OPTIMAL POWER FLOW FOR UNITS WITH NON-SMOOTH FUEL COST USING POPULATION BASED METHODS

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

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Power Systems & Electric Drives

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Certificate

I hereby certify that the work which is being presented in the thesis entitled "**Optimal Power Flow For Units With Non-Smooth Fuel Cost Using Population Based Methods**" in partial fulfillment of award of degree of **Master of Engineering** in **Power Systems and Electric Drives** submitted in Electrical and Instrumentation Engineering department, Thapar University, Patiala is an authentic record of my own work carried under the supervision of **Dr. Sanjay Kumar Jain,** Associate Professor, Electrical and Instrumentation Engineering department, Thapar University, Patiala, Punjab.

The matter 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 optimal power flow (OPF) is being used to find the optimal settings to operate the system. When the operating cost is minimized, the generation schedule is calculated by OPF. Traditionally, the cost function of each generator is represented by a simple quadratic function. However, thermal units are sometimes made to run on multiple fuels like coal, natural gas and oil. The multiple fuel options lead the cost function to be piecewise quadratic cost functions. The discontinuities are further added in the cost function when valve point loading effects are included. The optimal power flow with units having valve-point loading and ramp rate limits is represented as a non-smooth optimization problem having complex and nonconvex features.

The work reported in this thesis is carried out with the objective to make use of population based methods (EP and PSO) for solving the optimal power flow (OPF) problem for units with non smooth fuel cost function. The effect of both the ramp rate limits and valve point loadings, which are the typical discontinuities, have been incorporated. The objective in the OPF problem has been decided as minimization of total cost of real power generation. The IEEE-30 bus system is considered to test the algorithms. Two case studies have been considered for different sets of cost curves and load demand. The effectiveness of the developed algorithms has been tested for quadratic, piecewise quadratics and quadratics with sine components.

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INTRODUCTION

1.1 OVERVIEW

An Optimal Power Flow (OPF) is carried out to schedule the power system controls to optimize an objective function while satisfying a set of nonlinear equality and inequality constraints. The equality constraints are the power balance equations and the inequality constraints are the limits on the control and operating variables of the system. The OPF is a nonlinear, nonconvex, large-scale, static optimization problem with both continuous and discrete control variables.

Traditionally the cost function of each generator is represented by a simple quadratic function. But now-a-days thermal units are sometimes made to run on multiple fuels like coal, natural gas and oil. The multiple fuel options lead the objective function to piecewise quadratic cost functions. The fuel cost function becomes more non-linear when valve point loading effects are included. The optimization problem with valve-point effects is represented as a nonsmooth optimization problem having complex and nonconvex features.

A wide variety of optimization techniques have been applied in solving the OPF problems. The conventional Newton based methods, which require derivational computations, suffer from the following limitations [1]:

- The convergence to an optimal solution depends on the chosen initial solution.
- Most algorithms tend to get stuck to a suboptimal solution.
- An algorithm efficient in solving one optimization problem may not be efficient in solving a different optimization problem.
- Algorithms are not efficient in handling problems having discrete variables.
- Algorithms cannot be efficiently used on a parallel machine.

To overcome the above difficulties of conventional methods, the population based search and optimization methods have been used. These methods search the solution with the help of a set of solutions instead of a solution and result toward optimal solution with the progress of iterations. Some of the population based methods are genetic algorithm (GA), evolutionary programming (EP), ant colony optimization (ACO), particle swarm optimization (PSO) etc. Population based methods are optimization techniques inspired by natural evolution processes. They handle a population of individuals that evolves with the help of information exchange procedures in each iteration. For example in the implementation of genetic algorithm, a population of candidate solutions, which are referred to as chromosomes, is evolved through genetic operators of reproduction, mutation and crossover to find a global solution.

These population based methods have the following advantages:

- Optimizes with continuous or discrete variables.
- Simultaneously searches from a wide sampling of the cost (objective) surface.
- Deals with a large number of variables.
- Can work with the variable or with the encoded variable.
- Differentiability of the objective function is not required.
- Computational simplicity and ease of implementation.
- Power-full search ability to attain the near global optimum.
- Extremely robust with respect to the complexity of the problem.
- Diversity of solutions can be maintained.
- Takes into account the overall effect on the system.

The valve point loading and ramp rate limits are the typical discontinues from the conventional continuous smooth cost function of the generator units. In view of the limitations of the conventional methods as mentioned above, the problem to carry out OPF of units with non-smooth cost function is attempted using population based search methods. The solution has been attempted using two approaches namely EP and PSO.

1.2 LITERATURE REVIEW

The optimal power flow (OPF) was first introduced by Carpentier in 1962 [2]. The OPF procedure consists of using mathematical methodology to find the optimal settings to operate power system satisfying various constraints. It has been considered as a basic tool for determining secure and economic operating conditions of power systems. Newton-Raphson method is widely used to solve power flow problem. Dommel and Tinney [3] reported a practical method based on power flow solution by Newton's method, for solving the power flow problem with control variables such as real and reactive power and transformer ratios to minimize costs or losses. Alsac and Stott [4] extended Dommel-Tinney's approach of calculation of optimal power-system load flows. The method incorporates the steady state security constraints into the optimal power flow solution using exact formulation, this enables reactive power and voltage constraints to be considered in the outage cases. The inclusion of steady-state security constraints makes the optimal load-flow calculation a more powerful and practical tool for system operation and design.

Chen and Chen [5] proposed a new algorithm based on Newton-Raphson (NR) method with sensitivity factors incorporated to solve emission dispatch in real-time. The Jacobian matrix and the B-coefficients were obtained, developed in terms of the generalized generation shift distribution factor.

Lobato *et al*. [6] proposed linear programming (LP) based OPF for minimization of transmission losses and generator reactive margins. The discrete nature of shunt reactors and capacitors was modeled by integer variables.

Classical methods suffer from many limitations, they rely on convexity to find the global optimum. However, due to the nondifferential, nonlinearity and nonconvex nature of the optimal power flow (OPF) problem, the methods based on these assumptions do not guarantee to find the global optimum. Therefore many other powerful deterministic, probalistic and stochastic techniques are used for solving the large dimensional optimization problem [7-14].

Pandya and Joshi [15] presented a comprehensive survey of various optimization methods used to solve OPF problems and suggested the suitable methods for solving the various optimization problems.

Tinney *et al.* [16] discussed various deficiencies that limit their practical value and scope of application of optimal power flow program and offered solution approaches to reduce the difficulties. Almeida and Galiana [17] presented a systematic analysis of the main reasons for the failure of solution algorithms in the general non-linear optimal power flow (OPF) problem.

The evolutionary programming (EP) technique is a stochastic optimization method in the area of evolutionary computation, which uses the mechanics of evolution to produce optimal solutions to a given problem. The EP technique is particularly well suited to non monotonic solution surfaces where many local minima may exist. A survey of various applications of evolutionary computation in electric power systems has been presented in [18]. Due to the advantages of adaptability to change, ability to generate good enough solutions and rapid convergence EP has been used for solving economic dispatch [19], combined economic emission dispatch [20].

Yuryevich and Wong [21] used gradient acceleration to develop an efficient and reliable evolutionary programming algorithm for solving the optimal power flow. The algorithm is enhanced with gradient information to improve the speed of convergence of the algorithm as well as its ability to handle larger systems

Sood [22] presented evolutionary programming based optimal power flow and tested its validation for deregulated power system analysis. Somasundaram *et al.* [23] solved the security constrained optimal power flow using EP.

Lo *et al.* [24] proposed a parallel EP-OPF algorithm in which the initial population was divided into several sub-populations, to improve the computational speed. This approach was found less sensitive to the choice of starting points and types of generator cost curves.

Ongsakula and Tantimaporn [25] proposed improved evolutionary programming (IEP). The IEP is a hybrid of EP and simulated annealing (SA) algorithm. IEP initially divides the solution space into several subspaces. Multiple mutation operators are employed to enhance the search diversity.

Eberhart and Kennedy [26] suggested a particle swarm optimization (PSO) based on the analogy of swarm of bird and school of fish. The PSO mimics the behavior of individuals in a swarm to maximize the survival of the species. Basic concepts, variants, hybridization perspectives and applications of particle swarm optimization in electric power systems have been discussed by many researchers [27-30]

PSO has widely used to solve economic load dispatch problem, power loss minimization [31], optimal design of power system stabilizers [32], reactive power and voltage control considering voltage stability [33], reactive power optimization [34].

The PSO has been successfully implemented for solving optimal power flow problem [35, 36]. Incorporation of PSO as a derivative free optimization algorithm significantly relieves the assumption imposed on the optimization objective function.

Kim *et al.* [37] developed modified particle swarm optimization for optimal power flow in which the mutation operator of genetic algorithm (GA) was incorporated into the conventional PSO to improve the search performance.

The fuel cost function of the generating units becomes more non-linear when valve point loading effects are included. Also the fuel cost characteristics of the combined cycle co-generation plants is non-smooth and non-differentiable. Gnanadassa *et al.* [38] presented Evolutionary Programming to solve OPF problem considering valve point loading and combined cycle cogeneration plants.

Djillani and Yacine [39] presented the algorithm for optimal flow with generating units having non-smooth fuel costs curves while satisfying the constraints such as generator capacity limits, power balance, line flow limits, bus voltages and transformer tap setting.

Park *et al.* [40] proposed an alternative approach is proposed to the non-smooth economic dispatch (ED) problem using a modified PSO (MPSO), focusing on the treatment of the equality and inequality constraints when modifying each individual's search. Kumar *et al.* [41] proposed strategies for the economic power dispatch with valve-point effects, which explore the vicinity of particle's best position found so far leads to a better result.

Chandram and Subrahmanyam [42] described secant method with PSO for solving the Economic Dispatch problem with valve point loading. The problem was solved in two stages. The range of output powers near the global optimal solution was determined by the Secant method and then the final optimal solution is obtained by PSO.

Pandian and Thanushkodi [43] proposed two hybrid algorithms to solve non-convex economic dispatch problem: namely NN-EPSO, a hybrid of neural network and efficient particle swarm optimization (EPSO) and EP-PSO, a hybrid of evolutionary programming (EP) and efficient particle swarm optimization (EPSO) .

Subramanian and Rajeswari [44] proposed a modified particle swarm optimization in which the particle adjusts its velocity according to two extremes. One is the best position of its own and the other extreme is not always the best one of the group, but selected randomly from the group.

Thitithamrongchai and Eua-arporn [45] presented a self-adaptive differential evolution with augmented lagrange multiplier method for solving optimal power flow (OPF) problems with non-smooth generator fuel cost curves, the method is a modified version of conventional differential evolution (DE) by integrating mutation factor and crossover constant as additional control variables.

A normative self-organizing migrating algorithm for power economic dispatch of thermal generators with valve point effects and multiple fuels was proposed by Mariani and Rodrigo [46].

Sriyanyong [47] presented enhanced particle swarm optimization combined with gaussian mutation (GM) for solving the dynamic economic dispatch (DED) problem considering the operating constraints of generators. The enhanced PSO consists of the standard PSO and a modified heuristic search approaches. Namely, the ability of the traditional PSO is enhanced by applying the modified heuristic search approach to prevent the solutions from violating the constraints. In addition, gaussian mutation is aimed at increasing the diversity of global search.

1.3 OBJECTIVES OF THE WORK

The work reported in this thesis has been carried out with the objective of applying population based search methods namely EP and PSO for solving optimal power flow for cost minimization of thermal generating units. The effects of valve point loading and ramp rate limits have been taken into account which makes the generator fuel cost to be non-smooth fuel cost function. The result obtained using EP and PSO are compared.

1.4 ORGANIZATION OF THE THESIS

The Thesis is organized into five Chapters. The **Chapter 1** highlights the brief introduction, literature survey, objective of the work and organization of the thesis. The **Chapter 2** briefly describes optimal power flow, valve point loading effect and the ramp rate limits. The **Chapter 3** describes evolutionary programming, algorithm for EP based OPF and obtained results using EP. The **Chapter 4** discusses PSO, its implementation for solving the optimal power flow and the obtained results using PSO. The results are also compared with EP. The **Chapter 5** summarizes the conclusions and the scope of future work.

CHAPTER- 2

OPF FOR UNITS WITH NON-SMOOTH FUEL COST

2.1 INTRODUCTION

The main objective in the operation of any of today's complex electric power systems is to meet the demand for power at the lowest possible cost, while operating it without violating any constraint. Reliability and continuity of service are essential goals that the electric power systems engineer strives to meet at all times. Reliability can be referred in terms of violation of limits. Even the realistic operating conditions including the environmental impact measures can be included in the optimal power flow for formulation [48].

An electric power system is physically a large electrical circuit consisting of generators and loads interconnected by transmission. The loads are modeled as real and reactive power demands, whereas, generation is a source of real and reactive power. In addition, there is a variety of subsidiary protection equipment that monitors for undesirable conditions such as:

- Overload conditions on generators and on the transmission and distribution lines,
- Under- or over-voltage conditions on loads, and
- Short-circuits due to lightning strikes on transmission lines.

The calculation of the power flows on the transmission lines and the voltages at various nodes provides the information about the normal and abnormal operating state like overloads etc. This calculation is called a power flow study. It is important to be able to predict the power flows on lines and the voltage magnitudes at loads in advance of actual operations so that overloads and under or over-voltage conditions can be anticipated and pre-emptive action taken.

The optimal power flow (OPF) was proposed by Carpentier in the 1962 [2]. Since then it is an area of active research and effort is to include more realistic formulation and solution methods. Optimal power flow is a large dimension nonlinear, nonconvex and highly constrained optimization problem that has been used widely for power system planning and operation. It is nonconvex due to existence of nonlinear AC power flow equations, nonsmooth or nonconvex fuel cost functions (e.g., valve-point effects, multiple fuels), or the flexible alternating current transmission system devices (FACTS) in the power system [45].

The optimal power flow problem solution aims to optimize a selected objective function such as fuel cost via optimal adjustment of the power system control variables, while at the same time satisfying various equality and inequality constraints. The equality constraints are the power flow equations, while the inequality constraints are the limits on control variables and the operating limits of power system dependent variables [35]. OPF has been widely used in power system operation and planning.

In its most general formulation, the OPF is a nonlinear, nonconvex, large-scale, static optimization problem with both continuous and discrete control variables. Even in the absence of nonconvex unit operating cost functions, unit prohibited operating zones, and discrete control variables, the OPF problem is nonconvex due to the existence of the nonlinear (AC) power flow equality constraints. The presence of discrete control variables, such as switchable shunt devices, transformer tap positions, and phase shifters, further complicates the problem solution. This non-convexity is further increased when valve-point loading effects of thermal generators have to be included or FACTS devices are included on the network [21].

Effective optimal power flow is limited by factors such as high dimensionality of power systems and incomplete domain dependent knowledge of power system engineers. High dimensionality is addressed by numerical optimization procedures based on successive linearization using the first and the second derivatives of objective functions and their constraints as the search directions or by linear programming solutions to imprecise models. The advantages of such methods are in their mathematical underpinnings, but disadvantages exist also in the sensitivity to problem formulation, algorithm selection and usually converge to a local minimum [13]. The second limitation, incomplete domain knowledge, precludes also the reliable use of expert systems where rule completeness is not possible. The OPF has many applications which include [49]:-

- 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.

- 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.
- In an emergency, that is when some component of the system is overloaded or a bus is experiencing a voltage violation, the OPF study can be used to provide a corrective dispatch, suggesting the kind of adjustments to be performed to mitigate the overload or voltage violation problems.
- 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).
- The OPF is routinely used in planning studies to determine the maximum stress that a planned transmission system can withstand.
- The OPF can be used in economic analysis of the power system by providing bus incremental costs.
- OPF can be used to calculate the incremental or marginal cost of transmitting power from one company through its system to another company.

2.2 SMOOTH AND NON-SMOOTH FUEL COST FUNCTIONS

The input-output characteristics (or the cost function) of a generator are approximated using quadratic functions, under the assumption that incremental cost curves of the units are monotonically increasing piecewise-linear functions [48].

$$F(P_{gi}) = (a_i P_{gi}^2 + b_i P_{gi} + c_i) \ \$/h \tag{2.1}$$

The active power generation P_{gi} should satisfy the maximum and lower limits.

$$P_{gi}^{max} \leq P_{gi} \leq P_{gi}^{min} \tag{2.2}$$

Where P_{gi}^{max} and P_{gi}^{min} are the minimum and maximum generation limits.

This cost function is considered as smooth fuel cost function. The increasing fuel prices, scarcity of energy resources and ever-growing demand for electric energy necessitates the replacement of expensive fuels by more abundant fuels. Therefore, thermal units use multiple fuels options like coal, natural gas and oil. The multiple fuel options lead the objective function to piecewise quadratic cost functions. The fuel cost function becomes more non-linear when valve point loading effects are included. Adding to this, the operating range of all on-line units is restricted by their ramp rate limits. To consider the accurate cost curve of each generating unit, the valve-point effects must be included in the cost model. The valve point loading and ramp rate limits are briefed hereafter.

2.2.1 VALVE POINT LOADING

Large steam turbine generators usually have a number of steam admission valves that are opened in sequence to obtain ever-increasing output from the unit. Loading (output) levels at which a new steam admission valve is opened are called valve points. At these levels, discontinuities in the cost curves and in the incremental heat rate curves occur as a result of the sharp increases in throttle losses [48]. As the unit loading increases, the input to the unit increases and the incremental heat rate decreases between the opening points for any two valves. However, when a valve is first opened, the throttling losses increase rapidly and the incremental heat rate rises suddenly. This gives rise to the discontinuous type of incremental heat rate characteristic.

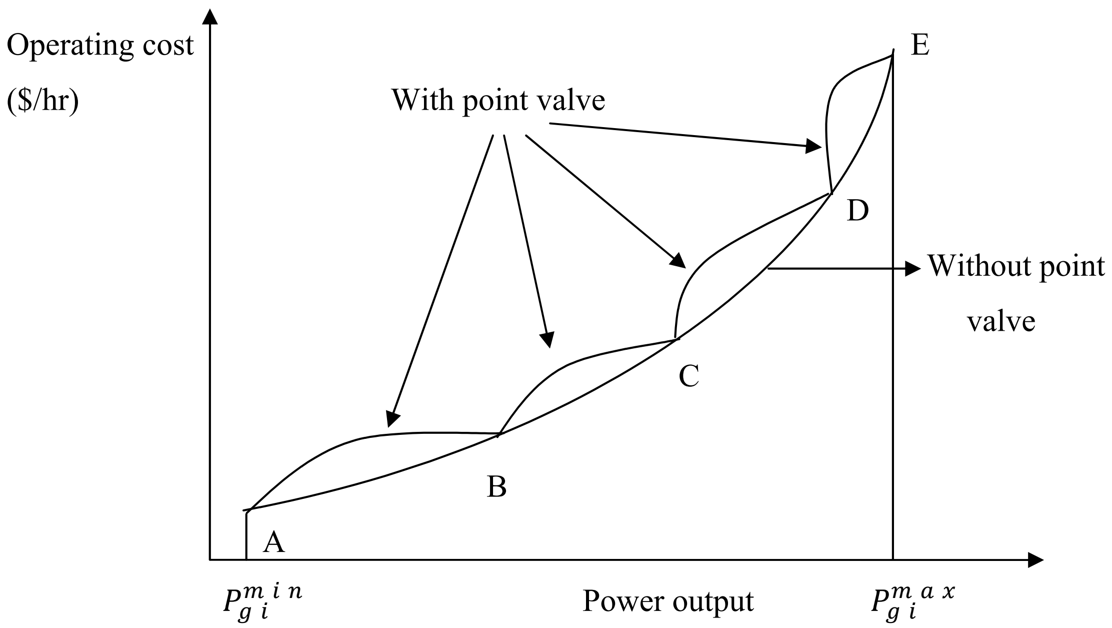

Figure 2.1: valve point loading effect

The nomenclature A, B, C, D and E in Fig. 2.1 stands for primary valve, secondary valve, tertiary valve, quaternary valve, quinary valve respectively. This type of characteristic should be used in order to schedule steam units accurately. The figure 2.1 shows the cost-output characteristics for a unit with steam admission valves for both smooth and non-smooth valve point loadings.

The real input-output characteristics display higher order nonlinearities and discontinuities due to valve-point loading. The valve point loading effect is the rippling effect added to the generating unit curve when each steam admission valve in a turbine starts to open. It has been modeled in as a recurring rectified sinusoidal function.

$$F(P_{g\,i}) = (a_i P_{g\,i}^2 + b_i P_{g\,i} + c_i) + |\, d_i * \sin\{ e_i * (P_{g\,i}^{min} - P_{g\,i})\} \,| \quad \$/h \qquad (2.3)$$

Where d_i and e_i are the coefficients of generator 'i' reflecting valve-point effects.

The addition of the valve-point effect poses a more challenging task to the proposed method since it increases the non-linearity of the search space as well as the number of local minima.

2.2.2 RAMP RATE LIMITS

Practically, the operating range of all the units is restricted. Their ramp rate limits the operation of units continually between two adjacent specific operation periods.

Figure 2.2 shows three possible situations in which a unit is on-line from time interval (t-1) to t. Figure 2.2(a) shows the unit operating in steady state conditions, Figure 2.2(b) shows the unit increasing its power generation whereas Figure 2.2(c) shows the unit decreasing the power generation output. Inequality constraints due to ramp rate limits that can be imposed are described below:

- In case generation increase

$$P_{g\,i} - P_{g\,i}^0 \leq UR_i \qquad (2.4)$$

Where UR_i is the up ramp limit of *i*th generator (MW/hr)

P_i^0 is the previous output power of *i*th generating unit.

- In case generation decreases

$$P_{g\,i}^0 - P_{g\,i} \leq DR_i \qquad (2.5)$$

Where DR_i is down ramp limit of *i*th generator (MW/hr).

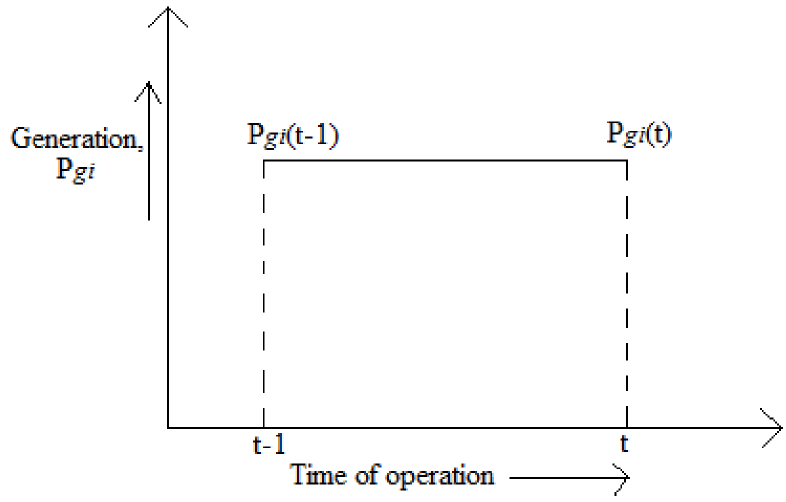

Figure 2.2(a) Steady state operation of ith generator.

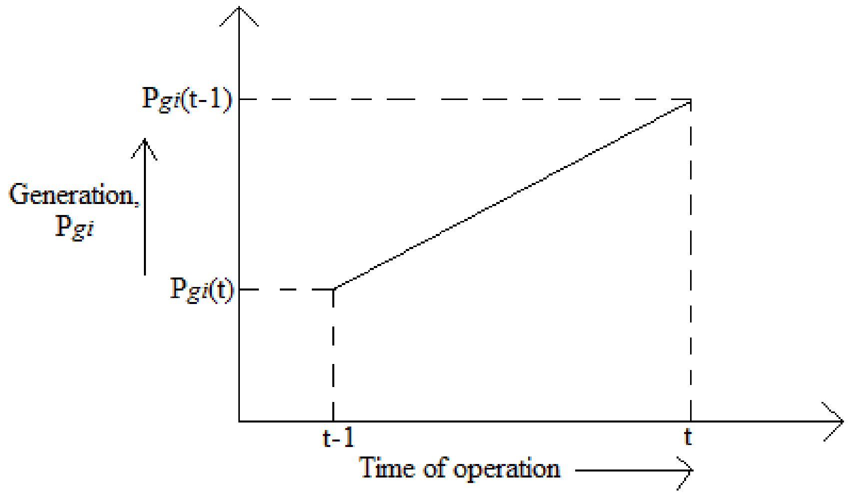

Figure 2.2(b) Ramp-up operation of ith generator.

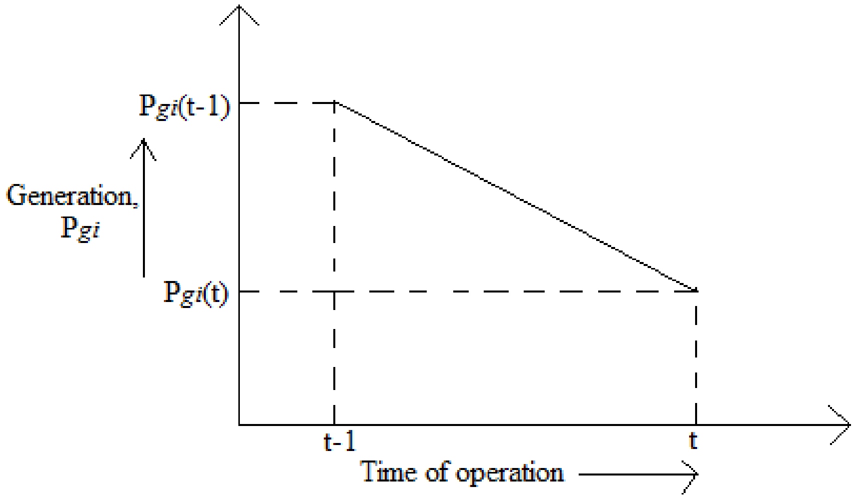

Figure 2.2(c) Ramp-down operation of ith generator.

Figure 2.2 Various states of operation of a generator.

The modified maximum and minimum limits on the active power generation for each generator are

$$P_{g\,i}^{min}{}_{(R)} = \max\left[P_{g\,i}^{min}, P_{g\,i}^{0} - DR_i\right] \quad (2.6)$$
$$P_{g\,i}^{max}{}_{(R)} = \min\left[P_{g\,i}^{max}, P_{g\,i}^{0} + UR_i\right] \quad (2.7)$$

Generator Ramp Rate inequality constraint is

$$\max\left(P_i^{min}, P_i^0 - DR_i\right) \leq P_i \leq \min(P_i^{max}, P_i^0 + UR_i) \quad (i = 1,2,\dots,NG) \quad (2.8)$$

2.3 OPF FORMULATION

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

$$\textit{Minimize } F(x,u) \quad (2.9)$$

$$\textit{Subject to}: g_E(x,u) = 0 \quad (2.10)$$

$$g_o(x,u) \leq 0 \quad (2.11)$$

Where:

1. 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.

2. The control variables (independent) are represented by x and the dependent variable are represented by u.

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

4. $g_o(x,u) \leq 0$ are the inequality constraints.

These terms applicable for OPF are described as follows :

2.3.1 OBJECTIVE FUNCTION

The most commonly used objective in the OPF problem formulation is the minimization of the total cost of real power generation.

Let the objective function to be minimized, is given below

$$f = \sum_{i}^{NG} F_i(P_{gi}) \tag{2.12}$$

Which is the sum of operating cost over all controllable power sources.

Where $F_i(P_{gi})$ is the generation cost function for P_{gi} generation at bus *i*.

NG is the number of generation including the slack bus.

The individual costs of each generating unit are assumed to be function, only, of active power generation and are represented by quadratic curves of second order. The objective function for the entire power system can then be written as the sum of the quadratic cost model at each generator [13].

The conventional quadratic fuel cost function of generating units is given by

$$F_i(P_{gi})quadratic = \left(a_i P_{gi}^2 + b_i P_{gi} + c_i\right) \ \$/hr \tag{2.13}$$

Where P_{gi} is the generated active power at bus i.

a_i, b_i and c_i are the unit costs curve for i^{th} generator.

Considering valve-point effects, the fuel cost function of generating units consists of rectified sine components superimposed on the quadratic function as follows:

$$F(P_{gi}) = \left(a_i P_{gi}^2 + b_i P_{gi} + c_i\right) + \left| d_i * \sin\{e_i * (P_{gi}^{min} - P_{gi})\}\right| \ \$/hr \tag{2.14}$$

The cost is optimized with the following constraints.

2.3.2 EQUALITY CONSTRAINTS

The equality constraints of the OPF reflect the physics of the power system as well as the desired voltage set points throughout the system. The dynamics of the Power System are enforced through the power flow equations which require that the net injection of real and reactive power at each bus sum to zero.

The equality constraint is

$$\sum P_{g\,i} = P_d + P_l \qquad (2.15)$$

where *Pd* is the total load of the system and *Pl* is the transmission losses of the system.

The power flow equation of the power network

$$g(V, \emptyset) = 0 \qquad (2.16)$$

Where

$$g(V, \emptyset) = \begin{cases} P_i(V, \emptyset) - P_i^{net} \\ Q_i(V, \emptyset) - Q_i^{net} \} \leftarrow For\ each\ PQ\ bus\ i \\ P_m(V, \emptyset) - P_m^{net} \} \leftarrow For\ each\ PV\ bus\ m, not\ including\ ref.bus \end{cases} \qquad (2.17)$$

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* bus i.

P_m and P_m^{net} are respectively calculated and specified real power for *PV* bus m.

V and $\emptyset$ are voltage magnitude and phase angles at different buses.

2.3.3 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. Physical devices that require enforcement of limits include generators, tap changing transformers, and phase shifting transformers. Some of the most common operating constraints are limitations on:

- Voltage magnitude at load buses
- Active or reactive power generation
- Branch currents, branch MW/MVAR/MVA flows
- Transformer load tap changer magnitudes
- Switched capacitor or reactors settings
- Phase shift transformer tap position

The formulation of common inequality constraints are -

- The inequality constraint on reactive power generation Q_{gi} at each *PV* bus

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max} \tag{2.18}$$

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 voltage magnitude V_i of each *PQ* bus

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{2.19}$$

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

- The inequality constraint on phase angle $\emptyset_i$ of voltage at all the buses *i*

$$\emptyset_i^{min} \leq \emptyset_i \leq \emptyset_i^{max} \tag{2.20}$$

where $\emptyset_i^{min}$ and $\emptyset_i^{max}$ are respectively minimum and maximum voltage angles allowed at bus *i*

- MVA flow limit on transmission line

$$MVAf_{ij} \leq MVAf_{ij}^{max} \tag{2.21}$$

where $MVAf_{ij}^{max}$ is the maximum rating of transmission line connecting bus *i* and *j*.

2.3.4. CONTROL VARIABLES

Control variables are the quantities whose value can be adjusted directly to help minimize the objective function and satisfy the constraints. In the problem formulation, P_{gi}s are selected as control variables (independent). The constraints on P_{gi} are

$$P_{gi}^{max} \leq P_{gi} \leq P_{gi}^{min} \tag{2.22}$$

Their modified limits are calculated using ramp rate. After this, P_{gi}s are selected randomly for all generators buses, except slack bus, within the modified limits.

CHAPTER- 3

OPF USING EVOLUTIONAY PROGRAMMING

3.1 EVOLUTIONARY PROGRAMMING: AN INTRODUCTION

Evolutionary Programming, originally conceived by Lawrence J. Fogel in 1960 [50], is a stochastic optimization method in the area of evolutionary computation, which uses the mechanics of evolution to search and produce optimal solutions to a given problem.

Mainly, the interest of using classical EP as the method for economic dispatch problem is because of its simplicity to GA where EP does not involve any special coding. Real number valued is used in the process. Secondly, EP does not impose any alteration of the objective function or constraints restriction. Hence, the transfer of the problem into algorithm is fairly simplified [19].

The main stages of this technique are initialization, creation of offspring vectors by mutation and competition and selection of best vectors to evaluate best fitness solution.

EP works by evolving a population of candidate solutions over a number of generations or iterations, toward the global minimum through the use of a mutation operator and selection scheme.

- Mutation create the necessary diversity and thereby facilitates novelty
- Selection acts as a force pushing quality

Initially a population of individuals is generated randomly, these are called "**Parents**". Each individual represents the candidate solution for the problem. During each iteration, a new population is formed from an existing population through the use of a mutation operator. The mutation operator randomly changes the value of one of the variable. The individuals of the new population generated are called "**Offsprings**". The degree of optimality of each individual is measured by their fitness, which can be defined as a function of the objective function of the problem. Through the use of a competition scheme, the individuals in population compete with other and with the parent population.

The winning individuals form a resultant population, which is regarded as “the next generation”. For optimization to occur, the competition scheme must be such that the more filter solutions have a greater chance of survival than the poorer solutions. If a child individual is fitter and has a better tournament score than a parent, it will take that parent's place in the next generation. The combined application of mutation and selection generally leads to improving fitness values in consecutive generations. Through this the population evolves towards the global optimal point. The EP technique is iterative. The process of generating new trials and selecting those with best function values is terminated by a stopping rule. The termination conditions or rules widely used are

- Stop after a specified number of iterations
- Stop when there is no appreciable change in the best solution for a certain number of generations.

The basic algorithm steps are as follows:

Step1. Initialize the population randomly, set the value for maximum iterations (gen_max) and iteration counter, $iter = 1$.

Step2. Compute the fitness

Step3. Select the population by completion and selection for next iteration. It is referred as parent population.

Step4. Generate child population by applying mutation to the parent population.

Step5. Compute the fitness of child individuals.

Step6. Combine the parent and child population.

Step7. Find and store the minimum cost among the parent and child population.

Step8. If iteration counter, $iter < gen\_max$ go to step 3.

Step9. Print the results.

This procedure is illustrated in figure 3.1.

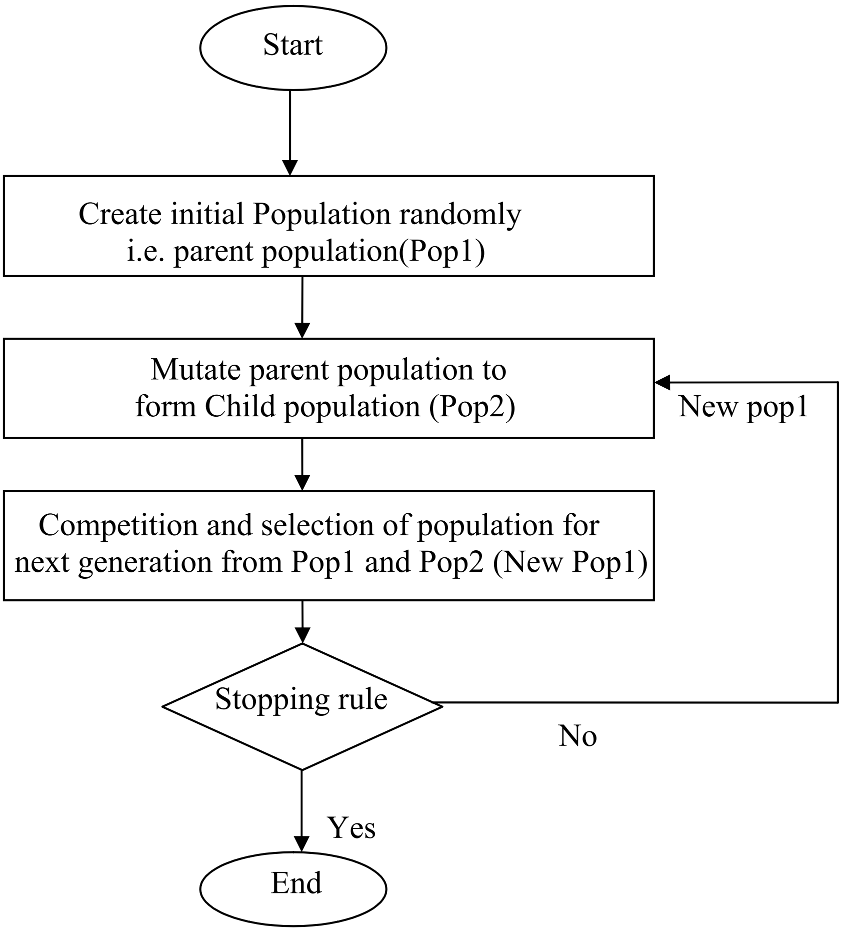

Figure 3.1: Algorithm of EP

3.2 OPF USING EP

Evolutionary programming emulates natural selection processes to find the global optimum of complex minimization and maximization problems. Based on the EP methodology, an algorithm for solving the OPF problem can be established. The implementation of EP algorithm is as follows:

3.2.1 OBJECTIVE FUNCTION

The objective function is the minimization of the generation fuel cost [21]. Generally, the OPF generation fuel cost function can be expressed by a quadratic function as follows:

$$f = \sum_{i}^{NG} F_i(P_{g\,i}) \tag{3.1}$$

Where $F_i(P_{g\,i})$ is the generation cost function for $P_{g\,i}$ generation at bus *i*.

NG is the number of generation including the slack bus

The individual costs of each generating unit are assumed to be function of active power generation.

$$F_i(P_{g\,i})quadratic = \left(a_i P_{g\,i}^2 + b_i P_{g\,i} + c_i\right) \;\$/hr \tag{3.2}$$

Where $P_{g\,i}$ is the generated active power at bus i.

a_i, b_i and c_i are the unit costs curve for i^{th} generator.

Considering valve-point effects, the fuel cost function of generating units consists of rectified sine components superimposed on the quadratic function as follows:

$$F(P_{g\,i}) = \left(a_i P_{g\,i}^2 + b_i P_{g\,i} + c_i\right) + |\, d_i * \sin\{e_i * (P_{g\,i}^{min} - P_{g\,i})\} \,| \;\$/hr \tag{3.3}$$

3.2.2 INITIALIZATION

To start with an initial (Parent) population vector ($P_{g\,i}$) is generated randomly for all generators except slack bus. The real encoding is used for population generation.

$$P_{g\,i} = P_{g\,i}^{min} + R(0,1)[P_{g\,i}^{max} - P_{g\,i}^{min}] \tag{3.4}$$

Where $R(0,1)$ is a random number distributed between 0 and 1.

With the above procedure, the $P_{g\,i}$ is computed within the respective lower and upper limits as

$$P_{g\,i}^{min} \le P_{g\,i} \le P_{g\,i}^{max} \tag{3.5}$$

These elements are the controllable real power outputs of the committed generating units (excluding the slack bus unit). The ramp-rate constraint modifies the physical lower and upper limits of generating units. The individuals in parent population represent a candidate OPF solution. The individuals generated randomly are represented as

$$[P_{g\,2}, P_{g\,3}, P_4, \dots\dots\dots\dots\dots\dots P_{g\,n}] \tag{3.6}$$

Slack bus generation is calculated using Newton Raphson method after the power flow.

$$[P_{g1}, P_{g2}, P_{g3}, P_4, \ldots \ldots \ldots \ldots \ldots \ldots P_{gn}] \quad (3.7)$$

3.2.3 MUTATION

An offspring vector (P'_{gi}) is created from each parent vector by adding Gaussian random variable with zero mean and standard deviation σ_i.

$$P'_{gi} = P_{gi} + N(0, \sigma_{ji}^2) \quad (3.7)$$

The expression designed for σ_{ji} is given below

$$\sigma_{ji} = \beta * \sum_{i=1}^{n-1} \left(\frac{F_i}{f_{min}}\right) * (P_{gi}^{max} - P_{gi}^{min}) \quad (3.8)$$

Where β is a scaling factor

F_i is the fuel cost of the generator

f_{min} is the minimum value of the fuel cost in the generation.

These offsprings must satisfy the minimum and maximum generation limits of the units. The slack bus generation is calculated using Newton Raphson method. The selection of value of scaling factor must be such that it provides a suitably high initial mutation level and does not cool too rapidly so as to present complete convergence to the global optimum. In the work presented, β is selected 0.01.

3.2.3 COMPETITION AND SELECTION

The parent individuals and the corresponding offspring compete with each other for survival. The competition is based on the objective function given by the equation (2.10). The lower cost individual, whether parent or offspring, is selected to from the new parent for the next generation. Initialization and mutation are repeated until there is no appreciable improvement in the fitness value.

3.2.4 ALGORITHM OF EP BASED OPF

The algorithm for Evolutionary Programming based optimal power flow (EP-OPF) is shown in Figure 3.3. The algorithm steps are described below as [21,38]:

Step1. Read system data that include bus and line data, generator cost functions with ramp rate and valve point loading. Assume suitably population size (pop_size), maximum number of generations or populations(gen_max). Set valid number of population counter $pop\_vn = 0$.

Step2. Modify the upper and lower limits of the generators using equations

$$P_{gi}^{min}(R) = \max\left[P_{gi}^{min}, P_{gi}^{0} - DR_i\right] \quad (3.9)$$

$$P_{gi}^{max}(R) = \min\left[P_{gi}^{max}, P_{gi}^{0} + UR_i\right] \quad (3.10)$$

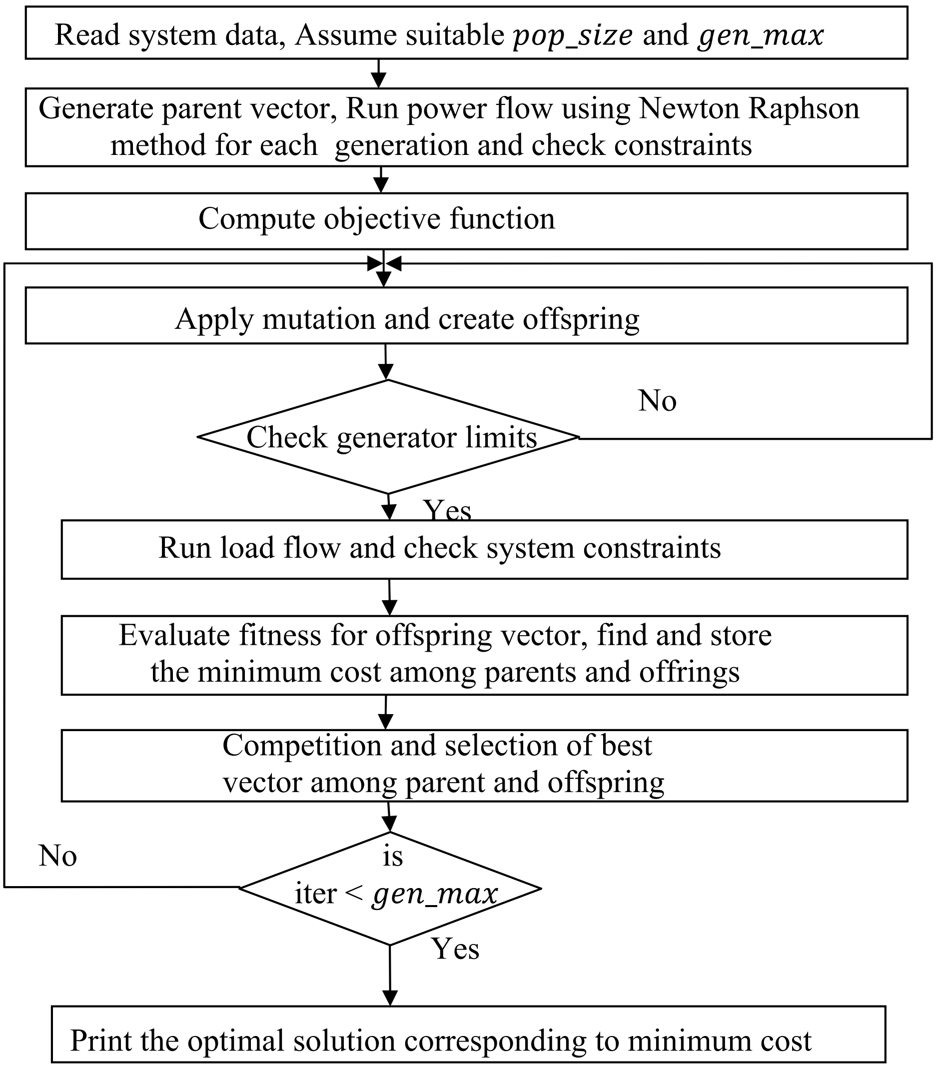

Figure 3.2: Flow chart of EP based OPF

Step3. Randomly initialize Parent vector (P_{gi}) of active power generation for all the units except the slack bus unit. The elements of parent vector must satisfy the constraint given in equation (3.5)

$$P_g = U[P_g^{min}, P_g^{max}] \quad (3.11)$$

Where, $U[P_g^{min}, P_g^{max}]$ is a uniform random number between P_g^{min} and P_g^{max}

P_g^{min} and P_g^{max} are the minimum and maximum limits of the generators.

Step4. Run power flow using the Newton–Raphson method for each set of generating patterns and calculate the slack bus generation.

Step5. Is slack bus Pg is within $P_{g(slack)}^{min}$ and $P_{g(slack)}^{max}$, go to step 6.

Step6. Increment pop_vn by 1. If pop_vn less than or equal to pop_size go to step 4, otherwise go to next step. Calculate cost function (described by the equation (2.14) in chapter 2), find and store minimum cost f_t^{min} corresponding to each valid generation pattern of an individual candidate in the population.

Step8. Set generation count $gen\_count = 1$.

Step9. A new population is generated from the existing parent population through the mutation operator. The j^{th} individual of the new population is calculated as

$$P_{ji}^{new} = P_{ji}^{old} + N(0, \sigma_{ji}^2) \quad (3.12)$$

Where, P_{ji}^{old} is the value of variable j in the parents P_i^{old}

$N(0, \sigma_{ji}^2)$ is a Gaussian random number with a mean of zero and a standard deviation of σ_{ji}

$$\sigma_{ji} = \beta * \sum_{i=1}^{n-1} \left(\frac{F_i}{f_{min}}\right) * (P_{gi}^{max} - P_{gi}^{min}) \quad (3.13)$$

Step10. Check the limits of the new generated individual. If any of the maximum or minimum limit is violated set the value of new individual to that respective limit. Run power flow using the Newton–Raphson method to calculate the slack bus generation. Check $P_{g(slack)}$, it should be within $P_{g(slack)}^{min}$ and $P_{g(slack)}^{max}$.

Step11. Find the minimum fitness among all individuals. If it is more than f^{min}, store this fitness in f_t^{min} and also store corresponding OPF variables.

Step12. Increment the generation count $iter$ by 1. If it is less than or equal to gen_max

Step13.Select the best individuals whether parents or offspring, as new parents for the next population and go to step 12 otherwise go to next step.

Step14. Find the optimal solution among all population groups.

3.3 RESULTS AND DISCUSSION

The developed algorithm has been applied on the IEEE-30 bus system shown as Fig. 3.4. This system consists of 6 generator units as well as 41 transmission lines. Correspondingly, the bus and line data is given in Appendix A as Table A1 and Table A2. For the studies, the population size is considered to be 25, and the number of iteration is considered 100. The study has been carried out for two cases depending on the difference in the generator cost data and load demand.

- Case- I : Cost data and load data [21].
- Case-II : Cost data and load data [38].

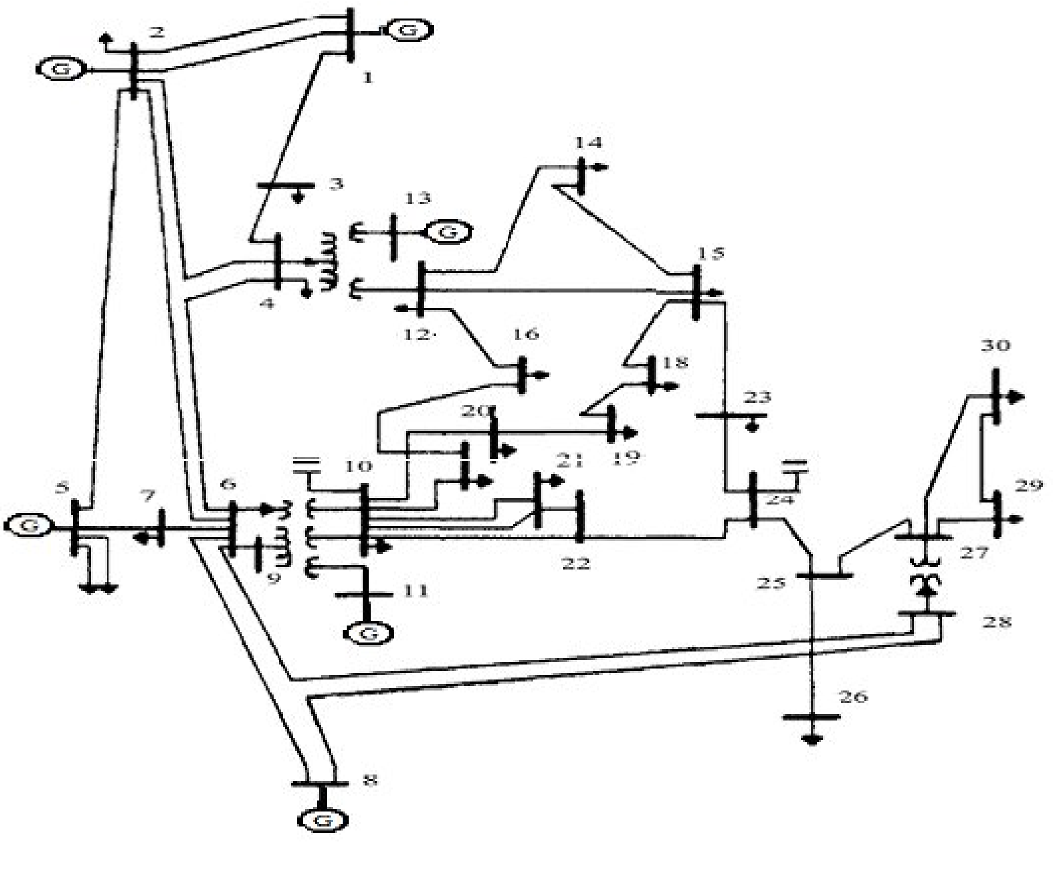

Figure 3.3: Single line diagram of IEEE-30 Bus system

3.3.1 CASE I

Three sets of generator cost curves are specified in the paper [21]. These curves are referred as quadratic, piecewise quadratics and quadratics with sine components. The performance has been studied for all three types of cost curves and the total load demand, as specified, is considered as 289.2 MW.

- Performance with quadratic cost curve
- Performance with piecewise quadratic cost curve
- Performance with quadratics curve with sine components

3.3.1.1 QUADRATIC COST CURVES

In this case the unit cost curves are represented by quadratic functions, summarized in Table 3.1. The minimum cost of solution using EP obtained is 802.749512$/hr. Resulted minimum with iterations graph is shown in figure 3.5. The solution details for the minimum cost are provided in Table 3.4.

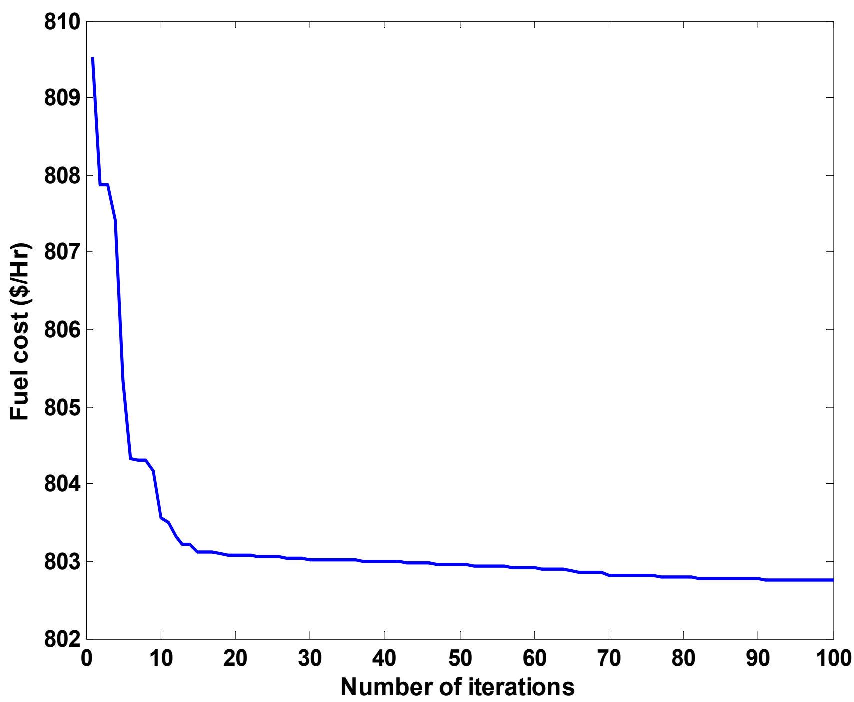

Figure 3.4: Resulted minimum cost with iterations by EP for Quadratic cost function.

Table 3.1. Generator Data and Quadratic Cost Coefficients

Generator No	Bus no.	$P_G^{min}\ (MW)$	$P_G^{max}\ (MW)$	Cost coefficients		
				A	b	c
1	1	50	200	0.00375	2.00	0.00
2	2	20	80	0.01750	1.75	0.00
3	5	15	50	0.006250	1.00	0.00
4	8	10	35	0.00834	3.25	0.00
5	11	10	30	0.02500	3.00	0.00
6	13	12	40	0.02500	3.00	0.00

3.3.1.2 PIECEWISE QUADRATIC

In this case, units 1 and 2 cost curves were replaced by piecewise quadratic curves as shown in Table 3.4. The minimum cost of solution using EP obtained is 652.652133$/hr. Figure 3.6 shows the graph of convergence of the algorithm toward the optimal solution. The solution details for the minimum cost are provided in Table 3.4.

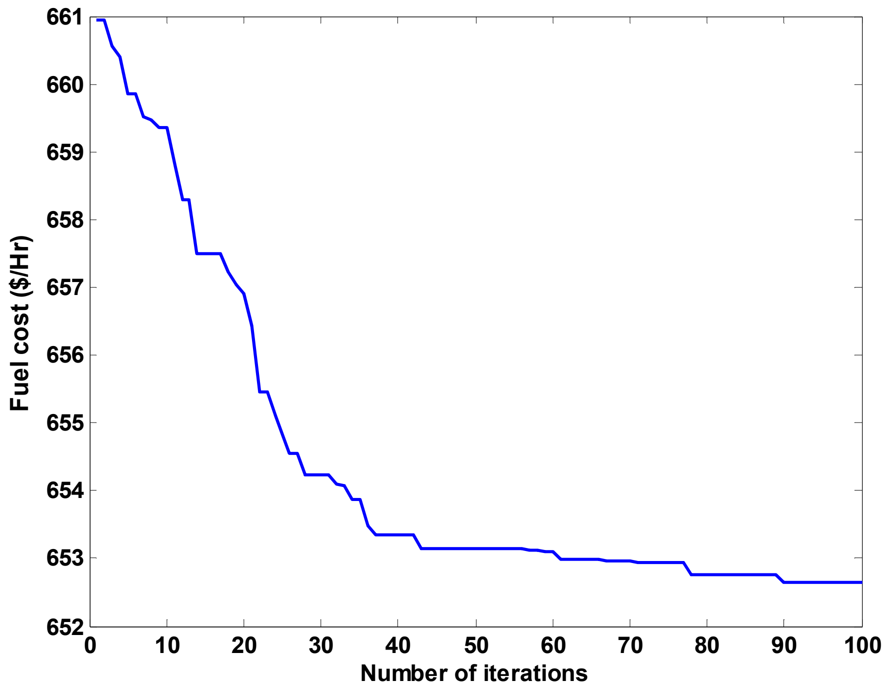

Figure 3.5: Resulted minimum cost with iterations by EP for Piecewise Quadratic cost function.

Table 3.2. Generator Data and Piecewise Cost Coefficients

Generator No.	Bus no.	P_G^{min} (MW)	P_G^{max} (MW)	Cost coefficients		
				a	b	c
1	1	50	140	0.0050	0.70	55.0
	1	140	200	0.0075	1.05	82.5
2	2	20	55	0.0100	0.30	40.0
	2	55	80	0.0200	0.60	80.0
3	5	15	50	0.006250	1.00	0.00
4	8	10	35	0.00834	3.25	0.00
5	11	10	30	0.02500	3.00	0.00
6	13	12	40	0.02500	3.00	0.00

3.3.1.3 QUADRATIC CURVE WITH SINE COMPONENTS

In this case the unit cost curves of the generators connected to buses 1 and 2 were quadratic with a sine component superimposed upon them. The sine component was used to represent the valve-point loading effects. The data for these curves is provided in Table 3.3. The minimum cost of solution using EP obtained is 923.570108$/hr. The solution details for the minimum cost are provided in Table 3.4.

Table 3.3. Generator Data and Quadratic with Sine Component Cost Coefficients

Generator No	Bus no.	P_G^{min} MW	P_G^{max} MW	Cost coefficients				
				a	b	c	d	e
1	1	50	200	0.0016	2.00	150	50.00	0.0630
2	2	20	80	0.0100	2.50	25.0	40.0	0.0980
3	5	15	50	0.006250	1.00	0.00	0.00	0.00
4	8	10	35	0.00834	3.25	0.00	0.00	0.00
5	11	10	30	0.02500	3.00	0.00	0.00	0.00
6	13	12	40	0.02500	3.00	0.00	0.00	0.00

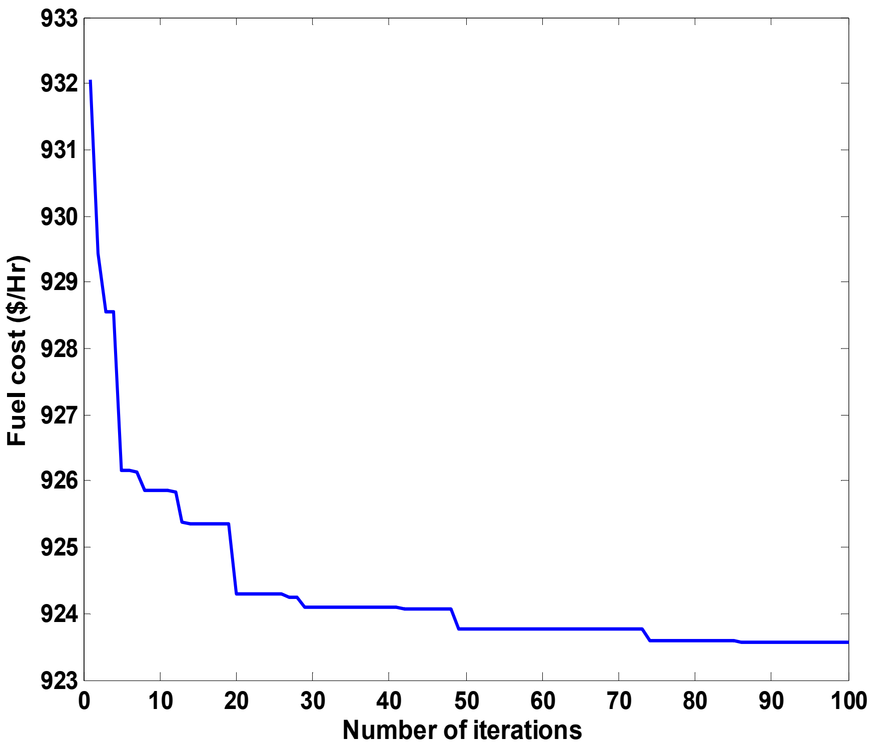

Figure 3.6 Resulted minimum cost with iterations by EP for Quadratic cost function with sine components.

Table 3.4. Optimal Results of EP for Case I

	Case(a)	Case(b)	Case(c)
P1	174.2669	139.9294	199.7317
P2	49.1097	54.9900	20.0564
P5	21.2623	28.4342	27.2023
P8	19.7780	23.7818	18.8089
P11	14.0508	19.3020	12.6459
P13	14.3069	24.1121	15.1032
Total cost($/hr)	**802.749512**	**652.652133**	**923.570108**
Total cost ($/hr) As reported in [21]	**803.51**	**649.67**	**921.45**

3.3.2 CASE II

IEEE 30 bus system given in literature [38] is considered in this case. The system consists of 6 generators. The first generator is assumed to be CCCP, second generator has piecewise and two generators having valve point loading and two, quadratic fuel functions, respectively. The cost coefficients the system are slightly modified to incorporate non-smooth fuel cost functions due to valve point loading and ramp rate limits effects, as shown in Table 3.5. The total system load demand is 283.4 MW. The best EPOPF solution obtained for the system with four types of non-smooth fuel cost functions reported in the literature is 747.3$/hr whereas the result obtained in the presented work is 726.301324$/hr.The results optained in each iteration are shown in figure 3.8. The solution details for the minimum cost are provided in Table 3.6.

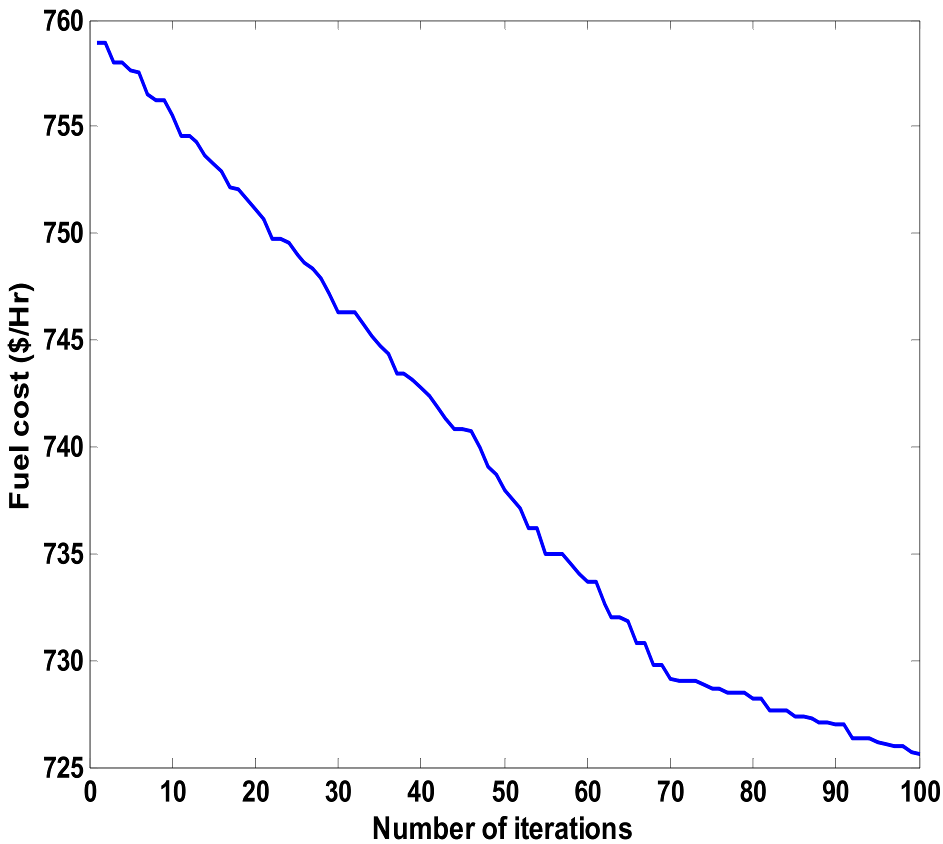

Figure 3.7: Resulted minimum cost with iterations by EP for minimization of generation cost.

Table 3.5. Generating Units Coefficients and Ramp Rate Limits for Case II

Gen. No.	$P_G^{m\ i}\ MW$	$P_G^{m\ a}\ MW$	a	b	c	D	e	k	P_G^0	ur	dr
	50	63.75	0	2.426	-11.95	0	0	0	135	65	85
	63.75	82.875	0	0	0	0	0	142	0	0	0
	82.875	93.75	0	7.146	-449.5	0	0	0	0	0	0
	93.75	157.5	0	2.942	-55.36	0	0	0	0	0	0
	157.5	176.625	0	0	0	0	0	408	0	0	0
1	176.625	200	0	6.074	-664.9	0	0	0	0	0	0
	43	53	0.01	0.3	35	0	0	0	65	12	22
2	53	77	0.02	0.6	60	0	0	0	0	0	0
3	20	47	0.07	0.095	45	40	0.08	0	35	12	15
4	10	33	0.09	0.025	30	30	0.09	0	25	8	16
5	11	26	0.025	3	0	0	0	0	20	6	9
6	14	38	0.025	3	0	0	0	0	30	8	16

Table 3.6. Optimal Results of EP for Case II

	Case 2
P1	176.7158
P2	51.9070
P5	22.9889
P8	10.7151
P11	15.0816
P13	15.6837
Total cost($/hr)	**726.301324**
Total cost ($/hr) As reported in [38]	**747.3**

CHAPTER- 4

OPF USING PARTICLE SWARM OPTIMIZATION

4.1 PARTICLE SWARM OPTIMIZATION: AN INTRODUCTION

Particle swarm optimization (PSO) is an optimization method developed by Kennedy and Eberhart [26]. It is a multi-agent search technique that simulates the motion of a flock of birds searching for food, where social sharing of information takes place and individuals can profit from the discoveries and previous experience. In a PSO system, particles change their positions by flying around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience and according to the experience of a neighboring particle.

Similar to evolutionary algorithms, the PSO technique conducts searches using a population of **particles**, corresponding to individuals [32]. Each particle represents a candidate solution to the problem at hand, a number of particles that constitute a **swarm**. An individual in a swarm approaches to the optimum or a quasi optimum through its present velocity, previous experience, and the experience of its neighbors. The fitness values of the population are found and population with best fitness is named as Particle best and best fitness among these particle best is taken as Global best. These Particle best and global best are updated for every iteration after obtaining the new population by adding velocities.

The position of each particle is updated by a new velocity calculated through equation

$$V(k,j,i+1) = W * V(k,j,i) + C1 * rand * \left(pbestx(j,k) - x(k,j,i)\right) + C2 * rand * gbestx(k) - x(k,j,i)) \quad (4.1)$$

Where, i is the iteration number

j is the particle number

W is the inertia weighting factor

C1, C2 are acceleration constant

This equation is based on its previous velocity, the position at which the best solution so far has been achieved by the particle ($pbest$ or pb), and the position at which the best solution so far has been achieved by the global population ($gbest$ orgb). The first term is the previous velocity of the agent. The second and third terms are used to change the velocity of the agent. Without the second and third terms, the agent will keep on flying in the same direction it hits the boundary. It is corresponds to a kind of inertia and tries to explore new areas. Therefore, the first term can realize the diversification in the search procedure. On the other hand, without the first term, the velocity of the flying agent is only determined by using its current position and its best solutions in search history. The agents will try to converge to their "$pbest$" and or "$gbest$" and, therefore the terms correspond to identification in the search procedure. The current position (searching point in the solution space) can be modified using the equation

$$X(k,j,i+1) = X(k,j-1,i) + V(k,j,i) \quad (4.2)$$

The movement of each particle naturally evolves to an optimal or near-optimal solution. The fitness value of each individual is compared and the best individual among the two is chosen.

The basic steps are shown in figure 4.1, correspondinglt the algorithm is as follows [35]:

Step1. Initialize the swarm i.e. position, and velocity, maximum number of iterations ($itermax$).

Step2. Identify the $pbest$ among. The $pbest$ is also $gbest$. Initialize iteration counter, $iter = 1$.

Step3. If $iter > itermax$, go to step 6 otherwise for each particle update velocity, update position. Compute objective function. Update the $pbest$.

Step4. Update $gbest$.

Step5. Increment $iter = iter + 1$ and go to step 3.

Step6. Print the optimal solution for $gbest$.

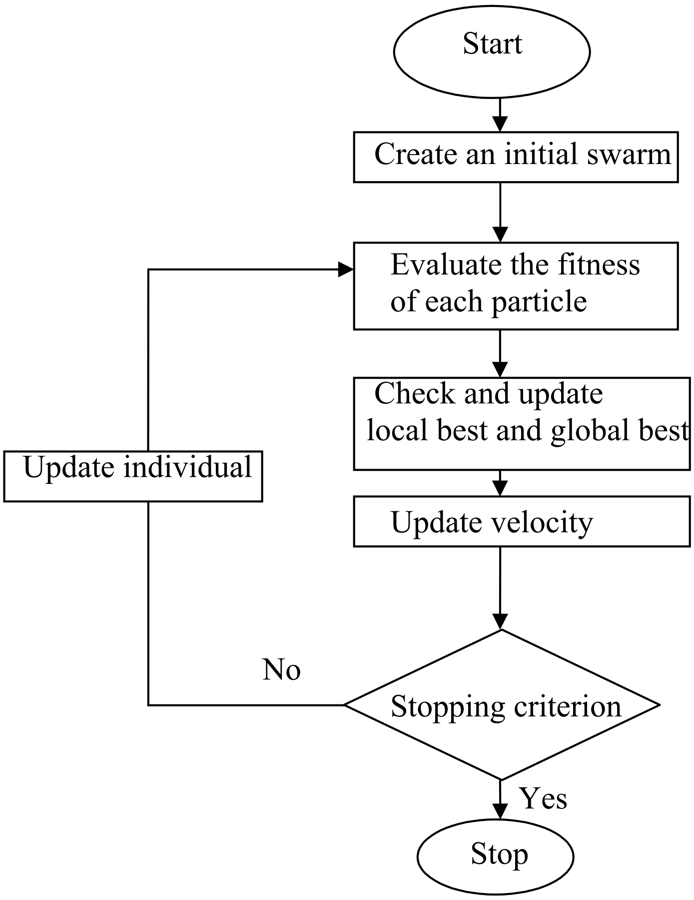

Figure 4.1: Flow chart of general PSO algorithm

4.2 OPF USING PARTICLE SWARM OPTIMIZATION

In PSO, a number of particles form a swarm that evolve or fly throughout the problem hyperspace to search for optimal or near optimal solution. The coordinates of each particle represent a possible solution with two vectors associated with it, the position and velocity vectors. Based on the PSO methodology, an algorithm for solving the OPF problem can be established. The implementation of PSO algorithm is as follows [35]:

4.2.1 INITIALIZATION

The initial particles for the generator buses except for slack bus, are chosen randomly. In the work presented, active power generation P_{gi} represents the particles in the swarm.

$$P_{gi} = P_{gi}^{min} + rand(P_{gi}^{max} - P_{gi}^{min}) \tag{4.3}$$

Where rand is a random number

The slack bus generation is computed by Newton Raphson method for each position

Similarly, initial velocities are also chosen randomly and would attempt to cover the entire parameter space uniformly.

$$V_i = V_i^{min} + rand(V_i^{max} - V_i^{min}) \quad (4.4)$$

P_{gi}^{max} and P_{gi}^{min} are the minimum and maximum limits of P_i

V_i^{max} and V_i^{min} are calculated as follows:

$$V_i^{max} = 0.5P_{gi}^{max} \quad (4.5)$$

$$V_i^{min} = -0.5P_{gi}^{min} \quad (4.6)$$

4.2.2 FINDING BEST

The objective function i.e. the minimization of generation cost represents the fitness function. The fitness values of the population are found and population with best fitness *i.e.* minimum cost is named as Particle best and best fitness among all the particle best is taken as Global best.

4.2.3 UPDATING VELOCITIES

To modify the position of each individual, it is necessary to calculate the velocity of each individual in the next stage. In this velocity updating process, the values of parameters such as W, C1, C2 should be determined in advance. The following weighting function is usually used in equation

$$W = W_{max} - \left(\frac{W_{max} - W_{min}}{itermax}\right) * iter \quad (4.7)$$

where $itermax$ is the maximum number of iterations or generations

W_{max}, W_{min} are the upper and lower limit of the inertia weight.

The inertia weight balances global and local explorations and it decreases linearly from 0.9 to 0.4 in each run.

The constants $C1$ and $C2$ pulls each particle toward $pbest$ and $gbest$ positions. The velocity is updated using equation (4.1)

4.2.4 UPDATING POSITION

Position of each individual is modified by adding the velocity of each individual using equation (4.2). If any element of an individual violates its inequality constraint due to over/under speed then the position of the individual is fixed to its maximum/minimum operating point.

4.2.5 STOP CRITERION

The search procedure can be stopped when the current iteration number reaches the predetermined maximum iteration number. The last "$gbest$" can be output as a solution.

4.3 PSO ALGORITHM FOR OPF PROBLEM

The various steps involved in the implementation of PSO to the OPF problem are shown in figure 4.2. corresponding algorithmic steps are:

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

Step 2: Modify the upper and lower limits of the generators using equations

$$P_{gi}^{min}(R) = \max\left[P_{gi}^{min}, P_{gi}^{0} - DR_i\right] \quad (4.8)$$

$$P_{gi}^{max}(R) = \min\left[P_{gi}^{max}, P_{gi}^{0} + UR_i\right] \quad (4.9)$$

Step3: Initialize randomly the particles of the population (the active power generation of the generators), except for the slack bus. These particles must satisfy the constraint

$$P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max} \quad (4.10)$$

Where P_{gi}^{max} is the minimum generation limits

and P_{gi}^{min} is maximum generation limit.

To each particles of the population, employ the Newton-Raphson method to calculate the slack bus generation, power flow.

Step 5: Calculate the fitness value of each particle, in the population using the evaluation function given by the equation

$$f = \sum_{i}^{NG} F_i(P_{gi}) \qquad (4.11)$$

Where, $F_i(P_{gi})$ is the generation cost function for P_{gi} generation at bus *i.*

NG is the number of generation including the slack bus.

Step 6: Compare each particle's fitness value with its $pbest$.

Step 7: Update the time counter t = t+1.

Step 8: Update the inertia weight W given by equation

$$W = W_{max} - \left(\frac{W_{max} - W_{min}}{itermax}\right) * iter \qquad (4.12)$$

Step 9: Modify the velocity v of each particle according to the equation

$$V(k,j,i+1) = W * V(k,j,i) + C1 * rand * \left(pbestx(j,k) - x(k,j,i)\right) + C2 * rand * gbestx(k) - x(k,j,i)) \qquad (4.13)$$

If $V > V_{max}$ then $V = V_{max}$ if $V < -V_{max}$ then if $V = -V_{max}$

Step 10: Modify the position of each particle according to the equation

$$P_g(k,j,i+1) = P_g(k,j-1,i) + V(k,j,i) \qquad (4.14)$$

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

Step11: 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.

Step12 .If the stopping criteria is satisfied then the whole process is stopped otherwise go to step3 $gbest$ is the solution.

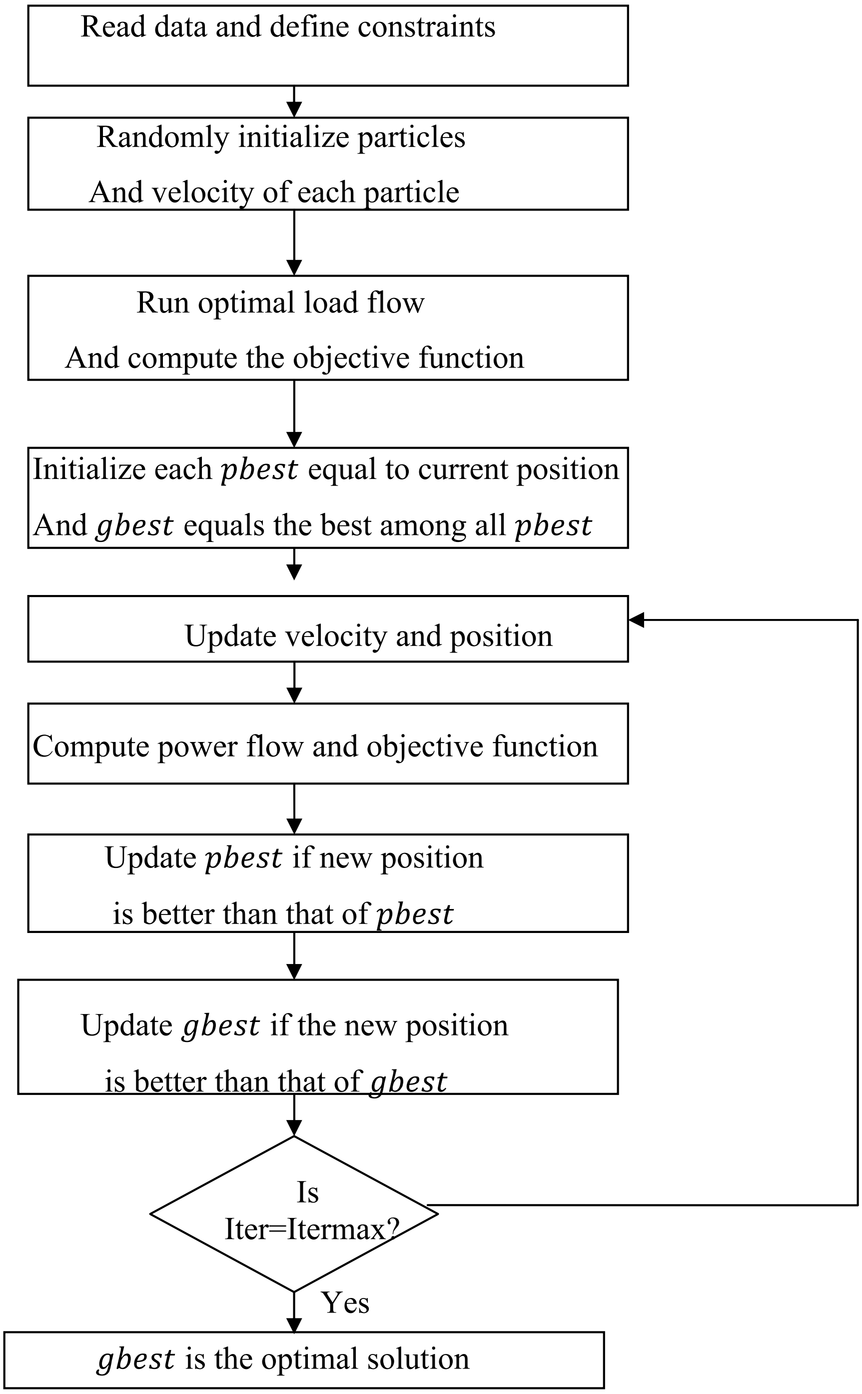

Figure 4.2: Flow chart of PSO based OPF

4.4 RESULTS

The test systems considered in chapter 3 are also tested using PSO. For the studies, the population size is considered to be 25, and the number of iteration is considered 100. The study has been carried out for two cases depending on the difference in the generator cost data and load demand.

- Case- I : Cost data and load data [21].
- Case-II : Cost data and load data [38].

4.4.1 CASE I

Three sets of generator cost curves are specified in the paper [21]. These curves are referred as quadratic, piecewise quadratics and quadratics with sine components. The performance has been studied for all three types of cost curves and the total load demand, as specified, is considered as 289.2 MW.

- Performance with quadratic cost curve
- Performance with piecewise quadratic cost curve
- Performance with quadratics curve with sine components

4.4.1.1 QUADRATIC COST CURVES

In this case the unit cost curves are represented by quadratic functions, summarized in Table 3.1 in chapter 3. The minimum cost of solution using PSO is obtained 802.452135$/hr. figure 4.3 shows the best solution obtained per iteration. The solution details for the minimum cost are provided in Table 4.1.

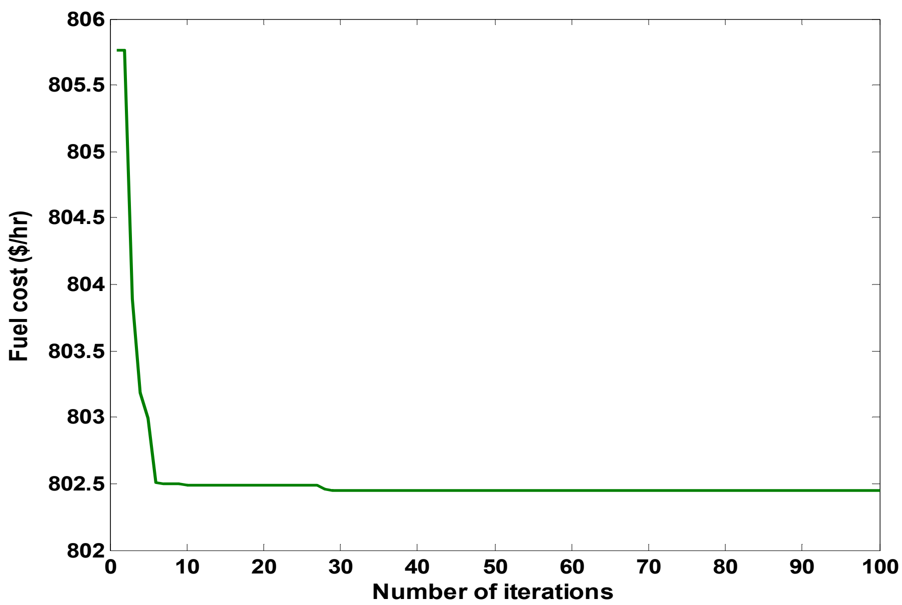

Figure 4.3: Resulted best cost with iterations by PSO for Quadratic cost function.

4.4.1.2 PIECEWISE QUADRATIC

In this case, units 1 and 2 cost curves were replaced by piecewise quadratic curves as shown in Table 3.2. The minimum cost of solution using PSO is 648.667177$/hr. The best solution obtained per iteration is shown in figure 4.4. The solution details for the minimum cost are provided in Table 4.1.

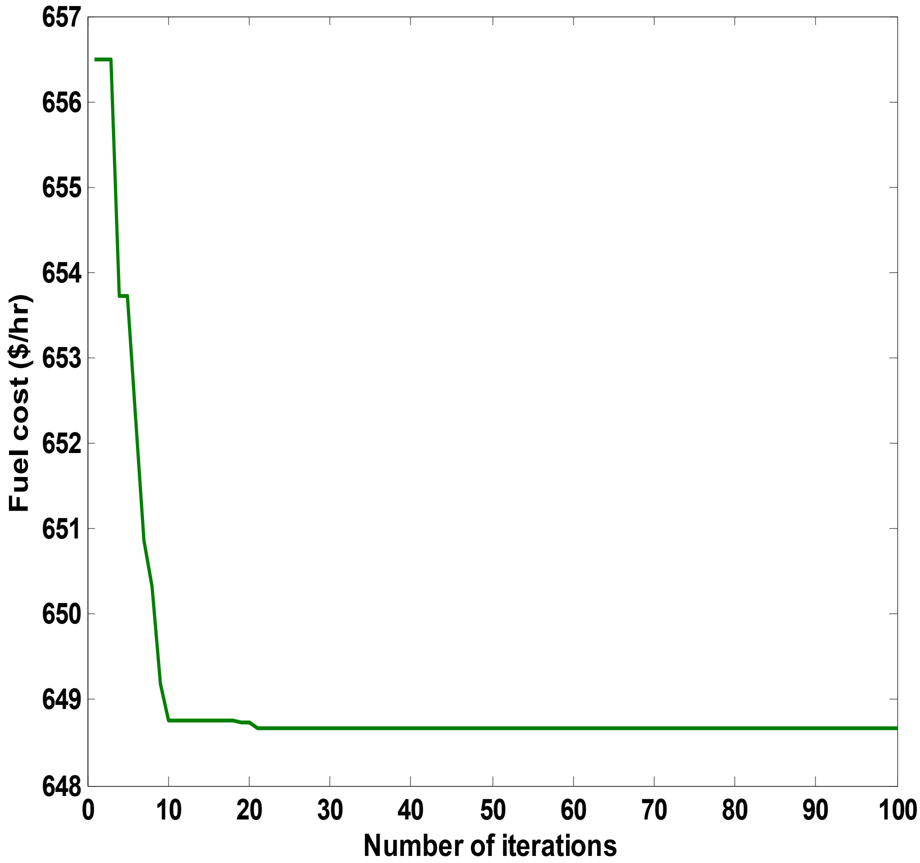

Figure 4.4: Resulted best cost with iterations by PSO for Piecewise Quadratic cost function.

4.4.1.3 SINE COMPONENTS

In this case the unit cost curves of the generators connected to buses 1 and 2 were quadratic with a sine component superimposed upon them. The sine component was used to represent the valve-point loading effects. The data for these curves is provided in Table 3.3. The minimum cost of solution using PSO is 921.229562$/hr. The best results per iteration are shown in figure 4.5. The solution details for the minimum cost are provided in Table 4.1.

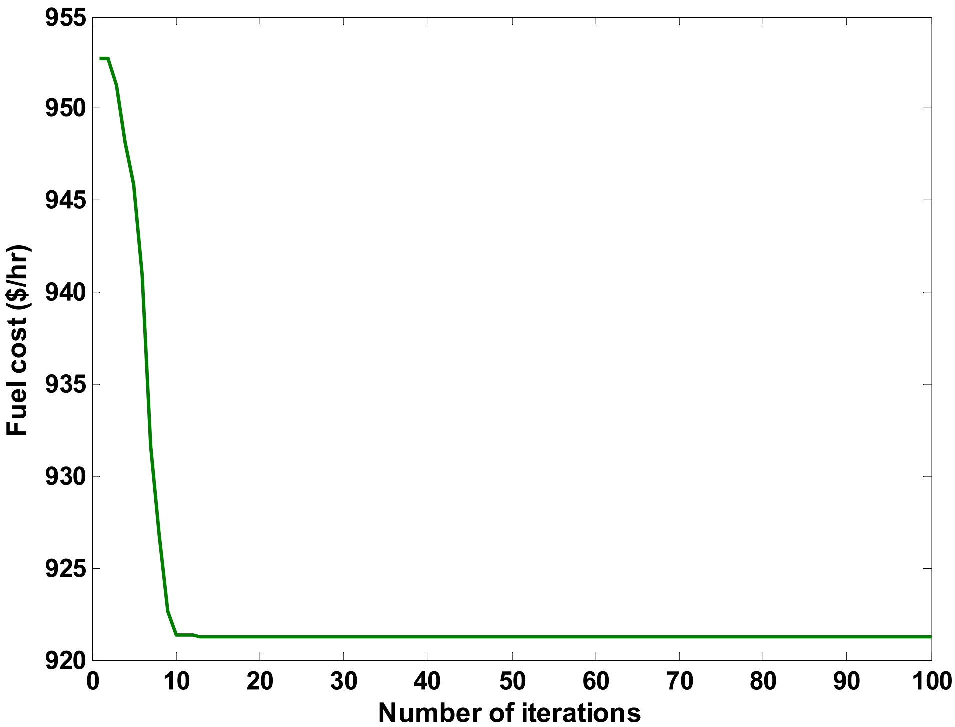

Figure 4.5: Resulted best cost with iterations by PSO for Quadratic cost function with sine components.

Table 4.1 Best Results of PSO for Case I

	Case(a)	Case(b)	Case(c)
P1	177.8342	140.0159	199.6144
P2	48.7318	54.9976	20.0000
P5	21.3873	21.8921	22.7838
P8	23.0496	34.4311	21.3595
P11	10.0000	20.0450	14.2388
P13	12.0000	19.2745	15.6423
Total cost($/hr)	**802.452135**	**648.667177**	**921.229562**
Total cost ($/hr) reported in literature [21]	**803.51**	**649.67**	**921.45**

4.4.2 CASE II

IEEE 30 bus system given in literature [38] is considered in this case. The system consists of 6 generators. The first generator is assumed to be CCCP, second generator has piecewise and two generators having valve point loading and two, quadratic fuel functions, respectively. The cost coefficients the system are slightly modified to incorporate non-smooth fuel cost functions due to valve point loading and ramp rate limits effects, as shown in Table 3.5. The total system load demand is 283.4 MW. The best EPOPF solution obtained for the system with four types of non-smooth fuel cost functions reported in the literature is 747.3$/hr whereas the result obtained in the presented work is 716.406541 $/hr.The best result obtained for each iteration is shown in figure 4.6. The solution details for the minimum cost are provided in Table 4.2.

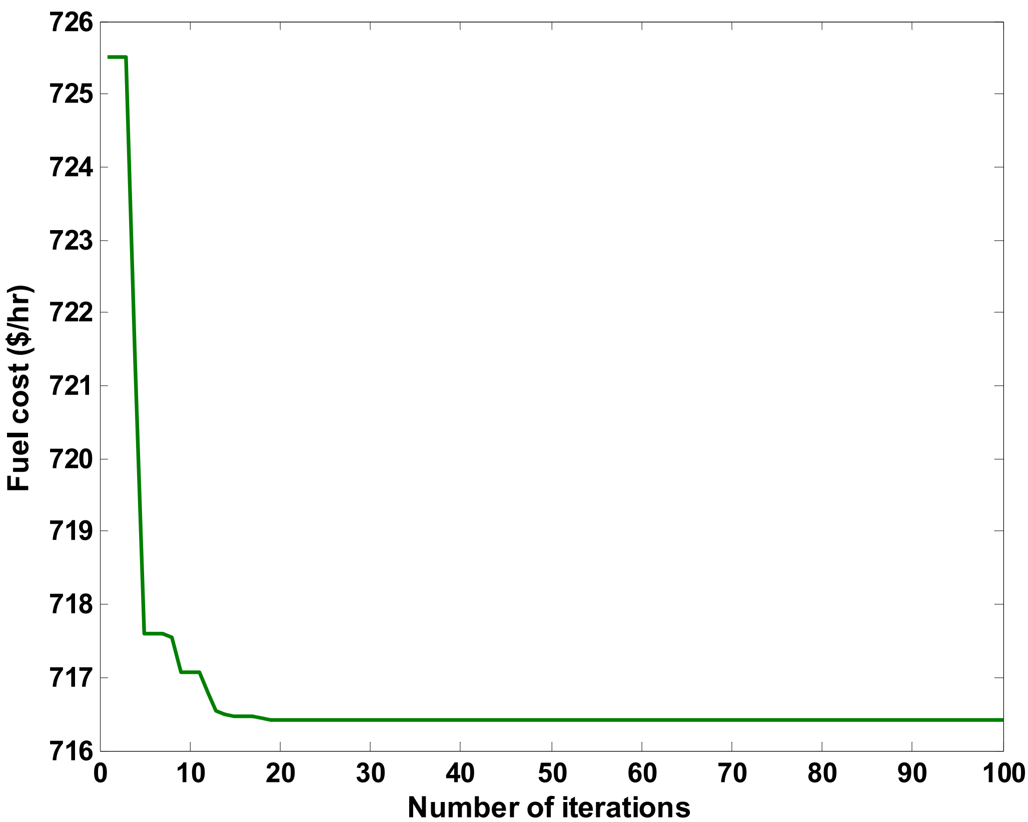

Figure 4.6: Resulted best cost with iterations by PSO for Quadratic cost function with sine components.

Table 4.2 Best Results of PSO for Case II

	Case 2
P1	176.6446
P2	52.9822
P5	20.0000
P8	10.0000
P11	14.2501
P13	19.3764
Total cost($/hr)	**716.406541**
Total cost ($/hr) reported in literature [38]	**747.3**

4.5 COMPARISON OF THE RESULTS

The results obtained with the implementation of EP and PSO based OPF, have been discussed in chapter 3 and chapter 4 respectively. In this section a comparison of the two population based methods has been presented. Figures (4.8-4.11) shows the comparison corresponding solution details are given in table 4.3 and 4.4 for the two cases respectively. The number of iterations for both the algorithms is 100 and population size is 25.

4.5.1 CASE I

IEEE-30 bus system given in the literature [21] is used for studies. This system consists of 6 generator units as well as 41 transmission lines. The total active power load is 289.2 MW. The optimal results obtained using EP and PSO for each iteration are shown in figures 4.7-4.10.

4.5.1.1 QUADRATIC COST CURVES

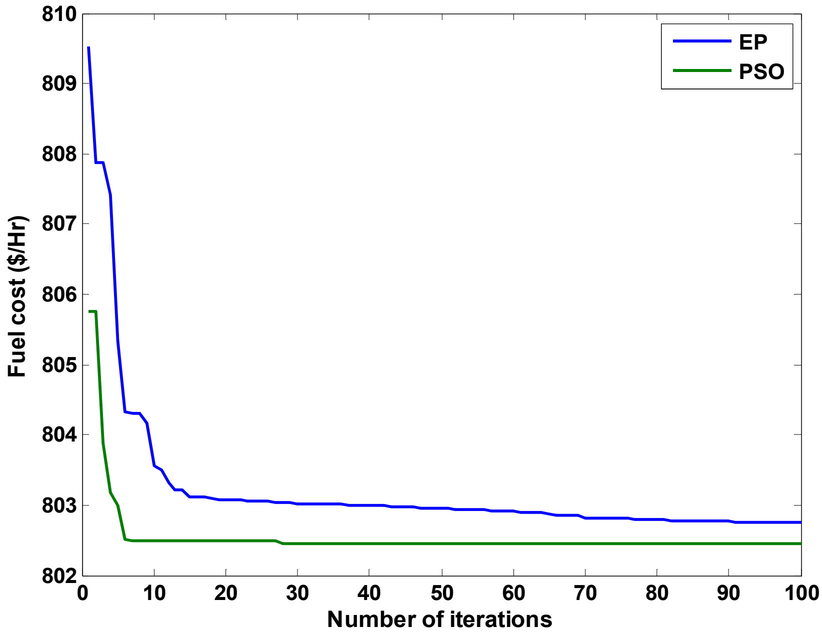

Figure 4.7: Comparison of Optimal cost with iterations using EP and PSO for Quadratic cost function.

4.5.1.2 PIECEWISE QUADRATIC

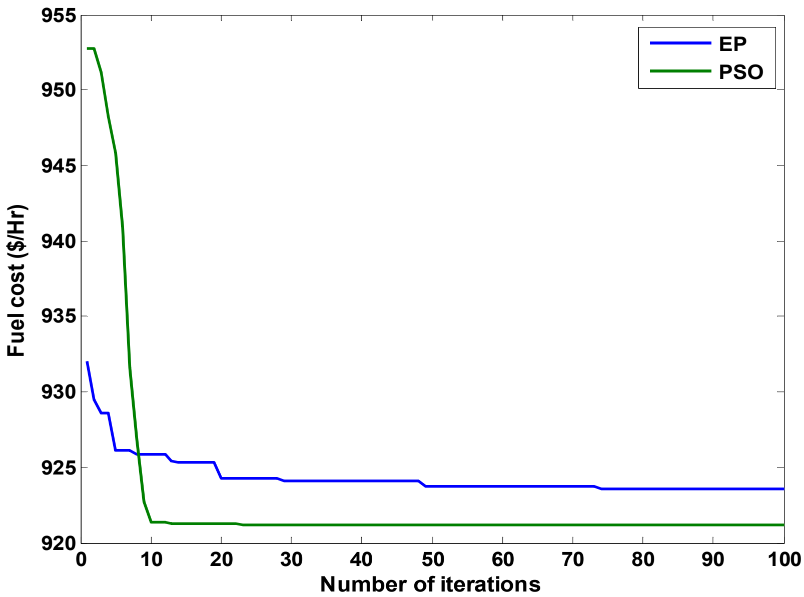

Figure 4.8: Comparison of Optimal cost with iteration using EP and PSO for Piecewise Quadratic cost function.

4.5.1.3 SINE COMPONENTS

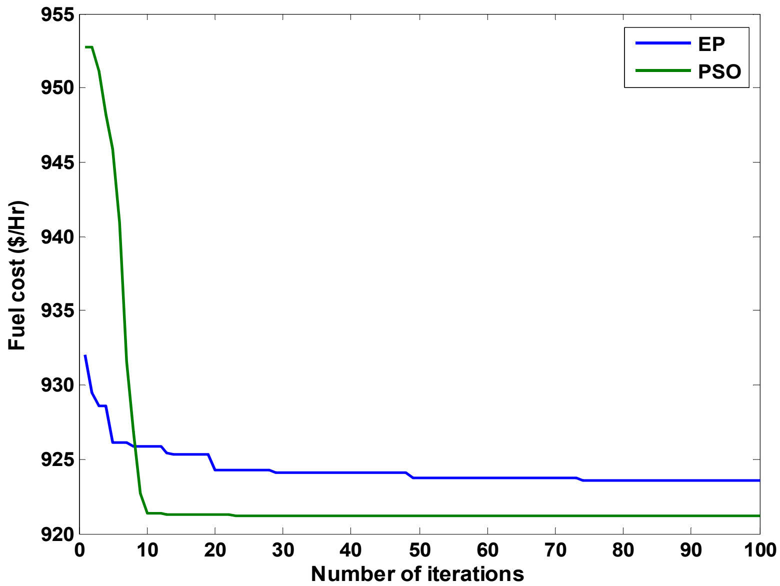

Figure 4.9: Comparison of Optimal cost with iterations using EP and PSO for Quadratic cost function with sine component.

Table 4.3. Best Results of EP and PSO for Case I

	Case (a)		Case (b)		Case (c)	
	EP	PSO	EP	PSO	EP	PSO
P1	174.2669	177.8342	139.9294	140.0159	199.7317	199.6144
P2	49.1097	48.7318	54.9900	54.9976	20.0564	20.0000
P5	21.2623	21.3873	28.4342	21.8921	27.2023	22.7838
P8	19.7780	23.0496	23.7818	34.4311	18.8089	21.3595
P11	14.0508	10.0000	19.3020	20.0450	12.6459	14.2388
P13	14.3069	12.0000	24.1121	19.2745	15.1032	15.6423
Total cost($/hr)	**802.749512**	**802.452135**	**652.652133**	**648.667177**	**923.570108**	**921.229562**
Total cost ($/hr) reported in literature [41]	**803.51**		**649.67**		**921.45**	

4.5.2 CASE II

IEEE 30 bus system given in literature [38] is considered as the test system. The total system load demand is 283.4 MW. The cost coefficients of IEEE-30 bus system are slightly modified to incorporate non-smooth fuel cost functions, as shown in Table 3.5.

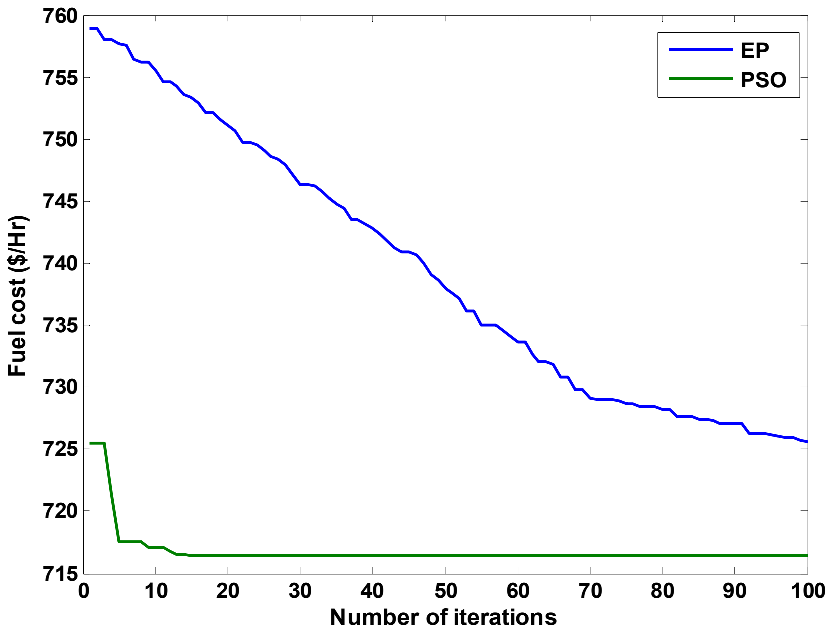

Figure 4.10: Comparison of Optimal cost with iterations using EP and PSO for minimizing generation cost.

Table 4.4 Best Results of EP and PSO for Case II

	Case 2	
	EP	PSO
P1	176.7158	176.6446
P2	51.9070	52.9822
P5	22.9889	20.0000
P8	10.7151	10.0000
P11	15.0816	14.2501
P13	15.6837	19.3764
Total cost($/hr)	**726.301324**	**716.406541**
Total cost ($/hr) reported in literature [41]	**747.3**	

CHAPTER- 5

CONCLUSION AND FUTURE SCOPE

5.1 CONCLUSION

The optimal power flow (OPF) problem for units with non-smooth fuel cost function has been solved using population based search methods namely evolutionary programming (EP) and particle swarm optimization (PSO). The discontinuities due to valve point loading effects and ramp rate limits have been incorporated. The objective in the OPF problem has been decided as minimization of total cost of real power generation. The performance of the developed algorithms has been demonstrated by their application on IEEE-30 bus system with different load demand and different sets of cost curves such as quadratic, piecewise quadratics and quadratics with sine components. The following conclusions have been drawn from the study.

- The obtained optimal results by both the methods i.e. EP and PSO are in close agreement to the respective reported results in the literature.
- PSO provides better solution as compared to EP and the PSO has a fast convergence rate.

5.2 FUTURE SCOPE

The scope of the work is identified as:

- These algorithms may be tested for power system having discrete variables like transformer tappings, switched shunt capacitors etc. Even the study can be extended to system having FACTS devices.
- The effectiveness of these algorithms may be compared with their variants and other population based search methods.
- Methodology may be identified to improve the speed of convergence of evolutionary programming based algorithm.

APPENDIX A

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

Bus no.	Bus code	Voltage Mag	Angle Degree	Load (MW)	Load (Mvar)	Gen. (MW)	Gen. (Mvar)	Gen. (Qmin)	Gen. (Qmax)	Injected (Mvar)
1	1	1.05	0.0	0.0	0.0	50	-20	0	150	0
2	2	1.033	0.0	21.70	12.7	20	-30	0	60	0
3	0	1.0	0.0	2.4	1.2	0	0.0	0	0	0
4	0	1.0	0.0	7.6	1.6	0	0.0	0	0	0
5	2	1.0058	0.0	94.2	19.0	15	-15	0	60	0
6	0	1.0	0.0	0.0	0.0	0	0.0	0	0	0
7	0	1.0	0.0	22.0	10.9	0	0.0	0	0	0
8	2	1.023	0.0	30.0	30.0	10	-15	0	50	0
9	0	1.0	0.0	0.0	0.0	0	0.0	0	0	0
10	0	1.0	0.0	5.8	2.0	0	0.0	0	0	19
11	2	1.0913	0.0	0.0	0.0	10	-10	0	-40	0
12	0	1.0	0.0	11.2	7.5	0	0	0	0	0
13	2	1.0883	0.0	0	0.0	12	-15	0	45	0
14	0	1.0	0.0	6.2	1.6	0	0	0	0	0
15	0	1.0	0.0	8.2	2.5	0	0	0	0	0
16	0	1.0	0.0	3.5	1.8	0	0	0	0	0
17	0	1.0	0.0	9.0	5.8	0	0	0	0	0
18	0	1.0	0.0	3.2	0.9	0	0	0	0	0
19	0	1.0	0.0	9.5	3.4	0	0	0	0	0
20	0	1.0	0.0	2.2	0.7	0	0	0	0	0
21	0	1.0	0.0	17.5	11.2	0	0	0	0	0
22	0	1.0	0.0	0	0.0	0	0	0	0	0
23	0	1.0	0.0	3.2	1.6	0	0	0	0	0
24	0	1.0	0.0	8.7	6.7	0	0	0	0	0
25	0	1.0	0.0	0	0.0	0	0	0	0	0
26	0	1.0	0.0	3.5	2.3	0	0	0	0	0
27	0	1.0	0.0	0	0.0	0	0	0	0	0
28	0	1.0	0.0	0	0.0	0	0	0	0	0
29	0	1.0	0.0	2.4	0.9	0	0	0	0	0
30	0	1.0	0.0	10.6	1.9	0	0	0	0	0

Table A.2 Line Data IEEE 30 Bus System

Bus from	Bus to	R p.u	X p.u	½ B p.u	Tap at bus
1	2	0.0192	0.0575	0.02640	1
1	3	0.0452	0.1852	0.02040	1
2	4	0.0570	0.1737	0.01840	1
3	4	0.0132	0.0379	0.00420	1
2	5	0.0472	0.1983	0.02090	1
2	6	0.0581	0.1763	0.01870	1
4	6	0.0119	0.0414	0.00450	1
5	7	0.0460	0.1160	0.01020	1
6	7	0.0267	0.0820	0.00850	1
6	8	0.0120	0.0420	0.00450	1
6	9	0.0000	0.2080	0.00000	0.978
6	10	0.0000	0.5560	0.00000	0.969
9	11	0.0000	0.2080	0.00000	1
9	10	0.0000	0.1100	0.00000	1
4	12	0.0000	0.2560	0.00000	0.932
12	13	0.0000	0.1400	0.00000	1
12	14	0.1231	0.2599	0.00000	1
12	15	0.0662	0.1304	0.00000	1
12	16	0.0945	0.1987	0.00000	1
14	15	0.2210	0.1997	0.00000	1
16	17	0.0824	0.1923	0.00000	1
15	18	0.1073	0.2185	0.00000	1
18	19	0.0639	0.2192	0.00000	1
19	20	0.0340	0.0680	0.00000	1
10	20	0.0936	0.2090	0.00000	1
10	17	0.0324	0.0845	0.00000	1
10	21	0.0348	0.0749	0.00000	1
10	22	0.0727	0.1499	0.00000	1
21	22	0.0116	0.0236	0.00000	1
15	23	0.1000	0.2020	0.00000	1
22	24	0.1150	0.1790	0.00000	1
23	24	0.1320	0.2700	0.00000	1
24	25	0.1885	0.3292	0.00000	1
25	26	0.2544	0.3800	0.00000	1
25	27	0.1093	0.2087	0.00000	1
28	27	0.000	0.3960	0.00000	01.968
27	29	0.2198	o.4153	0.00000	1
27	30	0.3202	0.6027	0.00000	1
29	30	0.2399	0.4533	0.00000	1
8	28	0.0636	0.2000	0.0214	1
6	28	0.0169	0.0599	0.065	1

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