OPTIMAL POWER DISPATCH IN DEREGULATED ENVIRONMENT

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in
Power Systems & Electric Drives

Thapar University, Patiala

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CERTIFICATE

I hereby certify that work which is being presented in the Thesis entitled **"Optimal Power Dispatch in Deregulated Environment"** in partial fulfillment of the requirement 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 supervision of **Dr. Sanjay K. Jain**, Asst. Prof., EIED and **Ms. Shivani Kansal**, Assistant Professor, EIED.

The matter presented in this Thesis has not been submitted for the award of any other degree of this or any other university.

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ABSTRACT

The deregulation of the electric power industry is one of the important aspect in power sector. The deregulation of the electric power industry is intended to create market conditions, competitions and innovation etc. Under deregulation, among various issues, managing dispatch is an important control activity in a power system. The control variables has to be obtained by optimizing different objectives of choice by satisfying the power flow.

In this thesis, bilateral transactions and multilateral transactions, which are likely to occur in deregulated energy markets, are simulated. The Particle Swarm Optimization (PSO) is applied to obtain optimal dispatch problem with bilateral and multilateral transactions. The performance is studied on IEEE 30 bus system for fuel cost minimization, minimization of active power loss and reactive power loss by considering real power generation and bus voltages as control variables. Generators with exponential and quadratic cost characteristics have been used.

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Introduction

1.1 Overview

The Optimal Power Flow (OPF) has been widely used for both the operation and planning of a power system. Therefore, a typical OPF solution adjusting the appropriate control variables, so that a specific objective in operating a power system network is optimized (maximizing or minimizing) with respect to the power system constraints, dictated by the electrical network. The OPF is also suited for deregulated environment and can solve some contractual dispatch, i.e. Bilateral and Multilateral dispatch.

By deregulation we basically mean that the generation portion of electricity service will be open to competition. However, the transmission and distribution of the electricity service will remain regulated. A bilateral transaction between a supplier and a buyer involves the injection of power at one location in the network and the extraction of the same amount of power, at the same time, at another location. Multilateral transactions are an extension of bilateral transactions. In a multilateral transaction, there are many generation points (at least more than one), similarly there are many load points (at least more than one). For optimization any optimization technique is required and Particle Swarm Optimization (PSO) is used in this thesis.Particle Swarm Optimization (PSO) 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, and emerged from earlier experiments with algorithms that modeled the flocking behavior seen in many species of birds.

1.2 Literature Review

The OPF has been developed a long time ago when Carpentier introduced a generalized formulation of the economic dispatch problem including voltage and other operating constraints. This formulation was later named the Optimal Power Flow problem (OPF) [1]. OPF programs based on mathematical programming approaches are used daily to solve very large OPF problems. But they are not guaranteed to converge. The existing OPF approaches have some problems, which include not only the robustness of optimization methodology used, but also the power system modelling.

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 [2], Quadratic Programming [3-4], Linear Programming [5-6], Newton-based techniques [7-9], Sequential unconstrained minimization technique [10], Interior point methods [11] and Parametric method [12]. 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.

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.

Difficulties arise because either the amount of computation required quickly becomes unmanageable as the size of the problem increases or the constraints violate the required assumptions, eg., differentiability or convexity. Unfortunately, the real world often poses such problems .

The evolutionary computation techniques can be constructed to cope effectively with the above difficulties. Evolutionary programming technique may provide more rapid and robust convergence on many function optimization problem. The reason, behind the scheme is that an evolutionary optimization algorithm is unlikely to be the best optimization procedure for any specific function in terms of efficiency convergence rate, solution accuracy, etc.

The various Evolutionary Programming techniques are Genetic Algorithm [13] , Tabu Search [14] and Particle Swarm Optimization (PSO) algorithm[15-20] etc. 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.

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 .In addition, the use of OPF, nowadays, is increasingly more important in solving the problem of inter-utility power transactions in deregulated electricity markets. [21].

In electricity markets, congestion issues and the right of the access to the grid are very important, because these factors can condition agent participation in the market[22]. Economic dispatch solutions using evolutionary programming in the presence of independent power producers (IPPs) and dispatch with bilateral transactions, multilateral transactions and pool transactions have been considered in various papers[23-36].

1.3 Objectives of the work

The objective of the thesis work is to study and simulate the Optimal Power Flow in Deregulated Environment using Particle Swarm Optimization. The particular emphasis is given to simulate the bilateral and multilateral transactions and their behavior under different objectives namely cost minimization, loss minimization and reactive power minimization. The effect of different cost functions is also to be studied,

1.4 Organization of Thesis

The work carried out has been summarized in five chapters.

The Chapter 1 highlights the brief introduction, summary of work carried out by various researchers. The objective of the work is also identified and the outline of the thesis is also given in this chapter.

The Chapter 2 briefly describes Particle Swarm Optimization along with its algorithm.

The Chapter 3 explains the Optimal Power Flow under Deregulated which includes explanation of Optimal Power Flow, Deregulation, Bilateral and Multilateral Transactions. The algorithm for OPF using PSO is also discussed.

The Chapter 4 discusses the Results and Discussions pertaining to various cases.

The conclusions and the scope of further work are detailed in Chapter 5.

Chapter 2

Particle Swarm Optimization

2.1 Overview of Particle Swarm Optimization

In many engineering disciplines a large spectrum of optimization problems has grown in size and complexity. In some instances, the solution to complex multidimensional problems by means of classical optimization techniques is extremely difficult and/or computational expensive.

This realization has led to an increased interest in a special class of searching algorithms, namely, heuristic algorithms. In general, they are referred to as “stochastic” optimization techniques and their foundations lie in the evolutionary patterns and behaviors observed in living organisms.

Particle Swarm Optimization (PSO) 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 James Kennedy and Russell Eberhart in 1995, and emerged from earlier experiments with algorithms that modeled the flocking behavior seen in many species of birds.

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 . 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 analogous to 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 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.

Particle swarm optimization (PSO) which is a population based stochastic optimization technique 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 .

In a PSO algorithm, particles change their positions by flying around in multidimensional search space until a relatively unchanged position has been encountered, or until computational limitations are exceeded . 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 finetune 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.

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.

2.1.1 Advantages of PSO

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

a) PSO is a population-based search algorithm. This property ensures PSO to be less susceptible in being trapped on local minima.

b) PSO makes use of the 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.

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

d) 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. Therefore, this method is different from traditional techniques.

e) 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 which makes it different from Genetic Algorithm (GA) and other heuristic algorithms.

2.2 PSO Algorithm

A general engineering optimization problem can be defined as follows:

Minimize

$$f(X), \qquad X = \{x_{1,} \quad x_2 \ldots\ldots\ldots\ldots\ldots\ldots . x_n\} \in R \ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.1)$$

Subject to

$$f_O(X) \le 0$$

$$f_E(X) = 0$$

Where:

$$X_i^{(L)} \le X_i \le X_i^{(U)}, i = 1, 2, \ldots\ldots., n \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.2)$$

Where (L) and (U) represents lower and upper limits of the i^{th} decision variable

Also,

f (X) represents the objective function.

$f_O(X) \le 0$ represents inequality constraint.

$f_E(X) = 0$ represents the equality constraint.

2.2.1 Basic Terms Used in PSO

The basic terms used in PSO technique are stated and defined as follows:

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 jth particle X (i,j) can be described as:

$$X_i(i) = [X_{j1}(i); X_{j2}(i); \ldots.X_{jk}(i); \ldots.X_{jd}(i);] \quad ..(2.3)$$

Where:

- x’s are the optimized parameters
- d represents number of control variables

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

$$pop(i) = [X_1(i), X_2(i), \ldots\ldots.X_n(i)]^T \quad \ldots\ldots\ldots..(2.4)$$

Where:

n represents the number of candidate solutions.

3. *Swarm:* Swarm may be defined as 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):* Particle velocity is the velocity of the moving particles represented by a d-dimensional real-valued vector. At iteration i, the jth particle Vj (i) can be described as:

$$V_j(i) = [V_{j1}(i); V_{j2}(i); \ldots.V_{jk}(i); \ldots.V_{jd}(i);] \quad \ldots\ldots\ldots\ldots..(2.5)$$

Where:

$V_{jk}(i)$ is the velocity component of the jth particle with respect to the kth dimension.

5. Individual best X* (i): When particles are moving 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 jth particle, individual best can be expressed as:

$$X_j(i) = [X_{j,1}*(i), X_{j,2.}*(i), ...X_{j,d}*(i)]^T \quad \text{……………………(2.6)}$$

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

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

7. Stopping criteria: Termination of search process will take place 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 kth 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 kth dimension is characterized by the range of the kth optimized parameter and given by:

$$V_k^{\max} = (X_k^{\max} - X_k^{\min}) / N \quad \text{………………..(2.7)}$$

Where:

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

2.2.2 The Algorithm

The general Particle Swarm Optimization algorithm may be applied to any optimization problem. 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 . Therefore, each optimized parameter represents a dimension of the problem space.

The steps taken to build up PSO basic algorithm are:

***Step 1*: Random Initialization**: Firstly we set i=0 and randomly generate n particles, $\{Xj(0), j=1,2,....n\}$. Each particle is considered to be a solution for the problem and it can be described
as

$$X_j(0)=[X_{i,1}(0);X_{i,2}(0);........;X_{i,k}(0)] \quad \text{.................................(2.8)}$$

Every control variable has a range $[X_{\min}, X_{\max}]$.

Random initialization of each particle and velocity is done using the objective function . If the candidate solution is a feasible solution, i.e. all the problem constraints have been met, then we go to step-2 else we repeat this step.

***Step 2*: Counter is Updated**: The next step we do is Updating the counter i= i +1.

***Step 3*: Calculation of the objective function:** Then the objective function is calculated.

***Step 4*: Velocity is updated**: By using the global best and individual best, the jth particle velocity in the kth dimension is updated according to the following equation:

$$V(k,j,i+1)=V(k,j,i)+C_1\times rand\times(p_{best}x(j,k)-x(k,j,i))+C_2\times rand\times(g_{best}x(k)-x(k,j,i)) \quad \text{.....(2.9)}$$

Where,

- i is the iteration number.
- j is the particle number.
- k is the kth control variable.
- c1, c2 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, the velocity limits are checked. If the velocity violates its limit, it is set 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 their own thinking and memory. The third term of the above equation represents the social part of PSO where the particle changes its velocity based on the social-psychological adaptation of knowledge.

***Step 5*: Position is updated**: On the basis of the updated velocity, each particle changes its position .

$$x(k,j,i+1) = x(k,j-1,i) + v(k,j,i) \qquad \text{……………………………………..(2.10)}$$

***Step 6*: Individual best updating**: Evaluation of each particle is done and particle is updated according to the update position.

***Step 7*: Search Minimum value:**The minimum value in the individual best is searched 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 the whole process is stopped otherwise go to step-2.

The flow chart for the above algorithm is shown in Fig. 2.1

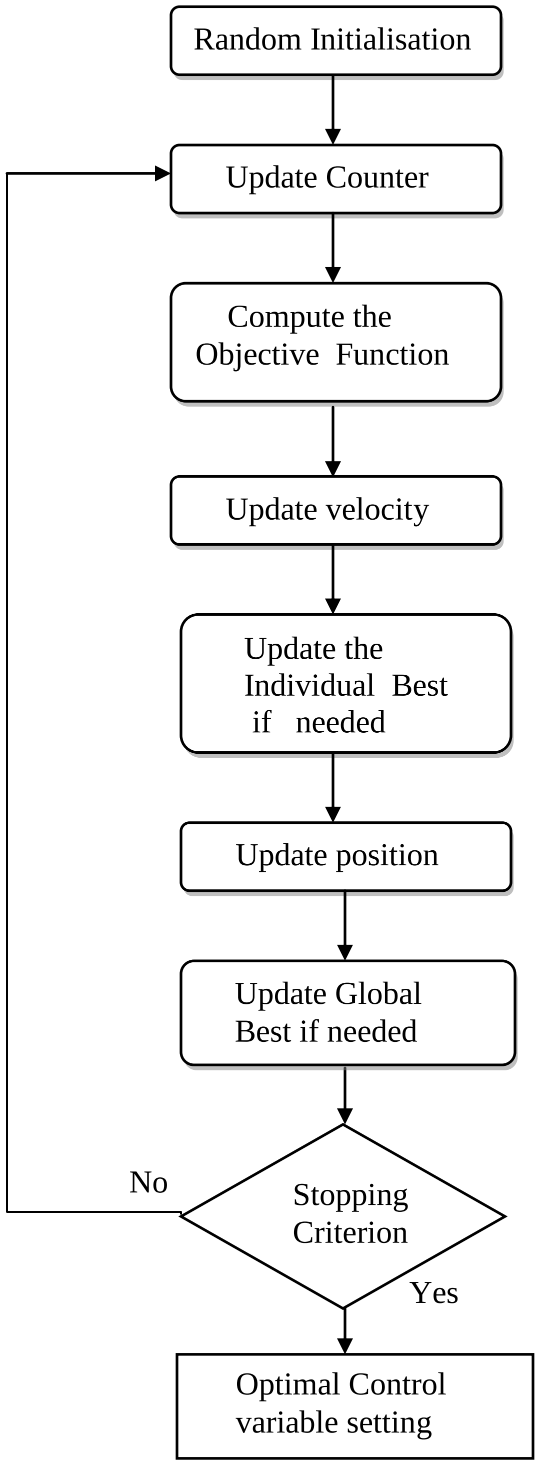


Fig.2.1 Flowchart for Basic Particle Swarm Optimization Algorithm

2.3 Concluding Remarks

The review of Particle Swarm Optimization algorithm has been presented. The background for Optimal Power Flow using PSO has been set.

Chapter 3

Optimal Power Flow under Deregulation

3.1 Optimal Power Flow

Optimal power flow (OPF) has been widely used in power system operation and planning. In deregulated environment of power sector, it is of increasing importance, for determination of electricity prices and also for congestion management.OPF is a computationally intensive tool when analyzing many generation plants, transmission lines and demands. Finally the engineering constraints and economic objectives for system operations are combined by formulating and solving the optimal power flow problem. OPF is used in economic analysis of the power system as well.

Optimal Power Flow (OPF) is a method to find steady state operation point which minimizes generation cost, loss etc. or maximizes social welfare, loadability etc while maintaining an acceptable system performance in terms of limits on generator’s real and reactive powers, line flow limits, output of various compensating devices etc.

The OPF problem may also have the formulation 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 .

On 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 can be used to obtain the settings of the control variables under the steady-state functions of the power system. These control variables may include generator control and transmission system control variables. For generators, the control variable can be generator MW outputs . For the transmission system, the control variable can be bus voltages of the generator buses, the tap ratio or phase shift angle for transformers, settings of switched shunt or flexible ac transmission system (FACTS) devices.

3.1.1 Features of OPF

Hence, the main features of Optimal Power Flow are:

a) OPF Minimize cost function, such as operating cost, taking into account realistic equality and inequality constraints.

b) OPF is basically a combination of economic dispatch and losses.

c) The Equality constraints while formulating OPF are Bus real and reactive power balance, generator voltage set points, area MW interchange etc.

d) The Inequality constraints while formulating OPF are transmission line/transformer/interface flow limits, generator MW limits, generator reactive power capability curves, bus voltage magnitudes.

e) The available Controls are generator MW outputs, transformer taps and phase angles etc.

3.1.2 Applications of OPF

The OPF has many applications which include :-

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

b) The OPF can be set up to provide a preventive dispatch if the security constraints are incorporated.

c) 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 can be performed in order to mitigate the overload or voltage violation problems.

d) 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.

e) 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).

3.2 General OPF Formulations

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

Minimize:

$$f(x,u) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.1)$$

Subject to:

$$f_E(x,u) = 0 \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.2)$$

$$f_o(x,u) \le 0 \quad \text{...(3.3)}$$

$$f_c(x,u) \le 0 \quad \text{...(3.4)}$$

Where:

The objective function is a scalar function. Two types of variables appear in the above optimization problem:

x is a set of state variables (voltage magnitudes v and phase angles θ for each node in the network) and u is the set of controllable quantities in the system(generator outputs, adjustable transformers)

$$x = \left(\frac{v}{\theta} \right) \quad \text{...(3.5)}$$

Also,

$$u = \left(\frac{\frac{\frac{P_g}{Q_g}}{t_b}}{\phi} \right) \quad \text{..(3.6)}$$

where, the number of control variables are active power (Pg) ,reactive power (Qg), tap changing transformers (tb), phase shifting transformers(ϕ).

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

- $f_E(x,u) = 0$ are the equality constraints.

- $f_o(x, u) \leq 0$ 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 limitations are:

  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.

- $f_c(x, u \leq 0$ 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.

3.2.1 The Objectives

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

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

Minimize

$$f_T = \sum_{i=1}^{Ng} f_i(P_{gi}) \quad \text{..} (3.7)$$

$$f_i(P_{gi}) = a_i + b_i P_{gi} + c_i P_{gi}^2 \quad \text{...}(3.8)$$

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

$$P_g = \left[P_{g1}, P_{g2}, ... P_{gn} \right]^T \quad \text{..................................}(3.9)$$

Minimization of Active Power Transmission Loss

Active power loss plays a great role in solving OPF problem. It can be obtained by subtracting active power (generation) from active power (demand). The expression for active power loss is as below:

$$P_L = \sum P_{gi} - \sum P_{di} \quad \text{...}(3.10)$$

The term P_L in the above two equations represents the total I^2R loss in the transmission lines and transformers of the network. The individual current in the various transmission lines of the network cannot be calculated unless both the voltage magnitude and angle at each bus in the electrical network are known. In practice, the Power loss is higher than zero.

Minimization of Reactive Power Transmission Loss

Static network-related system Voltage Stability Margin (VSM) depends on the availability of reactive power to support the transportation of real power from sources to sinks . In practice, the Q_L is not necessarily positive. The expression for reactive power loss minimization is as below:

$$Q_L = \sum Q_{gi} - \sum Q_{di} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.11)$$

3.2.2. The Constraints

The control variables for the OPF are active power at all generator units generator bus voltages; transformer tap positions; and switch-able shunt reactors. But before describing the various constraints it is important to describe the various types of buses in power system in brief.

The buses in electric power system are generally classified into three categories, generation bus, load bus and slack bus. Generation bus is also called PV bus, the voltage magnitude $|V|$ and real power P are specified on this bus. Whereas , Load bus is called PQ bus , the real power P and reactive power Q are specified on this bus. Also there is third type of bus called Slack bus or Reference bus where where voltage magnitude $|V|$ and phase angle Φ are specified.

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:

<u>Equality Constraints</u>

The equality constraints of the OPF reflect 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

$$f(V,\Phi)=0 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.12)$$

Where

$$f(V,\Phi)=P_i(V,\Phi)-P_i^{net} \quad \ldots\ldots\ldots\ldots..(3.13)$$

$$Q_i(V,\phi)-Q_i^{net} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots...(3.14)$$

$$P_m(V,\phi)-P_m^{net} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots...(3.15)$$

where:

- Pi and Qi 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.
- Pm and Pmi are respectively calculated and specified real power for PV bus m.
- V and f are voltage magnitude and phase angles at different buses.

Inequality Constraints

The inequality constraints of the OPF reflect the limits incorporated in the power system and also to ensure system security. The various 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 reactive power generation Qgi at each PV bus.

$$Q_{gi}^{\min} \leq Q_{gi} \leq Q_{gi}^{\max} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.16)$$

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

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

$$\phi_i^{min} \le \phi_i \le \phi_i^{max} \quad \text{……………………………………….(3.17)}$$

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

• MVA flow limit on transmission line

$$MVA_{jj} \le MVA_{jj}^{max} \quad \text{…………………………...........(3.18)}$$

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

3.2.3 The Control Variables

The control variables are described as below:

- Only Pg as a control variable

$$[P_1, P_2 \ldots\ldots\ldots\ldots\ldots\ldots P_n] \quad \text{………………………... (3.19)}$$

- Pg and generator bus voltages as control variable

$$[P_1, P_2 \ldots\ldots\ldots\ldots\ldots\ldots P_n, V_1, V_2 \ldots\ldots\ldots\ldots\ldots\ldots V_n] \quad \text{……………..(3.20)}$$

3.3 Deregulation

The electricity market has experienced enormous setbacks in delivering on the promise of deregulation. In theory, deregulating the electricity market would increase the efficiency of the industry by producing electricity at lower costs and passing those cost savings on to customers.

For the electric industry, deregulation means the generation portion of electricity service will be open to competition. However, the transmission and distribution of the electricity will remain regulated and our local utility company will continue to distribute electricity to us and provide customer services to us. The generation of electricity is being deregulated, which means we will have the opportunity to shop around for the electricity-generation supplier of choice.

The electricity market has experienced enormous setbacks in delivering on the promise of deregulation. In theory, deregulating the electricity market would increase the efficiency of the industry by producing electricity at lower costs and passing those cost savings on to customers.

India also had a centralized institutional environment for the provision of electricity. India's power generation management in India was structured by the Electricity (Supply) Act of 1948. The 1948 Act provided for the establishment of a Central Electricity Authority (CEA). The CEA was established with the purpose of developing a uniform national power policy and of providing clearance for power projects.

The 1948 Act also set up a network of state electricity boards (SEBs), power generation undertakings and management boards under central or joint partnership for the purpose of meeting regional power requirements. Currently, there are 18 SEBs that generate about two-thirds of the country's transmission, distribution and supply of electricity.

3.3.1 Requirements, Benefits, Effects and Impact of Deregulation.

The requirements of deregulation are:

- Good operations, planning and market design engineers.

- Sufficient supply and fuel diversity.
- Sufficient transmission infrastructure.
- Efficient demand side responsiveness and management.
- Provision of right incentives and good price signals.

The benefits of Deregulation include

- It involves issue of survival of the fittest i.e. efficient units live and others pernish.
- Cheaper electricity through competition and innovation.
- Improves generation and planning efficiency and economy.
- Revitalization of the power engineering profession means increased job and challenging opportunities.

Following are the effects of Deregulation:

After the deregulation of electricity there is a huge change in our electricity bills. Utility bills for electricity now include one total price for all these components: generation, transmission, distribution, and local service. There are separate additional charges for fuel adjustment and taxes.

Utility bills in the deregulated environment will be "unbundled," meaning that each of the components will be itemized separately with a price per kilowatt hour (kWh) for each. In addition, there may be a competitive transition charge or stranded investment charge for each kWh.

The impacts of deregulation on Power System Operation are following:

- Splitting into separate entities.

- Grid (network) operators turn into neutral system providers.

- Power plant operator’s turn into power production companies.

- Consumers are treated as customers.

- The interfaces especially of grid operators and power production companies changed to commercially sensitive ones.

- Investments are reduced to minimum with system operated closer to their limits.

- A high grade of system automation occurs.

- Early retirement programs reduce the number of operating personnel in the control centre.

3.4 Various Transaction Models

Following the success of liberalization of various sectors of the economy, electricity markets underwent transition. Vertically integrated utilities, which managed generation, transport and supply of electricity, were unbundled, and competition in generation and supply was introduced. Given the differences in electricity market structures and regulatory policies around the world, there is no single standard market model**.**

The transaction models are

- Bilateral transaction.
- Multilateral transaction.
- Pool model.

3.4.1 Bilateral Transactions

A bilateral transaction between a supplier and a buyer involves the injection of power at one location in the network and the extraction of the same amount of power, at the same time, at another location. Each bilateral transaction should, therefore, be represented by a Source (positive injection) connected to the point of injection and a sink (negative injection) connected to the point of extraction. The source and the sink are assumed to have the same size(transaction rate in MW). The power injections associated with different bilateral transactions can influence the loading on transmission facilities. As a result, power flows on lines and transmission interfaces can increase or decrease depending on the system operating conditions, transaction size, direction of power transfer and the number of transactions considered.

The conceptual model of bilateral structure is that gencos and discos enter into transaction contracts where the quantities traded and the prices are at their own discretion and not a matter for the ISO i.e. a bilateral transaction is made between a genco and a disco without third party intervention. These transactions are then submitted to the ISO.

In the absence of any congestion on the system, the ISO simply dispatches all the transactions that are requested, making an impartial charge for the service. In a bilateral trading model:

- Players arrange the purchase and sale transactions among themselves.

- Each schedule coordinator (SC) and each power exchange (PX) are responsible for ensuring supply/demand balance.

- The independent system operator (ISO) has the role to facilitate the undertaking of as many of the contemplated transactions as possible subject to ensuring that no system security and physical constraints are violated.

In a bilateral market mode, the purpose of the optimal transmission dispatch problem is to minimize deviations from transaction requests made by the market players. The goal is to make possible all transactions without curtailments arising from operating constraints.

The new set of rescheduled transactions thus obtained will be closest to the set of desired transactions, while simultaneously satisfying the power flow equations and operating constraints.

The power injections associated with different bilateral transactions can influence the loading on transmission facilities. As a result, power flow on lines and transmission interfaces can increase or decrease depending on the system operating conditions, transaction size, and the direction of power transfer and the number of transactions considered.

So, the utility is required to take an optimal decision in selecting the location of IPPs (invo1ved in transaction) and the magnitude of feasible transactions such that the economic dispatch solutions leads to either further optimized or unchanged.

Mathematically, each bilateral transaction between a seller at bus-*i* and power purchaser at bus-*j* satisfies the following power balance relationship.

$$P_{gi} - P_{dj} = 0 \qquad \text{……………………………………(3.21)}$$

where *Pgi* and *Pdj* represent the power injection into the seller bus-*i* and the power taken out at buyer bus-*j*.

3.4.2 Multilateral Transactions

Multilateral transactions are an extension of bilateral transactions. It is a trade that is arranged by energy brokers. In a multilateral transaction, there are many generation points (at least more than one), similarly there are many load points (at least more than one).

The scheduling coordinator (SC) of a group of multilateral transactions provides the maximum as well as proposed generation and demand at different generation and demand points, respectively. The coordinator also provides the maximum and proposed demands at different load points of the group. The SC determines the feasibility of this group of multilateral transaction and suggests minimum possible curtailments . After finalization, the feasible multilateral transaction is scheduled.

In the case of multi-lateral transaction, the summation of power injected in different buses *(i)* is equal to the summation of load powers taken out at various buses *(j)*.

$$\sum_i P_{gi}^k - \sum_j P_{dj}^k = 0 \qquad \text{......................(3.22)}$$

Where,

$$k = 1, 2, ...t_k$$

where *Pgi* and *Pdj* represent the power injection into the seller bus-*i* and the power taken out at buyer bus-*j*, t_k is the total number of transactions.

3.4.3 Pool Dispatch

The pool is the sole buyer and seller of electricity. The pool uses the offers of suppliers and bid of the demanders to determine the successful bidders whose offers and bid have been accepted.

The pool offers the "optimum" by solving a centralized economic dispatch model taking into account the network constraints. In case of congestion management in pool model, the pool model considers explicitly the impact of transmission network constraints. The pool model assumes implicitly the commitment of generators which are bidding to supply power. The determination of economic optimum is done with the explicit consideration of the congestion.

3.5 OPF using PSO

Particle Swarm Optimization (PSO) algorithm is reviewed in Chapter 2. The PSO is applied for OPF. The optimization is carried out using (i) Pg's as control variables. (ii) Both Pg's and generator bus voltages as control variables for minimizing the generation cost, minimization of active power loss and reactive power loss. The algorithm for generation cost optimization using Pg's as control variables is presented herewith.

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

Step 1: Firstly read the Input parameters of system (bus, line and generator data) and also specify the lower and upper boundaries of each variables. For N generators, optimization is carried out for N-1 generators and generator of large capacity is considered at slack bus.

Step 2: Then the particles of the population are randomly initialized i.e. P_i are randomly selected between the respective minimum and maximum values.Also assign the velocity V initially between [-1 and 1].

Step 3: Obtain power flow solution and compute losses by Newton-Raphson method. Calculate the fitness function as

$$= \sum_{i=1}^{N} c_i + k(abs([P_D - P_L - \sum P_g]) \qquad \text{……………………...(3.23)}$$

Step 4: The best fitness is assigned as *pBest* . At this stage the *pBest* is also the *gBest* .

Step 5: Iteration *i* = i+1 is updated.

Step 6:The velocity *v* of each particle is modified according to the mentioned equation.

$$V(k,j,i+1) = V(k,j,i) + C_1 \times rand \times (p_{best}x(j,k) - x(k,j,i)) + C_2 \times rand \times (g_{best}x(k) - x(k,j,i)) \quad (3.24)$$

Step7: The position of each particle is also modified according to the mentioned equation.

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

$$x(k, j, i+1) = x(k, j-1, i) + v(k, j, i) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.25)$$

Step 8: Evaluation of each particle is done according to its updated position by running power flow and calculate the fitness function. If the evaluation value of each particle is better than the previous *pBest* then the current value is set to be *pBest* . If the best *pBest* is better than *gBest* , the value is set to be gbest.

Step 9: If one of the stopping criteria is satisfied then we go to Step 10. Otherwise, we go to Step 5.

Step 10: *gBest* is the optimal value that is latestly generated by the particle.

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

a. Both acceleration factors C1 & C2.

b. Number of particles.

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

_ |gbestf(i) - gbestf(i-1)| < 0.0001 for 50 iterations

_ Maximum number of iteration reached (500 iterations)

The flow chart of PSO based OPF is shown in Fig. 3.1

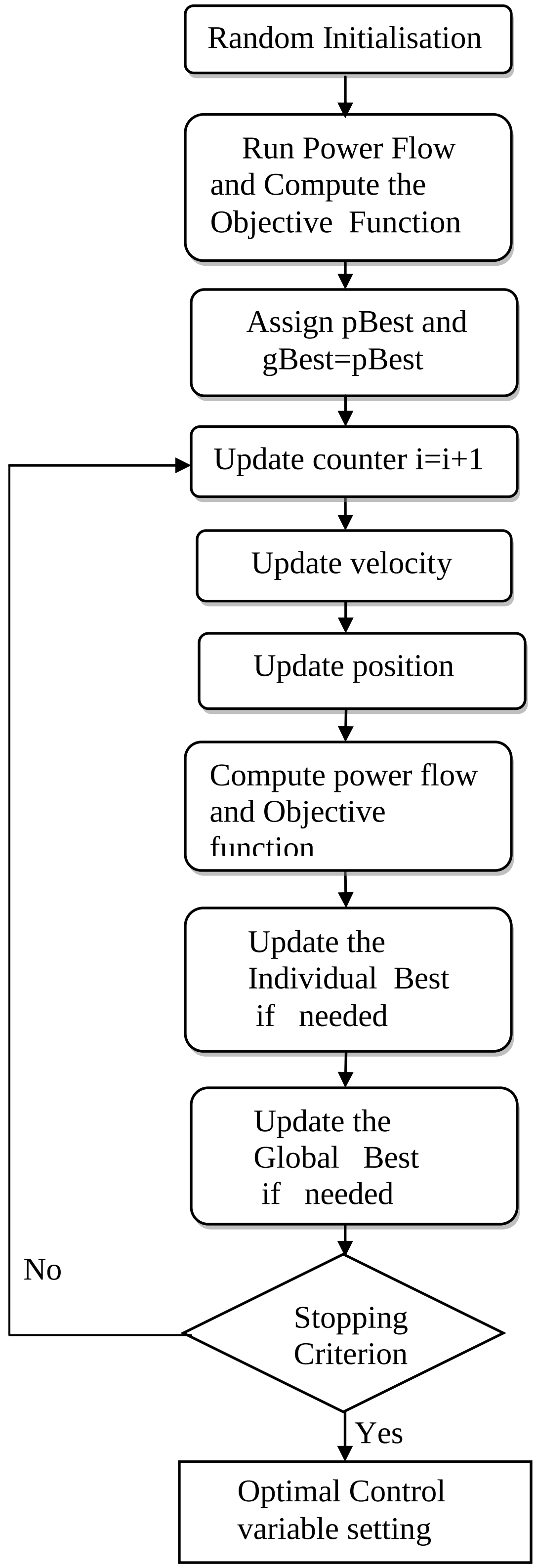


Fig.3.1 Flowchart of PSO based OPF

3.6 Concluding Remarks

The review of Optimal power flows, OPF formulation, the review of deregulation and transaction models namely Bilateral, Multilateral and Pool model are briefly explained in this chapter. The algorithm for OPF using PSO is also presented.

CHAPTER 4

Results and Discussion

The OPF using PSO has been carried out on the IEEE 30 bus system. The specifications of the IEEE 30 bus system and the cost functions are given in Appendix. The OPF solution has been attempted for minimizing the generation cost, active and reactive power loss by considering the (i) Generation Pg's, (ii) Generation Pg's and generator bus voltages as control variables.

The simulation has been carried out on system having 1.8 GHz Pentium 4 processor with 256 MB of RAM in MATLAB 7.5.0 environment. Results are viewed taking fuel cost as objective function, active power loss as objective function and reactive power loss as objective function. For the studies, the population size is considered as 100.

The various transactions for this system are taken from [23], [31]. The various transactions are -

Bilateral Transaction T1: 10MW of power is injected at the generator bus 5 and same net amount of power is consumed from load bus 29.

Bilateral Transaction T2: 10MW of power injected at the load bus 29 and same amount of power is consumed from generator bus 5.

Multilateral Transaction T3: With injection of 10 MW and 10MW in the generator buses 5 and 8 respectively and load of 5 MW, 15 MW in the load buses 20 and 29 respectively.

Multilateral Transaction T4: With injection of 10 MW and 10 MW in the load buses 20 and 29 respectively and load of 5 MW, 15 MW in the generator buses 5 and 8 respectively.

Various case studies

The above study has been summarized under the following Cases

CASE 1	Base case power flow solution.
CASE 2	Minimize generation cost with Pg's as Control variables (generation unit has Quadratic cost function) .
CASE 3	Minimize generation cost with both Pg's and generator bus voltages as Control variables (generating unit has Quadratic cost function).
CASE 4	Minimize generation cost with Pg's as Control variables (generation unit has Exponential cost function) .
CASE 5	Minimize generation cost with both Pg's and generator bus voltages as Control variables (generating unit has Exponential cost function).
CASE 6	Minimizing Active Power Loss with Pg's as control variables.
CASE 7	Minimizing Active power loss with both Pg's and generator bus voltages as control variables.
CASE 8	Minimizing Reactive Power Loss with Pg's as control variables.
CASE 9	Minimizing Reactive Power loss with both Pg's and generator bus voltages as control variables.

CASE 1 Base case power flow solution

The base case power flow results are obtained from Newton-Raphson method and the results are summarized in Table 4.1

TABLE 4.1 Basic Case OPF Solution

Bus No.	Bus Code	V(p.u)	Delta Angle	Pd (MW)	Qd (Mvar)	Pg (MW)	Qg (Mvar)	Qmin	Qmax	Tap set.
1	1	1.06	0.0000	0	0	260.2	0	-20	250	0
2	2	1.043	-5.3422	21.7	12.7	68.8834	0	-20	100	0
3	0	1.0235	-7.5693	2.4	1.2	0	0	0	0	0
4	0	1.0142	-9.3100	7.6	1.6	0	0	0	0	0
5	2	1.01	-14.148	94.2	19	0	0	-15	80	0
6	0	1.0122	- 11.0774	0	0	0	0	0	0	0
7	0	1.0044	-12.8796	22.8	10.9	0	0	0	0	0
8	2	1.01	-11.7929	30	30	0	0	-15	60	0
9	0	1.0512	-14.1071	0	0	0	0	0	0	0
10	0	1.0446	-15.694	5.8	2	0	0	0	0	19
11	2	1.082	-14.1071	0	0	0	0	-10	50	0
12	0	1.0577	-14.9574	11.2	7.5	0	0	0	0	0
13	2	1.071	-14.9574	0	0	0	0	-15	60	0
14	0	1.0427	-15.8476	6.2	1.6	0	0	0	0	0
15	0	1.038	-15.9358	8.2	2.5	0	0	0	0	0
16	0	1.0445	-15.5297	3.5	1.8	0	0	0	0	0
17	0	1.0396	-15.8594	9	5.8	0	0	0	0	0
18	0	1.0282	-16.5451	3.2	0.9	0	0	0	0	0
19	0	1.0255	-16.7159	9.5	3.4	0	0	0	0	0
20	0	1.0295	-16.5177	2.2	0.7	0	0	0	0	0
21	0	1.0323	-16.1372	17.5	11.2	0	0	0	0	0
22	0	1.0329	-16.1231	0	0	0	0	0	0	0
23	0	1.0274	-16.3221	3.2	1.6	0	0	0	0	0
24	0	1.0216	-16.4931	8.7	6.7	0	0	0	0	4.3
25	0	1.0184	-16.0813	0	0	0	0	0	0	0
26	0	1.0007	-16.5000	3.5	2.3	0	0	0	0	0
27	0	1.0249	-15.5666	0	0	0	0	0	0	0
28	0	1.0095	-11.7133	0	0	0	0	0	0	0
29	0	1.0051	-16.7924	2.4	0.9	0	0	0	0	0
30	0	0.9937	-17.6722	10.6	1.9	0	0	0	0	0

CASE 2 Minimize generation cost with Pg's as Control variables (generation unit has Quadratic cost function)

For case-2, the results are summarized in Table 4.2. As mentioned, Quadratic cost function is taken as the objective function considering Pg's only as the control variables. The various cases are discussed under this for example Generation Schedule MW by PSO, Generation Schedule (MW) introducing Bilateral transaction T1 and Generation Schedule (MW) introducing Bilateral transactionT2, Generation Schedule (MW) introducing Multilateral transaction T3, Generation Schedule (MW) introducing Multilateral transaction T4.

Table 4.2 Summary of OPF using PSO for generation cost minimization with Pg's as Control variables (generation unit has Quadratic cost function) .

Bus No	Generation Schedule MW by PSO	Generation Schedule (MW) introducing Bilateral transactions		Generation Schedule (MW) introducing Multilateral transactions	
		T1	T2	T3	T4
1	177.8944	175.8634	176.9928	176.8249	176.9499
2	48.8570	49.8589	48.4033	47.6176	48.7741
5	21.2318	21.5325	21.2489	21.5343	21.4396
8	21.1519	21.4411	22.2134	22.5360	22.6758
11	11.8220	12.2651	12.4263	12.4483	12.0401
13	12.0000	12.0000	12.0000	12.0000	12.0000
Total cost	802.1789	802.6471	803.6821	802.7257	805.8001
Active power loss	9.5578	9.5609	9.8845	9.5610	10.4795
Reactive power loss	-54.5679	-55.4990	-52.7109	-56.5745	-49.5556

Its clear from the above table that total cost is minimum in case of Generation Schedule MW by PSO. But in case of contracts , the total cost is minimum in case of Generation Schedule (MW) introducing Bilateral transaction T1. But it is having a limitation that reactive power loss comes out to be a little more than Generation Schedule MW by PSO.

The convergence of the cost function for OPF without and with different Transactions are plotted in Fig. 4.1 to Fig. 4.5 respectively.

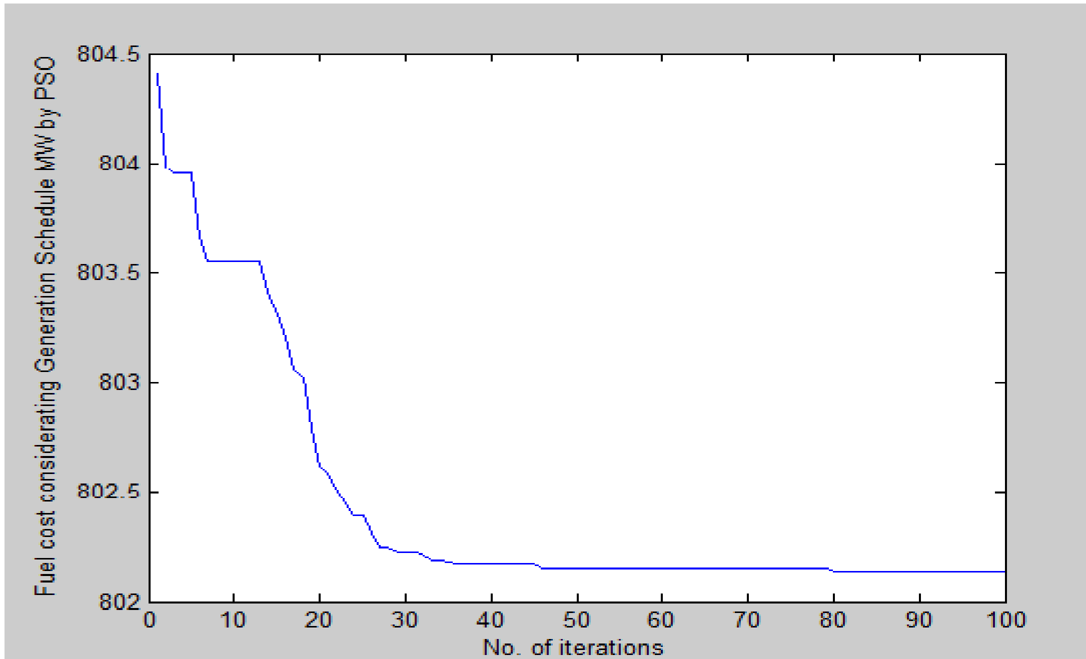


Fig.4.1 Variation of Fuel cost V/s iterations for Generation Schedule MW by PSO for minimizing generation cost with Pg’s as Control variables (generation unit has Quadratic cost function).

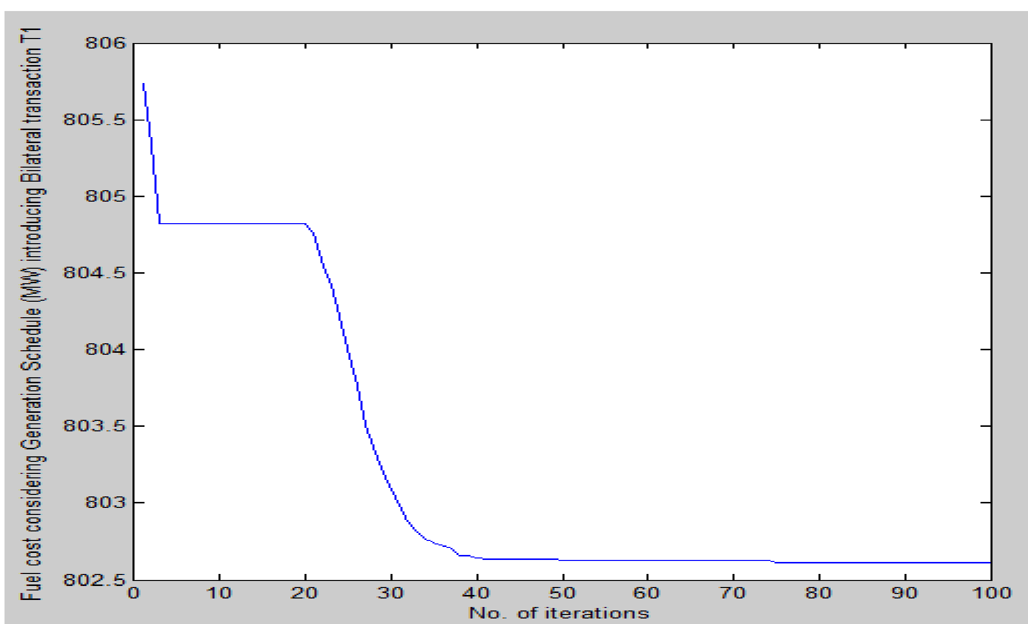


Fig.4.2 Variation of Fuel cost V/s iterations for Bilateral transaction T1 for minimizing generation cost with Pg’s as Control variables (generation unit has Quadratic cost function).

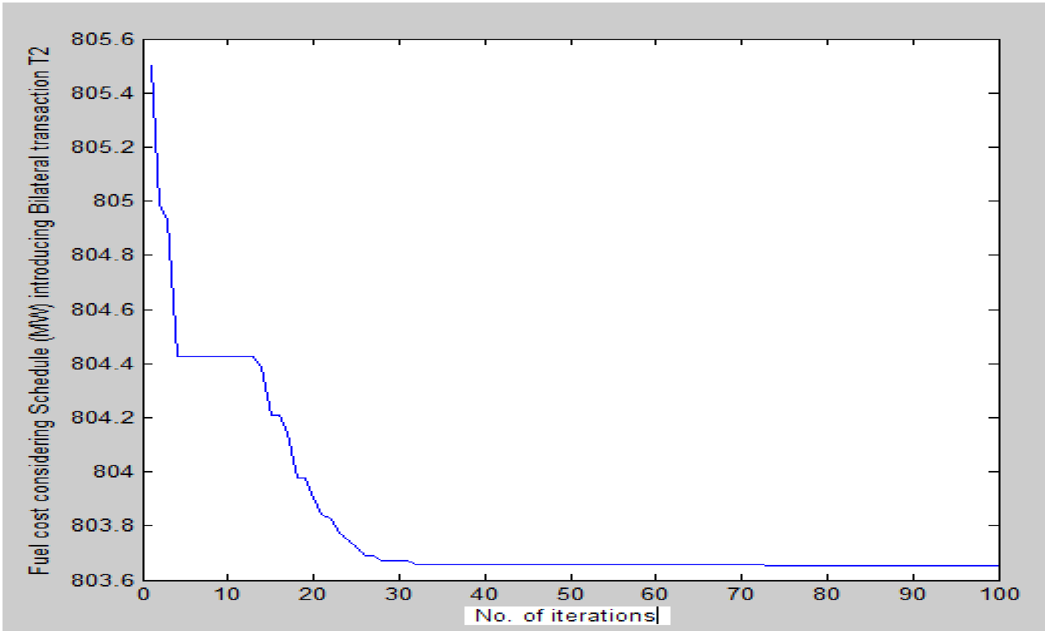


Fig.4.3 Variation of Fuel cost V/s iterations for Bilateral transaction T2 for minimizing generation cost with Pg's as Control variables (generation unit has Quadratic cost function).

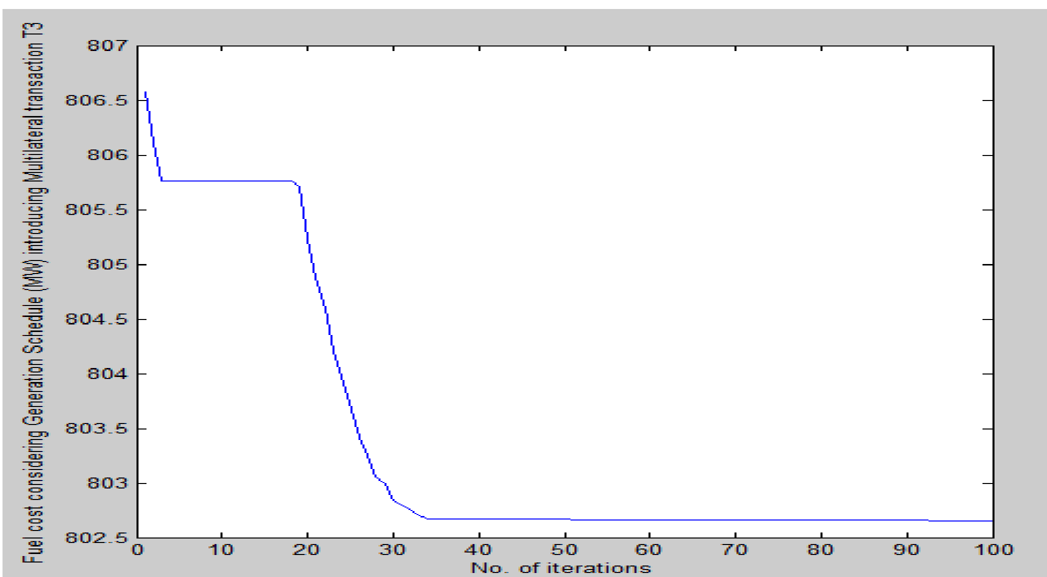


Fig.4.4 Variation of Fuel cost V/s iterations for Multilateral transaction T3 for minimizing generation cost with Pg's as Control variables (generation unit has Quadratic cost function).

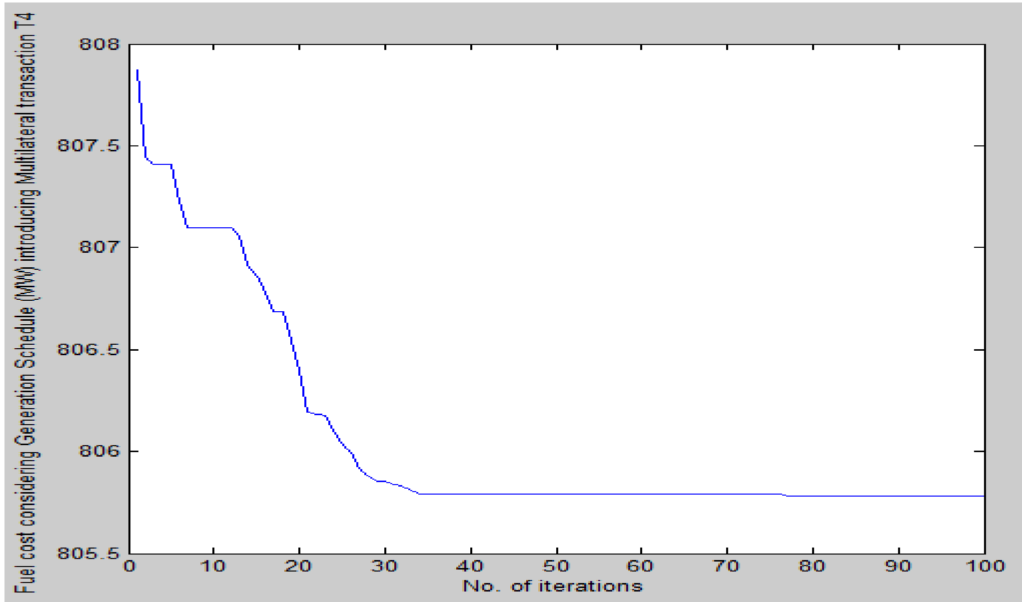


Fig.4.5 Variation of Fuel cost V/s iterations for Multilateral transaction T4 for minimizing generation cost with Pg's as Control variables (generation unit has Quadratic cost function).

The convergence for various Transactions is resulted in different number of iterations because the nature of the swarm optimization algorithm i.e. evolutionary nature.

CASE 3 Minimize generation cost with both Pg's and generator bus voltages as Control variables (generating unit has Quadratic cost function).

The minimization of generation cost with both Pg's and generator bus voltages as Control variables has been attempted and the results under various Transactions are summarized in Table 4.3. The generators are assumed to have Quadratic cost function. Its seen that the total cost is minimum in case of Generation Schedule (MW) introducing Multilateral transaction T3 but it has maximum reactive power loss. If we compare Table 4.2 and 4.3 (a) then it is observed that no doubt cost is a bit more but still reactive power loss are reduced a great amount.

Table 4.3(a) Summary of OPF using PSO for generation cost minimization with both Pg's and generator bus voltages as Control variables (generation unit has Quadratic cost function) .

Bus No	Generation Schedule MW by PSO	Generation Schedule (MW) introducing Bilateral transaction		Generation Schedule (MW) introducing Multilateral transaction	
		T1	T2	T3	T4
1	176.4507	177.2529	176.9100	176.5559	177.8972
2	49.1716	48.5905	48.4935	48.9261	48.8333
5	21.5114	21.6152	21.3602	21.4204	21.3991
8	22.1797	21.8971	23.3387	22.2178	21.2812
11	12.4079	12.4261	12.3588	12.3488	12.5459
13	12.0000	12.0000	12.0000	12.0000	12.0000
Total cost	805.3118	805.3963	807.9679	804.39905	805.7954
Active power loss	10.3213	10.3818	11.0617	10.0689	10.5567
Reactive power loss	-48.7238	-49.1265	-42.5362	-56.7739	-49.3192

Table 4.3 (b) Generation bus voltage profile for OPF (without Transactions) using PSO for generation cost minimization with both Pg's and generator bus voltages as Control variables (generation unit has Quadratic cost function) .

Bus No.	Base case power flow voltages	Power Flow voltages with OPF
1	1.060	1.050
2	1.043	1.050
5	1..010	1.046
8	1.010	1.000
11	1.082	1.050
13	1.071	1.050

While comparing with Table 4.2, the fuel cost with generator buses voltages as also control variables is slightly more because the voltage magnitude limits are considered between 0.95 and 1.05 whereas the base case power flow is resulting into slightly higher voltages at few buses.

CASE 4 Minimize generation cost with Pg's as Control variables (generation unit has Exponential cost function) .

The minimization of generation cost with Pg's as Control variables has been attempted and the results under various Transactions are summarized in Table 4.4. The generators are assumed to have Exponential cost function.

Table 4.4 Summary of OPF using PSO for generation cost minimization with Pg's as Control variables (generation unit has Exponential cost function) .

Bus No	Generation Schedule MW by PSO	Generation Schedule (MW) introducing Bilateral transaction		Generation Schedule (MW) introducing Multilateral transaction	
		T1	T2	T3	T4
1	60.6966	60.6353	60.5107	60.8857	61.1915
2	71.3473	71.4023	72.0948	71.0981	72.0948
5	50.0000	50.0000	50.0000	50.0000	50.0000
8	35.0000	35.0000	35.0000	35.0000	35.0000
11	30.0000	30.0000	30.0000	30.0000	30.0000
13	40.0000	40.0000	40.0000	40.0000	40.0000
Total cost	790.2818	790.2446	794.8216	789.7791	800.1609
Active power loss	3.6439	3.6380	4.2055	3.5837	4.8863
Reactive power loss	-75.1409	-75.6782	-72.9062	-76.3557	-70.0764

It is clear from table 4.2 and 4.4 that the fuel cost is minimum in case of Exponential cost function as objective function Considering Pg only as compared to Quadratic cost function as objective function Considering Pg only.

CASE 5 Minimize generation cost with both Pg's and generator bus voltages as Control variables (generating unit has Exponential cost function).

The minimization of generation cost with both Pg's and generator bus voltages as Control variables has been attempted and the results under various Transactions are summarized in Table 4.5. The generators are assumed to have exponential cost function.

Table 4.5 Summary of OPF using PSO for generation cost minimization with both Pg's and generator bus voltages as Control variables (generation unit has Exponential cost function) .

Bus No	Generation Schedule MW by PSO	Generation Schedule (MW) introducing Bilateral transaction		Generation Schedule (MW) introducing Multi lateral transition	
		T1	T2	T3	T4
1	60.8545	60.7927	61.2490	61.3525	61.7912
2	70.9701	71.1086	71.5257	72.2080	72.1247
5	50.0000	50.0000	50.0000	50.0000	50.0000
8	35.0000	35.0000	35.0000	35.0000	35.0000
11	30.0000	30.0000	30.0000	30.0000	30.0000
13	40.0000	40.0000	40.0000	40.0000	40.0000
Total cost	788.5189	789.1337	796.0468	802.3442	805.1552
Active power loss	3.4246	3.5013	4.374700	5.1604	5.5159
Reactive power loss	-77.1089	-75.4417	-70.1468	-63.2651	-62.0536

It is observed that in this case minimum cost occurs in case of Generation Schedule (MW) introducing Bilateral transaction T1. If we compare Table 4.5 and Table 4 .3 then it is observed that Fuel cost is minimum in case of Exponential cost function as objective function Considering Pg's and generator bus voltages as compared to Quadratic cost function as objective function Considering Pg's and generator bus voltages.

CASE 6 Minimizing Active Power Loss with Pg's as control variables.

The minimization of active power loss with Pg's as Control variables has been attempted and the results under various Transactions are summarized in Table 4.6. It is observed from the table that active power loss is minimum in case of Generation Schedule (MW) introducing Multilateral transaction T3 but reactive power loss is highest in this case.

Table 4.6 Summary of OPF using PSO for Active Power Loss minimization with Pg's as Control variables

Bus No	Generation Schedule MW by PSO	Generation Schedule (MW) introducing Bilateral transaction		Generation Schedule (MW) introducing Multilateral transaction	
		T1	T2	T3	T4
1	51.9758	51.9664	52.5474	51.9091	53.2268
2	80.0000	80.0000	80.0000	80.0000	80.0000
5	50.0000	50.0000	50.0000	50.0000	50.0000
8	35.0000	35.0000	35.0000	35.0000	35.0000
11	30.0000	29.9900	30.0000	30.0000	30.0000
13	40.0000	40.0000	40.0000	40.0000	40.0000
Total cost	968.7984	968.7312	970.1659	968.6392	971.7941
Active power loss	3.5757	3.5564	4.1474	3.5090	4.8268
Reactive power loss	-75.3501	-75.8966	-73.0875	-76.5840	-70.2607

CASE 7 Minimizing Active power loss with both Pg's and generator bus voltages as control variables.

The minimization of active power loss with both Pg's and generator bus voltages as Control variables has been attempted and the results under various Transactions are summarized in Table 4.7

Comparing Table 4.6 and 4.7 it is observed that in case of Generation Schedule MW by PSO active power loss is less in case of Active power loss as objective function Considering Pg's and generator bus voltages.

Table 4.7 Summary of OPF using PSO for Active Power Loss minimization with both Pg's and generator bus voltages as control variables.

Bus No	Generation Schedule MW by PSO	Generation Schedule (MW) introducing Bilateral transaction		Generation Schedule (MW) introducing Multilateral transaction	
		T1	T2	T3	T4
1	51.9090	51.8782	52.3200	52.2443	52.9540
2	80.0000	80.0000	80.0000	80.0000	80.0000
5	50.0000	50.0000	50.0000	50.0000	50.0000
8	35.0000	35.0000	35.0000	35.0000	35.0000
11	30.0000	30.0000	30.0000	30.0000	30.0000
13	40.0000	40.0000	40.0000	40.0000	40.0000
Total cost	968.6391	968.5654	969.6217	969.4405	971.1419
Active power loss	3.5090	3.4781	3.9200	3.8442	4.5548
Reactive power loss	-73.1640	-73.9061	-75.3162	-69.6775	-72.6493

CASE 8 Minimizing Reactive Power Loss with Pg's as control variables.

Table 4.8 Summary of OPF using PSO for Reactive Power Loss minimization with Pg's as Control variables.

Bus No	Generation Schedule MW by PSO	Generation Schedule (MW) introducing Bilateral transaction		Generation Schedule (MW) introducing Multilateral transaction	
		T1	T2	T3	T4
1	229.3559	229.5158	229.7993	229.5604	230.4193
2	20.0000	20.0000	20.0000	20.0000	20.0000
5	15.0000	15.0000	15.0000	15.0000	15.0000
8	10.0000	10.0000	10.0000	10.0000	10.0000
11	10.0000	10.0000	10.0000	10.0000	10.0000
13	12.0000	12.0000	12.0000	12.0000	12.0000
Total cost	832.4735	833.0686	834.1240	833.2845	836.4339
Active power loss	12.9558	13.1157	13.3931	13.1603	14.0192
Reactive power loss	-43.4700	-43.8719	-41.1889	-44.7783	-37.9587

The minimization of reactive power loss with Pg's as Control variables has been attempted and the results under various Transactions are summarized in Table 4.8. It is observed that Reactive power loss is minimum in case of Generation Schedule (MW) introducing Multilateral transaction T4.

CASE 9 Minimizing Reactive power loss with both Pg's and generator bus voltages as control variables.

The minimization of reactive power loss with both Pg's and generator bus voltages as Control variables has been attempted and the results under various Transactions are summarized in Table 4.9. As compared to Table 4.8 it is observed that Reactive power loss as objective function Considering Pg's and generator bus voltages is much less as compared to Reactive power loss as objective function Considering Pg's only.

Table 4.9 Summary of OPF using PSO for Reactive Power Loss minimization with both Pg's and generator bus voltages as control variables.

Bus No	Generation Schedule MW by PSO	Generation Schedule (MW) introducing Bilateral transaction		Generation Schedule (MW) introducing Multi lateral transaction	
		T1	T2	T3	T4
1	212.3940	219.4876	205.3305	209.9323	192.5656
2	20.0000	20.0000	26.6725	39.4749	42.6923
5	15.0000	15.0000	18.9307	15.0000	18.1699
8	10.0000	10.0000	14.6293	11.6319	19.5588
11	30.0000	19.0027	22.3100	12.6247	15.0980
13	12.0000	17.9040	12.0000	12.0000	12.0000
Total cost	850.4534	851.7889	837.5228	830.9379	826.9479
Active power loss	15.9945	17.9943	16.4729	17.2640	16.6866
Reactive power loss	-24.4584	-23.3000	-23.2999	-23.2999	-23.2994

Chapter 5

Conclusion and future Scope

5.1 Conclusions

In this Thesis, we are able to implement bilateral and multilateral dispatch in deregulated power system environment. The present algorithm is able to solve the optimal power dispatch in deregulated environment. The performance of the developed algorithm has been demonstrated by its application to the IEEE 30-bus test system for fuel cost minimization, minimization of active power loss and reactive power loss by considering real power generation and bus voltages as control variables. The Particle Swarm Optimization (PSO) is applied to obtain optimal dispatch problem with bilateral and multilateral transactions. Generators with input/output cost characteristic curves such as exponential cost curve, quadratic curve are used. The algorithm has accurately and reliably converged to the global optimum solution in each case.

- For active power loss minimization, generation levels at upper limit values are selected.
- For reactive power loss minimization, generation levels at lower limit values are selected.
- For generation cost minimization with quadratic cost function, the intermediate settings are selected.
- The cost by considering exponential cost function comes out to be less as compared to the other cases.

5.2 Scope of Future Work

The scope of work after studying Optimal Power Dispatch in Deregulated Environment is identified as:

- investigations including Facts devices shall be attempted.
- extend the problem with discrete variables like transformer tap setting.
- extend the problem for congestion management.

APPENDIX

Table A.1 Bus Data of IEEE 30 Bus-System.

basemva = 100; accuracy = 0.0001; maxiter = 10;

Bus No	Bus code	Voltage Mag.	Angle Deg.	Load		Generator				Injected Mvar
				MW	Mvar	MW	Mvar	Qmin	Qmax	
1	1	1.060	0.0	00.00	00.0	260.2	0.0	00	00	0
2	2	1.043	0.0	21.70	12.7	40.0	0.0	-40	50	0
3	0	1.000	0.0	02.40	01.2	0.0	0.0	00	00	0
4	0	1.060	0.0	07.60	01.6	0.0	0.0	00	00	0
5	2	1.010	0.0	94.20	19.0	0.0	0.0	-40	40	0
6	0	1.000	0.0	00.00	00.0	0.0	0.0	00	00	0
7	0	1.000	0.0	22.80	10.9	0.0	0.0	00	00	0
8	2	1.010	0.0	30.00	30.0	0.0	0.0	-10	40	0
9	0	1.000	0.0	00.00	00.0	0.0	0.0	00	00	0
10	0	1.000	0.0	05.80	02.0	0.0	0.0	00	00	19
11	2	1.082	0.0	00.00	00.0	0.0	0.0	-6	24	0
12	0	1.000	0.0	11.20	07.5	0.0	0.0	00	00	0
13	2	1.071	0.0	00.00	00.0	0.0	0.0	-6	24	0
14	0	1.000	0.0	06.20	01.6	0.0	0.0	00	00	0
15	0	1.000	0.0	08.20	02.5	0.0	0.0	00	00	0
16	0	1.000	0.0	03.50	01.8	0.0	0.0	00	00	0
17	0	1.000	0.0	09.00	05.8	0.0	0.0	00	00	0
18	0	1.000	0.0	03.20	00.9	0.0	0.0	00	00	0
19	0	1.000	0.0	09.50	03.4	0.0	0.0	00	00	0
20	0	1.000	0.0	02.20	00.7	0.0	0.0	00	00	0
21	0	1.000	0.0	17.50	11.2	0.0	0.0	00	00	0
22	0	1.000	0.0	00.00	00.0	0.0	0.0	00	00	0
23	0	1.000	0.0	03.20	01.6	0.0	0.0	00	00	0
24	0	1.000	0.0	08.70	06.7	0.0	0.0	00	00	4.3
25	0	1.000	0.0	00.00	00.0	0.0	0.0	00	00	0
26	0	1.000	0.0	03.50	02.3	0.0	0.0	00	00	0
27	0	1.000	0.0	00.00	00.0	0.0	0.0	00	00	0
28	0	1.000	0.0	00.00	00.0	0.0	0.0	00	00	0
29	0	1.00	0.0	02.40	00.9	0.0	0.0	00	00	0
30	0	1.000	0.0	10.60	01.9	0.0	0.0	00	00	0

Table A.2 Line Data of IEEE 30 Bus-System.

Bus nl	Bus nr	R p.u.	X p.u.	1/2 B p.u.	Line code = 1 for lines > 1 or < 1 tr. tap at bus
1	2	0.0192	0.0575	0.0528	1
1	3	0.0452	0.1652	0.0408	1
2	4	0.0570	0.1737	0.0368	1
3	4	0.0132	0.0379	0.0084	1
2	5	0.0472	0.1983	0.0418	1
2	6	0.0581	0.1763	0.0374	1
4	6	0.0119	0.0414	0.0090	1
5	7	0.0460	0.1160	0.0204	1
6	7	0.0267	0.0820	0.0170	1
6	8	0.0120	0.0420	0.0090	1
6	9	0.0000	0.2080	0.0000	0.978
6	10	0.0000	0.5560	0.0000	0.969
9	11	0.0000	0.2080	0.0000	1
9	10	0.0000	0.1100	0.0000	1
4	12	0.0000	0.2560	0.0000	0.932
12	13	0.0000	0.1400	0.0000	1
12	1	0.1231	0.2559	0.0000	1
12	15	0.0662	0.1304	0.0000	1
12	16	0.0945	0.1987	0.0000	1
14	15	0.2210	0.1997	0.0000	1
16	17	0.0524	0.1923	0.0000	1
15	18	0.1073	0.2185	0.0000	1
18	19	0.0639	0.1292	0.0000	1
19	20	0.0340	0.0680	0.0000	1

10	20	0.0936	0.2090	0.0000	1
10	17	0.0324	0.0845	0.0000	1
10	21	0.0348	0.0749	0.0000	1
10	22	0.0727	0.1499	0.0000	1
21	22	0.0116	0.0236	0.0000	1
15	23	0.1000	0.2020	0.0000	1
22	24	0.1150	0.1790	0.0000	1
23	24	0.1320	0.2700	0.0000	1
24	25	0.1885	0.3292	0.0000	1
25	26	0.2544	0.3800	0.0000	1
25	27	0.1093	0.2087	0.0000	1
28	27	0.0000	0.3960	0.0000	0.968
27	29	0.2198	0.4153	0.0000	1
27	30	0.3202	0.6027	0.0000	1
29	30	0.2399	0.4533	0.0000	1
8	28	0.0636	0.2000	0.0428	1
6	28	0.0169	0.0599	0.0130	1

Table A.3 Quadratic Cost Coefficients of generators.

Generator bus no.	**a**	**b**	**c**
1	0.00375	2.00	0
2	0.01750	1.75	0
5	0.06250	1.00	0
8	0.00834	3.25	0
11	0.02500	3.00	0
13	0.02500	3.00	0

The Quadratic cost function is expressed as:

$$FC_i(P_{gi}) = a_i P_{gi}^2 + b_i P_{gi} + c_i \quad \text{.........................} \quad (A.1)$$

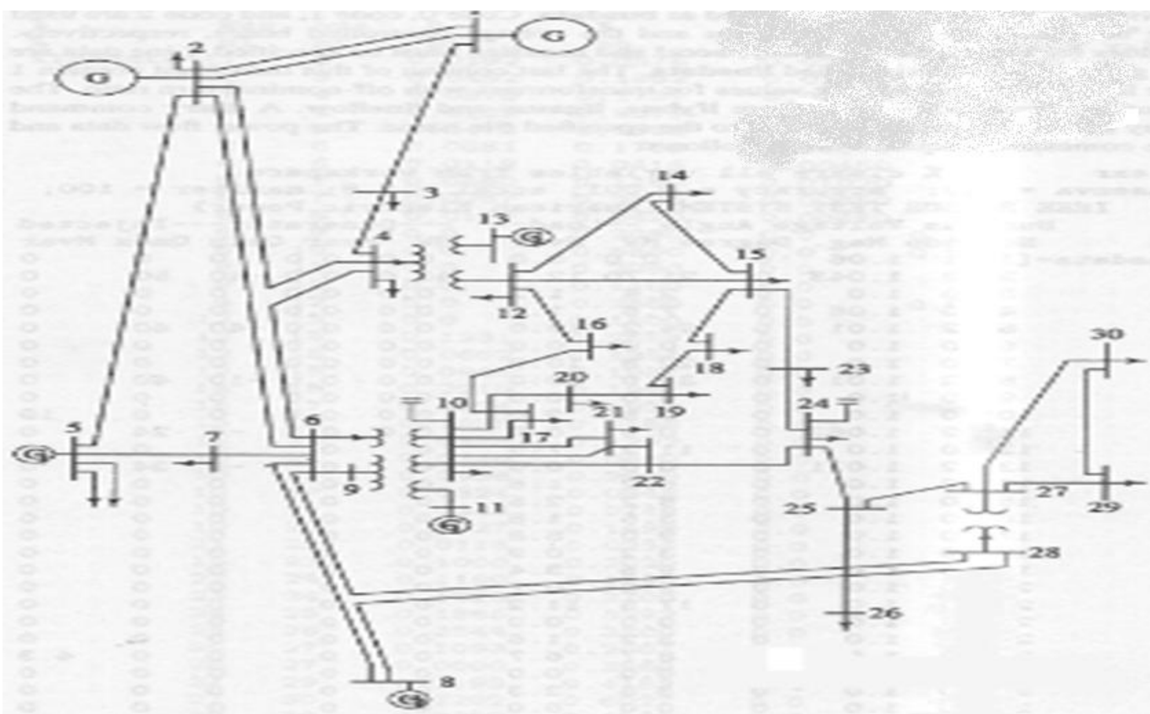
Table A.4 Exponential Cost Coefficients of generators.

Generator bus no.	a	b	c	d	e
1	0.0409	-0.0555	0.0649	0.0002	0.0285
2	0.0254	-0.0604	0.0563	0.0005	0.0333
5	0.0425	-0.0509	0.0458	0.0001	0.0800
8	0.0532	-0.0355	0.0338	0.0002	0.0200
11	0.0425	-0.0509	0.0458	0.0001	0.0800
13	0.0613	-0.0555	0.0515	0.0001	0.0666

The Exponential cost function is expressed as:

$$FC_i(P_{gi}) = a_i + b_iP_{gi} + c_iP_{gi}^2 + d_i \exp^{e^{-i}P_{gi}} \quad \text{……………………………….(A.2)}$$

Fig. A.1 IEEE-30 Bus Diagram



REFERENCES

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

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

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

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

[5] Torres G.L. and Quintana V.H., "Optimal Power Flow by a Nonlinear Complementarily Method", IEEE Transactions on Power Apparatus and Systems, Vol. 15, No. 3, pp. 1028-1033, 2000.

[6] Pudjianto S. A. and Strbac G., "Allocation of Var Support Using LP and NLP based Optimal Power Flows", IEE Proceedings on Generation, Transmission and Distribution., Vol. 149,No. 4, pp. 377-383, 2002.

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

[8] Saha T.N. and Maitra A., "Optimal Power Flow Using the Reduced Newton Approach in Rectangular Coordinates", International general of Electrical Power & Energy Systems, Vol. 20, No. 6pp. 383-389, 1998.

[9] Hong Y.Y. , Liao C.M. and Lu T. G., “Application of Newton Optimal Power Flow to Assessment of VAR Control Sequences on Voltage Security: Case Studies For A Practical Power System”, IEE Proceedings on Generation, transmission and distribution, Vol. 140, No. 6, pp. 539-543, 1993.

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

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

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

[13] Lai L.L. , Yokohoma R. and Zhao, M., “Improved Genetic Algorithm for Optimal Power Flow Under Both Normal and Contingent Operation States”, International general on Electrical Power Energy System, Vol.19, pp. 287-291, 1997.

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

[15] Abido M.A., “Optimal Power Flow Using Particle Swarm Optimization”, International general on Electrical Power and Energy Systems , Vol. 17, No. 2, pp. 563-571 , 2002.

[16] Lee K.Y., Park Y.M. and Ortiz J.L., " A Unified Approach to Optimal Real and Reactive Power Dispatch" ,IEEE Transactions on Power Apparatus and Systems, Vol. PAS-104, No. 5, 1985.

[17] Gaing, Z.L., "Particle Swarm Optimization to Solving the Economic Dispatch Considering the Generator Constraints", IEEE Transactions on Power Systems, Vol. 18, No. 3, pp. 11871-195 , 2003.

[18] Shi Y. and Eberhart, "A Modified Particle Swarm Optimizer", Proceedings of IEEE International Conference on Evolutionary Computation, Anchorage, pp. 69-73, 1998.

[19] Kennedy J., "The Particle Swarm: Social Adaptation of Knowledge", Proceedings of IEEE International Conference on Evolutionary Computation, Indianapolis, USA, pp. 303-308, 1997.

[20] Angeline P. ,"Evolutionary Optimization Verus Particle Swarm Optimization: Philosophy and Performance Differences", Proc 7th Annual Conference Evolutionary Programming, pp 601-610, 1998.

[21] Aguado J. A. and Quintana V.H., "Optimal Power Flows of Interconnected Power Systems", IEEE Power Engineering Society Summer Meeting, Vol. 2, pp. 814 –819, 1999.

[22] Ferreira J., Vale Z. and Cardoso J., "Firm Transmission Rights and Congestion Management in Electricity Markets", Proceedings of the 6th WSEAS International Conference on Power Systems, Lisbon, Portugal, 2006.

[23] Padhy N.P.and Kumari L., "Evolutionary Programming Based Economic Power Dispatch Solutions With Independent Power Producers", 2004 IEEE International Conference on Electric Utility Deregulation, Restructuring and Power Technologies (DRPT2004) Hong Kong Vol. 1, pp. 172-177, 2004.

[24] Kumar A. and Chanana S. , “Security Constrained Economic Dispatch with Secure Bilateral Transactions in Hybrid Electricity Markets”, Power System Technology and IEEE Power India Conference, pp.1-6, 2008.

[25] Cheng J. W. M., McGills D. T. and Galiana F. D., "Probabilistic security analysis of bilateral transactions in a deregulated environment, "IEEE Transaction on Power systems, Vol. 14, No. 3, pp. 1153-1159,1999.

[26] Vaisakh K., *Member, IEEE,* and G.V. Rao Siva Krishna, *Non-Member, IEEE* “Determination of Optimal Bilateral Power Contracts with Line Flow Constraints”.Power Symposium,NAPS’07, pp.448-455, Sept.30 2007- Oct 2 2007.

[27] Hamoud *G.* A**. ,** . “Feasibility Assessment of Simultaneous Bilateral Transactions in a Competitive Energy Market.” IEEE Power Engineering Society 1999 Winter Meeting, Newyork city, Newyork ,USA, Vol. 2 , pp.1253-1258, 31 Jan-4 Feb. 1999.

[28] Srivastava and Kumar Perveen , “Optimal Power Dispatch in Deregulated Market Considering Congestion Management” . Proceedings on Electric Utility Deregulation and Restructuring Power Technologies, London ,UK, pp. 53-59, 4-7 April,2000.

[29] Kumar A. and Wenzhong G. , Pattern of secure bilateral transactions ensuring power economic dispatch in hybrid electricity markets.” Power System Technology and Joint IEEE Power India Conference, New Delhi, pp.1-6, 12-15 Oct. 2008.

[30] Fang R.S. and David A.K., “Optimal Dispatch Under Transmission Contracts Department of Electrical Engineering” IEEE Transactions on Power Systems, Vol. 14, No. 2, 1999 .

[31] Raglend J., Karthikeyan P., and Kothari D. P., “Comparison of Intelligent Techniques to Solve Economic Load Dispatch with Bilateral and Multilateral

Transactions”, TENCON 2008 IEEE Region 10 Conference,Hyderabad, pp. 1-6,19-21 Nov. 2008.

[32] Qifeng D. and Ali A. , “ Optimal compensation of transmission losses in a multiple-transaction framework” ,Electrical Power and Energy Systems Vol.29 , pp. 14-20 ,Jan 2007.

[33] Gnanadass R., Padhy N.P. and Palanivelu T.G.,“A New method for the Transmission Congestion Management in the Restructured Power Market” Vol. 9, No. 1, 52-58, 2007.

[34] Padhy N. P. , Sood Yog Raj , Moamen Abdel. M. A. , Kumar M. and Gupta H. O. “A Hybrid Model for Congestion Management with Real and Reactive Power Transaction”.IEEE Power Engineering Society Summer Meeting, Chicago,USA, Vol.3, pp.1366-1372,25 July 2002.

[35] Garng Huang M. and Zhang H..“ Transmission Loss Allocations and Pricing Via Bilateral Energy Transactions”, IEEE Power Engineering Society Summer Meeting, Edmonton, Alta, Vol.2, pp.720-725,18-22 July,1999.

[36] Sood Y.R., Padhy N.P. and Gupta H.O. , “Deregulated model and locational marginal pricing” Electric Power Systems Research, Vol. 77 ,pp. 574–582, 2007 .

[37] Kothari D.P. and Nagrath I.J., *Modern Power System Analysis.* Tata McGraw-Hill, Third Edition, 2003.

[38] Saadat Hadi, “Power System Analysis”, McGraw-Hill, 1999.