PARTICLE SWARM OPTIMISATION APPLIED TO ECONOMIC LOAD DISPATCH PROBLEM

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR

THE DEGREE OF

Master of Technology
In
Power Control and Drives

By

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Department of Electrical Engineering

National Institute of Technology

Rourkela

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CERTIFICATE

This is to certify that the thesis report entitled "**PARTICLE SWARM OPTIMISATION APPLIED TO ECONOMIC LOAD DISPATCH PROBLEM**" submitted by Mr. SAUMENDRA SARANGI in partial fulfillment of the requirements for the award of Master of Technology degree in Electrical Engineering with specialization in "**Power Control and Drives**" during session 2008-2009 at National Institute of Technology, Rourkela (Deemed University) and is an authentic work by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other university/institute for the award of any degree or diploma.

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Saumendra Sarangi

ABSTRACT

The economic load dispatch plays an important role in the operation of power system, and several models by using different techniques have been used to solve these problems. Several traditional approaches, like lambda-iteration and gradient method are utilized to find out the optimal solution of non-linear problem. More recently, the soft computing techniques have received more attention and were used in a number of successful and practical applications. The purpose of this work is to find out the advantages of application of the evolutionary computing technique and Particle Swarm Optimization (PSO) in particular to the economic load dispatch problem. Here, an attempt has been made to find out the minimum cost by using PSO using the data of three and six generating units.

In this work, data has been taken from the published work in which loss coefficients are also given with the max-min power limit and cost function. All the techniques are implemented in MATLAB environment. PSO is applied to find out the minimum cost for different power demand which is finally compared with both lambda- iteration method and GA technique. When the results are compared with the traditional technique and GA, PSO seems to give a better result with better convergence characteristic.

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CHAPTER 1

INTRODUCTION

The economic operation of power system

Economic load dispatch

Overview of the thesis

1.1 THE ECONOMIC OPERATION OF POWER SYSTEM

Since an engineer is always concerned with the cost of products and services, the efficient optimum economic operation and planning of electric power generation system have always occupied an important position in the electric power industry. With large interconnection of the electric networks, the energy crisis in the world and continuous rise in prices, it is very essential to reduce the running charges of the electric energy. A saving in the operation of the system of a small percent represents a significant reduction in operating cost as well as in the quantities of fuel consumed. The classic problem is the economic load dispatch of generating systems to achieve minimum operating cost.

This problem area has taken a subtle twist as the public has become increasingly concerned with environmental matters, so that economic dispatch now includes the dispatch of systems to minimize pollutants and conserve various forms of fuel, as well as achieve minimum cost. In addition there is a need to expand the limited economic optimization problem to incorporate constraints on system operation to ensure the security of the system, there by preventing the collapse of the system due to unforeseen conditions. However closely associated with this economic dispatch problem is the problem of the proper commitment of any array of units out of a total array of units to serve the expected load demands in an 'optimal' manner. For the purpose of optimum economic operation of this large scale system, modern system theory and optimization techniques are being applied with the expectation of considerable cost savings.

1.2 ECONOMIC LOAD DISPATCH

The economic load dispatch (ELD) is an important function in modern power system like unit commitment, Load Forecasting, Available Transfer Capability (ATC) calculation, Security Analysis, Scheduling of fuel purchase etc. A bibliographical survey on ELD methods reveals that various numerical optimization techniques have been employed to approach the ELD problem. ELD is solved traditionally using mathematical programming based on optimization techniques such as lambda iteration, gradient method and so on [2],[3],[4],[5]and[6]. Economic load dispatch with piecewise linear cost functions is a highly heuristic, approximate and extremely fast form of economic dispatch [2].

Complex constrained ELD is addressed by intelligent methods. Among these methods, some of them are genetic algorithm (GA) [7]and [8], evolutionary programming (EP) [9]and[10], dynamic programming (DP)[11], tabu search [12], hybrid EP [13], neural network (NN)[14], adaptive Hopfield neural network (AHNN)[15], particle swarm optimization (PSO)[16], [17], [18], and [19], etc. For calculation simplicity, existing methods use second order fuel cost functions which involve approximation and constraints are handled separately, although sometimes valve-point effects are considered. However, the authors propose higher order cost functions for (a) better curve fitting of running cost, (b) less approximation, (c) more practical, accurate and reliable results, and modified particle swarm optimization (MPSO) is introduced to calculate the optimum dispatch of the proposed higher order cost polynomials. Constraint management is incorporated in the MPSO and no extra concentration is needed for the higher order cost functions of single or multiple fuel units in the proposed method.

Lambda iteration, gradient method [2], [3] and [4] can solve simple ELD calculations and they are not sufficient for real applications in deregulated market. However, they are fast. There are several Intelligent methods among them genetic algorithm applied to solve the real time problem of solving the economic load dispatch problem [7],[8].where as some of the works are done by Evolutionary algorithm [9],[10],[13].Few other methods like tabu search are applied to solve to solve the problem [12].Artificial neural network are also used to solve the optimization problem [14],[15].However many people applied the swarm behavior to the problem of optimum dispatch as well as unit commitment problem [16],[17],[18],[19],[20] and [21] are general purpose; however, they have randomness. For a practical problem, like ELD, the intelligent methods should be modified accordingly so that they are suitable to solve economic dispatch with more accurate multiple fuel cost functions and constraints, and they can reduce randomness.

Intelligent methods are iterative techniques that can search not only local optimal solutions but also a global optimal solution depending on problem domain and execution time limit. They are general-purpose searching techniques based on principles inspired from the genetic and evolution mechanisms observed in natural systems and populations of living beings. These methods have the advantage of searching the solution space more thoroughly. The main difficulty is their sensitivity to the choice of parameters. Among intelligent methods, PSO is simple and promising. It requires less computation time and memory. It has also standard values for its parameters.

In this thesis the Particle Swarm Optimization (PSO) is proposed as a methodology for economic load dispatch. The data of three generating units and six generating units has taken to which PSO with different population is applied and compared. The results are compared with the traditional method i.e. Lambda iteration method and Genetic Algorithm (GA).

1.3 OVERVIEW OF THE THESIS

Chapter 2 gives review of economic load dispatch. Different traditional methods are applied to find out solution the economic load dispatch problems has been discussed.

In Chapter 3, Particle Swarm Optimization (PSO) concept is explained. Benefits of PSO over conventional statistical methods are briefed. Basic parameters of PSO are explained to understand the operation how the swarms search their food.

In Chapter 4, different aspects of Genetic algorithm are discussed. A brief idea of different types of GA has given. Crossover and Mutation operation of the Genetic Algorithm are discussed with binary coded GA.

In Chapter 5, economic load dispatch problem using Lambda-iteration method and the steps to implement this using programming is discussed.

In Chapter 6, economic load dispatch problem using PSO and the steps to implement this using programming is discussed.

In Chapter 7, simulation results obtained from programming in MATLAB and details of the substation where the real time data of power consumption has taken are presented. Discussion on the results for the PSO and GA is also presented.

CHAPTER 2

ECONOMIC OPERATION OF POWER SYSTEM

Optimum economic dispatch

Cost function

System constraints

Previous approaches

INTRODUCTION

The Engineers have been very successful in increasing the efficiency of boilers, turbines and generators so continuously that each new added to the generating unit plants of a system operates more efficiently than any older unit on the system. In operating the system for any load condition the contribution from each plant and from ach unit within a plant must be determined so that the cost of the delivered power is a minimum.

Any plant may contain different units such as hydro, thermal, gas etc. These plants have different characteristic which gives different generating cost at any load. So there should be a proper scheduling of plants for the minimization of cost of operation. The cost characteristic of the each generating unit is also non-linear. So the problem of achieving the minimum cost becomes a non-linear problem and also difficult.

2.1 OPTIMUM LOAD DISPATCH

The optimum load dispatch problem involves the solution of two different problems. The first of these is the **unit commitment** or pre dispatch problem wherein it is required to select optimally out of the available generating sources to operate to meet the expected load and provide a specified margin of operating reserve over a specified period time .The second aspect of economic dispatch is the **on line economic dispatch** whereas it is required to distribute load among the generating units actually paralleled with the system in such manner as to minimize the total cost of supplying the minute to minute requirements of the system. The objective of this work is to find out the solution of non linear on line economic dispatch problem by using PSO algorithm.

2.2 COST FUNCTION

The Let C_i mean the cost, expressed for example in dollars per hour, of producing energy in the generator unit I. the total controllable system production cost therefore will be

$$C=\sum_{i=1}^{N} c(i) \text{ \$/h}$$

The generated real power P_{Gi} accounts for the major influence on c_i. The individual real generation are raised by increasing the prime mover torques ,and this requires an increased expenditure of fuel. The reactive generations Q_{Gi} do not have any measurable influence on c_i because they are controlled by controlling by field current.

The individual production cost c_i of generators unit I is therefore for all practical purposes a function only of P_{Gi}, and for the overall controllable production cost, we thus have

$$C = \sum_{i=1}^{N} ci(\text{PGi})$$

When the cost function C can be written as a sum of terms where each term depends only upon one independent variable

2.3 SYSTEM CONSTRAINTS:

Broadly speaking there are two types of constraints

i) Equality constraints
ii) Inequality constraints

The inequality constraints are of two types (i) Hard type and, (ii) Soft type. The hard type are those which are definite and specific like the tapping range of an on-load tap changing transformer whereas soft type are those which have some flexibility associated with them like the nodal voltages and phase angles between the nodal voltages, etc. Soft inequality constraints have been very efficiently handled by penalty function methods.

2.3.1 EQUALITY CONSTRAINTS

From observation we can conclude that cost function is not affected by the reactive power demand. So the full attention is given to the real power balance in the system. Power balance requires that the controlled generation variables P_{Gi} abbey the constraints equation

$$Pd = \sum_{i=1}^{N} PGi$$

2.3.2 INEQUALITY CONSTRAINTS:

i) Generator Constraints:

The KVA loading in a generator is given by $\sqrt{P^2 + Q^2}$ and this should not exceed a pre-specified value of power because of the temperature rise conditions

- The maximum active power generation of a source is limited again by thermal consideration and also minimum power generation is limited by the flame instability of a boiler. If the power output of a generator for optimum operation of the system is less than a pre-specified value P_{min} , the unit is not put on the bus bar because it is not possible to generate that low value of power from the unit .Hence the generator power P cannot be outside the range stated by the inequality

$$P_{min} \leq P \leq P_{max}$$

- Similarly the maximum and minimum reactive power generation of a source is limited. The maximum reactive power is limited because of overheating of rotor and minimum is limited because of the stability limit of machine. Hence the generator powers P_p cannot be outside the range stated by inequality, i.e.

$$Q_{p\,min} \leq Q_P \leq Q_{p\,max}$$

ii) Voltage Constraints:

It is essential that the voltage magnitudes and phase angles at various nodes should vary with in certain limits. The normal operating angle of transmission lies between 30 to 45 degrees for transient stability reasons. A lower limit of delta assures proper utilization of transmission capacity.

iii) Running Spare Capacity Constraints:

These constraints are required to meet

a) The forced outages of one or more alternators on the system and

b) The unexpected load on the system

The total generation should be such that in addition to meeting load demand and losses a minimum spare capacity should be available i.e.

$$G \geq P_p + P_{SO}$$

Where G is the total generation and P_{SO} is some pre-specified power. A well planned system is one in which this spare capacity P_{SO} is minimum.

iv) Transmission Line Constraints:

The flow of active and reactive power through the transmission line circuit is limited by the thermal capability of the circuit and is expressed as.

$$C_p \leq C_{p\ max}$$

Where $C_{p\ max}$ is the maximum loading capacity of the P_{TH} line

v) Transformer taps settings:

If an auto-transformer is used, the minimum tap setting could be zero and the maximum one, i.e.

$$0 \leq t \leq 1.0$$

Similarly for a two winding transformer if tapping are provided on the secondary side,

$$0 \leq t \leq n$$

Where n is the ratio of transformation.

vi) Network security constraints:

If initially a system is operating satisfactorily and there is an outage, may be scheduled or forced one, It is natural that is an outage, may be scheduled or forced one, it is natural that some of the constraints of the system will be violated. The complexity of these constraints (in terms of number of constraints) is increased when a large system is under study. In this a study is to be made with outage of one branch at a time and then more than one branch at a time. The natures of constraints are same as voltage and transmission line constraints.

2.4 PREVIOUS APPROACHES

2.4.1 The Lambda –Iteration Method:

In Lambda iteration method lambda is the variable introduced in solving constraint optimization problem and is called Lagrange multiplier. It is important to note that lambda can be solved at hand by solving systems of equation. Since all the inequality constraints to be satisfied in each trial the equations are solved by the iterative method

i) Assume a suitable value of $\lambda^{(0)}$ this value should be more than the largest intercept of the incremental cost characteristic of the various generators.

ii) Compute the individual generations

iii) Check the equality

$$Pd = \sum_{n=1}^{n} Pn \qquad \text{- - - - - - - - - - - - - - - - (2.1)}$$

is satisfied.

iv) If not, make the second guess λ repeat above steps

2.4.2 The Gradient Search Method:

This method works on the principle that the minimum of a function, f(x), can be found by a series of steps that always take us in a downward direction. From any starting point, x^0, we may find the direction of "steepest descent" by noting that the gradient f,

$$\nabla \mathrm{f} = \begin{bmatrix} \frac{\partial f}{\partial x1} \\ . \\ . \\ . \\ . \\ \frac{\partial f}{\partial xn} \end{bmatrix}$$

always points in the direction of maximum ascent. Therefore, if we want to move in the direction of maximum descent, we negate the gradient. Then we should go from x^0 to x^1 using:

$$x^1 = x^0 - \nabla f \alpha \quad \text{-----------------------(2.2)}$$

Where α is a scalar to allow us to guarantee that the process of convergence. The best value of α must be determined by experiment

In case of power system economic load dispatch f becomes

$$f = \sum_{i=1}^{N} F_i(P_i) \quad \text{-----------------(2.3)}$$

The object is to drive the function to its minimum. However we have to be concerned with the constraints function

$$\phi = (P_{load} - \sum_{i=1}^{N} P_i) \quad \text{----------------(2.4)}$$

To solve the economic load dispatch problem which involves minimizing the objective function and keeping the equality constraints, we must apply the gradient technique directly to the Lagrange function is:

$$\Im = \sum_{i=1}^{N} F_i(P_i) + \lambda(P_{load} - \sum_{i=1}^{N} P_i) \quad \text{------(2.5)}$$

And the gradient of this function is

$$\nabla \Im = \begin{bmatrix} \frac{\partial \Im}{\partial P1} \\ . \\ . \\ . \\ . \\ \frac{\partial \Im}{\partial Pn} \end{bmatrix}$$

The problem with the formulation is the lack of a guarantee that the new points generated each step will lie on the surface ϕ.

The economic dispatch algorithm requires a starting λ value and sarting values for $P_1, P_2,$ and P_3 .The gradient for $\Im$ is calculated as above and the new values of λ ,P_1,and P_2 etc, are found from

$$X^1 = X^0 - (\nabla \Im)\alpha \qquad \text{-------------(2.6)}$$

Where X is a vector

$$X = \begin{bmatrix} P_1 \\ P_2 \\ . \\ . \\ \lambda \end{bmatrix}$$

2.4.3 Newton's Method:

Newton's method goes a step beyond the simple gradient method and tries to solve the economic dispatch by observing that the aim is to always drive

$$\nabla \Psi x = 0$$

Since this is a vector function, we can formulate the problem as one of finding the correction that exactly drives the gradient to zero (i.e. to a vector, all of whose elements are zero).Suppose we wish to drive the function g(x) to zero. The function g is a vector and the unknown, x are also vectors. Then to use Newton's method, we observe

$$g(x+\Delta x)=g(x)+[g'(x)]\,\Delta x=0 \quad \text{------------------- (2.7)}$$

Where g'(x) is the familiar Jacobian matrix. The adjustment at each step is then

$$\Delta X = -[g'(x)]^{-1}\, g(x) \quad \text{-------------------- (2.8)}$$

Now, if we let the g function be the gradient vector $\nabla\Psi x$ we get

$$\Delta X = -[\frac{\partial}{\partial x}\nabla \psi_x]^{-1}\,\Delta\psi \quad \text{----------------- (2.9)}$$

For the economic load dispatch problem this takes the form:

$$\psi = \sum_{i=1}^{N} F_i(P_i) + \lambda(P_{load} - \sum_{i=1}^{N} P_i) \quad \text{------------ (2.10)}$$

The $\nabla \psi_x$ is a Jacobean matrix which has now second order derivatives is called Hessian matrix. Generally, Newton's method will solve for the correction that is much closer to the minimum generation cost in one cost in one step than would the gradient method

2.4.4 Economic Dispatch With Piecewise Linear Cost Functions:

In this method economic load dispatch problem of those generators are solved whose cost functions are represented as single or multiple segment linear cost functions. Here for all units running, we start with all of them at P_{min}, then begin to raise the output of the unit with the lowest incremental cost segment. If this unit hits the right-hand end of a segment, or if it hits P_{max}, we then find the unit with the next lowest incremental cost segment and raise its output. Eventually, we will reach a point where a units output is being raised and the total of all unit outputs equal the load, or load plus losses. At that point, we assign the last unit being adjusted to have a generation which is practically loaded for one segment. to make this procedure very fast, we can create a table giving each segment of each unit its MW contribution. Then we order this table by ascending order of incremental cost. By search in from the top down in this table we do not have to go and look for the next segment each time a new segment is to be chosen. This is an extremely fast form of economic dispatch.

2.4.5 Base Point and Participation Factor:

This method assumes that the economic dispatch problem has to be solved repeatedly by moving the generators from one economically optimum schedule to another as the load changes by a reasonably small amount. It is started from a given schedule called the base point . next assumes a load change and investigates how much each generating unit needs to be moved in order that the new load served at the most economic operating point.

2.4.6 Linear Programming:

Linear programming (LP) is a technique for optimization of a linear objective function subject to linear equality and linear in-equality constraints. Informally, linear programming determines the way to achieve the best outcome (such as maximum profit or lowest cost) in a given mathematical model and given some list of requirements represented as linear equations. For example if f is function defined as follows

$$f(x_1, x_2, ...x_n) = c_1x_1 + c_2x_2 + ...c_nx_n + d \qquad ---------- (2.11)$$

A linear programming method will find a point in the optimization surface where this function has the smallest (or largest) value. Such points may not exist, but if they do, searching through the optimization surface vertices is guaranteed to find at least one of them. Linear programs are problems that can be expressed in canonical form

Maximize $C^T X$

Subject to $AX \le b$

X represents the vector of variables (to be determined), while C and b are vectors of (known) coefficients and A is a (known) matrix of coefficients. The expression to be maximized or minimized is called the objective function (c^T in this case). The equations $AX \le b$ are the constraints which specify a convex polyhedron over which the objective function is to be optimized.

2.4.7 Dynamic Programming:

When cost functions are no-convex equal incremental cost methodology can not be applied. Under such circumstances, there is a way to find an optimum dispatch which use dynamic programming method. In dynamic Programming is an optimization technique that transforms a maximization (or minimization) problem involving n decision variables into n problems having only one decision variable each. This is done by defining a sequence of Value functions V_1, V_2, ... V_n, with an argument y representing the state of the system. The definition of $V_i(y)$ is the maximum obtainable if decisions 1, 2 ...I are available and the state of the system is y. The function V_1 is easy to find. For I=2,...n, V_i at any state y is calculated from V_{i-1} by maximizing, over the I-th decision a simple function (usually the sum) of the gain of decision i and the function V_{i-1} at the new state of the system if this decision is made. Since V_{i-1} has already been calculated, for the needed states, the above operation yields V_i for all the needed states. Finally, V_n at the initial state of the system is the value of the optimal solution. The optimal values of the decision variables can be recovered, one by one, by tracking back the calculations already performed.

SUMMARY

The optimum load dispatch of power system is discussed in this chapter. When the problem is to be solved few constraints has to be kept in mind. Different types of constraints are discussed in this chapter. Various traditional methods applied to solve the economic load dispatch problem is also discussed.

CHAPTER 3

PARTICLE SWARM OPTIMISATION

PSO An Optimization Tool

Back Ground of Artificial Intelligence

Algorithm of PSO

Flow chart

Artificial Neural Network and PSO

3. PSO AN OPTIMIZATION TOOL

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr.Ebehart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. The detailed information will be given in following sections. Compared to GA, the advantages of PSO are that PSO is easy to implement and there are few parameters to adjust. PSO has been successfully applied in many areas: function optimization, artificial neural network training, fuzzy system control, and other areas where GA can be applied.

3.1. BACK GROUND OF ARTIFICIAL INTELLIGENCE:

The term "Artificial Intelligence" (AI) is used to describe research into human-made systems that possess some of the essential properties of life. AI includes two-folded research topic.

- AI studies how computational techniques can help when studying biological phenomena
- AI studies how biological techniques can help out with computational problems

The focus of this report is on the second topic. Actually, there are already lots of computational techniques inspired by biological systems. For example, artificial neural network is a simplified model of human brain; genetic algorithm is inspired by the human evolution. Here we discuss another type of biological system - social system, more specifically, the collective behaviors of simple individuals interacting with their environment and each other. Someone called it as swarm intelligence. All of the simulations utilized local processes, such as those modeled by cellular automata, and might underlie the unpredictable group dynamics of social behavior. Some popular examples are bees and birds. Both of the simulations were created to interpret the movement of organisms in a bird flock or fish school. These simulations are normally used in computer animation or computer aided design. There are two popular swarm inspired methods in computational intelligence areas: Ant colony optimization (ACO) and particle swarm optimization (PSO). ACO was inspired by the behaviors of ants and has many successful applications in discrete optimization problems. The particle swarm concept originated as a simulation of simplified social system. The original intent was to graphically simulate the choreography of bird of a bird block or fish school. However, it was found that particle swarm model could be used as an optimizer.

3.2 PARTICLE SWARM OPTIMISATION:

PSO simulates the behaviors of bird flocking. Suppose the following scenario: a group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. But they know how far the food is in each iteration. So what's the best strategy to find the food? The effective one is to follow the bird, which is nearest to the food. PSO learned from the scenario and used it to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. We call it "particle". All of particles have fitness values, which are evaluated by the fitness function to be optimized, and have velocities, which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles.

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is 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 population. This best value is a global best and called g-best. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called p-best. After finding the two best values, the particle updates its velocity and positions with following equation (3.1) and (3.2).

$$V_i^{(u+1)} = w * V_i^{(u)} + C_1 * rand\,(\,) * (pbest_i - P_i^{(u)}) + C_2 * rand\,(\,) * (gbest_i - P_i^{(u)}) \quad \text{- - - - (3.1)}$$

$$P_i^{(u+1)} = P_i^{(u)} + V_i^{(u+1)} \quad \text{- - - - - - - - - - - - - - - - (3.2)}$$

In the above equation,
The term rand ( )*(pbest $_i$ -$P_i^{(u)}$) is called particle memory influence

The term rand ( )*($gbest_i$ -$P_i^{(u)}$) is called swarm influence.

$V_i^{(u)}$ which is the velocity of i^{th} particle at iteration 'u' must lie in the range

$$V_{min} \leq V_i(u) \leq V_{max}$$

- The parameter V_{max} determines the resolution, or fitness, with which regions are to be searched between the present position and the target position

- .If Vmax is too high, particles may fly past good solutions. If V_{min} is too small, particles may not explore sufficiently beyond local solutions.

- In many experiences with PSO, V_{max} was often set at 10-20% of the dynamic range on each dimension.

- The constants $C_1$and C_2 pull each particle towards pbest and *gbest* positions.

- Low values allow particles to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement towards, or past, target regions.

- The acceleration constants C_1 and C_2 are often set to be 2.0 according to past experiences
.
- Suitable selection of inertia weight 'ω' provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution.

- In general, the inertia weight *w* is set according to the following equation,

$$W = W_{max} - \left[\frac{W_{max} - W_{min}}{ITER_{max}} \right] \times ITER \qquad \text{- - - - - - - - (3.3)}$$

Where w -is the inertia weighting factor

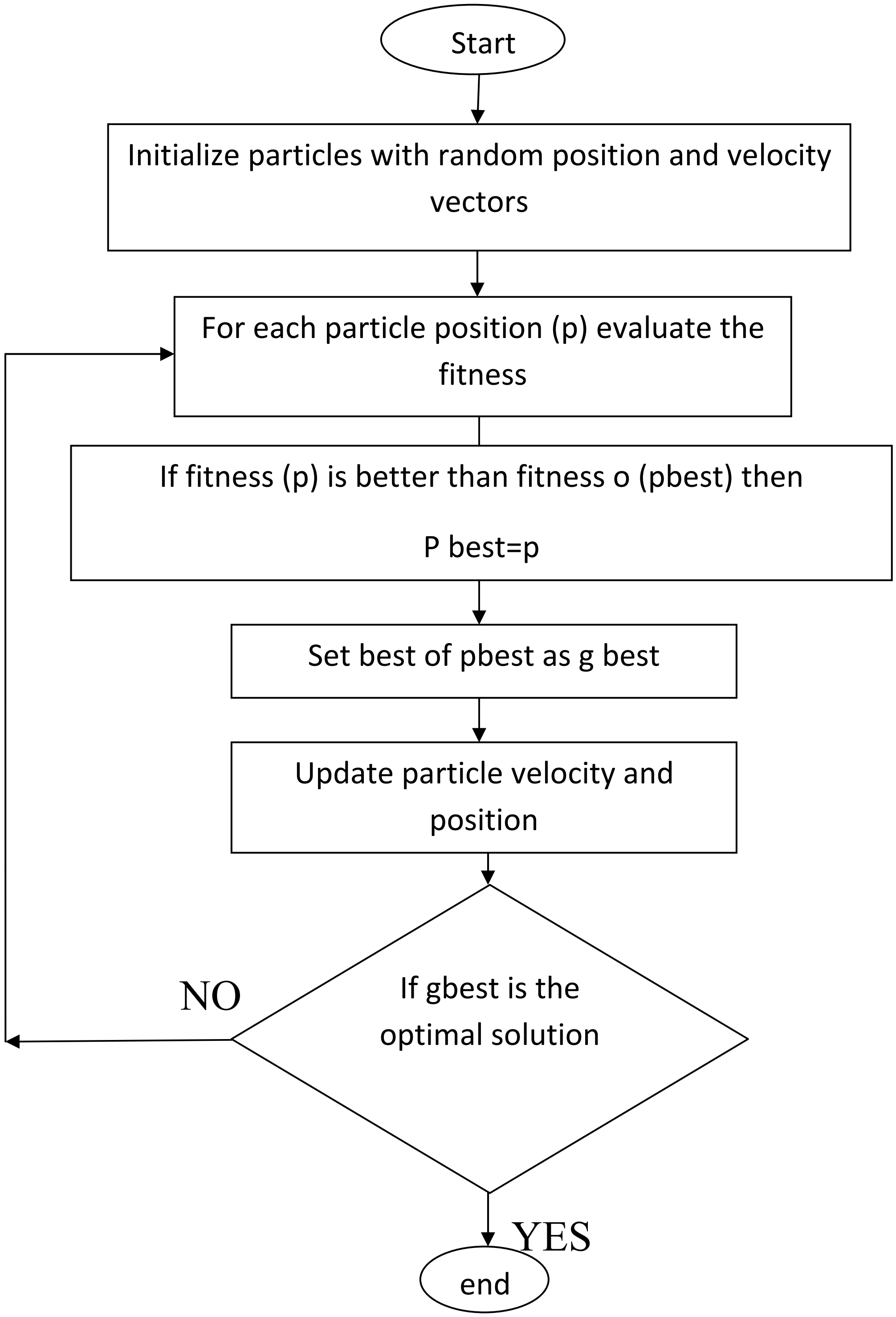
Wmax - maximum value of weighting factor

Wmin - minimum value of weighting factor

$ITER_{max}$ - maximum number of iterations

ITER - current number of iteration

3.3 FLOW CHART:



3.4. ARTIFICIAL NEURAL NETWORK AND PSO

An artificial neural network (ANN) is an analysis paradigm that is a simple model of the brain and the back-propagation algorithm is the one of the most popular method to train the artificial neural network. Recently there have been significant research efforts to apply evolutionary computation (EC) techniques for the purposes of evolving one or more aspects of artificial neural networks.

Evolutionary computation methodologies have been applied to three main attributes of neural networks: network connection weights, network architecture (network topology, transfer function), and network learning algorithms.

Most of the work involving the evolution of ANN has focused on the network weights and topological structure. Usually the weights and/or topological structure are encoded as a chromosome in GA. The selection of fitness function depends on the research goals. For a classification problem, the rate of misclassified patterns can be viewed as the fitness value. The advantage of the EC is that EC can be used in cases with non-differentiable PE transfer functions and no gradient information available.

The disadvantages are

1. The performance is not competitive in some problems.
2. Representation of the weights is difficult and the genetic operators have to be carefully selected or developed.

There are several papers reported using PSO to replace the back-propagation learning algorithm in ANN in the past several years. It showed PSO is a promising method to train ANN. It is faster and gets better results in most cases.

SUMMARY

The detail of particle swarm optimization technique is discussed in this chapter. Various parameters of PSO and their effects are also discussed. Algorithm of PSO optimization technique and the flow chart is discussed briefly. Finally a comparison of PSO and ANN considering various aspects is also discussed.

CHAPTER 4

GENETIC ALGORITHM

Overview of Genetic Algorithm

Operators of Genetic Algorithm

Properties of Genetic Algorithm

Flow Chart of GA

INTRODUCTION

Genetic algorithm is a search method that employs processes found in natural biological evolution. These algorithms search or operate on a given population of potential solutions to find those that approach some specification or criteria. To do this, the genetic algorithm applies the principle of survival of the fittest to find better and better approximations. At each generation, a new set of approximations is created by the process of selecting individual potential solutions (individuals) according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. This process leads to the evolution of population of individuals that are better suited to their environment than the individuals that they were created from, just as in natural adaptation.

4.1 OVERVIEW OF GENETIC ALGORITHM

Genetic algorithm (GAs) were invented by John Holland in the 1960s and were developed with his students and colleagues at the University of Michigan in the !(70s. Holland’s original goal was to investigate the mechanisms of adaptation in nature to develop methods in which these mechanisms could be imported into computer systems.

GA is a method for deriving from one population of “chromosomes” (e.g., strings of ones and zeroes, or bits) a new population. This is achieved by employing “natural selection” together with the genetics inspired operators of recombination (crossover), mutation, and inversion. Each chromosome consists of genes(e.g. bits), and each gene is an instance of a particular allele(e.g,0 or 1).The selection operator chooses those chromosomes in the population that will be allowed to reproduce, and on average those chromosomes that have a higher fitness factor(defined bellow),produce more offspring than the less fit ones. Crossover swaps subparts of two chromosomes, roughly imitating biological recombination between two single chromosome (“haploid”) organisms; mutation randomly changes the allele values of some locations (locus) in the chromosome; and inversion reverses the order of a contiguous section of chromosome

4.2 OPERATORS OF GENETIC ALGORITHM

A basic genetic algorithm comprises three genetic operators.

- Selection
- Crossover
- Mutation

Starting from an initial population of strings (representing possible solutions),the GA uses these operators to calculate successive generations. First, pairs of individuals of the current population are selected to mate with each other to form the offspring, which then form the next generation.

4.2.1 Selection

This operator selects the chromosome in the population for reproduction. The more fit the chromosome, the higher its probability of being selected for reproduction. The various methods Of selecting chromosomes for parents to crossover are

- Roulette-wheel selection
- Boltzmann selection
- Tournament selection
- Rank selection
- Steady-state selection

4.2.1.1 Roulette-wheel selection

The commonly used reproduction operator is the proportionate reproductive operator where a string is selected from the mating pool with a probability proportional to F_i where F_i is the fitness value for that string. Since the population size is usually kept fixed in a simple GA, The sum of the probabilities of each string being selected for the mating pool must be one. The probability of the ith selected string is

$$p_i = \frac{F_i}{\sum_{j=1}^{n} F_j} \qquad \text{----------------------- (4.1)}$$

Where n is the population size.

4.2.1.2 Tournament selection

GA uses a strategy to select the individuals from population and insert them into a mating pool. Individuals from the mating pool are used to generate new offspring, which are the basis for the next generation. As the individuals in the mating pool are the ones whose genes will be inherited by the next generation, it is desirable that the mating pool consists of good individuals .A selection strategy in GA is simply a process that the mating pool consists of good individuals .A selection strategy selection strategy in GA is simply a process that favors the selection of better individuals in the population for the mating pool.

4.2.2 Crossover

The cross over operator involves the swapping of genetic material (bit-values) between the two parent strings. This operator randomly chooses a locus (a bit position along the two chromosomes) and exchanges the sub-sequences before and after that locus between two chromosomes to create two offspring. For example, the strings 1110 0001 0011 and 1000 0110 0111. The crossover operator roughly imitates biological recombination between two haploid (single chromosome) organisms. The crossover may be a single bit cross over or two bit cross over. Incase of two bit crossover two points are chosen where the binary digits are swapped.

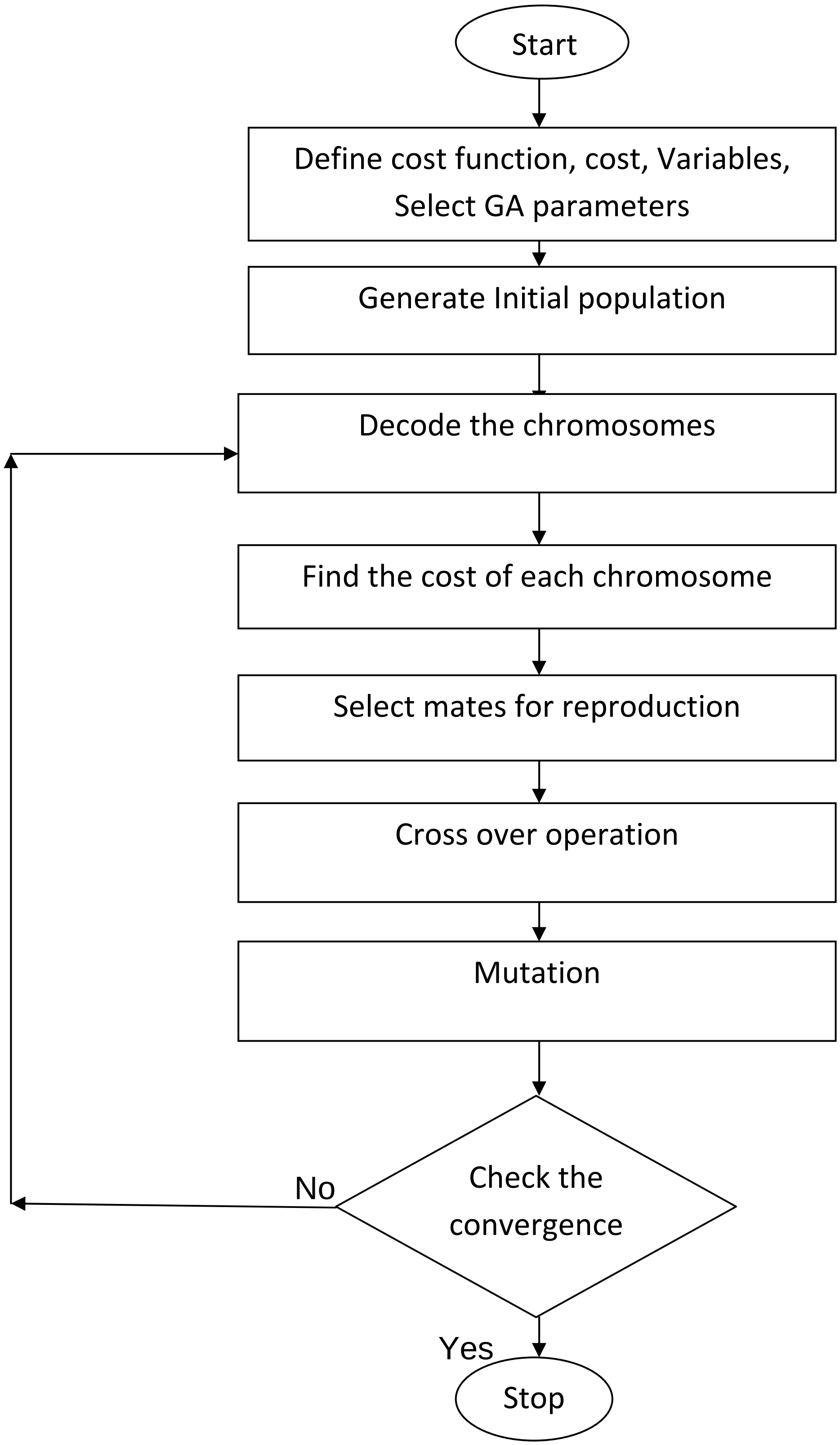
4.2.3 Mutation

The two individuals (children) resulting from each crossover operation will now be subjected to the mutation operator in the final step to forming the new generation. This operator randomly flips or alters one or more bit values at randomly selected locations in a chromosome. For example, the string 1000 0001 0011 might be mutated in its second position to yield 1**1**00 0001 0011. Mutation can occur at each bit position in a string with some probability and in accordance with its biological equivalent; usually this is very small, for example, 0.001. If 100% mutation occurs, then all of the bits in the chromosome have been inverted. The mutation operator enhances the ability of the GA to find a near optimal solution to a given problem by maintaining a sufficient level of genetic variety in the population, which is needed to make sure that the entire solution space is used in the search for the best solution. In a sense, it serves as an insurance policy; it helps prevent the loss of genetic material.

4.3 PROPERTIES OF GA

- Generally good at finding acceptable solutions to a problem reasonably quickly
- Free of mathematical derivatives
- No gradient information is required
- Free of restrictions on the structure of the evaluation function
- Fairly simple to develop
- Do not require complex mathematics to execute
- Able to vary not only the values, but also the structure of the solution
- Get a good set of answers, as opposed to a single optimal answer
- Make no assumptions about the problem space
- Blind without the fitness function. The fitness function drives the population toward better
- Solutions and is the most important part of the algorithm.
- Not guaranteed to find the global optimum solutions
- Probability and randomness are essential parts of GA
- Can by hybridized with conventional optimization methods
- Potential for executing many potential solutions in parallel
- Deals with large number of variables
- Provides a list of optimum variables

4.4 FLOW CHART OF GA



SUMMARY

In this chapter various operators of genetic algorithm like selection, crossover and mutation are discussed. Advantages and disadvantages of the Genetic Algorithm over the other optimization technique are also discussed. The Flow chart of GA is also discussed.

CHAPTER 5

ECONOMIC LOAD DIPSPATCH USING LAGRAGIAN METHOD

ELD with loss

ELD without loss

INTRODUCTION

The economic load dispatch problem deals with the minimization of cost of generating the power at any load demand. The study of this economic load can be classified into two different groups, one is economic load dispatch without the transmission line losses and other one is economic load dispatch with transmission line losses. In this chapter two different aspects are considered.

5.1 ELD WITHOUT LOSS

The economic load dispatch problem is defined as

$$\text{Min } F_T = \sum_{n=1}^{N} F_n \quad \text{- -} \quad (5.1)$$

$$\text{Subject to } P_D = \sum_{n=1}^{N} P_n \quad \text{- - - - - - - - - - - - - - - - - - - -} \quad (5.2)$$

Where F_T is total fuel input to the system, F_n the fuel input to nth unit, P_D the total load demand and P_n the generation of nth unit.

By making use of Lagrangian multiplier the auxiliary function is obtained as

$$F = F_T + \lambda\left(P_D - \sum_{n=1}^{n} P_n\right) \quad \text{- - - - - - - - - - - - - - - - - -} \quad (5.3)$$

Where λ is the Lagrangian multiplier.

Differentiating F with respect to the generation P_n and equating to zero gives the condition for optimal operation of the system.

$$\frac{\partial F}{\partial P_n} = \frac{\partial F_T}{\partial P_n} + \lambda(0-1) = 0 \quad \text{- - - - - - - - - - - - - - - - - - -} \quad (5.4)$$

$$= \frac{\partial F_T}{\partial P_n} - \lambda = 0$$

Since $F_T = F_1 + F_2 + F_3 + \text{- - - - - - - -} + F_n$

$$\therefore \qquad \frac{\partial F_T}{\partial P_n} = \frac{dF_n}{dP_n} = \lambda$$

And therefore the condition for optimum operation is

$$\frac{dF_1}{dP_1} = \frac{dF_2}{dP_2} = \cdots\cdots = \frac{dF_n}{dP_N} = \lambda \qquad \text{- - - - - - - - - - - - - - - - - (5.5)}$$

Here $\frac{dF_n}{dP_n}$ = incremental production cost of plant n in Rs.per MWhr.

The incremental production cost of a given plant over a limited range is represented by

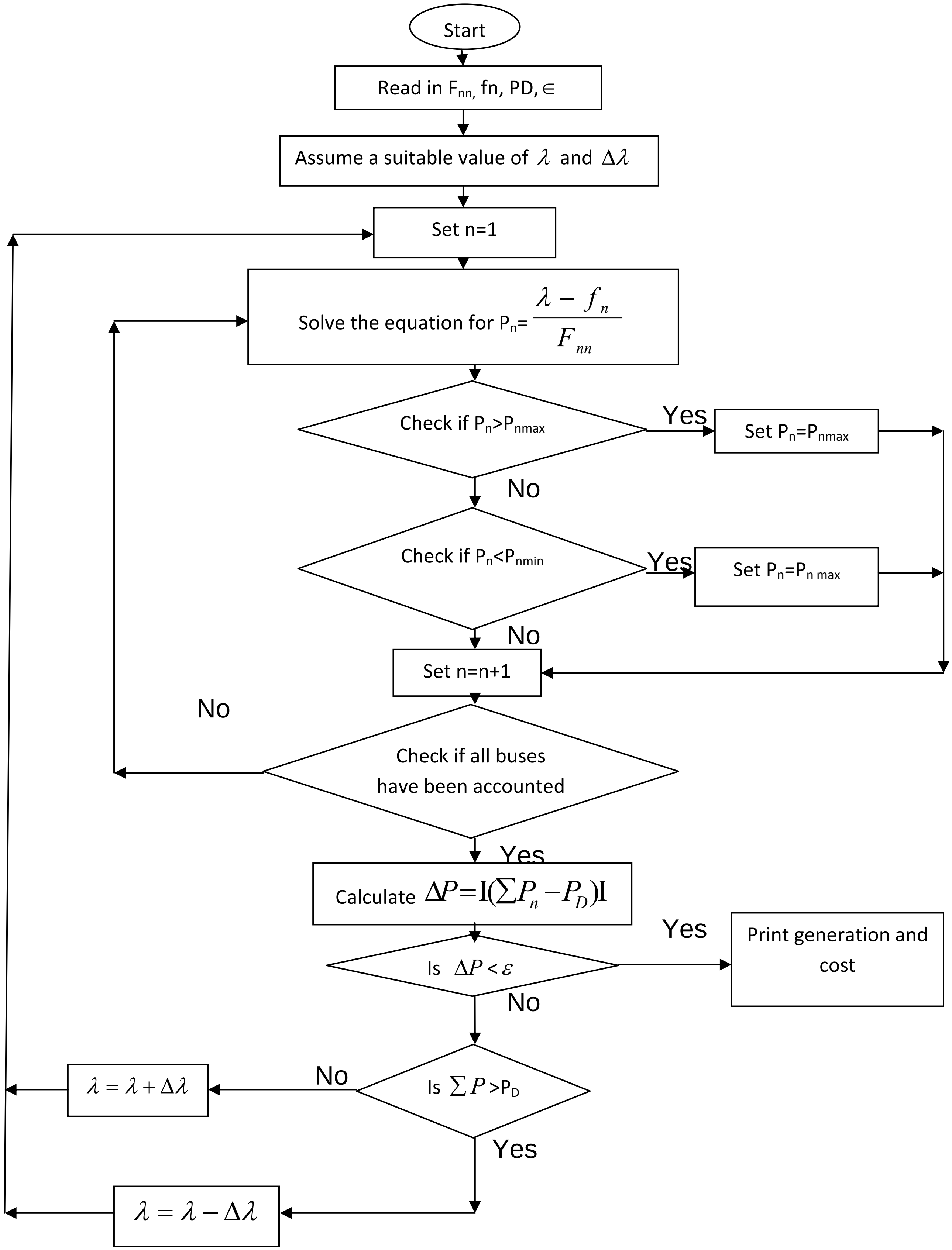
$$\frac{dF_n}{dP_n} = F_n P_n + f_n$$

Where F_{nn}=slope of incremental production cost curve

F_n =intercept of incremental production cost curve

The equation (5.5) mean that the machine be so loaded that the incremental cost of production of each machine is same. It is to be noted here that the active power generation constraints are taken into account while solving the equations which are derived above. If these constraints are violated for any generator it is tied to the corresponding limit and the rest of the load is distributed to the remaining generator units according to the equal incremental cost of production.

5.1.1 FLOW CHART OF ELD WITHOUT LOSS



5.2 ELD WITH LOSS

The optimal load dispatch problem including transmission losses is defined as

$$\text{Min } F_T = \sum_{n=1}^{N} F_n \quad \text{-------------------------- (5.6)}$$

$$\text{Subject to } P_D + P_L - \sum_{n=1}^{n} P_n \quad \text{-------------------------- (5.7)}$$

Where P_L is the total system loss which is assumed to be a function of generation and the other term have their usual significance.

Making use of the Lagrangian multiplier λ ,the auxiliary function is given by

$$F = F_T + \lambda (P_D + P_L - \sum P_N)$$

The partial differential of this expression when equated to zero gives the condition for optimal load dispatch, i.e.

$$\frac{\partial F}{\partial P_n} = \frac{\partial F_T}{\partial P_n} + \lambda\left(\frac{\partial P_L}{\partial P_n} - 1\right) = 0$$

$$\frac{dF}{dP_n} + \lambda \frac{\partial P}{\partial P_n} = \lambda \quad \text{------------------------ (5.8)}$$

Here the term $\frac{\partial P_L}{\partial P_n}$ is known as the incremental transmission loss at plant n and λ is known as the incremental cost of received power in Rs.per MWhr. The equation (5.8) is a set of n equations with (n+1) unknowns .Here n generations are unknown and λ is also unknown. These equations are known as coordination equations because they coordinate the incremental transmission losses with the incremental cost of production.

To solve these equations the loss formula equation is expressed in terms of generations and is approximately expressed as

$$P_L = \sum_m \sum_n P_m B_{mn} P_n \quad \text{------------------------} (5.9)$$

Where P_m and P_n are the source loadings, B_{mn} the transmission loss coefficient. The formula is derived under the following assumptions;

1. The equivalent load current at any bus remains a constant complex fraction of the total equivalent load current.
2. The generator bus voltage magnitudes and angles are constant
3. The power factor of each source is constant.

The solution of coordination equation requires the calculation of $\dfrac{\partial P_L}{\partial P_N} = 2\sum_m B_{mn} P_m$

Also
$$\frac{dF_n}{dP_n} = F_{nn} P_n + f_n \quad \text{------------------------} (5.10)$$

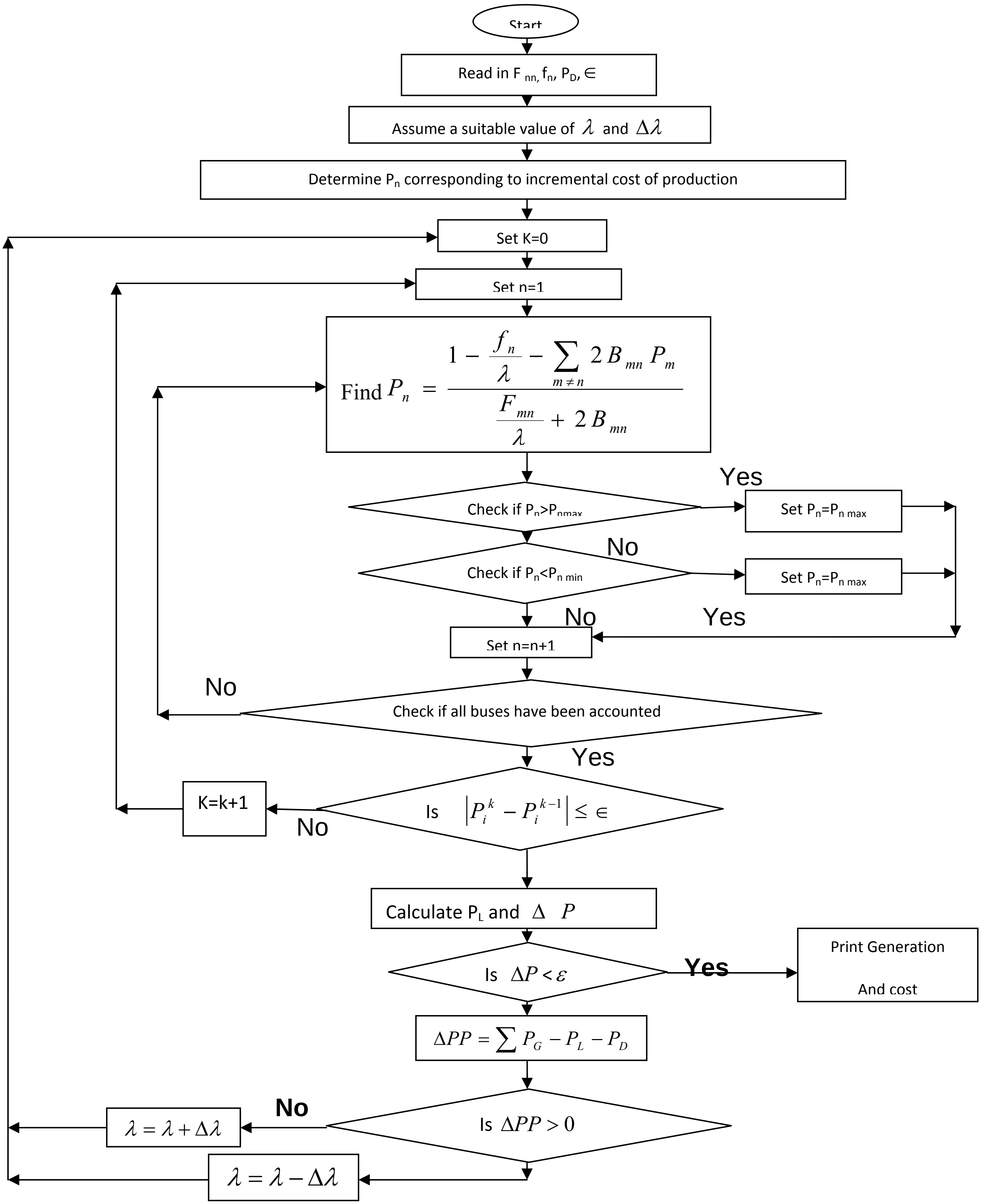
∴ The coordination equation can be rewritten as

$$F_{nn}P_n + f_n + \lambda \sum_m 2 B_{mn} P = \lambda$$

Solving for P_n we obtain

$$P_n = \frac{1 - \dfrac{f_n}{\lambda} - \sum_{m \neq n} 2 B_{mn} P_m}{\dfrac{F_{mn}}{\lambda} + 2 B_{mn}} \quad \text{----------------------} (5.11)$$

5.2.1 FLOW CHART OF ELD WITH LOSS



5.3 FEW IMPORTANT POINTS

When transmission losses are included and coordinated, the following points must be kept in mind for economic load dispatch solution

1. Whereas incremental transmission cost of production of a plant is always positive, the incremental transmission losses can be both positive and negative.

2. The individual generators will operate at different incremental costs of production.

3. The generation with highest positive incremental transmission loss will operate at the lowest incremental cost of production

SUMMARY

In this chapter the lambda iteration method for solving the economic load dispatch problem is discussed. Both the cases with transmission line losses and without transmission losses are discussed. The Flow charts of both cases are also discussed.

CHAPTER 6

ECONOMIC LOAD DISPATCH USING PSO AND GA

ELD without loss using PSO

ELD with loss using PSO

ELD with loss using GA

INTRODUCTION

Particle Swarm optimization (PSO) is a population based algorithm in which each particle is considered as s solution in the multimodal optimization space. There are several types of PSO proposed but here in this work very simplest form of PSO is taken to solve the Economic Load Dispatch (ELD) problem. The particles are generated keeping the constraints in mind for each generating unit. When economic load dispatch problem considered it can be classified in two different ways.

1. Economic load dispatch without considering the transmission line losses
2. Economic load dispatch considering the transmission line losses.

6.1 ELD WTHOUT LOSS USING PSO

When any optimization process is applied to the ELD problem some constraints are considered. In this work two different constraints are considered. Among them the equality constraint is summation of all the generating power must be equal to the load demand and the inequality constraint is the powers generated must be with in the limit of maximum and minimum active power of each unit. The sequential steps of the proposed PSO method are given below.

Step 1:

The individuals of the population are randomly initialized according to the limit of each unit including individual dimensions. The velocities of the different particles are also randomly generated keeping the velocity within the maximum and minimum value of the velocities. These initial individuals must be feasible candidate solutions that satisfy the practical operation constraints.

Step 2:

Each set of solution in the space should satisfy the equality constraints .So equality constraints are checked. If any combination doesn't satisfy the constraints then they are set according to the power balance equation.

Step 3:

The evaluation function of each individual P_{gi}, is calculated in the population using the evaluation function F .Here F is

$$F = a \times (P_{gi})^2 + b \times P_{gi} + c \quad \text{- (6.1)}$$

Where a, b, c are constants. The present value is set as the pbest value.

Step 4:

Each pbest values are compared with the other pbest values in the population. The best evaluation value among the p-bests is denoted as gbest.

Step 5:

The member velocity v of each individual Pg is modified according to the velocity update equation

$$V_{id}^{(u+1)} = w * V_i^{(u)} + C_1 * rand\,(\,) * (pbest_{id} - P_{gid}^{(u)}) + C_2 * rand\,(\,) * (gbest_{id} - P_{gid}^{(u)}) \quad (6.2)$$

Where u is the number of iteration.

Step 6:

The velocity components constraint occurring in the limits from the following conditions are checked

$$\mathbf{V_d^{min} = -0.5 * P_{min}}$$

$$\mathbf{V_d^{max} = +0.5 * P_{max}}$$

Step 7:

The position of each individual Pg is modified according to the position update equation

$$P_{gid}^{(u+1)} = P_{gid}^{(u)} + V_{id}^{(u+1)} \quad \text{- -.(6.3)}$$

Step 8:

If the evaluation value of each individual is better than previous ***pbest***, the current value is set to be ***pbest***. If the best ***pbest*** is better than ***gbest***, the value is set to be ***gbest.***

Step 9:

If the number of iterations reaches the maximum, then go to step 10.Otherwise,
go to step 2.

Step 10:

The individual that generates the latest **gbest** is the optimal generation power of each unit with the minimum total generation cost.

6.2 ELD WTH LOSS USING PSO

When the losses are considered the optimization process becomes little bit complicated. Since the losses are dependent on the power generated of the each unit, in each generation the loss changes. The P-loss can be found out by using the equation

$$P_L = \sum_m \sum_n P_m B_{mn} P_n \quad \text{------------------------------} \quad (6.4)$$

Where B_{mn} are the loss co-efficient. The loss co-efficient can be calculated from the load flow equations or it may be given in the problem. However in this work for simplicity the loss coefficient are given which are the approximate one. Some parts are neglected. The sequential steps to find the optimum solution are

Step 1:

The power of each unit, velocity of particles, is randomly generated which must be in the maximum and minimum limit. These initial individuals must be feasible candidate solutions that satisfy the practical operation constraints.

Step 2:

Each set of solution in the space should satisfy the following equation

$$\sum_{i=1}^{N} P_{gi} = P_D + P_L \text{ ---------------------- (6.5)}$$

P_L calculated by using above equation (6.4).Then equality constraints are checked. If any combination doesn't satisfy the constraints then they are set according to the power balance equation.

$$P_d = P_D + P_L - \sum_{\substack{i=1 \\ i \neq d}}^{N} P_i \text{ ---------------------- (6.6)}$$

Step 3:

The cost function of each individual P_{gi}, is calculated in the population using the evaluation function F .Here F is

$$F = a \times (P_{gi})^2 + b \times P_{gi} + c \text{ ---------------------- (6.7)}$$

Where a, b, c are constants. The present value is set as the pbest value.

Step 4:

Each pbest values are compared with the other pbest values in the population. The best evaluation value among the pbest is denoted as *gbest.*

Step 5:

The member velocity v of each individual Pg is updated according to the velocity update equation

$$V_{id}^{(u+1)} = w * V_i^{(u)} + C_1 * rand\,( ) * (pbest_{id} - P_{gid}^{(u)}) + C_2 * rand\,( ) * (gbest_{id} - P_{gid}^{(u)}) .(6.8)$$

Where u is the number of iteration.

Step 6:

The velocity components constraint occurring in the limits from the following conditions are checked

$$V_d^{min} = -0.5*P_{min}$$

$$V_d^{max} = +0.5*P_{max}$$

Step 7:

The position of each individual Pg is modified according to the position update equation

$$P_{gid}^{(u+1)} = P_{gid}^{(u)} + V_{id}^{(u+1)} \quad \text{-----------------(6.9)}$$

Step 8:

The cost function of each new is calculated If the evaluation value of each individual is better than previous *pbest;* the current value is set to be *pbest*. If the best *pbest* is better than *gbest*, the value is set to be *gbest*.

Step 9:

If the number of iterations reaches the maximum, then go to step 10.Otherwise, go to step 2.

Step 10:

The individual that generates the latest **gbest** is the optimal generation power of each unit with the minimum total generation cost.

6.3 ELD WTH LOSS USING GA

There are several types of GA can be applied to solve the optimization problem. In this work binary coded GA is applied. In GA, it is not required to put the generating units within the constraints. The generated value automatically remains with in the constraints. That is the advantage of GA over the PSO. The sequential steps of solving the given problem are given below.

Step1:

The initial strings are randomly generated. String length can chosen according to the problem complexity. Here in this work the string length is chosen is 10.

Step 2:

The generated string is converted in the feasible range by using following equation,

$$Actaul\_Value(i) = p\_\min + ((p\_\max - p\_\min) \times p\_m(i))/(2^{(L-1)}) \text{ --(6.10)}$$

Where L= the string length

P_min =minimum value of the generating unit

P_max= maximum value of the generating unit

p_m (i) = the decimal value of i^{th} generating unit in the string

Step 3:

Equality constraints are checked according to the equation (6.6)

Step 4:

The fitness of each chromosome is calculated according to the cost function mentioned in equation (6.1). the cost function is sorted and those has lowest cost function are selected for the next generation.

Step 5:

The selected chromosomes are considered for the crossover operation.

Step 6:

After the crossover operation the new off springs are considered for the mutation operation.

Step 7:

The fitness of the new offspring is calculated and they are sorted in the ascending order. The lowest cost function means better fitness. So lowest cost function values are selected for the next generation.

Step 8:

The process is repeated up to the maximum no of iterations.

SUMMARY

In this chapter the various steps to solve the economic load dispatch problem with transmission line losses and without transmission line losses are discussed. First particle swarm optimization (PSO) is discussed, and then genetic algorithm (GA) is also discussed.

CHAPTER 7

RESULTS AND DISCUSSION

Economic load dispatch of Three unit system

Economic load dispatch of Six unit system

7. RESULTS & DISCUSSION

The different methods discussed earlier are applied to two cases to find out the minimum cost for any demand. One is three generating units and other is six generating units. Results of Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) are compared with the conventional lambda iteration method. In the first case transmission losses are neglected and then transmission line losses are also considered. All these simulation are done on MATLAB 7.6 environment.

7.1 CASE STUDY-1: THREE UNIT SYSTEM

The three generating units considered are having different characteristic. Their cost function characteristics are given by following equations

$$F1=0.00156P_1^2+7.92P_1+561 \quad Rs/Hr$$

$$F2=0.00194P_2^2+7.85P_2+310 \quad Rs/Hr$$

$$F3=0.00482P_3^2+7.97P_3+78 \quad Rs/Hr$$

According to the constraints considered in this work among inequality constraints only active power constraints are constraints are considered. There operating limit of maximum and minimum power are also different. The unit operating ranges are:

$$100\ MW \leq P_1 \leq 600\ MW$$

$$100\ MW \leq P_2 \leq 400\ MW$$

$$50\ MW \leq P_3 \leq 200\ MW$$

The transmission line losses can be calculated by knowing the loss coefficient. The B_{mn} loss coefficient matrix is given by

$$B_{mn} = \begin{matrix} 0.000075 & 0.000005 & 0.0000075 \\ 0.001940 & 0.000015 & 0.0000100 \\ 0.004820 & 0.000100 & 0.0000450 \end{matrix}$$

7.1.1 ELD WITHOUT TRANSMISSION LINE LOSSES

7.1.1.1 Lambda iteration method

In this method initial value of lambda is guessed in the feasible reason that can be calculated from derivative of the cost function. For the convergence of the problem the delta lambda should be selected small. Here delta lambda is selected 0.0001 and the value of lambda must be chosen near the optimum point.

Table7.1: lambda iteration method without losses

SL NO	Power demand (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	F_t Rs/Hr	Time in secs
1	450	205.41	183.22	61.2	4651.8	4.84
2	585	268.85	234..27	81.83	5821.1	5.01
3	700	322.92	277.70	99.32	6838.4	8.01
4	800	369.93	315.52	114.54	7739.5	5.02
5	900	416.95	353.32	129.76	8653.6	3.9

It is observed that if the lambda value is not selected in the feasible range the cost is not converging. Also, the time taken to converge also depended on the lambda selection and delta lambda value. It nearly takes 1000-2000 iterations to converge.

7.1.1.2 Particle Swarm Optimization (PSO) method

In this method the initial particles are randomly generated within the feasible range. The parameters c1, c2 and inertia weight are selected for best convergence characteristic. Here c1 = 2.01 and c2 = 2.01 Here the maximum value of w is chosen 0.9 and minimum value is chosen 0.4.the velocity limits are selected as v_{max}= 0.5*P_{max} and the minimum velocity is selected as v_{min}= -0.5*P_{min}. There are 10 no of particles selected in the population.

Table7.2: PSO method without losses

SL NO	Power demand (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	F_t Rs/Hr	Time in secs
1	450	205.41	183.24	61.3	4652.3	8.56
2	585	268.85	234.26	81.84	5821.4	8.01
3	700	322.94	277.70	99.33	6838.4	8.44
4	800	369.93	315.52	114.54	7738.05	9.02
5	900	416.95	353.30	129.75	8653.25	9.3

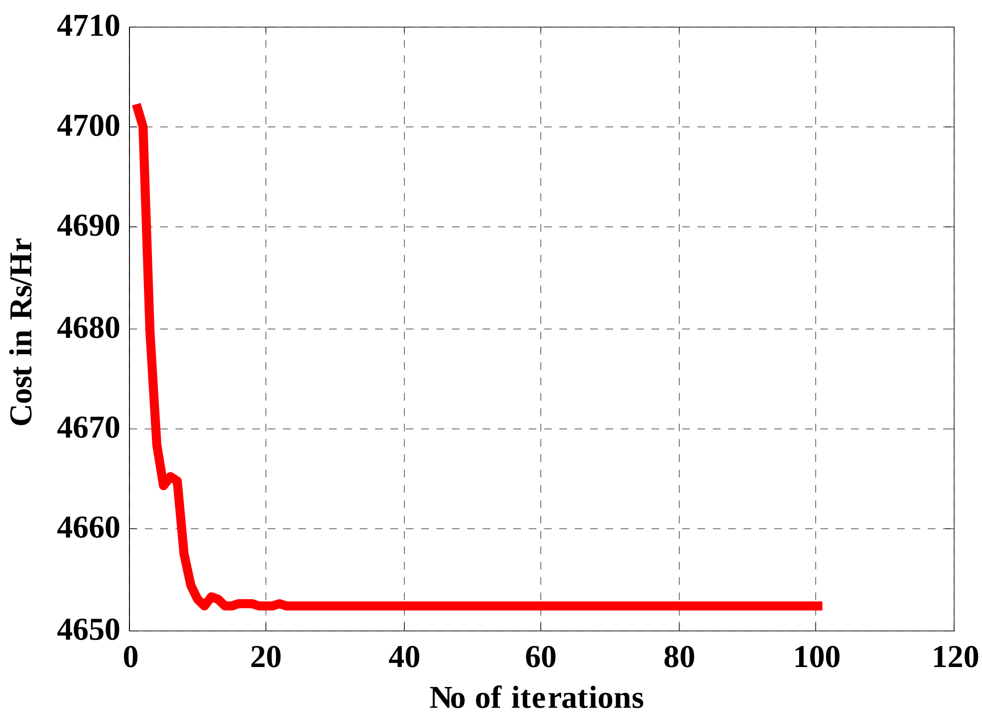


Fig 7.1: Cost curve of 450 MW demand by PSO method without loss

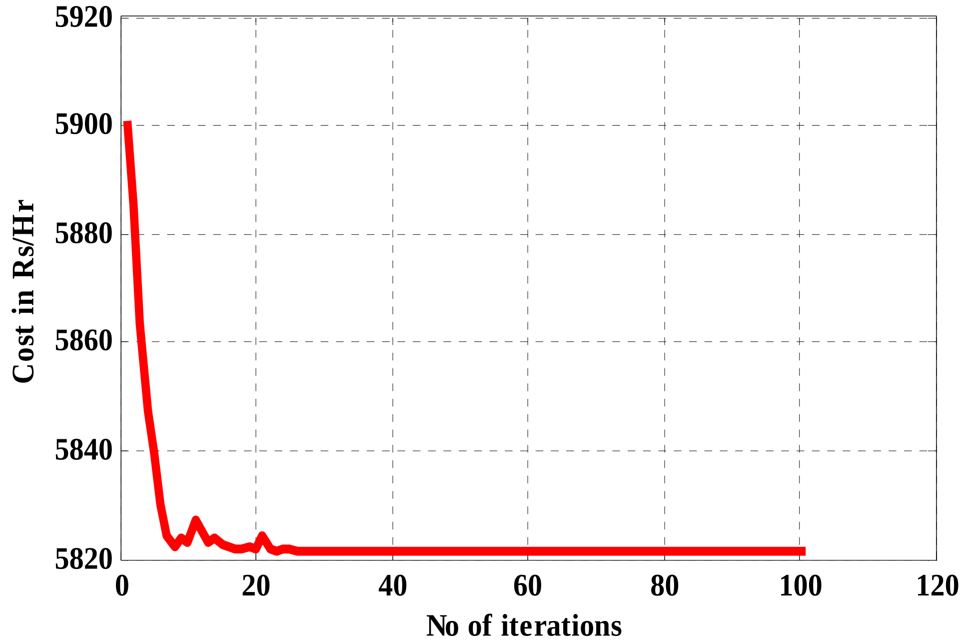


Fig 7.2: Cost curve of 585 MW demand by PSO method without loss

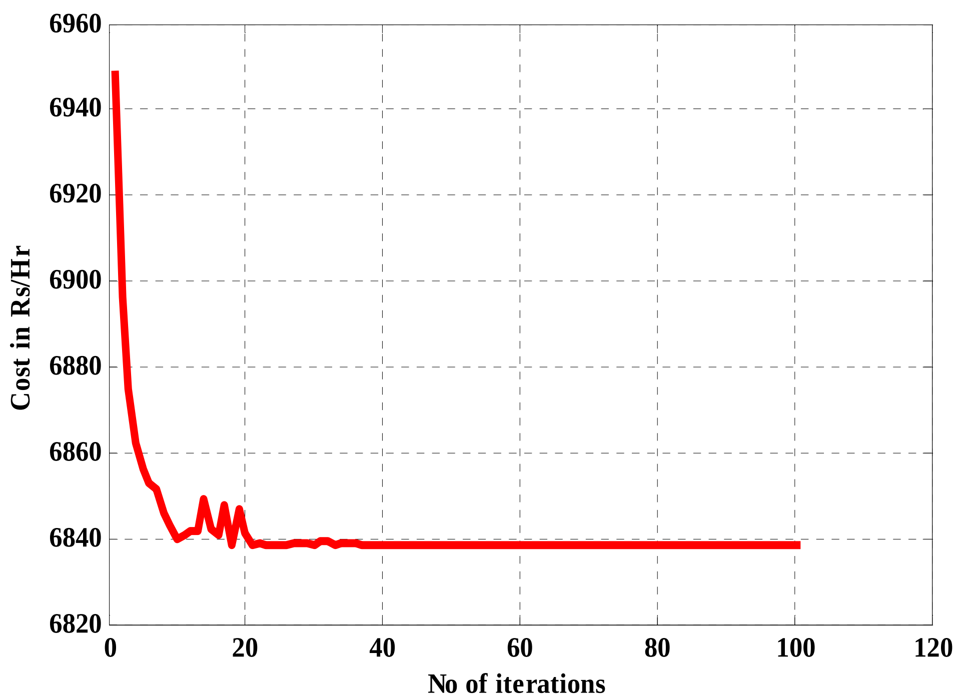


Fig 7.3: Cost curve of 700 MW demand by PSO method without loss

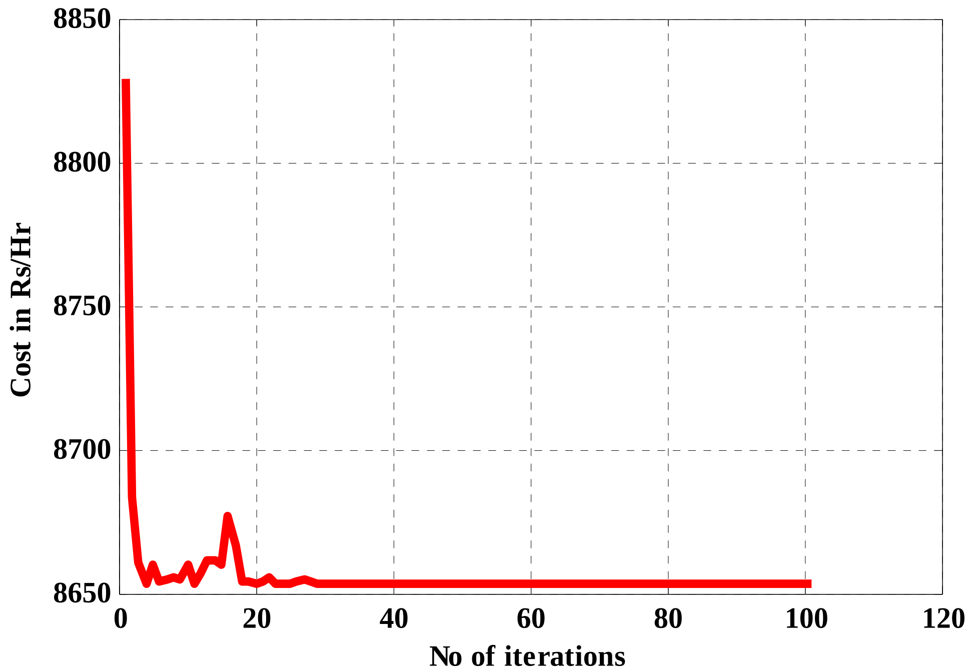


Fig 7.4: Cost curve of 900 MW demand by PSO method

7.1.1.3 GA method

In this method chromosomes are randomly generated. Since the problem is simple, 10 numbers of chromosomes are selected. The string length is also chosen 10. Probability of Selection for the crossover operation is 0.8. It means that for the next generation out of 10, eight best values are selected for crossover and mutation operation. In cross over operation single point crossover is applied.

Table7.3: GA method without losses

SL NO	Power demand (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	F_t Rs/Hr	Time in secs
1	450	205.41	183.21	61.37	4652.34	5.2
2	585	268.83	234.32	81.83	5821.4	4.74
3	700	322.5	277.6	99.64	6838.4	4.82
4	800	369.8	315.5	114.63	7738.5	5.44
5	900	417.95	352.72	129.55	8653.2	3.82

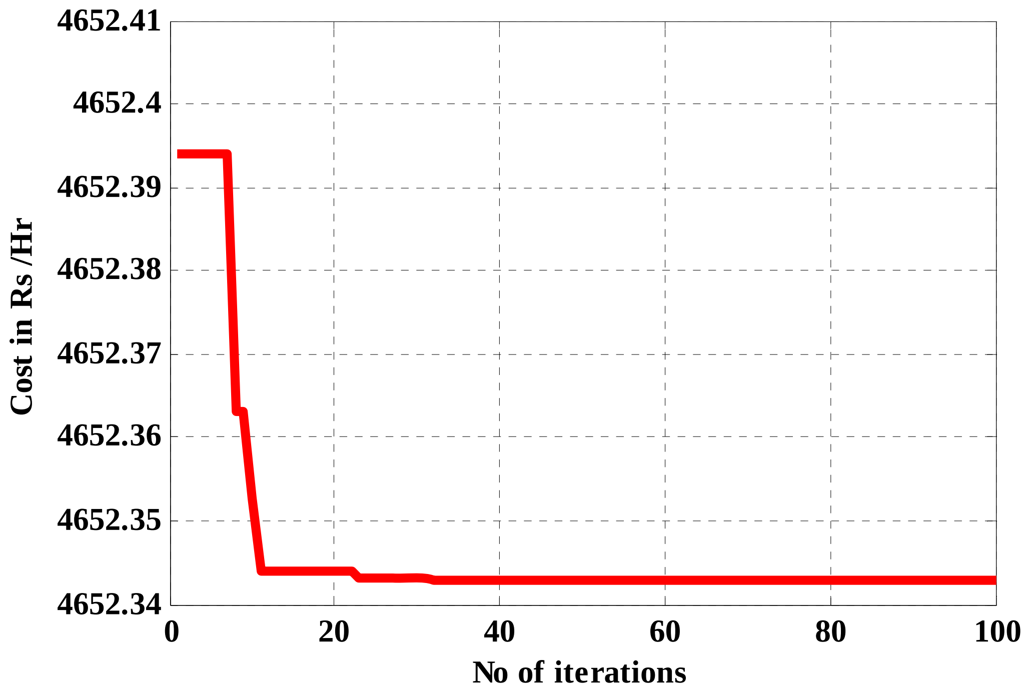


Fig 7.5: Cost curve of 450 MW demand by GA method

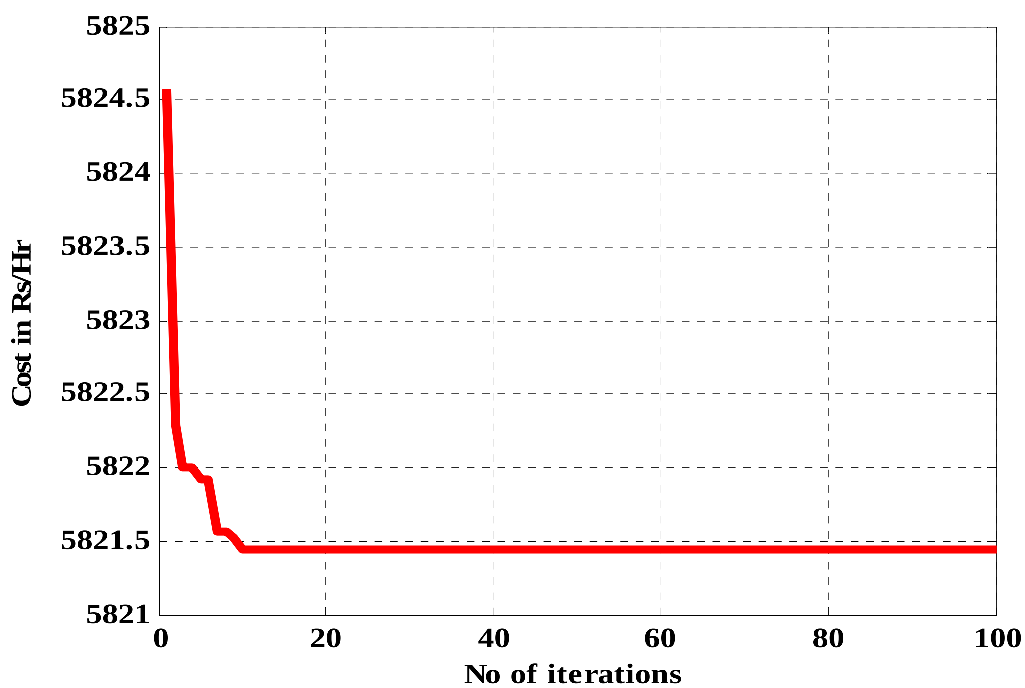


Fig 7.6: Cost curve of 585 MW demand by GA method

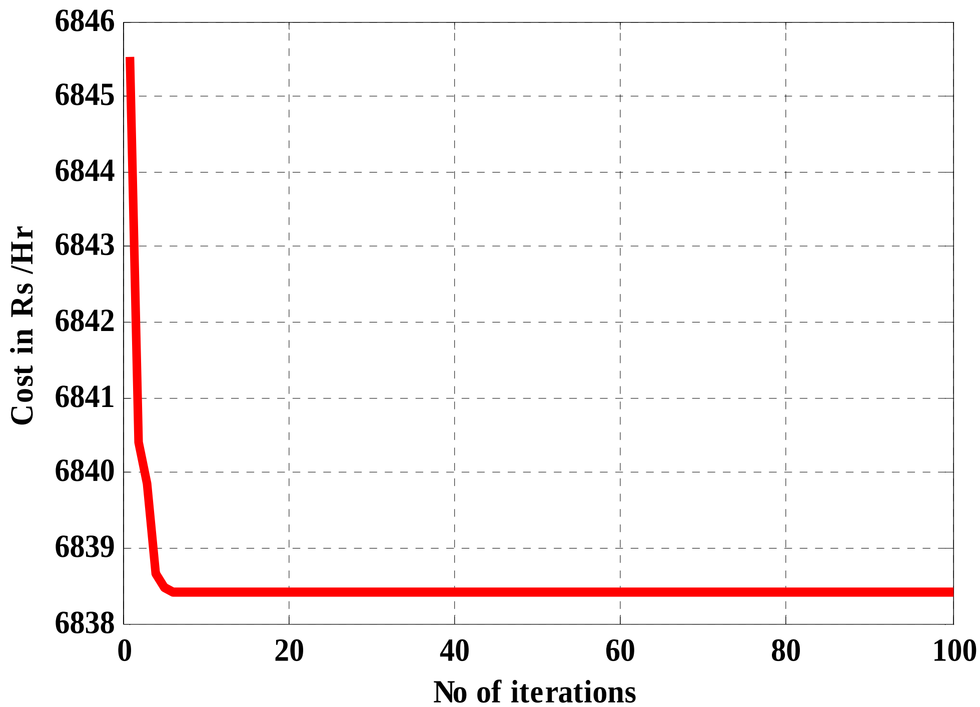


Fig 7.7: Cost curve of 700 MW demand by GA method

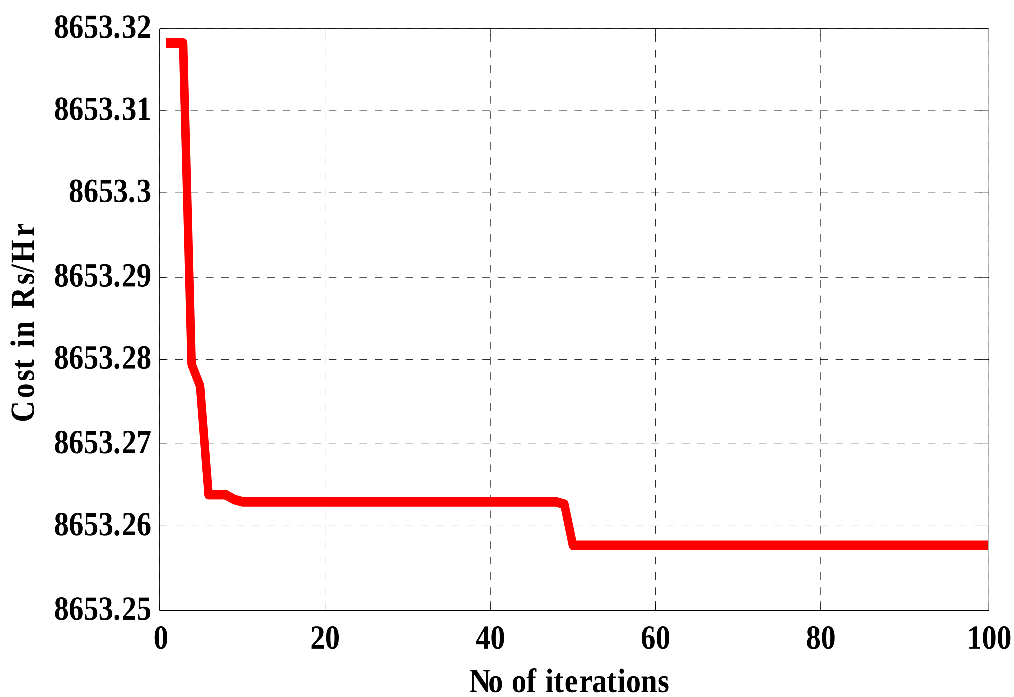


Fig 7.8: Cost curve of 900 MW demand by GA method

7.1.1.4 Comparison of cost in different method

The lowest costs obtained in three different methods are compared for five different power demands. It has been observed that for all the demand PSO and GA method gives same value of cost which nearly equal to the cost of lambda-iteration method. But in both PSO and GA method the cost curve converges within 20 to 40 iterations but conventional method takes more than 1000 iterations. In conventional method selection of lambda value in the feasible range is also required. If it is not selected in the feasible range then it will not converge.

Table7.4: Comparison of cost in three different methods

SL NO	Power demand (MW)	Cost in Rs/Hr Lambda iteration method	Cost in Rs/Hr PSO method	Cost in Rs/Hr GA method
1	450	4651.8	4652.3	4652.34
2	585	5821.1	5821.4	5821.4
3	700	6838.0	6838.4	6838.4
4	800	7739.1	7738.05	7738.5
5	900	8653.6	8653.25	8653.2

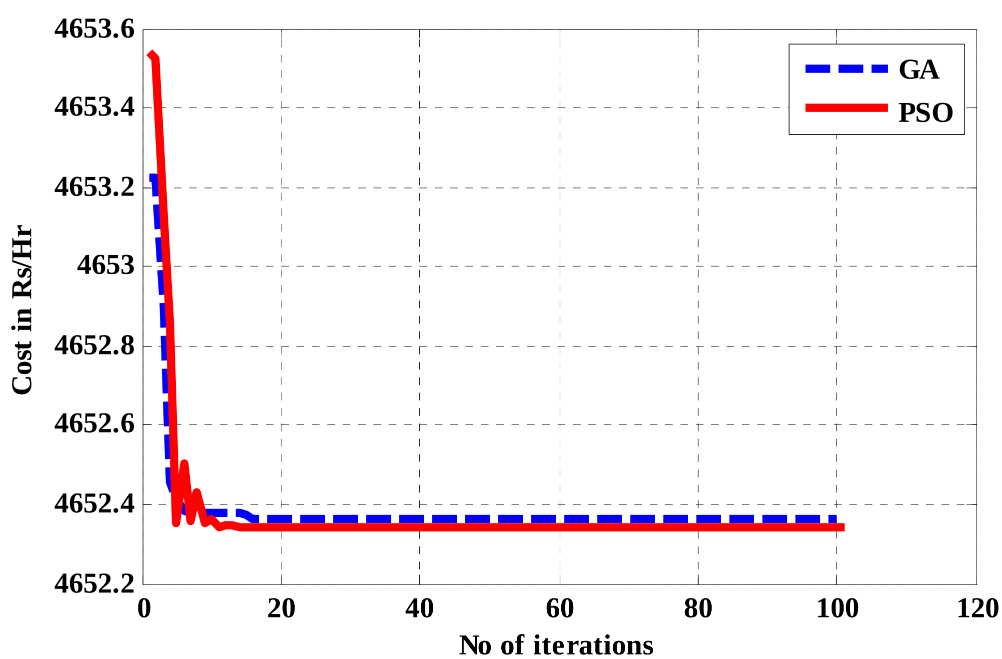


Fig 7.9: Comparison of Cost curve for 450 MW demand without loss for three units

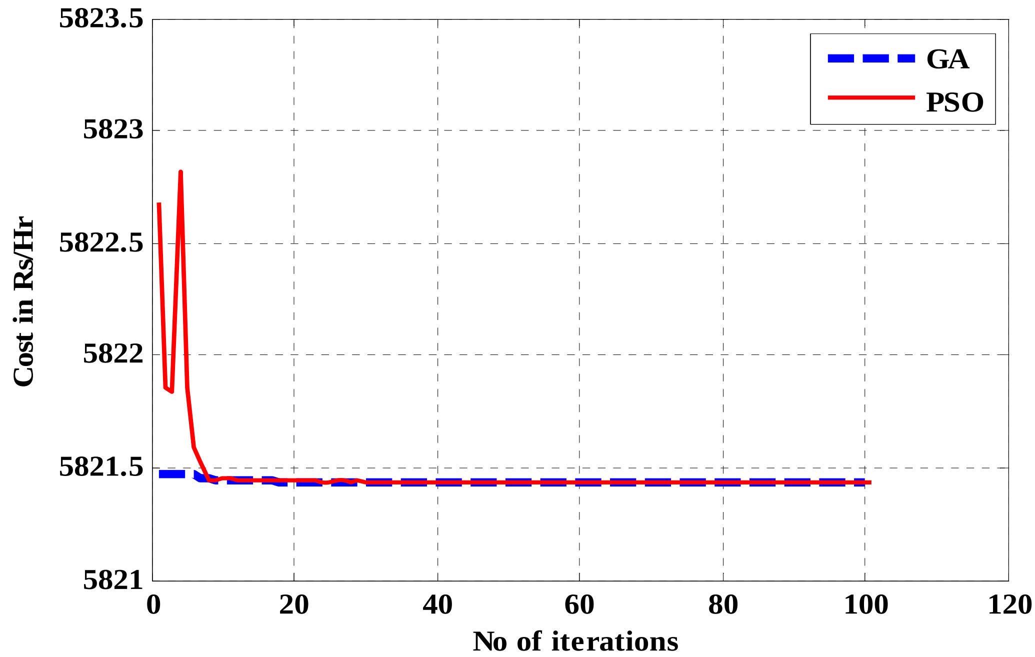


Fig 7.10: Comparison of Cost curve for 585 MW demand without loss for three units

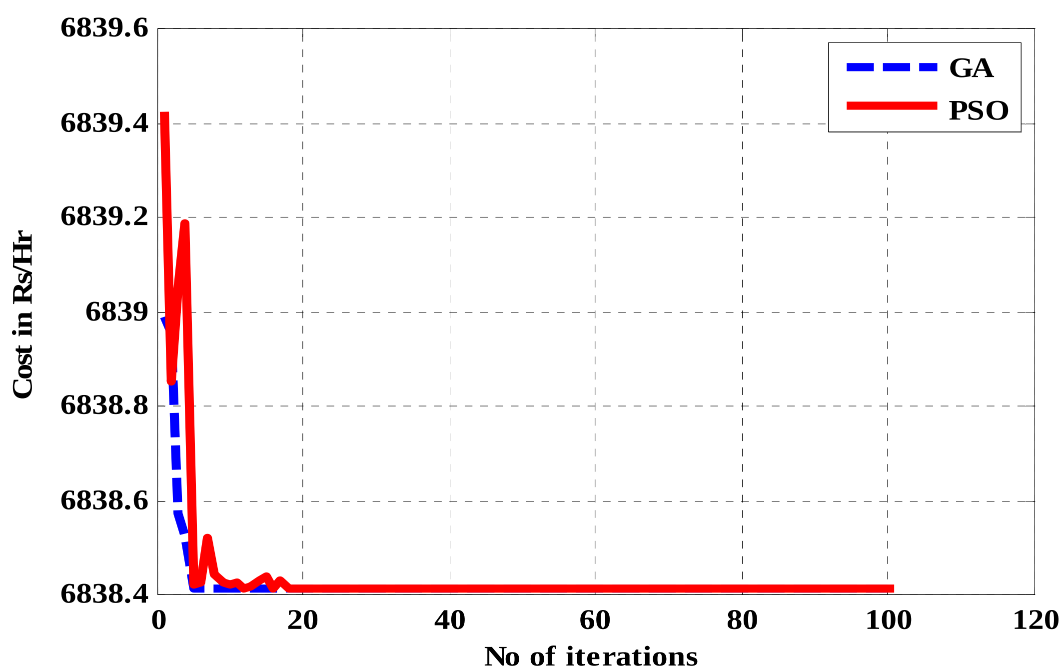


Fig 7.11: Comparison of Cost curve for 700 MW demand without loss for three units

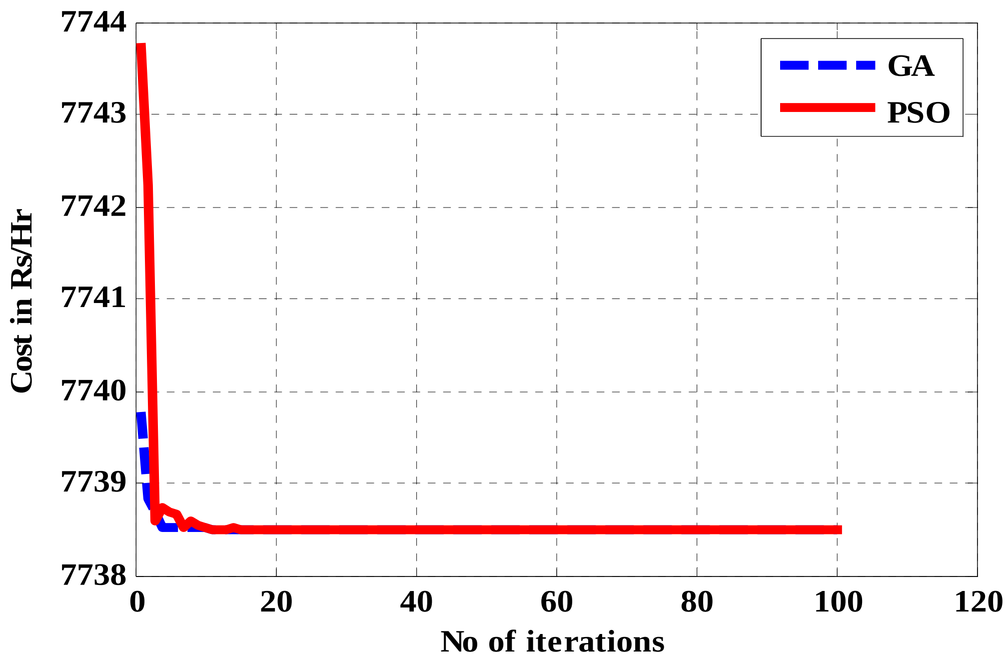


Fig 7.12: Comparison of Cost curve for 800 MW demand without loss for three units

7.1.2 ELD WITH TRANSMISSION LINE LOSSES

7.1.2.1 Lambda iteration method

In this method initial value of lambda is guessed in the feasible reason that can be calculated from derivative of the cost function. For the convergence of the problem the delta lambda should be selected small. Here delta lambda is selected 0.0001 and the value of lambda must be chosen near the optimum point. It has been observed that then minimum cost curve converges after so many iterations than in the no loss case. Here the cost curve converges within the range of 2000 to 5000 iterations. The lambda selection is important for convergence of cost curve.

Table7.5: lambda iteration method with losses

SL NO	Power demand (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	Loss in (MW)	F_t Rs/Hr	Time in sec s
1	450	184.8	198.36	68.16	1.36	4665.1	10.52
2	585	241.29	255.30	90.78	2.33	5844.7	6.67
3	700	289.2	304.02	110.13	3.36	6872.2	7.06
4	800	330.7	346.59	127.03	4.41	7783.37	7.71
5	900	372.22	389.39	144.01	5.06	8711.81	5.07

7.1.2.2 PSO method

In this method the initial particles are randomly generated within the feasible range. The parameters c1, c2 and inertia weight are selected for best convergence characteristic. Here, c1 = 1.99 and c2 = 1.99 Here the maximum value of w is chosen 0.9 and minimum value is chosen 0.4.the velocity limits are selected as v_{max}= 0.5*P_{max} and the minimum velocity is selected as v_{min}= -0.5*P_{min}. There are 10 no of particles are selected in the population. For different value of c1 and c2 the cost curve converges in the different region. So, the best value is taken for the minimum cost of the problem. If the no of particles are increased then cost curve converges faster. It can be observed the loss has no effect on the cost characteristic.

Table7.6: PSO method with losses

SL NO	Power demand (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	Loss in (MW)	F_t Rs/Hr	Time in sec s
1	450	204.71	188.59	58.06	1.37	4664.1	12.58
2	585	268.19	241.6	77.54	2.35	5842.7	6.31
3	700	322.35	286.90	94.13	3.38	6868.9	8.06
4	800	369.5	326.29	108.5	4.44	7779.37	8.81
5	900	416.7	365.9	122.9	5.64	8705.81	6.30

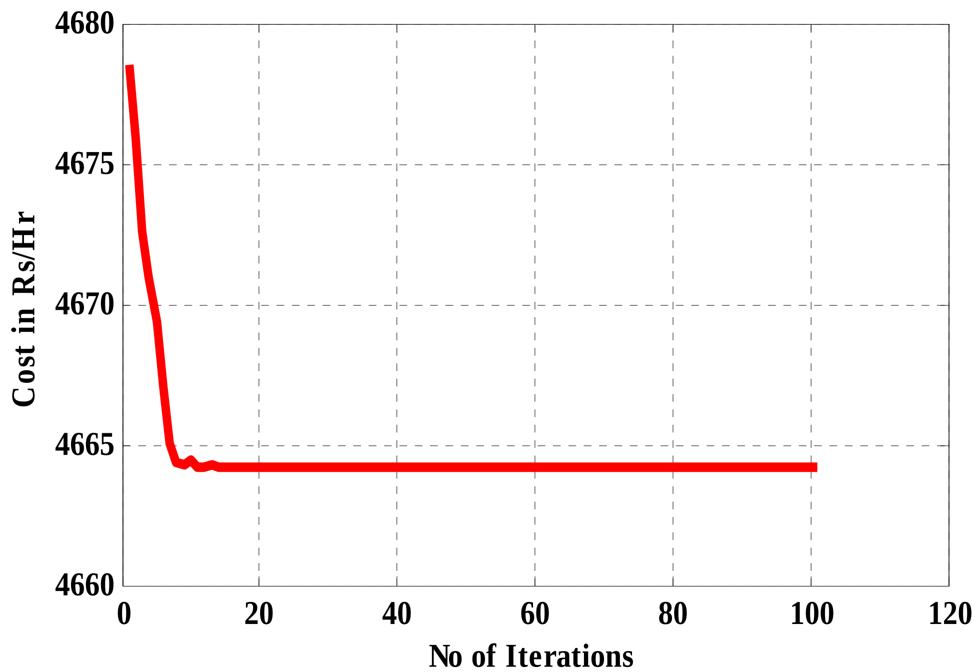


Fig 7.13:Cost curve of 450 MW demand by PSO method with loss

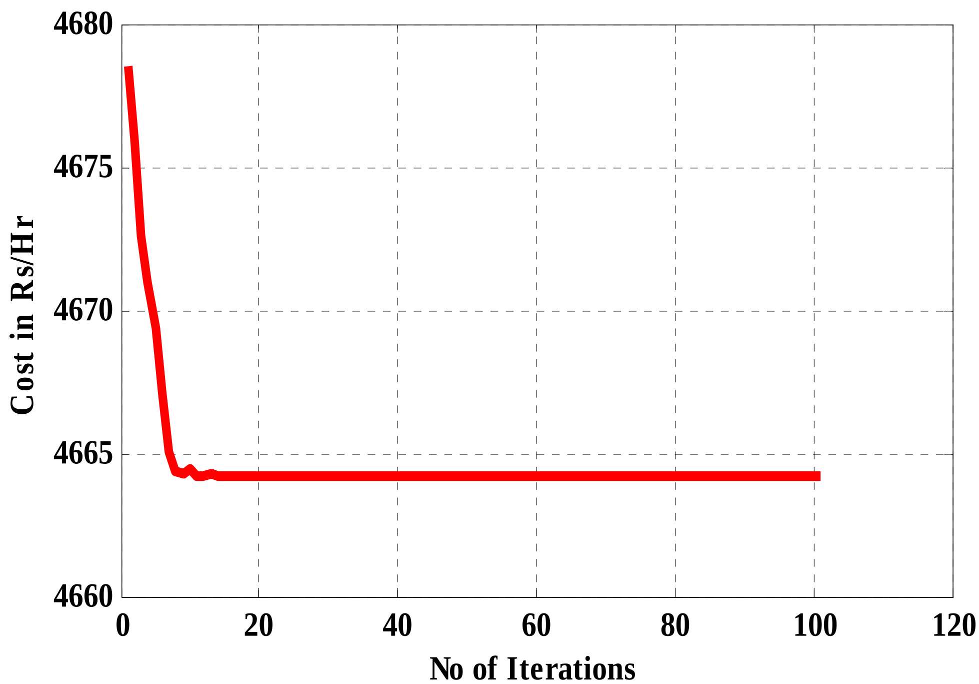


Fig 7.14: Cost curve of 585 MW demand by PSO method with loss

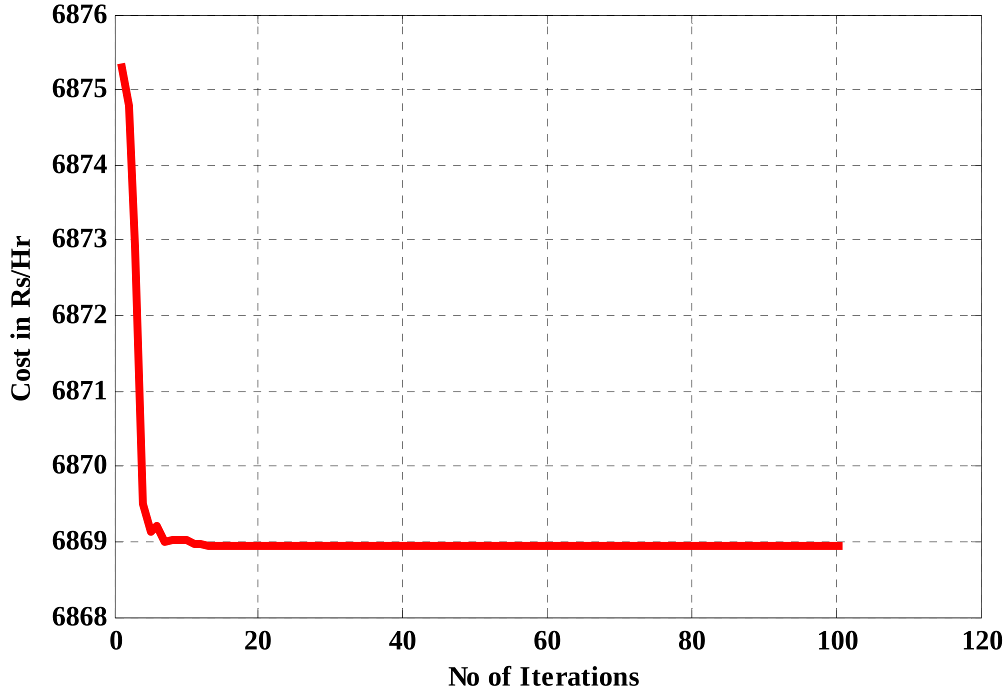


Fig 7.15: Cost curve of 700 MW demand by PSO method with loss

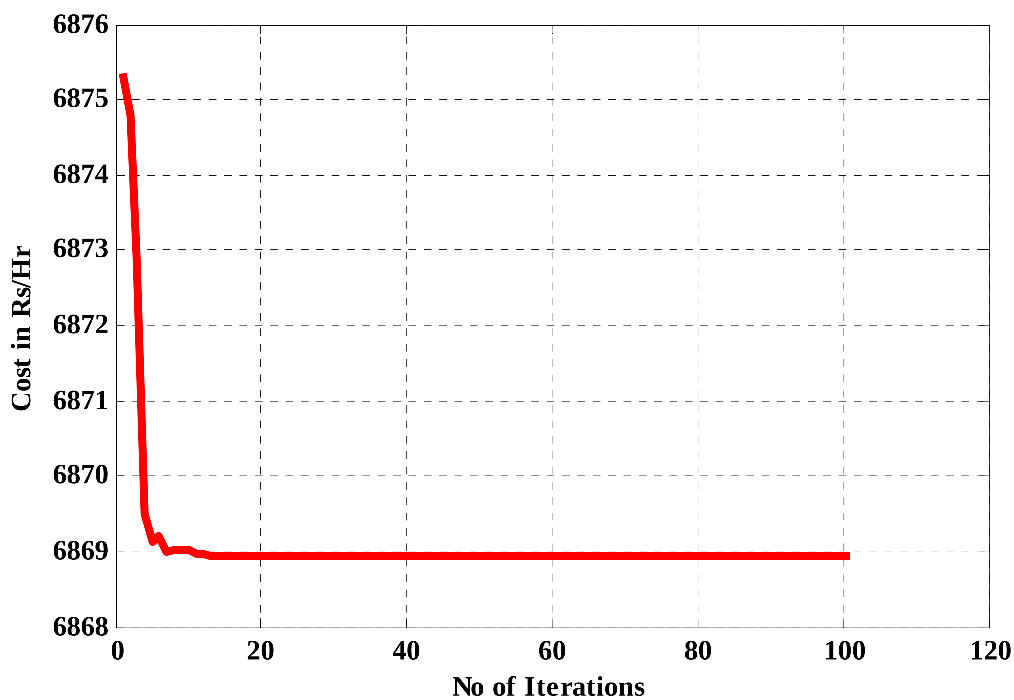


Fig 7.16: Cost curve of 900 MW demand by PSO method with loss

7.1.2.3 GA method

For solving the problem of ELD with considering the losses, 10 numbers of chromosomes are selected. The string length is also chosen as 10. Probability of selection for the cross over operation is chosen. In the crossover operation one point crossover method is applied. It has been observed that the minimum cost curve convergence is not different when transmission line losses are neglected as we found in conventional method.

Table7.7: GA method with losses

SL NO	Power demand (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	Loss in (MW)	F_t Rs/Hr	Time in sec s
1	450	203.1	189.8	57.7	1.36	4664.2	13.58
2	585	268.19	241.6	77.54	2.35	5842.7	6.31
3	700	321.45	287.63	94.29	3.38	6868.82	10.06
4	800	369.5	326.07	108.6	4.44	7779.37	7.45
5	900	416.04	366.9	122.61	5.63	8705.53	7.51

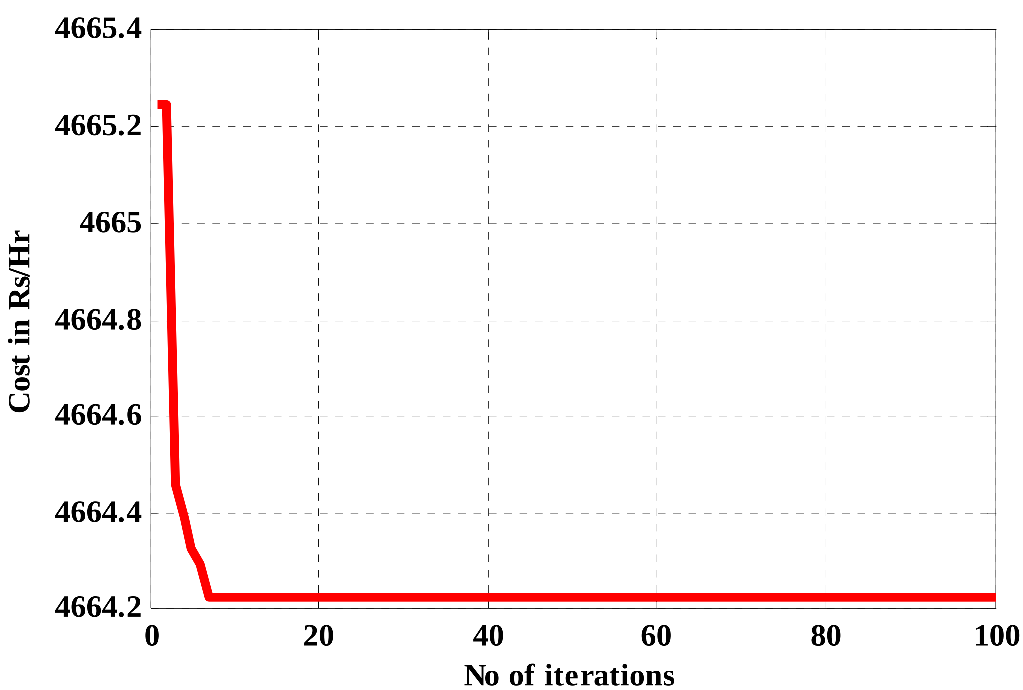


Fig 7.17: Cost curve of 450 MW demand by GA method with loss

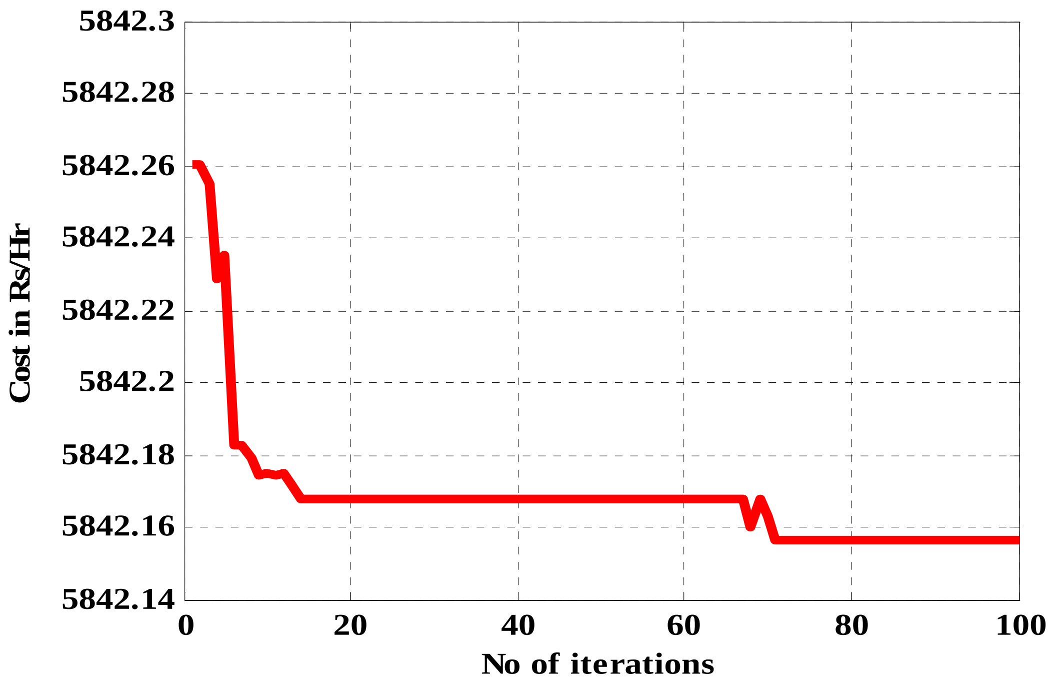


Fig 7.18: Cost curve of 585 MW demand by GA method with loss

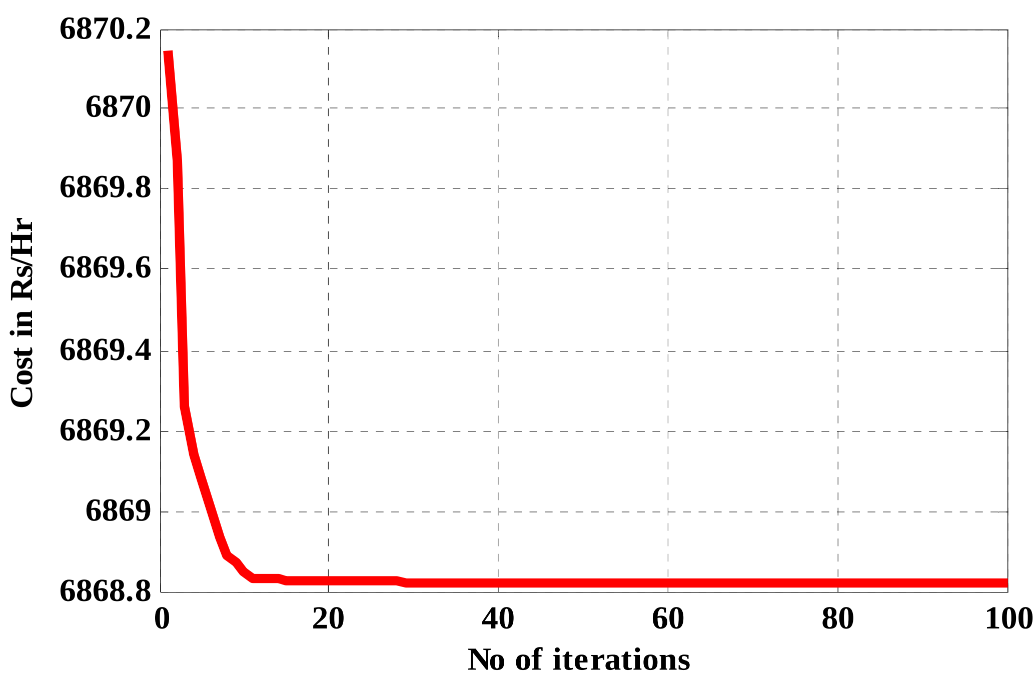


Fig 7.19: Cost curve of 700 MW demand by GA method with loss

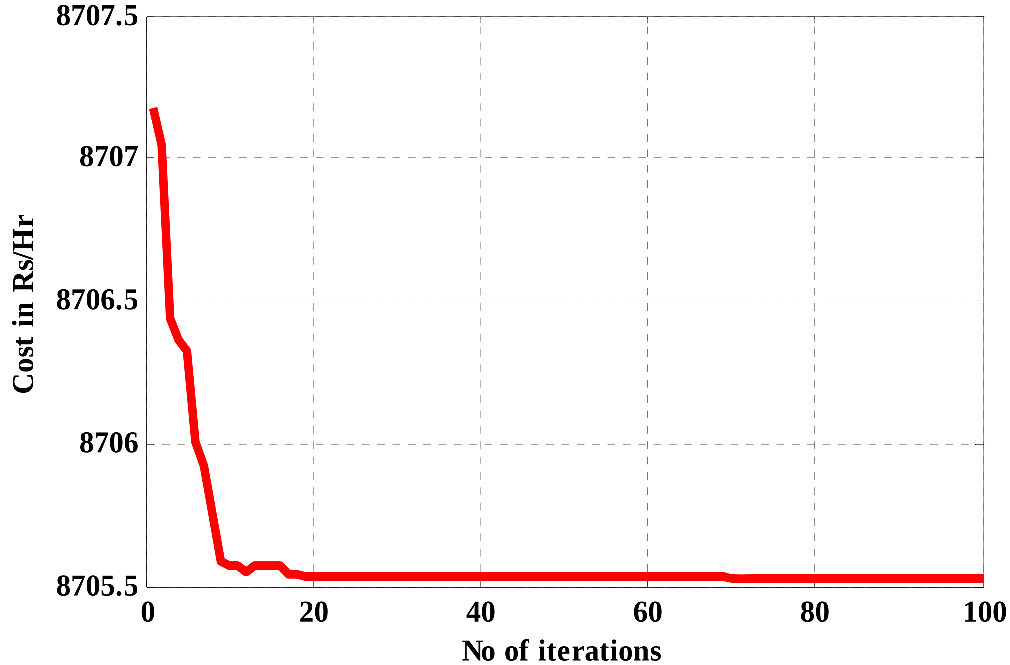


Fig 7.20: Cost curve of 900 MW demand by GA method with loss

7.1.2.4 Comparison of cost in different methods

It has been observed that when transmission line losses are included the minimum cost we found in the PSO and GA method are less than the conventional method. But both the methods PSO and GA gives the minimum cost nearly equal

Table7.8:Comparison of Cost between three methods with losses

	Power demand (MW)	Cost in Rs/Hr Lambda iteration method	Cost in Rs/Hr PSO method	Cost in Rs/Hr GA method
1	450	4665.18	4664.22	4664.2
2	585	5844.7	5842.2	5842.1
3	700	6872.2	6868.9	6868.82
4	800	7783.37	7779.2	7779.03
5	900	8711.81	8705.8	8705.53

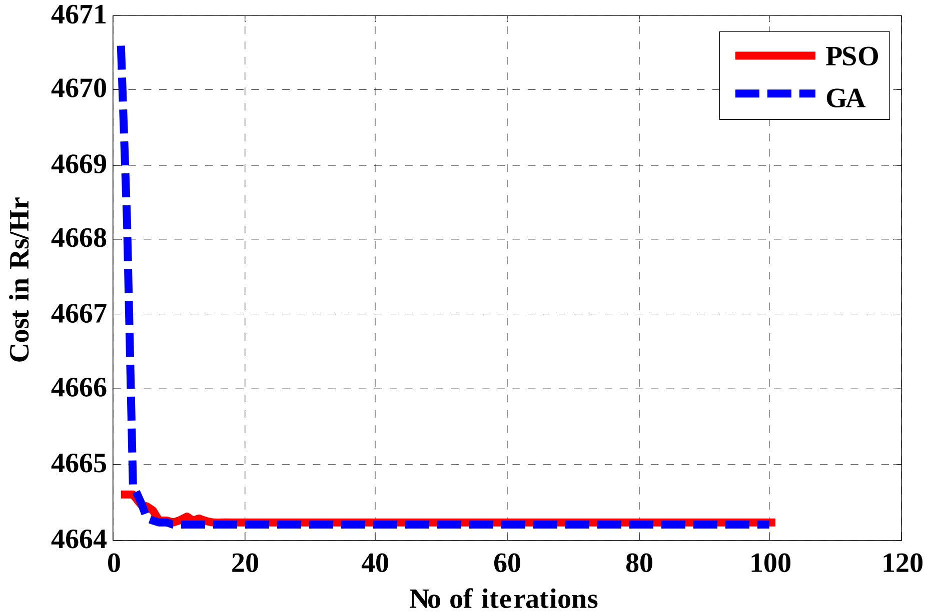


Fig 7.21:Comparison of Cost curve for 450 MW demand with loss for three units

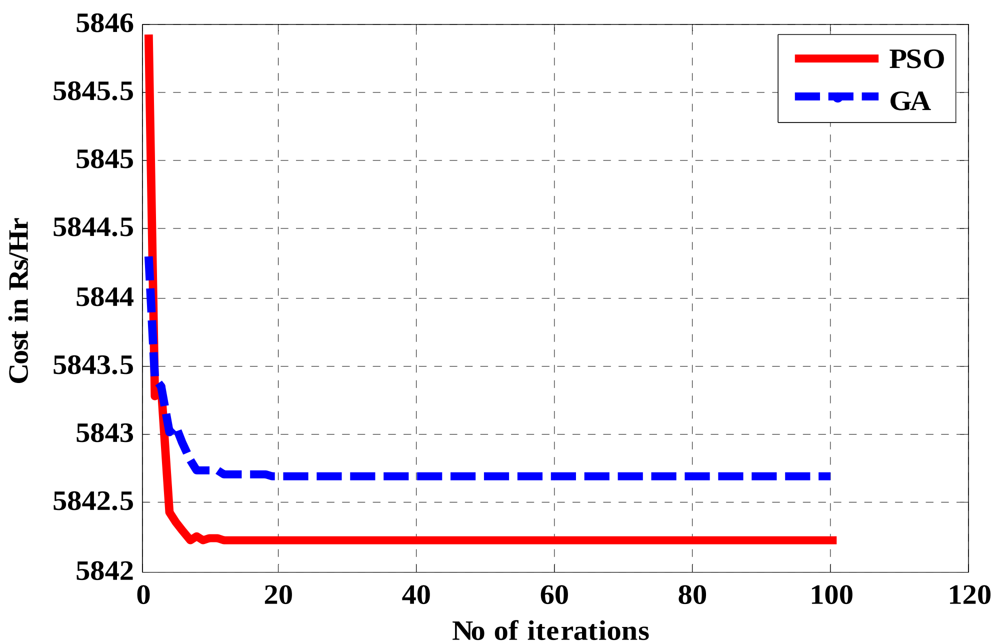


Fig 7.22:Comparison of Cost curve for 585 MW demand with loss for three units

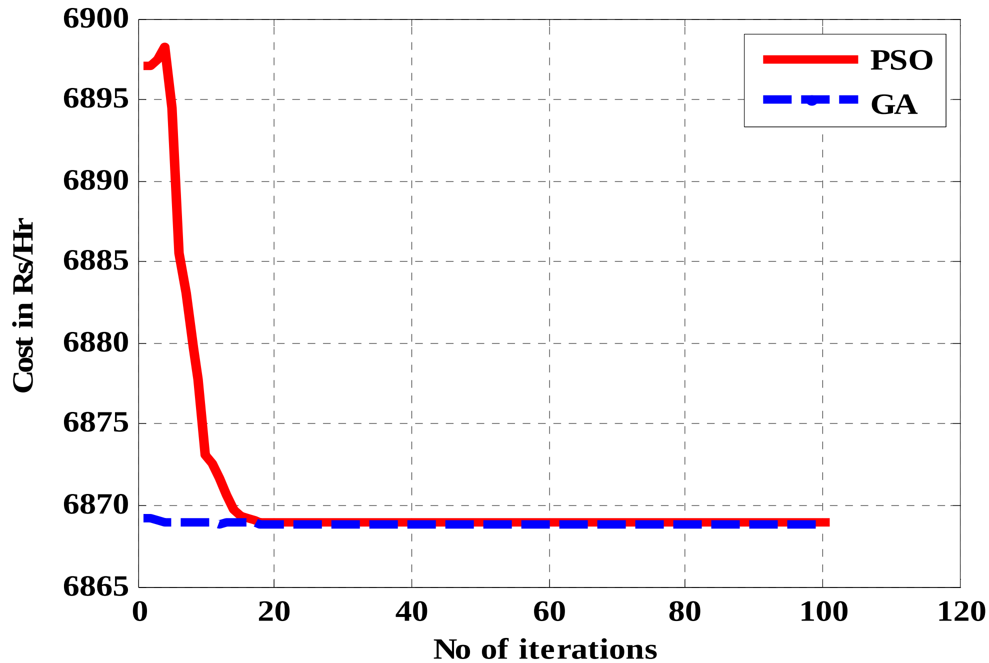


Fig 7.23:Comparison of Cost curve for 700 MW demand with loss for three units

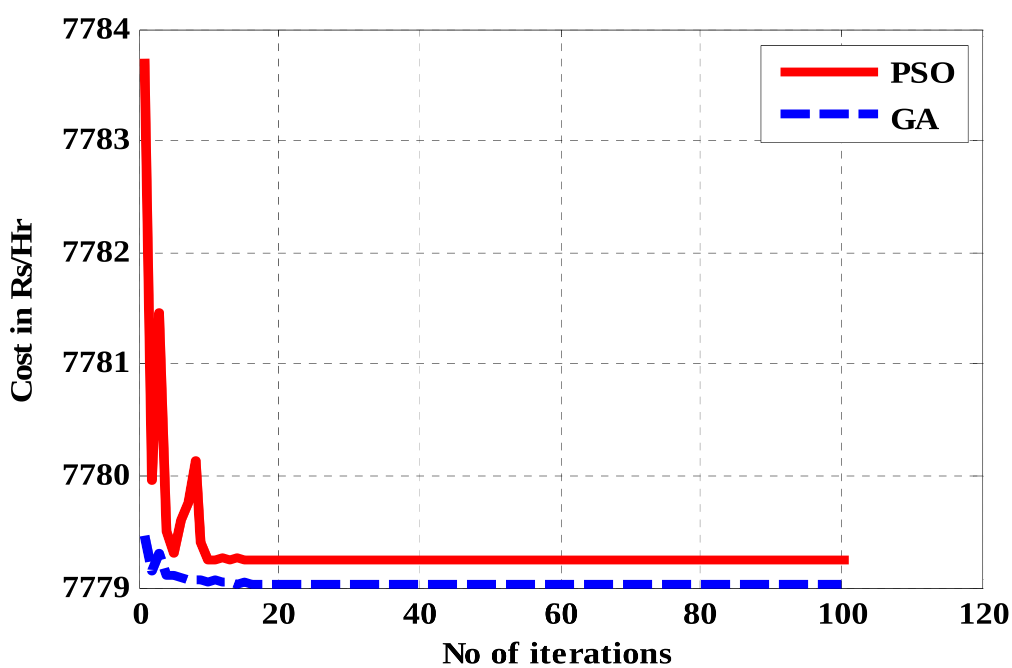


Fig 7.24:Comparison of Cost curve for 800 MW demand with loss for three units

7.2 CASE STUDY-2-SIX UNIT SYSTEM

The cost function of the six units are given as follows

$F1 = 0.15240P_1^2+38.53P_1+756.79886$ Rs/Hr

$F2 = 0.10587P_2^2+46.15916P_2+451.32513$ Rs/Hr

$F3 = 0.02803P_3^2+40.39655P_3+1049.9977$ Rs/Hr

$F4 = 0.03546P_4^2+38.30553P_4+1243.5311$ Rs/Hr

$F5 = 0.02111P_5^2+36.32782P_5+1658.5596$ Rs/Hr

$F6 = 0.01799P_3^2+38.27041P_3+1356.6592$ Rs/Hr

The unit operating ranges are

$$10\text{ MW} \leq P_1 \leq 125\text{ MW}$$

$$10\text{ MW} \leq P_2 \leq 150\text{ MW}$$

$$35\text{ MW} \leq P_3 \leq 225\text{ MW}$$

$$35\text{ MW} \leq P_4 \leq 210\text{ MW}$$

$$130\text{ MW} \leq P_5 \leq 325\text{ MW}$$

$$125\text{ MW} \leq P_6 \leq 315\text{ MW}$$

B_{mn} coefficient matrix is given as

$$\mathbf{B}_{mn} = \begin{bmatrix} 0.00014 & 0.000017 & 0.000015 & 0.000019 & 0.000026 & 0.000022 \\ 0.000017 & 0.000060 & 0.000013 & 0.000016 & 0.000015 & 0.000020 \\ 0.000015 & 0.000013 & 0.000065 & 0.000017 & 0.000024 & 0.000019 \\ 0.000019 & 0.000016 & 0.000017 & 0.000071 & 0.000030 & 0.000025 \\ 0.000026 & 0.000015 & 0.000024 & 0.000030 & 0.000069 & 0.000032 \\ 0.000022 & 0.000020 & 0.000019 & 0.000025 & 0.000032 & 0.000085 \end{bmatrix}$$

7.2.1 ELD WITHOUT TRANSMISSION LINE LOSSES

7.2.1.1 Lambda iteration method

The initial value of lambda is guessed in the feasible reason that can be calculated from derivative of the cost function. For the convergence of the problem the delta lambda should be selected small. Here delta lambda is selected 0.0001 and the value of lambda must be chosen near the optimum point. In this case also the convergence is largely affected by selection of lambda value and delta lambda The time taken for convergences increases than the three unit system.

Table7.9: lambda iteration method without losses

SL NO	Power demand (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	P_6 (MW)	F_t Rs/Hr	Time in secs
1	600	21.19	10	82.08	94.37	205.35	186.99	31446.4	7.9
2	700	24.97	10	102.664	110.63	232.67	219.05	36003.5	6.43
3	800	28.75	10	123.23	126.9	259.99	251.1	40676.1	6.29
4	850	30.650	10	133.52	135.03	273.65	267.13	43056.2	7.35
5	900	32.51	10.61	143.68	143.06	287.14	282.97	45464.1	5.79

7.2.1.2 PSO method

The initial particles are randomly generated within the feasible range. The parameters c1, c2 and inertia weight are selected for best convergence characteristic. Here c1=1.99 and c2=1.99. Here the maximum value of w is chosen 0.9 and minimum value is chosen 0.4.the velocity limits are selected as v_{max}= 0.5*P_{max} and the minimum velocity is selected as v_{min}= -0.5*P_{min}. There are 10 no of particles are selected in the population. For different value of c1 and c2 the cost curve converges in the different region. So the best value is taken for the minimum cost of the problem. If the no of particles are increased then cost curve converges faster. It can be observed the loss has no effect on the cost characteristic. It has been observed even if the no of units are increased the convergence is less affected.

Table7.10: Six unit system PSO method without losses

SL NO	Power demand (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	P_6 (MW)	F_t Rs/Hr	Time in secs
1	600	21.2	10	82.14	95.69	204.5	186.4	31445.7	9.62
2	700	24.62	10	104.10	111.7	234.67	214.9	36003.4	6.57
3	800	29.08	10	126.07	127.98	257.76	249.08	40676.4	6.89
4	850	33.19	13.08	197.5	144.67	216.6	243.67	43056.2	8.35
5	900	32.51	10.61	143.68	143.06	287.14	282.97	45464.1	5.79

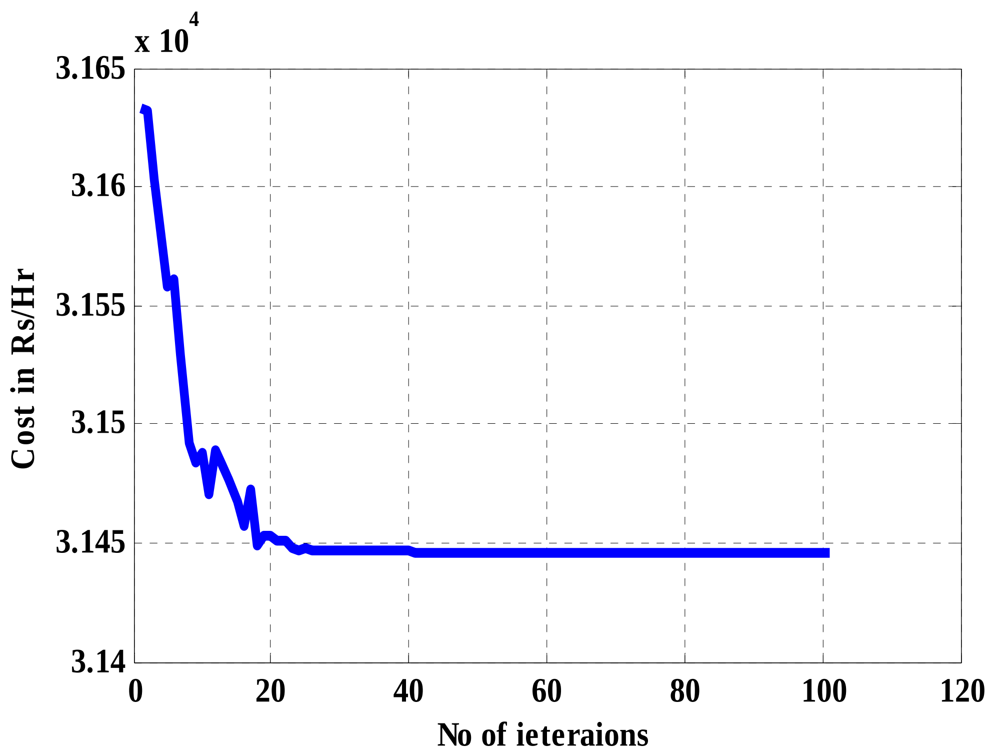


Fig 7.25: Cost curve of 600 MW demand by PSO method without loss

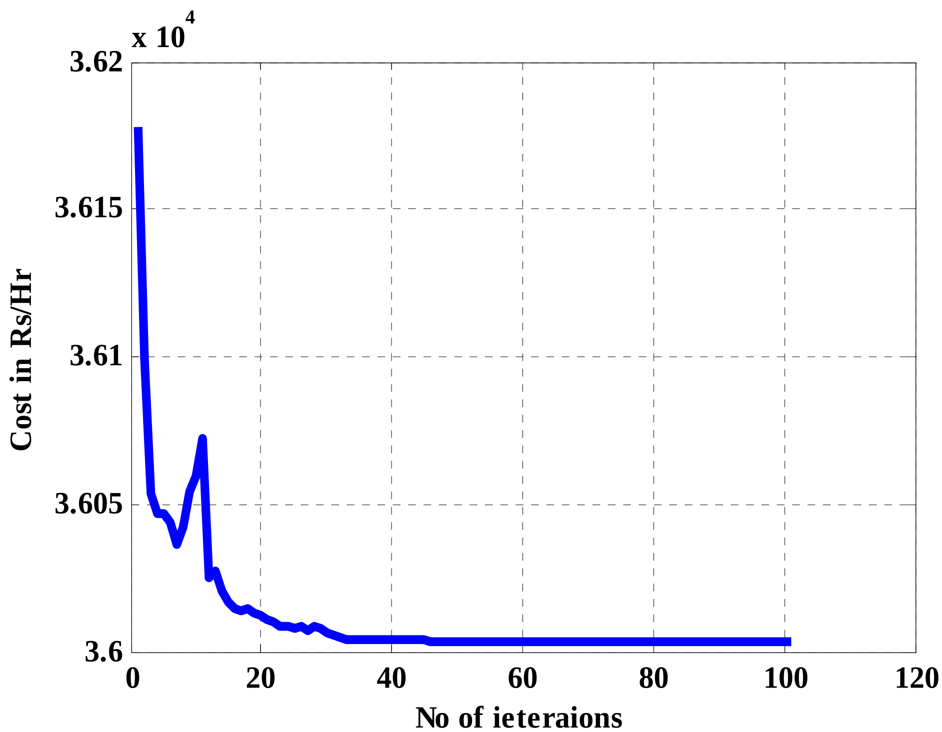


Fig 7.26: Cost curve of 700 MW demand by PSO method without loss

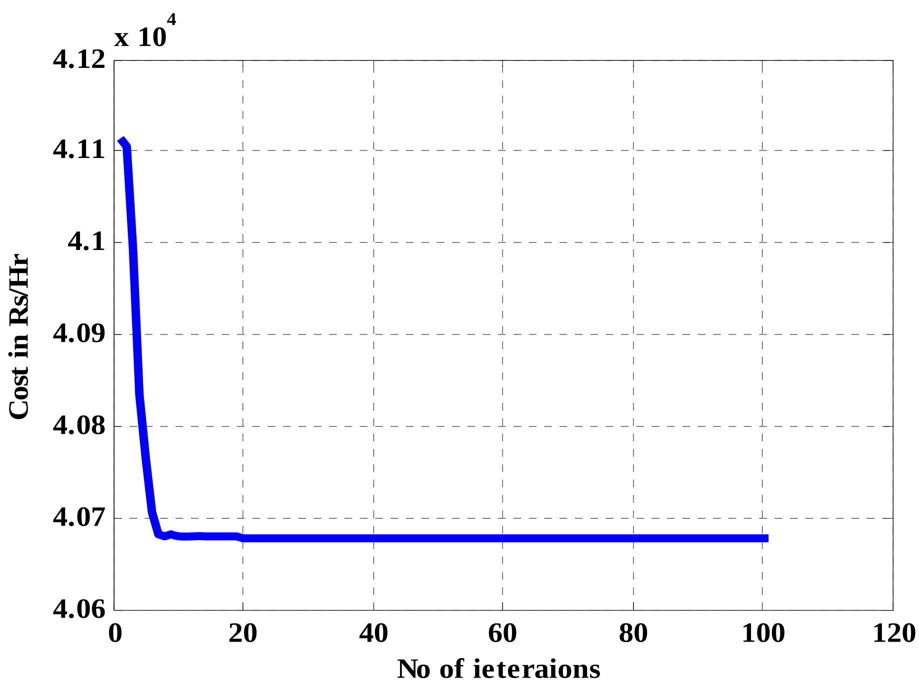


Fig 7.27: Cost curve of 800 MW demand by PSO method without loss

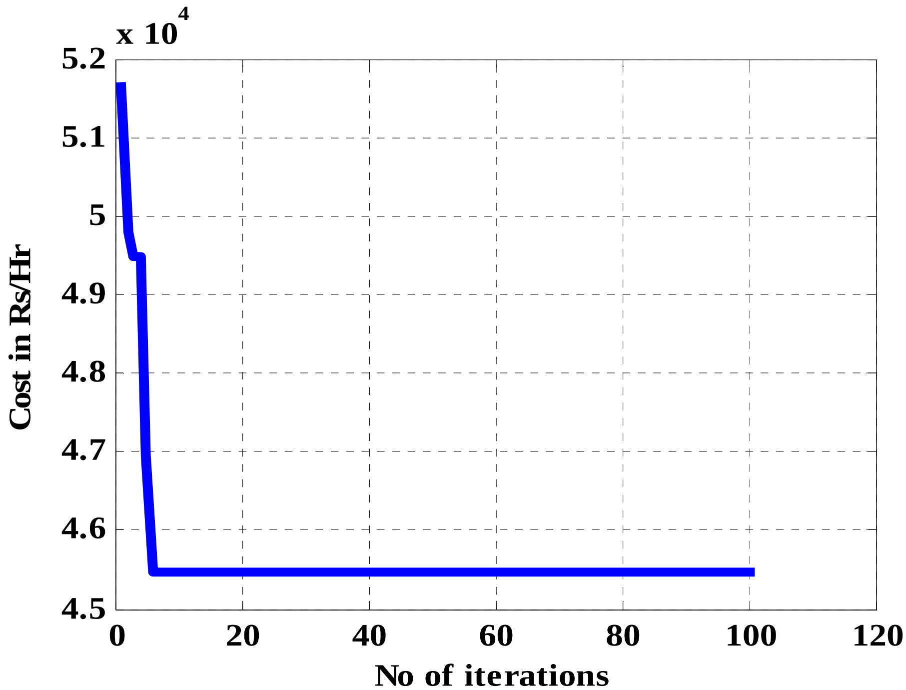


Fig 7.28: Cost curve of 900 MW demand by PSO method without loss

7.2.1.3 GA method

For solving the problem of ELD with considering the losses for six unit system 10 number of chromosomes are selected. If the no of chromosome s are increased then the convergence is not affected much more but the time of convergence is increased. The string length is also chosen 10.Probability of selection for the cross over operation is chosen 0.8. In the crossover operation one point crossover method is applied. It has been observed that the minimum cost curve convergence is not different when transmission line losses are neglected as we found in conventional method. When compared with the cost characteristic three unit system the convergence is not affected much more as it is affected in the conventional method. In three unit system the minimum cost curve converges within the 20-30 iterations whereas in six unit system the cost curve converges within 20-40 iterations. The time of convergence is also increased than the three unit problem.

Table7.11:Six unit system GA method without losses

SL NO	Power demand (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	P_6 (MW)	F_t Rs/Hr	Time in secs
1	600	23.25	10	73.32	96.68	208.5	188.21	31447.1	6.5
2	700	25.1	10.0	105.3	99.0	231.07	229.37	36010.7	6.57
3	800	29.16	10.0	126.00	117.9	263.36	253.52	40679.43	6.98
4	850	32.24	10.0	132.27	132.62	273.38	269.0	43059.3	5.21
5	900	32.34	10.0	145.03	143.09	286.93	282.58	45464.21	5.7

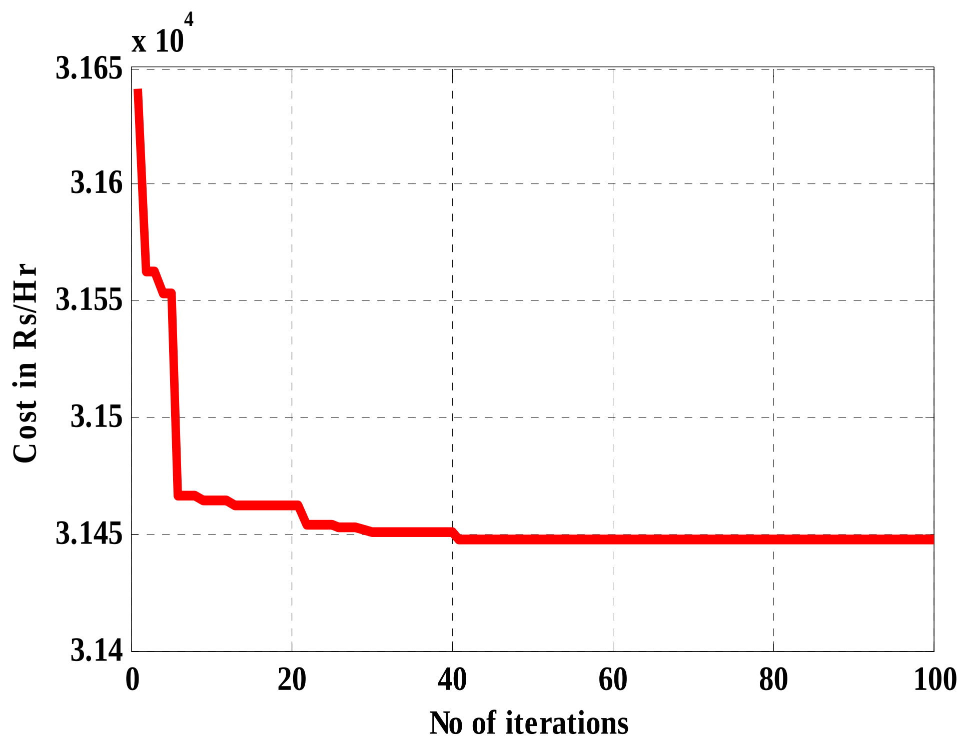


Fig 7.29: Cost curve of 600 MW demand by GA method without loss

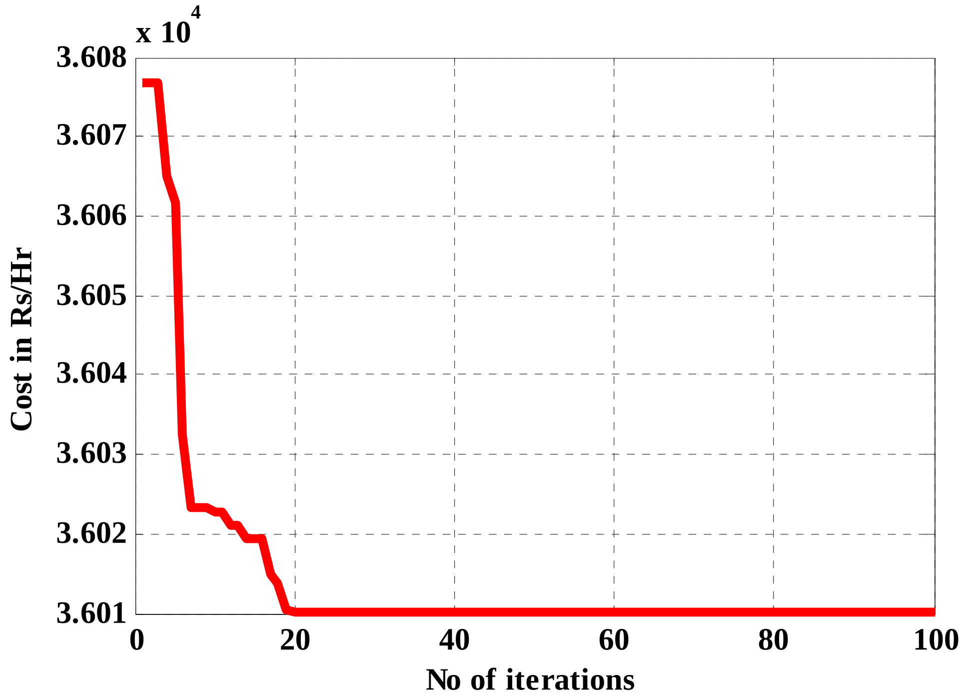


Fig 7.30: Cost curve of 700 MW demand by GA method without loss

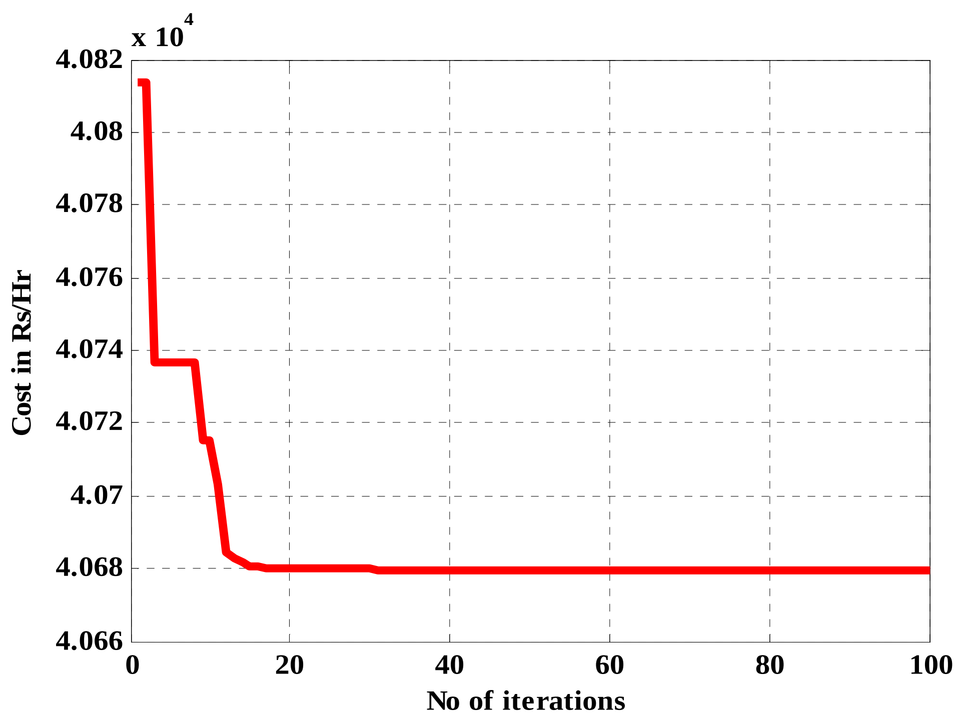


Fig 7.31: Cost curve of 800 MW demand by GA method without loss

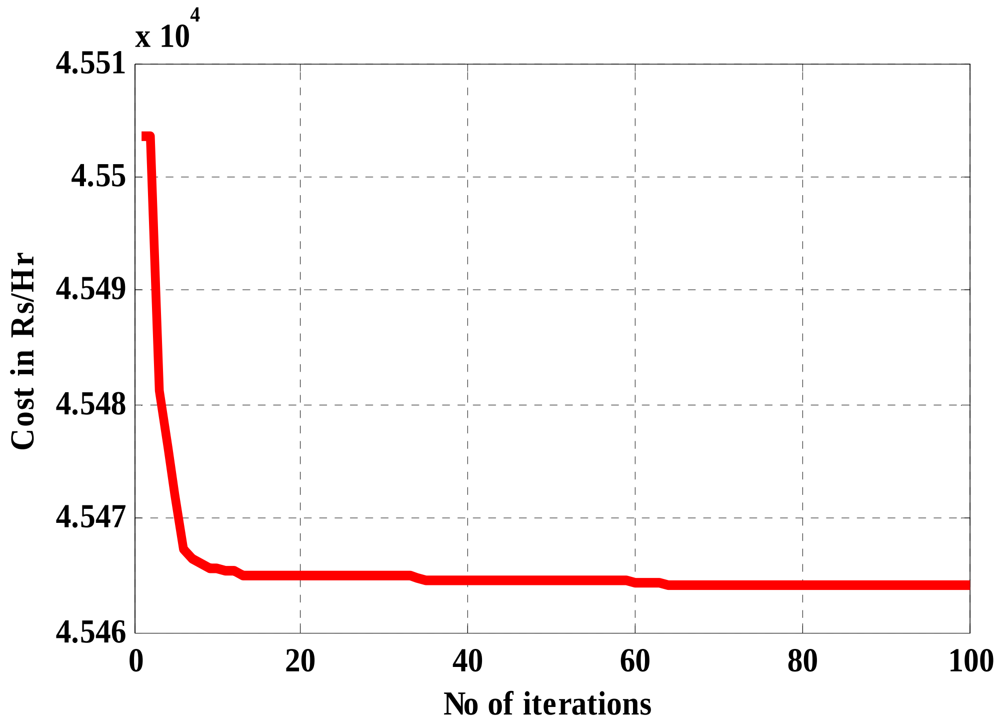


Fig 7.32: Cost curve of 900 MW demand by GA method without loss

7.2.1.4 Comparison of Cost in three different methods

It has been observed that when the numbers of units are increased the minimum cost we found in the PSO and GA method are less than or nearly equal to the conventional method. But both the methods PSO and GA give the minimum cost are not always equal. The performance depends on randomly generated particle in PSO and strings in GA. Sometimes PSO gives better result and sometimes GA gives better result.

Table7.12:Six unit system comparison of cost in different method without losses

SL NO	Power demand (MW)	Cost in Rs/Hr Lambda iteration method	Cost in Rs/Hr PSO method	Cost in Rs/Hr GA method
1	600	31446.4	31445.70	31447.1
2	700	36003.5	36003.4	36010.7
3	800	40676.1	40676.4	40679.43
4	850	43056.2	43056.2	43059.3
5	900	45464.1	45464.1	45464.21

7.2.2 ELD WITH TRANSMISSION LINE LOSSES

7.2.2.1 Lambda iteration method

The initial value of lambda is guessed in the feasible reason that can be calculated from derivative of the cost function. For the convergence of the problem the delta lambda should be selected small. Here delta lambda is selected 0.0001 and the value of lambda must be chosen near the optimum point. In this case also the convergence is largely affected by selection of lambda value and delta lambda The time taken for convergences increases than the three unit system. It is observed that the time taken convergence of six units with loss case is more than the without loss case.

Table7.13: lambda iteration method with losses

SL NO	Power demand (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	P_6 (MW)	Loss in (MW	F_t Rs/Hr	Time in secs
1	600	23.86	10	95.62	100.69	202.8	181.17	14.23	32132.1	6.84
2	700	28.30	10	118.96	118.68	230.76	212.75	19.43	36914.1	6.74
3	800	32.11	14.22	141.60	136.09	257.72	243.09	25.33	41927.1	9.9
4	850	34.74	17.44	152.78	144.67	270.97	257.96	28.56	44452.1	6.74
5	950	39.03	23.97	175.30	161.95	297.57	287.77	35.64	49683.1	9.9

7.2.2.2 PSO method

The initial particles are randomly generated within the feasible range. The parameters c1, c2 and inertia weight are selected for best convergence characteristic. Here c1=1.99 and c2=1.99. Here the maximum value of w is chosen 0.9 and minimum value is chosen 0.4.the velocity limits are selected as v_{max}= 0.5*P_{max} and the minimum velocity is selected as v_{min}= -0.5*P_{min}. There are 10 no of particles are selected in the population. For different value of c1 and c2 the cost curve converges in the different region. So the best value is taken for the minimum cost of the problem. If the no of particles are increased then cost curve converges faster. It can be observed the loss has no effect on the cost characteristic. It has been observed even if the no of units are increased the convergence is less affected.

Table7.14: PSO method with losses

SL NO	Power demand (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	P_6 (MW)	Loss in (MW	F_t Rs/Hr	Time in secs
1	600	23.8	10	95.7	100	202.6	181.2	14.24	32091.68	7.3
2	700	28.2	10	118.53	118.53	230.2	214.16	19.4	36912.2	8.7
3	800	31.95	10.8	153.2	151.8	247.3	229.69	24.95	41896.2	8.09
4	850	30.18	10	143.82	147.7	324.9	222.5	29.24	44452.08	9.8
5	950	39.05	24.4	191.8	172.56	294.5	262.4	34.90	49681.38	9.4

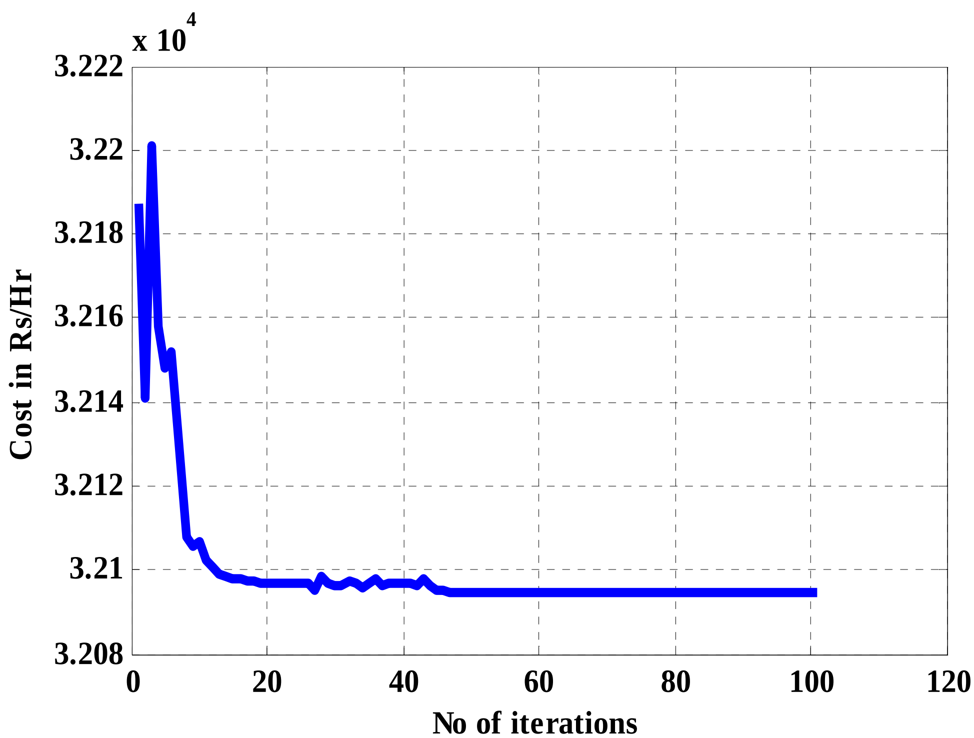


Fig 7.33: Cost curve of 600 MW demand by PSO method with loss

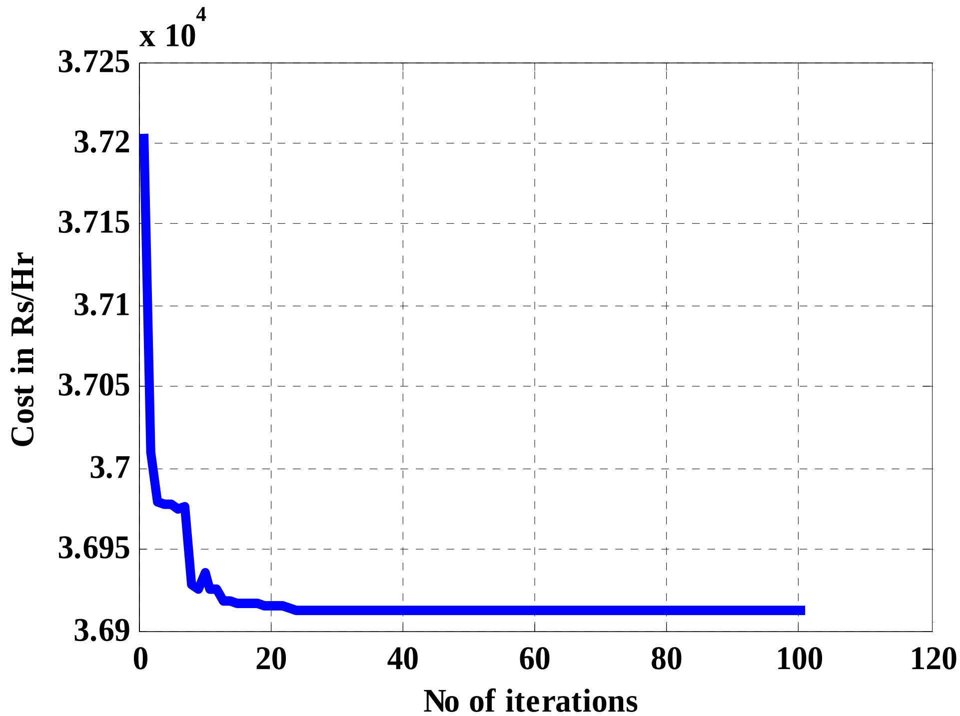


Fig 7.34: Cost curve of 700 MW demand by PSO method with loss

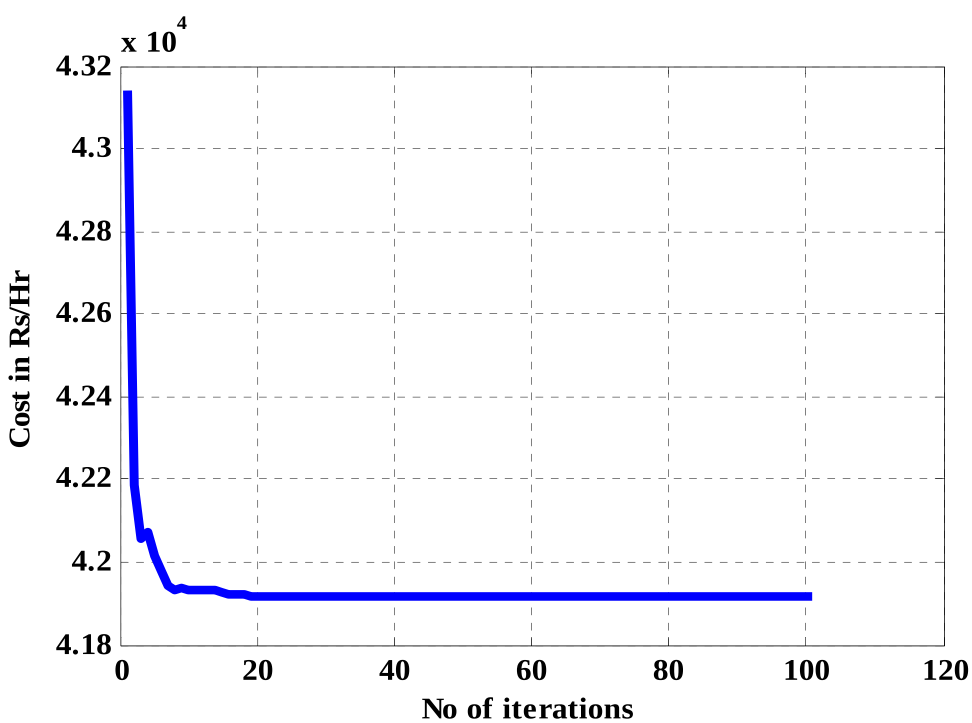


Fig 7.35: Cost curve of 800 MW demand by PSO method with loss

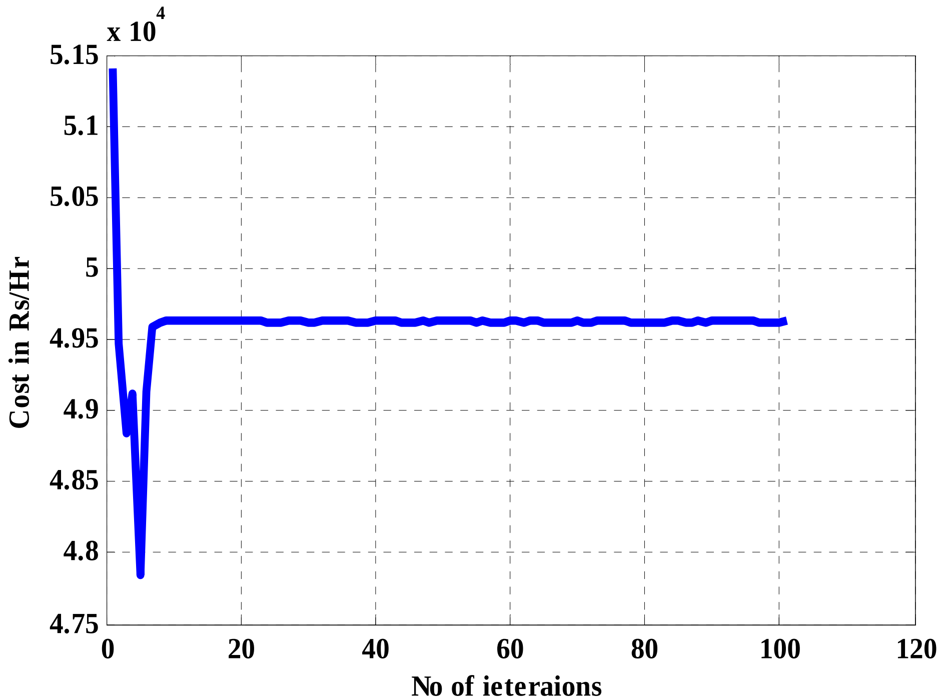


Fig 7.36: Cost curve of 950 MW demand by PSO method with loss

7.2.2.3 GA method

For solving the problem of ELD with considering the losses for six unit system 10 numbers of chromosomes are selected. If the no of chromosome s are increased then the convergence is not affected much more but the time of convergence is increased. The string length is also chosen 10.Probability of selection for the cross over operation is chosen 0.8. In the crossover operation one point crossover method is applied. It has been observed that the minimum cost curve convergence is not different when transmission line losses are neglected as we found in conventional method. When compared with the cost characteristic three unit systems the convergence is not affected much more as it is affected in the conventional method. In three unit system the minimum cost curve converges within the 20-30 iterations whereas in six unit system the cost curve converges within 20-40 iterations. The time of convergence is also increased than the three unit problem

Table7.15: GA method with losses

SL NO	Power demand (MW)	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	P_5 (MW)	P_6 (MW)	Loss in (MW	F_t Rs/Hr	Time in secs
1	600	22.8	10	100.3	98.9	194.23	187.5	14.2	32098.6	8.84
2	700	29.09	10	116.64	123.43	226.4	213.7	19.4	36913.7	9.74
3	800	32.5	12.4	140.51	136.2	258.28	245.3	25.44	41925.6	9.9
4	850	35.06	19.3	152.94	146.53	269.14	255.3	28.42	44456.28	9.74
5	950	39.7	24.9	179.17	163.13	288.4	290.1	35.4	49682.7	11.9

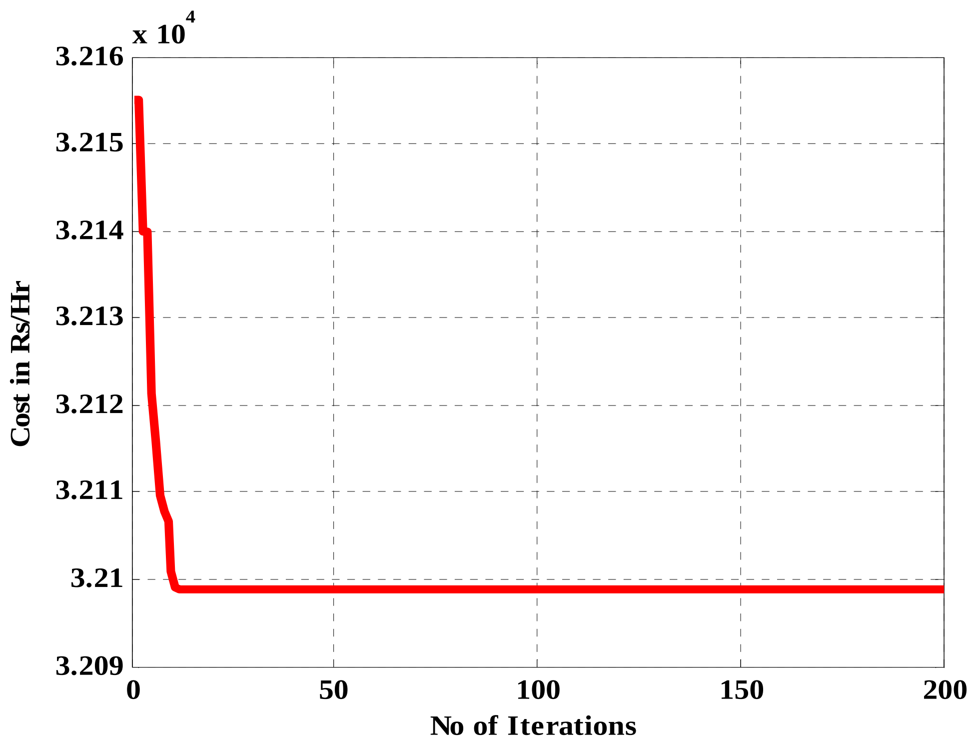


Fig 7.37: Cost curve of 600 MW demand by GA method with loss

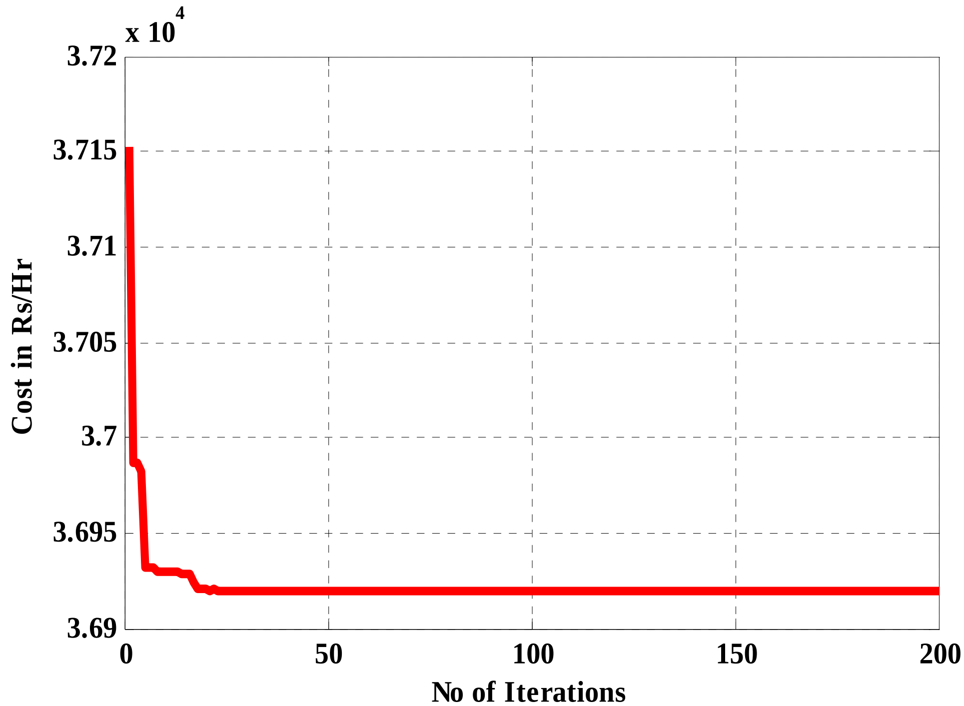


Fig 7.38: Cost curve of 700 MW demand by GA method with loss

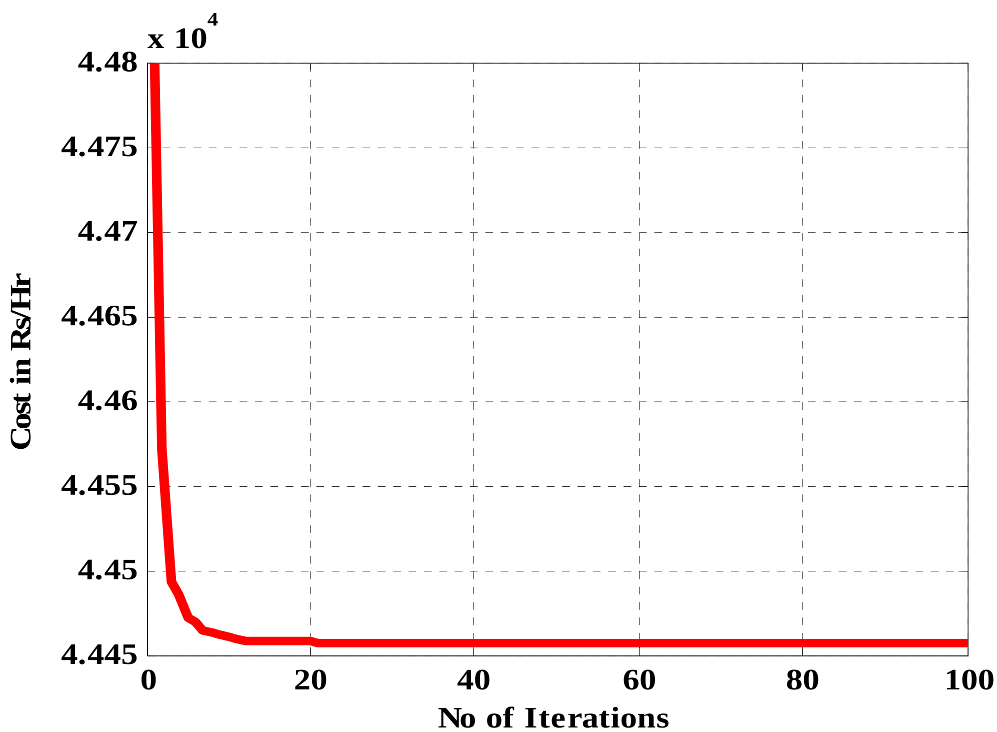


Fig 7.39: Cost curve of 850 MW demand by GA method with loss

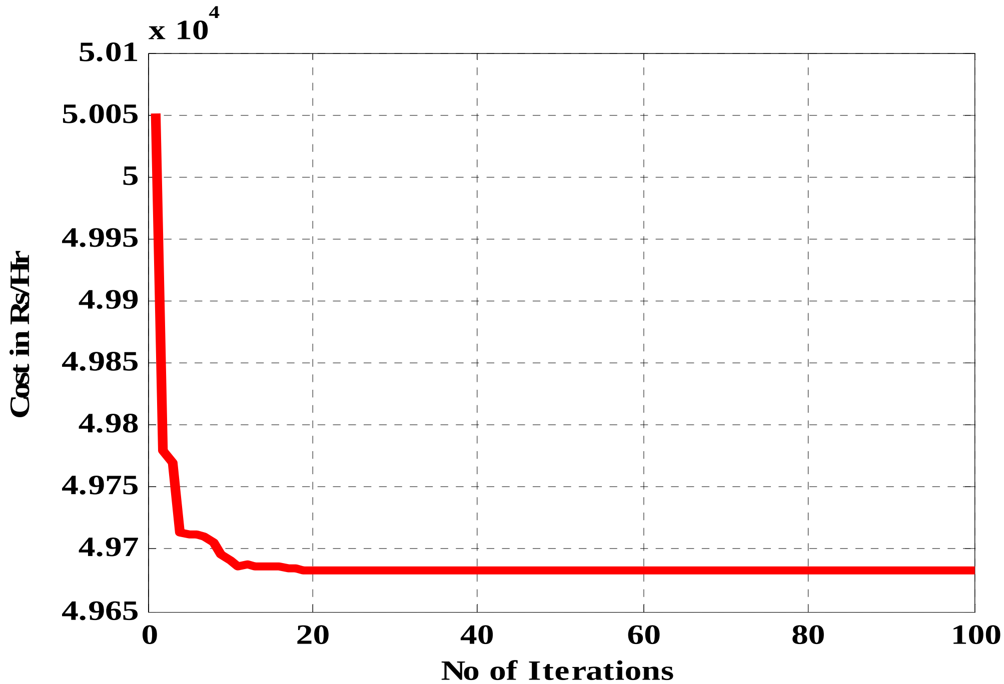


Fig 7.40: Cost curve of 950 MW demand by GA method with loss

7.2.2.4 Comparison of Cost in three different methods

It has been observed that when the numbers of units are increased the minimum cost we found in the PSO and GA method are less than the conventional method. But both the methods PSO and GA give the minimum cost are not always equal. The performance depends on randomly generated particle in PSO and strings in GA. Sometimes PSO gives better result and sometimes GA gives better result.

Table7.16: Six unit system comparison of cost in different method with losses

SL NO	Power demand (MW)	Cost in Rs/Hr Lambda iteration method	Cost in Rs/Hr PSO method	Cost in Rs/Hr GA method
1	600	32132.1	32091.68	32128.6
2	700	36914.1	36912.2	36913.7
3	800	41927.1	41896.2	41926.6
4	850	44452.1	44452.08	44456.28
5	950	49683.1	49681.38	49682.7

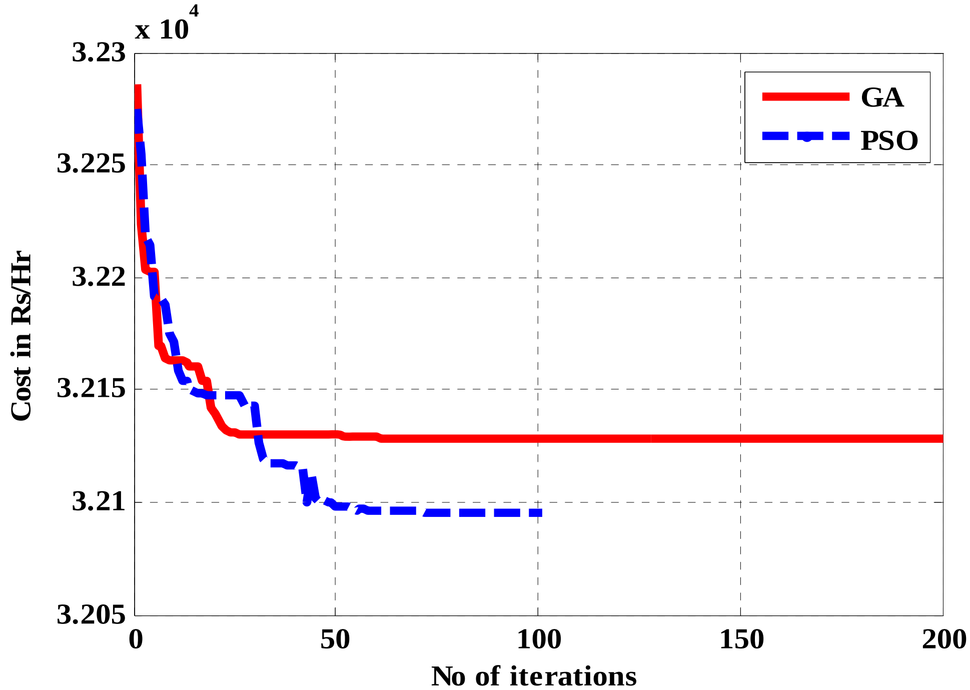


Fig 7.41: Comparison of Cost curve for 600 MW demand with loss for Six units

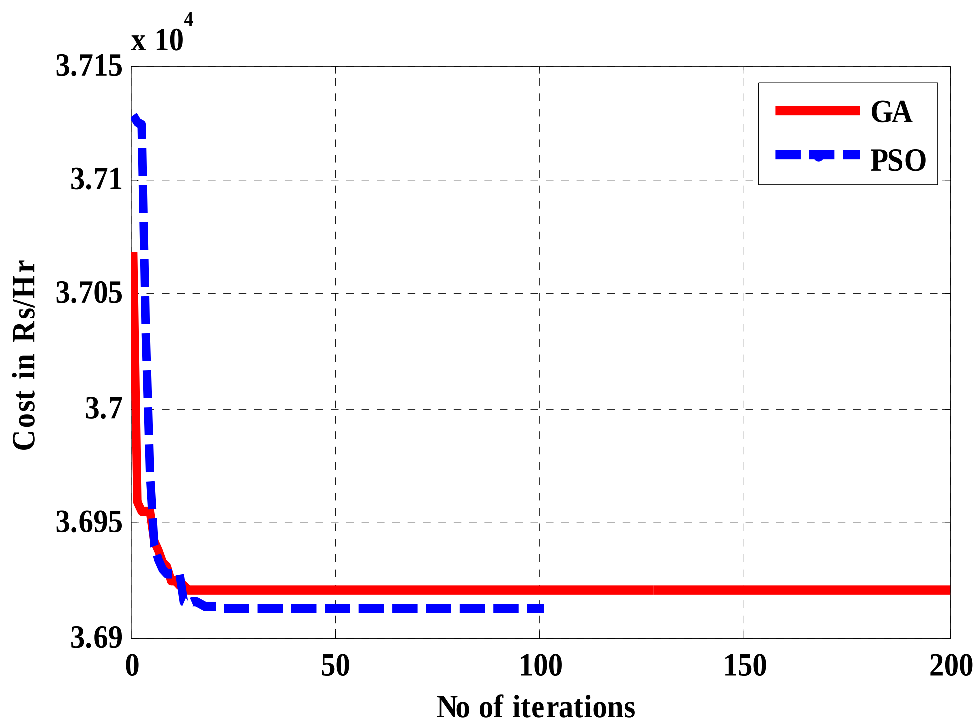


Fig 7.42: Comparison of Cost curve for 700 MW demand with loss for Six units

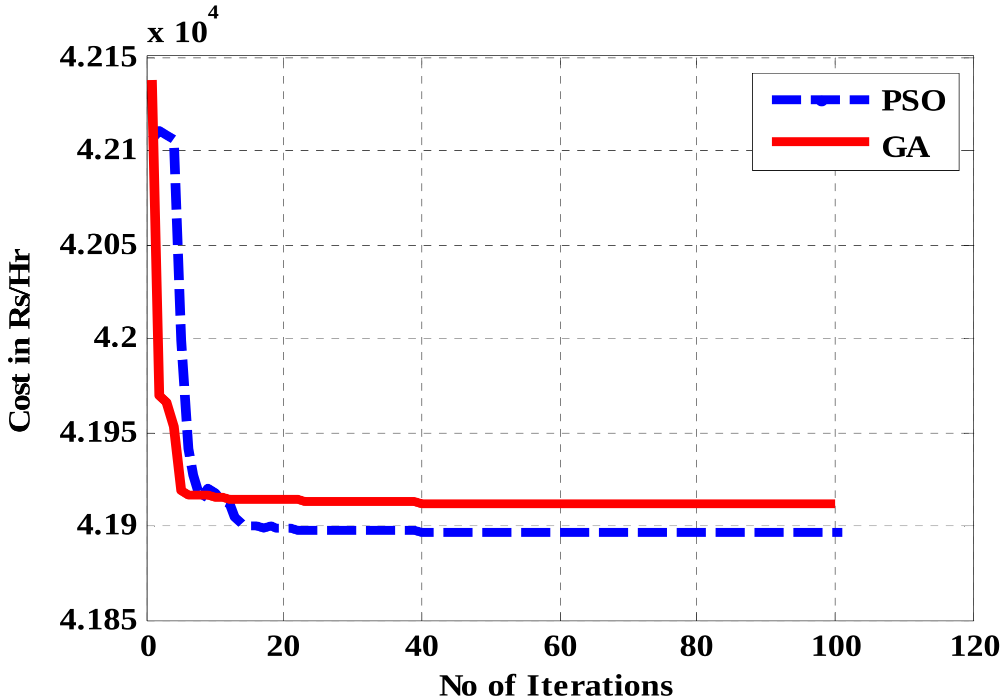


Fig 7.43: Comparison of Cost curve for 800 MW demand with loss for Six units

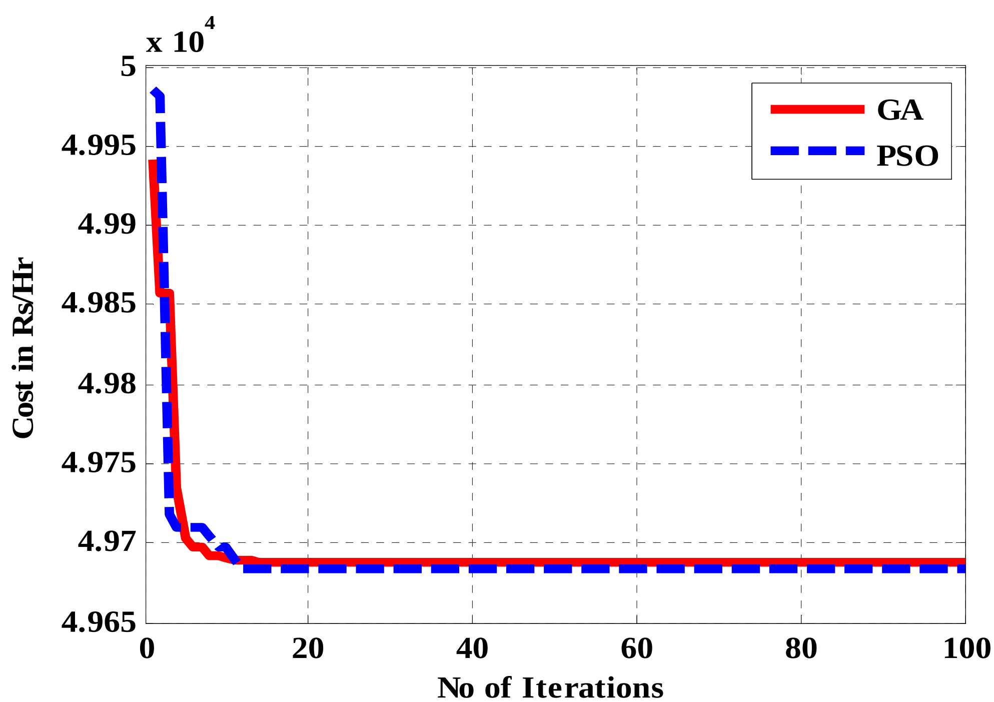


Fig 7.44: Comparison of Cost curve for 950 MW demand with loss for Six units

CHAPTER 8

CONCLUSION AND FUTURE WORK

Conclusion

Scope for Future work

8.1 CONCLUSION S

Economic load dispatch in electric power sector is an important task, as it is required to supply the power at the minimum cost which aids in profit-making. As the efficiency of newly added generating units are more than the previous units the economic load dispatch has to be efficiently solved for minimizing the cost of the generated power.

Load dispatch problem here solved for two different cases. One with three units in generating stations and other is six units in the generating stations. Each problem is solved by three different methods in the MATLAB environment.

Before the thesis draws to a close, major studies reported in this work and the general conclusions that emerge out from this work are highlighted. The conclusions are arrived at based on the performance and the capabilities of the PSO and GA application presented here. This finally leads to an outline of the future directions for research and development efforts in this area.

The main conclusions drawn are:

Three unit system:

Both the problem of three units system without loss and with loss is solved by three different methods. In Lambda-iteration method better cost is obtained but the problem converges when the lambda value is selected within the feasible range. But the cost characteristic takes many number of iteration converge. In PSO and GA method the cost characteristic converges in less number of iterations.

When transmission losses are considered PSO and GA methods gives a better result than the Lambda iteration method. In case of Lambda iteration method the number of iterations to converge is also increases. But in PSO and GA methods no of iterations are not affected when the transmission line losses are considered.

In PSO method selection of parameters c_1, c_2 and w is very much important. The best result obtained when c_1 = 2.01 and c_2= 2.01 and w value is chosen near 0.8. These results are similar when w is chosen according to the formula used.

Six unit system:

The problem of six units system without loss and with loss is solved by three different methods. In Lambda-iteration method better cost is obtained but the problem converges when the lambda value is selected within the feasible range. The cost characteristic takes many numbers of iterations to converge. In PSO and GA method the cost characteristic converges in less number of iterations.

When transmission losses are considered PSO and GA methods gives a better result than the Lambda iteration method. In case of Lambda iteration method the number of iterations to converge is also increases. But in PSO and GA methods no of iterations are not affected when the transmission line losses are considered. In both the methods the better result depends on the randomly generated particles. So, sometimes PSO gives better result and sometimes GA gives better result.

In PSO method selection of parameters c_1, c_2 and w is also important like above. The best result obtained when c_1=1.99 and c_2=1.99 and w value according to the formula used.

8.2 SCOPE FOR FUTURE WORK

Here the loss co-efficient are given in the problem. The work may be extended for the problem where transmission loss co-efficient are not given. In that case the loss co-efficient can be calculated by solving the load flow problem.

The two methods applies in this work are giving better result but GA convergence characteristic is better than PSO and in some cases the PSO gives better result than GA method. So, both the methods can be combined to find a better solution.

In PSO method selection of parameters are important. So, the parameters may be optimized by using the ANN method. Any other method can be applied with PSO to improve the performance of the PSO method.

This work may be extended for new optimization techniques, like Bacterial Foraging (BFO) and Artificial Immune Systems (AIS). This may be used to compare and find out the better optimization technique.

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