SINGLE OBJECTIVE OPTIMAL POWER FLOW USING PARTICLE SWARM OPTIMIZATION

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

Master of Engineering

in

Power Systems & Electrical Drives

.Thapar University, Patiala

By:

ANKUSH DUTTA

(Regn. No 80741002)

Under the supervision of:

Mr. Parag Nijhawan

Senior Lecturer, EIED

JULY, 2009

ELECTRICAL AND INSTRUMENTATION ENGINEERING DEPARTMENT

THAPAR UNIVERSITY

PATIALA – 147004

CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, **"Single Objective Optimal Power Flow using Particle Swarm Optimization"**, in partial fulfillment of the requirements for the award of degree of Master of Engineering in Power Systems & Electric Drives submitted in Electrical & Instrumentation Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of Mr. Parag Nijhawan, Senior Lecturer. The matter presented in this thesis has not been submitted for the award of any other degree of this or any other university

Ankush Dutta
15/7/09
(Ankush Dutta)
Regn. No. 80741002

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

Parag
15/07/09
(Mr. Parag Nijhawan)
Senior Lecturer
Electrical & Instrumentation Engg. Department
Thapar University
Patiala

Countersigned by

S. Ghosh
(Dr. Smarajit Gosh)
Professor & Head
Electrical & Instrumentation Engg. Department
Thapar University
Patiala

RK Sharma
22/7
(Dr. R.K. Sharma)
Dean (Academic Affairs)
Thapar University,
Patiala

ACKNOWLEDGEMENT

Acknowledgment is due to the esteemed and prestigious THAPAR UNIVERSITY carving the niche for many of the budding engineers by giving opportunities to expand their horizons of knowledge and giving them opportunities to implement their theoretical knowledge into practice in the shape of the projects.

I am grateful to my project guide Mr. Parag Nijhawan (Senior Lecturer) for his active role and leadership that was instrumental in directing the thesis work. I also acknowledge him for his excellent supervision, time, motivation, unlimited support and continuous encouragement.

Lastly but not the least I am also thankful to Dr. S. Ghosh (Prof. and Head) Electrical and Instrumentation Engineering Department for his ever supporting and encouraging nature. His cooperation throughout the thesis work has been remarkable.

Ankush Dutta
15/7/09
Ankush Dutta

ABSTRACT

Optimal Power Flow (OPF) problem in electrical power systems is considered as a static, non-linear, multi-objective or a single objective optimization problem. As the power industrial companies have been moving into a more competitive environment, OPF has been used as a tool to define the level of the inter-utility power exchange.

Basically, this thesis work provides a new approach to solve the single objective OPF problem considering critical objective function of generation fuel cost minimization for utility/industrial companies, while satisfying a set of system operating constraints, including constraints dictated by the electrical network. Particle Swarm Optimization technique (PSO) has been used for this purpose. Particle Swarm Optimization (PSO) is a population based stochastic optimization technique. The system is initialized with a population of random feasible solutions and searches for optima by updating generations. The IEEE-30 bus system is considered throughout this project work to test the proposed algorithm.

LIST OF TABLES

TABLE **Page**

LIST OF FIGURES

CONTENTS

CHAPTER 1
INTRODUCTION

1.1 Overview

In power system optimal operation problems transmission capacity is becoming increasingly important. There are pressures to optimize the operation of the generation resources and transmission system with regard to deregulation and open access in the utility industry occurring internationally. Many simplified network models have been incorporated in the past by various researchers for the scheduling problem formulation by using Lagrange relaxation (LR) and relaxing the transmission constraints with an additional set of Lagrange multipliers [1-3]. Price information for using the transmission lines is then fed to the sub-problems. It becomes really very difficult to model the full AC transmission system in this fashion since the problem is usually presented on DC power flow. Optimal Power Flow can represent the same objective as a scheduling problem at a particular instant while accounting for the full AC system network security.

The OPF problem has had a long history in its development. More than twenty five years ago, Carpentier introduced a generalized formulation of the economic dispatch problem including voltage and other operating constraints. This formulation was named as the Optimal Power Flow Problem [4]. OPF programs based on mathematical programming approaches are used daily to solve very large OPF problems. However , they are not guaranteed to converge to the global optimum of the general non-convex OPF problem, although there are some empirical evidences on the uniqueness of the OPF solution within the domain of interest. The existing OPF approaches have some problems, which include not only the robustness of optimization methodology used, but also the power system modeling.

Performance and reliability of optimal power flow algorithms remain important problems in power system control and planning areas. A new application of OPF in the solution of some problems requires especially high performance of optimization algorithms. A wide variety of classical optimization techniques have been applied in solving the OPF problems considering a single objective function such as Non-Linear Programming [5], Quadratic Programming [6], Linear Programming [7], Newton-based techniques [8], Sequential unconstrained minimization technique [9], Interior point methods [10] and Parametric method [11]. All these conventional optimization methods have many disadvantages associated with them such as insecure convergence, disadvantages associated with the piecewise quadratic cost approximation and may even fail to converge due to in appropriate initial conditions for Newton based method..

Most of the classical optimization techniques apply sensitivity analysis and gradient-based optimization algorithms by linearizing the objective function and the system constraints around an operating point. The OPF problem is often infeasible due to either badly posed or being under heavy operational stress [12]. If both active and reactive powers are dispatch-able in an electrical network then the usual criterion for optimal operation is the minimization of generation cost. If only a reactive power is dispatch-able then active power loss minimization is desired [13]. The OPF problem is a highly non-linear and a multimodal optimization problem, i.e. there exists more than one local optima. Hence local optimization techniques mentioned earlier are not suitable for such a problem and there is no criterion to decide whether a local solution is also the global solution. So it becomes essential to develop optimization techniques that are efficient to overcome these drawbacks and handle such difficulties.

A wide variety of advanced optimization techniques have been applied in solving the OPF problems considering a single objective function including Evolutionary programming [14], Genetic Algorithm [15], Tabu search [16] aad PSO [17] algorithm.

This thesis work presents the solution of OPF problem using PSO algorithm. PSO is less susceptible in being trapped on local minima, can easily deal with non differentiable objective functions, it is more flexible and robust and has no premature convergence problems. The results obtained using the proposed algorithm are compared with those already reported in the literature.

1.2 Scope of work

The aim of the proposed work is to apply the PSO optimization technique to solve the single objective OPF problem, to improve the quality of the solution. Here an objective function of minimization of generation fuel cost is achieved by using the PSO technique which gave a very promising and better results as compared to the other optimization techniques.

1.3 Organization of thesis

Chapter 1 It gives the overview of the thesis problem and also mentions the scope of this thesis work.

Chapter 2 Here a literature survey is done on the OPF problem and also contains a review on PSO technique.

Chapter 3 Tells about optimal power flow. Also, the goals of OPF and the objective of OPF is effectively described in this chapter. It also contains the proposed OPF problem and the various constraints are also defined.

Chapter 4 Describes about PSO, its description and an algorithm along with a flow chart is well described.

Chapter 5 Describes the various steps to solve PSO based OPF problem.

Chapter 6 It contains the results obtained after applying PSO algorithm.

Chapter 7 Shows the conclusion of this thesis work and also discusses the future scope of the work and future applications of PSO.

CHAPTER 2
LITERATURE SURVEY

During the past few decades, researchers have incorporated the simplified network model into the scheduling problem formulation by using the Lagrangian relaxation (LR) and the transmission constraints can be relaxed with an additional set of Lagrangian multipliers [1-3]. It is very difficult to model the full AC transmission system in this fashion. Carpentier introduced a general formulation of the economic dispatch problem including voltage and other operating constraints. This formulation was named the Optimal Power Flow problem [4].OPF programs based on mathematical programming approaches are used daily to solve very large OPF problems. However, they are not guaranteed to converge to the global optimum of the general non-convex OPF problem, although there are some empirical evidence on the uniqueness of the OPF solution within the domain of interest . The existing OPF approaches have some problems, which include not only the robustness of optimization methodology used, but also the power system modeling.

The OPF problem is known as twin sub-problems of active power generation dispatch (Economic Dispatch Problem, EDP) and reactive power generation dispatch. The main purpose of the EDP is to determine the generation schedule of the electrical energy system that minimizes the total generation and operation cost and does not violate any of the system operating constraints such as line overloading, bus voltage profiles and deviations . In the other hand, the objective of reactive power dispatch is to minimize the active power transmission losses in an electrical system while satisfying all the system operating constraints. The objective function of the OPF can take different forms other than minimizing the generation cost and the losses in the transmission system.

The OPF problem is often infeasible, due to either badly posed or being under heavy operational stress. In the latter case, the online calculation of OPF problem is a critical function. Therefore, in cases where the original OPF does not have a feasible solution, it is desirable to be able to relax some 'softer' constraints to produce the 'best' engineering solution representing a solved power system operating state. If the feasibility is the result of an operator or system error in the definition of some constraint limits, it is also very useful to remove or 'mark off' the offending constraints. If both active and reactive powers are dispatch-able, in an electrical network, then the usual criterion for optimal operation is the minimization of generation cost. If only a reactive power is dispatch-able, then active power loss minimization is frequently the desired objective. This is also a convenient dummy objective if the main problem is to determine a feasible reactive power/ voltage solution, or for the other purposes. Any other objective can be used based on utility's interests and needs. Performance and reliability of optimal power flow algorithms remain important problems in power system control and planning areas. A new application of OPF in the solution of some problems requires especially high performance of optimization algorithms. Some of the control variables of OPF problems can be adjusted only in discrete steps, but present OPF solution methods treat all variables as continuous. The adjustments, if any, for discrete variables are made by arbitrary suboptimal procedures. These procedures may result on a significant higher objective function cost than a solution in which the adjustment of the discrete variables is more nearly optimized. In conventional power flow solutions all of the control variables, including those that can be adjusted only in discrete steps, are treated as continuous until a first tentative solution has been reached. Then each discrete variable is rounded to its nearest step and a second and final solution is obtained using only the true continuous variables. This procedure is valid for the conventional power flow problem because the only solution requirement is the feasibility, but it is not the case with OPF problem where an objective function must also be minimized. Therefore, rounding to the nearest step does not minimize the objective function and it could make it impossible to obtain a feasible solution.

2.1 Classical Optimization Algorithms

A wide variety of classical optimization techniques have been applied in solving the OPF problems considering a single objective function such as Non-Linear Programming (NLP) [5], Quadratic Programming (QP) [6], Linear Programming (LP) [7], Newton-based techniques [8], sequential unconstrained minimization technique [9], Interior point methods [10], and Parametric Method [11]. The objective function employed for solving the Optimal Power Flow problem is whether power loss minimization or generation fuel cost minimization.

The Non-Linear Programming optimization algorithm deals with problems involving nonlinear objective and constraint functions. The constraints may consist of equality and/or inequality formulations. The inequality constraints can be specified as a variable that is restricted between predetermined values. Generally, nonlinear programming based procedures have many drawbacks such as insecure convergence properties and algorithmic complexity .

The Quadratic Programming technique is a special form of nonlinear programming whose objective function is quadratic with linear constraints. Quadratic programming based techniques have some disadvantages associated with the piecewise quadratic cost approximation .

In Newton method, the necessary conditions of optimality commonly referred to as the Kuhn-Tucker conditions are obtained. In general, these are non-linear equations requiring iterative methods of solution. Newton-based techniques have a drawback of the convergence characteristics that are sensitive to the initial conditions and they may even fail to converge due to the inappropriate initial conditions.

The sequential unconstrained minimization optimization techniques are known to exhibit numerical difficulties when the penalty factors become extremely large. Although the linear programming methods are fast and reliable, but they have some disadvantages associated with the piecewise linear cost approximation.

The Interior point (IP) method converts the inequality constraints to equalities by the introduction of nonnegative slack variables. This method has been reported as computationally efficient; however, if the step size is not chosen properly, the sub-linear problem may have a solution that is infeasible in the original nonlinear domain. In additional, this method suffers from initial, termination, and optimality criteria and, in the most cases, is unable to solve non-linear quadratic objective functions.

Mixed Integer Programming (MIP) is a particular type of linear programming whose constraint equations involve variables restricted to being integers. Integer programming and mixed integer programming like nonlinear programming are extremely demanding of computer resources and the number of discrete variables is an important indicator of how difficult is to solve a MIP problem

There are some empirical evidences on the uniqueness of the OPF problem within the domain of interest. To avoid the prohibitive computational requirements of mixed-integer programming, discrete control variables are initially treated as continuous and post-processing discretization logic is subsequently applied. Whereas the effects of discretization on load tap changing transformers are small and usually negligible, the rounding of switch-able shunt devices may lead to voltage infeasibility, especially when the discrete VAR steps are large, and require special logic. The handling of nonconvex OPF objective functions and the unit prohibited zones also present problems to mathematical programming OPF approaches.

2.2 Evolutionary Optimization Algorithms

Generally, most of the classical optimization techniques mentioned in the preceeding section apply sensitivity analysis and gradient-based optimization algorithms by linearzing the objective function and the system constraints around an operating point. The OPF problem is often infeasible due to either badly posed or being under heavy operational stress [12]. If both active and reactive powers are dispatch-able in an electrical network then the usual criterion for optimal operation is the minimization of generation cost. If only a reactive power is dispatch-able then active power loss minimization is desired [13]. Unfortunately, the OPF problem is a highly non-linear and a multimodal optimization problem, i.e. there exist more than one local optimum. Hence, local optimization techniques, which are well elaborated, are not suitable for such a problem. Moreover, there is no criterion to decide whether a local solution is also the

global solution. Therefore, conventional optimization methods that make use of derivatives and gradients are not able to identify the global optimum. Conversely, many mathematical assumptions such as convex, analytical, and differential objective functions have to be given to simplify the problem. However, the OPF problem is an optimization problem with in general nonconvex, nonsmooth, and non-differentiable objective functions. It becomes
essential to develop optimization techniques that are efficient to overcome these drawbacks and handle such difficulties.

More recently, OPF has enjoyed renewed interest in a variety of formulations through use of evolutionary optimization techniques to overcome the limitations of the mathematical programming approaches. A wide variety of advance optimization techniques have been applied in solving the OPF problems considering a single objective function including Genetic Algorithm (GA) [14], Simulated Annealing (SA) [15], Tabu Search (TS) [16], and PSO algorithm [17]. These are Evolutionary programming (EP) algorithms which use the mechanics of evolution to produce optimal solutions to a given problem. It works by evolving population of candidate solutions toward the global optimum. The EP algorithms give results better than the heuristic and the classical algorithm, The results reported were promising and encouraging for further research in this direction. Unfortunately, recent research has identified some deficiency in GA performance. The degradation in efficiency is apparent in applications with highly *epistatic* objective functions, i.e. where the parameters being optimized are highly correlated. In addition, the premature convergence of GA degrades its performance and reduces its search capability. The SA algorithm is a metaheuristic and many choices are required to turn it into an actual algorithm. There is a clear tradeoff between the quality of the solutions and the time required to compute them. The tailoring work required to account for different classes of constraints and to fine-tune the parameters of the algorithm can be rather delicate. The precision of the numbers used in implementation is of SA can have a significant effect upon the quality of the outcome.

In recent years, several evolutionary algorithms have been proposed for constrained engineering optimization problems. In recent years, many methods have been proposed for handling constraints, which is the key point of the optimization process. Recently a new evolutionary computational technique, called Particle Swarm Optimization (PSO), has been proposed and introduced [18-21]. Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Kennedy and Dr. Eberhart in 1995, inspired by social behavior of bird flocking or fish schooling [22]. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles [23]..Particles change their positions by flying around in a multidimensional search space until a relatively unchanged position has been encountered, or until computational limitations are exceeded. It has many advantages over the other optimization techniques mentioned ahead in the thesis. It has been successfully applied to various problems.[24-31] so I am going with this optimization technique to solve the problem of single objective OPF.

CHAPTER 3
OPTIMAL POWER FLOW

3.1 Introduction

. The Optimal Power flow module is an intelligent load flow that employs technique to automatically adjust the power system control settings while simultaneously solving the load flows and optimizing the operating conditions within specific constraints. Optimal Power Flow uses state-of-the-art techniques with barrier functions and infeasibility handling to achieve ultimate accuracy and flexibility in solving systems of any size. Basically the goal of an optimal power flow (OPF) is to determine the "best" way to instantaneously operate a power system. Usually "best" refers to minimizing the operating cost. OPF considers the impact of the transmission system. OPF functionally combines the power flow with economic dispatch. It minimizes cost function, such as operating cost, taking into account realistic equality and inequality constraints. A typical OPF problem seeks a dispatch of active power and/or reactive power by adjusting the appropriate control variables, so that a specific objective in operating a power system network is optimized (maximizing or minimizing) and the feasibility with respect to the power system constraints dictated by the electrical network is maintained. The OPF problem is considered as a static, non-linear, multi-objective optimization problem with both continuous and discrete control variables [4]. In addition it is a non-convex problem that has local minima. The non-linearity of the power flow equations makes the OPF problem a non-linear constrained problem. The importance of OPF problem in power system is not only due to operational security considerations, but also due to the projected annual saving resulted from operating the power system in an optimized state. OPF is one of the most important operational functions of the modern energy management system.

The continuous control variables model include unit active power outputs and generator-bus voltage magnitudes while the discrete variables include transformer tap settings and switch-able shunt devices.

OPF has been widely used in power system operation and planning. It has been used as a tool to define the level of inter-utility power exchange. The primary goal of a generic OPF is to minimize the costs of meeting the load demand for a power system while maintaining the security of the system. The costs associated with the power system may depend on the situation, but in general they can be attributed to the cost of generating power (MW) at each generator. In OPF the maintenance of system security needs to keep each device of power system within desired limits. It includes maximum and minimum outputs for generators, maximum MVA flows on transmission lines and generators and also keeping bus voltages within desired ranges. The OPF mainly addresses the steady-state of the power system. The OPF performs all the control functions of the power system to achieve these goals. The functions may include generator and transmission system control. The OPF will control generator MW outputs as well as generator voltage for the generators and for transmission system it may control the tap ratio or phase shift angle for variable transformers, switched shunt control and other FACTS devices. Secondary goal of OPF is to determine the system marginal cost data. It aids in the pricing of MW transactions as well as pricing auxillary services such as voltage support through MVAr support.

The OPF has many applications which include :-

1) The calculation of the optimum generation pattern, as well as all control variables, in order to achieve the minimum cost of the generation together with meeting the transmission system limitations.

2) Using either the current state of the power system or a short-term load forecast, the OPF can be set up to provide a preventive dispatch if the security constraints are incorporated.

3) In an emergency, that is when some component of the system is overloaded or a bus is experiencing a voltage violation, the OPF can provide a corrective dispatch, which tells the system's operators what kind of adjustments to perform in order to mitigate the overload or voltage violation problems.

4) The OPF can also be used periodically to find the optimum settings for generation voltages, transformers taps and switch-able capacitors or static VAr components (called "Voltage-VAr" optimization).

5) The OPF is routinely used in planning studies to determine the maximum stress that a planned transmission system can withstand.

3.2 General OPF Problem Formulation

In general, the mathematical formulation of the OPF problem can be formulated as a non-linearly constrained optimization problem as discussed below:

Minimize $F(x, u)$ (3.1)

Subject to: $g_E(x, u) = 0$ (3.2)

$g_O(x, u) \leq 0$ (3.3)

$g_C(x, u) \leq 0$ (3.4)

Where:

1. The vector of variables is partitioned into the controllable quantities (control variables) u and the dependent (state) variables x.

2. The objective function F (x, u) is scalar quantity and is considered objective function of any optimization problem. This function represents, for instance, economic and security oriented interests of the power utility.

3. g_E (x, u) = 0 are the equality constraints.

4. g_O (x, u) ≤ 0 are the operating constraints. Most network state variables are not allowed to exceed certain lower and upper limits. These limitations are "soft" constraints and corresponding to security and power quality based limitations and requirements. Some of the most common operating constraints are limitations on:

a. voltage magnitude at load buses

b. reactive power of PV-generators

c. branch currents, branch MW/MVAR/MVA flows

d. angle/voltage magnitude drop along a line

e. slack bus active power output limits

5. g_C (x, u) ≤ 0 are the control variables constraints. Control variables do not exceed lower and upper limits. These can be "hard" constraints, especially when corresponding to the operating range of physical apparatus. The most common control variable constraints are:

a. transformer load tap changer magnitudes

b. active generating power

c. voltage magnitude at PV buses

d. switched capacitor or reactors settings

e. MW interchange transactions

f. phase shift transformer tap position

g. reactive injection for a static VAR compensator

The OPF problem has many control variables to be adjusted, while the economic dispatch problem and reactive power generation dispatch have much less. The control variables **u** of the OPF problem can be stated in (3.5), while its state variables **x** are stated in (3.6).

$$\mathbf{u} = [Q^T{}_C \, TC^T \;\; V^T{}_G \;\; P^T{}_G] \tag{3.5}$$

Where:

Q_C = reactive power supplied by all shunt reactors

TC = transformer load tap changer magnitudes

V_G = voltage magnitude at PV buses

P_G = active power generated at the PV buses

$$\mathbf{x} = [V^T{}_L \;\; \theta^{\;T} \;\; P_{SG} \;\; Q^T{}_G] \tag{3.6}$$

Where:

N_L = number of load buses

NG = number of PV buses, generator buses

V_L = voltage magnitude at PQ buses, load buses

θ = voltage angles of all buses, except the slack bus

P_{SG} = active generating power of the slack bus

Q_G = reactive power of all generator units

3.3 Proposed OPF Problem Formulation

As any optimization problem, the OPF problem is formulated as a minimization or maximization to a certain objective function in which it is subjected to a variety of equality and inequality constraints. The proposed objective function is mentioned:

The Objective Function

<u>Minimization of Generation Fuel Cost</u>

The objective function is the minimization of the generation fuel cost of thermal units. Generally, the OPF generation fuel cost function can be expressed by a quadratic function as follows:

$$\text{Minimize } (F_T) = \sum_{i=1}^{N_G} F_i\,(P_{Gi})$$

$$F_i\,(P_{Gi}) = a_i + b_i\, P_{Gi} + c_i\, P^2_{Gi} \tag{3.7}$$

Where:

· N_G is the number of generators including the slack generator in any electric network

· a_i is the basic cost coefficient of the i_{th} generator

· b_i is the linear cost coefficient of the i_{th} generator

· c_i is the quadratic cost coefficient of the i_{th} generator

· P_{Gi} is the real power output of the i_{th} generator. P_G is the vector of real power outputs of all generator units and is defined as

$$P_G = [P_{G1}, P_{G2}, \ldots\ldots\ldots\ldots\ldots, P_{Gn}]^T \tag{3.8}$$

3.4 The Constraints

The control variables for the OPF include: active power at all generator units; generator bus voltages; transformer tap positions; and switch-able shunt reactors. The

OPF constraints are divided into equality and inequality constraints. The equality constraints are power/reactive power equalities, the inequality constraints include bus voltage constraints, generator reactive power constraints. reactive source reactive power capacity constraints and the transformer tap position constraints, etc. Therefore, the above objective function is subjected to the below constraints:

(i) Equality Constraints:

The equality constraints of the OPF reflect the physics of the power system. The physics of the power system are enforced through the power flow equation which require that the net injection of the real and reactive power at each bus to be zero as shown:-

The power flow equation of the network

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

$$\text{where } g(V,\phi) = \begin{cases} \left.\begin{array}{l} P_i(V,\phi) - P_i^{net} \\ Q_i(V,\phi) - Q_i^{net} \end{array}\right\} \leftarrow \text{For each PQ bus i} \\ P_m(V,\phi) - P_m^{net} \} \leftarrow \text{For each PV bus m, not including the Ref.bus} \end{cases}$$

where

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

P_i^{net} and Q_i^{net} are respectively specified real and reactive power for PQ buses i.

P_m and P_m^i are respectively calculated and specified real power for PV bus m.

V and ϕ are voltage magnitude and phase angles at different buses.

(ii) Inequality Constraints:

The inequality constraints of the OPF reflect the limits on physical devices in the power system as well as the limits created to ensure system security. This section will lay out all the necessary inequality constraints needed for the OPF implementation. The types of inequality constraints are bus voltage limits at generations, maximum line loading limits and limits on tap settings. The various inequality constraints are as follows:-

- The inequality constraint on real power generation at bus i

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

where Pg_i^{min} and Pg_i^{max} are resp. minimum and maximum values of real power generation allowed at generator bus i.

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

$$Q_{gi}^{min} \leq Qg_i \leq Qg_i^{max}$$

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

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

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

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

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

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

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

- MVA flow limit on transmission line

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

Where,

MVA_{ij}^{max} is the maximum rating of transmission line connecting bus i and j.

CHAPTER 4
PARTICLE SWARM OPTIMIZATION

4.1 Introduction

One of the most difficult parts encountered in practical engineering design optimizations is handling constraints. Real-world limitations frequently introduce multiple, nonlinear and non-trivial constraints in the engineering design problems. Constraints often limit the feasible solutions to a small subset of the design space. A general engineering optimization problem can be defined as follows:

Minimize $f(X)$, $X = \{x_1, x_2, \ldots\ldots, x_n\} \in R$

Subject to $g_i(X) \leq 0$, $i = 1, 2, \ldots, p$

$h_i(X) = 0$, $i = 1, 2, \ldots, m$

Where:

$x_i^{(L)} \leq x_i \leq x_i^{(U)}$, $i = 1, 2, \ldots, n$

Due to the complexity and unpredictability of constraints, a general deterministic solution is difficult to be found. In recent years, several evolutionary algorithms have been proposed for constrained engineering optimization problems. In recent years, many methods have been proposed for handling constraints, which is the key point of the optimization process. Recently a new evolutionary computational technique, called Particle Swarm Optimization (PSO), has been proposed and introduced [18-21] .

4.2 Particle Swarm Optimization Overview

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Kennedy and Dr. Eberhart in 1995, inspired by social behavior of bird flocking or fish schooling [22]. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random feasible solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. PSO algorithm has also been demonstrated to perform well on genetic algorithm test function. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles [23].

In a PSO algorithm, particles change their positions by flying around in a multidimensional search space until a relatively unchanged position has been encountered, or until computational limitations are exceeded [24]. In social science context, a PSO system combines a social-only model and a cognition-only model. The social-only component suggests that individuals ignore their own experience and fine-tune their behavior according to the successful beliefs of the individual in the neighborhood. On the other hand, the cognition-only component treats individuals as isolated beings. A particle changes its position using these models.

Each particle keeps track of its coordinates in the problem space, which are associated with the best solution, fitness, it has achieved so far. The fitness value is also stored. This value is called *pbest*. Another best value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the neighbours of the particle. This location is called *lbest*. When a particle takes all the population as its topological neighbours, the best value is a global best and is called *gbest*.

The concept of the PSO consists of, at each time step, changing the velocity of (accelerating) each particle toward its p*best* and *lbest* locations (local version of PSO). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward *pbest* and *lbest* locations. In past several years, PSO has been successfully applied in many research and application areas. It is demonstrated that PSO gets better results in a faster, cheaper way compared with other methods. As in the literature, PSO algorithm has been successfully applied to various problems [24-31].

Another reason that PSO is attractive is that there are few parameters to adjust. One version, with slight variations, works well in a wide variety of applications. Particle swarm optimization has been used for approaches that can be used across a wide range of applications, as well as for specific applications focused on a specific requirement.

Many advantages of PSO over other traditional optimization techniques can be summarized as follows [24]:

a) PSO is a population-based search algorithm (i.e., PSO has implicit parallelism). This property ensures PSO to be less susceptible in being trapped on local minima.

b) PSO uses payoff (performance index or objective function) information to guide the search in the problem space. Therefore, PSO can easily deal with non-differentiable objective functions. Additionally, this property relieves PSO of assumptions and approximations, which are often required by traditional optimization models.

c) PSO uses probabilistic transition rules and not deterministic rules. Hence, PSO is a kind of stochastic optimization algorithm that can search a complicated and uncertain area. This makes PSO more flexible and robust than conventional methods.

d) Unlike Genetic Algorithm (GA) and other heuristic algorithms, PSO has the flexibility to control the balance between the global and local exploration of the search space. This unique feature of a PSO overcomes the premature convergence problem and enhances the search capability

e) Unlike the traditional methods, the solution quality of the proposed approach does not depend on the initial population. Starting anywhere in the search space, the algorithm ensures the convergence to the optimal solution.

4.3 Basic Fundamental of PSO Algorithm

The basic fundamentals of the PSO technique are stated and defined as follows [24]:

1. **Particle *X* (i):** It is a candidate solution represented by a k-dimensional real-valued vector, where k is the number of optimized parameters. At iteration i, the j_{th} particle *X* (i, j) can be described as:

$$X_j(i) = [x_{j,1}(i); x_{j,2}(i); \ldots; x_{j,k}(i); \ldots\ldots; x_{j,d}(i)] \qquad (4.1)$$

Where: x's are the optimized parameters

$x_k(i,j)$ is the k^{th} optimized parameter in the j^{th} candidate solution

d represents number of control variables

2. **Population:** It is a set of n particles at iteration i.

$$pop(i) = [X_1(i), X_2(i), \ldots\ldots\ldots X_n(i)]^T \qquad (4.2)$$

Where: n represents the number of candidate solutions.

3. **Swarm:** it is an apparently disorganized population of moving particles that tend to cluster together while each particle seems to be moving in a random direction.

4. **Particle velocity V (i):** It is the velocity of the moving particles represented by a d-dimensional real-valued vector. At iteration i, the j_{th} particle $V_j(i)$ can be described as:

$$V_j(i) = [v_{j,1}(i); v_{j,2}(i); \ldots; v_{j,k}(i); \ldots\ldots; v_{j,d}(i)] \qquad (4.3)$$

Where: $v_{j,k}(i)$ is the velocity component of the j^{th} particle with respect to the k^{th} dimension.

5. **Inertia weight w (i):** It is a control parameter, which is used to control the impact of the previous velocity on the current velocity. Hence, it influences the trade-off between the global and local exploration abilities of the particles. For initial stages of the search process, large inertia weight to enhance the global exploration is recommended while it should be reduced at the last stages for better local exploration. Therefore, the inertia factor decreases linearly from about 0.9 to 0.4 during a run. In general, this factor is set according to the following equation [25]:

$$W = W_{max} - (W_{max} - W_{min}) / iter_{max} = iter \tag{4.4}$$

Where: $iter_{max}$ is the maximum number of iterations and iter is the current number of iterations.

6. **Individual best X^* (i):** During the movement of a particle through the search space, it compares its fitness value at the current position to the best fitness value it has ever reached at any iteration up to the current iteration. The best position that is associated with the best fitness encountered so far is called the individual best X^* (i). For each particle in the swarm, X^* (i) can be determined and updated during the search. For the j^{th} particle, individual best can be expressed as:

$$X_j^*(i) = [x_{j_1,*}(i), x_{j,2^*}(i), \ldots\ldots\ldots\ x_{j,d^*}(i)]^T \tag{4.5}$$

In a minimization problem with only one objective function f, the individual best of the j^{th} particle $X_j^*(i)$ is updated whenever $f(X_j^*(i)) < f(X_j^*(i-1))$. Otherwise, the individual best solution of the j^{th} particle will be kept as in the previous iteration.

7. **Global best X** (t):** It is the best position among all of the individual best positions achieved so far.

8. **Stopping criteria:** The search process will be terminated under whenever one of the following criteria is satisfied:

· The number of the iterations since the last change of the best solution is greater than a pre-specified number.

· The number of iterations reaches the maximum allowable number.

The particle velocity in the k^{th} dimension is limited by some maximum value, v_k^{max} This limit enhances the local exploration of the problem space and it realistically simulates the incremental changes of human learning. The maximum velocity in the k^{th} dimension is characterized by the range of the k_{th} optimized parameter and given by:

$$V_k^{max} = (x_k^{max} - x_k^{min})/N \tag{4.6}$$

Where: N is a chosen number of intervals in the k^{th} dimension.

4.4 General PSO Algorithm

In a PSO algorithm, the population has n particles that represent candidate solutions. Each particle is a k-dimensional real-valued vector, where k is the number of the optimized parameters [24]. Therefore, each optimized parameter represents a dimension of the problem space. The PSO technique steps can be described as below.

***Step 1*: Initialization**: Set i=0 and generate random n particles, $\{X_j(0), j=1,2,..n\}$.

Each particle is considered to be a solution for the problem and it can be described as $X_j(0)=[x_{i,1}(0); x_{i,2}(0); \ldots\ldots; x_{i,k}(0)]$. Each control variable has a range $[x_{min}, x_{max}]$. Each particle in the initial population is evaluated using the objective function f. If the candidate solution is a feasible solution, i.e. all problem constraints have been met, then go to step-2 else repeat this step.

***Step 2*: Counter Updating**: Update the counter i= i +1

***Step 3*: Compute the objective function**

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

$$V(k,j,i+1) = w*V(k,j,i) + C_1*rand*(pbestx(j,k) - x(k,j,i))$$

$$+ C_2*rand*(gbestx(k) - x(k,j,i)) \quad (4.7)$$

Where,

i is the iteration number

j is the particle number

k is the k_{th} control variable

w is the inertia weighting factor

c_1, c_2 are acceleration constant

rand () is a uniform random value in the range of [0,1] V(k,j,i) is the velocity of particle j at iteration I x(k,j,i) is the current position of particle j at iteration j

Then, check the velocity limits. If the velocity violates its limit, set it at its proper limit. The second term of the above equation represents the cognitive part of the PSO where the particle changes its velocity based on its own thinking and memory. The third term represents the social part of PSO where the particle changes its velocity based on the social-psychological adaptation of knowledge.

***Step 5*: Position updating**: Based on the updated velocity, each particle changes its position according to the equation (4.8).

$$x(k,j,i+1)=x(k,j-1,i)+v(k,j,i) \quad (4.8)$$

***Step 6*: Individual best updating**: Each particle is evaluated and updated according to the update position.

***Step 7*:** Search for the minimum value in the individual best and its solution, if it has ever been reached in any iteration and considered the minimum.

***Step 8*: Stopping criteria**: If one of the stopping criteria is satisfied, then stop otherwise go to step-2.

CHAPTER 5
PSO BASED OPF

5.1 Introduction

Though a wide variety of optimization techniques have been applied for solving the single objective OPF problem as mentioned earlier but the results obtained by using PSO method are much more promising and better as compared to other techniques. Many advantages of PSO over the other techniques include;-

- It is less susceptible in being trapped to local minima.
- It can deal with non differentiable objective functions.
- It is more flexible and robust.
- No problem of premature convergence.
- Solution quality independent of the initial population.

All these advantages priortise PSO technique over the other optimization techniques.

5.2 PSO Algorithm for OPF problem

The various steps involved in the implementation of PSO to the OPF problem are-

Step 1: Input parameters of system, and specify the lower and upper boundaries of each variable.

Step 2: Initialize randomly the particles of the population. These initial particles must be feasible candidate solution that satisfy the practical operation constraints.

Step 3: To each particles of the population, employ the Newton-Raphson method to calculate power flow and the transmission loss.

Step 4: Calculate the evaluation value of each particle, in the population using the evaluation function.

Step 5: Compare each particle's evaluation value with its *pBest* . The best evaluation value among the *pBest* is denoted as *gBest* .

Step 6: Update the time counter t = t+1

Step 7: Update the inertia weight w given by

$$W = W_{max} – (W_{max} - W_{min}) / iter_{max} = iter$$

Step 8: Modify the velocity v of each particle according to the mentioned equation.

V (k,j,i+1) = w*V(k,j,i) + C1*rand*(pbestx (j,k) - x(k,j,i)) + C2*rand*(gbestx (k) - x(k,j,i)) .

Step 9: Modify the position of each particle according to the mentioned equation. If a particle violates the its position limits in any dimension, set its position at the proper limit

x(k,j,i+1)=x(k,j-1,i)+v(k,j,i)

Step 10: Each particle is evaluated according to its updated position. If the evaluation value of each particle is better than the previous *pBest* , the current value is set to be *pBest* . If the best *pBest* is better than *gBest* , the value is set to be gbest.

Step 11 If one of the stopping criteria is satisfied then go to Step 12. Otherwise, go to Step 6.

Step 12: The particle that generates the latest *gBest* is the optimal value.

The parameters that must be selected carefully for the efficient performance of PSO algorithm are:-

a. Both acceleration factors C_1 & C_2.

b. Number of particles.

c. The inertia factor.

d. The search will terminate if one of the below scenario is encountered:

- $|g_{bestf}(i) - g_{bestf}(i-1)| < 0.0001$ for 50 iterations
- Maximum number of iteration reached (500 iterations)

e. Number of intervals N, which determine the maximum velocity v_k^{max}.

The PSO algorithm for solving the OPF problem with an objective function of minimization of generation fuel cost is shown on the next page.

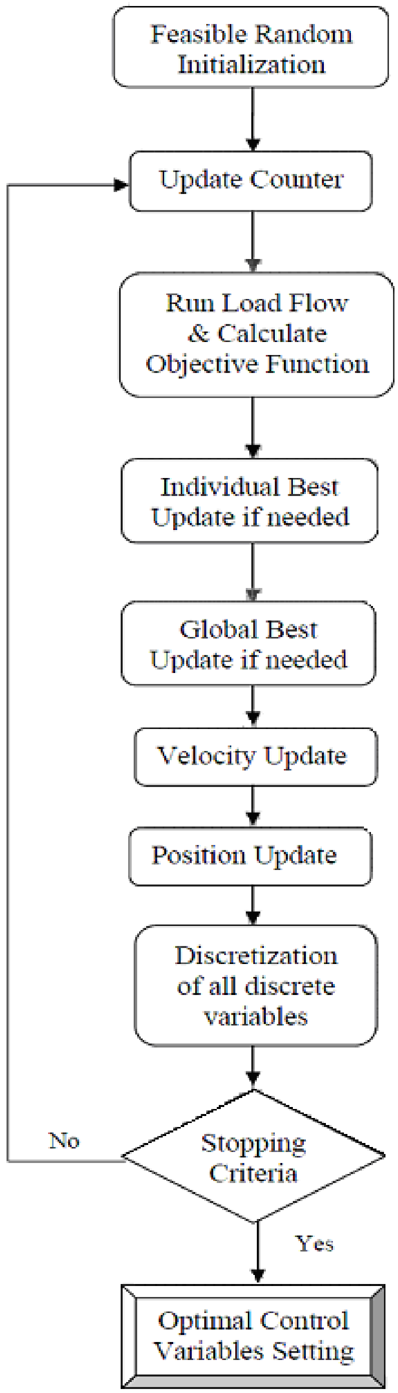

Fig. 5.1 PSO Algorithm for Single Objective OPF problem

CHAPTER 6
RESULTS AND DISCUSSION

6.1 The IEEE-30 Bus Power System

The IEEE-30 bus system is used throughout this work to test the proposed algorithm (PSO based OPF). This system is part of the American Power Service Cooperation Network that is used as a standard test system to study different power problems and evaluate programs to analyze such problems [33]. This system consists of 6 generator units as well as 41 transmission lines. The one line diagram of this system is shown in Figure 6.1. The detailed system parameters are presented in the Appendix Tables A.1 and A.2. The total active power load is 289.2 MW while the total reactive power is 126.2 MVAR. The values of fuel cost and emission coefficients of the six generators are given in Table A.3. The IEEE-30 control variables are also presented in details in Table A.4. Throughout all cases, the IEEE-30 bus system base MVA has assumed to be 100 MVA. The basic power flow results of the IEEE-30 bus system without applying optimization techniques are shown in Table 6.1. The outcomes of the transmission line flows as well as the active power losses are tabulated in Table 6.2. Furthermore, value of the objective function, before applying optimization is also mentioned following table 6.2. The results obtained using the proposed algorithm are compared with those reported in literature [17, 32].

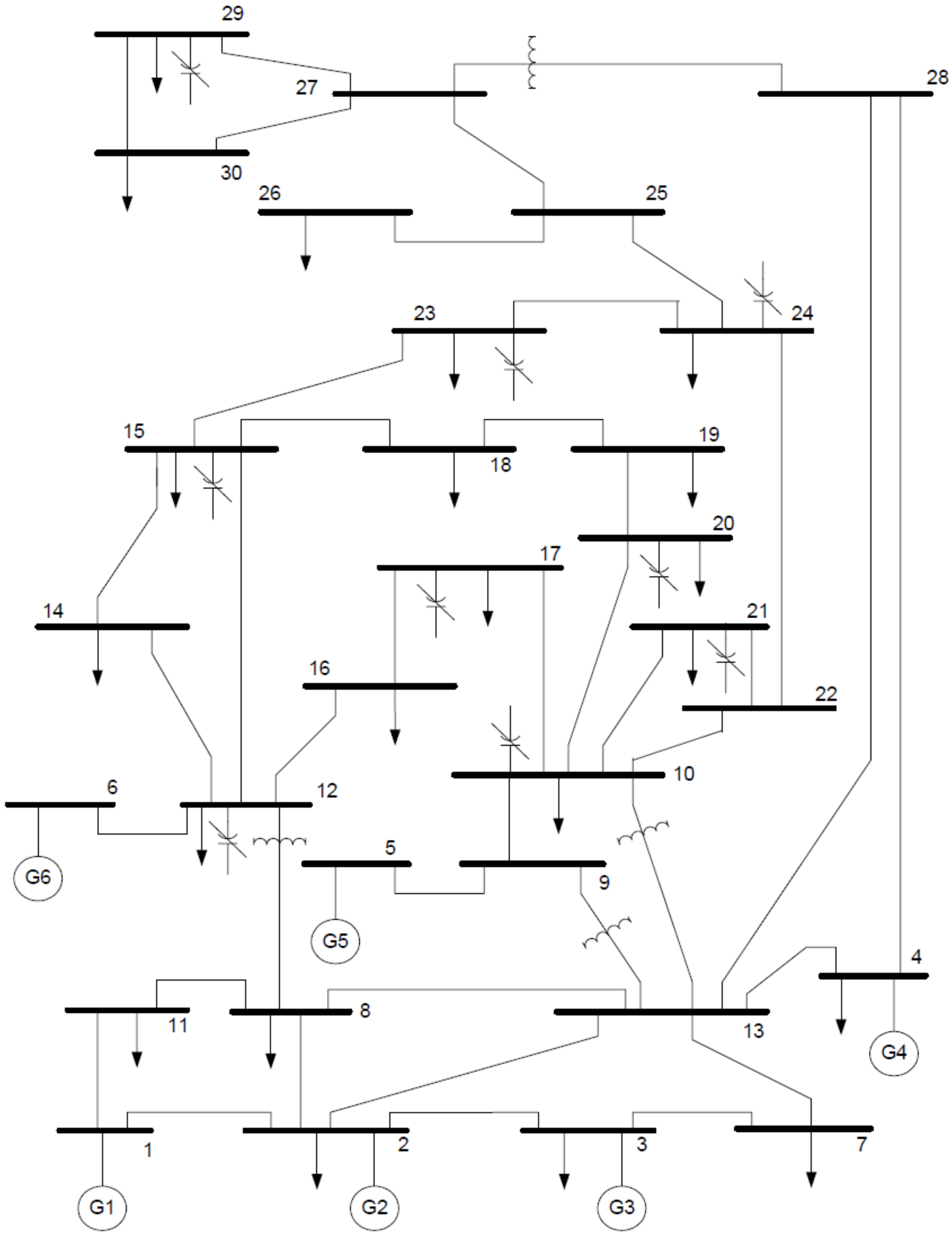

Figure 6.1 Single-line diagram of IEEE-30 bus test system [17]

Table 6.1: IEEE 30-Bus Basic Power Flow Results Before Applying Optimization (Bus Results)

Bus No.	V (p.u.)	Delta (degree)	P_D (MW)	Q_D (Mvar)	P_G (MW)	Q_G (Mvar)
1	1.0500	0	0.00	0.00	99.09	3.33
2	1.0400	-1.7735	21.70	12.70	80.00	28.70
3	1.0100	-6.5518	94.2.0	19.00	50.00	22.43
4	1.0100	-5.6968	30.00	30.00	20.00	47.38
5	1.0500	-4.4931	0.00	0.00	20.00	2.46
6	1.0500	-6.2527	0.00	0.00	20.00	12.50
7	0.9990	-6.3455	22.80	10.90	0	0
8	1.0117	-4.5008	7.60	1.60	0	0
9	1.0459	-6.6640	0.00	0.00	0	0
10	1.0267	-8.5971	5.80	2.00	0	0
11	1.0192	-3.7736	2.40	1.20	0	0
12	1.0337	-7.7310	11.20	7.50	0	0
13	1.0049	-5.3001	0.00	0.00	0	0
14	1.0192	-8.6704	6.20	1.60	0	0
15	1.0151	-8.7888	8.20	2.50	0	0
16	1.0233	-8.3863	3.50	1.80	0	0
17	1.0202	-8.7505	9.00	5.80	0	0
18	1.0067	-9.4455	3.20	0.90	0	0
19	1.0050	-9.6358	9.50	3.40	0	0
20	1.0096	-9.4362	2.20	0.70	0	0
21	1.0138	-9.0650	17.50	11.20	0	0
22	1.0143	-9.0530	0.00	0.00	0	0
23	1.0055	-9.2329	3.20	1.60	0	0
24	1.0014	-9.4651	8.70	6.70	0	0
25	1.0120	-9.6332	0.00	0.00	0	0
26	0.9943	-10.0574	3.50	2.30	0	0
27	1.0274	-9.4559	0.00	0.00	0	0
28	1.0003	-5.7960	0.00	0.00	0	0
29	1.0077	-10.6757	2.40	0.90	0	0
30	0.9962	-11.5510	10.60	1.90	0	0

**Table 6.2 IEEE 30-Bus Basic Power Flow Results
Before Applying Optimization
(Line Flow and Losses)**

--Line--		Power at bus and line flow			---Line loss--		Transformer tap
from	to	MW	Mvar	MVA	MW	Mvar	
1		99.1	4.2	99.2			
	2	58.8	-3.3	58.3	0.6	-4.0	
	3	40.3	7.5	41	0.7	-1.5	
2		58.3	15.9	60.4			
	1	-58.2	-0.6	58.2	0.6	-4.0	
	4	31.3	6.6	32.0	0.6	-2.2	
	5	45.7	4.4	45.9	0.9	-0.5	
	6	39.5	5.5	39.8	0.9	-1.3	
3		-2.4	-1.2	2.7			
	1	-39. 6	-9.0	40.6	0.7	-1.5	
	4	37.2	7.8	38.0	0.2	-0.3	
4		-7.6	-1.6	7.8			
	2	-30.8	-8.6	32.0	0.6	-2.2	
	3	-37.0	-8.2	37.9	0.2	-0.3	
	6	35.8	-4.0	36.0	0.2	-0.4	
	12	24.4	19.2	31.1	0	2.1	0.932
5		-44.2	2.3	44.3			
	2	-44.7	-4.9	45.0	0.9	-0.5	
	7	.0.5	7.2	7.2	0	-2.0	
6		0	0	0			
	2	-38.6	-6.8	39.2	0.9	-1.3	
	4	-35.6	3.6	35.8	0.2	-0.4	
	7	22.4	0.4	22.4	0.1	-1.3	
	8	12.1	-10.8	16.2	0	-0.8	
	9	13.11	4.1	13.8	-0.0	0.4	0.978
	10	11.5	7.0	13.5	-0.0	0.9	0.969
	28	15.0	2.5	15.2	0.0	-1.2	

7		-22.8	-10.9	25.3			
	5	-0.5	-9.2	9.2	0.0	-2.0	
	6	-22.3	-1.7	22.4	0.1	-1.3	
8		-10.0	10.8	14.7			
	6	-12.1	10.0	15.7	0.0	-0.8	
	28	2.1	0.8	2.2	0.0	-4.3	
9		0	0	0			
	6	-13.1	3.7	13.7	-0.0	-0.4	
	11	-20.0	-13.5	24.1	0.0	1.2	
	10	33.1	17.2	37.3	0.0	1.5	
10		-5.8	-2.0	6.1			
	6	-11.5	-6.0	13.0	-0.0	0.9	
	9	-33.1	-15.8	36.7	0.0	1.5	
	20	15.2	5.7	16.2	0.2	0.5	
	17	2.2	1.1	2.5	0.0	0.0	
	21	14.6	9.1	17.2	0.1	0.2	
	22	6.8	4.0	7.9	0.0	0.1	
11		20.0	14.6	24.8			
	9	20.0	14.6	24.8	0.0	1.2	
12		-11.2	-7.5	13.5			
	4	-24.4	-17.1	29.8	0.0	2.1	
	13	-20.0	-7.4	21.3	0.0	0.6	
	14	7.3	2.7	7.7	0.1	0.1	
	15	15.5	7.4	17.2	0.2	0.4	
	16	10.5	7.0	12.6	0.1	0.3	
13		20.0	8.0	21.5			
	12	20.0	8.0	21.5	0.0	0.6	
14		-6.2	-1.6	6.4			
	12	-6.19	-2. 55	7.555	0.1	0.1	
	15	0.010	0.9	1.4	0.0	0.0	
15		-8.2	-2.5	8.6			

	12	-15.3	-7.0	16.8	0.2	0.4	
	14	-1.0	-0.9	1.4	0.0	0.0	
	23	8.1	5.4	9.8	0.1	0.2	
16		-3.5	-1.8	3.9			
	12	-10.3	-6.7	12.3	0.1	0.3	
	17	6.8	4.9	8.4	0.1	0.1	
17		-9	-5.8	1.70			
	16	-6.8	-4.7	8.3	0.1	0.1	
	10	-2.2	-1.1	2.5	0.0	0.0	
18		-3.2	-0.9	3.3			
	19	-3.2	-0.9	3.3	0.0	0.0	
19		-9.5	-3.4	10.1			
	18	3.2	0.9	3.3	0.0	0.0	
	20	-12.7	-4.3	13.4	0.1	0.1	
20		-2.2	-0.7	2.3			
	19	12.8	4.4	13.5	0.1	0.1	
	10	-15.0	-5.1	15.8	0.2	0.5	
21		-17.5	-11.2	20.8			
	10	-14.5	-8.8	17.0	0.1	0.2	
	22	-3.0	-2.4	3.8	0.0	0.0	
22		0	0	0			
	10	-6.8	-3.9	7.8	0.0	0.1	
	21	3.0	2.4	3.8	0.0	0.0	
	24	3.8	1.5	4.1	0.0	0.0	
23		-3.2	-1.6	3.6			
	15	-8.0	-5.2	9.6	0.1	0.2	
	24	4.8	3.6	6.0	0.0	0.1	
24		-8.9	-8.4	0.1			
	22	-3.9	-3.1	4.1	0.0	0.0	
	23	-4.8	-3.6	5.9	0.0	0.01	

	25	-0.2	-1.7	1.7	0.0	0.0	
25		0	0	0			
	24	0.2	1.7	1.7	0.0	0.0	
	26	3.5	2.44.30.0	0.1	0.044	0.066	
	27	-3.7	-4.0	5.5	0.0	0.1	
26		-3.5	-2.3	4.2			
	25	-3.5	-2.3	4.2	0.0	0.1	
27		0	0	0			
	25	3.7	4.1	5.6	0.0	0.1	
	28	-17.0	-7.5	18.6	0.0	1.4	
	29	6.2	1.7	6.4	0.1	0.2	
	30	7.1	1.7	7.3	0.2	0.3	
28		0	0	0			
	27	17.0	8.8	19.2	0.0	1.4	0.968
	8	-2.1	-5.1	5.5	0.0	-4.3	
	6	-15.0	-3.7	15.4	0.0	-1.2	
29		-2.4	-0.9	2.6			
	27	-6.1	-1.5	6.3	0.1	0.2	
	30	3.7	0.6	3.8	0.0	0.1	
30		-10.6	-1.9	10.8			
	27	-6.93	-1.4	7.1	0.2	0.3	
	29	-3.67	-0.542	3.71	0.0	0.1	

The total generation fuel cost is 901.5892$/hr.

Table 6.3 Generation Fuel Cost Minimization (Bus Result)

(After applying PSO optimization technique)

Bus No.	V (pu)	Delta (degree)	P_D (MW)	Q_D (Mvar)	P_G (MW)	Q_G (Mvar)
1	1.0830	0	0.00	0.00	189.12	3.50
2	1.0631	-3.3786	21.70	12.70	47.55	19.30
3	1.0321	-9.8602	94.20	19.00	19.56	27.02
4	1.0369	-7.7451	30.00	30.00	10.00	33.65
5	1.0301	-8.1929	0.00	0.00	10.00	-2.29
6	1.0530	-9.6210	0.00	0.00	12.00	2.40
7	1.0268	-8.9493	22.80	10.90	0	0
8	1.0420	-6.3773	7.60	1.60	0	0
9	1.0350	-9.5272	0.00	0.00	0	0
10	1.0449	-11.2947	5.80	2.00	0	5.00
11	1.0500	-5.3115	2.40	1.20	0	0
12	1.0500	-10.4919	11.20	7.50	0	5.00
13	1.0359	-7.4570	0.00	0.00	0	0
14	1.0401	-11.4577	6.20	1.60	0	0
15	1.0400	-11.7255	8.20	2.50	0	4.00
16	1.0423	-11.1512	3.50	1.80	0	0
17	1.0416	-11.1512	9.00	5.80	0	5.00
18	1.0332	-12.3519	32.0	0.90	0	0
19	1.0322	-12.5337	9.50	3.0	0	0
20	1.0371	-12.3453	2.20	0.70	0	5.00
21	1.0364	-11.8398	17.50	11.20	0	5.00
22	1.0370	-11.8295	0.00	0.00	0	0
23	1.0380	-12.3124	3.20	1.60	0	5.00
24	1.0308	-12.3997	8.70	6.70	0	5.00
25	1.0328	-12.1585	0.00	0.00	0	0
26	1.0154	-12.5658	3.50	2.30	0	0
27	1.0426	-11.7520	0.00	0.00	0	0
28	1.0343	-7.9781	0.00	0.00	0	0
29	1.0376	-13.3450	2.40	0.90	0	5.00
30	1.0202	-14.0004	10.60	1.90	0	0

Table 6.4 Generation Fuel Cost Minimization (Line Flow and Losses)

(After applying PSO optimization technique)

--Line--		Power at bus and line flow			---Line loss--		Transformer tap
from	to	MW	Mvar	MVA	MW	Mvar	
1		196.1	-18.5	196.9			
	2	132.0	-23.6	134.1	3.1	3.5	
	3	64.1	5.2	64.3	1.7	2.6	
2		25.8	39.1	46.9			
	1	-128.9	27.2	131.7	3.1	3.5	
	4	37.3	6.5	37.9	0.8	-1.5	
	5	67.2	1.6	67.3	2.0	3.9	
	6	50.2	3.8	50.3	1.4	0.2	
3		-2.4	-1.2	2.7			
	1	-62.4	-2.5	62.5	1.7	2.6	
	4	60.0	1.3	60.0	0.5	0.5	
4		-7.6	-1.6	7.8			
	2	-36.5	-8.0	37.4	0.8	-1.5	
	3	-59.5	-0.9	59.5	0.5	0.5	
	6	55.9	-11.8	57.1	0.4	0.4	
	12	32.6	19.0	37.7	0.0	3.1	0.932
5		-74.6	14.3	76.0			
	2	-65.3	2.3	65.3	2.0	3.9	
	7	-9.4	12.0	15.2	0.1	-1.8	
6		0	0	0			
	2	-48.8	-3.6	48.9	1.4	0.2	
	4	-55.5	12.2	56.8	0.4	0.4	
	7	32.6	-3.7	32.8	0.3	-0.8	
	8	20.9	-17.3	27.2	0.1	-0.6	
	9	20.2	4.1	20.6	-0.0	0.8	0.978
	10	13.6	7.1	15.3	0.0	1.2	0.969
	28	17.0	1.3	17.0	0.0	-1.1	

7		-22.8	-10.9	25.3			
	5	9.5	-13.8	16.7	0.1	-1.8	
	6	-32.3	2.9	32.4	0.3	-0.8	
8		-20.0	18.6	27.3			
	6	-20.9	16.7	26.7	0.1	-0.6	
	28	0.9	1.9	2.1	0.0	-4.3	
9		0	0	0			
	6	-20.2	-3.2	20.5	-0.0	0.8	
	11	-10.0	-14.3	17.5	0.0	0.6	
	10	30.2	17.5	34.9	0.0	1.3	
10		-5.8	-2.0	6.1			
	6	-13.6	-5.9	14.8	0.0	1.2	
	9	-30.2	-16.2	34.3	0.0	1.3	
	20	15.2	5.7	16.2	0.2	0.5	
	17	2.0	1.1	2.3	0.0	0.0	
	21	14.2	9.2	16.9	0.1	0.2	
	22	6.6	4.1	7.7	0.0	0.1	
11		10.0	14.9	18.0			
	9	10.0	14.9	18.0	0.0	0.6	
12		-11.2	-7.5	13.5			
	4	-32.6	-15.9	36.3	0.0	3.1	
	13	-12.0	-8.6	14.7	-0.0	0.3	
	14	7.3	2.7	7.7	0.1	0.1	
	15	15.4	7.4	17.1	0.2	0.4	
	16	10.7	6.9	12.8	0.1	0.3	
13		12	8.8	14.9			
	12	12.0	8.8	14.9	-0.0	0.3	
14		-6.2	-1.6	6.403			
	12	-7.266	-2.286	7.617	0.1	0.1	
	15	1.066	0.9	1.4	0.0	0.0	

15		-8.2	-2.5	8.573			
	12	-15.2	-7.0	16.8	0.2	0.4	
	14	-1.063	0.9	1.3	0.0	0.0	
	23	8.0	5.5	9.7	0.1	0.2	
16		-3.5	-1.8	3.936			
	12	-10.6	-6.6	12.5	0.1	0.3	
	17	7.1	4.8	8.6	0.1	0.1	
17		-9	-5.8	10.707			
	16	-7.0	-4.7	8.4	0.1	0.1	
	10	-2.0	-1.1	2.3	0.0	0.0	
18		-3.2	-0.9	3.324			
	19	-3.2	-0.9	3.3	0.0	0.0	
19		-9.5	-3.4	10.09			
	18	3.2	0.9	3.30.0	0.0	0.01	
	20	-12.7	-4.3	13.4	0.1	0.1	
20		-2.2	-0.7	2.309			
	19	12.8	4.4	13.5	0.1	0.1	
	10	-15.0	-5.1	15.8	0.2	0.5	
21		-17.5	-11.2	20.777			
	10	--14.1	-9.0	16.7	0.1	0.2	
	22	--3.4	-2.2	4.1	0.0	0.0	
22		0	0	0			
	10	-6.5	-4.0	7.7	0.0	0.1	
	21	3.4	2.2	4.1	0.0	0.0	
	24	3.1	1.8	3.6	0.0	0.0	
23		-3.2	-1.6	3.578			
	15	-7.9	-5.3	9.5	0.1	0.2	
	24	4.7	3.7	6.0	0.0	0.1	
24		-8.7	-6.7	11.0			

	22	-3.1	-1.7	3.6	0.0	0.0	
	23	-4.7	-3.6	5.9	0.0	0.1	
	25	-0.9	-1.4	1.6	0.0	0.0	
25		0	0	0			
	24	0.9	1.4	1.7	0.0	0.0	
	26	3.5	2.4	4.3	0.0	0.1	
	27	-4.4	-3.8	5.8	0.0	0.1	
26		-3.5	-2.3	4.188			
	25	-3.5	-2.3	4.188	0.0	0.1	
27		0	0	0			
	25	4.5	3.8	5.9	0.0	0.1	
	28	-17.8	-7.2	19.2	-0.0	1.4	
	29	6.2	1.7	6.4	0.1	0.2	
	30	7.089	1.7	7.3	0.2	0.3	
28		0	0	0			
	27	17.8	8.6	19.8	-0.0	1.4	0.968
	8	-0.8	-6.2	6.2	0.0	-4.3	
	6	-16.9	-2.5	17.1	0.0	-1.1	
29		-2.4	-0.9	2.563			
	27	-6.103	-1.504	6.286	0.1	0.2	
	30	3.703	0.604	3.752	0.0	0.1	
30		-10.6	-1.9	10.769			
	27	-6.9	-1.4	7.1	0.2	0.3	
	29	-3.67	-0.542	3.71	0.0	0.1	
					Total	Total	
					11.8	12.8	

Total generation fuel cost after applying PSO is 786.0332$/hr.

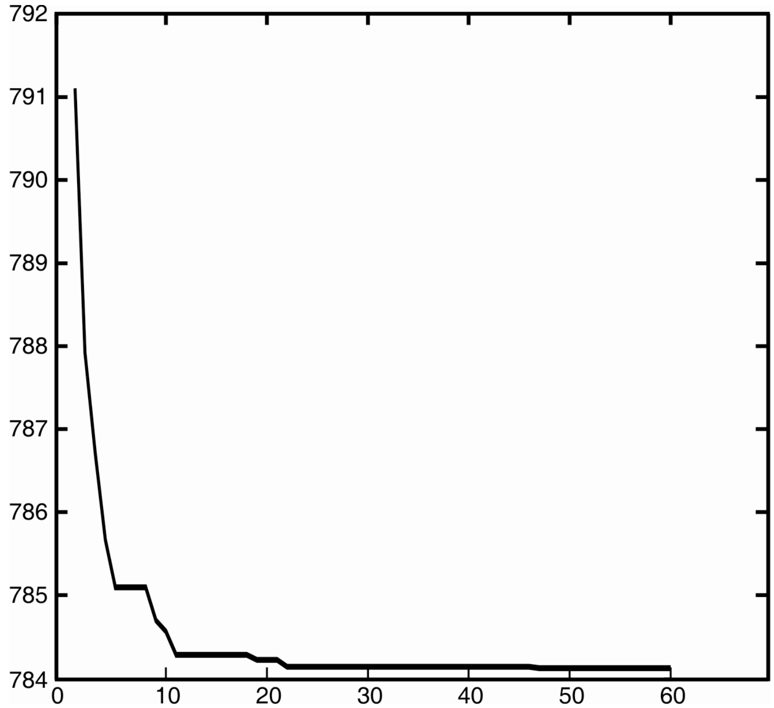

Figure 6.2 Generation Fuel Cost Minimization Using PSO Algorithm

Comparison of results reported in the literature and results obtained in the thesis:

Table 6.5 Literature Results [17]

Generator	MW
1	176.96
2	48.98
3	21.30
4	21.19
5	11.97
6	12.00
Total Loss	12.96
Fuel Cost	800.41$/hr

Table 6.6 Thesis Results

Generator	**MW**
1	**189.12**
2	**47.55**
3	**19.56**
4	**10.00**
5	**10.00**
6	**12.00**
Total Loss	**11.8**
Fuel Cost	**786.03$/hr**

The comparison of results reported in the literature and the results obtained in the thesis is shown above. The results obtained in the thesis are coming out to be better than those reported in the literature.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusion

This thesis work has significantly accomplished many attainments in the area under discussion which is the single objective Optimal Power Flow. The various achievements can be summarized as follows:

1. Implementing single OPF objective function optimization algorithm based on the Particle Swarm Optimization (PSO). An algorithm is developed and applied to a practical power system network. The developed OPF algorithm offers the following:

• Provides a flexibility to add or delete any system constraints and objective functions. Having this flexibility will help electrical engineers analyzing other system scenarios and contingency plans.

• Calculates the optimum generation pattern as well as all control variables in order to minimize the cost of generation together with meeting the transmission system limitations.

• Finds the optimum setting for system control variables that achieve minimum objective function. These control variables include: active power generation except the slack bus; all PV-bus voltages; all transformer load tap changers; and the setting of all switched reactors or static VAR components.

7.2 Future Work and Potential Applications

• To solve Optimal Power Flow problem considering the transient instability or excessive voltage decline at any electrical power system during a fault or as a result of switching.

• To incorporate the Power Factor Correction (PFC) to the developed OPF problem as an objective function,using PSO.

• To include the reactive power compensation requirement to the OPF problem in order to improve the voltage profile, using PSO.

• To redefine the OPF formulation to overcome the deregulation environment constraints.

APPENDIX

Table A.1 IEEE 30 Bus-System Line Data

Line No.	From Bus	To Bus	R (p.u.)	X (p.u.)	B/2 (p.u.)	Rating (MVA)	Tap Ratio (p.u.)
1	1	2	0.0192	0.0575	0.0264	130.0	1.0
2	1	11	0.0452	0.1852	0.0204	130.0	1.0
3	2	8	0.0570	0.1737	0.0184	65.0	1.0
4	11	8	0.0132	0.0379	0.0042	130.0	1.0
5	2	3	0.072	0.1983	0.0209	130.0	1.0
6	2	13	0.0581	0.1763	0.0187	65.0	1.0
7	8	13	0.0119	0.0414	0.0045	90.0	1.0
8	3	7	0.0460	0.1160	0.0102	70.0	1.0
9	13	7	0.0267	0.0820	0.0085	130.0	1.0
10	13	4	0.0120	0.0420	0.0045	32.0	1.0
11	13	9	0.0000	0.2080	0.0000	65.0	0.978
12	13	10	0.0000	0.5560	0.0000	32.0	0.969
13	9	5	0.0000	0.2080	0.0000	65.0	1.0
14	9	10	0.0000	0.1100	0.0000	65.0	1.0
15	8	12	0.0000	0.2560	0.0000	65.0	0.932
16	12	6	0.0000	0.1400	0.0000	65.0	1.0
17	12	14	0.1231	0.2559	0.0000	32.0	1.0
18	12	15	0.0662	0.1304	0.0000	32.0	1.0
19	12	16	0.0945	0.1987	0.0000	32.0	1.0
20	1	15	0.2210	0.1997	0.0000	16.0	1.0
21	16	17	0.0824	0.1923	0.0000	16.0	1.0
22	15	18	0.1070	0.2185	0.0000	16.0	1.0
23	18	19	0.0639	0.1292	0.0000	16.0	1.0
24	19	20	0.0340	0.0680	0.0000	32.0	1.0
25	10	20	0.0936	0.2090	0.0000	32.0	1.0
26	10	17	0.0324	0.0845	0.0000	32.0	1.0
27	10	21	0.0348	0.0749	0.0000	32.0	1.0
28	10	22	0.0727	0.1499	0.0000	32.0	1.0
29	21	22	0.0116	0.0236	0.0000	32.0	1.0
30	15	23	0.1000	0.2020	0.0000	16.0	1.0
31	22	24	0.1150	0.1790	0.0000	16.0	1.0
32	23	24	0.1320	0.2700	0.0000	16.0	1.0
33	24	25	0.1885	0.3292	0.0000	16.0	1.0
34	25	26	0.2544	0.3800	0.0000	16.0	1.0
35	25	27	0.1093	0.2087	0.0000	16.0	1.0

Contd......

36	28	27	0.0000	0.3960	0.0000	65.0	0.968
37	27	29	0.2198	0.4153	0.0000	16.0	1.0
38	27	30	0.3202	0.6027	0.0000	16.0	1.0
39	29	30	0.2399	0.4533	0.0000	16.0	1.0
40	4	28	0.0636	0.2000	0.0214	32.0	1.0
41	13	28	0.0169	0.0599	0.0065	32.0	1.0

Table A.2 IEEE 30 Bus-System Bus Data

Bus No.	V (pu)	P_G (pu)	Q_D (pu)	Q_{gmin} (pu)	Q_{gmin} (pu)	Q_{gmax} (pu)	P_{gmin} (MW)	P_{gmax} (MW)
1	1.0500	0.00	0.0000	0.0000	-0.200	2.00	0.500	2.000
2	1.0382	48.84	0.2170	0.1270	-0.200	1.00	0.200	0.800
3	1.0114	21.51	0.9420	0.1900	-0.150	0.80	0.150	0.500
4	1.0194	22.15	0.3000	0.3000	-0.150	0.60	0.100	0.350
5	1.0912	12.14	0.0000	0.0000	-0.100	0.50	0.100	0.300
6	1.0913	12.00	0.0000	0.0000	-0.150	0.60	0.120	0.400
7	1.0000	0.00	0.2280	0.1090	0.0	0.0	0.0	0.0
8	1.0000	0.00	0.0760	0.0160	0.0	0.0	0.0	0.0
9	1.0000	0.00	0.0000	0.0000	0.0	0.0	0.0	0.0
10	1.0000	0.00	0.0580	0.0200	0.0	0.05	0.0	0.0
11	1.0000	0.00	0.0240	0.0120	0.0	0.0	0.0	0.0
12	1.0000	0.00	0.1120	0.0750	0.0	0.05	0.0	0.0
13	1.0000	0.00	0.0000	0.0000	0.0	0.0	0.0	0.0
14	1.0000	0.00	0.0620	0.0160	0.0	0.0	0.0	0.0
15	1.0000	0.00	0.0820	0.0250	0.0	0.05	0.0	0.0
16	1.0000	0.00	0.0350	0.0180	0.0	0.0	0.0	0.0
17	1.0000	0.00	0.0900	0.0580	0.0	0.05	0.0	0.0
18	1.0000	0.00	0.0320	0.0090	0.0	0.0	0.0	0.0
19	1.0000	0.00	0.0950	0.0340	0.0	0.0	0.0	0.0
20	1.0000	0.00	0.0220	0.0070	0.0	0.05	0.0	0.0
21	1.0000	0.00	0.1750	0.1120	0.0	0.05	0.0	0.0
22	1.0000	0.00	0.0000	0.0000	0.0	0.0	0.0	0.0
23	1.0000	0.00	0.0320	0.0160	0.0	0.05	0.0	0.0
24	1.0000	0.00	0.0870	0.0670	0.0	0.05	0.0	0.0
25	1.0000	0.00	0.0000	0.0000	0.0	0.0	0.0	0.0
26	1.0000	0.00	0.0350	0.0230	0.0	0.0	0.0	0.0
27	1.0000	0.00	0.0000	0.0000	0.0	0.0	0.0	0.0
28	1.0000	0.00	0.0000	0.0000	0.0	0.0	0.0	0.0
29	1.0000	0.00	0.0240	0.0090	0.0	0.05	0.0	0.0
30	1.0000	0.00	0.1060	0.0190	0.0	0.0	0.0	0.0

Table A.3: IEEE 30-Bus System Generation Fuel Cost Coefficients

Generators		G1	G2	G3	G4	G5	G6
Cost Coefficients	**a**	0	0	0	0	0	0
	b	200	175	100	325	300	300
	c	37.5	175	625	83.4	250	250

Table A.4: IEEE 30-Bus System Control Variable Constraints

	Optimized Variable	Lower Limit	Upper Limit	Increment Value
Active Generated Power (MW	P_{G1}	0.50	2.00	N/A
	P_{G2}	0.20	0.80	
	P_{G3}	0.15	0.50	
	P_{G2}	0.10	0.35	
	P_{G5}	0.10	0.30	
	P_{G6}	0.12	0.40	
Generator Bus Voltage (pu)	V_{G1}	0.9	1.1	N/A
	V_{G2}			
	V_{G3}			
	V_{G1}			
	V_{G5}			
	V_{G6}			
Tap Position (pu)	TC_{L11}	0.9	1.1	0.9+16*1.25%
	TC_{L12}			
	TC_{L15}			
	TC_{L36}			
Capacitors	Q_{C10}	0	0.05	0.0 + 10*0.5%
	Q_{C12}	0	0.05	
	Q_{C15}	0	0.05	
	Q_{C17}	0	0.05	
	Q_{C20}	0	0.05	
	Q_{C21}	0	0.05	
	Q_{C23}	0	0.05	
	Q_{C24}	0	0.05	
	Q_{C29}	0	0.05	

REFERENCES

1. Carpinter, J., "Contribution to the Economic Dispatch Problem", Bulletin Society Francaise Electriciens, Vol.3, No.8, August 1962, pp. 431-447.

2. Xie, K., Song, Y.H., "Dynamic Optimal Power Flow by Interior Point Methods", IEE Proc-Generation, Transmission, Distribution, Vol. 148, No. 1, January 2001, pp. 76-84.

3. Xie, K., Song, Y.H., "Power Market Oriented Optimal Power Flow via an Interior Point Method", IEE Proc-Generation, Transmission, Distribution, Vol. 148, No. 6, January 2001, pp. 0549-556.

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

5. Alsac, O., Stott, B., "Optimal Load Flow with Steady State Security", IEEE Transactions on Power Apparatus and Systems, 1974, Vol.93, pp.745-751.

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

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

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

9. Rahli, M., “Optimal Power Flow Using Sequential Unconstrained Minimization Technique (SUMT) Method Under Power Transmission Losses Minimization”, Electric Power System Research 1999; 52:61-64.

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

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

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

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

14 Lai, L.L., MA, J.T., Yokohoma, R., Zhao, M., “Improved Genetic Algorithm for Optimal Power Flow Under Both Normal and Contingent Operation States”, Electrical Power Energy System, Vol.19, 1997, pp. 287-291.

15. Chen, L., Suzuki, H., Katou, K., “Mean Field Theory for Optimal Power Flow”, IEEE Transactions on Power Systems, Vol. 12, November 1997, pp. 1481-1486.

16. Kulworawanichpong, S.S., “Optimal Power Flow Using Tabu Search”,IEEE Power Engineering Review, June 2002, pp. 37-39.

17. Abido, M.A., “Optimal Power Flow Using Particle Swarm Optimization”, Electrical Power and Energy Systems 24 (2002). Power Systems, Vol. 17, No. 2, May 2002, pp. 563-571.

18. Kennedy, J., “The Particle Swarm: Social Adaptation of Knowledge”, Proc 1997 IEEE International Conference Evolutionary Computation ICEC 97, Indianapolis, IN, USA, 1997:303-8.

19. Angeline, P. “Evolutionary Optimization Versus Particle Swarm Optimization: Philosophy and Performance Differences”, Proc 7th Annual Conference Evolutionary Programming 1998:601-10.

20. Shi, Y., Eberhart, R., “Parameter Selection in Particle Swarm Optimization”, Proc 7th Annual Conference Evolutionary Programming 1998:591-600.

21. Ozcan, E., Mohan, C., “Analysis of a Simple Particle Swarm Optimization System”, Intelligent Engineering System Artificial Neural Networks, 1998; 8:253-258.

22. Stott, B., Marinho, J.L., “Linear Programming for Power System Network Security Applications”, ibid., PAS-98,1979, pp. 837-848.

23. Eberhart, R.C., Shi, Y., “Comparing Inertia Weights and Constriction Factors in Particle Swarm Optimization”, *IEEE int. Conf. Evolutionary Computation* ,2000.,pp.84-88.

24. Abido, M.A., “Optimal Design of Power-System Stabilizers Using Particle Swarm Optimization”, IEEE Transactions on Energy Conversion, Vol. 17, No.3, September 2002, pp. 406-413.

25. Gaing, Z.L., “Particle Swarm Optimization to Solving the Economic Dispatch Considering the Generator Constraints”, IEEE Transactions on Power Systems, Vol. 18, No. 3, August 2003, pp. 11871-195.

26. Hirotaka, Y., Kawata, K. Fukuyama, Y., “A Particle Swarm optimization for Reactive Power and Voltage Control Considering Voltage Security Assessment”, IEEE Transactions on Power Systems, Vol. 15, No. 4, , November 2000, pp.1232–1239.

27. Miranda, V., Fonseca, N., “EPSO-Evolutionary Particle Swarm Optimization, a New Algorithm with Applications in Power Systems”, IEEE Transactions on Power Systems, 2000, pp. 745–750.

28. Shi, Y., Eberhart, “A Modified Particle Swarm Optimizer”, Proceedings of IEEE International Conference on Evolutionary Computation, Anchorage, May 1998, pp. 69-73

29. Zhenya, H., et al., “Extracting Rules from Fuzzy Neural Network by Particle Swarm Optimization”, Proceedings of IEEE International Conference on Evolutionary Computation, , Anchorage, May 1998, pp. 74-77.

30. Kennedy, J., Spears, W., “Matching Algorithm to Problems: An Expermental Test of the Particle Swarm Optimization and Some Genetic Algorithms on the Multimodal Problem Generator, Proceedings of IEEE International Conference on Evolutionary Computation, Anchorage, May 1998, pp. 78-83.

31. Angeline, P, “Using Selection to Improve Particle Swarm Optimization”, Proceedings of IEEE International Conference on Evolutionary Computation, , Anchorage, May 1998, pp. 84-89.

32. Hadi Saadat, “Power System Analysis”, McGraw-Hill, 1999.