A NATURE INSPIRED HYBRID APPROACH TO SOLVE UNIT COMMITMENT SCHEDULING PROBLEM

A Thesis

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Computer Science Engineering

By

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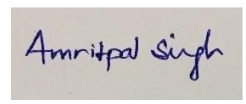
Declaration

I hereby declare that the thesis entitled "A NATURE INSPIRED HYBRID APPROACH TO SOLVE UNIT COMMITMENT SCHEDULING PROBLEM" submitted by me for the Degree of Doctor of Philosophy in Computer Science and Engineering is the result of my original and independent research work carried out under the guidance of Supervisor Dr. Aditya Khamparia, and it has not been submitted for to any university or institute for the award of any degree or diploma.



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Abstract

The research work illustrates the thoughts for addressing the unit commitment scheduling problem for thermal power plants. One of the key problems for power firms is the unit commitment scheduling problem. It involves how many units need to be put in a working state, how many units need to be put in an inactive state, and how much power one unit needs to generate to satisfy load demand. Unit commitment, popularly known as the UC problem, needs to be overcome by minimizing fuel costs, startup costs, and shutdown costs that come from the generating units. The UC scheduling problem is a mixed-integer non-linear programming problem intended to explore the schedule of generating units with the lowest operating costs based on forecasted demand.

A novel nature-inspired approach has been proposed, incorporating a Genetic Algorithm, Differential Evolution, and the Whale Optimization Algorithm. Two approaches have been described here; a single-objective approach which includes total operating cost minimization and a multi-objective approach which includes total emission minimization. Both binary commitment and continuous dispatch variables are included in UC. However, there is no universal optimizer that can perform both binary and continuous optimization. So, it motivated us to select the Genetic Algorithm, Differential Evolution, and Whale Optimization Algorithm.

We have also proposed a hybridized solution to the multi-objective unit commitment problem. Because of the conflicting nature of the economic and emissions targets, a Whale Optimization (WO)-differential evolution (DE) and genetic algorithm (GA) based hybrid approach, WODEGA, has been proposed which will satisfy two objectives: committing the generating units to meet electricity demand and reducing overall operational costs with minimal emissions. The average running cost is 142814.41 INR, which decreased to 142810.58 INR after optimization. The proposed method results in a large cost reduction, i.e. 142792.56 INR. A 100-unit system is being considered to test the scalability of the suggested technique. The average running cost is 135741.42 INR, which decreased to 135736.42 INR after optimization. The proposed approach results in a large cost reduction, i.e. 135732.83 INR. The results are cross-validated using neural networks and normalized using the critic method.

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First and foremost, on the successful completion of the research work and this thesis, I would like to pay all praise to the almighty God.

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Contents

Abstract iii

Acknowledgment v

Contents vi

List of Figures xi

List of Tables xiii

Glossary xiv

Chapter 1 Introduction **1**

1.1 Overview 1

1.2 Scope of Research 1

1.3 Main Goals 2

1.4 Research Contribution 2

1.5 Motivation 3

1.6 Problem Statement 3

1.6.1 Objective function: total operating cost minimization........ 3

1.6.1 Objective function: minimization of carbon emissions........ 5

1.7 Research Objectives 5

1.8 Research Questions 5

1.9 Unit Commitment 6

1.10 Economic Dispatch 6

1.11 Thesis Organization 7

Chapter 2 Basic Concepts and Unit Commitment Background............9
2.1 Overview............9
2.2 Optimal System Operation............9
2.3 Modeling Fossil Fuel Power Plants............10
2.4 Unit commitment Scheduling Problem............11
2.5 Types of unit commitment............15
2.5.1 Traditional fuel based environment............15
2.5.2 Stochastic environment............15
2.5.3 Profit based environment............15
2.6 Constraints in unit commitment............16
2.6.1 Unit Constraints............16
2.6.2 System Constraints............18
2.6.3 Other Constraints............20
2.7 Economic Dispatch Problem............21
2.8 Techniques for solving UC problem............23
2.8.1 Dynamic Programming Approach (DP)............24
2.9 Evolutionary Algorithms............25
2.9.1 Differential Evolution............26
2.9.2 Genetic Algorithm............27
2.10 Metaheuristic algorithms............30
2.10.1 Whale Optimization Algorithm............30
2.11 Optimization Methods for solving UC problem............32
2.12 Literature Survey of UC problem............41
2.13 Decomposition Methods for Stochastic UC............45

Chapter 3 Research Methodology 49
3.1 Overview 49
3.2 Pareto Optimal Solution 49
3.3 Proposed Methodology Adapted for single objective UC 50
3.4 Proposed Methodology Adapted for multi-objective UC 52
3.5 Inspiration behind GA and DE selection 59
3.6 Inspiration behind WOA selection 59
3.7 Role of Neural Networks 59
3.8 The Multiple Criteria Decision Making 62
3.8.1 Critic Method 63
Chapter 4 Experimental analysis **66**
4.1 Overview 66
4.2 Experimental environment 66
4.3 Input Data 66
4.4 Results 71
4.5 Summary 83
Chapter 5 Conclusion and Future Works **84**
5.1 Overview 84
5.2 Conclusion 84
5.3 Future research opportunities 85
Bibliography **86**

Research Publications..**98**

List of Figures

Chapter No.	Figure	Page
1.1	Fuel Cost Function	4
1.2	Start-Up Cost Function	4
1.3	A unit commitment Example	6
1.4	Economic Dispatch Example	7
2.1	Optimal System Operation	10
2.2	Peak Valley Load Pattern	13
2.3	UC schedule using shut down rule	14
2.4	Constraints in unit commitment	16
2.5	Types of Reserve	19
2.6	Network Constraint	20
2.7	Startup Cost	21
2.8	Generators committed to satisfy the load	22
2.9	N units serving P_{LOAD} through transmission network	22
2.10	Summarizing unit commitment and Economic Dispatch	23
2.11	Classification of UC problem solving techniques	24
2.12	Standard DP Logic	25
2.13	Structure of DE	27
2.14	Structure of GA	28
2.15	One-Point Crossover	29
2.16	Two-Point Crossover	29
2.17	Uniform Crossover	29
2.18	Mutation	30
2.19	Basic Elements of Metaheuristic Algorithm	30
2.20	WOA Phases	31
2.21	WOA Pseudocode	31
2.22	UC Problem development from 1940s to 2020	40

2.23	UC Problem evolution over the years	40
2.24	Decomposition Methods for Stochastic UC	46
3.1	Pareto-Optimal Solution	50
3.2	Working of hGADE algorithm	54
3.3	Modified hGADE algorithm	55
3.4	Working of proposed approach (single objective)	56
3.5	Working of proposed approach (multi objective)	57
3.6	Diagrammatical representation of proposed approach (multi objective)	58
3.7	Flowchart of proposed approach (multi objective)	58
3.8	Cross-Validation using neural network	60
3.9	Diagrammatical representation of neural network	61
3.10	Working of nntraintool	61
3.11	Methods in MADM	62
3.12	Working of CRITIC Method	65
4.1	Avg. Cost difference of generating units (6 units)	71
4.2	Avg. cost difference of generating units (100 units)	72
4.3	Unit Commitment Schedule	72
4.4	Slope Pattern of generators/units	73
4.5	MSE value for slopes	74
4.6	Comparison of hGADE with proposed approach	74
4.7	Validation performance using nntool	75
4.8	NN Training state	76
4.9	Carbon Emissions (Before Optimization)	80
4.10	Carbon Emissions (After Optimization)	80
4.11	Emission improvement percentage in generating units	81
4.12	Cost Comparison (6-unit system)	82
4.13	Cost Comparison (100-unit system)	83

List of Tables

Chapter No.	Table	Page
2.1	Unit Combination and Load Dispatch for load 550 MW	12
2.2	Shut Down Rule Derivation	14
2.3	Detailed Literature Survey with features, advantages, and limitations of proposed optimization methods	32
2.4	Literature Survey on Stochastic UC	47
4.1	Input Data	67
4.2	Load Pattern (Input)	67
4.3	Input Data (100 Units)	68
4.4	Parameter Setting	71
4.5	Comparative Analysis	72
4.6	Cost Comparison	75
4.7	Load Pattern	76
4.8	Carbon Emissions	78
4.9	Load Distribution	81
4.10	Cost Comparison (6-unit system)	82
4.11	Cost Comparison (100-unit system)	82

Glossary

GA	Genetic Algorithm
DE	Differential Evolution
WOA	Whale Optimization Algorithm
UC	Unit Commitment
ED	Economic Dispatch
hGADE	Hybridization of Genetic Algorithm and Differential Evolution
Minimum Down Time	Once the unit is running must not shut down immediately due to technical limitation and mechanical characteristic of the unit.
Ramp Up/Down	The ramp rate is the rate at which output increases or decreases per minute.
MINLP	Mixed Integer Non Linear Programming
PL	Priority List
PSO	Particle Swarm Optimization
DP	Dynamic Programming
MOP	Multi-Objective Optimization Problem
NLP	Non Linear Programming

Chapter 1

Introduction

1.1 Overview

The research work illustrates the thoughts for addressing the unit commitment scheduling problem for thermal power plants. One of the key problems for power firms is the unit commitment scheduling problem. It involves how many units need to be put in a working state, how many units need to be put in an inactive state, and how much power one unit needs to generate to satisfy load demand. Unit commitment, popularly known as the UC problem, needs to be overcome by minimizing fuel costs, startup costs, and shutdown costs which come from the generating units. The unit commitment scheduling problem is a mixed-integer non-linear programming problem intended to explore the schedule of generating units with the least operating costs based on forecasted demand.

1.2 Scope of the research

This research work intends to emphasize upon scheduling problem referred to as unit commitment in thermal power plants. Assume there is a specified load; now we must decide which units of the power station should be turned on to handle that load, and which units should be turned off if they are not needed [1]. It is not cost-effective to keep all of the units operational all of the time. This scheduling problem is only important for thermal power plants, it is not important for hydro nor it is important for nuclear. Nuclear power plants are baseload power plants. There is hardly any control, which one can have on the nuclear power plant. Similarly hydro, there is no fuel; there is no money involved. Fuel is water, water is available free of charge. So, there is no optimization involved as and when, and then the main reason is it is a quick starting unit [2]. It does not take long for a hydro unit to get up and running. Thermal power plants, on the other hand, can take anywhere from 2 to 8 hours to start up, depending on whether the boiler is coal-fired, if coal has just been added, whether there is no steam, and whether the unit is starting from a cold or hot start. Because of the aforementioned rationale, this issue is only relevant to thermal power plants.

There are several power plants in a power grid. There are multiple generating units in each power plant. At any given time, the generating units in various power plants are capable of meeting the entire load on the grid. Daily load patterns show signs of acute deviation amid the rush and off rush hours for the reason that the community utilizes a smaller amount of electrical energy on weekends than on weekdays. If adequate generation to fulfill the rush is kept online all through the day, it is promising that few of the units will be working near their least generating threshold during the off rush period. In most unified power systems, the power prerequisite is primarily fulfilled by thermal power generation. Quite a lot of working approaches are achievable to fulfill the requisite power requirement. It is recommended to use the most favorable operating approach based on the financial measure. That is to say, one of the most critical, if not the most important, factors in power system operation is meeting power demand at the lowest possible fuel cost. Furthermore, sequentially to provide first-rate electrical energy to consumers in a protected and cost-effective method, unit commitment (UC) is measured to be one of the best existing alternatives [3]. It thus comprehends that the most favorable unit commitment of thermal systems, dependent on unit and operating restrictions stem in a cutback for electric utilities. The general aim of the unit commitment issue is to reduce the total operational cost of the system when meeting all of the constraints.

1.3 Main Goals

1. Explore the problem of unit commitment.
2. Explore the sub-problem of unit commitment i.e. economic dispatch
3. Investigate the efficacy of the hGADE algorithm on-ramp up/down constraint.
4. Propose, implement and evaluate the nature-inspired methodology, by incorporating the various system and unit constraints.
5. Incorporation of proposed nature-inspired approach within multi-objective optimization framework to solve the multi-objective optimization problem.

1.4 Research Contribution

1. The proposed work aims to solve the unit commitment scheduling problem and its sub-problem Economic Dispatch, which are both mixed-integer optimization problems.

2. The methodology was put to the test on a six-unit system when taking into account a variety of system and unit constraints.
3. Differential Evolution, Genetic Algorithm, and Whale Optimization are all included in the proposed approach.
4. In terms of operation costs, the proposed methodology has shown promise.

1.5 Motivation

Every power station has several generating units. The entire load on the system is satisfied by generating units in power stations at any given time. The decisive factor in power generation is to satisfy the load (demand) at a lower fuel cost. Unit commitment (UC) is a challenge in the field of power systems engineering that is essential to a power system's safe, reliable, and cost-effective daily operation [4]. Unit commitment (UC) problem affiliated to the class of optimization problem comprising of binary UC variables and continual power dispatch variables.

1.6 Problem Statement

Unit commitment (UC) is a scheduling problem in the thermal power plant that is essential to a power system's safe, reliable, and cost-effective daily operation. Given a load profile (e.g., load values for each hour of the day) and a collection of available units, how should each unit be started and stopped, as well as how much power should it generate to satisfy the load at the lowest cost possible?

1.6.1 Objective function: total operating cost minimization

The objective function considered in the single objective UC problem is the minimization of overall costs. The three types of costs are generating costs, starting costs, and shutting down costs. Each generating unit is responsible for these costs at any given time.

Usually, producing costs, which are largely due to fuel consumption, is modeled as a quadratic function concerning production level. Figure 1.1 provides an example of the cost of the generation cost function.

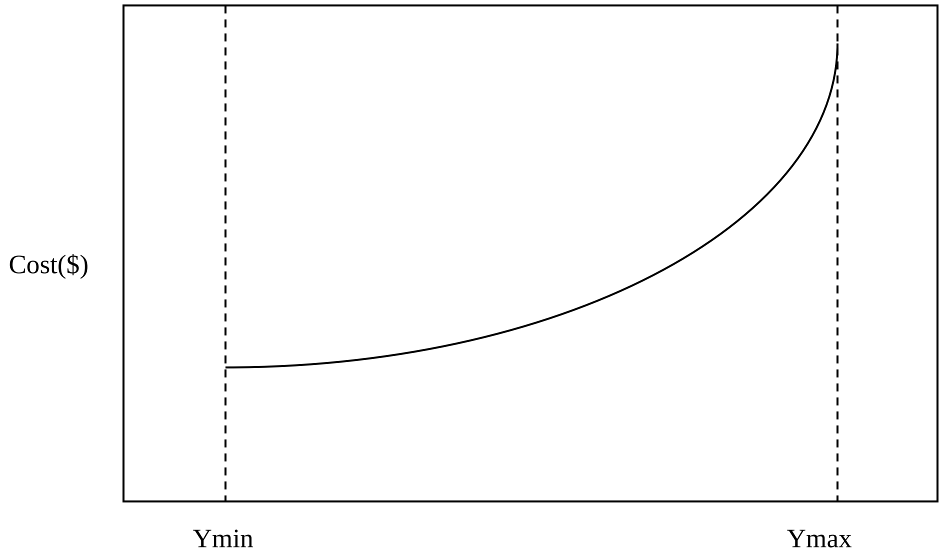

Figure 1.1 Fuel Cost Function

Every time a generating unit is turned on, start-up costs are incurred, and they are often believed to be constant. However, start-up costs for steam turbine plants are not constant because they differ depending on the amount of time the unit has been off and the state of the boiler, which may be hot or cold. The start-up cost function is represented graphically in Figure 1.2.

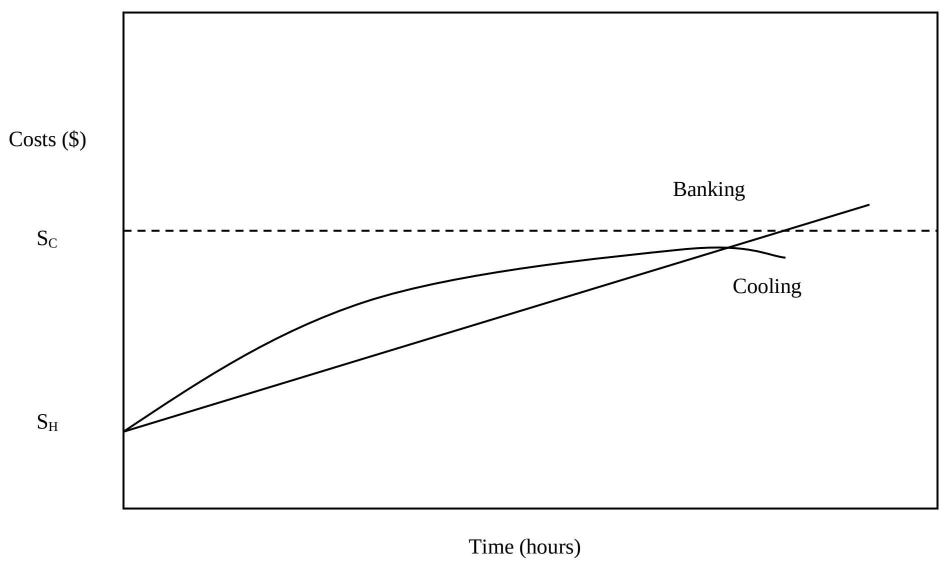

Figure 1.2 Start-Up Cost Function

1.6.2 Objective function: minimization of carbon emissions

The United Nations Framework Convention on Climate Change (UNFCCC), which began in 1992, and the Kyoto Protocol, which began in 1997, provide an international mechanism in which many countries around the world commit to reducing carbon emissions in reaction to changes such as the global climate change trend.

For example, between 2008 and 2012, the European Union was expected to reduce emissions by 8% relative to 1990 levels. It is important to note that the power industry is one of the major pollutant emitters, with fossil fuel combustion accounting for approximately 40% of CO2 emissions. For example, public heat and power output accounted for about 31% of Portuguese Carbon emissions in 2005. Emission strategies, technology, and operations in power plants must be developed to aid in the reduction of overall pollutant emissions. However, given the rising energy demand, reversing this pattern in the short term would be extremely difficult.

The UC dilemma, which involves minimizing operational costs and pollutant emissions at the same time (multi-objective function), can provide insight into the cost-pollutant trade-off.

1.7 Research Objectives

1. To investigate the efficacy of the hGADE algorithm on ramp up/down constraint.
2. To identify and propose a nature-inspired approach for solving unit commitment (UC) and economic dispatch (ED) problems.
3. Incorporation of proposed nature-inspired approach within multi-objective optimization framework to solve a multi-objective optimization problem.
4. To implement and evaluate the proposed approach using performance metrics with existing methodology

1.8 Research Questions

Unit commitment (UC) is a challenge in the field of power systems engineering that is essential to a power system's safe, reliable, and cost-effective daily operation. The questions used to seek researchers’ attention are like:

1. How has a unit commitment problem evolved?

2. What is a unit commitment problem and how it can be represented?
3. What are the different techniques used for solving unit commitment and economic dispatch problems, how nature-inspired approach could contribute to serving load at minimum fuel cost?
4. Given a load profile (e.g., load values for each hour of the day) and a collection of available units, how should each unit be started and stopped, as well as how much power should it generate to satisfy the load at the lowest cost possible?
5. On-line with a given load and collection of units. To satisfy this demand at the lowest possible cost, how much should each unit produce?

1.9 Unit Commitment

Unit commitment is a scheduling challenge in a thermal power plant that is critical to the safe, dependable, and cost-effective operation of a power system daily. How should each unit be started and stopped, as well as how much electricity should it create, given a load profile (Figure 1.3) (e.g., load values for each hour of the day) and a collection of available units (G) to satisfy the demand at the lowest cost possible?

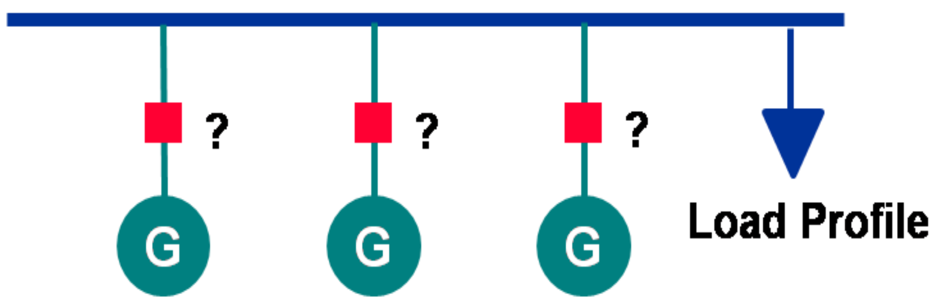

Figure 1.3. A unit commitment example

1.10 Economic Dispatch

Given a network of generating units, the economic dispatch problem deal with discovering the extent of power each generating unit should produce for given power demand, with the condition of reduction in aggregate operational cost [8]. On-line with a given load and collection of units. To satisfy this demand at the lowest possible cost, how much should each unit produce (Figure 1.4).

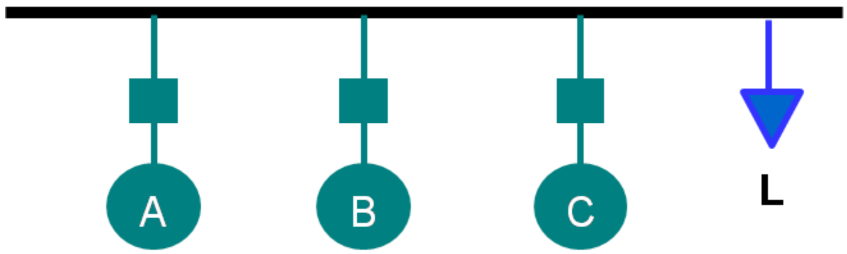

Figure 1.4. Economic Dispatch Example

1.11 Thesis Organization

The thesis is organized as under:

Chapter 2 Unit Commitment background

Chapter 2 illustrated the previous literature available on unit commitment and economic dispatch in thermal power systems. The research methods, algorithms, and models proposed for solving unit commitment scheduling problems have been discussed exhaustively. The chapter also describes the existing unit commitment and economic dispatch techniques with appropriate examples and critical evaluation.

Chapter 3 Methods and Materials

Chapter 3 discusses the methodology employed for solving unit commitment in thermal power plants. The algorithmic research methodology adopted has been discussed in detail. The chapter describes the nature-inspired hybrid technique used to determine the commitment of generating units and economic dispatch to generate power at the minimum cost possible. Further, it also describes a multi-objective approach to simultaneously address the emissions and operating costs.

Chapter 4 Experimental Analysis

Illustrates the experimental setup along with the analysis required to implement the proposed algorithm for the unit commitment scheduling problem. It also describes the tools and technology used for the implementation of nature-inspired hybrid techniques for solving the UC problem. The chapter describes the results and outcomes generated when the existing and proposed technique is applied. The performance metrics obtained have been critically analyzed and the technique proposed has been evaluated using cost and emission parameters.

Chapter 5 Conclusion

Chapter 5 concludes the research work undertaken for the unit commitment problem in thermal power plants. This chapter discusses the key outcomes for the objectives of the research work along with future challenges and research opportunities.

Chapter 2

Basic Concepts and Unit Commitment Background

2.1 Overview

In the first chapter, a brief introduction about the unit commitment scheduling problem in thermal power plants is given. It has been understood, what unit commitment and economic dispatch are and why it is so critical for power system operation. This chapter provides the background of unit commitment and economic dispatch in thermal power plant operation, particularly its definition and the methods proposed to address the problem. The chapter also explores the evolution of unit commitment along with its subproblem i.e. economic dispatch. Moreover, the techniques and metrics used for solving unit commitment and economic dispatch are thoroughly reviewed. It is worth mentioning here that we will discuss the conventional, non-conventional, and hybrid techniques in detail and will not discuss all of the existing methods as they are not in our scope of research.

2.2 Optimal System Operation

Optimal system operation is also known as economic operation. It is a hierarchical or multi-level process. The first problem that power system engineers address is load forecasting. Load forecasting is a very important problem. Once load forecasting is known, one should know what are power plants are going to supply the load. It is followed by the step in which one needs to decide which units of the power plants will undergo maintenance. It is a legal requirement for units to undergo maintenance. It means those units which are under maintenance will not participate in power generation. The step of maintenance is followed by the unit commitment problem. It means out of available units, which units will be on and which units will be off. Once the knowledge is obtained which units will be available, a final decision needs to be taken on how many units must be loaded which is called an economic dispatch problem. The optimal system generation is shown in figure 2.1.

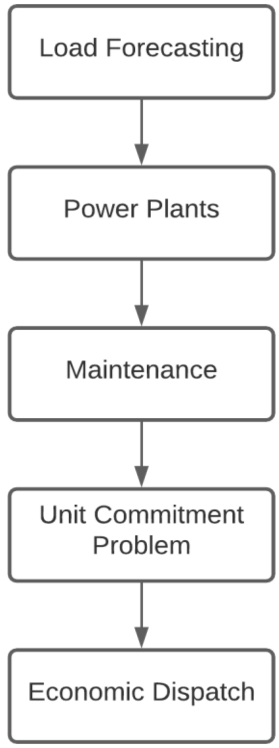

Figure 2.1 Optimal System Operations

2.3 Modeling Fossil Fuel Power Plants

Every power station has several generating units. The entire load on the system is satisfied by generating units in power stations at any given time. The decisive factor in power generation is to satisfy the load (demand) at least fuel cost. Unit commitment (UC) problem affiliated to the class of optimization problem comprising of binary UC variables and continual power dispatch variables.

Start-up costs – the cost of starting an offline power plant. It takes fuel so it takes a lot of fuel to ramp a power plant up to the point where it can be synchronized and producing electricity at the right frequency and so there are significant costs associated with that process.

Fixed costs – the cost of keeping a power plant online that occurs regardless of how much generation is being produced.

Variable costs – the cost of producing electricity that increases as a function of how much is being produced. These are costs that occur for the plant operator proportional or proportionally with how much electricity is being produced so for each power plant in our system.

Let's define three variables:

START = a binary {0,1} variable; 1 indicates a plant start

ON = a binary {0,1} variable; 1 indicates that the plant is online

GEN = a continuous variable indicating the level of electricity production

For any given fossil fuel power plant, we can describe the objective function in terms of all three:

$$Minimize\ Cost: START\ *\ a\ +\ ON\ *\ b\ +\ GEN\ *\ c \tag{2.1}$$

Where a = start cost (\$/event), b= fixed cost (\$/hour) and c = per cost of electricity (\$/MWh)

Here we are assuming that we can model the variable costs of a power plant using a constant marginal cost (\$/MWh rate), c. The aggregate variable costs of a power plant, at a given level of production, can be represented mathematically as presented in equation 2.2.

$$C(\$) = \ Heat\ Rate\ \left(\frac{MMBtu}{MWh}\right) *\ fuel\ price\ \left(\frac{\$}{MMBtu}\right) *\ Generation\ (MWh) \tag{2.2}$$

2.4 Unit commitment Scheduling Problem

Unit commitment belongs to the class of optimization problems which is used to decide the functioning agenda of generators with changeable loads. With the ever-changing demands, the importance of UC is rising. As a result, the power system must keep track of the most current procedures to enhance the operational steps of the generating units. A lot of methods using some form of estimation and generality have been planned. The following is a mathematical expression of the UC problem: (eq. 2.3):

$$\min_{x,u} \sum\nolimits_{I\in I} . \sum\nolimits_{t\in T} \mathrm{f_i}(\mathrm{x_{it}}, \mathrm{u_{it-1}}, \mathrm{u_{it}}) \tag{2.3}$$

$$s.t. \sum_{i\in I} \mathrm{x_{it}} \geq \mathrm{D_t}\ \ \mathrm{t} \in \mathrm{T}$$

$$\sum_{i\in I} \mathrm{X_i u_{it}} - \mathrm{x_{it}} \geq \mathrm{R_t} \quad \mathrm{t} \in \mathrm{T}$$

Where f_i *is cost function of each generating unit i*

x_{it} *is generation level*

u_{it} *is state of a unit*

D_t *and* R_t *is demand and reserve requirement for time period t respectively*

Suppose one had three generating units:

Unit 1: Minimum Generation = 150 MW, Maximum Generation = 600 MW

$$H_1 = 510 + 7.2P_1 + 0.00142P_1^2 \text{ MBtu/hr.}$$

Unit 2: Minimum Generation = 100 MW, Maximum Generation = 400 MW

$$H_2 = 310 + 7.85P_2 + 0.00194P_2^2 \text{ MBtu/hr.}$$

Unit 3: Minimum Generation = 50 MW, Maximum Generation = 200 MW

$$H_3 = 78 + 7.97P_3 + 0.00482P_3^2 \text{ MBtu/hr.}$$

What unit or combination of units must be used to provide a load of 550 MW cost-effectively? To solve this dilemma, try all three-unit combinations. If the sum of all maximum MW for the units combined is less than the load, or if the sum of all minimum MW for the units combined is greater than the load, such combinations are impossible. The results are shown in Table 2.1.

Table 2.1. Unit Combination and Load Dispatch for load 550 MW

Unit 1	Unit 2	Unit 3	Max Gen.	Min Gen.	P1	P2	P3	F1	F2	F3	Total Gen. Cost
Off	Off	Off	0	0	Infeasible						
Off	Off	On	200	50	Infeasible						
Off	On	Off	400	100	Infeasible						
Off	On	On	600	150	0	400	150	0	3760	1658	5418
On	Off	Off	600	150	550	0	0	5389	0	0	5389
On	Off	On	800	200	500	0	50	4911	0	586	5497
On	On	Off	1000	250	295	255	0	3030	2440	0	5471
On	On	On	1200	300	267	233	50	2787	2244	586	5617

Not operating all three units at the same time is by far the most cost-effective way to deliver the generation or even any combination of two units. Assume the load follows the basic "peak-valley" pattern depicted in Figure 2.2. If the system's operation is to be balanced, units must be turned off as the load decreases and then recommitted as the load increases.

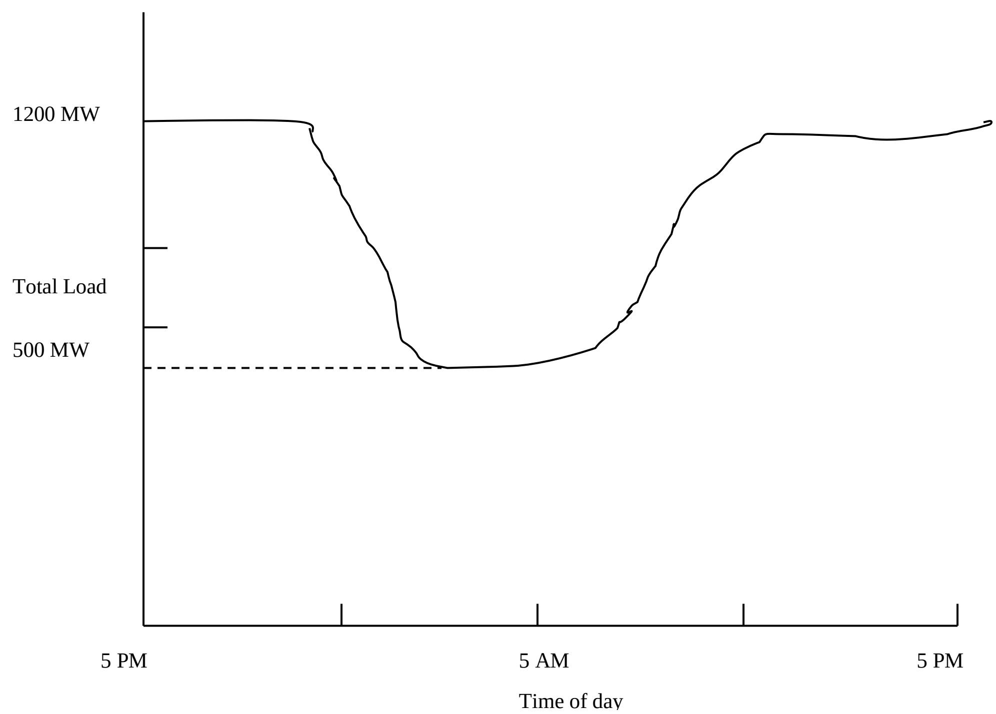

Figure 2.2. Peak Valley Load Pattern

The load fluctuates between a height of 1200 MW and a valley of 500 MW. Simply use a brute-force strategy to achieve a "shut-down law," in which all possible combinations of units are attempted. Run all three units when the load exceeds 1000 MW. Run units 1 and 2 when the load is between 1000 and 600 MW. If the load falls below 600 MW, just run unit 1.

The unit commitment schedule generated from this shut-down rule is shown in Figure 2.3. The unit commitment problem can be constrained in a variety of ways. The scheduling of units can be governed by different rules in each power system.

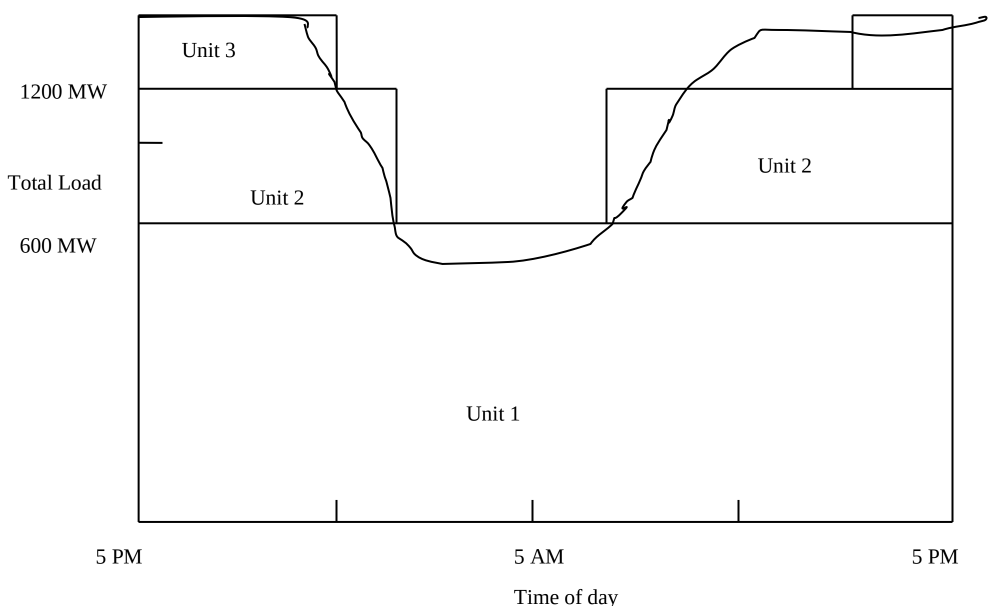

Figure 2.3. UC schedule using shut down rule

Table 2.2. Shut Down Rule Derivation

Load	Optimum Combination		
	Unit 1	Unit 2	Unit 3
1200	1	1	1
1150	1	1	1
1100	1	1	1
1050	1	1	1
1000	1	1	0
950	1	1	0
900	1	1	0
850	1	1	0
800	1	1	0
750	1	1	0
700	1	1	0
650	1	1	0
600	1	0	0
550	1	0	0
500	1	0	0

2.5 Types of unit commitment

The different types of objective functions are as follow that apply to different environments concerning unit commitment:

2.5.1 Traditional fuel-based environment:

In this environment, costs to decrease are fuel, shut down, and startup costs. The mathematical representation is given as equation 2.4.

$$\min \sum_{t=1}^{Nt} \sum_{i=1}^{Ni} \left[Ci\big(P(i,t)\big) I(i,t) + SU(i,t) + SD(i,t) \right] \tag{2.4}$$

Where *Ci(P(i,t))* denotes fuel cost of the ith unit at time t, *SU* and *SD* are startup cost and shutdown cost respectively.

2.5.2 Stochastic environment:

In this environment, randomness is added. In today's world uncertainty occurs due to the introduction of renewable sources of energy in power systems [9].

2.5.3 Profit based environment:

The main goal of a profit-based environment is to increase the earnings of Generation Company. Furthermore, the generation agenda need to fulfill several working constraints [10]. There are several constraints involved in UC which include Time based constraint, Emission based constraint, Fuel based constraint, Transmission based constraint, spinning reserve, and Ramp based constraint.

$$Notations$$

$$x(i,t){:}\ Status\ of\ ith\ unit\ at\ time\ t, 1\ indicates\ on\ and\ 0\ indicates\ off$$

$$o(i,t){:}\ Power\ produced\ by\ ith\ unit\ at\ time\ t$$

$$R(t){:}\ reserve\ requirement, L(t){:}\ load\ requirement$$

2.6 Constraints in unit commitment

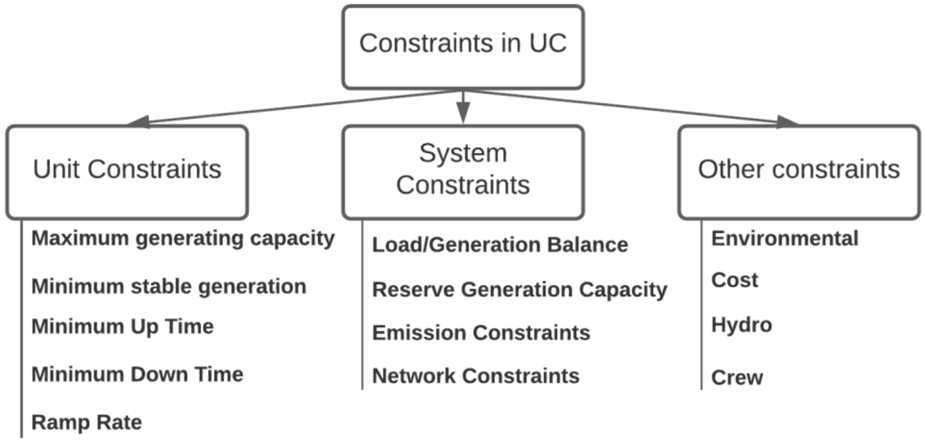

Figure 2.4. Constraints in unit commitment

2.6.1 Unit constraints

Constraints that are unique to each generating unit. The constraints which influence each generating unit individually are given below:

1. Maximum generating capacity
2. Minimum stable generation
3. Minimum uptime.
4. Minimum downtime.
5. Ramp rate

Maximum generating capacity:

This constraint state that the power generated from the unit must not exceed a specific value because of thermal stability of the unit exceeding this constraint cause damage to the unit. The mathematical representation of maximum generation capacity is given below:

$$X\ (i,t)\ <\ P\ max \tag{2.5}$$

where X (i,t) is the output power of unit *i*, in the time t.

Minimum stable generation:

As the above constraint, the power outage from the unit must not fall specific value because of technical limitations like flame stability in the gas and steam units. Equation 2.6 shows minimum stable generation where X (i,t) denotes output power of unit and Pmin and Pmax denote maximum and minimum generated power of each unit :

$$X\,(i,t)\ >\ P\,min \tag{2.6}$$

The maximum and minimum generated power of each scheduled unit must not be exceeded.

$$p\,min\ <\ X\,(i,t)\ <\ p\,max \tag{2.7}$$

Minimum up time:

This constraint state that once the unit is running must not shut down immediately due technical limitation and mechanical characteristic of the unit.

$$T_{u,on} \geq T_{u,up} \tag{2.8}$$

Where $T_{u,on}$ and $T_{u,up}$denotes on time and minimum uptime of unit *u* respectively.

Minimum downtime:

This constraint state that once the unit is running must not shut down immediately due technical limitation and mechanical characteristic of the unit.

Mathematical formula:

$$T_{u,off} \geq T_{u,down} \tag{2.9}$$

Where $T_{u,off}$ and $T_{u,down}$denotes off time and minimum downtime of unit *u* respectively.

Generation Limit Constraint: The power produced by each generating unit must be within certain limits and that is represented by

$$P_{i,minimum} \leq P_{i,t} \leq P_{i,maximum} \tag{2.10}$$

Where $P_{i,minimum}$ and $P_{i,maximum}$ are the minimum and maximum power output of generating unit i.

Ramp Up/Down Constraints:

The ramp rate is the rate at which output increases or decreases per minute, calculated in megawatts per minute (MW/min). Equations 2.11 and 2.12 show the mathematical representation of ramp up and down rates respectively. Here x(i,t) denotes power produced by unit *i* during period t.

Maximum ramp-up rate constraint:

$$x(i,t+1) - x(i,t) \le \Delta P_i^{up,\max} \quad \text{// Upper limit of power generation} \tag{2.11}$$

Maximum ramp-down rate constraint:

$$x(i,t+1) - x(i,t) \le \Delta P_i^{down,\max} \quad \text{// Lower limit of power generation} \tag{2.12}$$

2.6.2 System constraints

Load Balance Constraints:

Each hour's load must be equal to the total power generated and is represented by

$$P_{i,t} = \sum_{i=1}^{M} P_{i,t} U_{i,t} \tag{2.13}$$

Where $P_{i,t}$ is the system demand at time *t* and M denotes the set of available units.

Spinning Reserve:

The spinning reserve is the sum of spare capacity in online energy reserves that can be used to cover for power outages or frequency declines over a certain period. The spinning reserve can be fully deployed in minutes to meet increased load demand or to cover for an unexpected failure of an operational generator. Here L and R denote load and reserve requirement respectively (eq. 2.14).

$$\sum_{i=1}^{N} x(i,t) P_i^{max} \ge L(t) + R(t) \tag{2.14}$$

Following are the reasons to keep reserve power.

1. Sudden unexpected increase in the load demand.

2. Underestimating the load due to errors in load forecasting.
3. Local shortage in the generated power
4. Force outage of some generating units.
5. Force outage of supplementary equipment's due to the stability problem.

Force loss is a shutdown condition of a generating station, transmission line, or distribution line in electrical engineering when the generating unit is unable to generate power due to a sudden failure.

The condition of the reserve is given below:

1. Reserve must be higher than the largest unit.
2. Should be spread around the network.
3. The unit must operate at 80-85% of its rate.

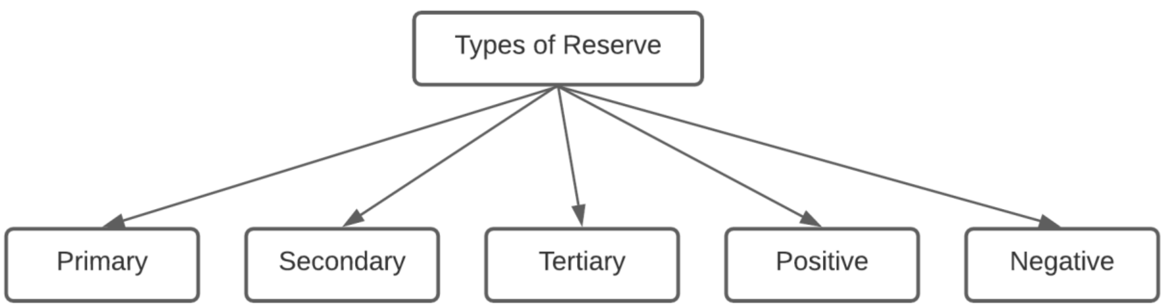

Figure 2.5. Types of Reserve

Primary Reserve:

For a short period, a quick response is required.

Secondary Reserve:

For a longer period, a slower response is preferred.

Tertiary Reserve:

To avoid another failure, replace the primary and secondary reserves. Units that can start up quickly provide this service.

Positive Reserve:

Positive Reserve states increase output when generation falls against demand (load).

Negative reserve

Negative Reserve states decrease output when generation is greater than demand (load).

Emission constraints:

Environmental constraints (such as SO2, NO) can affect generating unit scheduling.

Network constraints:

The transmission network can have an impact on unit commitment. Some units are required to run to provide voltage support. Some units' output could be restricted because their output will surpass the network's transmission capacity (Figure 2.6).

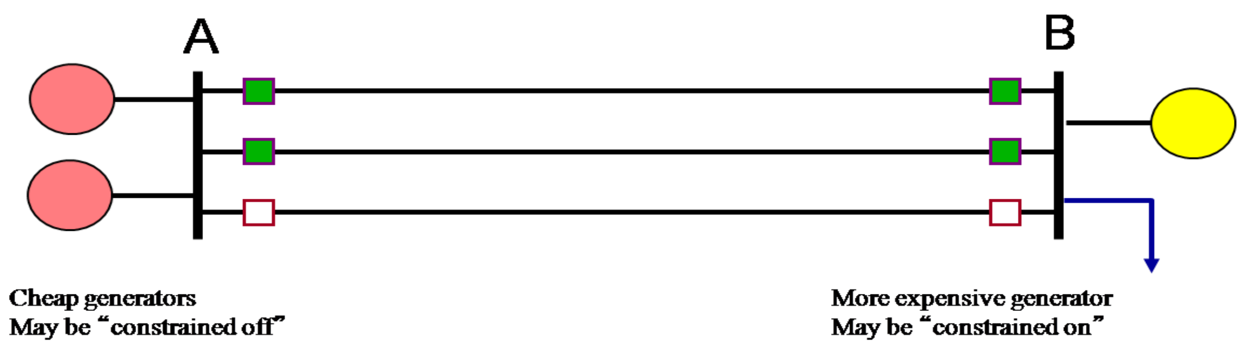

Figure 2.6. Network Constraint

2.6.3 Other constraints

Environmental Constraints:

Emission restrictions for fossil-fuel-fired generators and environmental guidelines for hydropower plants are among the environmental constraints.

Start-up costs:

Before they can be turned on, thermal units must be "warmed up." Warming up a generating unit is expensive. The cost of restarting a generating unit is determined by how long it has been off.

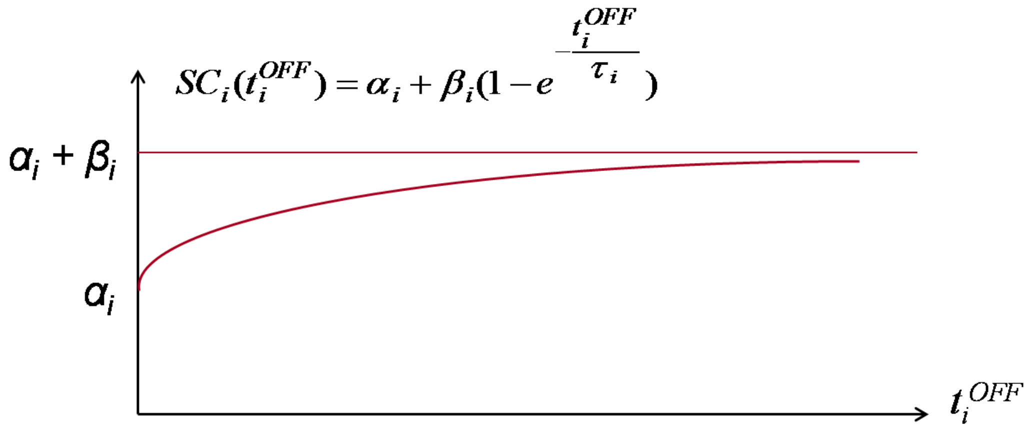

Figure 2.7. Startup cost

Hydro generation constraints:

1. Preservation of biodiversity
2. Recreation, navigation

Crew Constraints:

A plant with two or more units cannot be switched together at the same time because there are insufficient crewmen to react to both units at the same time.

2.7 Economic Dispatch Problem

Given a network of generating units, the economic dispatch problem deal with discovering the extent of power each generating unit should produce for given power demand, with the condition of reduction in aggregate operational cost.

$$\text{(Overall Cost) } F_T = F_1 + F_2 + F_3 + \ldots\ldots + F_N$$

$$= \sum_{i=1}^{N} F_i P_i$$

$$\phi = 0 = P_{load} - \sum_{i=1}^{N} P_i \tag{2.15}$$

Figure Fig.2.8 represents the configuration where N units are shown committed to satisfying a load P_{LOAD}.

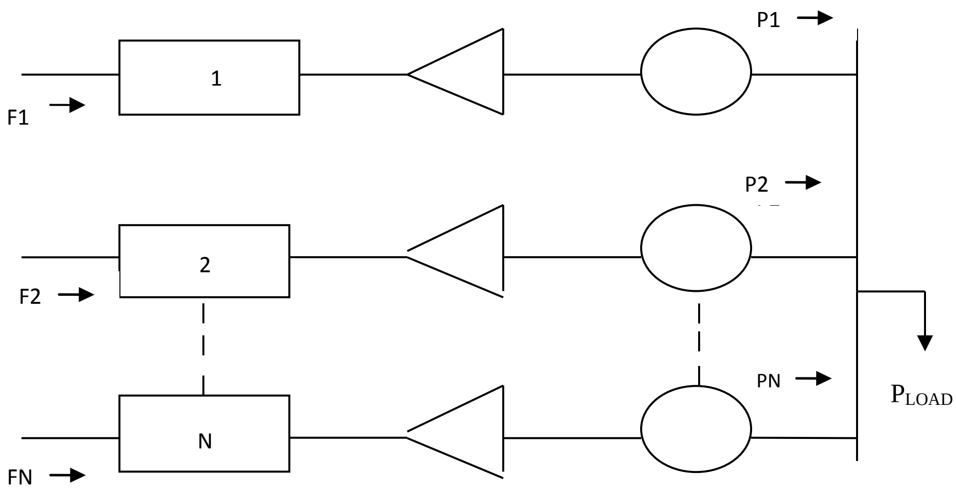

Figure 2.8. Generators committed to satisfying the load

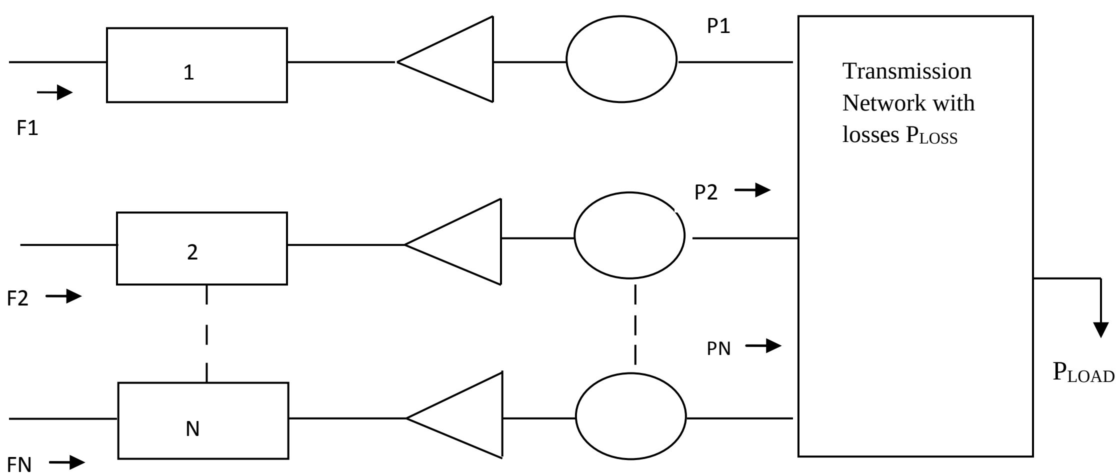

Figure 2.9. N units serving P_{LOAD} through a transmission network

The function of a standard Economic Dispatch problem is defined as follows (eq.2.16).

$$\min F_T = \sum_{i=1}^{n} \mathrm{F_i}(P_i) = \sum_{i=1}^{n} (\mathrm{a_i} + \mathrm{b_i P_i} + \mathrm{c_i P_i^2}) \tag{2.16}$$

$where \;\; F_T \; denotes \; overall \; fuel \; cost$

$F_i(P_i) \; denotes \; cost \; of \; ith \; generating \; unit \; in \; \$/h$

$P_i \; denotes \; ith \; unit's \; output \; power \; in \; MW$

$n \; denotes \; aggregate \; of \; generating \; units$

$$a_i, b_i, c_i \; denotes \; ith \; generating \; unit's \; cost \; coefficients$$

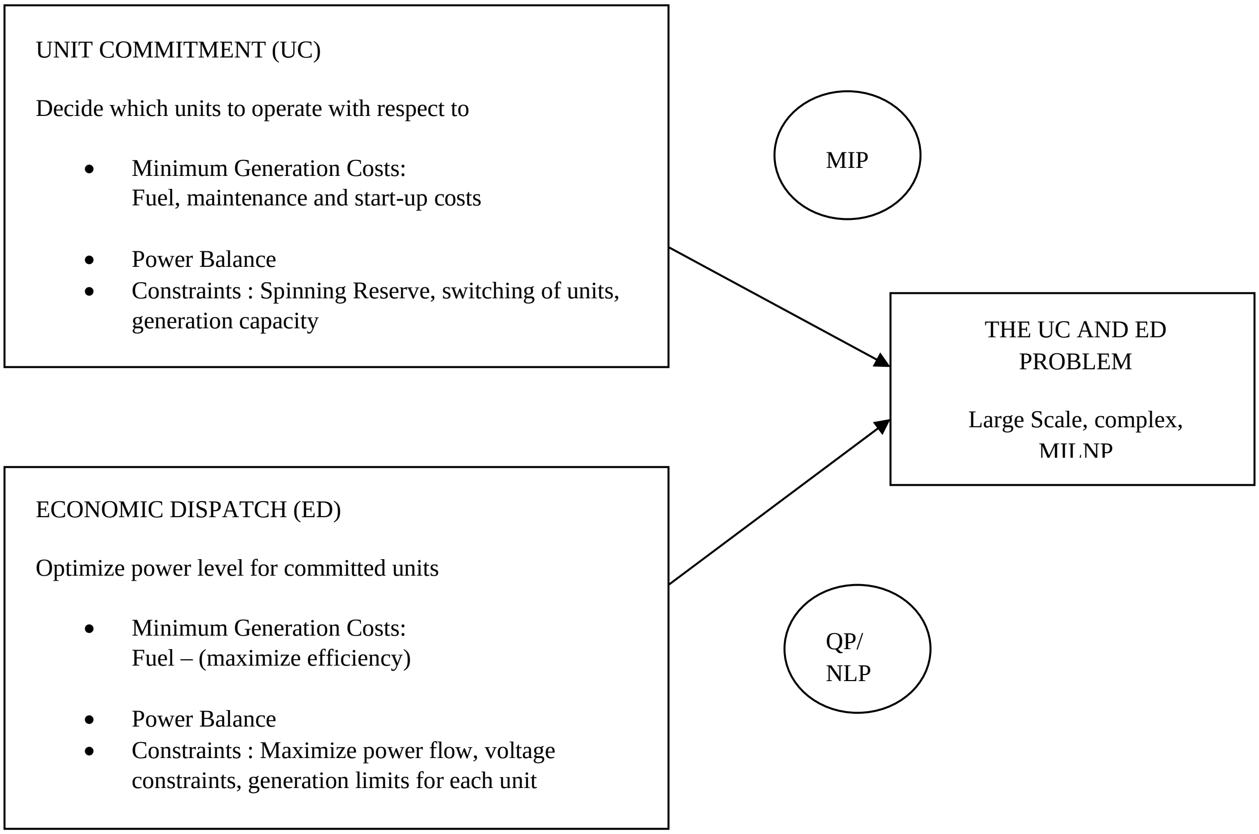

Figure 2.10. Summarizing unit commitment and economic dispatch

2.8 Techniques for solving UC problem

Several previous studies have attempted to solve the UC problem using different optimization techniques. Three types of solutions are:

1. Conventional Techniques [11,12]
2. Non-Conventional Techniques [13,14,15]
3. Hybrid Techniques [16,17,18,19]

Despite the availability of new solutions, UC solution techniques still use approximations of problems. Approximation may lead to inexact results, which is unacceptable. Dynamic Programming is one of the oldest techniques to solve the UC problem, but it's not capable of handling the complexity of the problem. Evolutionary algorithms are well known for handling complex problems in an effective way. Fuzzy techniques on the other hand are capable of handling the problem in situations where its parameters lack definiteness.

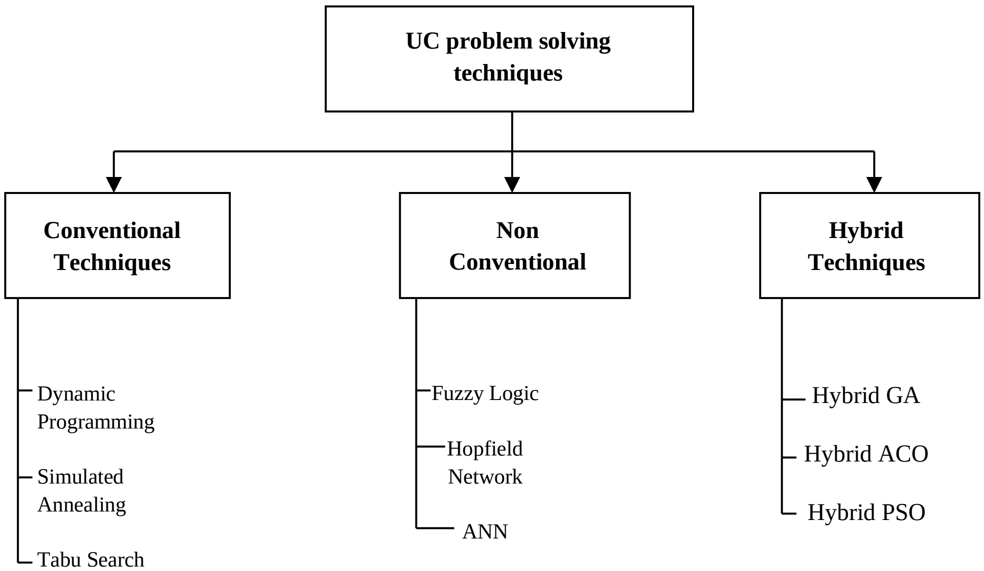

Figure 2.11. Classification of UC problem-solving techniques

2.8.1 Dynamic Programming Approach (DP)

DP is a tool for solving complex problems by breaking them down into stages. The exploration phase could take place in either a forward or backward direction. DP offers numerous benefits over the enumeration scheme. The advantage worth mentioning is its potential to lessen the dimensionality of the problem. For example, there are five units in the system then there will be $2^5 - 1 = 31$ combinations concerning testing. If priority order is maintained, there will be only five combinations to be worked upon. In conventional DP, numerous states will be under evaluation every hour to figure out the precursor path which leads to the lowest collective cost in that hour. As a result, the evaluated state will be having one precursor path and other possible precursors to that very state that got abandoned being sub-optimal. In Fig. 2.12, 4 states (P, Q, R, S) are taken into consideration for each of 3 hours. The lines in the graph which are solids show optimal paths and lines which are represented as dashed show sub-optimal paths which have been released. There are two methods for configuring DP: forward DP and backward DP. One can run a program in forwarding DP from the beginning to the end. In the case of backward DP, the program can be run from the closing hour to the first hour. The forward DP technique offers advantages in solving UC. The starting conditions can be easily identified and calculations can go forward as long as needed.

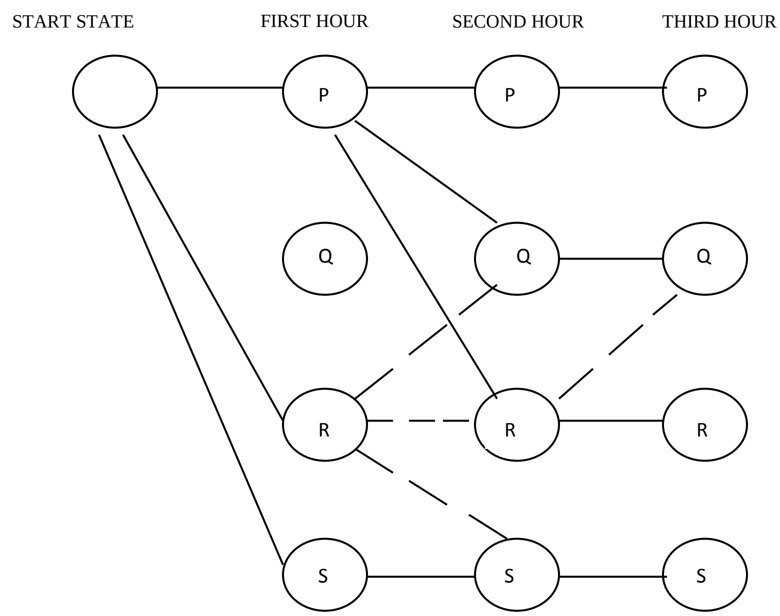

Figure.2.12. Standard DP Logic

2.9 Evolutionary Algorithms

In recent years, researchers have paid a lot of attention to global optimization. Since optimization problems prevail in engineering, economics, and other fields of research. Investigators need a robust optimization approach that can unravel optimization problems and are not too difficult to put into effect. Every species must reform its physical structures to remain fit in the world in which they live. The connection between optimization and evolution paves the way for the advancement of evolutionary computing approaches. Darwin's theory of evolution has made evolutionary algorithms one of the most appealing forms of directed random search techniques. During the search process, an evolutionary algorithm becomes accustomed, using the knowledge it collects to solve the problem of dimensionality, which makes non-random and detailed search methods computationally difficult to manage. The optimization technique must meet the following criteria:

i. Straightforward

ii. Parallelizability

iii. Dependable and adaptable function optimizer

iv. Robustness

v. Convergence Speed and Accuracy

Evolutionary techniques vary in the implementation details and the nature of the particular applied problem.

2.9.1 Differential Evolution

One of the most widely used optimization algorithms today is differential evolution (DE). DE functions in a similar way to a traditional evolutionary algorithm in terms of computational steps. Since its inception in 1995, DE has piqued the attention of numerous researchers all over the world, resulting in multiple variations of the original algorithm with improved results. The DE algorithm has steadily gained popularity and has been used in a variety of applications, owing to its strong convergence properties and ease of understanding. There are three operations, according to Storn and Price [20]: mutation, crossover, and selection. In several computer science contexts, such as image processing, big data, and other research fields, DE has been used to find an optimal solution.

Differential Evolution (DE) is a technique for optimization that has the following advantages:

1. In contrast to other evolutionary algorithms, differential evolution is very easy to implement.
2. Differential evolution outshines in terms of consistency, convergence rate, and durability.
3. The main body of the algorithm can be coded in a few lines in C or some other programming language.
4. In comparison to other algorithms, the space complexity is low.
5. In differential evolution, there are only a few control parameters that do not affect efficiency.

The structure of the DE algorithm is diagrammatically represented in figure 2.13:

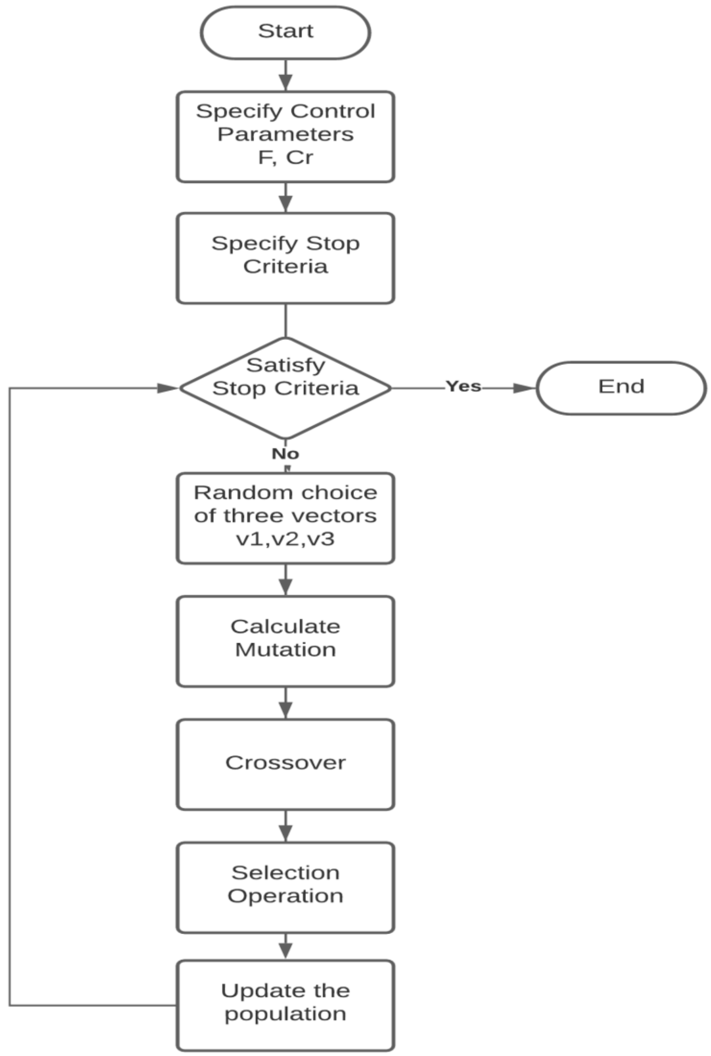

Figure 2.13. Structure of DE

2.9.2 Genetic Algorithm

Genetic algorithms are a form of global search heuristic that seeks solutions to optimization problems using techniques inspired by biological evolution, including mutation, selection, and crossover [21-23]. The Genetic Algorithms could be classified as part of a larger category of evolutionary algorithms. In general, chromosomes are taken as a population and must evolve to have the best solutions. Selection, mutation, and crossover are the most widely used genetic operators. The crossover causes the parents to be combined to create a new chromosome string of traits from both parents. The Genetic Algorithm is a technique that impersonates the natural selection process. A population of individual solutions is repeatedly modified by the genetic algorithm. Every individual in the population's fitness is assessed at each step; fitness is generally defined as the value of an objective function. The fittest individuals in the current population are selected at random to be parents, and their offspring are used to reproduce the next generation's children. The population progresses toward an optimum solution over subsequent generations. When the algorithm reaches a suitable fitness level or produces the maximum number of generations, it stops.

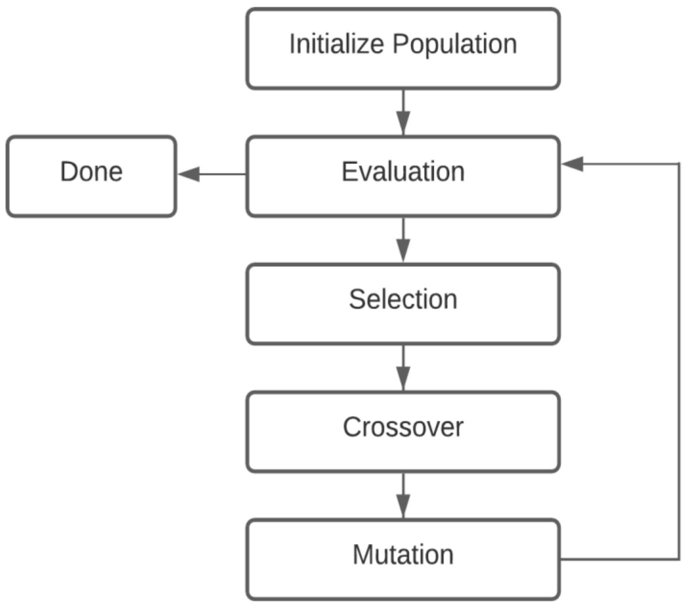

Figure 2.14. Structure of GA

Selection: Individuals may be selected at random or based on their fitness merit, with the optimal solution typically being chosen. Then a pair of parents are selected from the pool of parents already know, resulting in the creation of a new child by mutation and crossover.

The crossover technique is a method of reproducing a child solution from multiple parent solutions. Crossover methods (Figure 2.15-2.17) include one-point crossover, two-point crossover, and uniform crossover.

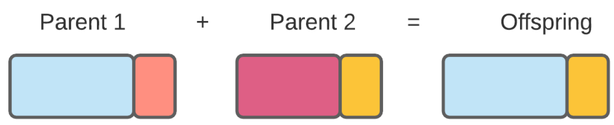

Figure 2.15. One-Point Crossover

Two crossover points are drawn at random from the parent chromosomes in the two-point crossover. Between the two stages, the bits are exchanged between the parent species.

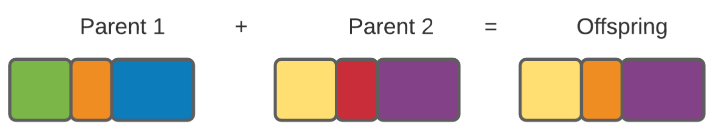

Figure 2.16. Two-Point Crossover

In the uniform crossover, each bit is usually chosen with equal probability from either parent. Other mixing ratios have been used in the past, resulting in offspring inheriting more genetic material from one parent than the other.

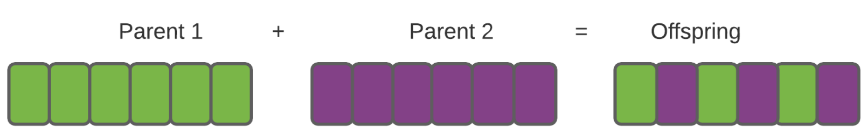

Figure 2.17. Uniform Crossover

Mutation in Genetic Algorithms aims to add diversity to the population being studied (Figure 2.18). Mutation operators are used to avoiding local minima by preventing chromosome populations from being too close to one another, delaying or stopping convergence to the global optimum.

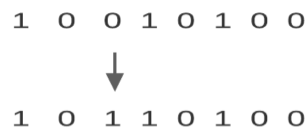

Figure 2.18. Mutation

2.10 Metaheuristic algorithms

Randomization and local search are attempted to be balanced by metaheuristic algorithms. As a result, the vast majority of these algorithms are used in global optimization.

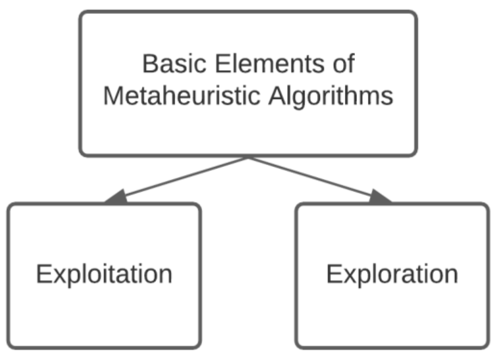

Figure 2.19. Basic Elements of Metaheuristic Algorithm

Exploitation and exploration are the two fundamental elements of metaheuristic algorithms (Figure 2.19). "Exploration" refers to making sure you look at several different parts of the search space so you don't get stuck in a local minimum. "Exploitation" refers to the process of analyzing a promising area of the search space to see if it contains a good local minimum.

2.10.1 Whale Optimization Algorithm

In 2016, Mirjalili and Lewis suggested the Whale Optimization Algorithm (WOA), which is also abbreviated as WOA [24]. It is often referred to as a nature-inspired metaheuristic algorithm. Mirjalili and Lewis suggested the algorithm to model humpback whale hunting activity (Figure 2.20). This is achieved in two ways: one, by following the prey with a random or strongest search agent, and second, by replicating the bubble net hunting technique (Figure 2.21).

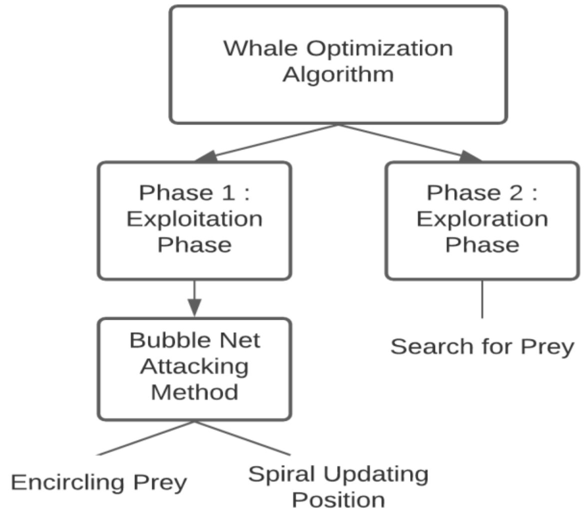

Figure 2.20. WOA Phases

```
(1) Initialize the whales population X_i (i = 1, 2, ..., n)
(2) Calculate the fitness of each search agent, X* = the best search agent
(3) while (t < maximum iteration number)
(4)     for each search agent
(5)     Update a, A, C, l, and p
(6)         if1 (p < 0.5)
(7)             if2 (|A| < 1)
(8)                 Update the position of the current search agent by
                    Equation (11)
(9)             else if2 (|A| ≥ 1)
(10)                Select a random search agent (X_rand)
(11)                Update the position of the current search agent by
                    Equation (11)
(12)            end if2
(13)        else if1 (p ≥ 0.5)
(14)            Update the position of the current search by Equation (11)
(15)        end if1
(16)    end for
(17)    Check if any search agent goes beyond the search space and amend it
(18)    Calculate the fitness of each search agent, Update X* if there is a better solution
(19)    if3 (|A| < 1)
(20)        Random variation of current best search agent for N times by
            Equation (13)
(21)    end if3
(22)    t = t + 1
(23) end while
(24) return X*
```

Figure 2.21. WOA Pseudocode [25]

2.11 Optimization Methods for solving UC problem

The detailed literature survey with features, advantages, and limitations of proposed optimization methods by the various researchers is tabulated below in Table 2.3. The development and evolution of the UC problem over the years are presented in Figures 2.22 and 2.23 respectively.

Table 2.3 Detailed literature survey with features, advantages, and limitations of proposed optimization methods

Researcher	Method	Advantages	Weakness
Senjyu et. al. [**26**]	Priority List	The simplest and quickest way to solve the UC problem	The solution is far from ideal.
Farhat et al. [2**7**]	Dynamic Programming	DP is a procedure used to compute complex problems by breaking them into stages	It suffers from imprecation of dimensionality.
Guan, et al. [2**8**]	Lagrangian Relaxation	It can be used to break down sub-problems even further.	The presence of a duality gap is a problem for it.
Shahidehpour, et. al. [2**9**]	Benders Decomposition	It helps break down the issue into smaller, more manageable chunks	Convergence speed is slow.
Madrigal et al. [3**0**]	Interior Point Optimization	It quickly converges on the best solution.	Slow down when looking for the best answer.
Sawa, et al. [**31**]	Quadratic Programming	It solves both the UC and the economic load dispatch problems at the same time.	Finding an answer takes a long time.

Hobbs, et al. [**32**]	Mixed Integer Linear Programming	Possibility of arriving at a globally optimal solution	As opposed to quick methods like heuristics, it takes a long time.
Chen et al. [**33**]	Branch-and-Bound	If the problem is small enough, it seeks the best solution.	For massive systems, the execution time increases exponentially.
Catalão, et al. [**34**]	Non-linear Programming	Modeling of power generation characteristics with accuracy.	It expands the scope and complexity of the problem.
Nagaraja [**35**]	Artificial Neural Network	Quite flexible with noisy data	With large problems, the computing time grows exponentially
G. Dudek [**36**]	Simulated Annealing	The algorithm will start with an initial solution and attempt to find a better one.	Finding a near-optimal solution takes a long time. The system is unable to determine whether or not an optimal solution has been found.
Mantawy, et al. [37]	Genetic Algorithm	The structural genetic algorithm can solve both the solution structure and parameter problems at the same time.	There's no assurance that a genetic algorithm can find the global best answer.
Rajan [3**8**]	Evolutionary Programming	It is capable of dealing with issues with multiple dimensions.	In most cases, it does not provide the global extremum.

Usami et. al. [3**9**]	Tabu Search	Its adaptive memory enables it to develop a more adaptable search behavior.	It can become stuck in a local optimal solution, with no way to explore other parts of the solution space.
Selvi et al. [**40**]	Ant Colony	Finding good ideas quickly is a good thing. Capable of dealing with large-scale issues such as the UC problem.	It is difficult to do a theoretical analysis.
Clerc et. al. [**41**]	Particle Swarm Optimization	It does not require a large number of parameters to tune. A simple way to find something in a complex problem with a lot of variables.	In local search, there is a slow convergence.
Abedinia, et al. [**42**]	FireFly	It's easy to understand and program. It is an appropriate approach for dealing with environmental and economic dispatch issues.	Convergence speed is slow
Saneifard, et al. [**43**]	Fuzzy Logic	It provides a qualitative account of a system's behavior and characteristics.	It is incapable of handling large-scale systems.
Li, et al. [**44**]	Expert Systems	They can store a large amount of data. They cut down on the time it takes to solve a problem.	It is unable to come up with novel solutions to the problems.

Najafi et al.[**45**]	Harmony search algorithm	It finds the best answer in a fair period. This method is capable of efficiently resolving both large and small-scale UC problems.	The number of iterations needed to find an optimal solution increases.
Yang et al. [**46**]	Fast heuristic algorithm	The algorithm's robustness and speed are two characteristics of this method.	To be quick and fast, some of the problem's requirements are ignored or even overpowered.
Sharma et al. [47]	Pattern Search Algorithm	This algorithm's definition is straightforward, computationally effective, and simple to implement.	It makes the technique more likely to get trapped in the local minimum.
Panwar et al. [4**8**]	Binary fireworks algorithm	Consistency is strong. Excellent precision in optimization	When a bad firework occurs, the best solution can become ineffective.
Anita et al. [4**9**]	Shuffled frog leaping algorithm	Does not need a lot of processing time.	The exploitation of solutions by the algorithm is not good.
Shukla et al. [**50**]	Gravitational search algorithm (GSA)	The benefit of an algorithm is that it is simple to implement.	It is easy to fall into the local optimal solution.
Li et al. [**51**]	Binary gravitational search algorithm (BGSA)	Solving the scheduling problem requires less time in terms of computation	Overly reliant on the randomization of the discovery process.

Devi et al. [5**2**]	Bat-inspired algorithm (BA)	The benefit of an algorithm is that it is simple to implement.	This algorithm suffers from incorrect convergence due to local optima.
Kamboj et al. [**53**]	Particle swarm optimization and grey wolf optimizer algorithm (PSOGWO)	Control parameters and computational performance are both relatively stable.	

(1940s) The unit commitment problem appears in electrical energy systems.

(1950s) The PL system was formulated, in which generators' positions were calculated by their average production costs.

(1960s) The study provided the first MIP formulation for the Unit Commitment problem, in which three binary variables (ON/OFF, start-up, and shutdown) are used to describe the unit status.

The unit commitment problem was solved by enumerating all available generating unit combinations

(1970s) To deal with the UC problem, the researchers used the Priority listing approach.

An extension of Lagrangian relaxation to power system scheduling.

MILP was used for the first time to formulate and solve the UC problem.

(1980-1983) Security Constrained UC have been developed.

The Unit Commitment problem is solved using the Branch-and-Bound approach.

Dynamic and Linear Programming utilized for scheduling of generating units

(1984-1987) DP was one of the first optimization techniques used to solve the UC problem.

(1988-90) For solving the UC problem, several studies have chosen the Lagrangian relaxation method.

The UC problem is solved using the fuzzy system approach.

Short Term UC problem is solved using Expert System approach

(1991-95) Artificial neural networks are used to solve the UC problem.

Tabu Search, Genetic Algorithm and Evolutionary programming utilized for finding solution to UC.

(1996-2000) To resolve the UC problem, the PSO with binary variables is proposed.

Benders Decomposition, Simulated Annealing algorithm utilized for UC problem.

(2001-2005) ACO algorithm, Hybrid PSO algorithm, Multi Agent Modeling used to solve UC problem.

The MIP method was used to formulate the PBUC problem.

(2006-2009) Renewable energy sources are being integrated into power grids.

To solve the UC problem, a new hybrid meta-heuristic approach combining Tabu search and Evolutionary PSO has been proposed.

(2010-2013) Several stochastic programming models for making optimal decisions in power grids under uncertainty have been presented.

The use of solar and wind energy in power systems has been investigated.

(2014-2017) The researchers looked at how to make decisions in power systems that have a large amount of wind power.

Researchers presented stochastic 2-stage reliability based SCUC in the context of smart grids

Using multi-objective unit commitment, the relationship between operating costs and wind curtailment is being investigated by researchers..

(2018) Authors have taken into consideration renewable energy in solving UC problem.

Authors have compared different Lagrangian relaxation strategies used for solving stochastic hydrothermal UC (unit commitment) problem.

Authors have addressed the concern of security and reliability caused by the wind speed uncertain nature and fluctuations. Authors have proposed the technique for solving security constraint unit commitment problem.

(2018) Authors have taken into consideration significance of renewable energy in power system operation.

Authors have combined Dragonfly algorithm and Particle Swarm Optimization to find optimal solution.

Authors have proposed a novel multi-objective model for smart grid technology.

(2018) Proposed data-driven approach for the UC optimization. Proposed model would increase the resilience of the stochastic UC.

Authors have presented a novel planning method for reducing operation cost and improving voltage stability of power units.

(2019) By considering the thermal, heat and DM-CHP (Dual Mode - Combined Heat and Power) components, the BPSO-PSO methodology was implemented to solve the UC challenge of Multi Objective economic and profit based models.

The complementary scheduling issue of hydrothermal-renewable power systems has been examined. The MOHGWO algorithm is formulated to address the multi objective problem.

(2019) Proposed system that has autonomy, expense and CO2 reductions as different goals with respect to power generation.

Examined the interaction between running costs and wind shortening in hybrid generation systems with thermal engines, wind turbines and battery-based energy storage

(2019) The scheduling of a CHP-based microgrid is studied taking into consideration three contradictory targets: production of pollutant gases, unit generation costs and the volume of electricity not supplied.

(2019) Optimum scheduling model is developed for Wind-Solar-Hydro power.

Authors have combined lambda iteration and simulated annealing techniques to solve ELD (Economic Load Dispatch) problem.

Authors have proposed a new variant of Differential Evolution Algorithm, MBDE to solve UC problem.

(2019) Authors have formulated the optimal unit commitment in hybrid DC/AC power systems

A multi-agent glowworm swarm optimization (MAGSO) algorithm has been suggested to solve the ELD issue of a large hydropower facility.

Authors have considered the ramp-rate constraint during investigation of Unit Commitment problem.

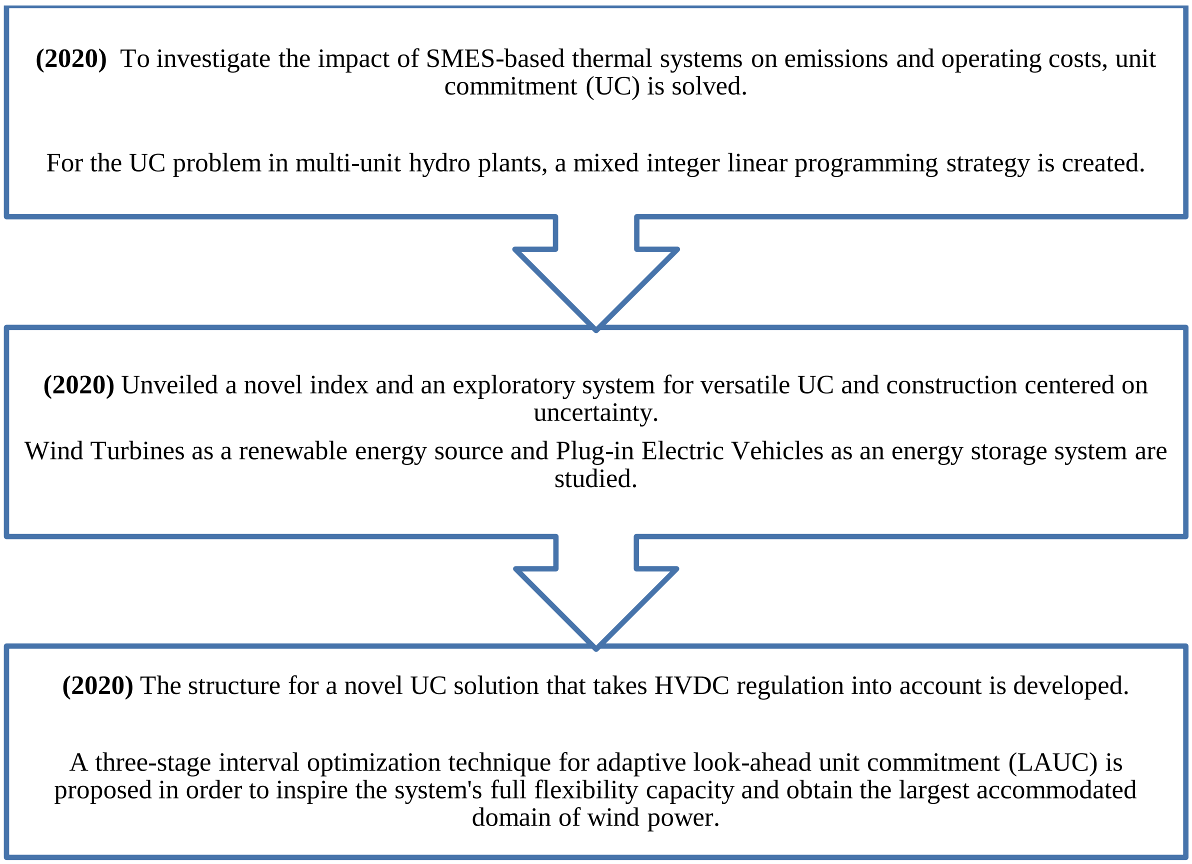

Figure 2.22. UC Problem development from the 1940s to 2020

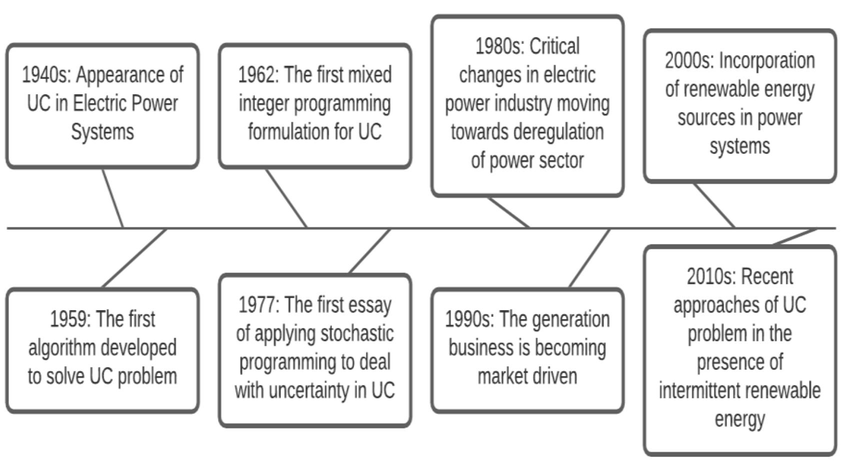

Figure 2.23. UC Problem evolution over the years

2.12 Literature Survey of UC problem

Kris Poncelet et al. [54] contribute to the existing literature by highlighting the significance of unit commitment (UC) constraints in generation expansion planning models. The impact of ignoring UC constraints in generation expansion planning models has been widely assessed and demonstrated in the research, especially in light of the growing emergence of renewable energy sources.

Lázaro Alvarado-Barrios et al. [55] have addressed the problem of optimal microgrid operation under uncertainties. The optimum functioning of the energy storage system has been implemented. In certain instances, the approach used a feasible guarantee. The key characteristics of the design process are demonstrated by some simulated case studies.

Mojtaba Rahmani et al. [56] suggested a security constraint unit commitment program that decreases network operating costs while deciding the best approach for implementation of Plug-in Electric Vehicles and Demand Response Programs. For power system modeling in a smart grid context, the authors used a 2-stage stochastic mixed-integer programming model.

Min Zhou et al. [57] have suggested a data-driven UC model deal with wind power and potential load uncertainties. Firstly, the non-parameter kernel density technique is used to denote hybrid uncertainties. Secondly, a new selection mechanism is proposed to figure out the correlation between UC and uncertainty representation.

Shuang Yuan et al. [58] have proposed a new multi-objective UC model incorporating cost and peak load regulation. The MRUCT algorithm, suggested by the authors, divides the problem into two stages. The primary issue is a multi-objective optimization problem that decides when the generating unit starts and stops. The sub-problem is a "min-max" issue that dictates the units' output.

Bo Wang et al. [59] examined the relationship between operating costs and wind reduction in generating mixed systems with thermal units, wind energy farms, and battery-based ES, taking into account the uncertainties of wind power and future load. A day ahead multi-objective UC model was built to reduce operational costs and wind reduction. As a possible solution to the complex model, a MOPSO based on reinforcement learning was proposed.

Xiaoyu Wang et al. [60] proposed a multi-agent glowworm swarm optimization algorithm, prefixed as the MAGSO algorithm, to address the Economic Load Dispatch problem of a hydropower station. The algorithm incorporates the principles of glowworm swarm optimization (GSO) evolution and the inter-individual cooperation of multi-agent systems (MAS).

Z. Soltani et al. [61] proposed a stochastic multi-objective UC problem combining smart grid technologies and renewable distributed generation. A modern mixed-integer linear programming (MILP) approach is used to conduct an economic emission analysis to reduce the overall estimated operating cost and pollution.

Pouya Pourghasem et al. [62] investigated the scheduling of a microgrid based on combined heat and power with three competing targets (environmental, reliability, and economic aspects). The multi-objective problem is solved using the stochastic programming method. Uncertainties in wind energy and load demand are taken into consideration. The multi-objective problem is addressed using the weighted sum method, and scenarios are constructed using a roulette wheel mechanism.

Hossein Narimani [63] et al. developed a new swarm-intelligence-based algorithm to address single and multi-objective forms of the UC problem, accounting for total operating costs as well as Total Expected Energy which is not supplied as Objective Functions. The proposed hybridization of the Grey Wolf Optimizer (GWO) and the Particle Swarm Optimization algorithm (PSO) has been thoroughly tested, with test cases ranging from 10 to 54 units (test systems of different sizes).

The topic of complementary planning of hydro-thermal-renewable energy systems has been investigated by Chaoshun Li et al. A novel economic/emission model is being developed, optimizing discrete variables and continuous variables [64].

Jie Li et al. [65] used the dragonfly algorithm to create an optimized scheduling model with the goals of increasing total power activity and lowering ecological discharge. They concentrate on the complementary generation of wind and solar power, wind and hydropower, or hydro and solar power, but are primarily used in distant regions in small-scale power systems.

Janez Brest et al. [66] proposed a unique method for controlling the parameter settings of classical DE. DE is a widely used optimization algorithm and has shown remarkable convergence properties. It has a handful of parameters that are kept permanently during the evolutionary process. Nevertheless, it is not a simple job to set the control parameters in DE properly. So, the authors devised a new algorithm called Self Adaptive Differential Evolution, which showed great performance on benchmark problems. The investigation results have shown that SADE outperforms DE when the quality of solutions is taken into consideration.

Masahiro Furukakoi et al. [67] have established a stochastic activity plan for reducing the issue of the photovoltaic power generation facility's output being uncertain. Using a multiobjective optimization approach, the authors have also proposed an optimized operation method designed to minimize operating costs and optimizing voltage stability of the presumed power system model.

Ali W. Mohamed et al. [68] proposed a novel DE algorithm to work out unconstrained problems of optimization. The authors proposed a better mutation law based on a weighted difference vector between a generation's fittest and worst individuals.

To improve the discovery ability of DE [69], Yong Wang et al. suggested a simple method for using an Orthogonal Crossover in DE equivalents.

Yiqiao Cai et al. [70] proposed hybrid linkage crossover as a novel linkage utilization technique (HLX). HLX aims to extract the linkage statistics for a specific problem and then uses linkage statistics to guide the crossover operation. The HLXDE was formed by assimilating HLX into DE.

An emerging surrogate model-based DE (ESMDE) approach was proposed by Rammohan Mallipeddi et al [71]. Josef Tvrdíka and Ivan proposed a novel technique combining DE and k-means [72]. Clustering is a technique for grouping objects into related classes based on their similarity. Hierarchical and non-hierarchical approaches are the two key methods for determining the clustering problem. The researchers used their algorithm to evaluate non-hierarchical clustering on eight well-known real-world data sets. The issue of optimal non-hierarchical clustering has been well addressed.

Dilip Datta et al. [73] put forward technique as an answer to the unit commitment problem. They named it binary-real-coded Differential Evolution. The issue of unit commitment scheduling is one of the most pressing issues for power companies. It involves how many units need to be put in a working state, how many units need to be put in an inactive state, and how much power one unit needs to generate to satisfy load demand. Unit commitment popularly known as the UC problem needs to be overcome by minimizing fuel cost, startup cost, and shutdown cost which come from the generating units.

Anupam Trivedi et al. [74] presented a novel solution to the power system optimization problem, also known as UC scheduling. The authors have given the algorithm the name hGADE (Hybridization GA and DE). The issue of unit commitment scheduling is one of the most pressing issues for power companies. It involves how many units need to be put in a working state, how many units need to be put in an inactive state, and how much power one unit needs to generate to satisfy load demand. Unit commitment popularly known as the UC problem needs to be overcome by minimizing fuel cost, startup cost, and shutdown cost which come from the generating units. The hGADE algorithm presented here is cross-disciplinary and can be used to solve optimization problems quickly.

Huifeng Zhang et al. [75] presented an enhanced multi-objective DE algorithm popularly known as MOHDE-SAT to resolve the dynamic economic emission dispatch problems (DEED). Economic Dispatch plays an important part in the working of power systems, it allows economic dispatch to be treated and the ultimate goal is to run power systems at minimal fuel cost and optimizing the pollutant discharge simultaneously. Furthermore, since pollutant emissions increase the cost of fuel, DEED can be viewed as a multi-objective issue.

Withironprasert et al. [76] suggested the hybrid ant system priority list as a new strategy (HASP). The technique consists of three important steps: Utilization Index calculation, Committing Process-Based Commitment Probability, and Pheromone Updating Process.

Calculation of Utilization Index :

$$UI_{i,t} = \frac{Pmax_i}{\left(\partial F_{i,t} / \partial P_{i,t}\right)_{\cdot Pmax_i}} \tag{2.17}$$

Committing Process-Based Commitment Probability:

$$CP_{i,t}(u) = \frac{\left[\tau_{i,t}(u)\right]^{\alpha}_{\cdot} \left[UI_{i,t}\right]^{\beta}_{\cdot}}{\sum_{i \in I_t^{cand}} \left[\tau_{i,t}(u)\right]^{\alpha}_{\cdot} \left[UI_{i,t}\right]^{\beta}} \tag{2.18}$$

2.13 Decomposition Methods for Stochastic UC

One of the most significant challenges for the economic, secure, and reliable operation of current power systems is the complexity associated with the massive integration of renewable energy sources (e.g., solar and wind power generation). One way to address this problem is to use a stochastic security constraint unit commitment (SSCUC) model.

Scenario decomposition is a common method for breaking down a stochastic problem into individual deterministic UC problems for each case.

Dual Decomposition employs Lagrangian relaxation to generate a separable Lagrangian dual function for each scenario.

A stochastic optimization problem in its most comprehensive form consists of a single mathematical model in which all constraints are written for all potential scenarios. Owing to a lack of computational resources, such formulation does not ensure a solution for large-scale problems. Progressive Hedging Algorithm is a scenario-based decomposition process suggested by Rockafellar and Wets as a solution alternative.

The primal-dual decomposition approach is used to solve two-stage problems that are both absolute UC problems. The algorithm does not make any assumptions on the set of technical constraints for the units and instead relies on methods that are already in place for deterministic UC.

The unit Decomposition method breaks down the problem into a single-generator stochastic program as an alternative to scenario decomposition, which can be solved separately, such as using dynamic programming.

The Lagrangian relaxation approach can be extended to the demand limit to decompose the unit commitment problem into the single-generator problem.

A cutting plane algorithm used to solve a wide variety of complicated combinatorial optimization problems is the Benders decomposition algorithm. In several models, Benders-like decomposition has been extended to the stochastic unit commitment problem. The decomposition methods for stochastic UC are presented below in figure 2.24. Table 2.4 presents the recent literature on stochastic UC.

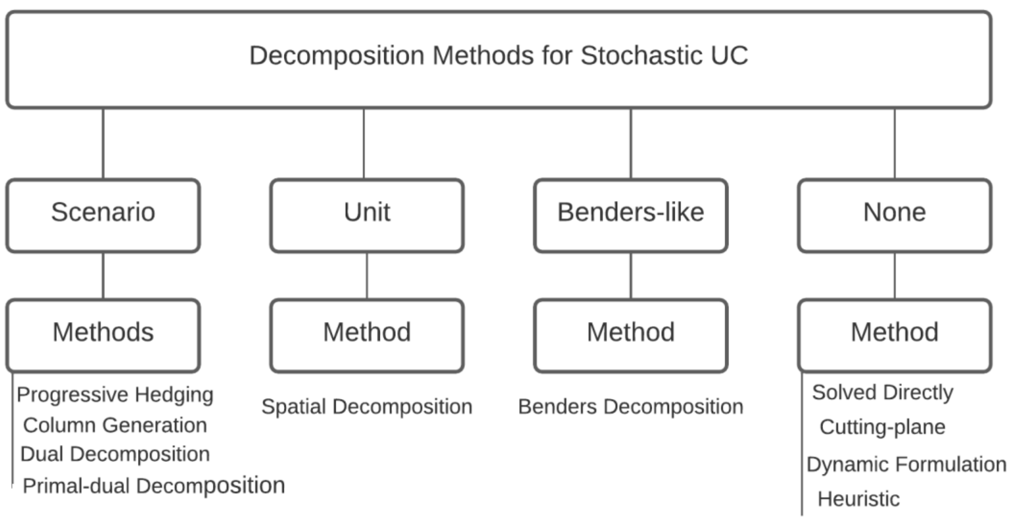

Figure 2.24. Decomposition Methods for Stochastic UC

Table 2.4 Literature Survey on Stochastic UC

Researcher	Decomposition	Method Used	Two-Stage/Multi-Stage
Kim K et al. [77]	Scenario-Based	Dual Decomposition	Two-Stage
Aravena I et al. [78]	Scenario-Based	Dual Decomposition	Two-Stage
Papavasiliou A. et al. [79]	Scenario-Based	Dual Decomposition	Two-Stage
Scuzziato MR et al. [80]	Scenario-Based	Dual Decomposition	Two-Stage
Feng Y et al. [81]	Scenario-Based	Progressive hedging	Two-Stage
Gade D et al. [82]	Scenario-Based	Progressive hedging	Two-Stage
Cheung K et al. [83]	Scenario-Based	Progressive hedging	Two-Stage
Rachunok B et al. [84]	Scenario-Based	Progressive hedging	Two-Stage
van Ackooij W et al. [85]	Scenario-Based	Primal-dual decomposition	Two-Stage
Schulze T et al. [86]	Scenario Based	Column generation	Multi-Stage
Nasri A et al. [87]	Benders-like	Benders decomposition	Two-Stage
Mehrtash M et al. [88]	Benders-like	Benders decomposition	Two-Stage
Vatanpour M et al. [89]	Benders-like	Benders decomposition	Two-Stage
Lopez-Salgado CJ et al. [90]	Benders-like	Benders decomposition	Two-Stage
Asensio M et al. [91]	None	Solved Directly	Two-Stage
Abbaspourtorbati F et al. [92]	None	Solved Directly	Two-Stage

Researcher	Decomposition	Method Used	Two-Stage/Multi-Stage
Uckun C et al. [93]	None	Solved Directly	Two-Stage
Bakirtzis EA et al. [94]	None	Solved Directly	Two-Stage
Valinejad J et al. [95]	None	Solved Directly	Two-Stage
Gomes IL et al. [96]	None	Solved Directly	Two-Stage
Du E et al. [97]	None	Solved Directly	Two-Stage
Wang B et al. [98]	None	Solved Directly	Multi-Stage
Shi J et al. [99]	None	Solved Directly	Multi-Stage
Jiang R et al. [100]	None	Cutting-plane	Multi-Stage
Analui B et al. [101]	None	Dynamic formulation	Multi-Stage
Shahbazitabar M et al. [102]	None	Heuristic	Two-Stage
Wang W et al. [103]	None	Heuristic	Two-Stage
Jo KH et al. [104]	None	Heuristic	Two-Stage

Chapter 3

Research Methodology

3.1 Overview

The literature review of unit commitment (UC) and economic dispatch (ED) in thermal power stations was presented in the previous chapter. Certain research problems have been drawn based on the critical study of the UC scheduling problem and the works suggested by previous researchers, discussed in chapter 1. In this chapter 3, the methodology adopted for addressing the UC scheduling problem along with the description of algorithms used for addressing unit commitment and economic dispatch is discussed. Various variants of nature-inspired approaches [105-114] have been proposed incorporating Genetic Algorithm, Differential Evolution [115], and Whale Optimization Algorithm. Two approaches have been described here; a single-objective approach which includes total operating cost minimization and the multi-objective approach which includes the total emission minimization. Both binary commitment and continuous dispatch variables are included in UC [116-120]. However, there is no universal optimizer that can perform both binary and continuous optimization. So, it motivated us to select the Genetic Algorithm, Differential Evolution, and Whale Optimization Algorithm. In addition to this, the chapter also describes a proposed hybridized solution to the multi-objective unit commitment problem. A Whale Optimization (WO)-differential evolution (DE) and genetic algorithm (GA) based hybrid approach (WODEGA) has been proposed which will satisfy two objectives: committing the generating units to meet electricity demand and reducing overall operational costs with minimal emissions.

3.2 Pareto Optimal Solution

Concerning one objective we may find a particular solution to be optimal, but concerning another objective one may find another solution to be optimal. These solutions are called Pareto optimal solutions. Multi-objective optimization can be thought of optimization problem where there is minimizing or maximizing a set of objective functions subject to some constraints. Objective functions may be conflicting with one another.

Pareto Optimal Solutions: Let us assume that we have a set of feasible solutions and there are different objective functions. So, if one takes two such feasible solutions, then Pareto improvement can be interpreted as a situation in which at least one objective function returns a good value while no other objective function becomes worse. So, one may say that going for the first one instead of the others is a kind of Pareto improvement. Now, consider one is left with a set of feasible solutions where no further Pareto improvement can be made, then those set of feasible solutions can be called the Pareto efficient or Pareto-optimal solutions.

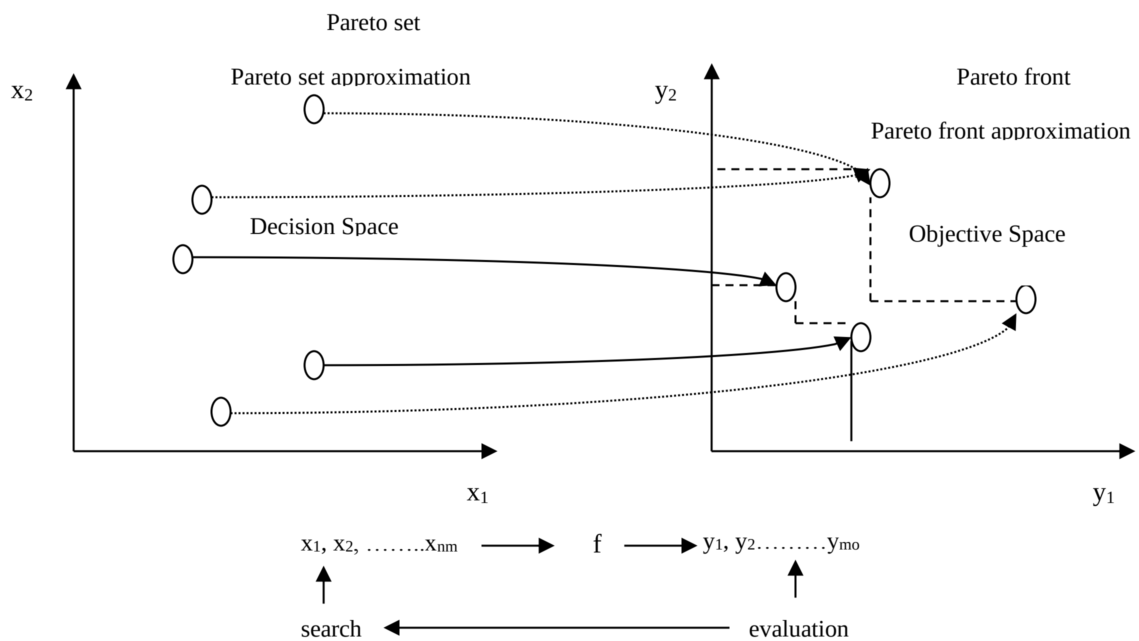

Figure 3.1. Pareto-Optimal Solution [121]

3.3 Proposed Methodology Adapted for single objective UC

Introduced a hybrid strategy to fix the UC problem, which is a mixed-integer optimization problem that is an enhancement of the hGADE algorithm. The Whale Optimization Algorithm (WOA) was used to figure out how much it costs to run a power system.

The initialization of the multiple parameters investigated in this work is the first step in the algorithm. An iterative approach is used in the algorithm. You can change the number of iterations to fit your needs. The working of the proposed approach is given below:

1. $GD = Take\ generator\ Data$
2. $Extract\ the\ Max\ Power\left(Ma_p\right)\ and\ \ Min\ Power\left(Mi_p\right)\ from\ GD$
3. $Power_{Difference} = Ma_p - Mi_p$
4. $Extract\ the\ Up\ and\ Down\ Time$
5. $For_{each} gen\ in\ Generation\ Compute\ Avg_{Cost_{Generator}}$
6. $Apply\ Genetic\ Algorithm\ keeping\ Average_{Cost_{Generator}} as\ main\ parameter$
7. $Generator\ Population$
8. $Evaluate\ Fitness\ over\ given\ Fitness\ Function\ using\ \frac{CrossoverRate}{Mutation\ Value}$

$$\begin{array}{lll} 0 & Otherwise & \\ 1 & if & (1-(\frac{e}{max(Fs)}) \times ramprate < Ft \end{array}$$

$$where\ Fs = Current\ Generator\ Cost$$

$$Ft = Average\ Generator\ Cost$$

9. Differential Evolution Computation with a Similar Fitness Function and a Separate Mutation and Crossover Rate is used.

$$\begin{array}{lll} 0 & Otherwise & \\ 1 & if & (Fs \times \frac{ramprate}{e}) < (\frac{Ft}{e}) \end{array}$$

$$where\ Fs = Current\ Generator\ Cost$$

$$Ft = Average\ Generator\ Cost$$

10. $For\ each\ value\ of\ mutation\ in\ list$
11. $Whale\ Prey\ =\ Mutation\ value$
12. If fitness function is fulfilled for prey in the Prey Group, hold the prey value with the same mutation value.
13. If the fitness function is not met, Prey Value should be updated with the average prey value.

$$Optimal_{Whales} = Initialize\ optimal\ whales\ to\ null$$

$$Food_{Change} = Radical$$

$$Fo\ all\ whales\ in\ Whale_{Group}$$

$$1\ \ If\ Whale_{Food_{Current}} \times Food_{Change} < Prey_{Food_{Threshold}} \times Prey_{Food_{Change}}$$

$$0\ \ Otherwise$$

14. Evaluate and Compare Parameters

3.4 Proposed Methodology Adapted for multi-objective UC

Due to global warming and environmental change, greenhouse gas emissions from electricity generation, in particular, have been a major concern over the past few years, thus committing the generating units to the minimum cost criterion is moving towards minimizing the cost with minimal emissions. So we have incorporated the minimization of emissions along with operational cost. The working of the proposed approach is given below:

1. $For_{each} output_{Vector}\ in\ GA_{Output}$
2. $Initialize\ Neural_{network} with\ n\ number\ of\ neurons$
3. $Total_{propagation}.Iteration = 100$
4. $Satisfy\ Training_{Behaviour}$
5. $Classified = Classify\ Test_{Data}$
    a. $If\ Classified.Label\ does\ not\ match\ with\ training\ label$
6. $Non_{Classified} ++$
7. $Load\ Emmision_{Rate}(Emmision_{Value})$
8. $Append\ Emmision\ to\ output_{Vector}$
9. $Initialize\ Multi_{Objective}\ Proportion$
10. $Whale_{Input} = NonSatisfied.Label \longrightarrow Attribute\ Set$
11. $DatatoLook = Whale_{Input}$
12. $For_{each}\ WI\ in\ Whale_{Input}$
13. $Current_{Prey} = WI$
14. $Other_{Prey}\ Value = Whale_{Input}(\sim WI)$

15. $Whale_{Value=}ApplyWhale\ Fitness(WI, Other_{Prey})$

16. $Replace\ GA_{Output}\ by\ Prey\ Output$

17. $End\ Algorithm$

Pseudocode for calculating Whale Fitness in multi-objective optimization:

1. $Initiate\ Total_{Simulations} = 10$
2. $Initialize\ fnf\ as\ zeros\ (Total_{Simulations})$
3. $For_{each} sm\ in\ Total_{Simulations}$
4. $Selection\ random\ prey\ Population$
5. $R = Select\ random\ population\ from\ prey\ population$
6. $Op = Other_{Prey_{Value}}(R)$
7. $Value_{To_{Check}} = Current_{Whale_{Prey}}$
8. $k1 = (Value_{to_{Check}} - \frac{\sum_{i=1}^{n} Prey_{Food_{Value}})/n}{Op}$
9. $k2 = \frac{\frac{\sum_{i=1}^{n} Prey_{Value}}{n}}{\sum_{j=1}^{k} \frac{Op}{n}}$
10. $if\ k1 < k2$
11. $fnf.append(0)$
12. $Else$
13. $fnf.append(1)$
14. End_{For}
15. $Find\ f1 = (fnf\ == 0)$
16. $Find\ f2 = (fnf\ == 1)$
17. $If\ f1 < f2$
18. $Apply\ Critic\ Method\ to\ Neutralize$
19. $Stop$

The working of the hGADE algorithm is presented in Figure 3.2. The modified hGADE algorithm is presented in Figure 3.3. The proposed algorithm which makes use of the Whale Optimization Algorithm for minimization of operation cost is shown in Figure 3.4. The proposed methodology for solving multi-objective UC is shown in Figure 3.5.

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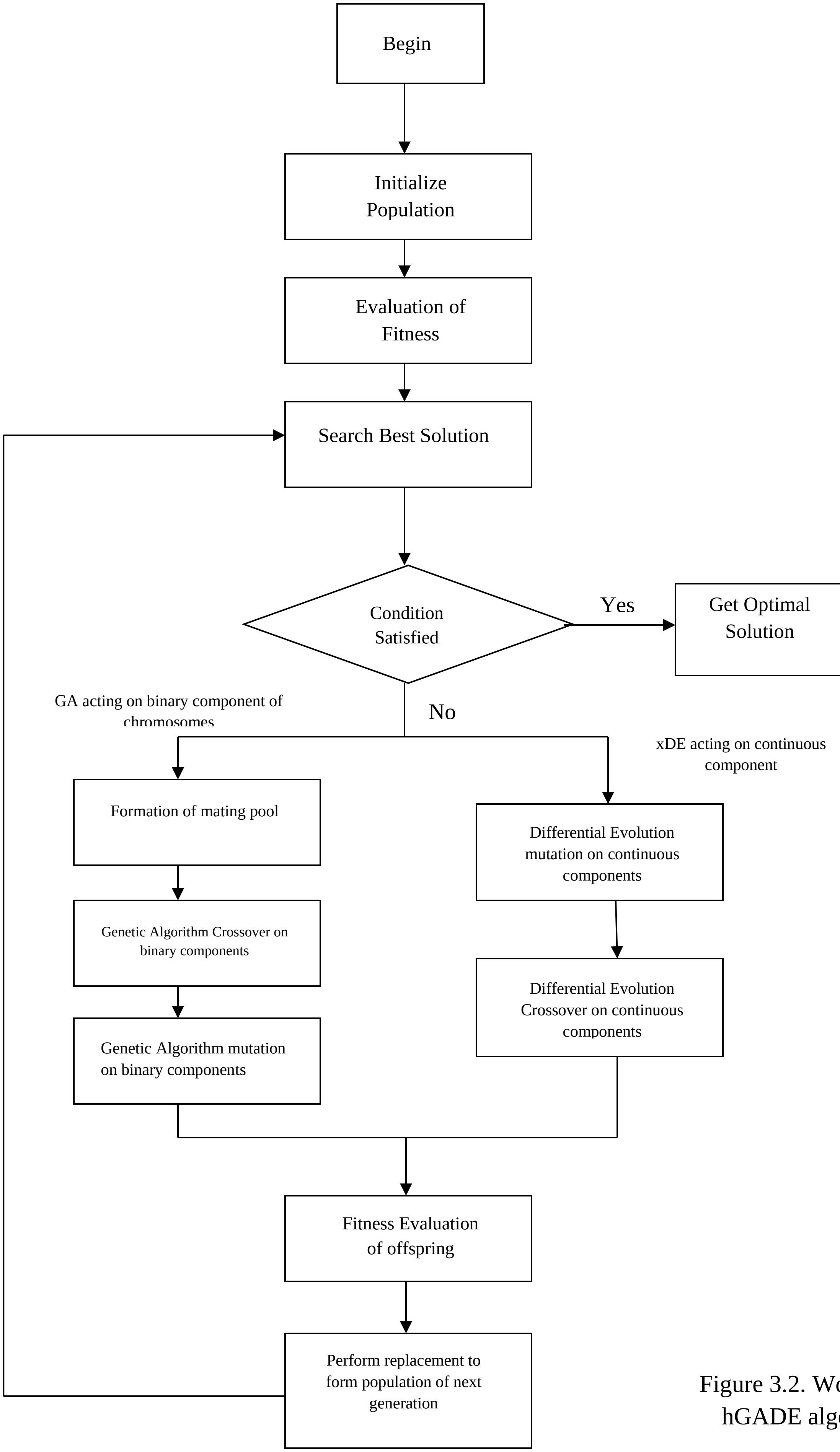

Figure 3.2. Working of hGADE algorithm

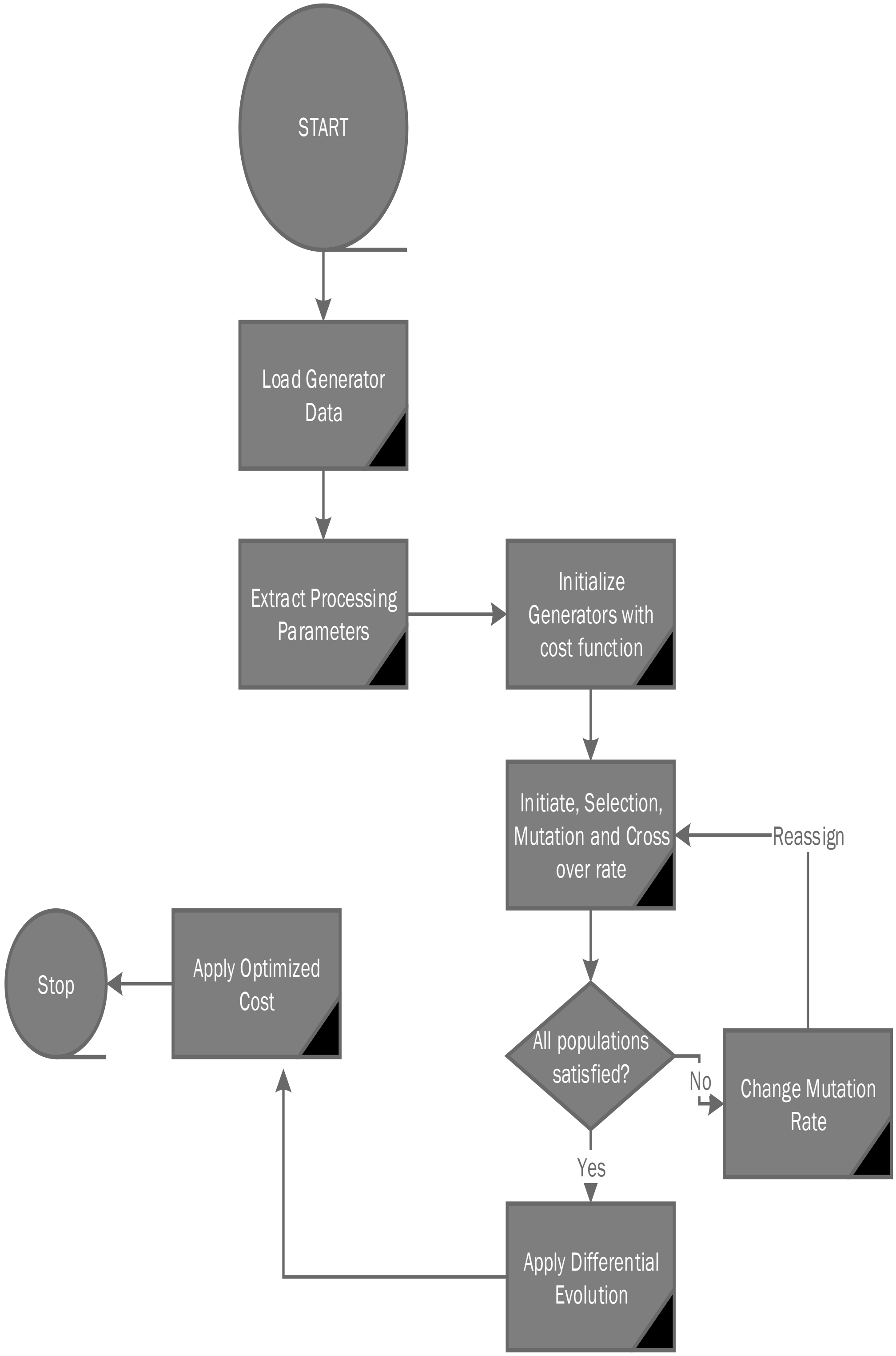

Figure 3.3 Modified hGADE algorithm

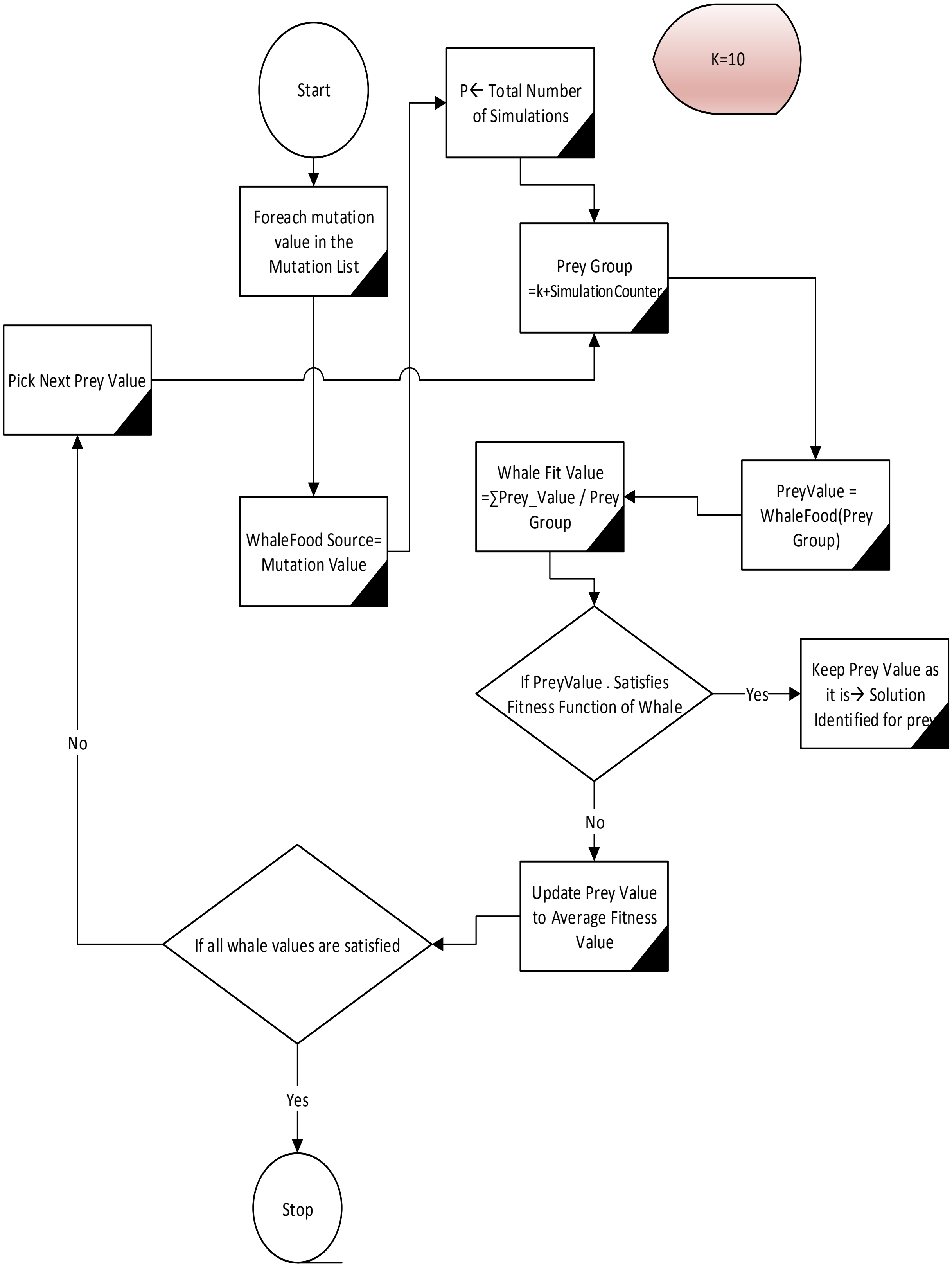

Figure 3.4 Working of proposed approach (single objective)

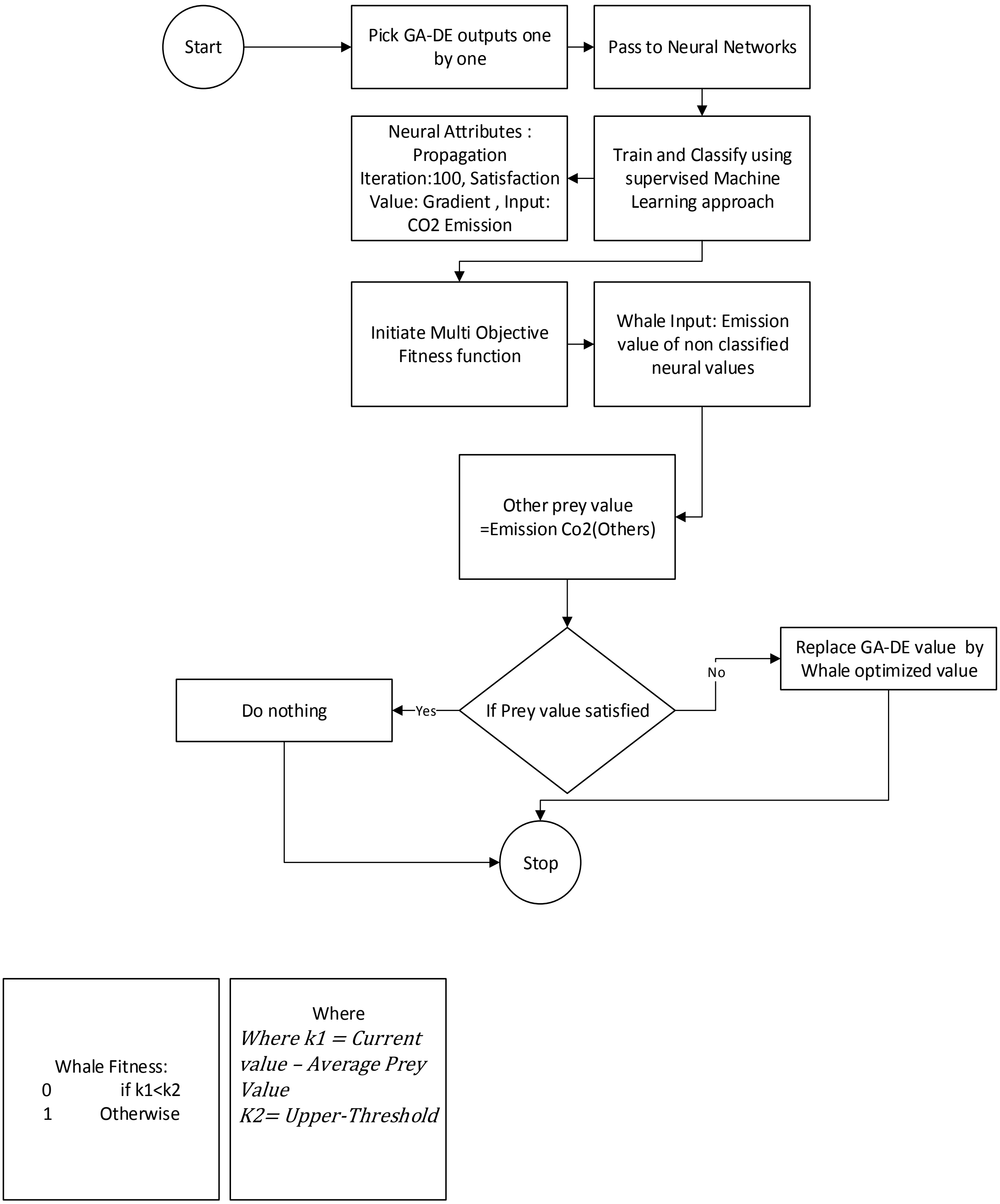

Figure 3.5 Working of proposed approach (multi objective)

Diagrammatical representation and flow chart of the proposed approach to solve multi-objective UC is shown below (Figure 3.6 and Figure 3.7 respectively)

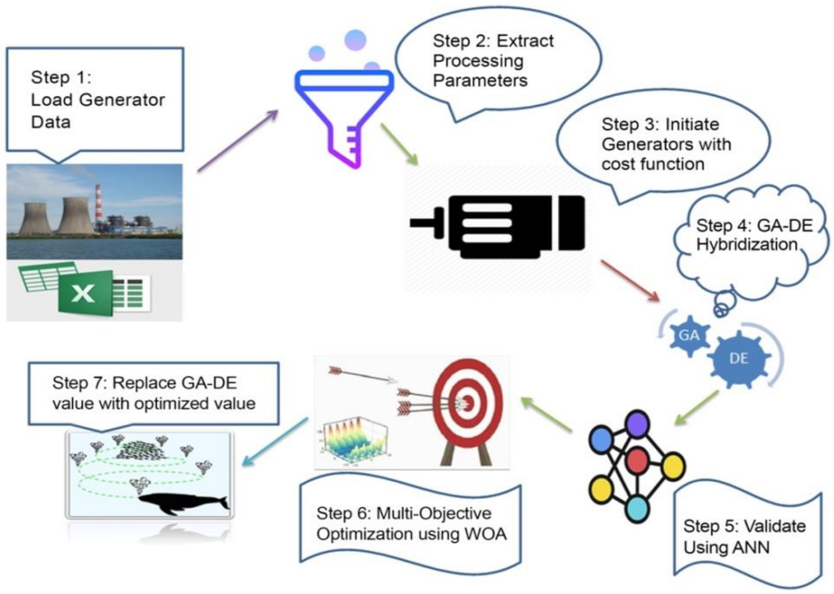

Figure 3.6 Diagrammatical representation of proposed approach (multi objective)

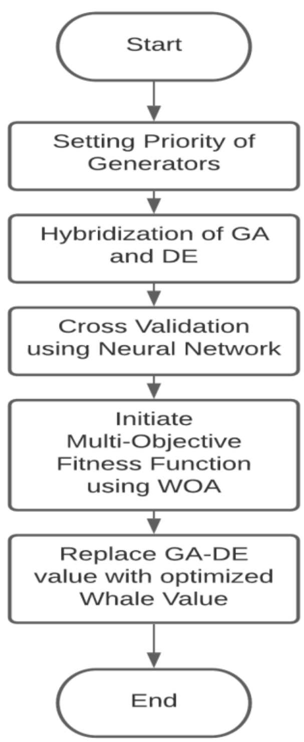

Figure 3.7 Flowchart of the proposed approach (multi-objective)

3.5 Inspiration behind GA and DE selection

While GA is capable of successfully managing binary variables [122], DE's performance is superior in real-world parameter optimization [123-130]. It inspired our decision to use differential evolution (DE) and a genetic algorithm (GA). Other factors contribute to GA's effectiveness as a global optimization method:

1) GA operates in a parallelized manner. It can simultaneously explore the solution's space in multiple directions.
2) GA has no idea what problems they've been sent to solve.
3) GA has proven to be successful in escaping local minima.
4) Perform well in situations involving a noisy fitness function, multiple local optima, or changes over time.

DE functions well for continuous variables, as already mentioned. Furthermore, it is one of the most common optimization tools that emerged for the following reasons:

1) To make it quick to execute, DE uses only a few control parameters.
2) DE is capable of locating true global minima.
3) DE has the potential to rapidly converge.

3.6 Inspiration behind WOA selection

The Whale Optimization Algorithm, or WOA, was introduced by Mirjalili and Lewis in 2016. Whales' unique hunting mechanism is the most interesting feature of them that motivates us to use WOA to solve the UC dilemma.

3.7 Role of Neural Networks

Neural Networks have numerous application areas. In our research work, it has been used for data validation. The neural networks play a significant role in cross-validation to check the optimality of an optimization algorithm.

The network is trained using nntraintool. It's very straightforward. Train, Validation, Test, and Best are the four lines that decide success measurement. The best line (dotted line) indicates that other lines should lie on or close this line, suggesting that training was successful. Convergence has occurred if either of the three lines (Training, Validation, and Testing) reach or move near the optimal (dotted) line; if not, the network should be retrained.

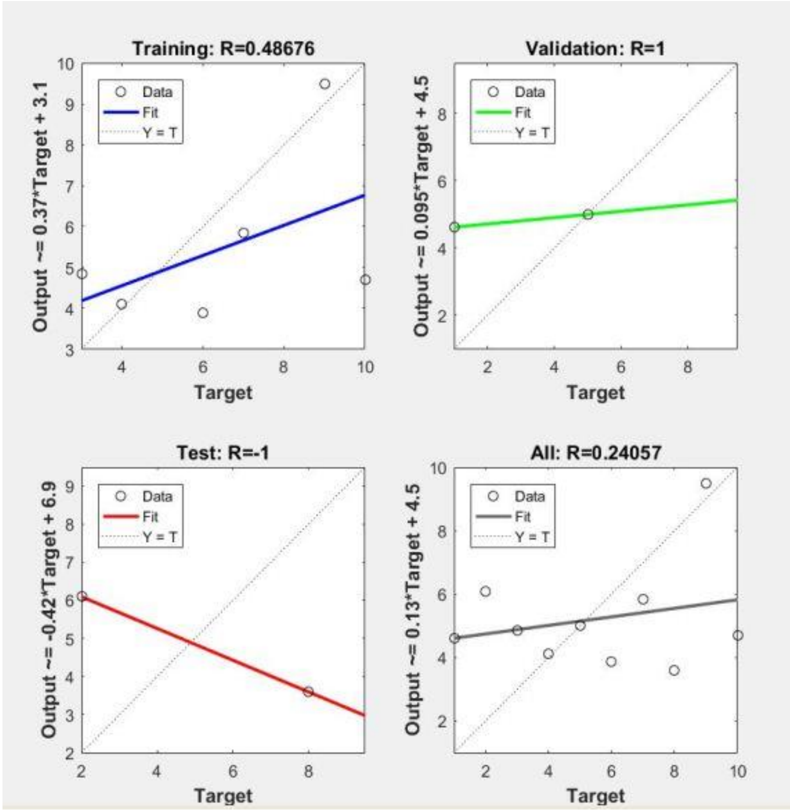

Figure 3.8 Cross-Validation using neural network

In the neural network terminology:

- Across all of the training instances, one epoch equals one forward as well as a backward pass.
- Batch size is the number of training examples in a single forward/backward pass. One will need more memory space as the batch size increases.
- The number of iterations refers to the number of passes, with each pass containing [batch size] instances. To explain, one pass is the total of one forward and one backward pass.

The cross-validation has been shown in figure 3.8. A diagrammatical representation of the neural network and nntool working is shown in figures 3.9 and 3.10 respectively.

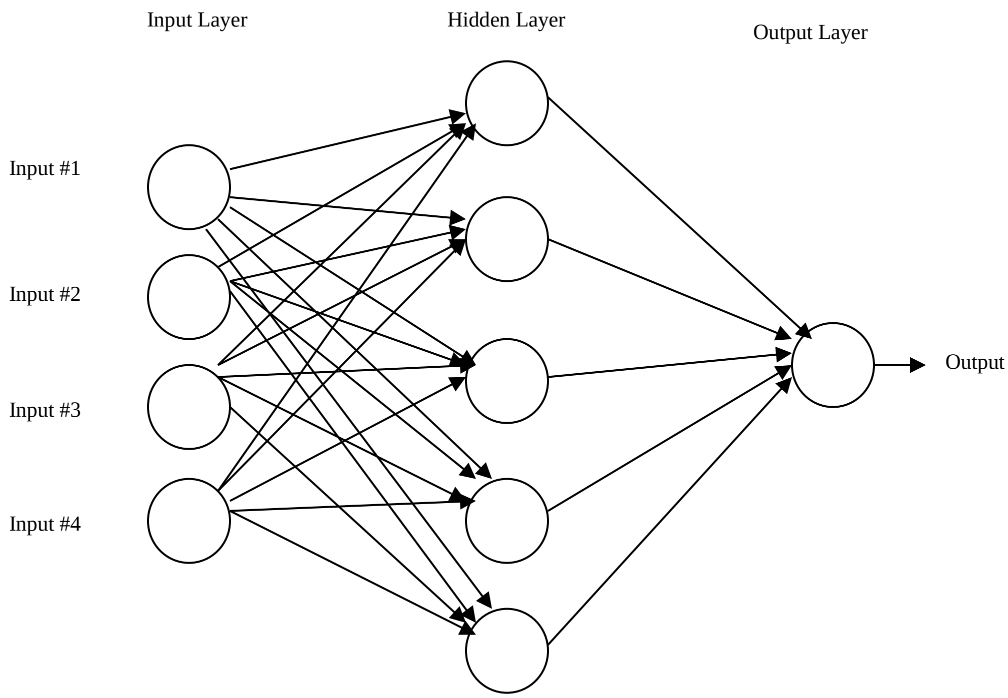

Figure 3.9 Diagrammatical representation of neural network

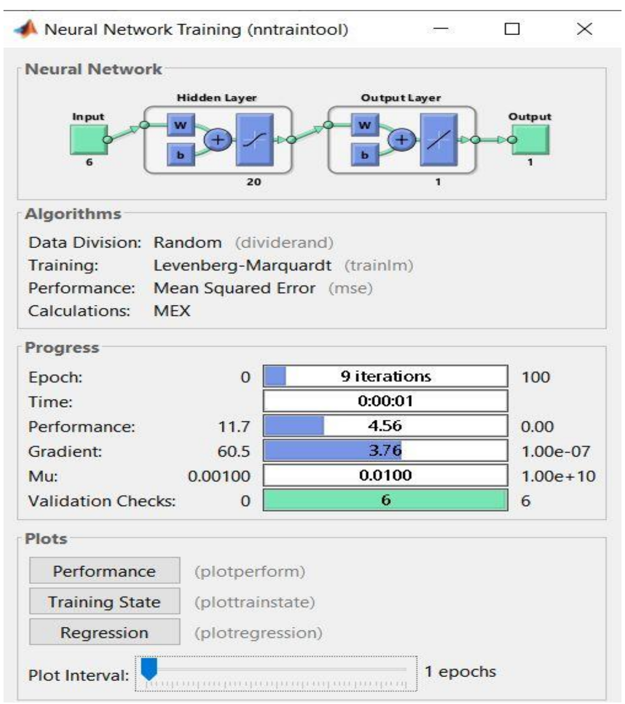

Figure 3.10 Working of nntraintool

When an entire dataset is only transmitted forward and backward through the neural network once, it is called an epoch. We split the dataset into batches because we can't feed an entire dataset into a neural network at once. Batch size is the number of training examples in a single batch. Iteration refers to the number of batches needed to complete one epoch. For example: when a dataset of 200 examples is divided into batches of size 50, it takes 4 iterations to complete one epoch. So here, 50 is the batch size and 4 is the number of iterations. Epoch and batch size are important hyperparameters that affect the performance of the neural network and deep learning models.

3.8 The Multiple Criteria Decision Making (MCDM)

Experts nowadays use a range of analytical and scientific approaches to select the best choice among many alternatives. Experiences can only be useful in a particular field and cannot be applied uniformly to all decision-making situations. Using a scientific method, on the other hand, is accurate and efficient in evaluating the best alternative in any case, regardless of the context is examined. Many experts consider Multiple Criteria Decision Making (MCDM) to be one of the most relevant scientific methods. The available methods in MADM are shown in figure 3.11.

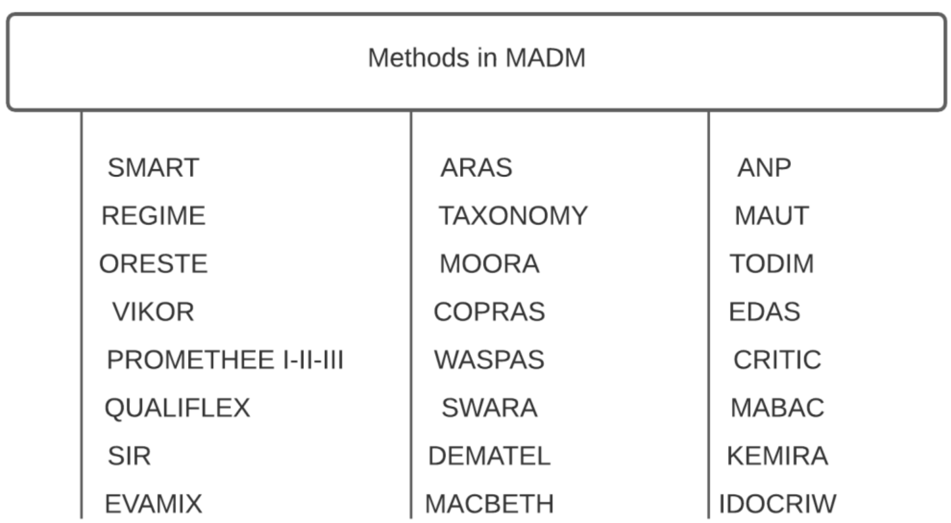

Figure 3.11 Methods in MADM [131]

3.8.1 Critic Method

The problem's complexity arises from the existence of more than one criterion. Diakoulaki, Mavrotas, and Papayannakis suggested the CRITIC form, which is specifically used to assess the weight of attributes. The CRiteria Importance Through Intercriteria Correlation (CRITIC) method has been taken into consideration as it is one of the significant methods in Multiple Attribute in Decision Making (MADM). It is used because both the objectives (overall operation cost and emissions) are not contradictory as both need to be reduced.

The CRITIC approach also has the following characteristics.

- No need for attributes to be independent.
- Qualitative characteristics are translated to quantitative characteristics.

This method has been applied to normalize the values of the decision matrix (equation 3.1).

$$X = \begin{bmatrix} r_{11} & \cdots & r_{ij} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r_{i1} & \cdots & r_{ij} & \cdots & r_{in} \\ \vdots & \ddots & \vdots & \ddots & \ddots \\ r_{m1} & \cdots & r_{mj} & \cdots & r_{mn} \end{bmatrix} \tag{3.1}$$

$$i = 1, \ldots., m, j = 1, \ldots., n$$

where r_{ij} represents the element of the decision matrix.

The normalized decision matrix

Eq. 3.2 and eq. 3.3 are used to normalize the positive attributes and negative attributes of the decision matrix.

$$x_{ij} = \frac{r_{ij} - r_i^-}{r_i^+ - r_i^-} \; ; i = 1, \ldots., m, j = 1, \ldots., n \tag{3.2}$$

$$x_{ij} = \frac{r_{ij} - r_i^+}{r_i^- - r_i^+} \; ; i = 1, \ldots., m, j = 1, \ldots., n \tag{3.3}$$

where x_{ij} indicates the normalized value of the decision matrix.

$$r_i^+ = \max(r_1, r_2, \ldots\ldots, r_m) \tag{3.4}$$

$$r_i^- = \min(r_1, r_2, \ldots\ldots, r_m) \tag{3.5}$$

Equations 3.4 and 3.5 have been used, respectively, to normalize the positive and negative properties of the decision matrix.

The steps of the CRITIC method are written below.

1. The Correlation Coefficient

Equation 3.6 determines the correlation coefficient among attributes. $\bar{x}_j$ is computed from equation 3.7. In the same way value of $\bar{x}_k$ is computed.

$$\rho_{jk} = \sum_{i=1}^{m}(x_{ij} - \bar{x}_j)(x_{ik} - \bar{x}_k) / \sqrt{\sum_{i=1}^{m}(x_{ij} - \bar{x}_j)^2 \sum_{i=1}^{m}(x_{ik} - \bar{x}_k)^2} \tag{3.6}$$

$$\bar{x}_j = \frac{1}{n}\sum_{j=1}^{n} x_{ij} \tag{3.7}$$

2. The Index (C)

Firstly, Equation 3.8 estimates the standard deviation of every attribute. Equation 3.9 is then used to determine the index (C).

$$\sigma_j = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}\left(x_{ij} - \bar{x}_j\right)} \quad i = 1, \dots, m \tag{3.8}$$

$$C_j = \sigma_j \sum_{k=1}^{n}(1 - \rho_{jk}); \quad j = 1, \dots, n \tag{3.9}$$

3. The Weight of Attributes

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \quad j = 1, \dots, n \tag{3.10}$$

4. The Final Ranking of Attributes

The working of CRITIC method is shown in figure 3.12

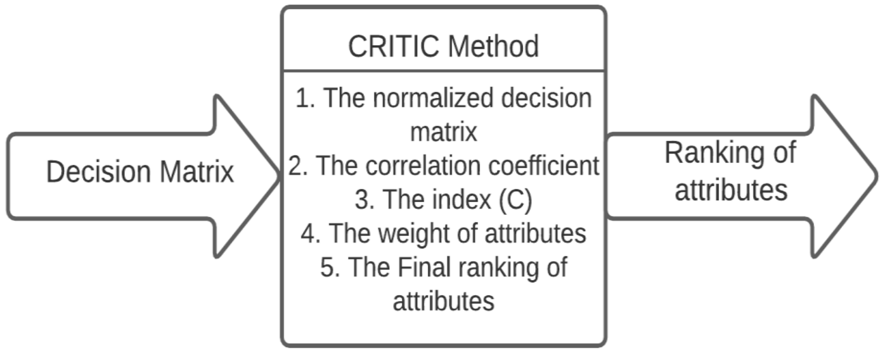

Figure 3.12 Working of CRITIC Method

Chapter 4

Experimental Analysis

4.1 Overview

In the previous chapter, the methodology used in addressing the unit commitment and economic dispatch is illustrated. This chapter describes the experimental environment required for implementing the methods proposed in the previous chapter. In this chapter, the data sources along with the description of datasets used in the research work are described. Moreover, the programming techniques and tools used are also being discussed. MATLAB has been used for implementing the similarity algorithm. Moreover, the results obtained after processing the real-time datasets have been illustrated and evaluated using state-of-the-art performance parameters.

4.2 Experimental Environment

The experiments for providing solutions to unit commitment and economic dispatch have been carried out using MATLAB, developed by Mathworks. It has been developed in the C/C++ language. In all branches of electrical engineering, MATLAB has been used to test and evaluate various circuits and controllers, as well as to easily implement various types of power systems and control structures in power engineering applications. The algorithm is tested by running on a PC with configuration Intel Core i5 3.30GHz 16GB RAM.

4.3 Input Data

For our research, data has been collected from thermal plants including Guru Gobind Singh Super Thermal Power Plant, JCT Phagwara, and Guru Hargobind Thermal Plant. Table 4.1 displays the input data for the 6-unit system, which contains cost coefficient values, minimum up costs, minimum down costs, and startup costs. Table 4.2 shows the load pattern. Table 4.3 and 4.4 display the input data for the 100-unit system and parameter setting respectively.

Here a,b,c denotes Cost Coefficients

Pmin stands for the power unit's minimum output power.

Pmax stands for the power unit's maximum output power.

Min. Up denotes the minimum uptime of the power unit.

Min. Down denotes maximum downtime of the power unit.

Startup Cost denotes the startup cost in firing up a unit includes hot startup and cold startup.

Ramp Rate (up/down) denotes that to avoid destroying the turbine, the output power of a generator cannot vary by more than a definite number over some time.

Table 4.1. Input Data

Unit	a (INR/hr.)	b (INR/MW hr.)	c (INR/MW^2 hr.)	P min (MW)	P max (MW)	Min. up (hours)	Min. Down (hours)	Startup Cost (INR)	Ramp Up (MW/hr)	Ramp Down (MW/hr)
1	0.00375	2	200	200	50	3	1	176	130	130
2	0.0175	1.75	257	80	20	2	2	187	130	130
3	0.0625	1	300	40	15	3	1	113	90	90
4	0.00834	3.25	400	35	10	3	2	267	60	60
5	0.025	3	515	30	10	2	1	180	60	60
6	0.05	3	515	25	12	3	1	113	40	40

Table 4.2. Load Pattern (Input)

Hour	Hour-1	Hour-2	Hour-3	Hour-4	Hour-5	Hour-6	Hour-7	Hour-8
Load (MW)	140	166	180	196	220	240	267	283.4

Hour	Hour-9	Hour-10	Hour-11	Hour-12	Hour-13	Hour-14	Hour-15	Hour-16
Load (MW)	308	323	340	350	300	267	220	196

Hour	Hour-17	Hour-18	Hour-19	Hour-20	Hour-21	Hour-22	Hour-23	Hour-24
Load (MW)	220	240	267	300	267	235	196	166

Table 4.3. Input Data (100 Units)

Unit	A	b	C	P_MAX	P_MIN	Min_Up	Min_Down	Start Up Cost
1	0.00375	2	200	200	50	3	1	176
2	0.0175	1.75	257	80	20	2	2	187
3	0.0625	1	300	40	15	3	1	113
4	0.00834	3.25	400	35	10	3	2	267
5	0.025	3	515	30	10	2	1	180
6	0.05	3	515	25	12	3	1	113
7	0.005383	1.25	447	47	11	2	1	180
8	0.028857	2.25	297	48	7	3	2	124
9	0.028284	2.25	220	3	18	2	1	104
10	0.005382	4.25	221	55	11	3	1	16
11	0.045635	1.25	369	4	19	3	2	103
12	0.02409	2.25	379	99	7	3	1	119
13	0.04306	3.25	131	9	9	3	1	91
14	0.06522	3.25	154	40	18	3	1	152
15	0.029093	2.25	3	37	9	1	1	49
16	0.093668	4.25	199	48	11	2	1	198
17	0.018368	4.25	16	33	15	3	1	190
18	0.054327	2.25	289	92	18	2	1	62
19	0.005531	3.25	66	36	8	4	1	169
20	0.028807	2.25	244	73	4	1	2	119
21	0.03044	4.25	448	19	1	3	2	24
22	0.003902	3.25	302	52	1	3	2	175
23	0.011328	2.25	121	56	12	1	2	159
24	0.078109	2.25	27	71	20	1	1	183
25	0.048166	4.25	405	19	5	1	1	155
26	0.051106	1.25	495	50	7	1	1	115
27	0.075099	1.25	178	14	17	1	1	1
28	0.080191	2.25	269	87	14	3	1	110
29	0.095988	3.25	404	98	18	1	1	90
30	0.001379	2.25	476	25	8	2	2	165
31	0.0453	2.25	463	74	15	4	1	158
32	0.045217	4.25	195	74	20	2	1	41
33	0.03234	1.25	188	33	7	3	1	104

34	0.077431	1.25	313	35	7	2	2	40
35	0.067245	4.25	100	30	10	4	1	55
36	0.053396	3.25	206	1	14	2	1	13
37	0.035858	2.25	102	81	8	1	1	155
38	0.01653	4.25	160	33	4	3	1	190
39	0.015821	2.25	344	14	10	3	2	146
40	0.074985	2.25	120	52	4	3	1	163
41	0.079388	2.25	155	69	20	3	2	141
42	0.059534	3.25	248	87	1	4	1	109
43	0.040297	1.25	362	61	16	2	2	115
44	0.094403	4.25	254	79	9	3	1	195
45	0.027821	1.25	376	83	18	1	2	108
46	0.046329	3.25	476	8	14	1	1	54
47	0.083251	4.25	325	70	19	3	1	76
48	0.063458	2.25	204	37	9	2	2	41
49	0.03386	3.25	243	26	12	4	1	88
50	0.008426	3.25	270	77	5	2	1	172
51	0.066084	2.25	174	25	19	1	1	72
52	0.074163	3.25	350	1	7	4	1	119
53	0.02978	1.25	194	82	20	3	1	68
54	0.023613	2.25	492	55	15	3	1	181
55	0.010512	3.25	365	72	3	2	1	106
56	0.085972	3.25	403	53	19	1	1	56
57	0.04809	3.25	104	61	7	4	1	20
58	0.095912	1.25	76	16	2	2	1	166
59	0.079024	3.25	236	71	19	2	1	158
60	0.023639	2.25	232	62	12	1	1	57
61	0.073573	2.25	414	94	8	1	1	150
62	0.032024	2.25	111	94	10	2	1	19
63	0.006017	3.25	386	20	18	3	1	198
64	0.003369	2.25	245	58	2	3	1	111
65	0.071203	2.25	309	21	13	2	1	76
66	0.026286	2.25	311	52	8	1	2	172
67	0.028394	3.25	390	95	18	2	1	159
68	0.011382	1.25	178	85	12	2	2	115
69	0.000998	3.25	304	48	5	1	1	45

70	0.00486	2.25	129	20	12	3	2	160
71	0.070811	4.25	391	20	20	1	1	43
72	0.024387	2.25	99	51	19	2	1	121
73	0.071464	2.25	429	92	15	1	2	29
74	0.050455	3.25	352	38	15	4	1	28
75	0.086306	2.25	206	96	15	4	1	19
76	0.038458	3.25	285	98	10	2	2	52
77	0.066532	4.25	336	30	11	1	2	81
78	0.030121	4.25	230	29	2	2	1	15
79	0.058056	2.25	181	72	17	1	2	191
80	0.020604	3.25	308	92	12	3	1	77
81	0.02515	1.25	236	65	6	2	1	60
82	0.065047	4.25	431	21	8	4	1	193
83	0.061916	1.25	413	66	11	1	1	47
84	0.036111	3.25	493	21	15	4	1	32
85	0.081092	2.25	58	88	13	1	2	7
86	0.003975	4.25	343	38	10	3	1	145
87	0.070133	2.25	291	34	3	2	2	45
88	0.036101	2.25	42	51	17	4	1	77
89	0.029802	3.25	440	92	2	2	1	51
90	0.088396	2.25	61	54	6	2	2	168
91	0.068024	2.25	321	21	12	3	1	69
92	0.03644	2.25	398	49	7	3	1	169
93	0.081653	4.25	185	38	17	2	1	139
94	0.096092	3.25	318	57	19	3	1	36
95	0.02435	3.25	100	98	14	1	2	182
96	0.096166	3.25	281	18	10	2	1	99
97	0.053512	2.25	312	3	6	2	1	120
98	0.036193	1.25	457	64	13	3	1	168
99	0.051666	1.25	190	82	3	1	2	161
100	0.022219	4.25	32	43	8	2	1	85

Table 4.4. Parameter Setting

Parameter	Value
GA mutation rate	0.35
GA crossover rate	0.6
DE mutation rate	1
DE crossover rate	0.98

4.4 Results

The outcomes seem to be promising. Over generations, the graph (Figures 4.1 and 4.2) depicts the average cost of generators (6 and 100 units). Figure 4.3 depicts a six-unit unit commitment schedule over ten generations. Here 0 means that the unit is involved in this iteration, while 1 indicates that the unit is not taken into account when calculating the overall operating expense. The total cost of service was discovered to be 142814.9603 INR, which was decreased to 142809.8944 INR after optimization. (hGADE) (Table 4.5). Case 1 reflects the overall cost of the operation without any optimization. Case 2 illustrates the effects of optimization. When the proposed solution is used, the comparative analysis indicates that there is a substantial cost reduction.

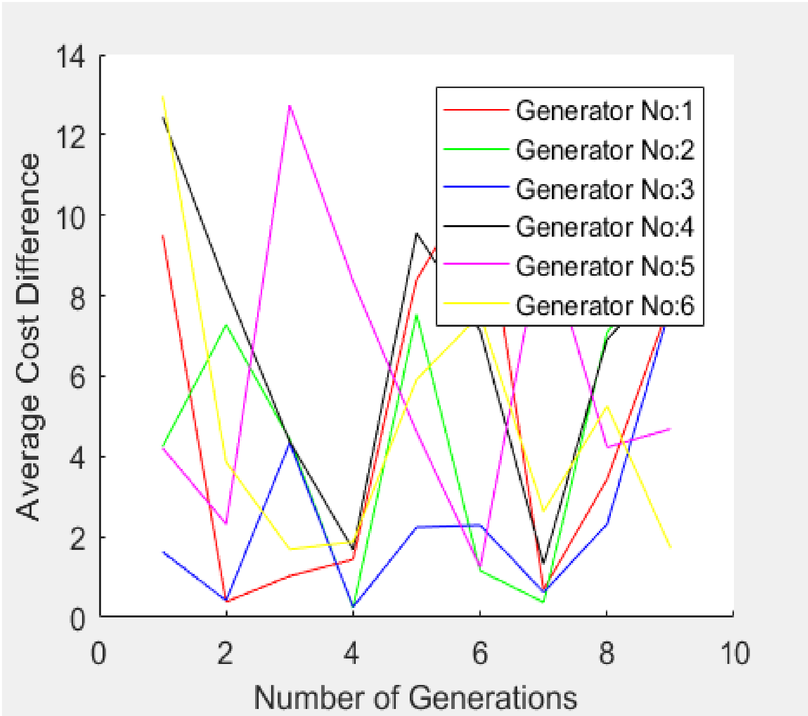

Figure 4.1 Average cost difference of generating units

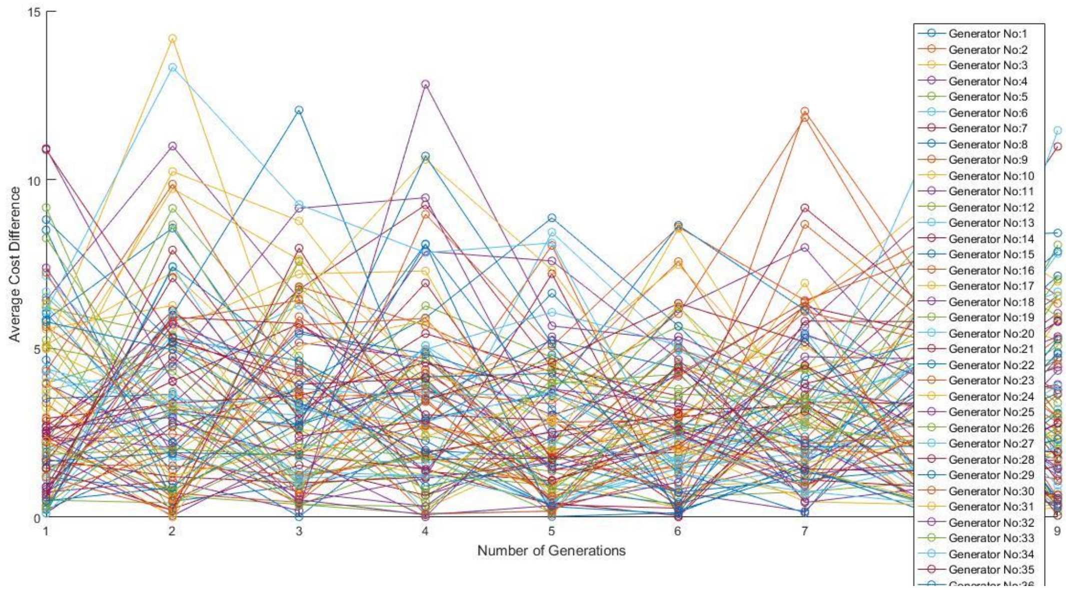

Figure 4.2 Avg. cost difference of generating units (100 units)

Generation	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6
1	0	1	0	0	1	0
2	1	1	0	0	1	1
3	1	0	1	1	0	1
4	1	1	1	0	1	1
5	1	0	0	0	1	0
6	1	0	0	0	0	0
7	0	1	1	0	1	0
8	1	1	0	0	0	0
9	1	0	0	1	0	0
10	1	1	1	0	0	1

Figure 4.3 Unit Commitment Schedule

Table 4.5. Comparative Analysis

Case	GA mutation rate	GA crossover rate	DE mutation rate	DE crossover rate	Cost
Case 1	0.35	0.60	1	0.98	142814.9603
Case 2	0.35	0.60	1	0.98	142809.8944

The slope pattern is depicted in the diagram. Since there are ten generations in this study, figure 4.4 depicts 9 slopes, as the slope is often measured as two minus one.

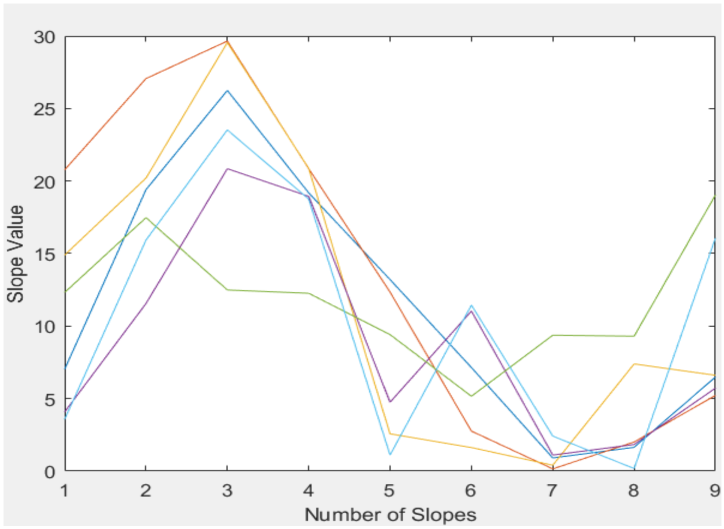

Figure 4.4 Slope pattern of generators/units

The slope needs to be linear. Either increase or decrease should be the case. The optimized result should match the previous result, which implies that if the previous data produced a linear slope, the optimized data should also produce a linear slope.

The graph (Figure 4.5) represents the relationship between the number of slopes and the Mean Square Error (MSE). Although there is no one-size-fits-all MSE value, it has been suggested that the lower the MSE, the better the model. A value that is close to zero is always the finest. Optimization is almost optimal since the value ends at zero.

The graph shows how hGADE corresponds to the suggested solution, which incorporates whale optimization. The line graph (Figure 4.6) shows three points: the initial cost, the cost after applying the GA and DE hybridization, and the final (best in terms of monetary value) cost achieved by using the WOA. The average cost of service was discovered to be 142814.9603 INR, which was reduced to 142809.8944 INR after optimization (hGADE). Following the implementation of the Whale Optimization Algorithm, the expense is further reduced to 142790.0 INR (WOA).

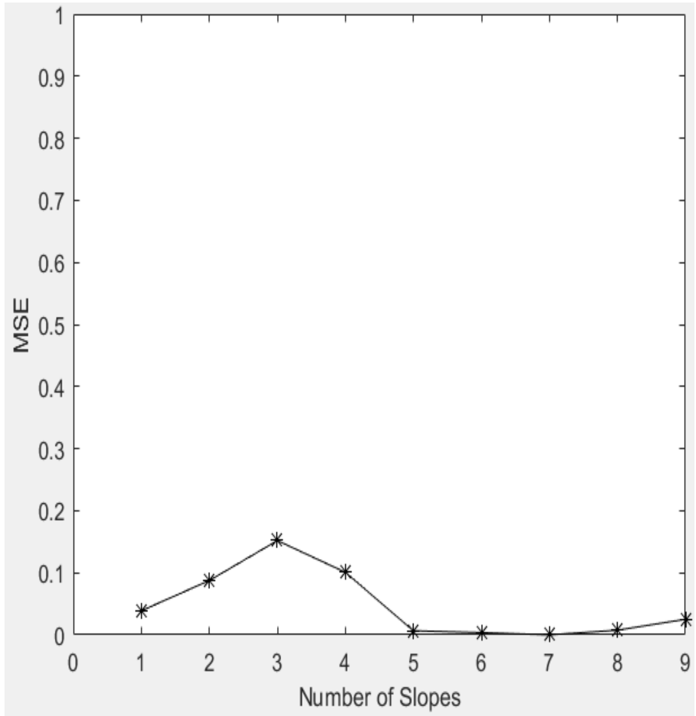

Figure 4.5 MSE value for slopes

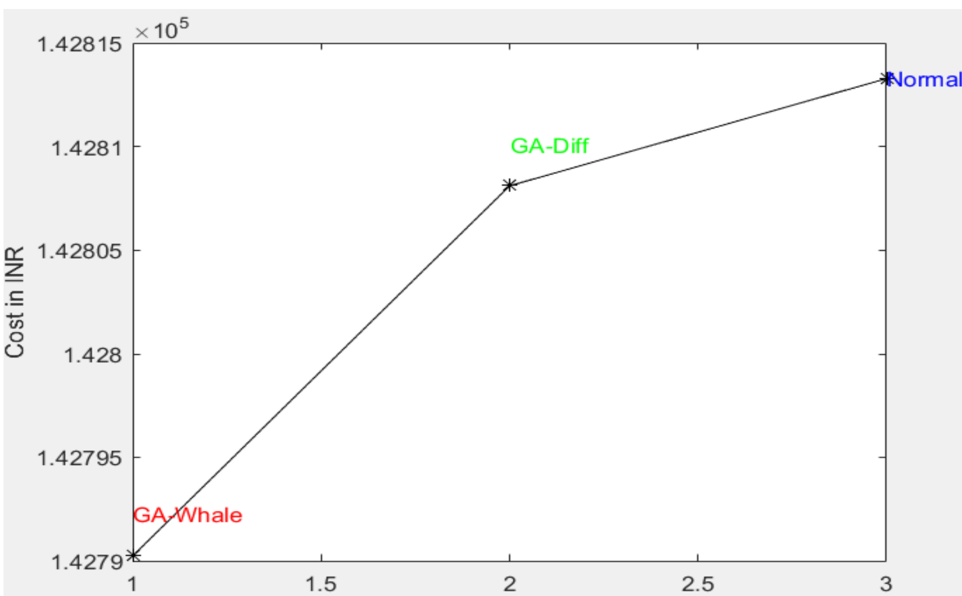

Figure 4.6 Comparison of hGADE with the proposed approach

Table 4.6 illustrates a comparison of the proposed and current methods. The data in the table clearly illustrates that the suggested solution decreases service costs dramatically. Without using any optimization techniques, the cost was estimated to be 142814.9 units. The hybridization of GA and DE reduces the operation cost even further. Then it went through the suggested solution, which resulted in the best cost-benefit.

Table 4.6 Cost Comparison

Case	GA mutation rate	GA crossover rate	DE mutation rate	DE crossover rate	Cost
Normal Cost	0.35	0.60	1	0.98	142814.9
hGADE	0.35	0.60	1	0.98	142809.8
Proposed Approach	0.35	0.60	1	0.98	142790.0

The methodology for solving UC and ED problems employs methods such as DE, GA, and WOA. The objective is to reduce the overall operational cost as well as emissions. Hence the proposed methodology will solve dual problems, thus becoming multi-objective problems.

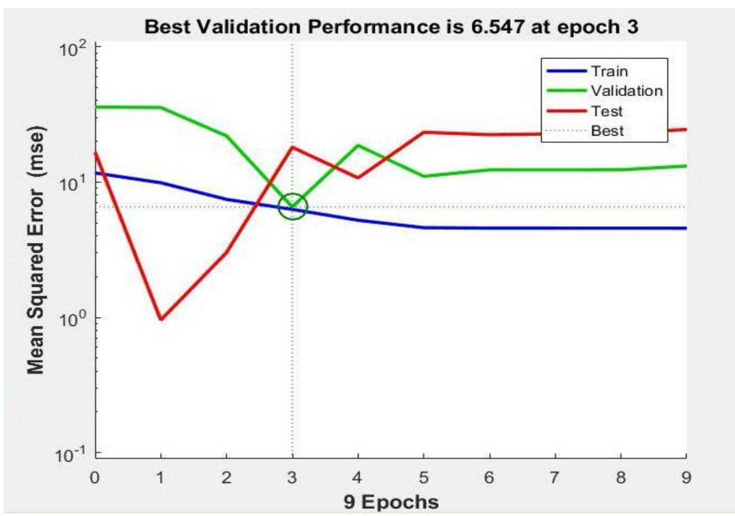

Figure 4.7 Validation performance using nntool

The results of genetic/differential evolution are fed as training data into neural networks. For the working of neural networks, 20 neurons have been taken into consideration. The number of neurons depends on input data. It helps in the propagation of data. As there are 6 generating units, there will be 6 inputs. The number of epochs is set to be 100. In terms of neural network efficiency, there are four lines: train, validation, evaluate, and best. Indeed, the best (pointed) line indicates that another line should be on or close these (pointed) lines, indicating that the training was completed successfully. If any of the three lines (Training, Validation, and Testing) reaches or approaches the best (pointed) line, convergence has occurred. The result has been shown in Figure 4.7. The training state outcome is shown in figure 4.8.

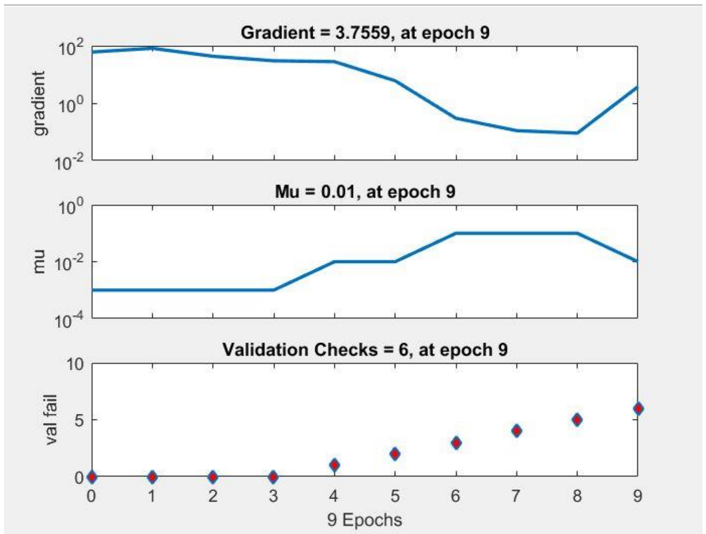

Figure 4.8 NN Training state

The load pattern (in MW) of interval 1 hour is shown in Table 4.7. The carbon emissions in pounds are shown in Table 4.8. (lb).

Table 4.7: Load Pattern

Hour	Hour-1	Hour-2	Hour-3	Hour-4	Hour-5	Hour-6	Hour-7	Hour-8
Load (MW)	140	166	180	196	220	240	267	283.4

Hour	Hour-9	Hour-10	Hour-11	Hour-12	Hour-13	Hour-14	Hour-15	Hour-16
Load (MW)	308	323	340	350	300	267	220	196

Hour	Hour-17	Hour-18	Hour-19	Hour-20	Hour-21	Hour-22	Hour-23	Hour-24
Load (MW)	220	240	267	300	267	235	196	166

Hour	Hour-25	Hour-26	Hour-27	Hour-28	Hour-29	Hour-30	Hour-31	Hour-32
Load (MW)	140	166	180	196	220	240	267	283.4

Hour	Hour-33	Hour-34	Hour-35	Hour-36	Hour-37	Hour-38	Hour-39	Hour-40
Load (MW)	308	323	340	350	300	267	220	196

Hour	Hour-41	Hour-42	Hour-43	Hour-44	Hour-45	Hour-46	Hour-47	Hour-48
Load (MW)	220	382	98	363	301	12	361	424

Hour	Hour-49	Hour-50	Hour-51	Hour-52	Hour-53	Hour-54	Hour-55	Hour-56
Load (MW)	226	383	60	349	425	383	119	97

Hour	Hour-57	Hour-58	Hour-59	Hour-60	Hour-61	Hour-62	Hour-63	Hour-64
Load (MW)	240	182	220	457	278	434	225	201

Hour	Hour-65	Hour-66	Hour-67	Hour-68	Hour-69	Hour-70	Hour-71	Hour-72
Load (MW)	355	342	203	24	40	367	301	14

Hour	Hour-73	Hour-74	Hour-75	Hour-76	Hour-77	Hour-78	Hour-79	Hour-80
Load (MW)	256	331	50	99	373	63	405	424

Hour	Hour-81	Hour-82	Hour-83	Hour-84	Hour-85	Hour-86	Hour-87	Hour-88
Load (MW)	5.86	173	77	248	46	18.0	429	446

Hour	Hour-89	Hour-90	Hour-91	Hour-92	Hour-93	Hour-94	Hour-95	Hour-96
Load (MW)	166	296	31	95	18.2	215	69	456

Hour	Hour-97	Hour-98	Hour-99	Hour-100
Load (MW)	196	439	333	267

Table 4.8 Carbon Emissions

Hour	Hour-1	Hour-2	Hour-3	Hour-4	Hour-5	Hour-6	Hour-7	Hour-8
Emission (lb)	16	18	21	17	22	24	22	29

Hour	Hour-9	Hour-10	Hour-11	Hour-12	Hour-13	Hour-14	Hour-15	Hour-16
Emission (lb)	26	25	17	28	20	21	31	31

Hour	Hour-17	Hour-18	Hour-19	Hour-20	Hour-21	Hour-22	Hour-23	Hour-24
Emission (lb)	27	23	30	22	15	19	18	23

Hour	Hour-25	Hour-26	Hour-27	Hour-28	Hour-29	Hour-30	Hour-31	Hour-32
Emission (lb)	13	13	15	31	28	26	31	32

Hour	Hour-33	Hour-34	Hour-35	Hour-36	Hour-37	Hour-38	Hour-39	Hour-40
Emission (lb)	32	15	31	23	13	18	30	29

Hour	Hour-41	Hour-42	Hour-43	Hour-44	Hour-45	Hour-46	Hour-47	Hour-48
Emission (lb)	12	25	28	17	13	17	14	22

Hour	Hour-49	Hour-50	Hour-51	Hour-52	Hour-53	Hour-54	Hour-55	Hour-56
Emission (lb)	20	20	30	20	18	13	16	17

Hour	Hour-57	Hour-58	Hour-59	Hour-60	Hour-61	Hour-62	Hour-63	Hour-64
Emission (lb)	13	26	12	24	20	17	25	18

Hour	Hour-65	Hour-66	Hour-67	Hour-68	Hour-69	Hour-70	Hour-71	Hour-72
Emission (lb)	14	23	15	30	25	29	27	28

Hour	Hour-73	Hour-74	Hour-75	Hour-76	Hour-77	Hour-78	Hour-79	Hour-80
Emission (lb)	25	26	26	18	23	29	13	22

Hour	Hour-81	Hour-82	Hour-83	Hour-84	Hour-85	Hour-86	Hour-87	Hour-88
Emission (lb)	21	30	25	32	24	29	21	23

Hour	Hour-89	Hour-90	Hour-91	Hour-92	Hour-93	Hour-94	Hour-95	Hour-96
Emission (lb)	16	25	31	23	22	28	14	30

Hour	Hour-97	Hour-98	Hour-99	Hour-100
Emission (lb)	12	22	26	23

Figure 4.9 indicates the emission rates (in-lb). Figure 4.10 indicates the graphical representation of emission rates undergoing optimization. Here asterisk (*) sign indicates the original value, the circle indicates those emission values which require optimization and the triangle indicates the prescribed emission after optimization. Figure 4.11 indicates the percentage improvement in emission. Here circles indicate the percentage value.

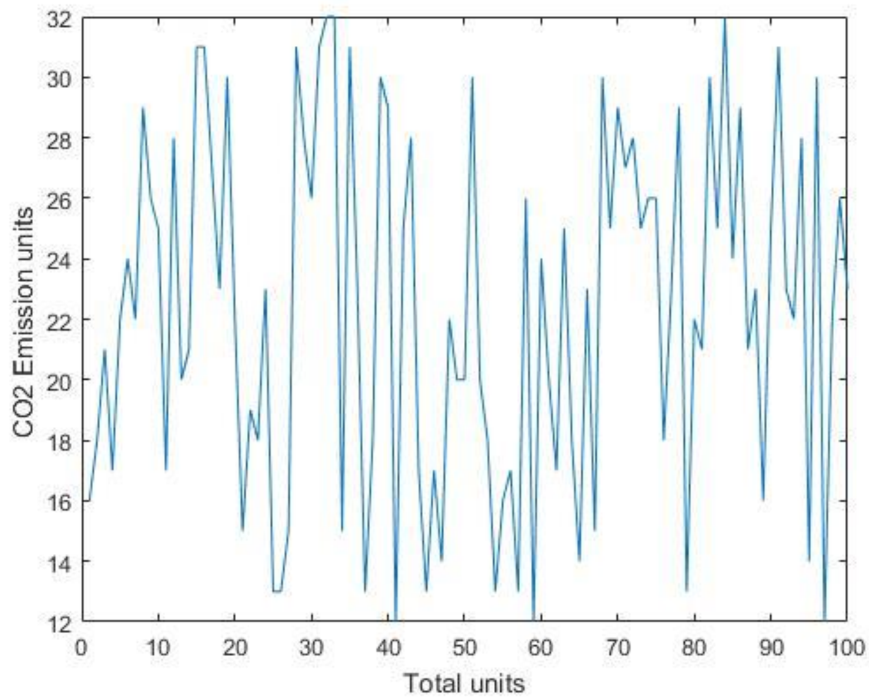

Figure 4.9 Carbon Emissions (Before Optimization)

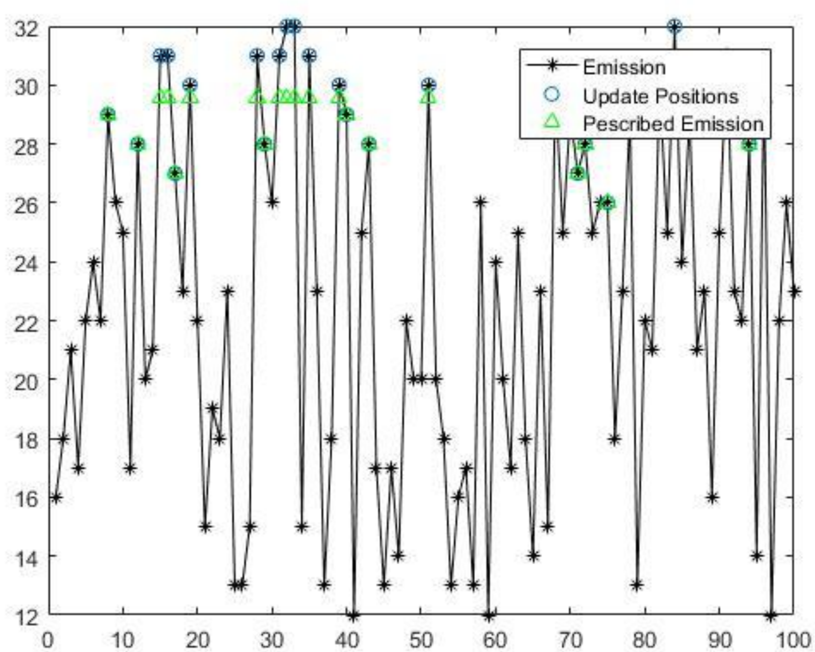

Figure 4.10 Carbon Emissions (After Optimization)

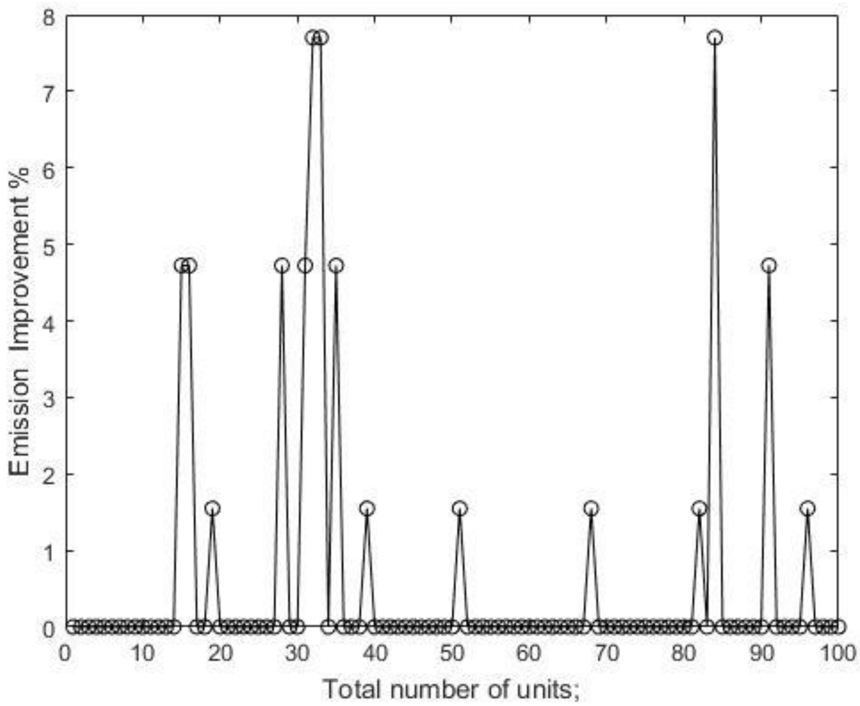

Figure 4.11 Emission improvement percentage in generating units

Table 4.9 represents the load distribution among the generating units. As per the tabular results, it is clear unit 1 has contributed more to satisfying the incoming load.

Table 4.9 Load Distribution

Generator/Unit	% Load Distribution
1	21.9822
2	12.6323
3	19.0725
4	16.1403
5	15.005
6	15.1677

Table 4.10 and 4.11 show the cost comparison using 6- and 100-unit systems respectively. Figures 4.12 and 4.13 show the graphical comparison of hGADE and optimization using the proposed approach (multi-objective) for 6 and 100 units respectively.

Table 4.10 Cost Comparison (6-unit system)

Case	Average Cost (in INR)
Without Optimization	142814.41
Optimization Using GA-DE (hGADE)	142810.58
Optimization Using MO WOA-DE-GA	142792.56

Table 4.11 Cost Comparison (100-unit system)

Case	Average Cost (in INR)
Without Optimization	135741.42
Optimization Using GA-DE (hGADE)	135736.42
Optimization Using MO WOA-DE-GA	135732.83

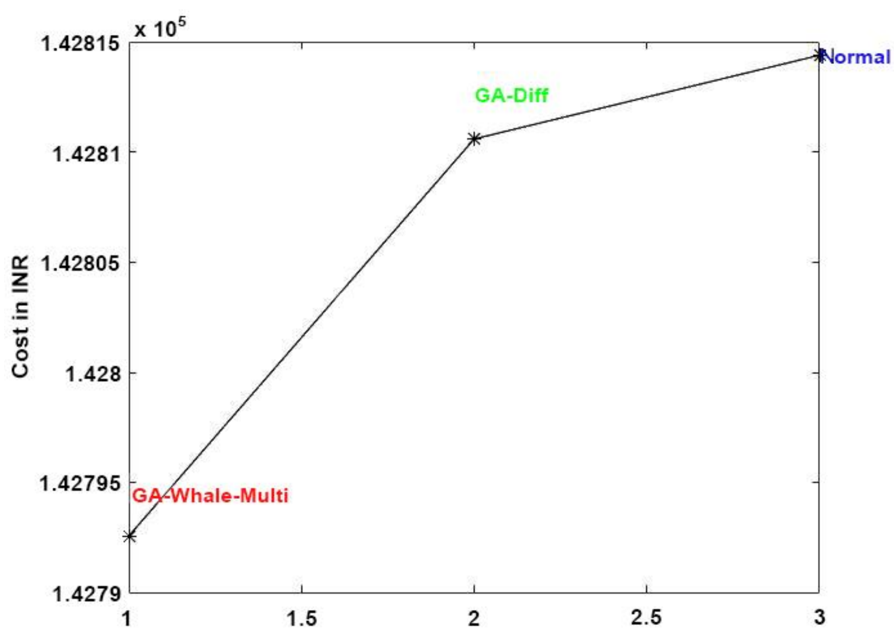

Figure 4.12 Cost Comparison (6-unit system)

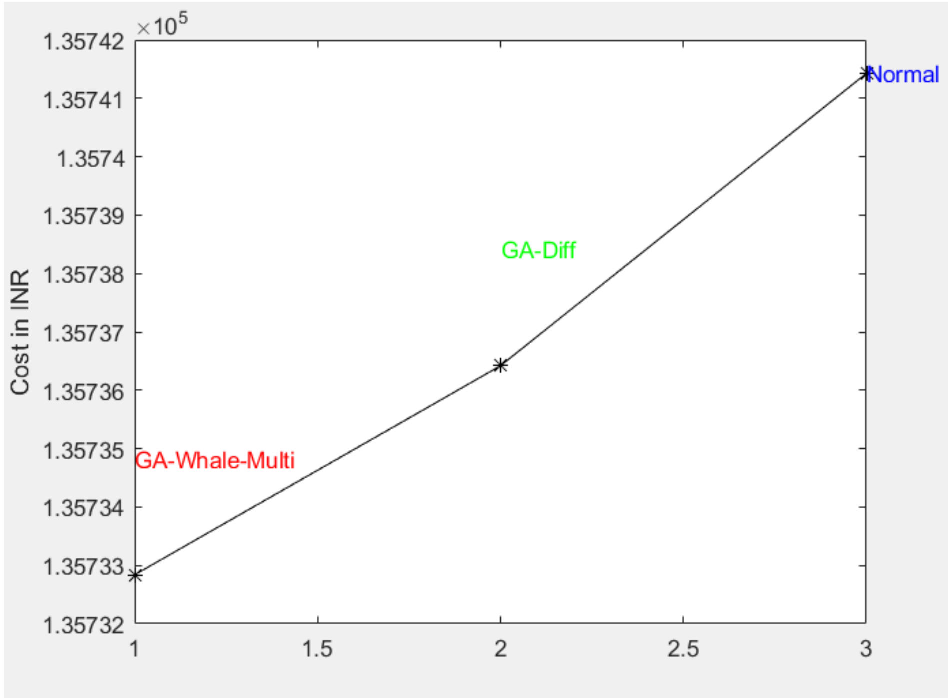

Figure 4.13 Cost Comparison (100-unit system)

In terms of computing time, typical hGADE clocks for single objectives average 24 and 451 seconds for 10 and 100 units, respectively (operation cost). In terms of computation, the recommended way will take a little longer. Three algorithms (GA, DE, and WOA) have been integrated to solve multi-objective problems. As a result, computation time will be longer than with normal hGADE.

4.5 Summary

Unit Commitment (UC) is a scheduling problem in the thermal power plant that is essential to a power system's safe, reliable, and cost-effective daily operation. This study aims to provide a solution to the issue of single-objective (cost minimization) and multi-objective (emission minimization) UC (MOUC).

Chapter 5

Conclusion and Future Works

5.1 Overview

In this research work, the main aim was to understand the UC and ED problem in power systems and minimization of total operating cost and pollutants emission. It was also to devise a multi-objective approach to simultaneously address the emissions and operating costs. The procedure for performing the research involves many processes for achieving the set objectives of the research. The chapter here concludes the work along with subsequent outcomes of the research undertaken.

5.2 Conclusion

The findings were compared to those of the hGADE algorithm, as the proposed technique was influenced by it. The proposed multi-objective system not only reduces total operating costs but also reduces overall emissions. The average running cost is 142814.41 INR, which is decreased to 142810.58 INR after optimization. The proposed method results in a large cost reduction, i.e. 142792.56 INR. A 100-unit system is being considered to test the scalability of the suggested technique. The average running cost is 135741.42 INR, which is decreased to 135736.42 INR after optimization. The proposed approach results in a large cost reduction, i.e. 135732.83 INR.

The goal of this work is to provide an idea to understand the optimal unit scheduling and economic dispatch by understanding the UC problem. Therefore, eventually, the thesis concludes the following contributions.

1) Critically analyzed the evolution of optimal power generation to understand the unit commitment and economic dispatch problem. In this process, the existing models and techniques had been studied by applying conventional and non-conventional techniques. The hGADE algorithm has been tested on ramp up/down constraints.
2) A novel nature-inspired approach has been proposed incorporating the Genetic Algorithm, Differential Evolution, and Whale Optimization Algorithm.

3) Proposed a hybridized solution to the multi-objective unit commitment problem. Because of the conflicting nature of the economic and emissions targets, Whale Optimization (WO)-differential evolution (DE) and genetic algorithm (GA) based hybrid approach; WODEGA has been proposed which will satisfy two objectives: committing the generating units to meet electricity demand and reduction of overall operational cost with minimal emissions.

5.3 Future research opportunities

The use of a hybrid nature-inspired algorithm to solve the electric power systems unit commitment problem is presented in this study. Investigators are often eager to work in this area, particularly with the widespread adoption of renewable energy in the power system. Extending the daily UC problem to more complex planning and operating activities, such as the weekly UC problem, is another promising research path. Finding better or optimal solutions with a less computational load of time is one of the most critical, and arguably the most fundamental, concerns that remains problematic in addressing the UC.

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List of Research Publications

1) Amritpal Singh, Aditya Khamparia (2020) **A hybrid whale optimization-differential evolution and genetic algorithm based approach to solve unit commitment scheduling problem:** WODEGA", Sustainable Computing: Informatics and Systems, Volume 28, 100442, 2020, https://doi.org/10.1016/j.suscom.2020.100442. **(SCI; Impact Factor 2.798) (Published)**

2) Singh A., Khamparia A. (2021) **Solution to Unit Commitment Problem: Modified hGADE Algorithm.** In: Khanna A., Singh A.K., Swaroop A. (eds) Recent Studies on Computational Intelligence. Studies in Computational Intelligence, vol 921. Springer, Singapore. https://doi.org/10.1007/978-981-15-8469-5_7 **(Scopus) (Published)**

3) Amritpal Singh, Aditya Khamparia, (2021) **Solution to Economic Dispatch problem using modified PSO algorithm**, Presented in ICICC-2021, Conference, **(Scopus) (Presented)**

4) Amritpal Singh, **Sushil Kumar**, (2016) Differential Evolution: An Overview, Advances in Intelligent Systems and Computing, pp. 209-217. **(Scopus) (Published)**

5) Amritpal Singh, Sushil Kumar (2016) **Solution to Unit Commitment Scheduling Problem-A Proposed Approach**, International Journal Of Control Theory And Applications. https://serialsjournals.com/index.php?route=product/product/volumearticle&issue_id=297&product_id=365 **(Published)**

6) Amritpal Singh, Aditya Khamparia (2021) **A Hybrid Evolutionary Approach for Multi-Objective Unit Commitment Problem in Power Systems**, IEEE Systems Journal **(SCI, Impact Factor 3.987) (Communicated)**

7) Amritpal Singh, Aditya Khamparia (2021) **Multi-agent Driven Smart Power Management Using an Improved Dynamic Programming,** International Journal of Network Management.**(Impact Factor 1.338) (Communicated)**