technique to get optimum solution of optimization problem. For this purpose, at the early stages, more diversity is introduced in the chromosomes i.e. by replacing fitter chromosome by weak child chromosome in controlled way. This can be done by probabilistic replacement test technique in component of Simulated Annealing instead of probabilistic acceptance test technique given in [31]. At initial conditions temperature is kept high but it decreases gradually when process is carried out. Therefore, the probability of replacement test also decreases accordingly. At later stages, chances of replacing fitter chromosome with weaker one reduce. It also checks whether mutated chromosome is included in population or not. The Mutation step is not included in Hybrid Genetic Algorithm method. The last step of Genetic Algorithm i.e. mutation is replaced by Simulated Annealing. So the algorithm becomes Hybrid Genetic Algorithm. Advantage of using Hybrid GA is that the Fuel Cost is minimized without violating the operating limits.

6.2 ALGORITHM AND FLOW CHART OF PROPOSED HYBRID GA METHOD TO SOLVE OPF PROBLEM

6.2.1 Algorithm

Step 1: Enter IEEE-30 bus system data i.e. generator data, bus data, line data, transformer data and capacitor/reactor data.

Step 2: Initialize suitable population size (pop size), crossover rate and maximum number of generations (gen_max).

Step 3: Set the population counter equals to zero initially.

Step 4: Generate chromosomes randomly.

Step 5: For calculating power flow for each set of Pg_i for each chromosome, run Newton Raphson and then calculate slack bus Generation, Voltage Magnitude at buses, phase angles at all buses.

Step 6: Check the Voltage Magnitude Constraints, Phase Angle Constraint and Reactive Power Limits at all generator buses.

If any of these is not satisfied then again go to Step 4 and repeat Step 5 and Step 6.

Step 7: If all the above constraints are satisfied then increase the population counter by 1. If the population size is less or equals to population size then again go to Step 4 otherwise go to next step.

Step 8: Calculate the fitness value of each chromosome and then store it.

Step 9: Now apply the Genetic Operator. Crossover will be applied to that population which is calculated in Step 8.

Step 10: Again check the power flow by Newton Raphson Method.

Step 11: Check the constraints that are mentioned in step 6. Those which do not satisfy the constraints, discard them.

Step 12: Add these chromosomes to the list so that best parents can be chosen for the next step.

Step 13: Apply Simulated Annealing by setting initial temperature T very high value.

Step 14: Calculate the Energy E by

$$E = \alpha \frac{\begin{bmatrix} \Delta P_P \\ \Delta Q_P \end{bmatrix}}{T} + \frac{F_i}{\beta}$$

Step 15: Check ΔE<0 then accept E otherwise go to next step.

Step 16: If ΔE is not less than zero then accept this with Probability δE.

$$P(\delta E) = \exp \frac{\delta E}{kT}$$

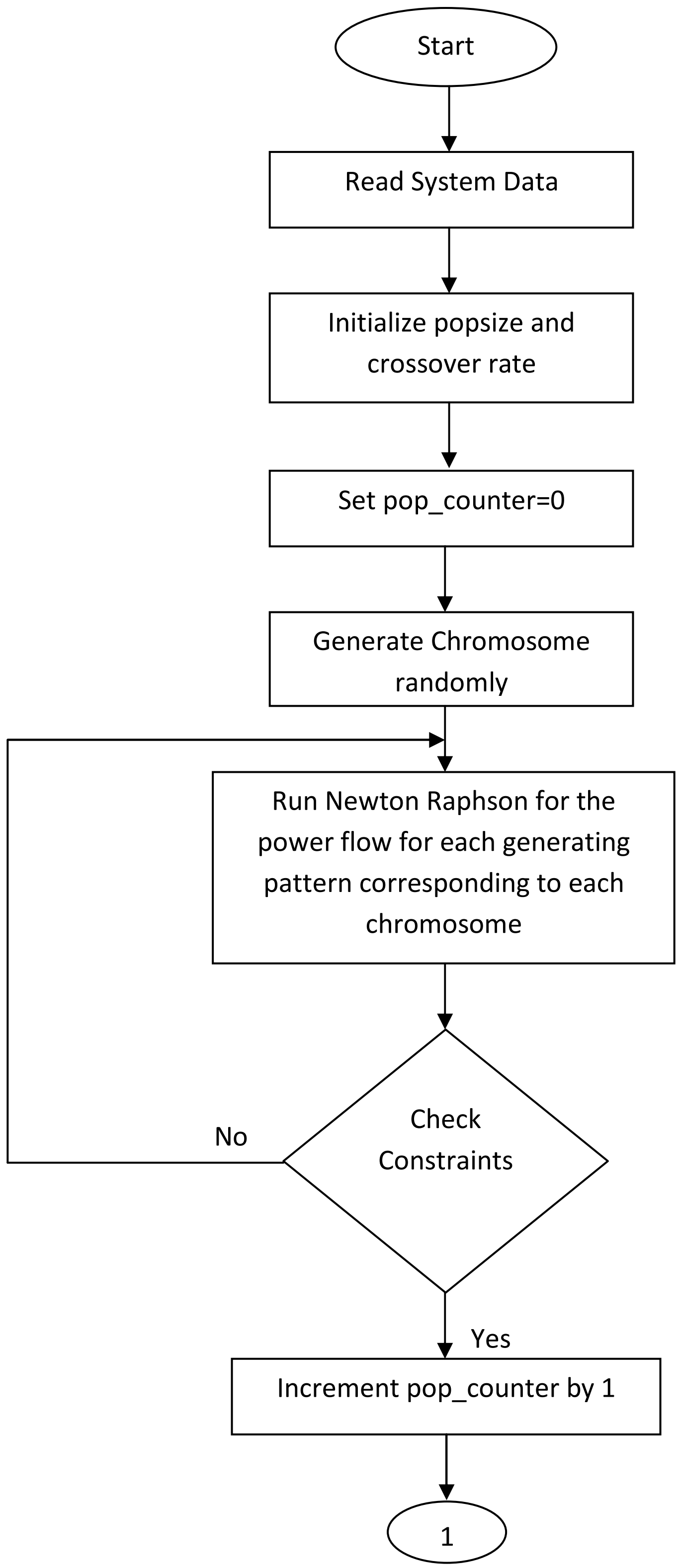
Step 17: Lower the temperature and then find the energy at the lowest temperature.

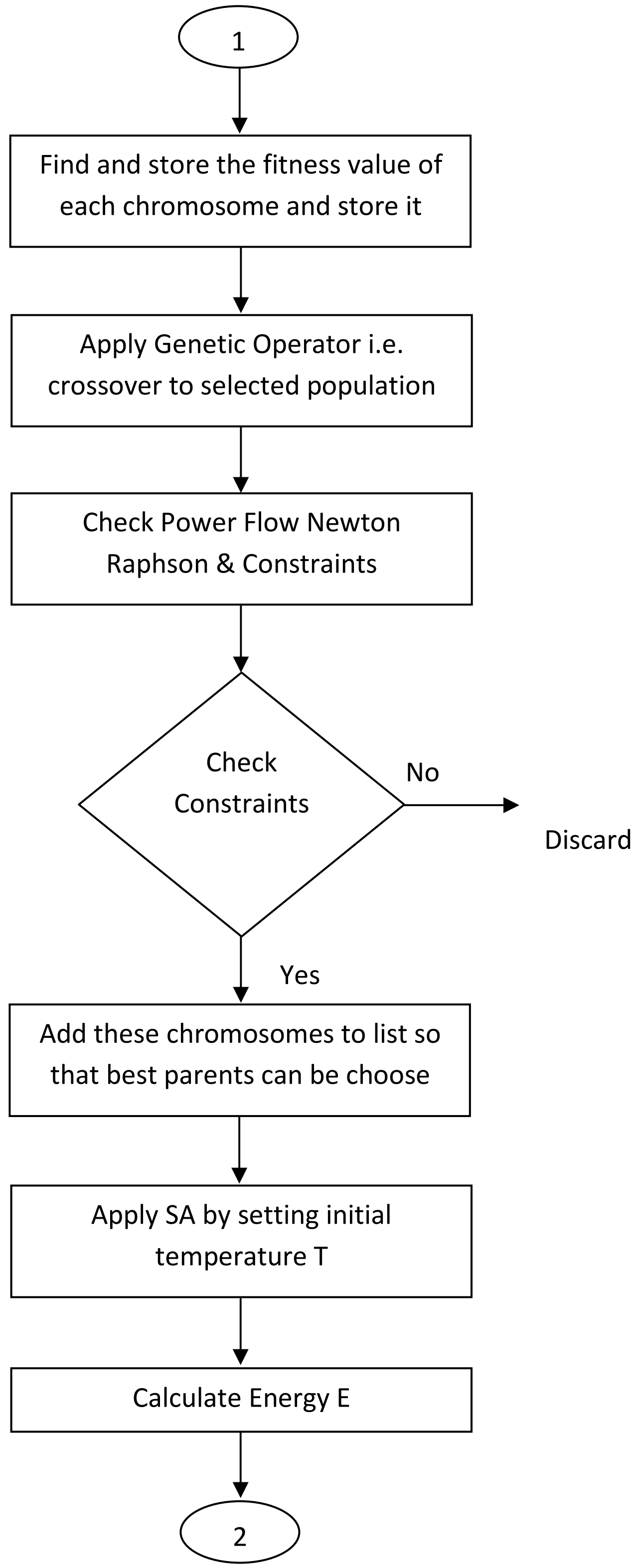
Step 18: Find the optimized value. Store it.

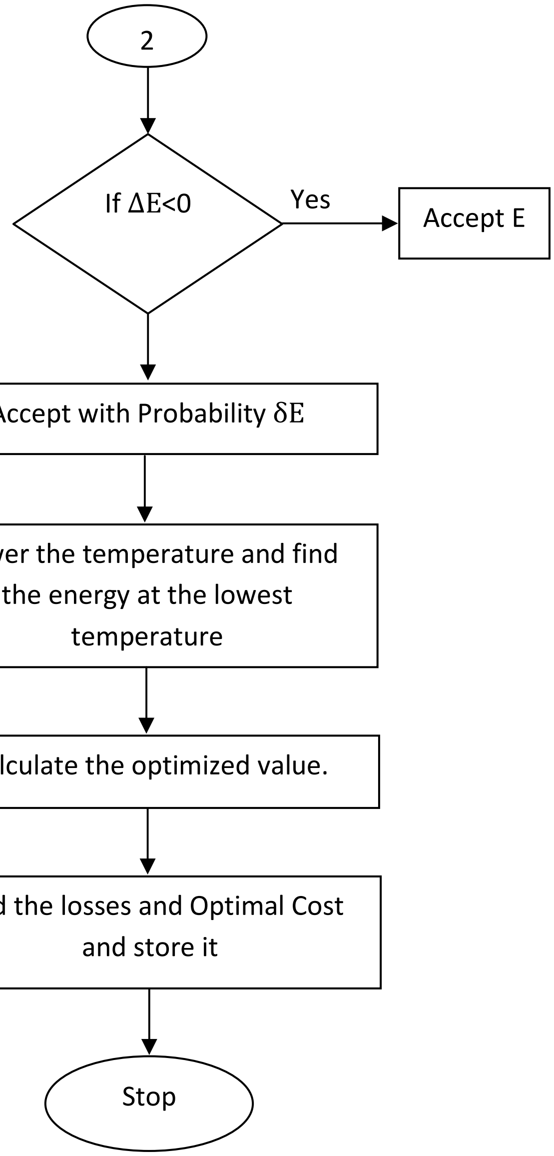
Step 19: Find the losses and Optimal Cost. Store it.

6.2.2 Flow Chart

Figure 6.1 Flow Chart of Hybrid GA




1
Find and store the fitness value of each chromosome and store it
Apply Genetic Operator i.e. crossover to selected population
Check Power Flow Newton Raphson & Constraints
Check Constraints
No
Discard
Yes
Add these chromosomes to list so that best parents can be choose
Apply SA by setting initial temperature T
Calculate Energy E
2


2
If ΔE<0
Yes
Accept E
Accept with Probability δE
Lower the temperature and find the energy at the lowest temperature
Calculate the optimized value.
Find the losses and Optimal Cost and store it
Stop

CHAPTER 7

RESULTS

7.1 PARAMETERS USED IN HYBRID GA BASED OPF

Simulated Annealing is combined with Genetic Algorithm and is applied to Optimal Power Flow Problem. This combination is called as Hybrid Genetic Algorithm. Following are the parameters that are used while carrying out the result for SA based OPF:

Table 7.1: List of Parameters

Population Size	20
Crossover Probability	0.8
Mutation Probability	0.8
Initial Temperature	10000
Alpha (α)	0.5
Beta (β)	0.5

7.2 RESULTS BASED ON HYBRID GENETIC ALGORITHM

In this thesis, IEEE 30 bus system data is taken. The Bus data, Line Data and Generator Limits are given in Appendix A. While Cost Coefficients and Emission Coefficients are given in Appendix B. The Optimization based on Hybrid Genetic Algorithm method is applied to IEEE 30 bus system. Here the control variable is generator's real power.

After running the Hybrid GA program, following results are there as the output of the program.

Table 7.2: Line Losses with Hybrid GA

Line		Power at Bus and Line Flow			Line Loss		Transformer Tap
From	To	MW	Mvar	MVA	MW	Mvar	
1		177.757	-2.530	177.775			
	2	120.334	-7.934	120.595	2.479	1.585	
	3	57.423	5.405	57.677	1.350	1.090	
2		22.300	16.867	27.960			
	1	-117.855	9.519	118.239	2.479	1.585	
	4	32.483	2.824	32.606	0.565	-2.188	
	5	63.681	3.590	63.782	1.774	3.049	
	6	43.990	0.934	44.000	1.038	-0.814	
3		-1.400	-1.200	1.844			
	1	-56.073	-4.314	56.239	1.350	1.090	
	4	54.673	3.114	54.762	0.376	0.201	
4		-5.600	-1.600	5.834			
	2	-31.918	-5.013	32.309	0.565	-2.188	
	3	-54.297	-2.913	54.375	0.376	0.201	
	6	50.377	-8.415	51.075	0.298	0.107	
	12	30.238	14.741	33.640	-0.000	2.426	0.932
5		-76.600	7.150	76.933			
	2	-61.907	-0.541	61.909	1.774	3.049	
	7	-14.693	7.690	16.584	0.132	-1.742	
6		0.000	0.000	0.000			
	2	-42.952	-1.749	42.988	1.038	-0.814	

	4	-50.079	8.522	50.799	0.298	0.107	
	7	31.889	0.537	31.893	0.263	-0.930	
	8	19.578	8.715	21.430	0.054	-0.733	
	9	18.529	-7.611	20.032	-0.000	0.773	0.978
	10	10.601	0.135	10.602	0.000	0.568	0.969
	28	12.434	-8.549	15.090	0.026	-13.317	
7		-16.800	-10.900	20.026			
	5	14.825	-9.433	17.571	0.132	-1.742	
	6	-31.625	-1.467	31.659	0.263	-0.930	
8		-20.000	-14.069	24.452			
	6	-19.524	-9.448	21.690	0.054	-0.733	
	28	-0.476	-4.620	4.645	0.004	-4.376	
9		0.000	0.000	0.000			
	6	-18.529	8.384	20.338	-0.000	0.773	
	11	0.000	-13.799	13.779	0.000	0.355	
	10	18.529	5.395	19.299	0.000	0.368	
10		-3.800	17.000	17.420			
	6	-10.601	0.434	10.610	0.000	0.568	
	9	-18.529	-5.027	19.199	0.000	0.368	
	20	6.798	3.329	7.570	0.049	0.109	
	17	6.416	4.322	7.736	0.018	0.046	
	21	7.999	9.552	12.459	0.049	0.106	
	22	4.117	4.390	6.019	0.024	0.049	
11		0.000	14.134	14.134			
	9	-0.000	14.134	14.134	0.000	0.355	

12		-7.200	-7.500	10.397			
	4	-30.238	-12.315	32.650	-0.000	2.426	
	13	0.000	-7.833	7.833	0.000	0.076	
	14	5.247	2.447	5.790	0.037	0.076	
	15	11.641	6.773	13.468	0.107	0.210	
	16	6.150	3.428	7.041	0.042	0.088	
13		0.000	7.910	7.910			
	12	-0.000	7.910	7.910	0.000	0.076	
14		-4.200	-1.600	4.494			
	12	-5.210	-2.371	5.724	0.037	0.076	
	15	1.010	0.771	1.271	0.003	0.003	
15		-3.200	-2.500	4.061			
	12	-11.534	-6.563	13.271	0.107	0.210	
	14	-1.007	-0.768	1.266	0.003	0.003	
	18	5.191	1.863	5.516	0.030	0.061	
	23	4.150	2.968	5.102	0.024	0.048	
16		-3.500	-1.800	3.936			
	12	-6.109	-3.340	6.962	0.042	0.088	
	17	2.609	1.540	3.029	0.007	0.016	
17		-9.000	-5.800	10.707			
	16	-2.602	-1.524	3.015	0.007	0.016	
	10	-6.398	-4.276	7.696	0.018	0.046	
18		-3.200	-0.900	3.324			

	15	-5.162	-1.802	5.467	0.030	0.061	
	19	1.962	0.902	2.159	0.003	0.006	
19		-6.500	-3.400	7.336			
	18	-1.959	-0.897	2.154	0.003	0.006	
	20	-4.541	-2.503	5.185	0.009	0.017	
20		-2.200	-0.700	2.309			
	19	4.550	2.521	5.201	0.009	0.017	
	10	-6.750	-3.221	7.479	0.049	0.109	
21		-7.500	-11.200	13.479			
	10	-7.950	-9.447	12.347	0.049	0.106	
	22	0.450	-1.753	1.810	0.000	0.001	
22		0.000	0.000	0.000			
	10	-4.093	-4.341	5.966	0.024	0.049	
	21	-0.449	1.754	1.811	0.000	0.001	
	24	4.542	2.587	5.227	0.029	0.045	
23		-3.200	-1.600	3.578			
	15	-4.126	-2.920	5.055	0.024	0.048	
	24	0.926	1.320	1.612	0.003	0.007	
24		-5.700	-2.400	6.185			
	22	-4.513	-2.542	5.180	0.029	0.045	
	23	-0.923	-1.313	1.605	0.003	0.007	
	25	-0.264	1.455	1.479	0.004	0.00	
25		0.000	0.000	0.000			

	24	0.268	-1.448	1.473	0.004	0.007	
	26	3.544	2.365	4.261	0.044	0.065	
	27	-3.811	-0.917	3.920	0.016	0.030	
26		-3.500	-2.300	4.188			
	25	-3.500	-2.300	4.188	0.044	0.065	
27		0.000	0.000	0.000			
	25	3.827	0.947	3.943	0.016	0.030	
	28	-11.928	-3.938	12.562	-0.000	0.586	
	29	4.065	1.519	4.340	0.039	0.073	
	30	4.036	1.471	4.296	0.055	0.104	
28		0.000	0.000	0.000			
	27	11.928	4.524	12.757	-0.000	0.586	0.968
	8	0.480	0.244	0.539	0.004	-4.376	
	6	-12.408	-4.768	13.293	0.026	-13.317	
29		-2.400	-0.900	2.563			
	27	-4.027	-1.446	4.278	0.039	0.073	
	30	1.627	0.546	1.716	0.007	0.013	
30		-5.600	-1.900	5.914			
	27	-3.980	-1.367	4.209	0.055	0.104	
	29	-1.620	-0.533	1.705	0.007	0.013	
				Total Losses		8.957 MW	

7.3 COMPARISON OF RESULTS

The obtained results are compared with those results which are there in literature [32].

Table 7.3 Comparison of Results

	ED+LF [32]	Alsac-Scott [32]	OPFSA [32]	**Hybrid GA (Results obtained from proposed algorithm)**
Unit 1(MW)	192.65	138.56	188.02	**185.21**
Unit 2 (MW)	48.92	57.56	47.45	**38.52**
Unit 5 (MW)	19.26	24.56	19.77	**22.13**
Unit 8 (MW)	10.58	35.0	13.40	**11.42**
Unit 11 (MW)	10.79	17.93	11.25	**15.71**
Unit 13 (MW)	12.24	16.91	14.09	**17.32**
Overall cost ($/hr)	805.45	813.74	804.43	**796.13**
Losses (MW)	11.04	7.13	10.58	**8.96**
Violating Limits	0	0	0	**0**

From the above table, the losses are minimum i.e. 7.13 MW computed by Alsac-Scott but the overall cost is high i.e. 813.74 ($/hr). The minimum cost is calculated by proposed algorithm i.e. 796.13 ($/hr). The losses calculated are not minimum among them but these are less as compared to others.

7.4 CONCLUSION

The various things that are concluded by this thesis are:

- Implementation of Hybrid GA on Optimal Power Flow Problem. This algorithm is developed and applied to a practical IEEE-30 Bus system.
- The algorithm calculates the optimum settings for system control variables to achieve minimum objective function. These control variables include active power generation except at slack bus, all PV bus voltages, all transformer load tap changers and the setting of all switched reactors.

The fuel cost and transmission losses are minimized with the help of this algorithm.

FUTURE SCOPE

The main objective of Optimal Power Flow is to minimize the Fuel Cost while taking Transmission Losses into consideration without violating the security limits. The artificial intelligence technique is mixed with heuristic technique to get better and promising results. In this thesis Hybrid GA i.e. GA and Simulated annealing method is used to solve single objective Optimal Power Flow Solutions. Only Fuel Cost is minimized in this work. For the future work, not only fuel cost but also Emission of Pollutants can be minimized by making it Multiobjective Optimal Power Flow Solution. Pollutants like SOx, COx, NOx can be minimized by setting emission coefficients in multiobjective problem. The solution can be obtained by using hybrid GA based on GA and Particle Swarm Optimization (PSO).

APPENDIX A

The data for six generator test system is given as below. The Bus data, Line Data and Generator Limits are given below in Table (A1 to A3).

TABLE A1: Bus Data

Bus No.	Bus Code	Voltage Mag.	Angle Deg.	Load (MW)	Load (Mvar)	Gen (MW)	Gen (Mvar)	Gen (Q_{min})	Gen Q_{max}	Injected (Mvar)
1	1	1.05	0.0	0.0	0.0	50	-20	0	150	0
2	2	1.033	0.0	21.70	12.7	20	-30	0	60	0
3	0	1.0	0.0	2.4	1.2	0	0.0	0	0	0
4	0	1.0	0.0	7.6	1.6	0	0.0	0	0	0
5	2	1.0058	0.0	94.2	19.0	15	-15	0	60	0
6	0	1.0	0.0	0.0	0.0	0	0.0	0	0	0
7	0	1.0	0.0	22.0	10.9	0	0.0	0	0	0
8	2	1.023	0.0	30.0	30.0	10	-15	0	50	0
9	0	1.0	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	0	19
11	2	1.0913	0.0	0.0	0.0	10	-10	0	-40	0
12	0	1.0	0.0	11.2	7.5	0	0	0	0	0
13	2	1.0883	0.0	0.0	0.0	12	-15	0	45	0
14	0	1.0	0.0	6.2	1.6	0	0	0	0	0
15	0	1.0	0.0	8.2	2.5	0	0	0	0	0
16	0	1.0	0.0	3.5	1.8	0	0	0	0	0
17	0	1.0	0.0	9.0	5.8	0	0	0	0	0
18	0	1.0	0.0	3.2	0.9	0	0	0	0	0
19	0	1.0	0.0	9.5	3.4	0	0	0	0	0
20	0	1.0	0.0	2.2	0.7	0	0	0	0	0
21	0	1.0	0.0	17.5	11.2	0	0	0	0	0
22	0	1.0	0.0	0.0	0.0	0	0	0	0	0

23	0	1.0	0.0	3.2	1.6	0	0	0	0	0
24	0	1.0	0.0	8.7	6.7	0	0	0	0	0
25	0	1.0	0.0	0.0	0.0	0	0	0	0	0
26	0	1.0	0.0	3.5	2.3	0	0	0	0	0
27	0	1.0	0.0	0.0	0.0	0	0	0	0	0
28	0	1.0	0.0	0.0	0.0	0	0	0	0	0
29	0	1.0	0.0	2.4	0.9	0	0	0	0	0
30	0	1.0	0.0	10.6	1.9	0	0	0	0	0

TABLE A2: Line Data

Bus From	Bus To	R (p.u)	X (p.u)	$\frac{1}{2}$B (p.u)	Tap at Bus
1	2	0.0192	0.0575	0.02640	1
1	3	0.0452	0.1852	0.02040	1
2	4	0.0570	0.1737	0.01840	1
3	4	0.0132	0.0379	0.00420	1
2	5	0.0472	0.1983	0.02090	1
2	6	0.0581	0.1763	0.01870	1
4	6	0.0119	0.0414	0.00450	1
5	7	0.0460	0.1160	0.01020	1
6	7	0.0267	0.0820	0.00850	1
6	8	0.0120	0.0420	0.00450	1
6	9	0.0000	0.2080	0.00000	0.978
6	10	0.0000	0.5560	0.00000	0.969
9	11	0.0000	0.2080	0.00000	1
9	10	0.0000	0.1100	0.00000	1
4	12	0.0000	0.2560	0.00000	0.932
12	13	0.0000	0.1400	0.00000	1

12	14	0.1231	0.2599	0.00000	1
12	15	0.0662	0.1304	0.00000	1
12	16	0.0945	0.1987	0.00000	1
14	15	0.2210	0.1997	0.00000	1
16	17	0.0824	0.1923	0.00000	1
15	18	0.1073	0.2185	0.00000	1
18	19	0.0639	0.2192	0.00000	1
19	20	0.0340	0.0680	0.00000	1
10	20	0.0936	0.2090	0.00000	1
10	17	0.0324	0.0845	0.00000	1
10	21	0.0348	0.0749	0.00000	1
10	22	0.0727	0.1499	0.00000	1
21	22	0.0116	0.0236	0.00000	1
15	23	0.1000	0.2020	0.00000	1
22	24	0.1150	0.1790	0.00000	1
23	24	0.1320	0.2700	0.00000	1
24	25	0.1885	0.3292	0.00000	1
25	26	0.2544	0.3800	0.00000	1
25	27	0.1093	0.2087	0.00000	1
28	27	0.0000	0.3960	0.00000	0.1968
27	29	0.2198	0.4153	0.00000	1
27	30	0.3202	0.6027	0.00000	1
29	30	0.2399	0.4533	0.00000	1
8	28	0.0636	0.2000	0.02140	1
6	28	0.0169	0.0599	0.06500	1

TABLE A3: Generator Limits

MW(minimum)	MW(maximum)	Mvar(minimum)	Mvar(maximum)
50	200	-30	150
20	80	-30	60
15	50	-15	60
10	35	-15	50
10	30	-10	40
12	40	-15	45

APPENDIX B

The data for six generator test system is given as below [34]. This test system consists of six generators provided with cost coefficients. The data related to these coefficients is given below in Table B1.

TABLE B1: Cost Coefficients

Bus No.	a	b	c
1	0.00375	2	0
2	0.01750	1.75	0
5	0.06250	1.00	0
8	0.00834	3.25	0
11	0.02500	3	0
13	0.02500	3	0

REFERENCES

[1] Hadi Saadat, “Power System Analysis”, Tata Mc-Grawhill, New Delhi, 15th Edition, 2002.

[2] J.A Momoh, R.J Koessler, M.S Bond, B.Stott, D.Sun, A.Papalexopoulos, P.Ristanovic, “Challenges to optimal power flow”, IEEE Power Engineering Society Vol. 12, No.1, pp. 445-455, February 1997.

[3] Papalexopoulos, A.D., Imparato, C.F., and Wu, F.F., “Large-Scale Optimal Power Flow: Effects of Initialization, Decoupling & Discretization”, IEEE Transactions on Power Systems, Vol. 4, No. 2 , pp. 748-759, May 1989.

[4] H.W. Dommel and W. F. Tinney, “Optimal power flow solutions”, IEEE Transactions on Power Apparatus Systems, Vol. PAS-87, pp. 1866–1876, Oct. 1968.

[5] Deb K., “Multi-objective optimization using evolutionary algorithms”, Wiley Interscience in systems and optimization, John Wiley & Sons, 2001.

[6] Kumari M. S. and Sydulu M., “Enhanced Genetic Algorithm based computation techniques for multiobjective optimal power flow solution”, Electric Power and Energy Systems, IEEE Transactions on Power Systems, Vol. 32, pp.736-742, 2002.

[7] K. Aoki, M. Kanezashi, “A Modified Newton Method for Optimal Power Flow Using Quadratic Approximation Power Flow”, IEEE Transactions on Power Apparatus and Systems, Vol. PAS-104, No. 8, pp. 2119-2124, August 1985.

[8] Almeida, K.C., Salgado, R., “Optimal Power Flow Solutions Under Variable Load Conditions”, IEEE Transactions on Power Apparatus and Systems, Vol. 15, No. 4, pp. 1204-1211, November 2000.

[9] Alsac, O., Stott, B., “Optimal Load Flow with Steady State Security”, IEEE Transactions on Power Apparatus and Systems, Vol.93, pp. 745-751, 1974.

[10] Grudinin, N., “Combined Quadratic-Separable Programming OPF Algorithm for Economic Dispatch and Security Control”, IEEE Transactions on Power Systems, Vol. 12, No. 4, pp. 1682-1688, November 1997.

[11] Liu Shengsong, Hou Zhijian, Wang Min, “A Hybrid Algorithm for Optimal Power Flow Using the Chaos Optimization and the Linear Interior Point Algorithm”, Power System Technology, 2002. Proceedings International Conference on Power Control 2002, Vol. 2, pp. 793-797, 13-17 October 2002.

[12] K.C. Almeida, F.D. Galiana, S. Soares, “A General Parametric Optimal Power Flow”, IEEE Transactions on Power Systems, Vol. 9, No. 1, pp. 540-547, Feb 1994.

[13] Rahli, M., “Optimal Power Flow Using Sequential Unconstrained Minimization Technique (SUMT) Method Under Power Transmission Losses Minimization”, Electric Power System Research, Vol. 52, pp. 61-64, 1999.

[14] Zhang S., Irving M.R., “Analytical Algorithm for Constraint Relaxation in LP-based Optimal Power Flow”, IEEE Proceedings, Vol. 140, No. 4, pp. 326-330, July 1993.

[15] K. L. Lo and Z. J. Meng, “Newton-like method for line outage simulation”, IEEE proceedings Generation Transmission Distribution, Vol. 151, No. 2, pp. 225-231, March 2004.

[16] X. Tong and M. Lin, “Semismooth Newton type algorithms for solving optimal power flow problems”, in Proceedings of IEEE/PES Transmission and Distribution Conference, Dalian, China, pp.1-7, 2005.

[17] M.K Pakhirs, “A Hybrid Genetic Algorithm using Probabilistic Selection”, IEEE Journal, Vol.84, May 2003.

[18] A. Rangel-Merino, J. L. López-Bonilla, R. Linares y Miranda , “Optimization Method based on Genetic Algorithm”, Apeiron, Vol. 12, No. 4, October 2005.

[19] Tomoyuki HIROYASU, Mitsunori MIKI, Maki OGURA, “Parallel Simulated Annealing Using Genetic Crossover”, Thesis submitted at Doshisha University, Japan.

[20] S. Kirkpatrick, C. D. Gelatt, Jr., M. P. Vecchi, “Optimization by Simulated Annealing”, Science, New Series, Vol. 220, No. 4598, pp. 671-680, May 13, 1983.

[21] Masaya Yoshikawa, Hironori Yamauchi, and Hidekazu Terai, “Hybrid Architecture of Genetic Algorithm and Simulated Annealing”, Advance on line publication, 20 Aug 2008.

[22] Y.J. Jeon and J.C. Kim, "Network reconfiguration in RDS using SA and TS", IEEE /PES, Winter Meeting, pp. 2329-2333, 2000.

[23] E. Carpaneto and G. Chicco, "Performance of the SA based algorithms for the optimal reconfiguration of distribution systems", Power Tech Proceeding, IEEE, Porto, Portugal, Vol. 3, pp.6, 2001.

[24] S. Gracia, F. Abu Chacra, H. Opazo and E. Lopez, "Minimal loss reconfiguration based on SA meta heuristic", Proceeding of the 5th International Conference on Electronics, Communication and Computers (CONLELECOMP 2005), pp. 1-5, 2005.

[25] J. Carpentier, "Contribution a.'l'etude du dispatching economique", Bull. Soc. Francaise Elect., Vol. 3, pp. 431–447, Aug. 1962.

[26] Jason Yuryevich, Kit Po Wong, "Evolutionary programming based optimal power flow algorithm", IEEE Transactions on Power Systems, Vol. 14, No. 4, Nov. 1999.

[27] Eliphas Shikongo, "Optimal power flow analysis based on evolutionary algorithm", Thesis submitted at University of Cape town, 23 October 2006.

[28] Allen J.Wood, Bruce F. Wollenberg, "Power generation operation and control", New York, John Wiley & Sons, Inc., 2nd edition, 1996.

[29] S.Rajasekaran, G.A Vijayalakshmi pai, "Neural Networks, Fuzzy Logic, and Genetic Algorithm Synthesis and Application", Prentice –Hall of India private Ltd. New Delhi, 2008.

[30] Mandira Chakraborty, Uday K. Chakraborty, "Applying genetic algorithm and Simulated annealing to a Combinatorial Optimization problem", International Conference on Information, Communication and signal Processing (ICICS), Singapore ,9-12 September, 1997.

[31] K.P.Wong and Y.W. Wong, "Thermal generator scheduling using hybrid genetic/simulated-annealing approach", to appear in IEEE Proceedings, Part C, 1995.

[32] C.A Rao – Sepulveda, B.J. Pavez-Lazo, "A solution to the optimal power flow using simulated annealing", IEEE Proto Power Tech Conference, Vol. 2, pp.10-13, September-2001.

[33] T.Yalcinoz, M.J Short "Large-scale economic dispatch using an improved Hopfield neural network", IEEE proceedings, Part C, Vol.144, No.2, pp.181-185, March 1997.

[34] Dhillon J. S. and Kothari D. P., "The surrogate worth trade-off approach for multiobjective thermal power dispatch problem", Electric Power Systems Research, Vol.56, pp.103-110, 2000.