COMPARATIVE STUDY OF PARTICLE SWARM OPTIMIZATION AND BEE SWARM OPTIMIZATION ON A DYNAMIC ECONOMIC LOAD DISPATCH PROBLEM

A Dissertation submitted in fulfillment of the requirements for the Degree
of

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In

Power System

Submitted by

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DECLARATION

I hereby certify that the work which is presented in dissertation entitled, **"Comparative Study Of Particle Swarm And Bee Swarm Optimization On A Dynamic Economic dispatch Problem"**, in partial fulfillment of the requirements for the award of the degree of Master of Engineering in Power Systems, submitted to Electrical & Instrumentation Engineering Department of Thapar University, Patiala is as authentic record of my own work carried under the supervision of Dr. S. K. Jain. It refers others researcher's work which are duly listed in the reference section. The matter contained in this dissertation has not been submitted, neither in part nor in full to any other degree to any other university or institute except as reported in text and references.

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It is certified that the above statement made by the student is correct to the best of my knowledge and belief.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

NOMENCLATURE

F_i	Fuel cost of the i^{th} generating unit in $^{\$}/_{MWh}$
P_i	Power produced by i^{th} generating unit in (MW)
$a_{i,}b_{i,}c_i,e_i,h_i$	Cost coefficients for i^{th} generating unit.
P_{imin}	Minimum power limit in MW
P_{imax}	Maximum power limit in MW
P_d	Load demand in MW
w	Inertial weights
w_{min}, w_{max}	Minimum and maximum value of weights in PSO
V_i^{k+1}	Velocity at $k+1$ iteration
$C1, C2$	Acceleration constants
$P_{best,i}^k$	Local best value at iteration k
G_{best}^k	Global best at iteration k
k	Current iteration number
$R1, R2$	Any random number between $(0,1)$
P_i^{k+1}	position of the particle at iteration $k+1$
V_{min}, V_{max}	Minimum and maximum limits of velocity
Pb_i	Probability value in the onlooker bee phase

ABBREVIATIONS

PSO	Particle swarm optimization
BSO	Bee swarm optimization
ELD	Economic load dispatch
DED	Dynamic economic dispatch
GA	Genetic algorithm
SQP	Sequential quadratic programming
MPSO	Modified particle swarm optimization
SOA	Seeker optimization algorithm
AIS	Artificial immune system
UR	Up rate
DR	Down rate

ABSTRACT

The economic operation of the generating systems has always occupied an important position in the electric power industry. The dynamic economic dispatch (DED) is one of the significant non-linear problems as optimization has to be carried out for the varying load demand. Mostly, 24-hr duration is accounted. The complexity further increases due to account of the valve-point loading effects and ramp-rate limits. The aim of the dynamic economic load dispatch problem is to find the optimal combination of generators in order to minimize the operating costs of the system. The load demand must be appropriately shared among the various generating units of the system.

In this dissertation, a comparative study of two optimization techniques namely Particle swarm optimization (PSO) and Bee swarm optimization (BSO) is done on a dynamic economic dispatch problem considering both valve-point loading and ramp rate limits of the generator. The algorithms are implemented on a ten unit system neglecting transmission losses. The results obtained by both the technique are compared.

CHAPTER 1

INTRODUCTION

1.1 Overview

Electrical power plays a very important role in our economy today. The entire economy depends on electricity as the basic need. Moreover, it is the most flexible forms of energy that is available to us. It helps us in operating domestic as well as industrial appliances which enhances its demand day by day. This rising demand has increased the number of power stations and the transmission lines which help in supplying electricity to the load centers. In order to fulfill these demands, electrical energy should be handled in the most efficient and economical manner. As a result, optimization of electrical energy is required and is therefore one of the most important areas of research in power systems today.

Electrical energy is produced largely by the use of non-conventional sources like coal, natural gas, hydro and nuclear. The major production depends on the thermal power plants which utilizes coal as the fuel. The heat produced by these fuels is ultimately converted to electricity. The fuel cost thus becomes an important economical factor. Thus the fuel cost is aimed to minimize taken into consideration the other available constraints. Therefore, electrical utilities aim to provide smooth supply of electricity to its customers at minimum cost. The major objectives taken into consideration are

- Cost minimization
- Reduction in losses
- Maximizing tariffs/profits

In order to fulfill the above mentioned objectives, economic scheduling is done. Economic scheduling can be done in the following three ways.

- **Economic load dispatch (ELD) -** The objective of economic load dispatch is to meet the load demand with the help of generating units at a reduced fuel cost, satisfying all operating constraints.
- **Unit commitment-** The main aim is to determine that which generating units are to be put in operation among the available units such that the load demand is met and the constraints are satisfied.

- **Optimal power flow-** The objective is to supply the real power to the available load centers with minimum system losses.

1.2 STATIC AND DYNAMIC ECONOMIC LOAD DISPATCH

Economic load dispatch is an important optimization problem in the field of power systems today. It could be static or dynamic in nature. Static economic dispatch is independent of time whereas dynamic economic load dispatch depends on the time period.

Static economic load dispatch aims to minimize the total fuel cost (Rs/h) of generating units satisfying certain equality and inequality constraints. The cost function to be minimized could be smooth or non-smooth depending upon the operating constraints of generating units. The cost function becomes non-convex or non-smooth if the generator constraints namely valve point loading [1] and ramp rate characteristics [2] are included.

Dynamic load dispatch on the other hand deals with the real time power system operations. It is dynamic in nature due to large variation in the load demand over a period of time. Traditionally, an economic load dispatch problem attempts to minimize the total generation cost subjected to certain constraints. It is assumed that the output power produced by the units is constant for a given time interval. However, in a real time power system, there is always an increase or decrease in the output power produced which is limited by the ramp rates of the generator. These limits distinguish between static and dynamic load dispatch problem. Thus dynamic load dispatch problem serves to schedule the outputs of the generator with the predicted load demands for certain time period thereby operating the system more economically. For precise modeling of a dynamic economic dispatch (DED) problem in the real system, the generator constraints like valve point loading and ramp rates are considered.

A number of optimization techniques have been used on economic load dispatch problems. Many researches are still ongoing in this field. A number of methods are used to solve the DED problem.

The classical methods used include Lagrangian multiplier method [3] and dynamic programming [4]. Most of these methods fail to give optimal solutions due to limitations in accuracy, efficiency and problem formulations. Recent researches have proposed certain heuristic methods to solve DED problem and reach to any optimal solution. One of these methods is the Tabu search method [5]. However, these methods also have certain disadvantages. The premature convergence doesn't guarantee an optimal global solution. In order to overcome these shortcomings, certain hybrid methods are introduced and implemented to obtain the best possible solution of a DED problem. These include stochastic search methods like evolutionary programming (EP) [6], genetic algorithm (GA) [7], and particle swarm optimization (PSO) [8], bee swarm optimization (BSO) [9] combined with sequential quadratic programming (SQP) etc.

1.3 LITERATURE REVIEW

Economic load dispatch has always been an area of concern for power system engineers. A number of optimization techniques have been applied on the stated problem including variety of constraints. These methods are broadly divided as classical methods, random search or stochastic methods, and hybrid methods. Recently intelligent search algorithms based on artificial intelligence have also been introduced. A detailed literature survey is discussed on these methods.

Liang *et al.* [4] presented a dynamic programming method to solve economic load dispatch problems including transmission line losses. A zoom feature is used in the proposed method which required less memory and time.

Walters *et al.* [7] implemented genetic algorithm on an ELD problem considering valve point discontinuities of the generators. The algorithm utilized the random and structured exchange of information between solutions to find the best optimal solution which was helpful in reducing the constraints of classical Lagrangian technique.

Attaviriyanupap *et al*. [10] proposed a hybrid methodology which combined evolutionary programming (EP) and sequential quadratic programming (SQP) over a dynamic ELD problem.

Attaviriyanupap *et al*. [11] proposed a fuzzy optimization method to DED problem from the view point of generator company which included all the uncertainties in deregulated markets. In this paper, the uncertainties were represented by fuzzy numbers which consists of demand and reserve requirement of market and prices cleared in the market.

Aruldoss *et al.* [12] combined an EP and SQP to implement a DED problem including valve point effects. SQP guide EP to obtain more optimal solution.

Park *et al.* [1] implemented a modified particle swarm optimization (MPSO) on an ELD problem with non-smooth cost function considering valve point effects and multiple fuel problems. Moreover, a reduction strategy was proposed to reduce dynamic search space and accelerate the process.

Pothiya *et al.* [5] implemented a multiple search tabu algorithm on a DED problem including generator constraints like ramp rate limits and prohibited operating zones. The algorithm introduced additional mechanisms namely initialization phase, adaptive search, multiple search, crossover and restart phase.

Karaboga *et al*. [13] proposed another swarm based algorithm named artificial bee colony to solve an ELD problem. The performance of algorithm is evaluated by comparing it with other random search algorithms.

Sivasubramani *et al.* [14] proposed a hybrid technique in which seeker optimization algorithm (SOA) and (SQP) are combined to solve DED problem with valve point effects. SOA is used for base level search and SQP tunes the solution obtained from SOA and hence guides SOA to obtain optimal solution.

Lee *et al.* [15] proposed a quantum GA on a economic dispatch problem along with the effect of wind power generation. The obtained results show that algorithm finds the optimal solution quickly and accurately as compared to other methods.

Hemamalini *et al.* [16] proposed an artificial immune system (AIS) algorithm on a dynamic economic dispatch problem considering valve point effects. The method is validated for ten and five unit test system for a time period of 24 hrs.

Lu *et al.* [17] implemented a chaotic differential evolution method on DED problem including valve point loading effects. The proposed technique was implemented in 3 stages. Initially chaotic sequences were applied to find the dynamic parameters in the problem. Secondly, a chaotic local search operation was designed to avoid premature convergence. Finally, heuristic constraint handling methods and selection strategy were implemented.

Pandi *et al*. [18] used a meta- heuristic optimization algorithm named harmony search with swarm based algorithm called (PSO). The proposed hybrid algorithm handle power balance, ramp rate limits, and power generation limits by using penalty function method.

Affijulla *et al.* [19] proposed an intelligent search algorithm called gravitational search algorithm. The stated algorithm is implemented on ELD problem with valve point loading effects and Kron's loss. The proposed algorithm imposes fewer burdens on memory size, population size, number of iterations, etc unlike other random search algorithms.

Manteaw *et al*. [20] combined two optimization techniques named Ant Bee Colony (ABC) and PSO to solve an ELD problem which aimed to minimize the generation cost and pollution emission.

Singh *et al.* [21] proposed a moderate random modified particle swarm optimization (MRPSO) algorithm to solve an ELD problem with emission as constraint. The paper aimed to minimize not only the cost of generation but also pollutant emission released by toxic gases.

Subhani *et al*. [22] presented a PSO algorithm with an automation strategy im which time varying acceleration coefficients are used to avoid premature convergence and to control the local and global search effectively.

Rahmat *et al*. [23] proposed a differential evolution ant colony optimization to optimize an ELD problem. The stated algorithm is implemented on the IEEE Reliability Test System (RTS) and is proved to be efficient.

Yang *et al*. [24] proposed firefly algorithm for a non-convex economic dispatch problems which included non-linear characteristics of power generators.

Niknam *et al.* [8] proposed an enhanced adaptive PSO technique on DED problem including valve-point loading and ramp rate limits. The proposed algorithm further formulated a mutation technique to avoid premature convergence.

Benhamida *et al*. [25] discussed a comparative study on QP method applied to solve a DED problem with and without ramp rate constraint neglecting the transmission losses.

Niknam *et al.* [9] proposed an enhanced bee swarm optimization algorithm on a dynamic ELD problem including ramp rate limits and valve point loading effects. The algorithm employed different moving patterns to search for the most feasible solution in the search space.

Zhu *et al.* [26] proposed a chaotic PSO algorithm to solve an ELD problem which used inertial weights to speed up the convergence process.

Dutt *et al*. [27] discussed one of the classical approaches to solve ELD problem. He proposed an improved Lambda iteration technique in Matlab environment which was fast and more reliable than the previous one.

Dasgupta [28**]** implemented a PSO algorithm with different variations on an ELD problem. He successfully implemented PSO, PSO with constriction factor, PSO with inertial weight factor and PSO with both the above combined factors.

Panigrahi *et al*. [29**]** proposed a heuristic optimization technique on an ELD problem using adaptive PSO method. The method was found to be capable enough to handle all constraints like ramp rate, system losses, and prohibited operating zones.

1.4 OBJECTIVE OF THE THESIS

The objective of the thesis is to optimize a DED problem considering the valve point loading effect and the ramp rate limits of the generating units using heuristic approaches and analyze the comparative results from two optimization techniques namely Particle swarm optimization (PSO) and Bee swarm optimization (BSO).

1.5 ORGANIZATION OF THE THESIS

The thesis work is summarized in six chapters.

Chapter 1 includes an overview of the topic and the detailed literature survey.

Chapter 2 covers the problem formulation stating the constraints and objective function to be optimized.

Chapter 3 gives a detailed description of PSO technique along with algorithm and flowchart.

Chapter 4 presented a detailed description of BSO technique along with algorithm and flowchart.

Chapter 5 includes the results obtained and the related discussions.

Chapter 6 discusses conclusion and scope for future work followed by references.

CHAPTER 2

ECONOMIC LOAD DISPATCH

2.1 INTRODUCTION

Economic load dispatch is an optimization scheme that aims to determine the best generation schedule which meets the load demand, at a minimum cost, satisfying the given constraints. The major challenge faced by electrical utilities is to meet the load demand at the minimal price. A power station comprises of a number of generating units. Each generating unit has its own typical characteristics depending on its operating parameters. The operating costs of these units are not proportional to the outputs produced by them. Thus the utilities make sure that the load demanded by the costumer is met with efficient running of units.

Electricity generation in power plants arises from three main sources i.e. thermal, nuclear and hydro plants. The major contribution is served by thermal and hydro plants. Nuclear plants are allowed to run at base loads only and hence don’t require scheduling just like thermal and hydro plants. The economic scheduling is more prominent in case of thermal plants as the variable costs incurred by them are much more than other plants.[30]

Table 2.1 Cost variation in different power plants. [30]

Cost	Thermal Plants	Hydro Plants	Nuclear Plants
Fixed Cost	20%	75%	70%
Fuel Cost	70%	0%	20%
Operational Cost	10%	25%	10%

As seen above, the cost from fuel comprises of major portion of the variable cost, therefore it needs to be reduced. The total operation cost includes labour cost, fuel cost, maintenance cost, and supply cost. All other costs do not vary much and therefore are considered as fixed percentage of the fuel costs.

2.2. COST CURVES

There are two significant costs in economic load dispatch of thermal units.

- Fuel cost (Rs/h)
- Incremental fuel cost. (Rs/MWh)

Input- Output curve

It is the curve between fuel cost in Rs/h to the power generation in MW.

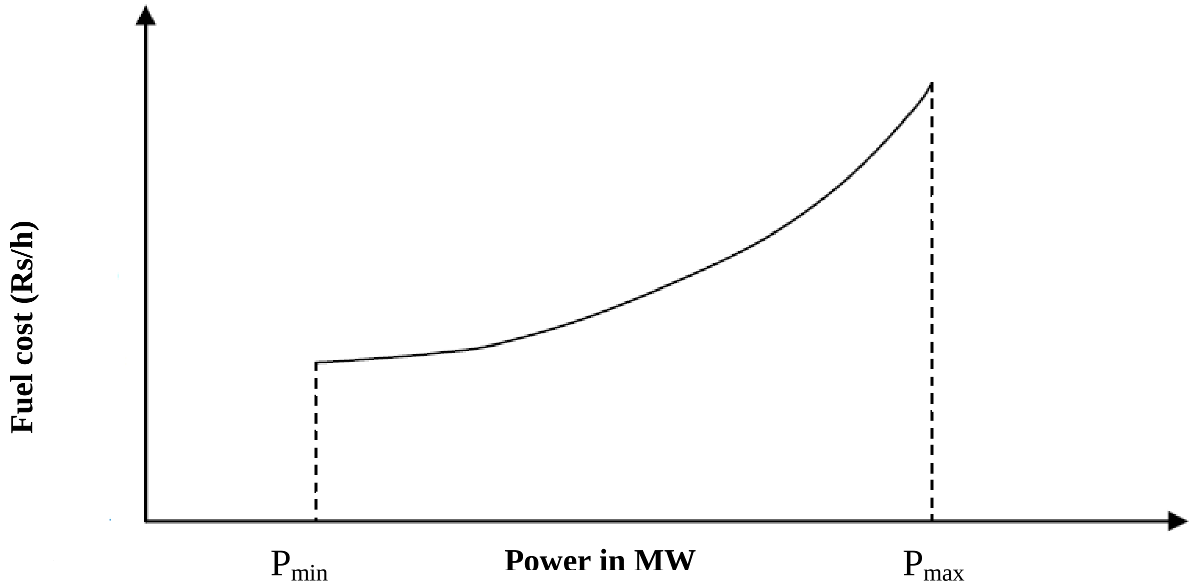


Fig. 2.1 Input Output curve. [30]

Incremental Fuel Cost Curve:

It is the curve between incremental fuel cost (Rs/h) and the power generated. (MW)

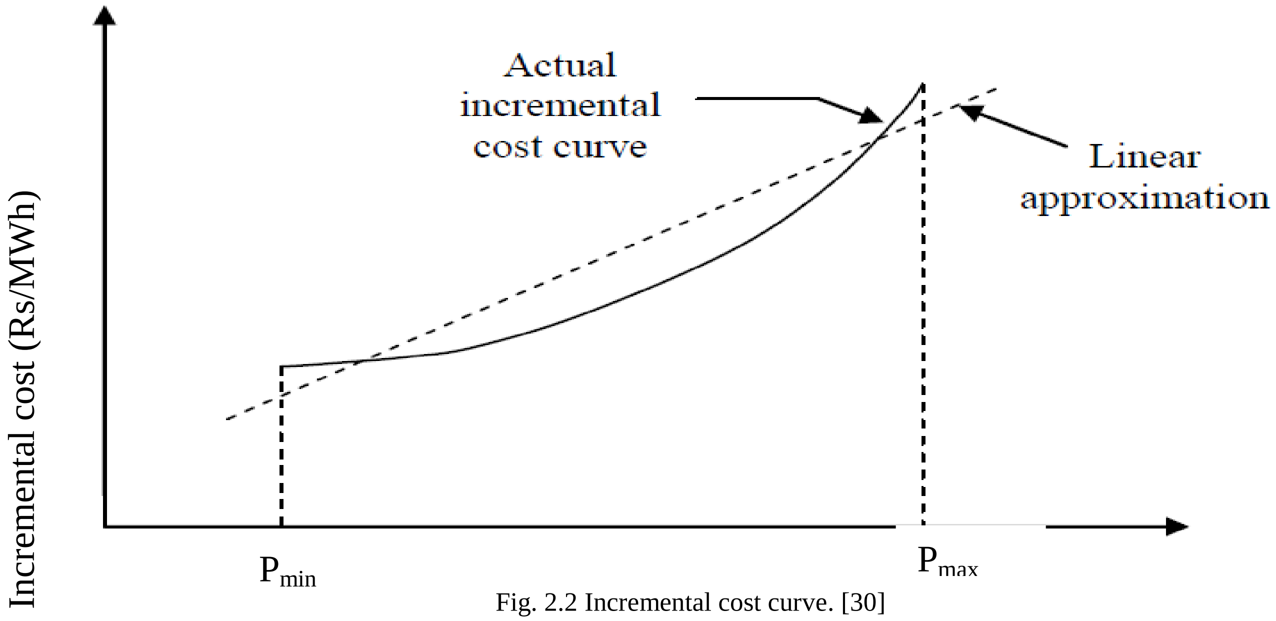


Fig. 2.2 Incremental cost curve. [30]

2.3 COST FUNCTION

Let us consider a simple example of a fossil plant.

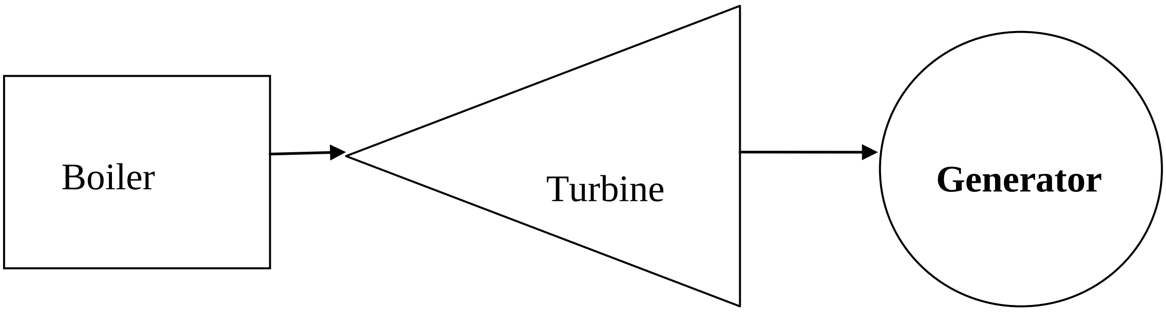


Fig 2.3 Simple Model of a fossil plant. [31]

The above figure shows a simple plant structure which shows conversion of mechanical energy to electrical energy. The steam produced in the boiler is sent to turbine which produces converts rotational motion of steam into electricity. The turbine consists of valves which affects the electrical output produced by the generator.

The output power generated can be increased by opening the steam inlet valve. The losses are high when valve opening is less and low when valve opening is high. Since the cost incurred by a generating unit is not proportional to the output generated, the fuel cost function takes up a quadratic form.

2.3.1 ELD with smooth cost function

The cost function or the objective function which is to be minimized is given as:

$$F_i(P_i) = \sum_{i=1}^{N}(a_i P_i^2 + b_i P_i + c_i\ ) \tag{2.1}$$

where,

$F_i =$ Fuel cost of the i^{th} generating unit (Rs/MWh)

$P_i =$ Power produced by i^{th} generating unit (MW)

a_i, b_i, c_i = Cost coefficients for i^{th} generating unit.

$N =$ Number of generators.

2.3.2 ELD with non smooth cost function

The cost function of an ELD problem becomes non-smooth owing to the valve point loading of the generating units. The generating units having multiple valves steam turbine shows a greater variation in the fuel cost characteristics. The cost function becomes highly non-linear due to the ripples that occur due to valve point loading effect. An extra sinusoidal term is added to the original cost function. The cost function now becomes

$$F_i(P_i) = \sum_{i=1}^{N}\{a_iP_i^2 + b_iP_i + c_i + [e_i * sinh_i * (P_{imin} - P_i)]\} \tag{2.2}$$

where,

e_i, h_i = Cost coefficients for i^{th} generating unit

P_{imin} = Minimum power of i^{th} generating unit in MW

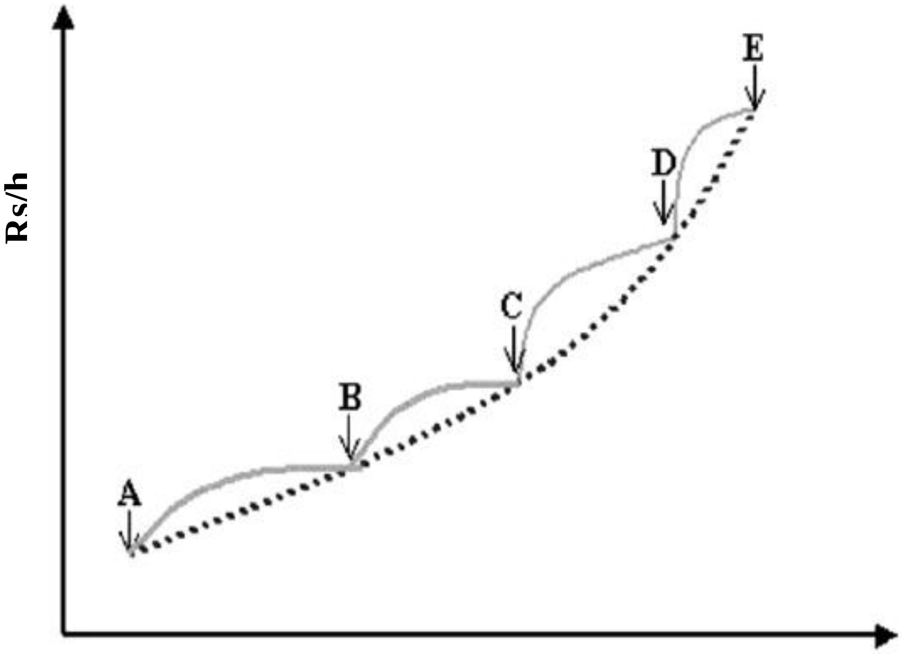


Fig. 2.4 Valve point loading effect. [1]

The above graph shows valve point loading effect in the generator units. The points A, B, C, D, and E are the valves in the generator units. Large steam turbine generators have a number of steam admission valves that are opened in sequence to obtain ever-increasing output of the unit. As the unit load increases, the input to the unit increases and the incremental heat rate decreases between the opening points for any two valves. However, when a valve is first opened, the throttling losses increase rapidly and the incremental heat rate rises suddenly. This gives rise to the discontinuous type of characteristics in order to schedule steam unit, although it is usually not done. It is possible to use this type of characteristic in order to schedule steam units. This type of input – output characteristics is non-convex. The number of valves is shown to be five which causes more non-linearity to the objective function.

2.4 DYNAMIC ECONOMIC LOAD DISPATCH

Dynamic economic load dispatch deals with real time systems. It is dynamic in nature and is therefore dependent on the time intervals. It schedules the power output considering the predicted load demand for a certain time interval. The objective function for dynamic economic load dispatch problem changes to

$$F_i(P_i^t) = \sum_{t=1}^{T} \sum_{i=1}^{N} \{a_i + b_i P_i^t + c_i (P_i^t)^2 + [\, e_i * sinh_i * (P_{imin} - P_i^t)]\} \qquad (2.3)$$

2.5 PROBLEM FORMULATION

The problem is a dynamic ELD problem which aims to minimize the fuel cost and schedule the power output of each unit for a time interval of 24 hours. The problem is subjected to various equality and inequality constraints.

Objective function

$$\boldsymbol{min}(F_i(P_i^t)) = \sum_{t=1}^{T} \sum_{i=1}^{N} \{a_i + b_i P_i^t + c_i (P_i^t)^2 + [\, e_i * sinh_i * (P_{imin} - P_i^t)]\}$$

Constraints

The dynamic economic load dispatch problem is subjected to certain equality and inequality constraints.

- **Equality constraints/ Power balance constraint**

The power generated for every specified time interval should meet the load demand if losses are neglected.

$$\sum_{i=1}^{N} P_i^t = P_d^t \qquad t=1\ldots\ldots24 \tag{2.4}$$

where

$N =$ Number of generators

P_i^t= generation by any unit at time t (MW)

P_d^t= load demand at any time t (MW)

- **Power limit constraints**

  The power generated should be within the maximum and minimum specified limits.

$$P_{imin} < P_i^t < P_{imax} \tag{2.5}$$

where

P_{imin}= minimum specified limit of i^{th} generating unit in MW

P_{imax}= maximum specified limit of i^{th}generating unit in MW.

- **Ramp rate limit constraints**

  Ramp rate is defined as the ability of the units to respond to power changes in a specified time interval.

For increase in generation

$$P_i^t - P_i^{t-1} \le UR_i \tag{2.6}$$

i.e. the successive increase in power for two time intervals must not exceed the ramp-up limit of generator i.

For decrease in generation

$$P_i^{t-1} - P_i^t \le DR_i \tag{2.7}$$

i.e. the successive decrease in power should not be less than the down rate limit of generator i.

where,

t =any time interval

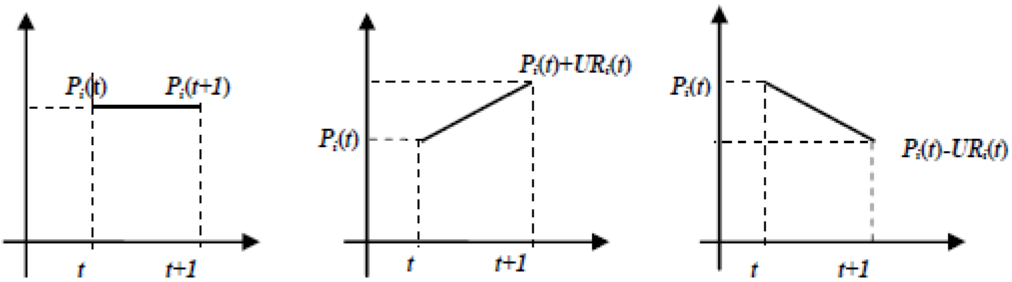
$UR_{i=}$ ramp up limit of any generator i

$DR_{i=}$ down rate limit of any generator i.

Thus the constraints for the maximum and minimum power limits can now be modified as,

$$\max\,(P_{imin}, P_i^{t-1} - DR_i) \leq P_i^t \leq \min\,(P_{imax}, P_i^{t-1} + UR_i) \tag{2.8}$$

The following graph indicates three different operations.



a) Steady state operation of units

b) Increase in generation

c) Decrease in generation

Fig. 2.5 Ramp rate characteristics of generating units. [32]

The above figure indicates three different possibilities when the generating units generate power which varies with time. Fig 2.5 a) indicates a steady state operation of a generating unit where the power generation is constant for two successive hours. So it does not require ramp rate limits. Fig 2.5 b) indicates an increase in generation for two successive hours. According to the constraints, the increase in generation should be equal to or less than the up rate limit specified. The line shows the maximum permissible increase allowed between two successive hours. Fig 2.5 c) indicates a decrease in generation for two hours. The constraints indicate that this decrease should be within the down rate specified. The decreasing line indicates the maximum permissible decrease allowed.

CHAPTER 3

PARTICLE SWARM OPTIMIZATION ALGORITHM

3.1 OVERVIEW OF PSO

PSO is a population based stochastic optimization technique developed by James Kennedy and Russell Eberhart in 1995 [33]. The algorithm like other population based optimization techniques is biologically inspired. It is based on the analogy of bird swarm or fish school. The swarms are a group of individuals or particles that serve a common purpose like food hunting. This algorithm is inspired from the relative behavior of swarms that live and move together in a group like birds, fishes etc.

PSO shares certain similarities with another population based optimization techniques like GA. A random population is initialized which searches for an optimal solution in the search space by updating its position. However, PSO differs from GA in certain aspects. It does not have operators like mutation and crossover. PSO has certain advantages over GA. It is easier to implement and has less parameters to adjust. PSO has been successfully applied to a number of areas in the power system like optimization problems, training of artificial neural network, and fuzzy control etc.

PSO is based on the behavior of bird flocking. Imagine a following situation: a group of birds are randomly searching for food in a given area. There is only one piece of food that needs to be searched. All the birds do not have the knowledge of where the food is but they are very well aware that how far the food is in every iteration. So the most effective way to search the food is to follow the bird which is nearest to the food. PSO uses this concept to solve an optimization problem. Thus each single food is referred to as 'bird' or 'particle' in the search space. Each particle has its own fitness valve computed by the fitness function to be optimized and a velocity which decides the flying trajectories of the particle. Thus the particle is able to search for the best optimal solution in the search space. PSO is initialized by a random population which searches for an optimal solution by updating its generation. Each particle is updated by two best values in every iteration. The first best value is the best solution or fitness achieved so far. This is called as the 'P_{best}'. Another best value is the value obtained so far by any particle in the defined population. This best value is called as'G_{best}'. The first best value is the local best value and the second best value is the global best value. After obtaining the two best values, the particle updates its position and velocity.

3.2 PARAMETER SELECTION IN PSO

The performance of PSO algorithm is strongly dependent on its parameter set. To achieve an optimal performance, tuning of these parameters is really important. Better convergence can be obtained by tuning its parameters effectively. Some of the parameters are inertial weights, acceleration constants, number of swarms, velocity and position updating.

3.2.1 Inertial weight

The inertial weight enables the swarms to fly in a larger search space. An appropriate value should be chosen to provide an adequate balance between local and global search. The weights are evaluated using the following formula.

$$w = w_{max} - \frac{(W_{max} - W_{\min}) * itr}{maxitr} \tag{3.1}$$

where

$w =$ Inertial weights

w_{max}= Maximum value of weights

w_{min}= Minimum value of weights

$maxitr =$ Maximum iteration number

$itr =$ Number of iterations

The maximum value of weights is taken to be 0.9 and the minimum value is taken to be 0.4.

3.2.2 Acceleration constants

C1 and C2 are the acceleration constants taken. These acceleration parameters help in better convergence as they try to pull the particles towards P_{best} and G_{best} values. The value of both $C1$ and $C2$ is taken as 2.

3.2.3 Velocity Updating

The velocities of the particle are updated by using the following equation

$$V_i^{k+1}=(w * V_i^k)+(C1 * R1(P_{best,i}^k-P_i^k) + (C2 * R2(G_{best}^k - P_i^k) \qquad (3.2)$$

where

V_i^{k+1}= velocity at $k+1$ iteration

$w =$ Inertial weights

$C1, C2 =$ Acceleration constants

$P_{best,i}^k$= local best value at iteration k

G_{best}^k= global best at iteration k

$k =$ previous iteration number

$R1, R2 =$ any random number between $(0,1)$

$k+1 =$ current iteration number

3.2.4 Position updating

The position is updated as follows

$$P_i^{k+1} = P_i^k+V_i^{k+1} \qquad (3.3)$$

where

P_i^k= position of the particle at iteration k

P_i^{k+1} = position of the particle at iteration $k+1$

V_i^{k+1}= velocity of the particle at iteration $k+1$

3.3 ADAPTIVE PARTICLE SWARM OPTIMIZATION

There are three control parameters which govern the performance of PSO algorithm. These parameters are acceleration parameters $C1$ and $C2$ and the inertial weight w. The convergence depends on these three parameters significantly. Acceleration parameters take the particle towards global optimum. The weights balance between local and global search. Therefore for better convergence and avoiding trapping in local minimum, the weights in the PSO are tuned by a non-linear approach [8]. The acceleration parameters $C1$ and $C2$ are self adaptively adjusted.

3.3.1 Self adaptive acceleration parameters

The acceleration parameters are self adaptively adjusted i.e. each parameter modifies its own position for next iteration. Normally the values of acceleration parameters are taken to be 2, but here the values will change in the form of following constraints.[34]

$$0 < C1, C2 \leq 3 \quad \text{and,}$$

$$C2 + C1 \leq 4$$

3.3.2 Non-linear weights

Weights are an important factor in a PSO algorithm as it balances between local and global search. A number of methods are proposed to adjust the weights. Usually weights decreases linearly from 0.9 to 0.4 as the algorithm progresses. The algorithm aims to enhance the global search in the beginning and local search at the end of the optimization process. However owing to the non-linear characteristics of the PSO, a non-linear weight approach is more flexible in balancing between local and global exploration. The weights are based on sinusoidal functions as follows

$$y = \sin\left(\frac{\pi}{r} * l\right) \tag{3.4}$$

Where l is defined as,

$$l = (maxitr - itr)/maxitr \tag{3.5}$$

where ,

r is any random number as $0 \leq r \leq 10$

The weights w are controlled by adjusting above mentioned parameters r and l. These parameters show a wide range of variation from approximately linear characteristics to periodic one. The value of y can be normalized as,

$$y_n = (y - y_{min})/(y_{max} - y_{min}) \tag{3.6}$$

where, y_{max} and y_{min} are the maximum and minimum value of the sinusoidal function.

The weight w is now linearly tuned using the equation:

$$w = y_n * (w_{max} - w_{min}) + w_{min} \tag{3.7}$$

Thus the weights vary from linear to periodic and hence are able to explore more effectively between local and global search.

3.4 PSO IMPLEMENTATION TO DYNAMIC ELD PROBLEM

PSO is implemented on a dynamic ELD problem considering both ramp rate limits and valve point loading. Therefore the optimization function becomes non-smooth and non-convex.

$$min(F_i(P_i^t)) = \sum_{t=1}^{T} \sum_{i=1}^{N} \{a_i + b_i P_i^t + c_i (P_i^t)^2 + [\, e_i * sinh_i * (P_{imin} - P_i^t)]\} \tag{3.8}$$

3.4.1 EVALUATING INITIAL CONDITION

The initial search points and velocities are randomly generated within the limits specified. The current search point is set to the P_{best}value for each particle. The best value among the local best value is set to global best value G_{best} and the best value is stored.

3.5 PSO ALGORITHM FOR SOLVING DYNAMIC ECONOMIC LOAD DISPATCH PROBLEM

The PSO algorithm is implemented on a dynamic economic load dispatch problem including ramp rate limits and valve point loading effect. The objective is to minimize the cost function. The algorithm is as follows:

Step 1: Input the system data consisting of cost coefficients of generators, ramp rate limits, load demand for each hour and maximum and minimum power limits. Also specify the parameters of PSO like acceleration parameters $C1$ and $C2$ as well as weights.

Step 2: Generate random population for every hour. Check whether the specified ramp rate limits are within specified range using the equation (2.6) and (2.7). If the limits are violated than specify new limits using equation (2.8).

Step 3: Since the generated power is random, it does not guarantee that it will satisfy the load demand. Calculate the mismatch and run the program till the error reduces close to zero.

Step 4: Evaluate the fitness function using equation (3.8)

Step 5: Compare the cost values for each particle in the population

Step 6: Particle corresponding to the lowest fitness value is called asP_{best}

Step 7: Modify the velocity of each particle using equation (3.2).

Step 8: Check for the limits

$$if\ (V_i < V_{min}) \tag{3.9}$$

$$V_i = V_{min} \quad \text{or}$$

$$if\ (V_i > V_{max})$$

$$V_i = V_{max}$$

Step 9: Modify the position of each particle using equation (3.3)

Step 10: Check for the maximum or minimum power limits.

$$if\ (P_i < P_{min}) \tag{3.10}$$

$$P_i = P_{min} \quad \text{or}$$

$$if\ (P_i > P_{max})$$

$$P_i = P_{max}$$

Step 11: Compare the fitness values of P_{best} of all the particles and determine the best. Store the coordinates of best particles asG_{best}.

Step 12: If the number of iterations reaches the maximum

Step 13: The particle that generates latest G_{best} is the solution.

Step 14: Stop

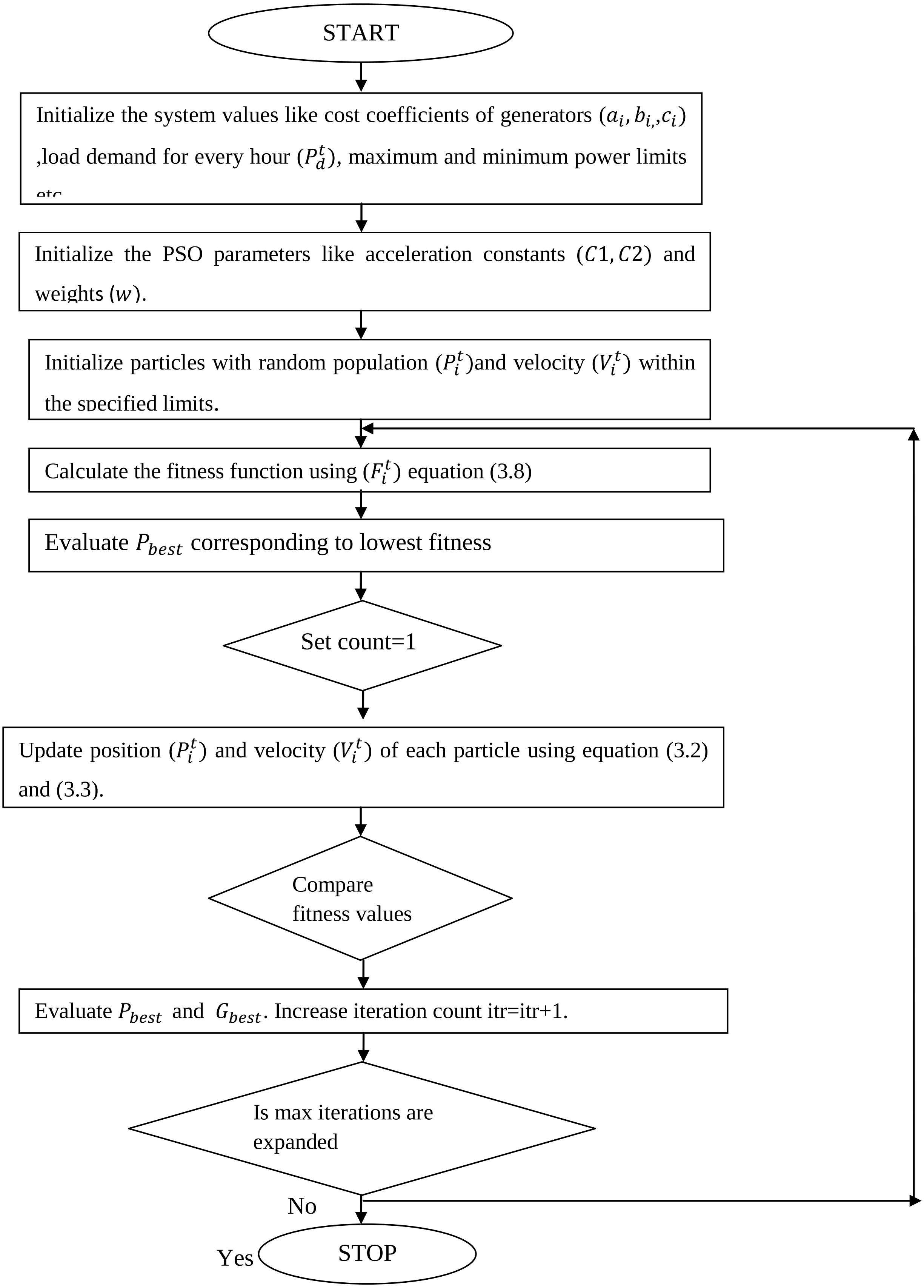


Fig 3.1 Flowchart for PSO

CHAPTER 4

BEE SWARM OPTIMIZATION

4.1 INTRODUCTION

Bee swarm algorithm is another swarm based algorithm which was developed by Dervis Karaboga [36] in 2005. The algorithm is based on the foraging behavior of honey bees. A number of swarm intelligence algorithms have been developed till now. These include particle swarm optimization (PSO), Ant colony algorithm, Bees algorithm etc. These algorithms are biologically inspired. They depend upon the behavior of a group of species like birds, fishes, ants, bees etc.

Bee swarm is a population based optimization algorithm which is inspired by the foraging behavior of the bees. Similar algorithms have already been developed for the purpose of numerical optimization. Artificial Bee Colony (ABC) and Virtual bee algorithm (VBA) are the examples. These algorithms have proved to give better performance than other population based algorithm like PSO, GA etc. In, most of the optimization problems, individuals follow a certain homologous pattern to search the feasible space and then update their positions. This homologous searching could ignore the search space with more optimal solution. Thus there is a need to employ certain algorithm which follows different moving patterns. Bee Swarm is one such technique. Since it is based on the varying behavior of honey bees, each bee follows a different moving pattern in the search space to reach an optimal solution. Hence there is an effective balance between exploitation and exploration.

4.2 BASIC WORKING OF BEE SWARM OPTIMIZATION

Bee swarm optimization (BSO) is inspired from the foraging behavior of the honey bees. These bee fly in a multi-dimensional search space to produce the most optimal solution. There are three types of bee:

- Employed bee or forager bee
- Onlooker bee
- Scout bee

Employed bee- These are the employed bees which search for the best food sources having more nectar content.

Onlooker bee- Employed bee share their information with the onlooker bees waiting in the hive. The onlooker bees choose their food source probabilistically on the basis of information given to them. The probability is calculated using the fitness value provided by employed bees.

Scout bee- Scout bees are the unemployed bees which choose their food source randomly.

4.2.1 PARAMETERS IN BSO

There are certain control parameters in BSO. The colony size is equal to the number of population which is equal to 50. The number of employed bees and onlooker bees are equal. The number of employed bees is taken as 40% of the colony size. The number of onlooker bees is taken as 40% of the colony size. The number of scout bees is selected as 10. The increase in the number of scout bees increases exploration whereas the increase in the number of onlooker bees increases exploitation.

4.2.2 BASIC STEPS

The basic working of the algorithm can be summarized in these basic steps.

1. Initialize the population
2. Place the employed bees on the food sources
3. Place the onlooker bees on the food sources depending on the nectar amounts which is obtained probabilistically.
4. Send the scout bees to the search area for generating random food sources.
5. Memorize the best solution obtained so far.
6. Stop

4.3 IMPLEMENTATION OF BSO ON DYNAMIC ELD PROBLEM

The algorithm is implemented on a dynamic ELD problem including the valve point effect and ramp rate limits which make the cost function non-smooth and non-convex.

The objective function to be optimized is

$$\boldsymbol{min}(F_i(P_i^t)) = a_i + b_i P_i^t + c_i(P_i^t)^2 + [\, e_i * sinh_i * (P_{imin} - P_i^t)] \qquad (4.1)$$

with certain equality and non-equality constraints.

The constraints include are:

- Equality constraints/power balance
- Power limit constraints
- Ramp rate limit constraints

Steps of algorithm

Step 1: Specify the generator cost coefficient, ramp rate limits of generator, load demand for every hour and generator power limits.

Step 2: Initialize control parameters of the algorithm like colony size, number of employed bees, onlooker bees and scout bees.

Step 3: Generate the population randomly within the specified power limits.

Step 4: Check for the ramp rate limits of generator for every hour. If the limits violate, specify new limits using the equation (2.8).

Step 5: Evaluate the fitness function using equation (4.1)

Step 6: Sort fitness in ascending order.

Step 7: Check for the power mismatch using equation (2.4)

Step 8: Employed Bee phase- The employed bee produces a new food source. The new food source is produced by the help of following equation

$$P_{ij} = P_{ij} + \Omega_{ij}(P_{ij} - P_{kj}) \qquad (4.2)$$

where $k =$ any random number between 1 and colony size i.e. 50

$$\Omega_{ij} = \Omega_{min} + (\Omega_{max} - \Omega_{min}) * rand \qquad (4.3)$$

Ω_{max} = 1 and

Ω_{min}= -1

Step 9: Check for the power limits. If the limits are violated, set them within pre specified value as follows

$$if\ (P_i < P_{min})$$

$$P_i = P_{min} \quad \text{or}$$

$$if\ (P_i > P_{max})$$

$$P_i = P_{max}$$

Step 10: Evaluate the fitness function in the employed bee phase.

Step 11: Apply greedy selection between the fitness values evaluated. Store the best value.

Step 12: Onlooker Bee Phase: The employed bee exchange the information related to the nectar amount and their position with onlooker bee

A probabilistic selection occurs depending on the fitness value of employed bee. As the nectar amount increases, the number of onlooker bees increases. The probability is evaluated as follows.

$$Pb_i = \frac{F_i}{sum(F_i)} \tag{4.4}$$

Step 13: Onlooker bees update the position of food source depending on the probability evaluated similar to employed bee using equation (4.2)

Step 14: Fitness value is evaluated and greedy selection is made. The best solution is stored.

Step 15: If the solution is not improved in predefined trials, it is abandoned and scout discovers a new food source randomly.

Step 16: Memorize the best solution obtained so far. Increment the cycle count.

Step 17: Stop the process when the maximum iterations are reached.

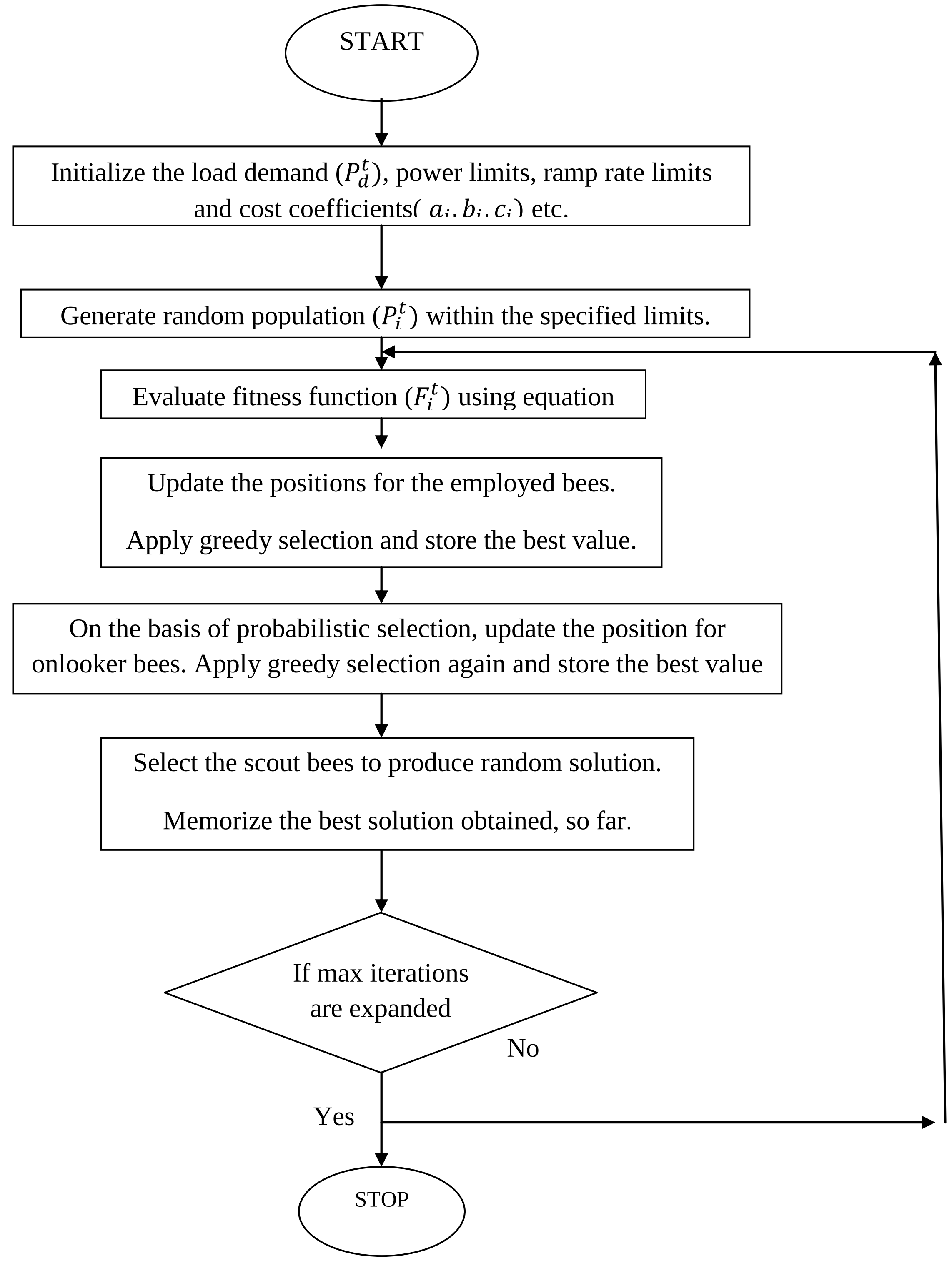


Fig 4.1 Flowchart for BSO

CHAPTER 5

RESULTS AND DISCUSSIONS

The proposed thesis work includes implementation of two swarm based optimization technique namely Particle Swarm Optimization (PSO) and Bee Swarm Optimization (BSO) on a dynamic ELD problem with varying load demand involving valve point loading and ramp rate limits of the generator. The above mentioned techniques are tested on a 10 unit system for a period of 24 hours neglecting transmission losses.

With valve point loading, the cost function takes a simple quadratic form. The convergence characteristics are also smooth as compared to with valve point loading effects. The cost obtained is also less.

These results are obtained considering the valve point loading effect in which the cost function attains an added sinusoidal term. Initially classical PSO is applied on a 10 unit system with linear weights and acceleration parameters values equal to 2 as proposed in method. The method is easy to implement but shows premature convergence and doesn't give a desired solution. For this purpose, an adaptive approach is used. In adaptive PSO approach, its control parameters adapt different values and the method is proved to be effective. The weights are non-linear due to their sinusoidal nature. The acceleration parameters are as per the constraints already specified. These control parameters improve the performance of the algorithm significantly. The weights provide an effective balance between local and global search. The acceleration parameters help in reaching towards global optima. Since DED problem is non linear due to the varying load demand with time (24 hrs), non-linearity in weights causes better exploration between local and global search. The algorithm aims to accelerate the global search in the beginning and local search at the end of the optimization process. The weights are tuned such that it decreases non-linearly in the beginning and linearly at the end. The initial non- linearity in weights encourages global search and linearity at the last stage promotes local search. Thus, the weights and acceleration parameters together provide a more effective convergence than classical method.

PSO uses a homologous pattern of finding velocities and updating positions. Such methods may ignore feasible search space. Thus it is necessary to employ methods which use different flying patterns. Therefore, BSO is applied on the similar 10 unit system. Due to its different flying patterns, it produces more optimum results than PSO.

The results for the three methods are shown. Table 5.1, 5.2, and 5.3 shows the power generated per hour with the change in load demand.

Table 5.1 Best solution obtained by Classical PSO method

Hour	Unit1 MW	Unit2 MW	Unit3 MW	Unit4 MW	Unit5 MW	Unit6 MW	Unit7 MW	Unit8 MW	Unit9 MW	Unit10 MW	P_D MW
1	215.9186	429.7281	258.2290	210.1140	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1036
2	215.9186	439.7685	258.2290	165.1450	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1110
3	215.9186	453.7957	258.2290	206.6764	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1258
4	215.9186	428.4791	258.2290	157.4798	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1406
5	215.9186	437.1336	258.2290	175.0498	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1480
6	215.9186	440.9876	258.2290	148.9385	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1628
7	215.9186	551.6475	258.2290	233.3944	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1702
8	215.9186	503.2023	258.2290	132.0466	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1776
9	215.9186	435.3082	258.2290	140.2182	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1924
10	215.9186	410.7055	258.2290	192.4115	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	2072
11	215.9186	554.1205	258.2290	239.9014	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	2146
12	215.9186	469.6028	258.2290	180.1367	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	2220
13	215.9186	440.5225	258.2290	180.5625	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	2072
14	215.9186	427.9371	258.2290	199.5456	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1924
15	215.9186	433.1167	258.2290	209.6446	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1776
16	215.9186	515.4292	258.2290	210.6885	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1554
17	215.9186	448.8162	258.2290	248.9816	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1480
18	215.9186	410.0429	258.2290	170.9838	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1628
19	215.9186	427.0203	258.2290	239.9280	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1776
20	215.9186	455.6555	258.2290	138.2293	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	2072
21	215.9186	423.9592	258.2290	156.9030	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1924
22	215.9186	416.0369	258.2290	218.5118	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1628
23	215.9186	457.5774	258.2290	240.9621	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1332
24	215.9186	448.3376	258.2290	112.7932	192.7778	107.1104	99.8328	77.0175	50.2629	55.00	1184

Table 5.2 Best solution obtained by Adaptive PSO method

Hour	Unit1 MW	Unit2 MW	Unit3 MW	Unit4 MW	Unit5 MW	Unit6 MW	Unit7 MW	Unit8 MW	Unit9 MW	Unit10 MW	P_D MW
1	215.0152	476.2088	215.0152	181.8720	192.5720	107.2842	99.8695	89.9033	50.1683	55.00	1036
2	215.0152	489.5224	259.2961	232.2348	123.1520	107.2842	50.0609	89.9033	50.1683	55.00	1110
3	215.0152	504.8129	259.2961	177.4278	123.1520	107.2842	99.8695	89.9033	50.1683	55.00	1258
4	215.0152	494.3328	259.2961	187.3957	123.1520	107.2842	50.0609	89.9033	50.1683	55.00	1406
5	215.0152	426.1037	259.2961	248.8584	123.1520	107.2842	99.8695	77.0915	50.1683	55.00	1480
6	215.0152	549.5336	259.2961	130.5252	192.5720	109.9693	50.0609	89.9033	50.1683	55.00	1628
7	215.0152	452.7472	259.2961	195.2912	123.1520	107.2842	99.8695	89.9033	50.1683	55.00	1702
8	215.0152	557.7789	215.0152	163.3709	123.1520	107.2842	99.8695	77.0915	50.1683	55.00	1776
9	215.0152	617.7966	215.0152	204.4863	123.1520	109.9693	50.0609	77.0915	50.1683	55.00	1924
10	215.0152	466.9154	259.2961	160.0752	192.5720	107.2842	50.0609	89.9033	50.1683	55.00	2072
11	215.0152	448.5860	259.2961	203.4267	123.1520	107.2842	99.8695	77.0915	50.1683	55.00	2146
12	215.0152	531.7396	215.0152	153.2578	123.1520	107.2842	50.0609	89.9033	50.1683	55.00	2220
13	215.0152	503.5327	259.2961	219.0874	1925720	107.2842	50.0609	89.9033	50.1683	55.00	2072
14	215.0152	581.5737	259.2961	141.4758	123.1520	109.9693	99.8695	89.9033	50.1683	55.00	1924
15	215.0152	563.9052	259.2961	139.0638	192.5720	107.2842	50.0609	89.9033	50.1683	55.00	1776
16	215.0152	476.2872	259.2961	115.1312	192.5720	107.2842	99.8695	89.9033	50.1683	55.00	1554
17	215.0152	546.0304	259.2961	216.3969	123.1520	107.2842	99.8695	89.9033	50.1683	55.00	1480
18	215.0152	649.4338	259.2961	243.1954	123.1520	107.2842	99.8695	89.9033	50.1683	55.00	1628
19	215.0152	522.5975	215.0152	242.6891	123.1520	107.2842	50.0609	77.0915	50.1683	55.00	1776
20	215.0152	549.5955	259.2961	218.3708	192.5720	107.2842	50.0609	89.9033	50.1683	55.00	2072
21	215.0152	527.2714	259.2961	125.4184	123.1520	107.2842	50.0609	89.9033	50.1683	55.00	1924
22	215.0152	564.9840	215.0152	125.7310	123.1520	109.9693	50.0609	77.0915	50.1683	55.00	1628
23	215.0152	493.3053	259.2961	221.9923	123.1520	107.2842	99.8328	89.9033	50.1683	55.00	1332
24	215.0152	510.8222	259.2961	234.3104	123.1520	107.2842	99.8328	89.9033	50.1683	55.00	1184

Table 5.3 Best solution obtained by Bee Swarm method

Hour	Unit1 MW	Unit2 MW	Unit3 MW	Unit4 MW	Unit5 MW	Unit6 MW	Unit7 MW	Unit8 MW	Unit9 MW	Unit10 MW	P_D MW
1	273.0132	366.4255	223.0393	124.8391	183.6461	108.0158	77.0078	87.3948	49.9491	55.00	1036
2	383.2296	215.7812	204.3221	112.8165	168.2891	107.4107	75.2691	85.7475	49.9565	55.00	1110
3	294.7478	286.5975	192.4441	238.7787	148.6876	108.4817	73.1329	77.8778	49.9079	55.00	1258
4	242.6667	371.4890	192.9103	217.1976	135.1720	107.1565	96.0204	89.7966	49.9404	55.00	1406
5	375.8107	251.9107	237.3124	170.2707	123.3509	108.7924	65.3569	82.1629	49.9552	55.00	1480
6	248.1495	353.3143	215.4390	227.9223	172.0643	109.1397	57.3458	81.0585	50.0061	55.00	1628
7	296.5535	371.8345	182.8754	210.4106	136.1568	108.1335	82.3958	83.5268	49.9190	55.00	1702
8	363.6050	354.1557	177.4223	130.5018	141.8241	107.9111	99.6559	80.0683	49.9330	55.00	1776
9	364.6663	372.5065	174.7567	178.9266	165.4149	108.1950	93.2155	87.6768	49.9114	55.00	1924
10	374.2720	261.9231	222.8654	126.1636	172.0960	107.4515	59.3865	83.3527	49.9835	55.00	2072
11	284.5905	319.1329	228.5875	193.3209	154.1078	108.4484	83.7465	83.9701	49.9483	55.00	2146
12	336.1250	247.2081	192.9573	127.3703	146.9308	107.6786	70.2779	88.2373	50.0205	55.00	2220
13	262.4958	362.5587	202.4570	188.7859	191.7712	107.7383	68.8149	87.7571	50.0245	55.00	2072
14	290.3030	358.9179	246.2526	207.8854	179.6463	107.5316	77.9386	80.0747	49.9284	55.00	1924
15	364.0615	333.0635	234.7396	209.7859	126.8887	108.9038	99.3776	82.2102	50.0030	55.00	1776
16	277.5850	252.7040	169.9497	112.0826	131.1697	109.2270	52.9920	81.7447	49.9771	55.00	1554
17	337.1896	278.2040	153.6609	227.8600	187.3396	108.2540	68.2221	84.8329	49.9853	55.00	1480
18	270.5400	252.7040	158.6125	202.0045	154.0749	108.2121	86.3864	86.0172	49.9395	55.00	1628
19	281.2527	300.7661	226.7436	234.5792	185.2885	109.7340	86.3864	87.0963	50.0103	55.00	1776
20	387.1746	215.9611	224.4311	233.4358	145.2480	107.8733	72.9165	83.7678	49.9658	55.00	2072
21	252.5285	363.7850	255.2042	207.5920	130.0226	109.1149	69.4322	87.9740	49.9975	55.00	1924
22	324.4898	242.8570	218.9978	218.9735	126.9247	108.7996	82.5877	77.7249	49.9401	55.00	1628
23	234.7529	375.0655	237.1605	219.2470	137.9195	109.3310	68.7936	83.6858	49.9526	55.00	1332
24	291.9432	280.4084	227.7418	249.8630	149.8161	107.2379	73.0382	83.1091	50.0180	55.00	1184

Table 5.4 Comparison of cost obtained by different methods implemented

Method	Cost(Rs/h)
Classical PSO	1027900
Adaptive PSO	1021100
Bee Swarm	1013300

Table 5.4 shows the comparison of costs evaluated by all the three methods. The algorithm runs for 100 iterations. The minimum cost is found for Bee Swarm followed by adaptive and classical PSO.

Bee swarm shows a steady convergence and reaches to the most optimal solution. Classical PSO converges prematurely due to ineffective local and global search. Better convergence characteristics are shown by adaptive PSO due to self tuning of its control parameters.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1 CONCLUSION

Bee Swarm converges steadily and reaches to the most feasible solution in the search space. It effectively balances between local and global search. This is due to the different flying patterns of the bee unlike in other swarm based optimization algorithms.

The classical PSO method is easy to implement but converges prematurely. The adaptive PSO shows better performance than classical PSO due to the changes in its control parameters which govern its performance. The weights are taken to be non-linear which prove to be more flexible in controlling the local and global search. This non-linearity proves to be effective due to the non linear characteristics of the dynamic economic dispatch problem where the environment changes dynamically with time.

6.2 SCOPE FOR FUTURE WORK

The scope for future work may include

- A hybrid implementation of both PSO and BSO.
- It could be implemented on a economic dispatch problem with prohibited operating zones.
- The cost function could include a constraint of multiple fuels.

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APPENDIX-1

The data for the ten unit system on which the optimization techniques are applied is:

Table A.1: System data for a ten unit system

Unit	P_{imax} (MW)	P_{imin} (MW)	a_i $\$/_h$	b_i $\$/_{MWh}$	c_i $\$/_{MW^2h}$	e_i $\$/_h$	h_i $rad/_{MW}$	UR_i (MW)	DR_i (MW)
1	470	150	958.2	21.6	0.00043	450	0.041	80	80
2	460	135	1313.6	21.05	0.00063	600	0.036	80	80
3	340	73	604.97	20.81	0.00039	320	0.028	80	80
4	300	60	471.6	23.9	0.0007	260	0.052	50	50
5	243	73	480.29	21.62	0.00079	280	0.063	50	50
6	160	57	601.75	17.87	0.00056	310	0.048	50	50
7	130	20	502.7	16.51	1.00211	300	0.086	30	30
8	120	47	639.4	23.23	0.0048	340	0.082	30	30
9	80	20	455.6	19.58	0.10908	270	0.098	30	30
10	55	55	692.4	22.54	0.00951	380	0.094	30	30

Table A.2 : Load Demand for 10 unit system

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

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