The Islamic University of Gaza
Electrical Engineering Department

Voltage-Control Based on Fuzzy Adaptive Particle Swarm Optimization Strategy

By
Hossam Hosni Shaheen

Advisor
Dr. Assad Abu-Jasser

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DEDICATION

To my father, Hosni, to my brothers and sisters

To my wife Asma and lovely kids Mohammed, Mariem and Samieh

To the memory of my beloved mother, Mariem

To the memory of my uncle, Dr. Samieh

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I address my sincere gratitude to God as whenever I faced any difficulty I used to pray to God to help me and He always was there protecting and saving me. Then, I would like to express my profound gratitude to my advisor Dr. Assad Abu-Jasser, who spared no effort in supporting me with all care and patience. I enjoyed working with him, making every moment I spent in this research work as enjoyable as can be imagined.

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ABSTRACT

It is of great importance to keep the voltage profile at a power system buses within a prescribed tolerance of ± 10%. Keeping an acceptable voltage profile at the system buses is a challenging and a system-wide task. The reactive power flow in the lines of a power system dictates the voltage profile at the system buses. Voltage-control is rooted in rescheduling of this flow of reactive power. Despite the fact that many voltage-control techniques are available to electric power system operators, these systems around the world have been subjected to voltage instability problems and voltage collapses that cause in many occasions complete system breakdowns.

In this thesis, a new voltage–control methodology is presented, which is originated on the use of multi-objective function based on fuzzy set theory and adaptive particle swarm optimization. The fuzzy logic is used to adapt the parameters of the adaptive particle swarm optimization. This methodology is applied to get a solution to the mathematical model that represents the voltage-control problem of a power system. The purpose is to ensure acceptable voltage profile and to minimize both the voltage deviation and the real power loss. The IEEE 30-Bus system model is used to employ and investigate the mathematical model built for the new voltage-control methodology using Matlab code. The findings will be documented and compared with other voltage-control strategies.

Keywords

Voltage profile, voltage collapse, voltage deviation, multi-objective, fuzzy logic, adaptive particle swarm optimization, and fuzzy adaptive particle swarm optimization.

ملخص البحث

التحكم في الجهد الكهربائي بإستخدام التحكم الضبابي والبرمجة المتطورة

من المهم جداً أن يكون الجهد الكهربائي فى المناطق المختلفة لأنظمة القوي الكهربائية عند مستوي معين بحيث لايتعدى ± 10% من القيمة الاسمية وذلك للمحافظة على الاجهزة والمعدات الكهربائية المختلفة ولضمان تشغيل أمثل للنظام. إن المحافظة علي الجهد عند مستوي مقبول في شبكات النقل وخطوط التوزيع يعتبر من أكبر التحديات والمهام. تعتبرعملية التحكم في الجهد الكهربائي من المشاكل غير الخطية وتعتمد بشكل أساسي على توزيع ومرور القدرة التخيلية فى شبكات النقل, وبالرغم من وجود عدة طرق مختلفة للتحكم بالجهد الكهربائي إلا أن أغلب هذه الوسائل تعانى من بعض العيوب حيث تؤدي إلي عدم إستقرار النظام الكهربائي وفي بعض الحالات ينتج إنهيار كامل للنظام.

في هذه الرسالة سيتم تطبيق طريقة تحكم جديدة للتعامل مع المعادلات الرياضية التى تمثل النظام حيث سيتم من خلالها العمل على تحقيق ثلاث أهداف أساسية وهي المحافظة على الجهد الكهربائي ضمن النطاق المقبول وتقليل الأنحراف في الجهد الكهربائي وكذللك تقليل الفاقد في القدرة الحقيقية. السمة البارزة للنهج المقترح هو أنه يجمع بين أنظمة التحكم الضبابي المنطقي Fuzzy logic والبرمجة المتطورة Adaptive Particle Swarm Optimization. حيث أن التحكم الضبابي المنطقي يستخدم فى تعديل معاملات البرمجة المتطورة. سيتم تطبيق هذه الطريقة على نظام IEEE 30-Bus System للحصول على حل للمعادلات الرياضية التي تمثل النظام بإستخدام برنامج Matlab. وسيتم تدوين النتائج التى يتم الحصول عليها ومقارنتها بالطرق الأخرى للتحكم.

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LIST OF SYMBOLS AND ABBREVIATIONS

P-problem	Active Power Problem
Q-problem	Reactive Power Problem
EA	Evolutionary Algorithm
IEEE	Institute of Electrical and Electronic Engineering
OED	Optimal Economic Dispatch
PSO	Particle Swarm Optimization
APSO	Adaptive Particle Swarm Optimization
FPSO	Fuzzy Particle Swarm Optimization
FAPSO	Fuzzy Adaptive Particle Swarm Optimization
SQP	Successive Quadratic Programming
NLP	Non Linear Programming
NLCNFP	Nonlinear Convex Network Flow Programming
ORPF	Optimal Reactive Power Flow
OPF	Optimal Power Flow
GA	Genetic Algorithm
ED	Economic Dispatch
VVC	Voltage VAR Compensator
V	Voltage Magnitude
P	Real Power
Q	Reactive Power
TSL	Total System Loss
VD	Voltage Deviation
λ	Lambda
TC	Total Cost

PV	Voltage Control Bus
pu	Per Unit
$	US Dollar
MWH	Mega Watt Hour
H	Hour

CHAPTER 1

1. INTRODUCTION

1.1 Background

In all conducting systems, whether overhead lines or underground cables, there will be a drop of volts along the system when current is flowing and this drop will vary with the current and the power factor. The voltage drop should not exceed values which are outside the capacities of automatic voltage regulators, which control the generator terminal voltage. Practically all present day equipments which utilize electric power such as lights, motors, thermal appliances, and electronic appliances are designed for use with a certain definite terminal voltage, the nameplate voltage. If the voltage deviates from this value, the efficiency, life expectancy, and the quality of performance of the equipment will suffer. Some electrical equipment is more sensitive to voltage variation than others such as motors. However, it is not economically possible to maintain voltage absolutely constant at every consumer's service terminals [1]. This means that the variations in voltage are permissible, but with favorable zones, for example the rise or drop in voltage should not exceed a prescribed tolerance of ± 10% of the nominal voltage.

Day-by-day, the evaluation of stability and voltage-control in power systems become very important especially when the system subjected to a disturbance. The disturbance may be small or large. The system must be able to operate satisfactorily under these conditions and successfully supply the maximum amount of load. It must also be capable of surviving numerous disturbances, such as a short circuit on a transmission line, loss of a large generator or load, or loss of a tie between two subsystems. This could lead to voltage instability and eventually to a voltage collapse.

Many mathematical assumptions, such as analytic and differentiable properties of the objective functions and unique minima existing in problem domains, have to be given to simplify the problem, otherwise it is very difficult to calculate the gradient variables, and a large amount of computation is involved in the conventional methods. In the conventional approaches to the Q-problem, the gradient of the objective function with respect to voltages is used as a search direction, while assuming active power and reactive power uninfluenced by voltage and angle changes respectively, based on the P-Q decomposition concept. However, in practice the phase angles will vary as active power changes and have a great influence on the active power loss in the network. Therefore, based on the mathematical assumptions in the Q-problem, use of the gradients may result in wrong search directions and the optimization tends to diverge when the system becomes large [2].

Although a large spectrum of optimization problems has grown in size and complexity, the solution to complex multidimensional problems by means of classical optimization techniques is extremely difficult and computational expensive. In general, heuristic algorithms which are referred to as "stochastic" optimization techniques have facilitated solving optimization problems that were previously very difficult or impossible to solve. These tools include: genetic algorithms, evolutionary strategies, evolutionary programming, simulated annealing, and particle swarm optimization.

The Evolutionary Algorithms (EA) can be applied to difficult search problems based on simulating natural evolution. Optimization using the EA is more efficient and effective than conventional gradient-based optimization algorithms. The EA does not require the mathematical assumptions applied in the conventional methods and offers a powerful global search over the control variable space. A population of solutions is maintained at each of the iterations. These solutions propagate into future generations probabilistically, as function of their overall merit. The EA can therefore discover the globally optimal point [2]. Due to these advantages, the EA offers a new promising tool for optimal reactive power dispatch of power systems. Reports of applications of each of these tools have been widely published. Recently, these new heuristic tools have been combined (or hybridized) among themselves and with more traditional approaches, to solve extremely challenging problems.

1.2 Thesis Objectives

The main objective of this thesis is to propose and employ a new methodology to control the system voltage profile through controlling reactive power flow based on the Fuzzy Adaptive Particle Swarm Optimization technique. In addition, the technique proposed aims at keeping the voltage deviation at the system buses as small as possible, and at minimizing of the real power loss, while satisfying a lot of constraints. These constraints are fundamental to ensure acceptable performance such as: satisfying of the reactive power generation limits, maintaining acceptable voltage magnitudes at the load buses, meeting the reactive power compensation limits, and satisfying the power balance within the system.

Various optimization techniques will be employed to obtain a valid solution to the mathematical model. The methods employed are: Optimal Economic Dispatch, Particle Swarm Optimization, Adaptive Particle Swarm Optimization, Fuzzy Particle Swarm Optimization and Fuzzy Adaptive Particle Swarm Optimization. At the end, the results will be compared and the superiority of the Fuzzy Adaptive Particle Swarm Optimization technique will be demonstrated.

1.3 Research Methodology

In order to achieve these objectives, the following procedure will be carried out:

1. Using the well known standard test system, the IEEE 30-bus system to validate and compare the results.
2. Formulating the problems of voltage-control, voltage deviation, and real power loss as mathematical optimization problems subject to the applicable constraints using Matlab code.
3. optimization models and then the proposed Fuzzy Adaptive Particle Swarm Optimization model to the problems addressed.
4. Tabulating and comparing the results obtained by the various control strategies with the proposed strategy.

1.4 Literature Review

Power system economical operation consists of two aspects: active power regulation and reactive power dispatch. This forms a multi-objective global optimization problem of a large-scale industrial system. This problem is considered conventionally as two separate problems: active power problem (P-problem) and reactive power problem (Q-problem) [2]. There is a strong relationship between the active power (P-problem) and phase angle, also between the reactive power (Q-problem) and voltage magnitude. The Q-problem is more difficult to solve than the P-problem due to its more complex relationship between variables. The P-problem is to regulate active power outputs of generators to minimize fuel costs. The Q-problem is to improve voltage stability.

A first comprehensive survey regarding optimal power dispatch was given by H. H. Happ [3] and subsequently an IEEE working group [4] presented bibliography survey of major economic-security functions in 1981. Thereafter in 1985, Carpentair [5] presented a survey and classified the OPF algorithms based on their solution methodology. In 1990, Chowdhury [6] did a survey on economic dispatch methods. E. Lobato et al. [7] proposed LP based OPF for minimization of transmission losses and Generator reactive margins of the Spanish power system. N. Grudinin [8] proposed a reactive power optimization model that was based on Successive Quadratic Programming (SQP) methods. Six optimization methods were used to test the IEEE 30-bus and 278 bus systems. It is found that the developed SQP methods provide more fast and reliable optimization in comparison with the usual Successive Linear Programming method (SLP).

Nonlinear programming (NLP) deals with problems involving nonlinear objective and constraint functions. J. A. Momoh et al. [9] proposed a new nonlinear convex network flow programming (NLCNFP) model and algorithm for solving the security constrained multi-area economic dispatch (MAED) problem. Karmarkar proposed a new method in 1984 for solving large-scale linear programming problems very efficiently. It is known as an interior method since it finds improved search directions strictly in the interior of the feasible space. Sergio Granville [10] presented an application of an Interior Point Method to the optimal reactive power dispatch problem. It is based on the primal dual logarithmic barrier method as described by Monteiro and Adler. Wei Yan et al. [11] presented the solution of the Optimal Reactive Power Flow (ORPF) problem by the Predictor Corrector Primal Dual Interior Point Method (PCPDIPM). V. C. Ramesh et al. [12] presented a Fuzzy Logic approach for the contingency constrained OPF problem formulated in a decomposed form that allows for post-contingency corrective rescheduling. Linear membership function is used. Walters et al. [13] applied a Genetic Algorithm (GA) to solve an economic dispatch problem for valve point discontinuities. Po-H. Chen et al. [14] proposed a new genetic algorithm for solving the Economic Dispatch (ED) problem in large-scale systems. It is a subset of evolutionary computation, a generic population based metaheuristic optimization algorithm. P. Somasundaram et al. [15] proposed an algorithm for solving security constrained optimal power flow problem through the application of EA.

Particle Swarm Optimization (PSO) refers to a relatively new family of algorithms that may be used to find optimal or near optimal solutions to numerical and qualitative problems. Particle Swarm Optimization was introduced by Russell Eberhart and James Kennedy in 1995 [16], inspired by social behavior of bird flocking or fish schooling. H. Yoshida et al. [17] proposed a Particle Swarm Optimization (PSO) for reactive power and Voltage/VAR Control (VVC) considering voltage security assessment. It determines an on-line VVC strategy with continuous and discrete control variables such as AVR operating values of generators, tap positions of on line tap changing of transformers and the number of reactive power compensation equipment. In adaptive particle swarm, the inertia weight (*w)* was modified according to linearly decreased equation. Cui-Ru Wang et al. [18] presented Adaptive (Modified) Particle Swarm Optimization (APSO) algorithm to solve economic dispatch problem. Wen Zhang and Yutian Liu [19] presented FPSO to solve voltage control and reactive power problem. In the FPSO, the fuzzy system was used to modify all of the parameter of particle swarm optimization to improve the performance of the system.

In this work a new methodology will be introduced that may help overcome some of the problem that appear in previous models. This new control methodology suggest the combination between the APSO and Fuzzy logic which known as FAPSO, in this method the w is linearly decreased while social parameter and cognitive parameter are modified by fuzzy system. By modifying these parameters, the overall objective of this work is to use this modern heuristic optimization algorithm (FAPSO) for solving voltage control and voltage stability problems through rescheduling of reactive power dispatch.

1.5 Contribution

The main contribution of this work is the introduction of a new modern heuristic technique based on Fuzzy Adaptive Particle Swarm Optimization to handle the voltage control problem in power systems. This new control methodology takes advantage of the Fuzzy Logic to adapt the parameters of the APSO. The second contribution is that: the voltage tolerance considered is ± 5% which narrower than any other previous work where a tolerance value of ± 10% was considered, also the precision index which is tackled in the iterative Newton Raphson methods is 10^{-4}. All of this has been dealt with while satisfying all constraints. Finally Matlab codes have been developed for each of the optimization techniques.

1.6 Outline of the Thesis

This thesis is organized into six chapters to report on the whole research activities and to discuss and analyze the results. Each of the following paragraphs generally describes the contents of each chapter. Chapter-1 explains the objectives and scope of this thesis, and gives the reasoning for such a study. It also summarizes a general methodology and the main activities involved in this research. Chapter-2 presents and describes the statement of the problem to be handled. Chapter-3 presents an overview of the voltage stability and voltage-control of power systems. Chapter-4 introduces the concept of optimization and describes the optimization methods. It also summarizes briefly the concept of particle swarm optimization and fuzzy logic system and describes its various configurations. Chapter-5 presents the Application of the Optimization technique to the Selected Power System Model to enhance voltage stability by controlling the voltage levels through reactive power dispatch. Finally, Chapter-6 presents the general conclusions and recommendations for future work.

CHAPTER 2

2. STATEMENT OF THE PROBLEM

2.1 Introduction

The voltage-control is very important especially when the system is heavily loaded or subject to a disturbance. Different methods were proposed in literatures to solve voltage-control such as linear programming [20], Newton-Raphson, quadratic programming, interior point and nonlinear programming methods [21-24]. Although these methods solve the power flow equation, they may sometimes have problems that appear as voltage instabilities and in some occasions as voltage collapses. From this point of view, voltage stability is very important in power systems and cause researchers to develop and upgrade different methods controlling power system bus voltages. This objective can be addressed through absorb or inject of reactive power from/into the system.

The problem to be dealt with is to examine and validate a new control methodology through selecting an appropriate power system model, to develop a mathematical model for this selected system (IEEE 30-bus system) and to employ various optimization techniques. In all techniques, the purpose is to sustain an acceptable voltage profile, to minimize the voltage deviation, and to reduce the real power loss, while satisfying all constraints. The optimal economic dispatch, the particle swarm, the adaptive particle swarm, and the fuzzy particle swarm optimization techniques will be employed separately to obtain a solution to the mathematical model that describes the selected system. To highlight the merits of the new optimization technique, The Fuzzy Adaptive Particle Swarm Optimization, the results obtained will be documented, graphed, and compared.

CHAPTER 3

3. VOLTAGE STABILITY AND VOLTAGE-CONTROL

3.1 Introduction

Power system stability is defined as the property of a power system that enables it to remain in a state of operating equilibrium under normal operating condition and to regain an acceptable state of equilibrium after being subjected to a physical disturbance. Stability is a condition of equilibrium between opposing forces, instability results when a disturbance leads to a sustained imbalance between the opposing forces [25].

The power system is highly nonlinear system that operates in a constantly changing environment, loads, generator outputs, topology and key operating parameters change continually. When subjected to a transient disturbance, the stability of the system depends on the nature of the disturbance as well as the initial operating condition. The disturbance may be small or large, small disturbance in the form of load changes and the system must be able to operate satisfactory and successfully under these conditions to meet the load demand. In the following, we will first review the classification of power system stability, and then briefly review voltage stability and its types. Finally, we will discuss the methods of voltage-control.

3.2 Classification of Power System Stability

We classify the stability of the power system based on the following considerations: the physical nature of the resulting instability related to the main system parameters in which instability can be observed. The size of the disturbance considered indicates the most appropriate method of calculation and prediction of stability. The devices, processes and the time span must be taken into consideration in order to determine stability. Figure 3.1 shows the classification of power system stability into various categories [25]:

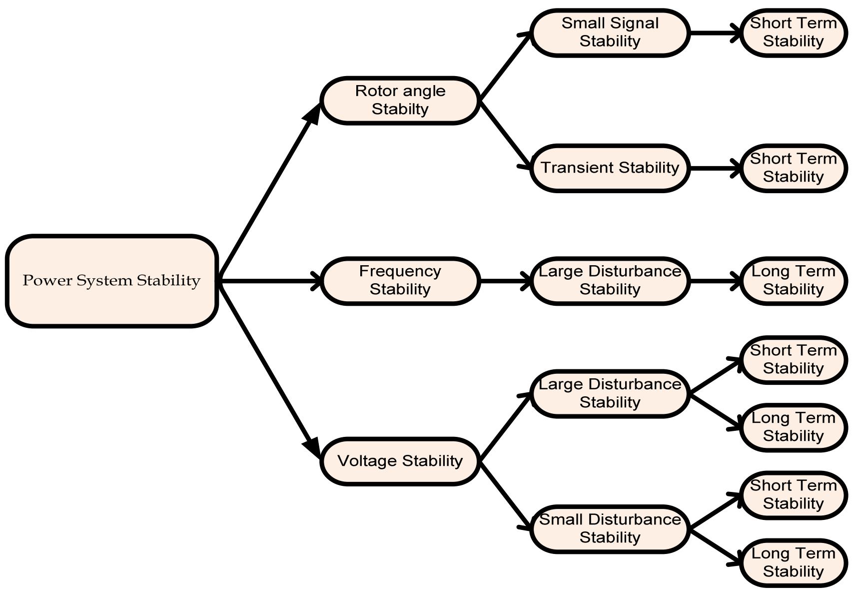

Figure 3.1: Classification of Power System Stability

Now, in the following, each type of stability will be considered in the brief but with concentration on the voltage stability.

3.2.1 Rotor Angle Stability

Rotor angle stability is the ability of interconnected synchronous machines of power system to remain in synchronism under normal operating conditions and after being subjected to a disturbance. It depends on the ability to maintain or restore equilibrium between electromagnetic torque and mechanical torque of each synchronous machine in the system. Instability that results occurs in the form of increasing angular swings of some generators leading to their loss of synchronous with other generators. A fundamental factor in this problem is that the power outputs of synchronous machines vary as their rotor angles change, since under steady state condition, there is an equilibrium between the input mechanical torque and the output electrical torque and the speed remains constant [25].

3.2.2 Frequency Stability

Frequency stability is the ability of the power system to maintain steady frequency within a nominal range following a severe system upset resulting in a significant imbalance between generation and load. It depends on the ability to restore balance between system generation and load with minimum loss of load [25].

3.2.3 Voltage Stability

Voltage stability is the ability of a power system to maintain steady voltages at all buses in the system under normal operating conditions, and after being subjected to a disturbance. Instability occurs when voltage fall or rise at some buses. Possible reasons of voltage instability are: loss of load in the area where voltages reach unacceptable low values and loss of integrity of the power system. This limits the capability of transmission network for power transfer. The power transfer is limited when some of generators hit their reactive power capability limits. The driving force for voltage instability is the loads, in response to a disturbance; power consumed by the loads tends to be restored by the action of distribution voltage regulators, tap-changing transformers and capacitor banks sizes. The voltage collapse is the catastrophic result of a sequence of events leading to a low voltage profile suddenly in a major part of the power system [25]. Voltage stability is classified into two types.

3.2.3.1 Large Disturbance Voltage Stability

This type is concerned with system ability to control voltages, following large disturbances such as system faults, loss of generation or circuit contingencies. The ability is determined by the system-load characteristics and interaction of both continuous and discrete controls and protections. Determination of large disturbance stability requires the examinations of the nonlinear dynamic performance of a system over a period of time [25].

3.2.3.2 Small Disturbance Voltage Stability

This type is concerned with a system ability to control voltages following small perturbations such as incremental changes in system load. This form of stability is determined by the characteristics of the loads, continuous controls and discrete controls at a given instant of time. A criterion for small disturbance voltage stability is that at a given operating condition for every bus in the system, the bus voltage magnitude increases as the reactive power injected at the same bus is increased. This means that a system is voltage-unstable if at least one of the buses in the system has a voltage magnitude (V) that decreases as the reactive power injected (Q) at the same bus is increased [25].

3.3 Voltage and Reactive Power Control

For efficient and reliable operation of power systems, the control of voltage and reactive power should satisfy the following objectives:

- Voltages at terminals of all equipment in the system are within acceptable limits.
- System stability is enhanced to maximize utilization of the transmission system, as mentioned before; voltage and reactive power control have a significant impact on system stability.
- The reactive power flow is minimized to reduced I^2R and I^2X losses to practical minimum.

The problem of maintaining voltages within the required limits is complicated by the fact that the power system supplies power to many loads and is fed from many generating units. As loads vary, the reactive power requirements of the transmission system vary.

3.4 Methods of Voltage-Control

The control of voltage levels is accomplished by controlling the production, absorption and flow of reactive power at all levels in the system [25]. There are many devices required to control voltage throughout the system, these devices can be classified as follows:

- Sources or sinks of reactive power such as: shunt capacitors, shunt reactors, synchronous condensers and static VAR compensators.
- Line reactance compensators such as series capacitors.
- Regulating transformers such as tap-changing transformers.

Shunt capacitors and reactors and series capacitors provide passive compensation; they are either permanently connected to the transmission and distribution system or switched-off. Synchronous condensers and static VAR compensators provide active compensations: they absorb or supply reactive power to systems and automatically adjusted to maintain voltages with acceptable range.

3.5 Control Methodology

Previously, voltage magnitudes were controlled manually; this means that the human will raise or lower the voltage according to the state in any area. After that, the control of voltage was done in an almost entirely decentralized manner according to timing depending on previous forecasting, this done by regulating pre-assigned voltage levels at certain buses using local reactive power sources such as generators, synchronous condensers and various tap-changers. However, dynamic changes of system loads and its topological variations would require a sufficiently fast adjustment of reactive power flows which would suit the real-time nature of the power system operation. From this point of view, the researchers attend to automatic voltage-control and extensive studies have been presented to investigate and analyze the nature of this complex problem.

Voltage-control and reactive power optimization is a sub-problem of the optimal power-flow (OPF) calculation, Several optimization methods have been proposed to solve the OPF, among them: the reduced gradient method, the differential injection method, the projected Lagrangian method, sequential quadratic programming methods [24], specific algorithms based on the resolution of a sequence of linear programming problems or on the resolution of a sequence of quadratic programming problems, interior point methods [21] and so on.

In this thesis, a new voltage control methodology is proposed. The method combines the fuzzy logic and the adaptive particle swarm optimization.

CHAPTER 4

4. OPTIMIZATION TECHNIQUES

4.1 Introduction

The objective of optimization is to seek values for a set of parameters that maximize or minimize objective functions subject to certain constraints [26, 27]. A choice of values for the set of parameters that satisfy all constraints is called a feasible solution. Feasible solutions with objective function values are called optimal solutions. An example of an optimization problem is the arrangement of the transistors in a computer chip in such a way that the resulting layout occupies the smallest area and that as few as possible components are used to perform a certain job. Optimization techniques are used on a daily base for industrial planning, resource allocation, scheduling, decision making. Furthermore, optimization techniques are widely used in many fields such as business, industry, engineering, and computer science. Research in the optimization field is very active and new optimization methods are being developed regularly [28]. Optimization can be classified into maximization and minimization problems. Any maximization problem can be converted into a minimization problem by taking the negative of the objective function, and vice versa. In general, the problem of voltage-control tackled in this thesis is a minimization problem. Therefore, the remainder of the discussion focuses on minimization problems. The minimization problem can be defined as follows [29].

Given $f : S \rightarrow R$ Where $S \subseteq R^{Nd}$ and N_d is the dimension of the search space S

Find $x^* \in S$ such that $f(x^*) \leq f(x), \forall x \in S$.

The variable x^* is called the global minimizer of f and $f(x^*)$ is called the global minimum value of f. This can be illustrated as shown in Figure 4.1. The process of finding the global optimal solution is known as global optimization [30]. A true global optimization algorithm will find x^* regardless of the selected starting point $x_0 \in S$ [27]. Global optimization problems are generally very difficult and are categorized under the class of nonlinear programming (NLP).

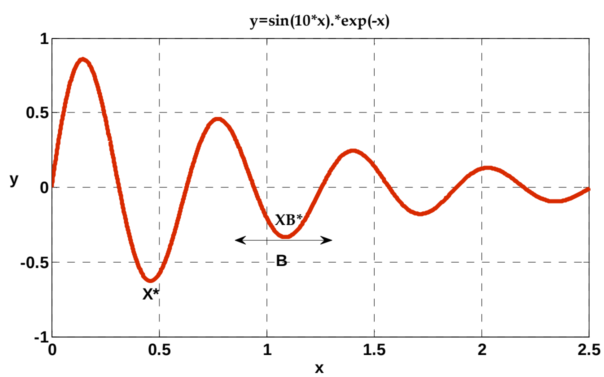

Figure 4.1: Example of a global minimizer x^* as well as a local minimize x^*_B

Examples of global optimization problems are [30]:

- Combinatorial problems: where a linear or nonlinear function is defined over a finite but very large set of solutions, for example, network problems and scheduling [29].
- General unconstrained problems: where a nonlinear function is defined over an unconstrained set of real values.
- General constrained problems: where a nonlinear function is defined over a constrained set of real values.

In Figure 4.1, x_B^* is called the local minimize of region B because $f(x_B^*)$ is the smallest value within a local neighborhood, B. Mathematically, the variable x_B^* is a local minimize of the region B if

$f(x_B^*) \leq f(x), \forall x \in B$

Where, $B \subset S$. Every global minimizer is a local minimizer, but a local minimizer is not necessarily a global minimizer. Generally, a local optimization method is guaranteed to find the local minimize x_B^* of the region B if a starting point x_0 is used with $x_0 \in B$. An optimization algorithm that converges to a local minimizer, regardless of the selected starting point $x_0 \in S$, is called a globally convergent algorithm.

4.2 Traditional Optimization Algorithms

Traditional optimization algorithms use exact methods to find the best solution. The idea is that if a problem can be solved, then the algorithm should find the global best solution. One exact method is the brute force (or exhaustive) search method where the algorithm tries every solution in the search space so that the global optimal solution is guaranteed to be found. Obviously, as the search space increases the cost of brute force algorithms increases. Therefore, brute force algorithms are not appropriate for the NLP-hard problems. The time to search an NLP-hard problem increases exponentially with problem size.

4.3 Stochastic Algorithms

Stochastic search algorithms are used to find near-optimal solutions for NLP-hard problems in polynomial time. This is achieved by assuming that good solutions are close to each other in the search space. This assumption is valid for most real world problems [31, 32] since the objective of a stochastic algorithm is to find a near-optimal solution, stochastic algorithms may fail to find a global optimal solution. While an exact algorithm generates a solution only after the run is completed, a stochastic algorithm can be stopped any time during the run and generate the best solution found so far. Stochastic search algorithms have several advantages compared to other algorithms [33]:

- Stochastic search algorithms are generally easy to implement.
- They can be used efficiently in a multiprocessor environment.
- They do not require the problem definition function to be continuous.
- They generally can find optimal or near-optimal solutions.
- They are suitable for discrete and combinatorial problems.

The major stochastic algorithms are Hill-Climbing [34], Simulated Annealing [35] and Tabu search [36, 37]. In Hill-Climbing, a potential solution is randomly chosen. The algorithm then searches the neighborhood of the current solution for a better solution. If a better solution is found, then it is set as the new potential solution. This process is repeated until no more improvement can be made. Simulated annealing is similar to Hill-Climbing in the sense that a potential solution is randomly chosen. A small value is then added to the current solution to generate a new solution. If the new solution is better than the original one then the solution moves to the new location. Otherwise, the solution will move to the new location with a probability that decreases as the run progresses [38]. Tabu search is a heuristic search algorithm where a tabu list memory of previously visited solutions is maintained in order to improve the performance of the search process. The tabu list is used to guide the movement from one solution to the next one to avoid cycling [39], thus, avoid being trapped in a local optimum. Tabu search starts with a randomly chosen current solution. A set of test solutions are generated via moves from the current solution. The best test solution is set as the current solution if it is not in the tabu list, or if it is in the tabu list, but satisfies an aspiration criterion. A test solution satisfies an aspiration criterion if it is in the tabu list and it is the best solution found so far [40]. This process is repeated until a stopping criterion is satisfied.

4.3.1 Particle Swarm Optimization Technique

Particle Swarm Optimization (PSO) is a population-based stochastic optimization algorithm modeled after the simulation of the social behavior of bird flocks. It is a relatively new evolutionary algorithm that may be used to find optimal (or near optimal) solutions to numerical and qualitative problems. Particle Swarm Optimization was originally developed by a social psychologist (James Kennedy) and an electrical engineer (Russell Eberhart) in 1995 [1, 3]. Although there were a number of such algorithms getting quite a bit of attention at the time, Kennedy and Eberhart became particularly interested in the models developed by biologist Frank Heppner [41]. Heppner studied birds in flocking behaviors mainly attracted to a roosting area. In simulations, birds would begin by flying around with no particular destination and spontaneously formed flocks until one of the birds flew over the roosting area.

Due to the simple rules the birds used to set their directions and velocities, a bird pulling away from the flock in order to land at the roost would result in nearby birds moving towards the roost. Once these birds discovered the roost, they would land there, pulling more birds towards it, and so on until the entire flock had landed. Finding a roost is like finding a solution in a field of possible solutions in a solution space. The manner in which a bird who has found the roost, leads its neighbors to move towards it, increases the chances that they will also find it. This is known as the "socio-cognitive view of mind". The "socio-cognitive view of mind" means that a particle learns primarily from the success of its neighbors. Eberhart and Kennedy revised Heppner's methodology [41] so that particles could fly over a solution space and land on the best solution simulating the birds' behavior.

Each particle should compare themselves to others and imitate the behavior of others who have achieved a particular objective successfully. Eberhart and Kennedy developed a model that balances the cooperation between particles in the swarm. An appropriate balance between exploration (individuals looking around for a good solution) and exploitation (individuals taking advantage of someone else's success), is a main concern in the Eberhart and Kennedy model. Too little exploration and the particles will all converge to the first good solution found (typically a local solution). Too little exploitation and the particle will take longer to converge (or may not converge at all). In summary, the Eberhart and Kennedy model attempts to find the best compromise between its two main components, individuality and sociality [16].

4.3.2 Particle Swarm Model for Continuous Variables

In Particle Swarm Optimization, the particles are “flown” through the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) that it has achieved so far. This implies that each particle has a memory, which allows it to remember the best position on the feasible search space that it has ever visited. This value is commonly called previous best (p-best). Another best value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the neighborhood of the particle. This location is commonly called global best (g-best). The basic concept behind the Particle Swarm Optimization technique consists of changing the velocity (or accelerating) of each particle toward its p-best and the g-best positions at each time step. This means that each particle tries to modify its current position and velocity according to the distance between its current position and p-best, and the distance between its current position and g-best. In its canonical form, Particle Swarm Optimization is modeled as follows:

$$v_i^{k+1} = v_i^k + c_1 \times rand(\quad)_1 \times \left(pbest_i - s_i^k\right) + c_2 \times rand(\quad)_2 \times \left(gbest - s_i^k\right) \qquad (4.1)$$

$$s_i^{k+1} = s_i^k + v_i^{k+1} \qquad (4.2)$$

Where,

v_i^{k+1} : $velocity\ of\ particle\ i\ at\ iteration\ k+1$

v_i^k : $velocity\ of\ particle\ i\ at\ iteration\ k$

S_i^{k+1} : $position\ of\ particle\ i\ at\ iteration\ k+1$

s_i^k : $position\ of\ particle\ i\ at\ iteration\ k$

c_1 : $constant\ weighting\ factor\ related\ to\ pbest$

c_2 : $constant\ weighting\ factor\ related\ to\ gbest$

$\mathrm{rand}()_1$: $random\ number\ between\ 0\ and\ 1$

$\mathrm{rand}()_2$: $random\ number\ between\ 0\ and\ 1$

$pbest_i$: $pbest\ position\ of\ particle\ i$

$gbest$: $gbest\ position\ of swarm$

Expressions in equations (4.1) and (4.2), [19] describe the velocity and position update, respectively. Expression in equation (4.1) calculates a new velocity for each particle based on the particle's previous velocity, the particle's location at which the best fitness has been achieved so far, and the population global location at which the best fitness has been achieved so far. In addition, c_1 and c_2 are positive constants called the cognitive parameter and the social parameter, respectively. These constants provide the correct balance between exploration and exploitation (individuality and sociality). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward p-best and g-best locations. The random numbers provide a stochastic characteristic for the particles velocities in order to simulate the real behavior of the birds in a flock. Figure 4.2 shows the concept of modification of searching points described by expression in equation (4.1). An inertia weight parameter w was introduced in order to improve the performance of the original Particle Swarm Optimization model. This parameter plays the role of balancing the global search and local search capability of Particle Swarm Optimization. It can be a positive constant or even a positive linear or non linear function of time.

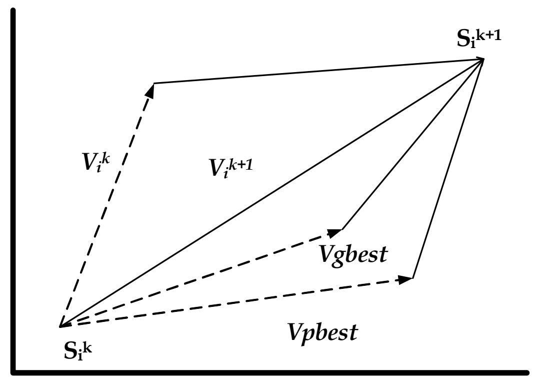

Figure 4.2: Concept of Modification of Searching Point

A better method of global optimum within a reasonable number of iterations can be achieved by incorporating this parameter into the velocity update expression in equation (4.1), as follows:

$$v_i^{k+1} = w \times v_i^k + c_1 \times rand(\quad)_1 \times \left(pbest_i - s_i^k\right) + c_2 \times rand(\quad)_2 \times \left(gbest - s_i^k\right) \tag{4.3}$$

Typical values for the inertia parameter are in the range [0.7, 1.2]. On the other hand some different approach using a construction factor K, which increase the algorithm's ability to converge to a good solution, and the expression used to update the particle's velocity becomes:

$$v_i^{k+1} = K \times \left(v_i^k + c_1 \times rand(\quad)_1 \times \left(pbest_i - s_i^k\right) + c_2 \times rand(\quad)_2 \times \left(gbest - s_i^k\right)\right) \tag{4.4}$$

Where,

$$K = \frac{2}{\left|2-\varphi-\sqrt{\varphi^2-4\varphi}\right|}, \varphi = c_1 + c_2, \varphi > 1 \tag{4.5}$$

The Particle Swarm Optimization algorithm with constriction factor can be considered as a special case of the algorithm with inertia weight since the parameters are connected through expression in equation (4.5). From experimental results, the best approach to use with Particle Swarm Optimization as a “rule of thumb” is to utilize the constriction factor approach or utilize the inertia weight approach while selecting w, c_1, and c_2 according to expression in equation (4.3). All parameters introduced in equations (4.3), (4.4) and (4.5) may vary depending of the characteristics of the problem at hand. Adjustments of these parameters are different for every kind of problem and need to be carefully adjusted in order to achieve better performance of the algorithm. In this thesis, we apply the inertia weight approach to use with particle swarm optimization on voltage-control problem.

4.4 Fuzzy System

The dictionary meaning of the word “fuzzy” is “not clear”. By contrast, in the technical sense, fuzzy systems are precisely defined systems, and fuzzy control is a precisely defined method of non-linear control. The main goal of fuzzy logic is to mimic (and improve on) “human-like” reasoning. “Fuzzy systems are knowledge-based or rule-based systems” [42], specifically, the key components of fuzzy system’s knowledge base are a set of IF-THEN rules obtained from human knowledge and expertise. The fuzzy systems are multi-input-multi-output mappings from a real-valued vector to a real-valued scalar.

4.4.1 Why Fuzzy?

Natural language is one of the most powerful forms of conveying information. The conventional mathematical methods have not fully tapped this potential of language. According to Timothy J. Ross [43], “scientists have said, the human thinking process is based primarily on conceptual patterns and mental images rather than on numerical quantities”. So if the problem of making computers with the ability to solve complex issues has to be solved, the human thought process has to be modeled. The best way to do this is to use models that attempt to emulate the natural language; the advent of fuzzy logic has put this power to proper use.

Most if not all of the physical processes are non-linear and to model them, a reasonable amount of approximation is necessary. For simple systems, mathematical expressions give precise descriptions of the system behavior. For more complicated systems with significant amounts of data available, model-free methods provide robust methods to reduce ambiguity and uncertainty in the system. But for complex systems where not much numerical data exists, fuzzy reasoning furnishes a way to understand the system behavior by relying on approximate input-output approaches. The underlying strength of fuzzy logic is that it makes use of linguistic variables rather than numerical variables to represent imprecise data.

4.4.2 Fuzzy Sets

The key difference between classical sets and fuzzy sets is that in the former, the transition for an element in the universe between membership and non-membership in a given set is well defined, that is the element either belongs or does not belong to the set. By contrast, for elements in fuzzy sets, the membership can be a gradual one, allowing for the boundaries for fuzzy sets to be vague and ambiguous.

4.4.3 Membership Function

A fuzzy set is characterized by a membership function whose value ranges from 0 to 1. It consists of members with varying degrees of membership based on the values of the membership function. In mathematical terms, the fuzzy set A in the universe U can be represented as a set of ordered pairs of an element x and its membership function $\mu_A(x)$. Formally we have

$$A = \{(x, \mu_A(x)) | x \in U, \text{where } U \text{ is continuous}\} \quad (4.6)$$

For more detailed description of fuzzy sets and the set operations that can be performed on them, see references [42] and [43]. A membership function is a continuous function in the range of 0 to 1. It is usually decided from human expertise and observations made and it can be either linear or nonlinear. Its choice is critical for the performance of the fuzzy logic system since it determines all the information contained in a fuzzy set. In the voltage and reactive power control problems under study in this research, the membership functions will help in automating the fuzzy control. The rules were framed through numerous simulations, which are carried out to determine the best possible set of rules aimed at pushing the stability limits of the system to its maximum. The membership functions can be estimated by studying the behavior of different conditions and for different contingency cases. They should be able to accommodate all the non-linearities of the system, making their determination a complex task.

4.4.4 Fuzzy Rule Base – IF-THEN Rules

Fuzzy logic has been centered on the point that it makes use of linguistic variables as its rule base. Li-Xin Wang [42] said that "*If a variable can take words in natural language as its values, it is called linguistic variable, where the words are characterized by fuzzy sets defined in the universe of discourse in which the variable is defined*". Examples of these linguistic variables are slow, medium, high, young and thin. There could be a combination of these variables too, i.e. "slow-young horse", "a thin young female". These characteristics are termed atomic terms while their combinations are called compounded terms. In real world, words are often used to describe characteristics rather than numerical values. For example, one would say "the car was going very fast" rather than say "the car was going at 100 miles per hour". Terms such as slightly, very, more or less, etc. are called linguistic hedges since they add extra description to the variables, i.e. very-slow, more or less red, slightly high.

4.4.5 Inference Systems Methods

There are a lot of inference methods which deals with fuzzy inference such as Mamdani method, Larsen method, Tsukamoto method, Sugeno style inference and Takagi- Sugeno-Kang (TSK) method. The most important and widely used in fuzzy controller are the Mamdani and Takagi-Sugeno methods.

4.4.5.1 Mamdani Method

This fuzzy inference method is the most commonly used. In 1974, Professor Ebrahim Mamdani of London University built one of the first fuzzy systems to control a steam engine and boiler combination. He applied a set of fuzzy rules supplied by experienced human operators [44]. The Mamdani style fuzzy inference process is performed in four steps:

- Fuzzification of the input variable.
- Rule evaluation.
- Aggregation of the rule output.
- Defuzzification.

The system shown in Figure 4.3 incorporates all the essential features of fuzzy systems. To illustrate the fuzzy inference, each step will be explained in more details.

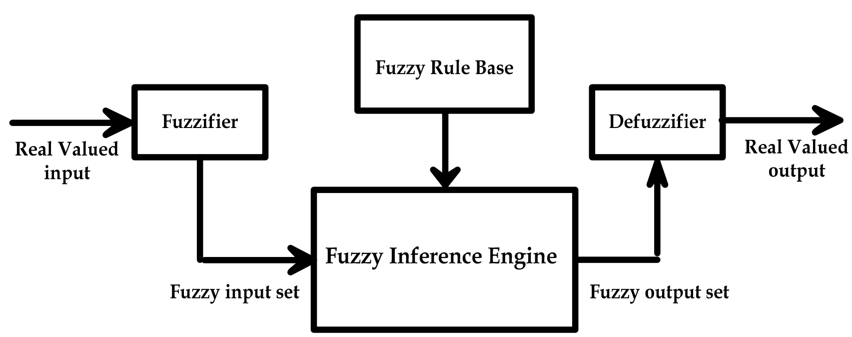

Figure 4.3: Configuration of a fuzzy system with fuzzifier and defuzzifier

Step 1: Fuzzification

The fuzzifier is a mapping from the real valued point, $x^* \in U$ to a corresponding fuzzy set $A^{'} \subset U$, which is the input to the fuzzy inference engine. The fuzzifier needs to account for certain criteria while performing this mapping. The first of these criteria states that the input is a crisp point x^*, so that its mapping in U is a fuzzy set $A^{'}$ that has a large membership value. The second criterion states that the fuzzifier must be able to suppress the noise inherent in real valued inputs. The third criterion is that the fuzzifier must be able to simplify the computations in the fuzzy inference engine. Three types of fuzzifiers have been proposed by Li-Xin Wang [42], which are singleton, Gaussian, and triangular fuzzifiers. They are defined as follows:

- **Singleton Fuzzifier:** This maps a real valued point $x^* \in U$, with a membership function $\mu_{A^{'}}(x)$ into a fuzzy singleton $A^{'}\ in\ U$. Specifically we have
- $\mu_{A'}(x) = \begin{cases} 1 & \text{if } x = x^* \\ 0 & \text{otherwise} \end{cases}$ 4.7

- **Gaussian Fuzzifier:** This maps a real valued point $x^* \in U$ into a fuzzy set $A^{'} \subset U$ with a membership function given by

$$\mu_{A^{'}}(x) = e^{-\left(\frac{x_1 - x_1^*}{a_1}\right)^2} \dots\ e^{-\left(\frac{x_n - x_n^*}{a_n}\right)^2} \qquad 4.8$$

Where: $\{a_i, i = 1, \dots, n\}$ are positive parameters

- **Triangular Fuzzifier:** This maps a real valued point $x^* \in U,$ into a fuzzy set $A' \subset U$ with a membership function written as

$$\mu_{A^{'}}(x) = \begin{cases} \left(1 - \frac{|x_1 - x_1^*|}{b_1}\right) \dots \left(1 - \frac{|x_n - x_n^*|}{b_n}\right) & \text{if } |x_i - x_i^*| \le b_i, i = 1,2, \dots.\ n \\ 0 & \text{otherwise} \end{cases} \qquad 4.9$$

Where: $\{b_i, i = 1, \dots, n\}$ are positive parameters

Note that all these fuzzifiers satisfy the first criterion as mentioned above, that is to say they have a large membership value at the input point. It can be observed that the singleton fuzzifier simplifies the computations involved in the fuzzy inference engine for any type of membership functions, while the other two fuzzifiers simplify the computations if the membership is either Gaussian or triangular, respectively. On the other hand, the Gaussian and triangular fuzzifiers can suppress noise while the singleton fuzzifier can't.

Step 2: Rule Evaluation

The second step is to take the fuzzified input, and apply them to the antecedents of the fuzzy rules. If a given fuzy rule has multiple antecedents, the fuzzy operator (AND or OR) is used to obtain a single number that represent the result of the antecedent evaluation.

Step 3: Aggregation of the Rule Output

Aggregation is the process of unification of the ouputs of all rules, we take the membership functions of all rule consequents and combine them into a single fuzzy set.

Step 4: Defuzzification

The defuzzifier's task is the reverse operation to the fuzzifier. It maps the fuzzy output set, $B^{'} \subset V$, from the fuzzy inference engine to a real valued point (crisp point), $y^{*} \in V$. In other words, it can be said that the defuzzifier gives the real point that best describes the fuzzy set $B^{'}$. Naturally, there exist many choices for choosing this point, but the most suitable point can be determined by considering certain criteria. The point y^{*} should represent $B^{'}$ from an intuitive point of view; for example it should exhibit a high membership in $B^{'}$. Furthermore, the defuzzifier has to have computational simplicity; this is particularly important because most of the fuzzy controllers are usually used in real time. Lastly, the defuzzifier must have continuity.

- **Centroid Defuzzifier**

The centroid defuzzifier specifies the crisp point y^* as the center of the area covered by the membership function of $B^{'}$. If the membership function is viewed as a probability density function of a random variable, the centroid defuzzifier gives its mean value. One inherent disadvantage of this method is that it is computational intensive.

- **Center Average Defuzzifier**

The center average defuzzifier takes the weighted averages of all the fuzzy sets that are output from the inference engine, where the weight of each set is based on the height of that particular set to determine the point y^*. This is a good approximation since the fuzzy set $B^{'}$is either a union or an intersection of the inference engine's output. This is the most commonly used defuzzifier in fuzzy systems because of it computational simplicity and intuitive plausibility.

- **Maximum Defuzzifier**

The maximum defuzzifier chooses y^* as the point at which the associated membership function achieves its maximum value. If more than one point satisfies this condition, then the maximum, or minimum, or mean of all such points is taken. While this type of defuzzifier is computationally simple and intuitively plausible, it lacks continuity wherein a small change in the value of $B^{'}$ results in a large change in y^*.

4.4.5.2 Sugeno Method

Most fuzzy controllers have been designed, based on human operator experience and/or control engineer knowledge. It is often the case that an operator can't tell linguistically what kind of action he takes in a particular situation. In this situation, it is useful to provide a method of modeling the control actions using numerical data [45]. In 1985 Takagi-Sugeno-Kang suggested to use a single spike, a singleton, as the membership function of the rule consequent, and they suggested another approach that using equation consequent in place off singleton consequent. Sugeno style fuzzy inference is very similar to the Mamdani method. Sugeno changed only a rule consequent, instead of a fuzzy set, he used a mathematical function of the input variable. The format of the Sugeno style fuzzy rule is

$$\text{If } \mathbf{X} \text{ is } \mathbf{A} \text{ AND } \mathbf{Y} \text{ is } \mathbf{B} \text{ THEN } \mathbf{Z} \text{ is } \boldsymbol{f}(\mathbf{x}, \mathbf{y}) \qquad 4.10$$

Where X, Y and Z are linguistic variables; *A* and *B* are fuzzy sets on universe of discourses X and Y, respectively; and *f*(x,y) is a mathematical function.

In this research the fuzzy logic with Mamdani inference system and centroid defuzzifier is used to adjust the parameters of particle swarm in order to improve the performance of the search for an optimized solution.

CHAPTER 5

5. APPLICATION OF THE OPTIMIZATION TECHNIQUES

5.1 Introduction

The optimal operating state of a power system network has been determined based on economic factors. However, the power quality and system security have forced power systems planners and operators to incorporate other criteria such as improved and maintain system voltage profile with acceptable value and minimization of transmission losses. Generally, the voltage-control and reactive power dispatch is one of the application functions of modern energy management systems, used to satisfy and maintain those criteria.

Scheduling of the reactive power in an optimum manner ensures better voltage profile which leads to real power saving on account of reduced system losses. Hence the reactive power dispatch plays an important role both in planning stages as well as in day-to-day operation of the power system. The reactive power dispatch determines the proper system settings required to control reactive power flows and allocate reactive power properly. Reactive power dispatch provides better system voltage-control and reduces power system losses. All these result in an improved voltage profile, system security, power transfer capability and overall system operation.

5.2 Power System Model Description

The IEEE 30-bus system was proposed as a model system in order to examine and validate the new approach. The following Figure and tables show the system topology and data:

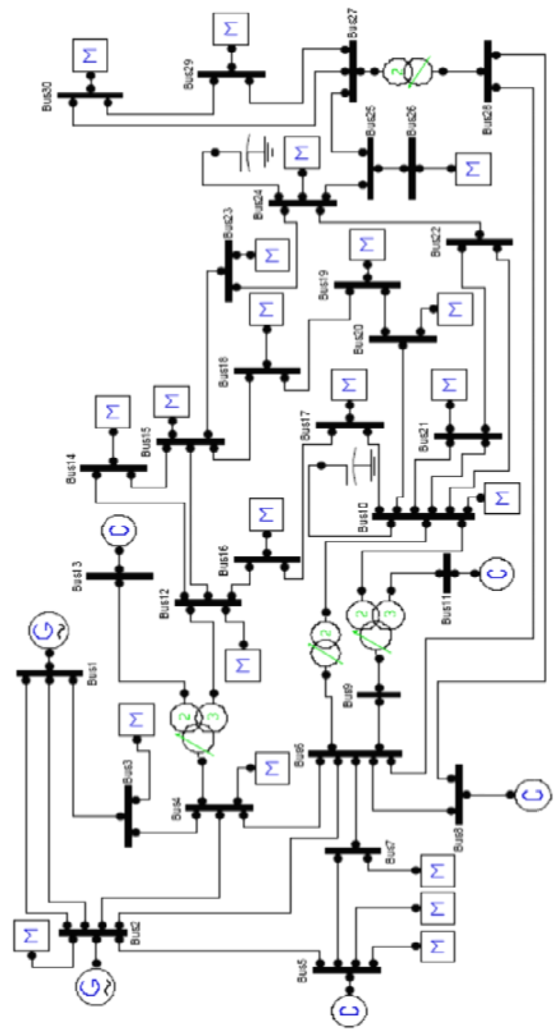

Figure 5.1: The IEEE 30-Bus system model

The system consists of thirty buses, bus number one is assigned as slack bus, while buses 2, 5, 8, 11, and 13 are taken as voltage controlled buses, and the remaining are load buses. Four tap changer transformers, the first transformer between bus number 6 and bus number 9, the second one between bus number 6 and bus number 10, the third transformer between bus number 4 and bus number 12, and the last transformer between bus number 28 and bus number 27. All four transformers are used as control variable. There are also two capacitor banks connected to bus 10 and bus 24.

Table 5.1: Bus data of IEEE 30-Bus system model

Bus data		Voltage	Angle	Load		Generation				Static Mvar
No	Code	PU	Degree	MW	Mvar	MW	Mvar	Q_{min}	Q_{max}	$+Q_c/Q_l$
1	1	1.05	0.0	0.0	0.0	0.0	0.0	0	0	0
2	2	1.05	0	21.70	12.7	40	0.0	-40	50	0
3	0	1.0	0	2.4	1.2	0	0	0	0	0
4	0	1.0	0	7.6	1.6	0	0	0	0	0
5	2	1.05	0	94.2	19.0	0	0	-40	60	0
6	0	1.0	0	0	0.0	0	0	0	0	0
7	0	1.0	0	22.8	10.9	0	0	0	0	0
8	2	1.05	0	30	30.0	0	0	-30	70	0
9	0	1.0	0	0	0	0	0	0	0	0
10	0	1.0	0	5.8	2	0	0	0	0	10
11	2	1.05	0	0	0	0	0	-6	24	0
12	0	1.0	0	11.2	7.5	0	0	0	0	0
13	2	1.05	0	0	0	0	0	-6	40	0
14	0	1	0	6.2	1.6	0	0	0	0	0
15	0	1	0	8.2	2.5	0	0	0	0	0
16	0	1	0	3.5	1.8	0	0	0	0	0
17	0	1	0	9.0	5.8	0	0	0	0	0
18	0	1	0	3.2	0.9	0	0	0	0	0
19	0	1	0	9.5	3.4	0	0	0	0	0
20	0	1	0	2.2	0.7	0	0	0	0	0
21	0	1	0	17.5	11.2	0	0	0	0	0
22	0	1	0	0	0	0	0	0	0	0
23	0	1	0	3.2	1.6	0	0	0	0	0
24	0	1	0	8.7	6.7	0	0	0	0	4.3
25	0	1	0	0	0	0	0	0	0	0
26	0	1	0	3.5	2.3	0	0	0	0	0
27	0	1	0	0	0	0	0	0	0	0
28	0	1	0	0	0	0	0	0	0	0
29	0	1	0	2.4	0.9	0	0	0	0	0
30	0	1	0	10.6	1.9	0	0	0	0	0

Table 5.1 contains the bus data, column two for the bus type: code 0: represents a load bus, code 1: represents a slack bus and code 2: represents a voltage controlled bus. Column 3 and column 4 present the voltage magnitude and phase angle in degrees respectively, while column 5 and column 6 describe the power load demand. Also column 7, column 8, column 9, and column 10 represent the power generations and their minimum and maximum limits. Finally column 11 states the capacitor bank size connected to the respective bus.

Table 5.2 contains the line data, column 1 and column 2 are reserved for line bus number, column 3, column 4 and column 5 are used for line resistance, reactance and one half of total line charging susceptance, and column 6 has the value of 1 for transmission line or transformer tap setting.

Table 5.2: Line data of IEEE 30-Bus system model

From Bus	To Bus	Type	R (p.u.)	X (p.u.)	½ B (p.u.)	Line code =1 for lines >1 or <1 for tr. Tap at from bus
1	2	T. L.*	0.0192	0.0575	0.02640	1
1	3	T. L.	0.0452	0.1852	0.02040	1
2	4	T. L.	0.0570	0.1737	0.01840	1
3	4	T. L.	0.0132	0.0379	0.00420	1
2	5	T. L.	0.0472	0.1983	0.02090	1
2	6	T. L.	0.0581	0.1763	0.01870	1
4	6	T. L.	0.0119	0.0414	0.00450	1
5	7	T. L.	0.0460	0.1160	0.01020	1
6	7	T. L.	0.0267	0.0820	0.00850	1
6	8	T. L.	0.0120	0.0420	0.00450	1
6	9	Transformer	0	0.2080	0	0.978
6	10	Transformer	0	0.5560	0	0.969
9	11	T. L.	0	0.2080	0	1
9	10	T. L.	0	0.1100	0	1
4	12	Transformer	0	0.2560	0	0.932
12	13	T. L.	0	0.1400	0	1
12	14	T. L.	0.1231	0.2559	0	1
12	15	T. L.	0.0662	0.1304	0	1
12	16	T. L.	0.0945	0.1987	0	1
14	15	T. L.	0.2210	0.1997	0	1
16	17	T. L.	0.0824	0.1923	0	1
15	18	T. L.	0.1073	0.2185	0	1
18	19	T. L.	0.0639	0.1292	0	1
19	20	T. L.	0.0340	0.0680	0	1
10	20	T. L.	0.0936	0.2090	0	1
10	17	T. L.	0.0324	0.0845	0	1
10	21	T. L.	0.0348	0.0749	0	1
10	22	T. L.	0.0727	0.1499	0	1
21	22	T. L.	0.0116	0.0236	0	1
15	23	T. L.	0.1000	0.2020	0	1
22	24	T. L.	0.1150	0.1790	0	1
23	24	T. L.	0.1320	0.2700	0	1
24	25	T. L.	0.1885	0.3292	0	1
25	26	T. L.	0.2544	0.3800	0	1
25	27	T. L.	0.1093	0.2087	0	1
28	27	Transformer	0	0.3960	0	0.968
27	29	T. L.	0.2198	0.4153	0	1
27	30	T. L.	0.3202	0.6027	0	1
29	30	T. L.	0.2399	0.4533	0	1
8	28	T. L.	0.0636	0.2000	0	1
6	28	T. L.	0.0169	0.0599	0	1

*T.L. is the transmission line

5.3 Mathematical model

The voltage-control and reactive power dispatch problem may be considered as a special case of optimal power flow (OPF). The main objective is to improve system voltage profile, minimize voltage deviation, and minimize the real power transmission loss, while satisfying a number of equality and inequality constraints. The equality constraints are the conventional power flow equations; the inequality constraints are the limits on the control and operating variables of the system. Mathematically, the voltage-control problem can be formulated as a constrained nonlinear optimization problem.

Voltage-control and Reactive power dispatch problem are complex combinatorial optimization problem involving continuous and discrete variables. The problem constraints include the reactive power limits of generation units, the voltage magnitude limits at load buses, the transformer tap positions, the voltage magnitude limits at generation buses, and settings of VARS compensators or shunt capacitor banks.

5.4 Objective functions

The objective function of voltage-control problem comprises three important terms, which are: maintaining acceptable system voltage profile, minimizing the voltage deviation at load buses, and minimizing the real power loss in the transmission grid.

5.4.1 System Voltage Profile

The first objective is to maintain the voltage at all buses in an acceptable range between (0.95 – 1.05).

5.4.2 Voltage Deviation

Bus voltage is one of the most important securities and service quality, one of the effective ways to avoid the voltages from moving toward their maximum or minimum limits after optimization, is to choose the deviation of voltage from the desired value as an objective function, that is

$$\min f_2 = \sum_{i=1}^{N_L} \frac{|v_i - v_i^*|}{N_L} \quad 5.1$$

Where f_2 is the per unit average voltage deviation, N_L is the total number of the system load buses, v_i and v_i^* are the actual voltage magnitude and the desired voltage magnitude at bus i.

5.4.3 Power Loss

The third objective is to minimize the total active power lose which can be expressed as follows:

$$\min f_1 = P_{loss}(x, u) \quad 5.2$$

Where f_1 is the total active power losses of the power system, x is the state variable vector consisting of load bus voltages V_L and generator reactive power outputs Q_G , u is the control variable vector consisting of generator voltages, V_G shunt VAR compensations Q_c and transformer tap settings T.

On the other hands, the mathematical formulation can be expressed as follow:

$$\min f_1 = \min\left\{\sum_{i=1}^{N} \sum_{j=1}^{N} \left[g_{ij} \times \left(|V_i|^2 + \left|V_j\right|^2 - 2 \times |V_i| \times \left|V_j\right| \times cos\left(\delta_i - \delta_j\right)\right)\right] \quad 5.3$$

Where,

N : Number of buses

$|V_i|$: Voltage magnitude at bus i

$\left|V_j\right|$: Voltage magnitude at bus j

g_{ij} : Conductance of transmission line between bus i and bus j

δ_i : Voltage angle at bus i

δ_j : Voltage angle at bus j

The following constraints are known as the power balance constraints. They guarantee that the load demand will be met considering the transmission losses of the system. These constraints are the main objective in a power flow analysis.

$$\sum P_G - \sum P_D - P_L = 0 \quad 5.4$$

$$\sum Q_G - \sum Q_D - Q_L = 0 \quad 5.5$$

Where,

P_G : Real power generation

P_D : Real power demand

P_L : Real power loss

Q_G : Reactive power generation

Q_D : Reactive power demand

Q_L : Reactive power loss

The operational constraints guarantee a safe operation of the system. The capacity limits should be met at all time to avoid damage to power system components and maintain system stability. The following constraints state real and reactive power generation limits for each generation unit:

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \quad 5.6$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \quad 5.7$$

Where,

P_{Gi}^{min} : Lower real power generation limit of unit i

P_{Gi}^{max} : Upper real power generation limit of unit i

Q_{Gi}^{min} : Lower reactive power generation limit of unit i

Q_{Gi}^{max} : Upper reactive power generation limit of unit i

In order to maintain system stability, the voltage at each bus should be within its limits. The following constrain shows this operational condition:

$$V_i^{min} \leq |V_i| \leq V_i^{max} \qquad 5.8$$

Where:

V_i^{min} : Lower voltage magnitude limit at bus i

V_i^{max} : Upper voltage magnitude limit at bus i

The optimal voltage-control and reactive power dispatch can be achieved by employing reactive power compensator devices such as shunt capacitor banks, and by adjusting the transformer tap positions. Shunt capacitor banks and transformer tap positions are control variables for voltage-control problem. The operational limits of these devices are expressed in the following constrains:

$$Q_C^{min} \leq Q_C \leq Q_C^{max} \qquad 5.9$$

$$T_k^{min} \leq T_k \leq T_K^{max} \qquad 5.10$$

Where:

Q_C : Reactive power generated by the shunt capacitor bank C

Q_C^{min} : Lower limit of shunt capacitor bank C

Q_C^{max} : Upper limit of shunt capacitor bank C

T_k : Tap position of transformer k

T_k^{min} : Lower tap position limit of transformer k

T_k^{max} : Upper tap position limit of transformer k

The transformer tap settings and the adjustable shunt capacitor banks are the essential key elements in transmission loss reduction. In power systems, almost all transformers provide taps on windings to adjust the ratio of transformation, also have adjustable shunt capacitor banks located in specified buses in order to correct voltage and power factor problems. In a mathematical formulation, the transformers tap settings and the adjustable shunt capacitor banks may be represented either as continuous or discrete variables, depending on the study issued. In this work, the transformers tap settings and the adjustable shunt capacitor banks are considered as continuous variables.

In the following, the voltage-control problem will be solved by five different approaches. The results will be generated, analyzed, compared and discussed. The program code was developed using MATLAB R2008a on a Pentium 4 PC. The power flow equations were solved using the Newton-Raphson load flow method with a tolerance of 10^{-4}.

5.5 Optimal Economic Dispatch

Despite the voltage control problem is non linear control problem, hence the power flow equations become nonlinear and must be solved by iterative technique. The commonly used iterative technique is Newton-Raphson for power flow equation. This method was employed to IEEE 30-bus system, subject to the applicable constraints and the optimal economic dispatch was used to rearrangement of power generator in order to minimize the total generation cost according to the following equation

$$J = \sum_{i=1}^{g} f_i \qquad 5.11$$

Where: f_i is the fuel cost of i^{th} generator

$$f_i = a_i + b_i P_{Gi} + c_i P_{Gi}^2 \qquad 5.12$$

Where a_i, b_i, c_i are cost coefficients of unit i, g is the number of generator. P_{Gi} is the real power generation of unit i. The loss formula can be formulated and described in equation 5.13.

$$P_L = P \times B \times P^T + B_0 \times P^T + B_{00} \qquad 5.13$$

Where P is the real power generation, B, B_0 and B_{00} are coefficients of the loss formula. For more details see **Appendix A.**

At each iteration, the set of values for voltage magnitudes at PV buses, transformers tap positions and total capacity of each shunt capacitor bank are used to run a power flow, calculate the transmission losses, voltage deviation and evaluate the following fitness function:

$$\min f_1 = \min\left\{\sum_{i=1}^{N}\sum_{j=1}^{N}\left[g_{ij} \times \left(|V_i|^2 + \left|V_j\right|^2 - 2 \times |V_i| \times \left|V_j\right| \times cos\left(\delta_i - \delta_j\right)\right)\right]\right. \qquad 5.14$$

$$\min f_2 = \sum_{i=1}^{N_L} \frac{|v_i - v_i^*|}{N_L} \qquad 5.15$$

Subject to

$$P_{Gi} - P_{Di} - \sum_{j=1}^{N}\left[\left|Y_{ij}\right| \times |V_i| \times \left|V_j\right| \times \cos\left(\emptyset_{ij} + \delta_j - \delta_i\right)\right] = 0 \qquad 5.16$$

$$Q_{Gi} - Q_{Di} - \sum_{j=1}^{N}\left[\left|Y_{ij}\right| \times |V_i| \times \left|V_j\right| \times \sin\left(\emptyset_{ij} + \delta_j - \delta_i\right)\right] = 0 \qquad 5.17$$

Variables values were forced to be within their limits. Any parameter that violates the limits is replaced with values using equation (5.18):

$$u_i = \begin{cases} u_i^{min} & if\ u_i < u_i^{min} \\ u_i^{max} & if\ u_i > u_i^{max} \\ u_i & otherwise \end{cases} \qquad 5.18$$

Where: u_i is any parameter variable

5.6 Optimal Economic Dispatch Results

The main classical approach used for solving the voltage-control problem was Newton Raphson Optimal Power Flow method. The following table shows the bus data results obtained:

Table 5.3: The bus data solution by OED

Bus no.	Bus Code	Voltage Magnitude	Angle Degree	Load		Generation		Q_{min}	Q_{max}	Q_{sh}
				MW	Mvar	MW	Mvar			
1	1	1.050	0.000	0	0	150.73	-39.28	0	0	0
2	2	1.050	-3.401	21.7	12.7	42.54	26.07	-40	50	0
3	0	1.038	-4.687	2.4	1.2	0.00	0.00	0	0	0
4	0	1.035	-5.615	7.6	1.6	0.00	0.00	0	0	0
5	2	1.050	-10.053	94.2	19	18.50	51.76	-40	60	0
6	0	1.041	-6.859	0	0	0.00	0.00	0	0	0
7	0	1.037	-8.663	22.8	10.9	0.00	0.00	0	0	0
8	2	1.050	-7.491	30	30	10.00	61.03	-30	70	0
9	0	1.048	-7.022	0	0	0.00	0.00	0	0	0
10	0	1.040	-8.845	5.8	2	0.00	0.00	0	0	10
11	2	1.050	-3.771	0	0	30.00	1.81	-6	24	0
12	0	1.056	-7.136	11.2	7.5	0.00	0.00	0	0	0
13	2	1.050	-4.240	0	0	40.00	-3.15	-6	40	0
14	0	1.041	-8.176	6.2	1.6	0.00	0.00	0	0	0
15	0	1.036	-8.420	8.2	2.5	0.00	0.00	0	0	0
16	0	1.041	-8.127	3.5	1.8	0.00	0.00	0	0	0
17	0	1.035	-8.837	9	5.8	0.00	0.00	0	0	0
18	0	1.025	-9.267	3.2	0.9	0.00	0.00	0	0	0
19	0	1.022	-9.580	9.5	3.4	0.00	0.00	0	0	0
20	0	1.026	-9.455	2.2	0.7	0.00	0.00	0	0	0
21	0	1.029	-9.326	17.5	11.2	0.00	0.00	0	0	0
22	0	1.030	-9.323	0	0	0.00	0.00	0	0	0
23	0	1.026	-9.189	3.2	1.6	0.00	0.00	0	0	0
24	0	1.022	-9.874	8.7	6.7	0.00	0.00	0	0	4.3
25	0	1.029	-10.423	0	0	0.00	0.00	0	0	0
26	0	1.011	-10.834	3.5	2.3	0.00	0.00	0	0	0
27	0	1.041	-10.492	0	0	0.00	0.00	0	0	0
28	0	1.041	-7.374	0	0	0.00	0.00	0	0	0
29	0	1.022	-11.679	2.4	0.9	0.00	0.00	0	0	0
30	0	1.010	-12.530	10.6	1.9	0.00	0.00	0	0	0

The voltage magnitudes result in column 3 are within the range (0.95- 1.05), except the load bus number 12 has a magnitude of 1.056 also the real and reactive power generation are within the range.

Table 5.4: The control variable solution by OED

Variable	*Result*
T_{6-9}	0.9780
T_{6-10}	0.9690
T_{4-12}	0.9320
T_{28-27}	0.9680
Real Power Loss	8.3703
Reactive Power Loss	- 13.6527i
Voltage Deviation(pu)	0.0325
Time Elapsed (s)	0.2383

The variables in shaded cells indicate that all control variables are within the range specified and the output of simulation as follows:

The total system loss, TSL = 8.3703- 13.6527i MVA

The voltage deviation, VD = 0.0325 pu

The incremental fuel cost, λ = 3.3897 $/ MWH

The total cost, TC = 782.2480 $/H

The time elapsed for this simulation, t = 0.2383 S.

The system voltage profile is shown in Figure 5.2.

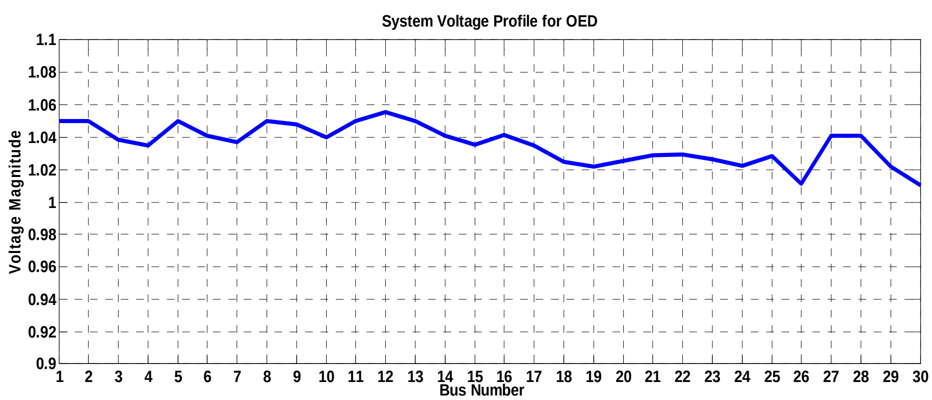

Figure 5.2: System Voltage Profile for OED

5.7 Particle Swarm Optimization

The control variables for voltage-control problem, which will be modified by the Particle Swarm optimization process, are:

1. Voltages magnitude at voltage-controlled buses (PV-buses) including the slack bus.
2. Transformers tap settings.
3. Adjustable shunt capacitor banks.

There are twelve control variables for IEEE 30-Bus system. The first position of control variables vector is the slack bus. The next five position for the five voltage magnitudes at PV-buses. The next four positions of the control variables vector are the transformers tap settings. These variables are considered as continuous variables, they are adjusted in the range [0.9-1.1]. The last two positions of the control variables vector are the adjustable shunt capacitor banks. These variables are also considered as continuous variables, they are adjusted in the range [0-10 MVAR]. All control variables were handled using the Particle Swarm Optimization and fuzzy system model for continuous variables. The following table shows the control variables vector.

Table 5.5: Control variable of IEEE 30-Bus system model

Control Variables Vector or Particle											
1	2	3	4	5	6	7	8	9	10	11	12
V_1	V_2	V_5	V_8	V_{11}	V_{13}	T_{6-9}	T_{6-10}	T_{4-12}	T_{28-27}	Q_{10}	Q_{24}

At each iteration, every particle determines a possible set of values for voltage magnitudes at PV buses, transformers tap positions and total capacity of each shunt capacitor bank. Subsequently, they are used to run a power flow, calculate the transmission losses, voltage deviation and evaluate the fitness function. The particle swarm optimization contains three tuning parameters w, c_1 and c_2 as shown in equations (4.2) and (4.3) that influences the algorithm performance, often stated as the exploration–exploitation tradeoff. Exploration is the ability to test various regions in the problem space in order to locate a good optimum, the global one. Exploitation is the ability to concentrate the search around a promising candidate solution in order to locate the optimum precisely. The inertia weight w is employed to control the impact of the previous history of velocities on the current velocity. A larger inertia weight w facilitates global exploration while a smaller inertia weight tends to facilitate local exploration to fine-tune the current search area. Suitable selection of the inertia weight w can provide a balance between global and local exploration abilities, thus require less iterations on average to find the optimum. The learning factors c_1 and c_2 determine the influence of personal best p-best and global best g-best, respectively as shown in equation (4.3). Since c_1 expresses how much the particle trusts its own past experience, it is called cognitive parameter. While c_2 expresses how much it trusts the swarm, it is called social parameter. In addition the PSO is influenced by the number of particles and the swarm size N, in the swarm. Since the parameters of PSO are influenced and deeply affect the algorithm performance, we concentrate in this thesis on these parameters. Each control variables vector or particle was evaluated according to the following algorithm:

Step 1: Initial search points and velocities are randomly generated for each of the three variables between their upper and lower bounds.

Step 2: Power loss and voltage deviation for each set (one value of voltage-controlled bus, transformer tap position and adjustable shunt capacitor) of particles is evaluated based on the fitness function. If the constraints are violated, the control variable is corrected according to equation 5.18.

Step 3: Assign the particle's position to p-best position and fitness to p-best fitness. Identify the best among the p-bests as the g-best.

Step 4: New velocities and new search points (directions) are formulated using the Equations (4.2) and (4.3) respectively.

Step 5: Power loss and voltage deviation corresponding to the new search points and velocities are evaluated.

Step 6: Compare the best current fitness evaluation with the population's g-best. If the current value is better than the g-best, reset g-best to the current best position and fitness value.

Step 7: If iteration reaches maximum number, then exit, otherwise go to step 4

The model of PSO can be shown below:

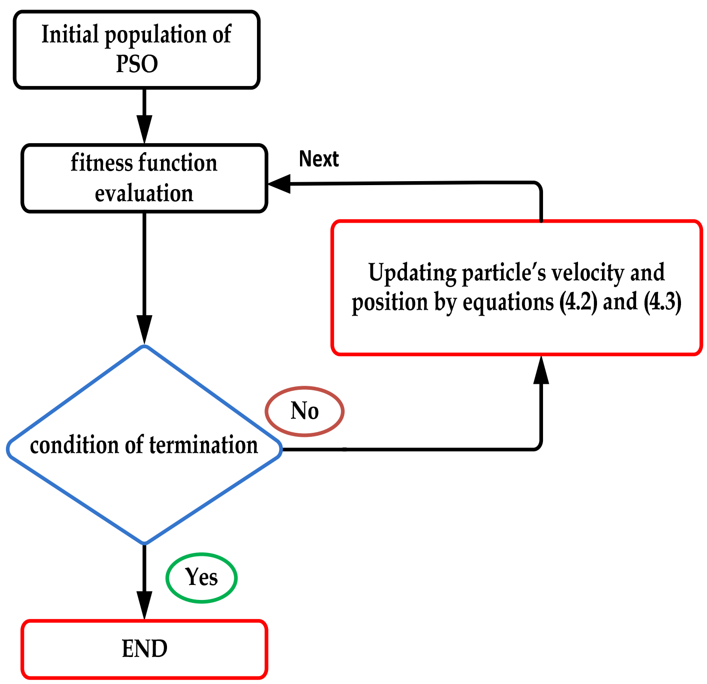

Figure 5.3: Flow Chart of the Particle Swarm Optimization

5.8 Particle Swarm Optimization Results

To improve the performance of voltage-control problem, the particle swarm optimization was employed with inertia weight 0.9, the cognitive parameter and social parameter equal 1, swarm size 50 and the number of iteration 20. The following tables show the bus data results and control variable solution obtained:

Table 5.6: The bus data solution by Particle Swarm Optimization

Bus no.	Bus Code	Voltage Magnitude	Angle Degree	Load		Generation		Q_{min}	Q_{max}	Q_{sh}
				MW	Mvar	MW	Mvar			
1	1	1.050	0.000	0	0	150.77	-22.93	0	0	0.00
2	2	1.042	-3.400	21.7	12.7	41.98	32.30	-40	50	0.00
3	0	1.033	-5.048	2.4	1.2	0.00	0.00	0	0	0.00
4	0	1.028	-6.053	7.6	1.6	0.00	0.00	0	0	0.00
5	2	1.013	-9.321	94.2	19	18.88	24.35	-40	60	0.00
6	0	1.020	-7.060	0	0	0.00	0.00	0	0	0.00
7	0	1.010	-8.512	22.8	10.9	0.00	0.00	0	0	0.00
8	2	1.025	-7.440	30	30	10.00	45.22	-30	70	0.00
9	0	0.980	-8.514	0	0	0.00	0.00	0	0	0.00
10	0	0.989	-10.442	5.8	2	0.00	0.00	0	0	7.73
11	2	0.969	-6.253	0	0	30.00	-4.62	-6	24	0.00
12	0	1.004	-9.299	11.2	7.5	0.00	0.00	0	0	0.00
13	2	1.050	-7.396	0	0	40.00	35.00	-6	40	0.00
14	0	0.988	-10.334	6.2	1.6	0.00	0.00	0	0	0.00
15	0	0.983	-10.481	8.2	2.5	0.00	0.00	0	0	0.00
16	0	0.990	-10.083	3.5	1.8	0.00	0.00	0	0	0.00
17	0	0.984	-10.565	9	5.8	0.00	0.00	0	0	0.00
18	0	0.972	-11.242	3.2	0.9	0.00	0.00	0	0	0.00
19	0	0.969	-11.482	9.5	3.4	0.00	0.00	0	0	0.00
20	0	0.973	-11.286	2.2	0.7	0.00	0.00	0	0	0.00
21	0	0.976	-10.939	17.5	11.2	0.00	0.00	0	0	0.00
22	0	0.977	-10.924	0	0	0.00	0.00	0	0	0.00
23	0	0.972	-11.022	3.2	1.6	0.00	0.00	0	0	0.00
24	0	0.967	-11.362	8.7	6.7	0.00	0.00	0	0	0.00
25	0	0.983	-11.622	0	0	0.00	0.00	0	0	0.00
26	0	0.964	-12.072	3.5	2.3	0.00	0.00	0	0	0.00
27	0	1.001	-11.477	0	0	0.00	0.00	0	0	0.00
28	0	1.018	-7.582	0	0	0.00	0.00	0	0	0.00
29	0	0.981	-12.763	2.4	0.9	0.00	0.00	0	0	0.00
30	0	0.969	-13.687	10.6	1.9	0.00	0.00	0	0	0.00

Column 3 in table 5.6 shows that the voltage magnitudes are within the range (0.95- 1.05). The real and reactive power generation also are within the range, note that the capacitor bank connected to bus number 10 equal 7.73 MVAR while the capacitor bank equal 0 on bus number 24.

Table 5.7: The control variable solution by Particle Swarm Optimization

Variable	*Result*
T_{6-9}	**1.0467**
T_{6-10}	**0.9000**
T_{4-12}	**1.0577**
T_{28-27}	**0.9758**
Real Power Loss	**8.0359**
Reactive Power Loss	**- 9.1446i**
Voltage Deviation(pu)	**0.0206**
Time Elapsed (s)	**13.3194**

In Particle swarm optimization methods, the variables in shaded cells indicate that all control variables are within the range specified and the output of simulation as follows:

The total system loss, TSL = 8.0359- 9.1446i MVA

The voltage deviation, VD = 0.0206 pu

The incremental fuel cost, λ = 3.3869 $ / MWH

The total cost, TC = 781.8074 $ /H

The time elapsed for this simulation, t = 13.3194 S.

The system voltage profile for this method is shown in Figure 5.4.

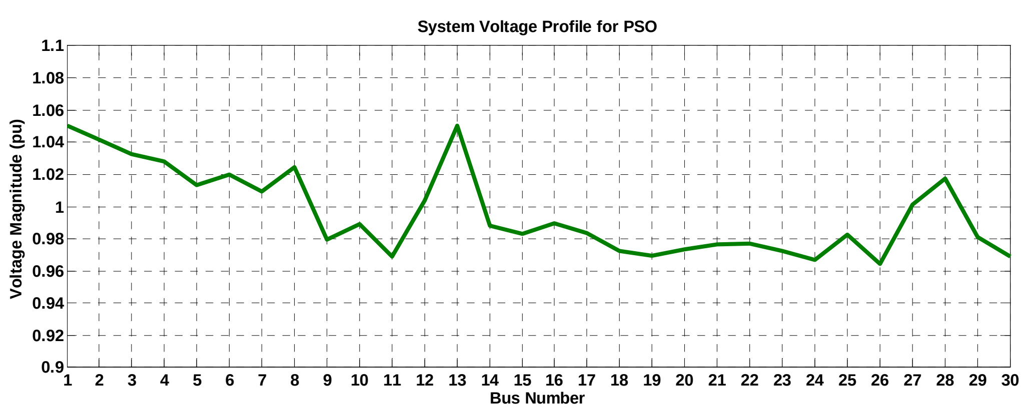

Figure 5.4: System Voltage Profile for PSO

5.9 Adaptive Particle Swarm Optimization algorithm

In the adaptive particle swarm optimization, the inertia weight decreased linearly according to the following equation

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{iter_{max}}\right) \times \ iter \qquad 5.19$$

Where:

$iter_{max}$: maximum number of iteration

$iter$: current iteration number

w_{max} : maximum inertia weight

w_{min} : minimum inertia weight

With setting c_1 and c_2= 1.0, which means that each particle will be attracted to the average of p-best and g-best. The swarm size is taken at 50 and the number of iterations is set at 20.

5.10 Adaptive Particle Swarm Optimization Results

The following table shows the bus data and control variable results obtained:

Table 5.8: The bus data solution by adaptive particle swarm optimization

Bus no.	Bus Code	Voltage Magnitude	Angle Degree	Load		Generation		Q_{min}	Q_{max}	Q_{sh}
				MW	Mvar	MW	Mvar			
1	1	1.050	0.000	0	0	150.45	-26.41	0	0	0.00
2	2	1.042	-3.388	21.7	12.7	42.10	29.11	-40	50	0.00
3	0	1.039	-5.132	2.4	1.2	0.00	0.00	0	0	0.00
4	0	1.035	-6.154	7.6	1.6	0.00	0.00	0	0	0.00
5	2	1.004	-9.165	94.2	19	19.01	11.22	-40	60	0.00
6	0	1.027	-7.167	0	0	0.00	0.00	0	0	0.00
7	0	1.010	-8.518	22.8	10.9	0.00	0.00	0	0	0.00
8	2	1.028	-7.479	30	30	10.00	33.37	-30	70	0.00
9	0	1.028	-8.724	0	0	0.00	0.00	0	0	0.00
10	0	0.998	-10.708	5.8	2	0.00	0.00	0	0	9.23
11	2	1.050	-6.737	0	0	30.00	11.38	-6	24	0.00
12	0	1.000	-9.359	11.2	7.5	0.00	0.00	0	0	0.00
13	2	1.050	-7.449	0	0	40.00	38.18	-6	40	0.00
14	0	0.987	-10.428	6.2	1.6	0.00	0.00	0	0	0.00
15	0	0.984	-10.664	8.2	2.5	0.00	0.00	0	0	0.00
16	0	0.991	-10.242	3.5	1.8	0.00	0.00	0	0	0.00
17	0	0.991	-10.799	9	5.8	0.00	0.00	0	0	0.00
18	0	0.976	-11.449	3.2	0.9	0.00	0.00	0	0	0.00
19	0	0.975	-11.703	9.5	3.4	0.00	0.00	0	0	0.00
20	0	0.980	-11.518	2.2	0.7	0.00	0.00	0	0	0.00
21	0	0.988	-11.247	17.5	11.2	0.00	0.00	0	0	0.00
22	0	0.989	-11.250	0	0	0.00	0.00	0	0	0.00
23	0	0.980	-11.381	3.2	1.6	0.00	0.00	0	0	0.00
24	0	0.985	-11.950	8.7	6.7	0.00	0.00	0	0	10.0
25	0	0.989	-11.897	0	0	0.00	0.00	0	0	0.00
26	0	0.971	-12.341	3.5	2.3	0.00	0.00	0	0	0.00
27	0	1.001	-11.580	0	0	0.00	0.00	0	0	0.00
28	0	1.025	-7.688	0	0	0.00	0.00	0	0	0.00
29	0	0.981	-12.866	2.4	0.9	0.00	0.00	0	0	0.00
30	0	0.969	-13.791	10.6	1.9	0.00	0.00	0	0	0.00

Note that the voltage magnitudes on load buses are within the range, also the capacitor banks on bus number 10 is increased to 9.23 MVAR and has a maximum (10 MVAR) on bus number 24.

Table 5.9: The control variable solution by APSO

Variable	*Result*
$T_{6\text{-}9}$	**0.9646**
$T_{6\text{-}10}$	**1.0948**
$T_{4\text{-}12}$	**1.1000**
$T_{28\text{-}27}$	**0.9954**
Real Power Loss	**7.9509**
Reactive Power Loss	**- 10.1218i**
Voltage Deviation(pu)	**0.0180**
Time Elapsed (s)	**12.5933**

In the adaptive particle swarm optimization methods, the variables in shaded cells indicate that all control variables are within the range specified and the output of simulation as follows:

The total system loss, TSL = 7.9509- 10.1218i MVA

The voltage deviation, VD = 0.018 pu

The incremental fuel cost, λ = 3.3846 \$ / MWH

The total cost, TC = 781.677 \$ / H

The time elapsed for this simulation, t = 12.5933 S.

The system voltage profile is shown in Figure 5.5.

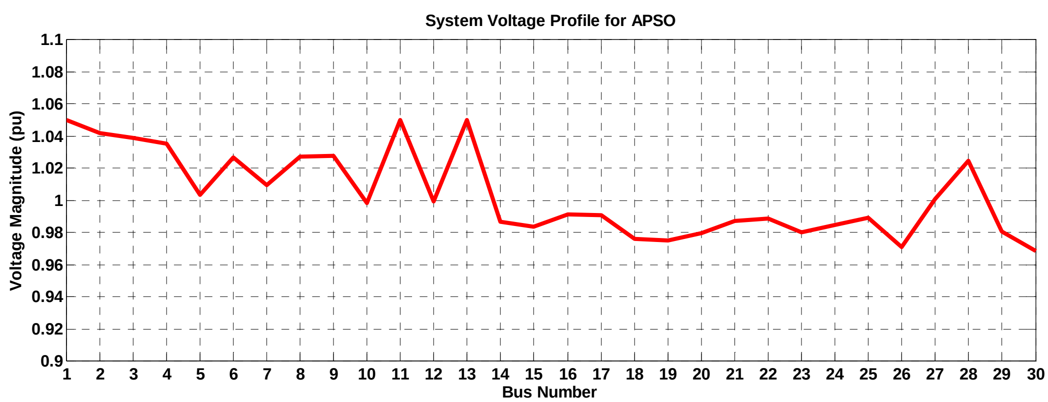

Figure 5.5: System Voltage Profile for APSO

5.11 Fuzzy Particle Swarm Optimization Algorithm

A fuzzy particle swarm optimization (FPSO) will be proposed to improve the performance of PSO; a fuzzy system will be employed to adjust the parameter of PSO, the inertia weight w and learning factors c_1 and c_2 during the evolution process. From experience, it is known that:

1. When the best fitness is low at the end of the run in the optimization of a minimum function, low inertia weight and high learning factors are often preferred.

2. When the best fitness is stuck at one value for a long time, number of generations for unchanged best fitness is large. The system is often stuck at a local minimum, so the system should probably concentrate on exploiting rather than exploring. That is, the inertia weight should be increased and learning factors should be decreased. Based on this kind of knowledge, a fuzzy system is developed to adjust the inertia weight, and learning factors with best fitness (BF) and number of generations for unchanged best fitness (NU) as the input variables, and the inertia weight (w) and learning factors (c_1 and c_2) as output variables.

The BF measures the performance of the best candidate solution found so far. Different optimization problems have different ranges of BF value. To design a FPSO applicable to a wide range of problems, the ranges of BF and NU are normalized into [0, 1.0]. To convert BF to a normalized BF format, we use equation (5.20):

$$NBF = \frac{(BF - BF_{min})}{(BF_{max} - BF_{min})} \quad 5.20$$

Where BF_{min} is the real minimum fitness value and BF_{max} is greater than the maximum fitness value. NU can be converted into [0, 1.0] in similar way. The value for w is bounded in $0.2 \leq w \leq 1.2$ and the values of c_1 and c_2 are bounded in $1.0 \leq c_1, c_2 \leq 2.0$.

In the fuzzy particle swarm optimization, each control variables vector or particle was evaluated according to the following algorithm:

Step (1) Input the power system data and the FPSO parameter limits.

Step (2) Generate the initial searching points and velocities of particles randomly and uniformly in the searching space. For each particle, calculate objective functions.

Step (3) Set each initial searching point to p-best; the initial best evaluated value among p-best is set to g-best.

Step (4) Update the FPSO control parameters (w, c_1 and c_2) by the fuzzy system.

Step (5) New velocities and searching points are calculated using (4.2) and (4.3).

Step (6) Evaluate all the particles in the new position. That is to calculate objective functions.

Step (7) If the evaluation value of each particle is better than the previous p-best, the value is set to p-best; if the best p-best is better than g-best, the value is set to g-best. All of g-bests are stored as candidates for the final solution.

Step (8) Check the stop criterion, usually a sufficiently good fitness value or a maximum number of iteration. If the stop criterion is not satisfied, then continue the process by returning to **step 4**. Otherwise, proceed to next step.

The model of FPSO can be described as follows:

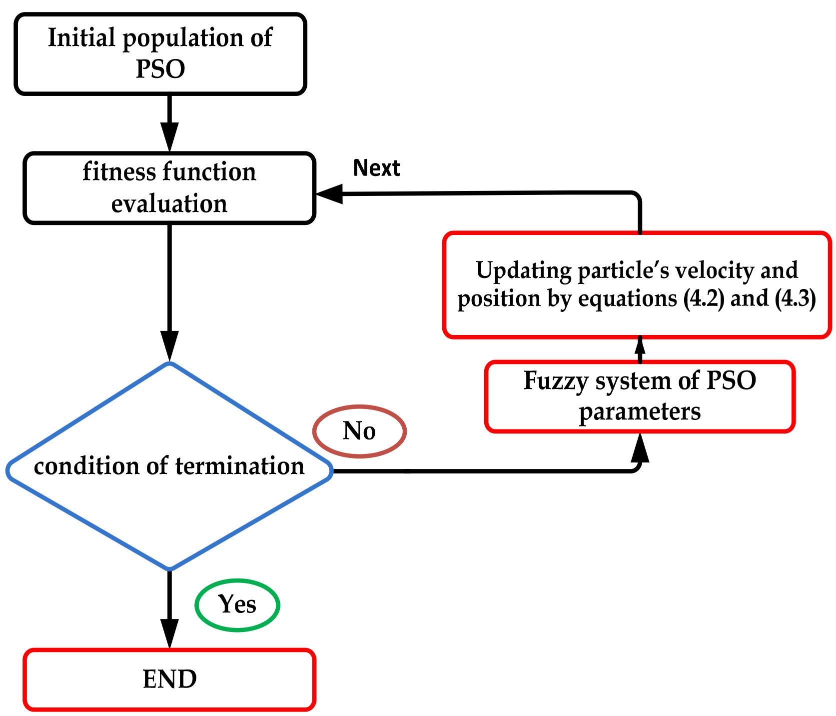

Figure 5.6: Flow Chart of the Fuzzy Particle Swarm Optimization Method

The membership function of inputs and outputs of FPSO model shown below

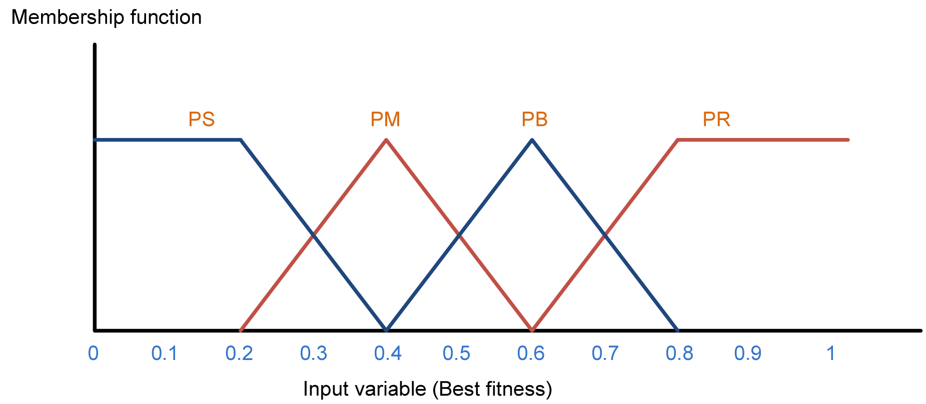

Figure 5.7: Membership function of Best fitness BF

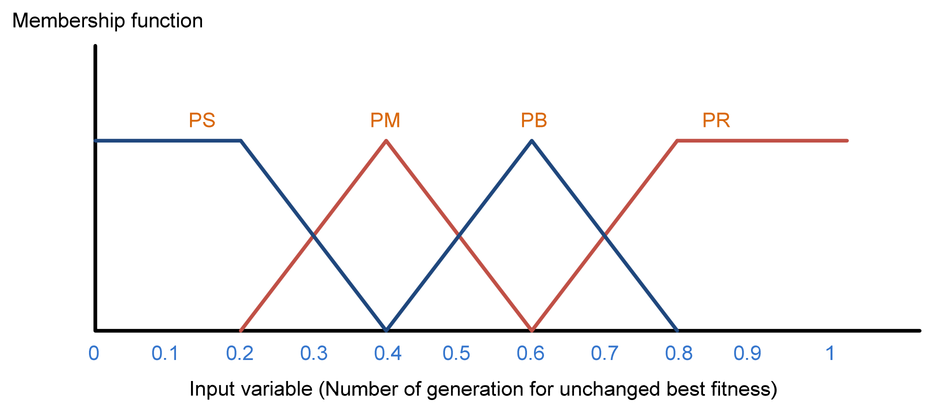

Figure 5.8: Membership function of number of generations for unchanged best fitness NU

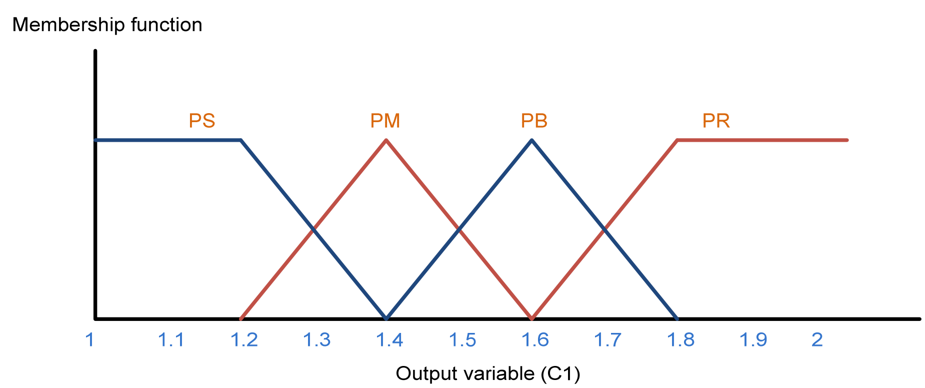

Figure 5.9: Membership function for learning factor C_1

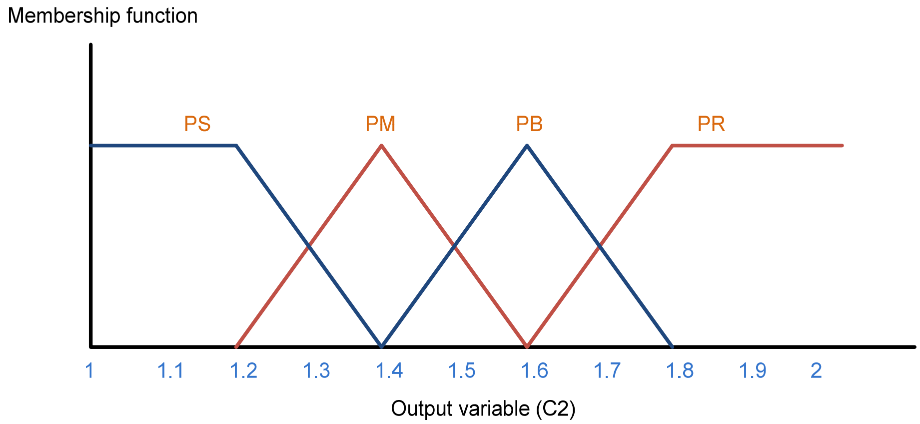

Figure 5.10: Membership function for learning factor C_2

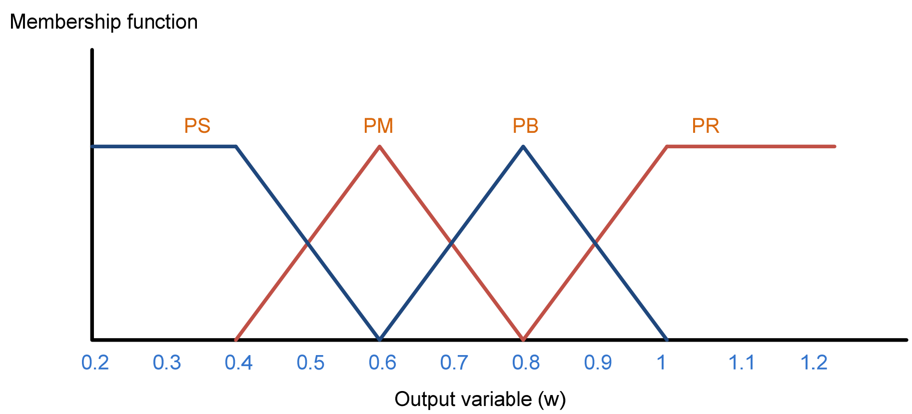

Figure 5.11: Membership function of inertia weight w

The fuzzy system consists of four principal components: fuzzification, fuzzy rules, fuzzy reasoning and defuzzification, which are described as following:

5.11.1 Fuzzification

Among a set of membership functions, left-triangle, triangle and right-triangle membership functions are used for every input and output as illustrated in Figure 5.7, Figure 5.8, Figure 5.9, Figure 5.10 and Figure 5.11. Four membership function were used in this thesis PS (positive small), PM (positive medium), PB (positive big) and PR (positive bigger) are the linguist variables for the inputs and outputs.

5.11.2 Fuzzy Rules

The Mamdani-type fuzzy rule is used to formulate the conditional statements that comprise fuzzy logic. The fuzzy rules in Table 5.10, Table 5.11 and Table 5.12 are used to adjust the inertia weight (w) and learning factors (c_1 and c_2), respectively. Each rule represents a mapping from the input space to the output space. The base rule can be formulated as follows:

R_1: If NBF is PS and NU is PS then w is PS; c_1 is PR and c_2 is PR.

R_2: If NBF is PM and NU is PS then w is PM; c_1 is PB and c_2 is PB.

R_3: If NBF is PB and NU is PS then w is PB; c_1 is PB and c_2 is PM.

R_4: If NBF is PR and NU is PS then w is PB; c_1 is PM and c_2 is PM.

R_5: If NBF is PS and NU is PM then w is PM; c_1 is PB and c_2 is PB.

R_6: If NBF is PM and NU is PM then w is PM; c_1 is PM and c_2 is PM.

R_7: If NBF is PB and NU is PM then w is PB; c_1 is PM and c_2 is PM.

R_8: If NBF is PR and NU is PM then w is PB; c_1 is PM and c_2 is PS.

R_9: If NBF is PS and NU is PB then w is PB; c_1 is PB and c_2 is PM.

R_{10}: If NBF is PM and NU is PB then w is PB; c_1 is PM and c_2 is PS.

R_{11}: If NBF is PB and NU is PB then w is PB; c_1 is PS and c_2 is PS.

R_{12}: If NBF is PR and NU is PB then w is PR; c_1 is PS and c_2 is PS.

R_{13}: If NBF is PS and NU is PR then w is PB; c_1 is PM and c_2 is PM.

R_{14}: If NBF is PM and NU is PR then w is PR; c_1 is PS and c_2 is PS.

R_{15}: If NBF is PB and NU is PR then w is PR; c_1 is PS and c_2 is PS.

R_{16}: If NBF is PR and NU is PR then w is PR; c_1 is PS and c_2 is PS.

Table 5.10: Fuzzy rules for inertia weight (w)

W		NU			
		PS	**PM**	**PB**	**PR**
NBF	**PS**	**PS**	**PM**	**PB**	**PB**
	PM	**PM**	**PM**	**PB**	**PR**
	PB	**PB**	**PB**	**PB**	**PR**
	PR	**PB**	**PB**	**PR**	**PR**

Table 5.11: Fuzzy rules for learning factor c_1

C_1		NU			
		PS	PM	PB	PR
NBF	PS	PR	PB	PB	PM
	PM	PB	PM	PM	PS
	PB	PB	PM	PS	PS
	PR	PM	PM	PS	PS

Table 5.12: Fuzzy rules for learning factor c_2

C_2		NU			
		PS	PM	PB	PR
NBF	PS	PR	PB	PM	PM
	PM	PB	PM	PS	PS
	PB	PM	PM	PS	PS
	PR	PM	PS	PS	PS

5.11.3 Fuzzy Reasoning

The fuzzy control strategy is used to map from the given inputs to the outputs. Mamdani's fuzzy inference method is used in this thesis. The AND operator is typically used to combine the membership values for each fired rule to generate the membership values for the fuzzy sets of output variables in the consequent part of the rule. Since there may be several rules fired in the rule sets, for some fuzzy sets of the output variables there may be different membership values obtained from different fired rules. These output fuzzy sets are then aggregated into a single output fuzzy set by OR operator. That is to take the maximum value as the membership value of that fuzzy set.

5.11.4 Defuzzification

To obtain a deterministic control action, a defuzzification strategy is required. The method of centroid (center-of-sums) is used as shown below:

$$y = \frac{\int_y \sum_{i=1}^{n} y.\mu_{Bi}(y)dy}{\int_y \sum_{i=1}^{n} \mu_{Bi}(y)dy} \qquad 5.21$$

Defuzzified value is directly acceptable values of PSO parameters, where the input for the defuzzification process is a fuzzy set $\mu_{Bi}(y)$ (the aggregate output fuzzy set) and the output is a single number y.

5.12 Fuzzy Particle Swarm Optimization Results

The following table shows the bus data and control variable results obtained:

Table 5.13: The bus data solution by fuzzy Particle Swarm Optimization

Bus no.	Bus Code	Voltage Magnitude	Angle Degree	Load		Generation		Q_{min}	Q_{max}	Q_{sh}
				MW	Mvar	MW	Mvar			
1	1	1.0500	0.0000	0	0	150.413	-15.208	0	0	0
2	2	1.0383	-3.3422	21.7	12.7	42.158	20.858	-40	50	0
3	0	1.0301	-5.0272	2.4	1.2	0.000	0.000	0	0	0
4	0	1.0249	-6.0279	7.6	1.6	0.000	0.000	0	0	0
5	2	1.0135	-9.3240	94.2	19	18.850	25.524	-40	60	0
6	0	1.0216	-7.0879	0	0	0.000	0.000	0	0	0
7	0	1.0105	-8.5293	22.8	10.9	0.000	0.000	0	0	0
8	2	1.0213	-7.3766	30	30	10.000	29.355	-30	70	0
9	0	1.0086	-8.5925	0	0	0.000	0.000	0	0	0
10	0	1.0163	-10.4547	5.8	2	0.000	0.000	0	0	9.84
11	2	1.0403	-6.5476	0	0	30.000	16.144	-6	24	0
12	0	1.0264	-9.1728	11.2	7.5	0.000	0.000	0	0	0
13	2	1.0500	-7.3118	0	0	40.000	18.074	-6	40	0
14	0	1.0121	-10.2028	6.2	1.6	0.000	0.000	0	0	0
15	0	1.0077	-10.4052	8.2	2.5	0.000	0.000	0	0	0
16	0	1.0146	-10.0048	3.5	1.8	0.000	0.000	0	0	0
17	0	1.0102	-10.5394	9	5.8	0.000	0.000	0	0	0
18	0	0.9982	-11.1587	3.2	0.9	0.000	0.000	0	0	0
19	0	0.9958	-11.4041	9.5	3.4	0.000	0.000	0	0	0
20	0	1.0001	-11.2278	2.2	0.7	0.000	0.000	0	0	0
21	0	1.0046	-10.9782	17.5	11.2	0.000	0.000	0	0	0
22	0	1.0055	-10.9814	0	0	0.000	0.000	0	0	0
23	0	0.9997	-11.0907	3.2	1.6	0.000	0.000	0	0	0
24	0	0.9977	-11.6420	8.7	6.7	0.000	0.000	0	0	10
25	0	0.9874	-11.5470	0	0	0.000	0.000	0	0	0
26	0	0.9692	-11.9929	3.5	2.3	0.000	0.000	0	0	0
27	0	0.9899	-11.2194	0	0	0.000	0.000	0	0	0
28	0	1.0216	-7.5912	0	0	0.000	0.000	0	0	0
29	0	0.9693	-12.5355	2.4	0.9	0.000	0.000	0	0	0
30	0	0.9574	-13.4822	10.6	1.9	0.000	0.000	0	0	0

Note that the voltage magnitudes result in column 3 are within the range (0.95- 1.05) with decreased in voltage deviation, also the real and reactive power generation are within the range. The capacitor banks are increased and within its range.

Table 5.14: The control variable solution by fuzzy Particle Swarm Optimization

Variable	*Result*
$T_{6\text{-}9}$	1.0592
$T_{6\text{-}10}$	0.9000
$T_{4\text{-}12}$	0.9980
$T_{28\text{-}27}$	1.0167
Real Power Loss	7.8699
Reactive Power Loss	- 11.6112i
Voltage Deviation (pu)	0.0146
Time Elapsed (s)	14.0566

In the fuzzy particle swarm optimization methods, the variables in shaded cells indicate that all control variables are within the range specified and the output of simulation as follows:

The total system loss, TSL = 7.8699 - 11.6112i MVA

The voltage deviation, VD = 0.0146 pu

The incremental fuel cost, λ = 3.3836 $ / MWH

The total cost,   TC = 781.1845 $ / H

The time elapsed for this simulation, t = 14.0566 S

The system voltage profile is shown in Figure 5.5.

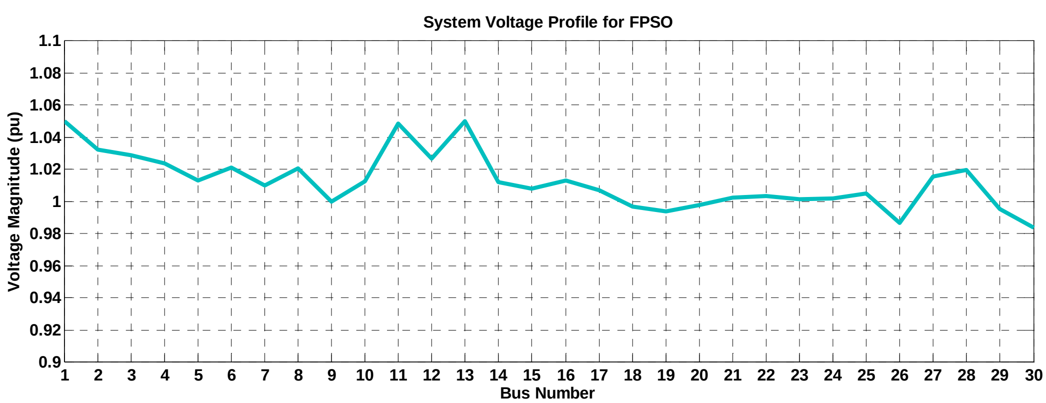

Figure 5.12: System Voltage Profile for FPSO

5.13 Fuzzy Adaptive Particle Swarm Optimization Algorithm

This new control method combined both fuzzy system and adaptive particle swarm optimization, where the inertia weight was modified according to equation (5.21), while c_1 and c_2 are modified according to fuzzy logic presented in the previous section. The fuzzy rule base and membership functions used in FAPSO are the same in the FPSO apart from the inertia weight.

5.14 Fuzzy Adaptive Particle Swarm Optimization Results

The following table shows the bus data and control variable results obtained

Table 5.15: The bus data solution by Fuzzy Adaptive Particle Swarm Optimization

Bus no.	Bus Code	Voltage Magnitude	Angle Degree	Load		Generation		Q_{min}	Q_{max}	Q_{sh}
				MW	Mvar	MW	Mvar			
1	1	1.050	0.000	0	0	150.42	-17.63	0	0	0
2	2	1.039	-3.358	21.7	12.7	42.05	25.32	-40	50	0
3	0	1.031	-5.031	2.4	1.2	0.00	0.00	0	0	0
4	0	1.026	-6.033	7.6	1.6	0.00	0.00	0	0	0
5	2	1.011	-9.298	94.2	19	18.89	22.83	-40	60	0
6	0	1.021	-7.086	0	0	0.00	0.00	0	0	0
7	0	1.009	-8.520	22.8	10.9	0.00	0.00	0	0	0
8	2	1.023	-7.423	30	30	10.00	37.32	-30	70	0
9	0	1.021	-8.550	0	0	0.00	0.00	0	0	0
10	0	1.012	-10.421	5.8	2	0.00	0.00	0	0	0
11	2	1.050	-6.549	0	0	30.00	14.89	-6	24	0
12	0	1.016	-9.089	11.2	7.5	0.00	0.00	0	0	0
13	2	1.043	-7.196	0	0	40.00	20.91	-6	40	0
14	0	1.003	-10.130	6.2	1.6	0.00	0.00	0	0	0
15	0	1.000	-10.357	8.2	2.5	0.00	0.00	0	0	0
16	0	1.007	-9.953	3.5	1.8	0.00	0.00	0	0	0
17	0	1.005	-10.505	9	5.8	0.00	0.00	0	0	0
18	0	0.991	-11.126	3.2	0.9	0.00	0.00	0	0	0
19	0	0.990	-11.377	9.5	3.4	0.00	0.00	0	0	0
20	0	0.995	-11.200	2.2	0.7	0.00	0.00	0	0	0
21	0	1.002	-10.945	17.5	11.2	0.00	0.00	0	0	0
22	0	1.003	-10.947	0	0	0.00	0.00	0	0	0
23	0	0.995	-11.058	3.2	1.6	0.00	0.00	0	0	0
24	0	0.998	-11.619	8.7	6.7	0.00	0.00	0	0	9.43
25	0	1.002	-11.619	0	0	0.00	0.00	0	0	0
26	0	0.984	-12.052	3.5	2.3	0.00	0.00	0	0	0
27	0	1.013	-11.343	0	0	0.00	0.00	0	0	0
28	0	1.019	-7.610	0	0	0.00	0.00	0	0	0
29	0	0.993	-12.599	2.4	0.9	0.00	0.00	0	0	0
30	0	0.981	-13.502	10.6	1.9	0.00	0.00	0	0	0

The voltage magnitudes result in column 3 are within the range (0.95- 1.05) with decreased in voltage deviation to 0.0109. The real and reactive power generations are within the range, while the capacitor bank equal 9.43 on bus number 24 and equal 0 on bus number 10.

Table 5.16: The control variable solution by FAPSO

Variable	*Result*
T_{6-9}	1.0099
T_{6-10}	0.9234
T_{4-12}	1.0254
T_{28-27}	0.9796
Real Power Loss	7.8369
Reactive Power Loss	- 13.1478i
Voltage Deviation (pu)	0.0109
Time Elapsed (s)	14.1275

In the fuzzy adapted particle swarm optimization method, the variables in shaded cells indicate that all control variables are within the range specified and the output of simulation as follows:

The total system loss, TSL = 7.8369 - 13.1478i MVA

The voltage deviation, VD = 0.0109 pu

The incremental fuel cost, λ = 3.3829 $/MWH

The total cost, TC = 780.9932 $ / H

The time elapsed for this simulation is t = 14.1275 S

The system voltage profile is shown in Figure 5.13.

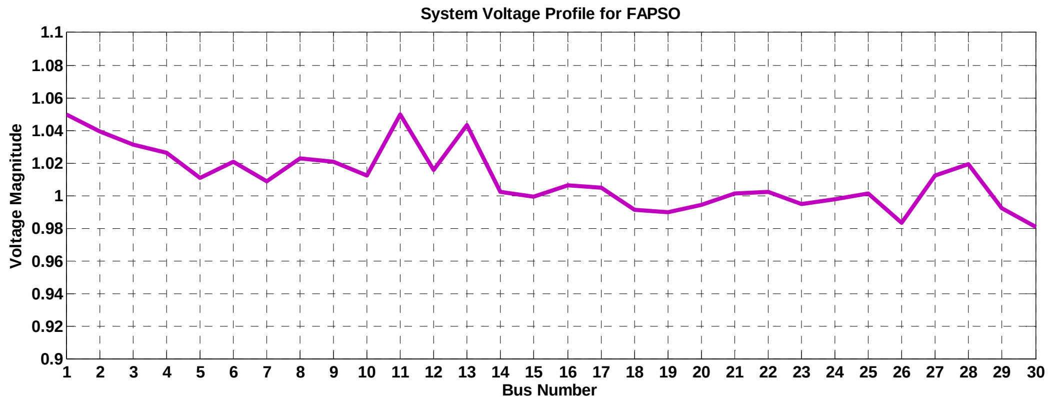

Figure 5.13: System Voltage Profile for FAPSO

5.15 Discussion of Results

The control variable limits and optimal control of IEEE-30 bus power system can be summarized in the following table

Table 5.17: The control variable limits and optimal control value

Control Variable	Control variable limit		OED	PSO	APSO	FPSO	FAPSO
	Min	Max					
V_{G1}	**0.95**	**1.05**	1.050	1.050	1.050	1.0500	1.050
V_{G2}	**0.95**	**1.05**	1.05	1.042	1.042	1.0383	1.039
V_{G5}	**0.95**	**1.05**	1.05	1.013	1.004	1.0135	1.011
V_{G8}	**0.95**	**1.05**	1.05	1.025	1.028	1.0213	1.023
V_{G11}	**0.95**	**1.05**	1.05	0.969	1.050	1.0403	1.050
V_{G13}	**0.95**	**1.05**	1.05	1.05	1.050	1.0500	1.043
$T_{6\text{-}9}$	**0.9**	**1.1**	0.978	1.047	0.965	1.059	1.010
$T_{6\text{-}10}$	**0.9**	**1.1**	0.969	0.900	1.095	0.900	0.923
$T_{4\text{-}12}$	**0.9**	**1.1**	0.932	1.058	1.100	0.998	1.025
$T_{28\text{-}27}$	**0.9**	**1.1**	0.968	0.976	0.995	1.017	0.980
Q_{c10}	**0**	**0.1**	0.1	0.773	0.923	0.984	0
Q_{c24}	**0**	**0.1**	0.43	0	0.1	0.1	0.943

In general, all variables met their operational limits for all cases. The following table summarizes the result obtained.

Table 5.18: Results from various voltage control methodology

Control strategy	VD (pu)	R (MW)	λ ($/MWH)	TC ($/H)	t (s)	Reduction in VD (%)	Reduction in R (%)
OED	0.0325	8.3703	3.3897	782.2480	0.2383	Original	Original
PSO	0.021	8.0359	3.3869	781.8074	13.3194	1.15	33.44
APSO	0.0180	7.9509	3.3846	781.677	12.5933	1.45	41.94
FPSO	0.0146	7.8699	3.383691	781.1845	14.0566	1.79	52.16
FAPSO	0.0109	7.8369	3.382931	780.9932	14.1275	2.16	53.34

Note that OED, PSO, APSO, FPSO and FAPSO approaches adjusted the voltage magnitudes of all PV buses, transformers tap settings and shunt capacitor banks. In comparison with the OED, the PSO gives a reduction in the VD of 1.15 %, while the APSO gives 1.45% reduction, the FPSO gives 1.79%, and finally the FAPSO gives a reduction of 2.16%. Moreover, there is a reduction in the real power loss of 33.44% using PSO, while a reduction of 41.94% is obtained using APSO, the FPSO gives a reduction of 52.16 and the reduction using the FAPSO reaches the 53.34%. The time elapsed for OED is 0.2383 second which is the smallest for all optimization technique because all control variable values are constant, thus has only a single solution, while for the PSO technique was 13.3194 second, the APSO takes 12.5933 second, also the FPSO elapse 14. 0566 second and FAPSO time elapsed is 14.1275, which is the largest one. This small incremental in time for FAPSO technique can be ignored corresponding to a large improvement in voltage deviation and real power loss reduction.

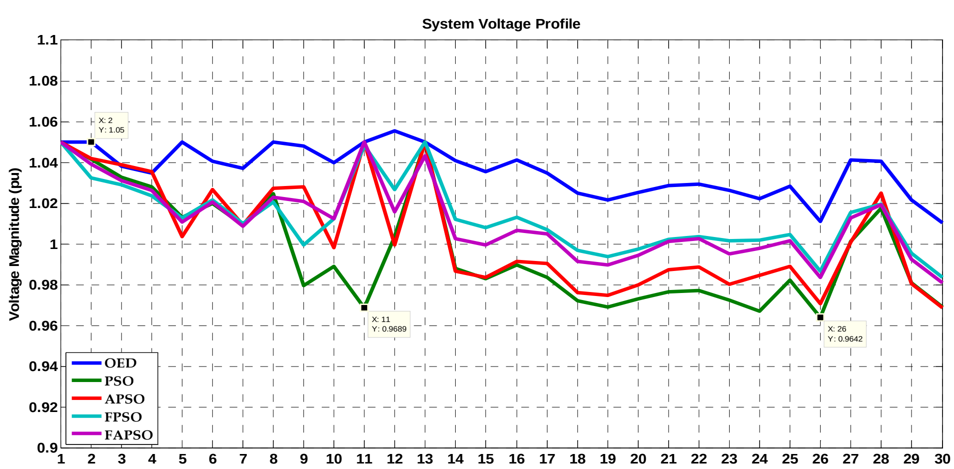

Figure 5.14: System Voltage Profile

Figure 5.14 shows the voltage profile for all voltage control strategies, it shows that the voltage magnitudes are within the acceptable margin (0.95-1.05) pu. It is notable that the voltage profile for fuzzy adaptive particle swarm optimization lies in the range of (0.981–1.05) pu, but for all other control strategies it lies in the range of (0.9574–1.05) pu.

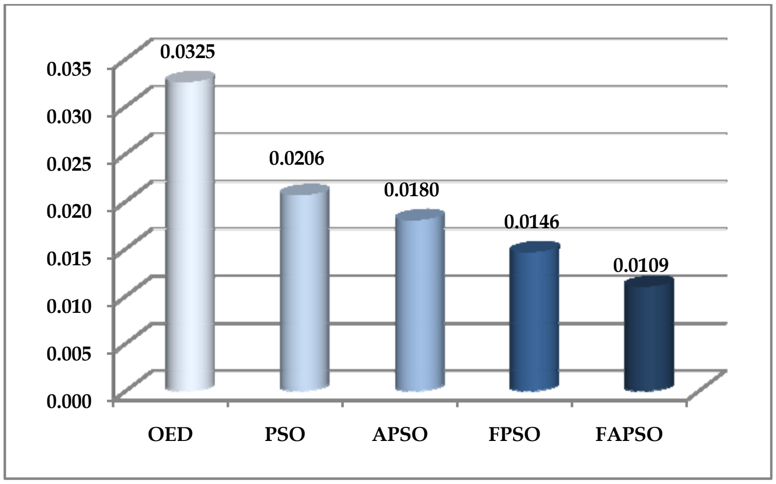

Figure 5.15: Voltage Deviation

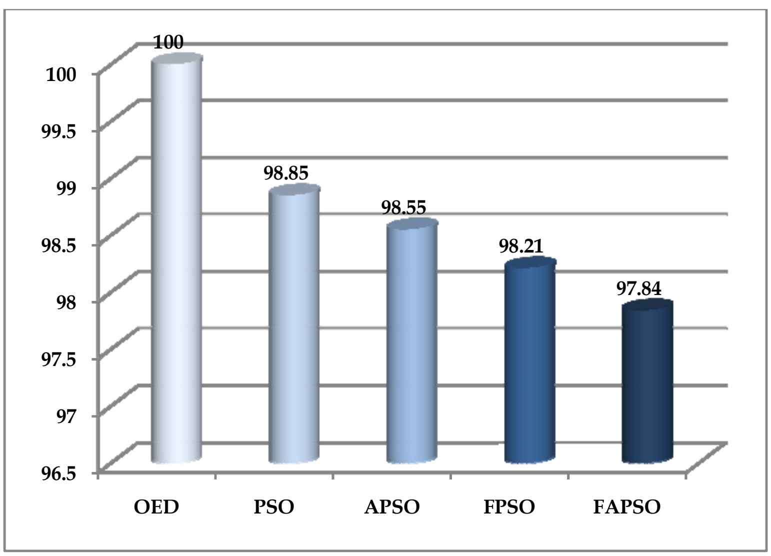

Figure 5.16: Voltage Deviation Reduction

Figure 5.15 represents the magnitude of voltage deviations after obtaining the final solution for the five voltage control strategy. For all cases, the magnitudes of the voltage deviation lie within a tolerable range. It is noted that the magnitude of this deviation is largest for the OED and is smallest for the FAPSO. This shows that one of the main objectives has been satisfied. Figure 5.16 presents the voltage deviation reduction.

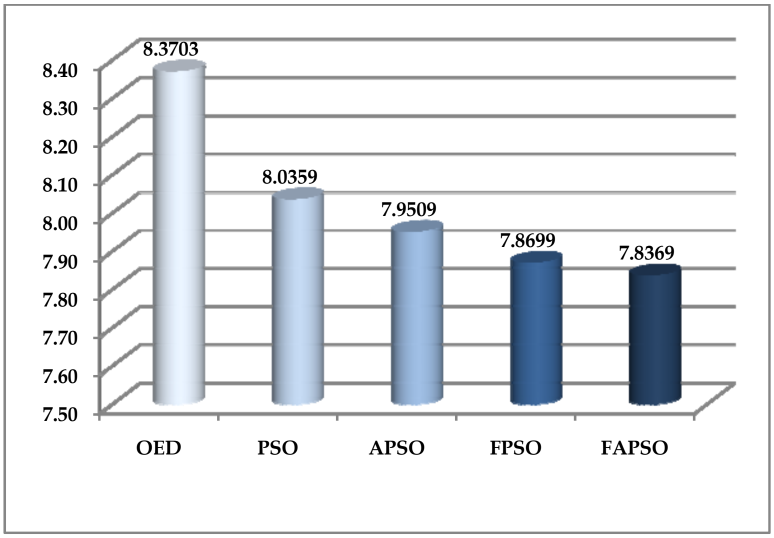

Figure 5.17: Real Power Loss

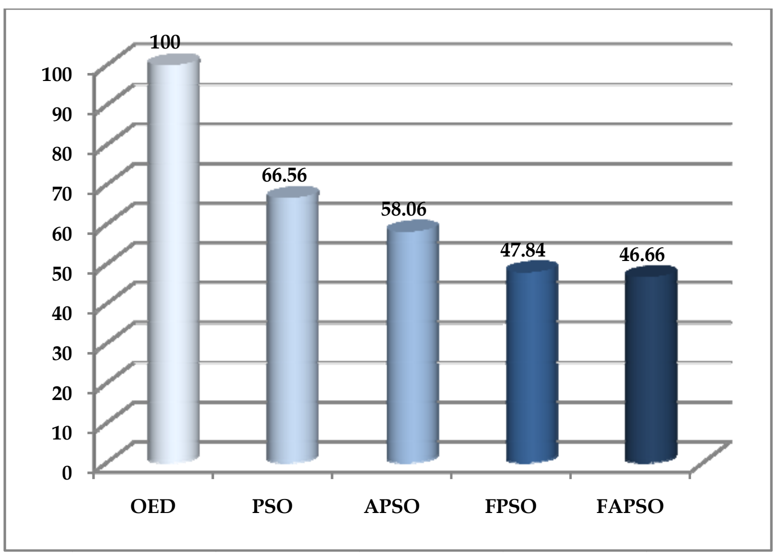

Figure 5.18: Real Power Loss Reduction

Figure 5.17 presents the real power loss for all voltage control strategies. It shows that the real power loss for OED is the largest at 8.3703 MW, while it is the smallest for FAPSO 7.8369, and this also satisfies the second objective. Figure 5.18 presents the real power loss reduction.

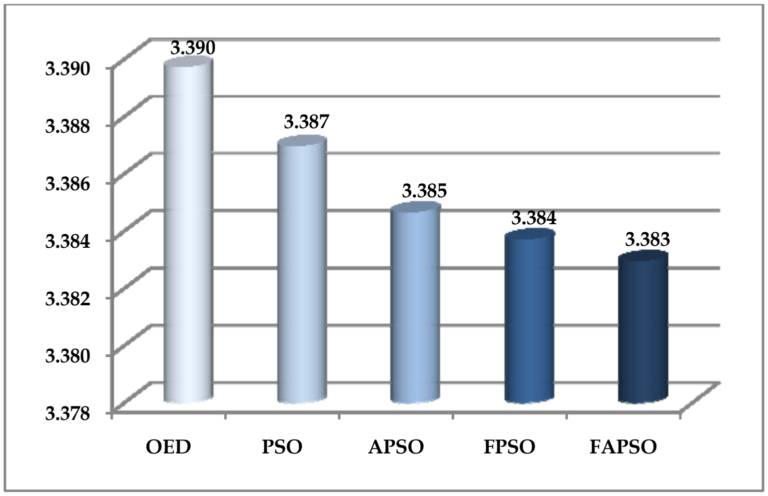

Figure 5.19: Incremental Fuel Cost λ

Figure 5.19 presents the incremental fuel cost for all voltage control strategies. It shows that the incremental fuel cost for OED is the largest at 3.39 $/MWH, while it is the smallest for FAPSO 3.383 $/MWH.

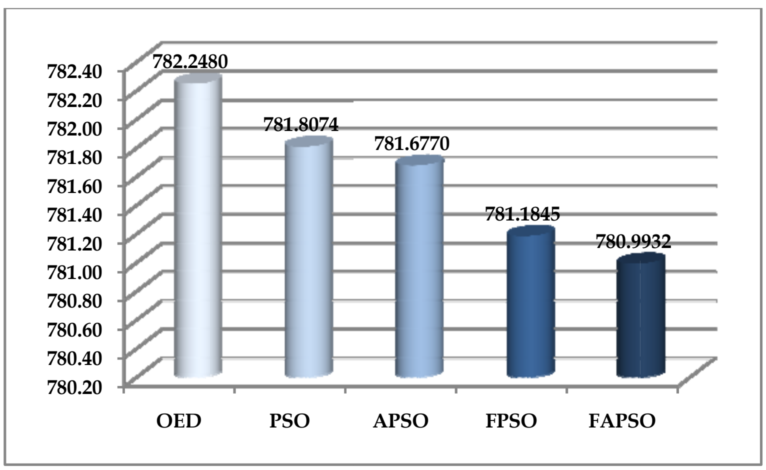

Figure 5.20: Total Cost

Figure 5.20 represents the total cost for the five voltage control strategy. It is noted that the total cost is largest for the OED 782.248 $/H and is smallest for the FAPSO at 780.9932 $/H.

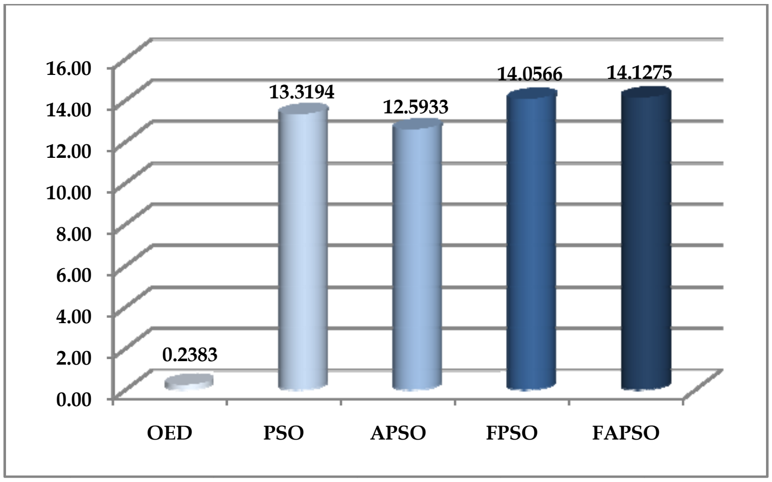

Figure 5.21: Time Elapsed

Figure 5.21 presents the Time Elapsed for all voltage control strategies. It shows that the time elapsed for OED is the smallest at 0.238 S, while it is the largest for FAPSO 14.1275 S. Despite the time elapsed for FAPSO is the biggest one, but this is not significant compared with other best result obtained such as voltage deviation, real power loss, total cost, and incremental fuel cost.

CHAPTER 6

6. CONCLUSION

6.1 General

The purpose of this work was to develop and apply an optimization technique for handling the mathematical model of the voltage-control problem in a power system through reactive power dispatch and to compare the outcomes with the results achieved by previous solving methods. Although all methods have achieved acceptable results to the objective functions the proposed technique exploiting evolutionary programming has accomplished best results.

6.2 Conclusion

Different optimization techniques were employed using combination of all control tools such as tap setting, static VAR compensations and voltage-control buses to solve the voltage-control problem. The PSO technique was first considered, the second was the Adaptive PSO technique then FPSO was employed and last a combination of fuzzy-logic and APSO technique were used, which known as FAPSO. It has been demonstrated that application of these optimization techniques gave acceptable results as far as the voltage magnitudes at the system buses are concerned. As well as the voltage deviations have been also within tolerable margins. The real power loss was also in a narrow range. However, we have noticed that the proposed optimization technique has achieved better results. In the adaptive particle swarm optimization, the inertia weight was decreased linearly to explore the search space from global to local area, the fuzzy system used to modify the particle swarm optimization parameters such inertia weight, cognitive and social. Suitable selection of these parameters has led to better voltage deviation and minimum real power loss. Therefore, the implementation of Particle Swarm Optimization to the voltage-control problem is a contribution to the modern heuristics research in the power system engineering area. The voltage-control and reactive power dispatch problem were formulated as mathematical optimization problem subject to applicable constraints. All optimization techniques tackled in this thesis were programmed using the MATLAB code and applied to the standard IEEE 30-bus system model. In general, the results obtained show the effectiveness, flexibility, and applicability of the Particle Swarm Optimization and Fuzzy Adaptive Particle Swarm Optimization technique for the proposed control problem.

6.3 Recommendations and Future Work

Several heuristic tools have evolved in the last decade that facilitated solving optimization problems that were previously difficult or impossible to solve. A general recommendation for future work is to apply Particle Swarm Optimization and Fuzzy Adaptive Particle Swarm Optimization to problems that arise continuously. Also, it is recommended to test the approaches using larger systems and to optimize the program code to reduce the execution time in order to improve the algorithm's performance.

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Appendixes

Appendix A: B - Coefficients

B =

$$
\begin{bmatrix}
0.0235 & 0.0082 & 0.0025 & -0.0033 & 0.0009 & 0.0036 \\
0.0082 & 0.0202 & 0.0008 & -0.0055 & 0.0010 & 0.0026 \\
0.0025 & 0.0008 & 0.0559 & -0.0467 & -0.0029 & -0.0011 \\
-0.0033 & -0.0055 & -0.0467 & 0.1423 & 0.0046 & -0.0000 \\
0.0009 & 0.0010 & -0.0029 & 0.0046 & 0.0107 & -0.0002 \\
0.0036 & 0.0026 & -0.0011 & -0.0000 & -0.0002 & 0.0248
\end{bmatrix}
$$

B0 =

$$
\begin{bmatrix} -0.0015 & 0.0025 & -0.0061 & 0.0097 & 0.0006 & 0.0004 \end{bmatrix}
$$

B00 =

$$
\begin{bmatrix} 0.0014 \end{bmatrix}
$$