# Optimal Power Flow with FACTS Devices

BY

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**To my Family**

# ACKNOWLEDGMENT

*In the name of Allah, the most gracious, the most merciful*

All praise be to Almighty Allah for having guided me all over my life.

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# Abstract

**Name:** Muhammad Mahdi Ibrahim Al-Hulail

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Optimal power flow (OPF) is one of the main tools for optimal operation and planning of modern power systems. Needs of OPF development rise, as power systems get more complicated. One of those main needs is the incorporation of power flow flexibility, which the flexible AC transmission systems (FACTS) devices play the main role in it.

Incorporating FACTS devices to be among the OPF problem control variables is the main concern of this thesis. A new formulation of OPF was developed taking into account FACTS devices representations. The developed formulation was solved for the optimal control variable settings with respect to single objective as well as to multi-objective optimization problems. Those objectives were total fuel cost minimization, voltage profile improvement, and voltage stability enhancement. Because of the complicated nature of the resulted problem, an efficient optimization technique was developed and implemented in this study. Particle swarm optimization (PSO) technique was employed for solving the formulated OPF problem. The effectiveness of PSO was compared to that of genetic algorithm (GA). The potential and superiority of PSO have been demonstrated through the results of different optimization runs. A novel hybrid GA/PSO has been proposed in this study for solving the problem of optimal FACTS devices location. The developed techniques have been tested on a standard IEEE test system. The results have been compared with those reported in the literature. The results of the developed and proposed techniques demonstrate their potential and effectiveness in handling power system optimization problems.

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# خلاصة الرسالة


| | |
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التشغيل الأمثل لأنظمة الطاقة الكهربائية هي إستراتيجية يتبناها جميع المهتمين بقطاع الكهرباء. و هذه الإستراتيجية تزداد إلحاحاً كلما ازدادت هذه الأنظمة اتساعاً و ترابطاً. من هنا تبرز محاكاة التدفق الأمثل للطاقة الكهربائية كواحدة من أبرز الوسائل التي يستعان بها لتخطيطٍ و تشغيلٍ مثاليين لشبكات الطاقة. و لا تنفك هذه الوسيلة (محاكاة التدفق الأمثل للطاقة الكهربائية) عن حاجتها للتطوير للتماشى و التطور المتسارع في هذه النظم. و يعد التدفق المرن و المتكيف أحد أهم التطورات في أنظمة الطاقة الكهربائية في الآونة الأخيرة.

هذه الدراسة تهتم بتطوير حساب التدفق الأمثل للطاقة و ذلك بإدخال إمكانيات المرونة و التكيف لأنظمة الطاقة الكهربائية لتكون أحد وسائل ضبط التدفق الأمثل. لقد تم تطوير النموذج الرياضي للتدفق الأمثل للطاقة بإدخال عناصر المرونة و من ثم إيجاد الضبط اللازم لعناصر التحكم و التي تشتمل على عناصر المرونة. تمت الإستعانة بطريقة جديدة تحاكي الأسراب الطائرة لإيجاد الضبط الأمثل و قد تم إثبات فاعليتها و تفوقها على الطرق الجينية في حدود ما تمت دراسته. كما تم تطوير طريقة مزدوجة بين الطريقة الجينية و الأسراب الطائرة. استخدمت هذه الطريقة لتعيين المواقع المثلى لأجهزة المرونة.


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# NOMENCLATURE

| | |
|---|---|
| OPF | Optimal Power Flow |
| FACTS | Flexible AC Transmission System |
| PSO | Particle Swarm Optimization |
| GA | Genetic Algorithm |
| ES | Evolutionary Strategy |
| EP | Evolutionary Programming |
| SVC | Static Var Compensator |
| TCSC | Thyristor Control Series Capacitor |
| TCPS | Thyristor Control Series Capacitor |
| FC/TCR | Fixed Capacitor/ Thyristor-Controlled Reactor |
| TSC/TCR | Thyristor Switched Capacitor/Thyristor-Controlled Reactor |

# CHAPTER ONE

# INTRODUCTION

## 1.1 Overview

Serving customers with reliable, good quality, and low cost electric power supply is the ultimate goal of every electric utility. Meeting this goal needs a proper power system planning and operation which is a great and growing challenge. Utilities and power producers put a great effort in beating such a challenge. This can be noticed in the continuing developments and attentions in two directions. The first is related to the power system analysis and control tools. *Optimal Power Flow* (OPF) is the most leading tool belongs to this direction. The second direction is related to the power system equipment and devices developments. Flexible AC Transmission Systems (FACTS) is believed to be the top in this trend.

Optimal power flow (OPF) is a special type of power flow where some variables are adjusted (controlled) so as to optimize a predefined objective while respecting various constraints [1-3]. The OPF was raised in the early sixties as an extension of the conventional economic dispatch [1]. Its usages have been widened since then to cover many power system applications ranging from long range planning to on-line operation. So, it has deserved a great attention in the past two decades [3].

Flexible AC Transmission System (FACTS), on the other hand, have opened a new world in power system control. They have made the power systems operation more flexible and secure. They have the ability to control, in a fast and effective manner, the three effective players in power flow. These are circuit impedance, voltage magnitude and phase angle. Gaining flexibility in power flow is not a little achievement. The great economic and technical benefits of this to the power systems have been well proven [4,5].

The question now is what can the OPF add to the FACT devices in terms of analysis? Also, what can the OPF gain from incorporating the FACTS devices in terms of solution? The answer to these questions is enough to justify this research direction and clarify its motivations.

## 1.2 Thesis Motivation

Incorporating FACTS devices in OPF problem contributes in developing OPF to be more beneficial tool for power systems planning and operation. Specifically it can help in the following:

### 1.2.1 Widening OPF Solution Space

Solution space of conventional OPF is usually limited by the operation and control variable limits of the power system. This limitation usually prevents from attaining the hoped improvements in the OPF objective or objectives. Therefore, it became necessary to widen the operating margins and increases the controllability of the power system. FACTS devices, with its introduced flexibility and controllability of power flow, release some of the imposed constraints on the OPF and so help in widening the solution space [6-9].

### 1.2.2 Assessment of FACTS Devices

Installing FACTS devices in any power system is an investment issue. It offers some flexibility to the power system (as explained in chapter 3) at the expense of cost. Therefore, it is necessary for any new installation of FACTS to be very well justified [10-14]. This justification needs an off-line simulation of the power system with the different candidate FACTS installations to assess the value added to the system. Among the different assessment tools used for this purpose, OPF seems to be the best. By incorporating FACTS devices in OPF with some modification, it can give scalar measures of its benefits. This can help a lot in deciding for the optimal location of new FACTS installation.

### 1.2.3 Limitation of Traditional Optimization Algorithms

Generally, most of the conventional optimization techniques apply sensitivity analysis and gradient-based optimization algorithms by linearzing the objective function and the system constraints around an operating point. Unfortunately, the problem of the OPF is a highly nonlinear and a multimode optimization problem, i.e. there exists more than one local optimum. Hence, local optimization techniques are not suitable for such a problem.

Moreover, many mathematical assumptions such as convex, analytic, and differential objective functions have to be taken [15]. However, the OPF problem is an optimization problem with, in general, nonconvex, nonsmooth, and nondifferentiable objective functions. Therefore, conventional optimization methods are not that efficient in solving OPF problem [16-18].

Recently, a new evolutionary algorithm, called particle swarm optimization (PSO), has been used for solving power system problems [19-22]. The results reported were promising and encouraging for further research.

## 1.3 Thesis Objectives

Objectives of this thesis can be listed as follows:

1. Developing an OPF formulation where FACTS devices are incorporated and considered as control variables.
2. Assessing FACTS devices using the developed OPF from different objective perspectives.
3. Formulating OPF as a multi-objective optimization problem and using fuzzy logic to extract the best compromised solution.
4. Employing two of the latest evolutionary algorithms in searching for the solution of the above objectives and comparing their results. Those two are the *Genetic Algorithms* (GA) and the *Particle Swarm Optimization (PSO)*.

5. Proposing a new GA/PSO algorithm to be used in searching for optimal FACTS devices location with respect to certain objective using the formulated OPF. This can help in FACTS devices investment.

## 1.4 Thesis Overview

Following is briefing of the nine chapters comprise this thesis. Chapter 2 gives a literature review of OPF. This includes a review of OPF applications, OPF formulation trends, and OPF solution techniques. The following chapter, chapter 3, describes the FACTS devices and their concepts. The most common used FACTS devices and their modeling for power flow studies are explained in this chapter. Detailed OPF formulation with FACTS devices is developed in chapter 4 whereas detailed explanation of GA and PSO solution techniques, used for solving this formulated problem, are given in chapter 5. This chapter also gives an explanation of the new GA/PSO algorithm used for searching for optimal FACTS location.

Case studies and simulation using IEEE-30-bus system are given in chapters 6, 7, and 8. Chapter 6 is devoted for the comparison between GA and PSO in terms of speed of convergence, robustness, and solution quality. OPF with FACTS is solved for different objective functions in chapter 7 using PSO. In chapter 8, the new GA/PSO is used for searching for optimal FACTS location with respect to a specified objective. The report is concluded in chapter 9 by summarizing the main findings of the study and pointing to some directions for future studies

# CHAPTER TWO

# LITERATURE REVIEW OF OPTIMAL POWER FLOW

This chapter presents the literature survey of the optimal power flow applications and solution methods. It seems essential at the beginning to name two comprehensive surveys on this matter. The first one is that of Huneault and Galiana [1]. Their work looks back, as they mentioned, on OPF field and economic power dispatch from the early 1930's up to 1989. The second survey is that of Al-Hawary et. al. [2]. It reviewed the optimization techniques that were applied to the OPF problem up to 1993.

## 2.1 Overview

Enormous efforts have been spent for improving OPF to make it of great help for all sorts of power system engineering. The OPF have been widened to include objectives other than minimizing fuel cost and system losses which are the most common objectives. New constraints have been added to the OPF over the power balance equations and the generator VAR limits. Also the control variables have received some attention. One of the newly introduced control variables to the OPF is the FACTS devices setting. All this together with the non-linear and non-convex nature of OPF problem contributed to came up with a complicated and difficult OPF problem to solve.

This chapter introduces first the optimal power flow problem and compares it with the conventional power flow in section 2.2. Then it gives in a three sections a review to the optimal power flow and its developments. It reviews in section 2.3 the applications to the OPF. Then it reviews the problem formulation and handling approaches in section 2.4. In section 2.5, it reviews the solution techniques employed for OPF solving.

## 2.2 Conventional Power Flow Versus Optimal Power Flow

### 2.2.1 Conventional Power Flow

Power flow calculation is the most common power system simulation tool. It is essential in evaluating the operation conditions of power systems, taking the proper control actions, and planning for future expansions. Power flow calculation can be described as finding the voltage magnitude and angle at each bus of the power system and in turn finding the real and reactive power flow through transmission lines and transformers among other valuable information. This is done by solving a series of simultaneous nonlinear equations known as *power-balanced equations* which state that the power injected at each bus is equivalent to the sum of power flows on all branches connected to that bus. More specifically, the net real power $P_i$ and reactive power $Q_i$ entering the network at bus $i$ in figure (2.1) are given respectively as:

$$P_i = P_{Gi} - P_{Di} \tag{2.1}$$

$$Q_i = Q_{Gi} - Q_{Di} \tag{2.2}$$

where $P_{Gi}$ and $Q_{Gi}$ are the generated real and reactive power at bus $i$, and $P_{Di}$ and $Q_{Di}$ are the real and reactive power demand at the same bus. The complex conjugate power injected at bus $i$ of a system consists of $NB$ number of buses can be expressed in terms of the network bus voltages and admittances as follows.

$$\begin{aligned} P_i - jQ_i &= V^*{}_i I_i \\ &= V_i^* \left[ \sum_{j=1}^{NB} Y_{ij} V_j \right] \end{aligned} \tag{2.3}$$

where

$V_i = |V_i| \angle \delta_i$ is the voltage magnitude and angle at bus $i$.

$V_j = |V_j| \angle \delta_j$ is the voltage magnitude and angle at bus $j$.

$Y_{ij} = |Y_{ij}| \angle \theta_{ij}$ is the negative summation of admittances connected between buses $i$ and $j$ where $i \neq j$.

Taking the real and imaginary parts of (2.3) and substituting for $P_i$ and $Q_i$ in (2.1) and (2.2) results in the following two equations:

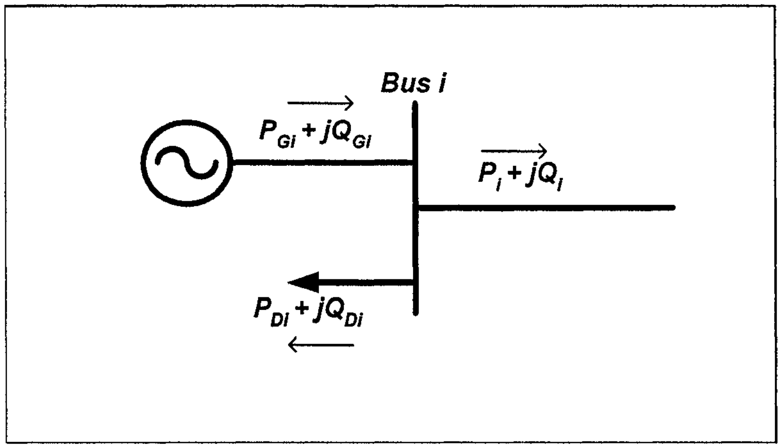


Figure 2.1: General bus *i* with generation and load

$$P_{G_i} - P_{D_i} = \sum_{j=1}^{NB} V_i V_j Y_{ij} \cos(\theta_{ij} + \delta_j - \delta_i) = 0; \qquad \forall\, i, j \in NB \tag{2.4}$$

$$Q_{G_i} - Q_{D_i} = \sum_{j=1}^{NB} V_i V_j Y_{ij} \sin(\theta_{ij} + \delta_j - \delta_i) = 0; \qquad \forall\, i, j \in NB \tag{2.5}$$

The power flow problem is to solve the above two equations for values of unknown bus voltage magnitudes and angles. Iterative numerical techniques are needed to solve such non-linear equations and the resulted solutions represent the power system operation conditions for a specific equipment setting.

Dependent variables such as load bus voltages and branch flow are the measure of the power flow solution quality. Load flow model offers a set of independent control variables whose value can be adjusted to provide an acceptable solution. Generator reactive output, transformer tap, and phase shifter angles are the common control variables for power flow. Experiences, unfortunately, showed that conventional power flow is not sufficient for large number of control adjustments to satisfy a system global objective rather that local objective such as bus voltage control. *Optimal power flow* has found its way for emergence from here [23].

### 2.2.2 Optimal Power Flow

Unlike conventional power flow, optimal power flow is a special power flow problem which, optimally, adjusts system control variables to achieve certain results while satisfying the power flow equations and other inequality constraints. It is an optimization problem with objective and constraints as given below in its general form [23].

$$Min \quad J(x,u) \tag{2.6}$$

Subject to: $$g(x,u)=0 \tag{2.7}$$

$$h(x,u)\leq 0 \tag{2.8}$$

Where $x$ is the vector of state variables (dependent variables), $u$ is the vector of controlled variables (independent variables), $f$ is the objective function to be optimized, $g$ is the set of power flow equality constraints, and $h$ is the set of inequality constraints on the dependent and the independent variables. Table 2.1 summarizes the main differences between the conventional power flow and the optimal power flow.

Table 2.1: Main differences between conventional and optimal power flow

| | Conventional Power Flow | Optimal Power Flow |
|---|---|---|
| Objectives | Local such as bus voltage control | Global such as fuel cost minimization in the entire system |
| Constraints | Power-balanced equations | Power-balanced equations, generator Var limits, transformer tap ranges, shunt Var limits, …etc. |
| Controls | Generator reactive output, transformer taps, and phase shifter angles | Generator MW output, transformer taps, and phase shifter angles, shunt capacitors, series compensation, …etc. |

## 2.3 OPF Applications

Applications of OPF may be classified into operational and planning applications. Operational applications can be separated into economical and technical. Several of applications come under each class. The most common applications can be explained as follows.

### 2.3.1 Fuel Cost Minimization

The starting point for OPF is minimizing the operation cost of power systems. The minimization of the fuel cost is the main objective under this class. It seeks to find the optimal active power outputs of the generation plants so as to minimize the total fuel cost [1,2,15-19,23-25].

### 2.3.2 Loss Minimization

Transmission losses minimization is considered to be one of the cost minimization objectives as well. This objective together with the fuel cost minimization is among the most common used objectives [1, 2, 23-25].

### 2.3.3 Voltage Profile Improvement

This objective has been taken into consideration in many OPF works [19,26-27]. In most OPF problems, voltages are bounded between upper and lower limits in inequality constraints [16-18]. Other OPF problems look for the operating settings that minimize the summation of the total voltage deviation at the load buses [19,26].

### 2.3.4 Voltage Stability Enhancement

Voltage profile improvement does not necessary implies a voltage secure system. Voltage instability problems have been experienced in systems where voltage profile was acceptable [28]. Voltage secure system is the system that is able to maintain constantly acceptable bus voltage at each bus under normal operating conditions, after load increase, changing system configuration, or when the system is subjected to a disturbance. This objective has been given a great attention in previous OPF researches where it has been formulated in different ways [19, 29-34]

### 2.3.5 Power Transfer Maximizing

Power transfer maximizing is a valuable goal for interconnected systems. It can help in minimizing the operation cost of power system in addition to other advantages such as reliability enhancement. This can be best managed by optimal adjustment of Var sources [27,35]. One use of FACTS devices is to enhance the power transfer and OPF can play a major role for optimal settings of those devices for this purpose.

### 2.3.6 Optimal System Planning

Like power system operation, OPF has taken a leading place in today's power system planning [3]. Reactive power planning is the most active application area of OPF and this can be a research subject by itself. Var planning aims to minimize the cost of additional expansion of new reactive resources to maintain the system in a secure and economic manner. It consists of identification of optimal Var location and size. The attribute in

Var planning may involves voltage stability enhancement, losses minimization, or any other evaluation index. An evaluation of three optimal Var planning tools is given in [36]. Different Var planning approaches have been tried [37-38].

## 2.4 OPF Problem Formulation

OPF, like any optimization problem, needs to be put in such a way where the candidate solution can be evaluated and the searching process is directed to the optimal solution. Most of time, the optimization techniques used to find the optimal solution formulate the problem in a shape convenient to work well. What follows is a generalization of the formulation approaches and solution strategy to the OPF problem.

### 2.4.1 Objective Formulation

An optimization process, by definition, looks for the best of all feasible solutions in terms of certain objective or objectives. So it has to have a tool to evaluate and rank those feasible solutions. There are two known classes of strategies for evaluating candidate solutions: the first class relies on objective function while the other relies on rule.

#### 1. Function-based objective

This approach is possible when each solution can be assigned a single numerical value. Due to its easy handling, it is more common than the other approach. Classical OPF problems usually relay on this approach [15-19,23-27]. An advantage of this approach is that it gives a value to every possible solution. This allows for a fair comparison between all candidate solutions.

**2. Rules-based objective**

It is sometimes easier for the user to state rules to select between candidate solutions rather than building an objective function. This approach has been in used recently with the revolution of expert systems. This approach is found to great helpful in multi-objective optimization with conflicting nature [39-40].

### 2.4.2 Control Variables

The only control variable for OPF problems, at their launching, was the MW output of the generators. Various control variables have been incorporated since then. The standard OPF nowadays treat generator terminal voltages, transformer tap settings, and Var shunt together with the MW output as controlled variables.

FACTS devices settings were treated lately as control variables in very few OPF problems [41-44]. The only objective considered in [41-44] was the minimization of the generation cost. A comprehensive study of FACTS devices effect on OPF problem is still needed and this is one objective of this thesis.

### 2.4.3 Constraints Treatment

As any optimization problem, there are some constraints that have to be satisfied in the course of the OPF problem solution. The way of dealing with constrains has developed and new constraints have been added. Load flow needs, which usually come with FACTS devices, are some of those new constraints lately introduced in OPF problems [8,45-46].

Constraints can be usually treated either as ***hard*** or ***soft*** constraint. In hard constraint approach, no violation is accepted at all while in soft constraints approach, violations are reflected in the objective with some certain penalty. The later approach is used in this thesis.

## 2.5 OPF Solution Techniques

OPF goes hand in hand with the development in optimization techniques. One can judge that almost all optimization technique have been applied to solve OPF problem. Literature is full with comparisons and evaluations of such algorithms. Those algorithms and optimization techniques can be broadly classified into two classes, namely, conventional techniques and modern techniques.

### 2.5.1 Conventional Optimization Techniques

Nonlinear programming [47,48], quadratic programming [49], Newton-based solutions [50-52], linear programming [53,54], and interior point methods [55,56] are some of the most common techniques of this type. Most of those optimization techniques are gradient-based. Literature is full of applications of those techniques for OPF solutions. Interested readers are directed to consult the comprehensive survey presented in [2].

What is common in all of these techniques is that they make use of the first and second derivatives of objective function and its constraints to find out the optimal solution. Hence, a differentiable and convex objective function has to be assured in order for those optimization techniques to work well. Unfortunately, the OPF problem in general comes with a nonconvex, nonsmooth, nonlinear, and nondifferentiable objective function. This has encouraged the OPF developers to try some more efficient optimization techniques.

### 2.5.2 Modern Evolutionary-based Optimization Techniques

These algorithms simulate the evolutionary pattern observed in nature. The reported results of these techniques often out perform the conventional optimization techniques when applied to complicated problems such as OPF. Genetic algorithm (GA), evolutionary strategy (ES), evolutionary programming (EP), and particle swarm optimization (PSO) are the four major algorithms of this direction.

GA has received a great attention from OPF developers. It has been applied in many OPF problems with a variety of objectives [17,18,42-43]. Nevertheless, EP and ES [15,16] have been applied to the same purpose. PSO is the latest algorithm of the four. It has been applied in many field of engineering including power system problems [20-22]. However, up to writing of this thesis, it has been applied to OPF problem only once so far [19]. The above techniques did not consider the FACTS devices in their formulation. This gap will be covered in this thesis.

This thesis is an effort to include FACTS devices settings into consideration in OPF studies. It tries also to utilize the latest advances in optimization techniques for OPF solving.

# CHAPTER THREE

# FACTS DEVICES AND POWER FLOW CONTROL

## 3.1 Overview

FACTS are AC transmission components incorporating power electronic controlled devices (FACTS devices or controllers) to enhance flexibility in power flow control. The word "flexibility" here means the power system ability to accommodate changes in electric transmission network or rapid operating conditions. Power system flexibility implies enhancing the power transfer capability, improving the security and stability of the system, and improving the transmission system performance in general.

FACTS devices are power electronic-based system and other solid-state control (no moving parts) that provide a rapid control of one or more of the three AC transmission system parameters affecting power flow. The three parameters are bus voltages, line impedances, and phase angles [57]. This chapter explains how those parameters influence power flow and clarifies the different controlling techniques. A description of three of the most known FACTS devices will be given. Specifically the effectiveness and potential of static Var compensator (SVC), thyristor controlled series compensator (TCSC), and thyristor controlled phase shifter (TCPS) will be explained.

## 3.2 Power Flow Control

Figure 3.1 is a simplified power transmission system that will be used to derive the basic relationships of AC power transmission in order to understand the power flow control offered by FACTS devices. It is a simple two-bus system where the sending and the receiving ends are interconnected via a short transmission line with a series reactance $X$ and a neglected shunt capacitance.

For simplicity and clarification, it has been assumed that the sending end voltage $V_S$ and the receiving end voltage $V_R$ have the same magnitude. That is $|V_S|=|V_R|=V$:

$$V_S = Ve^{j\frac{\delta}{2}} = V(\cos\frac{\delta}{2} + j\sin\frac{\delta}{2}) \tag{3.1}$$

$$V_R = Ve^{-j\frac{\delta}{2}} = V(\cos\frac{\delta}{2} - j\sin\frac{\delta}{2}) \tag{3.2}$$

The current through the line is given by

$$I = \frac{V_S - V_R}{jX} = \frac{2V}{X}\sin\frac{\delta}{2} \tag{3.3}$$

The midpoint voltage $V_M$ is

$$V_M = V_S - j\frac{X}{2}I = V\cos\frac{\delta}{2} \tag{3.4}$$

Assuming a lossless line, the power is the same at both ends as well as the midpoint, i.e.,

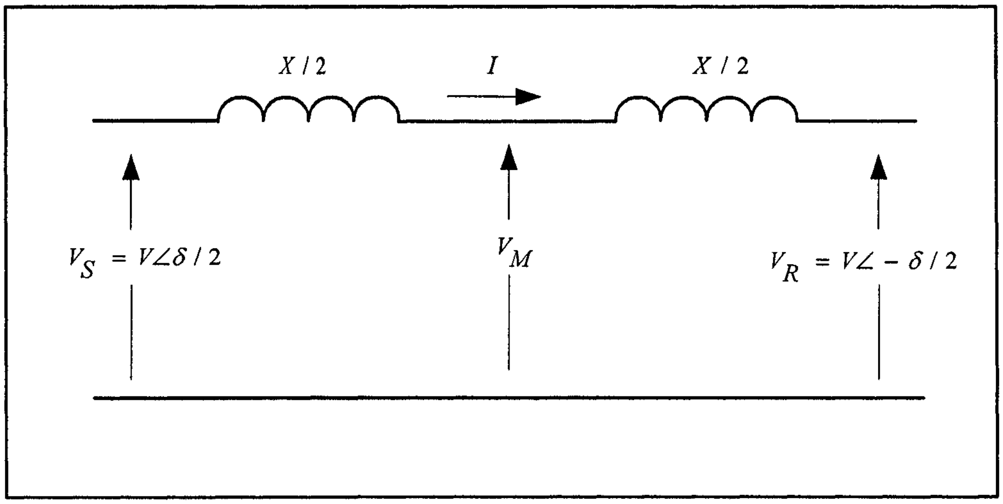


Figure 3.1: Simple power system model

$$P = V_M I = \frac{V^2}{X}\sin\delta \tag{3.5}$$

The reactive power provided for the line at each end is

$$Q_s = -Q_r = I * V\sin(\frac{\delta}{2}) = \frac{2V^2}{X}(1-\cos\delta) \tag{3.6}$$

Figure 3.2 shows the relationships between the real power $P$, the reactive power $Q$, and the angle $\delta$.

It is clear from (3.5) how the voltage magnitude and angle at the sending and receiving bus and the electric length of the transmission line (i.e. the effective series line reactance $X$) direct the power transmission. Shunt var compensation, series compensation, and phase angle controller are three approaches to control those parameters. Following is a brief illustration of the effect of each approach on the transmittable power.

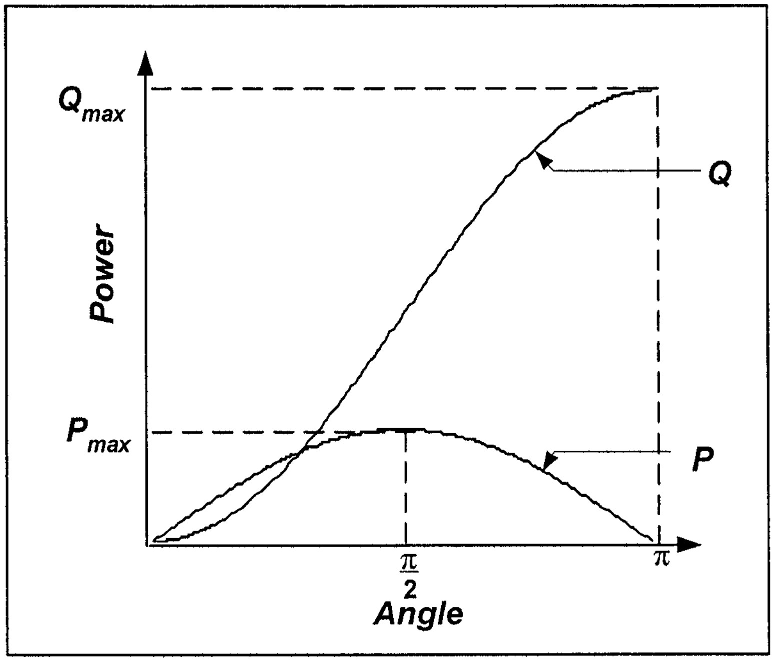


Figure 3.2: Power transmission characteristic for the simple system in figure 3.1

### 3.2.1 Shunt Compensation

The magnitude of the voltage $V_M$ at the middle of the uncompensated line in figure 3.1 is equals to $V\cos \delta/2$, which is less than the voltage magnitude at the line ends. To maintain a flat voltage profile ($|V_S| = |V_R| = |V_M| = V$), a capacitive current $I_M$ needs to be drawn at the middle of the line as shown in Figure 3.3.

The drawing of capacitive current is equivalent to applying a shunt compensator at that point. Since the compensator voltage $V_M$ and its current $I_M$ are in quadrature, the compensator does not consume any real power. Therefore, the power transferred from sending end to the mid-point is equal to the power transfer from the mid-point to the receiving end and it is given by:

$$P = \frac{V^2}{X/2}\sin\frac{\delta}{2} = \frac{2V^2}{X}\sin\frac{\delta}{2} \qquad (3.7)$$

Figure 3.4 shows the plot of the power transfer $P$ against the angle $\delta$ [58].

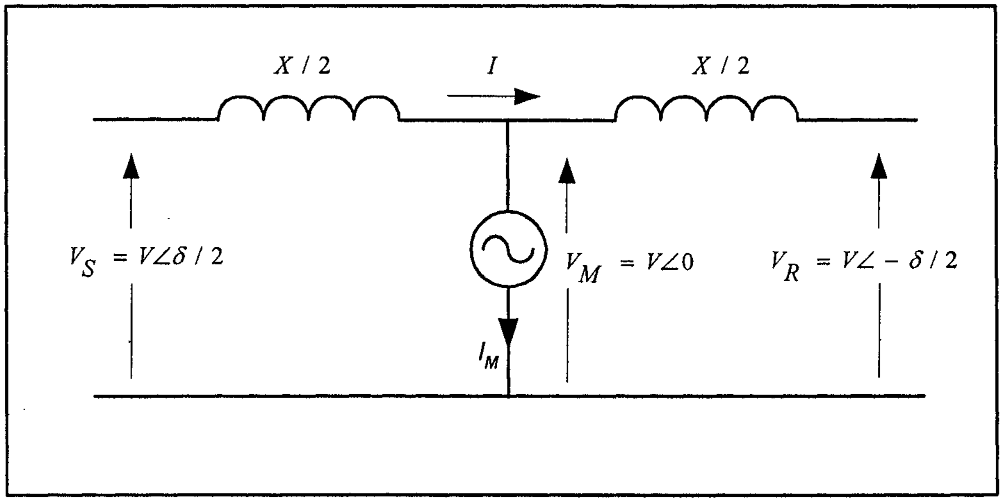


Figure 3.3: Simple power system model with mid-point shunt compensation

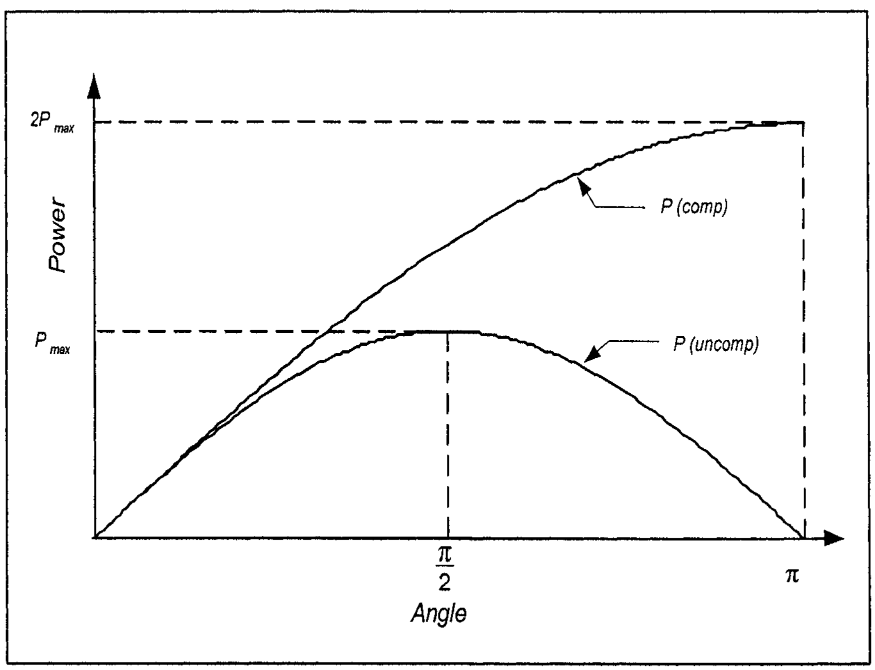


Figure 3.4: Power transmission characteristic for the shunt compensated line

### 3.2.2 Series Capacitance Compensation

Figure 3.5 shows the arrangement of series compensation of a line using a mid-point capacitor to reduce the overall line reactance. This method makes the line appears electrically shorter than in the actual case.

The overall reactance of the line will become $X$-$X_c$, or alternatively, $X(1$-$s)$, where $s$ is the degree of compensation given by:

$$s = \frac{X_c}{X} \qquad ;0 \leq s \leq 1 \tag{3.8}$$

The current in the compensated line and the real power transmitted are the same as (3.3) and (3.5) except that $X(1$-$s)$ is substituted for $X$, i.e;

$$I = \frac{2V}{X(1-s)} \sin\frac{\delta}{2} \tag{3.9}$$

$$P = \frac{V^2}{X(1-s)} \sin\delta \tag{3.10}$$

Figure 3.6 shows how the transmitted real power $P$ varies as the degree of compensation $s$ changes [58].

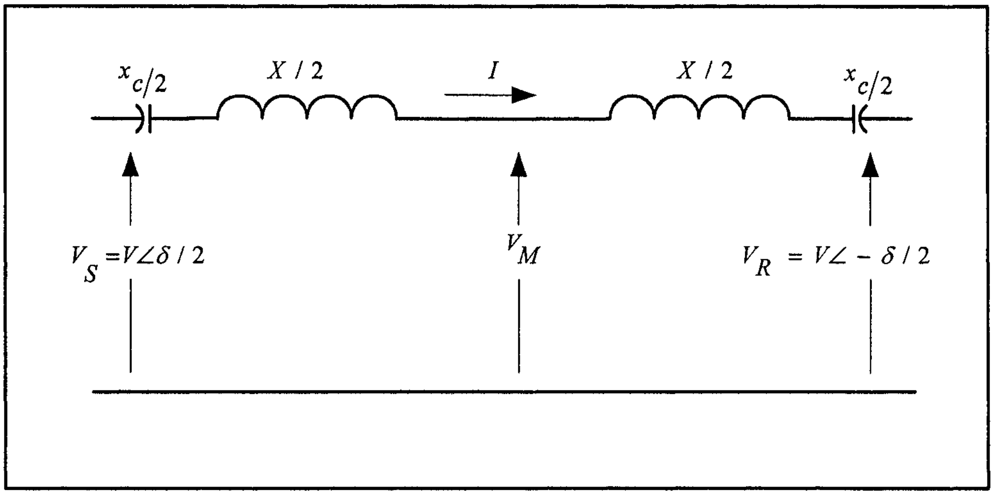


Figure 3.5: Simple power system model with series compensation

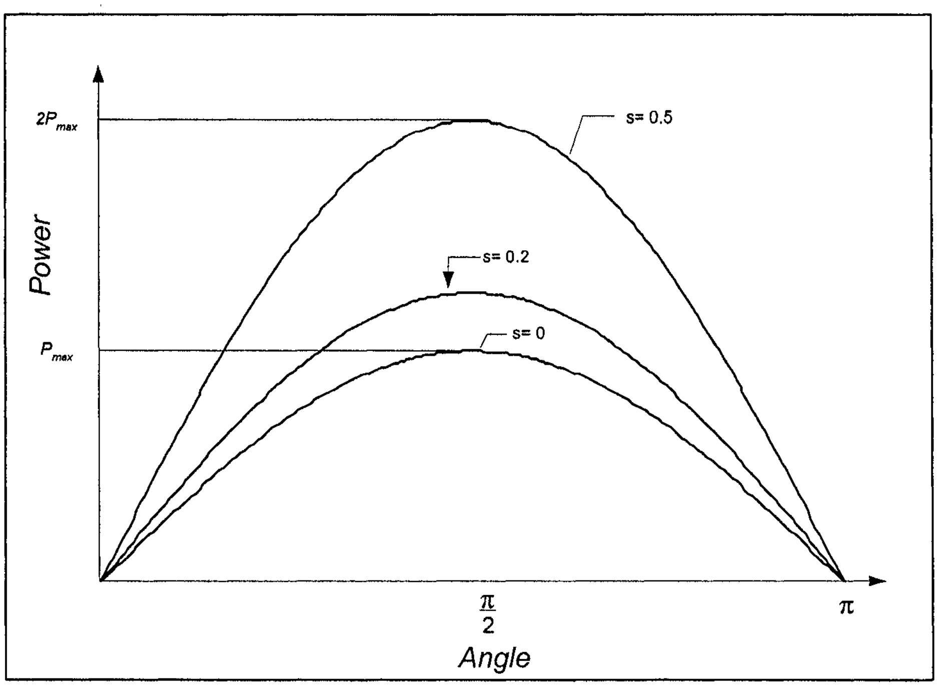


Figure 3.6: Power transmission characteristic for the series compensation

### 3.2.3 Phase Angle Control

A line compensated by a phase shifter is shown in figure 3.7. The voltage from the phase shifter, $V_{\sigma}$, is adjustable in phase and magnitude to produce the desired σ phase shift (leading or lagging). In this way, the sending-end voltage $V_S$ becomes the sum of the generator voltage $V_G$ and the phase shifter voltage $V_{\sigma}$. This can keep the transmitted power at a desired level independent of the angle δ between the sending and the receiving ends. Thus, the power can be kept at its peak value after the angle δ exceeds π/2 (the peak power angle) by controlling the effective phase angle (δ-σ) between the sending and the receiving ends.

The transmitted power can be expressed as follows:

$$P = \frac{V^2}{X}\sin(\delta - \sigma) \tag{3.11}$$

The phase shifter does not increase the maximum power transfer capability of the line as in the case of series and shunt compensation. However, it allows the maximum power transfer to occur at a wide range of the phase angle. This can be noticed from figure 3.8 which shows the transmitted power against the angle δ [58].

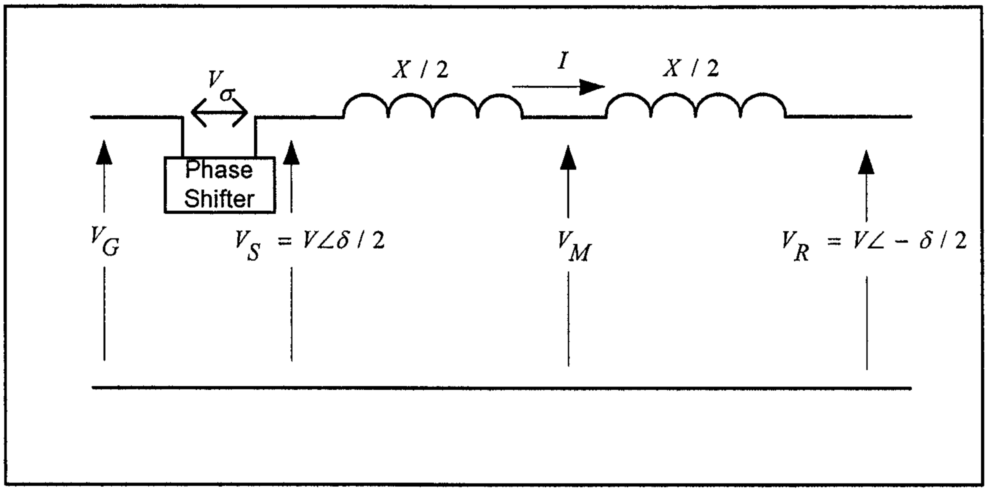


Figure 3.7: Simple power system model with phase shifter control

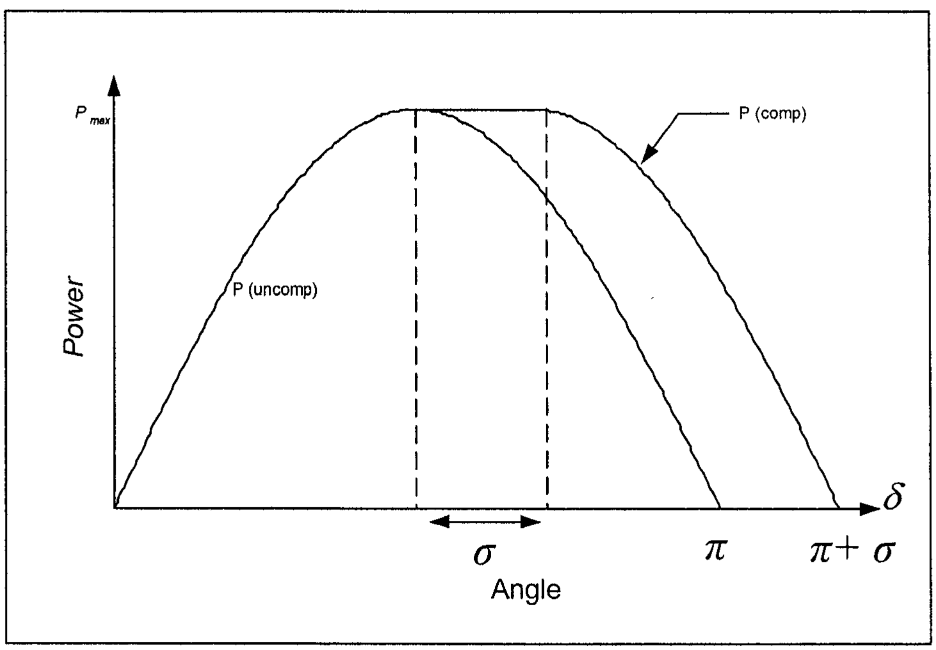


Figure 3.8: Power transmission characteristic for the phase shifter

## 3.3 FACTS Devices

Static Var compensator (SVC), Thyristor controlled series capacitor (TCSC), and Thyristor controlled phase shifter (TCPS) are FACT devices that act on the three parameters to determine the power transfer. What is common to those FACTS devices is that they employ thyristor reactive impedances or tap-changing transformer with thyristor switches as controlled elements.

### 3.3.1 Static Var Compensator

The early start of today's FACTS devices was a thyristor-controlled static var compensator (SVC) [4]. It has been identified by the word *static* because it does not have inertia or any rotating components. It has been defined by the IEEE as "a shunt-connected static Var generator or absorber whose output is adjusted to exchange capacitive or inductive current so as to maintain or control specific parameters of the electric power system (typically bus voltage)" [57].

Figure 3.9 shows the two most popular SVC configurations, namely, the fixed capacitor with a thyristor controlled reactor (FC/TCR) and the thyristor switched capacitor with the thyristor controlled reactor (TSC/TCR). The former is preferred in industrial application due to the less thyristor valves required whereas the later offer smoother control on reactive power.

From an operation point of view, the SVC can be seen as a variable shunt susceptance. Therefore, we choose to model the SVC as a total variable susceptance between certain limits as shown in figure 3.10. The effect of this on load flow can be taken care of in building the Y-Bus matrix [59].

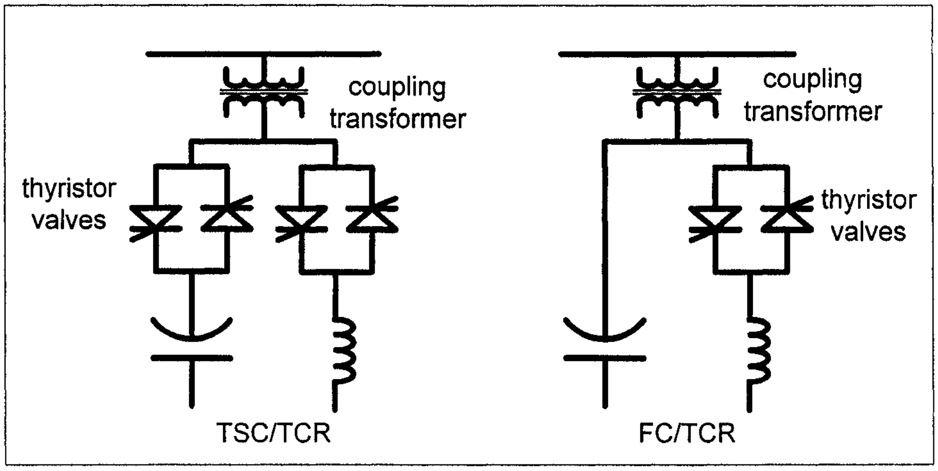


Figure 3.9: Static Var Compensator

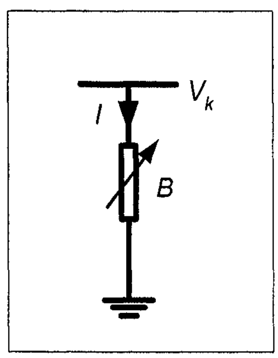


Figure 3.10: SVC model for power flow studies

### 3.3.2 Thyristor-Controlled Series Capacitor

Thyristor-controlled series capacitor (TCSC) is a more flexible way of series compensation which has been in use since early 1960s. It is the incorporation of thyristor valves that has led to that great flexibility in active power flow control and oscillation damping. Figure 3.10 shows one common scheme of TCSC. It is a fixed capacitor bank in parallel with a thyristor-controlled reactor in order to provide a smoothly variable series capacitive reactance. In addition to its effectiveness in steady state control of power flow, TCSC has been so effective in transient stability improvement and power oscillation damping [60]. According to [4], there have been three installation of TCSC in the United State of America (USA).

The effect of TCSC on power system can be seen as a controllable reactance $x_c$ inserted in the transmission line as shown in figure 3.12 [45,61].

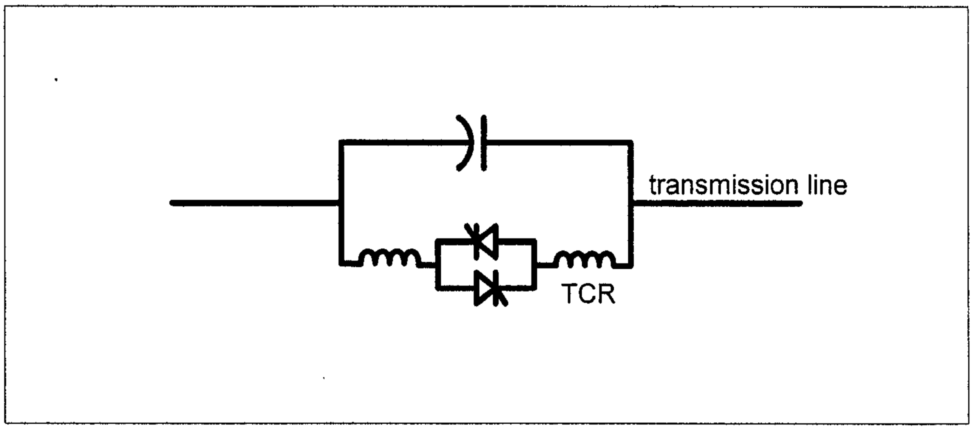


Figure 3.11: Thyristor Controlled Series Capacitor

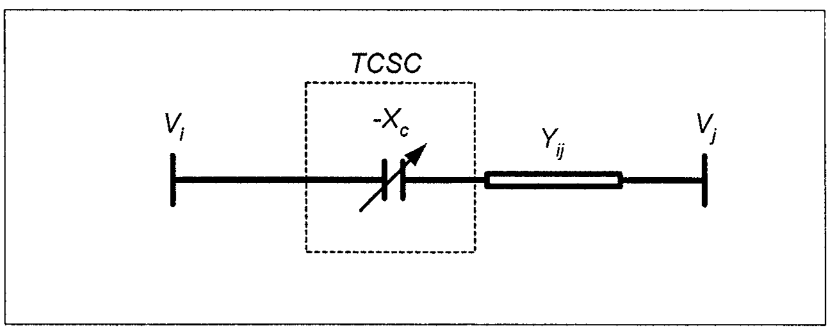


Figure 3.12: TCSC model in power flow calculation

### 3.3.3 Thyristor-Controlled Phase Shifter

The thyristor-controlled phase shifter (TCPS) is a phase-shifting transformer employs thyristor-controlled tap changer instead of the mechanical one to allow for a high speed operation. TCPS, as shown in figure 3.11, consists of a shunt-connected excitation transformer with appropriate taps, a series insertion transformer and a thyristor switch arrangement.

Similar to TCSC, TCPS allows for the control of power flow through the network and power sharing between parallel circuits. However, TCSC are more suitable for long distance lines while TCPS performs better in compact high density network [60].

The effect of the phase shifter can be seen to be equivalent to an ideal transformer with complex taps as shown in Figure 3.14.

The modification to the $Y$-Bus matrix is as follows [62]:

$$Y_{Bus} = \begin{pmatrix} t^2 Y_{ii} & -tY_{ij}e^{-j\Phi} \\ -tY_{ij}e^{-j\Phi} & Y_{jj} \end{pmatrix} \tag{3.12}$$

OPF with FACTS devices is formulated in the next chapter, chapter 4, using the modeling of FACTS explained in this chapter.

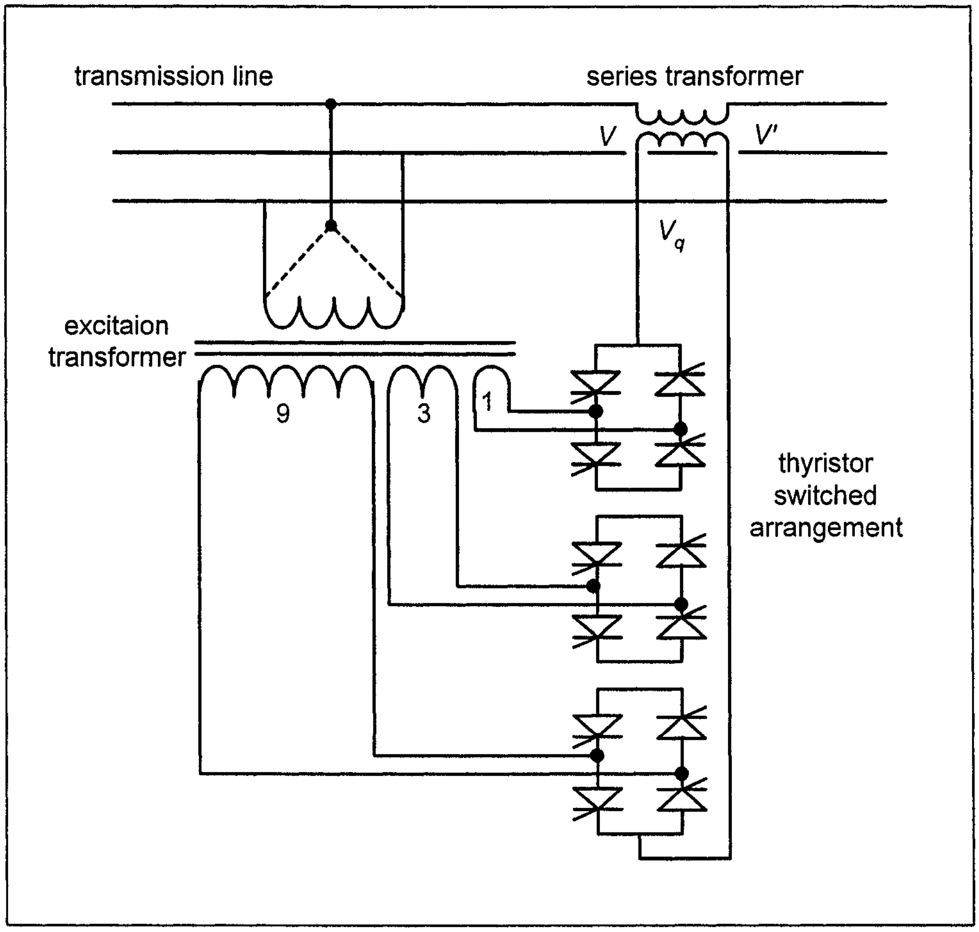


Figure 3.13: Thyristor-controlled phase shifter

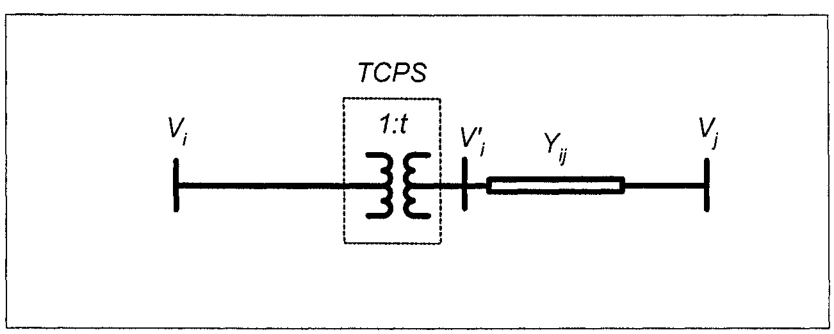


Figure 3.14: TCPS model in power flow calculation

# CHAPTER FOUR

# OPF FORMULATION WITH FACTS DEVICES

## 4.1 Overview

The OPF problem seeks to optimize the steady state performance of a power system in terms of an objective function while satisfying several equality and inequality constraints. OPF in its general form is expressed as follows:

$$Min \quad J(x,u) \tag{4.1}$$

$$\text{Subject to:} \quad g(x,u)=0 \tag{4.2}$$

$$h(x,u)\leq 0 \tag{4.3}$$

Where $x$ is the vector of state variables. This includes the slack bus power $P_{G1}$, load bus voltage $V_L$, generator reactive power output $Q_G$, and transmission line loadings $S_l$. Hence, $x$ can be expressed as

$$x^T = [P_{G_1}, V_{L_1},...., V_{L_{NL}}, Q_{G_1}, Q_{G_{NG}}, S_{l_1},...., S_{l_{nl}}] \tag{4.4}$$

Where *NL*, *NG*, and *nl* are number of load buses, number of generators, and number of transmission lines, respectively.

*u* is the vector of control parameters (independent variables). It consists of generator voltages $V_G$, generator real power outputs $P_G$ except the slack bus $P_{G1}$, transformer tap settings *T*, and *FACTS* devices control parameters. FACTS devices control parameters consists of the SVC susceptances *B*, TCSC reactances $x_C$, TCPS angles $\Phi$. Hence, *u* can be expressed as

$$\begin{aligned} u^T = [&V_{G_1} \ldots V_{G_{NG}}, P_{G_2} \ldots P_{G_{NG}}, T_1 \ldots T_{NT}, \\ &B_1 \ldots B_{NSVC}, x_{c_1} \ldots x_{C_{NTCSC}}, \Phi_1 \ldots \Phi_{NTCPS}] \end{aligned} \tag{4.5}$$

Where *NT*, *NSVC*, *NTCSC*, and *NTCPS* are number of regulating transformers, number of SVCs, number of TCSCs, and number of TCPSs, respectively.

## 4.2 Objectives

*J* is the objective function to be minimized. Most OPF objectives are related to the enhancement of the operation performance of the power system by looking for the optimal setting of some controlled variables. Another main objective of OPF is related to the optimal future planning of the power systems. This includes the optimal allocation of new equipments and expansion of transmission network. The control variables and the constraints are assumed to be common for the different objectives. Following are the objectives that are considered in this study.

### 4.2.1 Fuel Cost Minimization

Fuel cost minimization is the most classical objective. It is an expansion of the economic dispatch. It seeks to find the optimal active power outputs of the generation plants so as to minimize the total fuel cost.

$$J = \sum_{i}^{NG} f_i (\$ / h) \tag{4.6}$$

where $f_i$ is the fuel cost curve of the $i^{th}$ generator and it is assumed here to be represented by the following quadratic function:

$$f_i = a_i + b_i P_{G_i} + c_i P_{G_i}^2 \ (\$ / h) \tag{4.7}$$

where $a_i$, $b_i$, and $c_i$ are the cost coefficients of the $i^{th}$ generator.

### 4.2.2 Voltage Profile Improvement

Previous objective function seeks to improve the cost of operation regardless of the power quality. It may result in an unattractive state from the power quality point of view [19]. Optimal power system operation requires some kind of compromise between the operation cost and quality. Voltage profile is one of the quality measures for power system. It can be improved by minimizing the load bus voltage deviations from 1.0 per unit. The objective function can be expressed as

$$J = \sum_{i \in NL} \left| V_i - 1 \right| \tag{4.8}$$

### 4.2.3 Voltage Stability Enhancement

Voltage profile is not all for power system operation quality. Voltage profile improvement does not necessary implies a voltage secure system. Voltage instability problems have been experienced in systems where voltage profile was acceptable [28]. Voltage secure system can be assured by enhancing the voltage stability profile throughout the whole power system.

An indicator L-index is used in this study to evaluate the voltage stability at each bus of the system. The indicator value varies between 0 (no load case) and 1 (voltage collapse) [32,63,64]. L-index at load bus $j$ can be expressed as:

$$L_j = \left| L_j \right| = \left| 1 - \frac{\sum_{i \in \alpha_G} C_{ji} V_i}{V_j} \right| \qquad j \in \alpha_L \tag{4.9}$$

Where:

$\alpha_L$ : set of load buses

$\alpha_G$ : set of generator buses

$V_j$ : complex voltage at load bus $j$

$V_i$ : complex voltage at generator bus $i$

$C_{ji}$ : elements of matrix C determined by:

$$[C] = -\left[Y_{LL}\right]^{-1}\left[Y_{LG}\right] \tag{4.10}$$

Matrix $[Y_{LL}]$ and $[Y_{LG}]$ are submatrices of Y-bus matrix in equation (4.11)

$$\begin{bmatrix} I_L \\ I_G \end{bmatrix} = \begin{bmatrix} Y_{LL} & Y_{LG} \\ Y_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} V_L \\ V_G \end{bmatrix} \tag{4.11}$$

Some of the best features of the L-index is that the computation speed of very fast and so can be used for on-line monitoring of power system. Enhancing the voltage stability and moving the system far from voltage collapse point can be achieved by minimizing the following objective function

$$J = L_{\max} \tag{4.12}$$

Where $L_{max}$ is the maximum value of L-index defined as

$$L_{\max} = \max \{L_K, K = 1, \ldots\ldots, NL\} \tag{4.13}$$

## 4.3 Constraints

The functions $g$ and $h$ are the equality and inequality constraints to be satisfied while searching for the optimal solution.

### 4.3.1 Equality constraints

The function $g$ represents the equality constraints which are the power flow equations corresponding to both real and reactive power balance equations, which can be written as:

$$P_{G_i} - P_{D_i} = \sum_{j=1}^{NB} V_i V_j Y_{ij}(FACTS)\cos(\theta_{ij}(FACTS) + \delta_j - \delta_i) = 0 \quad ; \forall\, i \in NB \tag{4.14}$$

$$Q_{G_i} - Q_{D_i} = \sum_{j=1}^{NB} V_i V_j Y_{ij}(FACTS)\sin(\theta_{ij}(FACTS) + \delta_j - \delta_i) = 0 \quad ; \forall\, i \in NB \tag{4.15}$$

Where:

$NB$ is the number of buses;

$P_{Gi}$ 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 $i$;

$V_i$ and $\delta_i$ are voltage magnitude and angle at bus $i$;

$Y_{ij}(FACTS)$ and $\theta_{ji}(FACTS)$ are magnitude and phase angle of elements in Y-bus matrix where the effects of FACTS have been taken into consideration.

### 4.3.2 Inequality constraints

$h$ is the system inequality operation constraints that include:

i) Generation constraints: Generator voltages, real power outputs, and reactive power outputs are restricted by their lower and upper limits as follows:

$$V_{G_i}^{\min} \le V_{G_i} \le V_{G_i}^{\max}, \qquad i = 1,\ldots\ldots, NG \tag{4.16}$$

$$P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max}, \qquad i = 1,\ldots\ldots, NG \tag{4.17}$$

$$Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max}, \qquad i = 1,\ldots\ldots, NG \tag{4.18}$$

ii)Transformer constraints: Transformer tap settings are bounded as follows:

$$T_i^{\min} \le T_i \le T_i^{\max}, \quad i = 1,\ldots\ldots, NT \tag{4.19}$$

iii) Security constraints: These include the constraints of voltages at load buses and transmission lines loadings as follows

$$V_{L_i}^{\min} \le V_{L_i} \le V_{L_i}^{\max} \ , \ i = 1,\ldots\ldots, NL \tag{4.20}$$

$$S_l \le S_{l_i}^{\max} \ , \qquad i = 1,\ldots\ldots, nl \tag{4.21}$$

iv) FACTS devices constraints: SVC, TCSC, and TCPS settings are bounded as follows:

$$B_i^{\min} \le B_i \le B_i^{\max} \ , \quad i = 1,\ldots\ldots, NSVC \tag{4.22}$$

$$x_{C_i}^{\min} \le x_{C_i} \le x_{C_i}^{\max} \ , \quad i = 1,\ldots\ldots, NTCSC \tag{4.23}$$

$$\Phi_i^{\min} \le \Phi_i \le \Phi_i^{\max} \ , i = 1,\ldots\ldots, NTCPS \tag{4.24}$$

Where $B$ is the SVC susceptance, $x_c$ is the TCSC reactance, and $\Phi$ is the TCPS angle. It is worth mentioning that the control variables are self constrained. The hard inequalities of $P_{G1}$, $V_L$, $Q_G$, and $S_l$ can be incorporated in the objective function as quadratic penalty terms. Therefore, the objective function can be augmented as follows:

$$\begin{aligned} J_{aug} &= J + \lambda_P (P_{G_1} - P_{G_1}^{\lim})^2 + \lambda_V \sum_{i=1}^{NL} (V_{L_i} - V_{L_i}^{\lim})^2 \\ &+ \lambda_Q \sum_{i=1}^{NG} (Q_{G_i} - Q_{G_i}^{\lim})^2 + \lambda_S \sum_{i=1}^{nl} (S_{l_i} - S_{l_i}^{\max})^2 \end{aligned} \tag{4.25}$$

where $\lambda_P$, $\lambda_V$, $\lambda_Q$, and $\lambda_S$ are penalty factors and $x^{lim}$ is the limit value of the dependent variable $x$ given as

$$x^{\lim} = \begin{cases} x^{\max} ; x \succ x^{\max} \\ x^{\min} ; x \prec x^{\min} \end{cases} \tag{4.26}$$

The solution methodology for solving the OPF problem formulated above will be presented in the following chapter.

# CHAPTER FIVE

# SOLUTION METHODOLOGY

This chapter explains the optimization techniques employed for solving the OPF for the different objectives formulated in chapter four. It starts by a general overview that highlights the general tasks of the optimization algorithms and the nature of the evolutionary algorithms in general. This is followed by an explanation of the Genetic Algorithm and Particle Swarm Optimization in sections 5.2 and 5.3 respectively. The implementation details of the two algorithms for OPF solving are also given. Section 5.4 describes a new GA/PSO for solving the optimal FACTS devices location problems.

## 5.1 Overview

OPF is an optimization problem and the quality of its solution depends greatly on the optimization technique employed for this purpose. Optimization algorithms are needed in this study for the following purposes:

- Solving single objective OPF with/without FACTS devices.
- Solving multi-objective OPF with/without FACTS devices.

- Finding optimal locations and settings of FACTS with respect to a certain objective.

Genetic algorithm (GA) and Particle swarm optimization (PSO) have been selected for those purposes. They are two of the leading optimization algorithms belonging to the class of algorithms known as *stochastic iterative search methods*. Algorithms of this class take the following general shape shown in figure 5.1.

| |
|---|
| 1. Begin: generate and evaluate an initial collection of candidate solutions *S*. <br> 2. Operate: produce and evaluate a collection of new candidate solution *S'* by making randomized changes to the initial solution *S*. <br> 3. Renew replace some of the members of S with some better members of *S'*, and then (unless some termination criteria has been reached) return to 2. |

Figure 5.1: Generalized stochastic iterative search

These methods outperform other traditional methods for the following main reasons:

1. They search the problem space using a population of trials representing possible solutions to the problem, not a single point. This property ensures these algorithms to be less susceptible to getting trapped on local minima and moving over hills and across valleys. It provides also some kind of parallelism.
2. They use objective functions assessment to guide the search in the problem space. Therefore, they are very general and can deal with non-smooth, non-continuous and non-differentiable functions.

3. They use probabilistic transition rules, not deterministic rules. Hence, they can search a complicated and uncertain area. This makes them more flexible and robust than conventional methods.

The following two sections explain these two algorithms.

## 5.2 Genetic Algorithm (GA)

Genetic Algorithms (GAs) were invented by *John Holland* and developed by him and his students and colleagues [65]. GA typical structure was described by David Goldberg [66].

In general, GA is started with a *set of solutions* (represented by *chromosomes*) called *population*. Solutions from one population are taken and used to form a new population. This is done by evolving the chromosomes through successive iterations, called *generations*. During each generation, the chromosomes are evaluated using some measure of *fitness*. To create the next generation, new chromosomes called *offspring*, are formed by a *crossover* operator or/and a *mutation* operator. This is repeated until some condition (for example number of populations or improvement of the best solution) is satisfied. Following is a detailed explanation of the algorithm.

### 5.2.1 GA Basic Elements and Operators

- ***Chromosome, X(t),:*** It is a string structure representing a candidate solution usually, but not necessary, coded in terms of binary alphabet. Real coded chromosomes can be used and in this case each chromosome is represented by an $m$-dimensional real-valued vector, where $m$ is the number of optimized parameters. At time $t$, the $j^{th}$ chromosome $X_j(t)$ can be described as $X_j(t)=[x_{j,1}(t), x_{j,2}(t),\ldots, x_{j,m}(t)]$, where $xs$ are the optimized parameters and $x_{j,k}(t)$ is the position of the $j^{th}$ chromosomes with respect to the $k^{th}$ dimension, i.e., the value of the $k^{th}$ optimized parameter in the $j^{th}$ candidate solution.

- ***Population, pop(t),***: It is a set of $n$ chromosomes at time $t$, i.e., $pop(t)=[X_1(t), X_2(t), \ldots, X_n(t)]$.
- ***Crossover,:*** It is the most dominant operator in GA, and is responsible for producing new children by selecting two strings among the potential parents and exchanging portions of their structures. The new children may replace the weaker individuals in the population. A *blend crossover operator (BLX-α)* has been employed in this study. This operator starts by choosing randomly a number from the interval $[x_i-\alpha(y_i-x_i), y_i+\alpha(y_i-x_i)]$, where $x_i$ and $y_i$ are the $i^{th}$ parameter values of the parent solutions and $x_i < y_i$. To ensure the balance between exploitation and exploration of the search space, $\alpha = 0.5$ is selected. This operator is depicted in Figure 5.2. In this way, the excellent characteristics of the parents will be inherited in the next generation. The probability of crossover is set arbitrarily and is typically greater than or equal to 0.6. When a random number generated between 0 and 1 is less than the preset value of crossover probability, crossover will take place.

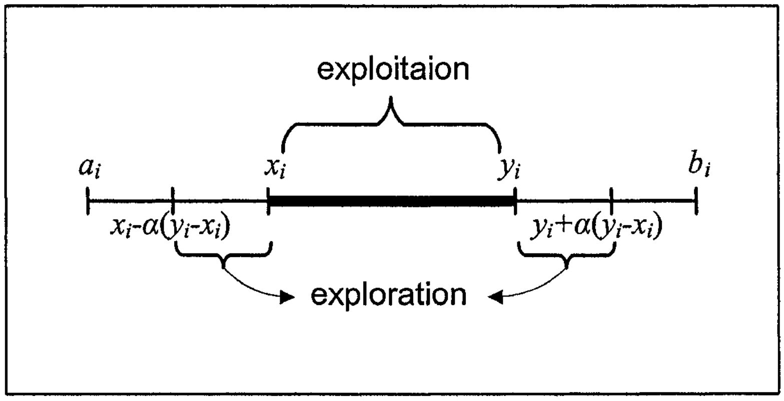


Figure 5.2: Blend crossover operator (BLX-α)

- ***Mutation,:*** It is a local operator, which is applied with a very low probability of occurrence. Its function is to alter the value of a random position in a string. This avoids the loss of important information at a particular position in the string. Similar to crossover probability, the mutation probability is set arbitrarily and is typically 0.1 per individual. When a random number generated between 0 and 1 is less than the preset value of mutation probability, a string will be mutated. Random mutation operator has been employed in this study.
- ***Global best, $X^*(t)$,:*** As a chromosomes move through the search space, it compares its fitness value at the current position to the best fitness value the algorithm has ever attained at any time up to the current time. The best position that is associated with the best fitness encountered so far is the global best, $X^*(t)$. Hence, the global best can be determined such that $J(X^*(t)) \leq J(X_j(t)),\ j = 1,\ldots\ldots, n$.
- ***Stopping criteria:*** These are the conditions under which the search process will terminate. In this study, the search will terminate if one of the following criteria is satisfied: (a) the number of iterations since the last change of the best solution is greater than a prespecified number; or (b) the number of iterations reaches the maximum allowable number.

### 5.2.2 GA Searching Technique

In GA algorithm, the population has $n$ chromosomes that represent candidate solutions. Each chromosome is an $m$-dimensional real-valued vector, where $m$ is the number of optimized parameters. Therefore, each optimized parameter represents a dimension of the problem space.

The GA technique can be described in the following steps:

***Step 1 (Initialization):*** Set the time counter $t=0$ and generate randomly $n$ chromosomes, $\{X_j(0), j = 1,\ldots\ldots, n\}$, where $X_j(0) = [x_{j,1}(0),\ldots\ldots, x_{j,m}(0)]$. $x_{j,k}(0)$ is generated by randomly selecting a value with uniform probability over the $k^{th}$ optimized parameter search space $[x_k^{\min}, x_k^{\max}]$.

***Step 2 (Fitness):*** Evaluate each chromosome in the initial population using the objective function, $J$. Search for the best value of the objective function $J_{best}$. Set the chromosome associated with $J_{best}$ as the global best.

***Step 3 (Time updating):*** Update the time counter $t=t+1$.

***Step 4 (New population):*** Create a new population by repeating the following steps until the new population is complete:

- ***Selection:*** Select two parent chromosomes from a population according to their fitness (the better fitness, the bigger chance to be selected)
- ***Crossover:*** With a crossover probability, cross over the parents to form a new offspring (children). If no crossover was performed, offspring is an exact copy of parents.
- ***Mutation:*** With a mutation probability, mutate new offspring at each locus (position in chromosome).

- *Accepting*: Place new offspring in a new population

***Step 5 (Replace):*** Use new generated population for a further run of algorithm.

***Step 6 (Stopping criteria):*** If one of the stopping criteria is satisfied then stop; else go to step 2.

### 5.2.3 GA Implementation for OPF

Figure 5.3 represents the contents of the chromosomes for a real coded GA used for OPF solving. It consists of the looked for control variables settings. *n* number of these chromosomes are generated based on the population size of the algorithm.

Figure 5.4 shows the flow chart of OPF using GA. The load flow is simulated for each candidate solution to evaluate its fitness. That is because the fitness function takes into consideration the violation such as load bus voltages, generator Mvar limits, and line loading as was declared in chapter 4.

| Generator MW Output | | | Generator Voltages | | | Transformer Settings | | | FACTS Settings | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $G_1$ | $G_2$ | - - - - - - - | $V_1$ | $V_2$ | - - - - - - - | $T_1$ | $T_2$ | - - - - - - - | $FACTS_1$ | $FACTS_2$ | - - - - - - - |

Figure 5.3: GA string

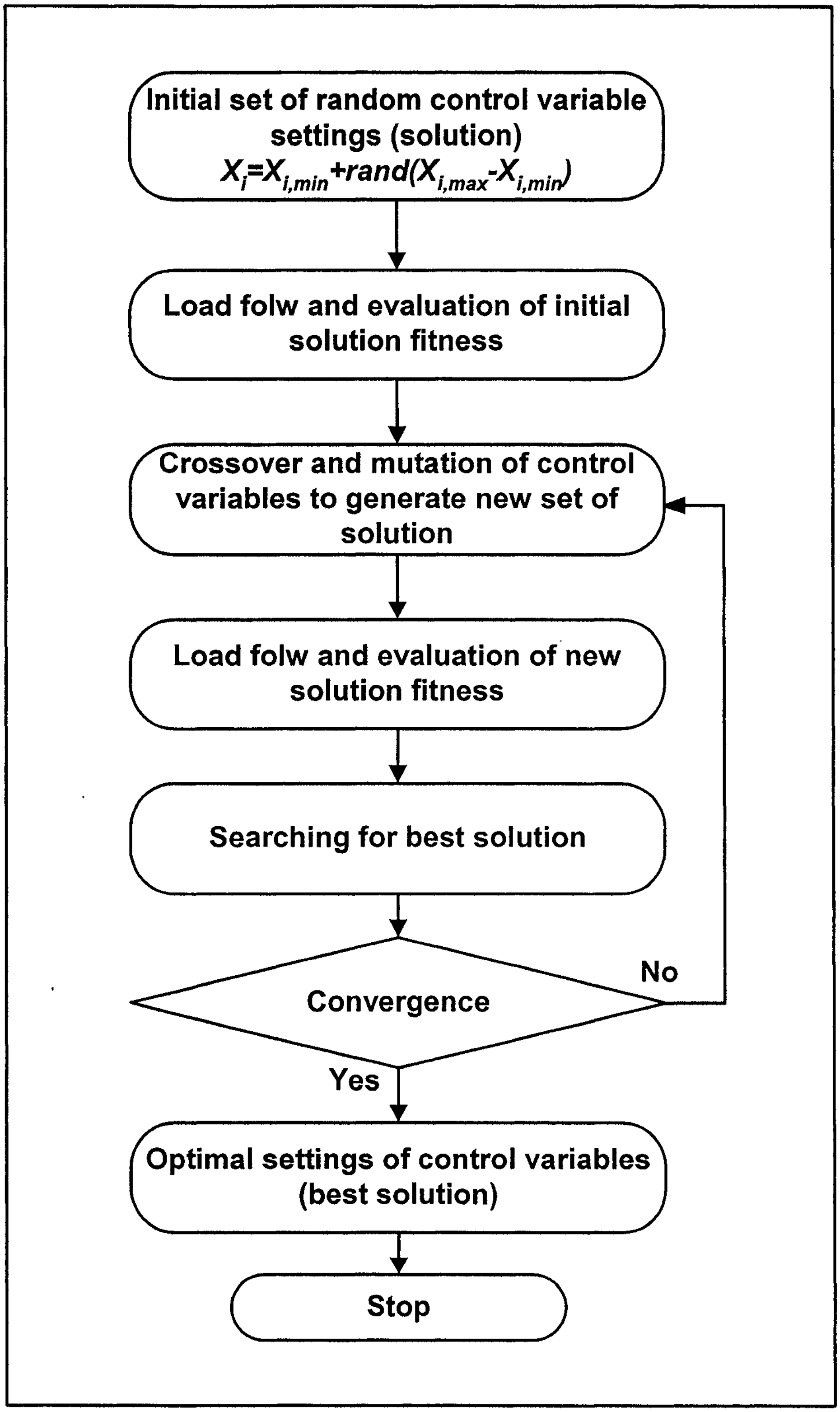


Figure 5.4: GA for OPF solution

## 5.3 Particle Swarm Optimization (PSO)

Like evolutionary algorithms, PSO technique conducts searching using a population of particles, corresponding to individuals. Each particle represents a candidate solution to the problem at hand. In a PSO system, particles change their positions by flying around in a multi-dimensional search space until a relatively unchanging position has been encountered, or until computational limitations are exceeded. Unlike GA and other heuristic algorithms, PSO has the flexibility to control the balance between the global and local exploration of the search space. This unique feature of PSO overcomes the premature convergence problem and enhances the search capability [67-72].

### 5.3.1 PSO Basic Elements and Operators

- ***Particle, X(t),:*** This is analogous to chromosome in GA. It is a candidate solution represented by an $m$-dimensional real-valued vector, where $m$ is the number of optimized parameters. At time $t$, the $j^{th}$ particle $X_j(t)$ can be described as $X_j(t)=[x_{j,1}(t),\ x_{j,2}(t),\dots,\ x_{j,m}(t)]$, where $xs$ are the optimized parameters and $x_{j,k}(t)$ is the position of the $j^{th}$ particle with respect to the $k^{th}$ dimension, i.e., the value of the $k^{th}$ optimized parameter in the $j^{th}$ candidate solution.
- ***Population, pop(t),***: It is a set of $n$ particles at time $t$, i.e., $pop(t)=[X_1(t),\ X_2(t),\ \dots,\ X_n(t)]$.
- ***Swarm:*** it is an apparently disorganized population of moving particles that tend to cluster together while each particle seems to be moving in a random direction.

- ***Particle velocity, V(t),:*** It is the velocity of the moving particles represented by an $m$-dimensional real-valued vector. At time $t$, the $j^{th}$ particle velocity $V_j(t)$ can be described as $V_j(t)=[v_{j,1}(t), v_{j,2}(t), \ldots, v_{j,m}(t)]$, where $v_{j,k}(t)$ is the velocity component of the $j^{th}$ particle with respect to the $k^{th}$ dimension. It is also limited by some maximum value, $v_k^{max}$. This limit enhances the local exploration of the problem space and it realistically simulates the incremental changes of human learning. The maximum velocity in the $k^{th}$ dimension is characterized by the range of the $k^{th}$ optimized parameter and given by

$$v_k^{\max} = \left(x_k^{\max} - x_k^{\min}\right)/N \qquad (5.1)$$

where $N$ is a chosen number of intervals.

- ***Inertia weight, w(t),:*** It is a control parameter that is used to control the impact of the previous velocities on the current velocity. Hence, it influences the trade-off between the global and local exploration abilities of the particles. For initial stages of the search process, large inertia weight to enhance the global exploration is recommended while, for last stages, the inertia weight is reduced for better local exploration. The decrement function for decreasing the inertia weight given as $w(t)=\alpha\, w(t-1)$, where $\alpha$ is a decrement constant smaller than but close to 1, is proposed in this study.

- ***Individual best, X (t),:*** As a particle moves through the search space, it compares its fitness value at the current position to the best fitness value it has ever attained at any time up to the current time. The best position that is associated with the best fitness encountered so far is called the individual best, $X^*(t)$. For each particle in the swarm, $X^*(t)$ can be determined and updated during the search. In a minimization problem with objective function $J$, the individual best of the $j^{th}$ particle $X_j^*(t)$ is determined such that $J(X_j^*(t)) \leq J(Xj(\tau))$, $\tau \leq t$. For simplicity, assume that $J_j^* = J(Xj(\tau))$. For the $j^{th}$ particle, individual best can be expressed as $X_j^*(t) = [x_{j,1}^*(t), \ldots\ldots, x_{j,m}^*(t)]$.

- ***Global best, $X^{**}(t)$,:*** It is the best position among all individual positions achieved so far. Hence, the global best can be determined such that $J(X^{**}(t)) \leq J(X_j^*(t)), j = 1, \ldots\ldots, n$. For simplicity, assume that $J^{**} = J(X^{**}(t))$.
- ***Stopping criteria:*** Same as with GA.

### 5.3.2 PSO Searching Technique

In PSO algorithm, the population has $n$ particles that represent candidate solutions. Each particle is an $m$-dimensional real-valued vector, where $m$ is the number of optimized parameters. Therefore, each optimized parameter represents a dimension of the problem space.

The PSO technique can be described in the following steps:

***Step 1 (Initialization):*** Set the time counter $t=0$ and generate randomly $n$ particles, $\{X_j(0), j = 1, \ldots\ldots, n\}$, where $X_j(0) = [x_{j,1}(0), \ldots\ldots, x_{j,m}(0)]$. $x_{j,k}(0)$ is generated by randomly selecting a value with uniform probability over the $k^{th}$ optimized parameter search space $[x_k^{\min}, x_k^{\max}]$. Similarly, generate randomly initial velocities of all particles, $\{V_j(0), j = 1, \ldots\ldots, n\}$, where $V_j(0) = [v_{j,1}(0), \ldots\ldots, v_{j,m}(0)]$. $V_{j,k}(0)$ is generated by randomly selecting a value with uniform probability over the $k^{th}$ dimension $v_k^{\min}, v_k^{\max}]$. Each particle in the initial population is evaluated using the objective function, $J$. For each particle, set $X_j^*(0) = X_j(0)$ and $J_j^* = J_j$, $j=1, 2, \ldots, n$. Search for the best value of the objective function $J_{best}$. Set the particle associated with $J_{best}$ as the global best, $X^{**}(0)$, with an objective function of $J^{**}$. Set the initial value of the inertia weight $w(0)$.

***Step 2 (Time updating):*** Update the time counter $t=t+1$.

***Step 3 (Weight updating):*** Update the inertia weight $w(t)=\alpha\, w(t-1)$.

***Step 4 (Velocity updating):*** Using the global best and individual best, the $j^{th}$ particle velocity in the $k^{th}$ dimension is updated according to the following equation:

$$\begin{aligned} v_{j,k}(t) &= w(t)v_{j,k}(t-1) + c_1 r_1\left(x^*_{j,k}(t-1) - x_{j,k}(t-1)\right) \\ &\quad + c_2 r_2\left(x^*_{j,k}(t-1) - x_{j,k}(t-1)\right) \end{aligned} \tag{5.2}$$

where $c_1$, and $c_2$ are positive constants and $r_1$, and $r_2$ are uniformly distributed random numbers in [0,1]. Check the velocity limits. If the velocity violates its limit set it at its proper limit.

***Step 5 (Position updating):*** Based on the updated velocities, each particle changes its position according to the following equation

$$x_{j,k}(t) = v_{j,k}(t) + x_{j,k}(t-1) \tag{5.3}$$

If a particle violates its position limits in any dimension, set its position at the proper limit.

***Step 6 (Individual best updating):*** Each particle is evaluated according to the updated position. If $J_j < J^*_j$, $j=1, 2, ..., n$, then update individual best as $X^*_j(t)=X_j(t)$ and $J^*_j = J_j$ and go to step 7; else go to step 7.

***Step 7 (Global best updating):*** Search for the minimum value $J_{\min}$ among $J^*_j$ where *min* is the index of the particle with minimum objective function value, i.e., min $\in \{j; j=1, 2, ..., n\}$. If $J_{min}<J^{**}$ then update global best as $X^{**}= X_{min}(t)$ and $J^{**}=J_{min}$ and go to step 8; else go to step 8.

***Step 8 (Stopping criteria):*** If one of the stopping criteria is satisfied then stop ;else go to step 2.

### 5.3.3 PSO Implementation for OPF

In using PSO for OPF solving, the particles represents the sought control variables. Similar to GA, figure 5.3 shows the contents of the particles and based on the population size, *n* number of these particles are generated. Figure 5.5 shows the whole algorithm.

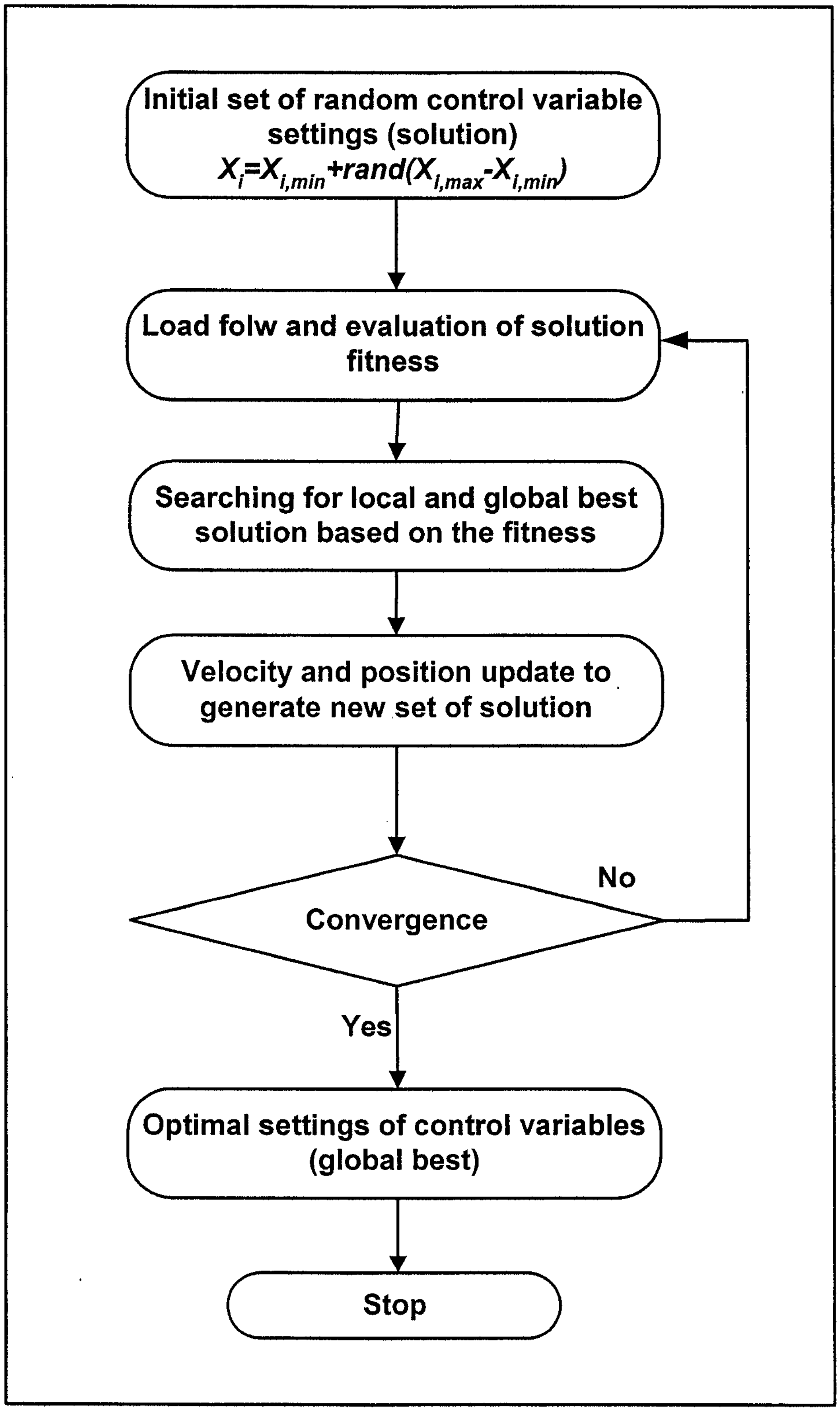


Figure 5.5: PSO for OPF solution

## 5.4 New Proposed GA/PSO

This is a searching technique developed for a complex and complicated problem related to OPF. That problem is finding the optimal FACTS device location and settings with respect to one of the OPF objectives discussed in chapter 4.

### 5.4.1 Motivation of GA/PSO

The problem above consists of two parts. The first is the optimal FACTS devices locations while the second is the OPF that generates the optimal settings of the FACTS devices together with the other control variables.

The result of the first part is an integer which is either bus number and/or branch numbers where FACTS devices are suggested to be installed. This needs an integer-based optimization algorithm. GA has been chosen to play this role because of its attractive quality. Fitness candidate solution is part of GA which requires OPF solving. From here the need for PSO appears. PSO has fast convergence ability which is greatly attractive property for such a large iterative and time consuming problem [69-72].

### 5.4.2 OPF Using GA/PSO

The interaction between the two algorithms as shown in figure 5.6 goes as follows. GA generates candidate FACTS locations and PSO evaluate them by solving the OPF with those FACTS locations. This yields to the optimal settings for those FACTS devices together with the other control variables and so the corresponding fitness of for each

FACTS location. The GA then takes that information and processes in generating another solution set by crossing over and mutating the old FACTS locations set. PSO is then consulted again for OPF solving with those new FACTS locations. This process is repeated until one of the stopping criteria for GA is satisfied. The final output of the process is an optimal setting of the OPF control variables with an optimal, or rather close to optimal, FACTS devices location with their corresponding optimal settings.

The new GA/PSO technique can be described in the following steps:

***Step 1 (Initialization):*** Set the time counter $t=0$ and generate randomly $n$ chromosomes, $\{X_j(0), j = 1,\ldots\ldots, n\}$ that represent n initial candidate FACTS devices locations.

***Step 2 (Fitness using PSO):*** Evaluate each chromosome (candidate FACTS location) in the initial population using the objective function, $J$. This is done by solving the OPF with each candidate location using PSO. Search for the best value of the objective function $J_{best}$. Set the chromosome (FACTS location) associated with $J_{best}$ as the global best.

***Step 3 (Time updating):*** Update the time counter $t=t+1$.

***Step 4 (New population):*** Create a new population of FACTS location by repeating the following steps until the new population is complete:

- ***Selection:*** Select two parent chromosomes from a population according to their fitness (the better fitness, the bigger chance to be selected)
- ***Crossover:*** With a crossover probability, cross over the parents to form a new offspring (children). If no crossover was performed, offspring is an exact copy of parents.
- ***Mutation:*** With a mutation probability, mutate new offspring at each locus (position in chromosome).
- ***Accepting***: Place new offspring in a new population

***Step 5 (fitness using PSO and time updating):*** repeat step 2 and 3 with the new FACTS locations.

***Step 6 (Stopping criteria):*** If one of the stopping criteria is satisfied then stop; else go to step 4. Figure 5.6 shows those steps.

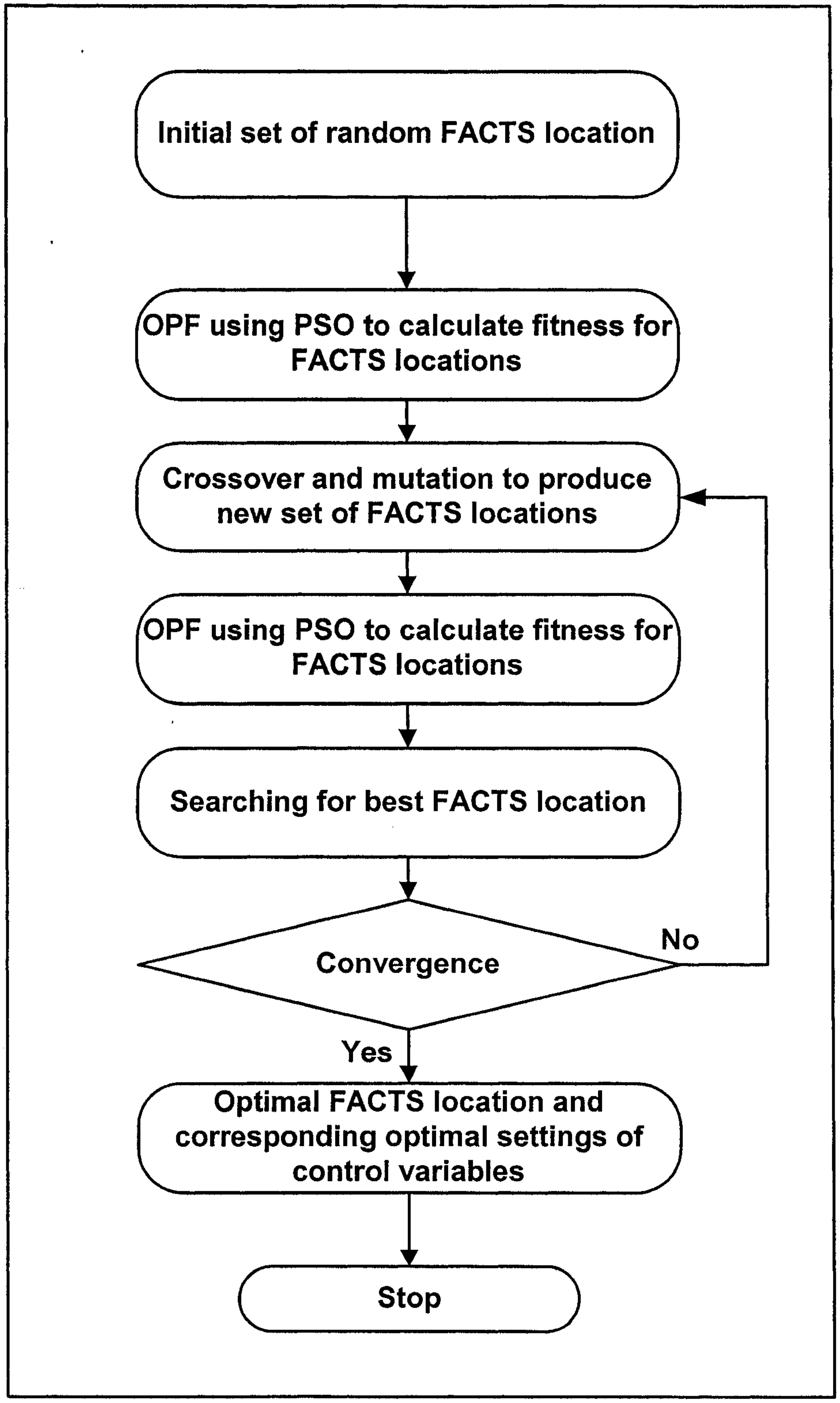


Figure 5.6: The new proposed GA/PSO

# CHAPTER SIX

# SOLUTION OF OPF USING GA AND PSO

This chapter uses the GA and PSO to solve the traditional OPF without FACTS control devices. The purpose is to assess the potential of PSO against those of the GA. The objective function used is the fuel cost minimization and standard IEEE-30 bus system is used in all simulations.

Both the GA and the PSO were developed and implemented on 2.0GHz PC using FORTRAN language. The population size, maximum number of generation and other settings for the two algorithms are stated before each simulation case.

## 6.1 IEEE 30-Bus System

Figure 6.1 shows the standard IEEE 30-bus system used for simulation. The system line and bus data are given by [73] and shown in Appendix I. The system has six generators at buses 1, 2, 5, 8, 11, and 13 and four transformers with off-nominal tap ratio in line 6-9, 6-10, 4-12, and 28-27. No shunt Var compensation buses have been selected.

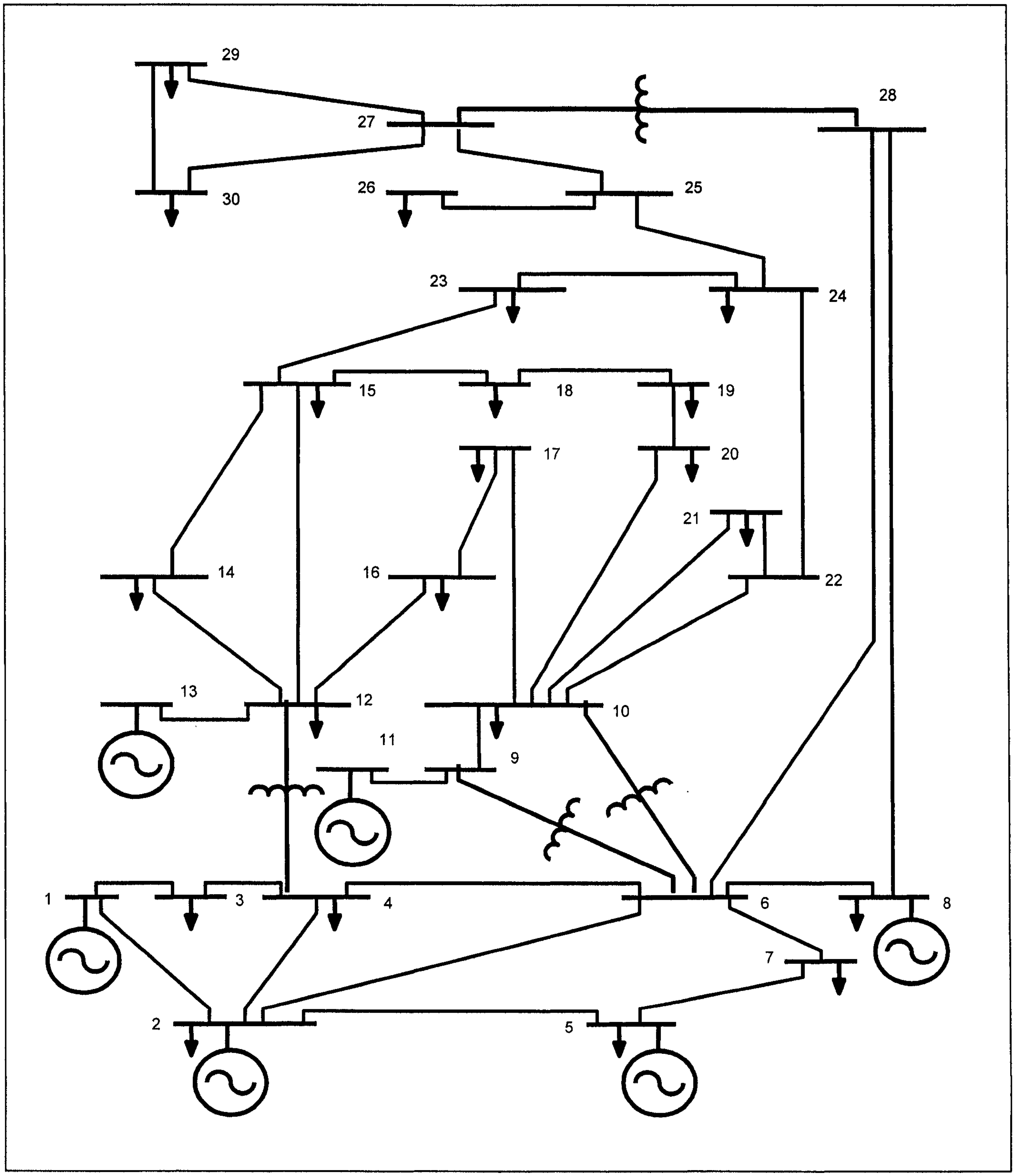


Figure 6.1: Single line diagram of IEEE 30-bus system

## 6.2 Fuel Cost Minimization Using GA and PSO

The effectiveness and robustness of GA and PSO have been evaluated and assessed. Both algorithms have been employed for finding OPF solution that best minimize the total fuel cost. Several runs of both algorithms with different population size have been conducted. The maximum number of generation has been kept equal to 300 in all simulations.

The objective function is the total fuel cost, i.e.

$$J = \sum_{i}^{NG} f_i (\$ / h) \tag{6.1}$$

where $f_i$ is the fuel cost of the $i^{th}$ generator.

The generator cost curves are represented by quadratic functions as [73]

$$f_i = a_i + b_i P_{G_i} + c_i P_{G_i}^2 \ (\$ / h) \tag{6.2}$$

where $a_i$, $b_i$, and $c_i$ are the cost coefficients of the $i^{th}$ generator. The values of these coefficients are given in Table 6.1.

Table 6.1: Generation cost coefficients [73]

| | G1 | G2 | G3 | G8 | G11 | G13 |
|---|---|---|---|---|---|---|
| a | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| b | 200 | 175 | 100 | 325 | 300 | 300 |
| c | 37.5 | 175 | 625 | 83.4 | 250 | 250 |

The controlled variables were the generator MW outputs, the generator terminal voltages, and the transformer tap settings. No FACTS devices were assumed in the system.

### 6.2.1 Settings of the Searching Algorithms

As stated earlier, the number of population and the initial solutions were varied to see how robust both algorithms are to those two factors.

**GA settings:**

The maximum number of generation for each algorithm was kept as 300. Population sizes of 5, 10, 25, and 50 were used to see the effect of that on the algorithm performance. Real GA coding was implemented with a crossover probability of 0.9 and mutation probability of 0.1 per individual.

**PSO settings:**

PSO has more key parameters than GA. The maximum number of generation and the population size were analogous to those used for GA. The initial inertia weight $w(0)$ and the number of intervals in each space dimension $N$ were selected as 1.0 and 10, respectively. The decrement constant $\alpha=0.9$ and $c_1=c_2=1.0$.

## 6.3 Convergence of GA and PSO

How fast an optimization algorithm converges to the optimal solution is an important issue. The two algorithms were tested using four different number of population, specifically, five (5), ten (10), twenty five (25), and fifty (50). Each was tested using same ten different initial solutions. Figures 6.2-6.5 show the average fuel cost variation versus iteration for both algorithms. It is clear that with all population sizes considered, PSO performs better than GA in terms of the best value of the objective function as well as the speed of convergence.

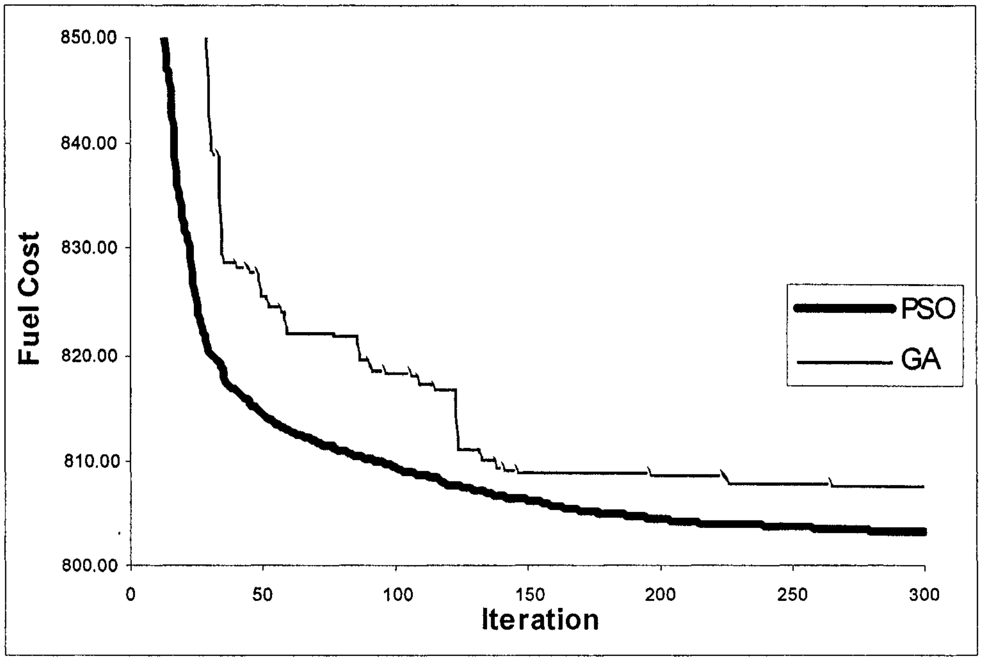


Figure 6.2: Average fuel cost variation of GA and PSO with population of five (5)

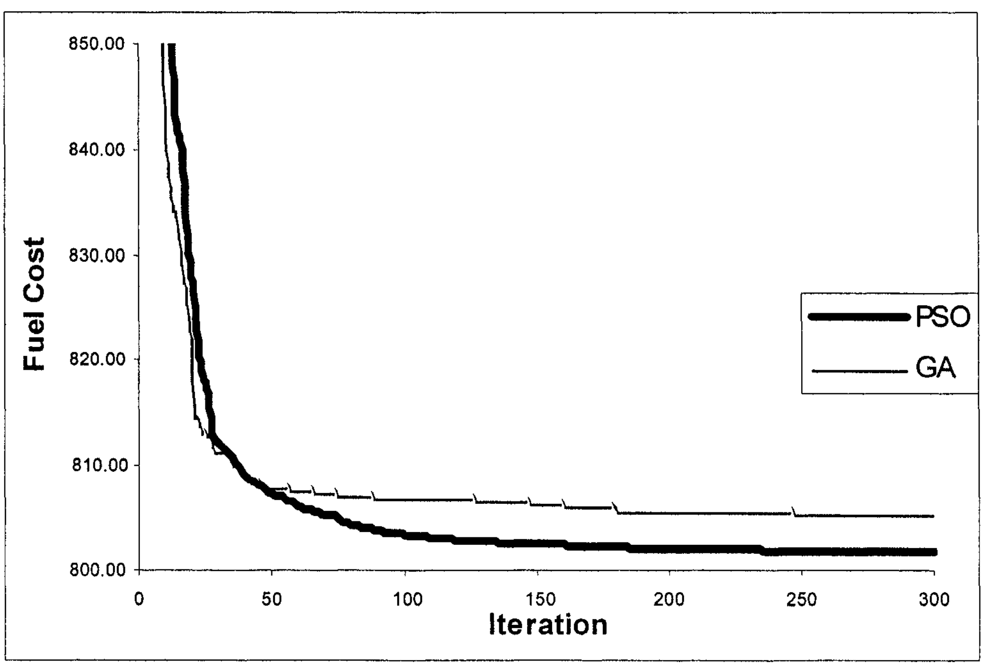


Figure 6.3: Average fuel cost variation of GA and PSO with population of ten (10)

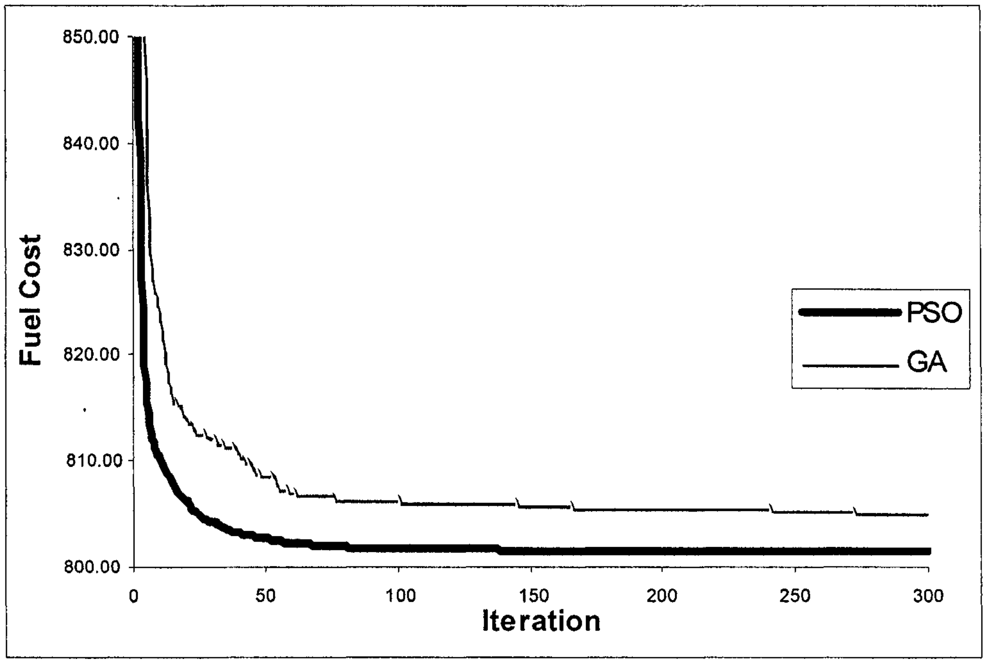


Figure 6.4: Average fuel cost variation of GA & PSO with population of twenty-five (25)

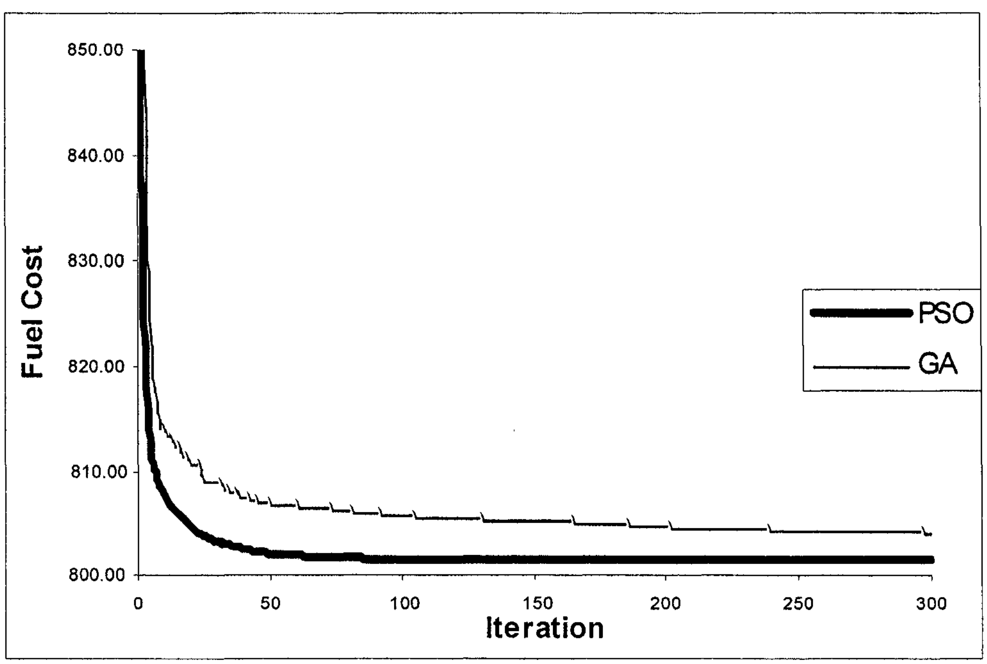


Figure 6.5: Average fuel cost variation of GA and PSO with population of fifty (50)

## 6.4 Robustness of GA and PSO

Like any evolutionary algorithms, randomness plays a major role in the searching process of both PSO and GA. Robustness to the sequence of the random numbers generated is an important property since the difference in random sequence implies difference in the start with initial solution. Figure 6.6 shows the convergence of ten (10) GA runs with different random number sequences. Figure 6.7 shows the same for PSO using the same ten (10) random sequences.

It is clear for GA that the ten cases converged to different optimal solution while in case of PSO all the ten cases converged approximately to the same optimal solution. It can be concluded that the PSO is more robust and effective in solving the OPF problem considered.

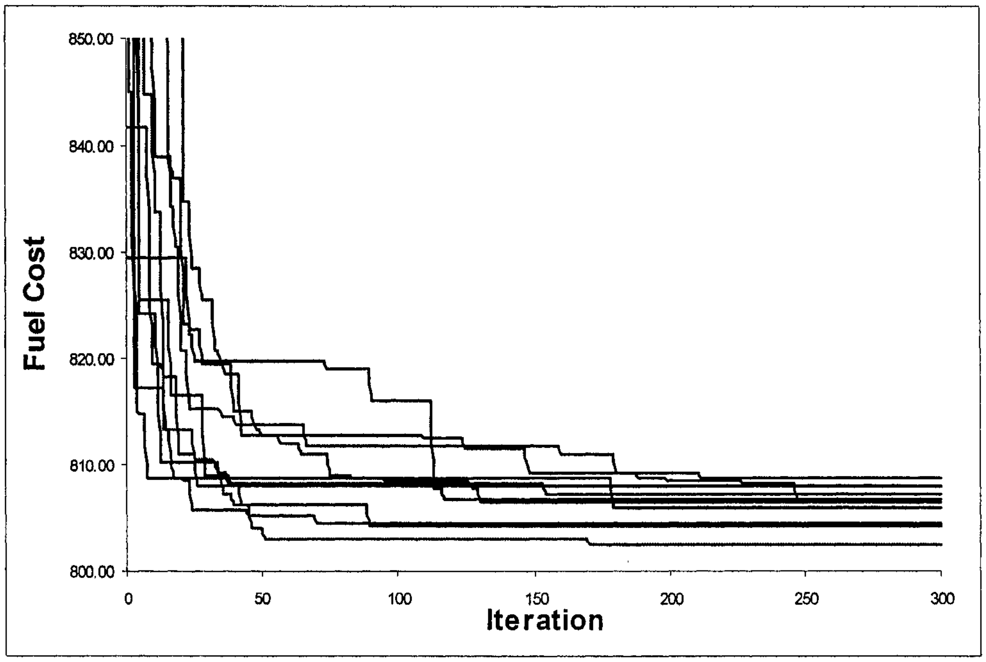


Figure 6.6: Fuel cost variation of GA for ten (10) different random sequences

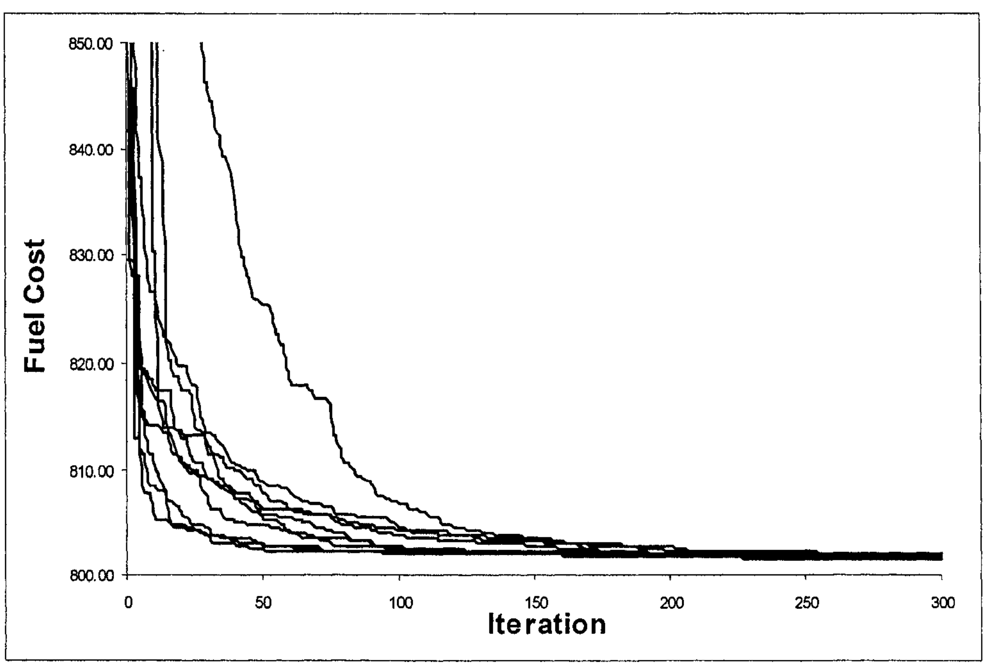


Figure 6.7: Fuel cost variation of PSO for ten (10) different random sequences

## 6.5 Solution Quality of GA and PSO

As a summary of the performance of both algorithms, Table 6.2 below shows the best, worst, and average of the ten (10) runs with the four different population sizes considered in section 6.3. It is clear that, the best, the worst, and the average solutions obtained by PSO are much better than those obtained by GA.

Table 6.2: Summary of results

| # Population | Best | | Worst | | Average | |
|---|---|---|---|---|---|---|
| | PSO | GA | POS | GA | POS | GA |
| 5 | 801.7002 | 805.0526 | 806.8203 | 811.5003 | 803.2220 | 807.6068 |
| 10 | 801.5617 | 802.4138 | 802.1005 | 808.7361 | 801.7816 | 806.1232 |
| 25 | 801.3532 | 802.8127 | 802.0516 | 806.7349 | 801.5172 | 805.0736 |
| 50 | 801.3175 | 802.1296 | 801.5186 | 805.1086 | 801.3972 | 804.1000 |

## 6.6 Results of PSO Compared with Published Results

For a comprehensive comparison, some published results have been traced. In [15], Evolutionary Programming (EP) was employed to solve OPF for the same system as in this research. The program was run 100 times with a population size of 20 and a total number of generations of 50. With the same control variable limits, initial conditions, and other system data, the average cost of solution obtained was $803.51 with the minimum being \$802.62 and maximum of \$805.61. It is clear that the proposed PSO approach outperforms the EP.

In terms of conventional optimization algorithms, the same problem was solved using gradient-based approach in [73]. Nine (9) shunt Var capacitors were controlled there in addition to the control variables considered in our study. Nevertheless, the optimal resulted fuel cost was \$804.583.

The cases considered justify clearly the choice of PSO for solving OPF. The following two chapters, chapter 7 and 8, employ PSO for OPF solving whenever possible.

# CHAPTER SEVEN

# OPF STUDIES USING PSO

## 7.1 Overview

In this chapter, PSO is used to solve single objective OPF. This single objective is one of the three objectives explained in chapter 4, namely, total fuel cost minimization, voltage deviation minimization, and voltage stability enhancement. To show the impact of the FACTS devices on the OPF results, studies with and without FACTS are simulated using IEEE-30 given in Appendix I. Five (5) FACTS devices are assumed in the IEEE-30 bus system at some arbitrary locations. Those FACTS devices are: two (2) SVC at buses 11 and 27, two (2) TCSC on branches 4, and 24, and one (1) TCPS on branched 8. In general, the following cases are considered.

Case 1: Fuel cost minimization ***without*** FACTS

Case 2: Fuel cost minimization ***with*** FACTS

Case 3: Voltage profile improvement ***without*** FACTS

Case 4: Voltage profile improvement ***with*** FACTS

Case 5: Voltage stability enhancement ***without*** FACTS

Case 6: Voltage stability enhancement ***with*** FACTS

The normal power flow case is shown in the table as well for a comprehensive view.

## 7.2 Total Fuel Cost Minimization

The objective function is as given in equation (6.1) with the quadratic generator cost curves in equation (6.2) and cost coefficient given in Table 6.1. PSO with a population size of ten (10) and maximum number of generation equals to 300 was simulated to find the optimal setting of the control variables that minimize the total fuel cost.

Table 7.1 shows the optimal settings of the control variables for the IEEE-30 bus system and the resulted total fuel cost. The table shows two cases in addition to the normal power flow case. Case 1, without FACTS devices where the control variables were the generator MW outputs, the generator terminal voltages, and the transformer tap settings. Case 2 has, in addition to the former mentioned controlled variables, five (5) FACTS devices at arbitrary locations as mentioned earlier.

The final results in Table 7.1 show that the fuel cost with normal power flow was \$902.3224 whereas it has been decreased to \$801.5616 with OPF in case 1 without FACTS devices which means a saving of about 11.17%. The table also shows that the reduction in fuel cost in case 2 with FACTS devices is not more than 0.05% from that of case 1 without FACTS. This is expected since FACTS are not fuel minimization-based devices. Part of the variation of the total fuel cost for the cases 1 and 2 are shown in figure 7.1. The figure shows that the convergence of the case with FACTS devices is greatly much faster than without FACTS.

Table 7.1: Optimal settings of control variables for total fuel minimization case

| | Limits Max | Min | Normal Power Flow | Case 1 (without FACTS) | Case 2 (with FACTS) |
|---|---|---|---|---|---|
| $P_1$ | 0.50 | 2.00 | 0.9880 | 1.7335 | 1.7289 |
| $P_2$ | 0.20 | 0.80 | 0.8000 | 0.4804 | 0.4943 |
| $P_5$ | 0.15 | 0.50 | 0.4998 | 0.2384 | 0.2381 |
| $P_8$ | 0.10 | 0.32 | 0.2000 | 0.2303 | 0.2107 |
| $P_{11}$ | 0.10 | 0.30 | 0.2000 | 0.1190 | 0.1270 |
| $P_{13}$ | 0.12 | 0.40 | 0.2000 | 0.1207 | 0.1224 |
| $V_1$ | 0.95 | 1.10 | 1.0500 | 1.0790 | 1.0845 |
| $V_2$ | 0.95 | 1.10 | 1.0450 | 1.0600 | 1.0663 |
| $V_5$ | 0.95 | 1.10 | 1.0100 | 1.0254 | 1.0373 |
| $V_8$ | 0.95 | 1.10 | 1.0100 | 1.0371 | 1.0371 |
| $V_{11}$ | 0.95 | 1.10 | 1.0500 | 1.0610 | 1.0685 |
| $V_{13}$ | 0.95 | 1.10 | 1.0500 | 1.0719 | 1.0602 |
| $T_{11}$ | 0.90 | 1.10 | 1.0780 | 1.0021 | 1.0056 |
| $T_{12}$ | 0.90 | 1.10 | 1.0690 | 1.0126 | 0.9875 |
| $T_{15}$ | 0.90 | 1.10 | 1.0320 | 1.0239 | 0.9802 |
| $T_{36}$ | 0.90 | 1.10 | 1.0680 | 0.9680 | 0.9567 |
| $SVC_{11}$ | -0.02 | 0.05 | - | - | 0.0120 |
| $SVC_{27}$ | -0.02 | 0.05 | - | - | -0.0001 |
| $TCSC_4$ *(% of $X_L$)* | 0.00 | 50% | - | - | 0.1739 |
| $TCSC_{24}$ *(% of $X_L$)* | 0.00 | 50% | - | - | 0.0960 |
| $TCPS_8$ *(radian)* | -0.20 | 0.20 | - | - | 0.0288 |
| ***Cost ($/H)*** | | | ***902.3224*** | ***801.5616*** | ***801.1727*** |
| $\sum$ *voltage deviation* | | | 0.8632 | 0.5760 | 0.7775 |
| *Voltage stab. Index* | | | 0.1644 | 0.1439 | 0.1388 |

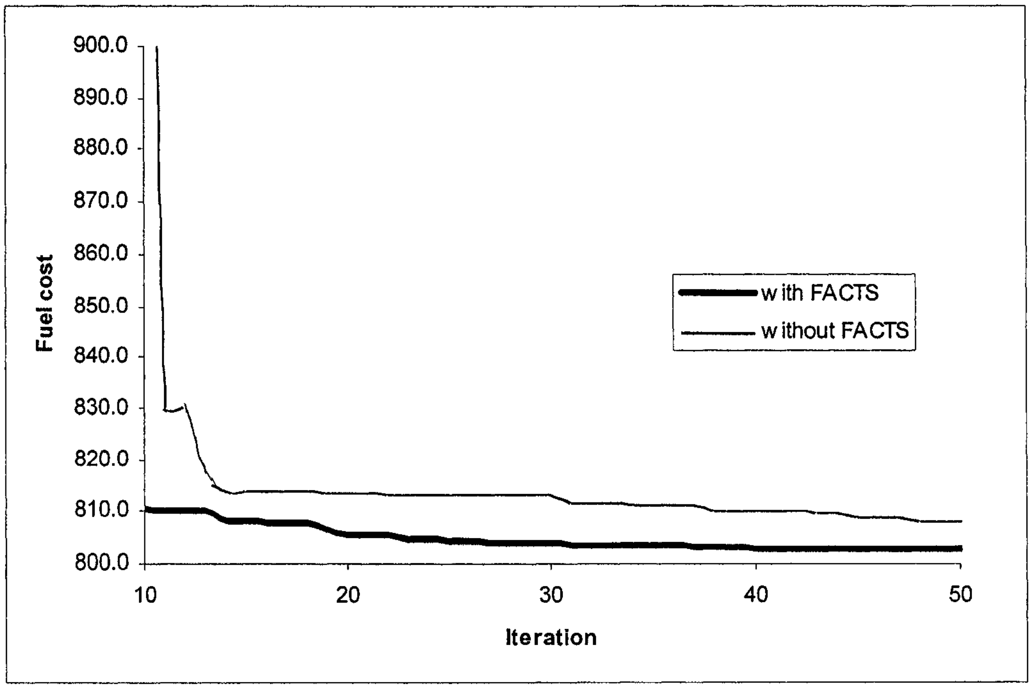


Figure 7.1: Part of fuel cost variation of cases 1 & 2

## 7.3 Voltage Profile Improvement

In the following two cases, the objective considered is to improve the voltage profile of the system. This objective can be expressed as has been shown in chapter 4 as

$$J = \sum_{i \in NL} |V_i - 1| \tag{7.1}$$

As in the previous two cases, PSO with a population size of ten (10) and maximum number of generation equals to 300 has been used to find the optimal setting of the control variables that best minimize equation (7.1).

Table 7.2 shows the setting of the control variables and the resulted summation of voltage deviation. The table shows two cases in addition to normal power flow. Case 3, without FACTS devices where the control variables are the generator MW outputs, the generators voltages, and the transformer tap settings. The other case (case 4) has, in addition to the former mentioned control variables, five (5) FACTS devices at arbitrary locations same as case 2. .

The final results in Table 7.2 show that the total sum of voltage deviations was reduced from 0.8632 in normal power flow to 0.1572 in case 3. The table also shows that the deviations were reduced further with the FACTS devices in case 4. The total sum of voltage deviation in this case was reduced to 0.1437 which means a reduction of about 8.6 % over that in case 3. This shows that FACTS devices have a considerable effect on voltage deviation. Part of the variation of the summation of the voltage deviation for cases 3 and 4 are shown in figure 7.2. As was noticed before in the case of fuel cost minimization, the summation of the voltage deviation with FACTS devices converges much faster than the case without FACTS.

Table 7.2: Optimal settings of control variables for voltage profile improvement

| | Limits Max | Min | Normal Power Flow | Case 3 (without FACTS) | Case 4 (with FACTS) |
|---|---|---|---|---|---|
| $P_1$ | 0.50 | 2.00 | 0.9880 | 1.3294 | 1.3836 |
| $P_2$ | 0.20 | 0.80 | 0.8000 | 0.5671 | 0.4896 |
| $P_5$ | 0.15 | 0.50 | 0.4998 | 0.4524 | 0.3420 |
| $P_8$ | 0.10 | 0.32 | 0.2000 | 0.1645 | 0.2478 |
| $P_{11}$ | 0.10 | 0.30 | 0.2000 | 0.1745 | 0.1959 |
| $P_{13}$ | 0.12 | 0.40 | 0.2000 | 0.2210 | 0.2578 |
| $V_1$ | 0.95 | 1.10 | 1.0500 | 1.0053 | 1.0133 |
| $V_2$ | 0.95 | 1.10 | 1.0450 | 0.9966 | 1.0044 |
| $V_5$ | 0.95 | 1.10 | 1.0100 | 1.0158 | 1.0199 |
| $V_8$ | 0.95 | 1.10 | 1.0100 | 1.0080 | 1.0092 |
| $V_{11}$ | 0.95 | 1.10 | 1.0500 | 1.0887 | 1.0184 |
| $V_{13}$ | 0.95 | 1.10 | 1.0500 | 1.0420 | 1.0286 |
| $T_{11}$ | 0.90 | 1.10 | 1.0780 | 1.0499 | 1.0214 |
| $T_{12}$ | 0.90 | 1.10 | 1.0690 | 0.9829 | 0.9254 |
| $T_{15}$ | 0.90 | 1.10 | 1.0320 | 0.9845 | 0.9598 |
| $T_{36}$ | 0.90 | 1.10 | 1.0680 | 0.9452 | 0.9626 |
| $SVC_{11}$ | -0.02 | 0.05 | - | - | 0.0065 |
| $SVC_{27}$ | -0.02 | 0.05 | - | - | 0.0491 |
| $TCSC_4$ *(% of $X_L$)* | 0.00 | 50% | - | - | 0.2216 |
| $TCSC_{24}$ *(% of $X_L$)* | 0.00 | 50% | - | - | 0.3176 |
| $TCPS_8$ *(radian)* | -0.20 | 0.20 | - | - | -0.0764 |
| *Cost ($/H)* | | | 902.3224 | 855.0492 | 831.4172 |
| ***$\sum$ voltage deviation*** | | | ***0.8632*** | ***0.1572*** | ***0.1437*** |
| *Voltage stab. Index* | | | 0.1644 | 0.1516 | 0.1583 |

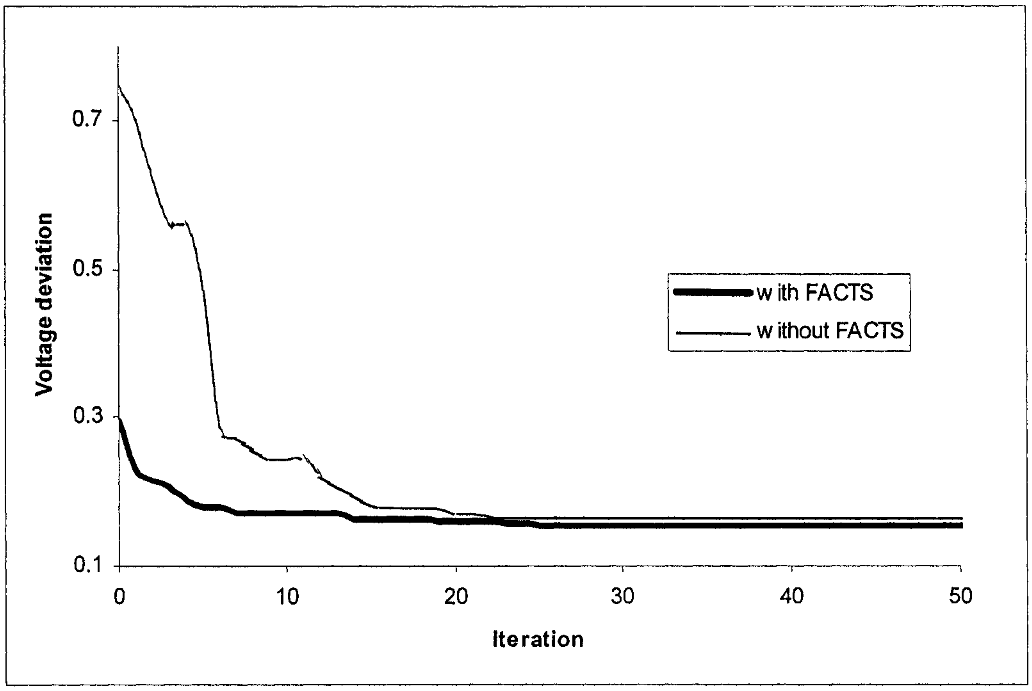


Figure 7.2: Part of the voltage deviation variation of cases 3 & 4

## 7.4 Voltage Stability Enhancement

As mentioned earlier, voltage instability problems have been experienced in systems where voltage profile was acceptable [28]. Therefore, a voltage secure system can only be assured by enhancing the voltage stability profile throughout the whole power system.

The indicator L-index, explained in chapter 4, is used here to evaluate the voltage stability at each bus of the system. The indicator value varies between 0 (no load case) and 1 (voltage collapse) [63,64]. The following objective function is proposed for this purpose

$$J = L_{\max} \tag{7.2}$$

where $L_{max}$ is the maximum value if L-index defined as

$$L_{\max} = \max \{L_k, K = 1,2,\ldots\ldots, NL\} \tag{7.3}$$

and L-index at load bus $j$ can is determined by equation (4.9)

It is aimed here to minimize the maximum L-index. Again, PSO with a population size of ten (10) and maximum number of generation equals to 300 has been used to find the optimal setting of the control variables that best minimize equation (6.4). Table 7.3 shows the setting of the control variables and the resulted $L_{max}$. Again, two cases were considered. Case 5 was without FACTS devices whereas case 6 was with five (5) FACTS devices at arbitrary locations.

The final results in Table 7.3 show that the value of $L_{max}$ was reduced from 0.1644 in normal power flow to 0.1399 in case 5 which means a reduction of about 14.9 %. The table also shows that an additional reduction of about 13.9 % has been achieved because of the existing of FACTS devices in case 6. As a result, the distance from collapse has increased further. Part of the variation of vale of $L_{max}$ at load buses is shown in figure 7.3. Again, the convergence with FACTS devices is much faster than the case without FACTS.

Table 7.3: Optimal settings of control variables for voltage stability enhancement

| | Limits | | Normal Power Flow | Case 5 (without FACTS) | Case 6 (with FACTS) |
|---|---|---|---|---|---|
| | Max | Min | | | |
| $P_1$ | 0.50 | 2.00 | 0.9880 | 1.1345 | 1.4242 |
| $P_2$ | 0.20 | 0.80 | 0.8000 | 0.5610 | 0.5897 |
| $P_5$ | 0.15 | 0.50 | 0.4998 | 0.5112 | 0.3881 |
| $P_8$ | 0.10 | 0.32 | 0.2000 | 0.3482 | 0.2229 |
| $P_{11}$ | 0.10 | 0.30 | 0.2000 | 0.2173 | 0.1845 |
| $P_{13}$ | 0.12 | 0.40 | 0.2000 | 0.1200 | 0.1200 |
| $V_1$ | 0.95 | 1.10 | 1.0500 | 1.0261 | 1.0839 |
| $V_2$ | 0.95 | 1.10 | 1.0450 | 1.0194 | 1.0788 |
| $V_5$ | 0.95 | 1.10 | 1.0100 | 1.0479 | 1.0857 |
| $V_8$ | 0.95 | 1.10 | 1.0100 | 1.0287 | 1.0423 |
| $V_{11}$ | 0.95 | 1.10 | 1.0500 | 1.0379 | 1.0304 |
| $V_{13}$ | 0.95 | 1.10 | 1.0500 | 1.0840 | 1.0312 |
| $T_{11}$ | 0.90 | 1.10 | 1.0780 | 0.9574 | 0.9833 |
| $T_{12}$ | 0.90 | 1.10 | 1.0690 | 0.9445 | 0.9379 |
| $T_{15}$ | 0.90 | 1.10 | 1.0320 | 0.9886 | 0.9263 |
| $T_{36}$ | 0.90 | 1.10 | 1.0680 | 0.9404 | 0.9393 |
| $SVC_{11}$ | -0.02 | 0.05 | - | - | 0.0186 |
| $SVC_{27}$ | -0.02 | 0.05 | - | - | -0.0500 |
| $TCSC_4$ (% of $X_L$) | 0.00 | 50% | - | - | 0.0699 |
| $TCSC_{24}$ (% of $X_L$) | 0.00 | 50% | - | - | 0.1669 |
| $TCPS_8$ (radian) | -0.20 | 0.20 | - | - | 0.2000 |
| *Cost ($/H)* | | | 902.3224 | 882.7579 | 837.9752 |
| *$\sum$ voltage deviation* | | | 0.8632 | 0.7824 | 0.9068 |
| ***Voltage stab. Index*** | | | ***0.1644*** | ***0.1399*** | ***0.1205*** |

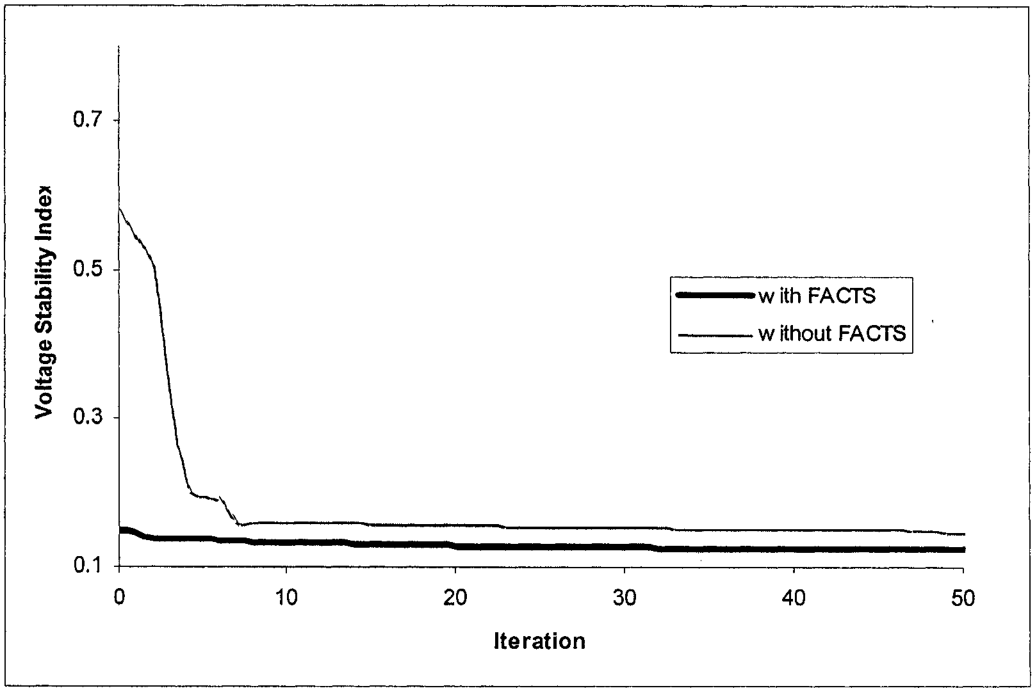


Figure 7.3: Part of $L_{max}$ variation of cases 5 & 6

# CHAPTER EIGHT

# OPTIMAL FACTS LOCATION USING PROPOSED GA/PSO

## 8.1 Overview

The cases simulated in the chapter 7 are to be simulated again here but with optimal FACTS devices location. More specifically, close to optimal FACTS locations are to be found using the proposed PSO/GA algorithm developed in section 5.4. Cases to be simulated are:

Case 1: Optimal FACTS devices locations for fuel cost minimization.

Case 2: Optimal FACTS devices locations for voltage profile improvement.

Case 3: Optimal FACTS devices locations for voltage stability enhancement.

In addition, two more cases that demonstrate the multi-objective optimization using PSO with and without FACTS devices are to be studied. Those cases are:

Case 4: Fuel cost minimization and voltage stability enhancement ***without*** FACTS.

Case 5: Fuel cost minimization and voltage stability enhancement ***with*** FACTS.

## 8.2 Optimal FACTS Location for Fuel Const Minimization

As stated earlier, the benefit of FACTS devices in fuel cost minimization is insignificant. This is because FACTS devices are not cost minimization devices. This fact has been seen in section 7.2 with FACTS devices at some arbitrary locations. The case is the same even if one tries to search for an optimal FACTS location.

The new PSO/GA described in chapter 5 was implemented to search for an optimal, or rather close to optimal, FACTS device locations that best minimize the total fuel cost. The optimal FACTS locations were found to be as follows: SVCs at buses 20 and 21, TCSCs on branches 2 and 5, and TCPS on branch 34. Table 8.1 shows the optimal settings of the control variables for OPF with optimal and arbitrary FACTS device locations and their corresponding fuel costs. The total fuel cost, as can be noticed from the table, has reduced from \$801.1727 to \$800.7393. FACTS devices, as indicated earlier, are not fuel minimization-based devices. So, such little reduction is expected.

Table 8.1: Optimal FACTS locations and settings of control variables for total fuel cost minimization

| | | Limits Min | Limits Max | Case with Arbitrary FACTS Locations | Case 1 (optimal FACTS Location) |
|---|---|---|---|---|---|
| | $P_1$ | 0.50 | 2.00 | 1.7289 | 1.7634 |
| | $P_2$ | 0.20 | 0.80 | 0.4943 | 0.4770 |
| | $P_5$ | 0.15 | 0.50 | 0.2381 | 0.2388 |
| | $P_8$ | 0.10 | 0.32 | 0.2107 | 0.2068 |
| | $P_{11}$ | 0.10 | 0.30 | 0.1270 | 0.1165 |
| | $P_{13}$ | 0.12 | 0.40 | 0.1224 | 0.1200 |
| | $V_1$ | 0.95 | 1.10 | 1.0845 | 1.0837 |
| | $V_2$ | 0.95 | 1.10 | 1.0663 | 1.0666 |
| | $V_5$ | 0.95 | 1.10 | 1.0373 | 1.0377 |
| | $V_8$ | 0.95 | 1.10 | 1.0371 | 1.0391 |
| | $V_{11}$ | 0.95 | 1.10 | 1.0685 | 1.0638 |
| | $V_{13}$ | 0.95 | 1.10 | 1.0602 | 1.0472 |
| | $T_{11}$ | 0.90 | 1.10 | 1.0056 | 1.0605 |
| | $T_{12}$ | 0.90 | 1.10 | 0.9875 | 0.9443 |
| | $T_{15}$ | 0.90 | 1.10 | 0.9802 | 0.9666 |
| | $T_{36}$ | 0.90 | 1.10 | 0.9567 | 0.9750 |
| Arbitrary Location | $SVC_{11}$ | -0.05 | 0.05 | 0.0120 | - |
| | $SVC_{27}$ | -0.05 | 0.05 | -0.0001 | - |
| | $TCSC_4$ (% of $X_L$) | 0.00 | 50% | 0.1739 | - |
| | $TCSC_{24}$ (% of $X_L$) | 0.00 | 50% | 0.0960 | - |
| | $TCPS_8$ (radian) | -0.20 | 0.20 | 0.0288 | - |
| Optimal Location | $SVC_{20}$ | -0.05 | 0.05 | - | 0.0432 |
| | $SVC_{21}$ | -0.05 | 0.05 | - | 0.0219 |
| | $TCSC_2$ (% of $X_L$) | 0.00 | 50% | - | 0.2035 |
| | $TCSC_5$ (% of $X_L$) | 0.00 | 50% | - | 0.2410 |
| | $TCPS_{34}$ (radian) | -0.20 | 0.20 | - | -0.0052 |
| | ***Cost ($/H)*** | | | ***801.1727*** | ***800.7393*** |
| | *∑ voltage deviation* | | | 0.7775 | 0.7393 |
| | *Voltage stab. Index* | | | 0.1388 | 0.1426 |

## 8.3 Optimal FACTS Location for Voltage Profile Improvement

It has been shown in section 7.3 that a great reduction in the summation of voltage deviations was gained with optimal settings of FACTS devices at some arbitrary locations. Further reduction can be gained if FACTS devices are installed at an optimal location as has been verified here.

The new PSO/GA was used to search for an optimal FACTS device location that may lead to the best reduction in summation voltage deviations. The optimal locations were as follows: SVCs at buses 19 and 26, TCSCs on branches 16 and 18, and TCPS on branch 26. Table 8.2 shows the optimal control variable settings for both OPF with arbitrary and close to optimal FACTS location. The resulted summation of voltage deviation with the close to optimal FACTS device locations is 0.0961 which means a reduction of about 33.12% from that with the arbitrary FACTS location.

Table 8.2: Optimal FACTS locations and settings of control variables for voltage profile improvement

| | | Limits Max | Limits Min | Case with Arbitrary FACTS Locations | Case 2 (optimal FACTS Location) |
|---|---|---|---|---|---|
| | $P_1$ | 0.50 | 2.00 | 1.3836 | 1.3969 |
| | $P_2$ | 0.20 | 0.80 | 0.4896 | 0.4067 |
| | $P_5$ | 0.15 | 0.50 | 0.3420 | 0.4102 |
| | $P_8$ | 0.10 | 0.32 | 0.2478 | 0.2649 |
| | $P_{11}$ | 0.10 | 0.30 | 0.1959 | 0.2111 |
| | $P_{13}$ | 0.12 | 0.40 | 0.2578 | 0.2358 |
| | $V_1$ | 0.95 | 1.10 | 1.0133 | 1.0140 |
| | $V_2$ | 0.95 | 1.10 | 1.0044 | 1.0041 |
| | $V_5$ | 0.95 | 1.10 | 1.0199 | 1.0178 |
| | $V_8$ | 0.95 | 1.10 | 1.0092 | 1.0107 |
| | $V_{11}$ | 0.95 | 1.10 | 1.0184 | 1.0316 |
| | $V_{13}$ | 0.95 | 1.10 | 1.0286 | 1.0197 |
| | $T_{11}$ | 0.90 | 1.10 | 1.0214 | 1.0517 |
| | $T_{12}$ | 0.90 | 1.10 | 0.9254 | 0.9000 |
| | $T_{15}$ | 0.90 | 1.10 | 0.9598 | 0.9666 |
| | $T_{36}$ | 0.90 | 1.10 | 0.9626 | 0.9505 |
| Arbitrary Location | $SVC_{11}$ | -0.05 | 0.05 | 0.0065 | - |
| | $SVC_{27}$ | -0.05 | 0.05 | 0.0491 | - |
| | $TCSC_4$ *(% of $X_L$)* | 0.00 | 50% | 0.2216 | - |
| | $TCSC_{24}$ *(% of $X_L$)* | 0.00 | 50% | 0.3176 | - |
| | $TCPS_8$ *(radian)* | -0.20 | 0.20 | -0.0764 | - |
| Optimal Location | $SVC_{19}$ | -0.05 | 0.05 | - | 0.0500 |
| | $SVC_{26}$ | -0.05 | 0.05 | - | 0.0273 |
| | $TCSC_{16}$ *(% of $X_L$)* | 0.00 | 50% | - | 0.2916 |
| | $TCSC_{18}$ *(% of $X_L$)* | 0.00 | 50% | - | 0.1999 |
| | $TCPS_{26}$ *(radian)* | -0.20 | 0.20 | - | -0.2000 |
| | *Cost ($/H)* | | | 831.4172 | 849.9176 |
| | ***∑ voltage deviation*** | | | ***0.1437*** | ***0.0961*** |
| | *Voltage stab. Index* | | | 0.1583 | 0.2242 |

## 8.4 Optimal FACTS Location for Voltage Stability Enhancement

The new PSO/GA algorithm was used once again here but to search for the close to optimal FACTS locations that lead to the best voltage stability enhancement. The close to optimal locations found were as follows: SVCs at buses 19 and 29, TCSC on braches 36 and 38, and TCPS on branch 10. OPF results of this case have been compared with that of the case with the arbitrary FACTS locations. Both are shown in Table 8.3. The voltage stability index has been improved and reduced from 0.1205 to 0.0598. (50.37% reduction)

Table 8.3: Optimal FACTS locations and settings of control variables for voltage stability enhancement

| | | Limits Min | Limits Max | Case with Arbitrary FACTS Locations | Case 3 (optimal FACTS Location) |
|---|---|---|---|---|---|
| | $P_1$ | 0.50 | 2.00 | 1.4242 | 1.2281 |
| | $P_2$ | 0.20 | 0.80 | 0.5897 | 0.6274 |
| | $P_5$ | 0.15 | 0.50 | 0.3881 | 0.3012 |
| | $P_8$ | 0.10 | 0.32 | 0.2229 | 0.2245 |
| | $P_{11}$ | 0.10 | 0.30 | 0.1845 | 0.2996 |
| | $P_{13}$ | 0.12 | 0.40 | 0.1200 | 0.2414 |
| | $V_1$ | 0.95 | 1.10 | 1.0839 | 1.0688 |
| | $V_2$ | 0.95 | 1.10 | 1.0788 | 1.0553 |
| | $V_5$ | 0.95 | 1.10 | 1.0857 | 1.0349 |
| | $V_8$ | 0.95 | 1.10 | 1.0423 | 1.0189 |
| | $V_{11}$ | 0.95 | 1.10 | 1.0304 | 1.0626 |
| | $V_{13}$ | 0.95 | 1.10 | 1.0312 | 1.0373 |
| | $T_{11}$ | 0.90 | 1.10 | 0.9833 | 1.0381 |
| | $T_{12}$ | 0.90 | 1.10 | 0.9379 | 0.9017 |
| | $T_{15}$ | 0.90 | 1.10 | 0.9263 | 0.9107 |
| | $T_{36}$ | 0.90 | 1.10 | 0.9393 | 0.9418 |
| Arbitrary Location | $SVC_{11}$ | -0.05 | 0.05 | 0.0186 | - |
| Arbitrary Location | $SVC_{27}$ | -0.05 | 0.05 | -0.0500 | - |
| Arbitrary Location | $TCSC_4$ (% of $X_L$) | 0.00 | 50% | 0.0699 | - |
| Arbitrary Location | $TCSC_{24}$ (% of $X_L$) | 0.00 | 50% | 0.1669 | - |
| Arbitrary Location | $TCPS_8$ (radian) | -0.20 | 0.20 | 0.2000 | - |
| Optimal Location | $SVC_{19}$ | -0.05 | 0.05 | - | -0.0500 |
| Optimal Location | $SVC_{29}$ | -0.05 | 0.05 | - | -0.0320 |
| Optimal Location | $TCSC_{36}$ (% of $X_L$) | 0.00 | 50% | - | 0.4988 |
| Optimal Location | $TCSC_{38}$ (% of $X_L$) | 0.00 | 50% | - | 0.1340 |
| Optimal Location | $TCPS_{10}$ (radian) | -0.20 | 0.20 | - | -0.1520 |
| | *Cost ($/H)* | | | 837.9752 | 844.1146 |
| | *$\sum$ voltage deviation* | | | 0.9068 | 0.6090 |
| | ***Voltage stab. Index*** | | | ***0.1205*** | ***0.0598*** |

## 8.5 Multi-objective OPF Using PSO

In real life, economic power system operation does not make much sense apart from power quality and vice versa. This has led to OPF problem with multiple objectives instead of a single objective.

The multi-objective optimization seeks the solution $x=(x_1,x_2,.....,x_n)$ which minimize or maximize the values of a set of objective functions $f=(f_1,f_2,.....,f_n)$. For the PSO or any optimization technique to be applicable for such type of optimization, the objectives have to be combined into a single objective according to some utility function. In many applications, however, the objectives to be optimized are non-commensurable and often competing and conflicting. In our study for instance, economic and qualitative operation of power system can not be ideally combined in one single objective and therefore single solution may not exist because of the trade off characteristic among the two objectives. Hence a set of optimal solution known as *Pareto-optimal set* is introduced [74,75].

The Pareto-optimal set is a family of points which is optimized in the sense that no improvement can be achieved in any objective without degradation in others. This set is obtained by applying PSO to solve single objective optimization problems that are formulated by combining the objectives with a proper weighting. In our study here, the multi-objective optimization problem consists of two objectives. They can be combined as follows:

$$J = w\lambda_1 J_1 + (1-w)\lambda_2 J_2 \tag{8.1}$$

where $\lambda_1$ and $\lambda_2$ are properly selected scaling factors. To generate a Pareto-optimal set of 50 solutions, PSO has to be applied 50 times with varying $w$ as a random number $w$ = *rand[0,1]*. This part of simulation tries to show how far FACTS devices can help in multi-objective optimizing.

### 8.5.1 Fuel Cost Minimization and Voltage Stability Enhancement

Total fuel cost minimization and voltage stability enhancement are the two objectives considered. PSO was employed to find the Pareto-optimal solutions where the two objectives were combined in a single objective as follows:

$$J = w \sum_{i}^{NG} f_i (\$ / h) + (1 - w) \lambda L_{\max} \tag{8.2}$$

where $\lambda$ is scaling factor selected as 7000 so that the voltage stability index be comparable with the fuel cost. $w$ is a weighting factor between 0 and 1. Twenty (20) solutions were generated by running PSO twenty (20) times starting with $w$=1 with a step reduction of 0.05.

Two cases were simulated. Case 4 without any FACTS devices where the control variables are: generator MW outputs, generator terminal voltages, and transformer tap settings. It is clear from the graph shown in figure 8.1 that no significant enhancement in the voltage stability can be attained even with high weight. The worst voltage stability index was attained if $w$=1 which means a fuel cost minimization problem (Table 7.1). The value of the maximum voltage stability index at this point of simulation is 0.1439. On the other hand, the best voltage stability index was attained where $w$=0 which means a voltage stability enhancement problem. The value of the maximum voltage stability index at this instance was 0.1399 (Table 7.3)

The other case, Case 5, was with FACTS devices at close to optimal location that lead to the best voltage stability enhancement. Those locations were as found in section 8.4 as follows: two (2) SVC at buses 19 and 29, two (2) TCSC on branches 36 and 38, and one (1) TCPS on branch 10. It is clear from figure 8.1 that a great improvement in the voltage stability enhancement was attained. In this case, we were able to move the voltage stability from 0.1277 when $w$=1 to 0.0598 when $w$=0.

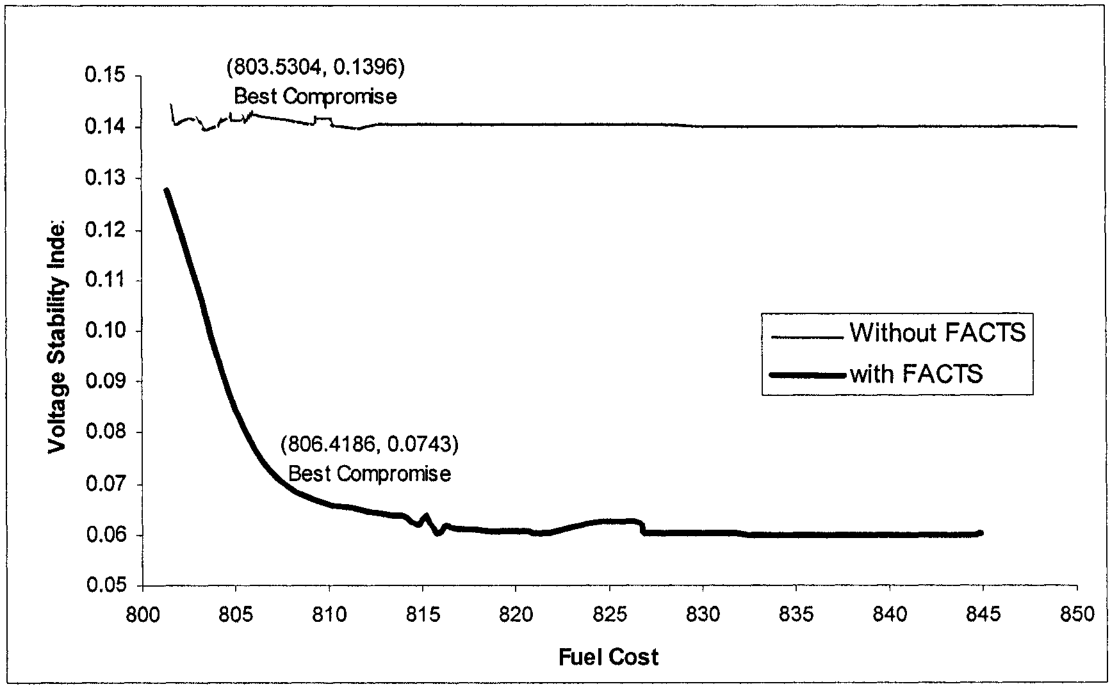


Figure 8.1: Pareto-optimal set of fuel cost minimization and voltage stability enhancement for cases 4 and 5

### 8.5.2 The Best Compromise Solution

The Pareto-optimal set provides the decision maker with insight into the characteristic of the problem before a final solution is chosen. The final chosen solution should be the best compromise one. Due to imprecise nature of the decision maker's judgment, the $i$-$^{th}$ objective function of each solution is represented by a membership function $\mu_i$ defined as [75]

$$\mu_i = \begin{cases} 1 & F_i \le F_i^{\min} \\ \dfrac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}} & F_i^{\min} \prec F_i \prec F_i^{\max} \\ 0 & F_i \ge F_i^{\max} \end{cases} \tag{8.3}$$

For each solution $k$, the normalized membership function $\mu^k$ is calculated as

$$\mu^k = \frac{\sum_{i=1}^{N_{obj}} \mu_i^k}{\sum_{k=1}^{M} \sum_{i=1}^{N_{obj}} \mu_i^k} \tag{8.4}$$

where M is the number of solution in the Pareto-optimal set. The best compromise solution is the one having the maximum value of $\mu^k$ [75].

Tables 8.4 and 8.5 show the membership value for each objective and the normalized membership value for both cases. The best compromise solution in each Table is highlighted. Table 8.4 shows that the maximum normalized membership value for case 4 was with $w$=0.55. The corresponding optimal fuel cost and voltage stability were \$803.5305 and 0.1396 respectively. On the other hand, the maximum normalized membership value for case 5 was with $w$=0.95. The corresponding optimal fuel cost and voltage stability were $806.4186 and 0.0743 respectively. Table 8.6 shows the optimal settings of the control variables for the two cases.

Table 8.4: Pareto-optimal solutions of fuel cost ($F_1$) and voltage stability index ($F_2$) without FACTS devices (Case 4)

| K(Solution Number) | $w$ | $F_1$ | $F_2$ | $\mu_{F1}$ | $\mu_{F2}$ | $\mu^k$ |
|---|---|---|---|---|---|---|
| 0 | 1.0000 | 801.5617 | 0.1439 | 1.0000 | 0.0000 | 0.0330 |
| 1 | 0.9500 | 801.7877 | 0.1407 | 0.9972 | 0.7482 | 0.0576 |
| 2 | 0.9000 | 802.7057 | 0.1420 | 0.9859 | 0.4306 | 0.0468 |
| 3 | 0.8500 | 804.7781 | 0.1422 | 0.9604 | 0.3835 | 0.0444 |
| 4 | 0.8000 | 804.7829 | 0.1417 | 0.9603 | 0.5200 | 0.0489 |
| 5 | 0.7500 | 805.3603 | 0.1417 | 0.9532 | 0.5059 | 0.0482 |
| 6 | 0.7000 | 805.5995 | 0.1413 | 0.9503 | 0.6071 | 0.0514 |
| 7 | 0.6500 | 805.9551 | 0.1429 | 0.9459 | 0.2259 | 0.0387 |
| 8 | 0.6000 | 804.4946 | 0.1417 | 0.9639 | 0.5200 | 0.0490 |
| 9* | 0.5500 | 803.5304 | 0.1396 | 0.9758 | 1.0000 | 0.0652 |
| 10 | 0.5000 | 805.4332 | 0.1420 | 0.9523 | 0.4447 | 0.0461 |
| 11 | 0.4500 | 809.9317 | 0.1421 | 0.8969 | 0.4141 | 0.0433 |
| 12 | 0.4000 | 809.2023 | 0.1410 | 0.9059 | 0.6800 | 0.0524 |
| 13 | 0.3500 | 813.3117 | 0.1409 | 0.8553 | 0.6894 | 0.0510 |
| 14 | 0.3000 | 808.5170 | 0.1413 | 0.9143 | 0.6047 | 0.0502 |
| 15 | 0.2500 | 809.2062 | 0.1422 | 0.9059 | 0.3835 | 0.0426 |
| 16 | 0.2000 | 810.0323 | 0.1417 | 0.8957 | 0.5106 | 0.0464 |
| 17 | 0.1500 | 809.2367 | 0.1420 | 0.9055 | 0.4447 | 0.0446 |
| 18 | 0.1000 | 810.2235 | 0.1410 | 0.8933 | 0.6847 | 0.0521 |
| 19 | 0.0500 | 811.5054 | 0.1402 | 0.8775 | 0.8518 | 0.0571 |
| 20 | 0.0000 | 882.7579 | 0.1399 | 0.0000 | 0.9365 | 0.0309 |

* The best compromise solution

Table 8.5: Pareto-optimal solutions of fuel cost ($F_1$) and voltage stability index ($F_2$) with FACTS devices (Case 5)

| *K(Solution Number)* | *w* | $F_1$ | $F_2$ | $\mu_{F1}$ | $\mu_{F2}$ | $\mu^k$ |
|---|---|---|---|---|---|---|
| 0 | 1.0000 | 801.3192 | 0.1277 | 1.0000 | 0.0000 | 0.0328 |
| 1* | 0.9500 | 806.4186 | 0.0743 | 0.8829 | 0.7863 | 0.0548 |
| 2 | 0.9000 | 813.3733 | 0.0638 | 0.7233 | 0.9409 | 0.0546 |
| 3 | 0.8500 | 813.8952 | 0.0636 | 0.7113 | 0.9445 | 0.0544 |
| 4 | 0.8000 | 815.6752 | 0.0604 | 0.6705 | 0.9920 | 0.0546 |
| 5 | 0.7500 | 814.7359 | 0.0619 | 0.6920 | 0.9698 | 0.0546 |
| 6 | 0.7000 | 816.2138 | 0.0618 | 0.6581 | 0.9713 | 0.0535 |
| 7 | 0.6500 | 815.1653 | 0.0637 | 0.6822 | 0.9426 | 0.0534 |
| 8 | 0.6000 | 816.9478 | 0.0611 | 0.6413 | 0.9814 | 0.0533 |
| 9 | 0.5500 | 816.1738 | 0.0618 | 0.6590 | 0.9714 | 0.0535 |
| 10 | 0.5000 | 820.3843 | 0.0608 | 0.5624 | 0.9860 | 0.0508 |
| 11 | 0.4500 | 821.3663 | 0.0603 | 0.5398 | 0.9932 | 0.0503 |
| 12 | 0.4000 | 824.6737 | 0.0625 | 0.4639 | 0.9608 | 0.0468 |
| 13 | 0.3500 | 826.6745 | 0.0621 | 0.4180 | 0.9673 | 0.0455 |
| 14 | 0.3000 | 826.8526 | 0.0607 | 0.4139 | 0.9873 | 0.0460 |
| 15 | 0.2500 | 827.2492 | 0.0605 | 0.4048 | 0.9906 | 0.0458 |
| 16 | 0.2000 | 830.7644 | 0.0603 | 0.3241 | 0.9934 | 0.0433 |
| 17 | 0.1500 | 833.6497 | 0.0600 | 0.2579 | 0.9975 | 0.0412 |
| 18 | 0.1000 | 828.8583 | 0.0603 | 0.3679 | 0.9937 | 0.0447 |
| 19 | 0.0500 | 844.8850 | 0.0603 | 0.0000 | 0.9925 | 0.0326 |
| 20 | 0.0000 | 844.1146 | 0.0598 | 0.0177 | 1.0000 | 0.0334 |

* The best compromise solution

Table 8.6: Optimal settings of control variables for best compromise solution of fuel cost minimization and voltage stability enhancement

| | Limits | | Normal Power Flow | Case 4 (without FACTS) | Case 5 (with FACTS) |
|---|---|---|---|---|---|
| | Min | Max | | | |
| $P_1$ | 0.50 | 2.00 | 0.9880 | 1.6642 | 1.7316 |
| $P_2$ | 0.20 | 0.80 | 0.8000 | 0.4913 | 0.4836 |
| $P_5$ | 0.15 | 0.50 | 0.4998 | 0.2369 | 0.2492 |
| $P_8$ | 0.10 | 0.32 | 0.2000 | 0.2418 | 0.2160 |
| $P_{11}$ | 0.10 | 0.30 | 0.2000 | 0.1645 | 0.1327 |
| $P_{13}$ | 0.12 | 0.40 | 0.2000 | 0.1219 | 0.1200 |
| $V_1$ | 0.95 | 1.10 | 1.0500 | 1.0612 | 1.0853 |
| $V_2$ | 0.95 | 1.10 | 1.0450 | 1.0472 | 1.0615 |
| $V_5$ | 0.95 | 1.10 | 1.0100 | 1.0239 | 1.0263 |
| $V_8$ | 0.95 | 1.10 | 1.0100 | 1.0282 | 1.0356 |
| $V_{11}$ | 0.95 | 1.10 | 1.0500 | 1.0283 | 1.0594 |
| $V_{13}$ | 0.95 | 1.10 | 1.0500 | 1.0668 | 1.0380 |
| $T_{11}$ | 0.90 | 1.10 | 1.0780 | 0.9538 | 0.9870 |
| $T_{12}$ | 0.90 | 1.10 | 1.0690 | 0.9357 | 0.9531 |
| $T_{15}$ | 0.90 | 1.10 | 1.0320 | 0.9717 | 0.9362 |
| $T_{36}$ | 0.90 | 1.10 | 1.0680 | 0.9418 | 0.9622 |
| $SVC_{19}$ | -0.02 | 0.05 | - | - | -0.0117 |
| $SVC_{29}$ | -0.02 | 0.05 | - | - | -0.0052 |
| $TCSC_{36}$ (% of $X_L$) | 0.00 | 50% | - | - | 0.4127 |
| $TCSC_{38}$ (% of $X_L$) | 0.00 | 50% | - | - | 0.2355 |
| $TCPS_{10}$ (radian) | -0.20 | 0.20 | - | - | -0.0977 |
| ***Cost ($/H)*** | | | ***902.3224*** | ***803.5304*** | ***806.4186*** |
| *$\sum$ voltage deviation* | | | 0.8632 | 0.7892 | 0.7727 |
| ***Voltage stab. Index*** | | | ***0.1644*** | ***0.1396*** | ***0.0743*** |

# CHAPTER NINE

# CONCLUSIONS AND FUTURE WORK

Following are some conclusions and some proposed future work related to the concern subject.

## 9.1 Conclusions and Findings

The optimal power flow problem incorporating FACTS devices has been investigated and discussed in this thesis. OPF has been then formulated as an optimization problem taking into consideration the FACTS representations. Different objective functions with several equality and inequality constraints have been considered.

Two different optimization techniques have been implemented and compare to each other. Namely, GA and PSO have been evaluated and assessed in this study. The comparison results between GA and PSO show the potential and effectiveness of PSO compared to GA in terms of robustness, convergence speed, and quality of the optimal solution obtained. Therefore, PSO is the optimization tool employed for solving the formulated OPF problem. OPF incorporating FACTS devices at some arbitrary location has been solved using PSO for a single objective. Minimization of total fuel cost, voltage deviation, and L-index have been considered individually.

A new proposed GA/PSO algorithm has been proposed for solving the optimal location and settings of FACTS devices with respect to a certain objective. In the proposed technique, the capability of GA to solve the optimal location problem has been merged with the potential of PSO to solve the optimal settings problem.

In addition, the OPF problem has been formulated as a multi-objective optimization problem where more than one objective function has been considered. The Pareto-optimal front of the multi-objective OPF problem has been generated. A fuzzy-based procedure is employed to extract the best compromise solution out of the Pareto optimal solutions.

Generally speaking, the main findings and conclusions of this work can be summarized as follows:

- There is a great need for incorporating FACTS devices effect in OPF. This can help in optimal planning and optimal operation of FACTS devices.
- PSO is more effective and more robust algorithm compared to GA in all cases considered in this study.
- FACTS devices greatly improve voltage deviation and significantly enhance voltage stability of power systems while they have a slight improvement on fuel cost.
- A new GA/PSO was proposed and tested in this study where the advantages of GA and advantages of PSO were merged.

- A further great improvement on the results can be achieved by investigating the optimal locations of FACTS devices.

## 9.2 Future Work Directions

Following are some extensions that may be taken into consideration in future:

- Developing the presented techniques to handle the continuous variables as well as the discrete variables of the problem.
- More objectives can be considered in solving OPF with FACTS devices such as maximizing power transfer and enhancing system reliability.
- Developing a multi-objective PSO and implementing it for solving OPF problem as a true multi-objective optimization problem.
- Investigate the injection model of FACTS as opposed to the Y-bus modification method.
- Finally, the OPF problem with FACTS proposed in this study can be expanded to come up with a comprehensive operation and planning tool. This requires mainly inclusion of some more operational objectives and at the same time paying attention to the cost in general (i.e. operational and planning cost).

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# APPENDIX I

# IEEE-30 BUS SYSTEM DATA

Table I-1: Transmission line and transformer data for IEEE-30 bus system

| Line No. | Line Designation | p.u. resistance on 100 MVA | p.u. reactance on 100 MVA | p.u. line charging on 100 MVA | Transformer Tap Setting | Rating MVA |
|---|---|---|---|---|---|---|
| 1 | 1 _ 2 | 0.0192 | 0.0575 | 0.0264 | | 130 |
| 2 | 1 _ 3 | 0.0452 | 0.1852 | 0.0204 | | 130 |
| 3 | 2 _ 4 | 0.0570 | 0.1737 | 0.0184 | | 65 |
| 4 | 3 _ 4 | 0.0132 | 0.0379 | 0.0042 | | 130 |
| 5 | 2 _ 5 | 0.0472 | 0.1983 | 0.0209 | | 130 |
| 6 | 2 _ 6 | 0.0581 | 0.1763 | 0.0187 | | 65 |
| 7 | 4 _ 6 | 0.0119 | 0.0414 | 0.0045 | | 90 |
| 8 | 5 _ 7 | 0.0460 | 0.1160 | 0.0102 | | 70 |
| 9 | 6 _ 7 | 0.0267 | 0.0820 | 0.0085 | | 130 |
| 10 | 6 _ 8 | 0.0120 | 0.0420 | 0.0045 | | 32 |
| 11 | 6 _ 9 | 0.0000 | 0.2080 | 0.0000 | 0.978 | 65 |
| 12 | 6 _ 10 | 0.0000 | 0.5560 | 0.0000 | 0.969 | 32 |
| 13 | 9 _ 11 | 0.0000 | 0.2080 | 0.0000 | | 65 |
| 14 | 9 _ 10 | 0.0000 | 0.1100 | 0.0000 | | 65 |
| 15 | 4 _ 12 | 0.0000 | 0.2560 | 0.0000 | 0.932 | 65 |
| 16 | 12 _ 13 | 0.0000 | 0.1400 | 0.0000 | | 65 |
| 17 | 12 _ 14 | 0.1231 | 0.2559 | 0.0000 | | 32 |
| 18 | 12 _ 15 | 0.0662 | 0.1304 | 0.0000 | | 32 |
| 19 | 12 _ 16 | 0.0945 | 0.1987 | 0.0000 | | 32 |
| 20 | 14 _ 15 | 0.2210 | 0.1997 | 0.0000 | | 16 |
| 21 | 16 _ 17 | 0.0824 | 0.1923 | 0.0000 | | 16 |
| 22 | 15 _ 18 | 0.1070 | 0.2185 | 0.0000 | | 16 |
| 23 | 18 _ 19 | 0.0639 | 0.1292 | 0.0000 | | 16 |
| 24 | 19 _ 20 | 0.0340 | 0.0680 | 0.0000 | | 32 |
| 25 | 10 _ 20 | 0.0936 | 0.2090 | 0.0000 | | 32 |
| 26 | 10 _ 17 | 0.0324 | 0.0845 | 0.0000 | | 32 |
| 27 | 10 _ 21 | 0.0348 | 0.0749 | 0.0000 | | 32 |
| 28 | 10 _ 22 | 0.0727 | 0.1499 | 0.0000 | | 32 |
| 29 | 21 _ 22 | 0.0116 | 0.0236 | 0.0000 | | 32 |
| 30 | 15 _ 23 | 0.1000 | 0.2020 | 0.0000 | | 16 |
| 31 | 22 _ 24 | 0.1150 | 0.1790 | 0.0000 | | 16 |
| 32 | 23 _ 24 | 0.1320 | 0.2700 | 0.0000 | | 16 |
| 33 | 24 _ 25 | 0.1885 | 0.3292 | 0.0000 | | 16 |
| 34 | 25 _ 26 | 0.2544 | 0.3800 | 0.0000 | | 16 |
| 35 | 25 _ 27 | 0.1093 | 0.2087 | 0.0000 | | 16 |
| 36 | 28 _ 27 | 0.0000 | 0.3960 | 0.0000 | 0.968 | 65 |
| 37 | 27 _ 29 | 0.2198 | 0.4153 | 0.0000 | | 16 |
| 38 | 27 _ 30 | 0.3202 | 0.6027 | 0.0000 | | 16 |
| 39 | 29 _ 30 | 0.2399 | 0.4533 | 0.0000 | | 16 |
| 40 | 8 _ 28 | 0.0636 | 0.2000 | 0.0214 | | 32 |
| 41 | 6 _ 28 | 0.0169 | 0.0599 | 0.0065 | | 32 |

Table I-2: Bus data of the IEEE-30 bus system

| Bus No. | Voltage Magnitude | Generation* | | Load* | |
|---|---|---|---|---|---|
| | | MW | Mvar | MW | Mvar |
| 1 | 1.05 | 0.9880 | 0.0000 | 0.0000 | 0.0000 |
| 2 | 1.05 | 0.8000 | 0.0000 | 0.2170 | 0.1270 |
| 3 | 1.00 | 0.0000 | 0.0000 | 0.0240 | 0.0120 |
| 4 | 1.00 | 0.0000 | 0.0000 | 0.0760 | 0.0160 |
| 5 | 1.01 | 0.5000 | 0.0000 | 0.9420 | 0.1900 |
| 6 | 1.00 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| 7 | 1.00 | 0.0000 | 0.0000 | 0.2280 | 0.1090 |
| 8 | 1.01 | 0.2000 | 0.0000 | 0.3000 | 0.3000 |
| 9 | 1.00 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| 10 | 1.00 | 0.0000 | 0.0000 | 0.0580 | 0.0200 |
| 11 | 1.05 | 0.2000 | 0.0000 | 0.0000 | 0.0000 |
| 12 | 1.00 | 0.0000 | 0.0000 | 0.1120 | 0.0750 |
| 13 | 1.05 | 0.2000 | 0.0000 | 0.0000 | 0.0000 |
| 14 | 1.00 | 0.0000 | 0.0000 | 0.0620 | 0.0160 |
| 15 | 1.00 | 0.0000 | 0.0000 | 0.0820 | 0.0250 |
| 16 | 1.00 | 0.0000 | 0.0000 | 0.0350 | 0.0180 |
| 17 | 1.00 | 0.0000 | 0.0000 | 0.0900 | 0.0580 |
| 18 | 1.00 | 0.0000 | 0.0000 | 0.0320 | 0.0090 |
| 19 | 1.00 | 0.0000 | 0.0000 | 0.0950 | 0.0340 |
| 20 | 1.00 | 0.0000 | 0.0000 | 0.0220 | 0.0070 |
| 21 | 1.00 | 0.0000 | 0.0000 | 0.1750 | 0.1120 |
| 22 | 1.00 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| 23 | 1.00 | 0.0000 | 0.0000 | 0.0320 | 0.0160 |
| 24 | 1.00 | 0.0000 | 0.0000 | 0.0870 | 0.0670 |
| 25 | 1.00 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| 26 | 1.00 | 0.0000 | 0.0000 | 0.0350 | 0.0230 |
| 27 | 1.00 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| 28 | 1.00 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| 29 | 1.00 | 0.0000 | 0.0000 | 0.0240 | 0.0090 |
| 30 | 1.00 | 0.0000 | 0.0000 | 0.1060 | 0.0190 |

* p.u. on 100 MVA base

Table I-3: Generation capacity data of the IEEE-30 bus system

| Bus No. | Min. MW | Max. MW | Min. MVAR | Max. MVAR |
|---|---|---|---|---|
| 1 | 50 | 200 | -20 | 200 |
| 2 | 20 | 80 | -20 | 100 |
| 5 | 15 | 50 | -15 | 80 |
| 8 | 10 | 35 | -15 | 60 |
| 11 | 10 | 30 | -10 | 50 |
| 13 | 12 | 40 | -15 | 60 |

Table I-4: Static capacitor data of the IEEE-30 bus system

| Bus No. | p.u. susceptance on 100 MVA |
|---|---|
| 10 | 0.190 |
| 24 | 0.043 |

# APPENDIX II

# PUBLICATIONS

1. Al-Hulail M. and Abido M., "optimal power flow incorporating FACTS devices using particle swarm optimization", *the first GCC industrial electrical & electronics conference*, May 13-14 2003.
2. "A New Proposed GA/PSO Algorithm for FACTS Devices Allocation" to be submitted.

# VITA

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