ECONOMIC DISPATCH PROBLEM INCLUDING RENEWABLE ENERGY USING GENERALIZED NORMAL DISTRIBUTION OPTIMIZATION AND BALD EAGLE SEARCH OPTIMIZATION ALGORITHM

by

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CERTIFICATE OF APPROVAL

The thesis/project entitled as "**Economic Dispatch Problem Including Renewable Energy using Generalized Normal Distribution Optimization and Bald Eagle Search Optimization**" submitted by **Saymun Adnan**, bearing Matric ID. **ET 171081** and **Sadmanul Hoque**, bearing Matric ID. **ET 171050** of session **Spring 2017**, to the Department of Electrical and Electronic Engineering, International Islamic University Chittagong, has been accepted as satisfactory in partial fulfilment of the requirements for the degree of Bachelor of Science in Engineering and approved for the examination held on **16th April, 2022**.

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DECLARATION

It is hereby declared that this work has been done by us and no portion of the work contained in this thesis/project has been submitted elsewhere for the award of any degree or diploma.

Saymun Adnan

Sadmanul Hoque

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Authors

ABSTRACT

Economic Dispatch (ED) problem is an essential optimization problem in electrical power system.It is to schedule the committed generating units outputs so as to meet the required load demand at minimum operating cost while satisfying all units and system equality and inequality constraints. Furthermore, renewable energy resources such as wind and solar have been a promising option due to environmental concerns as fossil fuel reserves are depleted, fuel prices rise quickly, and emissions rise. However, the uncertain nature of wind and solar irradiation due to weather and climate change and the integration of renewable power generation systems complicates the ED formulation. The Bald Eagle Search (BES) Optimization algorithm and Generalized Normal Distribution Optimization (GNDO) are proposed to solve the ED problem. To show the effectiveness of the proposed algorithm, four case studies are used to illustrate the proposed algorithm's ability. Finally, the results of the proposed algorithm are compared to other optimization techniques such as WOA, FPA, MODE, GA, PSO, and GSA. The results indicate that BES and GNDO can achieve lower total costs than the other optimization techniques.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

ED	Economic Dispatch
GA	Genetic algorithm
PSO	Particle swarm optimization
FPA	Flower pollination algorithm
WOA	Whale optimization algorithm
GNDO	Generalized normal distribution optimization
BES	Bald eagle search optimization algorithm
GSA	Gravitational search algorithm
RE	Renewable Energy
EMOCA	An evolutionary multi-objective crowding algorithm

CHAPTER 1

INTRODUCTION

1.1 Introduction

Economic dispatch (ED) is a cost-effective optimization strategy that provides a set of generators and levels of power output for satisfying demand at a minimum possible cost. It is one of the major optimization challenges in power systems. Its primary goal is to plan the committed producing unit outputs in such a method that all equality and inequality values are constraints, while the required load demand is met at the lowest possible operational cost. To minimize costs, ED often expands the use of more energy-efficient power plants to save costs, as well as result in terms of increased fuel economy, lower fuel consumption, and lower pollutant levels than if inefficient power plants were employed. It was designed to control fossil-fuel-burning power plants using calculations based on the power station's input and output parameters. For a practical power system, valve point effects, Prohibited Operating Zones (POZ), transmission loss, multi-fuel option, and ramp rate limitations are some of the most widespread solutions for ED problem formulation [1]. Nowadays, with the increasing environmental awareness, protecting the ecological environment has become the consensus of the majority of the world. Fossil fuels used in power systems cause air pollution and global warming by emitting greenhouse gases. Recently, the use of Renewable Energy (RE) has become more attractive for researchers and the power industries because of the growing of demand for electric power, increasing of fuel cost, depletion of resources and the global concern about the environmental pollution. Wind and solar power are the most popular among renewable energy sources. They are sustainable and nature friendly because it has no harmful by product that can lead to air pollution or emission in atmosphere. It is cost-effective and saves the fuel costs compared with thermal power generation. Moreover, renewable energy has no cost except for capital and initial cost.

ED is a very large topic so exploration of recent optimization techniques which are more efficient and reliable. The ED problem entails the resolution of two separate issues. The first is the Unit Commitment or Pre-Dispatch problem, in which the best producing sources must be chosen from among those available in order to fulfil expected demand and offer a particular margin of operating reserve over a set period of time. On-line economic dispatch is the second element, in which the load is allocated among the generating units that are actually paralleled with the system to lower the total cost of fulfilling the system's minute-to-minute requirements. The major goal is to reduce the cost of energy production while also accounting for transmission losses. While the problem can be solved simply if the generators' incremental cost curves are assumed to be piece-wise linear functions that increase monotonically, this technique will not work in real-world systems with nonlinear functions.

1.2 Background

Solving the Economic Dispatch (ED) problems has been an essential task for researchers since 1920s due to their importance in electrical power systems. Over the years, substantial improvements have been applied to the ED and different algorithms have been proposed to solve this problem. The issue first occurred when engineers were trying to figure out how to correctly distribute the load across the various generating units [2]. Various rudimentary approaches, such as "the base load" and "best point loading" [2], were utilized at first. Carpentier of Electricite de France made a breakthrough in mathematical formulation in the early 1960s, when he approached the entire network as an exact nonlinear optimization problem [2]. Most individual utilities and power pools have used ED as a mechanism for both supplying basis points and participation factors for Automatic Generation Control (AGC) and off-line or breakdown studies [2]. One of the most significant responsibilities for system control engineers is to discover the best combination of the units' power generation in order to reduce the total cost. Furthermore, incorporating an environmental component into the ED elevates the solution's value and places it in a larger context. As a result, numerous researchers have spent a long time investigating ED issues and developing relevant approaches. Most studies aimed to discover the best power flow approach, which 4 includes of strategies that use load flow techniques for ED [3]. Various optimization techniques such as conventional and nonconventional are used to solve ED problems which define the best operating level for electric power plants to meet the demands. Conventional methods are based on several complex mathematical formula like as gradient method [4], the newton-Raphson method [5], and lambda iteration [6]. Conventional methods have a basic mathematical model as well as high search speed but they have failed in solving such a problem. However, non-conventional methods such as Genetic Algorithm [7], [8], Particle Swarm Optimization (PSO) [7], Cuckoo Search (CS) algorithm [9], Flower Pollination Algorithm [10], Moth-Flame Optimization (MFO) algorithm [11], Hybrid Grey Wolf Optimizer (GWO) algorithm [12] and Woodpecker Mating Algorithm (WMA) [13], Simulated Annealing

(SA) [14], s Multi-Objective Differential Evolution (MODE) [15], gravitational search algorithm (GSA) [16] have been attempting to find the result of ED problem. All of them are excellent optimization techniques for finding the optimum global solution. To solve ED difficulties, a variety of optimization strategies have been used. Some of these strategies rely on traditional optimization techniques, while others rely on artificial intelligence or heuristic algorithms. Classic optimization approaches, such as linear programming or quadratic programming, are used in many references. These traditional approaches are quite sensitive to starting points, and they frequently converge to a local optimum or diverge entirely. Linear programming methods are quick and dependable, however the piecewise linear cost approximation has a drawback. Convergence and algorithmic complexity are known issues with non-linear programming methods. When dealing with a high number of inequality restrictions, Newton-based algorithms struggle. To solve the ED with the evolutionary based strategy, the Particle Swarm Optimization (PSO) technique was used.

1.3 Motivation

The Economic Dispatch (ED) problem is individual of the most essential operational functions of the modern clay energy managing system. The ED's purpose is to locate the best generation among the existing units so that the overall generation cost is as low as possible while also satisfying the power balance equations and other system limitations. The ED problem's literature and techniques for solving it are reviewed. However, it is recognized that traditional procedures become extremely complicated when dealing with increasingly complex dispatch problems, and are further constrained in a number of practical applications by their lack of robustness and efficiency. Many metaheuristics technique has been developed to solve economic dispatch problem. Recently, two developed metaheuristics optimization technique known as Bald eagle search optimization algorithm and Generalized Normal Distribution Optimization is proposed to solve ED problem. BES algorithm is a nature-inspired meta-heuristic optimization algorithm, that mimics the pursuing strategy or smart social behaviour of bald eagles as they search for fish. Hunting by BES is divided into three stages. In the first phase (selecting space), an eagle selects the space with the most number of prey. In the second phase (searching in space), the eagle moves inside the selected space to search for prey. In the third phase (swooping), the eagle swipes from the best location identified in the additional stage and determines the top point to hunt. Swooping starts from the best point and all other movements are directed towards this point. BES is tested by adopting a three-part evaluation methodology that (1) describes the benchmarking of the optimiation problem to estimate the algorithm performance, (2) compares the algorithm performance with that of other intelligent computation techniques and parameter settings and (3) evaluates the algorithm based on mean, standard deviation, best point and Wilcoxon signed-rank test statistic of the function values. Today, electric power systems are required to have a significant percentage of renewable energy sources, and there are numerous initiatives to integrate renewable energy resources into ED issues. Solar energy, biomass energy, wind energy, geothermal energy, and other resources that can be used to produce energy repeatedly are examples of renewable energy. Because of the fluctuation of wind and solar, there is a lot of interest in calculating the increase in auxiliary services needed to integrate wind and solar across different durations. It has probable benefits in limitation emissions and reducing the consumption of irreplaceable fuel reserves. The variability and intermittency of these resources provide important obstacles that must be overcome in the generation scheduling problem.

The suggested method, generalized normal distribution optimization (GNDO), is inspired by the generalized normal distribution method, which requires each individual to update its location using a generalized normal distribution curve. The developed generalized normal distribution model keeps track of each person's current position. The most notable aspect of GNDO is that it does not require any effort to fine-tune starting settings, unlike most other metaheuristic algorithms. Unlike other metaheuristics, the suggested technique solves optimization problems using only the necessary population size and terminal condition. The most notable feature of GNDO is that it requires only the essential population size and terminal condition to be established before running the algorithm. Furthermore, GNDO has a relatively simple structure and uses the built-in generalized normal distribution formula to update the individual's location.

1.4 Objective: The overall aim of this thesis is to advance the knowledge, understanding, and modelling capabilities of the Economic Dispatch (ED) including RE sources through the propose of recent optimization techniques. The details objectives of the thesis work are listed below-

- To solve the ED problem, a novel meta-heuristic optimization algorithm called GNDO and BES algorithm are proposed.
- To schedule the committed generating unit's outputs so as to meet the required load demand at minimum operating cost while satisfying all units and system equality and inequality constraints.
- To compare the GNDO and BES results with other optimization techniques such as WOA, GA, PSO, and GSA.
- To integrate RE sources (i.e. solar and wind) with thermal sources in ED problem.

1.5 Thesis Outline*:* The remainder of this thesis is organised as follows:

- **Chapter 1 (Introduction)** describes the introduction of the ED problem, Background, and Objectives of this study .
- **Chapter 2 (Literature Review)** describes the literature review on ED problems and renewable energy (RE). It is in four parts. The first part of RE introduces solar energy and wind energy system. The second part is optimization as a problem-solving tool; electrical energy and power, power generation, power transmission, and power distribution. The third part presents the various concept of optimization: optimization process, categories of optimization, and optimization on a problem-solving technique. The fourth part describe the literature review on optimization algorithm.
- **Chapter 3 (Problem Formulation)** goes on to describe the various formulations of ED problems. Objective function, power balance constrains, and power output limits are discussed in this section.
- **Chapter 4 (Methodology)** describes and evaluates a recent optimization algorithm for the ED problem where details on Bald Eagle Search Optimization and Generalized Normal Distribution Optimization are discussed with flowchart.
- **Chapter 5 (Results and Discussion)** describes the simulation results & discussion. In this section, three, six and ten generators with thermal generators

with solar and wind energy details are given and comparative results of GA, PSO, FPA, WOA, GSA and EMOCA are discussed.

- **Chapter 6 (Conclusion)** concludes the thesis. It shows a summary of each chapter as well as the main findings, and future scope with our suggestions regarding potentially important and fruitful lines of follow-on research that builds on what has been contributed in this thesis.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In this chapter, literature review of Economic Dispatch (ED) will be discussed in details. Sequence of contribution in ED are briefly mentioned. Literature review on ED and optimization algorithms are discussed in **section 2.2**, **section 2.3, and section 2.4** respectively.

2.2 Literature review on Economic Dispatch (ED)

Many studies have used various mathematical programming optimization approaches for tackling ED problems [18] since Carpentier established a network limited ED problem in 1962 [9] and Bechert and Kwatny published the first paper in the domain of dynamic dispatching in 1972 [17]. These optimization methods can be categorized into three groups. The linear programming algorithm [19], quadratic programming algorithm [20], non-linear programming algorithm [21], and other deterministic approaches are included in the first group. Stott and Marinho [19] used the LP approach to the power-system rescheduling problem with security-constrained economic dispatch/control for multiple-valved-turbine units. SLP looks to be a superior tool than SQP for the economic dispatch problem, according to Rosehart et al. [22]. . Zehar and Sayah [23] provided a multi-objective environmental/economic load dispatch solution based on efficient SLP techniques. Granelli and colleagues [20] used modified SQP approaches to tackle a security-constrained economic dispatch problem. The dual quadratic algorithm is used to find a dual viable starting point by reducing transmission limitations and enforcing constraint violations. SLP and the interior point dual-affine scaling technique were used to address a security constrained ED problem [24] and [25]. Momoh et al. [26] proposed a linear and convex QP-based IPM for the ED problem. However, each of the standard methods has flaws: using the linear programming algorithm to linearize the ED model would result in huge inaccuracies; the objective function for the quadratic and nonlinear programming algorithms should be continuous and differentiable [18]. The artificial intelligence-based methods fall into the second category. The application of artificial intelligence technologies to solve the ED problem has been successful. Jiang et al. devised a chaos optimization method (CAO) to solve the economic dispatch problem of a hydropower plant. Zhijiang et al. [27] used a COA as well, and the simulation results showed that the proposed method is both effective and exact. The economic functioning of power plants was studied by Xu et al. using a mutative scale COA. The procedure, however, is time-consuming, according to the results. Han and Lu [28] have created a more better mutative scale COA. The authors claim that their method is highly efficient and that it may be used to solve a variety of power system challenges, including economic operation, OPF, system identification, and optimal control. Mahdad et al. suggested a deconstructed parallel GA for solving the multi-objective environmental/economic dispatch problem in [29]. The problem is modified to optimize the active power consumption associated with each partitioned network in the first stage, which decomposes the original network into many sub-systems. An active power dispatch technique is proposed in the second stage to improve the ultimate solution of the original network's optimal power flow. On the Algerian 59-bus test system, the proposed method was put to the test. The computational findings revealed convergence at a near solution and the ability to produce a competitive solution in less time. Song et al. solved a mixed environmental ED problem using GAs with fuzzy logic controllers to modify crossover and mutation probability.

2.3 Renewable Energy (RE)

Renewable energy (RE), also known as clean energy, is derived from naturally regenerated sources or processes. Sunlight and wind, for example, continue to shine and blow despite the fact that their availability is dependent on time and weather. While harnessing nature's power is typically considered of as a novel technology, it has long been used for heating, transportation, lighting, and other purposes. Wind has propelled ships across the oceans and mills that process grain. The sun has supplied warmth throughout the day and has assisted in the lighting of fires that have lasted well into the evening. However, during the last 500 years or so, mankind have increasingly turned to dirtier, less expensive energy sources like coal and fracking gas. During the 1973 oil crisis, there was a surge of interest in RE as an alternative electric power source. Countries with limited fossil fuel resources and a reliance on oil imports from producing states began looking for alternate ways to ensure the reliability of their electric power supply. Furthermore, many of these countries' leaders had removed nuclear power stations from their list of nominated alternative energy sources due to popular pressure. As a result of their availability, safety, and environmental friendliness, RE sources were the most suitable alternatives. The most appropriate energy substitute was wind, with solar sources coming in second. Since the oil crisis, 35 years of research and development have led to significant achievement in the production of renewable energy in some countries. The utilization of renewable energy (RE) resources has piqued the interest of researchers in recent years as a result of rising oil costs, depletion of fuel supplies, ever-increasing demand for electrical power, and global concerns about air pollution and environmental protection. Environmentally friendly, these resources have no or low operating costs. Furthermore, power generation from renewable energy sources has been proven to be reliable, and if correctly scheduled and operated, might result in a significant reduction in the total cost of any power system. Wind and solar-powered homes can operate independently or be connected to the wider electrical grid via their power supplier. In most areas, electric companies enable households to pay just the difference between the electricity they consume from the grid and the electricity they generate, a procedure known as net metering.

2.3.1 Solar energy system

Solar energy systems are already a well-established technology that is innately safer than certain potentially hazardous electricity-generating methods. A 100 watt module will prevent the emission of over two tons of greenhouse emissions. Solar energy systems also do not pollute the environment during installation, operation, or maintenance. When compared to other types of electric energy sources, photovoltaic cell technologies pose a reduced environmental risk. Chemicals used in the production of PV cells, on the other hand, may be released into the air, surface water, and groundwater at the manufacturing facility, installation site, and disposal or recycling facility. During the production of electricity and heat, solar energy systems do not pollute the air, water, or emit greenhouse gases. Solar energy for electricity generating and heating can, without a doubt, have a good, indirect impact on the environment.

Fig.2.1 depicts a concentrated solar thermal system. The rationale for this is simple: it substitutes or reduces the consumption of other energy sources.

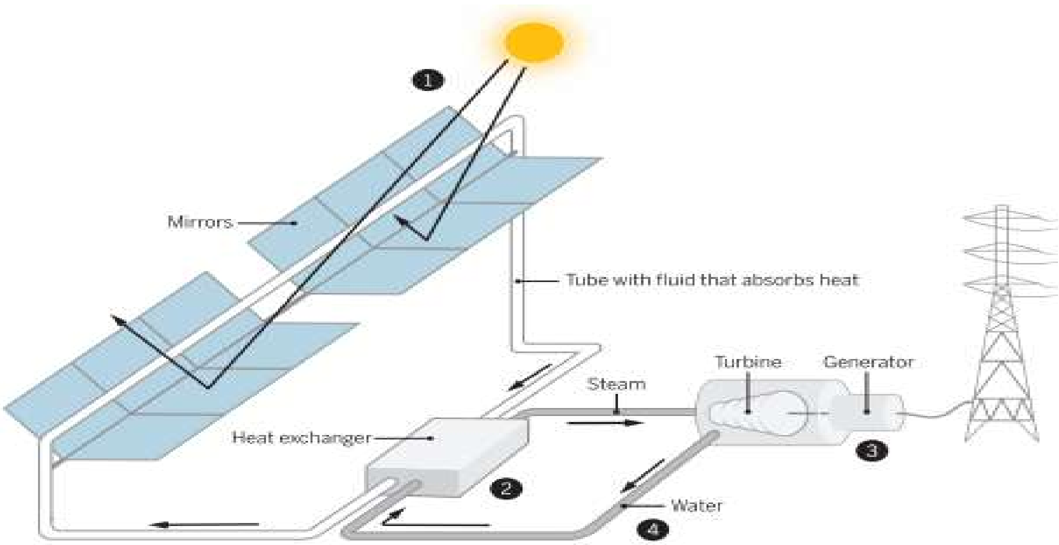

Fig.2.1 Concentrating solar thermal system [30].

for the same purposes but with larger negative effects on the environment. Solar energy, like any other type of power plant, has environmental issues in terms of land utilization, water use, pollutants, and hazardous material use.

2.3.2 Wind energy system

The usage of wind turbines to generate electricity is referred to as wind power or wind energy. Wind energy is a popular, sustainable, renewable energy source with a lower environmental impact than burning fossil fuels. The rotor with the turbine blades, perhaps a gearbox (which is abolished in direct-drive solutions), an electric generator, a power electronics converter, and a transformer are the major components used in a conventional WTS for energy conversion from wind to electricity as illustrated in **Fig.2.2** and wind turbine shown in **Fig.2.3**.

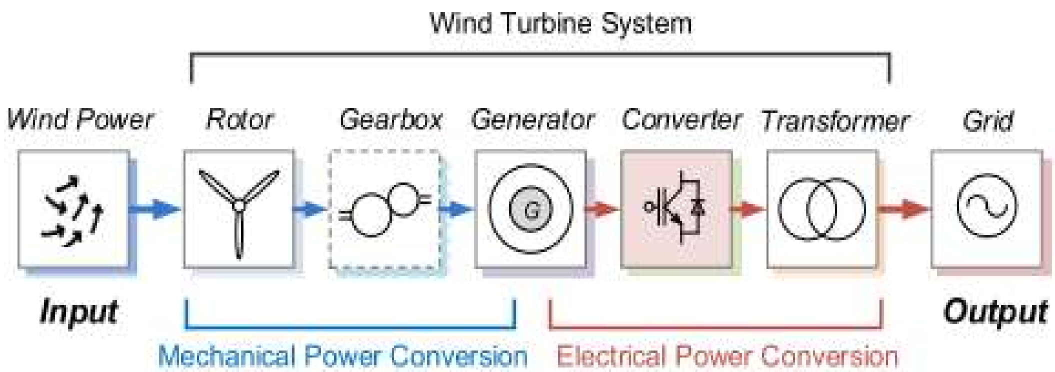

Fig.2.2 Power conversion stages in a typical WTS [31].

Fig.2.3 Figure of wind turbine [32].

In power distribution networks, large wind turbines (with capacity of up to 6-8 MW) are widely placed. Onshore and offshore wind farms are increasingly being connected directly to electricity transmission networks with capacities of hundreds of megawatts. Wind power is beginning to have a substantial impact on the operation of the current grid system as its grid penetration has increased dramatically. To improve the characteristics of wind turbines and make them more appropriate for integration into the power grid, advanced power electronics technologies are being deployed. Meanwhile, certain new difficulties have emerged that must be handled.

2.4 Electrical power and energy system

The phrases energy and power are frequently interchanged. As a result, it's important to understand the difference between the two terms as they're employed in this article. The ability to work is what energy is. It is an essential instrument for any nation's socioeconomic growth and development, and it comes in two varieties: renewable and nonrenewable. A typical power system representation showing the problem is shown in **Fig.2.4**.

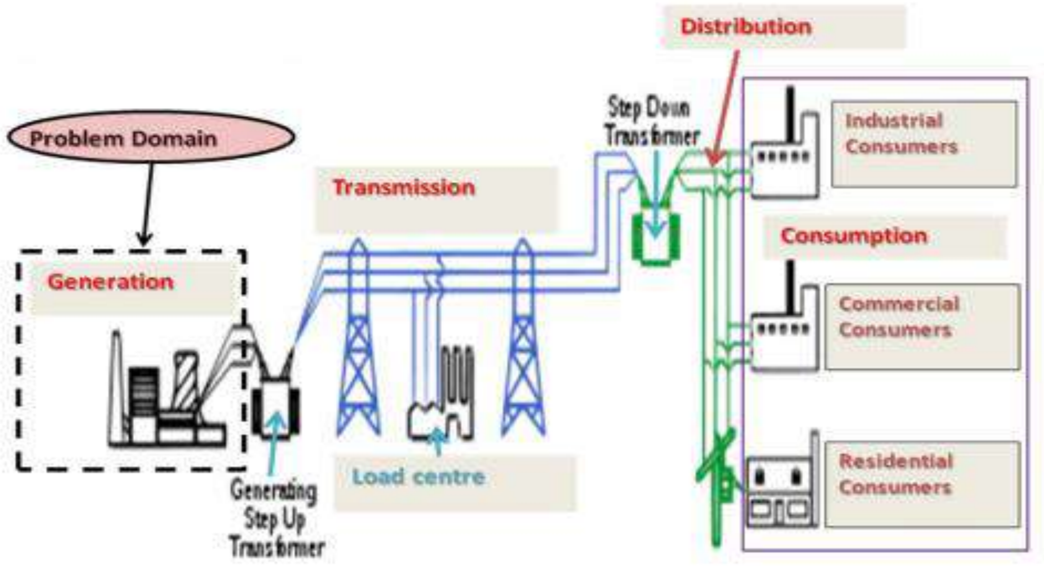

Fig.2.4 A typical power system representation showing the problem domain [33].

Renewable energy is obtained from naturally renewed natural resources such as the sun, wind, and water, whereas non-renewable energy is derived from fossil fuels (coal, petroleum, natural gas), and nuclear energy. On the other hand, power is the rate at which work is completed. It is the amount of work or energy expended in a given amount of time. The rate of flow of electrical energy is referred to as electrical power. The world's energy demand is rising, and in order to keep up with this trend, proper and timely up-to-date studies must be conducted on a regular basis. Because the operations of other businesses and sectors rely on electricity, the electrical energy industry is the world's largest energy industry. Power is essential to all areas of a country's economy, and both industrialized and developing countries strive to construct and maintain a functional electricity sector. Electrical Power Engineers are continually involved at every step of the electrical energy generation, transmission, distribution, and use process, and they face 15 difficult difficulties in their drive to deliver rising volumes of electrical energy in a cost-effective manner. Analysis and computation of electrical power flow is a systematic procedure that includes not only the electricity grid (generation, transmission, and distribution of electric power), but also the devices connected to the systems, such as generators, motors, and transformers, as well as system performance evaluation.

2.4.1 Power generation

This is the procedure of finding electricity from the source. Electricity is generated at power stations by electro-mechanical generators determined by heat engines, fuelled by nuclear fission, chemical combustion, and kinetic energy of flowing water, solar, wind, geothermal power and photovoltaic. **Fig.2.5** illustrates the power generation from an electric turbine.

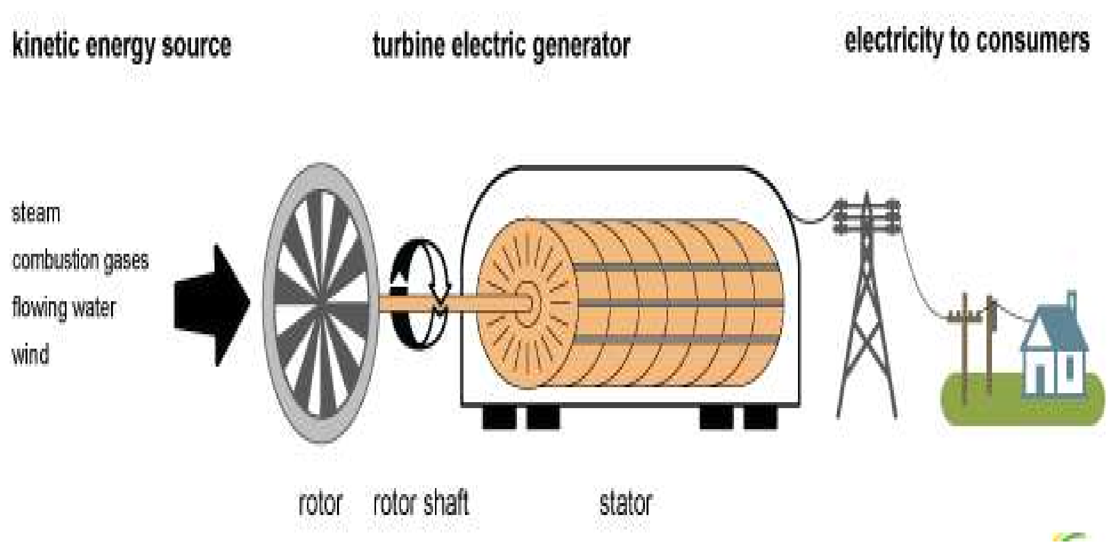

Fig.2.5 Power generation from an electric turbine [34].

Power generation can be divided into two types: centralised and distributed. Centralised generating offers good economies of scale, but also results in power losses due to long-distance transmission of electricity. On-site, dispersed, embedded, or decentralised generation, often known as distributed generation, generates electricity from a variety of modest energy sources. It minimizes the amount of energy wasted in transmission while also reducing the size and number of power lines that must be built. Solar panels, wind turbines, natural gas-fired micro-turbines, photovoltaic sources, and other distributed power sources are examples. The main disadvantage of dispersed generating is its high cost. Even though it offers significant advantages over the old method of burning fossil fuels, the distributed generating system is highly unusual. The production of power from fossil fuels emits hydrocarbons, which are harmful to the environment.

2.4.2 Power transmission

The transport of electrical energy from generating stations to substations in the vicinity of demand or customers is known as power transmission. Transmission lines become high-voltage transmission networks when they are interconnected (power grids). To prevent energy loss during long-distance transmission, electrical power is carried at high voltages. Overhead power lines and underground power cables are used for transmission. Electrical power transmission system is shown in **Fig.2.6**:

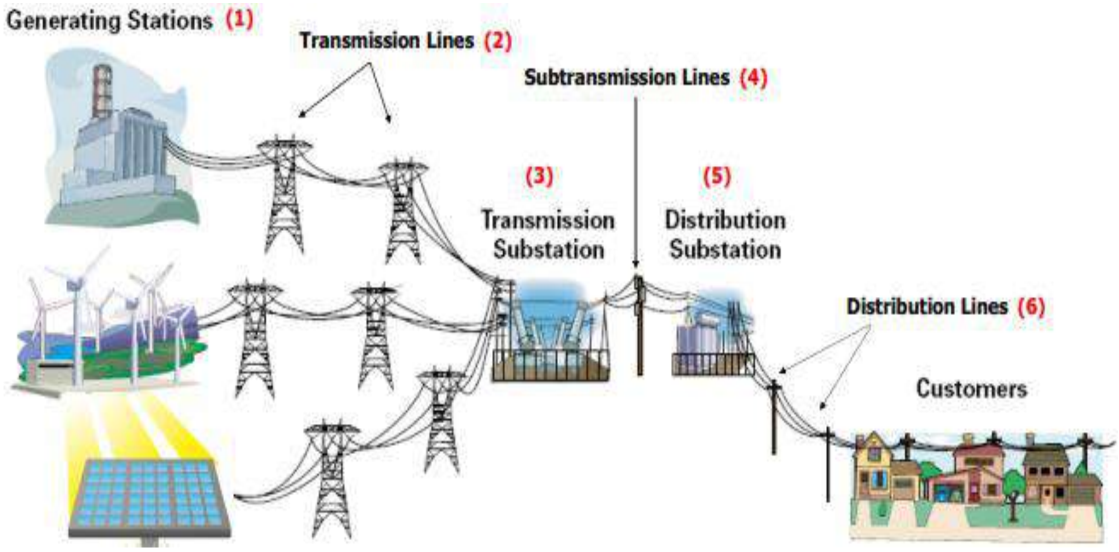

Fig.2.6 Electrical power transmission system [34].

A transmission substation lowers the voltage of incoming power, allowing it to link from long-distance high-voltage transmission to local distribution at lower voltage. Increase the voltage with a step-up transformer, which reduces the current in the conductors while balancing the power transmitted with the power generated, to enhance transmission efficiency. In the physical layer, transmission power is the most common area where inter-cell-group dependency exists. Although each cell group's power setting is unique, laws specify the maximum transmission power per device, creating a power sharing dependency between cell groups. When the device achieves its maximum transmission power, the power of the individual channels in the different cell groups must be scaled. This may appear simple, but the fact that cell groupings might be unsynchronized further complicates the situation. Changes in transmission power should only occur at subframe boundaries for a specific cell group, as the receiver may presume that transmission power is constant across a subframe.

2.4.3 Power distribution and consumption

The final stage of electric power delivery is distribution, which transports electricity from the transmission system to individual consumers. With the help of transformers, distribution substations connect to the transmission system and reduce the transmission voltage to a medium voltage of between 2 and 35 kV. The medium voltage power is delivered to distribution transformers near the customer's location by primary distribution lines. Lighting, industrial equipment, and residential appliances use the usage voltage, which is reduced via distribution transformers. Secondary distribution lines are frequently used to supply multiple consumers from a single transformer. Consumers are connected to the secondary distribution lines via service drops, which are used to connect commercial and residential customers. Customers who require a lot of power can be connected directly to the major distribution or subtransmission level. Over the last twelve decades, power distribution systems have grown into massive linked equipment systems centered on big centralized power plants. Significant amounts of decentralized, distributed generation and storage, much of it based on renewable and'micro-grid' technologies, will be included in the evolution in the twenty-first century. Power utilities will not totally transform their systems to this design, but rather pragmatically combine their traditional central-station systems with additions and augmentation based on distributed generation and micro-grids when needed. Future power systems will be a mix of old and new types, with far more flexibility in terms of dependability, economy, and fit to extreme aesthetic and user demand needs than traditional systems, but with far more context-responsive and dynamic control than in the past.

2.5 The concept of optimization

The term "optimization" refers to the process of improving thing. An optimization problem is one in which a set of possible solutions is used to discover an optimal or near-optimal answer using some well-established measurements or procedures for assessing them. The ED problem is an optimization problem that asks how energy generating businesses may meet their customers' power requests while minimizing under/over generation and operating costs (the costs of running the generating units). The term "optimization" refers to the process of fine-tuning anything. It entails minimizing or maximising a particular quantity; it is both an art and a science of resource allocation.

2.5.1 Optimization process

An optimization process is a technique for attempting to discover the optimum solution to a problem given a set of restrictions or limitations. **Fig. 2.7** depicts the principle of the optimization process. The independent quantity is the input (variables), the dependent quantity is the output (cost), and the evaluation function measures the quality of the current solution supplied by the input. The optimization procedure is iterated in the feedback loop until a stopping criterion is achieved. This is a quantitative decision, and it could mean finding the best feasible (optimal) outcome or reaching the maximum number of evaluation function runs allowed. The root-finding procedure in calculus is similar to optimization, except instead of looking for zeros of a function, the former looks for zeros of the function derivatives. Unlike root-finding, establishing whether a given minimum or maximum is a global optimum (the best possible solution) or a local optimum is a major challenge with optimization.

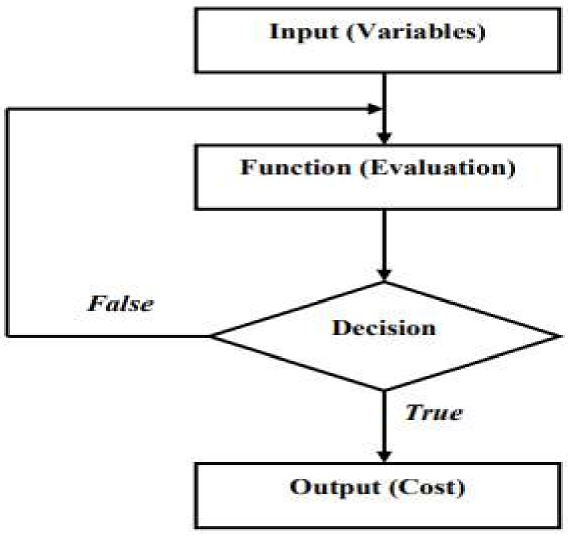

Fig.2.7 A flow diagram showing the concept of optimization [33].

The concept of optimization is very important in industrial planning and control, resource allocation, scheduling, decision making, and almost every other area of industry and science.

2.5.2 Catagories of optimization

There are several categories of optimization : Trial/error and function optimization; single-objective and multi-objective optimization; static and dynamic optimization; discrete and continuous variables optimization; constrained and unconstrained optimization; randomised and minimum/maximum seeking optimization. The variables are adjusted without much knowledge of the process that generates the output in trial and error optimization (preferred by most experimentalists), whereas function optimizations (preferred by theoreticians) are described by tried/proven formulae, and optimal solutions are found by manipulating these formulae mathematically. A single variable is involved in single-objective optimization, but multiple variables are involved in multi-objective optimization. The output of dynamic optimization evolves over time, whereas static optimization's output remains constant. Variables in discrete optimizations have a finite number of values within a certain range, but variables in continuous optimizations have an infinite number of values. Variable equalities or inequalities are embedded inside the functions to be optimized in constrained optimizations, but variables in unconstrained optimizations can take any value. Traditional optimization seeks to minimize or maximize a function's value. When moving from one solution to another, some planned steps are used, whereas random optimization makes advantage of probability during computations.

2.5.3 Optimization as a problem solving technique

Optimization is a problem-solving method that can be used to solve difficulties in any field of human endeavor. When there is a gap between the current state and the intended state, an optimization problem emerges. Problems are solved by allocating existing resources in such a way that disparities are reduced, with the goal of transforming the former into the latter. Identification and consideration of stakeholders in the issue-solving approach, the objectives to be attained, the variables involved in the problem, constraints (if any), solution methods, and evaluation of the final solution are all necessary components of a good problem-solving process. ED is an optimization work that aims to find the best/optimal combination of power generator outputs with the lowest generation cost while minimizing under/over generation and assisting electricity generating stations in meeting their customers' requests. Each of these goals is equally significant, and no new information about the situation is available.

2.6 Literature review on optimization algorithms

Various optimization techniques, conventional & nonconventional, are used to solve optimization problems. Meta-heuristics optimization techniques have become very popular over the last two decades especially Genetic Algorithm (GA), Particle Swarm Optimization (PSO) a Ant Colony Optimization (ACO). PSO first proposed by Kennedy and Eberhart , which is a method for determining the global optimization that has already been applied to handle real-time difficulties, has actuated the interest of researchers due to its efficiency and flexibility [35]. It is a modern heuristic algorithm that was developed by simulating a simplified social system that consists of the mutation operator as well as self-adaptive regulation of social parameters. Due to its simplicity, outstanding convergence characteristics, and good solution quality, this method solves a wide range of power system issues. Its disadvantage is that in high-dimensional space, it's simple to fall into a local optimum, and the iterative process's convergence rate is the iterative process. Moreover, the honey bee foraging behavior inspired the BSO algorithm, which is a technique for population-based optimization [36]. It's been proven to be effective in the solution of continuous nonlinear optimization problems. Although GA methods have been effectively used to handle difficult optimization problems, the current experiment has shown a deficiency in their performance. This deterioration inefficiency is observed when using strongly differentially expressed objective functions, hampered mutation and crossover processes, and compromised offspring fitness because population chromosomes contain analogous structures [36]. However, its disadvantage is that it takes a long time to count and there is no guarantee that a globally optimal solution will always be revealed. Firefly Algorithm (FA), proposed by Yang (2008), is based on the mating and social behavior of nocturnal light insects known as fireflies. The intenseness of a firefly's light is influenced by the background of the objective function to be maximized. However, it has the disadvantage of high computing complexity and low convergence accuracy, particularly when handling complicated problems. Xin-She Yang and Suash Deb established Cuckoo Search (CS) Algorithm in 2009 as a novel metaheuristic optimization algorithm [37]. This algorithm is based on the oblige offspring parasitism performance of several cuckoo species, as well as Levy flight activities of birds and fruit flies However, in comparison to the phase diversity method, its benefits include few parameters, a basic model and ease of implementation.

CHAPTER 3
PROBLEM FORMULATION

3.1 Introduction

An optimization problem is usually expressed as a mathematical model with the goal of minimizing unwanted quantities or increasing desirable ones while adhering to certain constraints. Cost of running producing units, transmission loss, and distribution mistakes are all unwanted characteristics in power system management and planning. The model is made up of a set of linear or nonlinear equations that describe the system's optimal or steady-state behavior. In this chapter, equation of fuel cost, Power balance constraint, and Power output limits are discussed.

3.2 Objective function

The conventional definition of the Economic Dispatch (ED) problem is the minimization of the sum of the fuel costs of the individual dispatchable generators, subject to real power balanced with total load demand and output limitations on generators. The cost function is a quadratic function that may be stated mathematically:

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

Where F_i denotes the quadratic form of the system's total cost function of unit i, N is the number of generators, Pi is the power generation of unit i and a_i, b_i and c_i are the coefficients of generator i. The summation of the cost function in (1) is the objective function to be minimized which may be represented as follows:

The objective of the economic dispatch problem is to minimize the total fuel cost.

$$F_t = \sum_{i=1}^{n} F_i(P_i) \tag{2}$$

Where F_t is the total generation cost, n is the number of intervals in the study period.

3.3 Power balance constraint:

Equations (1) and (2) are subject to an equality constraint attributed by the power balancing equation, which is written as follows:

$$\sum_{i=1}^{n} P_i = P_{Demand} + P_{loss} \tag{3}$$

Where P_{Demand} denotes total load demand, P_{Loss} denotes total power system loss. It's worth noting at this point that in the previous formulations, the B-coefficients, also known as loss coefficients, were used to simulate system losses. When B-constants are obtained, the B-coefficients approach should compute the system losses with reasonable precision. In other words, when the loss coefficients are estimated for a typical operating condition and there are no exceptionally large shifts in load between plants or in the overall load, using constant values for the loss coefficients in the equation for transmission losses produces good results. The B-coefficient approach is used to calculate losses, as follows:

$$P_{Loss} = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00} \tag{4}$$

Where B_{ij} is the ij^{th} element of the loss coefficient square matrix, B_{0i} is the ith element of the loss coefficient, and B_{00} is the constant loss coefficient

3.4 Power output limits

The goal of the ED issue is to find the most cost-effective generation level in a given area, as well as the power exchange across areas, that minimizes total operation costs while meeting a set of limitations. The power generation must be operated within its individual limits to meet the inequality constraint as follows:

$$P_{i(min)} \leq P_i \leq P_{i(max)} \qquad i = 1,2, \dots \dots .. n \tag{5}$$

where, P_i the active power generation of generator number i.

CHAPTER 4
METHODOLOGY

4.1 Introduction

In this chapter, the details of the BES and GNDO algorithm with flowchart are discussed. Method of finding best solution for Economic Dispatch (ED) are briefly discussed with flow chart and equation.

4.2 Bald Eagle Search (BES) Algorithm

The proposed BES algorithm simulates the behaviour of bald eagles during hunting to validate the significances of each step of hunting [38]. Large birds of prey, bald eagles are only found in North America. They will also consume smaller birds, bird eggs, and small animals like rabbits, lizards, and crabs, with salmon being their preferred meal. They have devised an intellectual strategy that involves picking the best place where prey is available, searching that place, and then swooping down on the prey at the appropriate time. For an effective hunting technique, these bald eagles take advantage of wind speed and stormy weather. The purpose of the ED problem be distributed into three sub-processes: selecting the space, searching the space, and, finally, swooping in on the prey (see **Fig.4.1**). These eagles flew away in a precise direction and select a specific region when they begin their search for food above a water source. It is possible to justify the provided available search space because the initial step in hunting behaviour is space selection. The selection step allows bald eagles to choose an area based on the information gathered in the earlier step. The eagles choose a different search area at random that differs from the earlier one however nearby to it. Seeing the prey is the second stage of hunting behaviour. When the eagles have located the prey, they will move on to the final stage of the hunt behaviour, which involves dropping slowly in order to snatching the fish from the water and reaching the prey at a high speed. The BES algorithm runs in three stages as illustrated in **Fig.4.2**.The three main steps of the bald eagle search algorithm are as follows:

- Selecting the space
- Search stage
- Swooping stage

4.2.1 Selecting the space

The blades select the space at random based on the prior search data in this stage. Equation (6) is expressed as below:

$$P_{i,new} = P_{best} + \propto \times r(P_{mean} - P_i) \quad (6)$$

Where α is the parameter for controlling position changes that may be derived from the equation below (7):

$$\propto = \frac{1.5\ .\ (Max_{iter} - t + 1)}{Max\_iter} \quad (7)$$

4.2.2 Search stage

The eagles begin their search for prey in this space by traveling in a spiral shape to speed up the process after picking the search space in the previous step. In this stage, the eagle location is restructured based on the following equation (8):

$$P_{i,new} = P_i + y(i) \times (P_i - P_{i+1}) + x(i) \times (P_i - P_{mean}) \quad (8)$$

$x(i) = \frac{xr(i)}{max|(xr)|}$, $y(i) = \frac{yr(i)}{max|(yr)|}$

$xr(i) = r(i) \times sin(\theta(i))$, $yr(i) = r(i) \times cos(\theta(i))$

$$\theta(i) = \alpha \times \pi \times rand$$

$$r(i) = \theta(i) \times R \times rand$$

Where R is a parameter with a range of 0.5 to 2 and α is a parameter with a range of 5 to 10.

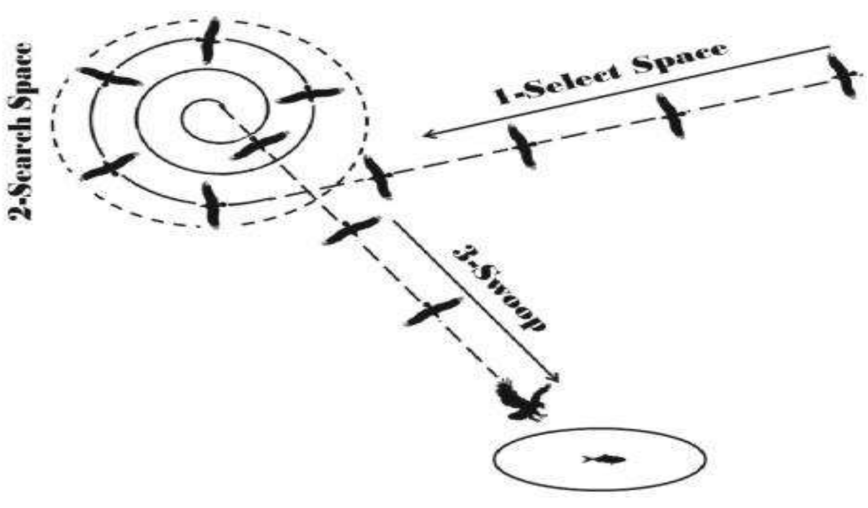

Fig. 4.1 Co-sequences for the three main stages of hunting by BES [38].

4.2.3 Swooping stage

In this stage, the eagles start to move from best search position towards their prey in a swing movement described in Equation (9)

$$P_{i,new} = rand * P_{best} + x_1(i) \times (P_i - c_1 * P_{max}) + y_1(i) \times (P_i - c_2 * P_{best}) \quad (9)$$

$x1(i) = \frac{xr(i)}{max|(xr)|}$, $y1(i) = \frac{yr(i)}{max|(yr)|}$

$xr(i) = r(i) * sinh[\theta(i)]$, $yr = r(i) \times \cosh[(\theta(i))]$

$\theta(i) = \alpha \times \pi \times rand$ $r(i) = \theta(i)$

Where $c1, c2 \in [1, 2]$.

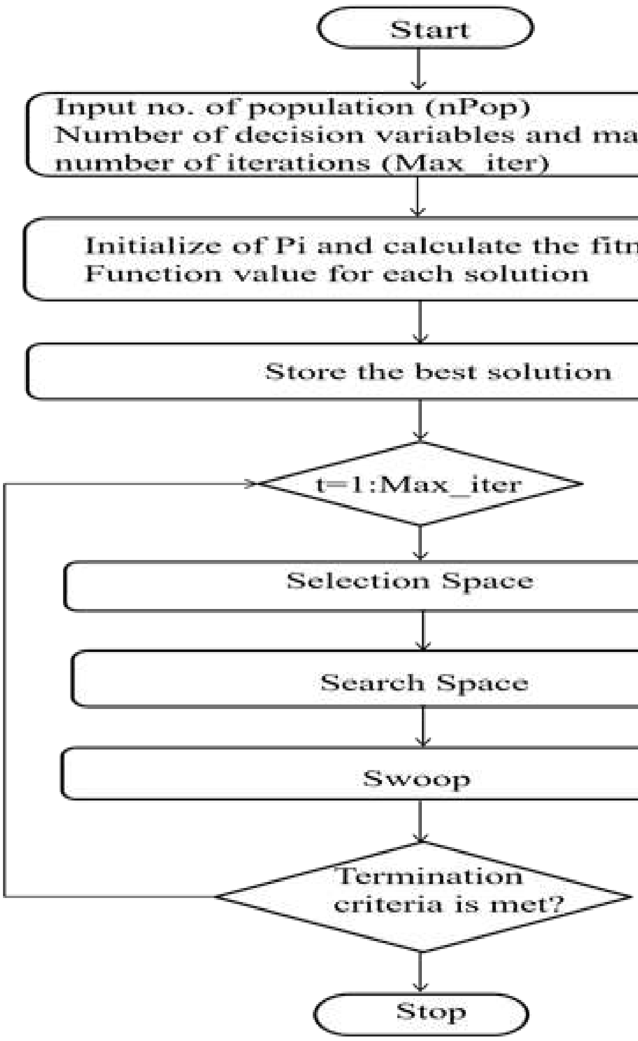

Fig. 4.2 Flowchart of the BES.

4.3 Generalized Normal Distribution Optimization (GNDO)

4.3.1 Description

A generalized normal distribution model is built according to population location data, and it is utilized to bring the individual's position up to date. Normal distribution theory influenced GNDO. The normal distribution, commonly known as the Gaussian distribution, is an important tool for describing natural phenomena. The following is a definition of a normal distribution. Assume that x is a random variable that follows a probability distribution with scale parameters and location, and that its probability density function is:

$$f(x) = \frac{1}{\sqrt{2\pi\delta}} exp\left(-\frac{(x-\mu)^2}{2\delta^2}\right) \tag{10}$$

Normal distribution has two variables, according to Eq. (10). The scale parameter δ and the location parameter μ. Random variables have a mean value and a standard variance are expressed using the location and scale parameters, respectively.

In general, there are three stages to the search process for population-based optimization approaches. To begin, the dispersed distribution contains all initialized persons. Previously, all individuals began to proceed in the direction of the global optimum solution under the guidance of the designed exploration and exploitation strategies. Finally, everyone gathers around the best solution that has been found. In reality, numerous normal distributions can be used to construct this search procedure. To put it another way, all people's positions can be thought of as random variables with a normal distribution. The ideal position and Random variables have a mean value and a standard variance. The ideal position and the mean position are wider apart in the first stage. The standard deviation of all individuals' rankings is even higher. The disparity between the mean and optimum positions is steadily reduced in the second step. The average change in all people's positions is getting smaller and smaller. The distance between the mean and optimum positions, as well as the standard variance of all individual positions, can be reduced to zero in the final stage. The computational methodology of GNDO algorithm has given in **Fig.4.4**.

4.3.2 Local exploitation

Local exploitation is the process of looking for better explanations in a search space that encompasses all of a person's current locations. The relationship between the distribution of people in the population and normal distribution can be used to create the generalized normal distribution model for optimization. .

$$v_i^t = \mu_i + \delta_i \times \eta, i = 1,2,3, \dots, N \tag{11}$$

Where v_i^t is the ith individual trail vector at time t, μ_i is the ith individual generalized mean position, δi is generalized standard variance and η is penalty factor. Furthermore, μ_i , δ_i and η can be defined as

$$\mu_i = \frac{1}{3}(x_i^t + x_{Best}^t + M) \tag{12}$$

$$\delta_i = \sqrt{\frac{1}{3}[(x_i^t - \mu)^2 + (x_{Best}^t - \mu)^2 + (M - \mu)^2]} \tag{13}$$

$$\eta = \begin{cases} \sqrt{-log(\gamma_1)} \times cos(2\pi\gamma_2), if\ a <= b \\ \sqrt{-log(\gamma_1)} \times cos(2\pi\gamma_2 + \pi), otherwise \end{cases} \tag{14}$$

Where, a, b, γ_1 and γ_2 are random values between 0 and 1, $x_{Best}{}^t$ is the current best position and M is the current population's mean position. In addition, M can be calculated by:

$$M = \frac{\sum_{i=1}^{N} x_i^t}{N} \tag{15}$$

4.3.3 Global exploration

Global exploration is the process of searching a speech space around the globe for promising places. In GNDO, the global exploration on the basis of three persons chosen at random, which can be stated as:

$$v_i^t = x_i^t + \beta \times (|\gamma_3| \times v_1) + (1 - \beta) \times (|\gamma_4| \times v_2) \tag{16}$$

In equation (15),

$\beta \times (|\gamma_3| \times v_1)$ = Local information sharing

$(1 - \beta) \times (|\gamma_4| \times v_2)$ = Global information sharing

Where γ_3 and γ_4 are two random values with a conventional normal distribution, β called adjust parameter is a random number between 0 and 1, and v1 and v2 are two trail vectors, respectively. Furthermore, v_1 and v_2 can be calculated by:

$$v_1 = \begin{cases} x_i^t - x_{p1}^t, if\ f(x_i^t) < f\left(x_{p1}^t\right) \\ x_{p1}^t - x_i^t, \text{otherwise} \end{cases} \tag{17}$$

$$v_2 = \begin{cases} x_{p2}^t - x_{p3}^t, if\ f\left(x_{p2}^t\right) < f\left(x_{p3}^t\right) \\ x_{p3}^t - x_{p2}^t, \text{otherwise} \end{cases} \tag{18}$$

Where, p1, p2 and p3 are three random integers between 1 to N, that satisfy p1 ≠ p2≠ p3 ≠ i. Given Eq. (17) and (18), the second term on the right of Eq. (16) can be referred to as local learning term, indicating referred to as the solution p1 shares information with the solution i; the third term on the right of Eq. (16) can be called global information sharing, that the individual i is given information by the individuals p2 and p3. The adjust parameter β is used to balance the two information distributing strategies. Moreover, γ_3 and γ_4 are random numbers with conventional normal distribution, which can make GNDO has larger search space during the global search. The absolute symbol in Eq. (16) is to stay reliable with the screening mechanism in Eq. (17) and Eq. (18).

4.3.4 The implementation of the proposed method for optimization

The implementation of GNDO is discussed in this section. Pseudocode of the GNDO is shown in **Fig.4.3**. The suggested GNDO is based on local exploitation and global exploration tactics that have been established. The two strategies are equally important to GNDO and have the same chance of being chosen. Furthermore, like with other population-based optimization techniques, GNDO population is initialized by

$$x_{i,j}^t = I_j + \left(u_j - I_j\right) \times \gamma_5, i = 1,2,3,\dots,N, j = 1,2,3,\dots,D \tag{19}$$

Where D is the number of design variables, lj denotes the jth design variable's lower boundary, uj denotes the jth design variable's upper boundary, and γ_5 is a random number between 0 and 1. It should be noted that a local exploitation strategy or a global exploration strategy may not provide a superior solution for the ith individual. A screening process is built in order to bring the better answer to the next generation population, which may be represented as-

$$x_i^{t+1} = \begin{cases} v_i^t, \text{if}\ f(v_i^t) < f(x_i^t) \\ x_i^t,\ \text{otherwise} \end{cases} \tag{20}$$

GNDO Algorithm

Input: population size N, the upper limits of variables $\boldsymbol{u}$, the lower limits of variables $\boldsymbol{l}$, the current number of iterations $t = 0$ and the maximum number of iterations $T_{\max}$.

/ Initialization */*
Initialize population by Eq. (26)
Calculate the fitness value of every individual and achieve the optimal solution $\boldsymbol{x}_{\text{Best}}$
Update the current number of iterations t by t=t+1
/ Main loop */*
while $t \leq T_{\max}$ **do**
    for $i = 1 : N$
        Generate a random number α between 0 and 1
        if $\alpha > 0.5$
/ Local exploitation strategy */*
            Select the current optimal solution $\boldsymbol{x}_{\text{Best}}$ and calculate the mean position $\boldsymbol{M}$ by Eq. (22)
            Compute generalized mean position μ, generalized standard variance δ and penalty factor by Eq. (19), Eq. (20) and Eq. (21), respectively.
            Perform the local exploitation strategy by Eq. (18) and Eq. (27).
        else
/ Global exploration strategy */*
            Perform the global exploration strategy by Eq. (23), Eq. 24), Eq. (25) and Eq. (27)
        end if
    end for
    Update the current number of iterations t by t=t+1
end while

Output: the optimal solution $\boldsymbol{x}_{\text{Best}}$

Fig. 4.3 Pseudocode of the GNDO.

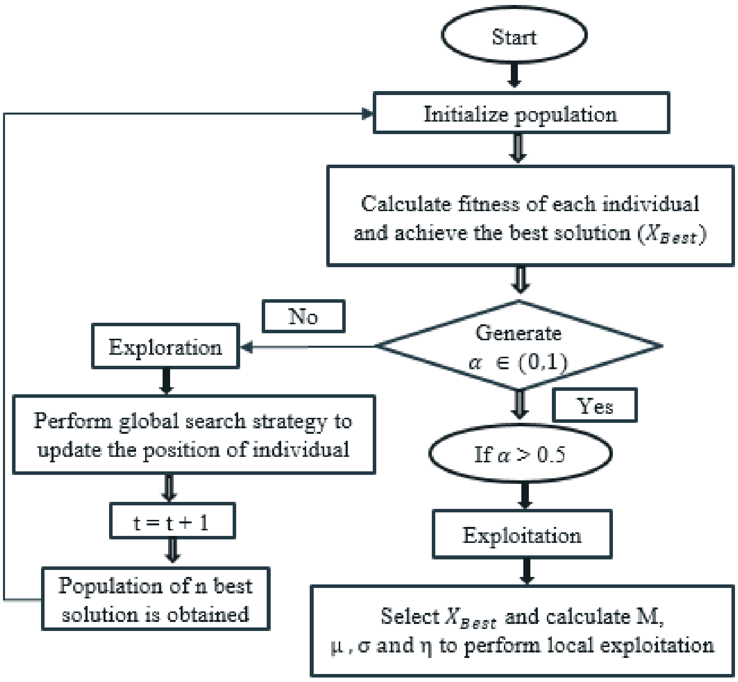

Fig. 4.4 Flowchart of the GNDO.

4.3.5 The computation complexity of the proposed algorithm

Computation complexity is an important statistic for estimating the execution time of an algorithm. The computational complexity of GNDO is made up of the time spent comparing and updating positions, which is dependent on the number of participants, variables, and iterations. N people must update their locations in each cycle, and N comparisons must be made. As a result, GNDO's overall computing complexity can be expressed as (NDT_{max} + NT_{max}).

CHAPTER 5
RESULTS AND DISCUSSIONS

5.1 Introduction

In this chapter, Simulation results for four-test networks are compared with different algorithms and discussed in details. The Simulated graph also attached in every case. Table content and figure are also discussed in every case.

5.2 Simulation results and discussion

A MATLAB-based simulation of four-test system is used to test the efficiency of the BES and GNDO. The BES and GNDO results are compared against other algorithms, where all the parameter values remain the same for all algorithms

5.2.1 Three thermal unit system

The three-generating unit system is presented here where the power system load demand (PD) is 400 MW and the fuel cost coefficients are given in **Table 5.1**. The results for this study case are provided in **Table 5.2,** where we can see that the BES and GNDO has a lower cost of $20815.54 and $20829.4509. The cost convergence characteristic of 3 generator system obtained from WOA, GNDO and BES is shown in **Fig.5.1 and Fig. 5.2**. It shows that the technique converges in relatively fewer cycles thereby possessing good convergence property and resulting in low operating cost.

The result obtained by the three thermal unit system by using BES and GNDO and compared with other algorithms in **Table 5.2**. And in **Table 5.1** fuel cost coefficient are given.

Table 5.1 Fuel cost coefficient for three thermal system .

Unit	P_{min} (MW)	P_{max} (MW)	a	b	c
1	35	210	1243.5311	38.30553	0.03546
2	130	325	1658.5696	36.32782	0.02111
3	125	315	1356.6592	38.27041	0.01799

Table 5.2 Three thermal unit system fuel cost at power demand 400 MW **.**

Power Output (MW)	GA	FPA	WOA	GNDO	BES
P1	102.61	102.446	110.597	89.8975	83.091
P2	153.82	153.834	130	166.3071	182.349
P3	151.01	151.132	166.918	151.5967	142.129
Total generation	407.42	407.412	407.456	407.526	407.571
Loss (MW)	7.4132	7.4126	7.45641	7.52634	7.571
Total cost ($/h)	20840	20838.1	20897.638	20829.45	20815.54

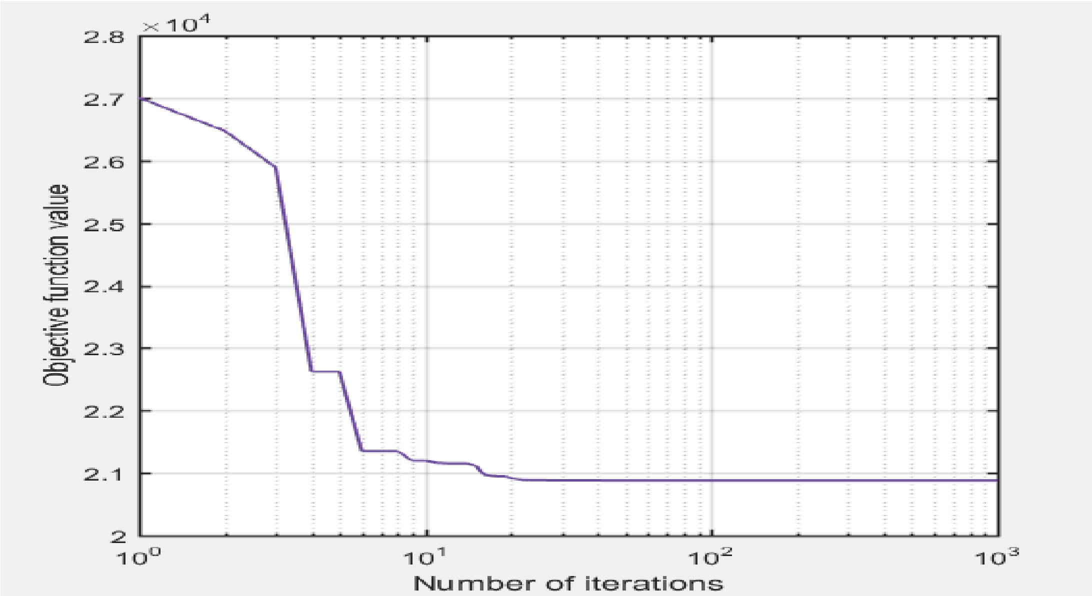

Fig. 5.1 Cost convergence characteristics of three thermal units by using GNDO.

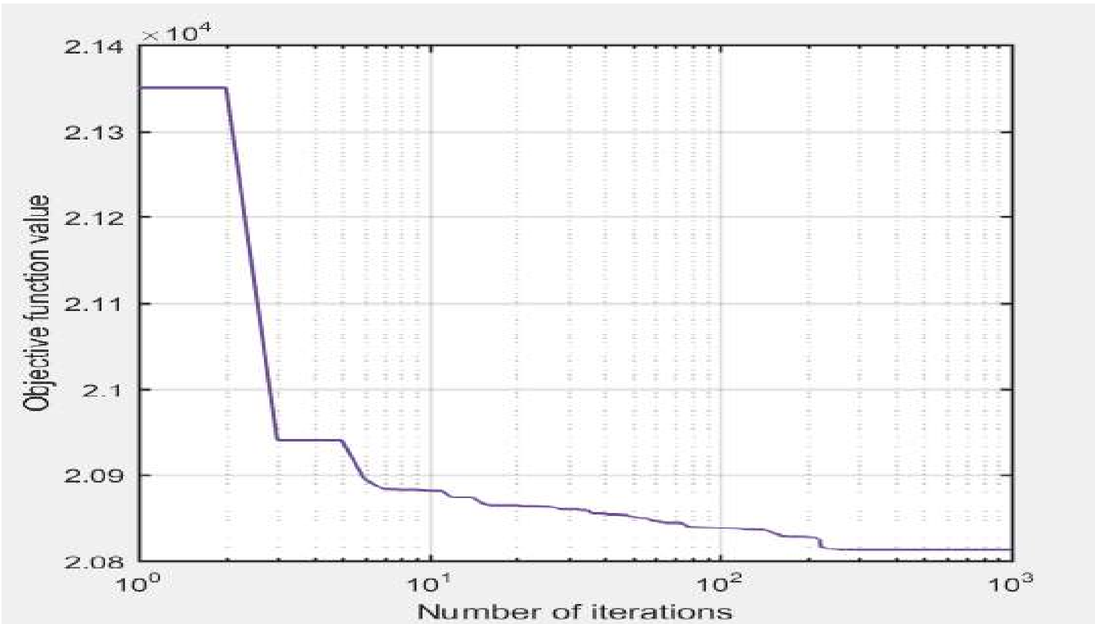

Fig. 5.2 Cost convergence characteristics of three thermal units by using BES.

The cost convergence characteristic of 3 generator system obtained from WOA, GNDO and BES is shown in **Fig. 5.1** and **Fig. 5.2**. It shows that the technique converges in relatively fewer cycles thereby possessing good convergence property and resulting in low operating cost.

5.2.2 Six thermal unit system

The load demand is set to 1263 MW. The best results of BES with other methods such as Particle Swarm Optimization (PSO) Genetic Algorithm (GA), Whale Optimization Algorithm(WOA), are tabulated in **Table 5.4**. From this table, it can be seen that the proposed BES and GNDO has a better solution in terms of total cost generated compared to others. The proposed algorithm gave the best results in terms of lower cost which is 15456.731 $/hr and 15490.4048 $/hr. The convergence characteristic of six thermal units by using WOA, GNDO, and BES is given in **Fig. 5.3 and Fig. 5.4**. The result obtained by the six thermal unit system by using BES and GNDO and compared with other algorithms in **Table 5.4** And in **Table 5.3** fuel cost coefficient are given.

Table 5.3 Fuel cost coefficient for six thermal system .

GEN	P_{min} (MW)	P_{max} (MW)	c	b	a
1	100	500	0.007	7	240
2	50	200	0.0095	10	200
3	80	300	0.009	8.5	220
4	50	150	0.009	11	200
5	50	200	0.008	10.5	220
6	50	120	0.0075	12	120

Table 5.4 Comparison of six thermal unit system fuel cost at power demand 1263 MW.

Power Output (MW)	PSO	WOA	GNDO	BES
P1	447.49	499.982022	487.688832	446.501
P2	173.32	188.194883	141.318573	178.778
P3	263.47	299.989213	295.863194	272.833
P4	139.05	101.265548	110.905167	143.926
P5	165.47	68.0683781	162.394377	145.095
P6	87.12	119.995685	78.587142	88.722
Total generation (MW)	1275.95	1277.4949	1276.7572543	1275.856
Loss (MW)	12.95	14.4949	13.7572543	12.856
Total cost ($/h)	15450	15603.95	15490.4048	15456.731

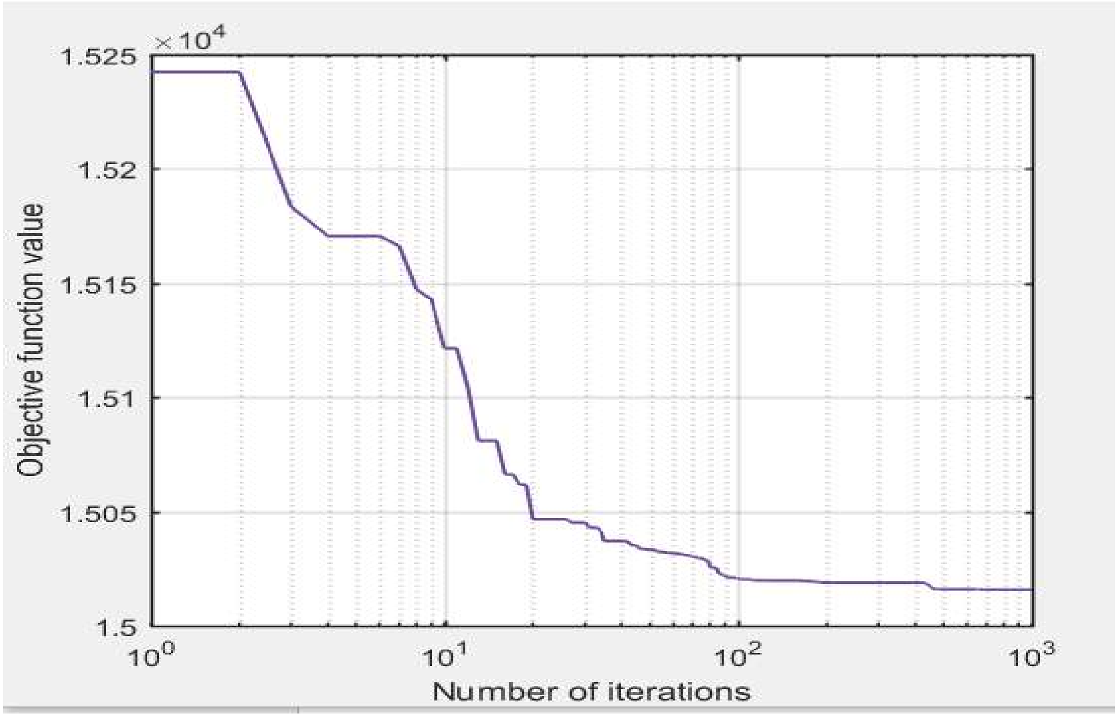

Fig. 5.3 Cost convergence characteristics of six thermal units by using GNDO.

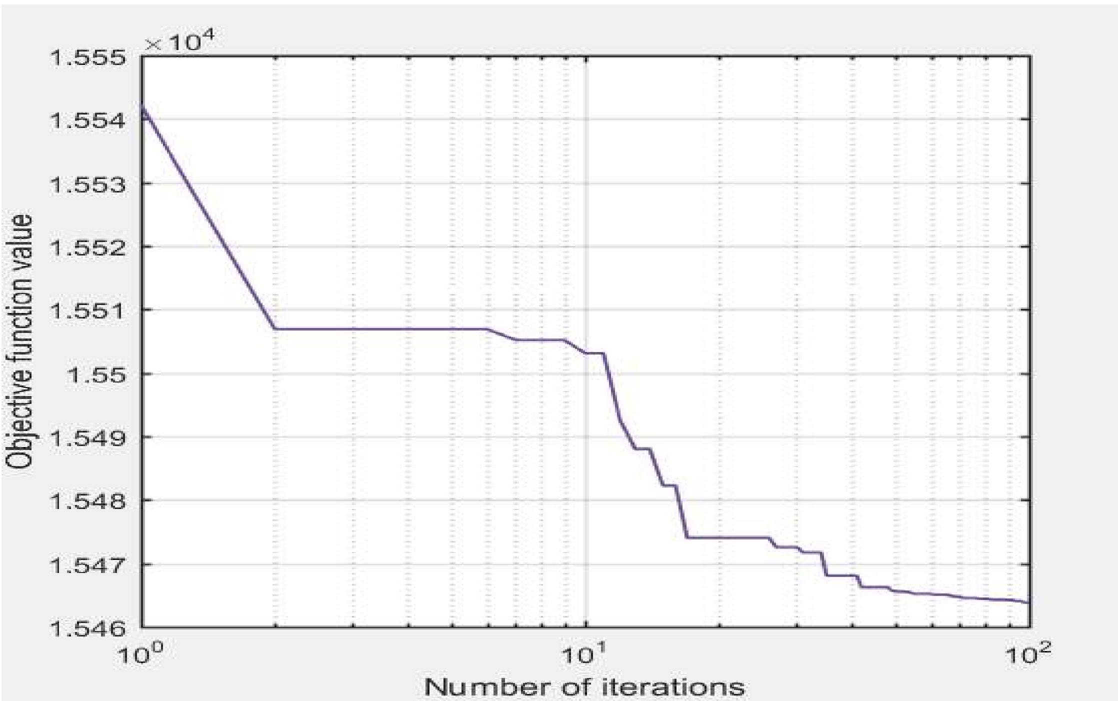

Fig. 5.4 Cost convergence characteristics of six thermal units by using BES.

5.2.3 Ten thermal unit system

For this system, the load demand is set to 2000MW. A detailed results of the optimal ED solution for this system of BES together with FPA, WOA, BES, GNDO are tabulated in **Table 5.6**. It can be noted that BES and GNDO gave the best results in terms of minimum cost of generation: 111287.448$/hr and 113921.9518$/hr which is less compared to WOA. However, the total loss obtained by BES is better where BES produces 87.125 MW compared to WOA, which is 87.137 MW. The convergence characteristic of ten thermal units by using WOA, GNDO, and BES is given in **Fig. 5. 5** and **Fig. 5.6**.

Table 5.5 Comparison of Ten-unit system fuel cost at power demand 2000 MW.

Power Output (MW)	FPA	WOA	GNDO	BES
P1	53.188	20.26523205	52.33272868	54.9999
P2	79.975	61.61721743	71.2235408	79.9999
P3	78.105	112.5742502	97.79843605	119.4089
P4	97.119	111.1567949	74.7906761	95.5084
P5	152.74	139.1779407	58.4030271	79.1377
P6	163.08	222.0725668	220.3267133	78.0774
P7	258.61	263.2965642	293.9334673	299.9997
P8	302.22	301.358806	297.4914138	339.9999
P9	433.21	415.202566	461.9720116	469.9997
P10	466.07	435.6976109	458.2473334	469.9931
Loss (MW)	84.3	82.17245719	85.49073141	87.125
Total cost ($/h)	113370.01	115345.3745	113921.9518	111287.448

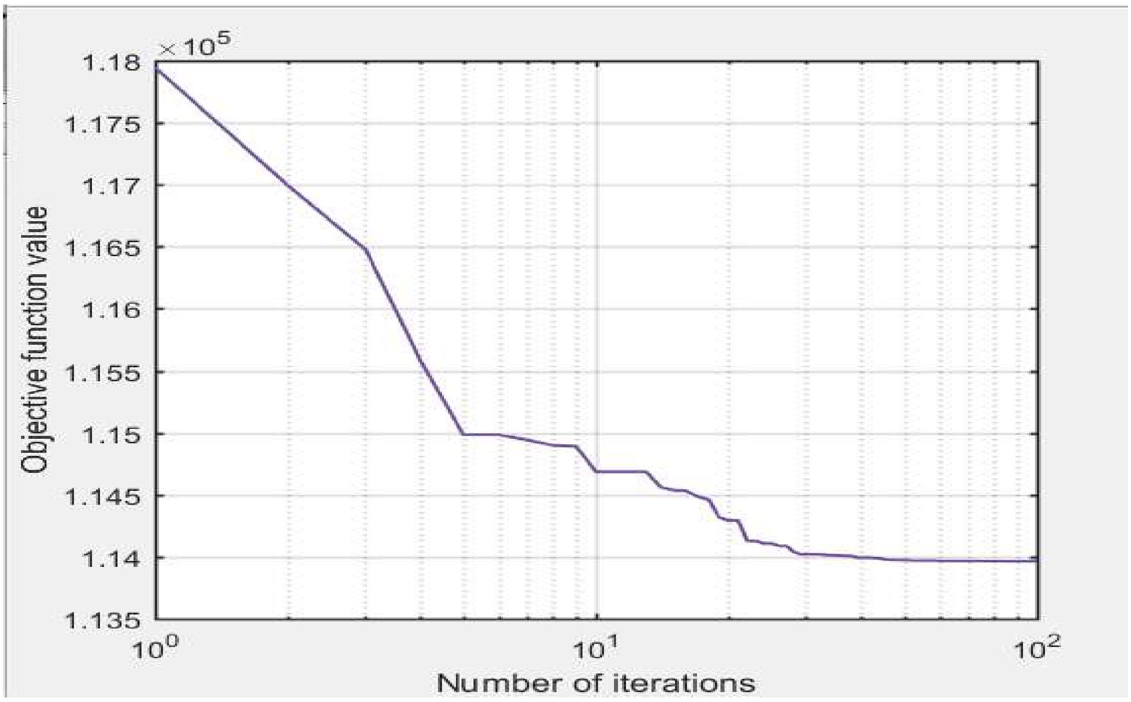

Fig. 5.5 Cost convergence characteristics of ten thermal units by using GNDO.

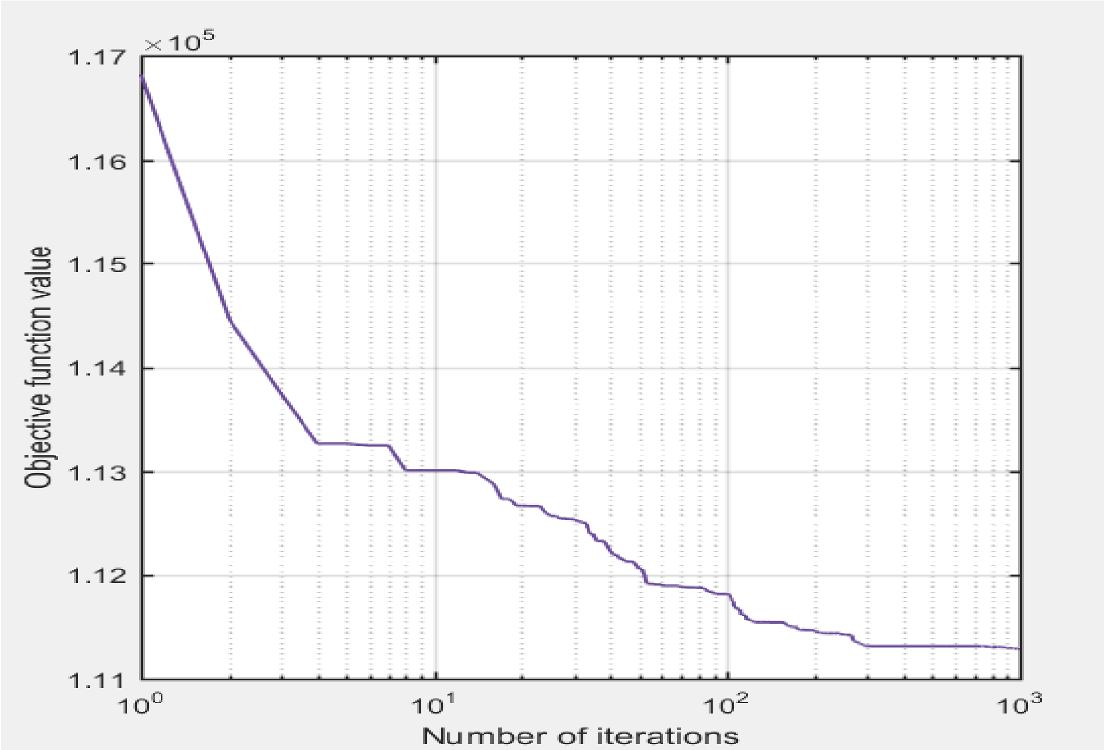

Fig. 5.6 Cost convergence characteristics of ten thermal units by using BES.

5.2.4 Three thermal with two renewable unit system:

The BES and GNDO algorithm is applied to a three-unit thermal system with renewable energy sources for a time period of 24 h in order to get the optimal economic power dispatch. It can be seen that the BES comparatively gives less operating cost, i.e., 188810.07 $/hr than that of the GNDO, which gives 189100.13 $/hr. The Cost convergence characteristics of three thermal and two renewable units by using WOA, GNDO and BES accordingly shown in **Fig. 5.7** and **Fig. 5.8**.

The result obtained by the three thermal two renewable unit system by using BES and GNDO and compared with other algorithms in **Table 5.9**. In **Table 5.7** fuel cost coefficient and in **Table 5.8** wind and solar generation data for 24 hours are given.

Table 5.6 Fuel cost coefficient for three thermal two renewable unit system.

Unit	P_{min} (MW)	P_{max} (MW)	a	b	c
1	37	150	1530	21	0.024
2	40	160	992	20.16	0.029
3	50	190	600	20.4	0.021

Table 5.7 Data of solar and wind generation (24 hours).

Time (Hours)	Wind (MW)	Solar (MW)	Time (Hours)	Wind (MW)	Solar (MW)
1	1.7	0	13	14.35	31.94
2	8.5	0	14	10.35	26.81
3	9.27	0	15	8.26	10.08
4	16.66	0	16	13.71	5.30
5	7.22	0	17	3.44	9.57
6	4.91	0.03	18	1.87	2.31
7	14.66	6.27	19	0.75	0
8	26.56	16.18	20	0.17	0
9	20.58	24.05	21	0.15	0
10	17.85	39.37	22	0.31	0
11	12.80	7.41	23	1.07	0
12	18.65	3.65	24	0.58	0

Table 5.8 Fuel cost comparison of three thermal two renewable unit system**.**

Time (hr)	PD (MW)	P1	P2	P3	WOA	GNDO	BES
1	140	45.39	43.03	50.71	6838.7529	6838.658	6837.0828
2	150	48.76	40.08	53.54	6997.1312	6994.1197	6991.1688
3	155	53.88	42.18	50.60	7103.8773	7104.2898	7097.9545
4	160	38.12	52.42	53.72	7133.7483	7131.5943	7130.3116
5	165	40.39	62.05	56.45	7376.6341	7359.4043	7358.5938
6	170	51.46	42.11	72.72	7530.8445	7503.3254	7500.4666
7	175	48.13	40.00	67.02	7447.308	7433.2132	7433.9652
8	180	39.37	48.64	50.08	7305.503	7302.374	7302.0221
9	210	49.56	61.37	55.65	7992.5498	7983.7174	7980.5083
10	230	39.85	45.04	89.31	8339.3612	8325.3536	8318.6049
11	240	77.75	92.74	51.47	9047.6505	9046.3342	9002.6216
12	250	39.40	63.87	127.02	9360.2706	9270.6585	9217.9454
13	240	38.16	55.83	101.54	8770.2232	8699.3773	8686.5409
14	220	57.96	40.03	86.39	8316.8728	8318.8556	8314.3733
15	200	82.19	41.60	59.35	8111.7395	8083.2572	8062.9923
16	180	46.00	40.53	75.66	7595.1488	7574.9859	7574.0647
17	170	44.93	61.77	51.38	7418.9297	7410.3802	7405.5416
18	185	49.95	44.15	88.25	7923.1343	7874.2525	7863.2393
19	200	77.01	50.53	73.49	8376.4831	8279.8308	8266.5120
20	240	92.64	41.93	107.94	9344.5874	9302.7113	9260.0190
21	225	40.91	90.46	95.87	9044.122	8916.9142	8886.0058
22	190	77.37	40.29	73.65	8110.0634	8054.1819	8037.7726
23	160	42.75	65.94	51.36	7329.1478	7319.0993	7315.8603
24	145	37.00	58.31	50.03	6970.5224	6970.438	6965.2241
Total	4580	1260.9	1266.9	1695.2	189780.01	189100.13	188810.07

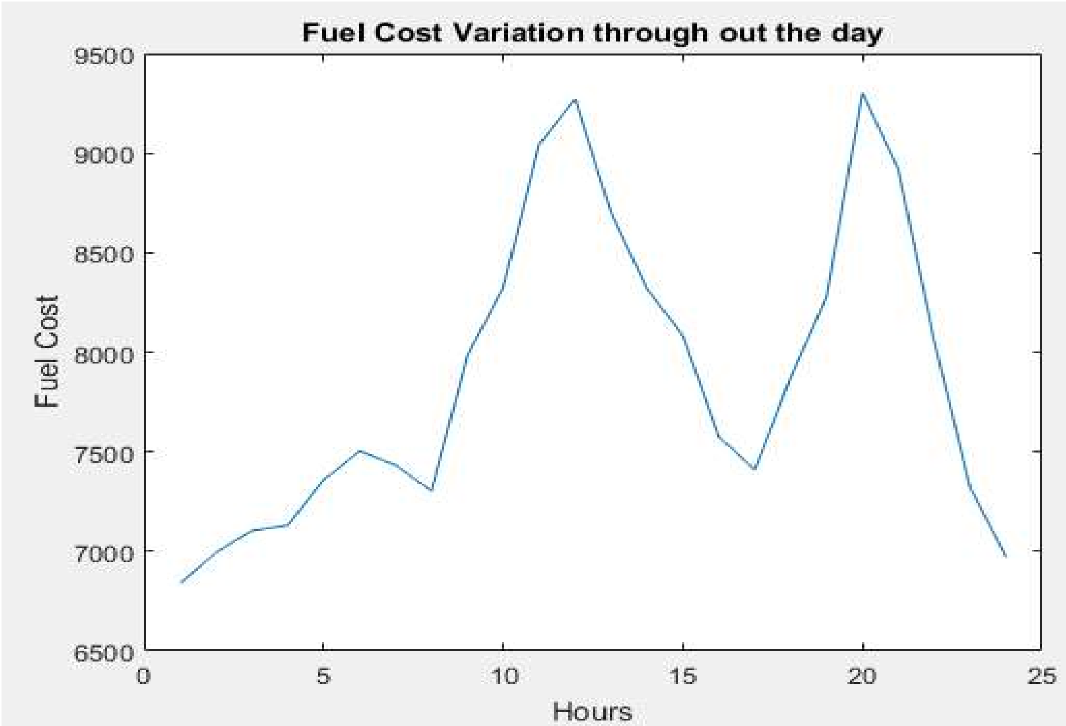

Fig. 5.7 Convergence characteristics of three thermal and two renewable units by using GNDO.

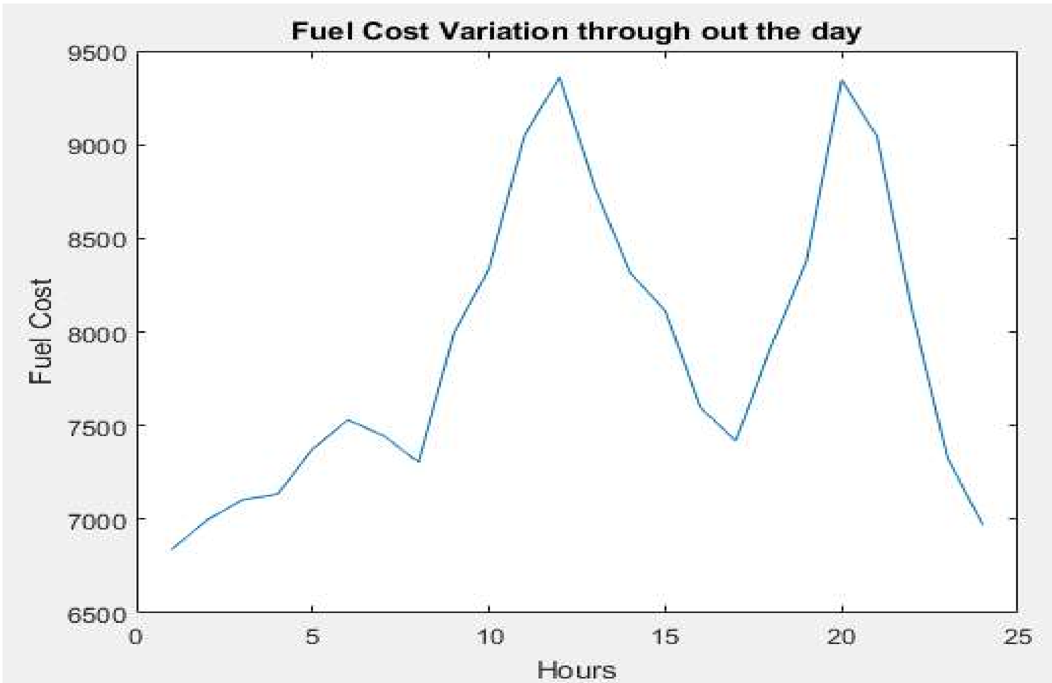

Fig. 5.8 Convergence characteristics of three thermal and two renewable units by using BES.

CHAPTER 6
CONCLUSION

6.1 Introduction

In this chapter, overall contribution of this thesis is discussed and also discussed the implementation of GNDO and BES may become very promising for solving some more complex optimization probems for future researches.

6.2 Conclusion

In this thesis, the Bald Eagle Search (BES) optimization algorithm and Generalized Normal Distribution Optimization(GNDO) are successfully implemented to produce the best solution of Economic Dispatch (ED) problem. Since there is no general procedure for determining the optimum solution of ED. This is where BES and GNDO plays an important role to find out the optimum solution. BES and GNDO are able to provide high-quality solutions with stable convergence. In the case of the proposed technique, the overall cost of generating looks to be lower than in the case of the other optimization technique. The effectiveness of BES and GNDO are demonstrated using 3, 6 and 10 thermal generators systems. Simulation results indicated that the proposed algorithm is better compared to other selected algorithms in terms of determining the minimum cost of generation in $/hr. In addition, we discussed wind and solar energy as a renewable energy source. We observed the reduction in the total cost of generation. The results are calculated for 24 hours fuel cost. The results obtained with BES and GNDO gives lowest fuel cost as compared to other optimization techniques such as with Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Flower Pollination Algorithm (FPA), Simulated Annealing (SA), and Whale Optimization Algorithm (WOA) in obtaining the minimum operating cost. In the future, BES and GNDO could also be used to solve the problems of ramp rate limits, prohibited operating zone and emission.

REFERENCES

[1] M. H. Sulaiman, W. Lo Ing, Z. Mustaffa, and M. R. Mohamed, “Grey wolf optimizer for solving economic dispatch problem with valve-loading effects,” *ARPN J. Eng. Appl. Sci.*, vol. 10, no. 21, pp. 9796–9801, 2015.

[2] H. H. Happ, “Optimal power dispatch — a comprehensive survey,” *IEEE Trans. Power Appar. Syst.*, vol. 96, no. 3, pp. 841–854, 1977, doi: 10.1109/T-PAS.1977.32397.

[3] B. H. Chowdhury and S. Rahman, “A review of recent advances in economic dispatch,” *IEEE Trans. Power Syst.*, vol. 5, no. 4, pp. 1248–1259, 1990, doi: 10.1109/59.99376.

[4] Q. Qin, S. Cheng, X. Chu, X. Lei, and Y. Shi, “Solving non-convex/non-smooth economic load dispatch problems via an enhanced particle swarm optimization,” *Appl. Soft Comput. J.*, vol. 59, pp. 229–242, 2017, doi: 10.1016/j.asoc.2017.05.034.

[5] C. E. Lin, S. T. Chen, and C. L. Huang, “A Direct Newton-Raphson Economic Dispatch,” *IEEE Trans. Power Syst.*, vol. 7, no. 3, pp. 1149–1154, 1992, doi: 10.1109/59.207328.

[6] Z. L. Gaing, “Particle swarm optimization to solving the economic dispatch considering the generator constraints,” *IEEE Trans. Power Syst.*, vol. 18, no. 3, pp. 1187–1195, 2003, doi: 10.1109/TPWRS.2003.814889.

[7] A. Devi and O. Krishna, “Combined economic and emission dispatch using Evolutionary algorithms-a case study,” *ARPN J. Eng. Appl. Sci.*, vol. 3, no. 6, pp. 28–35, 2008, [Online]. Available: http://www.doaj.org/doaj?func=fulltext&aId=1034686.

[8] T. A. A. Victoire and A. E. Jeyakumar, “Discussion of ‘Particle swarm optimization to solving the economic dispatch considering the generator constraints,’” *IEEE Trans. Power Syst.*, vol. 19, no. 4, pp. 2121–2123, 2004, doi: 10.1109/TPWRS.2004.831709.

[9] M. Basu and A. Chowdhury, “Cuckoo search algorithm for economic dispatch,” *Energy*, vol. 60, pp. 99–108, 2013, doi: 10.1016/j.energy.2013.07.011.

[10] A. Y. Abdelaziz, E. S. Ali, and S. M. Abd Elazim, “Flower pollination algorithm to solve combined economic and emission dispatch problems,” *Eng. Sci. Technol. an Int. J.*, vol. 19, no. 2, pp. 980–990, 2016, doi: 10.1016/j.jestch.2015.11.005.

[11] M. H. Sulaiman, Z. Mustaffa, M. I. M. Rashid, and H. Daniyal, “Economic Dispatch Solution Using Moth-Flame Optimization Algorithm,” *MATEC Web Conf.*, vol. 214, pp. 1–6, 2018, doi: 10.1051/matecconf/201821403007.

[12] T. Jayabarathi, T. Raghunathan, B. R. Adarsh, and P. N. Suganthan, “Economic dispatch using hybrid grey wolf optimizer,” *Energy*, vol. 111, pp. 630–641, 2016, doi: 10.1016/j.energy.2016.05.105.

[13] M. Karimzadeh Parizi, F. Keynia, and A. Khatibi Bardsiri, “Woodpecker Mating Algorithm for Optimal Economic Load Dispatch in a Power System with Conventional Generators,” *Int. J. Ind. Electron. Control Optim.*, vol. 4, no. 2, pp. 9–11, 2021.

[14] S. Pothiya, I. Ngamroo, and W. Kongprawechnon, “Application of multiple tabu search algorithm to solve dynamic economic dispatch considering generator constraints,” *Energy Convers. Manag.*, vol. 49, no. 4, pp. 506–516, 2008, doi: 10.1016/j.enconman.2007.08.012.

[15] M. Basu, “Economic environmental dispatch using multi-objective differential evolution,” *Appl. Soft Comput. J.*, vol. 11, no. 2, pp. 2845–2853, 2011, doi: 10.1016/j.asoc.2010.11.014.

[16] U. Güvenç, Y. Sönmez, S. Duman, and N. Yörükeren, “Combined economic and emission dispatch solution using gravitational search algorithm,” *Sci. Iran.*, vol. 19, no. 6, pp. 1754–1762, 2012, doi: 10.1016/j.scient.2012.02.030.

[17] T. E. Bechert and H. G. Kwatny, “Analysis Presented Below.”

[18] J. Cai, X. Ma, L. Li, and P. Haipeng, “Chaotic particle swarm optimization for economic dispatch considering the generator constraints,” *Energy Convers. Manag.*, vol. 48, no. 2, pp. 645–653, 2007, doi: 10.1016/j.enconman.2006.05.020.

[19] B. Stott and J. L. Marinho, “Linear Programming for Power-System Network Security Applications.,” no. 3, 1978.

[20] G. P. Granelli and M. Montagna, “Security-constrained economic dispatch using dual quadratic programming,” *Electr. Power Syst. Res.*, vol. 56, no. 1, pp. 71–80,

2000, doi: 10.1016/S0378-7796(00)00097-3.

[21] L. Hari, "Constraints Using a Classical Technique."

[22] R. A. Johnson, "Sequential Methods in Statistics," *Technometrics*, vol. 10, no. 2, pp. 405–406, 1968, doi: 10.1080/00401706.1968.10490575.

[23] K. Zehar and S. Sayah, "Optimal power flow with environmental constraint using a fast successive linear programming algorithm: Application to the algerian power system," *Energy Convers. Manag.*, vol. 49, no. 11, pp. 3362–3366, 2008, doi: 10.1016/j.enconman.2007.10.033.

[24] L. S. Vargas, V. H. Quintana, and A. Vannelli, "A tutorial description of an interior point method and its applications to security-constrained economic dispatch," *IEEE Trans. Power Syst.*, vol. 8, no. 3, pp. 1315–1324, 1993, doi: 10.1109/59.260862.

[25] M. R. Unum and P. Box, "Electrical Efigineering National Sun Yat-Sen University Kaohsiung, Taiwan, R.O.C.," *IEEE Trans. Power Syst.*, vol. 8, no. 3, pp. 1068–1076, 1993.

[26] J. A. Momoh, S. X. Guo, E. C. Ogbuobiri, and R. Adapa, "Quadratic Interior Point Method Solving Power System Optimization Problems," *IEEE Trans. Power Syst.*, vol. 9, no. 3, pp. 1327–1336, 1994, doi: 10.1109/59.336133.

[27] J. Chuanwen, "01047197.Pdf," pp. 2313–2317, 2002.

[28] F. Han and Q. S. Lu, "An improved chaos optimization algorithm and its application in the economic load dispatch problem," *Int. J. Comput. Math.*, vol. 85, no. 6, pp. 969–982, 2008, doi: 10.1080/00207160701305388.

[29] Erastus Mosha and A. A. B. Ruíz, "No 主観的健康感を中心とした在宅高齢者における 健康関連指標に関する共分散構造分析Title," *Theor. Appl. Genet.*, vol. 7, no. 2, pp. 1–7, 2010, [Online]. Available: http://repositorio.unan.edu.ni/2986/1/5624.pdf%0Ahttp://dx.doi.org/10.1016/j.tplants.2011.03.004%0Ahttp://dx.doi.org/10.1016/j.pbi.2010.01.004%0Ahttp://www.biomedcentral.com/1471-2156/12/42%0Ahttp://dx.doi.org/10.1016/j.biotechadv.2009.11.005%0Ahttp://www.

[30] G. A. Labrador, "Heat energy recapture and recycle and its new applications," doi:

10.1126/science.aad1920.22.

[31] F. Blaabjerg and K. Ma, "Wind Energy Systems, reviews application of power electronics in wind energy systems," *IEEE Power Energy Soc.*, vol. 105, no. 11, pp. 2116–2131, 2017, [Online]. Available: http://linkinghub.elsevier.com/retrieve/pii/B9780123972705000133.

[32] Wind turbine, Accessed :June 14 ,2022, [online]. Available: https://www.pexels.com/search/wind%20turbine/

[33] S. Orike, "Investigating Evolutionary Computation with Smart Mutation for three types of Economic Load Dispatch Optimisation Problem," 2015.

[34] how-electricity-is generated, Accessed :June 14,2022 , Available: https://www.eia.gov/energyexplained/electricity/how-electricity-is generated.php" .

[35] D. Karaboga and B. Basturk, "A powerful and efficient algorithm for numerical function optimization: Artificial bee colony (ABC) algorithm," *J. Glob. Optim.*, vol. 39, no. 3, pp. 459–471, 2007, doi: 10.1007/s10898-007-9149-x.

[36] V. Karthikeyan, S. Senthilkumar, and V. J. Vijayalakshmi, "A New Approach to the Solution of Economic Dispatch Using Particle Swarm Optimization with Simulated Annealing," *Int. J. Comput. Sci. Appl.*, vol. 3, no. 3, pp. 37–49, 2013, doi: 10.5121/ijcsa.2013.3304.

[37] X.-S. Yang and S. Deb, "Cuckoo Search via Levy Flights," 2010.

[38] H. A. Alsattar, A. A. Zaidan, and B. B. Zaidan, "Novel meta-heuristic bald eagle search optimisation algorithm," *Artif. Intell. Rev.*, vol. 53, no. 3, pp. 2237–2264, 2020, doi: 10.1007/s10462-019-09732-5.

APPENDIX

NOMENCLATURE

F_t	The total fuel cost of generation in $
F_i	The quadratic form of the system's total cost function of unit i
$F_i P_i$	The fuel cost function of i th generator in $
a_i, b_i, c_i	The coefficients of generator *i*.
Pi	The real power generation of i th generator in MW
P_{Demand}	The total load of the system in MW
P_{loss}	The transmission losses of the system in MW
P_i , P_j	The real power injections at i th and j th buses respectively
B_{ij} , B_{0i}, B_{00}	The loss-coefficients of transmission loss formula
$P_{i(min)}$, $P_{i(max)}$	The minimum and maximum generation limit (MW) of i^{th} generator respectively.