### A HYBRID GENETIC-ARTIFICIAL FISH SWARM ALGORITHM FOR ECONOMIC LOAD DISPATCH WITH VALVE-POINT AND MULTIPLE FUEL EFFECTS

**By**

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### AHMADU BELLO UNIVERSITY ZARIA, NIGERIA

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### DECLARATION

I declare that the work in this Dissertation entitled “A Hybrid Genetic-Artificial Fish Swarm Algorithm for Economic Load Dispatch with Valve- Point Loading and Multiple Fuel Effects” has been carried out by me in the Department of Electrical Engineering as part of the requirements for the award of degree of Master of Science (M.Sc.) degree in Electrical Engineering. The information derived from the literature has been duly acknowledged in the text and a list of references provided. No part of this dissertation was previously presented for another degree or diploma at this or any other Institution.

Musa Aliyu YAKUBU

(Student) Signature Date

### CERTIFICATION

This dissertation entitled **“A HYBRID GENETIC-ARTIFICIAL FISH SWARM ALGORITHM FOR ECONOMIC LOAD DISPATCH WITH VALVE-POINT LOADING**

**AND MULTIPLE FUEL EFFECTS”** by Musa Aliyu YAKUBU meets the regulations governing the award of Master of Science (M.Sc.) Degree in Electrical Engineering of the Ahmadu Bello University, and is approved for its contribution to knowledge and literary presentation.

Prof. Boyi Jimoh

(Chairman, Supervisory Committee) Signature Date

Dr. Y. Jibril

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(Dean, School of Postgraduate Studies) Signature Date

### DEDICATION

I dedicate this project to Almighty ALLAH (SWT) for his faithfulness to me throughout the entire period of this research and at all times.

### ACKNOWLEDGEMENT

My first gratitude goes to Almighty ALLAH (SWT) for guiding me through the research. My thanks go to my supervisors, Prof. Boyi Jimoh and Dr. Yusuf Jibril for the supervision and advisory role they played during the course of the research. I would like to also appreciate Prof.

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### ABSTRACT

The restructuring of the electrical power industry has given rise to a high degree of vibrancy and competitive market, which changed many features of the power industry. Energy resources become scarce, the cost of power generation increases, environmental concerns are raised, and an ever-increasing demand for electrical energy characterizes this now-altered scenario. In this perspective, Economic Load Dispatch (ELD) is necessitated. Strong heuristic techniques can go a long way in determining the optimum solution to such technical problems having large number of possible solutions. In the proposed research work, two heuristic algorithms namely: Genetic Algorithm (GA) and Artificial Fish Swarm Algorithm (AFSA) are hybridized to yield a more robust technique called “Hybrid Genetic-Artificial Fish Swarm Algorithm”, (HGAFSA) that is suitable for solving complex ELD problems. The technique is then applied to solve a multi- objective ELD problem involving higher order cost functions that includes the effects of valve- point loading and multiple fuel cost function. The proposed approach was validated using five standard IEEE test systems for 13, 40, 110, 140, and 160 generating unit systems. Testing of the developed HGAFSA based ELD algorithm (HGAFSAELDA) yielded reduction in fuel cost by 1.53%, 0.03%, 0.07%, 0.00012% and 1.37% for the 13, 40, 110, 140 and 160 generating units respectively. An annual savings in fuel cost of $3.254e+06, $3.8235e+05, $2135.7,

$9.5563e+06, and $1.1588e+06 for the 13, 40, 110, 140, and 160-generating-units respectively were achieved over the existing best costs presented in (Pradhan *et al*., 2017). HGAFSA based optimization curves and the Cumulative Power Generation curves are also presented to demonstrate how the inequality constraints are satisfied by each of the generating units.

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### LIST OF ABBREVIATIONS

### Acronyms Definition

AFSA Artificial Fish Swarm Algorithm

ANN Artificial Neural Network

BBO Biography Based Optimization

DSP Digital Signal Processor

ELD Economic Load Dispatch

EPUSPSO Efficient Population Utilization Strategy for Particle Swarm Optimization

FA Firefly Algorithm

FM Frequency Modulation

GA Genetic Algorithm

GAAPI Genetic Algorithm -Ant Colony Algorithm for Continuous domains

GWO Grey Wolf Optimization

HGAFSA Hybrid Genetic-Artificial Fish Swarm Algorithm

HGAFSAELDA Hybrid Genetic Artificial Fish Swarm Based Economic Load Dispatch Algorithm

ICA-PSO Improved Coordinated Aggregation Based Particle Swarm Optimization

KHA Krill Herd Algorithm

LIM Lambda Iteration Method

|  |  |
| --- | --- |
| LR | Lagragian Relaxation |
| MATLAB | Matrix Laboratory |
| MFCFE | Multiple Fuel Cost Function Effect |
| MVMOS | Mean Variance Mapping Optimization Strategy |
| MSSA | Modified Social Spider Algorithm |
| NLP | Non Linear Programming |
| NTA | Novel TANAN’s Algorithm |
| OGWO | Oppositional Grey Wolf Optimization |
| OIWO | Oppositional Invasive Weed Optimization |
| PSO | Particle Swarm Optimization |
| QOTLBO | Quasi- Oppositional Teaching Learning Based |
|  | Optimization |
| QP | Quadratic Programming |
| RCGA | Real Coded Genetic Algorithm |
| SDE | Shuffled Differential Evolution |
| SSA | Social Spider Algorithm |
| VPLE | Valve Point Loading Effect |

### NOMENCLATURE

|  |  |
| --- | --- |
| **Symbol** | **Meaning** |
| Ω | Set of updated population |
| S | List of steps to be executed in chronological order |
| Ρ | Combined population of GA and AFSA |
| K | Population counter |
| *S* | Step counter |
| *P* | No. of parameters |
| Q | Quantization level |
| qnorm | Quantization level normalization |
| N | No. of bits in chromosome (X) |
| Nbits | No. of bits per parameter |
| X | Chromosome (main parameter of decoder function) |
| χmin | Lower boundary of desired decoded output |
| χmax | Higher boundary of desired decoded output |

### CHAPTER ONE GENERAL INTRODUCTION

### BACKGROUND OF RESEARCH

The efficient and optimum economic operation and planning of electric power generation systems have always occupied a vital position in the electric power industry (Gargeya & Pabba, 2013). Economic load dispatch (ELD) is a process of allocating generation levels to dispersed generating power plants so that the system is fully supplied in the most economical way (Harpreet Kaur *et al*., 2015). It can also be defined as the operation of generation facilities to produce energy at the lowest cost to reliably serve consumers recognizing any operational limits of generation and transmission facilities. ELD is simply a technique used to schedule the outputs of available generating units for a particular time that minimizes the total production cost while satisfying equality and inequality constraints (Pothiya *et al*., 2008), Prior to 1973 and the oil embargo that caused the rapid increase in fuel prices, electric utilities in the United States spent about 20% of their total income on fuel for the production of electrical energy (Alsumait *et al*., 2010). An idea of magnitude of the amounts of money was under consideration, and could be obtained by considering the annual operating expenses of a large utility for buying fuel. Based on assumption proposed by Gargeya & Pabba, 2013, the following parameters for a moderately large power system:

* + 1. Annual peak load= 10,000MW;
    2. Annual load factor= 60%;
    3. Average annual heat rate for converting fuel to electric energy= 10,550.56KJ/kWh;
    4. Average fuel cost= $3.00/1.055GJ, corresponding to oil price at $18/Bbl.

With these assumptions, the total annual fuel cost for the system is as follows:

* + - 1. Annual energy produced =107 MW \* 8760h/year \* 0.60 = 5.256 \* 1010kWh;
      2. Annual fuel consumption= 10,550.56KJ/kWh \* 5.256 \* 1010 kWh = 55.45 \* 1013KJ;

III. Annual fuel cost = 55.45\* 1013 \* 3/1.055\* 10-9 $/J = $1.5767million.

This cost represents a direct requirement for revenues for the average customer of the system of 3.15cents/kWh aimed at recovering the expense for fuel. A savings in the operation of the system of small percent represents a significant reduction in operating cost, as well as in the quantities of fuel consumed. It is not surprising that this area has warranted a great deal of attention from the engineers through the years.

However, periodic changes in basic fuel price levels serve to accentuate the problem and increase its economic significance. Inflation also causes problems in developing and presenting methods, techniques, and examples of economic operation of electric power generating systems (Al-Othman & El-Naggar, 2008).

Moreover, rapid growth in power system size and electrical power demand has resulted into a problem of reducing the operating cost while maintaining voltage security and thermal limits of transmission line branches (Alsumait et al., 2010). A large number of mathematical Optimization Technique such as: GA based ELD; PSO based ELD; Hybrid GA-PSO based ELD; Dynamic Programming based ELD; Evolutionary Programming based ELD; to mention but a few have been applied to solve ELD problems. In most general formulation, the ELD problem is modeled as a non-linear, non-convex, large scale, static optimization problem with both continuous and discrete control variables (Burns & Gibson, 1975).

Furthermore, the non-linear convex nature of ELD problems has led most researchers such as: (Burns & Gibson, 1975), (Pothiya et al., 2008), (Al-Othman & El-Naggar, 2008), and others to model ELD problem using purely quadratic functions in which the quadratic coefficients are defined at the beginning of the solution search process. Whereas, more realistic models have also been developed in some other research works which includes those of: (Alsumait et al., 2010), (Sinha & Chakrabarti, 2003)*,* (Sun *et al*., 2014), (Mohammadi-Ivatloo & Rabiee, 2013), (Jubril & Komolafe, 2013); etc. These models incorporated the effect of valve point loading and multiple fuel cost functions into ELD problem formulation.

However, the proposed research work will try to address an ELD problem through the development of a more realistic model that will account for the following effects of Valve-Point Loading (VPL), Multiple Fuel Cost Function (MFCF), Ramp Rate (RR) and Prohibited Operating Zone (POZ).

These result into a multi-objective optimization problem that tends to minimize the cost of fueling the generating units during the operation. This kind of complex optimization problem requires the use of robust techniques to achieve a reliable solution. Although, this optimization problem can be solved to some extent, using the heuristic techniques earlier mentioned, but the effectiveness of the solution cannot be guaranteed in the case of large power system.

In order to proffer solution that can be reliable and more efficient, a hybridization of two conventional heuristic techniques (Genetic Algorithm and Artificial Fish Swarm Algorithm) is proposed for solving the complex optimization problem, which give rise to a technique called “ Hybrid G-AFS Algorithm” or simply HGAFSA. The choice of GA and AFSA were based on the following reasons:

* + - * 1. GA is a widely known heuristic technique that has a well-defined set of search equations that have been proven to be effective in solving problems such as: Optimal Location and Sizing of Distributed Generators and Capacitor Banks, (Moradi & Abedinie, 2010), (Atwa *et al*., 2010); Optimal Power Flow, (López-Lezama *et al*., 2012); Optimal Location of Tie and Sectionalizing Switches in Distribution System, (Rao *et al*., 2013); Optimal Network Expansion (Bernardon et al., 2014), A hybrid GA–PS–SQP method to solve power system valve-point economic dispatch problems (Alsumait et al., 2010); etc.
        2. AFSA on the other hand is a relatively new heuristic technique that is made up of well refined and sophisticated solution-search equations and has gained large application in areas like: Controller Design, (Fang *et al*., 2014); Optimal PID Tuning, (Amir Ghoreishi *et al*., 2011); Objective Function Minimization/ Maximization, (Wei Guo *et al*., 2011) (Huang *et al*., 2006); etc.

### Motivation/Justification

I derive my motivation from the fact that over the years researchers have tried to address the problem of economic load dispatch with the main focus of how to commit the online generating units economically in order to generate electricity at a minimum cost while addressing generator constraints. The modern power systems encounter numerous technical and economic difficulties under competitive deregulated environment. The generation companies’ (GENCOs) aim is to produce electric power at minimum cost therefore; proper allocation of power generation of the existing units may lead to significant savings in cost. This could be achieved by incorporating multiple fuel option into the economic dispatch problems.

### Problem Statement

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 and environmental concern necessitates 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 that will result in lowest cost of generation. Practical economic dispatch (ED) problems have highly nonlinear objective function with equality and inequality constraints. Conventional methods such as lambda iteration method, gradient method and non-conventional method such as the heuristic method earlier discussed have been applied to solve the Economic Load Dispatch (ELD) problem. However, these techniques may not give optimal solution because they require incremental fuel cost curves which are piecewise linear and monotonically increasing to find the global optimal solution. In the proposed research work, a hybridization of two heuristic techniques namely: Artificial Fish Swarm Algorithm (AFSA); and Binary Coded Genetic Algorithm (BCGA), will be carried out in order to form a more robust technique called “Hybrid Genetic-Artificial Fish Swarm Algorithm”, (HGAFSA). The technique will then be applied to solve a non-linear ELD problem considering the effects of valve-point loading, multiple fuel cost functions, ramp rate and prohibited operating zone. The effectiveness of the proposed approach will be demonstrated using five standard IEEE test systems (13, 40, 110, 140, and 160 generating unit systems); and finally comparing the results with those presented in (Pradhan *et al*., 2017)

### Aim and Objectives

The aim of the proposed research work is to develop a Hybrid Genetic-Artificial Fish Swarm Algorithm (HGAFSA) and use it in solving a non-linear ELD problem considering the effects of: valve-point loading and multiple fuel cost. In achieving this, the following objectives will be met:

1. To hybridize Genetic Algorithm (GA) with Artificial Fish Swarm Algorithm (AFSA) to form a more robust algorithm called HGAFSA.
2. To model a higher order ELD problem while considering the effects of valve-point loading, multiple fuel cost function, ramp rate and prohibited operating zone.
3. To solve the resulting ELD problem in (2) using the developed algorithm in (1) and demonstrate the effectiveness of the proposed approach using five standard test systems (13, 40, 110, 140, and 160 generating unit systems); and finally comparing the results

with those presented in (Pradhan *et al*., 2017).

### Scope of Work and Limitation

The following items are the step by step approach that will constitute the scope of the proposed research work:

1. For the ELD, valve point loading, multi fuel cost function, ramp rate and prohibited operating zone effects were considered while emissions were not considered; hence the impact of emissions to ELD objective function was not quantified.
2. GA and AFSA algorithms were formulated using matrix definition method to aid hybridization.
3. A simulation test framework is developed in MATLAB to demonstrate the effectiveness of the formulated multi-objective ELD problem using five standard IEEE test systems. Actual transmission network was not considered.
4. The power demand considered for the networks were based on the reference in Pradhan

*et al*., (2017).

1. The proposed ELD uses Encoder and Decoder to serve as an interface between GA and AFSA.

### Dissertation Organization Outline

This chapter describes ELD problem and a brief overview of its solution strategies. However, it forms the introductory chapter. The aim and objectives together with problem statement, methodology and significant contributions are also presented in this chapter. The rest of the chapters are organized as follows. Chapter two presents the literature review of the fundamental concepts and similar works regarding ELD problem formulation and solution approaches. Chapter three presents the methods and materials used for this research work. Chapter four presents the simulation setup, results and analysis. Finally Chapter five presents the conclusion, recommendations and limitations. Quoted references and appendices are also provided at the end of the dissertation.

### CHAPTER TWO LITERATURE REVIEW

### Introduction

In carrying out the research work, some literatures were reviewed, which served as a guide towards achieving the set goals. The review of these relevant literatures is categorized into two parts namely: review of fundamental concepts, and review of similar works, which are further discussed as follows.

### Review of Fundamental Concepts

Some of the fundamental concepts regarding the proposed research work are discussed as follows.

### Thermal power plant

A thermal power plant is a power plant in which its prime mover is driven by steam. Water is the working fluid. It is heated at the boiler and circulated with energy to be expanded at the steam turbine. To give work to the rotor shaft of the generator after it passes through the turbine, it is condensed in a condenser and then pumped to feed the boiler where it is heated (Vanita & Thanushkodi, 2011). For simplification, thermal power plants can be modeled as energy conversion from fossil fuel to electricity as described in Figure 2.1.

### P

**Fuel**

**Input**

**Boiler**

**Generator**

**Stream turbine**

Figure 2.1: Energy conversion in a thermal power plant (Vanita & Thanushkodi, 2011)

The thermal unit system generally consists of the boiler, steam turbine and generator. The input of the boiler is fuel and the output is steam. The relationship between the input and output can be expressed as a convex curve (Vanita & Thanushkodi, 2011). The input of the turbine – generator unit is the volume of steam and the output is electrical power, the overall input-output characteristic of the whole generation unit can be obtained by combining directly the input- output characteristics of the boiler and the input-output characteristic of the turbine-generator unit (Vanita & Thanushkodi, 2011).

### Generator operating cost

The total cost of operation includes the fuel cost, cost of labour, supplies and maintenance. Generally, cost of labour, supplies and maintenance are fixed percentages of incoming fuel cost. Other factors influencing power generation are operating efficiencies of generators and transmission losses (Vlachos, 2011). The total cost 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 operating cost is minimum. The input of the thermal plant is generally measured in Btu/hr and the output power is the active power in MW. A simplified input – output curve of a thermal unit is known as heat – rate curve and it is

shown in Figure 2.2 (Vlachos, 2011). Where 𝑃𝑖,𝑚𝑖𝑛 and 𝑃𝑖,𝑚𝑎𝑥 are minimum and maximum power generation by the *ith* generating unit.

**Fuel input (Btu/hr) Or Cost in ($/hr)**

P min

**Power generated, pg (in MW)** P max

Figure 2.2: Heat rate curve (Vlachos, 2011)

### Fuel efficiency

This is the ratio of power output in megawatt (MW) to fuel input in Btu/hr. The criterion of distributing the load between any two units is based on whether increasing the load in one unit as the load is decreased on the other unit by the same amount results in the increase or decrease in total load (Surekha & Sumathi, 2012).

* + 1. **Incremental *cost (*IC*)***

This is the limit of the ratio of increase in cost of fuel input in dollars per hour to corresponding increase in power output in megawatts as the increase in power output approaches zero. Incremental cost is the slope of the fuel cost curve, and the unit of *IC* is in dollars per megawatt hour (MWh). *IC* tells us how much it will cost to run a generator to produce an additional1MW

of power. All units in power plant must operate at the same incremental fuel cost for minimum cost in dollars per hour (Yun *et al*., 2011).

### Economic Load Dispatch (ELD) formulation

The objective of an ELD problem is to find the optimal combination of power generations that minimizes the total generation cost while satisfying equality and inequality constraints. The fuel cost curve for any unit is an approximation of segments of quadratic functions of the active power output of the generator by assumption (Balamurugan & Subramanian, 2008).

### The cost function

Cost function is a financial term used for expressing how differently costs can behave under a variety of circumstances. It shows how monetary outputs, everything from overhead and operating expenses to charges and fees change as the levels of an activity relating to those outputs change (Balamurugan & Subramanian, 2008). There are three basic types of linear cost functions:

* + - 1. Fixed cost functions.
      2. Variable cost functions.
      3. Mixed cost functions.

In a mixed circumstance, the cost will be fixed to a certain point that can be changed based on related activity. Analysts use these sorts of functions to make important predictions about the market place and to inform a variety of decision making tasks (Balamurugan & Subramanian, 2008).

For a given power system network, the problem may be described as optimization (minimization) of total fuel cost as defined by equation (2.1) under a set of operating constraints (Vlachos, 2011).

𝑖=1

𝑖

𝐹𝑇 = ∑𝑛

𝑖=1

𝐹(𝑃𝑖) = ∑𝑛

𝑎𝑖 + 𝑏𝑖𝑃𝑖 + 𝑐𝑖 𝑃2 (2.1)

Where *FT* represents the total fuel cost of generation in the system ($/hr), *ai*, *bi*, and *ci* are the cost coefficients of the *i*th generator, *Pi* is the power generated by the *i*th unit and *n* is the number of generators (Vlachos, 2011).

The cost is minimized subject to the following generator capacities (inequality) and active power balance (equality) constraints, as given by equations (2.2) and (2.3) respectively (Vlachos, 2011):

𝑃𝑖,𝑚𝑖𝑛 ≤ 𝑃𝑖 ≤ 𝑃𝑖,𝑚𝑎𝑥 𝑓𝑜𝑟 𝑖 = 1,2, … . , 𝑛 (2.2) Where *Pi,min* and *Pi,max* are the minimum and maximum power output respectively of the *ith* unit.

𝑃𝐷 = ∑𝑛

𝑖=1

𝑃𝑖 − 𝑃𝐿𝑜𝑠𝑠

(2.3)

Where *PD* is the total power demand and *PLoss* is total transmission loss. The transmission loss

*PLoss* is defined by (2.4) as follows (Vlachos, 2011),

𝑃𝐿𝑜𝑠𝑠 = ∑𝑛

𝑖=1

𝑛

∑

𝑗=1

𝑃𝑖 𝐵𝑖𝑗𝑃𝑗 + ∑𝑛

𝐵𝑖0𝑃𝑖

+ 𝐵00 (2.4)

Where the *Bij*s are the elements of loss coefficient matrix ***B***.

𝑖=1

The cost function defined by *FT* in equation (2.1) assumed a smooth quadratic fuel cost function without valve point (valve-point effects are ignored) loadings of the generating units. Such curve can be represented by the dotted line shown on Figure 2.3. The generating units with multi-valve steam turbines exhibit a greater variation in the fuel-cost functions. Since the valve point results

in ripples, a cost function contains higher order nonlinearity. Therefore, the function *F(Pi)* in equation (2.1) should be replaced by equation (2.5) when considering the valve-point effects (Vanita & Thanushkodi, 2011).

Sinusoidal functions are thus added to the quadratic cost function to account for the valve-point effect:

𝐹(𝑃𝑖) = 𝑎𝑖 + 𝑏𝑖𝑃𝑖 + 𝑐𝑖𝑃2 + |𝑒𝑖 × sin(𝑓𝑖 × (𝑃𝑖,𝑚𝑖𝑛 − 𝑃𝑖))| (2.5)

𝑖

Where *e*i and *f*i are the fuel cost coefficients of the *ith* unit with valve point effects. In figure 2.3 below, a, b, c, d, e and f are valve points.

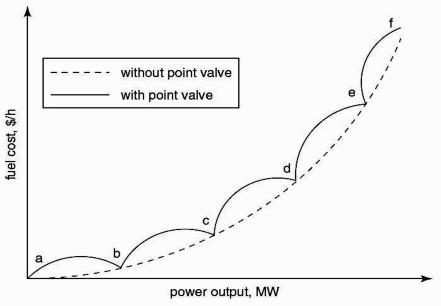


Figure 2.3: Incremental Fuel Cost Curve of a Typical Generating Unit (Vanita & Thanushkodi, 2011)

It is to be noted here that the fuel cost coefficients *ei* and *fi* are introduced in equation (2.5) to model the valve point loadings.

In practical situations, generating units are made up of subunits. These subunits combine to give rise to the overall installed capacity of the unit. Most units are designed to operate using more than one fuel type (source), particularly in the case where there is a great fluctuation in the price and availability of the dominant fuel types (Balamurugan & Subramanian, 2008). In the case of moderately large units, a combination of the available fuel types may be used to cover the power demand over the specified period of time. This type of scenario introduces a greater non-linearity into the overall fuel cost function. Therefore, the fuel cost function of such system can be modeled using multiple fuel cost function which is only defined for a particular range of power output within the specified maximum and minimum power generation. Considering both the valve point loading effect and multiple fuels, the cost function of the system may be easily represented using equation (2.6) (Balamurugan & Subramanian, 2008).

ai1 + bi1Pi + ci1P2 + |ei1 × sin(fi1 × (Pi1,min − Pi1))| Fuel1: Pmin ≤ Pi ≤ Pi1

i i

ai2 + bi2Pi + ci2P2 + |ei2 × sin(fi2 × (Pi2,min − Pi2))| Fuel2: P min ≤ Pi ≤ Pi2

F(Pi) =

\_ i \_ \_ \_

i1 \_

\_ \_ \_ \_ \_

𝗅aik + bikPi + cikP2 + |eik × sin(fik × (Pik,min − Pik))| Fuelk: P min ≤ Pi ≤ Pmax

i ik−1

ik

(2.6)

### Solution by Lagrange method

The Lagrange cost minimization function may easily be represented using (2.7) as follows (Sinha & Chakrabarti, 2003):

𝐿 = 𝐹𝑇 + 𝜆∅ (2.7)

In other words, the Lagrange function is defined by cost function *FT* plus the constraint function φ multiplied by a penalty coefficient *λ*. This penalty coefficient is set in order to limit the extent to which a set of predefined constraints are violated. Then to minimize *L*, its derivative with respect to *Pi* needs to be set to zero. This will generate a system of simultaneous equations which can be termed as "Coordination Equations", and their solution minimizes the costs, as in equation (2.8) (Sinha & Chakrabarti, 2003):

𝜕𝐿

= 𝑑𝐹𝑖 − 𝜆 (1 − 𝜕𝑃𝐿) = 0 (2.8)

𝜕𝑃𝑖

𝑑𝑃𝑖

𝜕𝑃𝑖

With this, the inequality conditions specified in equation (2.2) expand to the following set of equations (2.9) to (2.11) (Sinha & Chakrabarti, 2003):

𝑑𝐹𝑖 = 𝜆: 𝑃

≤ 𝑃

≤ 𝑃

(2.9)

𝑑𝑃𝑖

𝑖,𝑚𝑖𝑛 𝑖

𝑖,𝑚𝑎𝑥

𝑑𝐹𝑖 < 𝜆: 𝑃

= 𝑃

(2.10)

𝑑𝑃𝑖

𝑖 𝑖,𝑚𝑎𝑥

𝑑𝐹𝑖 > 𝜆: 𝑃

= 𝑃

(2.11)

𝑑𝑃𝑖

𝑖 𝑖,𝑚𝑖𝑚

These inequalities signify the fact that any unit with incremental cost higher than λ is "expensive" and should be set to operate at lowest level of production. In this way all equations are solved until all conditions are satisfied. The main point of concern is analyzing and limiting the level of production for each unit. In this Lagrange method, the transmission loss function defined in (2.4) is also applied during loss estimation (Sinha & Chakrabarti, 2003).

### Solution by Dynamic programming method

Dynamic programming is a method of solving complex problems by breaking them down into simpler sub-problems. It is applicable to problems exhibiting the properties of overlapping sub- problems and optimal substructure. When applicable the method takes far less time than naïve methods which don’t take advantage of the sub-problem overlap. The idea behind DP is quite simple. In general, to solve a given sub-problem, we need to solve different parts of the problem, and then combine the different parts of the solution to get an overall solution. Often when using a more naïve method, many of the sub-problems are generated and solved many times. DP approach seeks to solve each sub-problem only once, thus reducing the number of computations. Once the solution to a given sub-problem has been computed it is stored. The next time the same solution is needed it is simply looked up. The approach is especially useful when the number of repeating sub-problems grow exponentially as a function of the size of the input (Sun *et al*., 2014).

### Solution by Quadratic programming method

A linearly constrained optimization problem with a quadratic objective function is called a Quadratic Program (QP). Due to its numerous applications; quadratic programming is often viewed as a discipline in and of itself (Jubril & Komolafe, 2013). Quadratic programming is an efficient optimization technique to trace the global minimum if the objective function is quadratic and the constraints are linear. Quadratic programming is used recursively from the lowest incremental cost regions to highest incremental cost region to find the optimum allocation. Once the limits are obtained and the data are rearranged in such a manner that the incremental cost limits of all the plants are in ascending order. The general quadratic programming can be written as in equation (2.12) and (2.13) (Jubril & Komolafe, 2013):

𝑀𝑖𝑛𝑖𝑚𝑖𝑧𝑒:

𝑓(𝑥)

= 𝑐𝑥 +

1 𝑥𝑇𝑄

2

(2.12)

𝑆𝑢𝑏𝑗𝑒𝑐𝑡 𝑡𝑜:

𝐴𝑥 ≤ 𝑏 (2.13)

and

𝑥 ≥ 0 (2.14)

Where ***c*** is an *n*-dimensional row vector describing the coefficients of the linear terms in the objective function, and ***Q*** is an (*n* × *n*) symmetric matrix describing the coefficients of the quadratic terms. If a constant term exists it is dropped from the model. As in linear programming, the decision variables are denoted by the *n*-dimensional column vector ***x***, and the constraints are defined by an (*m*×*n*) **matrix** *A* and an *m*-dimensional column vector ***b*** of right- hand-side coefficients (Jubril & Komolafe, 2013). We assume that a feasible solution exists and that the constraint region is bounded. When the objective function *f*(**x**) is strictly convex for all feasible points the problem has a unique local minimum which is also the global minimum. A sufficient condition to guarantee strictly convexity is for ***Q*** to be positively definite. If there are only equality constraints, then the *QP* can be solved by a linear system. Otherwise, a variety of methods for solving the *QP* are commonly used, namely; interior point, active set, conjugate gradient, extensions of the simplex algorithm etc. (Jubril & Komolafe, 2013).

### Solution by Non-linear programming method

Power system operation problems are nonlinear. Thus nonlinear programming (NLP) based techniques can easily handle power system operation problems with nonlinear programming problem, the first step in this method is to choose a search direction in the iterative procedure

which is determined by first partial derivatives of the equations (Pothiya *et al*., 2008). Therefore, these methods are referred to as the first order methods, such as generalized reduced gradient method. NLP based methods have higher accuracy than linear programming based approaches and also have global convergence, which means that the convergence can be guaranteed independent of the starting point, but a slow convergence rate may occur because of zig-zagging in the search direction (Pothiya *et al*., 2008).

### Solution by Newton’s method

Newton’s method requires the computation of the second order partial derivatives of the power flow equation and other constraints and is therefore called a second – order method. The necessary conditions of optimality commonly are the Kuhn –Tucker conditions. Newton’s method is favored for its quadratic convergence properties (Pothiya *et al*., 2008).

### Solution by Heuristic approaches

Nature-inspired meta-heuristics are currently among the most effective tools for optimizing many NP-hard combinatorial problems. These methods are fundamental principles on which existing mechanisms of a biological phenomenon of nature are based. The natural systems are the most interesting inspiration for designing new methods to solve many optimization problems. The ant systems, artificial fish swarm, particle swarm optimization and bee algorithms are the techniques inspired from observing nature. These algorithms use the behavior of swarm intelligence. So they are based on a live insects or simple interactions among individual entities (Holland, 1975).

* + - 1. *Particle swarm optimization*

Particle swarm optimization (PSO) is a population based stochastic optimization technique inspired by the social behavior of flocks of birds or schools of fish. In PSO the potential solutions called particles, fly through the problem space by following the current optimum particles. The particles change their positions by flying around in a multidimensional search space until a relatively unchanged position has been exceeded (Li *et al*., 2013). A particle bases its search not only on its personal experiences but also by the information given by its neighbors in the swarm. Each particle keeps track of its coordinates in the problem space, which is associated with 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 lbest value obtained thus far by any particles in the neighbors of the particle (Li *et al*., 2013). This location is called lbest. When a particle takes the whole population as its topological neighbors, the best value is a global best and is called gbest. The main advantages of PSO are: easy implementation, single concept, robustness to control the parameters and less computational time compared to other optimization techniques while its disadvantages are: possibility of being trapped in local optimum, problems of dependency on initial point and parameter and difficulty in finding optimal design parameters and stochastic characteristic of the final outputs (Li *et al*., 2013).

* + - 1. *Artificial fish swarm algorithm*

Artificial fish swarm algorithm (AFSA) is a novel method for searching global optimum, which is typical of behaviorism in artificial intelligence. If there are *N* artificial fish in a swarm and that the vector *X* is the individual state of the artificial fish, 𝑋 = (𝑥1, 𝑥2, … , 𝑥𝑛) where 𝑥1(𝑖 = 1, … , 𝑛) is the variable to be optimized of AFSA, *Y=f(X)* is the food concentration of the

artificial fish at the current position and *Y* is the objective function of practical problems.

*Dij=||Xi-Xj||* is the distance between the individual artificial fish *i* and the individual artificial fish

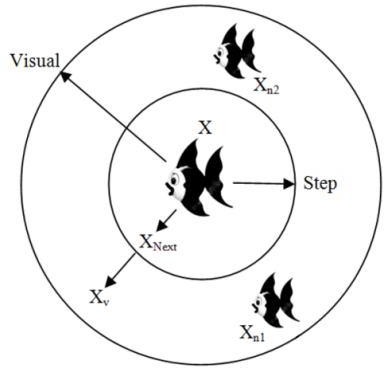
*j*. The other important parameters such as the visual field of the artificial fish, the maximum moving step, the congestion factor and the maximum number of tries in every forage are expressed as *Visual*, *Step*, *d* and *Try-number* (Azad *et al*., 2014). The congestion factor is to limit the fish swarm size of the artificial fish swarm so as to make more artificial fish individuals gather in the region with better state rather than the neighborhood with suboptimal state (Azad *et al*., 2014).

Figure 2.4: The visual and step of artificial fish (Azad *et al*., 2014) The behaviors of artificial fish include: forage, swarm and follow.

1. **Forage:** If we assume that the current state of artificial fish is *Xi* and let this artificial fish carries out forage, it will at first select a state *Xj* randomly within its visual field. In seeking minimum, if *Yi*≥*Yj,* then forage will be completed if moving one step towards this direction; if *Yi*≤*Yj,* reselect a state *X*j randomly and judge whether it satisfies the condition to move forward. After repeating this for a *Try-number* times, if it does not fulfill the forwarding condition, randomly move one step. This can be represented

mathematically as in equation (2.15)(Costa *et al*., 2014):

.

𝑥𝑗𝑘−𝑥𝑖𝑘

𝑥 = 𝑥 + . 𝑅𝑎𝑛𝑑𝑜𝑚 (𝑠𝑡𝑒𝑝) 𝑌 > 𝑌

{ 𝑖𝑛𝑒𝑥𝑡𝑘

𝑖𝑘

||𝑋𝑗−𝑋𝑖||

𝑗 𝑖

(2.15)

𝑥𝑖𝑛𝑒𝑥𝑡𝑘 = 𝑥𝑖𝑘 + 𝑅𝑎𝑛𝑑𝑜𝑚(𝑠𝑡𝑒𝑝) 𝑌𝑗 ≤ 𝑌𝑖

Where: *k*=1, 2, , *n*,

*xij* represents the *k-*th element of the current state vector *Xj* of artificial fish.

*x*jk represents the k-th element of the state vector *Xj* after random movement *x*inextk represents the k-th element of the next state vector *X*inext of artificial fish. *Y*i represents the objective function value of the current state.

*Y*j denotes the objective function value after random movement, Random (step) denotes a random number within [0 step].

1. **Swarm:** While swarming, fish has the natural ability to share the food and avoid any causes of distraction in the way. If the current state of the artificial fish is *Xj* and the number of companions in its visual domain is n. If *nf*= 0, it means that there is no companion in its visual domain and then implement forage, If *n*f≥0, it shows that there

are companions in its visual domain and then search the central position *X*c ( i.e centre between the fishes) of its companions according to equation (2.15)(Costa *et al*., 2014).

𝑋𝑐𝑘

𝑛𝑓

( ∑ 𝑥𝑗𝑘)

𝑗=1

=

𝑛𝑓

(2.16)

*Xc* represents the state vector of the central position between fishes;

*Xc*k represents the *k*-th element of the state vector *X*c of the central position;

*X*jk represents the *k*-th element of the *j (j = 1, 2,…., n,*) companion *Xj*; *Y*c represents the objective function value of the central position.

Calculate the food concentration *Yc* of the central position. Satisfying the following condition: *Yc.nf /Yi>*1. It indicates that the central position is not very congested and it is quite safe and then move toward this central position according to equation (2.16); otherwise, implement forage (Costa *et al*., 2014).

𝑥𝑖𝑛𝑒𝑥𝑡𝑘

= 𝑥𝑖𝑘

+ 𝑥𝑐𝑘−𝑥𝑖𝑘 . 𝑅𝑎𝑛𝑑𝑜𝑚. (𝑠𝑡𝑒𝑝) (2.17)

||𝑋𝑐−𝑋𝑖||

1. **Follow:** In the moving process of artificial fish swarm, when a single fish or several ones find food, the neighborhood partners have the natural ability to trail and reach the food quickly. If the current state of the artificial fish is *Xi* and the number of companions in its visual domain is *n*. If *nf*=0, it implies that there is no companion in its visual domain and then implement forage; If *nf*≥1, it is an indication that there are companions in its visual domain and then search the companion with the minimum corresponding function value *X*max in its visual domain. If it satisfies *Ymax.nf /Yi>1***.** It shows that the companion has small fitness value and that it is not very congested around here and then implement (2.18); otherwise, implement forage (Costa *et al*., 2014).

𝑥𝑖𝑛𝑒𝑥𝑡𝑘

= 𝑥𝑖𝑘

+ 𝑥𝑚𝑎𝑥,𝑘−𝑥𝑖𝑘 . 𝑅𝑎𝑛𝑑𝑜𝑚. (𝑠𝑡𝑒𝑝) (2.18)

||𝑋𝑚𝑎𝑥−𝑋𝑖||

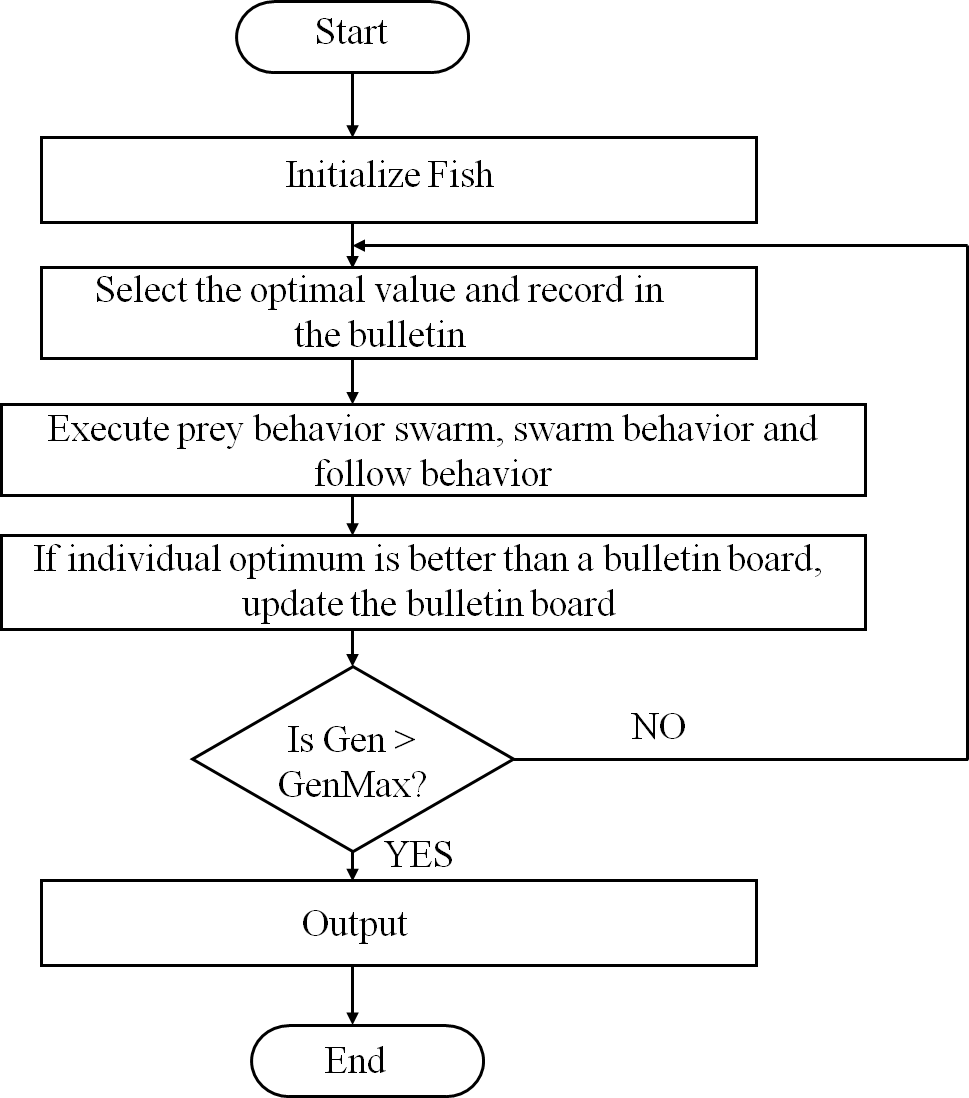
*Xmaxk* represents the *k*-th element of the state vector *Xmax*.

1. **Bulletin board:** The function of bulletin board is to record the state of the optimal artificial fish. At the optimization iteration, each artificial fish individual examines and makes comparison of its own state with the current state on the bulletin board. If the state on the bulletin board is inferior to its own state, it substitutes the state on the board with its own state; in this way, the historical optimal state can always be recorded on the bulletin board and the final recorded optimal value is the optimal solution (Costa *et al*., 2014).

Based on the behavior description of the above-mentioned artificial fish, every artificial fish searches its environmental conditions and its companions to choose an appropriate behavior in order to move rapidly towards optimal direction. Finally, the artificial fish gathers around several local optimums. The algorithm of implementation flow includes (Fang *et al*., 2014):

1. Initialization: define the population size as *N*; generate randomly *N* individuals within the definition domain of the variable and assign the maximum generation Gen max, the generation Gen, the visual field of the artificial fish Visual, the moving step of the artificial fish Step, the congestion factor *d* and the trials *Try-number*.
2. Assign the value on the bulletin board: calculate and compare the corresponding fitness value to every individual fish; choose the optimal state of the artificial fish and assign its value to the bulletin board.
3. Choose implementation behavior: every artificial fish simulates swarm and follow; implement the optimal behavior by comparing the fitness value; the default behavior is forage and *Gen=Gen* +l.
4. Update the bulletin board: compare the fitness value of every artificial fish and the value on the bulletin board, replace it if it is better than the value on the bulletin board; otherwise, keep the value on the bulletin board unchanged.
5. Judge end condition: when *Gen*>*Gen max*, end the algorithm and output the optimal value; otherwise, turn to step (III).

Figure 2.5 shows the flow chart of the AFSA algorithm



**Start**

**Initialize Fish**

**NO**

**YES**

**Output the result**

**End**

**Is Gen > Gen max ?**

**Select the optimal value and record in the bulletin**

**If individual optimum is better than a bulletin board, update the bulletin board**

**Execute prey behavior, swarm behavior and follow behavior**

Figure 2.5: Flowchart of Artificial Fish Swarm Algorithm (Fang *et al*., 2014)

* + - 1. *Genetic algorithm*

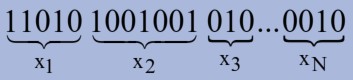
The idea of evolutionary computing was introduced in 1960 by Rechenberg in his work “Evolutionary strategies”. GA is a computerized search and optimization algorithm based on mechanics of natural genetics and natural selection. Prof. John Holland of University of Michigan conceived the concept of these algorithms in the mid-sixties and published (Chatterjee *et al*., 1996).

A genetic algorithm (GA) is a search and optimization method which works by mimicking the evolutionary principles and chromosomal processing in natural genetics. A GA begins its search with a random set of solutions usually coded in binary strings. Every solution is assigned a fitness which is directly related to the objective function of the search and optimization problem. Thereafter, the population of solutions is modified to a new population by applying three operators similar to natural genetic operator (Chatterjee *et al*., 1996):

* + - * 1. Reproduction;
        2. Crossover; and
        3. Mutation.

It works iteratively by successively applying these three operators in each generation till a termination criterion is satisfied. Over the past decade and more, GA has been successfully applied to a wide variety of problems, because of their simplicity, global perspective, and inherent parallel processing (Chatterjee *et al*., 1996)...

The GA is an iterative optimization procedure which works with a number of solutions (collectively known as population) instead of working with a single solution in each iteration. The steps involved in genetic algorithm are further described as follows (Chatterjee *et al*., 1996):

1. **Representation:** In a binary coded GA, every variable is first coded in a fixed-length of binary string. For example, a string representing *N* problem variables is illustrated below:

String Representation of *N*-problem Variables (x) (Chatterjee *et al*., 1996)

The *ith* problem variable is coded in a binary substring of length *l*i, so that total number of alternatives allowed in that variable is *2li*. The lower bound solution *Ximi*n is represented by

solution (0, 0… 0) and the upper bound solution *Ximax* is represented by the solution (1, 1… 1). And other substring si decodes to a solution *X*i as follows;

𝑚𝑖𝑛

𝑋𝑚𝑎𝑥−𝑋𝑚𝑖𝑛 .

𝑋𝑖 = 𝑋 +  𝑖 𝑖 𝐷𝑉(𝑠 ) (2.19)

𝑖 𝑙

𝑖

||2

−1|| 𝑖

Where 𝐷𝑉(𝑠.) is decoded value of string 𝑠.. The decoded value of a binary substring 𝑠. = (*si-1,si-*

𝑖 𝑖 𝑖

*2*,….,*s2,s1,s0*) is calculated as∑𝑙−1 2𝑗𝑠𝑗, where𝑠𝑗𝜖[0,1]. The length of substring is usually decided by precision needed in a variable. For example if three decimal places of accuracy are needed in

𝑗=0

the *ith* variable, total number of alternatives in the variable must be 𝑋𝑚𝑎𝑥−𝑋𝑚𝑖𝑛, which can be set

𝑖 𝑖

0.001

equal to 2li and *li* can be computed as follows:

𝑚𝑎𝑥 𝑚𝑖𝑛

𝑋 −𝑋

𝑙𝑖 = 𝑙𝑜𝑔2 𝑖 𝑖

ℇ𝑖

(2.20)

Here, the parameter ℇ𝑖 is desired precision in *i*-th variable. The total string length of an *N*-

variable solution is then 𝑙 = ∑𝑁 𝑙𝑖 in the population, l-bit strings are created at random (at each

𝑖=1

of *I* positions, there is an equal probability of creating a 0 or 1). Once such string is created, the first Ii bits can be extracted from the complete string and corresponding value of the variable xi can be calculated using equation (2.20) and using the chosen lower and upper limits of variable *xI*. This process is continued until all N-variables are obtained from complete string. Thus, an l- bit string represents a complete solution specifying all *N* variables uniquely. Once these values are known, the objective function *f(x1,x2, ... xN*) can be computed (Chatterjee *et al*., 1996).

In a GA, each string created either in the initial population or in the subsequent generations must be assigned a fitness value which is related to objective function value. For maximization problem, a string’s fitness can be equal to string’s objective function value. However, for minimization problems, the goal is to find a solution having minimum objective function value.

Thus, the fitness can be calculated as the negative of the objective function so that solutions with similar objective function value get larger fitness. There are number of advantages of using a string representation to code variables. First, this allows a shielding between working of GA and actual problem. The same GA code can be used for different problems by only changing definition of coding a string. This allows a GA to have widespread applicability. Secondly, a GA can exploit the similarities in string coding to make its search faster, this is important in working of a GA (Chatterjee *et al*., 1996).

1. **Reproduction:** Reproduction (or selection) is usually the first operator applied to a population. Reproduction selects good strings in a population and forms a mating pool. The essential idea is that above-average strings are picked from the current population and duplicates of them are inserted in the mating pool. The commonly used reproduction operator is the proportionate selection operator, where a string in the current population is selected with probability proportional to the string’s fitness. Thus, the *i*th string in the population is selected with probability proportional to ℇ𝑖. Since the population size is usually kept fixed in a simple GA, the cumulative probability for all string in the population must be one.

Therefore, the probability for selecting *i*th string is given in equation (2.21)

𝑃(𝑠𝑖) = 𝑓𝑖⁄ 𝑁

∑𝑖=1

𝑓𝑖

2.21

Where *N* is the population size and 𝑓𝑖 is the fitness of the *i*th string.

One way to achieve this proportionate selection is to use a roulette-wheel with the circumference marked for each string proportionate to the string’s fitness (Chatterjee *et al*., 1996).

1. **Crossover:** The crossover operator is applied next to the string of the mating pool. In crossover operator, two strings are picked from the mating pool at random and some portion of the strings is exchanged between the strings. In a single-point crossover operator, both strings are cut at an arbitrary place and right-side portion of both strings are swapped among themselves to create two new strings, as illustrated below:

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Parent 1 | 0 | 0 | 0 | 0 | 0  0 | 0 | 1 | 1 | 1 | Child 1 |
| Parent 2 | 1 | 1 | 1 | 1 | 1 1 | 1 | 0 | 0 | 0 | Child 2 |

An Illustration of Genetic Crossover (Dhebar and Deb, 2017)

It is interesting to note from the construction that good substrings from either parent string can be combined to form better child string if an appropriate site is chosen. Since the knowledge of an appropriate site is usually not known, a random site is usually chosen (Dhebar & Deb, 2017).

However, it is important to realize that the choice of a random site does not make this search operation random. With a single-point crossover on two *l*-bit parent strings, the solution search can only find at most different strings in the search space, whereas there are a total of strings in the search space. With a random site, the children strings produce 2i which may or may not have a combination of good substrings from parent strings depending on whether the crossing site falls in the appropriate site or not. But we do not worry about this aspect too much, because if good strings are created by crossover, there will be more copies of them in the next mating pool generated by the reproduction operator. But good strings are not created by crossover; they will not survive beyond next generation, because reproduction will not select bad strings for the next mating pool. In a two-point crossover operator, two random sites are chosen. This idea can be extended to create multi-point crossover operator and the extreme of this extension is known as a

uniform crossover operator. In a uniform crossover for binary strings, each bit from either parent is selected with a probability of 0.5 (Dhebar & Deb, 2017).

The main purpose of the crossover operator is to search the parameter space. Other aspect is that the search need to be performed in a way to preserve the information stored in the parent string maximally, because these parent strings are instances of good strings selected using the reproduction operator. In the single-point crossover operator search is not extensive, but the maximum information is preserved from parent to children. On the other hand, in the uniform crossover, the search is very extensive but minimum information is preserved between parent and children strings. If a crossover probability of Pc is used then 100Pc% strings in the population are used in the crossover operation and 100(1-Pc) % of the population are simply copied to the new population (Dhebar & Deb, 2017).

1. **Mutation:** Crossover operator is mainly responsible for the search aspect of genetic algorithms, even though the mutation operator is also used for this purpose sparingly. The mutation operator changes a 1 to a 0 and vice versa with a small mutation probability *P*m. An example of mutation operation is as illustrated below:

0 0 0 0 0  0 0 0 1 0

An Illustration of mutation operation (Dhebar and Deb, 2017)

In the above example, fourth gene has changed its value, thereby creating a new solution. The need for mutation is to maintain diversity in population. For instance, if in a particular position along the string length all strings in the population have a value 0, and a 1 is needed in that position to obtain optimum or a near-optimum solution, then mutation operator described above

will be able to create a 1 in that position. The inclusion of mutation introduces some probability of changing that 0 into 1. Furthermore, for local improvement of a solution, mutation is useful (Dhebar & Deb, 2017).

After reproduction, crossover, and mutation are applied to whole population, one generation of GA is completed. The reproduction operator selects good strings and the crossover operator recombines good substrings from two good strings together to hopefully form a better substring. The mutation operator alters a string locally to create a better string. Even though none of these claims is guaranteed and / or tested while creating a new population strings, it is expected that if bad strings are created they will be eliminated by the reproduction operator in next generation and if good strings are created, they will be emphasized. To make a faster convergence of a GA to real-world problems, problem-specific operators are often developed and used, but the above three operators portray fundamental operations of a genetic algorithm and facilitate a comparatively easier mathematical treatment (Dhebar & Deb, 2017).

The flow chart for the GA algorithm is shown in Figure 2.6.

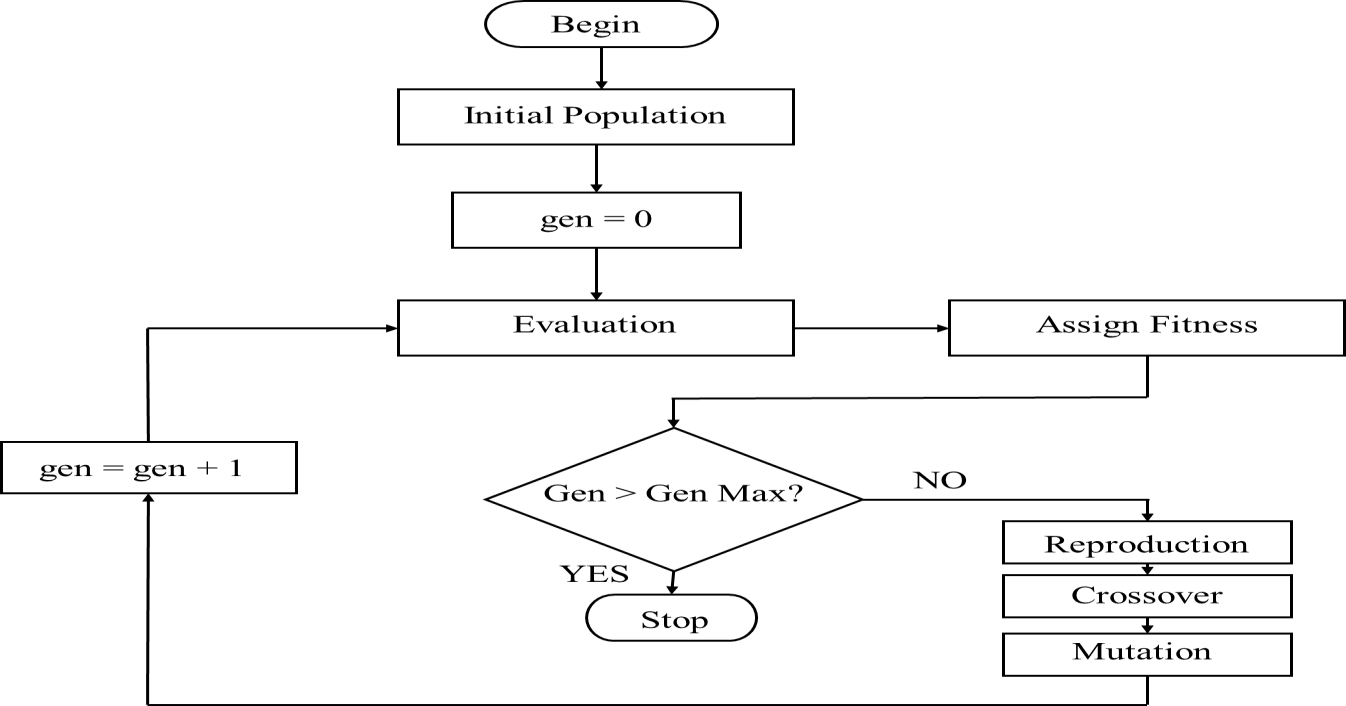


Figure 2.6: Flow chart of Binary Coded GA (Dhebar & Deb, 2017)

* + - 1. *Hybrid algorithms*

Hybrid algorithms try to make use of the merits of different methods to improve the performance of algorithms that are based on a single method. The main aim of proposing an algorithm as a hybrid of two or more methods is to speed up the convergence and to get better quality of solutions than that obtained when applying the individual methods by utilizing their strength and mitigating their weaknesses. A new algorithm integrating Genetic Algorithm (GA) and Artificial Fish Swarm Algorithm (AFSA) can be used to solve an economic dispatch problem. The core of the algorithm is based on GA. AFSA is used to generate new population members in the reproduction phase of the GA. AFSA method is used to accelerate the convergence of the GA by applying the AFSA for all the population members. In other words, GA is used for local search while AFSA is used for global search (Fang *et al*., 2014).

### Review of Similar Works

In the literature, a large number of publications have been made on the various aspects of power system distribution network. Quite a number of such publications have been consulted which served as a guide towards achieving the aim and objectives of the research work. Some of these publications are reviewed below.

**Bouktir & Slimani, (2005)** presented a solution of optimal power flow (OPF) problem of electrical power system using real type genetic algorithm. The objective was to minimize the total fuel cost of generation and environmental pollution caused by fossil based thermal generating units and also maintain an acceptable system performance in terms of limits on generator real and reactive power outputs, bus voltages, shunt capacitors/reactors, transformers tap-setting and power flow of transmission lines. The algorithm was developed in an Object Oriented environment using C++ programming language. The economic power dispatch was applied to an IEEE 30-bus model system (6-generator, 41-line and 20-load). The numerical results have demonstrated the effectiveness of the stochastic search algorithms. Further analyses indicated that this method can be effective for large-scale power systems. However, the rate of convergence of the proposed method can be improved by hybridization with other heuristic algorithm such as AFSA.

**Chiang, C.-L. (2005)** presented an improved genetic algorithm with multiplier dating (IGA\_MU) for power economic dispatch of units with valve-point effects and multiple fuels. The IGA was equipped with an improved evolutionary direction operator and a migration operation in order to efficiently search and actively explore solutions, while the MU was employed to handle the equality and inequality constraints of the PED problem. In order to demonstrate the effectiveness of the proposed approach, it was applied on four test systems comprising 20, 40, 80

and 160 generating units. Additionally, the proposed algorithm was compared with previous methods and the conventional genetic algorithm (CGA) with the MU (CGA\_MU). However, the major setback of this approach is its high computational time. This can be improved by hybridizing GA with AFSA.

**DosSantosCoelho, L., & Mariani, V. C. (2006)** proposed a new approach for solving economic load dispatch problems with valve-point effect. The proposed method combines the DE algorithm with the generator of chaos sequences and sequential quadratic programming (SQP) technique to optimize the performance of economic dispatch problems. The DE with chaos sequences is the global optimizer, and the SQP is used to ﬁne-tune the DE run in a sequential manner. The combined methodology and its variants are validated for two test systems consisting of 13 and 40 thermal units whose incremental fuel cost function takes into account the valve- point loading effects. The proposed combined method outperforms other state-of-the-art algorithms in solving load dispatch problems with the valve-point effect. However, the solution can be made more robust if hybridized with AFSA.

**Vlachogiannis & Lee, (2009a)** presented an improved coordinated aggregation-based particle swarm optimization (ICA-PSO) algorithm for solving the optimal economic load dispatch (ELD) problem in power systems. In the ICA-PSO algorithm, the number of search intervals for the particles was selected adaptively and the particles searched the decision space with accuracy up to two decimal places resulting in the improved convergence of the process. The ICA-PSO algorithm was tested on a number of power systems, including the systems with 6, 13, 15, and 40 generating units, the island power system of Crete in Greece and the Hellenic bulk power system, and is compared with other state-of-the-art heuristic optimization techniques (HOTs), demonstrating improved performance over them. However, PSO has the possibility of being

trapped in a local optimum. In addition to that, it always has difficulty in finding optimal design parameters and the stochastic characteristic of the final output. Hence the rate of convergence of the algorithm may be reduced when non linear constraints are considered.

**Rahmat Azami, (2011)** incorporated two approaches into the EDC and DCOPF problems. One of them was a mathematical optimization technique, Lagrangian Relaxation (LR) and the second was a heuristic one, Particle Swarm Optimization. The LR technique was based on the derivatives while the PSO was a non-derivative technique. The DCOPF methodology has been considered for Locational Marginal Pricing (LMP) calculation in LR, which is not available in PSO techniques. On the other hand, PSO technique may be able to provide the optimal solution, LR usually gets stuck at a local optimum in large scale power system and it takes much time in calculating LMP which makes its convergence difficult when large power systems are involved. This limits its application.

**Gargeya & Pabba, (2013)** presented Economic Load Dispatch of real power generation. The work considers valve point loading effects of the generating units. Two intelligent search methods were considered, namely, genetic algorithm and pattern search methods. Equality constraint was satisfied by penalty approach method. Two typical test cases of 5-generator, and 13-generator were carried out. The effectiveness of the approach can be made more realistic by incorporating no linear constraints such as multiple fuel cost function into the objective function. **Azad *et al*., (2014)** proposed an improved binary artificial fish swarm algorithm for 0-1 the multidimensional knapsack problem. The algorithm uses population of points in space to represent the position of fish in school; a point is represented by binary string of 0/1 bits. Each bit of a trial point is generated by copying the corresponding bit from the current point or from some other speciﬁed point, with equal probability. Some randomly chosen bits of a selected point

were occasionally changed from 0 to 1, or 1 to 0, with a user deﬁned probability. The infeasible solutions were made feasible by a decoding algorithm. The comparison with other methods shows that the proposed method gives a competitive performance. HGAFSA could perform better in terms of execution time.

**Fang *et al.*, (2014)** presented a hybrid real coded genetic algorithm and artificial fish swarm algorithm for short-term optimal hydrothermal scheduling (SHS). RCGA was used for global search while AFSA was used for local search in order to improve the exploitation capability of the algorithm. The water transport delay between connected reservoirs was taken into account. Moreover, new coarse and ﬁne adjustment methods without any penalty factors and extra parameters were proposed to deal with all equality and inequality constraints. The feasibility and effectiveness of the proposed RCGA–AFSA method was tested on two hydrothermal systems and compared with other method, the simulation results obtained by hybrid RCGA–AFSA showed superiority in fuel cost and computation time. However, HGAFSA still showed lower fuel cost and faster convergence rate.

**Gupta & Chawala, (2015)** presented a new efficient approach to economic load dispatch (ELD) problem with cost functions using curve fitting, ANN and particle swarm optimization. The ELD problem was modeled using multiple fuel cost function typically for coal power plants with varying quality. Curve fitting technique was used to obtain the coefficients of the cost curve. The same data is used for the training of the artificial neural network. The effectiveness of the algorithm was validated by carrying out extensive test on a power system involving eight (8) thermal generating units. The variation in calorific values of the coal used in different generators results in cost curve coefficients change. This effect was incorporated using curve fitting, ANN and PSO approaches. The ELD problem was then optimized. The comparison showed a better

result. However, the effectiveness of the technique can be improved by considering higher order cost functions.

**Khoa *et al*., (2015)** proposed a Swarm based Mean-variance mapping optimization (MVMOS) for solving the economic dispatch. The proposed optimization algorithm was the extension of the original single particle mean-variance mapping optimization (MVMO). The novel feature was the special mapping function applied for the mutation based on the mean and variance of n-best population. The MVMOS was investigated on four test power systems, including 3, 13, 20 thermal generating units and large-scale system of 140 units with quadratic cost function and the obtained results were compared with many other known methods in the literature. Test results showed that the method was quite efficient and can be implemented for solving economic dispatch. However, the effectiveness of the technique can be improved by incorporating non linear parameters such as valve point loading.

**Sharma *et al*., (2015)** presented Grey Wolf Optimization (GWO) to solve convex economic load dispatch (ELD) problem. Grey Wolf Optimization (GWO) is a new meta-heuristic inspired by grey wolves. The leadership hierarchy and hunting mechanism of the grey wolves was mimicked in GWO. The technique was implemented on two different test systems for solving the ELD with various load demands. The results were compared with other existing techniques. However, the ELD problem was modeled based on the quadratic fuel cost function, which is less effective than the higher order cost function (when non linear constraints parameters are considered).

**Aref Jalili *et al*., (2015)** presented a hybrid method based on Firefly Algorithm (FA) and Fuzzy Mechanism (FM) for solving Economic Load Dispatch (ELD) problem by considering the valve point in power system. Nonlinear constraints of generators, such as ramp rate limits, prohibited

operating zone, generation limits, transmission line loss and non-smooth cost functions were all considered. An attempt was made to find out the minimum cost by using FA using the data of six and forty generating units. Results were also presented. Though the problem definition was quite impressive, but the results failed in demonstrating the effectiveness of the method as compared with other similar methods in the literature.

**H Kaur *et al*., (2015)** presented a method for solving Economic Load Dispatch problem in order to operate an electric thermal power station within estimated load demand limits. The ELD objective function was formulated within the limits of equality and inequality constrains. The aim is to minimize fuel cost. The simulation results presented were quite good compared to the results so far in literature, but cannot be relied upon in the case of practical scenario simulation as they were based on quadratic cost function. Therefore, the accuracy of the method can be improved by considering other non linear constraints.

**Kumar Sharma & Kasniya, (2015)** applied Fuzzy Logic in combination with Genetic Algorithm (GA) to solve various power system problems. The computational results revealed that the proposed algorithm had excellent convergence characteristics and was superior to the GA and LIM. However, the work was only based on comparative analysis. Its effectiveness in solving multi-objective ELD problem can be improved.

**Wu *et al*., (2015)** presented an Efficient Population Utilization Strategy for Particle Swarm Optimization (EPUSPSO) to solve the ELD problem of power system. The algorithm was tested on three different ELD cases of power system including 3, 13 and 40 IEEE generating units, and the obtained results were compared with those obtained from other algorithms using the same system parameters. The compared results showed that the algorithm was able to find optimal

solution effectively and accurately. However, a quadratic fuel cost function based ELD model was used, but in practical scenarios, fuel cost functions are highly non-linear and can best be represented by higher order cost functions.

**Kasarapu & Sri, (2015)** solved economic load dispatch problem by Lagrange Multiplier method for a network of 8 bus system with 4 thermal units under competitive electricity market with inclusion of demand response programs using different strategies for peak load reduction with the application of fuzzy logic principles and independent power producers (IPPs). However, the method presented is not suitable for highly non-linear fuel cost functions (which is one of the typical properties of ELD problems). Therefore, the flexibility of the method can be improved.

**Subramanian *et al*., (2015)** presented a Novel TANAN’s Algorithm (NTA) for solving convex Economic Load Dispatch (ELD) problems considering transmission line losses. The main objective of NTA was to minimize the total fuel cost of the generating units, subject to limits on generator power output. The NTA was a simple numerical random search approach based on a parabolic TANAN function. The work therefore presented an application of NTA to ELD problems for different IEEE standard test systems. The simulation results showed that the simplicity of the proposed algorithm vary widely with increase in the number of generating units. This limits its application in real ELD problems.

**Dewangan *et al*., (2015)** presented lambda iteration method to solve an ELD problem using MATLAB for three and six generating units with and without transmission line losses. However, the method may not be suitable for application when other non linear constraints such as valve point loading and multiple fuel cost are considered.

**Achana N, (2015)** proposed a solution for unit commitment and economic load dispatch problem using hybrid Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The work showed lower operating cost and execution time when compared to several state-of-the-art techniques. The proposed system was tested on the seven unit Neyveli thermal power station system data. The algorithm was developed and executed using C++ and MATLAB 7.1 software. The work looks promising in addressing ELD problem but its guarantee can be made stronger by incorporating multiple fuel cost function into the proposed ELD model.

**Elsayed *et al*., (2016)** proposed a Modified Social Spider Algorithm for solving non-convex Economic Load Dispatch problem (MSSA). In their work, the binary mask based random walk used for generating new solution in the social spider algorithm (SSA) was replaced with mutation process after application of selection process. The performance and efficacy of the proposed MSSA were tested using four IEEE test systems having 6, 40, 80 and 140 generating units. The method proved effective in addressing generation fuel cost.

**Pradhan *et al*., (2017)** proposed an oppositional grey wolf optimization algorithm (OGWOA) for resolving the optimal economic load dispatch (ELD) problem. Their approach was based on the two common wolf behaviors namely: the hunting and social behavior. The opposition characteristics of grey wolves was mimicked and integrated into the solution strategy in order to ensure optimality and accelerate the rate of convergence of the conventional GWO algorithm. The performance of the proposed algorithm was demonstrated by applying it to a small, medium and large scale hypothetical test systems comprising of 13, 40 and 160 generating units. The results were further compared with that of the conventional GWO and other similar heuristic algorithm based techniques. Its effectiveness could be enhanced if it is hybridized with Artificial Fish Swarm Algorithm.

However, HGAFSA demonstrated superiority in terms of convergence rate, computational expensiveness and objective function minimization. Despite its effectiveness in solving ELD problems, hybrid heuristic algorithms based technique could perform better especially in the case of large number of generators (since ELD problem involves large number of possible solutions).

The reviewed literature so far covered a wide variety of ELD problem formulations and their respective solutions, the accuracy, efficiency, robustness, and flexibility of the approach presented in these literatures can be improved. It is worth noting that, Practical economic dispatch (ED) problems have highly nonlinear objective function with equality and inequality constraints. Conventional methods such as lambda iteration method and gradient method are not suitable for solving such problems. Heuristic techniques on the other hand (if not robust enough) may fail to provide optimal solution to the ELD problems (especially when the fuel cost function is highly non-linear). In the proposed research work, a more robust method was developed by hybridizing AFSA and BCGA to form a method called “HGAFSA”. Some of the target features of the HGAFSA algorithm are:

* Speed (able to overcome the computational complexity introduced by the sinusoidal component of the fuel cost function);
* Flexibility (able to optimally solve ELD problems with either quadratic or higher ordered cost function); and
* Accuracy (provide accurate results for five standard IEEE test cases [13, 40, 110, 140 and 160 generating units] and 463 generating units obtained by the combination of the five generating units.

Detailed characteristics of the proposed HGAFSA method will be presented in the subsequent parts of the proposed research work.

### CHAPTER THREE METHODOLOGY

### Introduction

This chapter presents detailed procedure that was used in achieving the set aim and objectives of the proposed research work, some useful findings and a set of pseudo codes describing the algorithm steps that were adopted.

### Formulation of the Proposed HGAFSA

The proposed Hybrid Binary Coded Genetic Algorithm and Artificial Fish Swarm Algorithm (HGAFSA) are designed based on the available parameter dredging steps present in the conventional GA and AFSA. However, each of the separate algorithms (GA and AFSA) is assumed to be composed of three major steps as described in the following.

* + 1. GA
       1. Reproduction;
       2. Crossover;
       3. Mutation.
    2. AFSA
       1. Preying;
       2. Swarming;
       3. Chasing.

The mathematical formulation of these steps has been earlier described in Chapter two of this work.

The proposed HGAFSA is a logical combination of the six (6) steps listed above. It is worthy of noting that, the BCGA uses binary operation on a set of binary codes known as chromosomes which further comprises of genes whereas, the AFSA uses real numbers ranging between zero and one as parameters of artificial fish. As such, a Decoder function and an Encoder function are required to serve as converters from GA to AFSA and vice versa. These functions are intended to decode binary code into real numbers and later encode real numbers into binary respectively.

### Decoder Function

The decoder function takes in four parameters as inputs and generates a decoded version of the main parameter as output. Here, the main parameter is the chromosome (*X*), whereas the remaining three parameters are:

i.

ii. iii.

*x*min

*x*max

*Nbits*

 Lower boundary of the desired decoded output;

 Higher boundary of the desired decoded output;

 Number of bits per parameter.

The steps involved in decoding a single chromosome can be described using Decoder function as follows:

Algorithm 3.1: The Decoder Function

* + 1. Input: *X*,

*x*min ,

*x*max and

*Nbits* ;

* + 1. Evaluate: *N* = number of bits in *X*;
    2. Evaluate: p =

*N* \**N* 1

(number of parameters);

*bits*

* + 1. Evaluate:

*q*  0.5[1,2,......*Nbits* ] (quantization levels);

 *Nbits*

1

* + 1. Evaluate:

*qnorm*  *q* \*  *qi* 

(quantization level normalization);

 *i*1 

* + 1. Evaluate:

*Xdecoded*(*i*)  [*q*(1) \* *X* ( *j* 1)

*q*(2) \* *X* ( *j*  2)

*q*(3) \* *X* ( *j*  3)

# ...

*q*(*Nbits* ) \* *X* ( *j*  *Nbits* )]

*for i*  1: *p* and

*j*  (*i* 1) \* *Nbits*) (decoding the bits forming the ith parameter)

* + 1. Output:

*Xdecoded*  *Xdecoded*(1)

*Xdecoded*(2)

*Xdecoded*(3)

# ....

*Xdecoded*( *p*)\* (*x*max  *x*min )  *x*min

Using the Decoder function, a vector *X* with *p\* Nbits* elements is decoded into a vector

*X decoded*

with *p* elements. As an illustration, consider *X= [110110110111011110111011111011]*, if

*x*min

= 0 and

*x*max =1, let

*Nbits* =6. Algorithm 3.1 will yield

*X decoded* = *[0.8571 0.8730 0.4762 0.9365*

*0.9365]*

In the proposed HGAFSA once any of the GA steps is executed, the resulting output/population must be decoded before their respective finesses can be evaluated. Whereas, the resulting output/population from the AFSA steps are directly evaluated using the fitness function without been decoded.

### Encoder Function

The encoder function was also written to counter the effect of the decoder function presented in Algorithm 3.1. However, a reversed procedure was adopted based on Algorithm 3.1 (moving from step 7 to 1). Here, the decoder function was intended to generate chromosome (X) given its

decoded version *Xdecode, xmin, xmax and Nbits.* However, the Encoder Function formulation was omitted from this manuscript for brevity.

Generally, it can be said that: The Decoder function converts a chromosome into a fish; whereas, the Encoder function converts a fish back to a chromosome. (This can be further illustrated using Figure 3.1).

Figure 3.1: Illustration of Chromosome-Fish Conversion and vice versa

Furthermore, it is worthy of noting that, both *X* and

*Xdecoded* are kept for reference during the

optimization process using the proposed HGAFSA. However, either *X* or

*X decoded*

is later

discarded depending on which of GA or AFSA steps (listed above) performs better at a given generation and at a given step in the HGAFSA dredging process. In the proposed HGAFSA, *X*

represents a chromosome whereas

*X decoded* represents a fish. At first, the entire population is

stored as chromosomes. However, each chromosome is either left as a chromosome (*X*) or

transformed into a fish

*X decoded* depending on which of the HGAFSA step (GA step or AFSA

step) performs better.

### Population Update

The proposed HGAFSA is composed of two unique algorithms (GA and AFSA) with totally different parameter dredging procedure. When one of the GA steps is executed on an encoded fish (chromosome), the resulting chromosome might be of poor fitness than it would have had if an AFSA step was directly performed on the fish itself. However, this consequence might be on the reverse side. Therefore, the population must be carefully updated for optimality and improved convergence rate. Algorithm 3.2 further describes the population update procedure.

Algorithm 3.2: Population Updater

* + 1. Input: S  (list of steps to be executed in chronological order); P (combined population of fish and chromosomes)
    2. Define:    
    3. For *k = 1* to *popsize*
    4. For s = 1 to Nsteps
    5. If P(k) = fish & S(s)AFSA
    6. Evaluate: *f* = Fobj(P(k))
    7. Execute:

*P*(*k*)  *S*(*s*)  *P*(*k*)*new*

* + 1. Evaluate: *f*new= Fobj(P(k)new)
    2. If *f*new is better than *f*
    3. Store : *f*

*new*

*P*(*k*)  

* + 1. Else

*new*

* + 1. Store :  *f*
    2. End

*P*(*k* )  

* + 1. Elseif P(k) = fish & S(s)GA
    2. Evaluate: *f* = Fobj(P(k))
    3. Execute:

*P*(*k*)  *Encoder*  *P*(*k*)*Encoded*

* + 1. Execute:

*P*(*k*)*Encoded*  *S*(*s*)  *P*(*k*)*Encoded*,*new*

* + 1. Evaluate: *f*new= Fobj( *P*(*k*)*Encoded*,*new* )
    2. If *f*new is better than *f*
    3. Store : *f*

*new*

*Encoded*,*new*

*P*(*k*)  

* + 1. Else
    2. Store :  *f*
    3. End

*P*(*k* )  

* + 1. Elseif P(k) = chromosome & S(s)AFSA
    2. Execute:

*P*(*k*)  *Decoder*  *P*(*k*)*Decoded*

* + 1. Evaluate: *f* = Fobj(P(k)Decoded)
    2. Execute:

*P*(*k*)*Decoded*  *S*(*s*)  *P*(*k*)*Decoded*,*new*

* + 1. Evaluate: *f*new= Fobj( *P*(*k*)*Decoded*,*new* )
    2. If *f*new is better than *f*
    3. Store : *f*

*new*

*Decoded*,*new*

*P*(*k*)  

* + 1. Else
    2. Store :  *f*
    3. End

*P*(*k* )  

* + 1. Elseif P(k) = chromosome & S(s)GA

|  |  |  |  |
| --- | --- | --- | --- |
| 35. | Execute: | | *P*(*k*)  *Decoder*  *P*(*k*)*Decoded* |
| 36. | Evaluate: | | *f* = Fobj(P(k)Decoded) |
| 37. | Execute: | | *P*(*k*)  *S*(*s*)  *P*(*k*)*new* |
| 38. | Execute: | | *P*(*k*)*new*  *Decoder*  *P*(*k*)*new*,*Decode* |
| 39. |  | Evaluate: *f*new= Fobj( *P*(*k*)*new*,*Decode* ) | |
| 40. |  | If *f*new is better than *f* | |
| 41. |  | Store : *f P*(*k*)    *new new*,*Decode* | |
| 42. |  | Else | |
| 43. |  | Store :  *f P*(*k* )  | |
| 44. |  | End | |
| 45. | End |  | |
| 46. | End |  | |
| 47. End |  |  | |

48. Sorting: Rearrage the vectors in  (in the order of optimality)

The Flow Chart of the proposed HGAFSA is presented in Figure 3.2





Decode Population

Crossover

Encode Population



Sort Population based on Finesses

Evaluate Fitness



Sort population based on finesses

Evaluate Fitness

Decode Population

Mutation

Encode Population

**GA**

**AFSA**

Start



Evaluate Fitness

Decode Population

Reproduction

Parameters of HGAFSA

|  |  |
| --- | --- |
| Evaluate Fitness    Sort Population based on Finesses    Encode Population    Crossover Decode Population Evaluate Fitness  Sort Population based on Finesses    Encode Population    Mutation    Decode Population Evaluate Fitness  Sort Population based on Finesses  Swarming Evaluate Fitness | |
| Sort Population based on Finesses |  |
|  |

Figure 3.2: Flow Chart of Proposed Hybrid GA and AFSA (HGAFSA)



Gen < Gen max

Yes

No

Stop

Print Optimum Result & Plot the necessary curves

Preying

Sort Population based on Finesses

Gen = 1



Gen = Gen + 1

Sort Population based on Finesses

Evaluate Fitness

Chasing

### Model of the ELD Problem

To solve ELD problem using the proposed HGAFSA, a function is required to convert the random numbers generated by it into electrical power demand scheduled to the set of generating units. Let ***P*** be a set of power to be generated by the available generating units forming the ELD problem. Let ***Pmax*** be the maximum power allowable for each of the units. Let also ***Pmin*** be the minimum power allowable for each of the units. Let *NG* be the number of generating units. Then:

*G*

*N*

*G*

*P*  [*P*1 *P*2

*P*3 ...

*PN* 2

*PN* 1 *P* ]

(3.1)

*P*max  [*P*max,1

*G*

*P*max,2

*P*max,3

...

*P*max,*N* 2

*P*max,*N* 1

*P*max,*N* ]

(3.2)

*P*min

*G*

*G*

*G*

[*P*min,1

*P*min,2

*P*min,3

...

*P*min,*N* 2

*P*min,*N* 1

*P*min,*N* ]

(3.3)

The next important parameter of ELD problem formulation is the total power (PG) to be generated by the generating units to meet both the power demand and the power losses along the network. This can be described using the equality constraint as in equation (3.4).

*G*

*G*

*G*

*PG*  *PD*  *PL*

(3.4)

Where, *PD* is the total power demand by the consumers; and *PL* is the total power losses in the

network.

*PG* can be expressed using equation (3.5).

*N*

*G*

*PG*   *Pi*

*i*

(3.5)

As described earlier, to evaluate the fitness of a population generated by HGAFSA, the population must be decoded into a fish ( *X decoded* ). However, this fish must be further converted

into real power demand *P.* To achieve this, let

*X decoded* be replaced by  having *p* elements, such

that equation (3.6) holds.

  *x*

1

*x*2 *x*3

...

*xp*2

*xp*1 *x* 

(3.6)

An ELD Encoder function is developed to transform  into an equivalent *P*. The overall process can be described using Figure 3.3.

*p*

Chromosome

Chromosome Decoder

Fish χ

ELD Encoder

P= [P1… Pp]

Fobj,ELD

Figure 3.3: Evaluating the Fitness of a Chromosome/Fish

The function

*Fobj*,*ELD* is the objective function of ELD problem described in equation (2.12). The

ELD Encoder function is given in Algorithm 3.3.

Algorithm 3.3: ELD Encoder

1. Input:  ,*p*, *NG* , *P* , *P* , and *PG*

max min

1. Create: 

  

3. For g = [1, 2, 3, …,

*NG* ]

4.   (*P*max (*g*)  *P*min (*g*)) \*  / max()

 

 

5. 

 

1. End
2. Create:    

8. For *par* = [1, 2, 3, …, *p*]

9. For g = [1, 2, 3, …,

*NG* ]

10. (*g*)   (*g*, *par*)

11. End

12. For h = [1, 2, 3, …,

*NG* ]

13.

 (*h*) 

*N*

(*PG*   *P*min (*g*)) \* 

*G*

*g*  *P*

(*h*)

 *NG* 

min

  (*g*) 

 *g* 

1. End
2. While max(  *P*max )  0

(enforce the upper limit constraint for each generating unit)

1. 16.

  *rand*(1, *NG* ).\*   *rand*(1, *NG* )

1. Re-execute steps 12 to 14
2. End
3. 19.

 

 

 

 

1. End

21. For *s* = [1, 2, 3, …, *p*]

1. Evaluate: *Fit*(*s*)  *Fobj*,*ELD* ([(*s*,1)

(*s*,2)

(*s*,3)

## ...

(*s*, *NG* 1)

(*s*, *NG* )])

1. End
2. Determine:   *Fit*( )  min( *Fit*)
3. Assign:

*P*  [ (,1)

 (,2)

 (,3)

...

 (, *NG* 1)

 (, *NG* )]

The proposed ELD encoder has the advantage that no generating unit can generate below its minimum allowable generating limit. However, its generation may exceed the allowable maximum. To prevent this, steps 15 to 18 were added to Algorithm 3.3 to enforce the maximum limit constraint.

However, it can be observed from step 22 of Algorithm 3.3, that the proposed ELD Encoder performs optimization during the encoding process. Therefore, it could be termed as an optimal ELD encoder of order *p*.

To further increase the performance of the proposed ELD Encoder, the dimension of  can be extended for every given  generated by the proposed HGAFSA. This extension was modeled as in equation 3.7.

*ext*  [

.\* sin(2 \* )

.\* cos(2 \* ) ]

(3.7)

With this extension, a new optimal ELD encoder of order 3\**p* can be formed by modifying steps 8 and 21 of the former optimal ELD encoder (order *p*) described earlier. This can be achieved using equation (3.8) and (3.9) respectively.

*par* = [1, 2, 3, …, 3\**p*] (3.8)

*s* = [1, 2, 3, …, 3\**p*] (3.9)

### The Proposed HGAFSA based Higher Order ELD Algorithm

ELD problem is one of the power system analysis problems with large number of possible solutions. However, such solutions form a set of local optimums. As the number of generating units increases, the possible solutions increase exponentially. As such, an algorithm that can deeply search into the solution domain is required to locate the global optimum solution. In this work, HGAFSA optimization algorithm with high computation capability and fast rate of convergence is developed for complex ELD problem solving. The flow chart for the proposed HGAFSA based higher order ELD problem solver is shown in Figure 3.4.



START

Input: ELD parameters,



NO

Is initial population available?

Reproduce initial population

YES

Is minimum cost accepted?

YES

NO

Set the best population as the starting point

Print minimum cost as global optimum cost

HGAFSA

Select suitable HGAFSA parameters

Generate Optimization Curve

Output Power allocation for each Generator

STOP

Figure 3 4: HGAFSA based ELD Algorithm

### CHAPTER FOUR RESULTS AND DISCUSSION

### Introduction

In this chapter, five-test systems are used in simulation and the results are compared with those presented in (Pradhan *et al*., 2017) and other similar literatures regarding ELD problem solving.

### Simulation Setup

To demonstrate the effectiveness of the developed HGAFSA for ELD problem solving, six test systems were used. The data of the test systems used for the simulation is provided in Appendix A1-A5. The developed algorithm was programmed in MALAB R2016a environment on a HP 8GB-RAM 2.3GHz Core-I3 Computer running Windows 10.1. Some of the M-Files used are also provided in the Appendix section of this work. A set of suitable parameters used for simulation are provided in Table 4.1. To achieve the desired objective, the best solution generated by HGAFSA is set as starting point if it did not meet the desired goal. This process is repeated as far as the optimum cost is higher than the best cost presented in Pradhan *et al*., (2017).

Table 4.1: HGAFSA Simulation Parameter Settings

|  |  |  |
| --- | --- | --- |
| **S/No.** | **Name** | **Value** |
| 1 | Population Size | 64 |
| 2 | Number of Parameters | 32 |
| 3 | Visual Distance AFSA | 0.875 to 1 |
| 4 | Crowding Factor AFSA | 0.09 to 0.5 |
| 5 | Step Size AFSA | 0.00125 to 0.1 |
| 6 | Max. Iteration | 100 |
| 7 | Min Cost | 0 |
| 8 | Mutation Rate GA | 0.4 to 0.75 |
| 9 | Selection Probability GA | 0.375 to 0.5 |
| 10 | Optimization Type | 2 |
| 11 | Min GA par | 0 |
| 12 | Max GA par | 1 |
| 13 | Number of Bits GA | 8 |

### Test system 1

In order to demonstrate the effectiveness of the proposed HGAFSA algorithm compared to the OGWO algorithm (Pradhan et al., 2017), a thirteen-unit test system with valve point effect is used. The system data including fuel cost coefficients and limiting value of active power of various generators are adopted from (dosSantosCoelho & Mariani, 2006). The power demand, in this case is assumed to be 2520 MW. To judge the superiority of OGWO and HGAFSA methods,

the test results are compared with the results obtained by other algorithms such as Oppositional

Invasive Weed Optimization (OIWO) (Barisal & Prusty, 2015), Oppositional Real Coded Chemical Reaction Optimization (ORCCRO) (Bhattacharjee, Bhattacharya, & Dey, 2014), Biogeography Based Optimization (BBO) (Bhattacharya & Chattopadhyay, 2010), hybrid Differential Evolution based BBO (DE/BBO) (Bhattacharya & Chattopadhyay, 2010) and Improved Coordinated Aggregation based PSO (ICA-PSO) (Vlachogiannis & Lee, 2009b) available in the literature.

The comparative results of active power generation and fuel cost using the OGWO and HGAFSA methods along with other methods are given in Table 4.2. The results show that the HGAFSA based approach performed better than all other approaches presented in this work. Figure 4.1a shows the HGAFSA based optimization curve. It may be observed from Figure 4.1a that the algorithm converges at the thirteenth generation to a cost of **$24,141.2687/h.** This resulted in an annual savings of $3,253,957.

Figure 4.1b presents the cumulative power generated by the units. In economic load dispatch (ELD), power generated by each unit must lie within its maximum and the minimum allowable power output (Upper and Lower Limits). Therefore, the power allocations must lie within this limit. It is clear that, the optimum power allocated to each unit (*Pi*) lie within its limits. Finally, the cost functions of the various generating units influence the optimum power allocated to the units and thus, defines the pattern of the ‘Optimum *Pi*’ curves for each of the five-test systems in this work. In general, the peak of the cumulative power curves can be described as follows.

* + 1. Optimum *Pi* Curve: - Defines the total power generated (Demand + Losses) by the system of generating units;
    2. Upper Limit *Pmax* Curve: - Defines the maximum power that can be generated by the system of generating units;
    3. Lower Limit *Pmin* Curve: - Defines the minimum power generated by the system of generating units.

In the case of Figure 4.1b,

*P peak*  2560  4 , *P peak*  550 , and *Ppeak*  2960

*i* min max

Table 4.2: Comparison of Results for 13-Units System

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **S/No.** | **HGAFSA** | **OGWO** | **GWO** | **OIWO** | **SDE** | **ORCCRO** |
| 1 | 628.320 | 628.294 | 628.1678 | 628.3185 | 628.32 | 628.32 |
| 2 | 299.200 | 299.1803 | 298.9229 | 299.1989 | 299.2 | 299.2 |
| 3 | 299.300 | 297.5041 | 298.2269 | 299.1991 | 299.2 | 299.2 |
| 4 | 159.730 | 159.7284 | 159.7232 | 159.7331 | 159.73 | 159.73 |
| 5 | 159.730 | 159.7325 | 159.721 | 159.7331 | 159.73 | 159.73 |
| 6 | 159.730 | 159.7295 | 159.727 | 159.7331 | 159.73 | 159.73 |
| 7 | 159.730 | 159.7334 | 159.7173 | 159.733 | 159.73 | 159.73 |
| 8 | 159.730 | 159.7323 | 159.6793 | 159.7331 | 159.73 | 159.73 |
| 9 | 159.730 | 159.7327 | 159.6673 | 159.733 | 77.4 | 77.4 |
| 10 | 77.394 | 77.3963 | 77.3971 | 77.3953 | 113.12 | 112.14 |
| 11 | 113.307 | 114.7487 | 114.6051 | 113.1079 | 92.4 | 92.4 |
| 12 | 92.1300 | 92.3974 | 92.3886 | 92.3594 | 92.4 | 92.4 |
| 13 | 92.2300 | 92.378 | 92.355 | 92.3911 | 92.4 | 92.4 |
| ***Fuel Cost $/h*** | ***24,141.2687*** | ***24,512.725*** | ***24,514.477*** | ***24514.83*** | ***24,514.9*** | ***24,513.91*** |
| ***Power Loss MW*** | **40.2686** | ***40.2874*** | ***40.2983*** | ***40.3686*** | ***40.43*** | ***39.43*** |

2.415

10 4

**HGAFSA Optimization Curve for 13 - Units**

2.4149

2.4148

2.4147

2.4146

2.4145

Cost

2.4144

2.4143

2.4142

2.4141

0 10 20 30 40 50 60 70 80 90 100

generation

Figure 4.1a: 13-Units: (a) Optimization Curve

3000

**HGAFSA Optimal Power Allocation**

2500

**0ptimum P1**

**Upper Limit P max**

**Lower Limit P min**

Cumulative Power Generated (MW)

2000

1500

1000

500

0

0 2 4 6 8 10 12 14

Generating Unit

Figure 4.1b: Cumulative Power Generated

### Test system 2

To compare the effectiveness of the OGWO (Pradhan et al., 2017) and HGAFSA approaches, a medium size ELD problem having 40 generating units with valve-point and multiple fuel effects are used. The input data for 40 generating Units system is taken from (Srinivasa Reddy & Vaisakh, 2013). The total power demand is taken as 10,500 MW. The real power generation output and the fuel cost obtained for 40 unit systems using various intelligent techniques like HGAFSA, GWO, OGWO (Pradhan et al., 2017), OIWO (Barisal & Prusty, 2015), Shuffled Differential Evolution (SDE) (Srinivasa Reddy & Vaisakh, 2013), ORCCRO (Bhattacharjee et al., 2014), GAAPI (Ciornei & Kyriakides, 2012), Quasi-Oppositional Teaching-Learning Based Optimization (QOTLBO) (Roy & Mandal, 2014) and Krill Herd Algorithm (KHA) (Roy & Mandal, 2014) are given in Table 4.3. The results show that the HGAFSA based approach

performed better than all other approaches presented in this work. Figure 4.2a shows the HGAFSA based optimization curve. It can be observed from Figure 4.2a that the algorithm converges at the fifty-first generation to a cost of **$136,396.9727/h.** This resulted in an annual savings of $382,350. Furthermore, Figure 4.2b shows that all generators satisfy their inequality constraint.

Table 4.3: Comparison of Results for 40-Units System

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **S/No.** | **HGAFSA** | **OGWO** | **GWO** | **OIWO** | **SDE** | **ORCCRO** | **GAAPI** | **QOTLBO** | **KHA** |
| 1 | 113.96 | 114 | 114 | 113.9908 | 110.06 | 111.68 | 114 | 114 | 114 |
| 2 | 113.69 | 114 | 114 | 114 | 112.41 | 112.16 | 114 | 114 | 114 |
| 3 | 120 | 120 | 120 | 119.9977 | 120 | 119.98 | 120 | 107.8221 | 120 |
| 4 | 179.74 | 183.5725 | 181.049 | 182.5131 | 188.72 | 182.18 | 190 | 190 | 190 |
| 5 | 96.975 | 87.8151 | 87.8351 | 88.4227 | 85.91 | 87.28 | 97 | 88.3702 | 88.5944 |
| 6 | 140 | 140 | 140 | 140 | 140 | 139.85 | 140 | 140 | 105.5166 |
| 7 | 300 | 300 | 300 | 299.9999 | 250.19 | 298.15 | 300 | 300 | 300 |
| 8 | 284.8 | 300 | 300 | 292.0654 | 290.68 | 286.89 | 300 | 300 | 300 |
| 9 | 289.02 | 300 | 300 | 299.8817 | 300 | 293.38 | 300 | 300 | 300 |
| 10 | 279.65 | 279.7201 | 279.9786 | 279.7073 | 282.01 | 279.34 | 205.25 | 211.2071 | 280.6777 |
| 11 | 168.81 | 243.617 | 243.6274 | 168.8149 | 180.82 | 162.35 | 226.3 | 317.2766 | 243.5399 |
| 12 | 94 | 94.1781 | 94.1436 | 94 | 168.74 | 94.12 | 204.72 | 163.7603 | 168.8017 |
| 13 | 484.04 | 484.27 | 484.4562 | 484.0758 | 469.96 | 486.44 | 346.48 | 481.5709 | 484.1198 |
| 14 | 484.05 | 484.3324 | 484.2306 | 484.0477 | 484.17 | 487.02 | 434.32 | 480.5462 | 484.1662 |
| 15 | 484.04 | 484.0484 | 484.2463 | 484.0396 | 487.73 | 483.39 | 431.34 | 483.7683 | 485.2375 |
| 16 | 484.08 | 484.0791 | 484.0333 | 484.0886 | 482.3 | 484.51 | 440.22 | 480.2998 | 485.0698 |
| 17 | 489.28 | 489.2147 | 489.6295 | 489.2813 | 499.64 | 494.22 | 500 | 489.2488 | 489.4539 |
| 18 | 489.3 | 489.2607 | 489.3228 | 489.2966 | 411.32 | 489.48 | 500 | 489.5524 | 489.3035 |
| 19 | 511.32 | 511.3341 | 511.4616 | 511.3219 | 510.47 | 512.2 | 550 | 512.5482 | 510.7127 |
| 20 | 511.33 | 511.4991 | 511.4932 | 511.335 | 542.04 | 513.13 | 550 | 514.2914 | 511.304 |
| 21 | 549.94 | 523.476 | 523.4767 | 549.9412 | 544.81 | 543.85 | 550 | 527.0877 | 524.4678 |
| 22 | 549.94 | 546.6445 | 547.6868 | 549.9999 | 550 | 548 | 550 | 530.1025 | 535.5799 |
| 23 | 523.3 | 523.3857 | 523.3738 | 523.2804 | 550 | 521.21 | 550 | 524.2912 | 523.3795 |
| 24 | 523.32 | 523.3344 | 523.135 | 523.3213 | 528.16 | 525.01 | 550 | 524.6512 | 523.15527 |
| 25 | 523.27 | 523.407 | 523.3472 | 523.5804 | 524.16 | 529.84 | 550 | 525.0586 | 524.1916 |
| 26 | 523.28 | 523.302 | 523.3578 | 523.5847 | 539.1 | 540.04 | 550 | 524.4654 | 523.5453 |
| 27 | 10.013 | 10.0076 | 10.0678 | 10.0086 | 10 | 12.59 | 11.44 | 10.8929 | 10.1245 |
| 28 | 10.007 | 10.0104 | 10.6337 | 10.0068 | 10.37 | 10.06 | 11.56 | 17.4312 | 10.1815 |
| 29 | 10.012 | 10.0622 | 10.5181 | 10.0123 | 10 | 10.79 | 11.42 | 12.7839 | 10.0229 |
| 30 | 96.966 | 87.8011 | 87.8029 | 87.8664 | 96.1 | 89.7 | 97 | 88.8119 | 87.8154 |
| 31 | 190 | 190 | 190 | 190 | 185.33 | 189.59 | 190 | 190 | 190 |
| 32 | 190 | 190 | 190 | 189.9983 | 189.54 | 189.96 | 190 | 190 | 190 |
| 33 | 190 | 190 | 190 | 190 | 189.96 | 187.61 | 190 | 190 | 190 |
| 34 | 199.99 | 200 | 200 | 199.994 | 199.9 | 198.91 | 200 | 200 | 200 |
| 35 | 200 | 200 | 200 | 200 | 196.25 | 199.98 | 200 | 168.0873 | 164.9199 |
| 36 | 169.2 | 164.8986 | 164.8334 | 164.8283 | 185.85 | 165.68 | 200 | 165.5072 | 164.9787 |
| 37 | 110 | 110 | 110 | 110 | 109.72 | 109.98 | 110 | 110 | 110 |
| 38 | 109.99 | 110 | 110 | 109.994 | 110 | 109.82 | 110 | 110 | 110 |
| 39 | 110 | 110 | 110 | 110 | 95.71 | 109.88 | 110 | 110 | 110 |
| 40 | 550 | 511.8527 | 511.5471 | 550 | 532.43 | 548.5 | 550 | 511.5313 | 512.06775 |
| ***Fuel Cost*** | ***136396.9727*** | ***136440.62*** | ***136446.85*** | ***136452.7*** | ***138157*** | ***136855.19*** | ***139865*** | ***137329.86*** | ***136670*** |

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| ***$/h*** | ***957.2965*** | ***973.1235*** | ***973.2874*** | ***957.2965*** | ***974.43*** | ***958.75*** | ***1045.06*** | ***1008.96*** | ***978.925*** |
| ***Power Loss***  ***MW*** |

1.363982

10 5

**HGAFSA Optimization Curve for 40 - Units**

1.36398

363978

1.

1.

1.

1.

363976

363974

Cost

363972

1.36397

1.363968

0 10 20 30 40 50 60 70 80 90 100

**generation**

Figure 4.2a: 40-units: (a) Optimization Curve

14000

**HGAFSA Optimal Power Allocation**

12000

**0ptimum P1**

**Upper Limit P max**

**Lower Limit P min**

Cumulative Power Generated (MW)

10000

8000

6000

4000

2000

0

0 5 10 15 20 25 30 35 40

Generating Unit

Figure 4.2b: Cumulative Power Generated

### Test system 3

This system comprises 110 generators with quadratic cost characteristic. The input system data were obtained from (Orero, 1997). The load demand is considered as 15, 000MW.The minimum fuel costs and their corresponding generation levels obtained by proposed HGAFSA and other method are provided in Table 4.4. The minimum fuel cost obtained for this system by all the methods are also provided in Table 4.4. From Tables 4.4, it is clear that the proposed method provides cheapest generation schedule of power generation. The results show that the HGAFSA based approach outperformed all other approaches presented in the literature so far. Figure 4.3a shows the HGAFSA based optimization curve. It may be observed from Figure 4.3a that the algorithm was truncated at the hundredth generation and at a cost of **$197,988.892/h.** This resulted in an annual savings of $2,135.69. The saving in cost was less because of the narrow margins for some of the generating units especially units 1 to 9 and the high cost of generation. Furthermore, Figure 4.3b shows that all generators satisfy their inequality constraints.

Table 4.4: Comparison of Results for 110-Units System

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **S/No.** | **HGAFSA** | **OIWO** |  | **HGAFSA** | **OIWO** |  | **HGAFSA** | **OIWO** |
| 1 | 2.4 | 2.4 | 38 | 69.9975178 | 69.981 | 75 | 89.99982 | 89.999 |
| 2 | 2.4004 | 2.4004 | 39 | 99.9999501 | 99.994 | 76 | 49.999 | 49.999 |
| 3 | 2.4026 | 2.4026 | 40 | 120 | 120 | 77 | 160 | 160.01 |
| 4 | 2.4 | 2.4 | 41 | 157.18324 | 156.8 | 78 | 295.7606 | 291.36 |
| 5 | 2.4 | 2.4 | 42 | 220 | 220 | 79 | 175.0589 | 177 |
| 6 | 4.0011 | 4.0011 | 43 | 440 | 440 | 80 | 98.0084 | 97.753 |
| 7 | 4 | 4 | 44 | 560 | 560 | 81 | 10.001 | 10.001 |
| 8 | 4 | 4 | 45 | 660 | 660 | 82 | 12.0124 | 12.305 |
| 9 | 4 | 4 | 46 | 616.436395 | 619.53 | 83 | 20.0153 | 20.042 |
| 10 | 64.3953156 | 63.055 | 47 | 5.40003807 | 5.4004 | 84 | 199.9893 | 199.99 |
| 11 | 62.16223 | 59.275 | 48 | 5.4 | 5.4 | 85 | 324.9917 | 324.51 |
| 12 | 36.2917819 | 35.658 | 49 | 8.4015 | 8.4015 | 86 | 439.998 | 439.99 |
| 13 | 56.6260119 | 57.438 | 50 | 8.4 | 8.4 | 87 | 14.42951 | 18.867 |
| 14 | 25 | 25 | 51 | 8.4 | 8.4 | 88 | 24.32679 | 23.334 |
| 15 | 25 | 25 | 52 | 12 | 12 | 89 | 82.44312 | 84.403 |
| 16 | 25 | 25 | 53 | 12 | 12 | 90 | 89.25027 | 91.9 |
| 17 | 155 | 155 | 54 | 12.001 | 12.001 | 91 | 57.61189 | 58.29 |
| 18 | 155 | 155 | 55 | 12 | 12 | 92 | 99.99727 | 98.071 |
| 19 | 155 | 155 | 56 | 25.2 | 25.2 | 93 | 440 | 440 |
| 20 | 155 | 155 | 57 | 25.2 | 25.2 | 94 | 499.9977 | 499.97 |
| 21 | 68.9 | 68.9 | 58 | 35 | 35 | 95 | 600 | 600 |

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 22 | 68.9 | 68.9 | 59 | 35.0004463 | 35 | 96 | 471.479 | 469.27 |
| 23 | 68.9 | 68.9 | 60 | 45.001 | 45.001 | 97 | 3.6 | 3.6 |
| 24 | 350 | 350 | 61 | 45.001 | 45.001 | 98 | 3.6 | 3.6 |
| 25 | 400 | 400 | 62 | 45 | 45 | 99 | 4.4 | 4.4 |
| 26 | 400 | 400 | 63 | 184.998222 | 185 | 100 | 4.400235 | 4.4005 |
| 27 | 500 | 500 | 64 | 185 | 184.99 | 101 | 10.00088 | 10.008 |
| 28 | 500 | 500 | 65 | 185 | 185 | 102 | 10.001 | 10.001 |
| 29 | 200 | 199.99 | 66 | 184.993084 | 185 | 103 | 20.005 | 20.005 |
| 30 | 100 | 100 | 67 | 70 | 70 | 104 | 20.00009 | 20.005 |
| 31 | 10.0005576 | 10.001 | 68 | 70 | 70 | 105 | 40 | 40 |
| 32 | 19.9992817 | 19.99 | 69 | 70.001 | 70.001 | 106 | 40.001 | 40.002 |
| 33 | 79.9983153 | 79.485 | 70 | 359.998903 | 360 | 107 | 50 | 50 |
| 34 | 250 | 250 | 71 | 400 | 400 | 108 | 30 | 30 |
| 35 | 360 | 360 | 72 | 400 | 400 | 109 | 40 | 40 |
| 36 | 400 | 399.99 | 73 | 104.96292 | 107.83 | 110 | 20 | 20 |
| 37 | 39.999 | 39.999 | 74 | 191.49755 | 188.81 | ***Fuel Cost***  ***$/h*** | ***197,988.892*** | ***197,989.1358*** |

1.97989

10 5

**HGAFSA Optimization Curve for 110 - Units**

1.9798898

1.9798896

1.9798894

Cost

1.9798892

1.979889

1.9798888

0 20 40 60 80 100

generation

Figure 4.3a: 110-Units: (a) Optimization Curve

2.5

10 4

**HGAFSA Optimal Power Allocation**

i

i

**0ptimum P1**

**Upper Limit P max**

**Lower Limit P min**

2

Cumulative Power Generated (MW)

1.5

1

0.5

0

0 20 40 60 80 100 120

Generating Unit

Figure 4.3b: Cumulative Power Generated

### Test system 4

In this case study, a complicated 140-unit test system is considered to verify the effectiveness of the proposed HGAFSA method. The non-linear constraints like valve-point effect prohibited operating zone and ramp rate limits are considered in this case. The load demand is assumed to be 49,342MW. In order to validate the superiority of the proposed methods, the results obtained from the HGAFSA and OGWO are compared with those of GWO, SDE and OIWA reported in the literature. The lowest cost for each of the 50 different trials using HGAFSA, OGWO, GWO, SDE (Srinivasa Reddy & Vaisakh, 2013), and OIWO (Barisal & Prusty, 2015) methods are illustrated in Table 4.5 from which HGAFSA method produces lowest cost compared to the OGWO and the other methods. It clearly suggests that though the performances of both HGAFSA and OGWO are satisfactory but HGAFSA is significantly better than OGWO. Figure

4.4a shows the HGAFSA based optimization curve. It may be observed from Figure 4.4a that the algorithm converges at the sixty-sixth generation to a cost of **$1,558,619.094/h.** This resulted in an annual savings of $2,128,680. Furthermore, Figure 4.4b shows that all generators satisfy their inequality constraints.

Table 4.5: Comparison of Results for 140-Units System

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **S/No.** | **HGAFSA** | **OGWO** | **GWO** |  | **HGAFSA** | **OGWO** | **GWO** |  | **HGAFSA** | **OGWO** | **GWO** |
| 1 | 113.5 | 114.5 | 119 | 48 | 250 | 250 | 250 | 95 | 978 | 978 | 978 |
| 2 | 189 | 189 | 189 | 49 | 250 | 250 | 250 | 96 | 682 | 682 | 682 |
| 3 | 190 | 190 | 190 | 50 | 250 | 250 | 250 | 97 | 720 | 720 | 720 |
| 4 | 190 | 190 | 190 | 51 | 165 | 165 | 165 | 98 | 718 | 718 | 718 |
| 5 | 168.54 | 168.54 | 168.5  4 | 52 | 165 | 165 | 165 | 99 | 720 | 720 | 720 |
| 6 | 190 | 190 | 190 | 53 | 165 | 165 | 165 | 100 | 964 | 964 | 964 |
| 7 | 490 | 490 | 490 | 54 | 165 | 165 | 165 | 101 | 958 | 958 | 958 |
| 8 | 490 | 490 | 490 | 55 | 180 | 180 | 180 | 102 | 1007 | 1007 | 1007 |
| 9 | 496 | 496 | 496 | 56 | 180 | 180 | 180 | 103 | 1006 | 1006 | 1006 |
| 10 | 496 | 496 | 496 | 57 | 103 | 103 | 103 | 104 | 1013 | 1013 | 1013 |
| 11 | 496 | 496 | 496 | 58 | 198 | 198 | 198 | 105 | 1020 | 1020 | 1020 |
| 12 | 496 | 496 | 496 | 59 | 312 | 312 | 312 | 106 | 954 | 954 | 954 |
| 13 | 506 | 506 | 506 | 60 | 277.85 | 280.85 | 282.89 | 107 | 952 | 952 | 952 |
| 14 | 509 | 509 | 509 | 61 | 163 | 163 | 163 | 108 | 1006 | 1006 | 1006 |
| 15 | 506 | 506 | 506 | 62 | 95 | 95 | 95 | 109 | 1013 | 1013 | 1013 |
| 16 | 505 | 505 | 505 | 63 | 159.42 | 160 | 160.88 | 110 | 1021 | 1021 | 1021 |
| 17 | 506 | 506 | 506 | 64 | 160 | 160 | 160 | 111 | 1015 | 1015 | 1015 |
| 18 | 506 | 506 | 506 | 65 | 490 | 490 | 490 | 112 | 94 | 94 | 94 |
| 19 | 505 | 505 | 505 | 66 | 196 | 196 | 196.26 | 113 | 94 | 94 | 94 |
| 20 | 505 | 505 | 505 | 67 | 490 | 490 | 490 | 114 | 94 | 94 | 94 |
| 21 | 505 | 505 | 505 | 68 | 489 | 490 | 489.6 | 115 | 244 | 244 | 244 |
| 22 | 505 | 505 | 505 | 69 | 130 | 130 | 130 | 116 | 244 | 244 | 244 |
| 23 | 505 | 505 | 505 | 70 | 234.71 | 234.71 | 234.7 | 117 | 244 | 244 | 244 |
| 24 | 505 | 505 | 505 | 71 | 137 | 137 | 137 | 118 | 95 | 95 | 95 |
| 25 | 537 | 537 | 537 | 72 | 324.5 | 325.5 | 325.82 | 119 | 95 | 95 | 95 |
| 26 | 537 | 537 | 537 | 73 | 195 | 195 | 195 | 120 | 116 | 116 | 116 |
| 27 | 549 | 549 | 549 | 74 | 175.39 | 175.39 | 175.39 | 121 | 175 | 175 | 175 |
| 28 | 549 | 549 | 549 | 75 | 175 | 175 | 175 | 122 | 2 | 2 | 2 |
| 29 | 501 | 501 | 501 | 76 | 175.99 | 175.99 | 175.99 | 123 | 4 | 4 | 4 |
| 30 | 501 | 501 | 501 | 77 | 175.41 | 175.41 | 175.41 | 124 | 15 | 15 | 15 |
| 31 | 506 | 506 | 506 | 78 | 330 | 330 | 330 | 125 | 9 | 9 | 9 |
| 32 | 506 | 506 | 506 | 79 | 531 | 531 | 531 | 126 | 12 | 12 | 12 |
| 33 | 506 | 506 | 506 | 80 | 531 | 531 | 531 | 127 | 10 | 10 | 10 |
| 34 | 506 | 506 | 506 | 81 | 395.1353 | 398.38 | 366.4 | 128 | 112 | 112 | 112 |
| 35 | 500 | 500 | 500 | 82 | 56 | 56 | 56 | 129 | 4 | 4 | 4 |
| 36 | 500 | 500 | 500 | 83 | 115 | 115 | 115 | 130 | 5 | 5 | 5 |
| 37 | 241 | 241 | 241 | 84 | 115 | 115 | 115 | 131 | 5 | 5 | 5 |
| 38 | 241 | 241 | 241 | 85 | 115 | 115 | 115 | 132 | 50 | 50 | 50 |
| 39 | 774 | 774 | 774 | 86 | 207 | 207 | 207 | 133 | 5 | 5 | 5 |
| 40 | 769 | 769 | 769 | 87 | 207 | 207 | 207 | 134 | 42 | 42 | 42 |
| 41 | 3 | 3 | 3 | 88 | 175 | 175 | 175 | 135 | 42 | 42 | 42 |
| 42 | 3 | 3 | 3 | 89 | 175 | 175 | 175 | 136 | 41 | 41 | 41 |
| 43 | 250 | 250 | 250 | 90 | 175 | 175 | 175 | 137 | 17 | 17 | 17 |
| 44 | 246.2765 | 246.39 | 250 | 91 | 175 | 175 | 175 | 138 | 15.35825 | 17 | 17 |

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 45 | 250 | 250 | 250 | 92 | 580 | 580 | 580 | 139 | 7 | 7 | 7 |
| 46 | 250 | 250 | 250 | 93 | 645 | 645 | 645 | 140 | 26 | 26 | 26.13 |
| 47 | 240.92 | 240.92 | 249.9  8 | 94 | 984 | 984 | 984 | ***Fuel Cost***  ***$/h*** | ***1558619.0935*** | ***1559710*** | ***1559953*** |

1.55866

10 6

**HGAFSA Optimization Curve for 140 - Units**

558655

1.

1.

1.

1.

1.55865

558645

1.55864

Cost

558635

1.55863

558625

1.55862

1.558615

0 10 20 30 40 50 60 70 80 90 100

generation

Figure 4.4a: 140-Units: (a) Optimization Curve

7

10 4

**HGAFSA Optimal Power Allocation**

**0ptimum P1**

**Upper Limit P max**

**Lower Limit P min**

6

5

4

Cost

3

2

1

0

0 20 40 60 80 100 120 140

Generating Unit

Figure 4.4b: Cumulative Power Generated

### 4.7 Test system 5

In this case, a 160-unit test system with non-smooth valve point and multiple fuel effects cost function are solved by the proposed GWO and HGAFSA methods. Transmission loss is ignored to verify the feasibility and effectiveness of the proposed algorithms for solving large scale ELD based power system problem. For this 160-units system, the 10-units multiple fuel system data taken from (Chiang, 2005) are duplicated and the demand is multiplied by 16 (i.e. load demand is taken as 43,200 MW). Table 4.6 presents the best cost and generation achieved by the different algorithms for the 160-unit system while satisfying the constraints. From Table 4.6, it can be inferred that the total minimum production cost obtained using HGAFSA technique is comparatively smaller with respect to other algorithms already mentioned in this work. Figure 4.5a shows the HGAFSA based optimization curve. It may be observed from Figure 4.5a that the algorithm converges at the eighth generation to a cost of **$9,612.8295/h.** This resulted in an

annual savings of $1,158,803.46. Furthermore, Figure 4.5b shows that all generators satisfy their inequality constraints.

Table 4.6: Comparison of Results for 160-Units System

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **S/No.** | **HGAFSA** | **OGWO** | **GWO** |  | **HGAFSA** | **OGWO** | **GWO** |  | **HGAFSA** | **OGWO** | **GWO** |
| 1 | 214.486 | 211.0548 | 224.4316 | 55 | 269.1426 | 207.4412 | 265.2612 | 109 | 438.9043 | 402.6279 | 430.8317 |
| 2 | 211.7117 | 208.8475 | 200.24 | 56 | 240.9831 | 254.7693 | 257.0533 | 110 | 275.8686 | 272.9789 | 260.2696 |
| 3 | 274.6078 | 335.1164 | 355.8632 | 57 | 290.0985 | 294.1646 | 277.1283 | 111 | 214.486 | 199.7646 | 217.9593 |
| 4 | 241.2519 | 243.6651 | 228.6577 | 58 | 240.8488 | 245.6809 | 235.9306 | 112 | 211.9596 | 204.8838 | 199.0124 |
| 5 | 269.1424 | 266.496 | 305.8538 | 59 | 439.0723 | 420.2064 | 394.7028 | 113 | 274.6078 | 351.507 | 357.91 |
| 6 | 240.58 | 237.7474 | 249.9548 | 60 | 275.8686 | 270.5752 | 278.4325 | 114 | 241.2519 | 249.6972 | 251.1044 |
| 7 | 290.0985 | 282.9036 | 309.7896 | 61 | 214.486 | 198.8766 | 240.6965 | 115 | 272.739 | 266.0942 | 267.0206 |
| 8 | 241.2519 | 239.4979 | 218.8214 | 62 | 211.4642 | 212.9224 | 213.3251 | 116 | 241.1175 | 240.0271 | 252.1589 |
| 9 | 439.0937 | 408.8918 | 335.8343 | 63 | 273.5996 | 348.4807 | 341.0975 | 117 | 290.0985 | 290.287 | 290.7761 |
| 10 | 275.8686 | 265.7794 | 270.5537 | 64 | 240.9831 | 259.8417 | 248.8005 | 118 | 241.2519 | 242.3206 | 233.9515 |
| 11 | 215.513 | 225.2013 | 187.6995 | 65 | 272.7397 | 292.9373 | 232.9769 | 119 | 439.0246 | 412.5941 | 329.9101 |
| 12 | 211.7117 | 217.9922 | 195.5662 | 66 | 241.2519 | 221.2448 | 245.9912 | 120 | 275.8686 | 242.8243 | 300.1967 |
| 13 | 273.5996 | 336.6158 | 353.7443 | 67 | 292.4695 | 286.6376 | 310.0164 | 121 | 215.513 | 211.0182 | 237.5402 |
| 14 | 241.3863 | 232.3276 | 241.0525 | 68 | 241.5206 | 242.6468 | 232.721 | 122 | 211.7117 | 210.7714 | 207.3365 |
| 15 | 269.1425 | 259.6177 | 273.3024 | 69 | 439.0756 | 348.3301 | 353.3462 | 123 | 274.6078 | 345.7508 | 337.0684 |
| 16 | 240.9831 | 237.6971 | 228.1355 | 70 | 275.8686 | 288.0821 | 281.0286 | 124 | 241.1175 | 227.1918 | 210.5269 |
| 17 | 292.4695 | 265.8324 | 277.3736 | 71 | 214.486 | 227.9132 | 219.8481 | 125 | 269.1424 | 273.9219 | 241.1325 |
| 18 | 240.9831 | 236.9454 | 224.3982 | 72 | 211.9593 | 215.0451 | 220.3933 | 126 | 241.5206 | 250.0678 | 246.6614 |
| 19 | 439.2471 | 414.7889 | 404.3422 | 73 | 273.5996 | 339.1038 | 343.6976 | 127 | 290.0985 | 258.3325 | 293.9444 |
| 20 | 275.8686 | 272.9817 | 314.3855 | 74 | 241.3862 | 244.8685 | 250.5153 | 128 | 240.9831 | 243.0127 | 245.9554 |
| 21 | 214.486 | 222.199 | 205.5031 | 75 | 269.1392 | 280.3173 | 273.4252 | 129 | 439.185 | 382.982 | 431.4487 |
| 22 | 211.9593 | 204.6515 | 200.7397 | 76 | 240.58 | 231.957 | 217.8772 | 130 | 275.8686 | 296.9508 | 248.3855 |
| 23 | 274.6078 | 333.0013 | 374.811 | 77 | 292.4695 | 286.6036 | 305.1259 | 131 | 214.486 | 200.3463 | 199.4532 |
| 24 | 241.2519 | 237.4739 | 234.0215 | 78 | 241.7894 | 225.9269 | 243.7327 | 132 | 211.7117 | 214.629 | 217.2444 |
| 25 | 272.7398 | 304.7814 | 284.8751 | 79 | 439.0763 | 382.9488 | 353.5211 | 133 | 274.6148 | 334.6046 | 342.2486 |
| 26 | 240.7144 | 245.5394 | 221.658 | 80 | 275.8686 | 265.3158 | 271.8637 | 134 | 241.5206 | 234.0886 | 229.6668 |
| 27 | 292.4751 | 265.8384 | 253.2492 | 81 | 215.513 | 223.9674 | 223.3807 | 135 | 269.1468 | 286.6132 | 250.7479 |
| 28 | 241.2519 | 237.482 | 223.1936 | 82 | 212.2069 | 200.5557 | 191.4945 | 136 | 241.7894 | 247.7709 | 236.0422 |
| 29 | 439.013 | 381.7295 | 421.8011 | 83 | 273.5996 | 334.5932 | 349.8148 | 137 | 290.0985 | 290.5292 | 305.7284 |
| 30 | 272.7219 | 267.3033 | 280.1477 | 84 | 241.1175 | 246.8674 | 234.8348 | 138 | 241.5206 | 229.8027 | 230.9169 |
| 31 | 214.486 | 223.8357 | 175.7028 | 85 | 269.1424 | 274.2033 | 275.2954 | 139 | 439.1252 | 391.0035 | 430.433 |
| 32 | 211.9593 | 214.3587 | 203.4868 | 86 | 241.1175 | 249.3916 | 208.8313 | 140 | 275.8686 | 270.6119 | 257.5185 |
| 33 | 274.6078 | 334.3914 | 348.5865 | 87 | 292.4695 | 297.4366 | 282.9046 | 141 | 214.486 | 212.7407 | 228.4485 |
| 34 | 241.5206 | 247.1993 | 219.6817 | 88 | 240.58 | 240.7596 | 255.2069 | 142 | 211.2166 | 226.1497 | 184.2037 |
| 35 | 269.1425 | 250.1068 | 283.914 | 89 | 439.0426 | 340.9873 | 409.1432 | 143 | 274.6078 | 335.9897 | 370.6009 |
| 36 | 241.5206 | 229.7748 | 244.5662 | 90 | 275.8686 | 291.238 | 269.0939 | 144 | 240.9831 | 245.3932 | 219.2088 |
| 37 | 292.4695 | 265.8045 | 313.7701 | 91 | 214.486 | 212.3306 | 192.5265 | 145 | 269.1424 | 261.9323 | 263.8981 |
| 38 | 240.7144 | 243.4346 | 236.54 | 92 | 210.969 | 210.493 | 201.0805 | 146 | 241.9237 | 244.4414 | 235.3311 |
| 39 | 439.0891 | 413.3884 | 340.5099 | 93 | 273.5995 | 337.77 | 350.8514 | 147 | 290.0985 | 294.0252 | 300.9854 |
| 40 | 275.8686 | 277.7058 | 333.2419 | 94 | 242.0581 | 236.8209 | 258.9069 | 148 | 241.3863 | 235.734 | 242.2109 |
| 41 | 214.486 | 202.7653 | 230.1267 | 95 | 269.1424 | 261.4802 | 290.5386 | 149 | 439.0389 | 390.4426 | 387.3228 |
| 42 | 211.7117 | 228.5107 | 209.9439 | 96 | 240.58 | 235.3425 | 226.8687 | 150 | 275.8686 | 253.1512 | 267.7898 |
| 43 | 273.5996 | 352.7008 | 341.696 | 97 | 292.4695 | 278.8739 | 299.7902 | 151 | 214.486 | 193.0014 | 184.8211 |
| 44 | 241.2519 | 227.3366 | 233.436 | 98 | 241.3862 | 237.8441 | 223.7707 | 152 | 212.2078 | 222.8983 | 212.4468 |
| 45 | 269.1424 | 272.1149 | 299.6092 | 99 | 439.1089 | 420.0762 | 366.8371 | 153 | 274.6078 | 355.9969 | 376.6391 |
| 46 | 240.7144 | 241.8475 | 263.4945 | 100 | 275.8684 | 268.9686 | 288.8294 | 154 | 240.58 | 242.056 | 248.5759 |
| 47 | 287.7275 | 266.7677 | 243.0096 | 101 | 214.486 | 224.3774 | 227.0085 | 155 | 269.1424 | 277.6386 | 278.2433 |
| 48 | 241.1175 | 230.7801 | 212.4306 | 102 | 211.9593 | 209.2698 | 210.8885 | 156 | 241.2519 | 246.0075 | 223.6107 |
| 49 | 439.0932 | 423.1378 | 362.973 | 103 | 273.5996 | 337.6392 | 363.4203 | 157 | 292.4695 | 318.3527 | 264.0864 |
| 50 | 275.8686 | 254.0386 | 303.2805 | 104 | 241.5206 | 230.3857 | 222.0259 | 158 | 241.1175 | 241.0144 | 234.1904 |
| 51 | 215.513 | 218.3367 | 181.5271 | 105 | 269.1424 | 269.3592 | 234.4937 | 159 | 439.097 | 341.9573 | 390.9912 |

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 52 | 211.2166 | 211.9849 | 211.2522 | 106 | 240.7144 | 235.2646 | 232.5588 | 160 | 275.8686 | 261.077 | 286.3951 |
| 53 | 274.6078 | 337.9485 | 364.7108 | 107 | 290.0985 | 274.0838 | 282.2891 | ***Fuel Cost***  ***$/h*** | **9,612.8295** | ***9,745.113*** | ***9,813.377*** |
| 54 | 241.7894 | 238.8923 | 234.0012 | 108 | 242.4612 | 244.0134 | 236.214 |

10000

**HGAFSA Optimization Curve for 160 - Units**

9950

9900

9850

9800

Cost

9750

9700

9650

9600

0 10 20 30 40 50 60 70 80 90 100

generation

Figure 4.5a: 160-Units: (a) Optimization Curve

5

10 4

**HGAFSA Optimal Power Allocation**

**0ptimum P1**

**Upper Limit P max**

**Lower Limit P min**

4.5

4

Cumulative Power Generated (MW)

3.5

3

2.5

2

1.5

1

0.5

0

0 20 40 60 80 100 120 140 160

Generating Unit

Figure 4.5b: Cumulative Power Generated

In General, the performance of HGAFSA over the best algorithms presented in literature so far and listed in this work can be further summarized as follows. The best cost so far for all the systems in Table 4.7 are obtained by OGWO except for the 110-Units system which was obtained using OIWO. In all the simulated cases, HGAFSA has demonstrated superiority and has yielded a considerable huge amount of annual savings in fuel cost. Figure 4.6 also show the bar charts of annual savings in fuel cost.

Table 4.7: Summary of Results for the Comparison of HGAFSA and OGWO/OIWO

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **System** | **Number of Units** | **HGAFSA**  **($)** | **OGWO**  **Best Cost so far ($)** | **Annual Savings ($)** | **Total Power** | **OGWO/OIWO**  **Iteration Time (s)** | **HGAFSA**  **Iteration Time (s)** |
| **1** | 13 | 24,141.2687 | 24,512.725 | 3,253,957.2 | 2,560.3686 | 5.16 | 5.023 |
| **2** | 40 | 136,396.9727 | 136,440.62 | 382,350.35 | 11,457.297 | 10.23 | 10.113 |
| **3** | 110 | 197,988.892 | 197,989.1358 | 2,135.688 | 15,000 | 31 | 104.3 |
| **4** | 140 | 1,558,619.094 | 1,559,710 | 9,556,340.9 | 49,342 | 41.77 | 41.123 |
| **5** | 160 | 9,612.8295 | 9,745.113 | 1,158,803.5 | 43,200 | 16.32 | 10.234 |

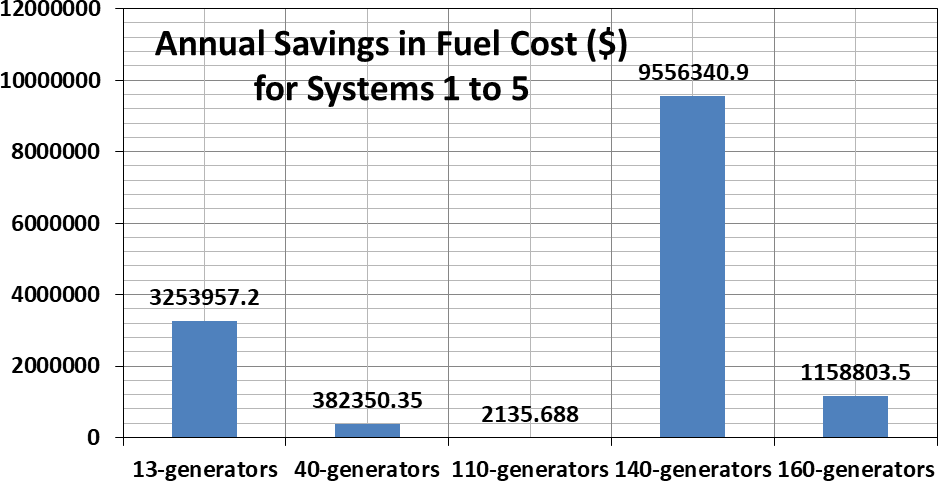


Figure 4.6: Annual Savings in Fuel Cost for Systems 1 to 5

### CHAPTER FIVE CONCLUSION AND RECOMMENDATION

### Introduction

This chapter presents the general conclusion drawn from the simulation carried out in this work, and itemize a set of recommendations that may be useful in future works regarding ELD problem and its solution strategy.

### Conclusion

In this work, a hybrid Genetic Algorithm and Artificial Fish Swarm Algorithm namely HGAFSA capable of solving a higher order economic load dispatch (ELD) has been developed and used to solve several higher order ELD problems including 13, 40, 110, 140 and 160-generating-Units system. An ELD Encoder algorithm that can be linked to any heuristic algorithm to solve ELD problem has been developed and linked to the developed HGAFSA to form a HGAFSA based ELD algorithm (HGAFSAELDA) that can minimize any ELD cost function lower than every algorithm available in the literature so far. The performance of the developed HGAFSAELDA has been demonstrated over five standard IEEE test systems. Reduction in fuel cost of 1.53%, 0.03%, 0.07%, 0.00012% and 1.37% were recorded on the 13, 40, 110, 140 and 160- generating- units. Annual savings in fuel cost of $3.254e+06, $3.8235e+05, $2135.7, $9.5563e+06, and

$1.1588e+06 for the 13, 40, 110, 140, and 160-generating-units respectively were achieved over the existing best costs presented in the (Pradhan *et al*., 2017). It can be generalized that this developed HGAFSAELDA can go a long way in providing solution to any given ELD problem. The simulation environment used was MATLAB R2016a Software running on a Windows 10.1 based 8GB-RAM, 2.3GHz-Core-I3 HP computer.

### Significant Contributions

The major contributions of this work to the existing body of knowledge are summarized in the following.

* + 1. A hybrid Genetic Algorithm and Artificial Fish Swarm Algorithm namely HGAFSA capable of solving a higher order economic load dispatch (ELD) have been developed and used to solve several higher order ELD problems including 13, 40, 110, 140 and 160- generating-Units system.
    2. An ELD Encoder algorithm that can be linked to any heuristic algorithm to solve ELD problem has been developed and linked to the developed HGAFSA to form a HGAFSA based ELD algorithm (HGAFSAELDA) that can minimize any ELD cost function lower than every algorithm available in the literature of this work.
    3. The performance of the developed HGAFSAELDA has been demonstrated over five ELD systems. Reduction in fuel cost of 1.53%, 0.03%, 0.07%, 0.00012% and 1.37% were recorded on the 13, 40, 110, 140 and 160- generating- units. An annual savings in fuel cost of $3.254e+06, $3.8235e+05, $2135.7, $9.5563e+06, and $1.1588e+06 for the 13, 40, 110, 140, and 160-generating-units respectively were achieved over the existing best costs presented in (Pradhan *et al*., 2017).

### Recommendations

In the case where a researcher wishes to work on ELD problem solving strategies. The following are some suggestions regarding possible research direction.

* + 1. Implementation of the developed Algorithm on a Digital Signal Processor (DSP) chip and testing it using a real power system to ascertain its effectiveness;
    2. Development of the proposed algorithm in a suitable java based software package for use by students in their respective course works;
    3. Linking the developed ELD encoder with other heuristics and testing their performance compared to the proposed HGAFSA.

### Limitation

The limitation encountered in this work is summarized in the following.

* + 1. The error due to approximation affected the results presented in some test system cases especially the 110-Unit case.

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### APPENDIX A1

Table 4a:13-Units Economic Load Dispatch Data

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Gen.**  **Unit.** | **Pmin** | **Pmax** | **a** | **B** | **c** | **e** | **f** |
| 1 | 0 | 680 | 0.0003 | 8.1 | 550 | 300 | 0.035 |
| 2 | 0 | 360 | 0.0006 | 8.1 | 309 | 200 | 0.042 |
| 3 | 0 | 360 | 0.0006 | 8.1 | 307 | 150 | 0.042 |
| 4 | 60 | 180 | 0.0032 | 7.74 | 240 | 150 | 0.063 |
| 5 | 60 | 180 | 0.0032 | 7.74 | 240 | 150 | 0.063 |
| 6 | 60 | 180 | 0.0032 | 7.74 | 240 | 150 | 0.063 |
| 7 | 60 | 180 | 0.0032 | 7.74 | 240 | 150 | 0.063 |
| 8 | 60 | 180 | 0.0032 | 7.74 | 240 | 150 | 0.063 |
| 9 | 60 | 180 | 0.0032 | 7.74 | 240 | 150 | 0.063 |
| 10 | 40 | 120 | 0.0028 | 8.6 | 126 | 100 | 0.084 |
| 11 | 40 | 120 | 0.0028 | 8.6 | 126 | 100 | 0.084 |
| 12 | 55 | 120 | 0.0028 | 8.6 | 126 | 100 | 0.084 |
| 13 | 55 | 120 | 0.0028 | 8.6 | 126 | 100 | 0.084 |

### APPENDIX A2

Table 4b: 40-Units Economic Load Dispatch Data

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Gen.**  **Unit.** | **Pmin** | **Pmax** | **a** | **B** | **c** | **e** | **f** |
| 1 | 36 | 114 | 0.0069 | 6.73 | 94.705 | 100 | 0.084 |
| 2 | 36 | 114 | 0.0069 | 6.73 | 94.705 | 100 | 0.084 |
| 3 | 60 | 120 | 0.02028 | 7.07 | 309.54 | 100 | 0.084 |
| 4 | 80 | 190 | 0.00942 | 8.18 | 369.03 | 150 | 0.063 |
| 5 | 47 | 97 | 0.0114 | 5.35 | 148.89 | 120 | 0.077 |
| 6 | 68 | 140 | 0.01142 | 8.05 | 222.33 | 100 | 0.084 |
| 7 | 110 | 300 | 0.00357 | 8.03 | 278.71 | 200 | 0.042 |
| 8 | 135 | 300 | 0.00492 | 6.99 | 391.98 | 200 | 0.042 |
| 9 | 135 | 300 | 0.00573 | 6.6 | 455.76 | 200 | 0.042 |
| 10 | 130 | 300 | 0.00605 | 12.9 | 722.82 | 200 | 0.042 |
| 11 | 94 | 375 | 0.00515 | 12.9 | 635.2 | 200 | 0.042 |
| 12 | 94 | 375 | 0.00569 | 12.8 | 654.69 | 200 | 0.042 |
| 13 | 125 | 500 | 0.00421 | 12.5 | 913.4 | 300 | 0.035 |
| 14 | 125 | 500 | 0.00752 | 8.84 | 1760.4 | 300 | 0.035 |
| 15 | 125 | 500 | 0.00708 | 9.15 | 1728.3 | 300 | 0.035 |
| 16 | 125 | 500 | 0.00708 | 9.15 | 1728.3 | 300 | 0.035 |
| 17 | 220 | 500 | 0.00313 | 7.97 | 647.85 | 300 | 0.035 |
| 18 | 220 | 500 | 0.00313 | 7.95 | 649.69 | 300 | 0.035 |
| 19 | 242 | 550 | 0.00313 | 7.97 | 647.83 | 300 | 0.035 |
| 20 | 242 | 550 | 0.00313 | 7.97 | 647.81 | 300 | 0.035 |
| 21 | 254 | 550 | 0.00298 | 6.63 | 785.96 | 300 | 0.035 |
| 22 | 254 | 550 | 0.00298 | 6.63 | 785.96 | 300 | 0.035 |
| 23 | 254 | 550 | 0.00284 | 6.66 | 794.53 | 300 | 0.035 |
| 24 | 254 | 550 | 0.00284 | 6.66 | 794.53 | 300 | 0.035 |
| 25 | 254 | 550 | 0.00277 | 7.1 | 801.32 | 300 | 0.035 |
| 26 | 254 | 550 | 0.00277 | 7.1 | 801.32 | 300 | 0.035 |
| 27 | 10 | 150 | 0.52124 | 3.33 | 1055.1 | 120 | 0.077 |
| 28 | 10 | 150 | 0.52124 | 3.33 | 1055.1 | 120 | 0.077 |
| 29 | 10 | 150 | 0.52124 | 3.33 | 1055.1 | 120 | 0.077 |
| 30 | 47 | 97 | 0.0114 | 5.35 | 148.89 | 120 | 0.077 |
| 31 | 60 | 190 | 0.0016 | 6.43 | 222.92 | 150 | 0.063 |
| 32 | 60 | 190 | 0.0016 | 6.43 | 222.92 | 150 | 0.063 |
| 33 | 60 | 190 | 0.0016 | 6.43 | 222.92 | 150 | 0.063 |
| 34 | 90 | 200 | 0.0001 | 8.95 | 107.87 | 200 | 0.042 |
| 35 | 90 | 200 | 0.0001 | 8.62 | 116.58 | 200 | 0.042 |
| 36 | 90 | 200 | 0.0001 | 8.62 | 116.58 | 200 | 0.042 |
| 37 | 25 | 110 | 0.0161 | 5.88 | 307.45 | 80 | 0.098 |
| 38 | 25 | 110 | 0.0161 | 5.88 | 307.45 | 80 | 0.098 |
| 39 | 25 | 110 | 0.0161 | 5.88 | 307.45 | 80 | 0.098 |
| 40 | 242 | 550 | 0.00313 | 7.97 | 647.83 | 300 | 0.035 |

### APPENDIX A3

Table 4c1: 110-Units Economic Load Dispatch Data

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Gen.**  **Unit.** | **Pmin** | **Pmax** | **a** | **B** | **c** | **e** | **f** |
| 1 | 2.4 | 12 | 0.0253 | 25.547 | 24.389 | 0 | 0 |
| 2 | 2.4 | 12 | 0.0265 | 25.675 | 24.411 | 0 | 0 |
| 3 | 2.4 | 12 | 0.028 | 25.803 | 24.638 | 0 | 0 |
| 4 | 2.4 | 12 | 0.0284 | 25.932 | 24.76 | 0 | 0 |
| 5 | 2.4 | 12 | 0.0286 | 26.061 | 24.888 | 0 | 0 |
| 6 | 4 | 20 | 0.012 | 37.551 | 117.76 | 0 | 0 |
| 7 | 4 | 20 | 0.0126 | 37.664 | 118.11 | 0 | 0 |
| 8 | 4 | 20 | 0.0136 | 37.777 | 118.46 | 0 | 0 |
| 9 | 4 | 20 | 0.0143 | 37.89 | 118.82 | 0 | 0 |
| 10 | 15.2 | 76 | 0.0088 | 13.327 | 81.136 | 0 | 0 |
| 11 | 15.2 | 76 | 0.0089 | 13.354 | 81.298 | 0 | 0 |
| 12 | 15.2 | 76 | 0.0091 | 13.8 | 81.464 | 0 | 0 |
| 13 | 15.2 | 76 | 0.0093 | 13.407 | 81.626 | 0 | 0 |
| 14 | 25 | 100 | 0.0062 | 18 | 217.9 | 0 | 0 |
| 15 | 25 | 100 | 0.0061 | 18.1 | 218.34 | 0 | 0 |
| 16 | 25 | 100 | 0.006 | 18.2 | 218.78 | 0 | 0 |
| 17 | 54.3 | 155 | 0.0046 | 10.694 | 142.74 | 0 | 0 |
| 18 | 54.3 | 155 | 0.0047 | 10.715 | 143.03 | 0 | 0 |
| 19 | 54.3 | 155 | 0.0048 | 10.737 | 143.32 | 0 | 0 |
| 20 | 54.3 | 155 | 0.0049 | 10.758 | 143.6 | 0 | 0 |
| 21 | 68.9 | 197 | 0.0026 | 23 | 259.13 | 0 | 0 |
| 22 | 68.9 | 197 | 0.0026 | 23.1 | 259.65 | 0 | 0 |
| 23 | 68.9 | 197 | 0.0026 | 23.2 | 260.18 | 0 | 0 |
| 24 | 140 | 350 | 0.0015 | 10.862 | 177.06 | 0 | 0 |
| 25 | 100 | 400 | 0.0019 | 7.492 | 210 | 0 | 0 |
| 26 | 100 | 400 | 0.0019 | 7.503 | 211.91 | 0 | 0 |
| 27 | 140 | 500 | 0.0014 | 12 | 210 | 0 | 0 |
| 28 | 140 | 500 | 0.0013 | 12.1 | 180 | 0 | 0 |
| 29 | 50 | 200 | 0.0026 | 12.2 | 240 | 0 | 0 |
| 30 | 25 | 100 | 0.0039 | 12.5 | 220 | 0 | 0 |
| 31 | 10 | 50 | 0.0051 | 23 | 60 | 0 | 0 |
| 32 | 5 | 20 | 0.005 | 13.5 | 50 | 0 | 0 |
| 33 | 20 | 80 | 0.0078 | 13.2 | 200 | 0 | 0 |
| 34 | 75 | 250 | 0.0012 | 12.4 | 140 | 0 | 0 |
| 35 | 110 | 360 | 0.0038 | 10.3 | 120 | 0 | 0 |
| 36 | 130 | 400 | 0.0043 | 9.9 | 90 | 0 | 0 |
| 37 | 10 | 40 | 0.0011 | 13.4 | 80 | 0 | 0 |
| 38 | 20 | 70 | 0.0023 | 13.3 | 70 | 0 | 0 |
| 39 | 25 | 100 | 0.0034 | 12.9 | 115 | 0 | 0 |
| 40 | 20 | 120 | 0.0067 | 12.8 | 150 | 0 | 0 |
| 41 | 40 | 180 | 0.0056 | 12.7 | 40 | 0 | 0 |
| 42 | 50 | 220 | 0.0023 | 12.6 | 300 | 0 | 0 |
| 43 | 120 | 440 | 0.0012 | 7.4 | 250 | 0 | 0 |
| 44 | 160 | 560 | 0.0045 | 6.6 | 100 | 0 | 0 |
| 45 | 150 | 660 | 0.0022 | 6.5 | 160 | 0 | 0 |
| 46 | 200 | 700 | 0.0067 | 6.2 | 130 | 0 | 0 |
| 47 | 5.4 | 32 | 0.0353 | 26.547 | 34.389 | 0 | 0 |
| 48 | 5.4 | 32 | 0.0365 | 26.675 | 34.411 | 0 | 0 |
| 49 | 8.4 | 52 | 0.038 | 26.803 | 34.638 | 0 | 0 |
| 50 | 8.4 | 52 | 0.0384 | 26.932 | 34.761 | 0 | 0 |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| 51 | 8.4 | 52 | 0.0386 | 17.061 | 34.888 | 0 | 0 |
| 52 | 12 | 60 | 0.032 | 38.551 | 127.76 | 0 | 0 |
| 53 | 12 | 60 | 0.0326 | 36.664 | 128.11 | 0 | 0 |
| 54 | 12 | 60 | 0.0236 | 38.777 | 128.46 | 0 | 0 |

Table 4c2: 110-Units Economic Load Dispatch Data (Continued)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Gen.**  **Unit.** | **Pmin** | **Pmax** | **a** | **b** | **c** | **e** | **f** |
| 55 | 12 | 60 | 0.0243 | 38.89 | 128.82 | 0 | 0 |
| 56 | 25.2 | 96 | 0.0098 | 14.327 | 82.136 | 0 | 0 |
| 57 | 25.2 | 96 | 0.0099 | 14.354 | 82.298 | 0 | 0 |
| 58 | 35 | 100 | 0.0092 | 14.38 | 82.464 | 0 | 0 |
| 59 | 35 | 100 | 0.0094 | 14.407 | 82.626 | 0 | 0 |
| 60 | 45 | 120 | 0.0072 | 19 | 218.9 | 0 | 0 |
| 61 | 45 | 120 | 0.0071 | 19.1 | 219.34 | 0 | 0 |
| 62 | 45 | 120 | 0.007 | 19.2 | 219.78 | 0 | 0 |
| 63 | 54.3 | 185 | 0.0066 | 11.694 | 143.74 | 0 | 0 |
| 64 | 54.3 | 185 | 0.0057 | 11.715 | 144.03 | 0 | 0 |
| 65 | 54.3 | 185 | 0.0058 | 11.737 | 144.32 | 0 | 0 |
| 66 | 54.3 | 185 | 0.0059 | 11.758 | 144.6 | 0 | 0 |
| 67 | 70 | 197 | 0.0036 | 24 | 269.13 | 0 | 0 |
| 68 | 70 | 197 | 0.0036 | 24.1 | 269.65 | 0 | 0 |
| 69 | 70 | 197 | 0.0036 | 24.2 | 270.18 | 0 | 0 |
| 70 | 150 | 360 | 0.0025 | 11.862 | 187.06 | 0 | 0 |
| 71 | 160 | 400 | 0.0029 | 8.492 | 320 | 0 | 0 |
| 72 | 160 | 400 | 0.003 | 8.503 | 321.91 | 0 | 0 |
| 73 | 60 | 300 | 0.0054 | 13.327 | 52.136 | 0 | 0 |
| 74 | 50 | 250 | 0.0055 | 12.354 | 42.298 | 0 | 0 |
| 75 | 30 | 90 | 0.0099 | 11.38 | 32.464 | 0 | 0 |
| 76 | 12 | 50 | 0.0031 | 9.407 | 23.626 | 0 | 0 |
| 77 | 160 | 450 | 0.0024 | 14 | 220 | 0 | 0 |
| 78 | 150 | 600 | 0.0023 | 13.1 | 190 | 0 | 0 |
| 79 | 50 | 200 | 0.0036 | 13.2 | 250 | 0 | 0 |
| 80 | 20 | 120 | 0.0049 | 13.5 | 230 | 0 | 0 |
| 81 | 10 | 55 | 0.0061 | 24 | 70 | 0 | 0 |
| 82 | 12 | 40 | 0.007 | 14.5 | 60 | 0 | 0 |
| 83 | 20 | 80 | 0.0088 | 14.2 | 210 | 0 | 0 |
| 84 | 50 | 200 | 0.0022 | 13.4 | 150 | 0 | 0 |
| 85 | 80 | 325 | 0.0048 | 11.3 | 130 | 0 | 0 |
| 86 | 120 | 440 | 0.0053 | 8.9 | 80 | 0 | 0 |
| 87 | 10 | 35 | 0.0021 | 14.4 | 90 | 0 | 0 |
| 88 | 20 | 55 | 0.0033 | 14.3 | 80 | 0 | 0 |
| 89 | 20 | 100 | 0.0034 | 13.9 | 125 | 0 | 0 |
| 90 | 40 | 220 | 0.0037 | 13.8 | 160 | 0 | 0 |
| 91 | 30 | 140 | 0.0066 | 13.7 | 50 | 0 | 0 |
| 92 | 40 | 100 | 0.0043 | 13.6 | 400 | 0 | 0 |
| 93 | 100 | 440 | 0.0022 | 8.4 | 260 | 0 | 0 |
| 94 | 100 | 500 | 0.0055 | 7.6 | 110 | 0 | 0 |
| 95 | 100 | 600 | 0.0032 | 7.5 | 170 | 0 | 0 |
| 96 | 200 | 700 | 0.0077 | 7.2 | 140 | 0 | 0 |
| 97 | 3.6 | 15 | 0.0353 | 26.547 | 26.389 | 0 | 0 |
| 98 | 3.6 | 15 | 0.0365 | 26.675 | 25.411 | 0 | 0 |
| 99 | 4.4 | 22 | 0.038 | 26.803 | 25.638 | 0 | 0 |
| 100 | 4.4 | 22 | 0.0384 | 26.932 | 25.76 | 0 | 0 |
| 101 | 10 | 60 | 0.021 | 15.3 | 65 | 0 | 0 |
| 102 | 10 | 80 | 0.023 | 16 | 82 | 0 | 0 |
| 103 | 20 | 100 | 0.024 | 20.2 | 86 | 0 | 0 |
| 104 | 20 | 120 | 0.035 | 20.2 | 84 | 0 | 0 |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| 105 | 40 | 150 | 0.034 | 25.6 | 75 | 0 | 0 |
| 106 | 40 | 280 | 0.037 | 30.5 | 56 | 0 | 0 |
| 107 | 50 | 520 | 0.039 | 32.5 | 67 | 0 | 0 |
| 108 | 30 | 150 | 0.035 | 26 | 68 | 0 | 0 |
| 109 | 40 | 320 | 0.028 | 25.8 | 69 | 0 | 0 |
| 110 | 20 | 200 | 0.026 | 27 | 72 | 0 | 0 |

### APPENDIX A4

Table 4d1: 140-Units Economic Load Dispatch Data

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Gen.**  **Unit.** | **Pmin** | **Pmax** | **a** | **b** | **c** | **e** | **f** |
| 1 | 71 | 119 | 0.032888 | 61.242 | 1220.6 | 0 | 0 |
| 2 | 120 | 189 | 0.00828 | 41.095 | 1315.1 | 0 | 0 |
| 3 | 125 | 190 | 0.003849 | 46.31 | 874.29 | 0 | 0 |
| 4 | 125 | 190 | 0.003849 | 46.31 | 874.29 | 0 | 0 |
| 5 | 90 | 190 | 0.042468 | 54.242 | 1976.5 | 0 | 0 |
| 6 | 90 | 190 | 0.014992 | 61.215 | 1338.1 | 0 | 0 |
| 7 | 280 | 490 | 0.007039 | 11.791 | 1818.3 | 0 | 0 |
| 8 | 280 | 490 | 0.003079 | 15.055 | 1134 | 0 | 0 |
| 9 | 260 | 496 | 0.005063 | 13.226 | 1320.6 | 0 | 0 |
| 10 | 260 | 496 | 0.005063 | 13.226 | 1320.6 | 0 | 0 |
| 11 | 260 | 496 | 0.005063 | 13.226 | 1320.6 | 0 | 0 |
| 12 | 260 | 496 | 0.003552 | 14.498 | 1106.5 | 0 | 0 |
| 13 | 260 | 506 | 0.003901 | 14.651 | 1176.5 | 0 | 0 |
| 14 | 260 | 509 | 0.003901 | 14.651 | 1176.5 | 0 | 0 |
| 15 | 260 | 506 | 0.003901 | 14.651 | 1176.5 | 0 | 0 |
| 16 | 260 | 505 | 0.003901 | 14.651 | 1176.5 | 0 | 0 |
| 17 | 260 | 506 | 0.002393 | 15.669 | 1017.4 | 0 | 0 |
| 18 | 260 | 506 | 0.002393 | 15.669 | 1017.4 | 0 | 0 |
| 19 | 260 | 505 | 0.003684 | 14.656 | 1229.1 | 0 | 0 |
| 20 | 260 | 505 | 0.003684 | 14.656 | 1229.1 | 0 | 0 |
| 21 | 260 | 505 | 0.003684 | 14.656 | 1229.1 | 0 | 0 |
| 22 | 260 | 505 | 0.003684 | 14.656 | 1229.1 | 0 | 0 |
| 23 | 260 | 505 | 0.004004 | 14.378 | 1267.9 | 0 | 0 |
| 24 | 260 | 505 | 0.003684 | 14.656 | 1229.1 | 0 | 0 |
| 25 | 280 | 537 | 0.001619 | 16.261 | 975.93 | 0 | 0 |
| 26 | 280 | 537 | 0.005093 | 13.362 | 1532.1 | 0 | 0 |
| 27 | 280 | 549 | 0.000993 | 17.203 | 641.99 | 0 | 0 |
| 28 | 280 | 549 | 0.000993 | 17.203 | 641.99 | 0 | 0 |
| 29 | 260 | 501 | 0.002473 | 15.274 | 911.53 | 0 | 0 |
| 30 | 260 | 501 | 0.002547 | 15.212 | 910.53 | 0 | 0 |
| 31 | 260 | 506 | 0.003542 | 15.033 | 1074.8 | 0 | 0 |
| 32 | 260 | 506 | 0.003542 | 15.033 | 1074.8 | 0 | 0 |
| 33 | 260 | 506 | 0.003542 | 15.033 | 1074.8 | 0 | 0 |
| 34 | 260 | 506 | 0.003542 | 15.033 | 1074.8 | 0 | 0 |
| 35 | 260 | 500 | 0.003132 | 13.992 | 1278.5 | 0 | 0 |
| 36 | 260 | 500 | 0.001323 | 15.679 | 861.74 | 0 | 0 |
| 37 | 120 | 241 | 0.00295 | 16.542 | 408.83 | 0 | 0 |
| 38 | 120 | 241 | 0.00295 | 16.542 | 408.83 | 0 | 0 |
| 39 | 423 | 774 | 0.000991 | 16.518 | 1288.8 | 0 | 0 |
| 40 | 423 | 769 | 0.001581 | 15.815 | 1436.3 | 0 | 0 |
| 41 | 3 | 19 | 0.90236 | 75.464 | 669.99 | 0 | 0 |
| 42 | 3 | 28 | 0.1103 | 129.54 | 134.54 | 0 | 0 |
| 43 | 160 | 250 | 0.024493 | 56.613 | 3427.9 | 0 | 0 |
| 44 | 160 | 250 | 0.029156 | 54.451 | 3751.8 | 0 | 0 |
| 45 | 160 | 250 | 0.024667 | 54.736 | 3918.8 | 0 | 0 |
| 46 | 160 | 250 | 0.016517 | 58.034 | 3379.6 | 0 | 0 |
| 47 | 160 | 250 | 0.026584 | 55.981 | 3345.3 | 0 | 0 |
| 48 | 160 | 250 | 0.00754 | 61.52 | 3138.8 | 0 | 0 |
| 49 | 160 | 250 | 0.01643 | 58.635 | 3453.1 | 0 | 0 |
| 50 | 160 | 250 | 0.045934 | 44.647 | 5119.3 | 0 | 0 |
| 51 | 165 | 504 | 4.40E-05 | 71.584 | 1898.4 | 0 | 0 |
| 52 | 165 | 504 | 4.40E-05 | 71.584 | 1898.4 | 0 | 0 |
| 53 | 165 | 504 | 4.40E-05 | 71.584 | 1898.4 | 0 | 0 |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| 54 | 165 | 504 | 4.40E-05 | 71.584 | 1898.4 | 0 | 0 |

Table 4d2: 140-Units Economic Load Dispatch Data (Continued)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Gen.**  **Unit.** | **Pmin** | **Pmax** | **a** | **b** | **c** | **e** | **f** |
| 55 | 180 | 471 | 0.002528 | 85.12 | 2473.4 | 0 | 0 |
| 56 | 180 | 561 | 0.000131 | 87.682 | 2781.7 | 0 | 0 |
| 57 | 103 | 341 | 0.010372 | 69.532 | 5515.5 | 0 | 0 |
| 58 | 198 | 617 | 0.007627 | 78.339 | 3478.3 | 0 | 0 |
| 59 | 100 | 312 | 0.012464 | 58.172 | 6240.9 | 0 | 0 |
| 60 | 153 | 471 | 0.039441 | 46.636 | 9960.1 | 0 | 0 |
| 61 | 163 | 500 | 0.007278 | 76.947 | 3672 | 0 | 0 |
| 62 | 95 | 302 | 4.40E-05 | 80.761 | 1837.4 | 0 | 0 |
| 63 | 160 | 511 | 4.40E-05 | 70.136 | 3108.4 | 0 | 0 |
| 64 | 160 | 511 | 4.40E-05 | 70.136 | 3108.4 | 0 | 0 |
| 65 | 196 | 490 | 0.018827 | 49.84 | 7095.5 | 0 | 0 |
| 66 | 196 | 490 | 0.010852 | 65.404 | 3392.7 | 0 | 0 |
| 67 | 196 | 490 | 0.018827 | 49.84 | 7095.5 | 0 | 0 |
| 68 | 196 | 490 | 0.018827 | 49.84 | 7095.5 | 0 | 0 |
| 69 | 130 | 432 | 0.03456 | 66.465 | 4288.3 | 0 | 0 |
| 70 | 130 | 432 | 0.08154 | 22.941 | 13813 | 0 | 0 |
| 71 | 137 | 455 | 0.023534 | 64.314 | 4435.5 | 0 | 0 |
| 72 | 137 | 455 | 0.035475 | 45.017 | 9750.8 | 0 | 0 |
| 73 | 195 | 541 | 0.000915 | 70.644 | 1042.4 | 0 | 0 |
| 74 | 175 | 536 | 4.40E-05 | 70.959 | 1159.9 | 0 | 0 |
| 75 | 175 | 540 | 4.40E-05 | 70.959 | 1159.9 | 0 | 0 |
| 76 | 175 | 538 | 0.001307 | 70.302 | 1304 | 0 | 0 |
| 77 | 175 | 540 | 0.000392 | 70.662 | 1156.2 | 0 | 0 |
| 78 | 330 | 574 | 8.70E-05 | 71.101 | 2119 | 0 | 0 |
| 79 | 160 | 531 | 0.000521 | 37.854 | 779.52 | 0 | 0 |
| 80 | 160 | 531 | 0.000498 | 37.768 | 829.89 | 0 | 0 |
| 81 | 200 | 542 | 0.001046 | 67.983 | 2333.7 | 0 | 0 |
| 82 | 56 | 132 | 0.13205 | 77.838 | 2029 | 0 | 0 |
| 83 | 115 | 245 | 0.096968 | 63.671 | 4412 | 0 | 0 |
| 84 | 115 | 245 | 0.054868 | 79.458 | 2982.2 | 0 | 0 |
| 85 | 115 | 245 | 0.054868 | 79.458 | 2982.2 | 0 | 0 |
| 86 | 207 | 307 | 0.014382 | 93.966 | 3174.9 | 0 | 0 |
| 87 | 207 | 307 | 0.013161 | 94.723 | 3218.4 | 0 | 0 |
| 88 | 175 | 345 | 0.016033 | 66.919 | 3723.8 | 0 | 0 |
| 89 | 175 | 345 | 0.013653 | 68.185 | 3551.4 | 0 | 0 |
| 90 | 175 | 345 | 0.028148 | 60.821 | 4322.6 | 0 | 0 |
| 91 | 175 | 345 | 0.01347 | 68.551 | 3493.7 | 0 | 0 |
| 92 | 360 | 580 | 6.40E-05 | 2.842 | 226.8 | 0 | 0 |
| 93 | 415 | 645 | 0.000252 | 2.946 | 382.93 | 0 | 0 |
| 94 | 795 | 984 | 2.20E-05 | 3.096 | 156.99 | 0 | 0 |
| 95 | 795 | 978 | 2.20E-05 | 3.04 | 154.48 | 0 | 0 |
| 96 | 578 | 682 | 0.000203 | 1.709 | 332.83 | 0 | 0 |
| 97 | 615 | 720 | 0.000198 | 1.668 | 326.6 | 0 | 0 |
| 98 | 612 | 718 | 0.000215 | 1.789 | 345.31 | 0 | 0 |
| 99 | 612 | 720 | 0.000218 | 1.815 | 350.37 | 0 | 0 |
| 100 | 758 | 964 | 0.000193 | 2.726 | 370.38 | 0 | 0 |
| 101 | 755 | 958 | 0.000197 | 2.732 | 367.07 | 0 | 0 |
| 102 | 750 | 1007 | 0.000324 | 2.651 | 124.88 | 0 | 0 |
| 103 | 750 | 1006 | 0.000344 | 2.798 | 130.79 | 0 | 0 |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| 104 | 713 | 1013 | 0.00069 | 1.595 | 878.75 | 0 | 0 |
| 105 | 718 | 1020 | 0.00065 | 1.503 | 827.96 | 0 | 0 |
| 106 | 791 | 954 | 0.000233 | 2.425 | 432.01 | 0 | 0 |
| 107 | 786 | 952 | 0.000239 | 2.499 | 445.61 | 0 | 0 |
| 108 | 795 | 1006 | 0.000261 | 2.674 | 467.22 | 0 | 0 |

Table 4d3: 140-Units Economic Load Dispatch Data (Continued)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Gen.**  **Unit.** | **Pmin** | **Pmax** | **a** | **b** | **c** | **e** | **f** |
| 109 | 795 | 1013 | 0.000259 | 2.692 | 475.94 | 0 | 0 |
| 110 | 795 | 1021 | 0.000707 | 1.633 | 899.46 | 0 | 0 |
| 111 | 795 | 1015 | 0.000786 | 1.816 | 1000.4 | 0 | 0 |
| 112 | 94 | 203 | 0.014355 | 89.83 | 1269.1 | 0 | 0 |
| 113 | 94 | 203 | 0.014355 | 89.83 | 1269.1 | 0 | 0 |
| 114 | 94 | 203 | 0.014355 | 89.83 | 1269.1 | 0 | 0 |
| 115 | 244 | 379 | 0.030266 | 64.125 | 4965.1 | 0 | 0 |
| 116 | 244 | 379 | 0.030266 | 64.125 | 4965.1 | 0 | 0 |
| 117 | 244 | 379 | 0.030266 | 64.125 | 4965.1 | 0 | 0 |
| 118 | 95 | 190 | 0.024027 | 76.129 | 2243.2 | 0 | 0 |
| 119 | 95 | 189 | 0.00158 | 81.805 | 2290.4 | 0 | 0 |
| 120 | 116 | 194 | 0.022095 | 81.14 | 1681.5 | 0 | 0 |
| 121 | 175 | 321 | 0.07681 | 46.665 | 6743.3 | 0 | 0 |
| 122 | 2 | 19 | 0.95344 | 78.412 | 394.4 | 0 | 0 |
| 123 | 4 | 59 | 4.40E-05 | 112.09 | 1243.2 | 0 | 0 |
| 124 | 15 | 83 | 0.072468 | 90.871 | 1454.7 | 0 | 0 |
| 125 | 9 | 53 | 0.000448 | 97.116 | 1011.1 | 0 | 0 |
| 126 | 12 | 37 | 0.59911 | 83.244 | 909.27 | 0 | 0 |
| 127 | 10 | 34 | 0.24471 | 95.665 | 689.38 | 0 | 0 |
| 128 | 112 | 373 | 4.20E-05 | 91.202 | 1443.8 | 0 | 0 |
| 129 | 4 | 20 | 0.085145 | 104.5 | 535.55 | 0 | 0 |
| 130 | 5 | 38 | 0.52472 | 83.015 | 617.73 | 0 | 0 |
| 131 | 5 | 19 | 0.17652 | 127.8 | 90.966 | 0 | 0 |
| 132 | 50 | 98 | 0.063414 | 77.929 | 974.45 | 0 | 0 |
| 133 | 5 | 10 | 2.7405 | 92.779 | 263.81 | 0 | 0 |
| 134 | 42 | 74 | 0.11244 | 80.95 | 1335.6 | 0 | 0 |
| 135 | 42 | 74 | 0.041529 | 89.073 | 1033.9 | 0 | 0 |
| 136 | 41 | 105 | 0.000911 | 161.29 | 1391.3 | 0 | 0 |
| 137 | 17 | 51 | 0.005245 | 161.83 | 4477.1 | 0 | 0 |
| 138 | 7 | 19 | 0.23479 | 84.972 | 57.794 | 0 | 0 |
| 139 | 7 | 19 | 0.23479 | 84.972 | 57.794 | 0 | 0 |
| 140 | 26 | 40 | 1.1119 | 16.087 | 1258.4 | 0 | 0 |

### APPENDIX A5

Table 4e1: 160-Units Economic Load Dispatch Data (Continued)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Gen.**  **Unit.** | **Pmin** | **Pmax** | **a** | **b** | **c** | **e** | **f** |
| 1 | 196 | 250 | 0.0019 | -0.3059 | 21.13 | 0.0211 | -3.059 |
| 2 | 157 | 230 | 0.0042 | -1.269 | 118.4 | 0.1184 | -12.69 |
| 3 | 200 | 332 | 0.0015 | -0.3116 | 39.79 | 0.0398 | -3.116 |
| 4 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 5 | 190 | 338 | 0.0011 | -0.0873 | 13.92 | 0.0139 | -0.8733 |
| 6 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 7 | 200 | 331 | 0.0011 | -0.1325 | 18.93 | 0.0189 | -1.325 |
| 8 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 9 | 370 | 440 | 0.0006 | -0.0182 | 14.23 | 0.0142 | -0.1817 |
| 10 | 200 | 362 | 0.0011 | -0.0994 | 13.97 | 0.014 | -0.9938 |
| 11 | 196 | 250 | 0.0019 | -0.3059 | 21.13 | 0.0211 | -3.059 |
| 12 | 157 | 230 | 0.0042 | -1.269 | 118.4 | 0.1184 | -12.69 |
| 13 | 200 | 332 | 0.0015 | -0.3116 | 39.79 | 0.0398 | -3.116 |
| 14 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 15 | 190 | 338 | 0.0011 | -0.0873 | 13.92 | 0.0139 | -0.8733 |
| 16 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 17 | 200 | 331 | 0.0011 | -0.1325 | 18.93 | 0.0189 | -1.325 |
| 18 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 19 | 370 | 440 | 0.0006 | -0.0182 | 14.23 | 0.0142 | -0.1817 |
| 20 | 200 | 362 | 0.0011 | -0.0994 | 13.97 | 0.014 | -0.9938 |
| 21 | 196 | 250 | 0.0019 | -0.3059 | 21.13 | 0.0211 | -3.059 |

Table 4e2: 160-Units Economic Load Dispatch Data (Continued)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Gen. Unit.** | **Pmin** | **Pmax** | **a** | **b** | **c** | **e** | **f** |
| 22 | 157 | 230 | 0.0042 | -1.269 | 118.4 | 0.1184 | -12.69 |
| 23 | 200 | 332 | 0.0015 | -0.3116 | 39.79 | 0.0398 | -3.116 |
| 24 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 25 | 190 | 338 | 0.0011 | -0.0873 | 13.92 | 0.0139 | -0.8733 |
| 26 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 27 | 200 | 331 | 0.0011 | -0.1325 | 18.93 | 0.0189 | -1.325 |
| 28 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 29 | 370 | 440 | 0.0006 | -0.0182 | 14.23 | 0.0142 | -0.1817 |
| 30 | 200 | 362 | 0.0011 | -0.0994 | 13.97 | 0.014 | -0.9938 |
| 31 | 196 | 250 | 0.0019 | -0.3059 | 21.13 | 0.0211 | -3.059 |
| 32 | 157 | 230 | 0.0042 | -1.269 | 118.4 | 0.1184 | -12.69 |
| 33 | 200 | 332 | 0.0015 | -0.3116 | 39.79 | 0.0398 | -3.116 |
| 34 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 35 | 190 | 338 | 0.0011 | -0.0873 | 13.92 | 0.0139 | -0.8733 |
| 36 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 37 | 200 | 331 | 0.0011 | -0.1325 | 18.93 | 0.0189 | -1.325 |
| 38 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 39 | 370 | 440 | 0.0006 | -0.0182 | 14.23 | 0.0142 | -0.1817 |
| 40 | 200 | 362 | 0.0011 | -0.0994 | 13.97 | 0.014 | -0.9938 |
| 41 | 196 | 250 | 0.0019 | -0.3059 | 21.13 | 0.0211 | -3.059 |
| 42 | 157 | 230 | 0.0042 | -1.269 | 118.4 | 0.1184 | -12.69 |
| 43 | 200 | 332 | 0.0015 | -0.3116 | 39.79 | 0.0398 | -3.116 |
| 44 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 45 | 190 | 338 | 0.0011 | -0.0873 | 13.92 | 0.0139 | -0.8733 |
| 46 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| 47 | 200 | 331 | 0.0011 | -0.1325 | 18.93 | 0.0189 | -1.325 |
| 48 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 49 | 370 | 440 | 0.0006 | -0.0182 | 14.23 | 0.0142 | -0.1817 |
| 50 | 200 | 362 | 0.0011 | -0.0994 | 13.97 | 0.014 | -0.9938 |
| 51 | 196 | 250 | 0.0019 | -0.3059 | 21.13 | 0.0211 | -3.059 |
| 52 | 157 | 230 | 0.0042 | -1.269 | 118.4 | 0.1184 | -12.69 |
| 53 | 200 | 332 | 0.0015 | -0.3116 | 39.79 | 0.0398 | -3.116 |
| 54 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 55 | 190 | 338 | 0.0011 | -0.0873 | 13.92 | 0.0139 | -0.8733 |
| 56 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 57 | 200 | 331 | 0.0011 | -0.1325 | 18.93 | 0.0189 | -1.325 |
| 58 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 59 | 370 | 440 | 0.0006 | -0.0182 | 14.23 | 0.0142 | -0.1817 |
| 60 | 200 | 362 | 0.0011 | -0.0994 | 13.97 | 0.014 | -0.9938 |
| 61 | 196 | 250 | 0.0019 | -0.3059 | 21.13 | 0.0211 | -3.059 |
| 62 | 157 | 230 | 0.0042 | -1.269 | 118.4 | 0.1184 | -12.69 |
| 63 | 200 | 332 | 0.0015 | -0.3116 | 39.79 | 0.0398 | -3.116 |
| 64 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 65 | 190 | 338 | 0.0011 | -0.0873 | 13.92 | 0.0139 | -0.8733 |
| 66 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 67 | 200 | 331 | 0.0011 | -0.1325 | 18.93 | 0.0189 | -1.325 |
| 68 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 69 | 370 | 440 | 0.0006 | -0.0182 | 14.23 | 0.0142 | -0.1817 |
| 70 | 200 | 362 | 0.0011 | -0.0994 | 13.97 | 0.014 | -0.9938 |
| 71 | 196 | 250 | 0.0019 | -0.3059 | 21.13 | 0.0211 | -3.059 |
| 72 | 157 | 230 | 0.0042 | -1.269 | 118.4 | 0.1184 | -12.69 |
| 73 | 200 | 332 | 0.0015 | -0.3116 | 39.79 | 0.0398 | -3.116 |
| 74 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 75 | 190 | 338 | 0.0011 | -0.0873 | 13.92 | 0.0139 | -0.8733 |

Table 4e3: 160-Units Economic Load Dispatch Data (Continued)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Gen. Unit.** | **Pmin** | **Pmax** | **a** | **b** | **c** | **e** | **f** |
| 76 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 77 | 200 | 331 | 0.0011 | -0.1325 | 18.93 | 0.0189 | -1.325 |
| 78 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 79 | 370 | 440 | 0.0006 | -0.0182 | 14.23 | 0.0142 | -0.1817 |
| 80 | 200 | 362 | 0.0011 | -0.0994 | 13.97 | 0.014 | -0.9938 |
| 81 | 196 | 250 | 0.0019 | -0.3059 | 21.13 | 0.0211 | -3.059 |
| 82 | 157 | 230 | 0.0042 | -1.269 | 118.4 | 0.1184 | -12.69 |
| 83 | 200 | 332 | 0.0015 | -0.3116 | 39.79 | 0.0398 | -3.116 |
| 84 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 85 | 190 | 338 | 0.0011 | -0.0873 | 13.92 | 0.0139 | -0.8733 |
| 86 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 87 | 200 | 331 | 0.0011 | -0.1325 | 18.93 | 0.0189 | -1.325 |
| 88 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 89 | 370 | 440 | 0.0006 | -0.0182 | 14.23 | 0.0142 | -0.1817 |
| 90 | 200 | 362 | 0.0011 | -0.0994 | 13.97 | 0.014 | -0.9938 |
| 91 | 196 | 250 | 0.0019 | -0.3059 | 21.13 | 0.0211 | -3.059 |
| 92 | 157 | 230 | 0.0042 | -1.269 | 118.4 | 0.1184 | -12.69 |
| 93 | 200 | 332 | 0.0015 | -0.3116 | 39.79 | 0.0398 | -3.116 |
| 94 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 95 | 190 | 338 | 0.0011 | -0.0873 | 13.92 | 0.0139 | -0.8733 |
| 96 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 97 | 200 | 331 | 0.0011 | -0.1325 | 18.93 | 0.0189 | -1.325 |
| 98 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 99 | 370 | 440 | 0.0006 | -0.0182 | 14.23 | 0.0142 | -0.1817 |
| 100 | 200 | 362 | 0.0011 | -0.0994 | 13.97 | 0.014 | -0.9938 |
| 101 | 196 | 250 | 0.0019 | -0.3059 | 21.13 | 0.0211 | -3.059 |
| 102 | 157 | 230 | 0.0042 | -1.269 | 118.4 | 0.1184 | -12.69 |
| 103 | 200 | 332 | 0.0015 | -0.3116 | 39.79 | 0.0398 | -3.116 |
| 104 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 105 | 190 | 338 | 0.0011 | -0.0873 | 13.92 | 0.0139 | -0.8733 |
| 106 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| 107 | 200 | 331 | 0.0011 | -0.1325 | 18.93 | 0.0189 | -1.325 |
| 108 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 109 | 370 | 440 | 0.0006 | -0.0182 | 14.23 | 0.0142 | -0.1817 |
| 110 | 200 | 362 | 0.0011 | -0.0994 | 13.97 | 0.014 | -0.9938 |
| 111 | 196 | 250 | 0.0019 | -0.3059 | 21.13 | 0.0211 | -3.059 |
| 112 | 157 | 230 | 0.0042 | -1.269 | 118.4 | 0.1184 | -12.69 |
| 113 | 200 | 332 | 0.0015 | -0.3116 | 39.79 | 0.0398 | -3.116 |
| 114 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 115 | 190 | 338 | 0.0011 | -0.0873 | 13.92 | 0.0139 | -0.8733 |
| 116 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 117 | 200 | 331 | 0.0011 | -0.1325 | 18.93 | 0.0189 | -1.325 |
| 118 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 119 | 370 | 440 | 0.0006 | -0.0182 | 14.23 | 0.0142 | -0.1817 |
| 120 | 200 | 362 | 0.0011 | -0.0994 | 13.97 | 0.014 | -0.9938 |
| 121 | 196 | 250 | 0.0019 | -0.3059 | 21.13 | 0.0211 | -3.059 |
| 122 | 157 | 230 | 0.0042 | -1.269 | 118.4 | 0.1184 | -12.69 |
| 123 | 200 | 332 | 0.0015 | -0.3116 | 39.79 | 0.0398 | -3.116 |
| 124 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 125 | 190 | 338 | 0.0011 | -0.0873 | 13.92 | 0.0139 | -0.8733 |
| 126 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 127 | 200 | 331 | 0.0011 | -0.1325 | 18.93 | 0.0189 | -1.325 |
| 128 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 129 | 370 | 440 | 0.0006 | -0.0182 | 14.23 | 0.0142 | -0.1817 |

Table 4e4: 160-Units Economic Load Dispatch Data (Continued)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Gen. Unit.** | **Pmin** | **Pmax** | **a** | **b** | **c** | **e** | **f** |
| 130 | 200 | 362 | 0.0011 | -0.0994 | 13.97 | 0.014 | -0.9938 |
| 131 | 196 | 250 | 0.0019 | -0.3059 | 21.13 | 0.0211 | -3.059 |
| 132 | 157 | 230 | 0.0042 | -1.269 | 118.4 | 0.1184 | -12.69 |
| 133 | 200 | 332 | 0.0015 | -0.3116 | 39.79 | 0.0398 | -3.116 |
| 134 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 135 | 190 | 338 | 0.0011 | -0.0873 | 13.92 | 0.0139 | -0.8733 |
| 136 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 137 | 200 | 331 | 0.0011 | -0.1325 | 18.93 | 0.0189 | -1.325 |
| 138 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 139 | 370 | 440 | 0.0006 | -0.0182 | 14.23 | 0.0142 | -0.1817 |
| 140 | 200 | 362 | 0.0011 | -0.0994 | 13.97 | 0.014 | -0.9938 |
| 141 | 196 | 250 | 0.0019 | -0.3059 | 21.13 | 0.0211 | -3.059 |
| 142 | 157 | 230 | 0.0042 | -1.269 | 118.4 | 0.1184 | -12.69 |
| 143 | 200 | 332 | 0.0015 | -0.3116 | 39.79 | 0.0398 | -3.116 |
| 144 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 145 | 190 | 338 | 0.0011 | -0.0873 | 13.92 | 0.0139 | -0.8733 |
| 146 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 147 | 200 | 331 | 0.0011 | -0.1325 | 18.93 | 0.0189 | -1.325 |
| 148 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 149 | 370 | 440 | 0.0006 | -0.0182 | 14.23 | 0.0142 | -0.1817 |
| 150 | 200 | 362 | 0.0011 | -0.0994 | 13.97 | 0.014 | -0.9938 |
| 151 | 196 | 250 | 0.0019 | -0.3059 | 21.13 | 0.0211 | -3.059 |
| 152 | 157 | 230 | 0.0042 | -1.269 | 118.4 | 0.1184 | -12.69 |
| 153 | 200 | 332 | 0.0015 | -0.3116 | 39.79 | 0.0398 | -3.116 |
| 154 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 155 | 190 | 338 | 0.0011 | -0.0873 | 13.92 | 0.0139 | -0.8733 |
| 156 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 157 | 200 | 331 | 0.0011 | -0.1325 | 18.93 | 0.0189 | -1.325 |
| 158 | 200 | 265 | 0.0059 | -2.338 | 266.8 | 0.2668 | -23.38 |
| 159 | 370 | 440 | 0.0006 | -0.0182 | 14.23 | 0.0142 | -0.1817 |
| 160 | 200 | 362 | 0.0011 | -0.0994 | 13.97 | 0.014 | -0.9938 |

### APPENDIX B

**m.File MATLAB Codes for the proposed ELD algorithm Appendix B1: Hybrid Genetic-Artificial Fish Swarm Algorithm**

1. function HGAFSA(Ngen)
2. addpath('AFSA');
3. addpath('BCGA');
4. addpath('Integrators'); 5. [

~,maxit,mincost,popsize,mutrate,selection,nbits,opt\_type,lo

,hi] = parameters\_bcga;

1. [nfish,npar,Visual\_distance,Crowdness\_factor,S,max\_iga,ntry

]=Parameters\_afsa;

1. [repparam,crosparam,mutatparam]=gengaparams;
2. [par,pop]=reproduction(repparam);
3. [Value,L]=objF(par);
4. % Vv=Value(1);

11. % Ll=L(1);

1. [cost,id]=sortrows([Value,L],1);
2. pop=pop(id,:);
3. if opt\_type==2
4. minc=cost(1,:);
5. else
6. minc=cost(end,:);
7. end

19. minc1=[];

20. mH=[];

1. if opt\_type==2
   1. minc1=sort([minc1,minc(:,1)'],'descend');
   2. mH=sort([mH,minc(:,2:end)'],'descend');
2. else
   1. minc1=sort([minc1,minc(:,1)']);
   2. mH=sort([mH,minc(:,2:end)']);
3. end
4. iga=1;
5. while iga<max\_iga

26. %@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@ @@@@@@@@@@@@@@@

1. New\_Fish=[];
2. Xi=par;
3. for Fish=1:size(par,1)

30. %

%%%%%%%%%%%%%%%%%%%%¬¬¬¬¬¬¬¬PREYING¬¬¬¬¬¬¬¬%%%%%%%%%%%%%%%%

%%%%

31. X\_new=feval('prey',Xi(Fish,:),Visual\_distance,S,iga,ma x\_iga,ntry,opt\_type);

32. %

%%%%%%%%%%%%%%%%%%%%¬¬¬¬¬¬¬¬£££££££¬¬¬¬¬¬¬¬%%%%%%%%%%%%%%%%

%%%%

1. if Fish==1
   1. if iga==1
2. X\_best=X\_new;
   1. end
3. else
   1. Y\_best=objF(X\_best);
   2. Y\_new=objF(X\_new);
   3. if opt\_type==1
      1. if Y\_new>Y\_best
      2. X\_best=X\_new;
      3. end
   4. end
   5. if opt\_type==2
      1. if Y\_new<Y\_best
      2. X\_best=X\_new;
      3. end
   6. end
4. end
5. New\_Fish=[New\_Fish;X\_new];
6. end
7. new\_par=New\_Fish;
8. new\_pop = transform\_ga\_afsa( New\_Fish,size(pop,2) );
9. [par,pop,Minc] = compare\_ga\_afsa( par,new\_par,pop,new\_pop,opt\_type);
10. if opt\_type==2
    1. minc=flipud(sortrows([minc;Minc],1));
11. else
    1. minc=sortrows([minc;Minc],1);
12. end
13. if opt\_type==2
    1. minc1=sort([minc1,minc(:,1)'],'descend');
    2. mH=sort([mH,minc(:,2:end)'],'descend');
14. else
    1. minc1=sort([minc1,minc(:,1)']);
    2. mH=sort([mH,minc(:,2:end)']);
15. end
16. [new\_par,new\_pop]=crossover(pop,crosparam);
17. [par,pop,Minc] = compare\_ga\_afsa( par,new\_par,pop,new\_pop,opt\_type);
18. if opt\_type==2
    1. minc=flipud(sortrows([minc;Minc],1));
19. else
    1. minc=sortrows([minc;Minc],1);
20. end
21. if opt\_type==2
    1. minc1=sort([minc1,minc(:,1)'],'descend');
    2. mH=sort([mH,minc(:,2:end)'],'descend');
22. else
    1. minc1=sort([minc1,minc(:,1)']);
    2. mH=sort([mH,minc(:,2:end)']);
23. end
24. [new\_par,new\_pop]=mutation(pop,mutatparam);
25. [par,pop,Minc] = compare\_ga\_afsa( par,new\_par,pop,new\_pop,opt\_type);
26. if opt\_type==2
    1. minc=flipud(sortrows([minc;Minc],1));
27. else
    1. minc=sortrows([minc;Minc],1);
28. end
29. if opt\_type==2
    1. minc1=sort([minc1,minc(:,1)'],'descend');
    2. mH=sort([mH,minc(:,2:end)'],'descend');
30. else
    1. minc1=sort([minc1,minc(:,1)']);
    2. mH=sort([mH,minc(:,2:end)']);
31. end

64. %@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@ @@@@@@@@@@@@@@@@

65. %@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@ @@@@@@@@@@@@@@@

1. New\_Fish=[];
2. Xi=par;
3. for Fish=1:size(par,1)

69. %

%%%%%%%%%%%%%%%%%%%%¬¬¬¬¬¬¬¬PREYING¬¬¬¬¬¬¬¬%%%%%%%%%%%%%%%%

%%%%

70. X\_new=feval('swarm',Xi(Fish,:),Visual\_distance,Crowdne ss\_factor,S,iga,max\_iga,ntry,opt\_type);

71. %

%%%%%%%%%%%%%%%%%%%%¬¬¬¬¬¬¬¬£££££££¬¬¬¬¬¬¬¬%%%%%%%%%%%%%%%%

%%%%

1. if Fish==1
   1. if iga==1
2. X\_best=X\_new;
   1. end
3. else
   1. Y\_best=objF(X\_best);
   2. Y\_new=objF(X\_new);
   3. if opt\_type==1
      1. if Y\_new>Y\_best
      2. X\_best=X\_new;
      3. end
   4. end
   5. if opt\_type==2
      1. if Y\_new<Y\_best
      2. X\_best=X\_new;
      3. end
   6. end
4. end
5. New\_Fish=[New\_Fish;X\_new];
6. end
7. new\_par=New\_Fish;
8. new\_pop = transform\_ga\_afsa( New\_Fish,size(pop,2) );
9. [par,pop,Minc] = compare\_ga\_afsa( par,new\_par,pop,new\_pop,opt\_type);
10. if opt\_type==2
    1. minc=flipud(sortrows([minc;Minc],1));
11. else
    1. minc=sortrows([minc;Minc],1);
12. end
13. if opt\_type==2
    1. minc1=sort([minc1,minc(:,1)'],'descend');
    2. mH=sort([mH,minc(:,2:end)'],'descend');
14. else
    1. minc1=sort([minc1,minc(:,1)']);
    2. mH=sort([mH,minc(:,2:end)']);
15. end
16. [new\_par,new\_pop]=crossover(pop,crosparam);
17. [par,pop,Minc] = compare\_ga\_afsa( par,new\_par,pop,new\_pop,opt\_type);
18. if opt\_type==2
    1. minc=flipud(sortrows([minc;Minc],1));
19. else
    1. minc=sortrows([minc;Minc],1);
20. end
21. if opt\_type==2
    1. minc1=sort([minc1,minc(:,1)'],'descend');
    2. mH=sort([mH,minc(:,2:end)'],'descend');
22. else
    1. minc1=sort([minc1,minc(:,1)']);
    2. mH=sort([mH,minc(:,2:end)']);
23. end
24. [new\_par,new\_pop]=mutation(pop,mutatparam);
25. [par,pop,Minc] = compare\_ga\_afsa( par,new\_par,pop,new\_pop,opt\_type);
26. if opt\_type==2
    1. minc=flipud(sortrows([minc;Minc],1));
27. else
    1. minc=sortrows([minc;Minc],1);
28. end
29. if opt\_type==2
    1. minc1=sort([minc1,minc(:,1)'],'descend');
    2. mH=sort([mH,minc(:,2:end)'],'descend');
30. else
    1. minc1=sort([minc1,minc(:,1)']);
    2. mH=sort([mH,minc(:,2:end)']);
31. end

103. %@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@ @@@@@@@@@@@@@@@@

104. %@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@ @@@@@@@@@@@@@@@

1. New\_Fish=[];
2. Xi=par;
3. for Fish=1:size(par,1)

108. %

%%%%%%%%%%%%%%%%%%%%¬¬¬¬¬¬¬¬PREYING¬¬¬¬¬¬¬¬%%%%%%%%%%%%%%%%

%%%%

109. X\_new=feval('chase',Xi(Fish,:),Visual\_distance,Crowdne ss\_factor,S,iga,max\_iga,ntry,opt\_type);

110. %

%%%%%%%%%%%%%%%%%%%%¬¬¬¬¬¬¬¬£££££££¬¬¬¬¬¬¬¬%%%%%%%%%%%%%%%%

%%%%

1. if Fish==1
   1. if iga==1
2. X\_best=X\_new;
   1. end
3. else
   1. Y\_best=objF(X\_best);
   2. Y\_new=objF(X\_new);
   3. if opt\_type==1
      1. if Y\_new>Y\_best
      2. X\_best=X\_new;
      3. end
   4. end
   5. if opt\_type==2
      1. if Y\_new<Y\_best
      2. X\_best=X\_new;
      3. end
   6. end
4. end
5. New\_Fish=[New\_Fish;X\_new];
6. end
7. new\_par=New\_Fish;
8. new\_pop = transform\_ga\_afsa( New\_Fish,size(pop,2) );
9. [par,pop,Minc] = compare\_ga\_afsa( par,new\_par,pop,new\_pop,opt\_type);
10. if opt\_type==2
    1. minc=flipud(sortrows([minc;Minc],1));
11. else
    1. minc=sortrows([minc;Minc],1);
12. end
13. if opt\_type==2
    1. minc1=sort([minc1,minc(:,1)'],'descend');
    2. mH=sort([mH,minc(:,2:end)'],'descend');
14. else
    1. minc1=sort([minc1,minc(:,1)']);
    2. mH=sort([mH,minc(:,2:end)']);
15. end
16. [new\_par,new\_pop]=crossover(pop,crosparam);
17. [par,pop,Minc] = compare\_ga\_afsa( par,new\_par,pop,new\_pop,opt\_type);
18. if opt\_type==2
    1. minc=flipud(sortrows([minc;Minc],1));
19. else
    1. minc=sortrows([minc;Minc],1);
20. end
21. if opt\_type==2
    1. minc1=sort([minc1,minc(:,1)'],'descend');
    2. mH=sort([mH,minc(:,2:end)'],'descend');
22. else
    1. minc1=sort([minc1,minc(:,1)']);
    2. mH=sort([mH,minc(:,2:end)']);
23. end
24. [new\_par,new\_pop]=mutation(pop,mutatparam);
25. [par,pop,Minc] = compare\_ga\_afsa( par,new\_par,pop,new\_pop,opt\_type);
26. if opt\_type==2
    1. minc=flipud(sortrows([minc;Minc],1));
27. else
    1. minc=sortrows([minc;Minc],1);
28. end
29. if opt\_type==2
    1. minc1=sort([minc1,minc(:,1)'],'descend');
    2. mH=sort([mH,minc(:,2:end)'],'descend');
30. else
    1. minc1=sort([minc1,minc(:,1)']);
    2. mH=sort([mH,minc(:,2:end)']);
31. end

142. %@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@ @@@@@@@@@@@@@@@@

1. iga=iga+1;
2. end
3. day=clock;
4. disp(datestr(datenum(day(1),day(2),day(3),day(4),day(5

),day(6)),0))

1. format shortg
2. disp(['popsize = ' num2str(popsize) ' mutrate = ' num2str(mutrate) ' # par = ' num2str(npar)])
3. disp(['#generations=' num2str(iga) ' best cost=' num2str(cost(1))])
4. disp('best solution')
5. disp(num2str(par(1,:)))
6. disp('Hybrid Genetic Algorithm and Artificial Fish Swarm Algorithm')
7. disp(['each parameter represented by ' num2str(nbits) ' bits'])
8. % % minc=minc(end-popsize+1:end,:);

155. % minc1=minc(:,1)';

156. % mH=minc(:,2:end)';

157. % % minc1(1)=Vv; 158. % % mH(1)=Ll;

1. for y=1:length(minc1)
2. if isnan(minc1(y))==0
   1. z=minc1(y);
   2. break
3. end
4. end
5. figure
6. % plot(1:Ngen,minc1(end-Ngen+1:end));
7. plot(0:Ngen,[z,minc1(end-Ngen+1:end)],'LineWidth',2);
8. xlabel('generation');ylabel('cost');
9. title(['HGAFSA Optimization Curve for ',num2str(size(mH,1)),' - Units'])
10. % figure
11. % for k=1:size(mH,1)

170. % plot(1:size(mH,2),mH(k,:));

1. % hold on
2. % end
3. % xlabel('generation');ylabel('parameter(X)');
4. % title('HGAFSA')
5. disp(['Optimum Cost = ',num2str(minc(end,1))])
6. disp(['Best Value of X = ',num2str(minc(end,2:end))])
7. %text(0,minc(1),'best');text(1,minc(2),'population average')
8. rmpath('AFSA');
9. rmpath('BCGA');
10. rmpath('Integrators');
11. end

### APPENDIX B2

**m.File: Sub-Function “ELD encoder algorithm”**

1. function Xeld=eldencoder(X)
2. [ Data,Ptotal] = generation\_data;
3. Xi=X;
4. X=abs([X,X.\*sin(2\*pi\*X),X.\*cos(2\*pi\*X),sin(2\*pi\*X),cos(2\*pi

\*X),log(X),cumsum(X,2),cumsum(X,1)]);

1. [a,b]=size(X);
2. % X=[X,rand(size(X)).X]; 7. % Xeld=[];
3. Ptotal=Ptotal-sum(Data(:,2));
4. % while size(Xeld,1)<size(X,1) 10. Xl=[];
5. for loc=1:size(Data,1)
6. for kk=1:size(X,1)

13. Xo(kk,:)=(Data(loc,3)-Data(loc,2))\*X(kk,:);

14. end

15. Xl=[Xl,{Xo}];

1. X=X(randperm(a),randperm(b));
2. end

18. X0=[];

1. for i=1:size(X,1)
2. for j=1:size(X,2)
   1. for loc=1:size(Data,1)
   2. Xx(1,loc)=Xl{loc}(i,j);
   3. end

d. X0=[X0;Xx];

1. end
2. end

23. % Xeld=[];

1. % while size(Xeld,1)<size(Xi,1)
2. Xmax=[];
3. for k=1:size(X0,1)

27. X0(k,:)=X0(k,:)\*Ptotal/sum(X0(k,:))+(Data(:,2))';

28. Xmax=[Xmax;Data(:,3)'];

29. % X0(k,:)=cenforce(X0(k,:),(Data(:,3)- Data(:,2))');

1. end
2. while isempty(find(sum((X0-Xmax)>0,2)'>0, 1))==0
3. for i=find(sum((X0-Xmax)>0,2)'>0)
4. for j=1:size(X0,2)
   1. if X0(i,j)>Data(j,3)
      1. Xs=X0(i,j);
      2. X0(i,j)=rand\*(Data(j,3)-Data(j,2))+Data(j,2);
      3. d=Xs-X0(i,j);
      4. while d~=0
      5. k=randi(size(X0,2));

34. % k=k+1;

35. % if k>size(X0,2) 36. % k=1;

1. % end
   1. if X0(i,k)<Data(k,3)

1. h=rand\*(-X0(i,k)+Data(k,3));

1. if d<h

a. X0(i,k)=X0(i,k)+d;

* 1. d=0;

1. else

a. d=d-h;

b. X0(i,k)=X0(i,k)+h;

1. end
   1. end
   2. end

b. end

1. end
2. end
3. clc
4. X0
5. end
6. Xeld=X0;

### APPENDIX B3

**m. File: Sub-Function “ObjF\_ELD\_fuel(X)”**

1. function [Cost,Xeld] = ObjF\_ELD\_fuel(X)
2. %OBJF\_ELD Summary of this function goes here
3. % Detailed explanation goes here
4. [ Data] = generation\_data;
5. Xeld=eldencoder(X);
6. Cost=0;
7. for i=1:size(Xeld,2)
8. Cost=Cost+Data(i,6)+Xeld(:,i)\*Data(i,5)+(Xeld(:,i).^2)\*Data (i,4)+abs(Data(i,7)\*sin(Data(i,8)\*(Data(i,2)-Xeld(:,i))));
9. end
10. [Cost,idc]=sort(Cost);
11. Xeld=Xeld(idc,:);
12. Cost=Cost(1:size(X,1),:);
13. Xeld=Xeld(1:size(X,1),:);

### APPENDIX B4

**m. File: Sub-Function “compare\_ga\_afsa(par,new\_par,pop,new\_pop,opt\_type)”**

1. function [Par,Pop,Minc] = compare\_ga\_afsa( par,new\_par,pop,new\_pop,opt\_type)
2. %COMPARE\_GA\_AFSA Summary of this function goes here
3. % Detailed explanation goes here
4. [Value,L]=objF(par);
5. [cost,id]=sortrows([Value,L],1);
6. pop=pop(id,:);
7. par=par(id,:);
8. if opt\_type==2
9. minc=cost(1,:);
10. else
11. minc=cost(end,:);
12. end
13. % NP=size(new\_par)
14. % P=size(par)
15. if size(new\_par,1)<size(par,1)
16. new\_par=[new\_par;par(end,:)];
17. end
18. % NP1=size(new\_par)
19. % P1=size(par)

20. %

1. % NP=size(new\_pop)
2. % P=size(pop)
3. if size(new\_pop,1)<size(pop,1)
4. new\_pop=[new\_pop;pop(end,:)];
5. end
6. % NP1=size(new\_pop)
7. % P1=size(pop)
8. [Value1,L]=objF(new\_par);
9. [cost1,id]=sortrows([Value1,L],1);
10. new\_pop=new\_pop(id,:);
11. new\_par=new\_par(id,:);
12. for r=1:size(cost,1)
13. if opt\_type==2
14. if cost(r,1)<cost1(r,1)
    1. Cost(r,:)=cost(r,:);
    2. Par(r,:)=par(r,:);
    3. Pop(r,:)=pop(r,:);
15. else
    1. Cost(r,:)=cost1(r,:);
    2. Par(r,:)=new\_par(r,:);
    3. Pop(r,:)=new\_pop(r,:);
16. end
17. else
18. if cost(r,1)>cost1(r,1)
    1. Cost(r,:)=cost(r,:);
    2. Par(r,:)=par(r,:);
    3. Pop(r,:)=pop(r,:);
19. else
    1. Cost(r,:)=cost1(r,:);
    2. Par(r,:)=new\_par(r,:);
    3. Pop(r,:)=new\_pop(r,:);
20. end
21. end
22. end
23. [Cost,id]=sortrows(Cost,1);
24. Pop=Pop(id,:);
25. Par=Par(id,:);
26. if opt\_type==2
27. Minc=Cost(1,:);
28. else
29. Minc=Cost(end,:);
30. end
31. end

### APPENDIX B5

**m. File: Sub-Function “reproduction (repparam)”**

1. function [par,pop]=reproduction(repparam)
2. lo=repparam{2}(1);
3. hi=repparam{2}(2);
4. nbits=repparam{2}(3);
5. pop=round(rand(repparam{1})); % random population of
6. % 1s and 0s
7. par=gadecode(pop,lo,hi,nbits); % convert binary to

### APPENDIX B6

**m. File: Sub-Function “mutation (pop, mutatparam)”**

1. function [par,pop]=mutation(pop,mutatparam)
2. mrow=mutatparam{1};
3. mcol=mutatparam{2};
4. nmut=mutatparam{3};
5. lo=mutatparam{4};
6. hi=mutatparam{5};
7. nbits=mutatparam{6};
8. for ii=1:nmut
9. pop(mrow(ii),mcol(ii))=abs(pop(mrow(ii),mcol(ii))-1);
10. % toggles bits
11. end% ii
12. par=gadecode(pop,lo,hi,nbits); % convert binary to

### APPENDIX B7

**m. File: Sub-Function “crossover(pop,crossparam)”**

1. function [par,pop]=crossover(pop,crosparam)
2. keep=crosparam{1};
3. ix=crosparam{2};
4. ma=crosparam{3};
5. xp=crosparam{4};
6. pa=crosparam{5};
7. Nt=crosparam{6};
8. lo=crosparam{7};
9. hi=crosparam{8};
10. nbits=crosparam{9};
11. pop(keep+ix,:)=[pop(ma,1:xp) pop(pa,xp+1:Nt)];
12. pop(keep+ix+1,:)=[pop(pa,1:xp) pop(ma,xp+1:Nt)]; 13. pop(end,:)=[];

14. par=gadecode(pop,lo,hi,nbits); % convert binary to

### APPENDIX B8

**m. File: Sub-Function “gadecode(chrom,lo,hi,bits)”**

1. function f=gadecode(chrom,lo,hi,bits)

|  |  |
| --- | --- |
| 2. % | gadecode.m |
| 3. % | Decodes binary encripted parameters |
| 4. % |  |
| 5. % | f=gadecode(chrom,lo,hi,bits,gray) |
| 6. % | chrom = population |
| 7. % | lo = minimum parameter value |
| 8. % | hi = maximum parameter value |
| 9. % | bits = number of bits/parameter |

10. % Haupt & Haupt 11. % 2003

1. [M,N]=size(chrom);
2. npar=N/bits; % number of variables
3. quant=(0.5.^(1:bits)'); % quantization levels
4. quant=quant/sum(quant); % quantization levels normalized
5. ct=reshape(chrom',bits,npar\*M)';% each column contains
6. % one variable
7. par=((ct\*quant)\*(hi-lo)+lo); % DA conversion and
8. % unnormalize varaibles
9. f=reshape(par,npar,M)';% reassemble population

### APPENDIX B9

**m. File: Sub-Function “prey(Xi,visual\_distance,S,itr,max\_itr,ntry,opt\_type)”**

1. function X\_new=prey(Xi,Visual\_distance,S,itr,max\_itr,ntry,opt\_type)

|  |  |
| --- | --- |
| 2. % | Execute the preying behaviour in an AFSA |
| 3. % | opt\_type is: |
| 4. % | 1 for maximization; and |
| 5. % | 2 for minimization. |

1. V=Visual\_distance;
2. T=0; % tested trials;
3. X\_new=feval('move\_fish',Xi,Visual\_distance,itr,max\_itr);
4. % for u=1:length(X\_new)
5. % if X\_new(u)>1
6. % X\_new(u)=X\_new(u)-floor(X\_new(u));
7. % end
8. % end
9. while T<ntry
10. Xj=feval('move\_fish',Xi,V,itr,max\_itr);
11. Yi=objF(Xi);
12. Yj=objF(Xj);
13. if opt\_type==1
14. if Yj>Yi
15. X\_new=feval('new\_fish',Xi,Xj,S);
16. % for u=1:length(X\_new)
17. % if X\_new(u)>1
18. % X\_new(u)=X\_new(u)-floor(X\_new(u));
19. % end
20. % end
21. break
22. end
23. end
24. if opt\_type==2
25. if Yj<Yi
26. X\_new=feval('new\_fish',Xi,Xj,S);
27. % for u=1:length(X\_new)
28. % if X\_new(u)>1
29. % X\_new(u)=X\_new(u)-floor(X\_new(u));
30. % end
31. % end
32. break
33. end
34. end

40. T=T+1;

41. End

### APPENDIX B10

**m. File: Sub-Function “swarm(Xi,Visual\_distance,Crowdness\_factor,S,itr,max\_itr,ntry,opt**

### \_type) ”

1. function X\_new=swarm(Xi,Visual\_distance,Crowdness\_factor,S,itr,max\_i tr,ntry,opt\_type)

|  |  |
| --- | --- |
| 2. % | Execute the swarmming behaviour in an AFSA |
| 3. % | opt\_type is: |
| 4. % | 1 for maximization; and |
| 5. % | 2 for minimization. |

1. V=Visual\_distance;
2. C=Crowdness\_factor;
3. Xj=feval('move\_fish',Xi,Visual\_distance,itr,max\_itr);
4. D=feval('distance',Xi,Xj);

10. [n,~]=size(Xi);

11. nf=sum(D<V\*ones(size(D)));

12. Xc=(Xi+Xj)/2;

1. Yi=objF(Xi);
2. Yc=objF(Xc);
3. if opt\_type==1
4. X\_new=feval('prey',Xi,Visual\_distance,S,itr,max\_itr,nt ry,opt\_type);
5. % for u=1:length(X\_new)
6. % if X\_new(u)>1
7. % X\_new(u)=X\_new(u)-floor(X\_new(u));
8. % end
9. % end
10. if Yc>Yi
11. if (nf/n)<C
12. X\_new=feval('new\_fish',Xi,Xc,S);
13. % for u=1:length(X\_new)
14. % if X\_new(u)>1
15. % X\_new(u)=X\_new(u)-floor(X\_new(u));
16. % end
17. % end
18. end
19. end
20. end
21. if opt\_type==2
22. X\_new=feval('prey',Xi,Visual\_distance,S,itr,max\_itr,nt ry,opt\_type);
23. % for u=1:length(X\_new)
24. % if X\_new(u)>1
25. % X\_new(u)=X\_new(u)-floor(X\_new(u));
26. % end
27. % end
28. if Yc<Yi
29. if (nf/n)<C
30. X\_new=feval('new\_fish',Xi,Xc,S);
31. % for u=1:length(X\_new)
32. % if X\_new(u)>1
33. % X\_new(u)=X\_new(u)-floor(X\_new(u));
34. % end
35. % end
36. else
37. end
38. end
39. end

### APPENDIX B11

**m. File: Sub-Function “chase(Xi,Visual\_distance,Crowdness\_factor,S,itr,max\_itr,ntry,opt**

### \_type)”

1. function X\_new=chase(Xi,Visual\_distance,Crowdness\_factor,S,itr,max\_i tr,ntry,opt\_type)

|  |  |
| --- | --- |
| 2. % | Execute the chasing behaviour in an AFSA |
| 3. % | opt\_type is: |
| 4. % | 1 for maximization; and |
| 5. % | 2 for minimization. |

1. V=Visual\_distance;
2. C=Crowdness\_factor;
3. Xj=feval('move\_fish',Xi,Visual\_distance,itr,max\_itr);
4. D=feval('distance',Xi,Xj);

10. [n,~]=size(Xi);

1. nf=sum(D<V\*ones(size(D)));
2. Yi=objF(Xi);
3. Yc=objF(Xj);
4. if opt\_type==1
5. X\_new=feval('prey',Xi,Visual\_distance,S,itr,max\_itr,nt ry,opt\_type);
6. % for u=1:length(X\_new)
7. % if X\_new(u)>1
8. % X\_new(u)=X\_new(u)-floor(X\_new(u));
9. % end
10. % end
11. if Yc>Yi
12. if (nf/n)<C
13. X\_new=feval('new\_fish',Xi,Xj,S);
14. % for u=1:length(X\_new)
15. % if X\_new(u)>1
16. % X\_new(u)=X\_new(u)-floor(X\_new(u));
17. % end
18. % end
19. end
20. end
21. end
22. if opt\_type==2
23. X\_new=feval('prey',Xi,Visual\_distance,S,itr,max\_itr,nt ry,opt\_type);
24. % for u=1:length(X\_new)
25. % if X\_new(u)>1
26. % X\_new(u)=X\_new(u)-floor(X\_new(u));
27. % end
28. % end
29. if Yc<Yi
30. if (nf/n)<C
31. X\_new=feval('new\_fish',Xi,Xj,S);
32. % for u=1:length(X\_new)
33. % if X\_new(u)>1
34. % X\_new(u)=X\_new(u)-floor(X\_new(u));
35. % end
36. % end
37. end
38. end
39. end