APPLICATION OF MAT-HEURISTICS ALGORITHM FOR ECONOMIC LOAD DISPATCH PROBLEM

Tesfaye Alemayehu Bekele

A Thesis Submitted to

The Department of Electrical Power and Control Engineering

School of Electrical Engineering and Computing

Presented in Partial Fulfillment of the Requirement for the Degree of Master of Science in Electrical power and control engineering

(Power System Engineering)

Office of Graduate Studies

Adama Science and Technology University

October 2020

Adama, Ethiopia

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APPROVAL SHEET

We, the undersigned, members of the board of examiners of the final open defense by Tesfaye Alemayehu have read and evaluated his thesis entitled "application of metaheuristics algorithm for economic load dispatch problem" and examine the candidate. this is, therefore, to certify that the thesis has been accepted in partial fulfillment of the requirement of the degree of Master of Science in electrical power and control engineering program (specialization in electrical power engineering).

Name of student	Signature	Date
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Internal examiner	Signature	Date
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Head of department	Signature	Date
School dean	Signature	Date
Postgraduate dean	signature	Date

DECLARATION

I hereby declare that this MSc Thesis is my original work and has not been presented for a degree in any other university, and all sources of material used for this thesis have been duly acknowledged.

Name: Tesfaye Alemayehu Bekele

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This MSc Thesis has been submitted for examination with my approval as thesis advisor.

Name: ____

Signature: ________________________________

Date of submission: ___________________________

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TABLE OF CONTENT

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS

ELDP	Economic load dispatch problem
SA	Simulated annealing
PSO	Particle swarm algorithm
ABC	Artificial bee colony algorithm
NN	Neural networks
GA	Genetic algorithm and
DE	Differential evolution algorithm optimization
MATLAB	Matrix laboratory
BFOA	Bacterial forging algorithm
LSM	New local search mechanism
HPSAO	A hybrid particle swarm optimization combined simulated annealing
MOABC	Multi objective artificial bee colony algorithm
AI	Artificial Intelligent techniques

LIST OF ACRONYMS

P_H	Output active hydro power (MW)
q	Rate of water discharge(m3/s)
h	Effective water head(m),
η_t	Efficiency
η_g	Generator efficiency
A	Area of the reservoir (m2)
Ho	Minimum water head(m)
α, β	Model coefficients
A_i, B_i & C_i	Coefficients of the input - output
Q	Operating flow function (m3)
N	Number of generating unit
P_D	Total load demand
P_L	Transmission loss power.
P_{best}	Particles best solution value
G_{best}	Particles global best solution value
V_i (t)	Velocity of the i_{th} particle at iteration 'i'
Vmax	particles maximum velocity
Vmin	particles minimum velocity
$V_{(i,j)}^{(k+1)}$	Velocity of particle at iteration k+1.
W	Inertia weighting factor,
W_{max}	Maximum value of weighting factor,
W_{min}	Minimum value of weighting factor
Iter	Current iteration number
Itermax	Maximum iteration number.
P_T (x)	Boltzmann distribution
Ex	Energy of state x,
K	Boltzmann's constant
T	Temperature
S_j	Neighboring solution

X_{ij}	Initially food source
S_N	Number of food sources
MCN	Maximum Cycle Number (MCN).
L	Limit for scout bee
D	Number of optimization parameters
V_{ij}	Neighboring food source for Xij.
Φ_{ij}	Uniformly distributed real random number
f (i)	Cost value of Vi.
P_i	Probability value
Np	Colony size

ABSTRACT

Economic load dispatch (ELD) is a process of finding optimal generation scheduling of available generators in an interconnected power system to meet the demand of the system, at lowest possible cost (fuel consumption), while satisfying various operational constraints on the system. The main aim of this thesis is to minimize the generator power production cost (water consumption) and to keep the power outputs of the generator within prescribed limit by using meta-heuristics technics like particle swarm optimization (PSO), artificial bee colony (ABC) and simulated annealing (SA) algorithm Optimization Techniques. And the algorithms will be tested on gibe III hydroelectric power plant. This optimization problem involves economically scheduling the generating units with some constraints like meeting total load demand and losses within the power generation limits. The algorithms presented in this thesis also consider the effect of loss formula coefficient (Bmn-coefficients) and these methods has been implemented using MATLAB software. Finally, the obtained solution quality and computation efficiency of these techniques are compared. And simulated annealing algorithm has better discharge consumption and computation time efficiency compared to the rest proposed technics.

Keywords- economic load dispatch problem, meta-heuristics optimization technic, constraint.

CHAPTER 1

INTRODUCTION

1.1 General background

Electric power grids are considered to be one of the most complex man-made systems mainly due to their wide geographical coverage, various transactions among different utilities and diversity in individual electric power companies' layouts, size, and equipment used. Engineers need special tools to optimally analyze, monitor, and control different aspects of such sophisticated system. Some of these tools are economic dispatch, unit commitment, state estimation, automatic generation control, and optimal power flow. The main objective of electrical power utility is to ensure that electrical energy requirement from the consumer is delivered. However, for doing so, the power utility has also to confirm that the electrical power is generated with reduced cost.

Power system optimization is an important area in the operation, planning and control of power systems. Economic Dispatch is a method to find the electrical power to be generated by the committed generating units in a power system so that the total generation cost of the system is minimized, with satisfying the load demand simultaneously [1]. So, for economic operation of the system, the total demand must be equally shared among the generating units with an objective to minimize the total generation operation cost for the system.

To show this problem, Optimization is a necessary in solving the cost minimization problems. Load variation depends upon the output of generators must be changed to meet the balance between loads and generation power to make the system efficient. Economic load dispatch is one of the basic problems in power system operation and planning.

It is defined as the process of giving generation levels to the generating units so that the system load is supplied fully and most economically [2]. It concerned on the reduction of an objective function, usually the total cost of generation (flow utilization), while considering both the equality and inequality constraints.

1.1.1 Economic load dispatch

Many deterministic & meta- heuristic techniques to the solution of complex power system optimization problems have been proposed, each differing in their procedure of representation, implementation and solution procedure. Most of the early methods proposed to solve the economic load dispatch problem used deterministic techniques. Now day's optimization based on swarm intelligence, known as meta-heuristic algorithms, gained popularity.

1.1.2 Deterministic techniques

Most of the early methods proposed to solve the economic load dispatch (ELD) problem used deterministic techniques such as non-linear programming (NLP), dynamic programming (DP), and variational techniques based on Lagrange multipliers [3-4]. These methods have a difficulty of getting trapped in local extrema, divergence situations and in solving complex and real-world optimization problems. In reality, a generating unit cannot exhibit a convex cost function, as there are various practical limitations in operation and control. None of these methods may be able to provide a global optimal solution, for they usually get stuck at a local optimum.

1.1.3 Meta-heuristics Algorithm

Optimization based on swarm intelligence, known as meta-heuristic algorithms, gained popularity in solving complex and real-world optimization problems years ago. modern heuristics stochastic search algorithm such as Simulated annealing (SA), Neural networks (NN), Differential evolution algorithm (DE), Genetic algorithm(GA) and Particle swarm optimization (PSO) may prove to be efficient in solving ELD problem with no restriction on the non-convex and nonlinear characteristic of the problem due to their powerful searching ability [5-6].

They solve non-convex optimization problems efficiently and often achieve a fast and near global optimal solution. Because the performance of most of the meta-heuristic methods are independent of the initial solutions and are derivative free, they overcome the main limitations of deterministic optimization.

To search for the optimal solution, classical deterministic methods, also known as derivative-based optimization methods, apply techniques such as the gradient and Hessian operators. They use single path search methods while heuristic methods use population-based search techniques to search the solution hyperspace. This difference, in fact, is an advantage for the heuristic methods as it helps searching in spaces with non-smooth characteristics. It also improves convergence for heuristic methods and makes it less dependent on the initial solution points. Being derivative-free, modern methods are applicable to any optimization problem regardless of the linearity or nonlinearity of its objective function and constraints. Another main difference between the two classes is that heuristic methods use stochastic techniques and include randomness in moving from one solution to the next while determinist methods follow deterministic transition rules. This, of course, gives an advantage to heuristic methods in avoiding local minima.

In this thesis, a hydro power plant consists of ten generating unit considered for the economic load dispatch problem. And among Meta-heuristics methods particle swarm optimization (PSO), simulated annealing algorithm (SA) & artificial bee colony algorithm (ABC) are chosen to solve the economic load dispatch (ELD) problem.

1.2 Statement of the problem

Hydro power plants have been used for electricity generation for a long time due to its low operational cost, high energy conversion efficiency, and because it uses a renewable primary resource, the water. Nevertheless, water is an important resource that must be handled with care, to ensure long term sustainability. In the hydropower system, for meeting for the system load and hydropower unit alternate requirements, and for the system running of technical constraints, the hydropower economic dispatch problem is to determine the status of the hydropower machine and to distribute the load of the hydropower unit for minimum total water consumption. The objective of the hydro economic load dispatch problem is to schedule committed generating unit outputs so as to meet the required load demand at minimum flow while satisfying all unit and system equality and inequality constraints. In

this thesis the economic load dispatch problem of a single objective problem is considered, which is minimization of the water discharge of the hydropower plant, its function is modeled as a quadratic function in terms of output active power subjected to system equality and inequality constraint. And meta- heuristics method is proposed to solve the optimization problem.

1.3 Significance of the study

The modern power system around the world has grown in complexity of interconnection and power demand. The focus has shifted towards the enhanced performance, increased customer focus, low cost, reliable and clean power. In this changed perspective, scarcity of energy resources, increasing power generation cost, environmental concern necessitates optimal economic load dispatch (ELD). In reality power stations neither are at equal distances from load nor have similar fuel cost functions. Hence for providing cheaper power, load has to be distributed among the various power stations in a way which results in lowest cost of generation.

Increasing load demand of power system leads to more complexity of the network. More and more generating units are added in the existing power system network, this increase in complexity results in uneconomical operation of the power system.

As we know electricity has become an important resource of our country and thus efficient use of it is a must for an electrical optimal power system operation. Economic dispatch benefits electricity users in a number of ways. By systematically seeking the lowest cost of energy production consistent with electricity demand, economic dispatch reduces total electricity costs. To minimize costs, economic dispatch typically increases the use of the more efficient generation units, which can lead to better fuel utilization, lower fuel usage from using less-efficient generation. As the geographic and electrical scope integrated under unified economic dispatch increases, additional cost savings result from pooled operating reserves, which allow an area to meet loads reliably using less total generation capacity than would be needed otherwise. Economic dispatch requires operators to pay close attention to system conditions and to maintain secure grid operation, thus increasing operational reliability without increasing costs.

1.4 Objective of the problem

Optimal economic operations of power generation systems are comprehensively investigated in this thesis considering various operational bounds. The proposed optimization technics for the hydro economic load dispatch problems are studied taking into account various constraints

1.4.1 General objective

To solve economic load dispatch problem (ELD) for scheduling the committed generating unit outputs so as to meet the required load demand at minimum flow consumption while satisfying constraints using Mata-heuristics swarm algorithm ABC, PSO and SA.

1.4.2 Specific objective

- To study and solve eld problem using pso, abc and sa optimization techniques.
- To simulate and demonstrate capability of these proposed techniques to find the global solution for the optimal dispatch power generations using matlab software.
- To compare the obtained solution quality and computation time efficiency of these proposed techniques.

1.5 Scope of the study

This thesis focuses on the solution for online economic load dispatch problem of a hydropower plant which controls the committed generators output such as the generation water flow utilization is minimized while satisfying the power demand and other constraints.

Particle swarm optimization simulated annealing algorithms and artificial bee colony algorithm are proposed for the economic load dispatch problem. The objective function which is flow function for the proposed optimization methods are single objective nonlinear characteristic function.

In addition, Bmn loss coefficient, the minimum and maximum active power limits are considered, and optimal economic dispatch of the power plant is carried out with mat-lab software for one-hour scheduling period.

1.6 Organization of the thesis

This thesis is organized in to five chapters.

Chapter 1: This chapter is the introduction part of the thesis. It discusses the statement of the problem, significance of the study, objectives of the study, and scope of the thesis.

Chapter 2: This chapter presents the background and literature review, involves a theoretical study of the objective function and optimization methods applied to hydropower plant.

Chapter 3: Presents the methodology; it includes problem formulation, formulation and implementation of the proposed method.

Chapter 4: Presents the result and discussion of the proposed technics for this thesis.

Chapter 5: Presents the conclusion and recommendation

Appendix A: gibe iii hydro power plant production data

Appendix B: Simulation algorithm for simulated annealing algorithm

Appendix C: Simulation algorithm for particle swarm optimization algorithm

Appendix D: Simulated algorithm for artificial bee algorithm

CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

2.1 Introduction

Economic operation and planning of electrical power systems have always been a primary concern in the electrical power industry. Optimal economic operation of power generation systems is achieved through the efficient use of the available fuel which comes mostly from irreplaceable natural resources. Operating costs of different generating units are dissimilar due to various reasons such as their characteristics and efficiencies and the distances between their locations and load centers. Consequently, an optimal power generation schedule that determines the generation level of each of the units is essential to meet the load demand at the minimum cost. Obtaining the optimal economic generation schedule can only be realized by considering various operational constraints. This chapter is devoted to the economic load dispatch of hydroelectric power systems.

2.2 Hydropower plant

For many years, hydroelectric power has been considered as one of the most efficient and magnificent sources of power generation. It played an essential role in the development of humanity. It is a conventional renewable energy source for generating electricity in small- and large-scale production. Hydroelectric power is also the most desirable and has a long and successful track record.

Hydropower is the power derived from the energy of falling water (as in waterfalls) or fast running water (as in rivers or long water streams). A schematic showing a cross-section of a typical hydroelectric power facility is shown in Figure 1. In this figure, water (the working fluid) is collected in a reservoir just behind a dam. The water accumulation behind the dam is normally dependent on several factors such as the intensity, distribution, and duration of rainfalls; the field moisture capacity of the basin or reservoir soil; and the direct evaporation, transpiration, and ground infiltration.

The working fluid is then transported through large pipes (called penstock) to the inlet of one or more hydro turbines at the base of the dam. The Hydro energy available from conversion to mechanical shaft work is the potential energy of the water in the main reservoir. The water makes the hydro turbine rotate by action of the available hydro energy contained in the water. Nowadays, hydro turbines are made more compact and usually operate at high rates of rotation and with high mechanical efficiency. The mechanical shaft work is then converted into electricity using the electric generator coupled with the hydro turbine shaft in the powerhouse. The power is then regulated using electric transformers before being transmitted through powerlines to the main electric grid.

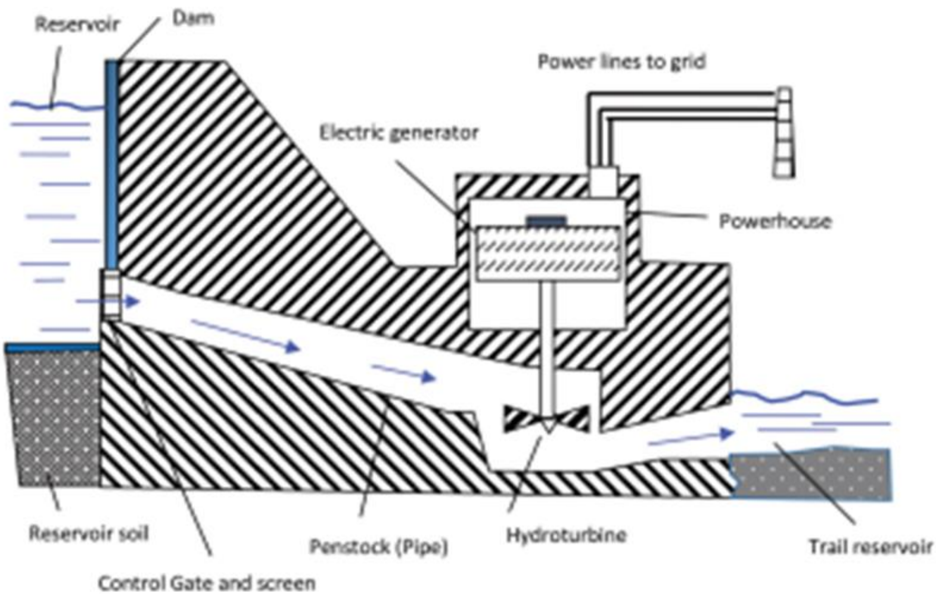

Figure 2.1. typical hydropower working mechanism

2.2.1 Hydro power plant modeling

Hydropower plant is the most important and widely used renewable source of energy. In a hydro plant, turbines convert the water potential energy into kinetic energy, which in turn is converted into electric form through the generators. Hydroelectric installations are classified into two types-conventional and pumped storage. The conventional type is further classified into two classes, storage and run-of-river".

- **pumped-storage plants**- A pumped-storage hydro plant consists of an upper and a lower reservoir. During light load periods, water is pumped from the lower to the upper reservoirs using the most economic energy available as surplus from other sources in the system. During peak load periods, water stored in the upper reservoir is released to generate power, displacing high cost fossil generation.

- **Run-of-river plants**- These plants have little storage capacity and use water as it becomes available. Water not utilized is spilled over. The power station can be located in the stream or alongside. The latter is commonly referred to as a canal-type power station. It is clear that in view of the unregulated flow, the generated electric power of a run-of-river plant is not a controllable variable. In economy dispatch studies for systems with run-of-river plants, the output of such a plant is considered as a negative load in arriving at the system load demand.

- **Storage plants**- Plants with reservoirs of significant storage capacity are termed storage plants. In periods with low power requirements water can be stored and utilized when the demand is high. Economic load dispatch problem of systems with storage-type hydro plants is the subject of further discussion in this thesis.

2.2.2 Hydro turbine modeling

Hydro turbines can be classified into two general types. These are; reaction type and impulse type. In the first type, water under pressure enters the turbine after it is partly converted into velocity. The most commonly used turbines of this type are the Francis wheel, the Kaplan wheel and propeller wheel. In the second type, water under pressure is entirely converted into velocity. The output active power of a hydro turbine is expressed in terms of rate of water discharge and the effective head as follows:

$$\mathrm{PH} = \left(\frac{\mathrm{qh}}{120}\right)\eta_t\eta_g \tag{2.1}$$

Where,

- PH: Output active hydro power (MW)
- q: Rate of water discharge(m3/s)
- H: Effective water head(m),

- η_t: Turbine efficiency
- η_g: Generator efficiency

Due to the diversity of installation characteristics, there exist several different models. All these models are principally based on Equation (2.1). The following are the most used models.

i. **Glimn-Kirchmayer Model**-This model is the most popular one in which the rate of discharge is mathematically expressed as a bi-quadratic function of the active power and net water head.

$$Q = K\varphi(h)\phi(p_h) \tag{2.2}$$

$$\varphi(h) = a_0 + a_1 h + a_2 h^2 \tag{2.3}$$

$$\phi(p_H) = b_0 + b_1 h + b_2 {p_H}^2 \tag{2.4}$$

Where,

- Q: Rate of water discharge(m3/s).
- P_H: Active power
- h: Net head of the power plant
- K: Constant of proportionality
- $\varphi(h), \phi(p_H)$: Independent function.

ii. **Hildebrand Model-**This model is a more generalized form than the Glimn-Kirchmayer model. The rate of discharge of this model is given by:

$$Q = \sum_{i=0}^{k} \sum_{j=0}^{l} c_{ij} {p_H}^i h^j \tag{2.5}$$

Where,

- Q: Rate of water discharge(m3/s).
- P_H: Active power
- h: Water head of the power plant
- Cij: Hydro turbine model coefficient
- k: Maximum exponent,
- l: Maximum exponent

iii. **Hamilton-Lamonts Model**-The mathematical representation of rate discharge of this model is given by:

$$Q = (a_0 + a_1 h + a_2 h^2)(b_0 + b_1 h + b_2 {p_H}^2) \qquad (2.6)$$

Where,

- Q: Rate of water discharge(m3/s).
- P_H: Active power.
- h: Water head of the power plant.
- a_0, a_1, a_2, b_0, b_1, b_2: Constant coefficient.

iv. **Arvanitidis-Rosing Model**-Unlike the previous models that describe the rate of water discharge in terms of net head and power generation, this model defines the output power as an exponential variation of net head and reservoir storage:

$$P_H = qh(\beta_R - e^{\alpha_R} A(h - h_0) \qquad (2.7)$$

Where,

- P_H: Active power
- q: Rate of water discharge(m^3/s)

- h: Water head of the power plant.
- A: Area of the reservoir (m^2).
- h, ho: Maximum, minimum water head.
- α, β : Model coefficients.

2.3 Economic load dispatch problem

The aim of real power economic dispatch (ED) is to make the generator' s fuel consumption or the operating cost of the whole system minimal by determining the power output of each generating unit under the constraint condition of the system load demands. The fundamental of the economic dispatch problem is the set of input - output characteristic of a power - generating unit.

2.3.1 Input-output characteristic

The factors influencing power generation are operating efficiencies of generators, water consumption and transmission losses. The total water consumption of generation is a function of the individual generation of the sources which can take values within certain constraints. The problem is to determine the generation of different plants such that total flow consumption is minimum. The input to the hydro plant is generally measured in m3/h and the output power is the active power in MW. A simplified input-output curve of a hydro unit known as flow-rate curve is shown in Figure 1. It can be observed from the input - output characteristic of the generating unit that the power output is limited by the minimal and maximal capacity of the generating unit. The lower limit of the output power Pmin is the minimum economical loading limit below which the operation is infeasible technically and/or economically. On the other hand, Pmax represents the upper limit and the maximum output power.

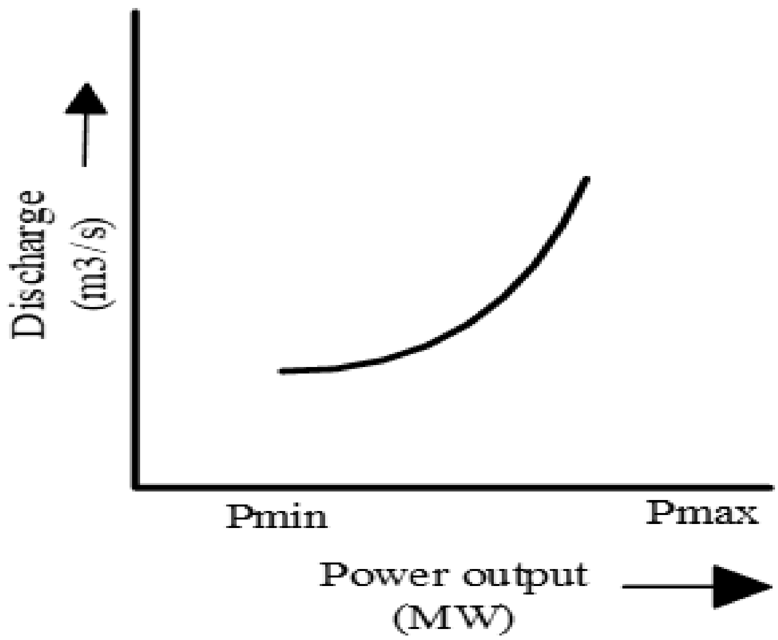

Figure 2.2-Input- output characteristics function curve

In all practical cases, the input-output characteristics function of any generator unit 'i' can be represented as a quadratic function of the real power generation [6] .

$$Q(p_i) = c_i + b_i * p_i + a_i * {p_i}^2 \quad (2.8)$$

Where,

- P_i: Output active hydro power (MW).
- Q (P_i): Rate of water discharge(m3/s).
- a_i, b_i & c_i coefficients of the input - output characteristic.

The derivative of the fuel cost curve with respect to the active power results in an important characteristic which is a measure of the flow consumption of the next increment of power.

$$\frac{\partial Q(p_{gi})}{\partial p_{gi}} = 2a_i * p_{gi} + b_i \quad (2.9)$$

2.3.2 Calculation of input-output characteristics parameter

The parameters of the input-output characteristic of any generating unit can be determined based on the experiments of the generating unit efficiency, based on the historic records of the generating unit operation, based on the design data of the generating unit provided by manufacturer. In the Practical power systems, we can easily obtain the flow rate data and power output statistics data. Through analyzing and computing data set we can determine the shape of the input-output characteristic and the corresponding parameters.

System constraints

The economic dispatch problem is designed to determine the optimal loading of all committed generating units to minimize the cost function by satisfying power system constraints while in operation. the ELD problem can be formulated with the following objective function:

$$MinQ = \sum_{i=1}^{n} Q_i \tag{2.10}$$

Where,

- Qi: Operating flow function.
- n: Number of generating unit.

Subjected to system constraints and this constraint can be classified into two [7].

Equality constraints - There is only one equality constraint in this system which is known as system power balance equation and it states the sum of all the generating units online must equal the system load plus the transmission losses. The system power balance constraint is given by:

$$\sum_{i=1}^{n} p_i = p_D + p_l \tag{2.11}$$

Where,

- Pi: Active power.

- PD: The total load demand.
- PL: The transmission loss.

The simplest form of loss equation is George's formula, which is given by:

$$P_L = \sum_i^n \sum_j^n p_{gi} \mathcal{B}_{ij} p_{gj} \qquad (2.12)$$

Where,

- P_L: Active power loss.
- P_{gi}: Active power of generator.
- B_{ij} : The loss coefficient.
- N: Number of generators

Inequality Constraints - Inequality constraints are constraints due to physical and operational limitations of the units and components will arise in economic scheduling. Generating unit capacity limit is one of the equality constraint limits in this system and it states there is a limit to the maximum amount of power system generator can generate. Similarly, the generators have a lower limit in terms of output below which the production would be uneconomical. This is given as an inequality constraint for a power system. It is usually given as below.

$$P_H^{min} \le p_H \le P_H^{max} \qquad (2.13)$$

Where,

- pH: Active power of hydropower plant.
- P_H^{min}, P_H^{max}: Min and max of active power of hydropower plant.

The proposed method is implemented to determine the optimal ELD of the case studies shown in the next chapter. The case study represents the ELD problem considering the system losses in the objective function and the algorithm was implemented in MATLAB 15a.

2.4 Meta-heuristics methods

In order to survive, the main objective of all creatures is foraging. Foraging behavior is cooperative in the same species. Each agent in the swarm communicates with others in such a way to find the food in the shortest time and way. Collective foraging behaviors of the lively beings are called swarm intelligence. This capability of all lively beings gives inspiration to the human being in order to find solutions to the optimization problems.

Optimization based on swarm intelligence, known as meta-heuristic algorithms, gained popularity in solving complex and real-world optimization problems. They solve non-convex optimization problems efficiently and often achieve a fast and near global optimal solution. Because the performance of most of the meta-heuristic methods are independent of the initial solutions and are derivative free, they overcome the main limitations of deterministic optimization [9].

2.4.1 Overview of particle swarm optimization

Natural creatures sometime behave as a Swarm. One of the main streams of artificial life researches is to examine how natural creatures behave as a Swarm and reconfigure the Swarm models inside the computer.

Particle swarm optimization is a population based stochastic optimization technique first described by Dr. Eberhart and Dr. Kennedy in the year of 1995 [10]. PSO is inspired by observation of swarming behaviors of fish schooling or bird flocking and field of evolutionary algorithm which is one of the modern meta-heuristic algorithms. The potential solution in PSO called particles swarms fly through the problem space following the optimum particles. The role of swarm is to gather data from each array built by their individual position and after that they refresh their Position by the use of velocity of the particles.

In PSO the swarm initially has a population of random solutions and each single solution is in the search space called particle. Each particle has fitness values, which are evaluated by the fitness function to be optimized, and have velocities, which direct the flying of the particles. All the particles have memory and each particle keeps track of its previous best position (Pbest) and the corresponding fitness value. The swarm has another value called Gbest, which is the best value of all the Pbest. After finding the two best values, the particle updates its velocity and positions [11-12].

2.4.2 Overview simulated annealing algorithm

The simulated annealing method is a heuristic optimization technique and it has the ability to find global solutions for large combinatorial optimization problems. The simulated annealing algorithm was originally inspired from the process of annealing in the metal works. Annealing involves heating and cooling a material to alter its physical properties due the changes in the internal structure. SA is a nature inspired method which is adapted from process of gradual cooling of metal in nature. The name and inspiration come from annealing in metallurgy, a technique involving heating and controlled cooling of a material to increase the size of its crystals and reduce their defects. The heat causes the atoms to become unstuck from their initial positions and wander randomly through states of higher energy; the slow cooling gives them more chances of finding configurations with lower internal energy than the initial one.

By analogy with this physical process, each step of the SA algorithm replaces the current solution by a random "nearby" solution, chosen with a probability that depends both on the difference between the corresponding function values and also on a global parameter temperature T, that is gradually decreased during the process. The dependency is such that the current solution changes almost randomly when T is large, but increasingly "downhill" as T goes to zero. The allowance for "uphill" moves potentially saves the method from becoming stuck at local optima which are the bane of greedier methods [13].

2.4.3 Overview of artificial bee colony algorithm

Artificial Bee Colony (ABC) is a swarm based a meta- heuristic search algorithm which imitates the scrounging behavior of honeybees. In ABC algorithm, the colony of artificial bees consists of three groups of bees: employed bees, onlookers and scouts.

Some of the bee of colony consists of employed artificial bees and the some includes the onlookers. Here, the number of employed bees is equal to the number of food sources around the hive. The employed bee whose food source has been abandoned becomes a scout. The position of food source determines the solution and the amount of nectar represents the fitness of the respective solution. An artificial onlooker bee chooses a food source depending on probability value associated with food source.

In ABC, provided that a position cannot be improved further through a predetermined number of cycles, that food source is assumed to be abandoned. The value of predetermined number of cycles is an important control parameter of the ABC algorithm, which is called limit for abandonment [14-15].

2.5 Literature review

The ELD problem has been widely studied and reported by different authors. Based on the research area of interest, this review covers published paper related to economic load dispatch problem. A variety of optimization methods and techniques have been proposed to solve the problems of power systems optimal operations. To search for the optimal solution, classical deterministic methods, also known as derivative-based optimization methods, apply techniques such as the gradient and Hessian operators. They use single path search methods while heuristic methods use population-based search techniques to search the solution hyperspace.

This difference, in fact, is an advantage for the heuristic methods as it helps searching in spaces with non- smooth characteristics. It also improves convergence for heuristic methods and makes it less dependent on the initial solution points. Being derivative-free, modern methods are applicable to any optimization problem regardless of the linearity or nonlinearity of its objective function and constraints.

In contrast, different deterministic methods are required for different optimization problems. Another main difference between the two classes is that heuristic methods use stochastic techniques and include randomness in moving from one solution to the next while determinist methods follow deterministic transition rules. This gives an advantage to heuristic methods in avoiding local minima.

Mirtunjay. K. Modi etal [1] In this paper, Stochastic Economic Load Dispatch (ELD) problem with multiple fuels is solved using Improved Particle Swarm Optimization (IPSO). Generally, ELD problem is solved using deterministic models, but data required for such studies are rarely available with complete certainty. So, uncertainties in unit’s generation, load demand and cost coefficients should be considered to get actual scenario. Thus, stochastic model for ELD problems is more suitable than deterministic model from the utilities point of view.

M. Nazari-Heris etal [2] The short-term hydrothermal scheduling (STHS) problem is providing a daily planning of hydro and thermal generations, aiming to minimize the total fuel cost of thermal plants. The minimization of total operation cost of hydrothermal power system is considered as a complex nonlinear hard optimization problem with a series of several equality and inequality constraints. This paper proposes real-coded genetic algorithm with an improved Mühlenbein mutation (RCGA-IMM) for the solution of STHS optimization problem, considering the minimization of operation cost which satisfies hydraulic and electrical constraints. The proposed optimization procedure is employed on two test systems in which different constraints have been considered including valve point loading effect of thermal units and transmission losses. The provided optimal solutions have been compared with recent studies in this area, which manifest superiority of the proposed method. It is found that the proposed RCGA-IMM has the capability of obtaining better solutions with respect to other optimization methods which are implemented on STHS problem.

Susheel Kumar et al [3] Economic load dispatch (ELD) problem is very important part of the power system. The purpose of economic dispatch is to determine the generation of different units in a plant such that the total fuel cost is minimum and at the same time the total demand and losses at any instant must be equal to the total generation. Many traditional methods such as lambda iteration, gradient method, Newton’s method etc. are applied to determine the optimal combination of power output of all generating units so as to meet the desired demand without violation of generator constraint.

This paper presents lambda iteration method to solve the ELD problem using MATLAB for three and six generating units with and without transmission losses.

Guozhong Wu [4] Bacterial Foraging Optimization Algorithm (BFOA) is a kind of algorithm of simulating the human E. Coli. The main characteristics of this method are distributed computation, good robustness and a good search efficiency. In this paper, the economic dispatch of hydropower system has been studied. Using BFOA, the method of solving the problem of economic dispatch of hydropower system is given. Simulation results show that the proposed method is higher efficiency than the conventional one.

Hari Mohan Dubey [5] This paper presents a comparative analysis of efficient and reliable modern programming approach using quadratic programming (QP) and general algebraic modeling system to solve economic load dispatch (ELD) problem. The proposed methodology easily takes care of different equality and inequality constraints of the power dispatch problem to find optimal solution. To validate the effectiveness of algorithm simulations have been performed over four different cases i.e. Crete Island system of 18 thermal generating units, twenty generating units' system with losses, practical Taiwan Power Company data which consists of 40 generating unit system and a very large system consisting of 110 generating unit. Results obtained with the proposed method have been compared with other existing relevant approaches available in literatures. Experimental results support the claim of proficiency of the method over other existing techniques in terms of robustness and most importantly its optimal search behavior.

Gaurav Prasad Dixit et al [6] this paper presents an artificial bee colony (ABC) algorithm-based method for solving the economic load dispatch (ELD) problem. The objective is to minimize the nonlinear function, which is the total fuel cost of thermal generating units, subject to the usual constraints. The proposed ABC method has been examined for Crete Island system consisting of 18 thermal generating units having quadratic (Convex) cost function, standard IEEE 30 bus system consisting of six generating units and a 15 generating unit system with emission constraints. ABC algorithm is easy to implement and capable of searching near global optimum solution at fast convergence and efficiency.

Pirmahamad [7] Optimal System operation involves the Consideration of economy of operation, system security, emission of certain fossil-fuel plant. The main aim of this study is to minimize the fuel cost and to keep the power outputs of the generator within prescribed limit with the use of An Ant colony Optimization Techniques. It is based on the ideas of ant foraging by pheromone communication to make path. Ant Colony Optimization technique is a metaheuristic approach for solving hard combinatorial optimization problems which can be applied for power system optimization. The work reported in this paper is carried out with the objective to make use of Ant colony Optimization for solving the economic load dispatch problem. IEEE-26 Bus 6 generator system is considered to test the Algorithm with quadratic cost functions.

M.Suman et al [9] In this paper Economic Load Dispatch solutions are solved by using Lambda Iteration and Back Propagation Neural Network Methods. A three-generator system is considered and by using lambda iteration method Economic Load Dispatch is determined and 150 patterns for different loads will be derived from same method to train neural network. As it is too slow method, a soft computing-based approach i.e. Back Propagation Neural Network (BPNN) proposed for determining the optimal flow. This method provides fast and accurate results when compared with the conventional method.

Fahad S. Abu-Mouti [14] In this paper, the artificial bee colony (ABC) algorithm– a recently introduced population-based technique is utilized to solve the DED problem. Integrating a renewable-energy source and analyzing its impact is considered as well. A sample test system five generating units with a dispatch period of 24-hour is designated to validate the outcomes. The promising results prove that the ABC algorithm has a great potential to be applied in different electric power system optimization areas.

Belkacem et al [15] this paper presents an improved artificial bee colony (IABC) optimization method to solving practical economic dispatch taking into account the nonlinear generator characteristics such as valve-point loading effects. In order to exploit the performance of this new variant based ABC method to solving practical economic dispatch, a new local search mechanism (LSM) associated to the original ABC algorithm; it allows exploiting effectively the promising region to locate the best solution. The proposed approach has been examined and applied to many practical electrical power systems, the 13 generating units, and to the large electrical system with 40 generating units considering valve point loading effects. From the different case studies, it is observed that the results compared with the other recent techniques demonstrate the potential of the proposed approach and show clearly its effectiveness to solve practical and large ED.

Abu Umar Attai [16] this paper presents the solution of economic load dispatch problem with quadratic cost function by using Particle Swarm Optimization (PSO). The method's capability of solving economic dispatch problem in power system is tested and validated ontwo sample networks: IEEE 3-generating units, 6-bus test system and the Nigerian network were considered in order to verify the performance of the approach in practical applications. The results show that PSO has the ability of minimizing cost of productions in power system operations.

Yongqiang Wang et al [17] A hybrid particle swarm optimization combined simulated annealing method (HPSAO) is proposed to solve economic load dispatch in this paper. The Simulated annealing (SA) algorithm is used to help PSO jump out the local optimum. Furthermore, a feasibility-based rule is introduced to deal with the constraints. Finally, HPSAO is tested on Three Gorges hydroelectric plant. The results are analyzed and compared with other methods, which show the feasibility and effectiveness of the HPSAO method in terms of solution quality and computation time.

Hardiansyah et al [18]. This paper presents particle swarm optimization (PSO) technique for the economic load dispatch problem. The results have been demonstrated for ELD of standard 3-generator and 6-generator systems with and without consideration of transmission losses. The final results obtained using PSO are compared with conventional quadratic programming. computation is capable of efficiently determining higher quality solutions addressing economic dispatch problems.

Y. S. Haruna et al [19] This paper deals with the optimization of economic load dispatch (ELD) problem using the particle swarm optimization (PSO) algorithm. PSO is applied to search for the optimal schedule of all the generator units that can supply the required demand at minimum fuel cost while satisfying all system constraints. The PSO algorithm has been implemented using MATLAB optimization toolbox and was applied to solve the ELD problem on thermal power stations. The results were compared with published results obtained via micro-GA, conventional-GA and differential evolution (DE) techniques.

Ismail Ziane and Farid Benhamida [21] This paper gives the optimal of economic load dispatch when the fuel cost function can be defined as cubic function. The fuel cost is described with 4 parameters. In this paper, simulated annealing method is used to find the optimal solution. The SA algorithm is used to minimize the fuel cost and the losses in the power systems. In this study, in order to evaluate the performance of the SA algorithm, it is tested on 2 different unit systems. The results obtained from the proposed method are compared other methods reported previously in the literature. The results show that the SA algorithm is better than the others at solving such a problem.

D. Reeshma et al [23] this paper presents Simulated Annealing (SA) algorithm for Optimum Static Load Dispatch optimization problem. The proposed approach is found to provide optimal results while working with the load balance constraint and the operating limit constraints of the generators. Transmission losses are incorporated in the algorithm. And also, it is investigated on two different standard test cases consisting of 3 unit and 6-unit test systems. The proposed method has been compared with other existing relevant approaches like Artificial Bee Colony (ABC) algorithm, Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and also with classical optimization technique i.e., lambda iteration method.

M. Venkatesh, Ramakrishna Raghutu [24] Economic load dispatch is the process of allocating the required load demand between the available generating units such that the cost of operation is minimized. There have been many algorithms proposed for economic dispatch such as genetic algorithm, particle swarm optimization, and differential evolution. Out of which a simulated annealing (SA) was found to be one of the best methods that is discussed in this paper. Simulated Annealing (SA) algorithm for optimization inspired by the process of annealing in thermodynamics to solve economic load dispatch (ELD) problems. The proposed approach is found to provide the optimal results while working with operating constraints in the ELD and valve point loading effects. In this paper the efficiency for the three (3) generators and forty (40) generators is tested by MAT Lab coding. Also, it is further extended for fifty (50) generators.

Ismail Ziane et al [25] this paper presents a multi-objective Simulated Annealing Optimization to solve a Dynamic Generation Dispatch problem. In this work, the problem is formulated as a multi-objective one with two competing functions, namely economic cost and emission functions, subject to different constraints. The inequality constraints considered are the generating unit capacity limits while the equality constraint is generation-demand balance. To show the advantages of the proposed algorithm, it has been applied for solving multi-objective EELD problems in a 3-generator system with NOx and SO2 emission. Results obtained with Simulated Annealing have been compared with other existing relevant approaches available in literatures. Experimental results show a proficiency of Simulated Annealing over other existing techniques in terms of robustness.

X. Liao et al [27]. This paper is aim to present multi-objective evolutionary algorithm named multi objective artificial bee colony (MOABC) algorithm and compares the efficiency of MOABC and established algorithms in long-term cascaded hydropower system dispatch. The performance of proposed MOABC has been demonstrated through a set of standard test functions on Three Gorges Project (TGP). The results showed the proposed method have a better convergence ability and distribution of the Pareto front.

Ganga Reddy Tankasala [28] This paper deals with optimization of fuel cost of coal fired generators of a modern power system. The conventional method of solving economic load dispatch (ELD) uses Newton Raphson, Gauss and Gauss Seidel techniques whose time of computation increases exponentially with the size. In order to overcome the drawbacks of conventional methods, Artificial Intelligent (AI) techniques likes like Genetic Algorithm (GA), Nueral Networks (NN), Artificial Immune systems (AIS) and Fuzzy Logics etc… are used. One such AI technique used is Artificial Bee Colony optimization (ABC) inspired from the foraging behaviour of bees. The ABC is applied for ELD and compared with the other

AI techniques. The results show that ABC promises global minimum of the solution while others may land in local minimum.

S. Lavanya, Dr. SP. Umayal [29] In this paper the problem of economic dispatch is solved by means of Artificial Bee Colony Algorithm (ABC). ABC is good at exploration the optimization problem involves economically scheduling the generating units with some constraints like meeting total load demand and losses within the power generation limits. The algorithm presented in this paper also considers the effect of Bmn coefficients. The performance of the algorithm is applied and tested on IEEE 6 units systems and is compared with the results of Genetic Algorithm and Simulated Annealing.

CHAPTER 3

METHODOLOGY

3.1 Introduction

In this chapter data required and data analysis for economic load dispatch problem as well as formulation of economic load dispatch problem and the proposed technics for the economic load dispatch problem are presented.

3.1.1 Location

The Gibe III hydropower plant is located within the Omo Gibe River Basin in Ethiopia, lies 6°50′50″N latitude and 37°18′5″E longitude about 62 km (39 mi) west of Sodo in the Southern Nations, Nationalities, and Peoples' Region.

Figure 3.1-Gibee III hydropower location

3.1.2 Gibe-III hydropower plant

Gibe III hydro-electric power plant was constructed on the Omo River in Ethiopia's Southern Nations, Nationalities, and People's Region State (SNNPRS). It is the largest hydroelectric power plant in Ethiopia with an estimated production capacity of 6,500GWh a year. The plant includes a 243m roller compacted concrete dam, the first of its kind in Ethiopia and one of the tallest in the world. And has a crest length of 610m and was constructed at an altitude ranging between 650m and 1,650m above sea level. Its reservoir has a total storage capacity of 14.7 billion cubic meters. The surface powerhouse is located on the left side of the river and contains ten vertical-axis Francis turbines each with a nominal power output of 187MW. It also includes two power tunnels both 11m in diameter. Each tunnel is connected to five generator units using two penstocks and manifolds.

Figure3.2-Gbee III hydropower plant dam

3.2 Data collection

For this thesis the collected data is the flow statistics data and power output statistics data from gibe III hydropower plant planning and generation operation main office Leghari, Addis Ababa and from site. The data contain the active power production capacity for available generating units and the load demand for each scheduling interval which one hour as well as the water discharge. In addition, it has the information about water availability and reservoir level. Sample of these data is placed at the appendix.

3.2.1 Data Analysis

Primary data from the site and secondary data obtained from office used for this thesis. By analyzing and computing the data obtained data sets are used to determine parameters like flow coefficients for flow function, loss coefficient, the maximum and minimum active power for the purpose of proposed optimization problem in this thesis.

Hourly load

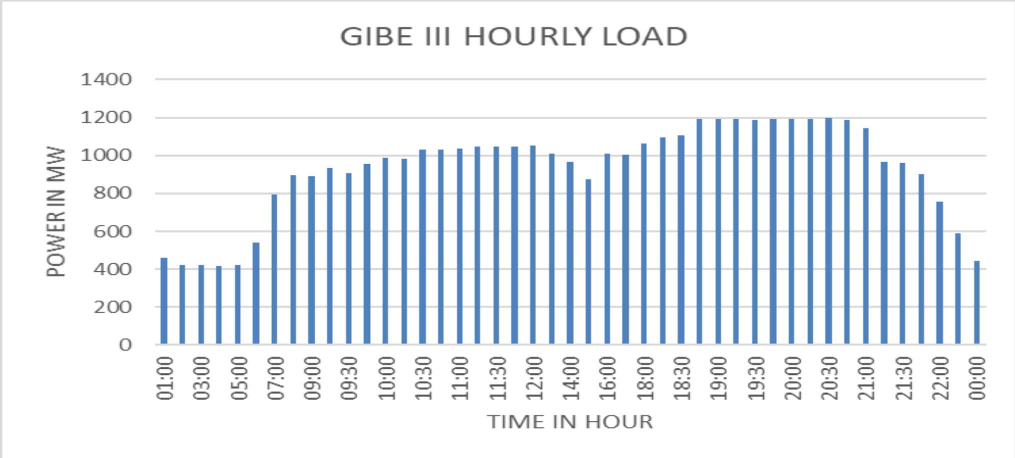

Figure 3.3-Gibe III hourly load

Case study

$$Q(t) = \begin{cases} 0.277 * P & for\ P \leq 760 \\ 0.5454 * P & for\ P > 760 \end{cases} \tag{3.1}$$

The water discharge rate in quadratic form is expressed as:

$$\text{Q(t)=0.5454P + 0.0000911p^2} \tag{3.2}$$

The water reservoir of the hydro plant is limited to a drawdown of 40331.9 m3 at reservoir level of 853.47 masl for 1 hour.

$$\int_0^t q(t)\, dt = 40331.94\ m^3 \tag{3.3}$$

The scheduling load is at systems peak and min load which are 1155 and 385.6 MW respectively

3.3 Hydro economic load dispatch problem

Economic Dispatch (ED) problem is an optimization problem that determines the power output of each online generator that will result in a least cost system operating state. The objective of the economic load dispatch is to minimize the total operation cost or fuel utilization (amount of water discharge) of each online generator. This power allocation is done considering system balance between generation and loads, and feasible regions of operation for each generating unit. Economic load dispatch problem can be formulated as follows.

3.3.1 Hydro model

As mentioned above in the earlier chapter, the input-output characteristics of a hydro-electric generating unit is formulated as a water discharge rate in terms of its reservoir's effective

water head and the output active power as defined by the Glimn-Kirchmayer model equation (3.4) below.

$$\mathrm{Q(t)} = \mathrm{K}\varphi(\mathrm{h})\phi(\mathrm{p_h}) \tag{3.4}$$

Where,

- Q(t): Water discharge rate for the reservoir at time t.
- $\varphi(\mathrm{h})\phi(\mathrm{p_h})$: Independent functions as defined in Equations.
- K: Constant of proportionality.

For a fixed-head reservoir, where the effective net head is assumed constant, the function $\varphi(h)$ is constant and hence, Equation (3.4) becomes as follows:

$$Q(t) = K\phi(p_h) \tag{3.5}$$

For the scheduling period, the amount of water available for each hydro plant is limited by a pre-specified quantity Vj:

$$\int_0^t q(t)dt = V_j \tag{3.6}$$

3.3.2 Constraints

The objective function represented by Equation (3.4) is subject to a number of constraints as follows:

I. Load balance equation-The total power generation must meet the total load demand over the scheduling period PD including the transmission power losses P. This is represented by equation (2.11).

II. Generation capacity limits-The maximum and minimum power of generating plants is expressed as inequality boundary constraints and represented by equation (2.13).

III. Transmission Loss-The loss formulas defined by Equations (2.12) are applied to model the transmission network losses. B-coefficients are used to express transmission losses as a function of generator powers. Under normal operating conditions, the transmission losses are found to be quadratic in the injected bus real powers. The simplest form of the loss formula using Georg's B-coefficients loss formula is expressed as follows:

3.4 Formulation of economic load dispatch

As stated above, the aim of hydro economic load dispatch problem is to minimize the total system flow consumption represented by the discharge rate of the hydro units. Mathematically, this objective function to be minimized is expressed as follows.

$$Q(p_i) = c_i + b_i * p_i + a_i * {p_i}^2 \qquad (3.7)$$

Where,

- Pi: Output active hydro power (MW).
- Q (Pi): Rate of water discharge(m3/s).
- ai, bi & ci coefficients of the input - output characteristic.

The minimization of this objective function is subject to load balance equation, generation boundary condition, water availability limit of the system equality and inequality constraints.

3.4.1 Economic load dispatch neglecting loses

Let there be a station with generators of number NG and the given power demand be PD . The actual power generation Pgi is to be allocated to generators so that operation cost or water discharge rate of generation is minimized. The optimization problem can be addressed as equation below:

$$Q(p_i) = c_i + b_i * p_i + a_i * {p_i}^2 \tag{3.8}$$

Subject to

I. Equality constraint

$$\sum_{i=1}^{n} p_i = p_D \tag{3.8a}$$

II. Inequality constraints

$$P_H^{min} \le p_H \le P_H^{max} \tag{3.8b}$$

3.4.2 Economic load dispatch considering losses

In case of power transmission for long distances, losses in transmission need to be considered to find out the economic scheduling of generators [3].

Mathematical statement:

$$Q(p_i) = c_i + b_i * p_i + a_i * {p_i}^2 \tag{3.9}$$

Subject to

I. Power balance constraint

$$\sum_{i=1}^{n} p_i = p_D + p_l \tag{3.9a}$$

Where,

- Pi: Active power.
- PD: The total load demand.

- PL: The transmission loss.

II. Inequality constraint

$$P_H^{min} \leq p_H \leq P_H^{max} \tag{3.9b}$$

Where,

- PH: Active power of hydropower plant.
- P_H^{min}, P_H^{max}: Min and max of active power of hydropower plant.

Transmission loss is expressed as a function of generated power with the help of B coefficients. The George's formula for transmission loss in terms of B-coefficients is

$$P_L = \sum_i^n \sum_j^n p_{gi} \mathcal{B}_{ij} p_{gj} \tag{3.9c}$$

Where,

- PL: Active power loss.
- Pgi: Active power of generator.
- Bij : The loss coefficient.
- N: Number of generators

3.5 Formulation of particle swarm optimization

PSO simulates the behaviors of bird flocking. In PSO, each single solution is a "bird" in the search space and it is called "particle". All of particles have fitness values, which are evaluated by the fitness function to be optimized, and have velocities, which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles [16].

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by the following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called Pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called g-best. After finding the two best values, the particle updates its velocity and positions with the following equations (3.18) and (3.19) [17].

$$V_{i,j}^{k+1} = w * v_i^k + c_1 * rand_1 * \left({P_{best}}_{i,j}^{k} - x_{i,j}^k\right) + c_2 * rand_2 * \left({G_{best}}_{i,j}^{k} - x_{i,j}^k\right) \quad (3.10)$$

$$X_{i,j}^{k+1} = X_{i,j}^k + V_{i,j}^{k+1} \quad (3.11)$$

Where,

- V_{ik} is velocity of agent i at iteration k,
- w is weighting function,
- c_1, c_2 is weighting coefficients,
- rand is random number between 0 and 1,
- X_{ik} is current position of agent i at iteration k,
- Pbest $_i$ is pbest of agent i, and
- Gbest is gbest of the group
- .$V_{i,j}^{k+1}$ is modified velocity of particle i at iteration k+1.

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

$$W = w_{max} - (w_{max} - w_{min} | iter_{max}) * iter \quad (3.12)$$

Where,

- W: The inertia weighting factor.

- wmax, wmin: Maximum and minimum value of weighting factor.
- iter: Current iteration number.
- itermax: Maximum iteration number.

3.5.1 Parameter of particle swarm optimization algorithm

I. Initial Velocity-Vi (t) which is the velocity of the ith particle at iteration 'i' should lie in the pre-specified range (Vmin, Vmax). The parameter Vmax determines the resolution with which regions are to be searched between the present position and the target position. If Vmax is too high, particles may fly past good solutions. If Vmax is too small particles may not explore sufficiently beyond local solutions.

II. Weighting factor-The constants C1and C2 pull each particle towards Pbest and Gbest positions. In the above equation (3.10), C1 is known as the self-confidence range and C2 is known as the swarm range. Low values allow particles to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement towards, or past, target regions.

III. Weighting parameter-This parameter controls the exploration of the search space. The inertia constant can be either implemented as a fixed value or can be dynamically changing. Suitable selection of inertia weight 'ω' provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution [17].

3.5.2 Application of particle swarm optimization

Particle Swarm optimization (PSO) is a population-based algorithm in which each particle is considered as solution in the multimodal optimization space. When any optimization process is applied to the ED problem some constraints are considered. In these work two different constraints are considered. Among them the equality constraint which is summation of all the generating power must be equal to the load demand and the inequality constraint is the powers generated must be within the limit of maximum and minimum active power of each unit. The sequential steps of the proposed PSO method are given below [18].

Step1: Generation of initial condition of each agent. The individuals of the population are randomly initialized according to the limit of each unit including individual dimensions. The velocities of different particles are also randomly generated keeping the velocity within the maximum and minimum value of the velocities. These initial individuals must be feasible candidate solutions that satisfy the practical operation constraints.

Step2: The objective function is evaluated for each individual.

Step3: The evaluation function of each individual is calculated. Each pbest values are compared with the other pbest values in the population. The best evaluation value among the p-bests is denoted as g-best.

Step4: The velocity v of each individual is modified according to the velocity update equation (3.17).

Step5: The velocity components constraint occurring in the limits from the following conditions are checked.

Step6: The position of each individual is modified according to the position update equation (3.18).

Step7: If the evaluation value of each individual is better than previous Pbest, the current value is set to be pbest. If the best pbest is better than gbest, the value is set to be gbest.

Step8: If the number of iterations reaches the maximum iteration, then go to step 10. Otherwise, go to step2.

Step9: The individual that generates the latest gbest is the optimal generation power of each unit with the minimum total generation cost.

3.5.3 Flow chart of particle swarm optimization

A simple block diagram showing the basics of particle swarm optimization works is shown in fig below.

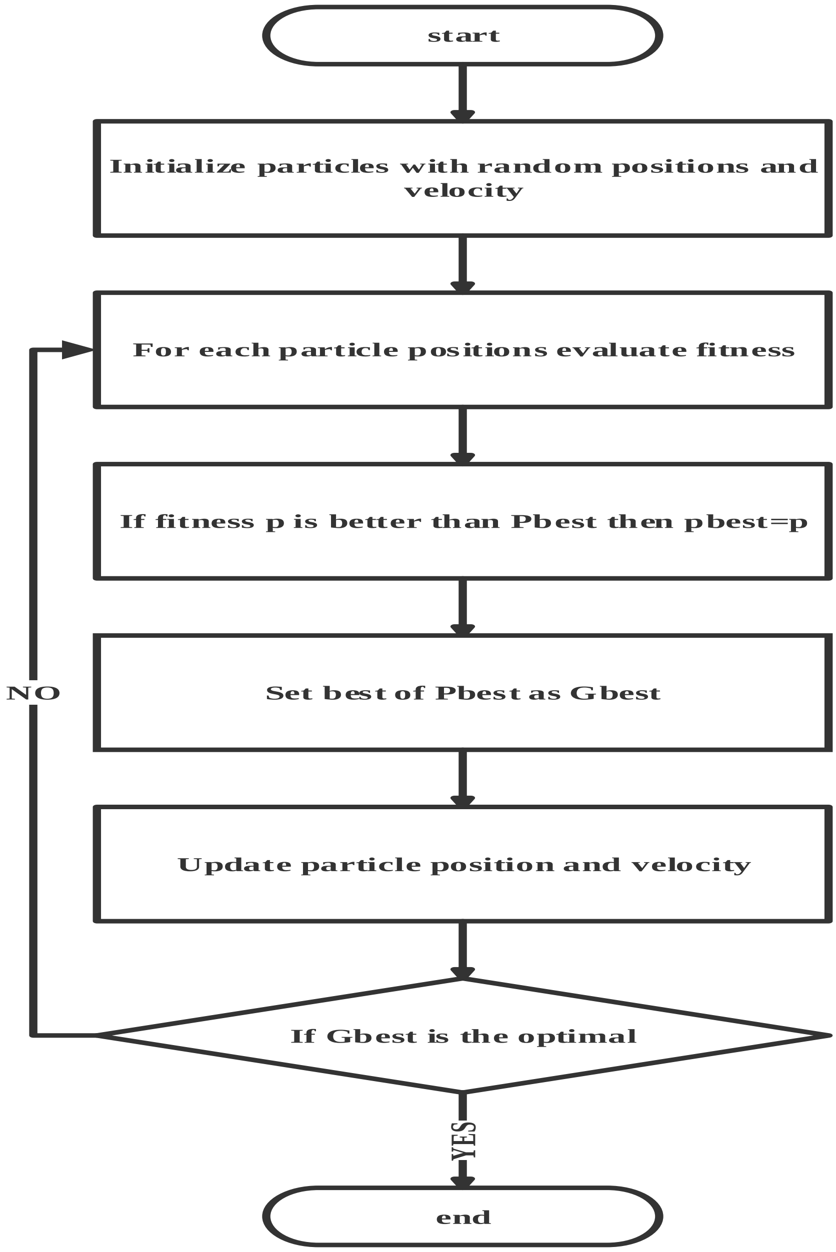

Figure 3.4-Particle swarm optimization flow chart

3.6 Formulation of simulated annealing algorithm

The concept of simulated annealing was first introduced in the field of optimization in the early 1980's by Kirkpatrick and independently by Cerny. Simulated annealing is a robust, general-purpose combinatorial optimization algorithm based on probabilistic method. Simulated Annealing (SA) algorithm is a nature inspired method which is adapted from process of gradual cooling of metal in nature. In the metallurgical annealing process, a solid is melted at high temperature until all molecules can move about freely and then a cooling process is performed until thermal mobility is lost. The same basic principle can be used in an optimization algorithm. [19].

3.6.1 Analogy to simulated annealing

The name simulated annealing comes from an analogy between combinatorial optimization and the physical process of annealing. In physical annealing a solid is cooled very slowly, starting from a high temperature, in order to achieve a state of minimum internal energy. It is cooled slowly so that thermal equilibrium is achieved at each temperature. Thermal equilibrium can be characterized by the Boltzmann distribution [20].

$$P_T(X) = e^{-Ex/kT} / \sum e^{-Ei/kT} \tag{3.13}$$

Where,

- Pt (x): Boltzmann distribution
- X: Random variable indicating the current state,
- Ex: The energy of state x,
- K: Boltzmann's constant and
- T: Temperature.

The evolution of the state of a solid in a heat bath toward thermal equilibrium can be efficiently simulated by a simple algorithm based on Monte Carlo techniques which was proposed by Metropolis in 1953 [21]. The Metropolis algorithm takes the current state x, and generates a new state y by applying some small perturbation. The transition from state x to state y is then accepted with probability. If accepted, y becomes the current state and the procedure is repeated. This acceptance rule is known as the Metropolis criterion.

$$P_{accept(x,y)} = \begin{cases} 1 & if\ E_x - E_y \leq 0 \\ e^{-(E_x - E_y)} & if\ E_x - E_y \geq 0 \end{cases} \tag{3.14}$$

Given a combinatorial optimization problem let the solution x correspond to the current state of the solid, the cost function corresponds to the energy of the current state, and the control parameter T correspond to the temperature of the solid. The simulated annealing algorithm consists simply of iterating the Metropolis algorithm for decreasing values of the artificial temperature parameter T.

Some of the analogies between the thermal process of physical annealing and the artificial process of simulated annealing in a combinatorial optimization problem are summarized in Table3.1.

Table 3.1-Analogies between physical and simulated annealing

Optimization problem	Physical system
Solution x	Current state of the solid
Objective value	Energy of the current state
Control parameter	Temperature
Optimal solution xopt	Ground state
Simulated annealing	Gradual cooling

3.6.2 Control parameter of simulated annealing algorithm

For the successful application of the SA algorithm, the annealing schedule is vital. There are four control parameters that are directly associated with its convergence (to an optimized solution) and its efficiency [22]. And they should be well set in order to achieve its best performance. These are-Initial temperature, Final temperature, Temperature decrement and Iterations at each temperature.

I. Initial temperature-At beginning, initial temperature must be set at a higher value, in order to get more probability of acceptance for non-optimized solutions during the first stages of the algorithm. Too much higher selection of initial temperature makes an algorithm slow and computationally inefficient. On the other hand, very low initial temperature may not be capable of searching a minimum especially for multi model function.

II. Final temperature-While working with SA algorithm generally the final temperature fall is set to zero degree Celsius. SA algorithm can take much longer time to execute the operation, if the decrement in the temperature is exponential in nature. Finally, the stopping criterion is selected, which can be either an appropriate low temperature or the value where the system get freeze at that temperature.

III. Temperature Decrement-As initial and final temperatures have predefined values; it is essential to find the approach of transition from starting to its final temperature as the success of algorithm depends on it. The decrement of temperature at time 't' is.

$$T(t) = {}^{d}/_{log\, t} \qquad 3.15$$

Where,

- d is a positive constant.

The temperature decrement can also be implemented using equation 3. below:

$$T(t+1) = \alpha * T \qquad (3.15a)$$

Where,

- α, is constant close to 1

IV. Iterations at each temperature-To enhance efficiency of the algorithm, selection of proper number of iterations is another important factor. The realization of only iteration for each temperature and the fall in temperature should take place at a really slow rate which can be expressed as:

$$T(t) = {}^{t}\!/_{1 + \beta t} \tag{3.15b}$$

Where,

- β takes very small value.

3.6.3 Application of SA Algorithm to ELD Problems

The simulated annealing algorithm for economic load dispatch problem is stepped as follows [23-24].

Step1: For initialization, choose temperature T, parameter α and maximum number of iterations 'max tries', to generate an initial feasible solution by random process and store it as current solution Si.

Step2: Set the iteration counter to μ=1

Step3: Find a neighboring solution Sj through a random perturbation of the counter one and calculate the new total Fcons.

Step4: If the new solution is better, we accept it but if it is worse, we calculate the deviation of Fcons ΔS=Sj-Si and generate a random number uniformly distributed over (0, 1). If $e^{-(\Delta s/t)} \geq \phi\varepsilon(0,1)$, Accept the new solution Sj to replace Si.

Step5: If the stopping criterion is not satisfied, reduce temperature using parameter α: T (t) =α. t and return to Step 2.

3.6.4 Flow chart of simulated annealing algorithm

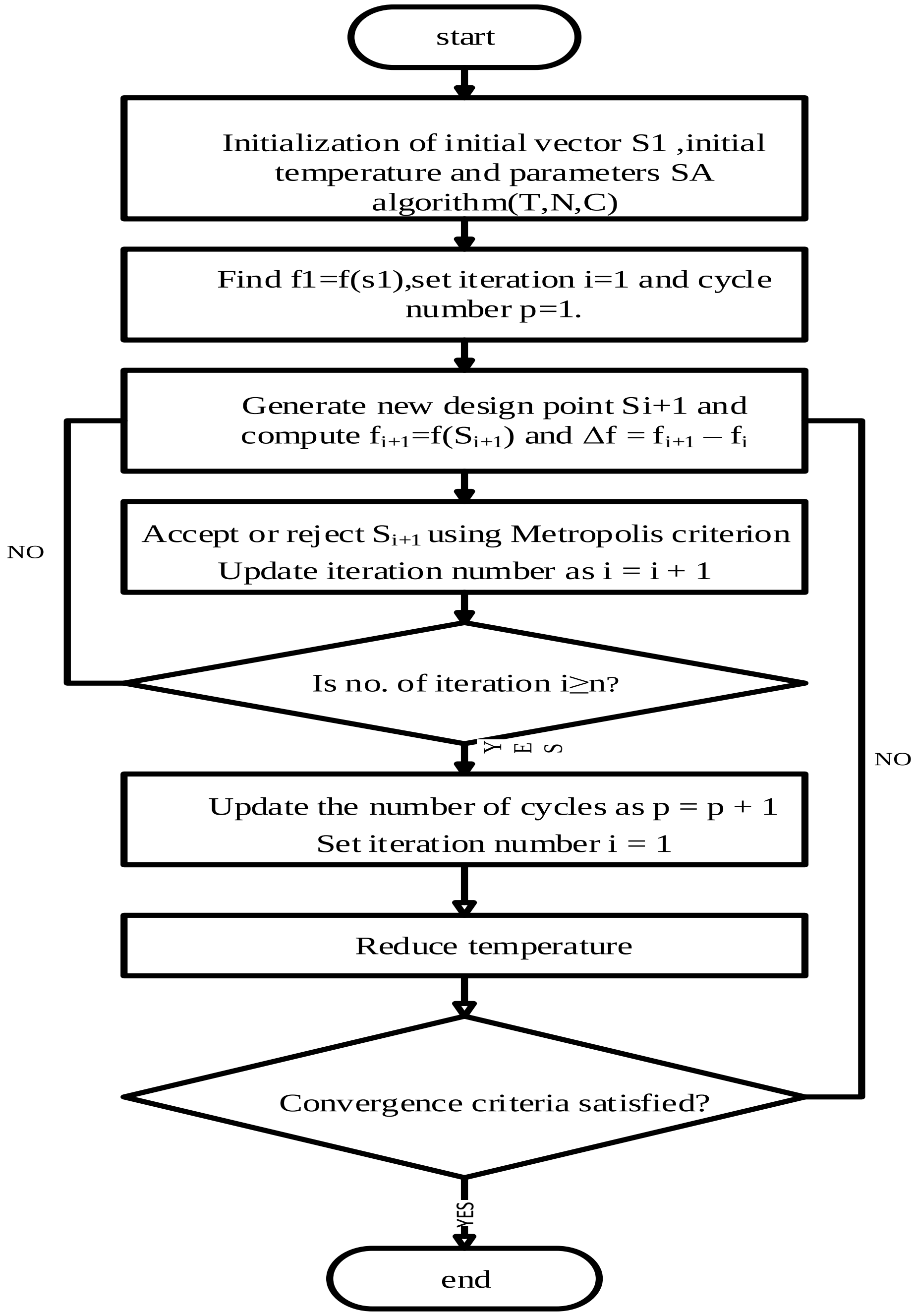

Figure 3.5-Flow chart of simulated annealing algorithm

3.7 Formulation of artificial bee colony algorithm

The artificial bee colony (ABC) algorithm, proposed by Karaboga in 2005 for real parameter optimization, is an optimized algorithm which simulates the forging behavior of a bee colony [25]. At the initial phase of the foraging bee, the bees start to explore the environment randomly in order to find a food source. After finding a food source, the bee becomes an employed forager and starts to exploit the discovered source. The employed bee returns to the hive with the nectar and unloads the nectar. After unloading the nectar, she can go back to her discovered source site directly or she can share information about her source site by performing a dance on the area. If her source is exhausted, she becomes a scout and starts to randomly search for a new source. Onlooker bees waiting in the hive watch the dances advertising the profitable sources and choose a sources site depending on the frequency of the dance proportional to the quality of the source.

The minimal model of swarm intelligent forage selection in a honey bee colony which the ABC algorithm simulates consists of three kinds of bees: employed bees, onlooker bees and scout bees. Half of the colony consists of employed bees, and the other half includes onlooker bees. Employed bees are responsible for exploiting the nectar sources explored before and giving information to the waiting bees (onlooker bees) in the hive about the quality of the food sources sites which they are exploiting. Onlooker bees wait in the hive and decide on a food source to exploit based on the information shared by the employed bees. Scout either randomly searches the environment in order to find a new food source depending on an internal motivation or based on possible external clues.

In the ABC algorithm the position of food source represents a possible solution to the optimization problem, and the nectar amount of a food source corresponds to the profitability (fitness) of associated solution. The number of employed bees is equal to the number of food sources existing around the hive (number of solutions in the population) and the employed bee whose food source has been abandoned becomes a scout [26-27].

3.7.1 Parameter initialization

The parameters of the basic ABC algorithm are the number of food sources (SN) which is equal to the number of the employed bees or onlooker bees, The colony size is 2*SN =

(NP),The number of trials after which a food source is assumed to be abandoned(limit),and a termination criterion (MCN).

In the basic ABC algorithm, the number of employed bees or the onlookers is set equal to the number of food sources in the population. In other words, for every food source, there is only one employed bee [28].

3.7.2 Producing initial food source

If the search spaces considered being the environment of the hive that contains the food source sites, initially food source is generated by control variable between their boundaries.

$$X_{ij} = x_i + rand(0,1) * (x_j^{max} + \ x_i^{min}) \tag{3.16}$$

Where,

- SN the number of food sources and
- D the number of optimization parameters
- i = 1…SN, j=1…D.

In addition, counters which store the number of trials of solutions are reset to zero in this phase. After initialization, the population of the food sources (solutions) is subjected to repeat cycles of the search process of the employed bees, the onlooker bees and the scout bees.

3.7.3 Sending employed bee

As mentioned earlier, each employed bee is associated with only one food source site. Hence the number of food source site is equal to the number of employed bees. An employed bee produces a modification on the position of the food source (solution) in her memory depending upon local information (visual information) and finds neighboring food source, and then evaluates its quality. In ABC, finding a neighboring food source is defined by equation.

$$V_{ij} = x_{ij} + \phi(\, x_{ij} - \ x_{ij} \,) \tag{3.17}$$

Where,

- Vij: The neighboring food source for Xi.
- ɸij: Uniformly distributed real random number in range [-1, 1.]
- j: random number in the range [1, D] and k ϵ {1, 2…SN}.

The difference between the parameters of the Xij and Xkj decreases, the perturbation on the position Xij decreases. Thus, as the search approaches to the optimal solution in the search space, the step length is adaptively reduced. If a parameter value produced by this operation exceeds its predetermined boundaries the parameter can be set to an acceptable value. If the value of the parameter exceeds its boundary is set to its corresponding boundaries as follows.

$$\begin{cases} x_i = x_i^{min} & if x_i > x_i^{min} \\ x_j = x_j^{max} & if x_j > x_j^{max} \end{cases} \tag{3.18}$$

After producing the Vi with the boundaries then find the fuel cost function for Vi.

$$fitness(i) = \begin{cases} 1 + abs\big(f(i)\big) & for\ x < 0 \\ 1/(1 + f(i) & for\ x \geq 0 \end{cases} \tag{3.19}$$

Where,

- f (i): the cost value of Vi.

A greedy selection is applied between Xi and Vi, the better one is selected depending on fitness values representing the nectar amount of the food sources at Xi and Vi. If the source at Vi is superior to that of Xi in terms of fitness values, the employed bees memorize the new position and forget the old one. Otherwise the previous position is kept in memory. If Xi cannot be improved its counter holding the number of trials is incremented by one, otherwise the counter is reset to zero.

3.7.4 Calculation of probability value

After all employed bees complete their searches, they share their information related to the nectar amount and the positions of their sources within the onlooker bees on the dance area.

This is the multiple interaction features of the artificial bees of ABC. Onlooker bees evaluate the nectar information taken from all employed bees and choose a food source site with a probability related to its nectar amount.

$$P_i = {fitness(i)}\Big/{\sum_i^n fitness(i)} \tag{3.20}$$

Where,

- Pi: The probability value.

3.7.5 Food site selection

In the basic ABC algorithm, a random real number within the range [0, 1] is generated for each source. If the probability value (Pi in Equation (3.29) of finding neighbor solution) associated with that source is greater than this random number, then the onlooker bee produces a modification on the position of this food source site by using Equation as in the case of the employed bee. After the source is evaluated, greedy selection is applied and the onlooker bee either memorizes the new position by forgetting the old one or keeps the old one. If solution Xi cannot be improved, its counter holding trial is increased by one; otherwise, the counter is reset to zero. This process is repeated until all onlookers are distributed onto food source sites.

3.7.6 Abandonment criteria

In a cycle, after all employed bees and onlooker bees complete their searches the algorithm checks to see if there is any exhausted source to be abandoned. In order to decide if a source is to be abandoned, the counters which have been updated during search are used. If the value of the counter is greater than the control parameter of the ABC algorithm, known as the "limit", then the source associated with this counter is assumed to be exhausted and is abandoned. The food source abandoned by its bee is replaced with a new food source is discovered by the scout, which represents the negative feedback mechanism and fluctuation property in the self-organization of ABC.

3.7.7 Application of artificial bee colony algorithm

The artificial bee colony algorithm for dispatch problem is stepped as follows [29]:

Step1: Initialize control parameter. The parameters of the basic ABC algorithm are the colony size (NP), the number of food sources (SN=NP/2), the limit for scout, L = SN*D, D is the dimension of the problem and a Maximum Cycle Number (MCN).

Step2: Producing initial food source site. Initialize the power loadings such that each element in the vector is determined by equation (3.26) with one generator as a dependent generator and evaluate the fitness value using Equation (3.28). Then select SN the best food source on the basis of highest fitness value as initial food sources and set the cycle=1, the trail number of each solution Xi, trial, is equal to zero.

$$fitneess(i) = {}^{1}\!/_{\sum_{i}^{n} fitness(p_i)} \tag{3.21}$$

Where,

- Fti is fuel utilization of each food source

Step3: Sending employed bees to the food sources [SN] and assigning the nectar amount. In this step each employed bee produces a new solution Vi by using Equation (4.2) and computes the fitness value of the new solution using Equation (4.5) satisfying with all constraints. If the fitness of the new one is higher than that of the previous one, the employed bee memorizes the new position and forgets the old one; otherwise the employed bee keeps the old solution.

Step4: Sending the onlooker bees to the food source depending on their amount of nectar this step required to calculate the probability value Pi of the solution Xi by means of their fitness value using Eq. (3.36). An onlooker bee selects a solution to update its solution depending on the probabilities and determines a neighbor solution around the chosen one. In the selection procedure for the first onlooker, a random number is generated between [0, 1] and if this number is less than P1, the solution is updated using Equation. Otherwise, the random number is compared with P2 and if less than that, the second solution is chosen. Otherwise, third probability of third solution is checked. This process is repeated until all onlookers have been distributed to solutions. The distributed onlooker bee updated its own solution just as the employed bees do.

Step5: Sending the scouts to the search area to discover new food source. If the solution Xi is not improved through step 3 and 4, the traili value of solution Xi will be increased by 1. If the traili of the solution is more than the predetermined "limit" the solution Xi is considered to be an abandoned solution, meanwhile the employed bee will be changed into a scout. The scout randomly produces the new solution and then compares the fitness of new solution with that its old one. If the new solution is better than the old solution, it is replaced with the old one and set its own traili into zero. This scout will be changed into employed bee. Otherwise, the old one is retained in the memory.

Step6: Record the best solution. In this step, the best solution so far is recorded and increased the cycle by 1.

Step7: Check the termination criterion. If the cycle is equal to the maximum cycle number (MCN) then the algorithm is finished; otherwise go to step-3.

3.7.8 Flow chart of artificial bee colony algorithm

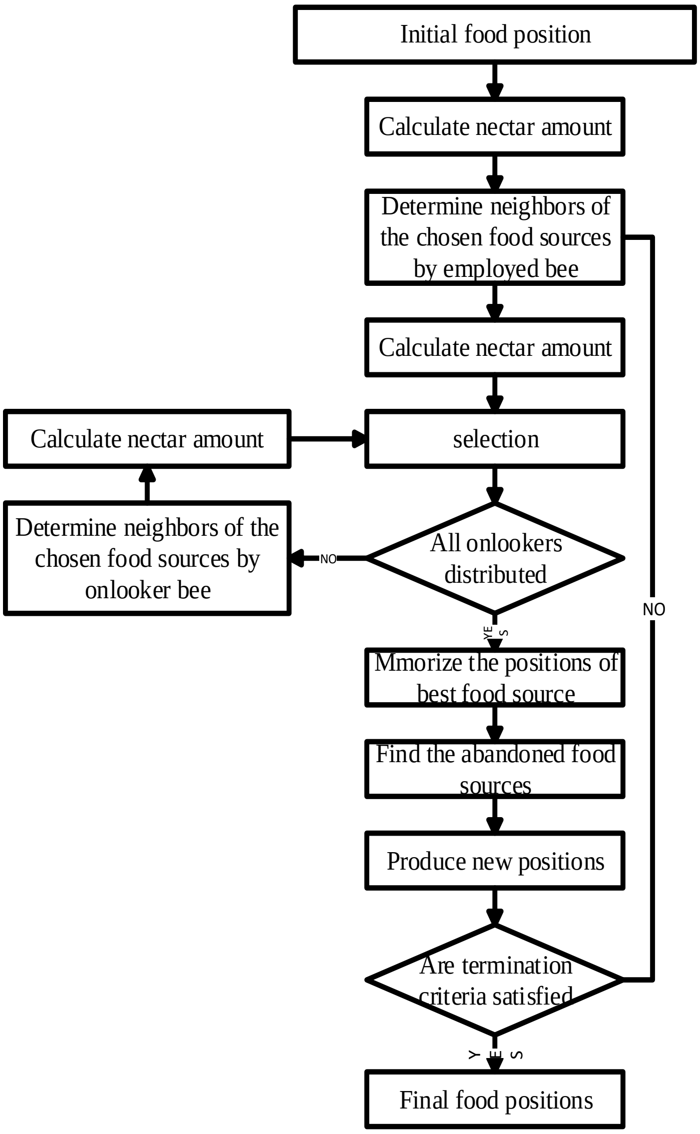

Figure 3.6-Flow chart of artificial bee algorithm

CHAPTER 4

RESULT AND DISCUSSION

4.1 Introduction

This chapter illustrates the application of meta-heuristics algorithm to economic load dispatch problem for gibe III hydropower plant. The results of ELD after the implementation of proposed algorithm are discussed and compared. The algorithms are coded in MATLAB to solve ELD problem. The performance is evaluated with no loss for ten sets of generator data.

4.2 Case study

In this case study the efficiency of the proposed technics for solving Economic Load Dispatch (ELD) problem has been tested on gibe III power generating units including the transmission losses. The performances of these algorithms are evaluated and compared. The algorithms are implemented in MATLAB R20015a platform on personal computer. Generating unit's capacity and consumption coefficients and the key parameters of algorithms are listed below in table 4.1, table 4.2.

Table 4.1-Unit performance parameter

Unit	a(1/(MW)2) h	b (1/MWh)	c	Pl (MW)	Pu (MW)
1-7	0.0000911	0.5454	0	0	187

Active power loads (MW)

Pmax=1146 MW

Pmin=354 MW

Pav=760 MW

4.3 Setting parameter for the proposed technics

Parameters chosen for simulated annealing algorithm in this thesis are initial temperature, final temperature and temperature decrement. For particle swarm optimization are number of particles, inertia weight, acceleration factor and max iteration and for artificial bee colony algorithm number of foods, max iteration and limit. And their value is given as shown below in table 4.2.

4.3.1 Parameters of proposed algorithm

Table 4.2-Control parameters of proposed algorithm

Proposed technics	Control parameter
Sa algorithm	Initial temperature=20
	Final temperature=2000
	Temperature decrement (α)=5
Pso algorithm	Number of particle (NP)=100
	Acceleration factor(W)=0.95
	Inertia weight (C1, C2) =2
	Maxi Iteration (T)=200
Abc algorithm	Number of foods=20
	Max iteration=2000
	Limit=200

4.4 Result

To test the feasibility and robustness of meta-heuristics technique is implemented in the economic load dispatch problem with the above parameters for generating unit test system with power generation limits and cost coefficients obtained using MATLAB-15a language. Generator data's, optimal load dispatch results and optimal fuel costs of the case study are presented in Table-4.3. And MATLAB simulation result for the proposed technics are presented in figure-4.1, figure-4.2 and figure-4.3

Table 4.3-loading, consumption, cpu time result

No. of units	Proposed technics	Load (MW)	Consumption (m^3/sec)	Loading (MW)	CPU time (sec)
7	Pso algorithm	354	195.09	50.67	2.46
		760	422.67	108.57	2.52
		1146.89	642.6	163.84	2.56
	Sa algorithm	354.7	192.3	50.57	1.56
		760	422.021	108.57	1.6
		1146.89	637.07	164	1.61
	Abc algorithm	354	192.177	50.57	0.792
		760	417.9	108.5	0.86
		1146	636.39	163.84	1.19

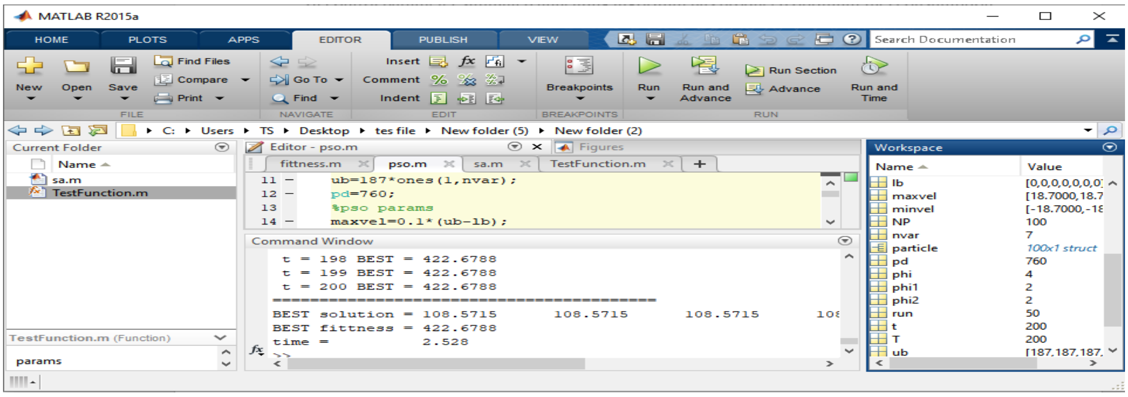

Figure 4.1-Simulation result for Pso algorithm

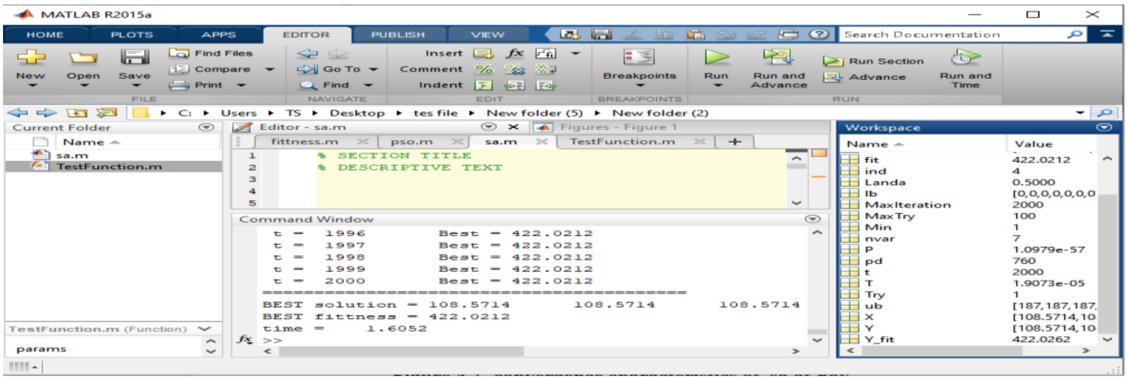

Figure 4.2-Simulation result for Sa algorithm

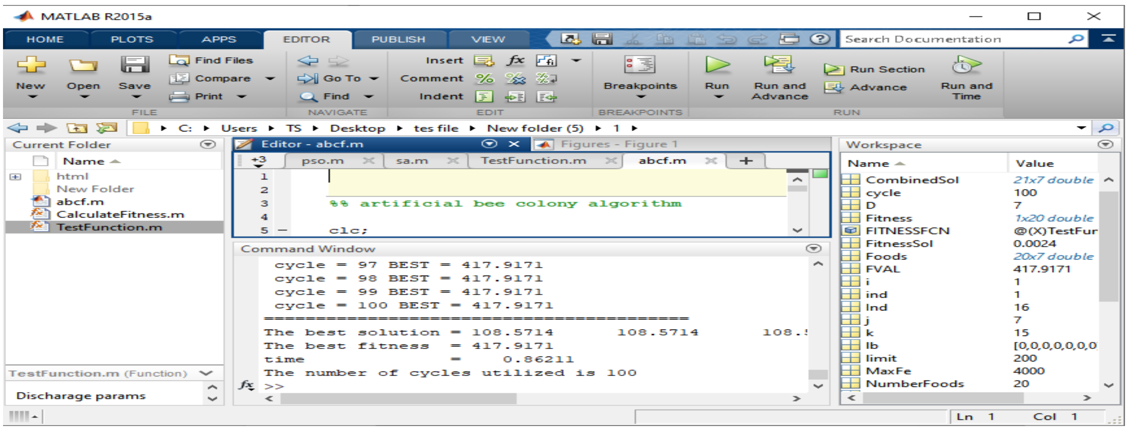

Figure 4.3-Simulation result for Abc algorithm

4.5 Discussion

4.5.1 Particle swarm optimization result

With the best values of NP= 100, C1=C2 = 2 and W= 0.999 obtained from Table III, the particle swarm optimization algorithm was run for different values of demand ranging for 1 hour. The individual generator powers, minimum fuel consumption, and the computational time required to obtain the simulation results are shown above in Table -4.3.1.And with the best value of control parameter particle swarm optimization algorithm has produced optimum fuel consumption of 422.67 m^3/sec and optimum loading 108.57 MW at cpu time period of 2.52 sec for average power load demand. The convergence characteristic curve at pav =760 MW is shown below at figure 4.4.

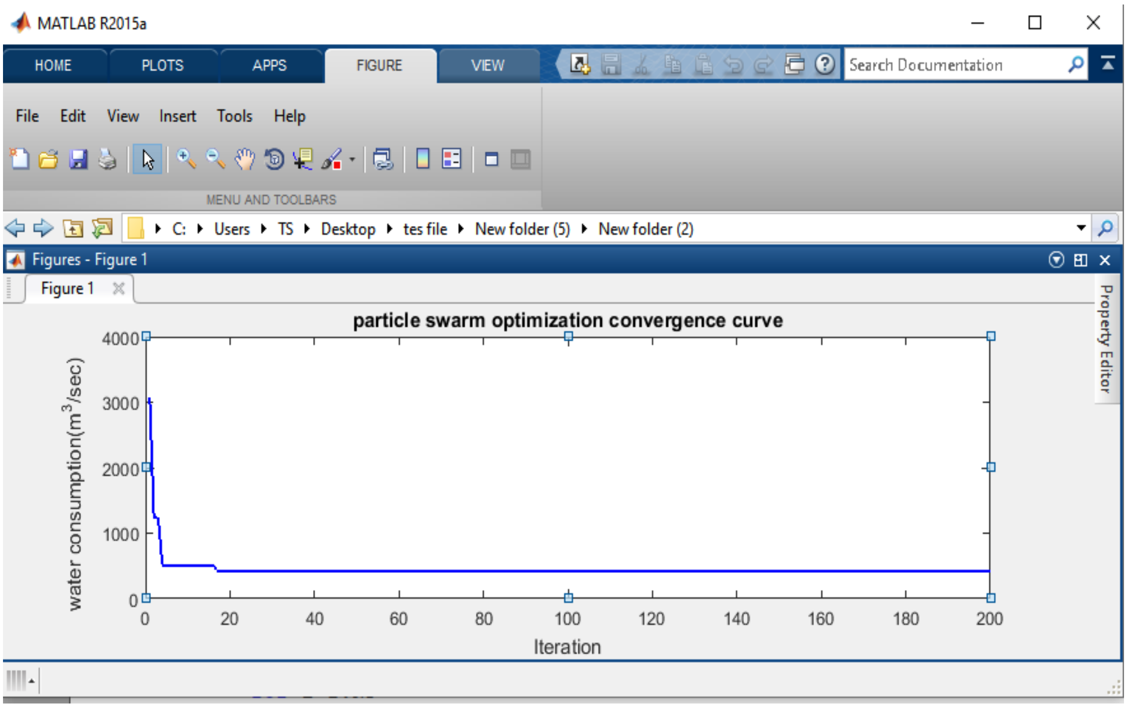

Figure 4.4- simulation result characteristic curve for pso algorithm

4.5.2 Simulated annealing algorithm result characteristic curve

With the best values of T init = 20, α = 0.5 and min T = 1 obtained from Table III, the SA algorithm was run for different values of demand ranging for 1 hours. The individual generator powers, minimum fuel cost, total power generated, and the computational time required to obtain the simulation results are shown in Table 4.2.2. And with the best value of control parameter simulated annealing algorithm has produced optimum fuel consumption of 422.02 m^3/sec and optimum loading 108.57 MW at cpu time period of 1.6 sec for average power load demand. The convergence characteristic curve for simulated annealing algorithm at pav =760 MW is shown below at figure 4.5.

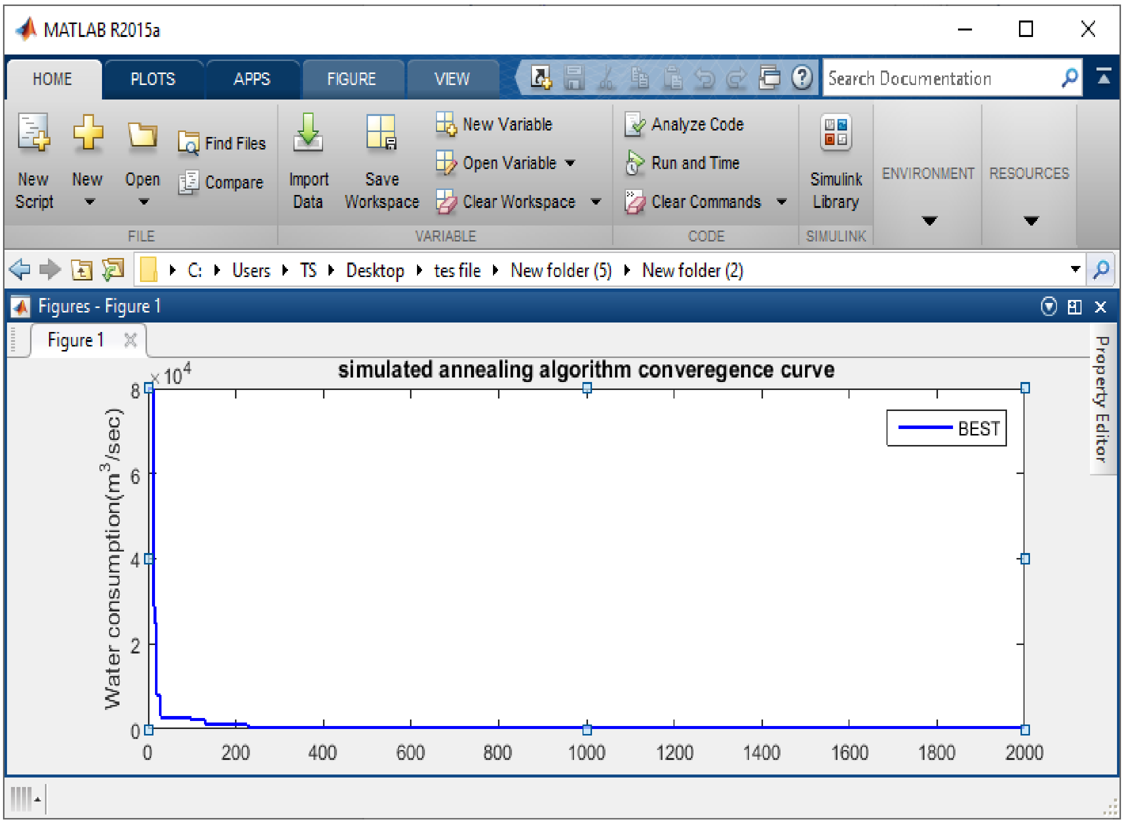

Figure 4.5-Convergence characteristics of sa algorithm at Pav

4.5.3 Artificial bee colony algorithm result

With the best values of number of food source= 100, max iteration= 4000 and limit = 200 obtained from Table III, the ABC algorithm was run for different values of demand ranging for 1hours at Pmax, Pmin, Pav. The individual generator powers, minimum fuel cost, and the computational time required to obtain the simulation results are shown in Table 4.3.3. And with the best value of artificial bee colony algorithm has produced optimum fuel consumption of 417.9 m^3/sec and optimum loading 108.5 MW at cpu time period of 0.86 sec for average power load demand. The convergence characteristic curve for artificial bee colony algorithm at pav =760 MW is shown below at figure 4.6.

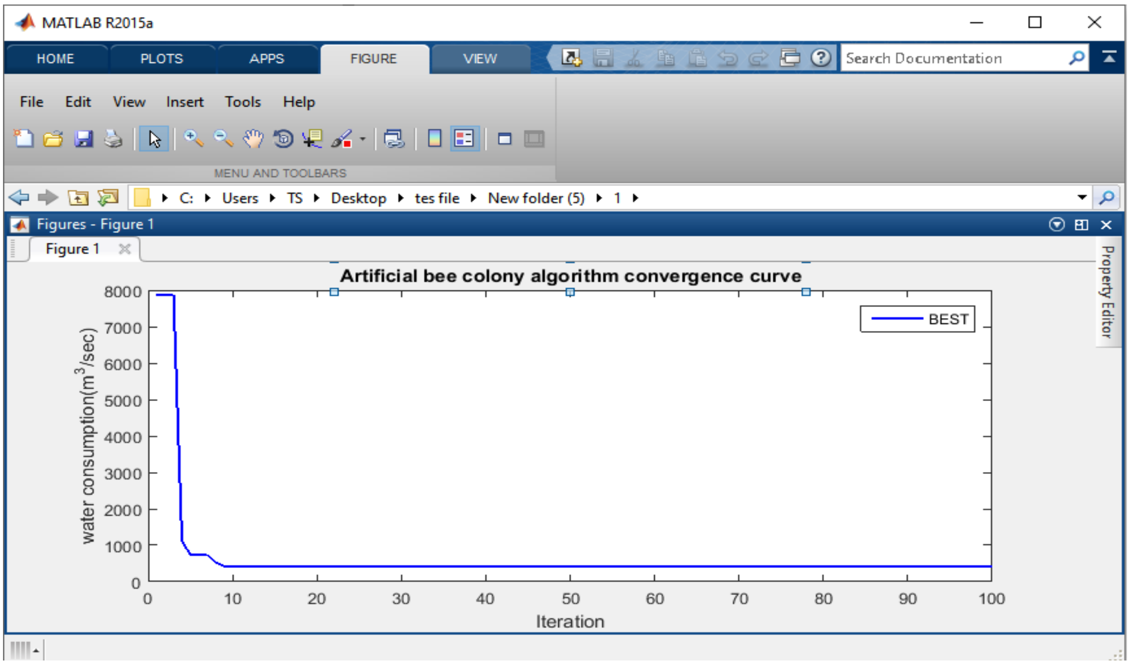

Figure 4.6-Convergence characteristics of Abc algorithm at Pav

4.5.4 Comparison of the result

In this thesis, the proposed simulated annealing algorithm, artificial bee colony algorithm and Particle swarm optimization were applied to solve the ELD problem of gibe III hydroelectric plant at different load demand load. For average load demand Simulation results of the proposed technics have been compared as shown below in Table-4.4.

Table 4.4-Simulation result comparison

	Simulated annealing algorithm	Particle swarm optimization	Artificialbee colony algorithm
Power loading	108.57	108.57	108.5
Flow consumption	422.02	422.62	417.9
Cpucomputation time	1.6	2.52	0.89

From table 4.4.4 the solutions found by these methods is clearly shown that the total flow consumption by the ABC method is smaller than those of the above methods on all hydroelectric units, and superior to the other mentioned method.

The total CPU time of these algorithms result tested using a Pentium (R)-2.2GHz CPU personal computer are shown from table 4.4. It is noticed that the proposed artificial bee colony algorithm is faster than SA and PSO in this system.

The solution of economic load dispatch problem for the test system are compared by proposed method such as PSO algorithm, SA algorithm and ABC algorithm. The minimum consumption for the demand for 1hr horizon is compared, while the proposed artificial bee colony algorithm produced a flow consumption of 417.9/s, promisingly optimal and consistent.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In this thesis, metaheuristics algorithm has been proposed. In order to prove the effectiveness of the algorithm it is applied to economic load dispatch problem (EELD) with 7 active generating units. The results obtained by proposed method were compared and the best fuel consumption is obtained by artificial bee colony algorithm (346.45 m3/s). The comparison shows that the Simulated Annealing performs better than particle swarm optimization method. SA has superior features, including quality of solution, stable convergence characteristics and better computational time but lesser than abc. Therefore, this result shows that abc optimization is a promising technique for solving complicated problems in power system.

5.2 Recommendation

In this thesis economic load dispatch problem in hydropower plant energy source is attempted using ABC, PSO and SA algorithm for gibe iii hydropower plant and among all the proposed method ABC algorithm is the best method to reach the near global optimal solution. the ELD problem in this thesis is single based only in gibe iii hydro power plant and our country has many hydropower plants. So, I recommend that these hydro power plants Can be combined with gibe iii and the economic load dispatch will be performed in large scale form.

The problem solved in this thesis is multi objective in the sense that it seeks to minimize the cost (fuel consumption) while at the same time optimizing the output of the renewable energy source. This has made its solution to be constrained to energy sources of hydropower only in this thesis. Since the renewable energy exploration is ongoing and gaining preference with time, I therefore recommend a solution to economic dispatch problem that includes other types of energy sources such as wind and solar energy.

In addition, hybrid methods can be used to ensure that an optimal solution to the dispatch problem is found, such that most of the constraints to the problem are taken care of and this makes the solution as practical as possible. Hybrid methodology is the useful tool for efficient solution by exploiting the strengths of PSO, SA and ABC with the powers of other techniques alongside the strengths of other methods incorporated

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APPENDIX A

YEKATIT/2010 E.C.	Active Power		
	Max.	Min.	Average
	MW	MW	MW
	716.45	301.80	437.21

DATE	GIBE III TOTAL GENERATED (MWH)	RESERVOR WATER LEVEL M	DISCHARGE
20/6/10	20340	853.47	40331.9358
21/6/10	17563	853.25	34825.4567
22/6/10	17343	853.02	34389.2214
23/6/10	16055	852.8	31835.262
24/6/10	16611	852.58	32937.7476
25/6/10	13530	852.35	26828.4706
26/6/10	15612	852.12	30956.8428
27/6/10	15189	851.95	30118.0813
28/6/10	16079	851.67	31882.8513
29/6/10	15548	851.44	30829.938
30/6/10	16854	851.22	33419.5893

APPENDIX B

Matlab code-pso.m

```
%% particle swarm optimization algorithm for eldp

clc;
clear;
close all;
global pd

%% parameter setting
nvar=7;
lb=0 *ones(1,nvar);
ub=187*ones(1,nvar);
pd=760;
%pso params
maxvel=0.1*(ub-lb);
minvel=-maxvel;
NP=100;
T=200;
W=0.999;
C1=2;
C2=2;


%%initialization
tic
empty.pos=[];
empty.velocity=[];
empty.cost=[];

particle = repmat(empty,NP,1);

for i=1:NP
    particle(i).pos=lb+rand().*(ub-lb);
    %particle(i).pos=unifrand(lb,ub,varsize);
    particle(i).cost=fittness(particle(i).pos);
    particle(i).velocity = zeros(1,1);
end

bparticle=particle;
[value,index]=min([particle(i).cost]);
gparticle=bparticle(index);



%% main loop

best=zeros(T,1);
AVR=zeros(T,1);
for t=1:T;
    for i=1:NP;
```

```
        particle(i).velocity= W* particle(i).velocity + C1*rand(1,1)...
            .*(bparticle(i).pos-particle(i).pos)+C2*rand(1,1)...
            .*(gparticle.pos-particle(i).pos);

        particle(i).velocity= min(particle(i).velocity,maxvel);
        particle(i).velocity=max(particle(i).velocity,minvel);

        particle(i).pos= particle(i).pos+ particle(i).velocity;
        particle(i).pos= min(particle(i).pos,ub);
        particle(i).pos= max(particle(i).pos,lb);


        particle(i).cost=fittness(particle(i).pos);

        if particle(i).cost<bparticle(i).cost;
            bparticle=particle;

            if bparticle(i).cost<gparticle.cost;
                gparticle=bparticle(i);
            end
        end
    end
%     W=W*Wd;
    best(t)=gparticle.cost;
    AVR(t)=mean([gparticle.cost]);
    run=50;
    gparticle_fittness=zeros(1,run);


    disp([' t = '   num2str(t)    ' BEST = '    num2str(best(t))]);

end


%% result
disp('========================================= ');
disp(['BEST solution = '    num2str(gparticle.pos)]);
disp(['BEST fittness = '    num2str(gparticle.cost)]);
disp(['time =          '    num2str(toc)]);

%% figure

figure(1)
plot(best(1:t), ' b ' , 'LineWidth' , 1.5 )
legend('BEST')
title('pso convergence curve')
```

matlab fittennes function.m

```
function z=fittness(x)
x=abs(x);
global pd

%generator params
a=0.0000911;
b=0.5454;
c=0;

%constraint
lmd=abs(sum(x)-pd);

%fittness fun
%z=sum(a*x.^2+b*x+c)+100*lmd;
z=sum(a*x.^2+b*x+c)+1000*lmd;
end
```

APPENDIX C

Matlab code-sa.m

```
%% simulated annealing algorithm for eldp

clc;
clear;
close all;
global pd

%% parameter setting

nvar=7;
lb=0*ones(1,nvar);
ub=187*ones(1,nvar);
pd=760;

%% sa parameter

T=20; %Temprature
MaxIteration=2000;
MaxTry=100;
Dx=(ub-lb)/10;
Landa=0.5;
Min=1;


%% Initialization

tic
X=lb+(ub-lb).*rand(1,nvar);
fit=TestFunction(X);
```

```
Ans=X;
Ans_fit=fit;

Try=1;



%% main loop

for t=1:MaxIteration;

    Y=X;
    ind=1+fix(rand*(nvar));

    Y(ind)=Y(ind)+Dx(ind)*(2*rand-1);

    Y=Y.*((Y>lb).*(Y<ub))+(lb+(ub-lb).*...
    rand(1,nvar)).*((Y<lb)+(Y>ub));

    Y=min(Y(ind),ub);
    Y=max(Y(ind),lb);
    Y_fit=TestFunction(Y);

    if ((Y_fit>fit)&&~Min)||(Y_fit<fit)&&Min;
        X=Y;
        fit=Y_fit;
    else
        P=exp(-abs(fit-Y_fit)/T);
        if rand<P
            X=Y;
            fit=Y_fit;
        end
    end

    if ((fit>Ans_fit)&&~Min)||(fit<Ans_fit)&&Min
        Ans=X;
        Ans_fit=fit;
    end

    BestSoFar(t)=Ans_fit;
    Try=Try+1;
    if Try>MaxTry
        Try=1;
        T=Landa*T;
        Dx=Dx*Landa;
    end


    disp(['t =  ' num2str(t)....
        'Best = ' num2str(BestSoFar(t))])

end
```

```
%% result
disp('======================================== ');
disp(['BEST solution = '    num2str(Ans)]);
disp(['BEST fittness = '    num2str(Ans_fit)]);
disp(['time =     '    num2str(toc)]);

figure(1)
plot(BestSoFar(1:t), ' b ' , 'LineWidth' , 1.5 )
legend('BEST')
title('simulated annealing algorithm')
```

Matlab Test function.m

```
function z=TestFunction(x)
x=abs(x);
global pd

%params
a=0.0000911;
b=0.5454;
c=0;
%constraint
lmd=abs(sum(x)-pd);

%fittness
z=sum(a*x.^2+b*x+c)+1000*lmd;
end
```

APPENDIX D

Matlab code-abcf.m

```
%% artificial bee colony algorithm

clc;
clear ;
close all;
global pd
%% problem parameter

FITNESSFCN=@(X)TestFunction(X);
D =7;
lb=0*ones(1,D);
ub=187*ones(1,D);
pd=760;

%% ABC algorithm parameter
NumberFoods = 20;
MaxFe = 4000;
%limit = NumberFoods*D;
limit = 200;

%% initialization of food source

tic
Foods = repmat(lb, NumberFoods,1) + rand(NumberFoods,D) .* repmat((ub-
lb),NumberFoods,1);
ObjVal = NaN(NumberFoods,1);
for i = 1: NumberFoods
    ObjVal(i) = FITNESSFCN(Foods(i,:));
end

% Determining the fitness function of the solutions

Fitness = CalculateFitness(ObjVal);
NumEval = NumberFoods;
trial = zeros(1,NumberFoods);

% The best food source is memorized

[FVAL, Ind] = min(ObjVal);
X = Foods(Ind,:);
cycle = 0;
BestFVALCycle = NaN(round((MaxFe -  NumberFoods)/(2*NumberFoods)),1);

%% mainloop
while ((NumEval < MaxFe))
    cycle = cycle + 1;
    % Employed Bees Phase
    for i = 1:NumberFoods
```

```
        j = randi(D,1);
        k = randi(NumberFoods,1);
        while (k == i)
            k = randi(NumberFoods,1);
        end
        sol = Foods(i,:);
        Phi = -1 + (1-(-1))*rand;
        sol(j) = Foods(i,j)+ Phi*(Foods(i,j) - Foods(k,j));
        sol = max(sol(j),lb);
        sol = min(sol(j),ub);
        % Determining the objective function and fitness value
        ObjValSol = FITNESSFCN(sol);
        FitnessSol = CalculateFitness(ObjValSol);
        NumEval = NumEval + 1;
        % Apply a greedy selection
        if (FitnessSol > Fitness(i))
            Foods(i,:) = sol;
            Fitness(i) = FitnessSol;
            ObjVal(i) = ObjValSol;
            trial(i) = 0;
        else
            % Increase the trial counter
            trial(i) = trial(i)+1;
        end
        if NumEval == MaxFe
            break % Terminate the algorithm
        end
    end

    % Onlooker Bee Phase
    prob = Fitness./sum(Fitness);
    i=1; t=1;
    while(t <= NumberFoods && NumEval < MaxFe)
        if(rand < prob(i))
            t = t + 1;
            j = randi(D,1);
            k = randi(NumberFoods,1);
            % Ensuring neighbour is d/t from the current solution i
            while (k == i)
                k = randi(NumberFoods,1);
            end
            sol = Foods(i,:);
            Phi = -1 + (1-(-1))*rand;
            % Generating a new solution
            sol(j) = Foods(i,j)+ Phi*(Foods(i,j) - Foods(k,j));
            sol = max(sol(j),lb);
            sol = min(sol(j),ub);
            % Determining the objective function and fitness value
            ObjValSol = FITNESSFCN(sol);
            FitnessSol = CalculateFitness(ObjValSol);
            NumEval = NumEval + 1;
            % Apply a greedy selection
            if(FitnessSol > Fitness(i))
                Foods(i,:) = sol;
                Fitness(i) = FitnessSol;
                ObjVal(i) = ObjValSol;
```

```
                trial(i) = 0;
            else
                trial(i) = trial(i)+1;
            end
            if NumEval == MaxFe
                break % Terminate the algorithm
            end
        end
        i = mod(i,NumberFoods) + 1;
    end
    % Scout Bee Phase
    if NumEval < MaxFe
        [val,ind] = max(trial);
        if (val > limit)
            trial(ind) = 0;
            % Generate a random solution
            Foods(ind,:) = (ub-lb).*rand(1,D)+lb;
            ObjVal(ind) = FITNESSFCN(Foods(ind,:));
            Fitness(ind) = CalculateFitness(ObjVal(ind));
            NumEval = NumEval + 1;
        end
    end
    % Keeping track of the best solution
    [BestFVALCycle(cycle),ind] = min([ObjVal;FVAL]);
    FVAL = BestFVALCycle(cycle);
    CombinedSol = [Foods;X];
    X = CombinedSol(ind,:);
    disp([' cycle = '   num2str(cycle)    ' BEST = '
num2str(BestFVALCycle(cycle))]);
end

% Removing the NaN entries in the vector
BestFVALCycle = BestFVALCycle(~isnan(BestFVALCycle));


%% result
disp('========================================== ');
display(['The best solution = ', num2str(X)])
display(['The best fitness  = ', num2str(FVAL)])
disp(   ['time              =    '    num2str(toc)]);
display(['The number of cycles utilized is ',
num2str(length(BestFVALCycle))])

%%figure
plot(BestFVALCycle, ' b ' , 'LineWidth' , 1.2)
legend('BEST')
title('artificial bee colony algorithm')
```

Matlab calculate fitness function.m

```
function Fitness = CalculateFitness(ObjVal)

% when obj fun is greater than or equal to 0
Fitness(ObjVal >= 0) = 1./(ObjVal(ObjVal >= 0)+1);

% when obj fun is less than 0
Fitness(ObjVal<0) = 1+abs(ObjVal(ObjVal<0));
```

Matlab test function.m

```
function z=TestFunction(x)
x= abs(x);
global pd
%Discharage params
a=0.0000911;
b=0.54;
c=0;
%constraint
lmd=abs(sum(x)-pd);

z= sum (a*x.^2+b*x+c)+ 1000*lmd ;
end
```