The Hong Kong Polytechnic University

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GENETIC ALGORITHM FOR OPTIMAL CAPACITOR SELECTION AND OPTIMAL POWER FLOW WITH FACTS DEVICES

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CERTIFICATE OF ORIGINIALITY

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_______________ (Signed)

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Abstract

As electric utility industry shifts from regulated monopolies to competitive market, it will place an increased reliance on the existing transmission systems. Flexible AC Transmission Systems (FACTS) become more important since they can enhance system flexibility and increase loadability. To address this need, the aim of this research is to develop the use of genetic algorithm for capacitor selection and to develop control strategies for FACTS devices in power systems.

The main contributions of this research work are thus to develop computer algorithms using Genetic Algorithms (GA) to solve the optimal capacitor allocation problem with harmonic distortion considerations and the optimal control setting problem of FACTS devices in optimal power flow (OPF).

The first part of this thesis reports the research findings of a genetic algorithm approach for optimizing shunt capacitor sizes and their placement in radial distribution systems with the consideration of harmonic distortion limit due to the presence of nonlinear power electronic devices. The algorithm is based on a genetic algorithm (GA) solution technique to minimize cost under the additional constraints of maximum limit in Harmonic Distortion Factor (HDF) and voltage. A harmonic distortion calculation is embedded in the genetic algorithm solution routine to enhance the optimal capacitor allocation solution. Results of simulation show that the approach is effective for such discrete value optimization problem. The improvement of the harmonic distortion is effective and the best allocation of capacitors is selected.

Secondly, the thesis would present the development of the equivalent modeling by Power Injected Method (PIM) of various types of FACTS devices including Thyristor Controlled Series Compensator (TCSC), Thyristor Controlled Phase Shifter (TCPS) and Unified Power Flow Controller (UPFC). A real-coded genetic algorithm method is presented to solve the optimal power flow problem of power system with flexible AC transmission systems (FACTS). The proposed method introduces the injected power model of FACTS devices into Newton-Raphson (NR) power flow problem to exploit the characteristic of FACTS devices. The advantage of this method is that it is easily incorporated into existing OPF of Energy Management Systems (EMS) since it

would reduce maintenance cost and software development. Moreover, the admittance matrix can be kept constant during the load flow calculation. Case studies on IEEE test systems demonstrate the potential for application of GA to determine the control parameter of the power flow controls with FACTS. It is shown that the FACTS device would not provide significant cost saving since cost depends mainly on the active power flow. However, it can increase the controllability and flexibility of the system; it can provide wider operating margin and improved voltage stability with higher reserve capacity. As deregulation and contract path are becoming more important, FACTS devices play an increasingly important role in such power system operation.

It is shown in the thesis that TCSC and TCPS can be employed to control the active power flow while UPFC can be used to control the real and reactive power. They can redistribute the power flow to the available transmission lines within the transmission capacity to achieve more efficient utilization of their capacity. As cost is the main objective of OPF, more constraints will increase the generation cost.

In the developed methodology, GA effectively finds the optimal setting of the control parameters using the conventional OPF method as an embedded calculation tool. Overall, the results show that GA is suitable in dealing with non-continuous, non-differentiable and non-convex optimization problems, such as the capacitor selection and optimal power flow problems with FACTS devices.

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Contents

List of Abbreviations

FACTS:	Flexible AC Transmission Systems
TCPS:	Thyristor Controlled Phase Shifter
TCSC:	Thyristor Controlled Series Compensator
UPFC:	Unified Power Flow Controller
EMS:	Energy Management System
OPF:	Optimal Power Flow
GA:	Genetic Algorithm
IPP:	Independent Power Producers
HDF:	Total Harmonic Distortion

List of Symbols and Notations 1

f_{max}	the maximum fitness of each generation in the population
N	the number of harmonic order is being considered
Q_c	the size of capacitor (kVar)
K_c	the equivalent capacitor cost ($/kVar)
K_l	the duration of the load period
K_p	the equivalent annual cost per unit of power losses ($/kW)
K_s	the capacitor bank size (kVar)
y_{ci}	frequency admittance of the capacitor at bus i (pu)
V_i	voltage magnitude at bus i (pu)
P_i, Q_i	active and reactive powers injected into network at bus i (pu)
P_{li}, Q_{li}	linear active and reactive load at bus i (pu)
P_{ni} Q_{ni}	nonlinear active and reactive load at bus i (pu)
θ_{ij}	voltage angle different between bus i and bus j (rad)
G_{ii}, B_{ii}	self conductance and susceptance of bus i (pu)
G_{ij}, B_{ij}	mutual conductance and susceptance between bus i and bus j (pu)
Superscript	
l	corresponds to the fundamental frequency value
n	corresponds to the nth harmonic order value

List of Symbols and Notations 2

X_c	vector of TCSC controllable parameters
ϕ	vector of TCPS controllable phase angles
U_T	vector of UPFC phases of the inserted voltage sources
φ_T	vector of UPFC magnitudes of the inserted voltage sources
I_q	vector of UPFC exciting transformer reactive current
P_{ij}	active power flow from bus i to bus j
Q_{ij}	reactive power flow from bus i to bus j
$P_{ij,UPFC}$	injected active power at bus i caused by the installation of UPFC
$Q_{ij,UPFC}$	injected reactive power at bus i caused by the installation of UPFC
$P_{ij,TCPS}$	injected active power at bus i caused by the installation of TCPS
$Q_{ip,TCPS}$	injected reactive power at bus i caused by the installation of TCPS

Chapter 1

Introduction

1.1 Introduction

Deregulation of electricity supply systems becomes an important issue in many countries. Flexible AC Transmission System (FACTS) [1] devices become more commonly used as the power market becomes more competitive. They may be used to improve the transient responses of power system and can also control the power flows (both active and reactive powers). The main advantages of FACTS are the ability in enhancing system flexibility and increasing the loadability. However, FACTS devices are also handicapped by the high cost of the components.

In steady state operation of power system, unwanted loop flow and parallel power flow between utilities are problems in heavily loaded interconnected power systems. These two power flow problems are sometimes beyond the control of generators or it may cost too much with generator regulations. However, with FACTS devices based on power electronics components in network, the unwanted power flow can be easily regulated. Several recent papers have been published dealing with power flow controls [2,3]

Flexible AC Transmission System (FACTS) is a concept promoting the use of high-speed power electronic controllers to enhance the controllability and usable capacity of AC transmission. These opportunities arise through the ability of FACTS to control the inter-related parameters that constrain today's transmission systems including series impedance, shunt impedance, phase angle and the occurrence of oscillations at various frequency below the rated frequency. The main contribution of the FACTS devices is to enable the transmission systems playing an active role in increasing the flexibility of power transfer requirement and in securing stability of dynamics of integrated power systems.

In general, transmission lines are under-utilized and uncontrolled. FACTS can contribute to control loop flow, power flow, reactive support and voltage stability. Moreover, as the electricity industry is moving towards a deregulation environment, the need to transport power between partners through defined line corridors would play an increasingly important role.

Rising energy costs, increased transmission distances and use of large generating machines are resulting in increased demands for reliable and more economic operation of transmission and distribution systems. FACTS devices are the most attractive devices and are being developed for meeting these needs. Optimal power flow with FACTS devices embedded in the transmission line would constitute a valuable tool in such operation.

1.2 Background of FACTS

Flexible AC Transmission Systems (FACTS) represent the application of power electronics in ac power systems in order to provide voltage and power flow control and thus better utilize the capability of existing transmission systems. The Electric Power System Research Institute (EPRI) in USA has been a strong proponent of the concept and Dr. Narain Hingorani is often credited with the idea [4]. Others have suggested the use of high power semiconductors in power systems and Dr. Hingorani focused on applications in high voltage systems. One of the earliest reference to FACTS was Hingorani's presentation at the American Power Conference in 1998. At that presentation, Hingorani, then Vice President of ERPI, advocated transmission controls that were virtually entirely based on silicon switches. Other overviews of the FACTS concept are found, with the focus of work being the modeling and control of the devices in dynamic situations.

The first generation of FACTS controllers employed thyristors as the power electronic switching elements, in combination with reactive components. Static VAR compensators are widely employed for shunt compensation of transmission systems, large industrial loads, and even remotely-located loads of moderate size. Series compensation by means of thyristor-controlled series capacitors (TSCS) and thyristor-controlled phase shifting transformers (TCPS) can provide power flow control to minimize system congestion problems.

The second generation of FACTS controllers uses Gate Turn-Off (GTO) or similar power semiconductors in voltage-source inverted configurations. Shunt compensation is provided by the static synchronous compensator (STATCOM), series compensation by static series synchronous compensator (SSSC) and combined series-shunt compensation by the unified power flow controller (UPFC) [5]

The main types of present FACTS devices include the following:

- Static Var Compensator (SVC)
- Static Synhronous Series Compensator (SSSC)
- Static Condensor (STATCON)
- Thyristor Controlled Series Compensator (TCSC)
- Thyristor Controlled Phase Shifter (TCPS)
- Thyristor Controlled Break Capacitor (TCBR)
- Thyristor Controlled Break Resistor (TCBR)
- Thyristor Controlled Series Reactor (TCSR)
- Phase Angle Regulator (PAR)
- Interface Power Controller (IPC)
- Unified Power Flow Controller (UPFC)
- Series Power Flow Controller (SPFC)
- Load Tap Changing Transformer (LTCT)
- Dynamic Voltage Limiter (DVL)
- Super-conducting Energy Storage System (SEMS)
- Solid State Circuit Breaker (SSCB)
- Solid State Current Limiter (SSCL)

1.3 The needs of FACTS

Large interconnected systems are developed for increasingly heavier loads especially if new lines cannot be built because of the lack of right-of-ways. Furthermore, the location for new generation is often far away from the load and the system takes over also the task of transmitting power over longer distances. The need for increase of the network transmission capacity has therefore increased in recent years. Due to deregulation in electric power industry, there are new requirements to transmit power through specified corridors. In some countries with remote power sources, it is necessary to fulfill the requirement to transmit power over long distance through weak transmission systems. Problems resulting from above mentioned developments may be improved by the use of Flexible AC Transmission (FACTS) system and controllers.

1.4 Power Flow Control with FACTS

FACTS controllers can increase the maximum power carrying capacity of existing transmission systems. It can control the power transfer between the power utility companies and to avoid unwanted power loop flows, parallel power flow and power fencing. It can also improve the power system damping stability and voltage profile.

Type of FACTS Devices	*Controlled Parameter*
UPFC	Series P and Q
TCSC, PAR	Series P
SVC, STATCON	Shunt Q

One of the current main researches on FACTS devices is on the power flow control and economic operation such as optimal power flow (OPF) [6]. OPF is part of the standard tools of the supervisory, control and data acquisition (SCADA) and energy management system (EMS). It schedules power system controls to optimize an objective function while satisfying non-linear equality and linear equality constraints.

The steady state of the power flow control [7] in the transmission line is based on three parameters: the impedance of transmission lines, the magnitude and the angle different of the voltage of sending end and receiving end.

$$P_{ij} = \frac{V_i V_j}{X_{ij}} \sin\theta_{ij} \tag{1.1}$$

The main function of FACTS is to use the power electronic controlled device [8] to control the power flows in a transmission network. The reasons of using FACTS are as follow:

1. To provide better control than conventional control.
2. To achieve fast control response time.
3. To develop reliable and flexible control.
4. To reduce the overall system losses (e.g. SVC reduces the reactive power flow).
5. To achieve more economic operation than the building of a power plant or transmission line.

The line impedance and the thermal capacity of the transmission line mainly dominate the power flow control in the transmission line. The line impedance of the transmission line totally governs the load sharing. The thermal capacity or series impedance of the transmission line limits the maximum power carrying capacity. For relatively short lines, the thermal limit is usually reached before the line impedance becomes a factor. However, with longer lines, line impedance often determines the upper limits. Moreover, new transmission lines cannot be built due to legal requirement or contractual restrictions. FACTS device can provide a more economic way than building up a new transmission line.

1.5 Recent work on power flow and OPF

The optimal power flow problem has been researched widely since its introduction by Carpentier in 1962 [9]. Because OPF is a very large, non-linear mathematical programming problem, it has taken decades to develop efficient algorithms for its solution. Many different mathematical techniques have been employed for its solution. The following are classifications of the types of solution methods reported in the literature:

1. Lambda iteration method - Also called the equal incremental cost criterion (EICC) method. This method has its roots in the common method of economic dispatch used since the 1930s. [10]
2. Gradient method - by Dommel and Tinney [11]
3. Newton's method - by Sun et al. [12]
4. Linear programming method - by Alsac et al. [13]
5. Interior point method - by Wu, Debs, and Marsten [14]
6. Evolutionary programming [15,16] , evolutionary strategy and simulated annealing [17]

An excellent literature survey of the different techniques can be found in a paper by Huneault and Galieana published in 1991 [18]. Though it does not discuss the interior point method [19], it does make reference to over 150 papers on the optimal power flow problem covering all the other methods for solving the OPF.

Solving the optimal active power flow dispatch problem incorporating with FACTS devices has been proposed by Taranto et al. using Bender decomposition method [20]. This method decomposes the active power OPF problem into two stages. In the first stage, the method decides a set of trial values of FACTS variable s based on the Benders theory. In the second stage, given the values of FACTS variables obtained from the first stage, it solves the linear OPF problem using LP based OPF method. However, this method can only deal with the DC representation of TCSC and TCPS. Moreover, this method can only deal with one type of FACTS devices (TCSC or TCPS) in each calculation, and the convergence property of this method was not reported. This method also does not consider the specified needs for power flow controls. Moreover, the static representation of UPFC is not included.

A method for solving the power flow control problem incorporating FACTS devices based on decomposition has been proposed by Noroozian [21,22]. The proposed optimal power flow control problem was to find the FACTS control values so that the predetermined line flow values and the power flow equation are all satisfied. This problem was decomposed into two sub-problems. The two sub-problems are solved successively by Newton's method in one iteration to yield the updated values of FACTS controls and state variables. Besides, the author also proposed the concept of feasible line flow region in this paper. However, this method does not combine the OPF problem with the power flow control problem. Hence the solution may not be the most economic solution. The FACTS devices considered are TCSC and TCPS while UPFC has not been considered.

A methodology using the existing Newton-type load flow algorithm to incorporate the UPFC model has been presented [23,24]. This paper proposed a new method based on a genetic algorithm technique to incorporate the power flow control needs with active power OPF using AC power flow model.

The main purpose of OPF is to determine the optimal operation state of a power system while meeting some specified constraints. Considerable amount of research on different optimization algorithms and solution methods have been done, especially in the recent three decades. The main existing techniques for solving the OPF problems include gradient method, Newton method, linear programming, quadratic method, decomposition method, interior point method (IPM) and Evolutionary Programming (EP). However, difficulties arise with the considerations of FACTS devices in OPF [25]. As an example, the controllable parameters of UPFC cannot be added directly to those existing OPF techniques because these parameters will change the admittance matrix.

1.6 GA-OPF Methodology

The conventional method used a succession of linear approximations with piecewise-linear relaxation linear programming such as gradient methods, quadratic programming, dynamic programming etc. and suffered from the drawback that it would usually be trapped in local minimum. In OPF, the objective function is highly non-linear and the solutions will have several local minima. Moreover, the control parameters of FACTS devices are discrete. By comparison, GA is a heuristics search algorithm and it possesses the advantage that it does not need to differentiate between the objective function and the constraint equations. Moreover, it improves the convergence rate.

In this thesis, a GA-OPF with FACTS approach is proposed to solve optimal power flow problem. An optimal power flow with FACTS devices belongs to the class of nonlinear constrained optimization problems where the objective functions are generation cost and system transmission loss. More than one FACTS devices are allocated within the system. FACTS devices can enhance the system flexibility and reduce the transmission losses within the security limits. Static power flow models are developed for TCSC (Thyristor Controlled Series Capacitor), TCPSR (Thyristor Controlled Phase Shifter Regulator) and UPFC (Unified Power Flow Controller). Real power losses and shunt capacitive admittances are included. These equations are embedded into the normal Newton-Raphson load flow equations to form an extended Newton-Raphson power flow with FACTS.

1.7 Project Objective

This thesis is comprised of two main sections. The first section (chapter 3) reports the research findings of a genetic algorithm approach for optimizing shunt capacitor sizes and their placement in radial distribution systems with the consideration of harmonic distortion limit due to the presence of nonlinear power electronic devices. The algorithm is based on a genetic algorithm (GA) solution technique to minimize cost under the additional constraints of maximum limit in Harmonic Distortion Factor (HDF) and voltage. A harmonic distortion calculation is embedded in the genetic algorithm solution routine to enhance the optimal capacitor allocation solution. Results of simulation show that the approach is effective for such discrete value optimization problem. The improvement of the harmonic distortion is effective and the best allocation of capacitors is selected.

The second section presents a new genetic algorithm method to achieve optimal power flow in power system incorporating flexible AC transmission systems. As powerful and versatile FACTS devices, TSCS, TCPS and UPFC are considered in the thesis. Unlike other FACTS devices, UPFC has a great flexibility that can control the active power, reactive power and voltage simultaneously. In the solution process, GA, coupled with full AC power flow, selects the best regulation to minimize the total generation fuel cost and keep the power flows within their security limits. The optimization process with GA is presented with case study examples using IEEE test system to demonstrate its applicability. The results are presented to show the feasibility and potential of this new approach.

1.8 Layout of the thesis

Chapter 1 provides an introduction to the Optimal Power Flow and Flexible AC Transmission

Chapter 2 gives an overview of genetic algorithm. Its strengths and weaknesses are compared to those of traditional search methods. Elements of genetic algorithms are presented.

Chapter 3 proposes genetic algorithm approach for optimizing shunt capacitor sizes and their placement in radical distribution systems. The consideration of harmonic distortion limit due to the presence of nonlinear power electronic devices is presented.

Chapter 4 develops static AC power flow models of FACTS devices. For TCPS and UPFC, the power injection method is developed to accommodate different applications. The static representation is shown to work well with the extended Newton-Raphson power flow method. Power mismatch equations are deduced based on power injection models of FACTS devices. The design is presented in this thesis together with test results.

Chapter 5 commences with a formulation of optimal power flow with FACTS devices using genetic algorithm. An application study of the proposed GA-based OPF is developed. The study result is examined and the performance of the algorithm is discussed.

Chapter 6 presents overall conclusion of the work reported in this thesis and further possible work directions.

1.9 Publications

Arising from this research project, three journal papers have already been published in leading international journals. In addition, six conference papers have been presented. These papers are listed below:

Referred Journal Paper Published:

1. T. S. Chung and **H.C. Leung**: "A GA approach in optimal capacitor selection with harmonics consideration", International Journal of Electrical Power and Energy Systems, Vol. 21, Nov 1999, pp.561-569

2. **H.C. Leung** and T.S. Chung: "A Hybrid GA Approach for Optimal Control Setting Determination of UPFC", IEEE Power Engineering Review, December 2001, pp. 62-65

3. T.S. Chung and **H.C. Leung**: "A New GA Approach for Optimal Control Setting Determination of UPFC in Power System Operation", Automation of Electric Power Systems, October 2002, vol.26, pp. 58-61

International Conference Papers:

1. T.S. Chung, H.C. Ling, **H.C. Leung** and D. Sutanto: "Optimal Shunt Capacitor Allocation with Harmonic Considerations", Proceedings of Australasian Universities Power Engineering Conference (AUPEC '97) and Institution of Engineers Australia Electric Energy Conference (EECON '97), Sydney, Australia, 1997, Volume 2, pp. 283-288

2. **H.C. Leung** and T.S. Chung: "Optimal Power Flow with FACTS devices by Refined Genetic Algorithm", Proceedings of SEV-ETH-IEE Conference EPSOM '98, International Conference on Electrical Power Systems Operation and Management, ETH Zürich, Switzerland, 23-25 September 1998 pp.LEUNG-26-(1-6)

3. **H.C. Leung** and T.S. Chung: "Optimal Placement of FACTS Controller in Power System by a Genetic-based Algorithm", Proceedings of The IEEE 1999 International Conference on Power Electronics and Drive Systems (PEDS'99), 26-29 July 1999, Hong Kong, Volume 2, pp. 833-836

4. **H.C. Leung** and T.S. Chung: "Optimal Power Flow with UPFC Genetic Algorithm", International Conference on Electrical Engineering (ICEE '99), 16-18 August 1999, Hong Kong, Volume 3, pp.12-15

5. **H.C. Leung** and T.S. Chung: "Optimal Power Flow with a Versatile FACTS Controller by Genetic-based Algorithm", IEEE PES Winter Meeting 2000, 24-27 January 2000, Singapore.

6. **H.C. Leung** and T.S. Chung: "OPF with a Versatile FACTS Controller by GA Approach", Proceedings of The IEE Hong Kong International Conference on Advances in Power System Control, Operation and Management, ASPCOM 2000, October 30 to November 1, 2000, Hong Kong

Chapter 2

BACKGROUND OF GENETIC ALGORITHMS

2.1 Introduction

Genetic algorithm [26] was first proposed by Holland in the early 1970s [27] and put into practical applications in the late 1980s. It is an adaptive method simulating the evolutionary process in nature and is based on the principle of natural selection and best survival.

In nature, individuals in a population have to compete with each other for scarce resources. The competition results in fitter individuals dominating the weaker one; a phenomenon called "survival of the fitness". The essential factor for the survival of an individual in a competition is the ability to adapt to a constantly changing environment. This survival capacity is determined by the unique set of genes that form the chromosomes individual. The fitness individuals therefore inherit a combination of genes from their parents that may further strengthen their survival capacity. The weaker ones will eventually die out together with the genes. Through the succession of natural selection and recombination of genes that occurs during reproduction, the evolution continues as the population becomes more adapted to the environment.

GA simulates an artificial environment of such genetic processes. A population of individuals, each representing a potential solution to a given problem, is maintained. Each individual is assigned a fitness value to indicate how good a solution is to the problem. The individuals then have to compete with others in the population to produce offspring. The highly fit individuals are those with higher fitness value and they have more chance to reproduce through crossover operations. The offspring inherits genes of their highly fit parents and will become even fitter and they represent a better solution to the problem concerned. The least fit individuals have less chance to reproduce and the trace of their genes will eventually disappear in the population. Between the newly produced offspring and their parents, the best individuals are chosen to form the population of the next generation. By repeating the process, the population will evolve into an optimal solution to the problem.

In power systems, GAs have recently been applied in solving various problems, such as distribution system configuration [28] optimization of generation expansion planning [29], economic dispatch [30], unit commitment [31], reactive power planning [32,33], voltage optimization [34] and load flow calculation [35,36]. GA is a powerful search algorithm based on the mechanics of natural selection and natural genetics. Its characteristics make GA a robust algorithm to adaptively search the global optimal point of certain class of engineering problems.

2.2.1 GA Vs Traditional methods

Optimization techniques have been widely used for solving power system operation and control problems, for example, such as generator scheduling and economic dispatch, etc. Traditional methods used include gradient search methods, integer and mixed-integer programming, linear programming [37]; non-linear programming [38], quadratic programming [39], dynamic programming. However, traditional methods of search and optimization are slow in finding a solution in a complex search space, even when they are implemented in supercomputers to determine global optimum solution. Unlike these traditional optimization methods, Genetic Algorithm is a robust search method requiring little information to search effectively in a large or poorly understood search space. Moreover, it has no prerequisite on the type of functions that it can handle, whether the function is discrete or multi-nodal in nature. In particular a genetic search progress through a population of points in contrast to the single point of focus of most search algorithms. Moreover, it is useful in the very tricky area of nonlinear problems. Its intrinsic parallelism (in evaluation functions, selections and so on) allows the uses of distributed processing machines.

2.2 Feature of GA and the best time to use GA

The advantages of GA over other traditional optimization techniques can be summarized as follows:

- It searches from a population of points, not a single point. The population can move over hills and across valleys. GA can therefore discover a globally optimal point, because the computation for each individual in the population is independent of others. GA has inherent parallel computation ability.

- It uses payoff (fitness or objective functions) information directly for the search direction, not derivatives or other auxiliary knowledge. GA therefore can deal with non-smooth, non-continuous and non-differentiable functions that are the real-life optimization problems. OPF in FACTS is one of such problems. This property also relieves GA of the approximate assumptions for a lot of practical optimization problems, which are quite often required in traditional optimization methods.

- It uses probabilistic transition rules to select generations, not deterministic rules. They can search a complicated and uncertain area to find the global optimum.

Although GA has been applied for many applications, not all the reported performances are successful. Moreover, there are no rules on how to determine whether GA should be used on a particular application. The disadvantages of GA are as follow:

- GA does not always produce an exact global optimum (premature convergence)
- GA requires long computation time since a large number of complicated fitness evaluations
- Population size, crossover rate and mutation rate are highly nonlinear. Therefore, some enhanced methods [40, 41] are recommended for the parameter settings to improve performance.

2.3 Basic Genetic Algorithm

Genetic algorithms belong to the class of population-based search strategies. They operate on a population of strings (chromosomes) that encode the parameter set of problem to be solved over some finite alphabets. Each encoding represents an individual in the GA population. The population is initialized to random individuals (random chromosomes) at the start of the GA run. The GA searches the space of possible chromosomes for better individuals. The search is guided by the fitness value return by the environment. This gives a measure of how well adapted each individual is in term of solving the problem and hence determines its probability of appearing in future generations. A binary encoding of the parameters of the problem is normally used. It has been mathematically proven that the cardinality of the binary alphabet maximizes the number of similarity template (schemata) on which the GA operates and hence improves the search mechanism.

A simple genetic algorithm involves the following steps:

1. Encoding – code parameters of the search space as binary strings of fixed length.
2. Initialization – randomly generate initial population strings which evolve to the next generation by genetic operators
3. Fitness – evaluates the quality of solutions coded by strings.
4. Selection – allows strings with higher fitness to appear with higher probability in the next generation.
5. Crossover and mutation – Crossover combines two parents by exchanging parts of their strings, starting from a randomly chosen crossover point. This leads to new solutions inheriting desirable qualities from both parents. Mutation flips single bits in a string, which prevents the GA from premature convergence, by exploiting new regions in the search space.
6. Termination – the new strings replace the existing string. The sequence continues until the termination criterion is reached.

A pseudo code of GA is as follows:

```
GA(..)
    Initialize and evaluate population;
    If (termination criteria is not reached) then
            Select chromosomes for next generation;
            Perform crossover and mutation;
            Evaluate population;
    End if
```

GA tends to take advantage of the fittest solutions by giving them greater weight, and concentrating the search in the regions which lead to fitter structures leading to better solutions of the problem.

2.3.1 Schema

A schema is a similarity template describing a subset of strings with similarities at certain string position. In a binary coding scheme, a string is made up of ones, zeros and asterisks, where asterisks represent all possible bits. A string that can be represented by a schema is called an instance of that schema. For example, the schema 00**01 in this example has four possible instances: 000001, 000101, 001001 and 001101. In this schema, the string positions that have non-asterisk bit, i.e. either 0 or 1 are described as the defined positions. The number of defined positions of a schema is its order. A schema's defining length is the distance between the two outer-most defined positions. Hence, the above example schema 00**01 has an order of 4 and a defining length of 5.

2.4 The operation of GA

2.4.1 Encoding / Solution Representation

Choosing a suitable coding method is the first step of designing a GA application. Since binary coding has been the most common encoding for the past, the existing GA theory is based on the assumption of fixed-length binary encoding. The first decision in applying an GA to seek optimal values for continuous variables is how to represent design parameters of an individual. Roughly speaking, there are two classes of representations: binary representations and floating-point representations.

The use of the binary representation originates in GAs that use a bit-string to model an individual. When a bit-string is used to represent an individual, however, it is required to transform real design parameters into binary numbers. Since binary substrings representing each parameter with the desired precision are concentrated to form a chromosome for GAs, the resulting chromosome encoding a large number of design variables would result in a huge string length. For example, for 100 variables with a precision of six digits, the string length is about 2000. GAs would perform poorly for such design problems. Previous applications have been kept away from this problem by sacrificing precision or narrowing down the search regions prior to the optimization. However, such approaches might exclude the region that actually has the global optimum. In addition, the binary representation of real design parameters presents the difficulty of so-called hamming cliffs, which comes from discrepancy between the representation space and the problem space. For instance, two points close to each other in the representation space might be far in the binary represented problem space. As a consequence, GAs using the binary representation is unable to focus the search effort in a close vicinity of the current population. It is still an open question to construct efficient genetic operators that suit to such a modified problem space.

Another drawback of the binary-coded GAs applied to parameter optimization problems in continuous domains comes from discrepancy between the binary representation space and the actual problem space. For example, two points close to each other in the representation space might be far in the binary represented problem space. It is still an open question to construct an efficient crossover operator that is suitable for such a modified problem space.

A simple solution to these problems is the use of the floating-point representation [42, 43] of parameters. In this real-coded GAs, an individual is coded as a vector of real numbers corresponding to the variables. The real-coded GAs is robust, accurate, and efficient because the floating point representation is conceptually closest to the real design space, and the string length reduces to the number of design variables. However, even the real-coded GAs would lead to premature convergence when it applied with a large number of variables.

Binary Coding
{1001,0110,110001,0010,10,0101}
or
Floating Point Vector
{25,1.34,900,-234,452,1.23,0.002}

The use of the floating-point representation originates in EP and ESs. In the floating-point representation, an individual is characterized by a vector of real numbers. It is more natural to use the floating-point representation for real parameter optimization problems because it is conceptually closest to the real design space and the string length is reduced to the number of design variables. It has been reported that real-coded GAs outperformed binary-coded GAs in many design problems. Therefore, GAs using the floating-point representation is used in OPF. An example of binary and floating-point representations is illustrated in Figure 2.1.

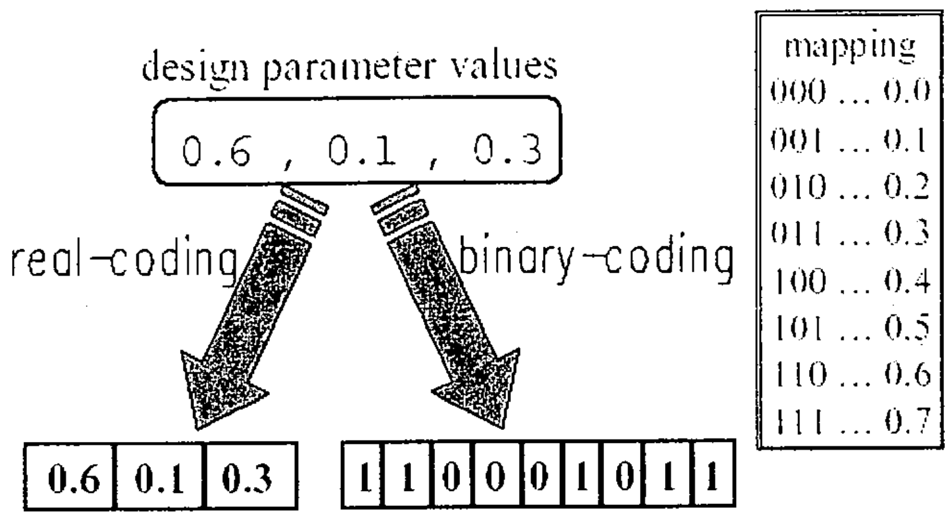


Figure 2.1 An example of binary and floating-point representations

2.4.2 Fitness

Each candidate solution must be assigned a fitness function to measure its optimality with respect to the objective being optimized. In the case of OPF, the fitness of an individual is adopted as follows:

$$Fitness = \frac{M}{1 + H + \lambda C^2} \tag{2.1}$$

In the above equation, M is the constant for amplifying the fitness value. H is the objective function (the generation cost) and λ is the penalty factor. The value of λ is set to an arbitrary number. Penalty cost has been added to discourage solutions, which violate the binding constraints. Finally, the penalty factor is tended to zero. C is the state variable / inequality constraint which add them as the quadratic penalty terms to the objective function to form a penalty function.

2.4.3 Selection

The selection rule is used to determine the individuals that will be represented in the next generation of GA. The selection mechanism is based on a fitness measure or objective function value, defined on each individual (chromosome) in the population. A widely used method is the fitness-proportional selection. In this method, the selection probability of each individual is calculated by dividing its fitness by the sum of the fitness of all individuals. Three major selection mechanisms are commonly adopted in the GA search: roulette selection, tournament selection and ranking selection.

2.4.3.1.Roulette selection

The parents are selected by roulette-wheel selection. Figure 2.2 shows the operation of the roulette-wheel selection that assigns a portion of the wheel proportional to the selection probability and starts spinning the roulette wheel: each time, a single individual is selected

$$p_{selection} = \frac{f(parent_i)}{\sum_i f(parent_i)}$$

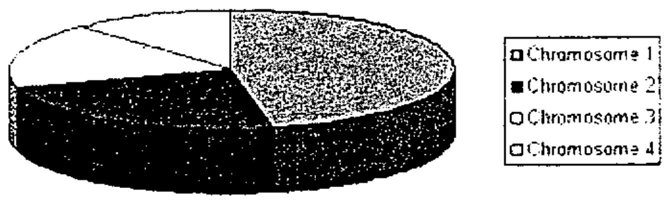


Figure 2.2: Roulette wheel selection

In roulette wheel selection the probability of being selected is proportional to an individual's fitness value. Therefore, highly fit individuals have a higher probability of being selected and hence of being represented in the next generation.

2.4.3.2. Tournament selection

Tournament selection [44] operates by choosing some individuals randomly from a population and selecting the best (highest fitness) from this group to survive into the next generation whereas discard all others. Binary tournaments where tournaments are held between pairs of individuals are the most common. A fraction of the individuals in the population are randomly selected into a subpopulation and competition is carried out to select the fittest individuals in each subpopulation.

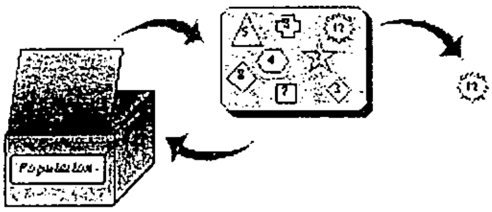


Figure 2.3 Tournament Selection

Figure 2.4 and 2.5 shows a comparison between roulette wheel and tournament selection for a population of 10 individuals with randomly initialized fitness between 0 and 100. The population is sampled 1000 times in each generation and the number of wins per individuals is averaged over 10 generations and tabulated. For tournament selection, the subpopulation size is set to half of the population size and it can be viewed as a noisy version of rank selection.

											Total
Fitness	10	34	42	43	49	62	63	75	80	100	**558**

Table 2.1 Fitness Function

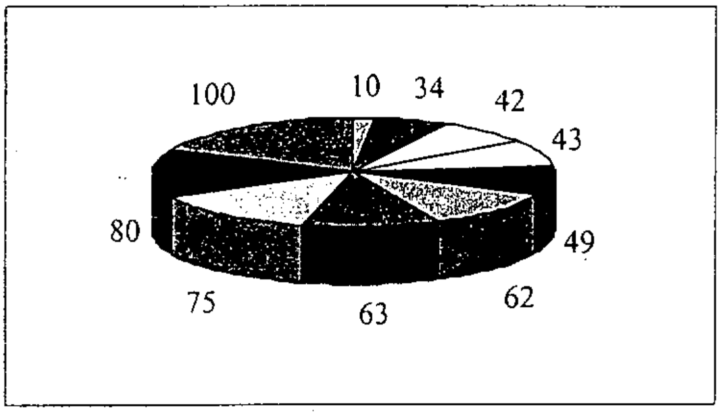


Figure 2.4 Roulette Wheel Selection

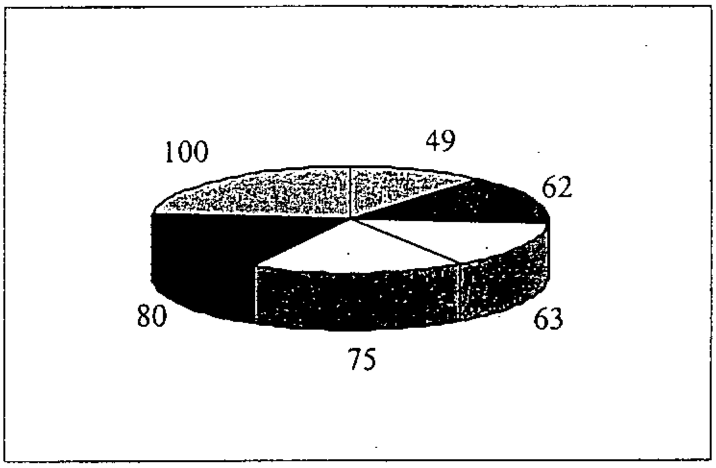


Figure 2.5 Tournament Selection

From Figure 2.4, it shows that roulette wheel selection given even the least fit members of the population a chance of being represented in the next generation. However, tournament selection is strongly in favour of the highest fitness individuals with a subset of the least fitness individuals guaranteed to disappear from the population in each generation.

2.4.3.3 Ranking selection

Ranking selection assigns selection probabilities on an individual's rank, ignoring absolute fitness value. In this method, the individuals in the mating pool are sorted according to their fitness values and then assigned a count that is solely a function of their rank. The selection probability is reassigned according to rank, for example, as an inverse of their rank values. In [45], Michalewicz proposed a nonlinear function to assign the selection probability as,

$$probability = c \cdot (1-c)^{(rank-1)} \tag{2.2}$$

where c is a user-defined parameter. Then, the parents are selected by either roulette-wheel selection or Stochastic Universal Sampling.

2.4.3.4 Elitism Strategy

GA adopting elitism can be viewed as steady-state GA with a large generation gap. During the generation of the next population, the best individuals of the previous generation are not always selected for reproduction, or they can be destroyed by crossover and mutation. Elitism is used in addition to selection method to retain a number of the best individuals from the previous population at each generation. Many researchers have found that elitism improves the performance of GA.

2.4.4 Crossover and mutation

2.4.4.1 Crossover

After selection is processed, new individuals was introduced into the current population or to create a new population based on the current population. In the combination process, crossover and mutation operators are commonly used. The combination rules act on individuals that have been previously selected by the selection mechanism. A reproduction process takes place between the selection individuals in the current generation to produce offspring that become individuals in the next generation. This kind of crossover operators includes one-point, two-point and uniform crossovers.

One-point crossover is the traditional crossover operator. Two new 'off-spring' chromosomes are generated from the exchange of the information in the two chosen 'parent' chromosomes. Of all the different form in crossover, the simplest and most original one is a single point crossover. A point is randomly decided as the crossover point where the genes of the two parent chromosomes before the point are exchanged to form two new chromosomes. Not every pair of chromosomes selected from the population takes part in the crossover process. Crossover probability, P_c is used to determined the frequency at which crossover is applied. If a number randomly generated between 0 and 1 is less than P_c, the two "off-spring" chromosomes will simply be duplicates of their parent chromosomes. Although simple in nature, it has some disadvantage that it cannot recombine all possible schemata. It is also more likely to destroy by a crossover depending strongly on the location of the genes in the chromosome. Furthermore, the genes exchanged between two parents always contain the endpoints of the strings.

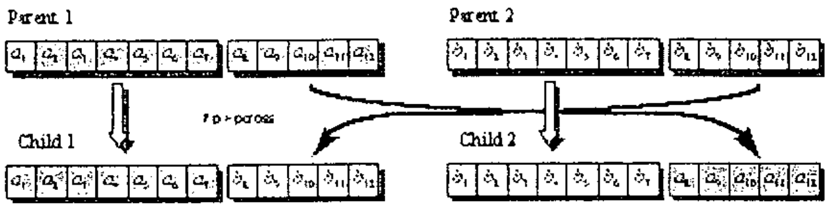


Fig 2.6 An illustration of a single point crossover operation

Two-point crossover [46] is used to reduce the effect of positional bias and the endpoint problem. Two points are chosen at random and the genes between them are exchanged to create two new offspring. Two-point crossover is likely to destroy schemata with large defining lengths and the genes exchanged do not necessarily contain endpoints.

Uniform crossover [47 is different from one-point or two-point crossover. Every gene of an individual in uniform crossover is probabilistically exchanged with some fixed probability. The exchange of one gene is independent of the exchange of genes at other positions. Uniform crossover can be highly disruptive to a schema and is said to have distributed bias where it is related to the number of genes exchanged by crossover operator .

In the floating-point representation, the vector components of two parents are swapped in groups at a random space of a vector between the vector components. For example, given a five dimensional space, Parent 1 has a vector (a_1, a_2, a_3, a_4, a_5) and Parent 2 has a vector (b_1, b_2, b_3, b_4, b_5) and the crossover point was selected to be 3, then the offsprings will carry vectors (a_1, a_2, a_3, b_4, b_5) and (b_1, b_2, b_3, a_4, a_5). An example of one-point crossover is illustrated in Fig 2.7

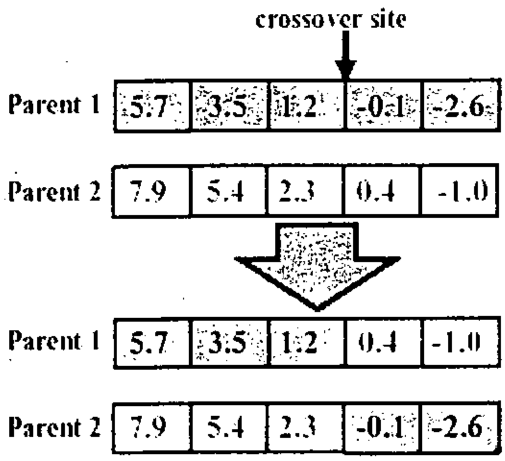


Figure 2.7 Two point, multi-point, and uniform crossovers for the floating-point implementation can be defined in the same manner.

2.4.4.2 Mutation

Mutation plays a secondary role to crossover in the genetic algorithm. It adds a small amount of randomness in the search process to allow the exploration of all regions in the search space. Genes in a chromosome are occasionally altered in the mutation process, thus increasing the diversity of the population. In Figure 2.8 the ninth gene is randomly chosen for mutation. Under the binary encoding scheme, mutation of any single bit is done by flipping the bit from 0 to 1, or vice versa. On the other hand, there is no strict definition on how to perform mutation under a real-valued encoding scheme. Similar to the crossover operator, mutation probability, P_m, governs the rate of performing mutation. Mutation is applied to the chromosomes when P_m is greater then a randomly generated number between 0 and 1. The value of P_m is usually small, for high mutation probability has a counter-effect of destroying the building blocks of the chromosomes.

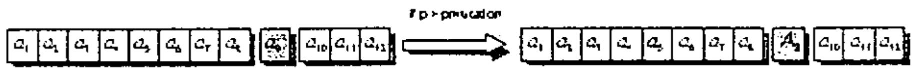


Figure 2.8 An illustration mutation being applied to a chromosome

2.5 Parameter setting of GA

Finding good parameter settings [48] that work for a particular problem is not a trivial task. The critical factors are to determine robust parameter settings for population size, encoding, selection criteria, genetic operator probabilities and evaluation (fitness) normalization techniques.

If the population is small, the genetic algorithm will converge quickly to a local optimal point and may not find the best solution. On the other hand, too many members in a population result in long waiting times for significant improvement, called slowing finishing but increase its diversity and reduces the chance of premature convergences.

Increasing the crossover rate will increase the recombination of building blocks at generation. Setting the crossover rate too high will destroy the good building blocks already present in the individuals of the current population. Two point crossover is quicker to get the same results and retain the solutions much longer than one point crossover.

The fitter member will have a greater chance of reproduction. The members with lower fitness are replaced by the offspring. Thus in successive generations, the members on average are fitter as solutions to the problem.

It is also accepted that high mutation introduces diversity and takes longer time to get the optimal solution. Too low mutation tends to miss some near-optimal points.

2.6 Constraint Satisfaction in GA

The basic genetic algorithm has been developed on the basis of unconstrained optimization problem. Despite the fact that GAs are often used in constrained optimization problems [49], the issue of handling infeasible individuals in the population has not been formally addressed in genetic algorithms. However, a number of techniques have been proposed to handle constraints in genetic algorithms. The most popular method is penalty method.

Penalty method transforms the constrained problem into an unconstrained problem by penalizing infeasible solutions. It is the most common technique used in the genetic algorithms for constrained optimization problems. A penalty function is usually added to the objective function to form the new fitness evaluation function shown as follows:

$$eval(x) = f(x) + p(x) \tag{2.3}$$

where x represents an individual in the population. $F(x)$ and $p(x)$ are the objective function and the penalty function respectively. For minimization problems, the penalty function is designed to have the following property

$$P(x) = 1;\ \text{if } x \text{ is feasible}$$

$$P(x) > 0;\ \text{otherwise}$$

In general, a constrained optimization problem can be transformed usefully into an unconstrained optimization problem by using a penalty method. There are general rules for designing penalty functions

2.6.1. Advantages and disadvantages of the penalty method

Advantage: It removes hard constraints on the parameter values.

Disadvantages:

1. Some constraints can be "slightly" violated e.g. by a good solution close to the border of the space of valid solutions, which the method does not prevent. This might be allowable for some problems.
2. In many constrained optimizations problems, the constraints actually enforce the syntactic correctness of the solutions rather than simply restrict the space of valid

solutions. i.e. solutions that violate the constraints are non-solutions. In this case, the penalty method is inadequate. One must resort to using special representations and genetic operators e.g. use a crossover method that prevents non-solution offspring from being generated.

2.7 Summary

This chapter gives a comprehensive overview of genetic algorithm. This includes the conceptual idea of GA and the application areas where GA has been used for optimization. The merits of GA over traditional search methods and the type of problem to which GA will be best suited are discussed. Binary encoding and floating point representation are also reviewed. Various constraint satisfaction methods previously employed in GA are presented.

Chapter 3

OPTIMAL CAPACITOR SELECTION WITH HARMONIC DISTORTION CONSIDERATION

3.1 Introduction

Capacitors have been commonly used to provide reactive power compensation in distribution systems. The capacitor placement problem is a well-researched topic. Earlier approaches differ in problem formulation and the solution methods. In some approaches, the objective function is considered as an unconstrained maximization of savings due to energy loss reduction and peak power loss reduction against the capacitor cost. Others formulated the problem with some variations of the above objective function. Some have also formulated the problem as constrained optimization and included voltage constraints into consideration.

In today's power system, there is a general trend to use more nonlinear loads such as energy-efficient fluorescent lamps and solid-state devices. The capacitors' sizing and allocation should be properly considered, if else they can amplify harmonic currents and voltages due to possible resonance at one or several harmonic frequencies. This condition could lead to potentially dangerous magnitudes of harmonic signals, additional stress on equipment insulation, increased capacitor failure and interference with communication system.

Capacitor values are often assumed as continuous variables whose costs are considered as proportional to capacitor size in past researches [50-58]. However, commercially available capacitors are discrete capacities and tuned in discrete steps. Moreover, the cost of capacitor is not linearly proportional to the size (kVar). Hence, if the continuous variable approach is used to choose integral capacitor size, the method may not result in an optimum solution and may even lead to undesirable harmonic resonance conditions. [59]

An innovative genetic algorithm approach is developed for optimizing shunt capacitor sizes and their placement in radical distribution systems with the consideration of harmonic distortion limit. The approach is based on a genetic algorithm (GA) solution technique to minimize cost under the additional constraints of maximum limit in harmonic distortion factor (HDF). A harmonic distortion calculation is embedded in the genetic algorithm solution routine to enhance the optimal capacitor allocation solution. One of the advantages of using GA is that the computation time is neither proportional nor dependent of the scale of radial system. Since the increase in the number of search due to combinatorial explosions brings an exponential increase in the search time, the enumeration based methods (Exhausive Search, Branch and Bound) become impossible for large scale problems [58]. Results of simulation show that the approach is effective for such discrete value optimization problem.

3.1.1 GA in Capacitor allocation

The following sections describe the method based on Genetic Algorithm (GA) [60,61] to solve the optimal capacitor allocation successfully. As GA is a multiple point probabilistic search technique and is characterized by the mechanism of natural selection and natural genetics, it is able to deal with discrete function in optimization. It is different from traditional methods in four ways:

1. GA can work with coding of the parameter set, not the parameters themselves.
2. GA searches from a population of points not a single point.
3 GA uses payoff (objective function) information not derivatives or auxiliary knowledge.
4 GA uses probabilistic transition rules not deterministic rules.

Simple Genetic Algorithm (SGA) method is a powerful optimization technique analogous to the natural genetic process in biology. Theoretically, this technique is a stochastic approach and it converges to the global optimum solution, provided that certain conditions are satisfied. This paper considers a distribution system with 9 possible locations for capacitors and 27 different sizes of capacitors. A critical discussion using the example with result is presented here.

3.2 Problem Formulation

3.2.1 Assumptions

The optimal capacitor placement problem has many variables including the capacitor size, capacitor cost, locations and voltage constraints on the system. There are switchable capacitors and fixed-type capacitors in practice. However, considering all variables in a nonlinear fashion will make the placement problem very complicated. In order to simplify the analysis, only fixed-type capacitors are considered with the following assumptions: 1) balanced conditions, 2) negligible line capacitance, 3) time-invariant loads and 4) harmonic generation is solely from the substation voltage supply.

3.2.2 Radial distribution system

Figure 3.1 clearly illustrates an m-bus radial distribution system where a general bus i contains a load and a shunt capacitor. The harmonic currents introduced by the nonlinear loads are injected at each bus

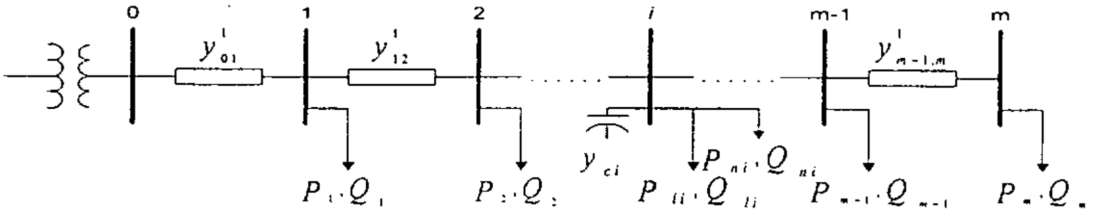


Figure 3.1 One-line diagram of the radial distribution feeder.

At the power frequency, the bus voltages are found by solving the following equations:

$$P_i = \left|V_i^1\right|^2 G_{ii} + \sum_{\substack{j=1 \\ j \neq i}}^{m} \left|V_i^1 V_j^1 Y_{ij}^1\right| \cos\left(\theta_{ij}^1 + \delta_j^1 - \delta_i^1\right) \qquad i = 1,2,3...m \quad (3.1)$$

$$Q_i = -\left|V_i^1\right|^2 B_{ii} + \sum_{\substack{j=1 \\ j \neq i}}^{m} \left|V_i^1 V_j^1 Y_{ij}^1\right| \sin\left(\theta_{ij}^1 + \delta_j^1 - \delta_i^1\right) \qquad i = 1,2,3...m \quad (3.2)$$

where

$$P_i = P_{li} + P_{ni} \quad (3.3)$$

$$Q_i = Q_{li} + Q_{ni} \quad (3.4)$$

$$Y_{ij}^1 = \left|Y_{ij}^1\right| \angle \theta_{ij}^1 = \begin{cases} -y_{ij}^1 & if \;\; i \neq j \\ y_{i-1,i}^1 + y_{i+1,i}^1 + y_{ci}^1 & if \;\; i = j \end{cases} \quad (3.5)$$

$$Y_{ii} = G_{ii} + B_{ii} \quad (3.6)$$

3.2.3 Real power losses

At fundamental frequency, the real power losses in the transmission line between buses i and $i+1$ is:

$$P^{1}_{loss(i,i+1)} = R_{i,i+1}\left(\left|V^{1}_{i+1} - V^{1}_{i}\right|\left|Y^{1}_{i,i+1}\right|\right)^{2} \tag{3.7}$$

So, the total real losses are:

$$P_{loss} = \sum_{n=1}^{N}\left(\sum_{i=0}^{m-1} P^{n}_{loss(i,i+1)}\right) \tag{3.8}$$

3.2.4 Objective Function and Constraints

The objective function of capacitor placement is to reduce the power loss and keep bus voltages and total harmonic distortion (HDF) within prescribed limits with minimum cost. The constraints are voltage limits and maximum harmonic distortion factor, with the harmonics taken into account. Following the above notation, the total annual cost function due to capacitor placement and power loss is written as :

Minimize $$f = K_l K_p P_{loss} + \sum_{j=1}^{m} Q_{cj} K_{cj} \tag{3.9}$$

where $j = 1,2,\ldots.m$ represents the capacitor sizes

$$Q_{cj} = j * K_s \tag{3.10}$$

The objective function (Equation 3.9) is minimized subject to

$$V_{min} \le |V_i| \le V_{max} \qquad i = 1,2,3...m \tag{3.11}$$

and

$$HDF_i \le HDF_{max} \qquad i = 1,2,3...m \tag{3.12}$$

According to IEEE Standard 519 [62] utility distribution buses should provide a voltage harmonic distortion level of less than 5% provided customers on the distribution feeder limit their load harmonic current injections to a prescribed level.

3.3 Proposed Algorithm

3.3.1 Harmonic power flow

At the higher frequencies, the entire power system is modelled as the combination of harmonic current sources and passive elements. Since the admittance of system components will vary with the harmonic order, the admittance matrix is modified for each harmonic order studied. If the skin effect is ignored, the resulting n-th harmonic frequency load admittance, shunt capacitor admittance and feeder admittance are respectively given by:

$$Y_{li}^{n} = \frac{P_{li}}{\left|V_i^1\right|^2} - j\frac{Q_{li}}{n\left|V_i^1\right|^2} \tag{3.13}$$

$$Y_{li}^{n} = nY_{ci}^{1} \tag{3.14}$$

$$Y_{i,i+1}^{n} = \frac{1}{R_{i,i+1} + jnX_{i,i+1}} \tag{3.15}$$

The linear loads are composed of a resistance in parallel with a reactance [63]. The nonlinear loads are treated as harmonic current sources, so the injection harmonic current source introduced by the nonlinear load at bus i is derived as follows:

$$I_i^1 = \left[\frac{P_{ni} + jQ_{ni}}{V_i^1} \right]^* \tag{3.16}$$

$$I_i^n = C(n) I_i^1 \tag{3.17}$$

In this study, $C(n)$ is obtained by field test and Fourier analysis for all the customers along the distribution feeder. The harmonic voltages are found by solving the load flow equation (3.18), which is derived from the node equations.

$$Y^n V^n = I^n \tag{3.18}$$

At any bus i, the r.m.s. value of voltage is defined by

$$|V_i| = \sqrt{\sum_{n=1}^{N} \left|V_i^n\right|^2} \tag{3.19}$$

where N is an upper limit of the harmonic orders being considered and is required to be within an acceptable range. After solving the load flow for different harmonic orders, the harmonic distortion factor (HDF) [64] that is used to describe harmonic pollution is calculated as follows:

$$HDF_i(\%) = \frac{\sqrt{\sum_{n=2}^{N} \left|V_i^n\right|^2}}{V_i^1} \times 100\% \tag{3.20}$$

It is required to be lower than the accepted maximum value.

3.3.2 Selection of optimal capacitor location

The general case of optimal capacitor locations can be selected for starting the iteration. GA calculates the optimal capacitor sizes according to the optimal capacitor locations. After the first iteration, the solution of capacitor locations and sizes will be recorded as an old solution and more locations are then considered. GA is used to calculate a new solution. If the new solution is better than the old solution, the old solution will be replaced by the new solution. If else, the old solution is the best solution. Therefore, this process will continue to consider more locations until no more optimal solution is found which is better than the previous solution. The selection of optimal capacitor location is based on the following criteria: voltage, real power loss, load reactive power and harmonic distortion factor with equal weighting.

3.3.3 Solution Algorithm

GA is a search algorithm based on the mechanism of natural selection and genetics. Simple GA consists of a population of bit strings transformed by three genetic operations: 1) Selection or reproduction, 2) Crossover, and 3) mutation. Each string is called chromosome and represents a possible solution. The algorithm starts from an initial population generated randomly. Using the genetic operations considering the fitness of a solution, it generates a new generation. The string's fitness is usually the reciprocal of the string's objective function in minimization problem. The fitness of solutions is improved through iterations of generations. For each chromosome population in the given generation, a Newton-Raphson load flow calculation is performed. When the algorithm converges, a group of solutions with better fitness is generated, and the optimal solution is obtained. The scheme of genetic operations, the structure of genetic string, its encode/decode technique and the fitness function are designed in this process. The implementation of GA components and the neighborhood searching are explained as follow.

3.4. Representation of candidate solutions

3.4.1 The Genetic String

The genetic string, which consists of "n+1" substrings of binary numbers, where n is the number of probable capacitor locations. The first substring is used to indicate the location of the capacitors, and is named as "location indicator". The length of the location indicator substring is equal to the number of probable capacitor locations and each location is represented by a bit of the string. A "1"in the bit position is used to select a location and a "0"bit indicates that the location is not selected. Each of the remaining "n" substrings is used to indicate the kVar value at the probable capacitor location. The kVar substring for a particular location may have a non-zero value when the selection bit for that location in the location indicator substring is zero. The kVar substring in such cases is ignored while determining the fitness function value of a genetic string; however, the genetic operators of the crossover and mutation are applied on each substring irrespective of the values of the location indictor bit for the location. The location indictor acts as a switch. Although capacitors are installed at each probable location, the capacitors of these locations are connected to the system, for which the location selector bit is 1.

An entire genetic algorithm string is selected during reproduction. The crossover operation is performed between the respective substrings. Thus, there are (n+1) crossover points in each genetic algorithm string. The crossover mechanism used in the present implementation is single-point crossover.

A string of length represents a candidate solution. The initial population of strings s_i, where i = 1, 2 ... m where m is the population size. The population size is 200 and is randomly selected. The maximum capacitor size is 27 (4050kVar) in this example. A 5-bit sub-string is used to represent the capacitor size (00001 to 11011) at each node and (00000) means no capacitor is needed. The above sub-string multiplied by the K_s is equal to the actual capacitor size at the node.

3.4.2 Reproduction

The function of reproduction is to select good strings in a population and put it into the mating pool based on their fitness. Proportionate selection operator is used and the i-th string in the population is selected based on the probability of the string fitness f_i .The higher of f_i, the higher chance of i-th string is selected. The probability for selecting i-th string is $f_i / \sum_{i=1}^{m} f_i$ where m is the population size. Roulette-wheel selection method is used and its circumference is marked proportional to the fitness of the string. The number of f_i / f_{ave} string are generated where f_{ave} is the average fitness of each generation in the population.

3.4.3 Crossover

The main purpose of crossover is to search the parameter space and it is the most important operator in GA. Typically, the probability of crossover is 0.6 for a population size of 100 [65] and it is arbitrarily set as 0.8 in this work. The crossover operator takes two strings from the old population and exchanges the next segment of their structures to form offspring. There are several different crossover operators such as two-point crossover operator and the uniform crossover operator but only single-point crossover is used in simple GA. In the single-point crossover, the search is not comprehensive and information may be retained.

3.4.4 Mutation

The function of mutation is to prevent the loss of the information. Mutation can keep the population more diverse so that it alters a string locally to create a better string. The mutation probability cannot be set too high or too low. If the mutation rate is too high, the information will be lost. If the mutation rate is too low, premature convergence will occur. Typically, the probability of mutation is 0.001 for a population size of 100 and it is arbitrarily set as 0.002 in this work. A random number is generated from a uniformly distributed curve within the range of 0 and 1. If the number is less or equal to the mutation probability, j-th bit of the string change 1 to 0 or vice versa. The trials will be chosen randomly by one trial for mutation and is placed to the optimal location and repeat again.

Once the new proportion is completed, the program will continue to generate new population. The iteration can be stopped either when no further significant change of the solution occurs or when the specified number of iteration is reached.

3.4.5 Fitness function

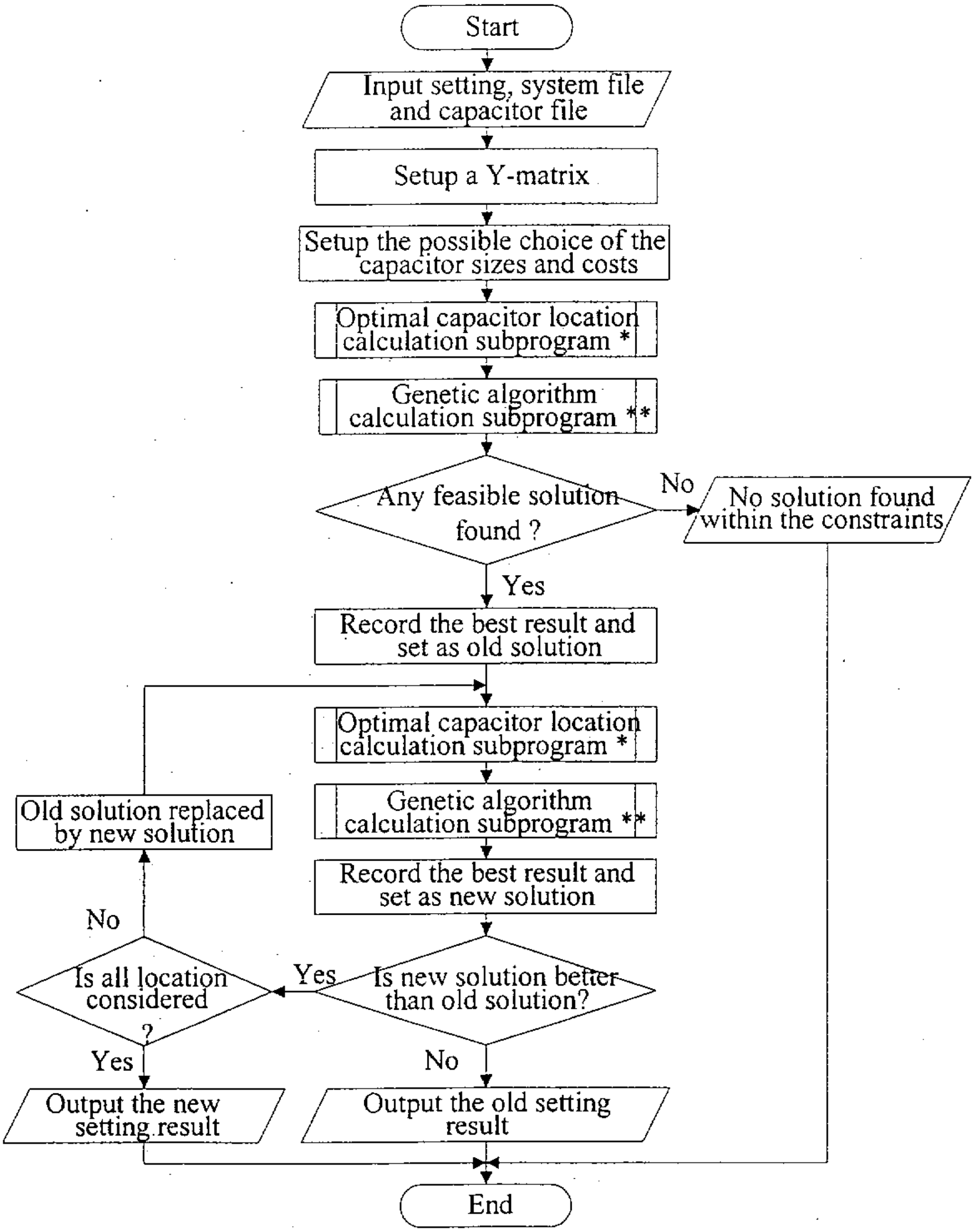
The fitness function is derived as equation (3.9). The objective function is to minimize f. It is composed of two parts; 1) the cost of the power loss in the transmission branch and 2) the cost of reactive power supply. Since GA is applied to maximization problem, minimization of the problem take the normalized relative fitness value of the population and the fitness function is defined as:

$$f_i = \frac{f_{\max} - f_a}{f_{\max}} \tag{3.21}$$

$$\text{where } f_a = K_l K_p P_{loss} + \sum_{j=1}^{m} Q_{cj} K_{cj} \tag{3.22}$$

3.5 Software Design

Figure 3.2 depicts the main steps in the process of this experiment. The predefined processes of optimal capacitor location and genetic algorithm calculation are illustrated in Figure 3.3 and Figure 3.4



* refer to Figure 3.3 and ** refer to Figure 3.4

Figure 3.2 Flow chart of main operation

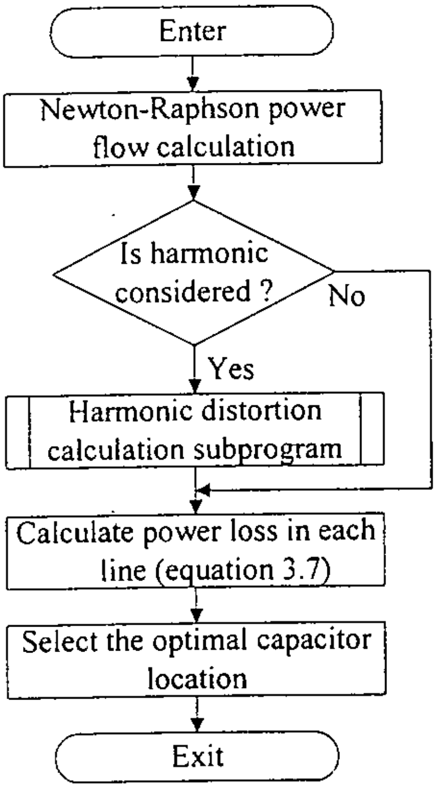


Figure 3.3 Flow chart of 'Optimal capacitor location calculation subprogram' in Figure 3.2

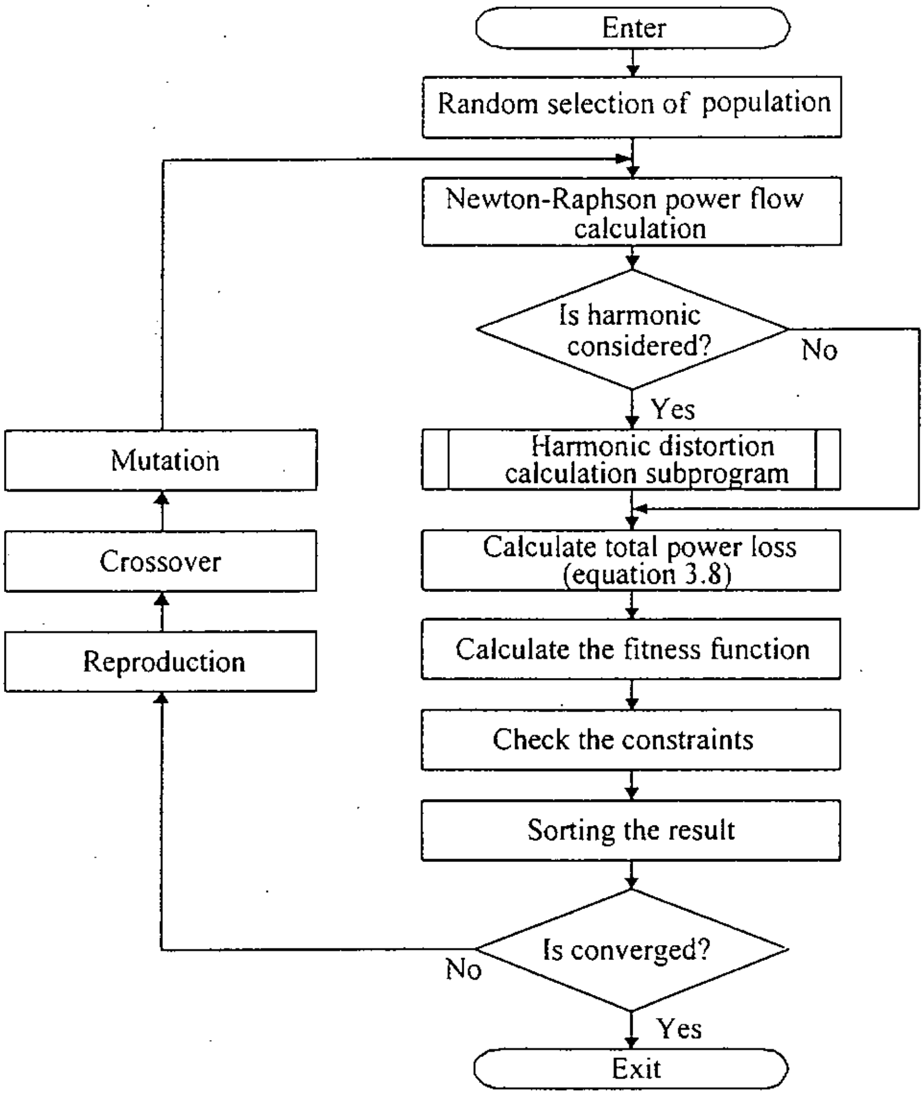


Figure 3.4 Flow chart of 'Genetic algorithm calculation subprogram' in Figure 3.2

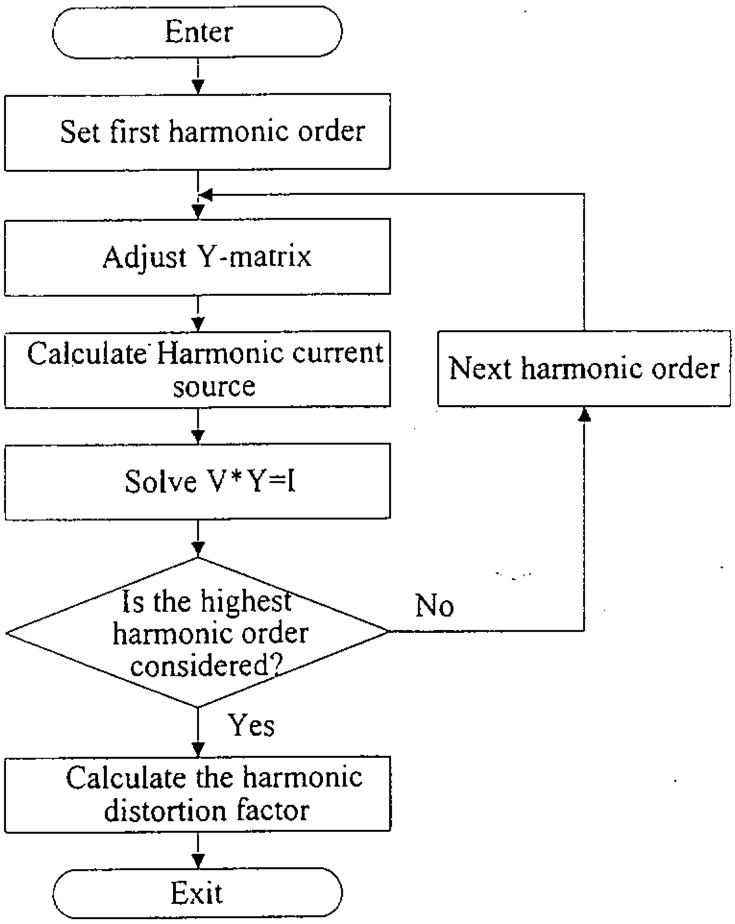


Figure 3.5 Flow chart of 'Harmonic distortion calculation subprogram' in Figure 3.3 and Figure 3.4

3.6 Numerical Example and Results

In this section, a radial distribution feeder [66] is used as the test system to show the effectiveness of this algorithm. This feeder has nine load buses at a rated voltage of 23kV. Table 3.1 and Table 3.2 show the loads and feeder line constants. The harmonic current sources are shown in Table 3.3, which are generated by each customer.

Bus	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
P(kW)	1840	980	1790	1598	1610	780	1150	980	1640
Q(kvar)	460	340	446	1840	600	110	60	130	200
Non-linear (%)	0	55.7	18.9	92.1	4.7	1.9	38.2	4.5	4.0

Table 3.1 Load data of the test system

From Bus i	**From Bus j**	$R_{i,i+1}(\Omega)$	$X_{i,i+1}(\Omega)$
0	1	0.1233	0.4127
1	2	0.0140	0.6051
2	3	0.7463	1.2050
3	4	0.6984	0.6084
4	5	1.9831	1.7276
5	6	0.9053	0.7886
6	7	2.0552	1.1640
7	8	4.7953	2.7160
8	9	5.3434	3.0264

Table 3.2 Feeder data of the test system

Bus	Harmonic current sources(%) in harmonic order 5	7	11	13	17	19	23	25
1	0	0	0	0	0	0	0	0
2	9.1	5.3	1.8	1.1	0.7	0.6	0.4	0.3
3	3.1	1.8	0.6	0.4	0.2	0.2	0.1	0.1
4	6.2	3.6	1.3	0.8	0.5	0.4	0.3	0.2
5	17.7	2.9	4.5	8.2	5.4	2.9	2.9	0
6	0	0	9.6	5.8	0	0	3.6	3.0
7	0.3	0	0	0	0	0	0	0
8	0.8	0.5	0.2	0	0	0	0	0
9	15.1	8.8	3.0	1.8	1.2	1.0	0.6	0.5

Table 3.3 The harmonic current sources

K_p is selected to be US \$168/kW in equation (3.9). The minimum and maximum voltages are 0.9 p.u. and 1.0 p.u. respectively. All voltage and power quantities are per-unit values. The base value of voltage and power is 23kV and 100MW respectively. Commercially available capacitor sizes are analyzed. Table 3.4 shows an example of such data provided by a supplier for 23kV distribution feeders. For reactive power compensation, the maximum capacitor size Q_c(max) should not exceed the reactive load, i.e. 4186 kVar. Capacitor sizes and costs are shown in Table 3.5 by assuming a life expectancy of ten years (the placement, maintenance, and running costs are assumed to be grouped as total cost.)

Size of capacitor (kVar)	150	300	450	600	900	1200
Cost of capacitor ($)	750	975	1140	1320	1650	2040

Table 3.4 Available 3-phase capacitor sizes and costs

j	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Q_{cj} (kvar)	150	300	450	600	750	900	1050	1200	1350
K_{cj} ($\$$ / kvar)	0.500	0.350	0.253	0.220	0.276	0.183	0.228	0.170	0.207
j	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
Q_{cj} (kvar)	1500	1650	1800	1950	2100	2250	2400	2550	2700
K_{cj} ($\$$ / kvar)	0.201	0.193	0.187	0.211	0.176	0.197	0.170	0.189	0.187
j	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**
Q_{cj} (kvar)	2850	3000	3150	3300	3450	3600	3750	3900	4050
K_{cj} ($\$$ / kvar)	0.183	0.180	0.195	0.174	0.188	0.170	0.183	0.182	0.179

Table 3.5 Possible choice of capacitor sizes and costs

The effectiveness of the method is illustrated by a comparative study of the following three cases. Case 1 is without capacitor installation and neglect the harmonic. Both case 2 and case 3 use GA approach for optimizing the size and the placement of the capacitor in the radial distribution system. However, case 2 does not take harmonic into consideration and case 3 takes harmonic into consideration. The optimal locations of capacitors are selected at bus 4, bus 5 and bus 9.

Before optimization (case 1), the voltages of bus 7, 8, 9 are violated. The cost function and the maximum HDF are \$132138 and 6.15% respectively. The harmonic distortion level on all buses is higher than 5%.

After optimization (case 2 and 3), the power losses become 0.007065 p.u. in case 2 and 0.007036 p.u. in case 3. Therefore, the power savings will be 0.000747 p.u. in case 2 and 0.000776 p.u. in case 3. It can also be seen that case 3 has more power saving than case 2.

The voltage profile of case 2 and case 3 are shown in Table 3.6 and Table 3.7 respectively. In both cases, all bus voltages are within the limit. The cost savings of case 2 and case 3 are \$2,744 (2.091%) and \$1,904 (1.451%) respectively with respect to case 1. Since harmonic distortion is considered in case 3, the sizes of capacitors are larger than case 2 so that the total cost of case 3 is higher than case 2.

The maximum HDF of case 2 of case 3 are 1.35% and 1.2% respectively. The HDF improvement of case 3 with respects to case 1 is

$$\text{HDF improvement \%} = \frac{6.15 - 1.20}{6.15} \times 100 = 80.49\%$$

The HDF improvement of case 3 with respects to case 2 is

$$\text{HDF improvement \%} = \frac{1.40 - 1.20}{1.40} = 14.29\%$$

The improvement of the harmonic distortion is quite attractive and it is clearly shown in Figure 3.6. The reductions in HDF are 80.49% and 14.29% with respect to case 1 and case 2.

The optimal cost and the corresponding capacitor sizes, power loss, minimum / maximum voltages, the average CPU time and harmonic distortion factor are also shown in Table 3.8.

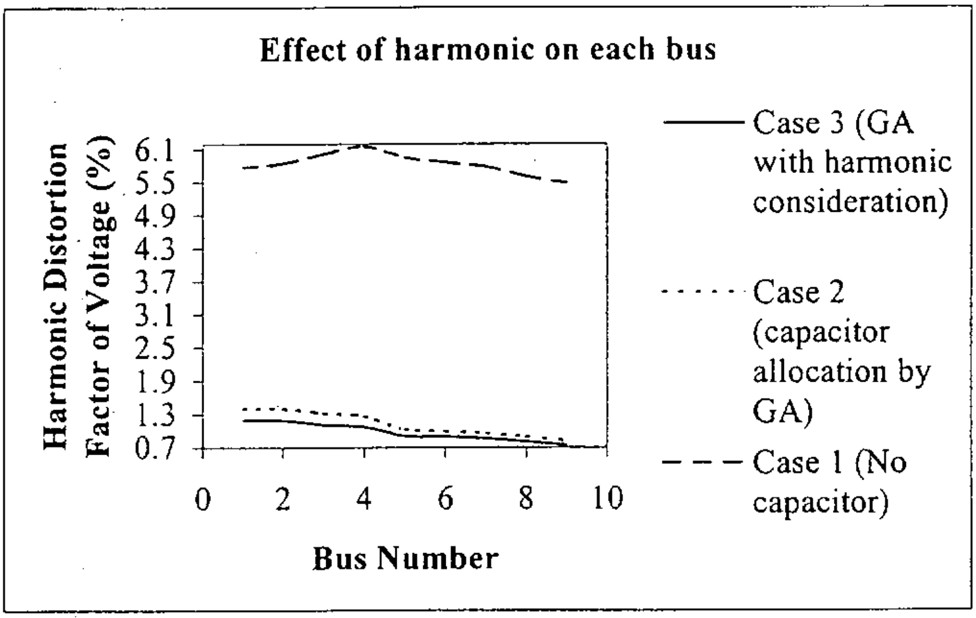


Figure 3.6 Harmonic effect on each bus

Bus	Voltages in harmonic order									V_{rms}	HDF
	1	5	7	11	13	17	19	23	25		
	x1	$x10^{-2}$	$x10^{-3}$	$x10^{-3}$	$X10^{-3}$	$x10^{-4}$	$x10^{-4}$	$x10^{-4}$	$x10^{-4}$	x1	%
1	0.993	4.41	2.96	1.57	1.25	9.60	8.12	7.47	4.72	0.992	5.78
2	0.987	4.43	2.98	1.58	1.26	9.69	8.19	7.53	4.76	0.987	5.85
3	0.963	4.45	2.98	1.58	1.26	9.70	8.18	7.54	4.74	0.963	6.02
4	0.948	4.47	3.00	1.59	1.27	9.76	8.21	7.59	4.75	0.947	6.15
5	0.917	4.23	2.78	1.46	1.18	9.02	7.49	6.98	4.24	0.916	5.95
6	0.907	4.14	2.71	1.41	1.14	8.61	7.14	6.65	4.05	0.907	5.86
7	0.889	4.02	2.61	1.34	1.08	8.11	6.72	6.22	3.79	0.888	5.78
8	0.859	3.80	2.43	1.23	0.98	7.31	6.05	5.57	3.40	0.858	5.60
9	0.838	3.66	2.32	1.15	0.91	6.79	5.61	5.13	3.15	0.837	5.49

Table 3.5 The voltage profile of Case 1

Bus	Voltages in harmonic order									V_{rms}	HDF
	1	5	7	11	13	17	19	23	25		
	x1	$x10^{-2}$	$x10^{-2}$	$x10^{-3}$	$x10^{-3}$	$x10^{-4}$	$x10^{-4}$	$x10^{-4}$	$x10^{-4}$	x1	%
1	0.997	1.190	5.86	1.93	1.22	7.45	6.27	4.49	3.33	0.999	1.40
2	0.999	1.190	5.90	1.94	1.23	7.51	6.32	4.53	3.36	0.988	1.40
3	0.988	1.130	5.34	1.62	0.99	5.51	4.37	2.94	2.05	0.980	1.32
4	0.980	1.100	5.02	1.44	0.85	4.36	3.23	2.05	1.29	0.980	1.26
5	0.962	0.887	3.42	0.81	0.52	2.29	1.33	0.96	0.29	0.962	1.02
6	0.954	0.861	3.28	0.79	0.51	2.12	1.24	1.12	0.49	0.954	0.99
7	0.939	0.827	3.10	0.73	0.46	1.90	1.12	0.97	0.44	0.939	0.95
8	0.915	0.751	2.72	0.60	0.36	1.45	0.89	0.68	0.34	0.915	0.89
9	0.900	0.682	2.37	0.47	0.25	1.04	0.69	0.39	0.25	0.901	0.82

Table 3.6 The voltage profile of Case 2

Bus	Voltages in harmonic order									V_{rms}	HDF
	1	5	7	11	13	17	19	23	25		
	x1	$x10^{-2}$	$x10^{-2}$	$x10^{-3}$	$x10^{-3}$	$x10^{-4}$	$x10^{-4}$	$x10^{-4}$	$x10^{-4}$	x1	%
1	0.998	1.05	5.08	1.64	1.03	6.41	5.45	3.95	2.98	0.998	1.20
2	1.000	1.06	5.11	1.65	1.04	6.46	5.50	3.98	3.00	1.000	1.19
3	0.991	0.99	4.54	1.33	0.80	4.42	3.53	2.38	1.69	0.991	1.11
4	0.983	0.95	4.20	1.14	0.66	3.25	2.36	1.47	0.91	0.983	1.07
5	0.963	0.81	3.08	0.75	0.52	2.35	1.36	1.05	0.28	0.963	0.90
6	0.955	0.79	2.96	0.74	0.50	2.18	1.26	1.20	0.49	0.955	0.89
7	0.944	0.76	2.81	0.68	0.45	1.95	1.14	1.04	0.44	0.940	0.86
8	0.917	0.69	2.48	0.57	0.35	1.49	0.90	0.73	0.34	0.917	0.80
9	0.902	0.63	2.18	0.45	0.25	1.05	0.69	0.40	0.25	0.902	0.74

Table 3.7 The voltage profile of Case 3

	Case 1	Case 2	Case 3
Maximum voltage (p.u.)	0.999	0.999	1.000
Minimum voltage (p.u.)	0.837	0.901	0.902
Total power loss (p.u.)	0.007812	0.007065	0.007036
$Q_c(4)$ (p.u.)		0.024	0.036
$Q_c(5)$ (p.u.)		0.024	0.018
$Q_c(9)$ (p.u.)		0.009	0.009
Cost ($ / year)	131238	128494	129334
Average CPU Time (sec.)	0.8	1.20	3.39
Maximum HDF (%)	6.15	1.40	1.20

Table 3.8 Summary of results using the GA method

3.7 Summary

This chapter presents a genetic algorithm (GA) approach to search for optimal shunt capacitor location and size in a distribution system. The cost or fitness function is constrained by voltage and Harmonic Distortion Factor (HDF). Since GA is a stochastic approach, performance should be evaluated using statistical value. The performance will be affected by initial condition but GA can give the optimal solution by increasing the population size. The result shows that GA method is suitable for discrete value optimization problem such as capacitor allocation and the consideration of harmonic distortion limit may be included with an integrated approach in the GA.

Chapter 4

Static Modeling of FACTS Devices for Power Flow Studies

4.1 Classification of FACTS Devices

Load flow control with power system components like UPFC (United Power Flow Controller has recently become an important issue because of the overload transmission corridors and bottlenecks. Additionally, existing transmission line reserves can be utilized more effectively by redistributing the power flows. In this chapter, the modeling of FACTS devices for power flow studies and the role of that modeling in the study of FACTS devices for power flow control are discussed. A number of power flow study programs are developed in order to model various types of FACTS devices.

The research approach employs the use of the FACTS devices at the bus rather than at the branch since the number of buses are fewer than the number of branches. Moreover, FACTS can be expressed by injected power to the related buses and most power flow programs and other analysis programs use bus admittance matrix. When the analysis of the power lines with FACTS is carried out, it will invert the branch-model to power-injected-bus model for convenience.

4.1.1 Development the mathematical model of FACTS devices

In some previous work, it is necessary to modify the nodal admittance matrix when the FACTS device is incorporated into the loadflow calculation. However, a power injection method is introduced in this thesis to represent TCPSR and UPFC. The concept is to introduce a power injection variable ΔS_{is} in bus i and ΔS_{js} in bus j. The advantage of this method is that it can retain the symmetry of the admittance matrix.

In order to build the model for the current FACTS devices, it is necessary to classify them into several types according to their characteristics. In general, there are three types of FACTS devices, i.e. series controller, shunt controller and unified controller respectively.

TCSC and thyristor-controlled phase-shifter (TCPS) are categorized as series controllers which control the series parameter P and/or Q. Series controller such as TCSC or variable series capactive compensation can be effective in power flow redistribution while TCPS can exchange both real and reactive power with ac system by changing the ratios and angles via the series insertion transformer. These series devices, especially of TCSC, will certainly play a major role in controlling power flow such as congestion management in the future. Static var compensator (SVC) and static synchronous compensator (STATCOM) are categorized as shunt controllers which are normally used for the voltage regulation of transmission system at a selected terminal. UPFC, as a unified controller with series and shunt inverter, regulates the real and reactive power flow (P and Q) independently on the transmission line while it also regulates the bus voltage (V) simultaneously.

4.2 Thyristor-Controlled Series Capacitor (TCSC)

4.2.1 Introduction

The world's first multi-module Thyristor-Controlled Series Capacitor (TCSC) system has been installed on Bonneville Power Administrations' transmission system. The TCSC is part of EPRI's Flexible AC Transmission System (FACTS) program. The installation is located at BPA's C.J. Slatt Substation on the Slatt-Buckley 500 kV line in Northern Oregon. The TCSC's high speed switching capability provides a mechanism for controlling line power flow, which permits increased loading of existing transmission lines, and allows for rapid readjustment of line power flow in response to various contingencies. The TCSC also can regulate steady-state power flow within its rating limits. The fast acting TCSC can provide a means of rapidly increasing power transfer upon detection of the critical contingencies, resulting in increased transient stability. The TCSC provides a mechanism for greatly reducing potential subsynchronous resonance problem at thermal generators electrically close to transmission lines with series compensation.

4.2.2 The Basic Principles of TCSC

Transmission lines can be compensated by fixed series capacitors or more effectively by controllable series capacitors using thyristor switches. Thyristor Controlled Series Compensator (TCSC) and Thyristor Switched Series Compensator (TSSC) are two types of controllable series capacitors. The use of series capacitors for compensating the inductive reactance of long distance lines is the most effective and economic method of improving power transfer. The configurations of TCSC use thyristor-controlled reactor (TCRs) in parallel with segments of a capacitor bank. Thus it can be controlled either in capactive or in inductive operating range depending on the different applications while TSSC uses thyristor switches in parallel with a segment of the series capacitor bank to insert / remove portions of the bank in discrete steps.

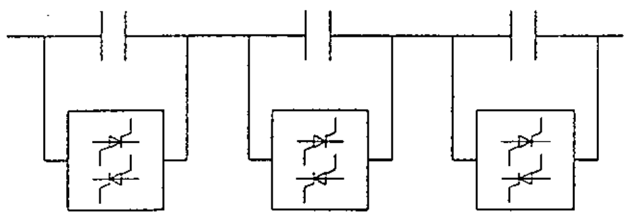


Figure 4.1 Thyristor Switched Series Compensator (TSSC)

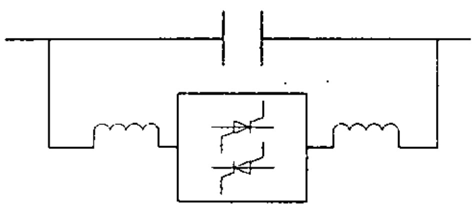


Figure 4.2 Thyristor Controlled Series Compensation (TCSC)

The TCSC's high speed switching capability provides a mechanism for controlling line power flow, which permits increased loading of existing transmission lines, and allows for rapid readjustment of line power flow in response to various contingencies. The TCSC also can regulate steady-state power flow within its rating limits.

Three FACTS devices, TCSC, TCPS and UPFC are derived by the Power Injection Method (PIM) [67]. PIM is a good model for FACTS devices because it will handle them well in load flow computation and OPF analysis. Since this method will not destroy existing admittance matrix B, it is easy for implementing in load flow programs. An alternative method that can be used is the load-equivalent method. However, load-equivalent method is only used when the control objectives of FACTS devices are known. The injected-power model is convenient and is considered relevant for our analysis here.

4.2.3 Mathematical Modeling of TCSC

The model of the network with TCSC is shown in Fig.4.3. The controllable reactance, x_c, is directly used as the control variable to be implemented in the bus susceptance matrices.

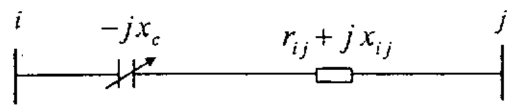


Figure 4.3 equivalent circuit of TCSC

The effect of the TCSC on the power system may be simulated as a controllable reactance $-x_c$ inserted in the transmission line. In general, TCSC is installed in the substation for operation. For simplicity, the line shunt impedance (B/2) is neglected since this approximation only has little effect on the accuracy. The above assumption will also be used in the model of TCPS and UPFC, which are shown in the next section.

TCSC thus consists of a discrete variable series capacitive reactance as shown.

$$P_{ij,TCSC} = U_i^2 G_{ij}^{'} - U_i U_j \left(G_{ij}^{'} \cos\theta_{ij} + B_{ij}^{'} \sin\theta_{ij} \right) \tag{4.1}$$

$$Q_{ij,TCSC} = -U_i^2 (B_{ij}^{'} + B/2) - U_i U_j \left(G_{ij}^{'} \sin\theta_{ij} - B_{ij}^{'} \cos\theta_{ij} \right) \tag{4.2}$$

$$P_{ji,TCSC} = U_j^2 G_{ij}^{'} - U_i U_j \left(G_{ij}^{'} \cos\theta_{ij} - B_{ij}^{'} \sin\theta_{ij} \right) \tag{4.3}$$

$$Q_{ji,TCSC} = -U_j^2 (B_{ij}^{'} + B/2) - U_i U_j \left(-G_{ij}^{'} \sin\theta_{ij} - B_{ij}^{'} \cos\theta_{ij} \right) \tag{4.4}$$

$$\text{where } G_{ij}^{'} = \frac{r_{ij}}{r_{ij}^2 + \left(x_{ij} - x_c\right)^2} \text{ and } B_{ij}^{'} = \frac{-\left(x_{ij} - x_c\right)}{r_{ij}^2 + \left(x_{ij} - x_c\right)^2} \tag{4.5}$$

If $Y_{ij} = jB_{ij}$, the active and reactive power parts of injection sources are (line resistance neglected)

$$P_{is,TCSC} = \frac{x_c}{x - x_c} \left(\frac{U_i U_j \sin\theta_{ij}}{x} \right) \tag{4.6}$$

$$P_{js,TCSC} = \frac{-x_c}{x - x_c} \left(\frac{U_i U_j \sin\theta_{ij}}{x} \right) \tag{4.7}$$

$$Q_{is,TCSC} = \frac{x_c}{x - x_c} \left(\frac{U_i^2 - U_i U_j \cos\theta_{ij}}{x} \right) \tag{4.8}$$

$$Q_{js,TCSC} = \frac{x_c}{x - x_c} \left(\frac{U_j^2 - U_i U_j \cos\theta_{ij}}{x} \right) \tag{4.9}$$

Equations (4.6)-(4.9) reveal that the series capacitor redistribute the active power through the compensated line. Moreover, the reactive power distribution is also affected at the same time since capacitor is a source of reactive power.

$$\Delta P_{is} = -\Delta P_{js} = \left(\frac{U_i U_j \sin\theta_{ij}}{x^2} \right) \Delta x_c \tag{4.10}$$

This indicates that the capability of a series capacitor to redistribute the active power flow depends on the level of line loading and it is the lowest when the line is unloaded.

The real power losses of the line k, when TCSC is installed, are as follows:

$$P_{ij,TCSC} + P_{ji,TCSC} = P_{loss,TCSC} = G_{ij}^{'}\left(U_i^2 + U_j^2 - 2U_iU_j\cos\theta_{ij}\right) \tag{4.11}$$

4.3 Thyristor-Controlled Phase Shifter (TCPS)

4.3.1 Introduction

Phase shifter (PS) is a transformer with turns ratio. Serially connected boosting transformer in transmission line achieves the phase angle shift of PS. PS does not produce nor consume the active and reactive power if the power losses are neglected.

4.3.2 The Basic Principle of TCPS

TCPS can provide a rapidly variable phase angle by the adjustment of thyristor switches. The real and reactive power flow from bus i to bus j and vice versa are controlled when TCPSR is installed. The typically value of the a_{ij} is $0.9\ p.u. \le a_{ij} \le 1.1$ $p.$u and the value of ϕ is $-20^o \le \phi \le +20^o$.

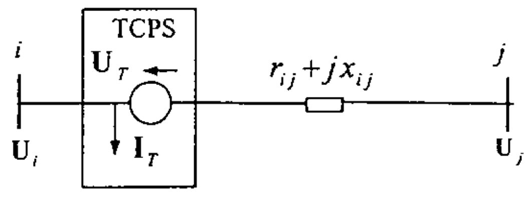


Figure 4.4 Equivalent circuit of TCPS

4.3.3 Mathematical Modeling of TCPS

$$P_{ij,TCPSR} = a_{ij}^2 U_i^2 G_{ij} - a_{ij} U_i U_j \left[G_{ij} \cos(\theta_{ij} + \phi) + B_{ij} \sin(\theta_{ij} + \phi) \right] \tag{4.12}$$

$$Q_{ij,TCPSR} = -a_{ij}^2 U_i^2 (B_{ij} + B_{shunt}) - a_{ij} U_i U_j \left[G_{ij} \sin(\theta_{ij} + \phi) - B_{ij} \cos(\theta_{ij} + \phi) \right] \tag{4.13}$$

$$P_{ji,TCPSR} = U_j^2 G_{ij} - a_{ij} U_i U_j \left[G_{ij} \cos(\theta_{ij} + \phi) - B_{ij} \sin(\theta_{ij} + \phi) \right] \tag{4.14}$$

$$Q_{ji,TCPSR} = -U_j^2 (B_{ij} + B_{shunt}) - a_{ij} U_i U_j \left[-G_{ij} \sin(\theta_{ij} + \phi) - B_{ij} \cos(\theta_{ij} + \phi) \right] \tag{4.15}$$

where $\theta_{ij} = \theta_i - \theta_j$ and $Y_{ij} = G_{ij} + jB_{ij}$ (4.16)

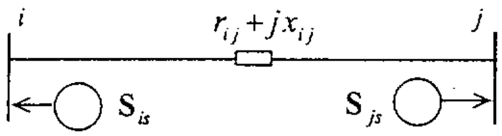


Figure 4.5 Injected model of TCPS

The injection power flow model equations are as follow:

$$P_{is,TCPSR} = B_{ij} U_i U_j \left[a_{ij} \sin(\theta_{ij} + \phi) - \sin\theta_{ij} \right] + G_{ij} (a_{ij}^2 - 1) U_i^2 - G_{ij} V_i V_j \left[a_{ij} \cos(\theta_{ij} + \phi) - \cos\theta_{ij} \right]$$
(4.17)

$$Q_{is,TCPSR} = -B_{ij} \left[a_{ij} U_i U_j \cos(\theta_{ij} + \phi) - U_i U_j \cos\theta_{ij} \right] - (B_{ij} + B_{shunt}) U_i^2 (1 - a_{ij}^2) \tag{4.18}$$

$$P_{js,TCPSR} = -B_{ij} U_i U_j \left[a_{ij} \sin(\theta_{ij} + \phi) - \sin\theta_{ij} \right] + G_{ij} U_i U_j \left[a_{ij} \cos(\theta_{ij} + \phi) + \cos\theta_{ij} \right] \tag{4.19}$$

$$Q_{js,TCPSR} = -B_{ij} U_i U_j \left[a_{ij} \cos(\theta_{ij} + \phi) - \cos\theta_{ij} \right] - G_{ij} U_i U_j \left[a_{ij} \sin(\theta_{ij} + \phi) + \sin\theta_{ij} \right] \tag{4.20}$$

If $Y_{ij} = jB_{ij}$ and $a_{ij}=1$, the active and reactive power parts of injection sources are

$$P_{is,TCPSR} = 2B_{ij} U_i U_j \sin\frac{\phi}{2} \cos\left(\theta_{ij} + \frac{\phi}{2} \right) \tag{4.21}$$

$$P_{js,TCPSR} = -2B_{ij} U_i U_j \sin\frac{\phi}{2} \cos\left(\theta_{ij} + \frac{\phi}{2} \right) \tag{4.22}$$

$$Q_{is,TCPSR} = 2B_{ij}U_iU_j \sin\frac{\phi}{2}\sin\left(\theta_{ij} + \frac{\phi}{2}\right) \tag{4.23}$$

$$Q_{js,TCPSR} = 2B_{ij}U_iU_j \sin\frac{\phi}{2}\sin\left(\theta_{ij} + \frac{\phi}{2}\right) \tag{4.24}$$

Equations (4.21)-(4.24) reveal that the reactive component of the injection source at each node is much smaller than the active component, i.e. $Q_{is} \ll P_{is}$ and $Q_{js} \gg P_{js}$. This means that the main function of an ideal phase shifter is to redistribute the active power flow through the compensated line. This is because an ideal phase shifter neither generates nor absorbs reactive power. Moreover, a small change in the phase shifter angle yields

$$\Delta P_{is} = -\Delta P_{js} = B_{ij}U_iU_j \cos\theta_{ij}\Delta\phi \tag{4.25}$$

which indicates that the capability of a phase shifter to redistribute the active power flow depends on the loading level of the compensated line. It is highest when the line is unloaded.

The real power losses of the line k, when TCPSR is installed, are as follows:

$$P_{ij,TCPSR} + P_{ji,TCPSR} = P_{loss,TCPSR} = G_{ij}\left[a_{ij}^2U_i^2 + U_j^2 - 2a_{ij}U_iU_j \cos(\theta_{ij} + \phi)\right] \tag{4.26}$$

4.4 Unified Power Flow Controller

4.4.1 Introduction

Gyugyi (1991) defined the concept of UPFC. The UPFC consists of shunt (exciting) and series (boosting) transformers, which are connected by two GTO converters (shunt and series) and a DC circuit represented by the capacitor.

Series converter is used to generate a voltage source at the fundamental frequency with variable amplitude $(0 \le U_T \le U_{T\max})$ and phase angle $(0 \le \varphi_T \le 2\pi)$ is added to the AC transmission line by the series connected boosting transformer.

4.4.2 The Basic Principle of UPFC

The basic UPFC concept is explained herewith. UPFC has three controllable parameters, namely magnitude of the boosting transformer injected voltage U_T, phase of this voltage φ_T and the exciting transformer reactive current I_q.

Injected-power model is a suitable model for FACTS devices in this application because it will handle settings well in load flow computation and OPF analysis. Since this method will not destroy existing admittance matrix B, it is easy for implementation in load flow programs. In this respect, load-equivalent method is only used when the control objectives of FACTS devices are known.

The basic structure of an UPFC consists of shunt (exciting) and series (boosting) transformers, which are connected by two GTO converters that operate from a common dc-circuit consisting of a dc-storage capacitor.

One of the inverters is used to generate a voltage source at the fundamental frequency with variable amplitude and phase angle, which is added to the AC transmission line by the series connected boosting transformer. It is assumed that the operation of converter is loss free so that the UPFC neither absorb nor inject the active power with respect to the system.

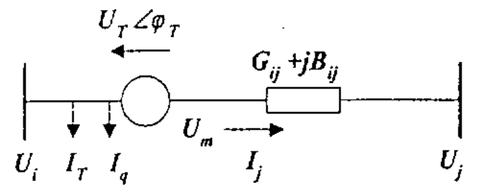


Figure 4.6 Basic configuration of UPFC

The effect of UPFC on network can be modelled by a series inserted voltage source U_T and two tapped currents I_T *and* I_q. The model of the network with UPFC is shown in Figure.4.7

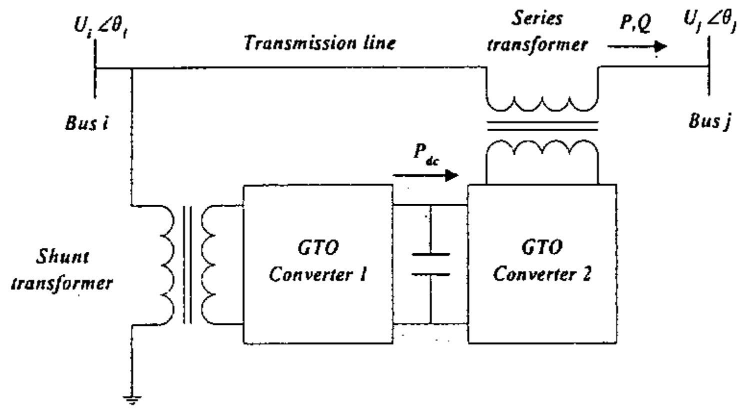


Figure 4.7 Equivalent circuit of UPFC

UPFC can control three parameters: the magnitude (U_T) and phase angle (φ_T) of inserted voltage which is in series with the branch and the terminal voltage of shunt branch (U_i) using reactive current source I_q control. The series branch voltage that is injected can be in any phase with respect to U_i and can have any magnitude from 0 to a defined maximum value, U_T^{max}. The operating area becomes the region limited by a circle with radius U_T^{max}. The phase angle of this voltage (φ_T) is independent of the line current (I_j). It has magnitude from -π to π. The reactive current source I_q is assumed as either capactive or inductive and the magnitude is between 0 and a defined maximum value I_q^{max}, which is independent of the terminal voltage.

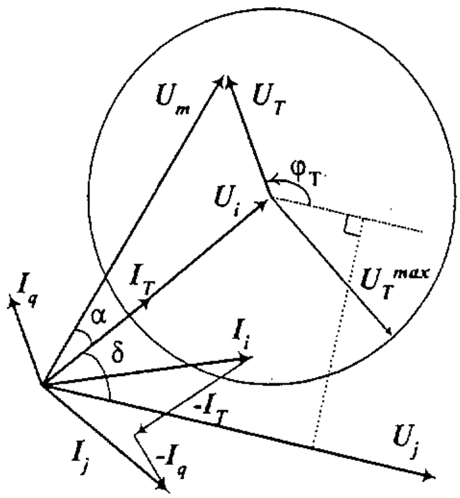


Figure 4.8 Vector diagram of the equivalent circuit of UPFC

Unified Power Flow Controller (UPFC) combines both the series and shunt controllers. This equipment can control both active and reactive power flows independently in a transmission line. $U_T = U_T \angle \phi_t$ is the injected voltage and I_q is the transformer reactive current. These three parameters can be controlled instantaneously.

Based on the basic principles of UPFC, the mathematical relations can be derived as follow:

$$U_j = U_i + U_T \tag{4.27}$$

$$Arg(I_q) = Arg(U_i) \pm 90^0 \tag{4.28}$$

$$Arg(I_T) = Arg(U_i) \tag{4.29}$$

$$I_T = \frac{\mathrm{Re}\left[U_T I_j^{\bullet}\right]}{V_i} \tag{4.30}$$

4.4.3 Mathematical Modeling of UPFC

Thus, based on the mathematical relationship, the derivation of the power flow equations of UPFC from bus i to bus j and from bus j to bus i is as follows:

$$S_{ij,UPFC} = P_{ij,UPFC} + jQ_{ij,UPFC} = U_i I_{ij}^{\bullet} = U_i \left(I_T + I_q + I_j\right)^{\bullet} \tag{4.31}$$

$$S_{ji,UPFC} = P_{ji,UPFC} + jQ_{ji,UPFC} = U_j I_{ji}^{\bullet} = U_j \left(-I_j\right)^{\bullet} \tag{4.32}$$

$$P_{ij,UPFC} = \left(U_i^2 + U_T^2\right) g_{ij} + 2U_i U_T g_{ij} \cos(\varphi_T - \delta_{ij}) - \\ U_i U_T \left(g_{ij} \cos\varphi_T + b_{ij} \sin\varphi_T\right) - U_i U_j \left(g_{ij} \cos\delta_{ij} + b_{ij} \sin\delta_{ij}\right) \tag{4.33}$$

$$Q_{ij,UPFC} = -U_i I_q - U_i^2 b_{ij} - U_i U_T \left[g_i \sin(\varphi_T - \delta_{ij}) + b_{ij} \cos(\varphi_T - \delta_{ij}) - U_i U_j \left(g_{ij} \sin\delta_{ij} - b_{ij} \cos\delta_{ij}\right)\right] \tag{4.34}$$

$$P_{ji,UPFC} = U_j^2 g_{ij} - U_j U_T \left(g_{ij} \cos\varphi_T - b_{ij} \sin\varphi_T\right) - U_i U_j \left(g_{ij} \cos\delta_{ij} - b_{ij} \sin\delta_{ij}\right) \tag{4.35}$$

$$Q_{ji,UPFC} = -U_j^2 b_{ij} - U_j U_T \left(g_{ij} \sin\varphi_T - b_{ij} \cos\varphi_T + U_i U_j \left(g_{ij} \sin\delta_{ij} + b_{ij} \cos\delta_{ij}\right)\right) \tag{4.36}$$

where δ_{ij} is the angle between U_i and U_j and φ_T is the angle of the U_t as taking U_j as reference $\forall\, i \in NU$

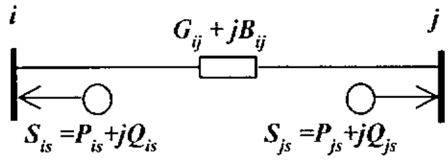


Figure 4.9 Injected Model of UPFC

According to basic principles, the power injection model of network with UPFC is shown in Figure.4.9

The injected power at bus i and bus j is as follows:

$$S_{is,UPFC}=U_i\left(-I_T-I_q-\frac{U_T}{r_{ij}+jx_{ij}}\right)^* \tag{4.37}$$

$$S_{js,UPFC}=U_j\left(\frac{U_T}{r_{ij}+jx_{ij}}\right)^* \tag{4.38}$$

The injected active and reactive power equations at two related buses are derived as follow:

$$P_{is,UPFC}=-U_T^2 g_{ij}-2U_iU_jg_{ij}\cos(\varphi_T-\delta_{ij})+U_iU_j(g_{ij}\cos\varphi_T+b_{ij}\sin\varphi_T) \tag{4.39}$$

$$Q_{is,UPFC}=U_iI_q+U_iU_j\left[g_{ij}\sin(\varphi_T-\delta_{ij})+b_{ij}\sin\varphi_T\right] \tag{4.40}$$

$$P_{js,UPFC}=U_jU_T(g_{ij}\cos\varphi_T-b_{ij}\sin\varphi_T) \tag{4.41}$$

$$Q_{js,UPFC}=-U_jU_T(g_{ij}\sin\varphi_T+b_{ij}\cos\varphi_T) \tag{4.42}$$

If $Y_{ij}=jB_{ij}$, the active and reactive power parts of injection sources are

$$P_{is,UPFC}=U_iU_jb_{ij}\sin\varphi_T \tag{4.43}$$

$$Q_{is,UPFC}=U_iI_q+U_iU_jb_{ij}\sin\varphi_T \tag{4.44}$$

$$P_{js,UPFC}=-U_jU_Tb_{ij}\sin\varphi_T \tag{4.45}$$

$$Q_{js,UPFC} = -U_j U_T b_{ij} \cos\varphi_T \tag{4.46}$$

The real power loss of the line k, which UPFC is installed, is as follows:

$$P_{ij,UPFC} + P_{ji,UPFC} = P_{loss,UPFC} = g_{ij}\left(U_i^2 + U_j^2 - 2U_i U_j \cos\theta_{ij}\right) + 2U_T g_{ij}\left[U_i \cos\left(\varphi_T - \theta_{ij}\right) - U_j \cos\varphi_T\right] \tag{4.47}$$

4.5 Modified Non-linear Power Flow Equations

The effect of TCSC on power system can be modeled by a reactance x_c inserted in the lines, the related node admittance matrix should change accordingly. The effect of TCPS and UPFC on the power system can be modeled by injected power flows at two related buses without change of node admittance matrix.

For each PQ and PV node, there is an active power mismatch equation and for each PQ node, there is a reactive power mismatch equation. These equations can be formulated as follow:

$$P_{Gi} + P_{iu} + P_{ip} - P_{di} - \sum_{j\in N} U_i U_j Y_{ij} \cos\left(\theta_{ij} + \delta_j - \delta_i\right) = 0 \qquad \forall i \in N-1 \tag{4.48}$$

$$Q_{Gi} + Q_{iu} + Q_{ip} - Q_{di} + \sum_{j\in N} U_i U_j Y_{ij} \sin\left(\theta_{ij} + \delta_j - \delta_i\right) = 0 \qquad \forall i \in M \tag{4.49}$$

P_{Gi} and Q_{Gi} are injected bus generator powers. P_{iu} is injected bus power caused by the installation of UPFC, while P_{ip} and Q_{ip} are injected powers caused by the installation of TCPS. P_{di} and Q_{di} are bus active and reactive loads. N is the network bus number and M is the network PQ bus number. N^{th} bus is supposed to be the slack bus. Thus, linear relationships are obtained for small variations in U and δ, by forming the total differentials as follow:

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = J_1 \begin{bmatrix} \Delta\delta \\ \Delta U \end{bmatrix} + J_2 \begin{bmatrix} \Delta\delta \\ \Delta U \end{bmatrix} + J_3 \begin{bmatrix} \Delta\delta \\ \Delta U \end{bmatrix} = J \begin{bmatrix} \Delta\delta \\ \Delta U \end{bmatrix} \tag{4.50}$$

$$J = J_1 + J_2 + J_3 \tag{4.51}$$

where J_1 is the NR power flow Jacobian and J_2 and J_3 are the partial derivative matrices of injected power with respect to the variables.

For TCPS : If bus i and j are PQ buses, the matrix J_2 may have 16 non-zero elements.

If bus i is a PV bus, then $\frac{\partial P_{is}}{\partial U_i} = \frac{\partial P_{js}}{\partial U_i} = \frac{\partial Q_{is}}{\partial U_i} = \frac{\partial Q_{js}}{\partial U_i} = \frac{\partial Q_{is}}{\partial U_j} = \frac{\partial Q_{is}}{\partial \theta_j} = \frac{\partial Q_{is}}{\partial \theta_i} = 0$ (4.52)

If bus j is a PV bus, then $\frac{\partial P_{is}}{\partial U_j} = \frac{\partial P_{js}}{\partial U_j} = \frac{\partial Q_{is}}{\partial U_j} = \frac{\partial Q_{js}}{\partial U_j} = \frac{\partial Q_{js}}{\partial U_i} = \frac{\partial Q_{js}}{\partial \theta_i} = \frac{\partial Q_{js}}{\partial \theta_j} = 0$ (4.53)

When more than one TCPS are installed in the network, their effects are accumulated to J_2 and non-zero elements may be more than 16.

For UPFC: If bus i and j are PQ buses, the matrix J_2 may have 9 non-zero elements.

If bus i is a PV bus, then $\frac{\partial P_{is}}{\partial U_i} = \frac{\partial P_{js}}{\partial U_i} = \frac{\partial Q_{is}}{\partial U_i} = \frac{\partial Q_{js}}{\partial U_i} = \frac{\partial Q_{is}}{\partial U_j} = \frac{\partial Q_{is}}{\partial \theta_j} = \frac{\partial Q_{is}}{\partial \theta_i} = 0$ (4.54)

If bus j is a PV bus, then $\frac{\partial P_{is}}{\partial U_j} = \frac{\partial P_{js}}{\partial U_j} = \frac{\partial Q_{is}}{\partial U_j} = \frac{\partial Q_{js}}{\partial U_j} = \frac{\partial Q_{js}}{\partial U_i} = \frac{\partial Q_{is}}{\partial \theta_i} = \frac{\partial Q_{is}}{\partial \theta_j} = 0$ (4.55)

When more than one UPFC's are installed in the network, their effects are accumulated to J_3 and non-zero elements may be more than 9.

The power flow can be solved by NR method in the normal way except the small difference in J matrix and the power mismatch equations. This derived extended NR power flow method can be shown to work well with the proposed OPF method in this thesis.

4.6 Summary

In this chapter, the static modelings of FACTS devices are developed based on their operating theory. Controlled series compensation (both TCSC and TCPS) is an effective means for power flow control in AC Transmission Systems. The efficiency of TCSC is higher in loaded lines than unloaded lines while the efficiency of TCPS is higher in unloaded lines than loaded lines. TCSC offers voltage support by generating reactive power. The reactive power exchanged by the TCPS, as a result of the quadrature voltage injection, can cause considerable voltage drops in the system. One point must be mentioned is that UPFC has three controllable parameters (I_q, U_T and ϕ_T) which have strong relationship between active and reactive power flows. The FACTS models developed would be used in OPF in the next chapter to show their applicability and effectiveness.

Chapter 5

OPTIMAL POWER FLOW WITH FACTS DEVICES BY GENETIC ALGORITHMS

5.1 Introduction

OPF is a constrained nonlinear programming problem to determine the optimal outputs of controlled generators in power system. In OPF calculations, both bus voltage and transformer tap setting are optimized with an objective to minimize total production cost within security constraints. Since OPF was introduced in 1968 [68], numerous methods have been employed to solve this problem. For example, various versions of Gradient based method, Linear programming methods [69] and Quadratic programming methods [70] have been employed.

Taranto et al. (1992) presented a Bender decomposition based solution method to solve active power OPF subproblem incorporating FACTS devices. In this method, the DC models of TCSC and TCPS are used in OPF separately. However, this method can only consider one type of FACTS device in each calculation. A comprehensive consideration of several typical FACTS devices still deserves to be researched. However, it is a DC network model based active power OPF method, an AC network model based method is also required to fit in different situations of steady-state operation and control.

The conventional optimization methods are based on successive linearization and use of first and second derivatives of objective functions and their constraint equations as the search directions. However, the conventional optimization methods suffer from three main drawbacks. Firstly, they may not be able to provide optimal solutions and may get stuck at a local optimal point. Secondly, these methods are based on the assumption of continuity and differentiability of objective function, which actually may not exist universally in a practical system. Thirdly, these methods may fail to converge well when they are applied to discrete variables. GA is proposed as a suitable method to overcome the above drawbacks.

GA, first proposed by Holland [71] in the early 1970s, is a stochastic global search method that mimics the metaphor of natural biological evaluation. GAs operate on a population of candidate solutions encoded to finite bit string called chromosomes. In order to obtain optimality, each chromosome exchanges information by using operators borrowed from natural genetic to produce the better solution. GAs differ from other optimization and search procedures in four ways [72]:

1. GAs work with a coding of the parameter set, not the parameters themselves. Therefore GAs can easily handle the integer or discrete variables.
2. GAs search from a population of points, not a single point. Therefore GAs can provide a globally optimal solution.
3. GAs use only objective function information, not derivatives or other auxiliary knowledge. Therefore GAs can deal with the non-smooth, non-continuous and non-differentiable functions.
4. GAs use probabilistic transition rules, not deterministic rules.

In this context, more control facilities may complicate the system operation. As control facilities influence each other, a good coordination is required in order to bring all devices to work together, without interfering with each other. Therefore, it becomes necessary to extend available system analysis tools, such as optimal power flow (OPF), to represent FACTS controls.

Optimal Power Flow (OPF) [73-74] generally involves a large number of parameters. The parameters can be either continuous or discrete and often include constraints in allowable values. The goal of the optimization is to find a solution that represents a global maximum or minimum. It has also been noted that OPF is a non-linear problem. The optimizations of control parameters of FACTS devices are also highly-nonlinear and non-convex problems which may lead the conventional optimization methods stuck into local minima.

This chapter presents a new genetic algorithm (GA) method to solve optimal power flow (OPF) in power system incorporating flexible AC transmission systems (FACTS). Several types of FACTS devices are considered in the chapter. Thyristor controlled phase shifter (TCPS) is used as a phase shifter, thyristor controlled series compensation (TCSC) is used to regulate the impedance of transmission lines and Unified Power Flow Controller (UPFC) is used to control the active power, reactive power and voltage simultaneously. The specified needs for power flow controls are related to use of FACTS devices to be included in the contingency-constrained OPF problem. A typical example of power flow control is that some predefined transmission lines should operate at specified power flow values. They are proposed to be formulated as a set of equality constraints to be implemented in the proposed OPF.

In the solution process, GA, coupled with full AC power flow, selects the best regulation to minimize the total generation fuel cost and keep the power flows within their security limits. The optimization process with GA is presented with case study examples using IEEE test systems to demonstrate its applicability. The results are presented to show the feasibility and potential of this new approach.

5.2 Optimal Power Flow with FACTS device

There are two categories of objective functions in OPF, the generation cost objective function and the real power losses objective function.

5.2.1 Economic objective (Active OPF)

Generation cost is the objective function of active power flow optimization. Minimization of the generation cost is formulated as follows:

$$F_{fuel} = \sum_{i \in NG} C_i(P_{Gi}) = \sum_{i \in NG} \alpha_i P_{Gi}^2 + \beta_i P_{Gi} + \gamma_i \tag{5.1}$$

where $C_i(P_{Gi})$ is the operating cost of producing P_{Gi} units of real power at the generating plant at bus i. α_i, β_i and γ_i are the cost coefficients of generator i. NG is the total number of generator. The constraints considered are power flow equations, specified needs for power flow controls, reactive power flow equations of UPFC branch, active power flow limits on all branches and limits on all control variables. The variables are defined as follow:

- Type 1 control variable – active optimal power flow dependent (x_c, ϕ, U_T and φ_T)
- Type 2 control variable – reactive optimal power flow dependent (I_q)

- Type 3 control variable – active and reactive optimal power flow dependent (I_q, U_T and φ_T)

As defined, the control variables include the type 1 and type 3 of control variables. During this optimization, the reactive power control variables type 2 is kept constant.

5.2.2 Transmission losses objective (Reactive OPF)

System transmission power loss is the objective function of reactive power flow optimization. Minimization the transmission active power losses is formulated as follows:

$$\sum_{i \in NB} P_{loss,i} = \sum P_{loss} + \sum P_{loss,TCSC} + \sum P_{loss,TCPSR} + \sum P_{loss,UPFC} \tag{5.2}$$

The objective function of RPOPF is to minimize the total active power transmission losses. The constraints considered are the power flow equations, reactive branch power flow limits and limits on all control variables. During this optimization, the active power control variables are kept constant.

$$\sum P_{loss} = \sum_{i=1}^{NB} G_{ij}\left[V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}\right] \tag{5.3}$$

where $P_{loss,TCSC}$, $P_{loss,TCPSR}$, $P_{loss,UPFC}$ are represented at (4.11), (4.26) and (4.47) respectively.

In this thesis, active power OPF is considered since it produces higher impact than reactive power OPF from the cost point of view.

5.3 The Classification of Control Variables

In the steady state operation of power systems, the major functions of TCSC and TCPS are to control the active power flow sharing among the transmission lines. We can, therefore, classify the controllable parameters x_c (TCSC) and ϕ (TCPS) as active related control variables. Static VAR compensators are capable of controlling the voltages of buses to which they are connected. Obviously, their output reactive powers can be classified as reactive power related variables. UPFC can control the voltages of related buses and the active and reactive power flows on a transmission line simultaneously. UPFC has three controllable parameters. The exciting transformer reactive current I_q is related with the voltage and reactive power flows and can be classified as reactive power related variable. For the magnitude and phase of the boosting transformer inserted voltage (U_T and φ_T), it is difficult to classify them as active power related variables or reactive power related variables. Both of them have strong relations with the active and reactive power flows. This means that they form the third type of control variables, which are both active and reactive power related variables.

	Objective	Controls	Constraints
Active OPF	Minimum the generation cost	➢ Real Power generations ➢ FACTS control x_c, ϕ, U_T and φ_T	➢ Power flow equation ➢ MW Branch Flow ➢ Specified MW flow constraint ➢ Reactive power equality constraint of UPFC
Reactive OPF	Minimum active power transmission loss	➢ Reactive Power generations ➢ FACTS control U_T, I_q and φ_T.	➢ Power flow equation ➢ MVar Branch Flow ➢ Voltage magnitude ➢ Active power equality constraint of UPFC

5.4 Equality and Inequality Constraint

5.4.1 Equality Constraints

The equations (4.15)-(4.18) and (4.41)-(4.44) are the general form of the injected power source. It shows that the derivatives:

$$\frac{\partial P_{is}}{\partial \theta_i} = \frac{\partial P_{is}}{\partial \theta_j} = \frac{\partial Q_{is}}{\partial V_i} = \frac{\partial Q_{is}}{\partial \theta_j} \approx 0 \tag{5.4}$$

It is relatively small for realistic systems and therefore the source of S_{is} and S_{js} can be treated as constant generation or loads in each load flow iteration. Moreover, the sensitivities of the injected power with respect to the magnitude and angles of voltage at the nodes i and j are smaller than the corresponding elements in the ordinary Jacobian matrix of power flow equation. It can be concluded that in power mismatch equations, the TSCS and UPFC injected powers can be treated as loads or generations within each iteration. Therefore, the Power flow equations, used as equality constraints, are as follows:

$$P_{Gi} + P_{is,FACTS} - P_{Di} - V_i^2 \sum G_{ij} - V_i \sum V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}\right) = 0 \qquad \forall i \in N_{B-1} \tag{5.5}$$

$$Q_{Gi} + Q_{is,FACTS} - Q_{Di} + V_i^2 \sum B_{ij} - V_i \sum V_j \left(B_{ij} \cos\theta_{ij} - G_{ij} \sin\theta_{ij}\right) = 0 \qquad \forall i \in N_{PQ} \tag{5.6}$$

where N_i = set of numbers of buses adjacent to bus i, including bus i

N_{B-1} = set of numbers of total buses, excluding slack bus

N_{PQ} = set of PQ-bus numbers

Using this method, $P_{is,FACTS}$ and $Q_{is,FACTS}$ will be computed after each iteration but it is not necessary to derive the Jacobian matrix at each iteration. Thus, the symmetry property of bus admittance matrix, Y_{BUS}, is maintained. P-Q coupled flow can be used without modification.

5.4.2 Inequality Constraint

5.4.2.1 Parameter of FACTS devices Constraints

The angle and magnitude of the voltage and the injected current, I_q of UPFC, the angle and tap setting of TCPS and the reactance of TCSC are the control parameters of the FACTS devices (i.e. $x_{FACTS}^{\min} \le x \le x_{FACTS}^{\max}$).

$$TCSC \left\{ \quad x_c^{\min} \le x_c \le x_c^{\max} \right. \tag{5.7}$$

$$TCPS \left\{ \phi^{\min} \le \phi \le \phi^{\max} \right. \tag{5.8}$$

$$UPFC \left\{ \begin{array}{ll} U_T^{\min} \le U_T \le U_T^{\max} & (5.9) \\ \varphi_T^{\min} \le \varphi_T \le \varphi_T^{\max} & (5.10) \\ I_q^{\min} \le I_q \le I_q^{\max} & (5.11) \end{array} \right.$$

5.4.2.2 Other Inequality Constraints

Other inequality constraints include active and reactive power generation, power carrying capacity of transmission line and bus voltage.

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \tag{5.12}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \tag{5.13}$$

$$V_i^{\min} \le V_i \le V_i^{\max} \tag{5.14}$$

5.5 Problem Formulation

In this project, a new GA approach to solve the optimal power flow control problem with FACTS is proposed. UPFC can provide the necessary functional flexibility for optimal power flow control. This approach allows the combined application of phase angle control with controlled series and shunt reactive compensation. The objective is to minimize the total cost of operating the spatially separated generating units subject to the set of equations that characterize the flow of power through the system and all operational and security constraints. The OPF problem is solved in FACTS and the variable parameters of FACTS devices are considered. Simulation studies are carried out in IEEE test systems to show the effectiveness of the method. The optimal power flow problem in flexible AC transmission systems is therefore expressed as follows:

$$Min \quad \sum_{i \in NG}\left(a_i P_{Gi}^2 + b_i P_{Gi} + c_i\right) + \sum_{i \in PQ} \lambda\left(V_i - 1.0\right)^2 \tag{5.15}$$

$$s.t. P_{Gi} + P_{iu} + P_{ip} - P_{di} - \sum_{j \in N} U_i U_j Y_{ij} \cos\left(\theta_{ij} + \delta_j - \delta_i\right) = 0 \qquad \forall i \in N \tag{5.16}$$

$$Q_{Gi} + Q_{iu} + Q_{ip} - Q_{di} + \sum_{j \in N} U_i U_j Y_{ij} \sin\left(\theta_{ij} + \delta_j - \delta_i\right) = 0 \qquad \forall i \in N \tag{5.17}$$

$$g_Q(U_T, \varphi_T, U, \delta) = 0 \tag{5.18}$$

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \qquad \forall i \in NG \tag{5.19}$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \qquad \forall i \in NG \tag{5.20}$$

$$T_{Gi}^{\min} \le T_{Gi} \le T_{Gi}^{\max} \qquad \forall i \in NT \tag{5.21}$$

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max} \qquad \forall i \in N \tag{5.22}$$

$$|I_i| \le I_i^{\max} \qquad \forall i \in NB \cup NT \tag{5.23}$$

$$0 \le U_{Ti} \le U_{Ti}^{\max} \qquad \forall i \in NU \tag{5.24}$$

$$-\pi \le \varphi_{Ti} \le \pi \qquad \forall i \in NU \tag{5.25}$$

$$x_{ci}^{\min} \le x_{ci} \le x_{ci}^{\max} \qquad \forall i \in NU \tag{5.26}$$

$$\phi^{\min} \le \phi \le \phi^{\max} \qquad \forall i \in NU \tag{5.27}$$

where

N is set of bus indices;

NG is set of generation bus indices;

NT is set of transformer indices;

NB is set of transmission line indices;

NU is set of UPFC indices

Y_{ij} and θ_{ij} are magnitude and phase angle of element in admittance matrix;

P_{Gi} and Q_{Gi} are active and reactive power generations at bus i;

P_{di} and Q_{di} are active and reactive power demands at bus i;

P_{iu} and Q_{iu} are injected active and reactive powers at bus i due to UPFC;

P_{ip} and Q_{ip} are injected active and reactive powers at bus i due to TCSC;

V_i and δ_i are voltage magnitude and angle at bus i;

I_i is current magnitude at transmission line i;

U_T is inserted voltage source magnitude of UPFC i;

φ_T is inserted voltage source angle of UPFC i.

X_c is the vector of TCSC controllable parameters

ϕ is the vector of TCPS controllable phase angles

$g_Q(U_T, \varphi_T, U, \delta)$ is the set of UPFC line reactive power flow equations (equation (4.34 or 4.36)).

It is difficult to solve this problem formulation directly. However, it is obvious that if the variables x_c, U_i , φ_i and I_q in the above formulation are defined, the optimal power flow in flexible AC transmission systems is the same as a conventional full AC OPF problem, which can be solved by a Han-Powell algorithm with a variable-reduction-procedure [75]. In other words, we can treat the OPF problem in FACTS with defined variables U_i, φ_i, x_{ci} and as a sub-set, and solve the OPF problem by the Han-Powell algorithm with a variable-reduction-procedure. The set of parameters of TCSC, TCPS and UPFC are considered as inputs and the cost of the network as outputs. The output of the OPF is the objective function to be minimized. The classical gradient method, that requires the derivative of the function, cannot be applied. Heuristic methods, that require only the value of the objective function, may be adapted to the current problem. It has been noted that the OPF problem with FACTS may be a non-convex problem and it is not possible to guarantee that the Two-stage LP approach will converge. With the big size of the search space, genetic algorithm is proposed.

5.6 Methodology Implementation of Genetic-Based Algorithm

5.6.1 Genetic algorithm

The general genetic algorithm, as well as the coding specific to this problem is presented in this section.

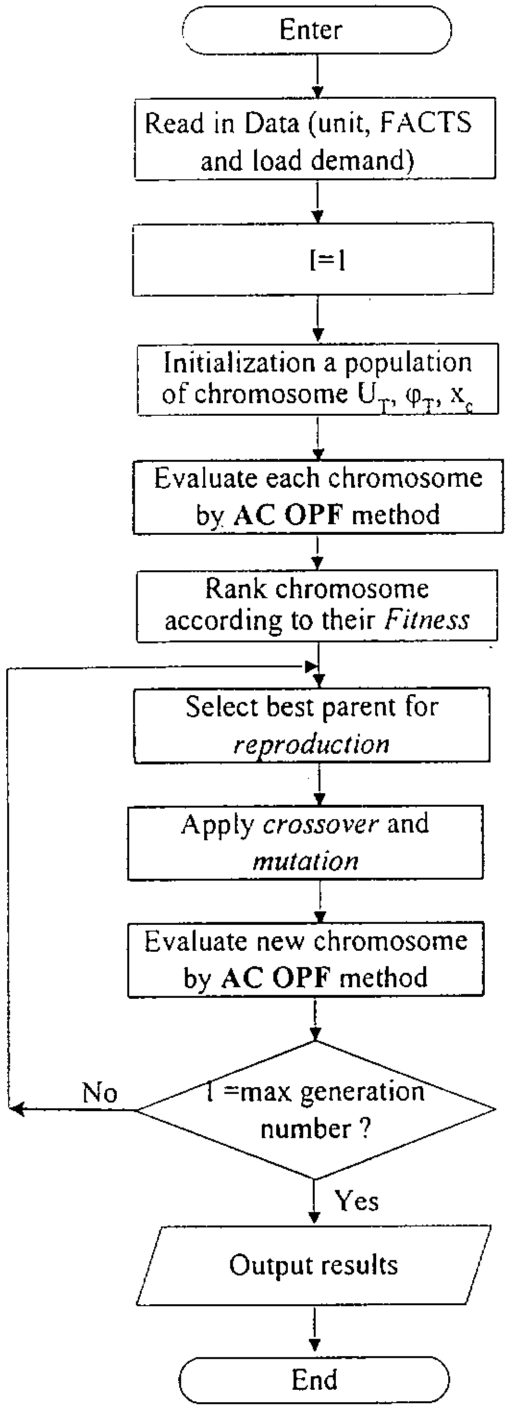


Figure.5.1 Flowchart of proposed method of optimization by a GA approach

This section explains the design and implementation of the genetic based algorithm. The implementation is based on the genetic algorithm reviewed in the previous chapter.

5.6.2 Solution Representation

As the control parameters are continuous, the binary bit string representation will fail to reflect the continuous nature of the loadings. The use of floating-point numbers to represent each parameter is being proposed. The lengths of the strings are given by the number of parameters. By this representation method, the string length is at its minimum and is much smaller than that based on binary bits. This method also avoids the need to convert binary numbers into their decimal equivalents.

Candidate solutions to OPF problem are represented by fixed length chromosomes. Each gene in a chromosome is a real number representing the control variable of FACTS, Thus, the length of the chromosomes is the total number of control variable of FACTS defined in the OPF problem. A real number of a binary bit is used because of the continuous power loading within the operating limits.

A floating-point number coding method is incorporated for solving the OPF problem. Floating-point representation of the control setting of the FACTS devices is adopted. By this method, it would eliminate any discretisation error, which may be introduced in the decoding process.

5.7 Genetic Algorithm

A genetic algorithm is governed by three factors: the mutation rate, the crossover rate and the population size. GAs are search processes, which can be applied to unconstrained optimization problems. Constraints may be included into the fitness function as added penalty terms.

5.7.1 Coding Scheme

The control variables of the FACTS devices have been treated as discrete. In most existing Optimal Power Flow (OPF) algorithms, discrete variable controls are treated as continuous variables and rounded off to their nearest discrete steps. This procedure gives acceptable solutions provided the step sizes for the discrete controls are sufficiently small.

Since the control variables of the FACTS devices are continuous values (especially the control parameter of UPFC), it is impossible to encode the parameter in binary coding where discretation error will occur. The real-coded GAs should have an advantage over binary coded GAs in exploiting continuities in optimization function. Moreover, the real-code schema can propagate and grow at a higher rate in successive generations than the binary-code schema. An additional merit of real coding is the equality constraints can be incorporated and satisfied directly.

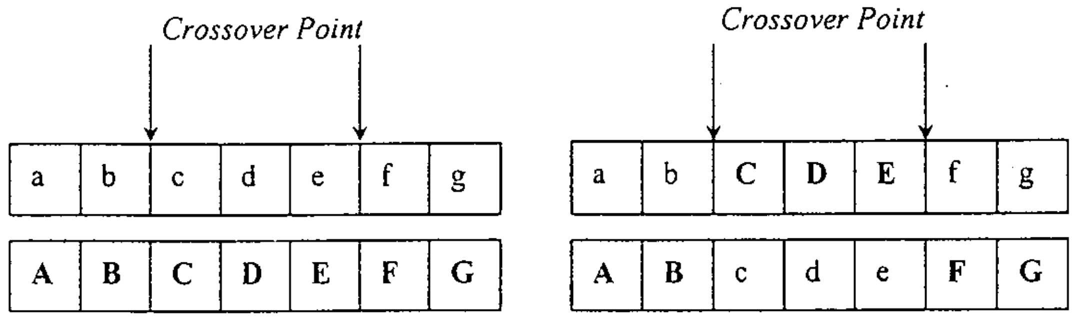
The first step of GA is the parameter encoding (*i.e.*, the representation of the problem). The encoding must be carefully designed to utilize the GA's ability to efficiently transfer information between chromosome strings and objective function of problem. The proposed approach uses a conventional OPF problem as a black box, the optimal value of which is the fitness value of GA. The encoded parameter is the variables x_c, ϕ, U_i, φ_i, where $x_c^{\min} \le x_c \le x_c^{\max}$, $\phi^{\min} \le \phi \le \phi^{\max}$, $0 \le U_i \le U_i^{\max}$, $-\pi \le \varphi_i \le \pi$ respectively. In the present work, the basic GA algorithm is adopted and the FACTS control settings are coded in chromosomes using floating-point algorithm. The proposed floating method is suitable for this optimization problem involving parameters with continuous values. A chromosome is coded by a string of *N* floating-point numbers.

5.7.2 Reproduction

Reproduction or selection is a process in which individual chromosomes are copied according to their fitness. The more fitness chromosomes would mean more changes to be copied into the next generation. The biased roulette wheel is used to archive a Darwinian survival of the fittest. In roulette wheel selection, each chromosome in the population has its interval. The size of each interval corresponds to the fitness value of individual and can be found from the ratio of $f / f_i \Sigma$, where $f \Sigma$ is a sum of fitness in population. To select a chromosome, a random number is generated in the interval [0, f Σ] and the chromosome whose segment spans the random number is selected. This process is repeated until the desired number of chromosomes is selected.

5.7.3 Crossover and Mutation

Crossover is a process that each individual will exchange information to explore new structure of chromosome. The crossover operator in the algorithm is implemented by two-point crossover. Although one-point crossover is generally used, more diversity in the population of chromosomes can be achieved by two-point crossover. The advantage is that every gene in chromosome produced by means of two-point crossover will always satisfy the operating limit constraint of active power generation and FACTS control variable. The crossover process will be initiated when the random number generated from [0, 1] is less than the defined probability of crossover. A crossover mask, the same length as the chromosome, is created randomly. If the mask bit is 1, the bit of parents that corresponds to the bit of the mask string will swap with each other, while the others stay unchanged.



Parent chromosomes children chromosomes

Figure 5.2 Mechanism of two-point crossover

Although reproduction and crossover are applied to chromosome in each generation to obtain a new set of better solutions, occasionally they may become overzealous and lose some useful information (1 or 0 at particular positions). To protect these irrecoverable losses, mutation is applied. Mutation is random alteration of bit of string with small probability called probability of mutation. At each bit position of chromosome, the bit will be changed from 1 to 0 or vice versa if a uniformly random number from [0,1] is less than probability of mutation..

Under the present real number coding scheme, the value of a selected gene of a chromosome is replaced by a value generated from a uniform distribution between $x_{FACTS}^{\min} \le x \le x_{FACTS}^{\max}$. Such a mutation method guarantees the satisfaction of operating limits in the chromosomes produced. For example, a gene representing x_c with an operating limit x_c^{min} and x_c^{max} will have a value anywhere between x_c^{min} and x_c^{max} after mutation.

5.7.4 Elitism

To guarantee that the new population is better, elitism is used in this paper. Elitism is a technique used to save early solutions by ensuring the survival of the best chromosome in each population. In each generation, the best chromosome will be passed to the next generation without any change on it.

5.7.5 Fitness Function

The performance of each string is evaluated according to its fitness. Fitness is used to provide a measure of how individuals perform in the problem domain. It is closely related with the objective function value in the optimization. In the case of this minimization, the fitness function adopted is given as:

$$Fitness = \frac{M}{1 + H + \lambda C^2} \tag{5.28}$$

M is the maximum possible cost of generation. H is the total the generation cost and λ is the penalty factor. The value of λ is set to an arbitrary number. Penalty cost has been added to discourage solutions, which violate the binding constraints. Finally, the penalty factor is tended to zero. C is the bus voltage magnitude ($0.95p.u. \leq V_i \leq 1.05p.u.$) add them as the quadratic penalty terms to the objective function to form a penalty function.

5.7.6 Termination criteria

Since GA is a stochastic optimization method, it is difficult to formally specify convergence criteria [76]. In this thesis, GA procedure will be terminated when the fitness function is less than 0.01 within 20 generations.

5.8 Genetic Algorithm for OPF with UPFC

The genetic algorithm to solve the optimal power flow with UPFC can be summarized as follow:

Step 1. Initialize the population by randomly generating i number of chromosome (x_c, U_T, φ_i), then solve the OPF problem for each chromosome and evaluate its fitness value

Step 2. For M number of generations, generate a new population from the present population using the following steps:

2.1.1 Scale the fitness of each chromosome using the fitness function.

2.1.2 Copy the chromosomes with the best fit to the new population.

2.1.3 The remaining offsprings can be generated by randomly selecting two parents with probability proportional to its corresponding scaled fitness. With mutation probability, apply the mutation process to the offspring until new population is filled.

2.1.4 Solve the OPF problem for all chromosome and re-evaluate the fitness value using the fitness function.

5.9 Numerical Results and discussion

The IEEE 30-bus system is used to test the effectiveness of the proposed method. Six cases have been studied. Case 1-5 is the GA-OPF with FACTS devices, while Case 6 is conventional OPF without FACTS. In the case, line 3, 18 and 28, are installed with different type of FACTS devices (Table 5.1). Three FACTS line power flows are assumed to be controlled at specified values. Their predefined power flow control is set on different cases. The initial values of the controllable FACTS devices parameters are set at zero. The main optimization results are listed in Table 5.2. Figure 5.3 show GA – AOPF IEEE 30 buses convergence (Piecewise Quadratic Cost Curve) Case 1

From these tables and figures, several points can be observed. First, when the power flow control constraints and the (N-1) security constraints are considered in OPF, the total generation cost of the test system is higher than the normal OPF

The network generation data, the branch impedance, loads and other necessary data are shown in Appendix A.

GA parameters

The population size = 100

Probability of crossover and method = 0.9; 2 point crossover

Probability of mutation = 0.01

Termination criteria for variable = 0.001

Termination criteria for objective function = 0.001

Maximum iteration = 1200.

The GA-OPF was run 100 times on the IEEE 30-bus system. Of the 100 trials conducted, 100 feasible solutions were returned with an average solution time of 24 seconds required. The average cost was $804.307, with a minimum of $802 for Case 1.

	Type of FACTS Device Installation / Line flow Constraint (p.u.)		
	Line 3	Line 18	Line 28
Case 1	TCSC (Line 3 = 0.30 p.u)	TCPS (Line 18 = 0.25 p.u.)	UPFC (Line 28 = 0.15 p.u.)
Case 2	TCSC (Line 3 = 0.30 p.u)	UPFC (Line 18 = 0.25 p.u.)	UPFC (Line 28 = 0.15 p.u.)
Case 3	TCPS (Line 3 = 0.45 p.u.)	UPFC (Line 18 = 0.25 p.u.)	UPFC (Line 28 = 0.20 p.u.)
Case 4	TCPS (Line 4 = 0.45 p.u.)	UPFC (Line 17 = 0.15 p.u.)	UPFC (Line 27 = 0.10 p.u.)
Case 5	UPFC (Line 3 = 0.45 p.u.)	UPFC (Line 18 = 0.25 p.u.)	UPFC (Line 28 = 0.15 p.u.)
Case 6	No FACTS device is installed		

Table 5.1 The installation of FACTS device in IEEE-30 bus system

	Line 3	Line 18	Line28
Case 1	$X_c = -0.0384$	$\phi = 0.1470^{\circ}$	$U_T = 0.0194$
			$\phi_T = -45.602^{\circ}$
Case 2	$X_c = -0.0565$	$U_T = 0.0197$	$U_T = 0.0164$
		$\phi_T = -77.025^{\circ}$	$\phi_T = -15.080^{\circ}$
Case 3	$\phi = 0.9406^{\circ}$	$\phi = 0.1470^{\circ}$	$U_T = 0.0186$
			$\phi_T = -33.080^{\circ}$
Case 4	$\phi = 0.9412^{\circ}$	$U_T = 0.0166$	$V_T = 0.0156$
		$\phi_T = -64.02^{\circ}$	$\phi_T = -22.025^{\circ}$
Case 5	$U_T = 0.0177$	$U_T = 0.0199$	$U_T = 0.0155$
	$\phi_T = 7.542^{\circ}$	$\phi_T = -76.080^{\circ}$	$\phi_T = -10.246^{o}$
Case 6	Conventional OPF without FACTS device -		

Table 5.2 Results of FACTS devices

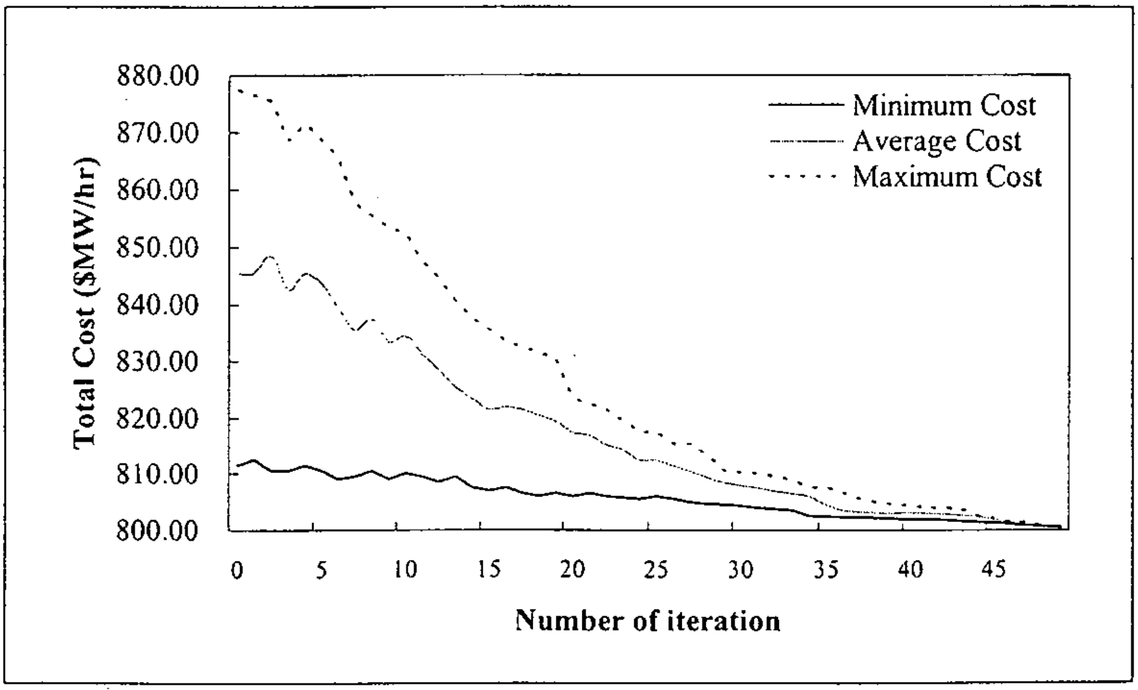


Figure 5.3 GA – AOPF IEEE 30 buses convergence (Piecewise Quadratic Cost Curve) Case 1

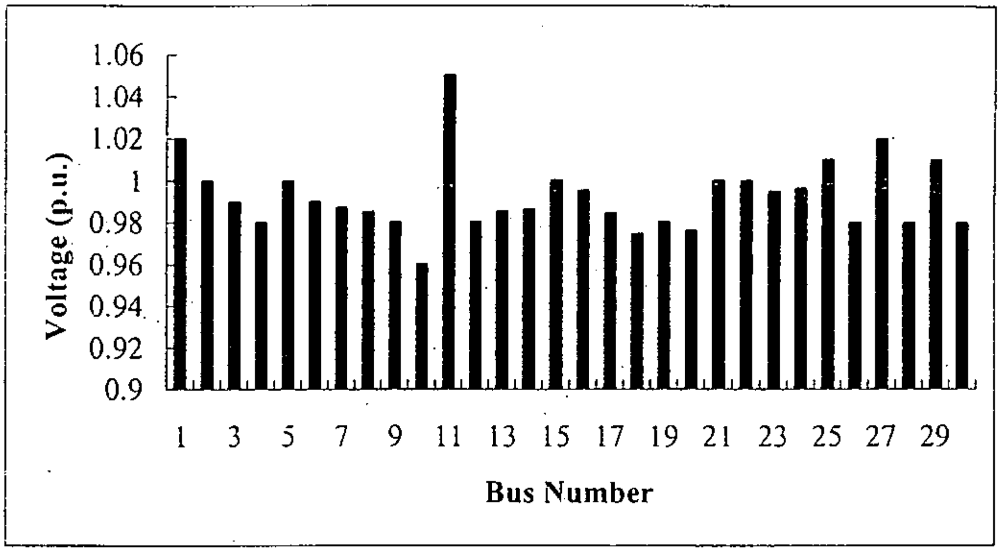


Figure 5.4 GA-OPF with IEEE 30 bus - Voltage profile of Case 1

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
P_{G1}	1.775	1.775	1.778	1.783	1.778	1.705
P_{G2}	0.488	0.488	0.488	0.488	0.488	0.485
P_{G5}	0.213	0.213	0.213	0.213	0.213	0.176
P_{G8}	0.210	0.210	0.210	0.213	0.209	0.300
P_{G11}	0.119	0.118	0.118	0.119	0.118	0.139
P_{G13}	0.120	0.120	0.120	0.120	0.120	0.120
ΣP_{gen}	2.925	2.924	2.927	2.936	2.926	2.924
ΣP_{loss}	0.09057	0.09023	0.09351	0.1021	0.09217	0.0901
Σ Cost	800.51	800.37	801.42	804.38	800.94	803.87

Table 5.3 The results of GA-OPF with IEEE 30 buses

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Shortest	120.02	125.32	130.56	132.53	142.23	50.72
Average	132.69	134.23	138.01	144.47	156.34	54.28
Longest	145.46	146.89	146.53	158.56	165.02	57.89

Table 5.4 Computation time (seconds) of the GA-OPF with IEEE 30 buses

Six cases have been studied. It is observed that the total generation cost of the test system with FACTS devices is higher than the normal system without FACTS controls. This is because more constraints are considered in the modified OPF problem.

The final result is shown in Table 5.3. Without FACTS devices, the cost of OPF is \$803.87. With FACTS device, the cost of OPF is \$804.38 (Case 4). The results show that the generation cost is increased with FACTS device application when the parameter constraint of UPFC is included.

The objective in improving the voltage profile is to adjust the voltage at supply or load nodes as close to the nominal 1.0 p.u. voltage as possible while minimising the generation cost. From Figure 5.4, the voltage profile is close to 1.0 p.u. In addition, the power flow control objectives can be met by different FACTS devices, and the final generation cost for different cases (case 1, 2, 3 and 5) is similar.

Since the exact reactive power flow equation of UPFC lines is introduced into this active power OPF, the reactive power flow of UPFC lines can also be controlled at pre-specified values obtained from reactive power OPF. Many tests have been done for different initial FACTS values. The results show that the introduction of this reactive power constraint of FACTS line can provide the uniqueness of the controllable UPFC parameter solution.

The computation time of GA is summarized in the Table 5.4.The time stated is the computation time required on a PC 586 1.6GHz machine. The table shows that Case 6 is the fastest cases because FACTS control parameters are not included. Although it is known that GA is much time-consuming compare with the traditional method, it has been found that it converges to the global optimum.

5.10 Summary

A proposed hybrid GA approach is implemented to solve the optimal power flow problem with FACTS devices. The proposed method uses the injected power model of FACTS devices in conjunction with AC optimal power flow to exploit the new characteristic of FACTS devices. Case studies on IEEE test system show the potential and effectiveness for application of GA to determine the FACTS control parameter controls. GA-OPF problem is formulated as a non-linear optimization problem. The reactive power equation of UPFC is introduced in OPF. It is shown that this may increase the controllability of the system and provide wider operating margin as well as better voltage security with more reserve capacity. GA effectively finds the optimal results by using the conventional OPF method as a black box. It shows that such a hybrid GA approach is able to deal with non-smooth, non-continuous, non-differentiable and non-convex optimization problems, such as the optimal power flow problem with FACTS. With deregulation, congestion management problems are becoming more common. FACTS devices optimal setting calculation may play an increasingly important role in modern power system operation and control.

The application of GA to various power system engineering problems is certainly useful. However, the results show that the use of GA in OPF greatly retards the solution speed. It is truly believed that every method has its advantage and disadvantage. Although GA is a very time-consuming method, it is still worthwhile to investigate its potential. Since planning and analysis of power system is an offline action, computation time is not a critical factor to consider. It is concluded that GA is not suitable for real-time operation, but it can find the global optimum and may provide high accuracy results.

Chapter 6

Conclusion

The main contribution of this research is to develop using Genetic Algorithm (GA) to solve the optimal capacitor allocation with harmonic distortion and the optimal control setting of FACTS devices in optimal power flow (OPF). Case studies on IEEE test systems demonstrate the potential for application of GA to determine the control parameter of the power flow controls with FACTS. It is shown that the FACTS device would not provide significant cost saving since cost depends mainly on the active power flow. However, it can increase the controllability and flexibility of the system; it can provide wider operating margin and improved voltage stability with higher reserve capacity. As deregulation and contract path are becoming more important, FACTS devices play an increasingly important role in such power system operation.

In conclusion, the following are the main findings and recommended future work of this research work.

6.1 Summary

1. The technology of FACTS devices, especially UPFC, provides huge potential opportunities for improved transmission line power flow. UPFC can be used to control the active and reactive power flows, whereas TCSC and TCPS can control the active power flow.

2. In GA, binary representation is replaced by floating point representation since the latter can represent continuous variable. It uses for real parameter optimization problems with no discretation error since it does need to encode and decode the variable. As the control variable in UPFC is continuous, it is more than suitable to use this approach.

3. It is hard to determine the value of control parameter setting of GA (crossover rate, mutation rate and population size). Although the effect of change the control parameter is known, it does not help us in determining the values. This is because they typically interact with one another nonlinearly.

4. In the capacitor placement problem, the objective function of capacitor placement is to reduce the power loss and keep bus voltages and total harmonic distortion (HDF) within prescribed limits with minimum cost. The constraints are voltage limits and maximum harmonic distortion factor, with the harmonics taken into account.

5. GA is a powerful optimization tools which improve the harmonic distortion is quite attractive. Moreover, it can reduce the active power losses. It can concluded that GA method is suitable for discrete value optimization problem such as capacitor allocation and

the consideration of harmonic distortion limit may be included with an integrated approach in the GA.

6. The mathematical modeling of FACTS device is developed. TCSC, TCPS and UPFC are wholly developed. The efficiency of TCSC control is higher in loaded lines than in unloaded lines whereas the efficiency of TCPS control is higher in unloaded lines than loaded lines.

7. In GA-OPF, the objective is to minimize the total production cost. The control variables are the first and third type of control variables, which include the conventional OPF control variables and FACTS control variables. The constraints include the active power flow constraint of specified lines and reactive power flow constraint of UPFC line. Genetic Algorithm solves this new formulated GA-OPF. However, in GA-ROPF, the objective is to minimize the total system losses and voltage deviation. The control variables are the second and third type of control variable, which include the conventional OPF control variable and FACTS control variable. The constraints include the reactive power flow constraint of specified lines and active power flow constraint of UPFC line

8. Power flow calculation is the basis for the steady and dynamic state analysis of the power system. However, due to the strong coupling relationship between active and reactive power in the bus line with FACTS devices, the decoupled power flow model is not appropriable to represent this scenario. Therefore, an extended Newton-Raphson power flow with four

typical FACTS device is introduced. At present the aim of active and reactive power optimization of public power systems is solved as a decoupled problem. Decoupled power flow solutions are extremely popular because of lesser storage and faster solution speed as compared to coupled power flow solution. However, it is generally believed that decoupling cannot be used near critical loading condition. Moreover, since the strong P-Q relationship of UPFC, coupled method has higher accuracy than the decoupled method. The decoupling of the optimization problem is only valid for weakly loaded network and it will probably fail to converge at the load flow iterations for highly loaded network. Separated solutions for economic load dispatch and optimal power flow are based on network specific characteristics concerning the X/R ratio.

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_{P\delta} & J_{PV} \\ J_{Q\delta} & J_{QV} \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta V \end{bmatrix}$$

where $J_{P\delta}$, J_{PV}, $J_{Q\delta}$ and J_{QV} are the usual Jacobian submatrices. Under normal loading condition the effect of J_{PV} and $J_{Q\delta}$ submatrices is insignificant. Hence, decoupled load-flow formulations neglecting these submatrices are feasible for moderately loaded power system. However, as system becomes under heavy loaded with the utilization of FACTS devices, especially the UPFC, these submatrices cannot completely ignored since there is highly physical P-Q coupling existing in power system network.

6.2 Future Work

The following work directions are recommended for future research.

1. As mentioned earlier, it requires much effort to find the best parameter setting in GA. With higher population size of the chromosomes, more computation time is required. To reduce the computation time, it is necessary to consider how to reduce the population size to as small as possible. Since high quality chromosomes are required, virtual population approach may be considered for introduction to improve performance. To eliminate premature convergence and to achieve robustness, it is also necessary to consider the diversity of chromosomes.

2. With open access and deregulation of power systems, FACTS devices are expected to play increasing roles in the control of active and reactive power flows with OPF schemes. The FACTS models are developed with hybrid GA-OPF tested on moderate size systems in this research work. These problems would need to be assessed on large scale networks' operation. Hence further research in such directions would be of much interest and very challenging.

Reference

1. Breuer, G. "Flexible AC Transmission Systems: Technology for the Future," Proceedings of 20th Annual Electrical / Electronics Insulation Conference, Boston, MA, October 7-10, 1991

2. Taranto. G.N., Pinto, L.M.V.G. and Pereira, M.V.F. "Representation of FACTS devices in power system economic dispatch", IEEE Trans. On Power Systems, PWRS-7, No.2, May 1992, pp. 572-576.

3. Papic, I. Zunko, P. and Povh, D. "Basic control of Unified Power Flow Controller " IEEE Trans. on Power Systems, Vol. 12, No. 4, November 1997, pp. 1734- 1739.

4. Hingorani, N.G. "Flexible AC Transmission", IEEE Spectrum, April 1993, pp. 40-45

5. Keri, A. J. F. Lombard, X. and Edris, A. A. "Unified Power Flow Controller (UPFC): Modelling and Analysis", IEEE Transaction Power Delivery, Vol. 14, No. 2, April 1999, pp. 648-654.

6. Huneault, M. and Galiana, F. D. "A Survey of the Optimal Power Flow Literature," IEEE Trans. Power Systems, Vol. 6, No. 2, 1991, pp. 762-770

7. Gotham, Douglas. J. and Heydt, G.T, "Power Flow Control and Poewr Flow Studies for Systems with FACTS devices", IEEE Transaction on Power Systems, Vol.13, No.1, Feb 1998

8. Zhang, B.M. and Ding, Q.F. "The development of FACTS and its control", Fourth International Conference on Advances in Power System Control, Operation & Management, Nov. 11-14, 1997, Hong Kong, China.

9. Carpienter, J. "Contribution e l'étude do Dispatching Economique," Bulletin Society Française Electriciens, Vol. 3, August 1962.

10. Wood, A. J. and Wollenberg, B. F. "Power Generation Operation and Control", New York, NY: John Wiley & Sons, Inc., 1996, pp. 39,517.

11. Dommel, H. W. and Tinney, W. F. "Optimal Power Flow Solutions," IEEE Transactions on Power Apparatus and Systems, Vol. PAS-87, October 1968, pp.1866-1876.

12. Sun, D. I. Ashley, B. Brewer, B. Hughes, A. and Tinney, W. F "Optimal Power Flow by Newton Approach," IEEE Transactions on Power Apparatus and Systems, Vol. PAS-103, October 1984, pp. 2864-2880.

13. Alsac, O. Bright, J. Prais, M. and Stott, B. "Further Developments in LP-Based Optimal Power Flow," IEEE Transactions on Power Systems, Vol. 5, No. 3, August 1990, pp. 697-711.

14. Wu, Y. Debs, A. S. and Marsten, R. E. "Direct Nonlinear Predictor-Corrector Primal-Dual Interior Point Algorithm for Optimal Power Flows," 1993 IEEE Power Industry Computer Applications Conference, pp. 138-145.

15. Lai, L. L. "Intelligent System Applications in Power Engineering, Evolutionary Programming and Neural Networks" New York, Wiley 1998

16. Yuryeich, J. and Wong, K.P. "Evolutionary Programming Based Optimal Power Flow Algorithm," IEEE Transactions on Power System, Vol.14, No.4, November 1999, pp.1245-1250

17. Tsoi, E, Wong, K.P. and Fung, C.C. "Hybrid GA/SA algorithms Evaluating Trade-off Between Economic Cost and Environmental Impact in Generation Dispatch", International Conference on Evolutionary Computing, Nov. 1995 , pp. 132-137

18. Huneault, M. and Galiana, F. D. "A Survey of the Optimal Power Flow Literature," IEEE Transactions on Power Systems, Vol. 6, No. 2, May 1991, pp.762-770.

19. Tinney, W. F. and Hart, C. E. "Power Flow Solution by Newton's Method," IEEE Transactions on Power Apparatus and Systems, Vol. PAS-86, No. 11, November 1967, pp. 1866-1876.

20. Geoffrion, A.M. "Generalized Benders decomposition", Journal of Optimization Theory and Applications, 1972, 10(4), pp.237-260

21. Noroozian. M. and G. Andersson, "Power flow control by use of controlled series components", IEEE Trans. on Power Delivery, PWRS-8, No.3, July 1993, pp.1420-1429.

22. Noroozian, M. Ängquist, L. Ghandhari, M. and Andersson, G. "Use of UPFC for Optimal Power Flow Control," IEEE Transactions on Power Delivery, Vol.12, No.4, October 1997, pp.1629-1634

23. Fuerte-Esquivel, C.R. and Acha, E. "Unified power flow controller: a critical comparison of Newton-Raphson UPFC algorithms in power flow studies," IEE Proc.-Gener. Transm. Distrib., Vol.144, No.5, September 1997, pp.437-444

24. C.R. Fuerte-Esquivel and E. Acha, "A Newron-type Algorithm for the control of power flow in electrical power network," IEEE Transactions on Power Systems, Vol.12, No.4, November 1997, pp.1474-1480

25. Lai, L.L. and Ma, J.T. "Genetic algorithm and UPFC for power flow control", Engineering Intelligent Systems, Vol. 4, No. 4, 1996, pp. 237-242.

26. Golderg, D.E., "Genetic Algorithms in Search, Optimization and Machine Learning", Addison-Wesley, 1989

27. Holland, J.H., "Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control and Artificial Intelligence " The University of Michigan Press, Ann Arbor, USA, 1975.

28. Nara, K., Shiose, A., Kitagama, M. and Ishihara, T., "Implementation of Genetic Algorithm for Distribution Systems Loss Minimum Re-Configuration", IEEE Transactions on Power System, Vol.7, No. 3, Aug 1992, pp.1044-1051

29. Fukuyama, Y. and Ueki, Y., "Application of Parallel Genetic Algorithms to Generation Expansion Planning Using Parallel Processors", Electrical Engineering in Japan, 1995, Vol. 115, No. 6, 71-81

30. Walters, D. C. and Sheble, G. B., "Genetic Algorithm Solution of Economic Dispatch with Valve Point Loading", IEEE Transaction on Power systems, 1993, Vol. 8, No. 3, pp. 1325-1332

31. Kazarlis, S. A., Bakirtzis, A. G. and Petridis, V., "A Genetic Algorithm Solution to the Unit Commitment Problem", IEEE Transaction on Power systems, 1996, Vol. 11, No. 1

32. Boone, G. and Chang, Hsiao-Dong, "Optimal Capacitor Placement in Distribution System by Genetic Algorithm", Electric Power & Energy System, 1993, Vol. 15, No. 3

33. Lai, L.L. and Ma, J.T. " Application of Evolutionary Programming to Reactive Power Planning – Comparison with Non-linear Programming Approach", IEEE Transactions on Power Systems, Vol.12, No.1, Feb 1997, pp.198-204

34. Haida, T. and Akimoto, Y., "Genetic Algorithms Approach to Voltage Optimization", Proceedings of First International Forum on Applications of Neural Network to Power System, 1991, pp.139-143

35. Wong, K.P. Li, A. and Law M.Y., "Development of Constrained-Genetic Algorithm Load-Flow Method", IEE Proceedings of Generation Transmission and Distribution, Vol. 144, No. 2, 1997, pp. 91-99

36. Yin, X. "Application of Genetic Algorithms to Multiple Load Flow Solution Problem in Electrical Power Systems", Proceedings of the 32nd IEEE Conference on Decision and Control, Vol.4. 1993. pp. 3734-3739

37. Stott, B. and Marinho, J. L., "Linear Programming for Power System Network Security Application", IEEE Trans. on Power Apparatus and Systems, Vol. PAS-98, May/June 1979, pp.837-848.

38. Luenberger, D. G. "Linear and Nonlinear Programming", 2th edition, Addison-Wesley, 1984.

39. Nanda, J., Kothari, D.P. and Srivatava S.C. "New optimal power-dispatch algorithm using Fletcher's quadratic programming method." Proceedings of the IEE. Vol.136, No.3, May 1989, pp.153-161.

40. De Jong, K.A. "An analysis of the Behaviour of a Class of Genetic Apaptive Systems, Ph.D. Dissertation, University of Michigan 1975

41. Grefenstette, J.J. "Optimization of control Parameters for Genetic Algorithms", IEEE Transactions on System, Man, and Cybernetics, Vol. SMC-16 No.1, Jan./Feb,1986, pp.122-128

42. Janikow, C.Z. and Michalewicz, Z. "An Experimental Comparison of Binary and Floating Point Representations in Genetic Algorithm", Proceedings of the Fourth International Conference on Genetic Algorithm 1991, Morgan Kaufmann Publishers, Inc., San Mateo, CA, 1991, pp. 31-36

43. Wong, K.P. and Wong, Y.W. "Floating-point Number Coding method for Genetic Algorithms" Proceedings ANZIIS-93, Perth, Western Australia, pp.512-516

44. Goldberg, D.E. and Derb, K. "A comparative analysis of selection schemes used in genetic algorithm" Foundations of Genetic Algorithm, Morgan Kaufmann Publishers, inc., San Mateo, CA, 1991. pp.69-93

45. Michalewicz, Z. "Genetic Algorithm + Data Structure = Evolution Program, 3rd revised edition, Springer-Verlag, Berlin, 1996

46. Booker, L. "Improving Search in Genetic Algorithm: Genetic Algorithms and Simulated Annealing", Davis, L. (Ed.) Morgan Kaufumann

47. Syswerda, G. "Uniform crossover in genetic algorithm." Proceedings of the Fifth International Conference on Genetic Algorithms. University of Illinois at Urbana-Champaign, 1993:2-9.

48. Grefenstette, J. J. "Optimization of control parameters for Genetic Algorithm", IEEE Transactions on Systems, Man and Cybernetics, Vol. SMC-16, No.1, Jan/Feb 1986, pp.122-128

49. Homaifar, A., Qi, C.X. and Lai, S.H. "Constrained Optimization via Genetic Algorithms", Simulation Vol. 62, No.4, 1994, pp.685-692.

50. Baghzouz, Y and Ertem, S. "Shunt capacitor sizing for radial distribution feeders with distorted substation voltages", IEEE Transaction on Power Delivery, 1990, pp.650-656

51. Grainer, J.J. and Stevenson, W.D. "Power System Analysis, New York, McGraw-Hill, 1991 ISBN No, 0-07-113338-0

52. Chang, R.E. "Locating shunt capacitors on primary feeder for voltage control and loss reduction" IEEE Transactions on Power Apparatus and Systems, Vol. 88, No.10, pp.1574-1577, October 1969

53. Grainger, J.J., Lee, S.H. "Optimum size and location of shunt capacitors for reduction of on distribution feeders" IEEE Transactions on Power Apparatus and Systems, Vol.100, No.3, pp.1105-1108, March 1981

54. Baran, M.E. and Wu, F.F. "Optimal capacitor placement on radial distribution systems" IEEE Transactions on Power Delivery, Vol. 4, No.1, pp.725-734, January 1989

55. Baran, M.E. and Wu, F.F. "Optimal sizing of capacitors placed on a radial distribution systems" IEEE Transactions on Power Delivery, Vol. 4, No.1, pp.735-743, January 1989

56. Chiang, Hsiao-Dong, et al, "Optimal capacitor placement in distribution systems: Part 1 & 2, " IEEE Transactions on Power Delivery, Vol. 5, No.2, pp.634-649, April 1990

57. Sundhararajan, S. and Pahwa, Anil "Optimal selection of capacitors for radial distribution systems using a genetic algorithm", IEEE Transaction on Power System, vol.93 Aug 1994, pp.1499-1507, August 1994

58. Zoka, Y, et al, "An optimal deployment of fuel cells to distribution systems by means of improved genetic algorithms", International Journal of Engineering Intelligence Systems, Vol.9, No.3, pp. 165-172, 2001

59. Sundhararajan, S. and Pahwa, A. "Optimal selection of capacitors for radial distribution systems using a genetic algorithm", IEEE Transaction on Power System, vol.93 Aug 1994, pp.1499-1507

60. Davix, L. "Handbook of genetic algorithm", New York, Van Nostrand Reinhold, 1991

61. Golderg, D.E., "Genetic Algorithms in Search, Optimization and Machine Learning", Addison-Wesley, 1989

62. IEEE standard 519-1981, IEEE guide for harmonic control and reactive power compensation of static power converters, IEEE, New York, 1981

63. Baghzouz, Y "Effects of nonlinear loads on optimal capacitor placement in radial feeders", IEEE Transaction on Power Delivery, 1991, pp.245-251

64. Arrillga, J. Bradley, D.A. and Boodger, P.S. "Power System Harmonics", New York Weily, 1985 ISBN No. 0-471-90640-9

65. De Jong, K.A. "An analysis of the Behaviour of a Class of Genetic Apaptive Systems, Ph.D. Dissertation, University of Michigan 1975

66. Chin, H.C. "Optimal shunt capacitor allocation by fuzzy dynamic programming", Electrical Power Systems Research 1995, vol.35, pp.133-139

67. Ge, Shaoyun "Optimal power system operation and control incorporating FACTS devices", Ph.D. Thesis, Department of Electrical Engineering, The Hong Kong Polytechnic University 1998

68. Dommel, H.W., "Optimal power dispatch" IEEE Transactions on Power Apparatus and Systems.Vol.PAS93, No.3, May/June 1974:820-830.

69. Alsac, O., Bright, J., Prais, M. and Stott, B., "Further developments in LP-based optimal power flow." IEEE Transaction of Power Systems. Vol.5, No.3, August 1990:697-711.

70. Nanda, J., Kothari, D.P. and Srivatava S.C. "New optimal power-dispatch algorithm using Fletcher's quadratic programming method." Proceedings of the IEE. Vol.136, No.3, May 1989:153-161.

71. Holland, J.H., "Adaptation in Natural and Artificial Systems." The University of Michigan Press, Ann Arbor, USA, 1975.

72. Goldberg, D.E., "Genetic Algorithms in Search, Optimization and Machine Learning." Addison Wesley Publishing Company, 1989.

73. H. Wei, H. Sasaki, J. Kubokawa, R. Yokoyama, "An Interior Point Nonlinear Programming for Optimal Power Flow Problems with A Novel Data Structure," IEEE Transactions on Power Systems, Vol. 13, No. 3, November, 1998, pp. 870-877

74. H. Wei, H. Sasaki, J. Kubokawa, "A Decoupled Solution of Hydro-Thermal Optimal Power Flow Problem by Means of Interior Point Method and Network Programming," IEEE Transactions on Power Systems, Vol. 13, No. 2, May, 1998, pp. 286-293

75. Talukdar, S.N. and Giras, T.C. "A fast and robust variable metric method for optimal power flows", IEEE Trans., PAS-101, No.2, Feb. 1982, pp. 120-140.

76. Ge, Shaoyun and Chung, T.S. 'Optimal active power flow incorporating power flow control needs in flexible AC transmission systems', IEEE Trans. on Power systems, Vol. 14, No.2, May 1999.

Appendix

Bus No.	Generation		Load		Voltage	
	Active MW	Reactive MVAR	Active MW	Reactive MVAR	Magnitude p.u.	Angle Radian
1	66.364	-4.656	0.0	0.0	1.067	.00
2	35.403	15.334	21.7	12.7	1.062	-.020
3	70.000	19.879	94.2	19.0	1.043	-.069
4	.000	.000	47.8	-3.9	1.033	-.071
5	.000	.000	7.6	1.6	1.040	-.057
6	30.557	10.455	11.2	7.5	1.040	-.082
7	.000	.000	0.0	0.0	1.040	-.042
8	60.000	-1.204	0.0	0.0	1.033	.056
9	.000	.000	29.5	16.6	1.037	-.087
10	.000	.000	9.0	5.8	1.030	-.092
11	.000	.000	3.5	1.8	1.032	-.089
12	.000	.000	6.1	1.6	1.028	-.092
13	.000	.000	13.5	5.8	1.023	-.097
14	.000	.000	14.9	5.0	1.012	-.110

Table A.1. IEEE 14-bus system network data

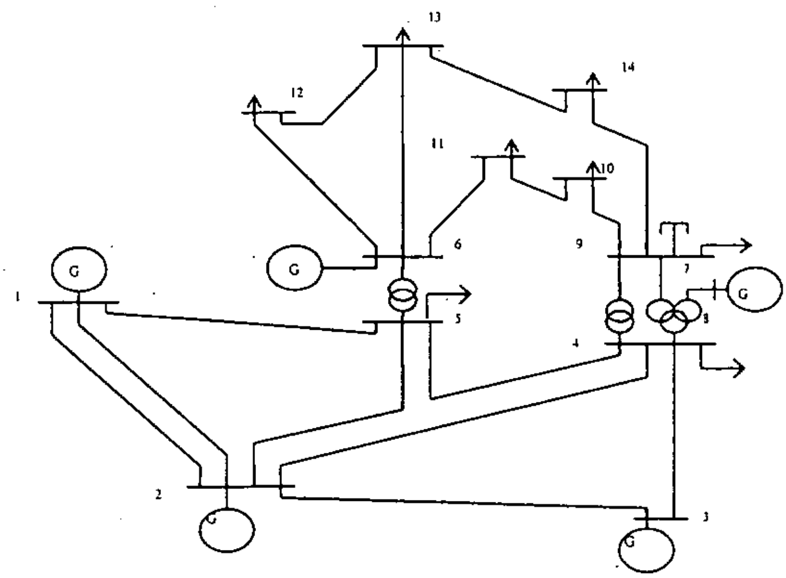


Figure A.1 The modified IEEE 14-bus system diagram with FACTS Devices

Table A.2 IEEE 14-bus system load data

Bus No.	Load MW	Load MVAR	Bus No.	Load MW	Load MVAR
1	0.00	0.00	8	0.00	0.00
2	21.70	12.70	9	29.50	16.60
3	94.20	19.00	10	9.00	5.80
4	47.80	-3.90	11	3.50	1.80
5	7.60	1.60	12	6.10	1.60
6	11.20	7.50	13	13.50	5.80
7	0.00	0.00	14	14.90	5.00

Table A.3 IEEE 14-bus test system line data

Branch No.	Bus No's	R p.u.	X p.u.	B/2 p.u.	Rating p.u.
1	1 – 2	0.01938	0.05917	0.0264	3.42
2	2 – 3	0.04699	0.19797	0.0219	1.71
3	2 – 4	0.05811	0.17632	0.0187	1.20
4	1 – 5	0.05403	0.22304	0.0264	1.71
5	2 – 5	0.05695	0.17388	0.0170	1.71
6	3 – 4	0.06701	0.17103	0.0173	1.71
7	4 – 5	0.01335	0.04211	0.0064	1.71
8	5 – 6	0.00000	0.25202	0.0000	0.65
9	4 – 7	0.00000	0.20912	0.0000	0.65
10	7 – 8	0.00000	0.17615	0.0000	0.65
11	4 – 9	0.00000	0.55618	0.0000	0.40
12	7 – 9	0.00000	0.11001	0.0000	0.65
13	9 – 10	0.03181	0.08450	0.0000	0.50
14	6 – 11	0.09498	0.19890	0.0000	0.50
15	6 – 12	0.12291	0.15581	0.0000	0.50
16	6 – 13	0.06615	0.13027	0.0000	0.50
17	9 – 14	0.12711	0.27038	0.0000	0.50
18	10 – 11	0.08205	0.19207	0.0000	0.50
19	12 – 13	0.22092	0.19988	0.0000	0.50
20	13 – 14	0.17093	0.34802	0.0000	0.50

Table A.4 Regulated bus data

Bus No.	Voltage Magnitude p.u.	Minimum MVAR capability	Maximum MVAR capability
2	1.045	-40.0	50.0
3	1.010	0.0	40.0
6	1.070	-6.0	24.0
8	1.090	-6.0	24.0

Table A.5 Transformer data

Transformer destination	Tap setting
5 ---- 6	0.932
4 ---- 7	0.978
4 ---- 9	0.969

Table A.6 Static capacitor data

Bus No.	Susceptance (p.u.)
9	0.190

The IEEE 30-bus system is shown in Figure A.2. The generation data, branch data, load data and other necessary data are listed in Table A.7. to Table A.12 respectively.

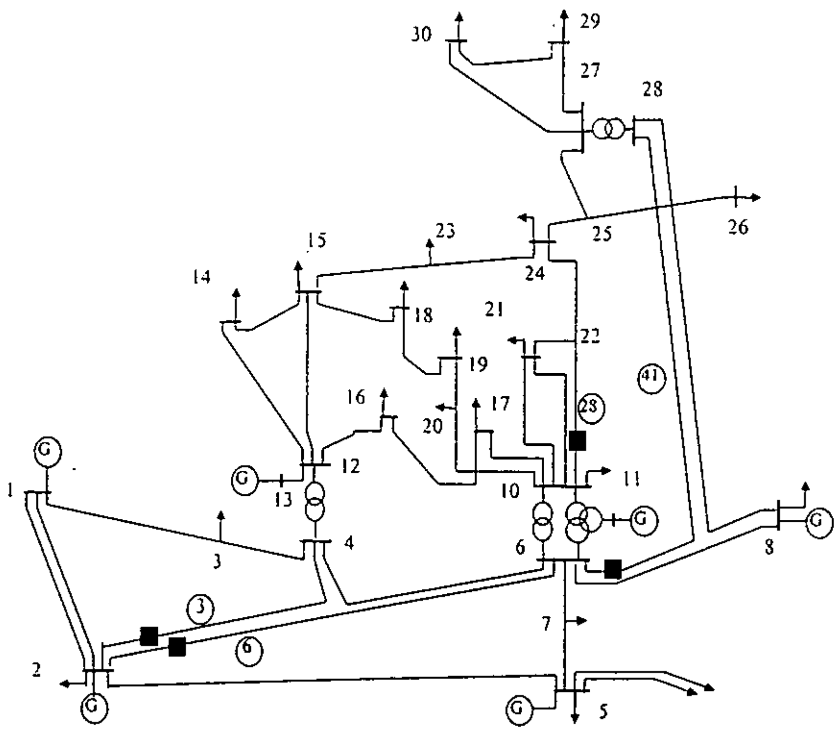


Figure A.2 IEEE 30-bus test system

Table A.7 IEEE 30-bus system generation data

Bus No.	P_G^{min} (MW)	P_G^{max} (MW)	Cost coefficient		
			a	*b*	*c*
1	50	200	0.0	2.00	0.00375
2	20	80	0.0	1.75	0.01750
5	15	50	0.0	1.00	0.06250
8	10	35	0.0	3.25	0.00834
11	10	30	0.0	3.00	0.02500
13	12	40	0.0	3.00	0.02500

* Generation cost $f_i = a_i + b_i P_{Gi} + c_i P_{Gi}^2$ £/hr

Table A.8 IEEE 30-bus test system line data

Branch No.	Bus No's	R (p.u.)	X (p.u.)	B/2 (p.u.)	Rating (p.u.)
1	1 – 2	0.0192	0.0575	0.0264	1.30
2	1 – 3	0.0452	0.1852	0.0204	1.30
3	2 – 4	0.0570	0.1737	0.0184	0.65
4	3 – 4	0.0132	0.0379	0.0042	1.30
5	2 – 5	0.0472	0.1983	0.0209	1.30
6	2 – 6	0.0581	0.1763	0.0187	0.65
7	4 – 6	0.0119	0.0414	0.0045	0.90
8	5 – 7	0.0460	0.1160	0.0102	0.70
9	6 – 7	0.0267	0.0820	0.0085	1.30
10	6 – 8	0.0120	0.0420	0.0045	0.32
11	6 – 9	0.0000	0.2080	0.0000	0.65
12	6 – 10	0.0000	0.5560	0.0000	0.32
13	9 – 11	0.0000	0.2080	0.0000	0.65
14	9 – 10	0.0000	0.1100	0.0000	0.65
15	4 – 12	0.0000	0.2560	0.0000	0.65
16	12 – 13	0.0000	0.1400	0.0000	0.65
17	12 – 14	0.1231	0.2259	0.0000	0.32
18	12 – 15	0.0662	0.1304	0.0000	0.32
19	12 – 16	0.0945	0.1987	0.0000	0.32
20	14 – 15	0.2210	0.1997	0.0000	0.16
21	16 – 17	0.0824	0.1932	0.0000	0.16
22	15 – 18	0.1070	0.2185	0.0000	0.16
23	18 – 19	0.0639	0.1292	0.0000	0.16
24	19 – 20	0.0340	0.0680	0.0000	0.32
25	10 – 20	0.0936	0.2090	0.0000	0.32
26	10 – 17	0.0324	0.0845	0.0000	0.32
27	10 – 21	0.0348	0.0749	0.0000	0.32
28	10 – 22	0.0727	0.1499	0.0000	0.32
29	21 – 22	0.0116	0.0236	0.0000	0.32
30	15 – 23	0.1000	0.2020	0.0000	0.16
31	22 – 24	0.1150	0.1790	0.0000	0.16
32	23 – 24	0.1320	0.2700	0.0000	0.16
33	24 – 25	0.1885	0.3292	0.0000	0.16
34	25 – 26	0.2544	0.3800	0.0000	0.16
35	25 – 27	0.1093	0.2087	0.0000	0.16
36	28 – 27	0.0000	0.3960	0.0000	0.65
37	27– 29	0.2198	0.4153	0.0000	0.16
38	27 – 30	0.3202	0.6027	0.0000	0.16
39	29 – 30	0.2399	0.4533	0.0000	16
40	8 – 28	0.0636	0.2000	0.0000	32
41	6 – 28	0.0169	0.0599	0.0000	32

Table A.9 IEEE 30-bus system load data

Bus No.	Load MW	Load MVAR	Bus No.	Load MW	Load MVAR
1	0.0	0.0	16	1.8	1.8
2	21.7	21.7	17	5.8	5.8
3	2.40	1.2	18	0.9	0.9
4	7.60	1.6	19	3.4	3.4
5	94.2	19.0	20	0.7	0.7
6	0.0	0.0	21	11.2	11.2
7	22.8	10.9	22	0.0	0.0
8	30.0	30.0	23	1.6	1.6
9	0.0	0.0	24	6.7	6.7
10	5.8	2.0	25	0.0	0.0
11	0.0	0.0	26	2.3	2.3
12	11.2	7.5	27	0.0	0.0
13	0.0	0.0	28	0.0	0.0
14	6.2	1.6	29	0.9	0.9
15	8.2	2.5	30	1.9	1.9

Table A.10 Regulated bus data

Bus No.	Voltage magnitude p.u.	Minimum MAVR capability	Maximum MVAR capability
2	1.045	-40.0	50.0
5	1.010	-40.0	40.0
8	1.010	-10.0	40.0
11	1.082	-6.0	24.0
13	1.071	-6.0	24.0

Table A.11 Transformer data

Transformer destination	Tap setting
4 --- 12	0.932
6 --- 9	0.978
6 --- 10	0.969
28 --- 27	0.968

Table A.12 Static capacitor data

Bus No.	Susceptance (p.u.)
10	**0.190**
24	**0.043**