Power Economic Dispatch with Valve-Point Loading Effects and Multiple Fuels Using Chaotic Based Differential Evolution

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

Master of Engineering
in
Power Systems and Electric Drives

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July 2011

CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, **"Power Economic Dispatch with Valve-Point Loading Effects and Multiple Fuels Using Chaotic Based Differential Evolution "**, in partial fulfillment of the requirements for the award of degree of Master of Engineering in *Power Systems and Electric Drives* submitted in *Electrical and Instrumentation Engineering Department* of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of ***Mrs. Manbir Kaur*** and refers other researcher's work which are duly listed in the reference section. The matter presented in the thesis has not been submitted for award of any other degree of this or any other University, except as reported in text and references.

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

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ACKNOWLEDGEMENT

First of all, I wish to express my profound gratefulness and appreciation to ***Mrs. Manbir Kaur*** , Assistant Professor of Electrical & Instrumentation Engineering Department, Thapar University, Patiala, for her patient guidance and support throughout the work. She has been my mentor for help and without whose encouragement the learning would not have been realized.

Before I get into thick of things, I would like to add a few words to express my thanks to ***Dr. Smarajit Ghosh***, Professor and Head of Electrical & Instrumentation Engineering Department, & all the faculty and staff members of EIED Department of Thapar University, Patiala, for their valuable and unstinted advice from time to time.

Thanks are due to my parents for their motivation and inspiration and providing me all time to time support which has made me to come on this platform.

In the last but not the least, multi million thanks to the Almighty God, who gave me the opportunity and strength to carry out this thesis work.

To conclude, my best regards and thanks to whom I have forgotten to mention who helped me directly or indirectly in the completion of my report successfully and also for the preparation of this work.

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ABSTRACT

The power economic dispatch (PED) problem is one of the fundamental issues in power system. In essence, it is an optimization problem and its main objective is to reduce the total generation cost of units, while satisfying constraints. The work done in this thesis presents differential evolution (DE) and an improved differential evolution (IDE) with self-adaptive parameters setting for DE with chaos theory. Among various evolutionary algorithms (EAs), DE which characterized by the different mutation operator and competition strategy from the other EAs, has shown great promise in many numerical benchmark problems and real-world optimization applications. The potentialities of DE are its simple structure, easy use, convergence speed and robustness. To improve the global optimization property of DE, its parameters CR and f_m that needs to be adjusted by the user are generally the key factors affecting the DE's convergence. The utilization of chaotic sequences in DE can be useful to escape more easily from local minima than with the standard DE and improve its global convergence.

. In this thesis work, differential evolution and improved differential evolution techniques are used to solve power economic dispatch (PED) problem of all thermal units with valve point loading effects and multiple fuels for no loss transmission line as well considering transmission loss.

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LIST OF SYMBOLS AND ABBREVIATIONS

AHNN---------------------------------------Adaptive Hopfield neural network

CR---Crossover rate

CGA--Conventional genetic algorithm

DE---Differential evaluation

d---Slack generator

DP---Dynamic programming

EA---Evolution algorithm

EP---Evolution programming

f_m ---Mutation factor

GA---Genetic algorithm

GS---Gauss seidal

HDE--Hybrid differential evolution

HM--Hierarchical method

HS---Harmony search

IDE--Improved differential evolution

IGA--Improved genetic algorithm

L--Population

LM--Lagrangian method

NG--Number of generator

NR--Newton raphson

p_{ij}^{t} --Real power output

PED--Power economic dispatch

P_D --Power demand

P_L --Power loss

PSO--Particle swarm optimization

rand()--Random number

RNG---Random number generator

SA--Simulated annealing

SQP---Sequential quadratic programming

T--Time

TC--Total cost

$t_{\max}$ --Maximum iteration

VSHDE---------------------------------------Variable scaling hybrid differential evolution

W---Weighting factor

Chapter-1
Introduction

1.1 Overview

The engineer of power system is faced with the challenging task of planning and operating successfully one of the most complex systems of today's civilization. The basic requirement is to meet the demand for electric energy by the area served by the system at the lowest possible cost.

It may be tempting to order the above objective on a priority list. However, these objectives interact, which makes it difficult for one to come up with a general clear-cut ordering. Not only does this vary with the system, but also with the times and socioeconomic factors. Economic dispatch ranks high among the major economy security functions in power system operation. Conventional economic dispatch is a static optimization procedure to pre-selected generating units. This is a procedure for the distribution of total thermal generation requirements among alternatives sources for optimal system economy with due consideration of generating costs, transmission losses, and several recognized constraints imposed by the requirements of reliable service and equipment. Considering transmission losses can increase the cost of power system, but it cannot be ignored if power is transmitting across far-off distances. Mathematical of unit power modeling in the power economic dispatch (PED) is critical to achieve optimal results. In the power economic dispatch problem, the classical formulation presents deficiencies due to the simplicity of the models. Here, the power system is modeled through the power balance equation and generation with their cost curve as highly non-linear, containing discontinuities owing to valve-point loading are modeled as a segmented piecewise nonlinear function rather than a single quadratic function and generator output side is based on the constraints imposed. The PED problem with valve-point effects is represented as a non-smooth optimization problem having complex and non-convex characteristics with heavy equality and inequality constraints, which makes the challenge of finding the global optimum hard. Moreover, many generating units, particularly those which are supplied with multi-fuel sources (coal, nature gas, or oil), lead to the problem of determining the most economic fuel to burn. Some studies of the PED problem, such as genetic algorithm (GA) **[1]**, evolutionary programming (EP) **[2,3],** dynamic programming (DP) **[4],** Tabu search **[5],** hybrid EP combined with sequential quadratic programming (SQP) **[6],** and the particle swarm optimization (PSO) technique with the SQP method (PSO-SQP) **[7],** consider only valve-point effects, while others, such as a hierarchical method (HM) **[8],** Hopfield neural network approach (HNN) **[9],** adaptive Hopfield neural network method (AHNN) **[10],** and evolutionary programming (EP) **[11],** have considered only the change fuels. However, few approaches for the PED problem, and none of the studies mentioned above, consider both valve-point loadings and multi-fuel effects, which always exist in real power systems simultaneously. To obtain an accurate and practical economic dispatch solution, the realistic operation of the PED problem should be taken both valve-point effects and multiple fuels into account.

Differential evolution (DE) is one of the most prominent new generation of evolutionary algorithm (EA), proposed by Storn and Price **[12],** to exhibit consistent and reliable performance in nonlinear and multimodal environment **[13]** and proven effective for constrained optimization problems. Due to its powerful and reliable search capability, it has got many real work applications in various fields such as pattern recognition, communication, mechanical and chemical engineering and biotechnology **[14].**

1.2 Literature Review

Several references in technical literature have reported the optimal scheduling of power plant generation with the all type of loading i.e. either smooth or non-smooth type, such that the determination of the generation for every committed generating unit, the total system generation cost is minimum, while satisfying the system constraints. However with insignificant marginal cost of thermal electric power, the problem of minimizing the operational cost of a thermal system essentially reduces to minimizing the fuel cost for thermal units constrained by the generating limits and the energy balance condition in a given period of time. Walters and Sheble [1] have presented a genetics-based algorithm to solve an economic dispatch problem for valve point discontinuities. The algorithm utilizes payoff information of candidate solutions to evaluate their optimality. Sinha *et.al*. [2] have investigated the performance of the algorithms on economic load dispatch problems of different sizes and complexity having non-convex cost curves where conventional gradient-based methods are inapplicable. Yang *et al.* [3,4] have presented economic load dispatch based on the evolutionary programming (EP) technique, the new algorithm is capable of determining the global or near global optimal dispatch solutions in the cases where the classical Lagrange based algorithms cease to be applicable whereas by Lin *et al.* [5] have solved this problem using an improved tabu search algorithm (ITS) considering non-continuous and non-smooth cost functions. Kit *et al.* [6,7] have presented a novel and efficient method for solving the economic dispatch problem (EDP), by integrating the particle swarm optimization (PSO) technique with the sequential quadratic programming (SQP) technique. Lin and Viviani [8] have proposed the solution of PED with piecewise quadratic cost functions. Park *et al.* [9,10] has presented a new method to solve the problem of economic power dispatch with piecewise quadratic cost function using the Hopfield neural network and have used slope adjustment and bias adjustment methods, in order to speed up the convergence of the Hopfield neural network system. Jayabarathi, G. Sadasivam have considered multiple fuel options and solved PED problem using evolutionary programming [11]. Dhillon and Kothari [15-16] present a new approach based on a constrained nominal search and pattern search respectively algorithm to solve well-known power system economic load dispatch problem (ELD) with valve-point effect. Wong and Wong [17] have presented a hybrid genetic simulated-annealing approach for solving the thermal generator scheduling problem. Coelho and Marian [18] have introduced a meta-heuristic algorithm called harmony search (HS), mimicking the improvisation process of music players. Base *et al* [19] have used a simulated annealing (SA) technique for the determination of the global or near global optimum dispatch solution. Pathom [20] have proposed solution of PED problem using hybrid EP and SQP for Dynamic Economic Dispatch with Nonsmooth Fuel Cost Function. Simon *et al* [21] have used the artificial bee colony algorithm based optimization technique based on the foraging behavior of honeybees for solving economic load dispatch problems with non-smooth cost functions exhibiting valve-point effect. Chiang [22] has presented a different algorithm for power economic dispatch of units with valve-point effects and multiple fuels. Noman and Iba [23] have studied differential evolution (DE) algorithm for solving economic load dispatch (ELD) problems in power systems. DE has proven to be effective in solving many real world constrained optimization problems in different domains. Ref. [24-25] present DE is a population-based, stochastic function optimizer using vector differences for perturbing the population. The DE is used to solve the Economic Dispatch problem (ED) with or without transmission loss by satisfying the linear equality and inequality constraints [26].

Ref.[27-28] present a variable scaling hybrid differential evolution (VSHDE) for solving the economic dispatch (ED) problem in large-scale systems. Different from the hybrid differential evolution (HDE), the concept of a variable scaling factor is used in the VSHDE method. Coelho *et al* [29] and [30] have presented a variable scaling hybrid differential evolution for solving the economic dispatch problem in large-scale systems. Different from the hybrid differential evolution (HDE), the concept of a variable scaling factor is used in the VSHDE method. Amjady *et al* [31] have presented a chaotic hybrid differential evolution algorithm so that chaos theory is applied to obtain self-adaptive parameter settings in differential evolution (DE). The effect of introducing chaotic sequences instead of random ones during all the phases of the evolution process has been investigated. The approach is based on the substitution of the random number generator (RNG) with chaotic sequences. Ref.[32] present the Improved Differential evolution (IDE) solution to economic dispatch problem is very useful when addressing heavily constrained optimization problem in terms of solution accuracy. Radhakrishnan [33] have presented an optimization task in fossil fuel fired power plant operation for allocating generation among the committed units such that fuel cost and emission level are optimized simultaneously while satisfying all operational constraints. Ref.[34-36] present an experimental analysis on the convergence of evolutionary algorithms (EAs). The effect of introducing chaotic sequences instead of random ones during all the phases of the evolution process is investigated. The approach is based on the substitution of the random number generator (RNG) with chaotic sequences. M.basu et al Ref.[37] present Power economic dispatch (PED) is an important optimization task in fossil fuel fired power plant operation for allocating generation among the committed units such that fuel cost . Padhay *et al* [38] have presented evolutionary programming (EP) algorithm is devoted to solve the OPF problem with non-smooth fuel cost functions like quadratic, piece-wise, valve point loading and combined cycle cogeneration plants.

1.3 Objectives

The main objectives of the present work are:

1. To formulate and solve power economic dispatch (PED) for all thermal units with valve point loading effect under the consideration of equality and inequality constraints using differential evolution.
2. To formulate and solve power economic dispatch (PED) for all thermal units with valve point loading and multiple fuels.
3. To improve the result of power economic dispatch or all thermal units with valve point loading with and without transmission losses by using chaotic based differential evolution.

1.4 Organization of work

The thesis is organized into five chapters. The organization of chapters is as follows:

Chapter-1 summarized the overview of the problem, brief literature review, scope of work and organization of the thesis.

Chapter-2 highlights the topic power economic dispatch (PED) and also gives the overview of various related aspects of thermal power plants and its perspectives.

Chapter-3 explores the structure of differential evolution (DE) & improved differential evolution (IDE), its methodology & algorithm and its overview aspects.

Chapter-4 presents the problem formulation, result and compares with other type of population based techniques for various test problems.

Chapter-5 presents the conclusions drawn and also presents the scope of future work followed by reference section.

The work is carried out using MATLAB R2010a.

Chapter-2
Power Economic Dispatch

2.1 Introduction

Electrical energy cannot be stored, but is generated from natural sources and delivered as demand arises. A transmission system is used for the delivery of bulk power over considerable distances, and a distribution system is used for local deliveries. As depicted in Figure 2.1**,** an interconnected power system consists of mainly three parts: the generators which produce the electrical energy, the transmission lines which transmit it to faraway places, and the loads which use it. Such a configuration applies to all interconnected networks (regional, national, international), where the number of element may vary**.**

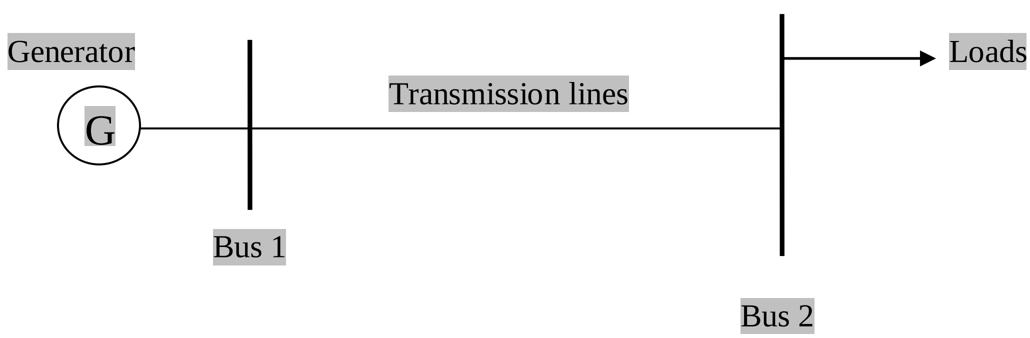


Figure 2.1: A simplified configuration of an interconnected power system

The size of electric power system is increasing rapidly to meet the energy requirements. A number of power plants are connected in parallel to supply the system load by interconnection of power stations. With the development of grid system it becomes necessary to operate the plant unit most economically. The economic generation scheduling problem involves two separate steps namely the unit commitment and the online economic dispatch. The unit commitment is the selection of unit that will supply the anticipated load of the system over a required period of time at minimum cost as well as provide a specified margin of the operating reserve. The function of the online economic dispatch is to distribute the load among the generating units actually paralleled with the system in such a manner as to minimize the total cost of supplying the minute to minute requirements of the system. Thus, economic load dispatch problem is the solution of a large number of load flow problems and choosing the one which is optimal in the sense that it needs minimum cost of electric power generation. Accounting for transmission losses results in considerable operating economy. Furthermore this consideration is equally important in future system planning and in particular, with regard to the location of plants and building of new transmission lines **[15].**

2.2 Performance Models for Thermal system

For a given generating unit the various generating plant using equal incremental cost criteria. It is, however, unrealistic to neglect transmission losses particularly when long distance transmission of power is involved. A modern electric utility serves over a vast area of relatively low load density. The transmission losses may vary from 5 to 15% of total load. The power economic dispatch problem is defined so as to minimize the total operating cost of a power system while meeting the total load plus transmission losses within generator limits **[16]**.

Mathematically, the problem is defined as:

Minimize $$\sum_{i=1}^{NG} F_i(P_i) \qquad (2.1)$$

Subject to (i) the energy balance equation (equality constraints)

$$\sum_{\substack{i=1 \\ i \neq d}}^{NG} P_i = P_D + P_L \qquad (2.2)$$

(ii) the inequality constraints

$$P_i^{min} \leq P_i \leq P_i^{\max} \quad (i=1,2,\ldots\ldots NG) \qquad (2.3)$$

where P_D is load demand

P_i is real power generation and will act as decision variable

P_L is power transmission loss

NG is the number of generation buses.

Function $F_i(P_i)$ can be expressed in two ways:

2.2.1 Without Valve Point Loading (Smooth quadratic function)

Each generator cost function establishes the relationship between the power injected to the system by the generator and the incurred costs to load the machine to that capacity. Typically, generators are modeled by smooth quadratic functions such as to simplify the optimization problem as Fig 2.1 below.

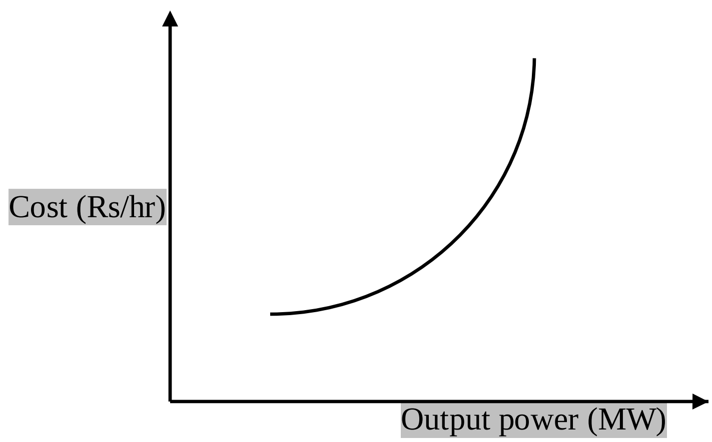


Figure 2.2: Fuel Cost for Thermal Units (Smooth quadratic function)

Mathematically, the cost curve can be expressed as:

$$F_i(P_i) = \sum_{i=1}^{NG} (a_i P_i^2 + b_i P_i + C_i) \qquad (2.4)$$

where a_i, b_i, c_i are cost coefficients of the thermal plants and

Pi =Power output of the generating units in MW for i^{th} unit.

2.2.2 With Valve Point Loading (Non-Smooth quadratic function)

Generators are commonly modeled using smooth quadratic functions (Fig 2.2) to relate power output to production cost. This type of cost function simplifies greatly the economic dispatch problem. For some cases, quadratic representations do not model properly generators, requiring more accurate models to provide better results in the solution of the economic dispatch problem. Power plants commonly have multiple valves that are used to control the power output of the unit. When steam admission valves in thermal units are first opened, a sudden increase in losses is registered which results in ripples in the cost function. This effect is known as a valve point loading. The cost function of thermal system with valve point loading which will result non-linier, non-smooth and non-convex cost function characteristics as shown in Fig 2.3 below **[17-21]**:

$$F_i(P_i) = \sum_{i=1}^{NG} (a_i P_i^2 + b_i P_i + C_i + | e_i \times \sin\{ f_i \times (P_i^{\min} - P_i)\} |) ....(2.5)$$

where

a_i, b_i, c_i are cost coefficients of the i^{th} unit. NG is the number of generating units.

e_i, f_i are fuel cost coefficient of the i^{th} unit with valve point effect.

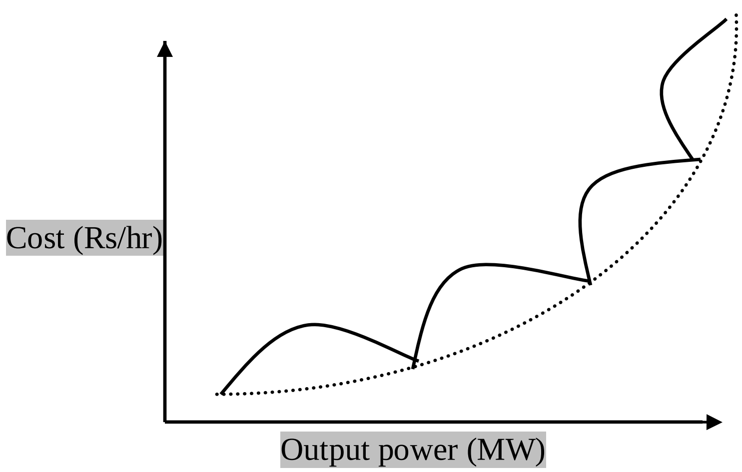


Figure 2.3: Fuel Cost function for a Thermal Unit with Valve Point Loading

2.3 Transmission Losses

The transmission losses which occur in the line when power is transferred from the generating station to the load centers increases with increase in distance between the two buses. The transmission losses may vary from 5 to 15 % of the total load. If the power factor of load at each bus is assumed to remain constant the system loss P_L can be shown to be a function of active power generation at each plants i.e.

$$P_L = P_L \left(P_{G1}, P_{G2} \ldots\ldots\ldots P_{GK} \right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2.6)$$

Approximately transmission losses are expressed as a function of generator powers is through B-Coefficients and is given by Kron’s loss formula as **[15]**:

Using Kron’s formula :

$$P_L = B_{00} + \sum_{i=1}^{NG} B_{io} P_i + \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_i B_{ij} P_j \text{.........................} (2.7)$$

where

B_{00}, B_{io}, B_{ij} are B-coefficients.

from equal constraints equation,

$$\sum_{\substack{i=1 \\ i \neq d}}^{NG} P_i = P_D + P_L \text{...} (2.8)$$

This equation can be rewritten considering transmission losses as:

$$P_d + \sum_{\substack{i=1 \\ i \neq d}}^{NG} P_i = \left[\sum_{\substack{i=1 \\ i \neq d}}^{NG} \sum_{\substack{j=1 \\ j \neq d}}^{NG} P_i B_{ij} P_j + \sum_{\substack{j=1 \\ j \neq d}}^{NG} P_j (B_{jd} + B_{dj}) P_d + B_{dd} P_d^2 + \sum_{\substack{i=1 \\ i \neq d}}^{NG} B_{io} P_i + B_{do} P_d + B_{oo} \right] + P_D \text{...} (2.9)$$

Above equation (2.3.4) can be simplified as:

$$X P_d^2 + Y P_d + Z = 0 \text{.................................. ....} (2.10)$$

where

$$X = B_{dd} \text{..} (2.11)$$

$$Y = \sum_{\substack{j=1 \\ j \neq d}}^{NG} (B_{jd} + B_{dj}) P_j + B_{do} - 1 \text{...} (2.12)$$

$$Z = P_D + B_{oo} + \sum_{\substack{i=1 \\ i \neq d}}^{NG} \sum_{\substack{j=1 \\ j \neq d}}^{NG} P_i B_{ij} P_j + \sum_{\substack{i=1 \\ i \neq d}}^{NG} B_{io} P_i - \sum_{\substack{i=1 \\ i \neq d}}^{NG} P_i \text{......................................} (2.13)$$

The positive roots of the equation are obtained as:

$$P_d = \frac{-Y \pm \sqrt{Y^2 - 4XZ}}{2X} \text{...} (2.14)$$

$$where Y^2 - 4XZ \geq 0 \qquad (2.15)$$

The positive values of roots, which lie within operating limits, are considered only, then the fuel cost is computed. In case, transmission losses are neglected, then

X=0, Y= -1 and

$$Z = P_D - \sum_{\substack{i=1 \\ i \neq d}}^{NG} P_i \qquad (2.16)$$

The value of dependent generator,

$$P_d = Z \qquad (2.17)$$

2.4 Power Economic Dispatch considering Multiple Fuels

Many generating unit, particularly those which are supplied with multi-fuel sources (coal, natural gas, or oil), lead to the problem of determining the most economical fuel to burn. Any given unit with multiple cost curves needs to operate on the lower contour of the intersecting curves. The resulting cost function is called a "hybrid cost function." Each segment of the hybrid cost function implies some information about the fuel being burned or the unit's operation. Since the dispatching units are practically supplied with multi-fuel sources, each unit should be represented with several piecewise quadratic functions reflecting the effects of fuel type changes, and the generator must identify the most economic fuel to burn. Thus, the fuel cost function should be practically expressed as **[22]**:

$$F_i(P_i) = \begin{cases} a_{i1}P_i^2 + b_{i1}P_i + c_{i1} + |e_{i1} \times \sin(f_{i1} \times (P_{i1}^{\min} - P_{i1}))|, for\_fuel1, P_i^{\min} \leq P_i \leq P_{i1} \\ a_{i2}P_i^2 + b_{i2}P_i + c_{i2} + |e_{i2} \times \sin(f_{i2} \times (P_{i2}^{\min} - P_{i2}))|, for\_fuel2, P_{i1} \leq P_i \leq P_{i2} \\ \vdots \\ a_{ik}P_i^2 + b_{ik}P_i + c_{ik} + |e_{ik} \times \sin(f_{ik} \times (P_{ik}^{\min} - P_{ik}))|, for\_fuelk, P_{ik-1} \leq P_i \leq P_i^{\max} \end{cases} \qquad (2.18)$$

where,

$a_{ik}, b_{ik}, c_{ik}, e_{ik}, f_{ik}$ are cost coefficients of the i^{th} generator unit using the fuel type k.

NG is the number of generating units.

2.5 Solution Methods for Power Economic Dispatch

A wide variety of technique has been reported to obtain solution of power economic dispatch problem. As it is an optimal problem, broadly optimization techniques are clamped as

1. Conventional method
2. Artificial neural method

2.5.1 Conventional method

When making a decision in order to achieve a certain goal, a optimization techniques such as mathematical programming have been utilized in cases where the largest problem can be expressed as a power economical dispatch (PED). On the other hand, if the target problem cannot be expressed in a mathematical equation, neural network, fuzzy logic, expert systems and other decision-making techniques have been utilized. The problem with conventional technique is the difficulty in guaranteeing the generation of good quality solutions for cases that have not been verified. It has also a slow convergence of optimization procedure. Some conventional methods are:

i. Lagrangian method

The method of Lagrange multipliers can also accommodate multiple constraints. To see how this is done, we need to reexamine the problem in a slightly different manner because the concept of "crossing" discussed above becomes rapidly unclear when we consider the types of constraints that are created when we have more than one constraint acting together.

ii. Gauss seidal method

The Gauss–Seidel method, also known as the Liebmann method or the method of successive displacement, is an iterative method used to solve a linear system of equations. It is named after the German mathematicians Carl Friedrich Gauss and Philipp Ludwig von Seidel, and is similar to the Jacobi method. Though it can be applied to any matrix with non-zero elements on the diagonals, convergence is only guaranteed if the matrix is either diagonally dominant, or symmetric and positive definite

iii. Gradient method

The gradient method is an algorithm for the numerical solution of particular systems of linear equations, namely those whose matrix is symmetric and positive-definite. The conjugate gradient method is an iterative method, so it can be applied to sparse systems that are too large to be handled by direct methods such as the Cholesky decomposition. Such systems often arise when numerically solving partial differential equations.

iv. Newton raphson method

Newton method is a method for finding successively better approximations to the roots (or zeroes) of a real-valued function. The idea of the method is as follows: one starts with an initial guess which is reasonably close to the true root, then the function is approximated by its tangent line (which can be computed using the tools of calculus), and one computes the x-intercept of this tangent line (which is easily done with elementary algebra). This x-intercept will typically be a better approximation to the function's root than the original guess, and the method can be iterated

2.5.2 Artificial neural method

Artificial method has an advantage in that a good quality solution can be obtained even in cases when the target problem cannot be expressed as an equation. Rather than optimization within a small range, as is often said, end users require "total optimization" over a broad range. In comparing with convergence time, it is able to do it in lesser time than conventional methods. Some artificial neural methods are:

i. Genetic Algorithm (GA):

A global optimization technique known as genetic algorithm (GA) has emerged as a candidate due to its flexibility and efficiency for many optimization applications. Genetic algorithm is a stochastic searching algorithm. It combines an artificial, i.e. the Darwinian survival of the fittest, principle with genetic operation, abstracted from nature to form a robust mechanism that is very effective at finding optimal solutions to complex-real world problem.

ii. **Evolutionary programming (EP)**

Evolutionary computing is an adaptive search technique based on the principles of genetics and natural selection. Evolutionary programming is a probabilistic, global search technique. It starts with a population of randomly generated candidate solutions and evolves towards better solutions over a number of generations or iterations. The main stages of this technique include initialization, mutation, competition and selection.

iii. **Particle swarm optimization (PSO)**

In 1995, kennedy and Eberhart [1995] first introduced the particle swarm optimization (PSO) method, motivated by social behavior of organisms such as fish schooling and bird flocking. PSO, as an optimization tool, provides a population-based search procedure in which individuals called particles change their positions (states) with time.

iv. **Adaptive neural network (ANN)**

Adaptive control theory has evolved as a powerful methodology for designing nonlinear feedback controllers for systems with parametric uncertainty. The fundamental issues of adaptive control for linear systems-selection of controller structures, assumptions of a priori system knowledge, parameterization of adaptive systems, establishment of error models, development of adaptive laws, persistency of excitation, and analysis of closed-loop stability have been extensively addressed.

v. **Differential Evolution (DE)**

Differential evolutionary Programming is a population-based stochastic function minimizes (or maximize) relating to evolutionary computation, whose simple yet powerful and straightforward features make it very attractive for numerical optimization. Differential evolution uses a rather greedy and less stochastic approach to problem solving than do evolutionary algorithms. Differential evolution combines simple arithmetic operators with the classical operators of recombination, mutation and selection to evolve from a randomly generated starting population to a final solution [28].

Chapter-3
Differential Evolution

3.1 Introduction

Differential evolution is a population-based stochastic technique that minimizes (or maximize) relating to evolutionary computation, whose simple yet powerful and straightforward features make it very attractive for numerical optimization. Differential evolution uses a rather greedy and less stochastic approach to problem solving than do evolutionary algorithms. Differential evolution combines simple arithmetic operators with the classical operators of recombination, mutation and selection to evolve from a randomly generated starting population to a final solution. Differential evolution differs from conventional genetic algorithm in its use of perturbing vectors, which are the difference between two randomly chosen parameter vectors, a concept borrowed from the operators of simplex optimization technique. The differential evolution algorithm was first introduced by Storn and price in 1995 and was successfully applied in the optimization of some well-known nonlinear, non-differentiable, and non-convex functions by Storn **[12]**.

The different variants of differentiable evolution are classified using the following notation: DE/α/β/δ, where α indicates the method for selecting the parent chromosome that will form the base of the mutated vector, β indicates the number of difference vectors used to perturb the base chromosome, and δ indicates the recombination mechanism used to create the offspring population. The bin acronym indicates that the recombination is controlled by a series of independent binomial experiments. The fundamental idea behind differential evolution is a scheme whereby it generates the trial parameter vectors. In each step, the differential evolution mutates vectors by adding weighted, random vector differentials to them. If the cost of the trial vector is better than that of the target, the trial vector replaces the target vector in the next generation. The variant implemented here was the DE/rand/l/bin, which involved the following steps and procedures. The differential evolution algorithm can be implemented by searching the generation of power plants, p_i within generator limits. The economic dispatch problem is defined by Eq. (2.4) or Eq. (2.5) and transmission losses are defined Eq. (2.7) **[23-27]**.

3.2 Methodology and Algorithm

This section provides the solution methodology to the power economic dispatch problems through differential evolution.

3.2.1 Parameter setup

The user must choose the key parameters that control the differential evolution, i.e. population size (L), boundary constraints of optimization variables (NG), mutation factor (f_m), crossover rate (CR), and the stopping criterion of maximum number of iterations (generations) t_{max}. The set of real power output (p_{ij}^t) of all generators is represented as the population. For a system with NG generators, the population is represented as a vector of length NG. If there are L members in the population, the complete population is represented as a matrix as below**:**

Population =

$$\begin{bmatrix} P_{11}^t & P_{12}^t & .. & P_{1NG}^t \\ P_{21}^t & P_{22}^t & .. & P_{2NG}^t \\ : & : & P_{ij}^t & : \\ P_{L1}^t & P_{L1}^t & .. & P_{LNG}^t \end{bmatrix} . \begin{matrix} i = 1, 2, ...NG \\ j = 1, 2, ...L \end{matrix} \quad \text{.......(3.1)}$$

where P_{ij}^t is the jth element of NG set of committed generators giving jth individual of a population. In other words it represents the real power generation of generator j of the possible solution i. Further, $P_{ij}^t = \left[P_{i1}^t, P_{i2}^t, ..., P_{iNG}^t \right]^T$ stands for the position of the ith individual of a population of real valued NG-dimensional vectors.

3.2.2 Initialization of an Individual Population

The initial population comprises combinations of only the candidate dispatch solutions, which satisfy all the constraints and are feasible solutions of economics dispatch. It consists of P_{ij}^t (i=1,2,..NG; j=1,2,..L) trial parent individuals. The element of a parent is the combinations of power outputs of the generating units, which are chosen randomly by a random number ranging over $\left[P_i^{\min}, P_i^{\max}\right]$.

$$P_{ij}^{t} = P_{ij}^{\min} + rand()(P_i^{\max} - P_i^{\min})(\text{ i} = 1,2,..\text{NG};\text{i} \neq d;\ j = 1,2,...L)..................(3.2)$$

where rand ( ) is uniform random number ranging over [0,1].

The element of parent/offspring P_i^j may violate inequality constraints. This violation is corrected by fixing them either at lower or upper limits as described below:

$$P_{ij}^{t} = \begin{cases} P_i^{\min}; P_{ij}^{t} < P_i^{\min} \\ P_i^{\max}; P_{ij}^{t} > P_i^{\max} \\ P_i^{j} : P_i^{\min} \le P_i^{j} \le P_i^{\max} \end{cases} \quad (i = 1,2,..NG; i \neq d;\ j = 1,2,...L).............(3.3)$$

3.2.3 Evaluation

In order to satisfy the power balance constraint, a generator is arbitrarily selected as a dependent generator d. $P_L=0$ means transmission losses are neglected. $P_L \neq 0$ means transmission losses are considered. Output of dependent or slack generator is obtained from Eq.(2.10) and is given below

$$P_{dj}^{t} = \begin{cases} Z^{j}; P_L = 0 \\ W^{j}; P_L \neq 0 \end{cases} (j = 1,2,....L)..(3.4)$$

where

$$W^{j} = \frac{-Y \pm \sqrt{Y^2 - 4XZ}}{2X} When Y^2 - 4XZ \ge 0...(3.5)$$

with

$$X = \begin{cases} 0; P_L = 0 \\ B_{dd;} P_L \neq 0 \end{cases}...(3.6)$$

$$Y^j = \begin{cases} -1.......................................\ ....; P_L = 0 \\ \sum_{\substack{j=1 \\ j \neq d}}^{NG} (B_{jd} + B_{dj}) P_j + B_{do} - 1...........; P_L \neq 0 \end{cases} ....(3.7)$$

$$Z^t = \begin{cases} P_D - \sum_{\substack{i=1 \\ i \neq d}}^{NG} P_i ....; P_L = 0 \\ P_D + B_{oo} + \sum_{\substack{i=1 \\ i \neq d}}^{NG} \sum_{\substack{j=1 \\ j \neq d}}^{NG} P_i B_{ij} P_j + \sum_{\substack{i=1 \\ i \neq d}}^{NG} B_{io} P_i - \sum_{\substack{i=1 \\ i \neq d}}^{NG} P_i ....; P_L \neq 0 \end{cases} ....(3.8)$$

Similarly, if the output of the dependent generator violates its limits, it is fixed using Eq. (3.2.2.2)

$$If P_d^t > P_d^{\max} then P_i^t = P_i^j + w \times rand()(P_i^{\max} - P_i^{\min})(i = 1, 2....NG; i \neq d)......(3.9)$$

$$If P_d^t < P_d^{\min} then P_i^t = P_i^j - w \times rand()(P_i^{\max} - P_i^{\min})(i = 1, 2....NG; i \neq d)......(3.10)$$

where w is some weighting factor nominally range [0,1].

3.2.4 Mutation operation (differential operation)

Mutation is an operation that adds a vector differential to a population vector of individuals according to the following equation:

$$Z_{ij}^t = P_{R_1 j}^t + f_m (P_{R_2 j}^t - P_{R_3 j}^t)(i = 1, 2, ...NG; i \neq d; j = 1, 2, ...L).....................................(3.11)$$

where

i=1,2…...NG is the individual's population index;

J=I,2,……L is the position in NG of the dimensional individual;

T is the time (generation);

$p_i^t = [P_{i1}^t, P_{i2}^t, ...P_{iNG}^t]^T$ stands for the position of the ith individual of a population of real valued NG-dimensional vectors.

$Z_i^t = \left[Z_{i1}^t, Z_{i2}^t, ..., Z_{iNG}^t \right]^T$ Stands for the position of the ith individual of a mutual vector

$R_1, R_2 and R_3$ are mutually different integers that are also different from the running index, i, randomly selected with uniform distribution from the set {1,2,….i-1,i+1,….L}

f_m is the mutation factor and f_m >0 is a real parameter, which controls the amplification of the difference between two individuals with indexes $R_2 and R_5(i) \in \{1, 2, ..., NG\}$ so as to avoid search stagnation and is usually a constant value taken from the range [0.4,1].

The mutation operation using the difference between two randomly selected individuals may cause the mutual individual to escape from the search domain. If an optimized variable for the mutant individual is outside is outside of the domain search, then this variable is replaced by its lower bound or its upper bound so that each individual can be restricted to remain within the search domain.

3.2.5 Recombination operation

Following the mutation operation, recombination is applied to the population. Recombination is employed to generate a trial vector by replacing certain parameters of the target vector by the corresponding parameters of a randomly generated donor vector.

For each vector, Z_i^{t+1}, an index $R_5(i) \in \{1, 2, ..., NG\}$ is randomly chosen using a uniform distribution, and a trial vector, $U_i^{t+1} = [U_{i1}^{t+1}, U_{i2}^{t+1}, ... U_{iNG}^{t+1}]^T$.

$$U_i^{t+1} = \begin{cases} Z_{ij}^t; if\,(R_4(j) \le CR) or (j = R_5(i)) \\ P_{ij}^t; if\,(R_4(j) > CR) or (j \ne R_5(i)) \end{cases} (i = 1, 2, ...NG; i \ne d;\ j = 1, 2, ...L)........(3.12)$$

where

$R_4(j)$ is the jth evaluation of a uniform random number generation with [0,1]

CR is the crossover or recombination rate in the range [0,1].

Usually, the performance of a DE algorithm depends on three variables: the population size, the mutation factor f_m and the CR.

3.2.6 Selection operation

Selection is the procedure whereby better offspring are produced. To decide whether the vector U_i^{t+1} should be a member of the population comprising the next generation, it is compared with the corresponding vector P_{ij}^{t}. Thus, if f denotes the cost function under minimization, then

$$P_{ij}^{t+1} = \begin{cases} U_{ij}^{t+1}; (i = 1, 2, ..., NG); if\,(U_i^{t+1}) < f\,(P_i^t) \\ P_{ij}^{t}; (i = 1, 2, ..., NG); otherwise \end{cases} (j = 1, 2, ..., L) ....(3.13)$$

In this case, the cost of each of trial vector U_i^{t+1} is compared with that of its parent target vector P_{ij}^{t}. If the cost f, of the target vector P_{ij}^{t}, is lower than that of the trial vector, the target is allowed to advance to the next generation. Otherwise, a trial vector replaces the target vector in the next generation.

3.2.7 Verification of the stopping criterion

Set the generation number for t=t+1. Repeat mutation, recombination and selection operation until a stopping criterion is met, usually a maximum number of iterations (generations), $t_{\max}$. The stopping criterion depends on the type of problem.

3.3 Various differential (mutation) strategies

There are several variations of differential evolution algorithm strategies that can be employed for optimization as mentioned by Sum-Im et al. [2009]. Ten variations, which are defined as the following mutation strategies.

Differential strategy 1: In this mutation strategy, the mutant vector can be generated according to the following equation from the randomly chosen base vector

$$Z_{ij}^{t} = P_{R_1 j}^{t} + f_m (P_{R_2 j}^{t} - P_{R_3 j}^{t})(i = 1, 2, ...NG; i \neq d; j = 1, 2, ...L) ....(3.14)$$

where

t is the time (generation)

$p_i^t = [P_{i1}^t, P_{i2}^t, ...P_{iNG}^t]^T$ stands for the position of the ith individual of a population of real valued NG-dimensional vectors.

$Z_i^t = \left[Z_{i1}^t, Z_{i2}^t, ..., Z_{iNG}^t \right]^T$ Stands for the position of the ith individual of a mutual vector

$R_1, R_2 and R_3$ are mutually different integers that are also different from the running index, i, randomly selected with uniform distribution from the set {1,2,….i-1,i+1,….L}.

$f_m(t)$ is the mutation factor and $f_m(t)$ >0 is a real parameter,

Differential Strategy 2: In this mutation strategy, the mutant vector can be generated according to the following equation from the best performing vector of the current generation by considering it as base vector

$$Z_{ij}^t = P_{R_5 j}^t + f_m(P_{R_1 j}^t + P_{R_2 j}^t - P_{R_3 j}^t - P_{R_4 j}^t)(i = 1, 2, ...NG; i \neq d; j = 1, 2, ...L) \qquad (3.15)$$

where P_{Bj}^t is the best performing vector of the current generation.

Differential Strategy 3: In this mutation strategy, the perturbation is applied at a location between the best performing vector and a randomly selected population vector according to the following equation

$$Z_{ij}^t = P_{ij}^t + f_B(P_{Bj}^t - P_{ij}^t) + f_m(P_{R_1 j}^t - P_{R_2 j}^t)(i = 1, 2, ...NG; i \neq d; j = 1, 2, ...L) \qquad (3.16)$$

where f_B is applied to control the greediness of the scheme, which usually it is set equally to f_B to reduce the number of control variables.

Differential Strategy 4: Two difference vectors are used as a perturbation in this mutation strategy.

$$Z_{ij}^t = P_{Bj}^t + f_m(P_{R_1 j}^t + P_{R_2 j}^t - P_{R_3 j}^t - P_{R_4 j}^t)(i = 1, 2, ...NG; i \neq d; j = 1, 2, ...L) \qquad (3.17)$$

Differential Strategy 5: This mutation strategy replace the best performing vector by a randomly selected vector

$$Z_{ij}^t = P_{R_5 j}^t + f_m(P_{R_1 j}^t + P_{R_2 j}^t - P_{R_3 j}^t - P_{R_4 j}^t)(i = 1, 2, ...NG; i \neq d; j = 1, 2, ...L) \qquad (3.18)$$

Differential Strategy 6: In this mutation strategy, the mutant vector can be generated according to the following equation

$$Z_{ij}^t = P_{Bj}^t + f_m(P_{Bj}^t - P_{ij}^t)(i = 1, 2, ...NG; i \neq d; j = 1, 2, ...L) \qquad (3.19)$$

Differential Strategy 7: The mutant vector can be generated according to the following equation for this mutation strategy

$$Z_{ij}^{t} = P_{Bj}^{t} + f_m(P_{Bj}^{t} - P_{ij}^{t} - P_{R_1 j}^{t} - P_{R_2 j}^{t})(i = 1, 2, ...NG; i \neq d; j = 1, 2, ...L) \text{............} (3.20)$$

Differential Strategy 8: This mutation strategy generates the mutant vector according to the following equation

$$Z_{ij}^{t} = P_{Bj}^{t} + f_B(P_{Bj}^{t} - P_{ij}^{t}) + f_m(P_{R_1 j}^{t} - P_{R_2 j}^{t})(i = 1, 2, ...NG; i \neq d; j = 1, 2, ...L) \text{............} (3.21)$$

Differential Strategy 9: This mutation strategy generates the mutant vector according to the following equation

$$Z_{ij}^{t} = P_{Bj}^{t} + f_m(P_{Bj}^{t} + P_{ij}^{t} - P_{R_1 j}^{t} - P_{R_2 j}^{t})(i = 1, 2, ...NG; i \neq d; j = 1, 2, ...L) \text{..........} (3.22)$$

Differential Strategy 10: This mutation strategy considers the previous generation's best performing vector in order to creat the mutant vector

$$Z_{ij}^{t} = P_{Bj}^{t} + f_m(P_{Bj}^{t} - P_{Bj}^{t-1})(i = 1, 2, ...NG; i \neq d; j = 1, 2, ...L) \text{.............} (3.23)$$

3.4 Flowchart of the Differential Evolution:

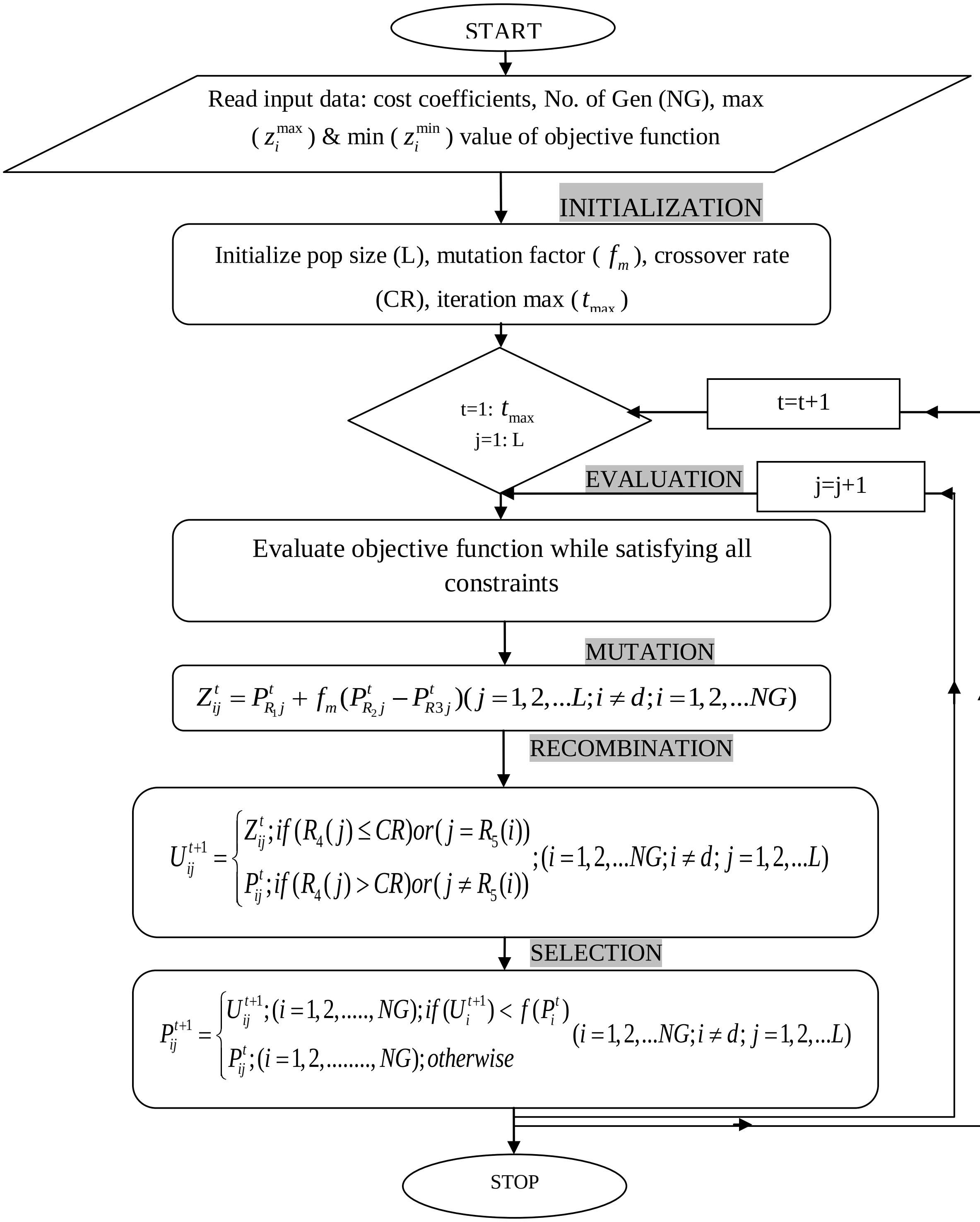


Figure 3.1 Flowchart of the Differential Evolution

3.5 Advantages

Differential evolution algorithm has a number of significant advantages which are summarized below **[15]**:

1. Differential evolution algorithm has the ability to find the true global minimum regardless of initial parameter values;
2. Differential evolution algorithm is fast and simple with regard to application;
3. Differential evolution algorithm requires few control parameter;
4. Differential evolution algorithm has parallel processing nature and fast convergence;
5. Differential evolution algorithm is capable of providing multiple solutions in a single run;
6. The method is effective on integer, discrete and mixed parameter optimization;
7. Differential evolution algorithm has the ability to find the optimal solution for a non-linear constrained optimization problem with penalty functions.

3.6 Disadvantages

Although differential evolution algorithm has many advantages explained above, there are also a number of disadvantages of differential evolution algorithm that are summarized below:

1. Differential evolution algorithm does not always give an exact global optimum due to premature convergence;
2. Differential evolution algorithm may require tremendously high-computation time because of a large number of fitness evaluations;
3. In differential evolution algorithm, there exist many trials vector generation strategies out of which a few may be suitable for solving a particular problem;
4. Moreover, three crucial control parameters involved in differential evolution algorithm, i.e, population size, scaling factor, and crossover rate, may significantly influence the optimization performance.

3.7 Improved Differential Evolution

Chaotic sequences display an unpredictable long-term behavior due to their sensitiveness to initial conditions. This feature is useful to track the chaotic variable as it travels ergodically over the space of interest, so it is can be applied in DE. In order to obtain high quality solution for thermal scheduling, an improved DE combination chaotic sequences for parameters setting with selection comparison technique based on individual feasibility and heuristic rules for constraints handling is proposed in this paper.

3.8 Self-adaptive parameters setting for DE with chaos theory

Recently, some applications of chaotic sequences in evolutionary algorithm (EA) have been investigated by the literature [31]. Numerous examples and statistical results show that some chaotic sequences applied to EA are able to increase the algorithm-exploitation capability in the search space and enhance its convergence. The DE's parameters CR and F that need to be adjusted by the user are generally the key factors affecting the DE's convergence. Choosing suitable parameter values are difficult for DE, which is usually a problem-dependent task. The trial-and-error method adopted frequently for tuning the parameters in DE requires multiple optimization runs. However, the parameter CR and f_m cannot ensure the optimization's ergodicity completely in the search phase because they are often constant factors in traditional DE. Therefore, this paper adopts chaotic sequences to self-adaptive adjust parameters CR and f_m during the evolutionary process. The utilization of chaotic sequences in DE can be useful to escape more easily from local minima than with the standard DE and improve its global convergence **[23-28]**.

Several characterizations of a chaotic system are possible. Before giving a definition of chaos, the following definitions are required **[31]**.

Definition 1: Given a dynamic system of the form dx/dt=f(x), not satisfying Liouville's Theorem (conservative systems theorem) and that contracts its volume in all (or at least some) parts of phase space, the set of points in the phase space where the volumes are contracted is called an attractor.

Definition 2: An attractor can have an integer dimension (e.g., points have dimension zero, lines have dimension one, plane surfaces have dimension two, etc.), or they have fractal dimension: in this case, they are called a strange attractor. For the case of a map dx/dt=G(x), a volume contraction or expansion is determined by computing the determinant J of Jacobian matrix. Then, all points for which J < 1 define the contraction subspace; correspondingly, all points for which J > 1 define the expansion subspace and, finally, the subset of the phase space where indicates a limit cycle.

From a time-series perspective, a chaotic system is characterized by signals with a broad-band spectrum that depend strongly on the initial conditions. A more analytical way to define it makes use of the Lyapunov exponents, which are closely related with the qualitative aspects reported above.

Consider an orbit x(t) whose long-term limit fills out the attractor. Now consider the initial condition for this orbit x(0) and a second initial condition $x^{'}(0)$, which is displaced from x(0) by an infinitesimal distance δx(0).

3.9 Various chaotic time series sequences strategies

There are several variations of chaotic time series sequences strategies that can be applicable in evolutionary algorithm (EA) which is able to increase the algorithm-exploitation capability in the search space and enhance its convergence **[31-33]**.

Strategy 1: Logistic Map (type1)

One of the simplest dynamic systems evidencing chaotic behavior is the iterator named logistic map [23], whose equation is the following:

$$x_{k+1} = ax_k(1-x_k) \qquad (3.24)$$

The following values for the parameters X_0 =0.20207 and a=4 have been used for simulation.

Strategy 2: Logistic Map (type2)

$$y(t) = \mu.y(t-1).[1-y(t-1)] \qquad (3.25)$$

where μ is a control parameter, $0 \le \mu \le 4$.

The parameter value of F and CR in DE are modified by the formula above through following expresses:

$$\begin{aligned} F(G) &= \mu.F(G-1).[1-F(G-1)] \\ CR(G) &= \mu.CR(G-1).[1-CR(G-1)] \end{aligned} \qquad (3.26)$$

where G is the current iteration generation; f_m (0) and CR(0) are randomly number between 0 and 1, respectively.

Strategy 3: self-adaptive control mechanism

A self-adaptive control mechanism is used to change the control parameter F during the run. At generation G=1 of the ELD sub-problem, the amplification factor $F_{k,G}$ for each individual in the population are randomly generated within the range [0.1,1].

New control parameters $F_{k,G+1}$ were calculated as follows:

$$F_{k,G+1} = \begin{cases} F_l + rand_l * F_u \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots & if rand < \tau \\ F_{k,G} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots & otherwise \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.27)$$

where rand are the uniform random values within the range [0,1], and τ represents the probability to adjust control parameter F . F_l and Fu were taken from fixed values 0.1 and 0.9, respectively. The new F takes a value from [0.1,1] in a random manner. This procedure produces new scaling factors F in a new parent vector.

Strategy 4: Tent Map

The Tent map resembles the logistic map and assumes the following form:

$$x_{k+1} = G(x_k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.28)$$

with

$$G(x) = \begin{cases} x_k / 0.7, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots & if x < 0.7 \\ \dfrac{1}{0.3} x_k (1 - x_k), \ldots\ldots\ldots\ldots\ldots & otherwise \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.29)$$

The initial condition of x has been fixed at x_0=0.27.

Strategy 5: Sinusoidal Iterator

A third chaotic generator used in this paper is the so-called sinusoidal iterator represented by

$$x_{k+1} = a x_k^2 \sin(\pi x_k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.30)$$

it is iterated with a=2.3 and x_0=0.7 and simplified by using the following relation:

$$x_{k+1} = \sin(\pi x_k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3.31)$$

Strategy 6: Gauss Map

This transformation is similar to a quadratic one and is adopted in the literature [24] for testing purposes because it allows a complete analysis of its chaotic qualitative and quantitative features. The equations are

$$x_{k+1} = G(x_k) \quad (3.32)$$

$$G(x) = \begin{cases} 0, & if x = 0.7 \\ \frac{1}{x} \bmod 1, & x \in (0,1) \end{cases} \quad (3.33)$$

Strategy 7: Lozi Map

Lozi's piecewise linear model is a simplified version of Henon's attractor and it admits a strange attractor. The transformation is given by

$$(x_{k+1}, y_{k+1}) = H(x_k, y_k) \quad (3.34)$$

$$H(x_k, y_k) = (1 + y_k - a|x_k|, bx_k) \quad (3.35)$$

Lozi suggested the values a=1.7 and b=0.5 for the parameters.

Strategy 8: Chua's Oscillator

Chua's oscillator has been studied extensively because of its extremely rich variety of dynamical behaviors together with a relatively simple mathematical model. Its dimensionless state equations are

$$\begin{aligned} \dot{x}(t) &= \alpha(y(t) - l(x(t))) \\ \dot{y}(t) &= x(t) - y(t) + z(t) \quad (3.36) \\ \dot{z}(t) &= -\beta y(t) - \gamma z(t) \end{aligned}$$

with

$$l(x) = m_1 x + 0.5(m_0 - m_1)(|x+1| - |x-1|) \quad (3.37)$$

x,y, and z being the state variables and α, β, γ, m_0 and m_1 the five dimensionless system parameters..

The double scroll attractor is observed in Chua's oscillator if

$$\alpha = 9, \beta = 14.286, \gamma = 0, m_0 = -1/7, m_1 = 2/7 \quad (3.38)$$

Discrete-time chaotic time series are derived by using the Chua oscillator signals at suitable sampling times.

3.10 Improved DE algorithm

1. Design of the parameters setup: The user must choose the key parameters that control the DE, i.e., population size (L), boundary constraints of optimization variables, mutation factor (f_m), recombination or crossover rate (CR), and the stopping criterion ($t_{\max}$).
2. Initialization: Initialize the generation's counter, t = 1, and also initialize a population of individuals (solution vectors) x(t) with random values generated according to a uniform probability distribution in the n-dimensional problem space.
3. Evaluation the objective function as given in Eq. (2.1) considering the equality and inequality constraints given by Eqs. (2.2) and (2.3).
4. Select the value of control parameters e.g. f_m and CR by using chaotic strategy mentioned in section 3.9.
5. Mutations carry out mutation operation on individual population.

$$Z_{ij}^{t} = P_{R_1 j}^{t} + f_m (P_{R_2 j}^{t} - P_{R_3 j}^{t}); (i = 1, 2, ...NG; i \neq d; j = 1, 2, ...L)$$

where

i=1,2…...Np is the individual‘s population index;

j=1,2,……L is the position in NG of the dimensional individual;

T is the time (generation);

$p_i^t = [P_{i1}^t, P_{i2}^t, ...P_{iNG}^t]^T$ stands for the position of the ith individual of a population of real valued NG-dimensional vectors.

6. Recombination is employed to generate a trial vector by replacing certain parameters of the target vector by the corresponding parameters of a randomly generated donor vector.

For each vector, Z_i^{t+1}, an index $R_5(i) \in \{1, 2, ..., NG\}$ is randomly chosen using a uniform distribution, and a trial vector, $U_i^{t+1} = [U_{i1}^{t+1}, U_{i2}^{t+1}, ...U_{iNG}^{t+1}]^T$.

$$U_i^{t+1} = \begin{cases} Z_{ij}^t; if\,(R_4(j) \le CR) or (j = R_5(i)) \\ P_{ij}^t; if\,(R_4(j) > CR) or (j \ne R_5(i)) \end{cases} (i = 1,2,...NG; i \ne d; j = 1,2,...L)$$

where

$R_4(j)$ is the j[th] evaluation of a uniform random number generation with [0,1]

CR is the crossover or recombination rate in the range [0,1].

7. Selection operation: Selection is the procedure whereby better offspring are produced. To decide whether the vector U_i^{t+1} should be a member of the population comprising the next generation, it is compared with the corresponding vector P_i^t. Thus, if f denotes the cost function under minimization, then

$$P_{ij}^{t+1} = \begin{cases} U_{ij}^{t+1}; (i = 1,2,.....,NG); if\,(U_i^{t+1}) < f\,(P_i^t) \\ P_{ij}^t; (i = 1,2,........,NG); otherwise \end{cases} (j = 1,2,...,L)$$

   In this case, the cost of each of trial vector U_i^{t+1} is compared with that of its parent target vector P_i^t. If the cost f_m, of the target vector P_i^t, is lower than that of the trial vector, the target is allowed to advance to the next generation. Otherwise, a trial vector replaces the target vector in the next generation.

8. Termination criterion: Set the generation number for t = t+1. Repeat mutation, recombination and selection operation until a stopping criterion is met, usually a maximum number of iterations (generations), $t_{\max}$.

3.11 Advantages

Application of chaotic sequences to obtain DE's parameters CR and f_m has two advantages:

1. User does not need to guess the good values for f_m and CR.
2. The rules for self-adapting adjusted parameters f_m and CR are quite simple.
3. It helps to increase the convergence of unit system using chaotic based differential evolution algorithm.

3.12 Flowchart of the Improve Differential Evolution:

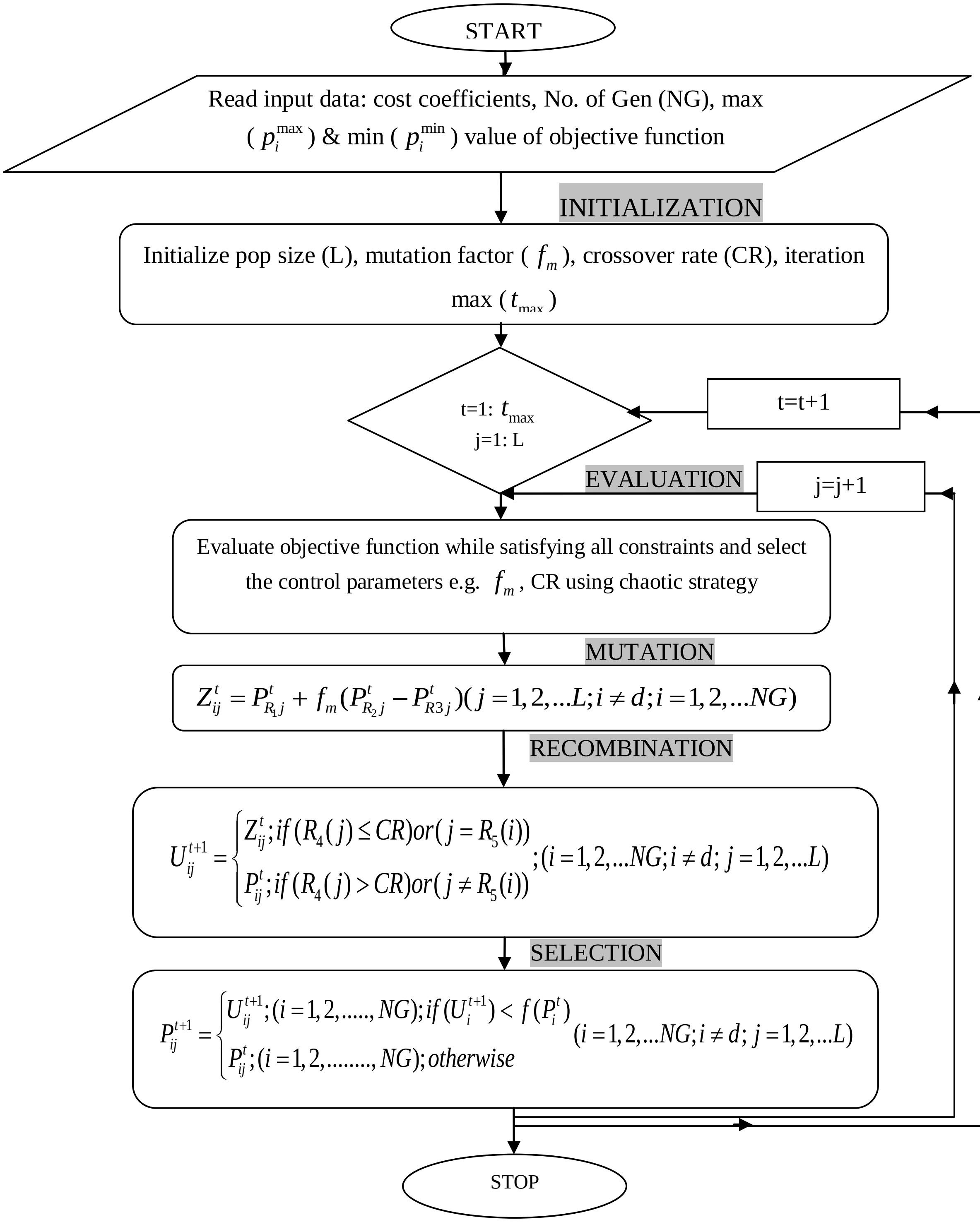


Figure 3.2 Flowchart of the Improved Differential Evolution

Chapter 4

Problem formulation and Result

4.1 Test 1: Power Economic Dispatch with neglecting transmission losses

To find the economic dispatch for different type of thermal unit power plant without considering transmission losses for valve point loading function (non-smooth type).

4.1.1 Problem formulation

The PED problem can be described as an optimization (minimization) problem with objective function as formulated in chapter 2:

Minimize

$$\sum_{i=1}^{NG} F_i(P_i) \qquad (4.1)$$

Subject to (i) the energy balance equation (equality constraints)

$$\sum_{\substack{i=1 \\ i \neq d}}^{NG} P_i = P_D + P_L \qquad (4.2)$$

(ii) the inequality constraints

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

(i=1,2,……NG)………………….……..(4.3)

where P_D is load demand

P_i is real power generation and will act as decision variable

P_L is power transmission loss which is taken as zero (P_L =0)

NG is the number of generation buses.

The cost function of thermal system with valve point loading is modeled as :

$$\sum_{i=1}^{NG} F_i(P_i) = \sum_{i=1}^{NG} (a_i P_i^2 + b_i P_i + C_i + | e_i \times \sin\{ f_i \times (P_i^{\min} - P_i)\} |) \qquad (4.4)$$

where

a_i, b_i, c_i, d_i, e_i are cost coefficients of the i^{th} unit. NG is the number of generating units.

4.1.2 Algorithm & Flowchart:

1. Read data, viz. cost coefficient, $a_i, b_i, c_i, e_i, f_i (i = 1, 2, ..., NG)$. Population size (L), boundary constraints of optimization variables (NG), mutation factor (f_m), crossover rate (CR), weighting factor (w), $t_{\max}$ and the $P_{ij}^{\min} and P_{ij}^{\max}$ for (i=1,2,…NG) etc are the limits of generating system.
2. Select reference generator, d=1
3. Set t counter, for t=0: $t_{\max}$ and increment iter counter, t=t+1
4. Generate an array of (NG $\times$ L) size of uniform random numbers.
5. In case of IDE solution, controlling parameter can be controlled by using various chaotic time series sequences strategies.
6. Set population counter, for j=0 and increment population counter, j=j+1
7. Set generation counter, for i=0 and increment generation counter, i=i+1
8. If ((i<d)||(i>d) for setting i $\neq$ d
9. Calculate the power generation for each unit except reference generator using equation

$$P_{ij}^t = P_{ij}^{\min} + rand()(P_{ij}^{\max} - P_{ij}^{\min})$$

10. Sum=sum+ P_{ij}^t for i=1:NG for i $\neq$ d
11. Calculate power generation for reference generator using equation

$$P_d^t = P_D - \sum_{\substack{i=1 \\ i \neq d}}^{NG} P_i$$

12. Check the limit of reference generator i.e. $P_{ij}^{\min} \leq P_{dj}^t \leq P_{ij}^{\max}$
13. If limit is violated than upgrade the other generation unit using equation

$$If P_d^t > P_d^{\max} then P_i^t = P_i^t + w \times rand()(P_i^{\max} - P_i^{\min})$$
$$If P_d^t < P_d^{\min} then P_i^t = P_i^t - w \times rand()(P_i^{\max} - P_i^{\min})$$

14. Check the limit of individual generator i.e. $P_{ij}^{\min} \leq P_{ij}^t \leq P_{ij}^{\max}$
15. Calculate cost function using equation

$$F(p_i)=\sum_{i=1}^{NG}(a_i p_i^2+b_i p_i+c_i+|e_i\times\sin\{f_i\times(p_i^{\max}-p_i)\}|)$$

16. End of the evaluation operation
17. Start of the mutation operation
18. Repeat the steps 6-9
19. Calculate power generation for each unit except scale generator using equation as refer section 3.3.

$$Z_{ij}^{t}=P_{R_1 j}^{t}+f_m(P_{R_2 j}^{t}-P_{R3 j}^{t})(j=1,2,...L;i\neq d;i=1,2,...NG)...........(3.14)$$

20. Repeat steps 10-15
21. End of the mutation operation
22. Start of the recombination operation
23. Set population counter, for j=0 and increment population counter, j=j+1
24. Set generation counter, for i=0 and increment generation counter, i=i+1
25. $U_{ij}^{t+1}=\begin{cases}Z_{ij}^{t} if(R_4(j)\le CR) or(j=R_5(i))\\ P_{ij}^{t} if(R_4(j)>CR) or(j\neq R_5(i))\end{cases}(i=1,2,...NG;i\neq d;\ j=1,2,...L)$

26. Repeat steps 10-15
27. End of the recombination operation
28. Start of the selection process
29. Set population counter, for j=0 and increment population counter, j=j+1
30. $P_{ij}^{t+1}=\begin{cases}U_{ij}^{t+1}(j=1,2,.....,NG); if(U_i^{t+1})<f(P_i^t)\\ P_{ij}^{t}(j=1,2,........,NG); otherwise\end{cases}(i=1,2,..NG)$
31. Select the best efficient cost among no of populations
32. Repeat steps for increment each iteration, steps 5-31
33. Stop

FLOWCHART FOR CASE 1

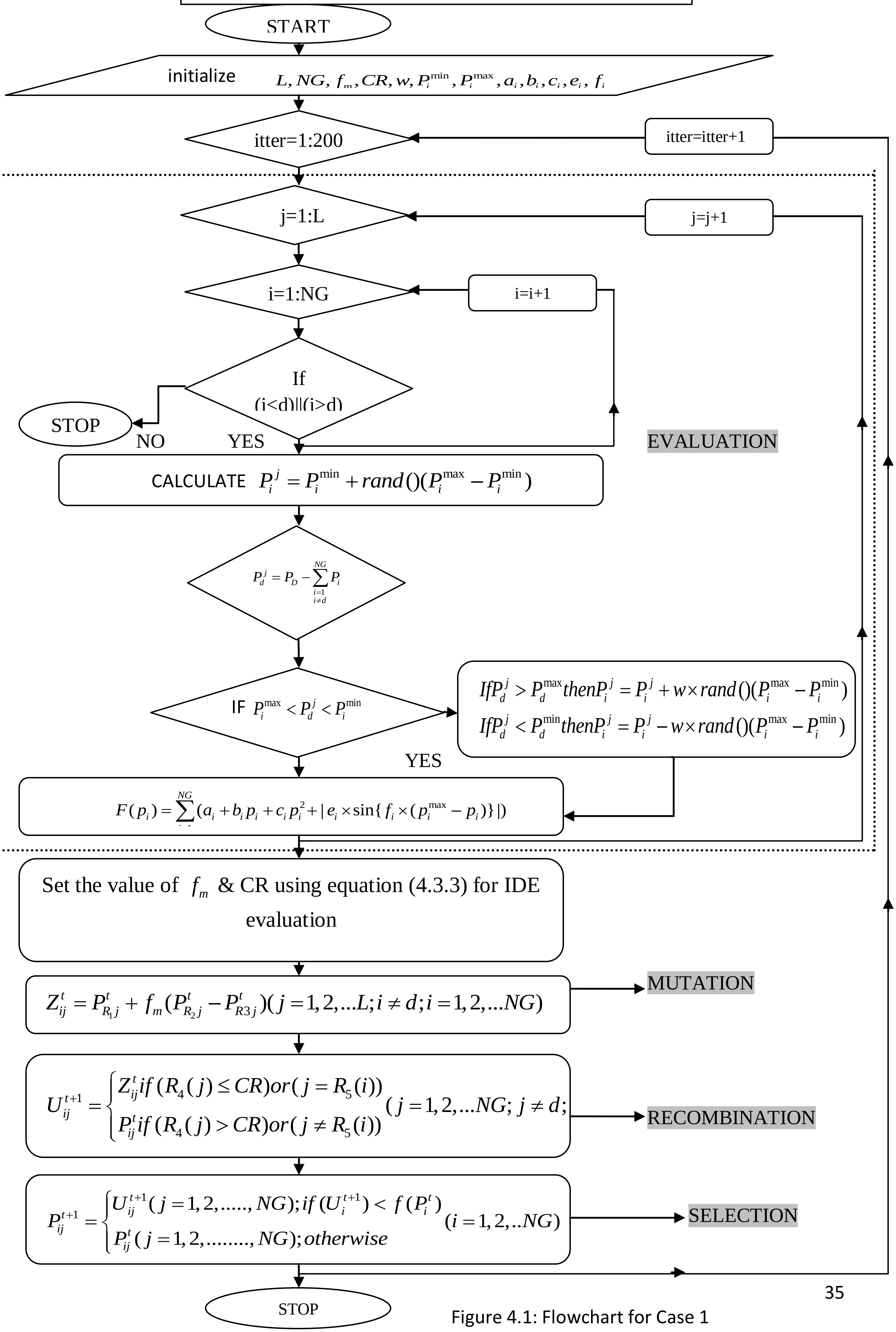


Figure 4.1: Flowchart for Case 1

4.1.3 CASE 1_TEST PROBLEM 1

A three unit test system in a simple six bus power system for 850 MW power demand, its constraints for these equations as well as unit operating ranges data are given below table **[1]**:

Table 4.1: Three unit cost coefficients data for Case1_Test problem1

UNIT	a_i	b_i	c_i	e_i	f_i
GEN 1	0.001562	7.92	561	300	0.0315
GEN 2	0.00194	7.85	310	200	0.042
GEN 3	0.00482	7.97	78	150	0.063

Table 4.2: Three unit operating range data for Case1_ Test problem1

UNIT	$P_i^{\min}(MW)$	$P_i^{\max}(MW)$
GEN 1	100	600
GEN 2	100	400
GEN 3	50	200

4.1.3.1 Results and Comparisons

Table 4.3: Result of Case1_Test problem 1**[7]**

METHOD	GA	EP	EP-SQP	PSO	PSO-SQP	DE	IDE
UNIT	**Gen power (MW)**	**Gen power (MW)**	**Gen power (MW)**	**Gen power (MW)**	**Gen power (MW)**	**Gen power (MW)**	**Gen power (MW)**
1	398.70	300.264	300.267	300.268	300.267	300.2320	300.1899
2	399.60	400.0	400.0	400.00	400.00	400	400
3	50.100	149.736	149.733	149.732	149.733	149.8280	149.810
P_D **(MW)**	848.40	850.0	850.0	850.0	850.0	850.0	850.0
Total Cost ($/h)	8240.3	8234.07	8234.07	8234.07	8234.07	**8234.01**	**8233.01**
TIME (sec)	35.8	6.78	5.12	4.37	3.37	**2.36**	**3.1**
Max iter	NA	30	30	30	30	500	1000

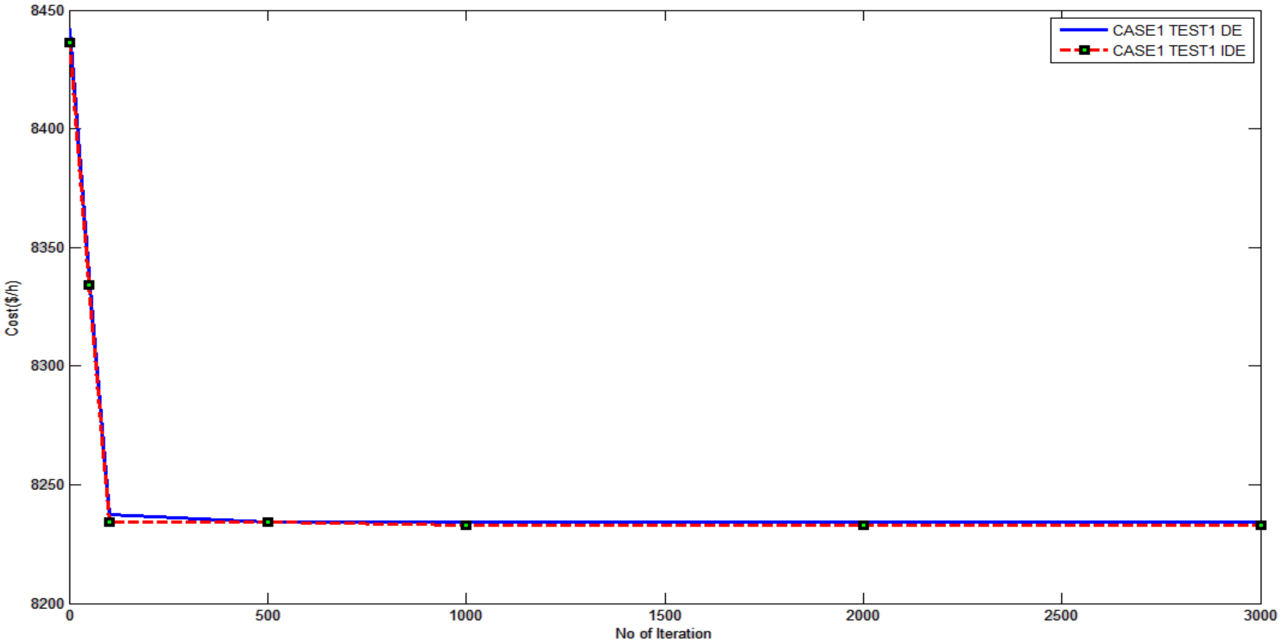


Figure 4.2: Convergence curve for Case1_Test problem1

It is observed from above table and graph that total cost (TC) of three unit systems is 8233.01 $/h in case of IDE which is lowest TC among other techniques and convergence time is also very fast in case of IDE i.e. 3.1 sec for 1000 iteration.

4.1.4 CASE 1_TEST PROBLEM 2

A five unit generation system to meet a demand of 730 MW, its cost coefficients as well as unit operating ranges data are given below table **[15]**:

Table 4.4: Five unit coefficients data for Case 1 _ Test problem 2

UNIT	a_i	b_i	c_i	e_i	f_i
GEN 1	0.0015	1.8	40.0	200.0	0.035
GEN 2	0.0030	1.8	60.0	140.0	0.040
GEN 3	0.0012	2.1	100.0	160.0	0.038
GEN 4	0.0080	2.0	25.0	100.0	0.042
GEN 5	0.0010	2.0	120.0	180.0	0.037

Table 4.5: Five unit operating range for Case1 _ Test problem 2

UNIT	$P_i^{\min}(MW)$	$P_i^{\max}(MW)$
GEN 1	50	300
GEN 2	20	125
GEN 3	30	175
GEN 4	10	75
GEN 5	40	250

4.1.4.1 Results and Comparison

Table 4.6: Result of Case1 _ Test problem 2

Method	**DE(Penalty)**	**DE(Penalty Less)**	**IDE(Penalty Less)**
UNIT	**Gen (MW)**	**Gen.(MW)**	**Gen(MW)**
1	225.3845	229.8646	233.7930
2	113.020	106.0144	98.0177
3	109.4146	108.9072	114.4977
4	73.11176	74.90	75
5	209.0692	210.3138	208.6916
P_D (MW)	730	730	730
Total Cost ($/h)	2140.97	**2074.70**	**2056.50**
TIME (sec)	NA	32.016538	45.1242
Max. Iteration	50	2000	3000
f_m	0.48	0.48	0.2504
CR	0.88	0.88	0.7504

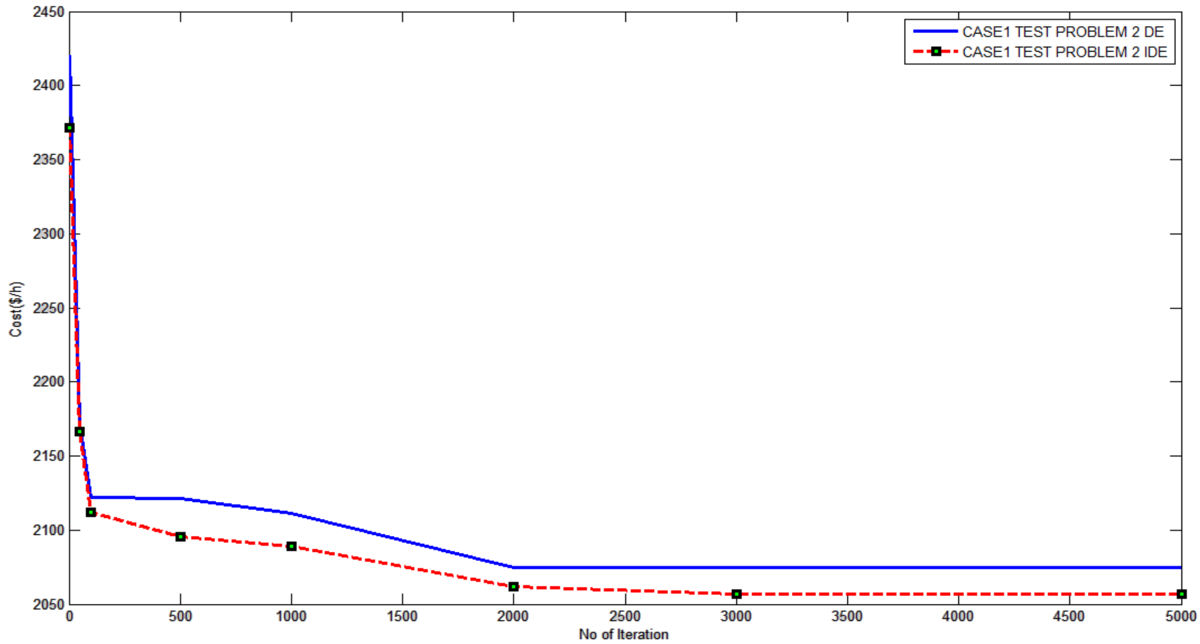


Figure 4.3: Convergence curve for Case1 _ Test problem 2

It is observed from above table and graph that total cost (TC) of five unit systems is 2056.01 $/h in case of IDE which is lowest TC among other techniques and convergence time is also very fast in case of IDE i.e. 45 sec for 3000 iteration.

4.1.5 CASE 1_ TEST PROBLEM 3

This test case comprises of thirteen unit generation system, the required power demand to be met by all the thirteen unit is 1800 MW **[2]** and 2520 MW **[7]**, its cost coefficients as well as unit operating ranges data are given below table:

Table 4.7: Thirteen unit cost coefficients for Case 1_Test problem 3

UNIT	a_i	b_i	c_i	e_i	f_i
GEN 1	0.00028	8.10	550	300	0.035
GEN 2	0.00056	8.10	309	200	0.042
GEN 3	0.00056	8.10	307	150	0.042
GEN 4	0.00324	7.74	240	150	0.063
GEN 5	0.00324	7.74	240	150	0.063
GEN 6	0.00324	7.74	240	150	0.063
GEN 7	0.00324	7.74	240	150	0.063

GEN 8	0.00324	7.74	240	150	0.063
GEN 9	0.00324	7.74	240	150	0.063
GEN 10	0.00284	8.60	126	100	0.084
GEN 11	0.00284	8.60	126	100	0.084
GEN 12	0.00284	8.60	126	100	0.084
GEN 13	0.00284	8.60	126	100	0.084

Table 4.8: Thirteen unit operating range for Case 1_Test problem 3

UNIT	$P_i^{\min}(MW)$	$P_i^{\max}(MW)$
GEN 1	0	680
GEN 2	0	360
GEN 3	0	360
GEN4	60	180
GEN 5	60	180
GEN 6	60	180
GEN 7	60	180
GEN 8	60	180
GEN 9	60	180
GEN 10	40	120
GEN 11	40	120
GEN 12	55	120
GEN 13	55	120

4.1.5.1 Result and Comparison for 1800 MW

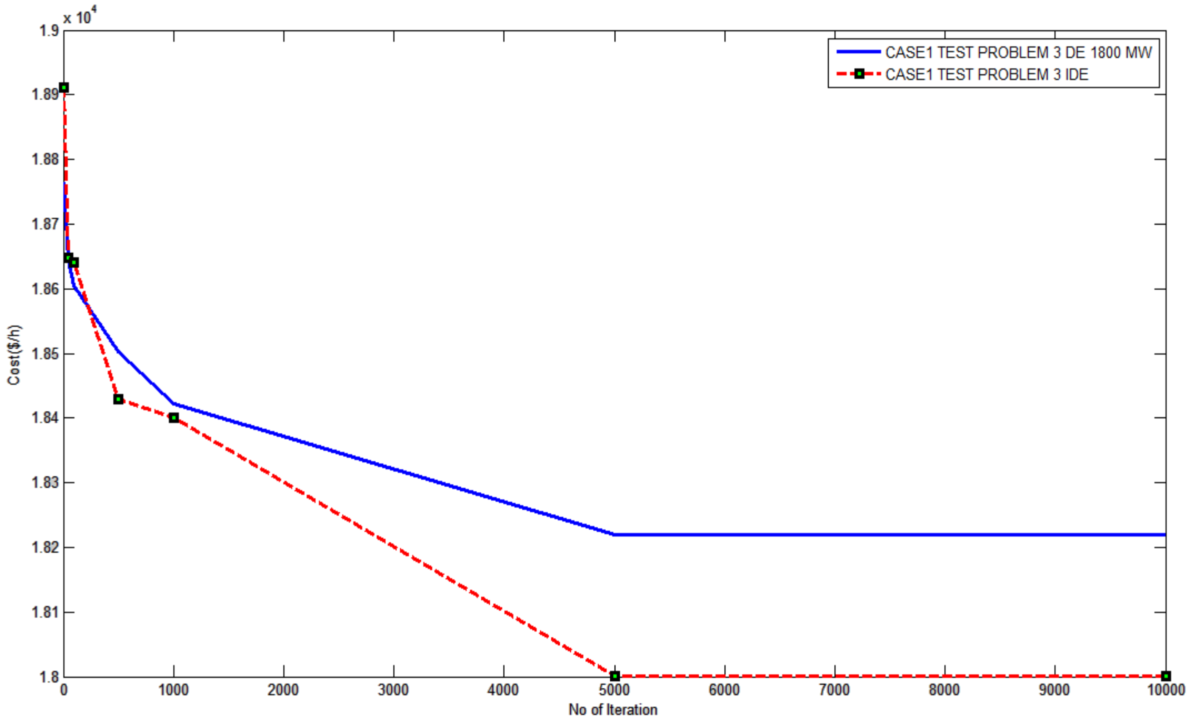
Table 4.9: Result of Case 1_Test problem3 1800 MW

METHOD	**UNIT**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
DE	Gen(MW)	639.6051	146.7967	161.6497	71.4466	110.0408	60	60
IDE	Gen(MW)	633.7855	0	293.1461	60	60	180	60

8	**9**	**10**	**11**	**12**	**13**	**TC($/h)**	f_m	CR
153.519	109.395	69.888	43.065	87.683	86.908	**18220.0**	0.48	0.9
169.258	105.661	40	86.460	56.687	55	**18001.0**	0.687	0.920

Table 4.10: Comparison of best results for Case 1_Test problem 3 for 1800 MW

Optimization Technique	**Best Objective Function ($/h)**	**Time (s)**
PSO [7]	18030.72	77.37
EP [2]	17994.07	157.43
EP-SQP [7]	17991.03	121.93
GA [22]	17975.3437	NA
PSO-SQP [7]	17969.93	33.97
Pattern Search Method [16]	17969.17	NA
IGA [22]	17963.9848	NA
Quantum PSO [18]	17963.95	NA
DE	**18220.0**	23.101463
IDE	**18001.0**	29.191158



It is observed from above table and graph that total cost (TC) of thirteen unit systems is 18001.0 $/h in case of IDE which is not the lowest TC among other techniques but its convergence time is very fast i.e. 29.1 sec for 5000 iteration..

4.1.5.2 Result and Comparison for 2520 MW

Table 4.11: Comparison of best results for Case1_ Test problem3 for 2520 MW

METHOD	GA	SA	GA-SA	EP-SQP	PSO-SQP	DE	IDE
UNIT	Gen(MW)	Gen(MW)	Gen(MW)	Gen(MW)	Gen(MW)	Gen(MW)	Gen(MW)
1	628.32	668.40	628.23	628.3136	628.3205	627.6124	630.4220
2	356.49	359.78	299.22	299.1715	299.0524	360	360
3	359.43	358.20	299.17	299.0474	298.9681	287.0098	360
4	159.73	104.28	159.12	159.6399	159.4680	160.2327	160.0952
5	109.86	60.36	159.95	159.6560	159.1429	133.5585	109.8103
6	159.73	110.64	158.85	158.4831	159.2724	157.3044	109.4807
7	159.63	162.12	157.26	159.6749	159.5371	115.0298	156.8051
8	159.73	163.03	159.93	159.7265	158.8522	113.9654	132.0457

9	159.73	161.52	159.86	159.6653	159.7845	180	106.0507
10	77.31	117.09	110.78	114.0334	110.9618	77.6178	115.3878
11	75.00	75.00	75.00	75.0000	75.0000	120	63.8452
12	60.00	60.00	60.00	60.00	60.00	93.1667	96.0574
13	55.00	119.58	92.62	87.5884	91.6401	94.5026	120
P_D (MW)	2520	2520	2520	2520	2520	2520	2520
Total Cost ($/h)	24,398.2	24,970.91	24,275.71	24,266.44	24261.05	**24520.10**	**24511.9**
TIME(S)	NA	NA	NA	NA	NA	6.6	7.7244

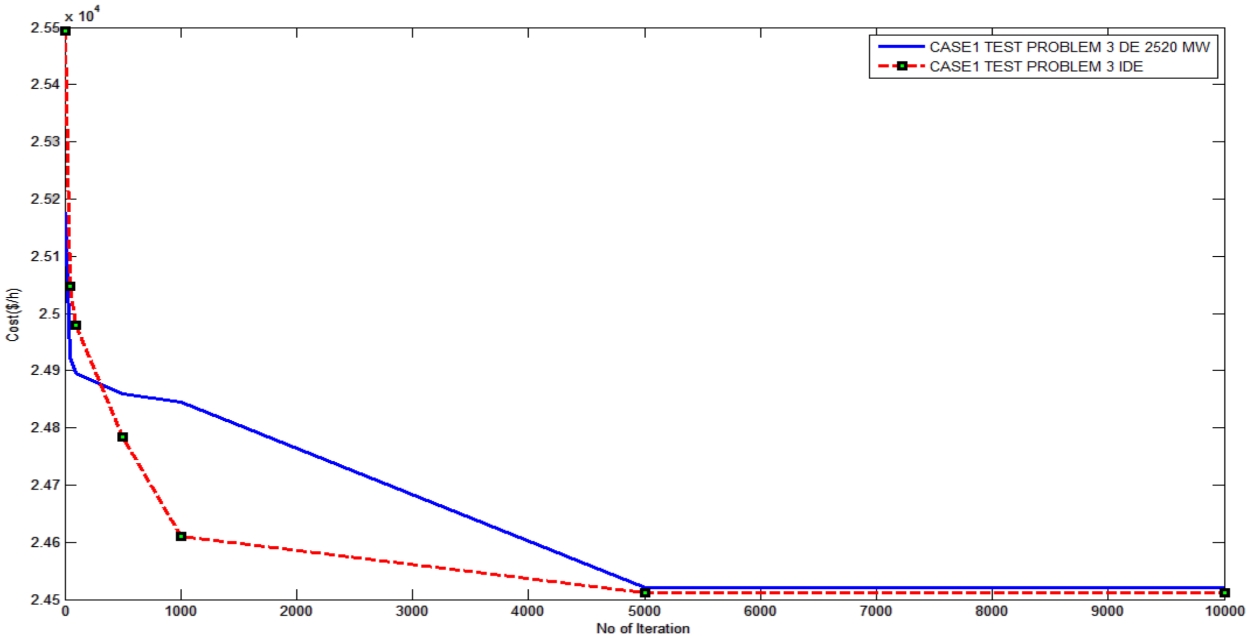


Figure 4.5: Convergence curve for Case1_ Test problem3 for 2520 MW

It is observed from above table and graph that total cost (TC) of thirteen unit systems is 24511.9 $/h in case of IDE which is not the lowest TC among other techniques but its convergence time is very fast in case of IDE i.e. 7.72 sec for 5000 iteration.

4.1.6 Case1_ Test problem 4

A ten unit generation system to meet a demand for 24 hours scheduling, its cost coefficients as well as unit operating ranges data are given below table **[20]:**

Table 4.12 Ten unit generator characteristics for Case1_Test problem 4

UNIT	a_i	b_i	c_i	e_i	f_i
GEN 1	0.00043	21.60	958.20	450	0.041
GEN 2	0.00063	21.05	1313.6	600	0.036
GEN 3	0.00039	20.81	604.97	320	0.028
GEN 4	0.00070	23.90	471.60	260	0.052
GEN 5	0.00079	21.62	480.29	280	0.063
GEN 6	0.00056	17.87	601.75	310	0.048
GEN 7	0.00211	16.51	502.70	300	0.086
GEN 8	0.00480	23.23	639.40	340	0.082
GEN 9	0.10908	19.58	455.60	270	0.098
GEN 10	0.00951	22.54	692.40	380	0.094

Table 4.13: Ten unit operating range for Case 1_Test problem 4

UNIT	$P_i^{\min}(MW)$	$P_i^{\max}(MW)$
GEN 1	150	470
GEN 2	135	460
GEN 3	73	340
GEN4	60	300
GEN 5	73	243
GEN 6	57	160
GEN 7	20	130
GEN 8	47	120
GEN 9	20	80
GEN 10	55	55

Table 4.14: Ten unit 24 hours load demand for Case 1_Test problem 4

HOUR	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
P_D **(MW)**	1036	1110	1258	1406	1480	1628	1702	1776
HOUR	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
P_D **(MW)**	1924	2072	2146	2220	2072	1924	1776	1554
HOUR	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
P_D **(MW)**	1480	1628	1776	2072	1924	1628	1332	1184

4.1.6.1 Results and Comparison

Table 4.15: Result of Ten unit for Case 1_Test problem 4

HOUR SCHEDULING	**DE ($/h)**	**IDE ($/h)**
1	29008	28653
2	30620	30357
3	34070	33604
4	36772	36980
5	38812	38317
6	42003	41933
7	43598	43517
8	45193	44758
9	48510	48380
10	51944	51903
11	53622	53707
12	55439	55452

13	51847	51941
14	48516	48432
15	45291	45220
16	40211	40124
17	38687	38479
18	41961	41593
19	45252	44715
20	52103	51928
21	48588	48384
22	42058	41798
23	35450	35243
24	32243	31859
TOTAL COST($)	**1.0318e6**	**1.0273e6**
TIME(SEC)	**1525.078**	**1909.832**

Table 4.16: Real power generation of Ten unit for Case 1_Test problem 4_IDE

	1(MW)	**2(MW)**	**3(MW)**	**4(MW)**	**5(MW)**	**6(MW)**	**7(MW)**	**8(MW)**	**9(MW)**	**10(MW)**
1	0.0153	0.0405	0.0073	0.0060	0.0073	0.0057	0.0094	0.0047	0.0020	0.0055
2	0.0153	0.0219	0.0170	0.0123	0.0073	0.0122	0.0125	0.0049	0.0020	0.0055
3	0.0153	0.0416	0.0183	0.0060	0.0113	0.0120	0.0091	0.0047	0.0020	0.0055
4	0.0381	0.0150	0.0297	0.0060	0.0073	0.0131	0.0130	0.0086	0.0043	0.0055
5	0.0223	0.0315	0.0291	0.0131	0.0166	0.0126	0.0106	0.0047	0.0020	0.0055
6	0.0333	0.0397	0.0306	0.0060	0.0113	0.0160	0.0130	0.0053	0.0021	0.0055

7	0.0384	0.0393	0.0311	0.0066	0.0089	0.0138	0.0130	0.0112	0.0024	0.0055
8	0.0309	0.0460	0.0302	0.0079	0.0227	0.0147	0.0130	0.0047	0.0020	0.0055
9	0.0443	0.0394	0.0298	0.0103	0.0199	0.0160	0.0130	0.0120	0.0022	0.0055
10	0.0453	0.0398	0.0337	0.0176	0.0243	0.0160	0.0130	0.0085	0.0034	0.0055
11	0.0456	0.0398	0.0340	0.0300	0.0226	0.0160	0.0130	0.0061	0.0020	0.0055
12	0.0457	0.0401	0.0340	0.0300	0.0234	0.0160	0.0130	0.0120	0.0022	0.0055
13	0.0452	0.0403	0.0306	0.0300	0.0173	0.0140	0.0130	0.0093	0.0020	0.0055
14	0.0463	0.0460	0.0293	0.0119	0.0167	0.0160	0.0130	0.0056	0.0021	0.0055
15	0.0447	0.0404	0.0321	0.0074	0.0074	0.0160	0.0130	0.0086	0.0025	0.0055
16	0.0383	0.0213	0.0294	0.0118	0.0079	0.0142	0.0130	0.0120	0.0020	0.0055
17	0.0371	0.0400	0.0287	0.0060	0.0081	0.0057	0.0095	0.0047	0.0027	0.0055
18	0.0311	0.0391	0.0313	0.0122	0.0076	0.0151	0.0130	0.0049	0.0031	0.0055
19	0.0468	0.0398	0.0286	0.0076	0.0115	0.0160	0.0130	0.0048	0.0040	0.0055
20	0.0454	0.0398	0.0340	0.0123	0.0243	0.0160	0.0130	0.0120	0.0049	0.0055
21	0.0454	0.0397	0.0313	0.0127	0.0165	0.0132	0.0130	0.0097	0.0054	0.0055
22	0.0451	0.0309	0.0201	0.0120	0.0163	0.0121	0.0096	0.0090	0.0023	0.0055
23	0.0153	0.0306	0.0286	0.0065	0.0179	0.0125	0.0095	0.0047	0.0020	0.0055
24	0.0151	0.0301	0.0159	0.0060	0.0073	0.0147	0.0126	0.0088	0.0025	0.0055

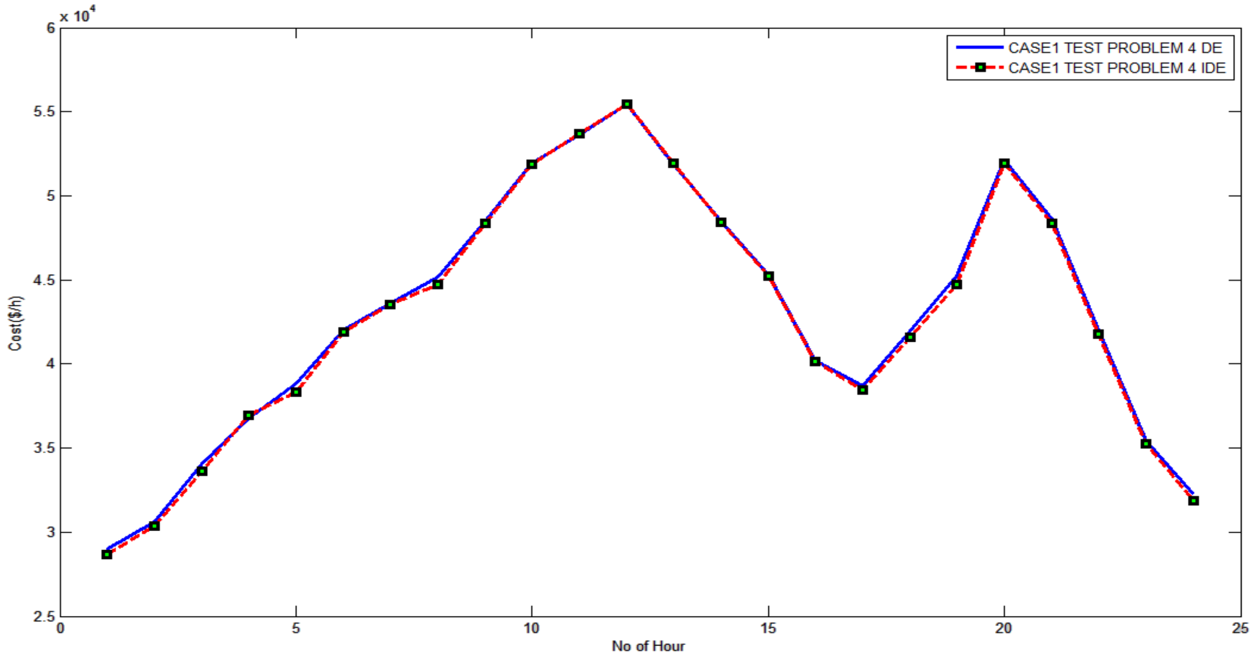


Figure 4.6: Cost-Load curve for Case1_ Test problem 4

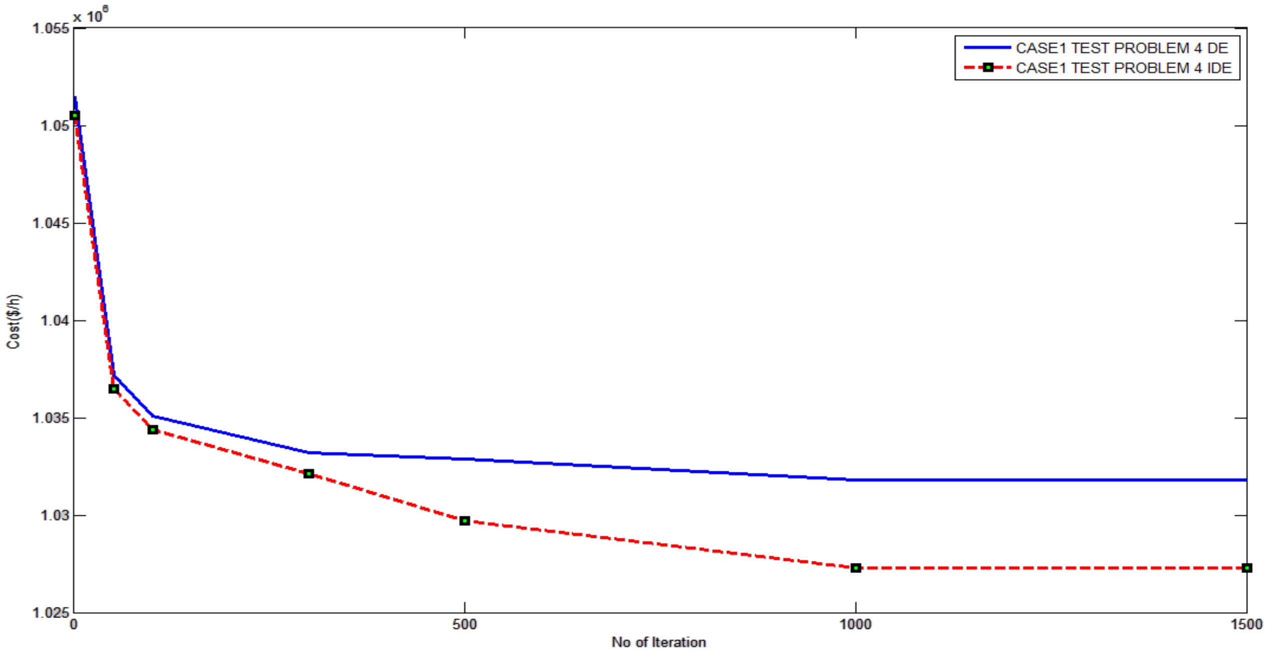


Figure 4.7: Convergence curve for Case1_ Test problem 4

It is observed from above table and graph that total cost (TC) of ten unit systems for IDE is 1.0273e6 $ for a 24 hour scheduling correspondence to its load demand which is lower TC than DE's TC.

4.2 Test 2: ELD for Thermal unit with transmission losses

To find the economic load dispatch for different type of thermal unit power plant with considering transmission losses for both quadratic function (smooth type) as well as valve point function (non-smooth type).

4.2.1 Problem formulation

The PED problem can be described as an optimization (minimization) process with objective expressed as equations in chapter 2:

Minimize

$$\sum_{i=1}^{NG} F_i(P_i) \qquad (2.1)$$

Subject to (i) the energy balance equation (equality constraints)

$$\sum_{\substack{i=1 \\ i\neq d}}^{NG} P_i = P_D + P_L \qquad (2.2)$$

(ii) the inequality constraints

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

(i=1,2,……NG)……………………...…..(2.3)

where P_D is load demand

P_i is real power generation and will act as decision variable

NG is the number of generation buses.

P_L is power transmission loss which can be calculate by using section 3.2

$$P_d + \sum_{\substack{i=1 \\ i\neq d}}^{NG} P_i = \left[\sum_{\substack{i=1 \\ i\neq d}}^{NG} \sum_{\substack{j=1 \\ j\neq d}}^{NG} P_i B_{ij} P_j + \sum_{\substack{j=1 \\ j\neq d}}^{NG} P_j (B_{jd} + B_{dj}) P_d + B_{dd} P_d^2 + \sum_{\substack{i=1 \\ i\neq d}}^{NG} B_{io} P_i + B_{do} P_d + B_{oo} \right] + P_D \qquad (2.9)$$

The cost function of thermal system with valve point loading is modeled as :

$$\sum_{i=1}^{NG} F_i(P_i) = \sum_{i=1}^{NG} (a_i P_i^2 + b_i P_i + C_i + | e_i \times \sin\{ f_i \times (P_i^{\min} - P_i)\} |) \qquad (2.5)$$

The cost function of thermal system with smooth point loading is modeled as :

$$F_i(P_i) = \sum_{i=1}^{NG} (a_i P_i^2 + b_i P_i + C_i) \quad \text{...(2.4)}$$

where

a_i, b_i, c_i, d_i, e_i are cost coefficients of the i^{th} unit. NG is the number of generating units.

4.2.2 Algorithm & Flowchart

1. Read data, viz. cost coefficient, $a_i, b_i, c_i, e_i, f_i (i = 1, 2, ..., NG)$. Population size (L), boundary constraints of optimization variables (NG), mutation factor (f_m), crossover rate (CR), weighting factor (w), t_{max} and the $P_i^{min} and P_i^{max}$ for (i=1,2,…NG) etc are the limits of generating system.
2. Repeat steps from 2-10 as section 4.1.2.
3. Calculate power generation for reference generator using section 3.2.3

$$P_d^j = \begin{cases} Z^j ; P_L = 0 \\ W^j ; P_L \neq 0 \end{cases} (j = 1, 2, ...L)$$

4. Repeat steps from 12-32 as section 4.1.2.
5. Stop

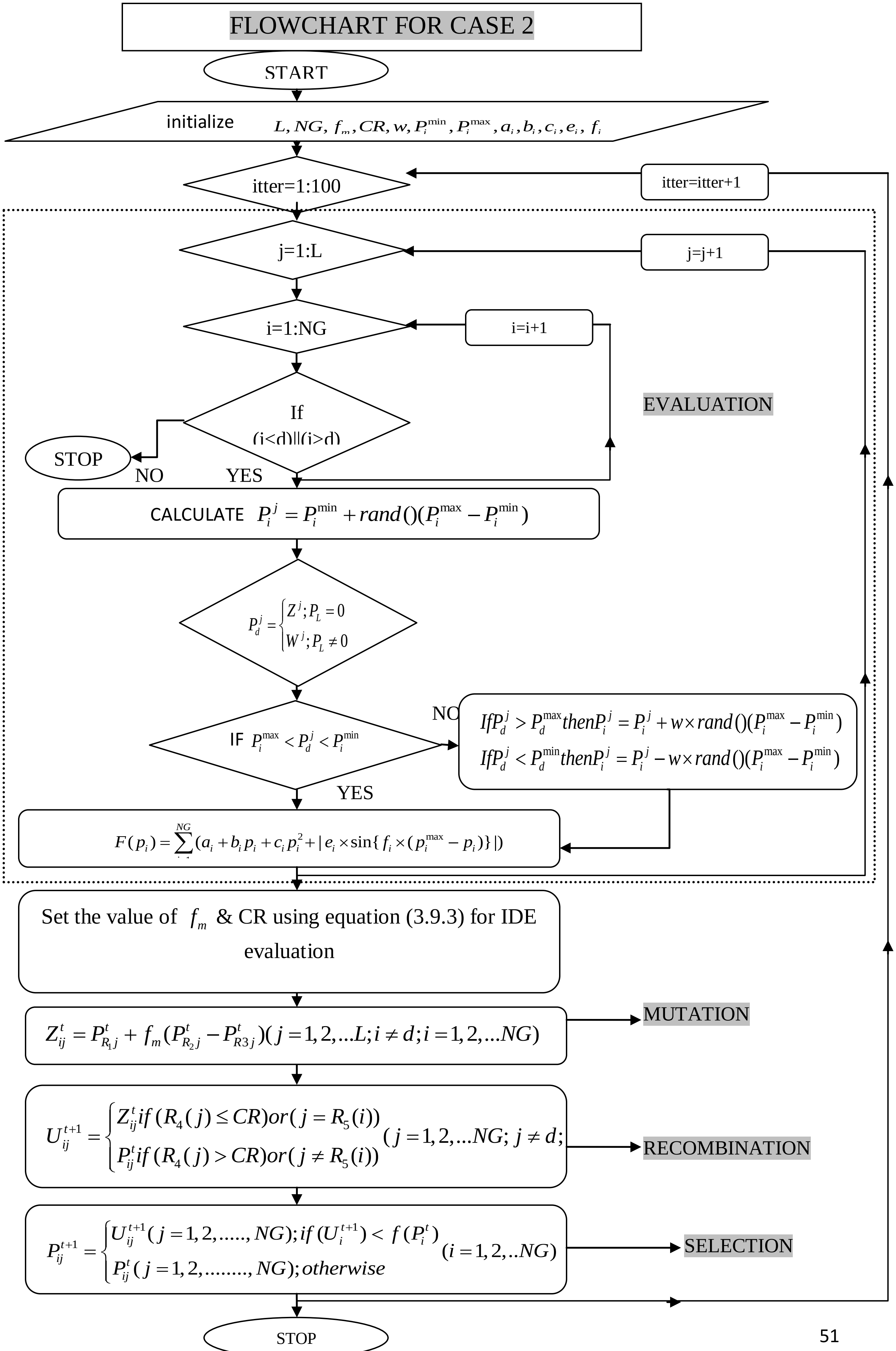


Figure4.8: Flowchart for Case2

4.2.3 CASE 2_ TEST PROBLEM 1

A six unit generation system to meet a demand of 1200 MW including transmission loss, its cost coefficients as well as unit operating ranges data are given below table **[37]:**

Table 4.17: Six unit generator characteristics for Case2_Test problem1

UNIT	a_i	b_i	c_i	$P_i^{min}(MW)$	$P_i^{max}(MW)$
GEN 1	0.15247	38.5390	756.7988	10	125
GEN 2	0.10587	46.1591	451.3251	10	150
GEN 3	0.03546	38.3055	1243.5311	35	210
GEN 4	0.02803	40.3965	1049.9977	35	225
GEN 5	0.01799	38.2704	1356.6592	125	315
GEN 6	0.02111	36.3278	1658.5696	130	325

The transmission loss formula coefficients of six-unit system are:

$$B = \begin{bmatrix} 0.000140 & 0.000017 & 0.000015 & 0.000019 & 0.000026 & 0.000022 \\ 0.000017 & 0.000060 & 0.000013 & 0.000016 & 0.000015 & 0.000020 \\ 0.000015 & 0.000013 & 0.000065 & 0.000017 & 0.000024 & 0.000019 \\ 0.000019 & 0.000016 & 0.000017 & 0.000071 & 0.000030 & 0.000025 \\ 0.000026 & 0.000015 & 0.000024 & 0.000030 & 0.000069 & 0.000032 \\ 0.000022 & 0.000020 & 0.000019 & 0.000025 & 0.000032 & 0.000085 \end{bmatrix}$$

4.2.3.1 Results and Comparison

Table 4.18: Six unit generator characteristics for Case2_Test problem1

METHOD	**DE(with penalty)**	**DE(penalty less)**	**IDE(penalty less)**
UNIT	**Gen(MW)**	**Gen(MW)**	**Gen(MW)**
1	84.4354	85.0160	84.6551
2	93.3638	93.4081	93.4078
3	225.0000	208.6408	210

4	209.9995	225	224
5	325.0000	315	315
6	314.9998	325	325
P_D (MW)	1200	1200	1200
P_L (MW)	52.7985	52.1	52.06
TC($/h)	64,083	**64050.23**	**64045.09**
TIME(S)	8.32	536.653895	926.832319
Max. Iterations		500	500

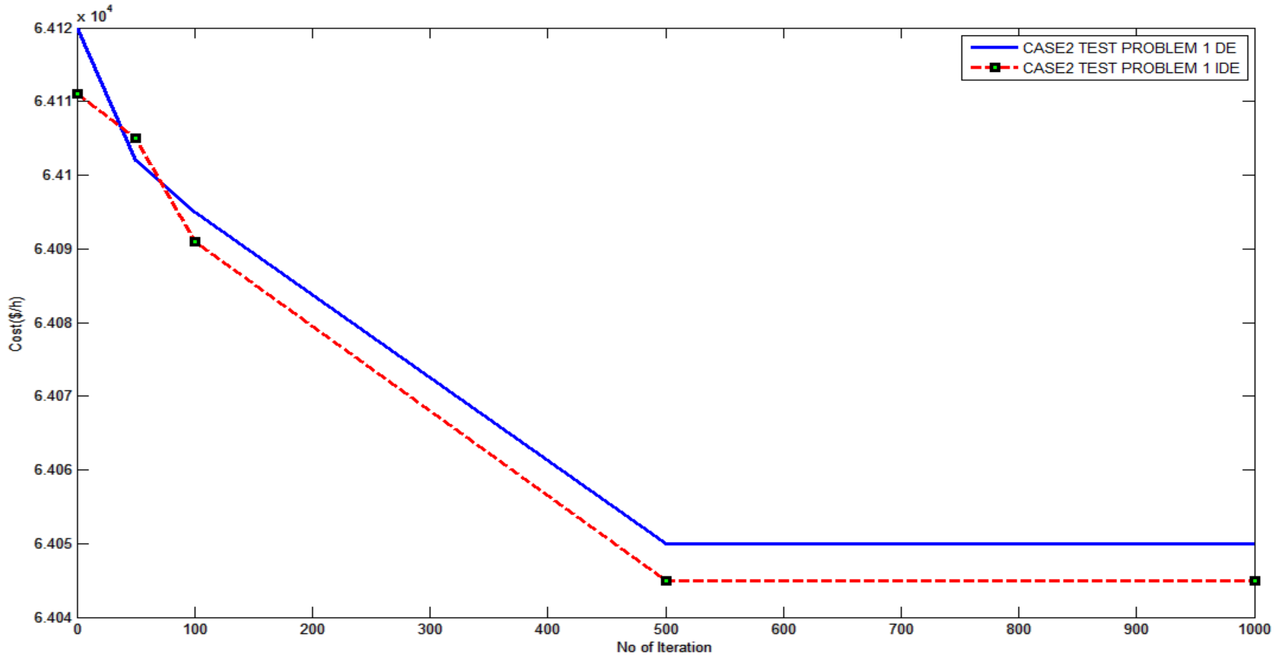


Figure 4.9: Convergence curve characteristics for Case2_Test problem 1

It is observed from above table and graph that total cost (TC) of six unit systems is 64045.09 $/h in case of IDE which is the lowest TC among other techniques.

4.2.4 CASE 2_TEST PROBLEM 2

A ten unit generation system to meet a demand of 2000 MW, its cost coefficients as well as unit operating ranges data are given below table **[37]**:

Table 4.19: Ten unit cost coefficients for Case 2_Test problem 2

	a_i	b_i	c_i	e_i	f_i
GEN 1	0.12951	40.5407	1000.403	33	0.0174
GEN 2	0.10908	39.5804	950.606	25	0.0178
GEN 3	0.12511	36.5104	900.705	32	0.0162
GEN 4	0.12111	39.5104	800.705	30	0.0168
GEN 5	0.15247	38.5390	756.799	30	0.0148
GEN 6	0.10587	46.1592	451.325	20	0.0163
GEN 7	0.03546	38.3055	1243.531	20	0.0152
GEN 8	0.02803	40.3965	1049.998	30	0.0128
GEN 9	0.02111	36.3278	1658.569	60	0.0136
GEN 10	0.01799	38.2704	1356.659	40	0.0141

Table 4.20: Ten unit operating range for Case 2_Test problem 2

	$P_i^{\min}$	$P_i^{\max}$
GEN 1	10	55
GEN 2	20	80
GEN 3	47	120
GEN4	20	130
GEN 5	50	160
GEN 6	70	240
GEN 7	60	300
GEN 8	70	340
GEN 9	135	470
GEN 10	150	470

The transmission loss formula coefficients of ten-unit system are:

$$B=\begin{bmatrix} 0.000049 & 0.000014 & 0.000015 & 0.000015 & 0.000016 & 0.000017 & 0.000017 & 0.000018 & 0.000019 & 0.000020 \\ 0.000014 & 0.000045 & 0.000016 & 0.000016 & 0.000017 & 0.000015 & 0.000015 & 0.000016 & 0.000018 & 0.000018 \\ 0.000015 & 0.000016 & 0.000039 & 0.000010 & 0.000012 & 0.000012 & 0.000014 & 0.000014 & 0.000016 & 0.000016 \\ 0.000015 & 0.000016 & 0.000010 & 0.000040 & 0.000014 & 0.000010 & 0.000011 & 0.000012 & 0.000014 & 0.000015 \\ 0.000016 & 0.000017 & 0.000012 & 0.000014 & 0.000035 & 0.000011 & 0.000013 & 0.000013 & 0.000015 & 0.000016 \\ 0.000017 & 0.000015 & 0.000012 & 0.000010 & 0.000011 & 0.000036 & 0.000012 & 0.000012 & 0.000014 & 0.000015 \\ 0.000017 & 0.000015 & 0.000014 & 0.000011 & 0.000013 & 0.000012 & 0.000038 & 0.000016 & 0.000016 & 0.000018 \\ 0.000018 & 0.000016 & 0.000014 & 0.000012 & 0.000013 & 0.000012 & 0.000016 & 0.000040 & 0.000015 & 0.000016 \\ 0.000019 & 0.000018 & 0.000016 & 0.000014 & 0.000015 & 0.000014 & 0.000016 & 0.000015 & 0.000042 & 0.000019 \\ 0.000020 & 0.000018 & 0.000016 & 0.000015 & 0.000016 & 0.000015 & 0.000018 & 0.000016 & 0.000019 & 0.000044 \end{bmatrix}$$

4.2.4.1 Results and Comparison for Case 2_Test problem 2

Table 4.21: Results for Case 2_Test problem 2 (Load Demand 2000MW)

METHOD	**DE(with penalty)**	**DE(penalty less)**	**IDE(penalty less)**
UNIT	**Gen(MW)**	**Gen(MW)**	**Gen(MW)**
1	55.0000	51.6911	51.9386
2	79.8063	80	80
3	106.8253	120	120
4	102.8307	86.8018	96.3210
5	82.2418	73.4797	80.8734
6	80.4352	95.0708	76.9473
7	300.0000	300	300
8	340.0000	340	340
9	470.0000	470	470
10	469.8975	470	470
P_L **(MW)**	87.0368	87.01	86.0803

Total Cost ($/h)	111500	**111495**	**111480**
TIME(S)	9.42	1293.976815	1301.8615
Max Iteration	NA	500	500

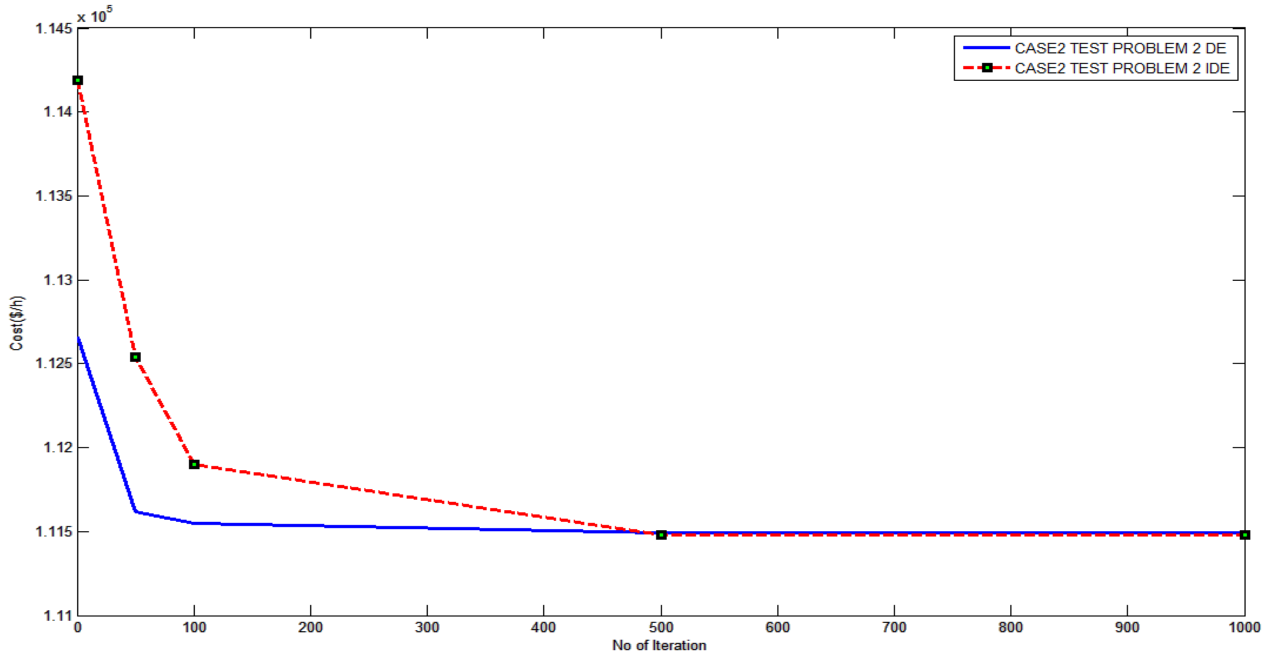


Figure 4.10: Convergence curve characteristics for Case 2_Test problem 2

It is observed from above table and graph that total cost (TC) of ten unit systems is 111480 $/h in case of IDE which is not the lowest TC among other techniques and also convergence time is very fast in case of IDE run for 5000 iteration.

4.2.5 Case 2_Test problem 3

A five unit generation system to meet a demand for 24 hours scheduling, its cost coefficients as well as unit operating ranges data are given below table **[19]:**

Table 4.22: Five unit cost coefficient for Case2_Test problem 3

UNIT	a_i	b_i	c_i	e_i	f_i
GEN 1	0.0080	2.0	25	100	0.042
GEN 2	0.0030	1.8	60	140	0.040
GEN 3	0.0012	2.1	100	160	0.038
GEN 4	0.0010	2.0	120	180	0.037
GEN 5	0.0015	1.8	40	200	0.035

Table 4.23: Five unit operating range for Case2 _ Test problem 3

UNIT	$P_i^{\min}(MW)$	$P_i^{\max}(MW)$
GEN 1	10	75
GEN 2	20	125
GEN 3	30	175
GEN 4	40	250
GEN 5	50	300

Table 4.24: Five unit 24 hours load demand for Case 2_Test problem 3

HOUR	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
P_D **(MW)**	410	435	475	530	558	608	626	654
HOUR	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
P_D **(MW)**	690	704	720	740	704	690	654	580
HOUR	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
P_D **(MW)**	558	608	654	704	680	605	527	463

4.2.5.1 Results and Comparison

Table 4.25: Result of Five unit for Case 2_Test problem 3

TIME INTERVAL	DE ($/h)	IDE ($/h)
1	1241.2	1262.6
2	1406.6	1409.9
3	1467.1	1467.8
4	1682.4	1654.6
5	1688.5	1696.0
6	1851.3	1863.7
7	1861.8	1861.3
8	1860.5	1887.4
9	2034.3	2061.1
10	2073.1	2117.7
11	2182.1	2131.9
12	2259.7	2232.5
13	2120.6	2053.2
14	2066.3	1994.8
15	1896.6	1930.8
16	1669.2	1666.1
17	1672.9	1653.0
18	1842.9	1854.5
19	1885.7	1886.8
20	2.0323	2091.2
21	1973.1	2016.0
22	1818.8	1846.6
23	1649.4	1631.7
24	1463.9	1475.3
TOTAL COST($/H)	**4.3746e4**	**4.360e4**
TIME(SEC)	1005	1118
Max. Iteartion	500	500

Table 4.26: Real power generation of Five unit for Case 2_Test problem 3_IDE

Hour	1 (MW)	2(MW)	3(MW)	4 (MW)	5(MW)
1	11.0	20.0	112.7	40.0	230.2
2	34.9	20.0	113.2	126.4	144.4
3	11.8	103.5	100.2	124.7	139.6
4	39.1	33.4	113.0	209.0	141.4
5	15.7	93.1	106.9	118.9	23.01
6	72.1	87.8	113.1	206.0	136.8
7	10.6	76.9	112.4	208.4	226.2
8	11.7	98.5	113.0	205.5	234.6
9	44.7	96.3	116.3	210.8	232.0
10	56.5	97.4	115.2	211.1	234.3
11	19.3	98.1	108.4	205.5	300.0
12	15.0	105.0	123.0	209.0	300.0
13	52.1	95.2	126.6	209.7	230.8
14	28.9	112.4	114.2	210.0	234.7
15	21.8	97.6	113.0	201.9	228.8
16	10.0	20.0	112.0	215.9	229.3
17	15.7	98.6	114.0	200.0	136.4
18	34.5	20.0	112.5	215.5	233.4
19	15.2	90.8	113.2	212.1	231.9
20	59.6	101.1	114.4	210.1	229.3
21	32.7	103.8	114.5	209.7	229.2
22	50.6	99.4	107.7	124.5	230.6
23	52.6	97.4	115.1	129.7	138.0
24	12.7	84.5	106.3	125.5	138.5

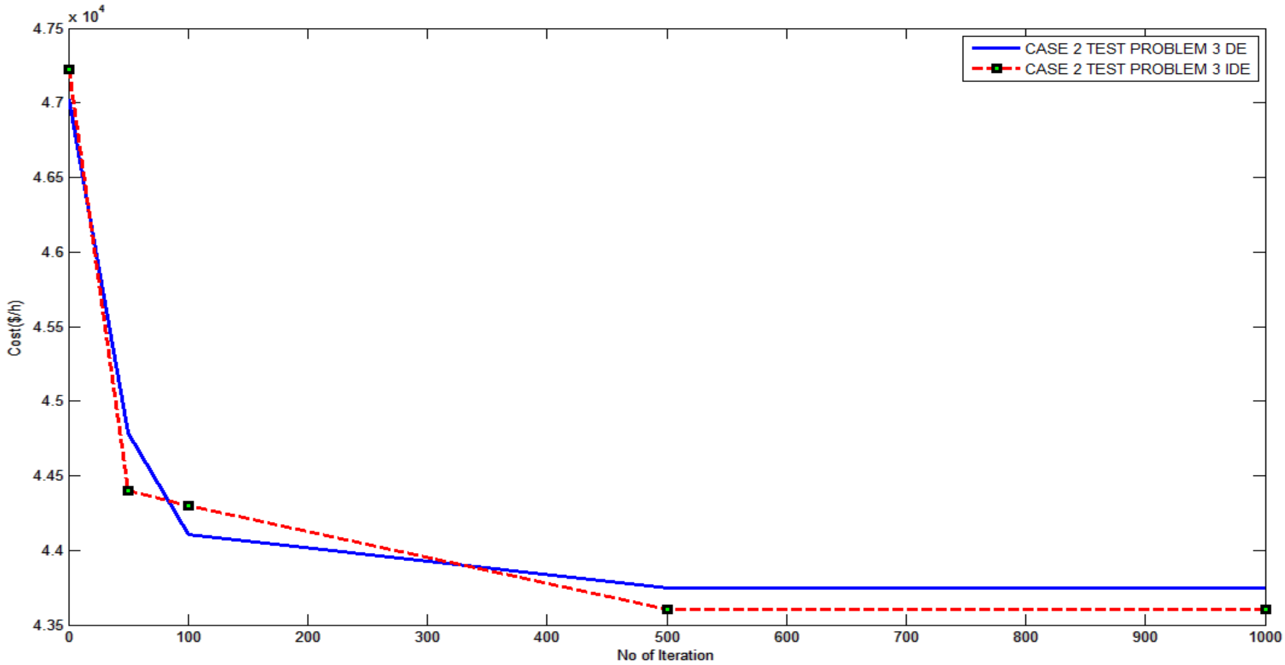


Figure 4.11: Convergence curve characteristics for Case 2_Test problem 3

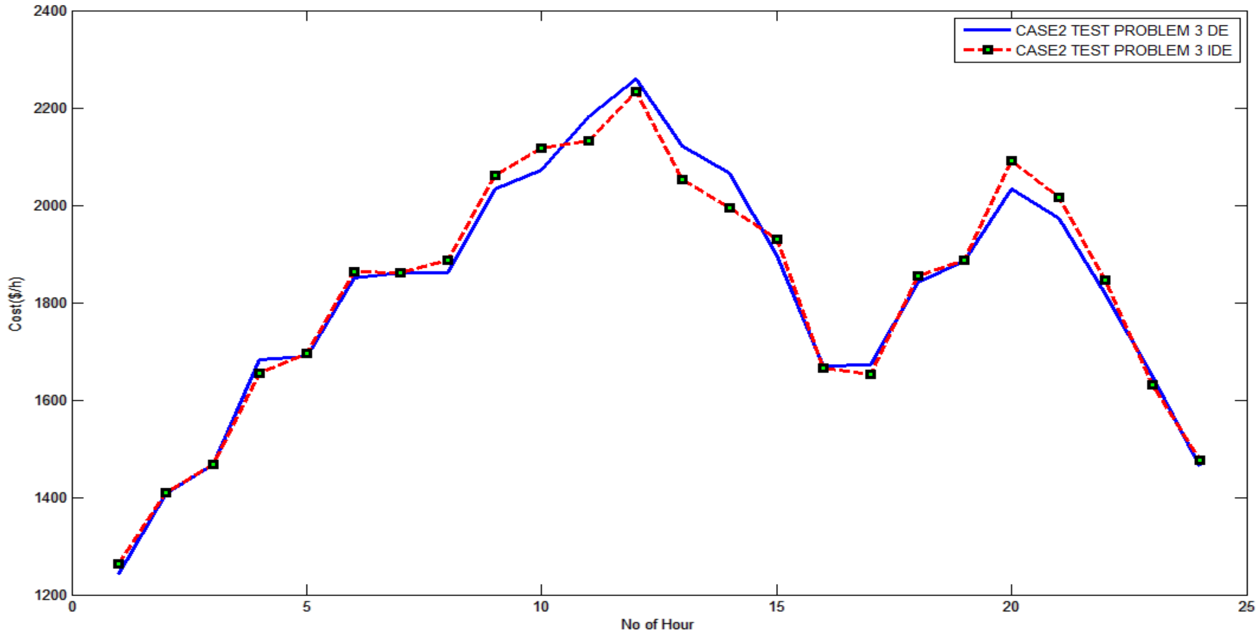


Figure 4.12: Cost curve characteristics for Case 2_Test problem 3

It is observed from above table and graph that total cost (TC) of five unit systems for IDE is 4360e4 $ for a 24 hour scheduling correspondence to its load demand which is lower TC than DE's TC.

4.3 Test 3: ELD for Thermal unit multiple-fuel type system

To find the economic load dispatch for different type of multiple-fuel type thermal unit power plant with neglecting transmission losses for valve point function (non-smooth type) **[38]**.

4.3.1 Problem formulation

The PED problem can be described as an optimization (minimization) process with objective expressed as equations in previous chapter:

Minimize

$$\sum_{i=1}^{NG} F_i(P_i) \quad \text{...}(2.1)$$

Subject to (i) the energy balance equation (equality constraints)

$$\sum_{\substack{i=1 \\ i\neq d}}^{NG} P_i = P_D + P_L \quad \text{...}(2.2)$$

(ii) the inequality constraints

$$P_i^{min} \le P_i \le P_i^{\max}$$

(i=1,2,……NG)……………….....(2.3)

where P_D is load demand

P_i is real power generation and will act as decision variable

P_L is power transmission loss which in neglecting (P_L =0)

NG is the number of generation buses.

The cost function of thermal system with valve point loading is modeled as :

$$F_i(P_i) = \begin{cases} a_{i1}P_i^2 + b_{i1}P_i + c_{i1} + |e_{i1} \times \sin(f_{i1} \times (P_{i1}^{\min} - P_{i1}))|, for\_fuel1, P_i^{\min} \le P_i \le P_{i1} \\ a_{i2}P_i^2 + b_{i2}P_i + c_{i2} + |e_{i2} \times \sin(f_{i2} \times (P_{i2}^{\min} - P_{i2}))|, for\_fuel2, P_{i1} \le P_i \le P_{i2} \\ \vdots \\ a_{ik}P_i^2 + b_{ik}P_i + c_{ik} + |e_{ik} \times \sin(f_{ik} \times (P_{ik}^{\min} - P_{ik}))|, for\_fuelk, P_{ik-1} \le P_i \le P_i^{\max} \end{cases} \quad \text{..........}(2.18)$$

where

$a_{ik}, b_{ik}, c_{ik}, e_{ik}, f_{ik}$ are cost coefficients of the i^{th} generator unit using the fuel type k.

NG is the number of generating units.

4.3.2 Algorithm & Flowchart

1. Read data, viz. cost coefficient, $a_i, b_i, c_i, e_i, f_i (i = 1, 2, ..., NG)$. Population size (L), boundary constraints of optimization variables (NG), mutation factor (f_m), crossover rate (CR), weighting factor (w)=0.10, $t_{\max}$ and the $P_i^{\min} and P_i^{\max}$ for (i=1,2,…NG, j=1,2,….L) etc are the limits of generating system.
2. Repeat steps from 2-14 as section 4.1.2
3. Select the fuel type by checking calculated power generated in between range.
4. Estimate cost function as equation (2.18)
5. In case of IDE solution, controlling parameter can be controlled by using various chaotic time series sequences strategies. So here selecting Strategy 3: self-adaptive control mechanism
6. Repeat steps from 16-32 as section 4.1.2
7. Stop

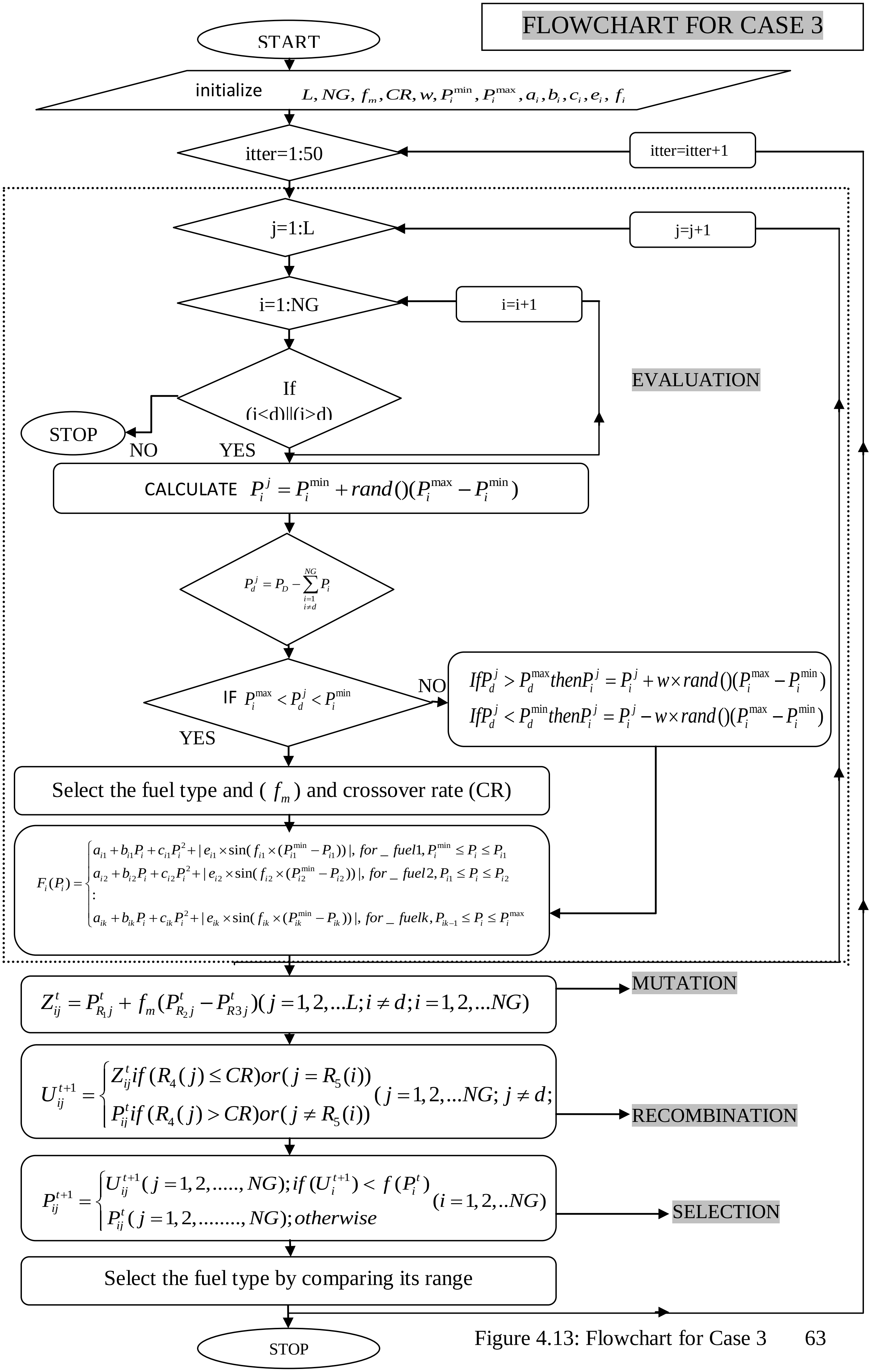


Figure 4.13: Flowchart for Case 3

4.3.3 TEST3

This test system contained ten dispatching units addressing both valve point effects and multiple fuels for a load demand of 2700 MW. Its unit characteristics are given below **[22]**:

Table 4.27 Ten unit generator characteristics with multiple fuels for Case 3

UNIT	P_i^{min}	P_i^{max}	FUEL TYPE	a_i	b_i	c_i	e_i	f_i
1	100	196	1	.2697e2	-.3975e0	.2176e-2	.2697e-1	-.3975e1
	196	250	2	.2113e2	-.3059e0	.1861e-2	.2113e-1	-.3059e1
2	157	230	1	.1184e3	-.1269e1	.4194e-2	.1184e0	-.1269e2
	50	114	2	.1865e1	-.3988e-1	.1138e-2	.1865e-2	.3988e0
	114	257	3	.1365e2	-.1980e0	.1620e-2	.1365e-1	-.1980e1
3	200	332	1	.3979e2	-.3116e0	.1457e-2	.3979e-1	-.3116e1
	388	500	2	-.5914e2	.4864e0	.1176e-4	-.5914e-1	.4864e1
	332	388	3	-.2875e1	.3389e-1	.8035e-3	-.2876e-2	.3389e0
4	99	138	1	.1983e1	-.3114-1	.1049e-2	.1983e-2	-.3114e0
	138	200	2	.5285e2	-.6348e0	.2785e-2	.5285e-1	-.6348e1
	200	265	3	.2668e3	-.2338e1	.5935e-2	.2668e0	-.2338e2
5	190	338	1	.1392e2	-.8733e-1	.1066e-2	.1392e-1	-.8733e0
	338	407	2	.9976e2	-.5206e0	.1597e-2	.9976e-1	-.5206e1
	407	490	3	-.5399e2	.4462e0	.1498e-3	-.5399e-1	.4462e1
6	138	200	1	.5285e2	-.6348e0	.2758e-2	.5285e-1	-.6348e1
	85	138	2	.1983e1	-.3114e-1	.1049e-2	.1983e-2	-.3114e0
	200	265	3	.2668e3	-.2338e1	.5935e-2	.2668e0	-.2338e2
7	200	331	1	.1893e2	-.1325e0	.1107e-2	.1893e-1	-.1325e1
	331	391	2	.4377e2	-.2267e0	.1165e-2	.4377e-1	-.2267e1
	391	500	3	-.4335e2	.3559e0	.2454e-3	-.4335e-1	.3559e1
8	99	138	1	.1983e1	-.3114e-1	.1049e-2	.1983e-2	-.3114e0
	138	200	2	.5285e2	-.6348e0	.2758e-2	.5285e-1	-.6348e1
	200	265	3	.2668e3	-.2338e1	.5935e-2	.2668e0	-.2338e2
9	213	370	1	.8853e2	-.5675e0	.1554e-2	.8853e-1	-.5675e1
	130	213	2	.1530e2	-.4514e-1	.7033e-2	.1423e-1	-.1817e0
	370	440	3	.1423e2	-.1817e-1	.6121e-3	.1423e-1	-.1817e0
10	200	362	1	.1397e2	-.9938e-1	.1102e-2	.1397e-1	-.9938e0
	407	490	2	-.6113e2	.5084e0	.4164e-4	-.6113e-1	.5084e1
	362	407	3	.4671e2	-0.2024e0	.1137e-2	.4671e-1	-.2024e1

4.3.4 Results and Comparison

Table 4.28 Result of Ten unit Test3

METHOD	CGA_MU		IGA_MU		DE_METHOD		IDE_METHOD	
Unit	**Fuel Type**	**Gen.**	**Fuel Type**	**Gen.**	**Fuel Type**	**Gen.**	**Fuel Type**	**Gen.**
1	2	222.0108	2	219.1261	2	246.7	2	229.7
2	1	211.6352	1	211.1645	1	230.0	1	230.0
3	1	283.9455	1	280.6572	1	300.3	3	338.6
4	3	237.8052	3	238.4770	1	136.7	1	137.1
5	1	280.4480	1	276.4179	1	324.1	1	264.1
6	3	236.0330	3	240.4672	3	242.1	3	254.8
7	1	292.0499	2	287.7399	1	341.6	1	296.6
8	3	241.9708	3	240.7614	3	227.1	3	219.5
9	3	424.2011	3	429.3370	1	374.4	3	440.0
10	1	269.9005	1	275.8518	1	276.8	1	289.6
P_D	2700.00		2700.00		2700.00		2700.00	
Total Cost ($/h)	624.7193		624.5178		**482.3**		**481.10**	
TIME(s)	26.17		7.25		49.803		55.5230	
Max. Iteration	NA		NA		2000		2000	

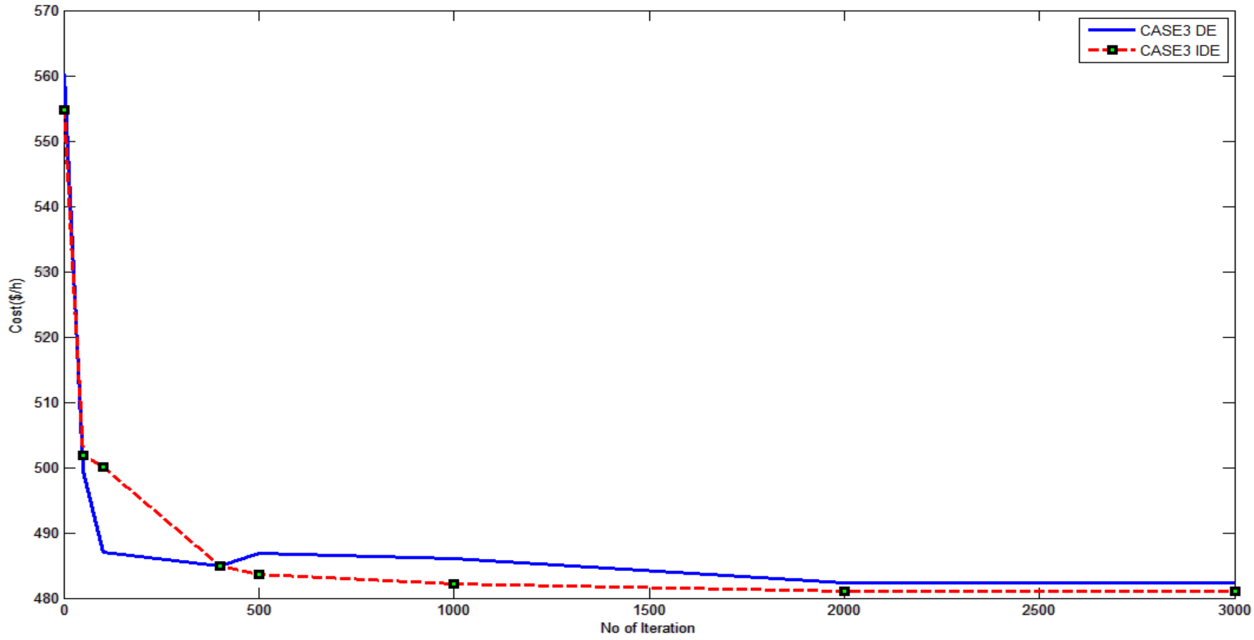


Figure 4.14: Convergence curve for Test3

It is observed from above table and graph that total cost (TC) of ten unit systems for IDE is 481.10 $/h for a 24 hour scheduling correspondence to its load demand which is lower TC than DE's TC and its rate of convergence is also very fast.

Chapter 5

Conclusions and Future scope

5.1 Conclusion

Conventional differential evolution (DE) algorithm is a simple but powerful stochastic global optimizer. In this thesis work a penalty less handling constraints DE algorithm is used to solve economical dispatch problems in more efficient way. The DE's parameters CR and f_m that need to be adjusted by the user are generally the key factors affecting the DE's convergence. Choosing suitable parameter values is difficult for DE, which is usually a problem-dependent task. The trial-and-error method adopted frequently for tuning the parameters in DE requires multiple optimization runs. Therefore to improve global convergence, chaotic sequence series to adjust parameters CR and f_m during the evolutionary process is adopted. Application of chaotic sequences based on logistic map to determine the values of parameters f_m and CR in the proposed algorithm is devised to effectively handling constraints which does not require a penalty function to bias the search towards the feasible region of a problem.

Improved differential evolution (IDE) has proven to be a high class technique for solving different types of real world problems from communication engineering to biotechnology. In this work we have investigated the potential of the algorithm in solving power economic dispatch problem with valve point loading effects and multiple fuels.

5.2 Future scope

1. Sensitivity analysis for the control parameters mutation constant, crossover rate and weight can be performed for better results.
2. This technique can be used to solve multi-objective problems of generation scheduling with non-commensurable objectives.