UNIT COMMITMENT PROBLEM ANALYSIS USING ADVANCED HEURISTICS ALGORITHMS CONSIDERING IMPACT OF COVID-19

Thesis Submitted for the Award of the Degree of

DOCTOR OF PHILOSOPHY

in

Electrical Engineering

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2025

Dedicated

To

My supervisors, My Parents, Spouse

& My Daughters

DECLARATION

I, hereby declared that the presented work in the thesis entitled "***Unit Commitment Problem Analysis Using Advanced Heuristics Algorithms Considering Impact of COVID-19 "*** in fulfilment of the degree of **Doctor of Philosophy (Ph. D.)** is the outcome of research work carried out by me under the supervision of Dr. Sobhit Saxena working as Professor in the School of Electronics and Electrical Engineering, Lovely Professional University, Punjab, India and co-supervision of Dr. Vikram Kumar working as Electrical Engineering Lead, TAG/ TAG Engineering, Yellowknife, NT, Canada. In keeping with the general practice of reporting scientific observations, due acknowledgments have been made whenever the work described here has been based on the findings of other investigators. This work has not been submitted in part or full to any other University or Institute for the award of any degree.

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CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled **"*Unit Commitment Problem Analysis Using Advanced Heuristics Algorithms Considering Impact of COVID-19*"** submitted in fulfillment of the requirement for the reward of the degree of **Doctor of Philosophy (Ph.D.)** in the School of Electronics and Electrical, is a research work carried out by SHRIKANT, 12009807, is bonafide record of his/her original work carried out under my supervision and that no part of the thesis has been submitted for any other degree, diploma or equivalent course.

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ABSTRACT

Electric power plays a crucial role in the economy and development of any country. To ensure sustainable economic growth, it is essential to have the appropriate infrastructure in place. The power sector significantly contributes to a country's development, as electricity is fundamental to modern societies. Electricity can be generated from various sources, including traditional ones like thermal, nuclear, hydroelectric, and oil and gas-based plants, as well as from modern sources such as solar, tidal, geothermal, and wind energy. In India, the demand for electricity is rapidly changing, requiring a substantial increase in power generation capacity to meet the growing needs.

COVID-19 has a large impact on humans and nature and changes electricity consumption among the nations. Individuals have been observed to staying home and many organizations have suspended or scaled back operations due to the pandemic. It is important to analyse the power demand and the impact on the power grid during this pandemic. Such analysis allows energy companies to prepare for future adverse events and pandemics. Many policy makers have set targets for renewable energy generation and analysing electricity demand can help improve contingency planning in the event of future pandemics or adverse impacts. The ever-increasing appetite for electricity has led practitioners to look for alternative energy options, which are becoming more prevalent. Global warming, habitat destruction and deteriorating air-quality require a comprehensive action plan.

A major challenge in the design and management of power systems is the Unit Commitment (UC) problem. This problem involves determining the optimal schedule for power-generating units to meet energy demands at the lowest cost while adhering to various operational and security constraints. The problem becomes more complex with the integration of oxygen concentrator, electrolyser, and renewable energy sources (RES) due to the intermittent and unpredictable nature of renewable energy.

The aim of the current study is to explore innovative solutions to the UC problem, taking into account the impacts of Oxygen Concentrator (OC), Electrolyser (EL) and the variability of renewable energy sources during COVID-19. The study introduces novel methodologies that fuse optimization algorithms, combining local and global search strategies to enhance the exploration and exploitation of the search space. This hybrid approach improves the effectiveness of solving the UC problem.

The introduction of the dissertation outlines the UC problem and its importance in modern power sectors. It also reviews the fundamentals of optimization techniques and renewable energy sources. The study proposes hybrid methods that blend meta-heuristic and classical optimization algorithms to address the UC problem effectively.

A significant section of the research explains the various optimization methodologies employed, providing justifications and detailed descriptions of each approach. It includes a review of impact of COVID-19 on power system and impact of OC, EL,

which are crucial in solving the UC problem. This section also includes a comprehensive literature review of various optimization techniques, highlighting the limitations of current methods and emphasizing that no single optimizer is suitable for all types of optimization problems. This underscores the need to explore new variations of metaheuristic algorithms.

The research goes on to present novel hybrid metaheuristic optimization methods inspired by behaviour of Beluga Whales, as well as various chaotic maps. Techniques like Levy flight are employed to enhance the exploitation capabilities of these optimizers. Specifically, chaotic map strategies are applied to Beluga Whale optimizers, resulting in enhanced performance when combined with chaotic and Levy flight. The effectiveness of these hybrid optimizers, chaotic beluga whale optimization algorithm (CBWO), is evaluated through hypothesis testing.

Further, the dissertation provides an overview of the exploitation and exploration capabilities of the existing Beluga Whale Optimization (BWO). Enhancements using chaotic tent functions, Levy flight strategies are implemented to improve the BWO’s performance. The improved CBWO optimizer have been successfully tested on various benchmark problems, including unimodal, multimodal, and fixed dimension challenges, as well as interdisciplinary engineering design problems. These optimizers are then applied to solve the UC problem, and their performance is assessed using standard test systems with thermal generating units across small, medium, and large power sectors.

The proposed algorithms were evaluated on systems with 10, 20, and 40 generators, demonstrating superior performance compared to existing methods. The CBWO optimizer consistently outperformed other algorithms, as shown by comparative analysis. The next chapter explores the application of the hybrid CBWO to solve the UC problem considering the impacts of COVID-19 and OC, EL with renewable energy sources (wind). Tests on systems with 10, 20, and 40 units revealed that the CBWO optimizer performed better than both traditional and newer heuristic, meta-heuristic, and evolutionary search algorithms, achieving the lowest fuel costs.

Statistical analysis of the proposed algorithms was conducted using metrics such as standard deviation, median value, best fitness, average fitness, and worst fitness. Hypothesis testing was supported by the t-test and the Wilcoxon rank-sum test. Additionally, computation times were tracked to assess the computational complexity of the methods.

The final chapter summarizes the significant contributions of the study and provides suggestions for further improving security constraints in power systems. It compares the effectiveness of the proposed optimizer against other competitive algorithms in solving the UC problem with OC, EL and RES. The study concludes with recommendations for future research directions, offering insights for new researchers in the field.

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LIST OF SYMBOLS

FC- Fuel Cost
g,h- Generating unit and time (hour)
a_g, b_g, c_g - Fuel cost coefficients
U_{gh}- Committed status of the g^{th} unit at h^{th} hour
SUC- start-up cost
NG- Number of generating units
CSC_g, HSC_g - Cold start-up and hot start-up cost of g^{th} unit
CSH_g - Cold start hour of g^{th} unit
MDT-Minimum down time of g^{th} unit
MUT_g - Minimum up time (in hrs)
T_{gh}^{OFF} - Duration for which the thermal g^{th} unit has been continuously off until hour h
T_{gh}^{ON} - Duration for which g^{th} unit is continuously ON
P_{gh}- Power generated by g^{th} unit
$P_g^{\max}$ - Maximum power generated by g^{th} unit
$P_g^{\min}$ - Minimum power generated by g^{th} unit
$P_h^{\mathrm{Re}serve}$ - Reserve power for the future
$P_{gh}U_{gh}$ - Total power generated by g^{th} units for h hour
$P_h^{Covid-19}$ - Power demand during COVID -19
P_h^{OC} - Power consumed by Oxygen concentrator
P_h^{EL} - Power consumed by Electrolysers
$pdf(v,k,\lambda)$- Probability density function of the wind speed
λ - Weibull scale parameter
k- Dimensionless Weibull shape parameter
v- Wind velocity
P- Wind power generated by a wind turbine
ρ_{air} - Air density kg/m^3
A_C $-$Swept Area of the turbine
v^3 $-$Wind Velocity in m/s
C_p- Power Coefficient.
OC- Oxygen Concentrator
EL- Electrolysers
RES- Renewable Energy Sources
$CBWO$- Chaotic Beluga Whale Optimizer
FL- Full Lockdown period during COVID
PL- Partial Lockdown period during COVID

LIST OF ABBREAVIATION

Acronym	Definition
ACO	Ant colony optimizer
ALO	Ant Lion Optimizer
AOA	Arithmetic Optimization Algorithm
BBO	Biogeography Based Optimization
CAOA	Chaotic Arithmetic Optimization Algorithm
CBWO	Chaotic beluga whale optimizer
CE	Constrained Engineering
COVID	Corona Virus Disease
DER	Distributed Energy Resources
DP	Dynamic Programming
DPS	Distributed power systems
DR	Demand Response
DT	Dynamic Technique
EA	Evolutionary Algorithm
EFO	Electromagnetic Field Optimization
EHO	Elephant Herding Optimization
EL	Electrolyser
ELD	Economic Load Dispatch
EMA	Exchange Market Algorithm
EOA	Equilibrium Optimization Algorithm
EPPSO	Evolutionary Parallel Particle Swarm Optimizer
EPSO	Evolutionary Particle Swarm Optimizer
ESF	Energy storage facilities
FCR	Frequency Containment Reserves
FPA	Flower Pollination Algorithm
GBO	Gradient Based Optimizer
HGSO	Henry gas solubility optimizer
HS	Harmony Search
LFAOA	Levy flight arithmetic optimization algorithm
MAPE	Mean Absolute Percentage Error
MBA	Mine Blast Algorithm
MBO	Monarch Butterfly Optimization
MDE	Modified Differential Evolution
MDP-PSO	Modified Dynamic Programming with Particle Swarm Optimization
MFO	Moth Flame Optimizer
MFO-HHO	Moth Flame Optimizer - Harris Hawks Optimizer
MFO-SVM	Moth Flame Optimizer with Support Vector Machine
MGSCA	Memory Guided Sine Cosine Algorithm
MGWO	Modified Grey Wolf Optimizer
MILP	Mixed Integer Linear Programming

MM	Muller Method
MO	Multi-objective Optimization
MOGA	Multi-Objective Genetic Algorithm
MOMBO	Multi-Objective Migrating Bird Optimization
MSESCA	Multi-Strategy Enhanced Sine Cosine Algorithm
MVO	Multi Verse Optimizer
NSGA	Non-Dominated Sorting Genetic Algorithm
NWOA	Novel Whale Optimization Algorithm
OC	Oxygen concentrator
PBUCP	Profit Based Unit Commitment Problem
PEM	Point Estimate Method
PEVs	Plug Electric Vehicles
PNACO	Parallel Nodal Ant Colony Optimization
PSA	Photon Search Algorithm
PSO	Particle Swarm Optimization
PSO	Particle Swarm Optimization
RES	Renewable Energy Sources
RWAOA	Random walk arithmetic optimization algorithm
SCA	Sine-Cosine algorithm
SCUC	Security Constrained Unit Commitment
TLBO	Teaching Learning Based Optimization
TS	Tabu Search
TSA	Tree Seed Algorithm
UCP	Unit commitment problem
V2G	Vehicle to Grid
WOA	Whale Optimization Algorithm
WSA	Wind Stride Algorithm

LIST OF PUBLICATION

Journal Publication

1. Bhardwaj, S., Saxena, S., Kamboj, V.K. *et al.* A sophisticated solution to numerical and engineering optimization problems using Chaotic Beluga Whale Optimizer. *Soft Computing* (2024), IF-3.2. https://doi.org/10.1007/s00500-024-09823-8.

Conference

1. Shrikant Bhardwaj, Sobhit Saxena, Vikram Kumar Kamboj, "Effect of Covid-19 on Power Generation, Distribution and Consumption: A Review", 4th International Conference on Intelligent Circuits and Systems (ICICS 2022)", April 8-9th, 2022.
2. Shrikant Bhardwaj, Sobhit Saxena, Vikram Kumar Kamboj and Suman Lata Tripathi, "Impact of Covid-19 on current electricity market and renewable energy: An extensive review" SOFA 2022 (Soft Computing and Applications).
3. Shrikant Bhardwaj, Sobhit Saxena, Vikram Kumar Kamboj, "Optimal Commitment of thermal power system with Impact of load demand of Oxygen Concentrator during Covid-19" ICICSO GOA, December 2023.

Publications in Communication

1. Shrikant Bhardwaj, Sobhit Saxena, Vikram Kumar Kamboj, "Pre & During Covid impact analyses on electricity Generation and Renewable Energy Usage", Engineering Research Express, ERX-105020, IOP-Science, 2024. [Status: Under Review]
2. Shrikant Bhardwaj, Sobhit Saxena, Vikram Kumar Kamboj, "Unit Commitment Problem considering the impact of covid 19 of Canadian provinces using CBWO", Soft Computing, 2024, [Status: Under Review].
3. Shrikant Bhardwaj, Sobhit Saxena, Vikram Kumar Kamboj, "Optimal Commitment of thermal power system with Impact of load demand of Electrolyser during Covid-19" AKGEC-2024. [Status: Presented in Conference, Publication under process].

Chapter-1

INTRODUCTION

1.1 INTRODUCTION

The contemporary world is heavily reliant on a reliable and efficient power infrastructure for its survival. This complex web of interacting system components like generation, transmission, distribution and consumption that forms a large part of the great machine that powers our household lighting, heating and air conditioning along with thousands of other people on earth. Electricity become necessary for all country to meet the demand for its industry and commercial needs.

The power generation in India is produced by thermal power plants, which emanate a lot of pollutants and have an enormous impact on the environment. Apparently, it is infeasible because we know that coal as an energy source has a limited supply and will eventually become completely mined. This is why the demand for thermal power plants accompanied by other energy sources as hydro, nuclear, solar and wind power becomes a necessity.

It is very difficult to create a balance between the production of electric power and the environment these days since every nation promotes industrialization, which has a negative impact on the environment. The greatest option is to produce electricity that is highly reliable, reasonably priced, and perhaps less harmful to the environment. The planning of electric power production systems, regulation, and cost-effective operation are the three most important concerns facing the electric power sector. Therefore, the ideal timing of producing units is crucial when weighing the costs and benefits of power economics. Determining an acceptable timeframe for operating the unit status, commonly termed to as unit commitment, is therefore expected.

Unit commitment, or the coordination of power plants, looks to be a financially ideal alternative for the generating station as it makes operational cost lesser and better reliability. In addition to defining the ON/OFF conditions, this problem often calls for figuring out the hourly thermal output power, which is sometimes referred to as economic load dispatch, and satisfying a sizable number of operational constraints and devices while minimizing fuel costs.

1.2 RENEWABLE ENERGY AND POWER SYSTEM

Worldwide, it is one of the fastest growing energy transition pathways. Renewable energy will the key that humanity needs in order to fulfil our need of seeking and saving. The daily production of electricity and increasing demands, wind energy showing stochastic behavior in modern power networks. This problem is worsened when a high wind velocity forces the grid to turn off its generation. The use of solar and wind energy is the overarching theme for an energy system that awaits us in the years ahead. The intermittent and unpredictable nature of these renewable resources creates serious difficulties for users and the economical functioning of electricity networks as well.

The Indian government announced that state-owned energy distribution companies would not be required to pay for the power they had purchased for a period of three months, despite the fact that the country's energy needs will increase over the coming years and that the power sector faces noteworthy price barriers. In addition, the government eliminated late payment penalties, lowered the payment security to 50% for future power purchases, and made sure that power would not be cut off continuously during COVID-19 outbreaks. In an effort to demonstrate unity and patriotism against the COVID-19 pandemic, the entire domestic sector shut down for nine minutes on April 5, 2020, at 9:00 PM. As a consequence, the grid load was reduced by 32,000 megawatts, meaning that India's residential lighting consumption is around 32 gigawatts, with a 10% error margin.

The increasing need for electricity has prompted practitioners to investigate alternative energy sources, which are gaining popularity. An extensive action plan is required in response to habitat loss, air quality deterioration, and global warming. There has to be more work done in this specific sector. The purpose of the proposed study, which is motivated by these research challenges, is to develop a hybrid meta-heuristic research approach that solves the unit commitment problem of the integrated electric power system while considering renewable energy sources.

1.3 UNIT COMMITMENT PROBLEM IN POWER SYSTEM

The unit commitment (UC) problem is one of the biggest barriers to operating a stable and cost-effective electrical power supply. Nowadays the key question is- How can power facilities be planned to remain operational at the lowest possible cost to meet unpredictable electricity demand? Electricity cannot be effectively stored in vast amounts like other commodities can. This implies that output and consumption must always coincide. Considering the many features and expenses involved in turning on and off electricity plants. The objective is to minimize costs, taking into account fuel prices, maintenance and operation costs, and any start up or shut down costs related to turning on or off power units. The UC solution must ensure that there is enough power producing potential to fulfil the anticipated need for energy for the span of the scheduling period.

Many methods like Mixed Integer Linear Programming (MILP), Dynamic Programming (DP), and meta-heuristics, can be used to solve the UC problem. UC problem divided into smaller phases and considering all potential unit states (ON/OFF), dynamic programming used to optimize the units. The bottommost possible cost of all probable earlier stages, including the fuel cost and start-up cost—of moving from prior states to the present one, can be used to get the lowest feasible cost of running the system at a given point.

MILP is a generally used method for tackling the UC problem in power systems. This tactic articulates the problem as a mathematical model that represents both the real-valued output power of each generating unit and their on/off status during specific time periods through linear equations, integrating both binary and continuous variables. Where 1 considered to be operational and 0 implies offline.

The meta-heuristics are useful optimization techniques inspired by natural developments such as simulated annealing or genetic algorithms. These tactics are particularly suited to solving complex problems like UC, where traditional methods, such as DP or MILP, can become computationally arduous for large-scale systems. Meta-heuristics provide an operative toolkit for solving the UC problem in power systems, exclusively for larger systems. They may not always guarantee the optimal solution but they are capable of producing high-quality results that meet the demands of power system operations.

The UC problem is a critical challenge in safeguarding the efficient and reliable operation of power systems. As electricity production is expensive, UC helps to categorize the most economical combination of power plants to run at a given time. To keep the grid stable, generation and consumption must always be equal. Throughout the planning process, UC makes sure there is sufficient power plant capacity available and planned to fulfil the anticipated demand for energy. Constraints such as minimum uptime and spinning reserve criteria are added into UC to ensure stable power output and the ability to respond to unforeseen swings in demand or unexpected power disruptions.

The requirement and supply predictions for the following day are the foundation for electricity market functions. System operators use UC technologies to ascertain the real dispatch schedule for power plants once market demand is known. This means specifying the power output and ON/OFF status of each unit for each time cycle all over the scheduling period.

Due to their erratic and fluctuating character, renewable energy sources like solar and wind are becoming more and more prevalent, which makes power system management more challenging. In order to guarantee dependable grid operation with renewable energy, UC systems are being modified to include probabilistic techniques that take into consideration anticipated uncertainties in renewable power.

1.4 COVID-19 PANDEMIC IN INDIA AND WORLD

The new corona virus SARS-CoV-2, which gave birth to COVID-19, arose in late 2019 and fast spread around the world, having a significant detrimental effect on economy, society, and public health. In December 2019, Wuhan, China, reported the first cases of COVID-19. The virus is likely to have begun in bats and transmitted to humans in a Wuhan seafood market, probably via an intermediate animal host [1]. Through international travel, it swiftly crossed borders and caused epidemics in many countries. The virus's high contagiousness and potential to propagate among asymptomatic individuals enabled for its speedy dissemination, which led to a global health disaster [2].

On or around November 16, 2019, Wuhan, People's Republic of China, observed the first human incidences of COVID-19. On January 21, 2020, the first human case of COVID-19 was reported in the United States., World Health Organization (WHO) declared the COVID-19 outbreak as a Public Health Emergency of International apprehension on 30-January 2020 and by 11-March 2020, they declared as a global pandemic [3]. The pandemic postured significant challenges to healthcare systems around the countries. COVID-19 spreads through respiratory droplets, causing a wide range of symptoms from mild respiratory illness to severe pneumonia and acute respiratory distress syndrome. The maximum risk of illness and death was observed in defenseless groups, such as the elder people and individuals having pre-existing health conditions [4].

To control the pandemic, governments implemented various approaches including lockdowns, social distancing measures, mask mandates, mass testing, and contact tracing. Vaccination plays a crucial impact to control the virus's spread and reducing the severity of infections [5]. The impact of pandemic was also seen on economy that leads to significant job losses, business closures, and interrupt to global supply chains. Government put restrictions on movement and lockdown imposed that reduced spending, lowered industrial output, and sharply decreased international trade. Due to the lockdown, small businesses, hotels and tourism sectors, were especially affected, and faced closures and financial difficulties [6].

Whilst macroeconomic policies and economic relief initiatives were putting in operation by governments to mitigate the impact on the economy, the pandemic's long-term repercussions are still getting encountered. The most powerful economies confronted the dilemma of increased unemployment and high inflation due to inefficiencies and overspending on treating and rehabilitating COVID-19 victims and their families [7]. The effects of COVID-19 on human health are the main cause of worry. Aside from cattle, pigs, and poultry, other affected agricultural industries include dairy, grains and oilseeds, fruits and veggies [8].

1.5 IMPACT OF COVID-19 PANDEMIC IN POWER SYSTEM

The COVID-19 epidemic has fundamentally affected global energy systems and electric power grids, resulting in many complex problems requiring careful consideration and long-term strategic planning. This work clarifies many significant results and observations on the influence of the epidemic on grid operations, energy infrastructure, and the general energy environment. Apart from reducing the need for electricity, the epidemic shifted load from large cities to outlying areas and from the business and manufacturing industries to the financial sector. Frequency variations and load forecasting errors significantly increased during lockdowns [9].

The production of power has decreased overall in tandem with demand and coal-fired generation bearing the brunt of this decline. Although curtailment rates have also risen, the percentage of renewable production has grown. Major markets have seen a sharp decline in the price of power, with European countries seeing the largest global price fall. Numerous utilities and coal-fired power plants have had financial difficulties. Long-term investments in the electrical industry and the upcoming switch to renewable energy sources are anticipated to be substantially unaffected, notwithstanding the suspension of the majority of investment projects [10].

The worldwide energy systems have been considerably impacted by the COVID-19 epidemic. The use of social distancing protocols and varying degrees of regulatory restrictions aimed at curbing the transmission of the highly infectious virus has led to significant decreases in commercial and industrial operations. As such, these listed activities directly affect the subsequent drop in the global usage of energy. Furthermore, at the most limited periods, it was rather evident that decreased activity related to transportation improved air quality and greenhouse gas emissions [11].

The impact of the epidemic on residential energy consumption varies significantly across months, seasons, and consumer activities in day hours that causes variations in loads. We found that 36.3% of consumers' profile patterns had a substantial shift from pre- to post-COVID-19 during the spring season. Conversely, after the pandemic, the profile pattern of 63.7% of clients showed a little shift, and daily demand increased significantly from 16.3% to 29.1% [12]. There was a noticeable change in the use of hot water and power in the middle of the day during the most severe phase of the lockdown. If we define the hours of 9 AM to 5 PM as the "middle of the day," power consumption jumped 46% in April. This is quite shocking given a 103% increase in hot water usage [13].

In Canada, Ontario, there is 14% decrease in demand throughout April, almost 1267 GW. Weekends showed the largest daily declines in demand, with an average of 18% per day and a maximum fall of 25%. For the month of April, savings of $131,844 were achieved [14]. Due to the interruption in the demand, the accuracy of the load forecasting tool decreased in Canada. More functional method was therefore required to control the load volatility. This city has the highest penetration of renewable energy ever because to the lower demand amid the COVID-19 shutdown. The lowered demand and higher amount of renewable energy changed the producing mix significantly [15].

Ottawa, the capital city of Canada, is a vibrant and diverse metropolis located in the province of Ontario. With a rich history, stunning architecture, and a thriving cultural scene, Ottawa offers a unique blend of natural beauty, national landmarks, and a high quality of life. As the capital city of Canada, Ottawa has a significant electricity consumption profile. The city's electricity demand is influenced by various factors, including residential, commercial, and industrial sectors. Residential consumption accounts for a substantial portion of the electricity demand, driven by heating and cooling needs, lighting, appliances, and other household activities. The commercial sector includes office buildings, retail establishments, and institutions, while the industrial sector encompasses manufacturing, data centers and other energy-intensive activities.

To achieve the evaluation of energy consumption in Ottawa, the required data is driven from the record of the Independent Electricity System Operator (IESO) of Ontario Canada. Demand data was collected from 24rd March to 22st April 2019 and similar time periods of 2020 and 2021.

Fig. 1.1 shows the average demand comparison between before COVID-19 period (2019), Strict lockdown during COVID-19 (2020) and partial lockdown during COVID-19 (2021) period of the Ottawa region. A decrement in average demand is seen during COVID-19 pandemic because of the lockdown that took place in 2020 in

Ottawa and also the shifting of electricity demand from industrial to residential load. Average demand reduced by approx. 110MW in 2020 and approx.105MW in 2021 as compared to 2019. During partial lockdown, electricity consumption shows a mixed type of demand response.

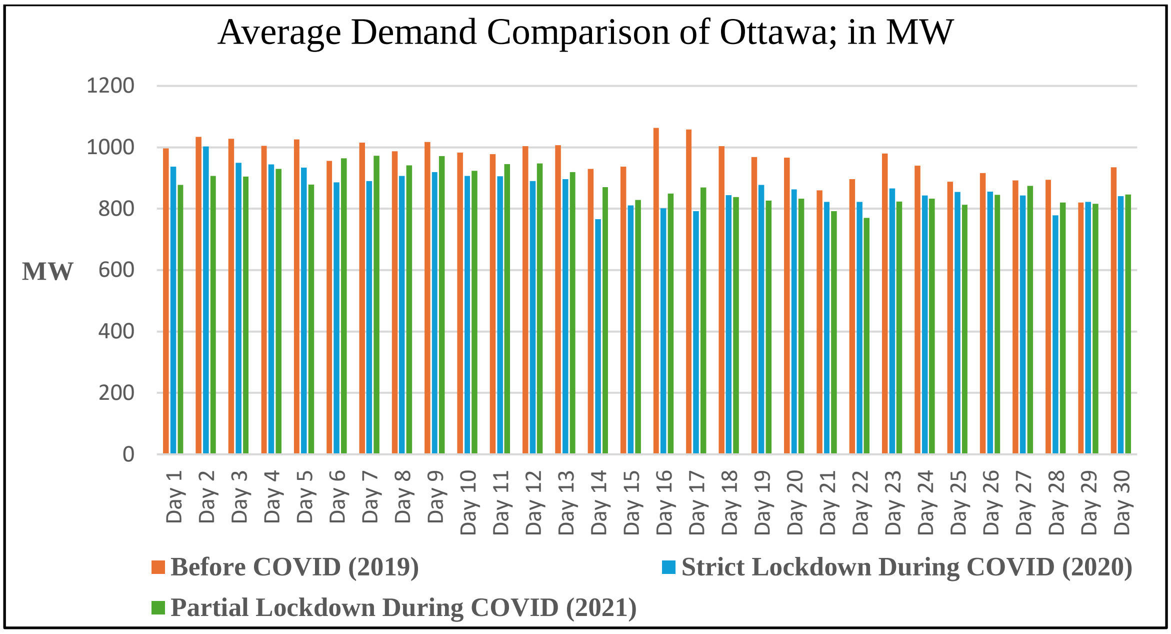


Fig. 1.1: Average Demand Comparison of Ottawa (Canada) in MW.

On 11th of March 2020, first confirm case of COVID-19 was recorded in city but there is no community spread evidence. On 16th March, all municipal facility in Ottawa city was closed. On 24th March, Ottawa mayor declare a state emergency due to the spread of COVID-19 and city confirmed its first death due to COVID-19. All non-essential businesses were shut-down while grocery stores and pharmacies were allowed to stay open. They put restrictions on restaurants and bars, only delivery and takeout order allowed. That’s why on 24th March or Day 1, shows less power consumption as compare to similar day in 2019. On 1st April, travel restriction with nearby states were imposed.

From 10 March to 15th of March 2021, COVID-19 cases were increased at a rate of 25% and government declared red zones in city. Movie theater were closed, limitations on gathering, only 5 people allowed to gather inside and 25 outdoor. Restaurants allowed only 10 people inside, limited people in gyms and no team sport allowed. Fig 1.1 Shows less power consumption during partial lockdown as compared to 2020 up to day 5. On 1st April, some pharmacies were allowed to vaccinate the adults over age of 55. During this time, people start to move outside, commercial electricity consumption increased. On 8th April, state declared stay at home order to people. From day 18, electricity consumption was reduced as compare to the 2020 [16-19].

1.6 OUTLINES OF DISSERTATION

This dissertation mainly investigates the problems of uncertainty in demand during COVID-19 and UC problem in contemporary power systems. The study is looked into the optimization and challenges of UC in the modern power grids. More specifically, it analyses how an oxygen concentrator and electrolyzer would affect the UC problem during COVID and considers the uncertainty of renewable energy sources (RES) by using a metaheuristic optimizer. Their aim is to physically operate at minimum cost while maintaining reliability, electricity demand-response, and other physical constraints over time. For the UC problem, Chaotic Beluga Whale Optimization (CBWO) algorithms appropriately evaluated and tested. Further CBWO is tested on various scenarios comprising small, medium and large test systems to find out best results.

The thesis is organized as follows:

Chapter 1 presents the impact of the COVID-19 pandemic on power system. It presents the UC problem in the power system, discussing its relevance in the current power sector. It also explores the incorporation of UC with OC, EL, and RES. The chapter suggests the importance of UC problem during COVID-19 pandemic and need of OC, EL and RES.

Chapter 2 presents the methodologies of various optimization techniques. It reviews the different algorithms used to address UC problem and observes some of the testing benchmarks for solving the UC problem. Additionally, the chapter offers a thorough review of the literature on OC, EL and RES.

Chapter 3 illustrates a new metaheuristic optimization method, CBWO. The effectiveness of this hybrid optimizer is evaluated through various test systems and hypothesis testing. The chapter converses the advance of CBWO to enhance exploration and exploitation across the entire search space. This hybrid algorithms have been successfully tested on various benchmark functions, including multidisciplinary engineering design problems.

Chapter 4 presents the efficacy and legitimacy of the proposed CBWO optimization techniques in addressing the UC problem. The hybrid optimization method was evaluated using a standard test system, incorporating thermal generating units. The results for UC problem and scheduling for units-10, 20, and 40 presented and indicating that the proposed optimizer surpasses existing optimizers in solving continuous, discrete, and non-linear optimization challenges.

Chapter 5 illustrates a consistent solution to the UC problem, taking into wind power as renewable energy source during lockdown and pre lockdown for both weekends and weekdays. A brief impact of OC and EL on the power system is presented. The optimizers were applied to systems with 10, 20, and 40 generating units, achieving cost-effective scheduling. Simulation results indicate that the CBWO optimizer outperforms other heuristic, metaheuristic, and evolutionary search methods in reducing costs. The study also analyses cost variations, including best, average, and worst-case scenarios, along with std and median values. Various hypothesis tests, such as the Wilcoxon rank-sum test and t-test, were directed to evaluate the results. The chapter concludes by brief the practical applications and contributions of CBWO in the UC problem.

1.7 CONCLUSION

This chapter plays a decisive role in the thesis, providing a comprehensive overview of the research conducted. It presents a broad summary of the various chapters, briefly highlighting each and accentuating the significance of the research. In addition, the chapter delves into the current state of unit commitment issues, offering various views and solutions within the field. The research in this thesis contributes to existing knowledge by introducing a novel approach to addressing this problem.

The chapter also acquaint with the thesis by offering background information on the research. It establishes the foundation for the research problem, delineation the objectives and methodology used in the study. The structure is projected to offer a clear understanding of the research problem, its importance, and the overall scope of the study.

Chapter- 2

LITERATURE REVIEW

2.1 INTRODUCTION

In order to minimise the cost of generation while meeting electricity demand and adhering to various technical constraints, the unit commitment problem (UCP), which is an essential element of power system functioning, seeks to arrange the on or off states and power outputs of generating units over a specified period of time (usually a day or week). The UCP has been the subject of considerable study in the last several decades due of its intricacy. The amount of research being done in the subject of optimisation is growing quickly. Diverse new approaches or strategies for distinct optimisation are becoming more prevalent. Research is moving quickly to create hybrid combinations of optimisation algorithms that can survive the shortcomings of the current approaches.

This chapter reviews the research on the effects of COVID-19 on power systems and the various optimisation techniques that may be used to effectively address unit commitment issues. The complexity of the UCP-related problems grew with the use of renewable energy sources. The decisions and distribution of power scheduling are more crucial factors in reducing fuel expenses.

2.2 LITERATURE REVIEW

Research projects often use several optimisation techniques in the broad field of power system optimisation. The goal of the study is to find sophisticated optimisation techniques to address various issues. A lot of study is being done to find novel approaches and to develop modified, hybrid, and chaotic methods to increase the effectiveness of current procedures in solving problems.

This section of the work includes the study of the impact of COVID-19 pandemic on power system and also in the field of unit commitment problems with the influence of renewable energy sources i.e., wind power, as well as the synchronization of conventional plants with RES. This section of the work includes the study of the impact of COVID-19 pandemic on power system and also in the field of unit commitment problems with the influence of renewable energy sources i.e., wind power, as well as the synchronization of conventional plants with RES. In the following sub-sections, a short review of several academic papers in the concerned area using various methodologies has been discussed. This section has been divided into the following subsection for a comprehensive literature review.

(i) A Comprehensive review on the impact of COVID-19 on power system

(ii) A Comprehensive Review on Optimization Algorithm

(iii) A Comprehensive Review on Unit Commitment Problem by considering renewable energy sources

2.2.1 A Comprehensive Review on the Impact of COVID-19 on Power System

In the Australian state Victoria, reported overall electrical demand profile, as the mean half-hourly power demand is lowered by 23.94 MW due to COVID-19, whereas in lockdowns particularly, an average half-hourly demand decrease by 210.55 MW. With a root mean square error of 136.44 and an overall average error of 100.38, the suggested regression model can estimate demand during lockdown times from the test set more accurately than any other forecasting approach that is thought to be a benchmark [21].

A thorough analysis of COVID 19's implications on sustainable development objectives is provided in an integrated approach to assessing energy and water availability, providing insights into how COVID-19 has affected the water-energy relationship. In 2020, there was a 5% global decline in the energy use. COVID-19 hindered manufacturing, trade, and transportation. The overabundance of supplies caused the oil market to crash in April 2020 [22].

Global energy systems and electric power grids have been significantly impacted by the COVID-19 pandemic, which has created a number of complicated issues that need for careful thinking and long-term strategic planning. Several important findings and observations on the pandemic's impact on energy infrastructure, grid operations, and the overall energy landscape have been clarified by this study.

In addition to lowering the demand for power, the pandemic also caused a shift in load from big cities to outlying communities and from the commercial and industrial sectors to the private sector. Frequency variances and load forecasting mistakes significantly increased during lockdowns [23].

The production of power has decreased overall in tandem with demand, with coal-fired generation bearing the brunt of this decline. Although curtailment rates have also risen, the percentage of renewable production has grown. Major markets have seen a sharp decline in the price of power, with European countries seeing the largest global price fall. Numerous utilities and coal-fired power plants have had financial difficulties. The majority of investment projects have been put on hold, while long-term investments in the electrical industry and the eventual switch to renewable energy sources should go mostly unaffected [24].

The worldwide energy systems have been considerably impacted by the COVID-19 epidemic. The use of social distancing protocols and varying degrees of regulatory restrictions aimed at curbing the transmission of the highly infectious virus has led to significant decreases in commercial and industrial operations. Consequently, these aforementioned actions have had a direct impact on the following decline in the world's energy consumption. Additionally, at the most restricted times, improvements in air quality and greenhouse gas emissions as a result of less transportation-related activities were clearly noticeable [25].

The impact of the epidemic on residential energy consumption varies significantly across months, seasons, and day types because to weather-related variations conditioning loads, daylight hours, and consumer activity [26].

The accuracy of the load forecasting tool decreased in Saskatchewan, Canada as a result of the interruption in the demand for energy. As a result, more operational reserve was needed to manage the load unpredictability. Because of the reduced demand during the COVID-19 business shutdown, this city had the greatest penetration of renewable energy ever [27]. The generating mix saw significant changes as a consequence of the reduced demand and increased percentage of renewable energy. Compared to a comparable time in 2019, CO_2 emissions significantly decreased between March and September of 2020 [28].

Widespread job losses, company closures, and disruptions to worldwide supply networks were among the many negative economic effects of the epidemic. Lockdown policies and mobility limitations resulted in lower consumer spending, lower industrial production, and a steep drop in international commerce [29].

Particularly heavily impacted small enterprises, the hotel industry, and the tourism industry, which all experienced closures and financial difficulty. Although monetary policies and fiscal stimulus programs were put in place by governments to lessen the effects on the economy, the pandemic's long-term effects are still being felt.

Most developed countries confronted the dilemma of increased unemployment and high inflation due to inefficiencies and overspending on treating and rehabilitating COVID-19 victims and their families. Workers in the agro-food supply chain are as, if not more, vulnerable to catching the virus than anybody else due to the disease's lack of discrimination. Other agricultural industries affected by these changes comprise dairy, fruits and vegetables, pigs, poultry, cattle, cereals and oilseeds [30].

Table 2.1: Impact of COVID-19 and change in load demand in different countries.

Countries	**Estimated Change in Load Demand (%)**	**Impact of COVID-19**	**Reference**
United States	-10% to -15%	Significant economic downturn, strain on healthcare system, high death toll	[31]
India	Varied: -5% to +5% (residential increase, commercial decrease)	Devastation of healthcare system, economic hardship, social unrest	[32]
Brazil	-15% to -20%	Overwhelmed hospitals, severe economic recession, travel restrictions	[33]
Italy	-20% to -25% during lockdowns	Early lockdown helped control spread, but resurgence caused strain	[34]
France	-10% to -15%	Lockdowns and travel restrictions slowed spread, but economic impact significant	[35]

Spain	-25% to -30%	High number of cases early on, tourism industry heavily impacted	[36]
Germany	-5% to -10%	Stringent social distancing measures helped control spread	[37]
United Kingdom	-15% to -20%	Multiple lockdowns throughout the pandemic, significant strain on NHS	[38]
South Africa	Varied: -10% to +5% (residential increase, commercial decrease)	Early emergence of new variant, significant economic impact	[39]
Mexico	-10% to -15%	High death toll, overwhelmed hospitals in some regions	[40]
Russia	-5% to -10% (limited data)	Initial downplaying of severity, later surges in cases	[41]
Indonesia	Varied: -10% to +5% (residential increase, commercial decrease)	Island nation faced challenges in containing spread	[42]
Japan	-5% to -10%	Relatively low death toll compared to population size	[43]
South Korea	-5% to -10%, with quick recovery	Aggressive testing and tracing program yielded success	[44]

Table 2.2: Impact of COVID-19 on different aspects

Country	Social	Economy	Environment	Load Demand Profile
United States	Lockdowns, travel restrictions, social unrest	Significant downturn, high unemployment	Temporary air quality improvement, increased waste from PPE	Decreased due to lockdowns and business closures
India	Stringent lockdowns caused social disruption	Severe economic hardship, job losses	Limited data, potential for temporary air quality improvement	Mixed impact: residential increase, commercial decrease
Italy	Strict social distancing measures	Early lockdown helped control spread, later economic struggles	Temporary air quality improvement, increased waste from PPE	Significant decrease during lockdowns
Brazil	Lockdowns and travel restrictions	Deep recession, high poverty rates	Limited data, potential for temporary air quality improvement in some areas	Decreased due to lockdowns and economic slowdown

Germany	Stringent social distancing measures	Relatively stable compared to others	Limited data, potential for temporary air quality improvement in some areas	Moderate decrease, some sectors less impacted
France	Social isolation, strain on healthcare system	Lockdowns and restrictions impacted businesses	Limited data, potential for temporary air quality improvement in some areas	Decrease due to lockdowns and business closures
Spain	Lockdowns and travel restrictions	Tourism industry heavily impacted, high unemployment	Temporary air quality improvement, increased waste from PPE	Significant decrease due to lockdowns and tourism collapse
South Africa	Lockdowns and travel restrictions	Economic downturn, job losses	Limited data, potential for temporary air quality improvement in some areas	Mixed impact: decreased commercial demand, increased residential demand
United Kingdom	Social isolation, increased mental health issues	Multiple lockdowns, strain on healthcare system	Limited data, potential for temporary air quality improvement in some areas	Decrease during lockdowns, impacting commercial and industrial sectors
Mexico	Lockdowns and travel restrictions	Economic slowdown, job losses	Limited data, potential for temporary air quality improvement in some areas	Moderate decrease, with pockets of more significant decrease due to lockdowns

Table 2.3: Comparison of pre COVID and during COVID period on different parameters

Parameter	Before COVID-19	During COVID-19 (Estimated Change)
Social	Relatively high social interaction	Social distancing events, lockdowns (decrease in interaction)
	Strong focus on in-person activities	Increased use of technology for communication and work (shift)
	Relatively low mental health concerns	Increased mental health concerns (potential increase)
Economy	Steady economic growth	Recession, job losses (decrease)
	Low unemployment rate	Increased unemployment rate (increase)
	Strong emphasis on international trade	Disruptions in global supply chains (potential decrease in trade)
Environment	Moderate air pollution levels	Temporary air quality improvement in some areas (decrease by -5% to -10%)
	Focus on sustainability initiatives	Increased waste generation from PPE (potential increase)
	Investment in renewable energy	Potential for continued investment (positive/neutral)
Load Demand	Steady increase in demand	Moderate decrease in demand (-5% to -10%)
	Seasonal fluctuations in demand	Potential for increased fluctuations due to changes in work/life patterns

2.2.2 A Comprehensive Review on Optimization Algorithm

The field of optimization is enormous and regularly sprouting. Researchers are working hard in advancement of new techniques and algorithms to resolve innumerable problems more competently. In this particular field, exploring different approaches and combining them to address the limitations of contemporary methods. In this part of research, recent algorithms are examined with their findings and research gaps.

Table 2.4: Literature review on the metaheuristic optimization algorithms

Algorithm	Findings / Test System	Conclusion/ Research gaps	Ref.
Harmony Search Algorithm	Effective at solving engineering optimization problems	Need for efficient update mechanisms, sensitivity to parameter settings.	[45]
Artificial Bee Colony	Effective at solving real-world optimization problems, outperforms other algorithms	Need for more efficient update mechanisms, sensitivity to parameter settings.	[46]
Cuckoo Search Algorithm	Effective at solving complex optimization problems	Need for efficient update mechanisms, sensitivity to parameter settings.	[47]
Bat Algorithm	Effective at solving continuous optimization problems with noisy objective functions	Need for efficient update mechanisms, sensitivity to parameter settings	[48]
Firefly Algorithm	High efficiency and flexibility, able to solve complex optimization problems	Need for better search strategy, parameter tuning.	[49]
Artificial Bee Colony Algorithm	Effective at solving continuous optimization problems	Need for efficient update mechanisms, sensitivity to parameter settings.	[50]
Krill Herd Algorithm	Effective at solving real-world optimization problems, outperforms other algorithms	Need for more efficient update mechanisms, sensitivity to parameter settings.	[51]
Flower Pollination Algorithm	Effective at solving continuous optimization problems with non-linear constraints	Need for efficient update mechanisms, sensitivity to parameter settings.	[52]
Grey Wolf Optimizer	Outperforms other optimization algorithms in accuracy and efficiency	Lack of diversity in population, sensitivity to parameter settings.	[53]
Teaching-Learning-Based Optimization Algorithm	Effective at solving a variety of optimization problems	Need for efficient update mechanisms, sensitivity to parameter settings.	[54]
Moth-Flame Optimization Algorithm	Outperforms other optimization algorithms in accuracy and efficiency	Need for more efficient update mechanisms, sensitivity to parameter settings.	[55]
Whale Optimization Algorithm	Effective at solving complex optimization problems, outperforms other algorithms	Need for more efficient update mechanisms, sensitivity to parameter settings.	[56]

Grasshopper Optimization Algorithm	Effective at solving real-world optimization problems	Need for efficient update mechanisms, sensitivity to parameter settings.	[57]
Biogeography-Based Optimization	Effective at solving real-world optimization problems	Need for efficient update mechanisms, sensitivity to parameter settings.	[58]
Arithmetic Optimization Algorithm (AOA)	Engineering design problem.	Arithmetic Operator for Exploration and Exploitation	[59]
Modified Bald Eagle Search Algorithm (MBES)	Standard 10-unit system	Handles uncertainties in renewables and flexible loads effectively.	[63]
Enhanced Grey Wolf Optimizer (GWO) for Ramp Constraints	Various systems	Efficiently handles generator ramp rate limitations.	[64]
Novel Chaotic Bat Algorithm (CBA)	IEEE 30-bus system	Considers valve-point effects on generator efficiency, achieving good solution quality.	[65]
Novel Multi-Objective Bee Colony Optimization (BO)	IEEE 30-bus system	Balances cost and carbon emissions for UC.	[66]
Novel Chaotic Krill Herd Algorithm (CKHA)	IEEE 30-bus system	Achieves good balance between objectives in multi-objective UC with ramp constraints.	[67]
Hybrid Grey Wolf Optimizer (GWO)	Various systems	Considers emissions and cost in multi-objective UC.	[68]
Enhanced Artificial Bee Colony Algorithm (ABC) for DR & Reserve	Various systems	Incorporates demand response and spinning reserve requirements.	[69]
Novel Chaotic Whale Optimization Algorithm (CWOA)	Various systems	Demonstrates promising results for solving UC.	[70]

2.2.3 A Comprehensive Review on Unit Commitment Problem

A novel approach regarding renewable energy producers was created by Maghsudlu S. et al. to address the scheduling issue in unit commitment. The Cuckoo search algorithm is a meta heuristic method that uses a high rate of convergence to solve the UC issue [71]. To investigate the effects of Plug-in Electric Vehicle (PEV) scheduling, an IEEE 10-unit system is used. In order to handle UC problems, which include mixed integer problems in optimisation coupled with PEVs, Zhile Yang et al. used a hybrid metaheuristic approach [72].

To determine the influence of the transfer function, which is used for binary optimisation to solve the integrated issue based on UC and PEVs, a 10-unit power system with 50,000 PEVs is taken into account. In a dynamic form of power pricing market, Pengcheng You et al. spoke about a novel cooperative technique for Electric Vehicles (EV) charging using smart charging stations. For the scheduling issue, MILP is developed to capture the characteristics of batteries, including charging and discharging. The MILP is proposed to be solved by a novel method that makes use of dual and Bender's decomposition [73].

Table 2.5: Literature review on the Unit Commitment Problem

Ref.	Paper Title	Test System	Summary	Conclusion
[74]	Effect of modelling choices in the unit commitment problem	N/A (Theoretical Analysis)	This paper analyzes how different modeling decisions, such as generator ramp rates or reserve requirements, can affect UC solutions.	Investigates how modeling choices in power system representation can influence UC results.
[75]	CO2 Emission-Constrained Short-Term Unit Commitment Problem Using Shuffled Frog Leaping Algorithm	IEEE 39-bus system	This paper introduces a novel optimization technique (SFLA) for UC that considers both economic and environmental objectives.	The proposed Shuffled Frog Leaping Algorithm (SFLA) effectively minimizes operating costs and CO_2 emissions for UC.
[76]	Stochastic Unit Commitment Study in a Power System with Flexible Load in Presence of High	Standard 10-unit system	This paper proposes an optimization method using a modified Bald Eagle Search Algorithm (MBES) to address uncertainties associated with renewable	Modified Bald Eagle Search Algorithm (MBES) effectively handles uncertainties in renewable generation and flexible loads.

	Penetration Renewable Farms		energy sources and flexible loads.	
[77]	An Intelligent Algorithm for Solving Unit Commitments Based on Deep Reinforcement Learning	Simulation examples	This work explores using Deep Reinforcement Learning, a form of artificial intelligence, to solve the UC problem, potentially leading to more efficient solutions.	Proposes a Deep Reinforcement Learning (DRL) based approach for UC, achieving promising results.
[78]	A Multi-Stage Unit Commitment with Demand Response and Renewable Energy Sources Considering Uncertainty	IEEE 118-bus system	This research introduces a multi-stage UC approach that incorporates factors like demand response programs, renewable energy sources, and uncertainties for better decision-making.	Proposes a multi-stage UC method considering demand response, renewables, and uncertainties, achieving good performance.
[79]	A novel intelligent global harmony search algorithm based on improved search stability strategy	IEEE 30-bus system	This research proposes a novel optimization method (CHSA) that incorporates valve-point effects, improving the accuracy of UC models.	Introduces a Chaotic Harmony Search Algorithm (CHSA) for UC, considering valve-point effects and achieving good solution quality.
[80]	A Novel Chaotic Bat Algorithm for Solving the Unit Commitment Problem with Valve Point Effects	IEEE 30-bus system	This research introduces a novel optimization technique (CBA) that considers the non-linear effects of valve points on generator efficiency in UC.	Proposes a Chaotic Bat Algorithm (CBA) for UC considering valve-point effects on generator efficiency.
[81]	A Distributionally Robust Unit Commitment Model with Photovoltaic Uncertainty	IEEE 24-bus system	This paper presents a UC model that considers uncertainties in solar power generation in a statistically robust way.	Introduces a distributionally robust UC model for handling photovoltaic power uncertainty.
[82]	Customized Benders Decomposition for Unit Commitment Integrated Generation Expansion Planning	Garver 6-bus system	This paper proposes a method for UC that can handle the additional complexity of optimizing transmission line switching decisions.	Develops a Benders decomposition approach for UC that incorporates the complexity of transmission line switching decisions.
[83]	Integration of smart grid technologies in stochastic multi-objective unit commitment: An	Modified IEEE 30-bus system	This work explores UC in smart grids with pumped hydro storage and electric vehicles, considering their charging/discharging	Presents a UC strategy for smart grids with pumped hydro storage and electric vehicles,

	economic emission analysis		patterns and energy storage capabilities.	accounting for their unique characteristics.
[84]	An economic/emission dispatch based on a new multi-objective artificial bee colony optimization algorithm and NSGA-II	IEEE 30-bus system	This research proposes a novel optimization method that simultaneously minimizes generation cost.	Introduces a multi-objective Bee Colony Optimization (BO) algorithm for UC, balancing cost and carbon emissions.

2.2.4 Unit Commitment Problem with Renewable Energy- A Comprehensive Review

The reliable and efficient operation of an electric power system hinges on a complex decision-making process known as the unit commitment problem. This critical task involves scheduling the operation of individual generating units within the system over a specific time horizon, typically a day or a week. The goal is to meet the ever-fluctuating electricity demand while minimizing the overall cost of generation. Electricity cannot be efficiently stored in large quantities. This necessitates real-time matching of generation with demand. UC considers various types of power plants, each with its own characteristics [85]. Nuclear and coal plants, for instance, are better suited for baseload generation due to their high start-up costs and slow response times. Conversely, natural gas and hydro plants offer more flexibility and can be ramped up or down quickly to meet peak demand periods [86].

Solving the UC problem involves complex optimization techniques that consider these constraints while minimizing the total generation cost. This cost typically includes fuel costs for fossil-fuel plants, variable operating and maintenance costs, and start-up costs associated with turning units on and off.

The increasing penetration of renewable energy sources like wind and solar adds another layer of complexity to UC. These renewable sources are variable and non-dispatchable, meaning their output depends on weather conditions and cannot be readily adjusted to meet demand. This necessitates incorporating forecasting models into the UC process to account for the variability of renewable generation [87].

Research into UC continues to evolve to address these new challenges. New approaches explore integrating renewable energy sources, accommodating the growing demand for distributed generation, and ensuring system resilience in the face of extreme weather events. In conclusion, the unit commitment problem plays a vital role in ensuring the efficient and reliable operation of electric power systems [88].

This plan emphases on handling energy in a virtual power plant (VPP) made up of wind farms, energy storage, and programs that inspire customers to regulate their energy use. This VPP runs at the transmission level and works organized with other VPPs to buy and sell energy and reserves. The goal is to make the VPP's revenues as close to its operating costs as possible. The system considers factors like power plant accessibility, reserve necessities, and the VPP's specific requirements. It also accounts for uncertainties in things like energy demand, market prices, and wind power production. [89].

To successfully accomplish power systems with erratic renewable energy sources like wind and solar, tools called stochastic unit commitment and economic dispatch are crucial. These tools help minimize the cost of producing electricity while considering the uncertainty in RES. An innovative technique has been developed to more precisely envisage the cost of electricity production. This technique is knowingly better than existing approaches, particularly on days with unanticipated weather conditions [90].

To competently accomplish power systems with a lot of RES, a new method using deep reinforcement learning has been developed. This technique helps scheduling of power plants more swiftly and efficiently. To account for the uncertainty in wind power, a system is used that pretends how changes in wind power distress the overall power system [91].

The anticipated technique is a multi-stage stochastic Mixed Integer Linear Program with binary recourse that optimizes the day-ahead UC of both predictable and virtual power plants. By associating the UC strategies of three diverse power plant types—natural gas-fired combined cycle, combined heat and power (CHP) with thermal storage, and a virtual power plant that fit in a mutual cycle with battery storage and photovoltaic fields. This optimization tactic can increase the returns of conventional power plants by up to 13.58%. It helps to create a viable and effective operational schedule for both CHP and virtual power plants [92].

To reinforce the flexibility of transmission systems with offshore wind farms ahead of approaching typhoons, a proactive UC strategy is presented. An exceptional set-up tree is developed to evaluate the uncertain effects of typhoons on offshore wind farms, transmission lines, and inclusive system circumstances, incorporating both inertia support from the wind farms and the unpredictability of system conditions [93].

It's imperative to account for the uncertainty of wind power in monthly forecast. To address this, a three-step watchlist approach is proposed to rapidly identify latent power flow constraints that may be encumbered during monthly UC. This tactic comprises of three key lists: a risk list, a concern list, and an interest list. A shift factor system is used to recognize potential overloads caused by the redispatch progression, helping to manage the effect of significant wind power uncertainties. [94].

To address the rising demand for electricity considering environmental apprehensions, a system is anticipated that efficiently integrates RES with conventional power sources and plug-in electric vehicles to meet energy consumption requirements [95]. As the power grid enlarges, the high computational costs and long processing times present noteworthy challenges for effective scheduling in UCP. To tackle these subjects, a reinforcement learning technique is presented, which suggests strong supervisory abilities and time-saving performance, making it perfect for handling the computational complications related with UCPs [96].

2.2.5 Literature Review of Oxygen Concentrator and Electrolyser

To produce oxygen more efficiently, use less energy, and provide better care for patients, oxygen concentrator operation must be optimised for changing load needs. A simulation model of a Pressure Swing Adsorption (PSA) oxygen concentrator is presented and suggests a demand-based control approach that modifies cycle duration and pressure, among other operational parameters, in response to the oxygen demand in real time. It uses less energy and guarantees an adequate supply of oxygen at times of high demand [97].

A PSA oxygen concentrator's experimental setup and simulation model are presented and create a model-predictive control strategy that predicts oxygen use and adjusts oxygen output in line with it. Compared with conventional techniques it basically consumes less energy [98]. Simulation model of PSA oxygen concentrator that uses a buttressing learning system to find the superlative control techniques based on demand data from the past and present. It makes available with an adaptive and nifty method for controlling OC with varying load profiles [99].

A battery storage unit is incorporated with PSA OC that used to investigate-how demand-responsive management and battery storage can be used to maximise the energy efficiency and lessen dependency on the grid. This system provides a feasible option for homecare applications, enhancing energy saving and a stable flow of oxygen [100]. A PSA type oxygen concentrator connected with the system and elaborate a hybrid control approach that optimises operation to save energy costs by taking into account both oxygen demand and grid restrictions for power system stability [101].

In a hospital context, the practical use of a demand-responsive control system, design and execution of a workable control system for allocating many oxygen concentrators according to patient demand that provide insightful information for using load control techniques in practical healthcare settings [102]. A combined model of a PSA oxygen concentrator and power grid is presented and create a control plan that takes demand changes and grid power fluctuations into account while adjusting operational settings to minimise energy use. They provide a multi-factor method for maximising grid stability and energy efficiency in the operation of oxygen concentrators [103].

A demand-based control system for a PSA oxygen concentrator is shown in a simulation model and influence of demand-based control techniques on oxygen concentrator problem detection and diagnostic procedures is examined in this research. They emphasise how crucial it is to modify defect detection algorithms to take load management's dynamic oxygen concentrator functioning into consideration [104]. A user-centric system with real-time feedback on energy and oxygen use is presented and create an easy-to-use system that enables patients to modify oxygen flow rates in response to current demand, therefore encouraging user awareness and energy economy [105].

A simulation model of an oxygen concentrator network in a smart hospital context is presented and create a multi-objective optimisation strategy that strikes a compromise between energy use, the price of producing oxygen, and the degree to which oxygen supply meets patient needs. They provide a viable method of controlling oxygen concentrators in intricate medical settings with various demand points [106].

A model of a hospital network with several oxygen concentrators and patients is presented and provide a comprehensive approach to managing oxygen concentrators in smart hospitals, taking into account a variety of optimisation objectives, and they also propose a multi-objective optimisation framework that balances energy consumption, oxygen supply reliability, and patient comfort under varying demand patterns [107].

A real-world dataset from a hospital context is presented in order to train machine learning models for the prediction of oxygen demand. They create a machine learning method based on patient data and historical data to forecast trends in oxygen consumption. They increase demand forecasting accuracy, which results in oxygen concentrator load control techniques that are more successful. These developments help to maximise oxygen production, save energy use, and provide a steady supply of oxygen for patients, especially during peak demand [108].

For cost-effective hydrogen generation, grid stability, and efficient hydrogen production, electrolyser operation must be optimised for fluctuating hydrogen demand. A hybrid model of a power grid with renewable energy sources and a proton exchange membrane electrolyser is presented in order to minimise operating costs and maximise hydrogen production at times when renewable energy is cheap, they build an optimisation algorithm that schedules electrolyser operation based on dynamic electricity prices and renewable energy availability [109].

A power grid model that incorporates electrolysers, other power producing units, and renewable energy sources is presented. They use a stochastic model-predictive control strategy that optimises unit commitment (scheduling power generating units) and electrolyser operation for dependable and economical grid behaviour while taking into account the uncertainty involved with renewable energy production [110].

A model of an electrolyser connected with the hydrogen market and power grid is presented. Demand-response programs, which allow electrolysers to modify their operations in response to dynamic hydrogen price signals, provide grid operators and hydrogen producers with an adaptable way to control electrolyser operation for financial gain [111].

A microgrid model with integrated battery storage, electrolysers, and renewable energy sources (PV) is presented. They provide a complete method for managing distributed energy resources and hydrogen generation in microgrids by developing an integrated energy management system that optimises energy flows within the microgrid while taking fluctuations in hydrogen demand into account [112].

A hybrid microgrid model of electrolyser with solar and wind power, hydrogen storage, and multiple loads that provide a feasible method for optimising microgrid operation with H_2 production and storage abilities for peak load and grid support. They optimise the microgrid's operation to save energy expenditures while taking H_2 demand-response possibilities into consideration [113].

A power grid and electrolyser integrated model is presented and provide a multi-objective optimisation strategy that considers both the economic feasibility and the influence on the grid when balancing the expenses of producing hydrogen with metrics for grid stability (frequency, voltage). They also provide a trade-off analysis for optimising the operation of electrolysers [114].

A PEM electrolyser model with an integrated deterioration model is presented and provide a scheduling strategy that takes into account how different load profiles affect the electrolyzer's deterioration over time and presents a novel method for maximising hydrogen generation while reducing the electrolyzer's long-term degradation [115].

A model of electrolysers, battery storage, and power grid that provide a method for using electrolysers for grid stability while controlling hydrogen production, and they provide an optimisation algorithm that schedules electrolyser operation and battery utilisation for grid support services including peak shaving and frequency management [116].

A model of an electrolyser integrated into the electrical grid is presented in order to account for uncertainties and estimate hydrogen demand, they use a machine learning methodology. They also provide a method for adjusting electrolyser operation to dynamic demand patterns and grid circumstances [117].

A multi-agent simulation model of a network of electrolysers taking part in a hydrogen marketplace is presented and provide a scalable method for controlling a network of electrolysers in a decentralised hydrogen market environment, and they create a decentralised multi-agent reinforcement learning methodology for individual electrolysers to optimise their operation based on local information and market signals [118].

2.3 SCOPE OF RESEARCH

The Unit Commitment Problem (UCP) remains a critical research area due to the growing complexity of power systems, especially with the integration of renewable energy sources, fluctuating demand patterns, and evolving market dynamics. This research aims to develop an efficient and robust meta-heuristic optimization algorithm to address large-scale UCP with enhanced accuracy, speed, and adaptability under uncertain conditions, such as those observed during the COVID-19 pandemic.

A comprehensive review of existing algorithms including SA, GA, PSO, HS, EP, DE, ABC, BFA, GSA, WOA, BA, and various hybrid methods reveals limitations such as premature convergence, computational inefficiency, and reduced accuracy in handling multi-objective and constrained problems. While several hybrid approaches have improved convergence and solution quality, challenges remain in optimizing UC for large-scale systems with renewable integration and demand uncertainty. The proposed research will focus on:

- Developing an improved hybrid meta-heuristic algorithm to enhance convergence speed and global search capability.
- Addressing the shortcomings of existing algorithms by balancing exploration and exploitation.
- Modelling UCP under realistic conditions including load uncertainty, renewable energy variability, and operational constraints.
- Evaluating the algorithm’s performance on standard test systems and during low-demand scenarios like COVID-19.

This research aims to contribute a more scalable and adaptive UC solution for modern and future power systems.

2.4 RESEARCH OBJECTIVES

The proposed research aims to develop an efficient meta-heuristic algorithm for a reliable, cost-effective unit commitment solution considering electricity demand during COVID-19. The objectives are outlined below:

(i). To study and analyse the impact of COVID-19 on the load profile of realistic power system.

(ii). To solve unit commitment problem of Thermal Power System considering impact of COVID-19 and power demand of oxygen concentrator and electrolyser.

(iii). To evaluate the cost-effective solution of the integrated unit commitment problem considering the effect of COVID-19 diseases and renewable energy sources.

2.5 CONCLUSION

In conclusion, the Unit Commitment problem is essential for efficient and reliable power system operation by scheduling generation to meet demand at minimal cost. While UC focuses on dependable and economical scheduling, it does not fully address demand variations. During COVID-19, grid management relied more on demand-side programs and renewable integration to balance demand and reduce fossil fuel use. Continuous improvements in UC models and technology integration are vital for future flexible and reliable generation planning. In the upcoming chapters, the impact of Covid-19 on Unit commitment problem has been studied and analysed considering the load demand of the electrolyser and oxygen concentrator.

Chapter-3

METHODOLOGIES

3.1 INTRODUCTION

The bedrock of modern-day economies is electricity. It powers industries, companies, light houses, and facilitates communication networks, among other aspects of economic activity. In order to operate equipment and industrial processes efficiently, which increases productivity and economic output, it is necessary to have access to inexpensive and reliable power. Having access to electricity, promotes company development and establishment, generating employment and boosting the economy. Long-term economic expansion is fuelled by electricity, which also supports the research and development that propels technical improvements. Essential services like lighting, communication, and refrigeration are made possible by electricity, which raises living standards and may even promote economic involvement.

Demand for power is heavily influenced by economic activities. Power usage is influenced by consumer purchasing patterns, industrial activity levels, and seasonal fluctuations. For both homes and companies, the price of power is a significant consideration. The cost of electricity production and transmission may be impacted by changes in fuel prices, infrastructure expenditures, and regulatory regulations. These factors can also have an influence on consumer spending and corporate operating expenses. Large sums of money are needed to build and maintain the infrastructure of the electrical grid. The amount of money invested in networks for the production, transmission, and distribution of electricity is mostly determined by political and economic factors.

The primary obstacle is figuring out how to best combine affordable energy with a dependable power source. While there may be demand for power prices to drop during economic downturns, maintaining system security and stability is crucial. There are advantages and disadvantages to the growing use of renewable energy sources like solar and wind power. These sources may have an influence on economic concerns since they are often fluctuating and need integration measures to ensure grid stability. Smart grids incorporate cutting-edge technology into the electrical system for communication, control, and monitoring. In the long term, this may reduce total costs and optimise resource allocation while enhancing efficiency.

The scheduling of electricity production from several sources (renewables and fossil fuels) to meet predicted demand at the lowest feasible cost is the goal of the optimisation issue. UCP solutions take into account variables such as fuel prices, initial investment costs, and power plant efficiency. Demand-Side Management (DSM) programs encourage customers to shift or cut down on their power consumption during times of high demand. By doing this, system costs are reduced overall and costly expenditures in extra generating capacity are avoided. Power companies may compete in the electrical market for the right to sell energy, which might result in more cost-effective production and resource allocation.

3.2 OPTIMIZATION PROBLEM

Economic growth and progress are largely dependent on electrical power. A strong and efficiently run electricity grid is necessary for a healthy economy. We can guarantee a sustainable and safe energy future by investing in smart grid technology, integrating renewable energy sources effectively, and striking a balance between economic concerns and dependability. Optimisation challenges are an effective way to identify the best feasible solutions in a variety of fields and make data-driven judgements. Optimisation methods will become more crucial in solving complicated issues in a variety of industries as research into algorithm development and processing capacity grow [119].

Several types of optimisation issues include integer programming, nonlinear optimisation, and linear optimisation. The objective function and restrictions in linear optimisation are linear functions of the decision variables. Techniques such as the simplex algorithm are often used to address these issues in an effective manner. The objective function or constraints in non-linear optimisation have non-linear interactions with the choice variables. These issues may be harder to resolve and can call for specific methods. Decision variables in integer programming are limited to integer values, or whole integers. This kind of issue comes up when allocating resources or scheduling work in situations where partial answers don't make sense.

Iterative procedures that draw inspiration from human behaviour or natural processes are known as heuristics and meta-heuristics. They are useful for solving complicated issues, particularly when determining the precise best solution proves to be challenging. Particle swarm optimisation, genetic algorithms, and simulated annealing are a few examples. Given its efficiency and possibility for optimum outcomes, a heuristic might be a viable option for a well-defined issue with easily accessible domain knowledge. Because of its adaptability and capacity to identify solutions even in the absence of comprehensive issue-specific information, a meta-heuristic may be a preferable choice when faced with a complicated problem that has little structure or expertise [120].

3.3 OPTIMIZATION METHODOLOGIES

When faced with optimisation difficulties, our goal is to find the optimal solution based on a given set of criteria. Finding the greatest answer inside a constrained neighbourhood rather than necessarily the best solution across the search space is the focus of local optimisation issues. The collection of all potential answers to the given issue is represented by the search space. Every solution is given a value, and the objective is to identify the maximum and minimum value depending on the problem. The collection of solutions in the search space that are deemed "close" to a certain answer is referred to as the neighbourhood. A local optimum is a solution that, in terms of the objective function, is better than all of its neighbours inside the search space. That may not be the greatest option available worldwide, however.

Several popular methods for local search include "hill climbing," which begins with a starting point and repeatedly advances to a better neighbour (a higher or lower objective function value, depending on the issue of minimisation or maximisation), until no better neighbours are found. In local optima, it may get trapped. Inspired by the annealing process, Simulated Annealing permits "bad" movements to sometimes break out of local optima and broaden the search area. For complicated issues with several local optima, it is helpful. By generating a population of potential solutions, using crossover and mutation operators, and choosing the "fittest" answers for the next generation, genetic algorithms are able to replicate biological behaviour. Avoiding local optima and generating a variety of options might be helpful [121].

Problems involving global optimisation seek the optimal answer across the search space, not only in a small area. Depending on the particular situation, this "best solution" either maximises or minimises the objective function. Locating the globally optimum solution may be much more difficult than local optimisation, particularly for complicated issues. Since there are many local optima in non-convex search spaces, it is challenging to ensure that suboptimal regions are avoided and the optimum solution is found. Extensive exploration of problems involving several variables may be computationally costly due to their large search areas.

Hybrid strategies take use of the advantages of many optimisation methods to more successfully address the UCP. A hybrid technique that combines heuristics and meta-heuristics may provide superior results. A heuristic may offer a solid starting answer, while a meta-heuristic may enhance it even more. Finding effective solutions while preserving computing efficiency may be possible by combining machine learning or meta-heuristic approaches with more conventional approaches like mixed-integer linear programming [122]. More investigation is required into successful hybrid strategies catered to the unique difficulties faced by UC.

3.4 PROPOSED OPTIMIZATION METHODOLOGY

3.4.1 Chaotic Beluga Whale Optimization

The Chaotic Beluga Whale Optimization (CBWO) algorithm mimics the characteristics of beluga whales throughout the optimization process, including swimming, hunting, and falling. Like other meta-heuristics, CBWO having essential stages, exploration and exploitation. During the exploration phase, beluga whales are scattered at random, which ensures that the design area is fully covered [123]. The intake phase facilitates localized neighbourhood searching within the design space. Within a search agent model, beluga whales possess the ability to navigate the search space through adjustments to their location vectors.

This unique combination of exploration, exploitation, and dynamic posture adjustments, inspired by the fascinating behaviors of beluga whales, endows CBWO with the capability to efficiently explore and optimize complex solution spaces in various real-world applications [124].

The matrix of position (M) of search agents is modelled as:

$$M = \begin{pmatrix} me_{1,1} & me_{1,2}\ldots\ldots & me_{1,d} \\ me_{2,1} & me_{2,2}\ldots\ldots & me_{2,d} \\ \vdots & \ddots & \vdots \\ me_{n,1} & me_{n,2}\ldots\ldots & me_{n,d} \end{pmatrix} \tag{3.1}$$

where d stands for the dimension of design variables and n is the beluga whale population size. The associated fitness values i.e., F_{me} for every beluga whale are kept as follows:

$$F_{me} = \begin{bmatrix} f(me_{1,1}, me_{1,2}, ..., me_{1,d}) \\ f(me_{2,1}, me_{2,2}, ..., me_{2,d}) \\ \vdots \\ \vdots \\ f(me_{n,1}, me_{n,2}, ..., me_{n,d}) \end{bmatrix} \tag{3.2}$$

Here, B_f (the balance factor) is:

$$B_f = B_o(1 - T_i / 2T_{i\max}) \tag{3.3}$$

Here, $T_{i\max}$ is the maximum number of iterations, B_o fluctuates between 0 and 1, and it determines the BWO algorithms' transitions from exploration to exploitation. T_i is the most recent iteration. The search phase begins when the balance factor is, $B_f > 0.5$ and the exploitation phase begins when $B_f \leq 0.5$. The range of B_f variable decreases from (0, 1) to (0, 0.5).

3.4.2 Exploration Phase

The beluga whale's swimming pattern, which is being considered the exploration of CBWO, shows that they can interact socially in a variety of various positions. Here, $A_{i,j}^{T+1}$ is the new location for the ith beluga whale on the jth dimension, P_j (j= 1, 2, …, d) is termed as a new position. $A_{r,P1}^{T}$ and $A_{i,Pj}^{T}$ is the latest position for the ith and rth (a randomly picked beluga whale). The locations are modified as follows:

$$\{A_{i,j}^{T+1} = A_{i,Pj}^{T} + (A_{r,P1}^{T} - A_{i,Pj}^{T})(1 + r_1)\sin(2\pi r_2), ... j = even \tag{3.4}$$

$$A_{i,j}^{T+1} = A_{i,Pj}^{T} + (A_{r,P1}^{T} - A_{i,Pj}^{T})(1 + r_1)\cos(2\pi r_2), ... j = odd \tag{3.5}$$

Here "r_1 and r_2 are arbitrary values between (0, 1). $\cos(2\pi r_2)$ and $\sin(2\pi r_2)$ are the mean of the mirrored beluga whale. The revised location shows, dependent on the factor given by odd and even numbers. Two random numbers, r_1 and r_2 are employed in the search phase to enhance the random operators".

3.4.3 Phase of Exploitation

This phase was influenced by how beluga whale feeds. They may move together, and hunt together based on their location. To choose the ideal choice, beluga whale exchange information regarding their position. A Levy flying method is incorporated to the CBWO exploitation step to enhance convergence and new position is given as follows:

$$A_i^{T+1} = r_3 A_{best}^T - r_4 A_i^T + C_1 . L_f . (A_r^T - A_i^T) \tag{3.6}$$

Here, A_i^T and A_r^T are the positions for the ith and rth beluga whale. A_i^{T+1} is new location, A_{best}^T is the strongest spot for beluga whales and r_3 & r_4 are random numbers between 0-1.

$C_1 = 2r_4(1 - T_i / T_{i\max})$ is the random jump power which stands for the strength of Levy flight (L_f). L_f and σ is calculated by equation 3.7 and 3.8 below.

$$L_f = 0.05 \times \frac{u \times \sigma}{|v|^{1/\beta}} \tag{3.7}$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\pi\beta / 2)}{\Gamma((1+\beta)/2) \times \beta \times 2^{(\beta-1)/2}} \right)^{1/\beta} \tag{3.8}$$

Where β = default constant; β=1.5; u, v are random values.

3.4.4 Optimizer for Local Space

Local optimization is a technique used to find good, but not necessarily perfect, solutions to problems. It works by iteratively improving a solution until a stopping criterion is met. Here's a breakdown of local optimization and its algorithms. We have a mathematical function or objective function that assigns a score to each possible solution. Our goal is to find the input value that minimize or maximize this score. This process starts by pick a random starting point or solution in the search space and look at nearby solutions (neighbours) of the current solution. Now, move to a neighbouring solution with a better score (lower for minimization, higher for maximization) and keep iterating steps 2 and 3 until we reach a stopping criterion, no better neighbours exist (stuck at local optima), a certain number of iterations are completed and the change in score falls below a threshold.

Local optimization algorithms can get trapped in local optima. These are points where the score is better than surrounding neighbours, but not necessarily the best globally (global optimum). Imagine a ball rolling downhill in a hilly landscape - it might get stuck in a valley instead of reaching the lowest point. Gradient descent is a popular algorithm that uses the derivative of the objective function to determine the direction of improvement (steeper downhill). Hill climbing, a simpler version that only considers the score difference between the current solution and its neighbours. Local optimization is a good choice when finding the absolute best solution isn't critical, and the search space is vast. It's often faster than searching the entire space for a perfect solution. Local optima can lead to suboptimal solutions. The quality of the result depends on the initial guess.

3.4.5 Chaotic Map

Chaotic maps offer a promising approach to enhancing the performance of local search optimization algorithms. They can help the algorithm explore the search space more effectively and potentially find better solutions. Chaotic maps are interesting mathematical tools that have been applied in optimization algorithms to address some of the challenges faced by traditional local search methods. Local search algorithms can get stuck in local optima, leading to suboptimal solutions. Imagine searching a hilly landscape and getting trapped in a valley instead of reaching the lowest point [125].

Chaotic maps are mathematical functions that exhibit seemingly random behaviour despite being deterministic (meaning they follow a specific rule). These maps can generate sequences of numbers that appear random but have specific properties, like good coverage within a defined range. Traditional local search algorithms often use random starting points. Chaotic maps can be used to generate these starting points, ensuring a more even distribution across the search space. This helps the algorithm explore a wider area and avoid getting stuck in local optima from the beginning.

During the search process, chaotic maps can be used to introduce random-like perturbations to the current solution. This helps the algorithm escape local optima by nudging it out of valleys and potentially towards better regions of the search space. By using chaotic maps, the algorithm can explore a wider range of solutions and potentially avoid getting stuck in local optima. Chaotic maps can help maintain diversity in the population of solutions considered by the algorithm, preventing premature convergence to suboptimal solutions.

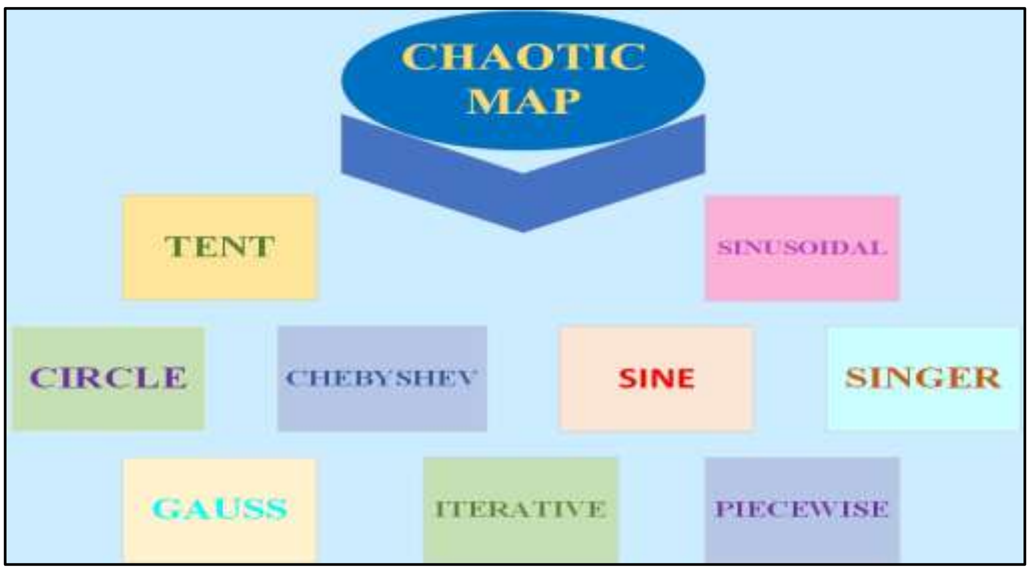


Fig. 3.1: Chaotic Map strategies

Fig. 3.1 shows chaotic map which includes a number of local optimization methods. Selecting an appropriate chaotic map with suitable properties is crucial for effective optimization. The way the chaotic map is integrated into the optimization algorithm (e.g., how much perturbation to introduce) might require some tuning for optimal performance.

3.4.6 Whale Fall

Polar bears, killer whales, and humans provide risks to beluga whales. By their intelligence, most beluga whales can avoid threats by sharing information within them. However, a few beluga whales died and plunged to the bottom of the sea. Numerous animals get food through the phenomenon known as "whale fall”.

To simulate small changes and forecast the manner of a whale's fall at each iteration, we choose the chance of a whale dropping from a group unit as a qualitative parameter. These beluga whales could have moved, or they might have taken asylum in a deeper body of water after being hurt by others. To keep steady population size, the updated sites are dependent on the beluga whales’ habitat and scope of the whale’s fall. The mathematical formulation is as follows:

$$A_i^{T+1} = r_{r5} A_i^T - r_{r6} A_r^T + r_{r7} A_{step} \tag{3.9}$$

Where, A_i^{T+1} is new location, r_{r5}, r_{r6} & r_{r7} are any numbers between (0, 1), A_{step} is the whale fall's step size, determined as follows:

$$A_{step} = (u_{ib} - l_{ib}) \exp(-C_2 T_i / T_{i\max}) \tag{3.10}$$

Here, C_2 is the step coefficient of whale drop probability and population size, calculated by- $C_2 = 2W_f \times n$. Where, u_{ib} and l_{ib} are the upper and lower limits of the variables. The whale falling (W_f) is calculated by:

$$W_f = 0.1 - 0.05 T_i / T_{i\max} \tag{3.11}$$

The risk of a whale falling is reduced from 0.1 in the initial iteration and 0.05 in the final, showing that the danger posed by beluga whales lowers as they get closer to their food source throughout the optimization process.

3.4.7 The PSEUDO Code of Proposed CBWO

Input: Algorithm parameters (population size, maximum iteration)

Output: The best solution

Pseudo Code-

Initialize population and fitness value, obtain best solution

While $T_i=T_{imax}$

Calculate W_f and B_f

For each A_i

If $B_f>0.5$ **(Exploration phase)**

Generate P_j and choose A_r randomly

Update new position

Else if $B_f<0.5$ **(Exploitation phase)**

Apply Chaotic strategy and evaluate levy flight function

Update latest position

End if

Check new position and find fitness value

End for

For each A_i

If $B_f= W_f$ **(Fall phase)**

Update C_2 and calculate A_{step}

Update new position

Check new position and find fitness value

End if

End for

To find current best solution $P*$

$T_{imax}=T_i+1$

End While

Fig.3.2: PSEUDO Code of CBWO

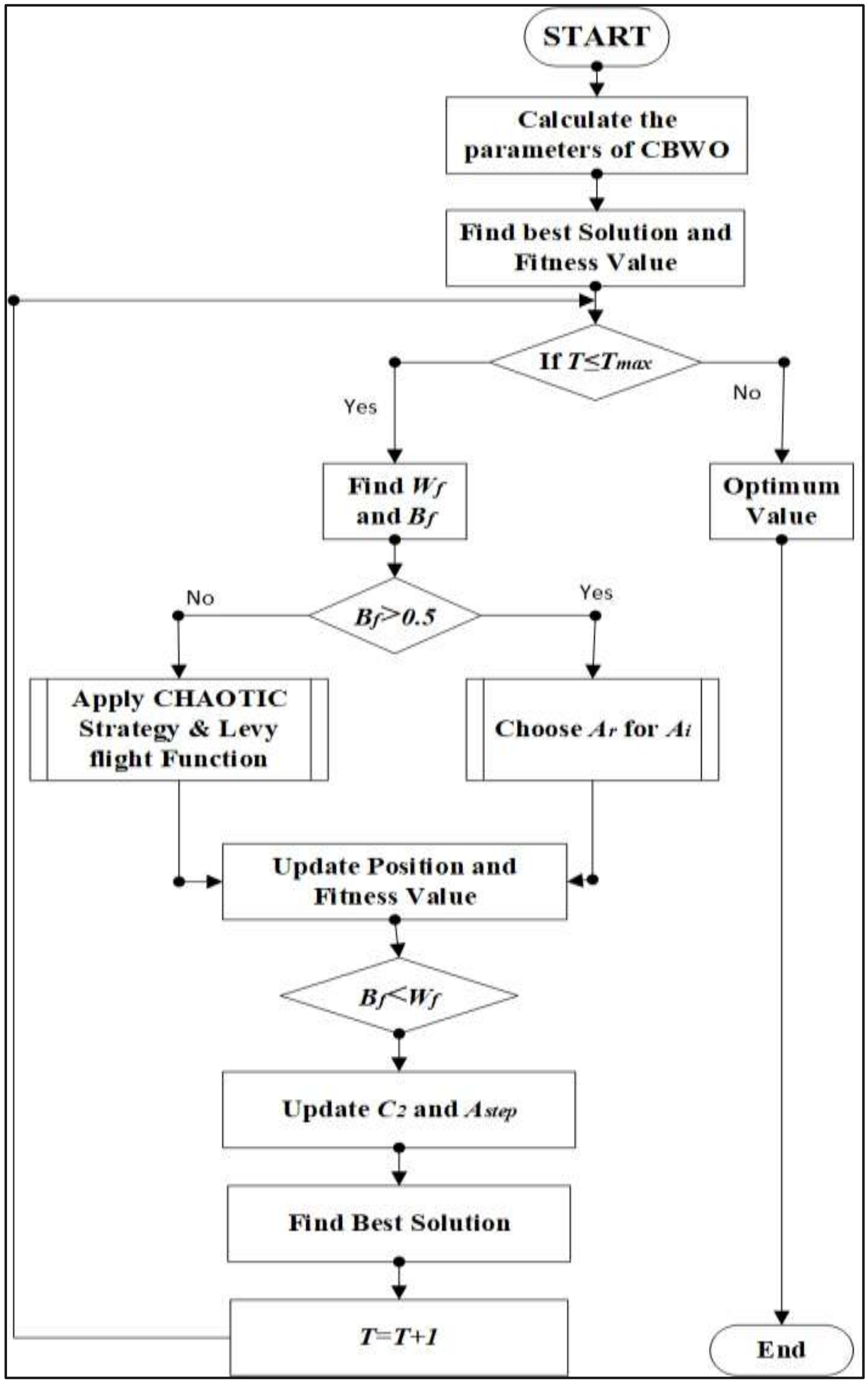


Fig. 3.3: Flowchart for CBWO

3.5 TEST SYSTEMS

The proposed CBWO method incorporates with the circular chaotic map to enhance its optimization capabilities. The distinct characteristics of the popular test functions, including their range, ideal value, and objective fitness within a specific parameter space and dimension (fmin) set them apart. The Uni-modal (UM) functions equations from F1 to F7 are presented in Table 3.1. The test benchmark functions corresponding to CEC 2005, for multi modal (MM) functions (F8 to F13) & (F14 to F23) are fixed dimension (FD) functions shown in Tables 3.2 and 3.3, respectively.

Table-3.1: Uni-modal Benchmark Functions

Functions	Dimensions	Range
$F_1(S)=\sum_{a=1}^{b} S_a^2$	30	[-100,100]
$F_2(S)=\sum_{a=1}^{b}\lvert S_a\rvert+\prod_{a=1}^{b}\lvert S_a\rvert$	30	[-10,10]
$F_3(S)=\sum_{a=1}^{b}\left(\sum_{c-1}^{a} S_c\right)^2$	30	[-100,100]
$F_4(S)=\max A\{\lvert S_a\rvert, 1\le a\le b\}$	30	[-100,100]
$F_5(S)=\sum_{a=1}^{b-1}[100(S_a+1-S_a^2)^2+(S_a-1)^2]$	30	[-30,30]
$F_6(S)=\sum_{a=1}^{b}(S_a+0.5)^2$	30	[-100,100]
$F_7(S)=\sum_{a=1}^{b} aS_a^4+rand[0,1]$	30	[-1.28,1.28]

Table-3.2: Multi Modal Benchmark Functions

Functions	**Dim**	**Range**
$F_8(S) = \sum_{a=1}^{b} -S_a \sin(\sqrt{\lvert S_a \rvert})$	30	[-500, 500]
$F_9(S) = \sum_{a=1}^{b} [S_a^2 - 10\cos(2\pi S_a) + 10]$	30	[-5.12, 5.12]
$F_{10}(S) = -20\exp(-0.2\sqrt{(\frac{1}{b}\sum_{a=1}^{z} S_a)}) - \exp\frac{1}{b}\sum_{a=1}^{b}\cos(2\pi S_a) + 20 + d$	30	[-32, 32]
$F_{11}(S) = 1 + \sum_{a=1}^{b} \frac{S_a^2}{4000} - \prod_{a=1}^{b} \cos\frac{S_a}{\sqrt{a}}$	30	[-600, 600]
$F_{12}(S) = \frac{\pi}{z}\left\{10\sin(\pi\tau_1) + \sum_{a=1}^{b-1}(\tau_a - 1)^2[1 + 10\sin^2(\pi\tau_{a+1})] + (\tau_b - 1)^2\right\} +$ $\sum_{a=1}^{b} g(S_a, 10, 100, 4)$ $\tau_a = 1 + \frac{S_a + 1}{4}$ $g(S_a, p, x, i) = \begin{Bmatrix} x(S_a - p)^i S_a > p \\ 0 \rightarrow -p < S_a < p \\ x(-S_a - p)^i S_a < -p \end{Bmatrix}$	30	[-50, 50]
$F_{13}(S) = 0.1\{\sin^2(3\pi S_a) + \sum_{a=1}^{b}(S_a - 1)^2[1 + \sin^2(3\pi S_a + 1)] + (x_b - 1)^2$ $[1 + \sin^2(2\pi S_a)]\} + \sum_{a=1}^{b} g(S_a, 5, 100, 4)$	30	[-50, 50]

Table-3.3: Fixed Dimensions Benchmark Functions

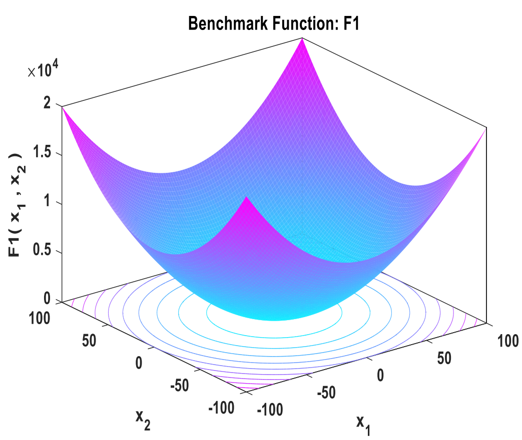
Functions	Dim	Range
$F_{14}(S)=\left[\frac{1}{500}+\sum_{c=1}^{2}5\frac{1}{c+\sum_{a=1}^{b}(S_a-b_{ac})^6}\right]^{-1}$	2	[65.536,65.536]
$F_{15}(S)=\sum_{a=1}^{11}\left[p_a-\frac{S_a(r_a^2+r_a\eta_2)}{r_a^2+r_a\eta_3+\eta_4}\right]^2$	4	[-5,5]
$F_{16}(S)=4S_1^2-2.1S_1^4+\frac{1}{3}S_1^6+S_1S_2-4S_2^2+4S_2^4$	2	[-5,5]
$F_{17}(S)=(S_2-\frac{5.1}{4\pi^2}S_1^2+\frac{5}{\pi}S_1-6)^2+10(1-\frac{1}{8\pi})\cos S_1+10$	2	[-5,5]
$F_{18}(S)=[1+(S_1+S_2+1)^2(19-14S_1+3S_1{}^2-14S_2+6S_1S_2+3S_2{}^2)]\times[30+(2S_1-3S_2)^2\times(18-32S_1+12S_1{}^2+48S_2-36S_1S_2+27S_2{}^2)]$	2	[-2,2]
$F_{19}(S)=-\sum_{a=1}^{4}d_a\exp(-\sum_{c=1}^{3}S_{ac}(S_a-q_{ac})^2)$	3	[1,3]
$F_{20}(S)=-\sum_{a=1}^{4}d_a\exp(-\sum_{c=1}^{6}S_{ac}(S_a-q_{ac})^2)$	6	[0,1]
$F_{21}(S)=-\sum_{a=1}^{5}[(S-p_a)(S-p_a)^T+d_a]^{-1}$	4	[0,10]
$F_{22}(S)=-\sum_{a=1}^{7}[(S-p_a)(S-p_a)^T+d_a]^{-1}$	4	[0,10]
$F_{23}(S)=-\sum_{a=1}^{10}[(S-p_a)(S-p_a)^T+d_a]^{-1}$	4	[0,10]

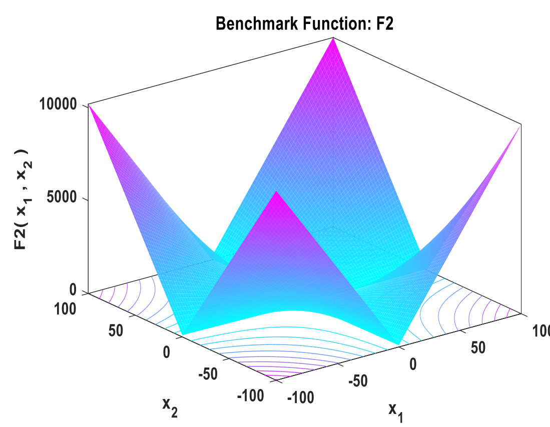
3.6 RESULTS AND DISCUSSION

This section summarizes the findings from testing the suggested approach against 23 frequently used benchmark functions. The simulation was done using MATLAB 2018a on a Windows 11 equipped with an Intel(R) Core (TM) i5-10300H CPU operating at 2.50GHz. To characterize the performance of the benchmark functions, tests measures done on mean, worst, best, median, and standard deviation by conducting 1000 iterations and 30 trial tests. These outcomes are then compared with other existing algorithms for the purpose of comprehensive analysis.

3.6.1 Testing Results of Unimodal Functions

The algorithms' capability to approach the origin determines how to trace the ideal place. There may be possibilities to be trapped far or close and characterized in the form of exploration and exploitation throughout the search procedure by numerous means. The uni-modal benchmark function's statistical analysis is displayed in Table 3.4 and 3.5. Table 3.6 displays the CBWO simulation time for UM benchmark functions.





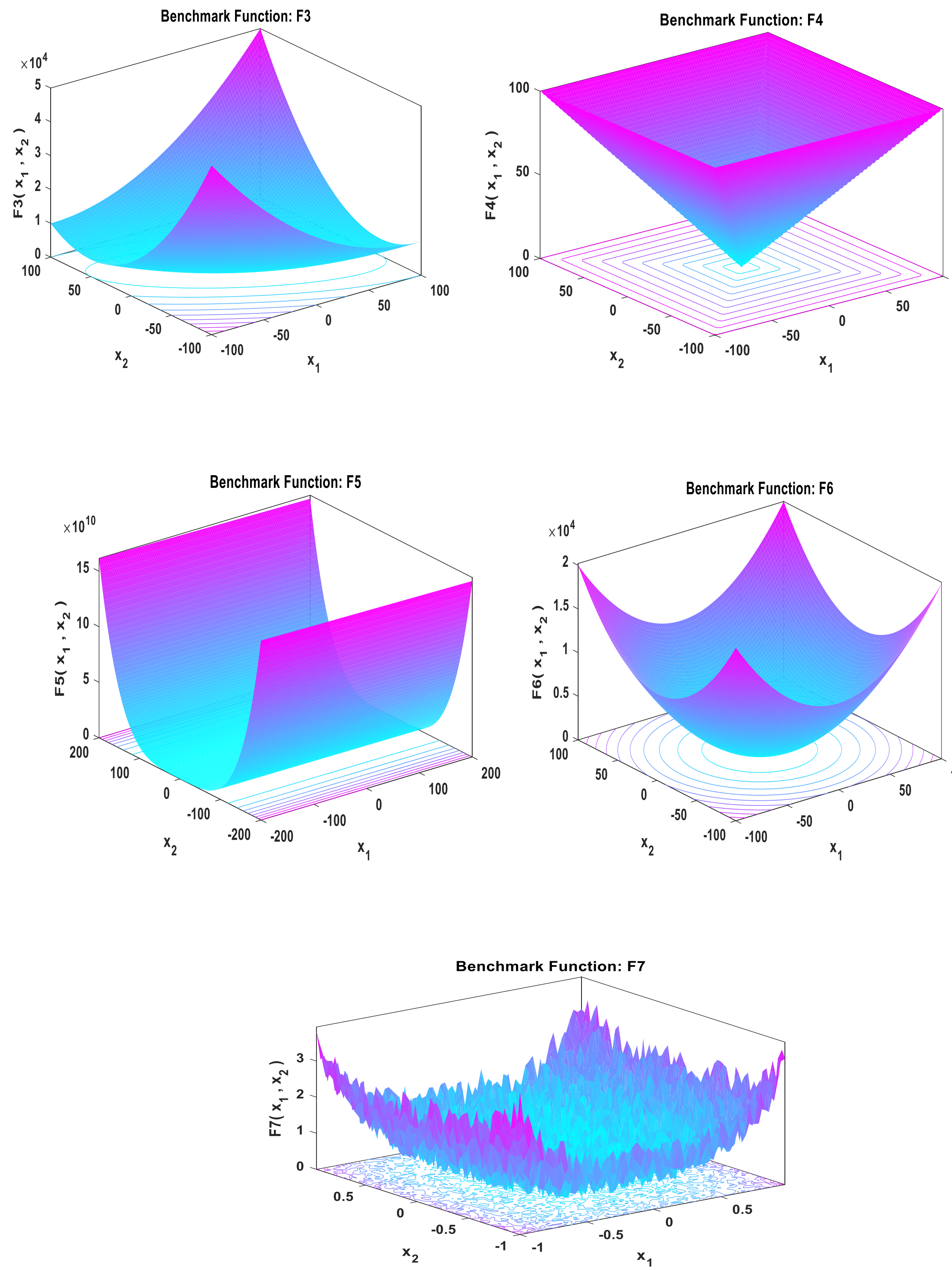


Fig.3.4: 3D View of Unimodal (F1-F7) Benchmark Functions

The results for benchmark UM functions implementing the Chaotic Beluga Whale Optimization technique are shown in Table 3.4. The table shows numerous statistical parameters characterizing the results from CBWO runs for each benchmark function (F1 to F7), including the std, which reflects the dispersion of values around the mean, and the Mean that provides the average value of the data received. The best and worst solutions discovered throughout the optimization process are shown in the best and worst columns, respectively.

Table-3.4: Test results for Unimodal Benchmark Functions using CBWO

Function No.	Mean	Std	Best	Worst	Median	Wilcoxon rank sum test (p-Value)	Wilcoxon rank sum test (h-Value)	t-test (p-Value)
F1	0	0	0	0	0	-	0	-
F2	0	0	0	0	0	1.21E-12	1	0
F3	0	0	0	0	0	-	0	-
F4	0	0	0	0	0	1.21E-12	1	0
F5	1.72E-12	6.31E-12	9.07E-17	3.33E-11	9.91E-15	0.001597	1	0.378396
F6	3.53E-27	9.43E-27	3.32E-30	3.93E-26	1.1E-28	0.077272	0	0.435751
F7	4.95E-05	6.04E-05	3.14E-07	0.000269	3.8E-05	0.019112	1	0.339088

The results of statistical analyses used to determine the significance of the algorithm. The Wilcoxon rank sum test (p-Value) reflects the chance of noticing the observed outcomes if there were no differences between CBWO and the comparable approaches. The Wilcoxon rank sum test (h-Value) denotes hypothesis test's outcome, 1 indicating a significant difference and 0 indicating no significant difference. Similarly, the t-test (p-value) provides insight into the probability of observing the results if there were no differences between CBWO and the compared methods.

Upon analysing the Table-3.4 and 3.5, it is evident that CBWO demonstrates highly competitive performance across the unimodal benchmark functions. The exceptionally low mean, standard deviation, and best values show that CBWO often produces optimum or almost optimal solutions. Furthermore, the statistical tests indicate that CBWO significantly outperforms other techniques for some benchmark functions (e.g., F2, F4, F5 and F7) as indicated by the h-value of 1 and small p-values in Wilcoxon rank sum and t-tests. However, for functions F1, F3 and F6, CBWO's performance is still competitive, although the statistical tests show less significant differences.

The Table-3.5 presents a summary of results obtained from conducting 30 trials of the "Chaotic Beluga Whale Optimization (CBWO) algorithm on UM benchmark functions (F1 to F7). The table shows statistical data for each function, including minimum and maximum values, means, medians, first quartiles (25th percentile), second quartiles (50th percentile), third quartiles (75th percentile), semi-interquartile deviation, number of outliers, and standard deviation. These findings give useful insights into the efficacy and unpredictability of CBWO when applied to diverse benchmark functions.

Table-3.5: Statistical Analysis of Results for Unimodal Benchmark Functions

Function No.	No. of trials	Minimum value	Maximum value	Mean Value	Median	First quartile (25th Percentile)	Second Quartile (50th Percentile)	Third quartile (75th Percentile)	Semi Interquartile Deviation	Number of outliers	Std
F1	30	0	0	0	0	-	0	-	-	0	0
F2	30	0	0	0	0	-	0	-	-	0	0
F3	30	0	0	0	0	-	0	-	-	0	0
F4	30	0	0	0	0	-	0	-	-	0	0
F5	30	9.07E-17	3.33E-11	1.72E-12	9.91E-15	8.92E-16	9.91E-15	5.6E-14	2.76E-14	4	6.31E-12
F6	30	3.32E-30	3.93E-26	3.53E-27	1.1E-28	2.01E-29	1.1E-28	5.98E-28	2.89E-28	5	9.43E-27
F7	30	3.14E-07	0.000269	4.95E-05	3.8E-05	8.14E-06	3.8E-05	5.06E-05	2.12E-05	2	6.04E-05

Table-3.6: Computational Time for Unimodal Benchmark Functions Using CBWO

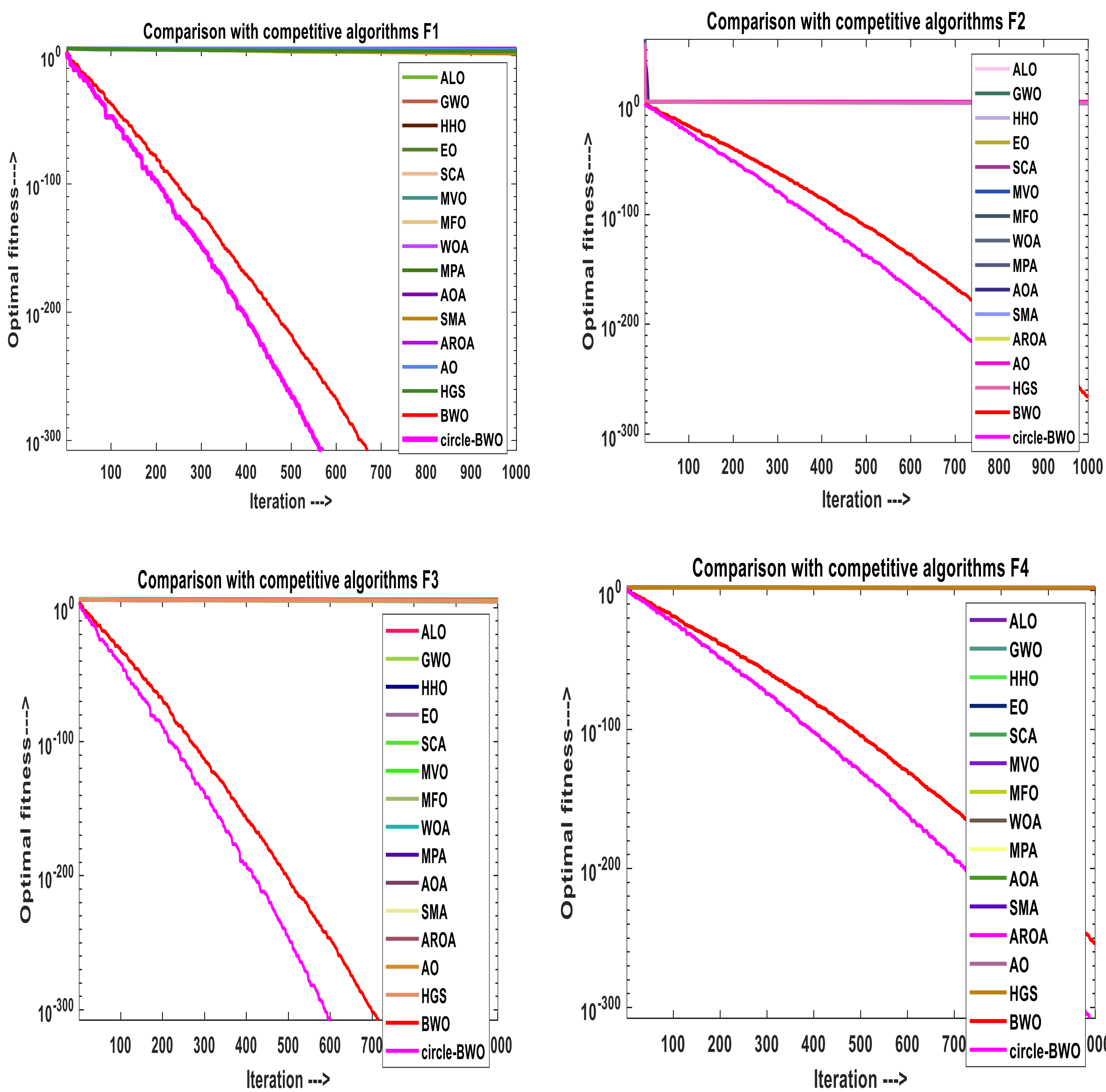
Function No.	Best Time (Sec)	Worst Time (Sec)	Average Time (Sec.)
F1	3.13E-01	8.44E-01	3.46E-01
F2	2.34E-01	5.63E-01	2.93E-01
F3	4.69E-01	5.94E-01	5.08E-01
F4	2.34E-01	3.59E-01	2.44E-01
F5	2.66E-01	3.28E-01	2.74E-01
F6	2.34E-01	2.81E-01	2.41E-01
F7	3.44E-01	3.91E-01	3.60E-01

The outcomes are shown in Table 3.7, in terms of std and mean deviation with various meta heuristic search algorithms including Aquila Optimization (AO), Grey Wolf Optimization (GWO), Marine Predator Algorithm (MPA), Harris Hawk Optimization (HHO), Arithmetic Optimization Algorithm (AOA), Hunger Game Search (HGS), Moth Fame Optimizer (MFO), Multi Verse Optimizer (MVO), Ant Lion Optimizer (ALO), Sine-Cosine Algorithm (SCA), Slime Mold Algorithm (SMA), Wolf Optimization Algorithm (WOA), Beluga Whale Optimization (BWO), and CBWO with 1000 iterations and 30 test runs used to assess this method.

Table-3.7: Comparison of Results for Unimodal Benchmark Functions

Algorithms	Parameters	F1	F2	F3	F4	F5	F6	F7
AO	AVG	1.90E-212	8.04E-102	2.03E-201	8.31E-100	9.74E-04	6.31E-05	4.69E-05
[127]	SD	0.0E+00	4.35E-101	0.0E+00	3.37E-99	1.66E-03	0.00015	3.94E-05
GWO	AVG	2.53E-70	4.36E-41	0.0E+00	1.61E-19	1.51E-17	2.64E+01	2.92E-01
[128]	SD	3.95E-70	3.94E-41	0.0E+00	5.60E-19	1.81E-17	7.05E-01	2.47E-01
MPA	AVG	5.54E-50	5.75E-28	1.14E-12	2.58E-19	2.34E+01	1.70E-09	6.79E-04
[129]	SD	7.76E-50	7.37E-28	2.99E-12	1.89E-19	5.09E-01	6.72E-10	4.10E-04
HHO	AVG	2.6E-193	1.9E-101	0.0E+00	2.30E-166	8.46E-98	1.11E-03	1.05E-05
[130]	SD	3.8E-192	7.6E-101	0.0E+00	1.20E-164	4.43E-97	1.25E-03	2.17E-05
AOA	AVG	1.47E-28	0.0E+00	0.0E+00	2.94E-03	1.99E-02	2.79E+01	2.42E+00
[131]	SD	8.03E-28	0.0E+00	0.0E+00	1.07E-02	2.07E-01	4.75E-01	2.14E-01
HGS	AVG	0.0E+00	4.80E-116	1.54E-152	2.32E-132	1.52E+01	8.72E-07	6.46E-04
[132]	SD	0.0E+00	0.0E+00	8.45E-152	1.27E-131	1.18E+01	1.16E-06	9.46E-04
MFO	AVG	2.00E+03	3.37E+01	2.49E+04	6.44E+01	5.35E+06	1.66E+03	4.62E+00
[133]	SD	4.07E+03	2.03E+01	1.41E+04	8.69E+00	2.03E+07	5.28E+03	1.31E+01
MVO	AVG	3.19E-01	3.89E-01	4.81E+01	1.08E+00	4.08E+02	3.24E-01	2.09E-02
[134]	SD	1.13E-01	1.39E-01	2.18E+01	3.11E-01	6.15E+02	9.73E-02	9.58E-03
ALO	AVG	1.05E-05	2.87E+01	1.29E+03	1.22E+01	2.99E+02	1.20E-05	1.04E-01
[135]	SD	7.83E-06	4.21E+01	5.96E+02	3.59E+00	4.31E+02	1.10E-05	3.43E-02
SCA	AVG	1.53E-02	1.15E-05	3.27E+03	2.04E+01	5.33E+02	4.55E+00	2.44E-02
[136]	SD	3.01E-02	2.75E-05	2.94E+03	1.10E+01	1.92E+03	3.57E-01	2.07E-02
SMA	AVG	0.0E+0	5.67E-188	0.0E+0	5.63E-195	1.99E+00	1.24E-03	9.89E-05
[137]	SD	0.0E+0	0.0E+0	0.0E+0	0.0E+0	6.81E+0	6.18E-04	1.00E-04
WOA	AVG	0.0E+0	0.0E+0	0.0E+0	0.0E+0	6.81E+0	6.18E-04	1.01E-04

[138]	SD	2.28E-152	1.59E-103	1.06E+04	2.99E+01	5.74E-01	1.11E-01	1.15E-03
BWO	AVG	0.0E+00	3.01E-261	0.0E+00	2.20E-252	1.09E-11	2.01E-27	6.36E-05
[123]	SD	0.0E+00	0.0E+00	0.0E+00	0.0E+00	5.57E-11	3.54E-27	4.44E-05
CBWO	**AVG**	**0.0E+00**	**0.0E+00**	**0.0E+00**	**0.0E+00**	**1.72E-12**	**3.53E-27**	**4.95E-05**
	SD	**0.0E+00**	**0.0E+00**	**0.0E+00**	**0.0E+00**	**6.31E-12**	**9.43E-27**	**6.04E-05**



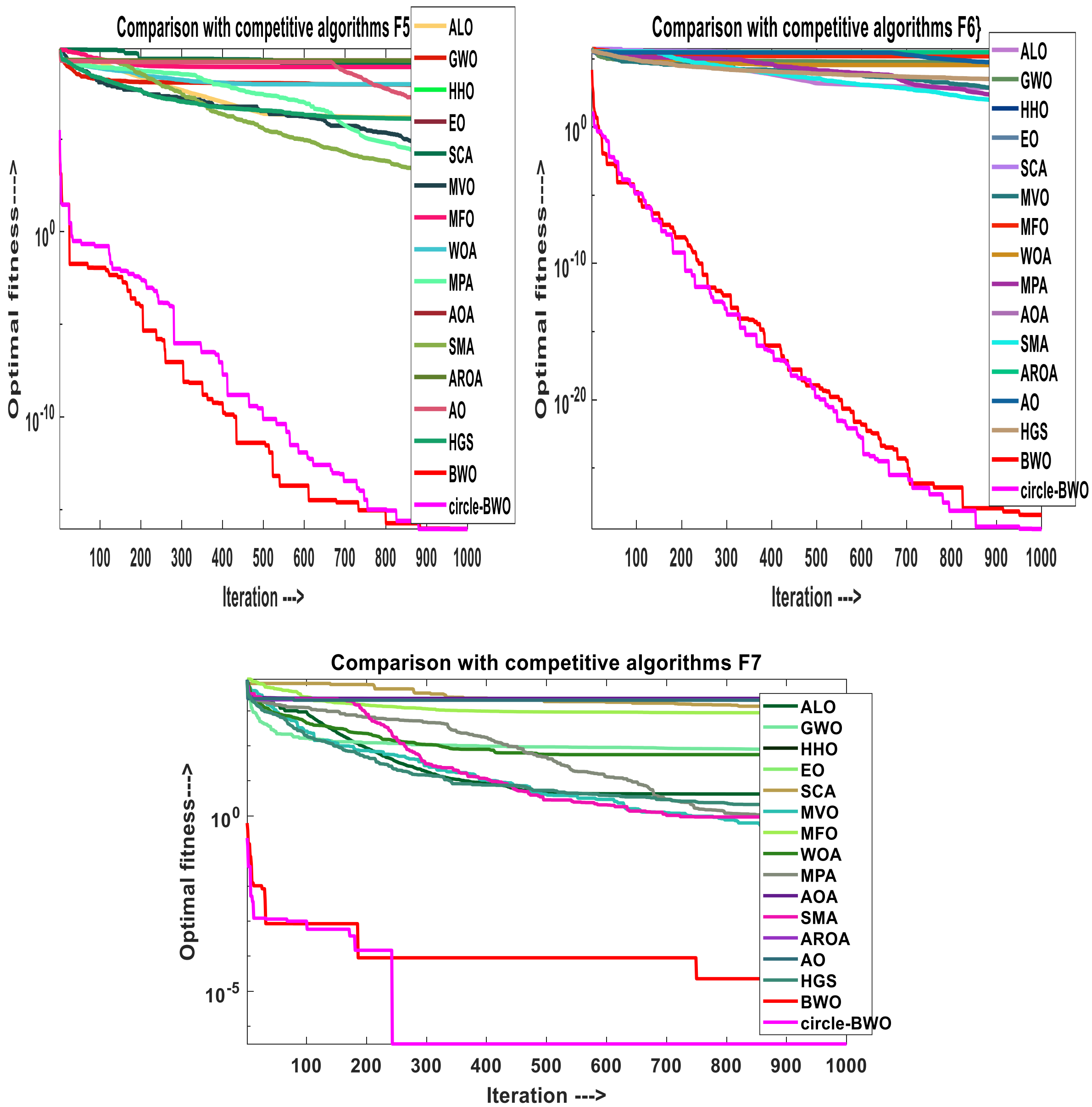
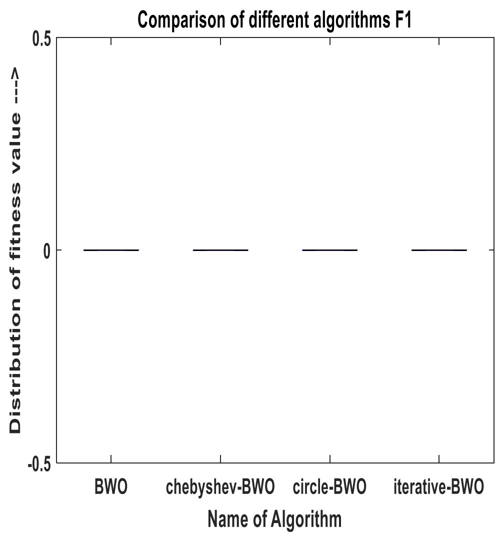
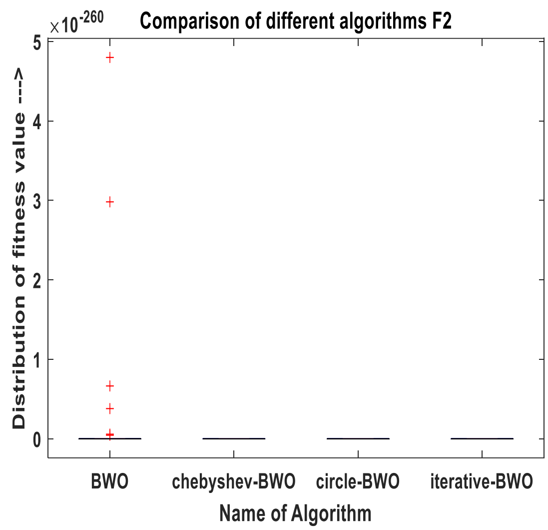


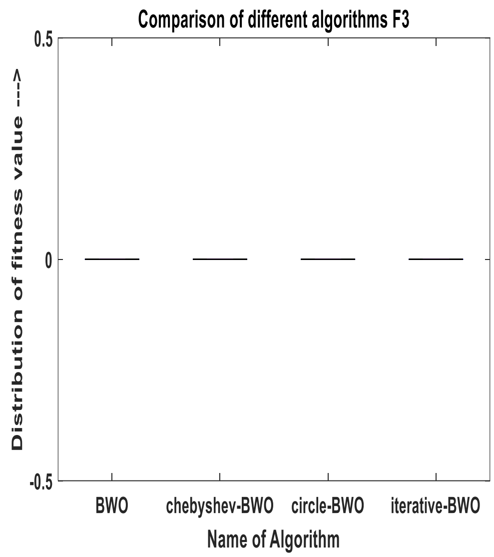
Fig.3.5: Comparison Graph of CBWO with other Algorithms for Unimodal Functions (F1- F7)

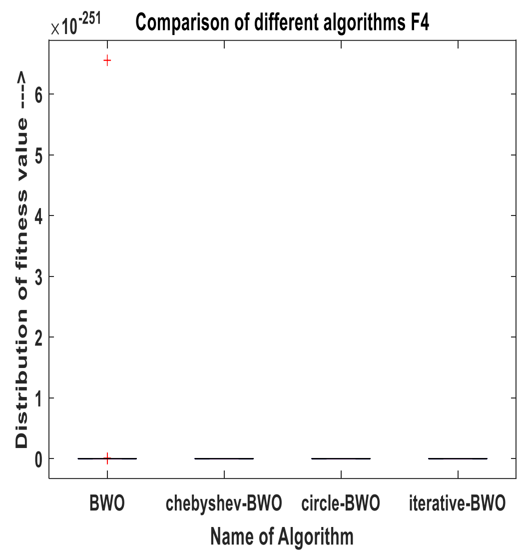
The UM test results (F1-F7) demonstrate the usefulness of the method by highlighting various improvements in convergence when employing CBWO. Fig. 3.6 shows the box plot comparison of BWO with their chaotic versions for F1- F7. Fig. 3.5 shows the standard benchmark functions and the comparison of CBWO with various meta-heuristic algorithms for all UM functions.

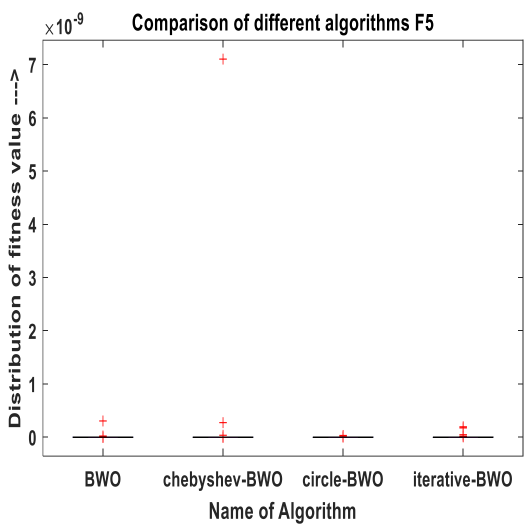
Overall, the test results affirm CBWO's effectiveness and competitiveness in solving uni-modal benchmark functions, showcasing its potential as a reliable and efficient optimization algorithm. Further investigations may be necessary to explore CBWO's performance on other types of benchmark functions and other applications.

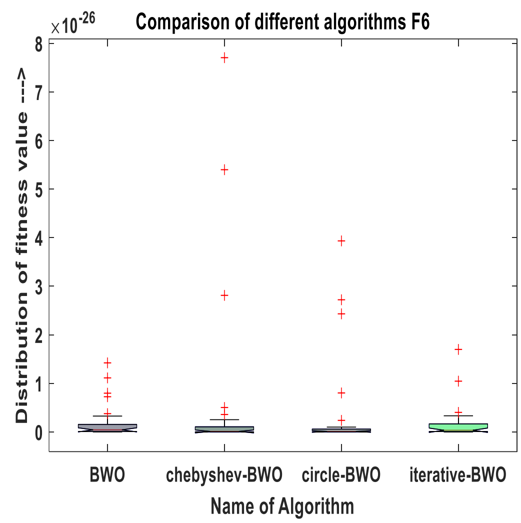





Comparison of different algorithms F3
Distribution of fitness value --->
0.5
0
-0.5
BWO
chebyshev-BWO
circle-BWO
iterative-BWO
Name of Algorithm


×10^-251
Comparison of different algorithms F4
Distribution of fitness value --->
0
1
2
3
4
5
6
BWO
chebyshev-BWO
circle-BWO
iterative-BWO
Name of Algorithm


×10^-9
Comparison of different algorithms F5
Distribution of fitness value --->
0
1
2
3
4
5
6
7
BWO
chebyshev-BWO
circle-BWO
iterative-BWO
Name of Algorithm


×10^-26
Comparison of different algorithms F6
Distribution of fitness value --->
0
1
2
3
4
5
6
7
8
BWO
chebyshev-BWO
circle-BWO
iterative-BWO
Name of Algorithm

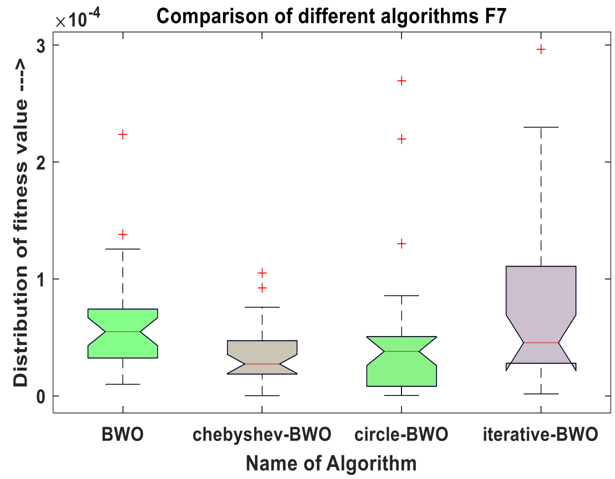
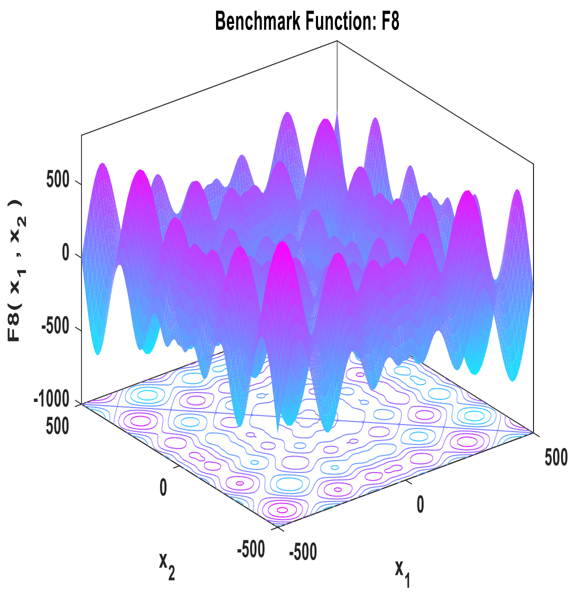
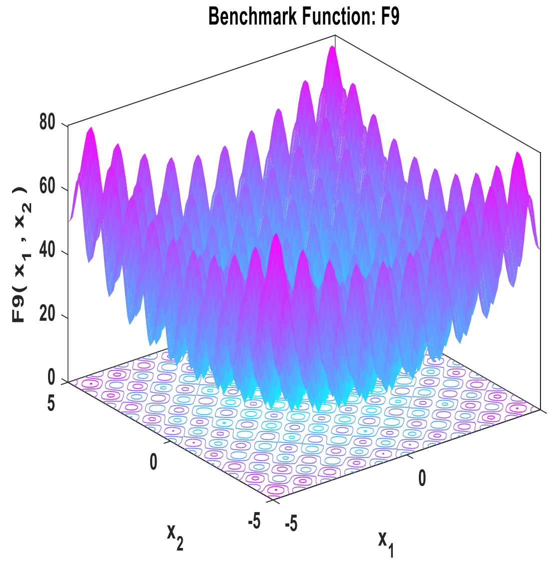


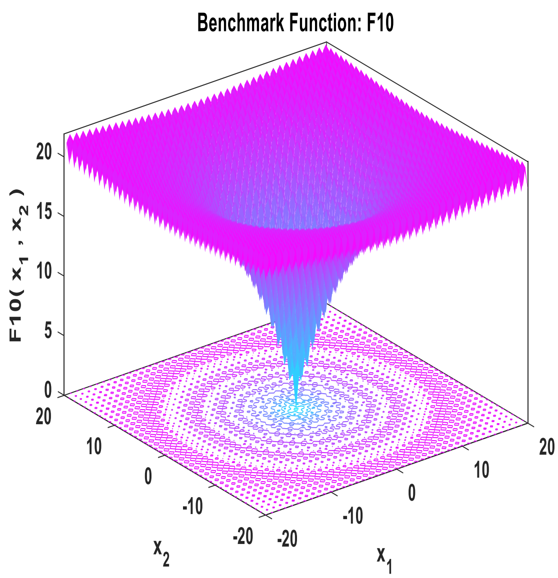
Fig.3.6: Boxplot figures for Unimodal Function of Various Chaotic Versions of BWO.

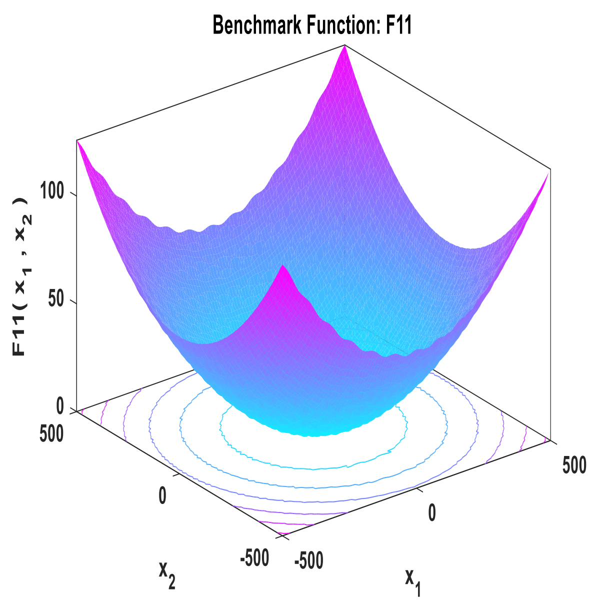
3.6.2 Testing of MM Test Functions

The suggested Chaotic Beluga Whale Optimization algorithm is rigorously evaluated for multi-modal test functions through 1000 iterations and 30 trial runs. The outcomes of the Multimodal test functions and simulation time are presented in Table 3.8 and Table 3.9, along with statistical analysis for benchmark functions. Table 3.10 compares the effectiveness of CBWO with various algorithms, including AO, GWO, MPA, HHO, AOA, HGS, MFO, MVO, ALO, SCA, SMA, WOA and BWO. CBWO exhibits higher convergence rates, with fewer peak spots in the results for MM functions F8 to F13, highlighting the method's efficiency. Box-plot trial runs of the MM benchmark functions are evaluated to alternative approaches, confirming the superior performance of CBWO. The comprehensive analysis underscores the effectiveness and potential of CBWO in tackling multi-modal optimization challenges across various domains.


Benchmark Function: F8
F8(x1 , x2)
500
0
-500
-1000
x2
x1
500
0
-500
-500
0
500


Benchmark Function: F9
F9(x1 , x2)
80
60
40
20
0
x2
x1
5
0
-5
-5
0
5


Benchmark Function: F10
F10(x1 , x2)
20
15
10
5
0
x2
x1
20
10
0
-10
-20
-20
-10
0
10
20


Benchmark Function: F11
F11(x1 , x2)
100
50
0
x2
x1
500
0
-500
-500
0
500

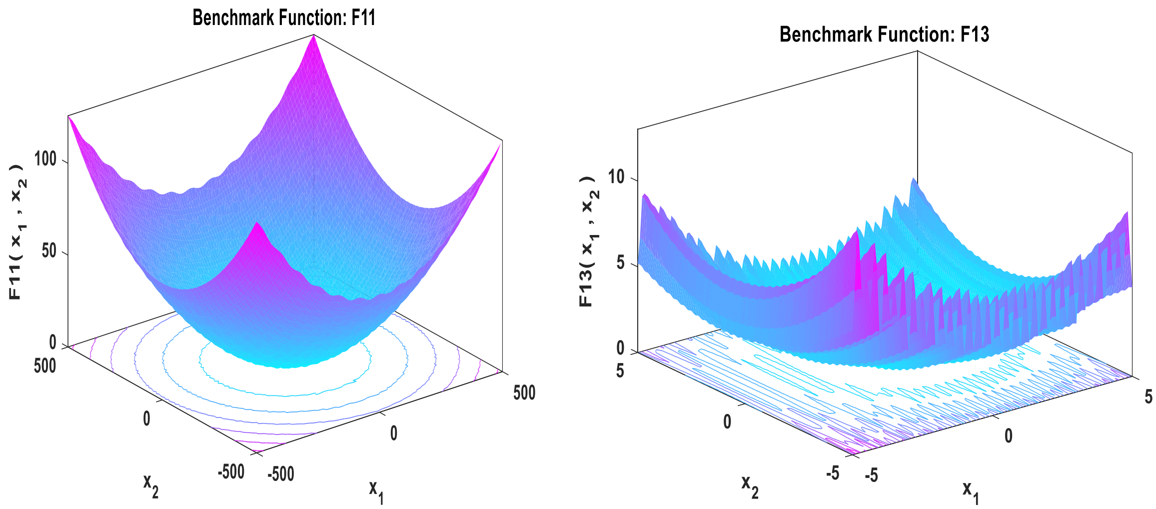


Fig.3.7: 3D view of Multimodal (F8-F13) Benchmark Functions

The relevance of the Chaotic Beluga Whale Optimization findings for MM benchmark functions (F8 to F13) is shown in Tables 3.8-3.9. In each function, the standard deviation which reflects the distribution of values around the mean, is represented by the Std., and the mean value of the results represented by the Mean. The best and worst solutions discovered throughout the optimization process are shown in the Best and Worst columns, respectively in Table 3.8.

To assess the importance of CBWO, the Table 3.8 also contains the results of the Wilcoxon rank sum test and the t-test. It denotes the hypothesis test's outcome, with 0 indicating no significant difference and 1 indicating a significant difference.

Table-3.8: Test Results of Multimodal Benchmark Functions

Function No.	Mean	Std	Best	Worst	Median	Wilcoxon rank sum test (p-value)	Wilcoxon rank sum test (h-value)	t- test (p-value)
F8	-12569.5	1.85E-12	-12569.5	-12569.5	-12569.5	-	0	-
F9	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	-	0	-
F10	8.88E-16	0.0E+00	8.80E-16	8.80E-16	8.80E-16	-	0	-
F11	0.0E+00	0.0E+00	0.0E+00	0.0E+00	0.0E+00	-	0	-
F12	9.18E-24	4.82E-23	3.82E-28	2.65E-22	7.67E-26	0.137323	0	0.359807
F13	3.75E-24	1.06E-23	2.75E-28	4.6E-23	1.42E-25	0.864994	0	0.996838

Table-3.9: Statistical Analysis of Results for Multimodal Benchmark Functions using CBWO

Function No.	No. of trials	Minimum value	Maximum value	Mean Value	Median	First quartile (25th Percentile)	Second Quartile (50th Percentile)	Third quartile (75th Percentile)	Semi Interquartile Deviation	Number of outliers	Standard Deviation
F8	30	-12569.5	-12569.5	-12569.5	-12569.5	-	-12569.5	-	-	0	1.85E-12
F9	30	0.0E+00	0.0E+00	0.0E+00	0.0E+00	-	0.0E+00	-	-	0.0E+00	0.0E+00
F10	30	8.8E-16	8.8E-16	8.8E-16	8.8E-16	-	8.8E-16	-	-	0.0E+00	0.0E+00
F11	30	0.0E+00	0.0E+00	0.0E+00	0.0E+00	-	0.0E+00	-	-	0.0E+00	0.0E+00
F12	30	3.82E-28	2.65E-22	9.18E-24	7.67E-26	1.95E-26	7.67E-26	3.82E-25	1.81E-25	3	4.82E-23
F13	30	2.75E-28	4.6E-23	3.75E-24	1.42E-25	2.29E-26	1.42E-25	4.88E-25	2.32E-25	5	1.06E-23

Table-3.10: Computational time for Multi-modal benchmark functions using CBWO

Function No.	Best Time (Sec)	Average Time (Sec.)	Worst Time (Sec)
F8	2.50E-01	2.70E-01	2.97E-01
F9	2.34E-01	2.52E-01	2.66E-01
F10	2.34E-01	2.53E-01	2.66E-01
F11	2.66E-01	2.81E-01	3.44E-01
F12	5.78E-01	6.86E-01	1.39E+00
F13	5.78E-01	6.17E-01	7.19E-01

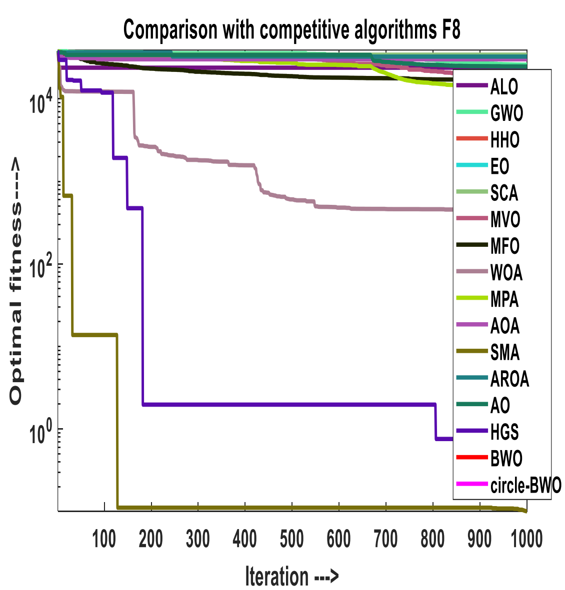
The findings show that CBWO routinely produces outcomes for multi-modal benchmark functions that are very effective. CBWO achieves optimum or close to perfect outcomes for functions F8, F9, F10, and F11, as shown by the exceptionally low mean, standard deviation, and best values. The statistical tests further support the significance of CBWO's results, with p-values suggesting the obtained outcomes are highly relevant and reliable. However, for functions F12 and F13, the statistical tests show less significant differences, implying that CBWO performs competitively, though with some variability in comparison to alternative approaches.

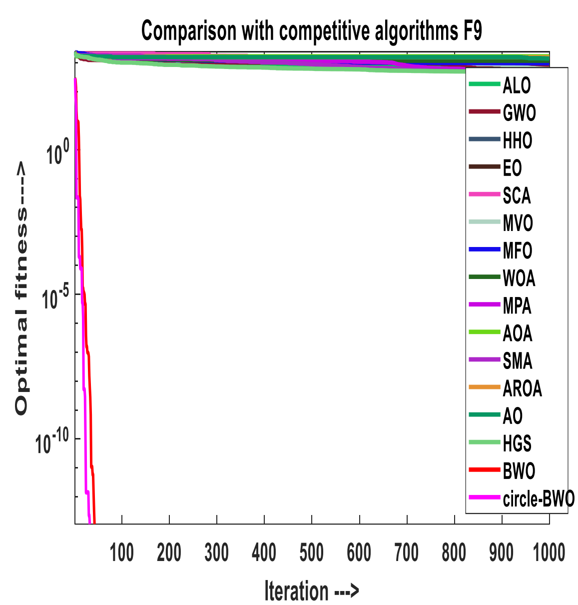
In conclusion, the Table 3.11 demonstrates the robustness and significance of CBWO in tackling multi-modal benchmark functions, affirming its potential as an effective and reliable optimization algorithm for complex real-world problems.

Table-3.11: Comparison of Results for Multi-Modal Benchmark Problems

Algorithms	P	F8	F9	F10	F11	F12	F13
AO [127]	AVG	1.90E-212	8.04E-102	2.03E-201	8.31E-100	9.74E-04	6.31E-05
	SD	0.0E+00	4.35E-101	0.0E+00	3.37E-99	1.66E-03	0.00015
GWO [128]	AVG	2.53E-70	4.36E-41	0.0E+00	1.61E-19	1.51E-17	2.64E+01
	SD	3.95E-70	3.94E-41	0.0E+00	5.60E-19	1.81E-17	7.05E-01
MPA [129]	AVG	5.54E-50	5.75E-28	1.14E-12	2.58E-19	2.34E+01	1.70E-09
	SD	7.76E-50	7.37E-28	2.99E-12	1.89E-19	5.09E-01	6.72E-10
HHO [130]	AVG	2.6E-193	1.9E-101	0.0E+00	2.30E-166	8.46E-98	1.11E-03
	SD	3.8E-192	7.6E-101	0.0E+00	1.20E-164	4.43E-97	1.25E-03
AOA [131]	AVG	1.47E-28	0.0E+00	0.0E+00	2.94E-03	1.99E-02	2.79E+01
	SD	8.03E-28	0.0E+00	0.0E+00	1.07E-02	2.07E-01	4.75E-01
HGS [132]	AVG	0.0E+00	4.80E-116	1.54E-152	2.32E-132	1.52E+01	8.72E-07
	SD	0.0E+00	0.0E+00	8.45E-152	1.27E-131	1.18E+01	1.16E-06
MFO [133]	AVG	2.00E+03	3.37E+01	2.49E+04	6.44E+01	5.35E+06	1.66E+03
	SD	4.07E+03	2.03E+01	1.41E+04	8.69E+00	2.03E+07	5.28E+03
MVO [134]	AVG	3.19E-01	3.89E-01	4.81E+01	1.08E+00	4.08E+02	3.24E-01
	SD	1.13E-01	1.39E-01	2.18E+01	3.11E-01	6.15E+02	9.73E-02
ALO [135]	AVG	1.05E-05	2.87E+01	1.29E+03	1.22E+01	2.99E+02	1.20E-05
	SD	7.83E-06	4.21E+01	5.96E+02	3.59E+00	4.31E+02	1.10E-05

SCA [136]	AVG	1.53E-02	1.15E-05	3.27E+03	2.04E+01	5.33E+02	4.55E+00
	SD	3.01E-02	2.75E-05	2.94E+03	1.10E+01	1.92E+03	3.57E-01
SMA [137]	AVG	0.0E+0	5.67E-188	0.0E+0	5.63E-195	1.99E+00	1.24E-03
	SD	0.0E+0	0.0E+0	0.0E+0	0.0E+0	6.81E+0	6.18E-04
WOA [138]	AVG	0.0E+0	0.0E+0	0.0E+0	0.0E+0	6.81E+0	6.18E-04
	SD	2.28E-152	1.59E-103	1.06E+04	2.99E+01	5.74E-01	1.11E-01
BWO [123]	AVG	0.0E+00	3.01E-261	0.0E+00	2.20E-252	1.09E-11	2.01E-27
	SD	0.0E+00	0.0E+00	0.0E+00	0.0E+00	5.57E-11	3.54E-27
CBWO	**AVG**	**0.0E+00**	**0.0E+00**	**0.0E+00**	**0.0E+00**	**1.72E-12**	**3.53E-27**
	SD	**0.0E+00**	**0.0E+00**	**0.0E+00**	**0.0E+00**	**6.31E-12**	**9.43E-27**





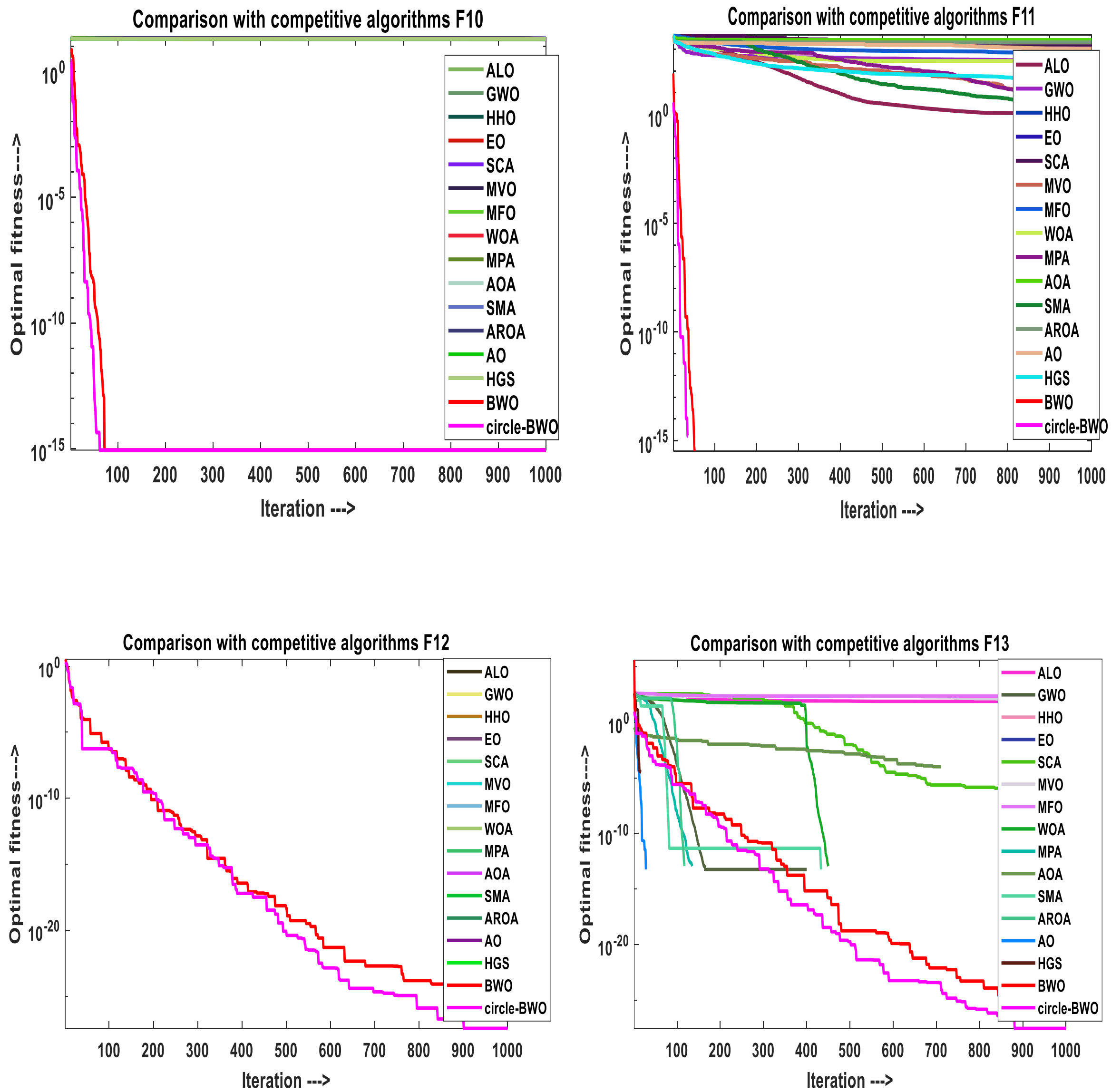
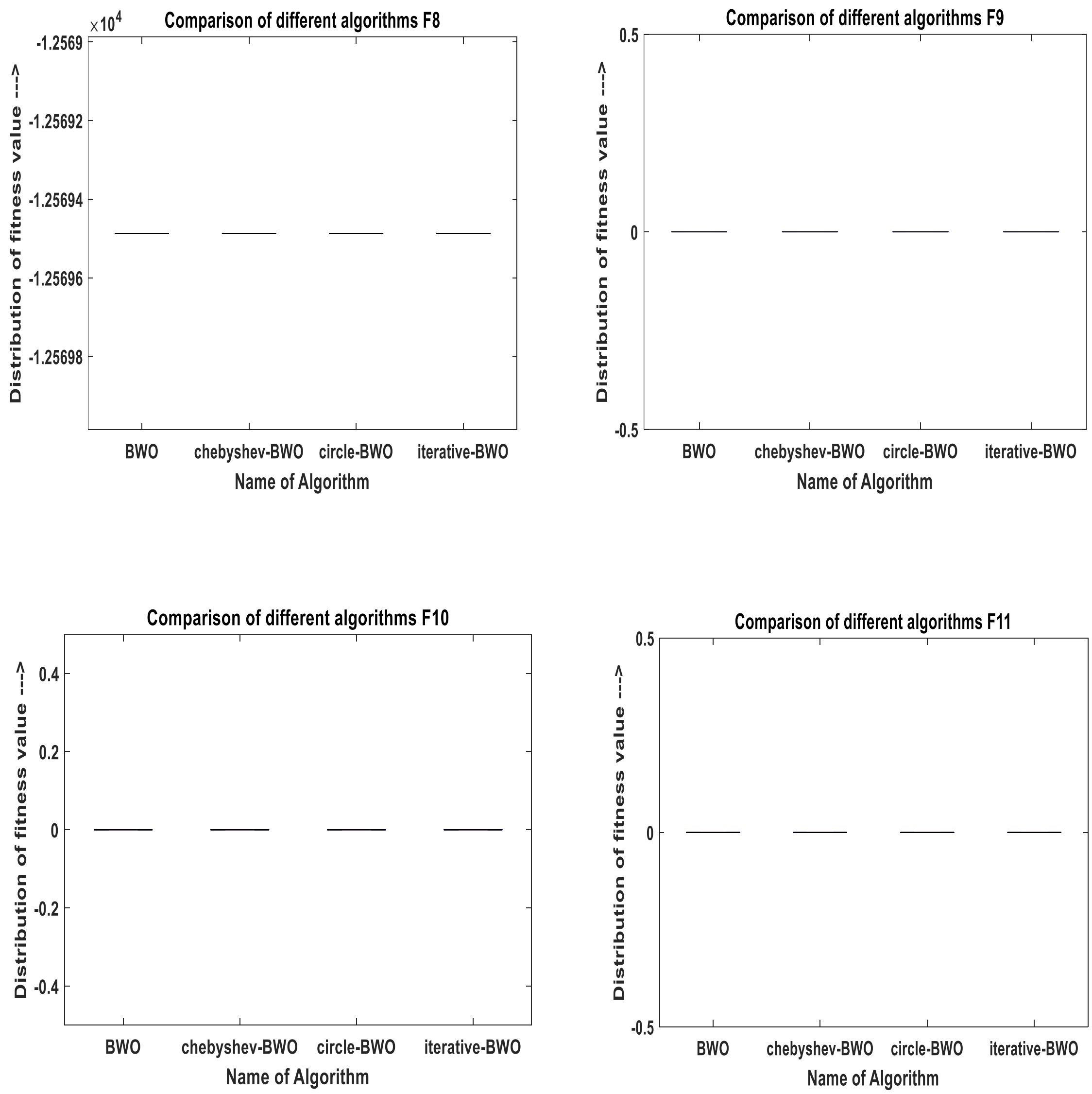


Fig.3.8: Comparison of convergence of CBWO with other algorithms for Multimodal functions (F8-F13)

The results for multimodal CBWO are shown in terms of std and mean deviation with other algorithms including AO, GWO, MPA, HHO, AOA, HGS, MFO, MVO, ALO, SCA, SMA, WOA and BWO. To evaluate the comparison results, number of iterations set to 1000 and 30 test runs. The MM test results (F8-F13) demonstrate the usefulness of the method by highlighting various improvements in convergence when employing CBWO. Fig. 3.9 (f8-f13) shows the box plot comparison of BWO with their chaotic versions, Fig. 3.8 shows the convergence graph and the comparison of CBWO with various metaheuristic algorithm for all the MM functions.



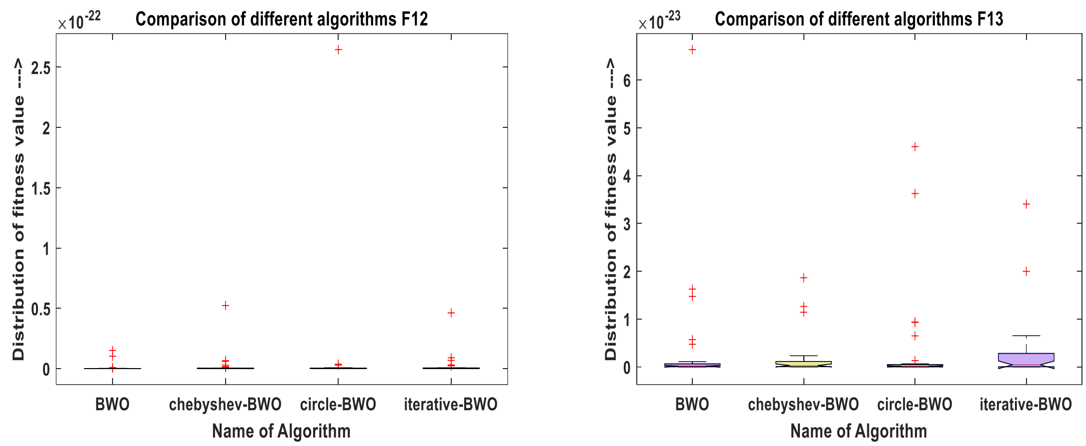
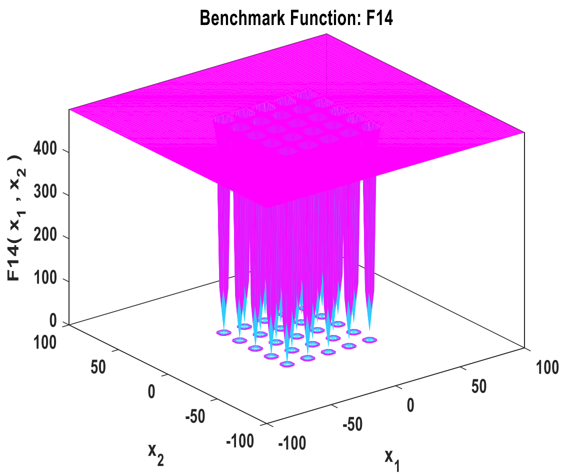


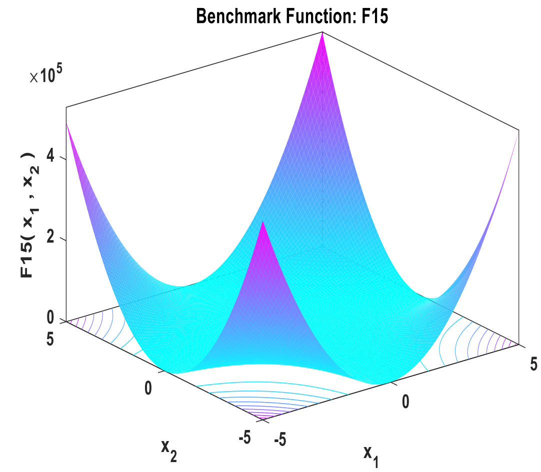
Fig.3.9: Boxplot for Various Chaotic Versions of CBWO.

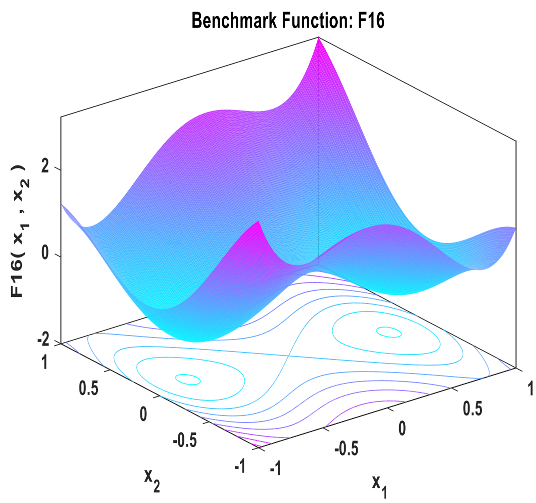
3.6.3 Testing of Fixed Dimension Benchmark Functions

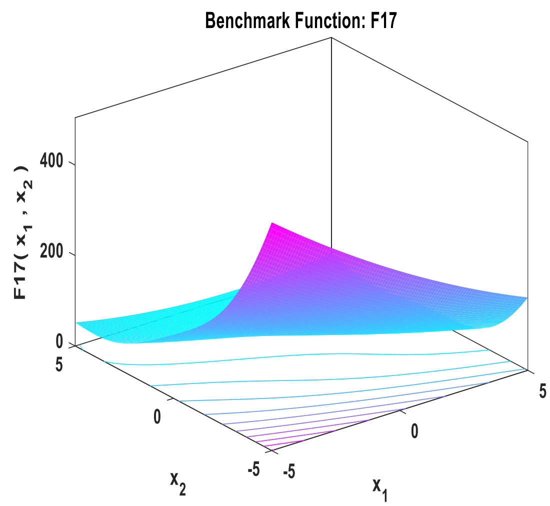
CBWO is thoroughly evaluated for FM functions (F14 to F23) with 30 trials & 1,000 iterations. The results for FD functions and numerical analysis for FD functions are presented in Table 3.12 and Table 3.13, respectively. Additionally, Table 3.14 compares the simulation time for FD Benchmark Problems using CBWO. Convergence results for FM functions compares with AO, GWO, MPA, HHO, AOA, HGS, MFO, MVO, ALO, SCA, SMA, WOA and BWO, in terms of std & mean in Table 3.15 and 3.16. Notably, the suggested circular chaotic BWO consistently demonstrates superior convergence outcomes, as evidenced by the comparison of convergence curves.

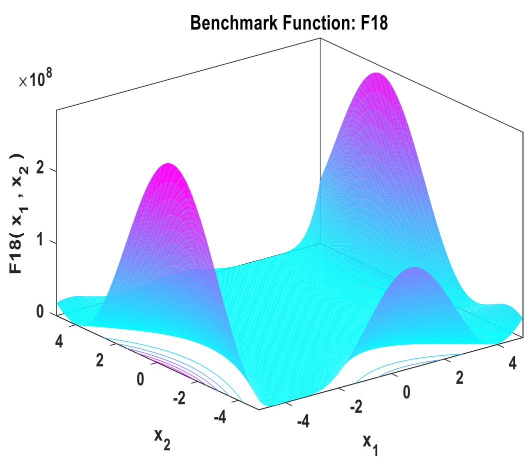
Overall, the comprehensive analysis highlights the effectiveness and efficiency of CBWO in solving FM functions and FD Benchmark Problems. The presented results and comparisons reinforce CBWO's potential as a competitive and promising optimization algorithm for addressing a wide range of complex optimization challenges.

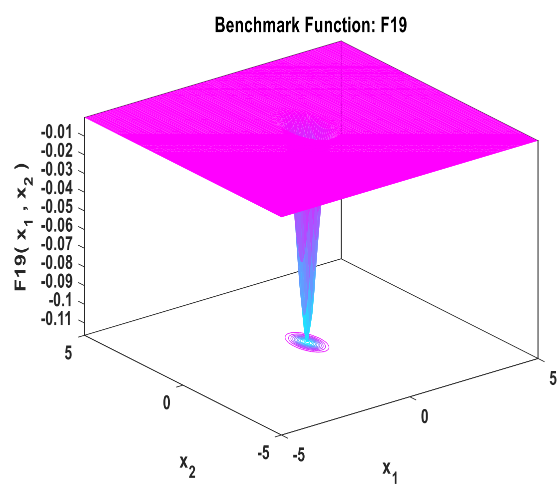

Benchmark Function: F14
F14(x1 , x2)
x2
x1


Benchmark Function: F15
×10^5
F15(x1 , x2)
x2
x1


Benchmark Function: F16
F16(x1 , x2)
x2
x1


Benchmark Function: F17
F17(x1 , x2)
x2
x1


Benchmark Function: F18
×10^8
F18(x1 , x2)
x2
x1


Benchmark Function: F19
F19(x1 , x2)
x2
x1

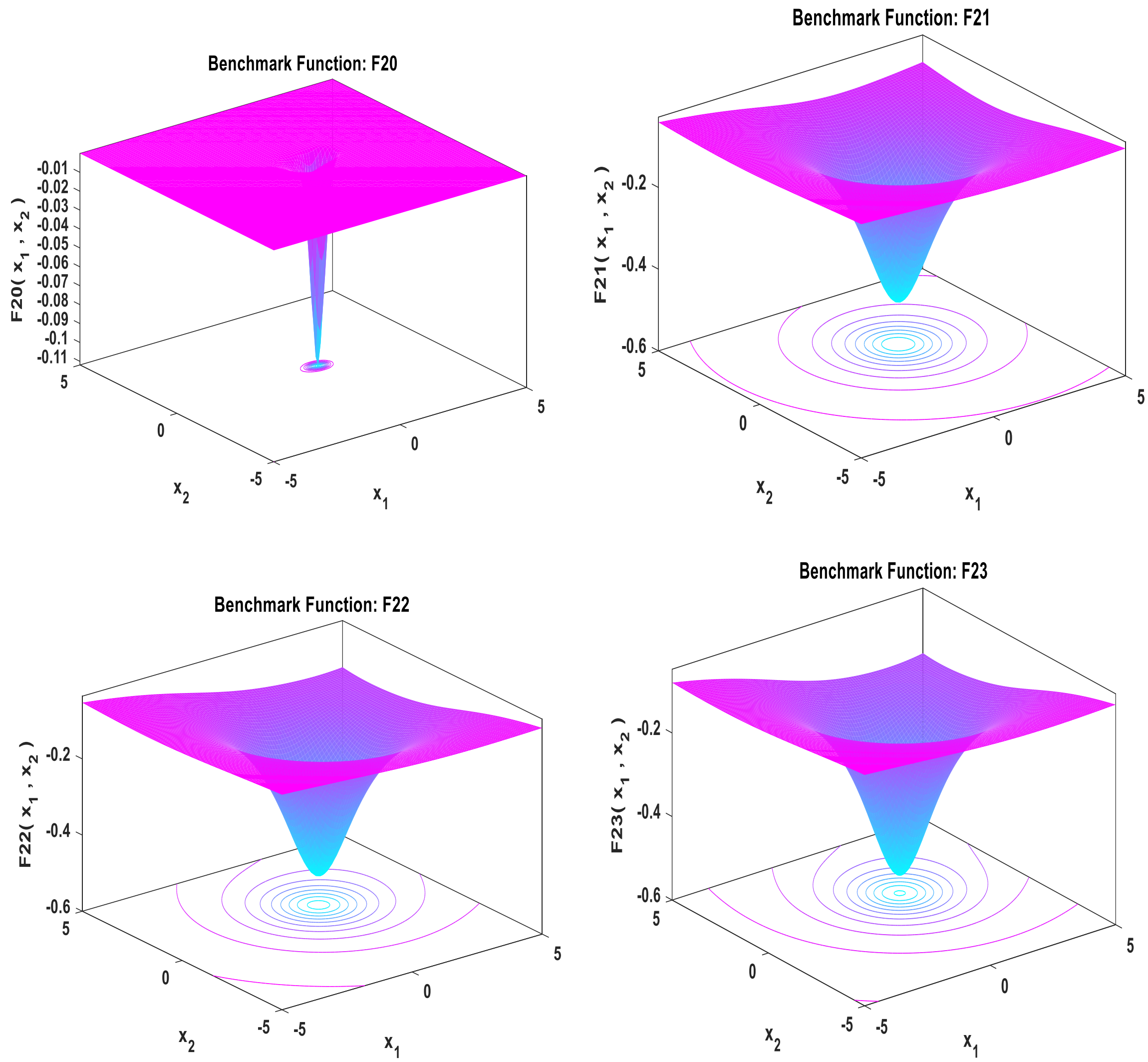


Fig.3.10: 3D view of Fixed benchmark functions

Table-3.12: Test results for fixed dimensions benchmark problems using CBWO

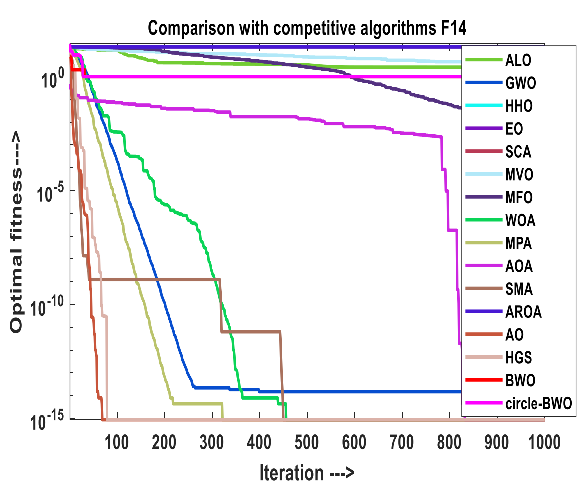
Function	Mean	Std	Best	Worst	Median	Wilcoxon rank sum test (p-value)	Wilcoxon rank sum test (h-value)	t-test (p-value)
F14	1.387087	2.131098	0.988004	12.67051	0.988004	0.00232	1	0.325582
F15	0.000391	0.000104	0.000317	0.000829	0.000365	0.000284	1	0.005703
F16	-1.03126	0.000375	-1.03159	-1.0301	-1.03142	5.19E-07	1	9.42E-05
F17	0.399869	0.002187	0.397892	0.408654	0.399388	0.662735	0	0.662748
F18	3.365409	0.367306	3.005133	4.290632	3.232937	0.05012	0	0.017677
F19	-3.86122	0.001618	-3.86267	-3.8541	-3.86173	0.000318	1	0.002648
F20	-3.30795	0.006881	-3.31826	-3.29077	-3.30916	0.662735	0	0.883057
F21	-10.1532	7.46E-06	-10.1532	-10.1532	-10.1532	3.09E-06	1	0.024276
F22	-10.4029	1.13E-05	-10.4029	-10.4029	-10.4029	7.66E-05	1	0.020185
F23	-10.5364	8.55E-06	-10.5364	-10.5364	-10.5364	2.32E-06	1	3.63E-05

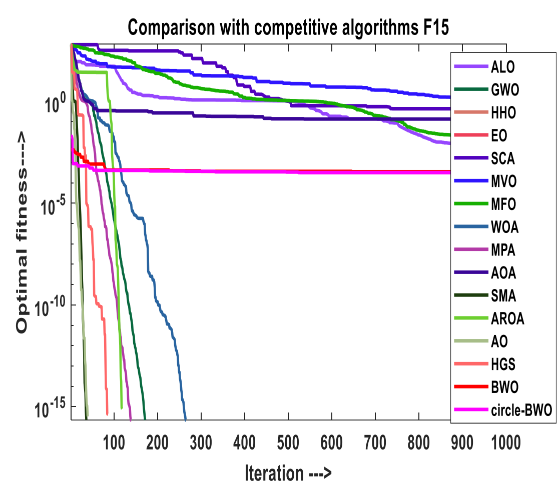
Table-3.13: Statistical analysis of results for fixed dimensions benchmark problems using CBWO

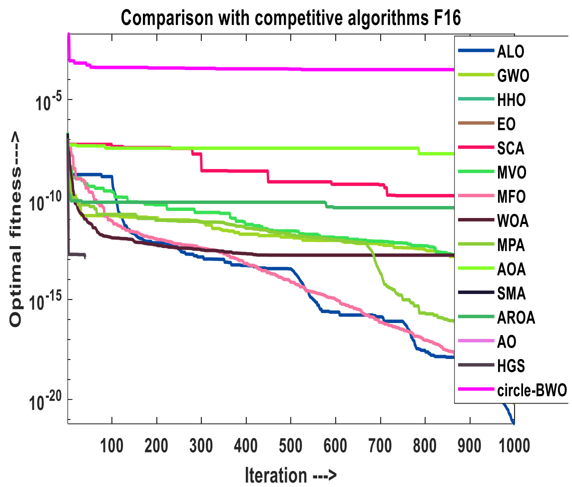
Function	No. of trials	Minimum value	Maximum value	Mean Value	Median	First quartile (25th Percentile)	Second quartile (50th Percentile)	Third quartile (75th Percentile)	Semi Interquartile Deviation	Number of outliers	Standard Deviation
F14	30	0.998004	12.67051	1.387	0.9980	0.998004	0.998004	0.998004	7.37E-12	4	2.13109
F15	30	0.000317	0.000829	0.0033	0.0003	0.000332	0.000365	0.000384	2.58E-05	3	0.00010
F16	30	-1.03159	-1.0301	-1.031	-1.0314	-1.03152	-1.03142	-1.03116	0.00018	2	0.00037
F17	30	0.397892	0.408654	0.398	0.3993	0.398513	0.399388	0.400289	0.000888	2	0.00218
F18	30	3.005133	4.290632	3.365	3.2329	3.067337	3.232937	3.628263	0.280463	0	0.36730
F19	30	-3.86267	-3.8541	-3.861	-3.8617	-3.86209	-3.86173	-3.8609	0.000597	1	0.00161
F20	30	-3.31826	-3.29077	-3.307	-3.3091	-3.31312	-3.30916	-3.30312	0.004999	0	0.006881
F21	30	-10.1532	-10.1532	-10.15	-10.153	-10.1532	-10.1532	-10.1532	8.56E-07	5	7.46E-06
F22	30	-10.4029	-10.4029	-10.40	-10.402	-10.4029	-10.4029	-10.4029	3.06E-06	2	1.13E-05
F23	30	-10.5364	-10.5364	-10.53	-10.536	-10.5364	-10.5364	-10.5364	5.91E-06	0	8.55E-06

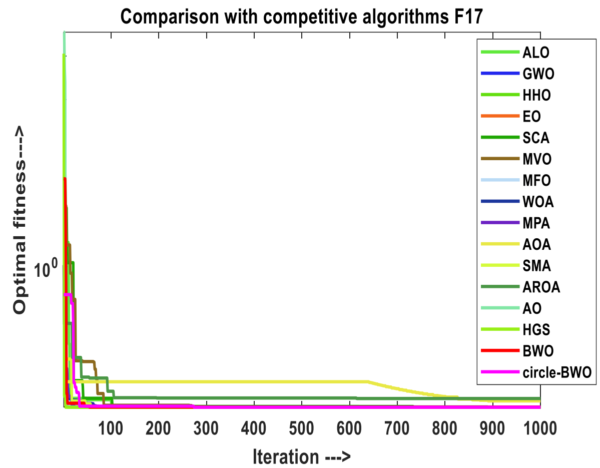
Table-3.14: Computational time for Fixed Modal benchmark functions using CBWO

Function No.	Best Time (Sec)	Average Time (Sec.)	Worst Time Sec)
F15	1.56E-01	1.76E-01	3.91E-01
F16	1.42E-01	1.58E-01	2.66E-01
F17	1.42E-01	1.45E-01	2.03E-01
F18	1.25E-01	1.44E-01	1.56E-01
F19	1.55E-01	1.72E-01	1.88E-01
F20	1.73E-01	1.82E-01	1.88E-01
F21	3.12E-01	3.28E-01	3.44E-01
F22	3.76E-01	3.98E-01	4.38E-01
F23	4.69E-01	4.94E-01	5.16E-01









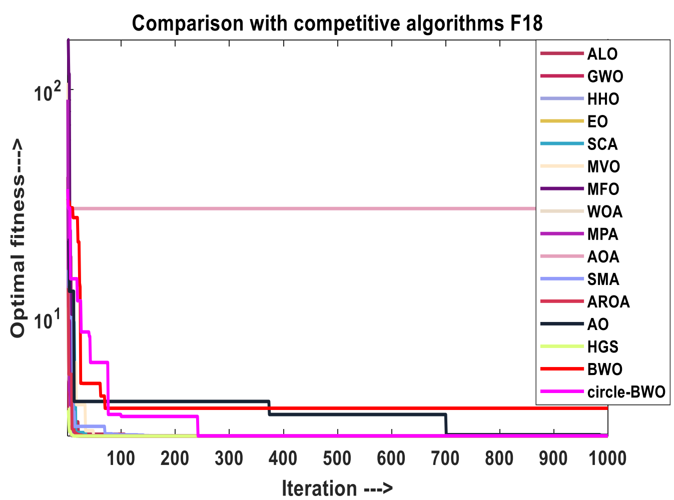
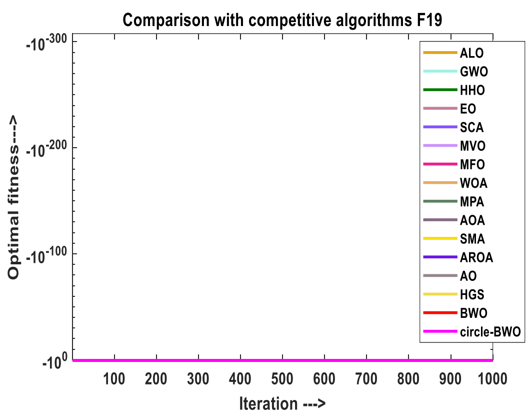


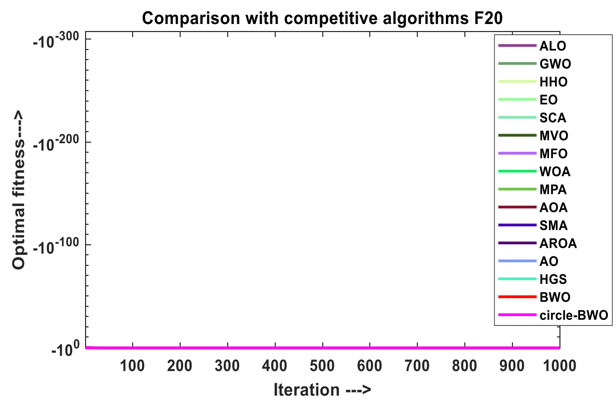
Fig.3.11: Comparison graphs for Fixed modal functions (F14-F18)

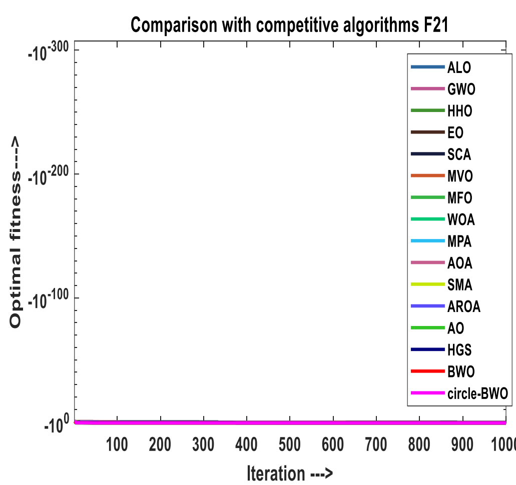
Table-3.15: Comparison of results for FD benchmark problems (F14-F19)

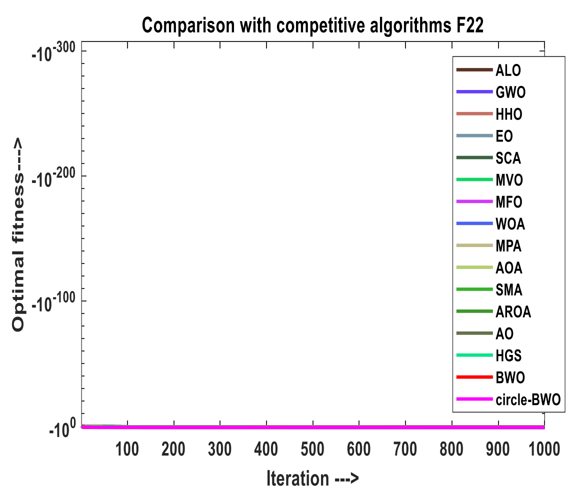
Algorithms	Parameters	F14	F15	F16	F17	F18	F19
AO [127]	AVG	1.49E+0	4.38E-04	-1.04E+0	3.99E-01	3.01E+0	-3.87E+0
	SD	8.14E-01	9.60E-05	1.79E-04	1.08E-04	1.41E-02	2.59E-03
GWO [128]	AVG	1.36E-14	1.68E-03	0.0E+0	2.58E-02	3.40E-01	2.45E+0
	SD	2.41E-15	4.46E-03	4.65E-17	1.25E-02	1.47E-01	2.99E+0
MPA [129]	AVG	9.99E-01	3.06E-04	-1.04E+0	3.99E-01	3.0E+0	-3.87E+0
	SD	5.83E-17	2.65E-19	6.38E-16	0.0E+0	1.31E-15	2.72E-15
HHO [130]	AVG	8.88E-16	0.0E+0	-1.0E+0	9.26E-07	1.15E-05	9.98E-01
	SD	0.0E+0	0.0E+0	0.0E+0	1.53E-06	1.30E-05	0.0E+0
AOA [131]	AVG	8.88E-16	7.38E-02	0.0E+0	3.11E-01	2.77E+0	8.64E+0
	SD	0.0E+0	4.24E-02	4.13E-08	4.58E-02	9.80E-02	4.41E+0
HGS [132]	AVG	1.65E+0	6.45E-04	-1.04E+0	3.99E-01	3.0E+0	-3.87E+0
	SD	2.48E+0	2.24E-04	5.14E-16	0.0E+0	2.16E-15	2.41E-15
MFO [133]	AVG	8.70E+07	1.34E+10	5.20E+02	6.23E+02	1.30E+03	1.43E+03
	SD	1.37E+08	7.69E+09	1.73E-01	2.71E+0	1.03E+0	2.07E+01
MVO [134]	AVG	1.49E+07	5.67E+05	5.21E+02	6.14E+02	1.30E+03	1.40E+03
	SD	6.24E+06	2.10E+05	1.03E-01	3.44E+0	1.15E-01	4.03E-01
ALO [135]	AVG	1.26E+07	1.26E+04	5.21E+02	6.26E+02	1.30E+03	1.40E+03
	SD	5.18E+06	9.06E+03	9.39E-02	3.62E+0	1.01E-01	4.76E-02
SCA [136]	AVG	4.26E+08	2.69E+10	5.21E+02	6.37E+02	1.30E+03	1.47E+03
	SD	9.72E-01	4.18E-04	2.66E-05	1.35E-03	1.59E-05	3.17E-03
SMA [137]	AVG	9.99E-01	5.19E-04	-1.04E+0	3.99E-01	3.0E+0	-3.85E+0
	SD	1.17E+08	5.43E+09	5.35E-02	2.24E+0	3.74E-01	1.55E+01
	AVG	1.54E-13	2.56E-04	2.77E-11	2.52E-08	2.05E-12	7.14E-08

WOA [138]	SD	6.93E+07	1.09E+09	1.20E-01	2.89E+0	2.61E-01	6.26E+0
BWO [123]	AVG	9.99E-01	3.37E-04	-1.04E+0	4.00E-01	3.97E+0	-3.87E+0
	SD	8.63E-11	3.80E-05	9.26E-05	3.06E-03	1.18E+0	2.43E-03
CBWO	**AVG**	**1.39E+0**	**3.91E-04**	**-1.02E+0**	**4.00E-01**	**3.37E+0**	**-3.86E+0**
	SD	**2.13E+0**	**1.04E-04**	**3.75E-04**	**2.19E-03**	**3.67E-01**	**1.62E-03**









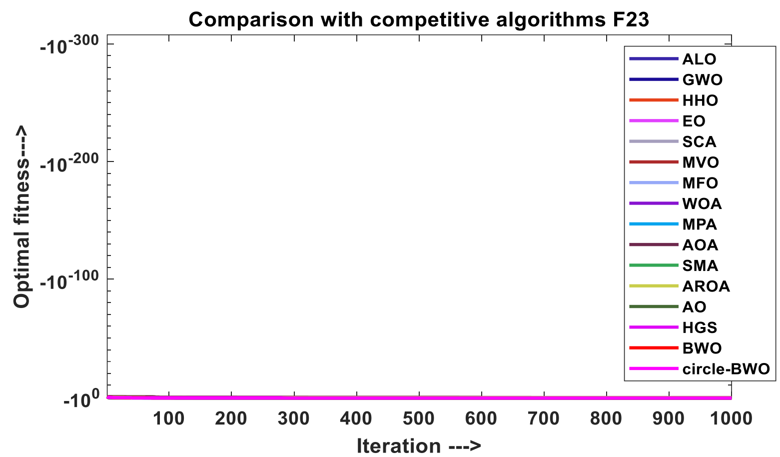
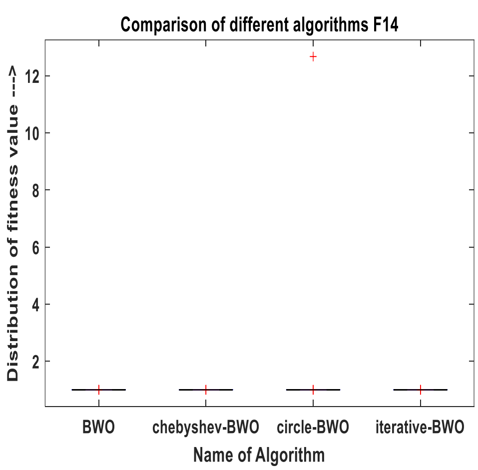


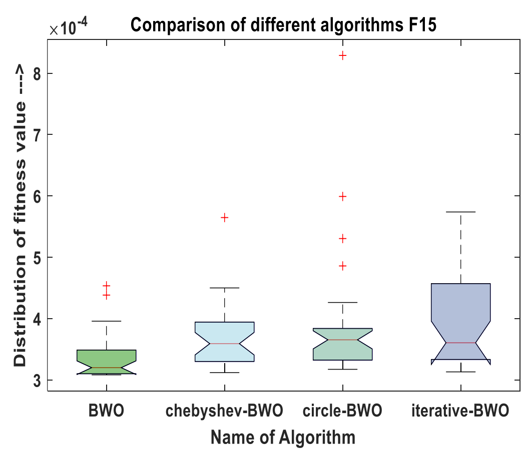
Fig.3.12: Convergence curve for Fixed modal functions (F19-F23)

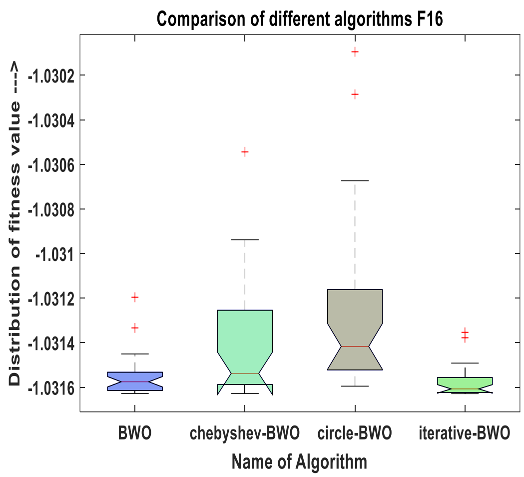
Table-3.16: Comparison of results for FD benchmark problems (F20-F23)

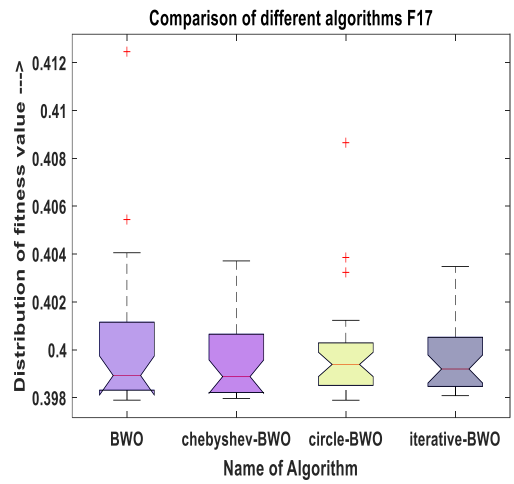
Algorithms	Parameters	F20	F21	F22	F23
AO [127]	AVG	-3.18	-1.02E+01	-1.04E+01	-1.05E+01
	SD	9.42E-02	1.17E-02	1.78E-02	2.68E-02
GWO [128]	AVG	4.38E-03	-1.03E+00	-9.62E+00	-1.02E+01
	SD	8.13E-03	2.31E-09	1.64E+00	9.70E-01
MPA [129]	AVG	-3.32	-1.03E+01	-1.03E+01	-1.06E+01
	SD	1.05E-15	5.96E-15	0.00E+00	1.58E-15
HHO [130]	AVG	3.51E-04	-1.03E+00	-5.39E+00	-5.44E+00
	SD	1.68E-04	2.48E-13	1.27E+00	1.35E+00
AOA [131]	AVG	1.86E-02	-1.03E+00	-4.34E+00	-4.40E+00
	SD	3.13E-02	5.27E-08	1.19E+00	1.04E+00
HGS [132]	AVG	-3.28E+00	-1.03E+01	-1.03E+01	-1.02E+01
	SD	7.29E-02	5.68E-15	1.19E-15	1.37E+00
MFO [133]	AVG	2.09E+05	1.61E+03	3.69E+06	3.01E+07
	SD	4.17E+05	5.36E-01	5.22E+06	1.15E+08

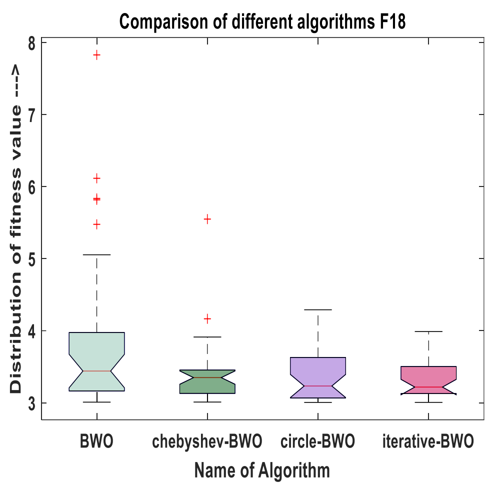
MVO [134]	AVG	1.51E+03	1.61E+03	6.48E+05	1.11E+04
	SD	3.70E+00	5.27E-01	4.23E+05	7.88E+03
ALO [135]	AVG	1.52E+03	1.62E+03	1.23E+06	3.77E+03
	SD	4.83E+00	5.73E-01	9.02E+05	1.98E+03
SCA [136]	AVG	1.69E+04	1.61E+03	1.48E+07	2.77E+08
	SD	3.25E-01	2.49E+00	2.18E+00	1.78E+00
SMA [137]	AVG	-3.24E+0	-1.03E+01	-1.05E+01	-1.04E+01
	SD	1.35E+04	2.42E-01	7.20E+06	1.77E+08
WOA [138]	SD	5.55E-02	1.09E-04	9.00E-05	9.75E-05
	SD	1.22E+02	4.63E-01	1.56E+07	2.99E+05
BWO [123]	AVG	-3.31E+0	-1.03E+01	-1.05E+01	-1.04E+01
	SD	8.29E-03	3.78E-07	3.57E-06	1.29E-06
CBWO	**AVG**	**-3.31E**	**-1.02E+01**	**-1.03E+01**	**-1.04E+01**
	SD	**6.88E-03**	**7.46E-06**	**1.13E-05**	**8.55E-06**

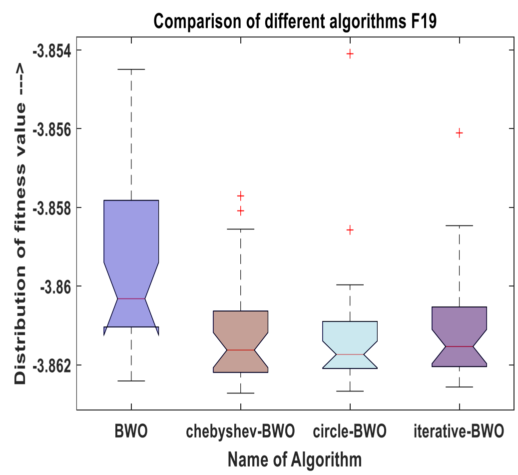


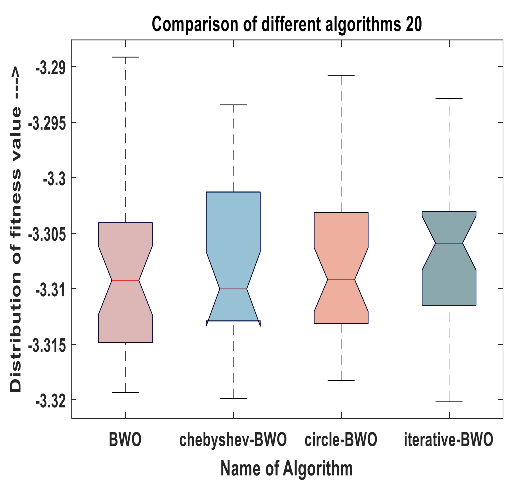


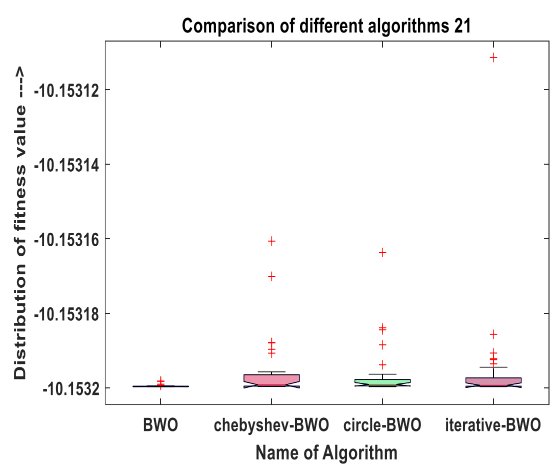

Comparison of different algorithms F16
Distribution of fitness value --->
-1.0302
-1.0304
-1.0306
-1.0308
-1.031
-1.0312
-1.0314
-1.0316
BWO
chebyshev-BWO
circle-BWO
iterative-BWO
Name of Algorithm


Comparison of different algorithms F17
Distribution of fitness value --->
0.412
0.41
0.408
0.406
0.404
0.402
0.4
0.398
BWO
chebyshev-BWO
circle-BWO
iterative-BWO
Name of Algorithm


Comparison of different algorithms F18
Distribution of fitness value --->
8
7
6
5
4
3
BWO
chebyshev-BWO
circle-BWO
iterative-BWO
Name of Algorithm


Comparison of different algorithms F19
Distribution of fitness value --->
-3.854
-3.856
-3.858
-3.86
-3.862
BWO
chebyshev-BWO
circle-BWO
iterative-BWO
Name of Algorithm


Comparison of different algorithms 20
Distribution of fitness value --->
-3.29
-3.295
-3.3
-3.305
-3.31
-3.315
-3.32
BWO
chebyshev-BWO
circle-BWO
iterative-BWO
Name of Algorithm


Comparison of different algorithms 21
Distribution of fitness value --->
-10.15312
-10.15314
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-10.15318
-10.1532
BWO
chebyshev-BWO
circle-BWO
iterative-BWO
Name of Algorithm

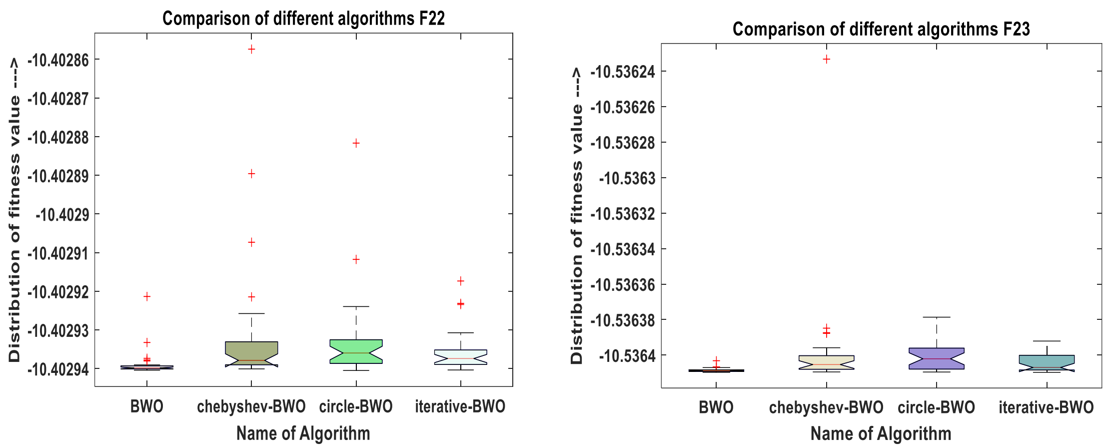

Fig.3.13: Boxplot of various chaotic versions of CBWO for Fixed Modal Functions.

3.7 MULTI-DISCIPLINARY ENGINEERING BENCHMARK PROBLEMS

There are 11 different design issues covered in this section including “3-rod truss problem, speed reducer problem, pressure vessel design, compression spring design, rolling element problem, welded beam design, Belleville spring problem, gear train design, multi-disc clutch brake problem, cantilever beam design and I-beam designs” [127], shown in Table 3.17.

All engineering design problems are highlighted, including their best, mean, std and p-value comparisons are displayed in Table-3.18. From EF1 to EF11 design challenges are all run via 1000 iterations and 30 test runs to confirm the usefulness of CBWO. To support the validity of test findings for each design challenge, a comparison with existing optimization methodologies is also included.

Table-3.17: Abbreviations of Engineering Design Problems

Engineering Functions	**Design Problem**
EF1	Three Truss Bar Problem
EF2	Pressure Vessel Problem
EF3	Speed Reducer Problem
EF4	Tension/Compression Spring Design Problem
EF5	Rolling Element Bearing
EF6	Welded Beam Problem
EF7	Multiple Disk Clutch Brake
EF8	Gear Train Design Problem
EF9	Cantilever Beam Design
EF10	Belleville Spring
EF11	I Beam Design

Table-3.18: Test results for Engineering Design Problems

Problem	Mean	Best value	Worst value	Std	Median	Wilcoxon rank sum test (p- value)
EF1	264.3468	263.9673	265.1561	0.327547	264.2663	0.340288
EF2	8085.476	6781.794	9216.884	647.5301	8037.506	0.000655
EF3	3101.192	3054.445	3214.915	39.15153	3090.442	0.02266
EF4	0.013153	0.012773	0.013483	0.000165	0.013196	0.024157
EF5	-72222.8	-80855.4	-64667	4897.792	-71867	0.200949
EF6	2.352601	1.933092	2.751438	0.231188	2.385073	0.061452
EF7	0.428177	0.397574	0.483591	0.019828	0.427697	0.079782
EF8	1.04E-10	4.73E-15	1.18E-09	2.69E-10	1.88E-11	0.3871
EF9	1.315083	1.308106	1.321584	0.003948	1.314907	0.166866
EF10	2.13313	1.992514	3.500604	0.266401	2.059073	0.446419
EF11	0.00663	0.006626	0.006636	3.13E-06	0.006629	0.200949

3.7.1 EF1-Three Truss Bar design problem

The commonly used engineering optimization problem i.e., "three-bar truss design problem" aims to reduce overall weight while fulfilling stress, deflection, and buckling limitations [246]. A three-bar truss is in Fig. 3.14. The challenge of design problem is to determine the cross-sectional areas of the bars that minimize the overall weight of the truss while fulfilling the limitations.

$$a = [a_1, a_2]; \tag{3.12}$$

$$f(a) = (2\sqrt{2}a_1 + a_2) * l; \tag{3.13}$$

$$t1(a) = \frac{\sqrt{2}a_1 + a_2}{\sqrt{2}a^2{}_1 + 2a_1 a_2} * P - \sigma \le 0 \tag{3.14}$$

$$t2(a) = \frac{a_\partial}{\sqrt{2}a^2{}_1 + 2a_1 a_2} * P - \sigma \le 0; \tag{3.15}$$

$$t3(a) = \frac{1}{\sqrt{2a_2 + a_1}} * P - \sigma \le 0; \tag{3.16}$$

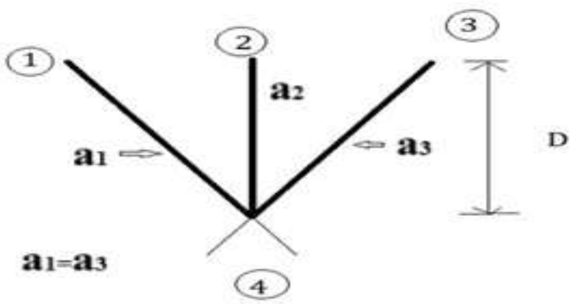

Fig. 3.14: Three Truss Bar Design

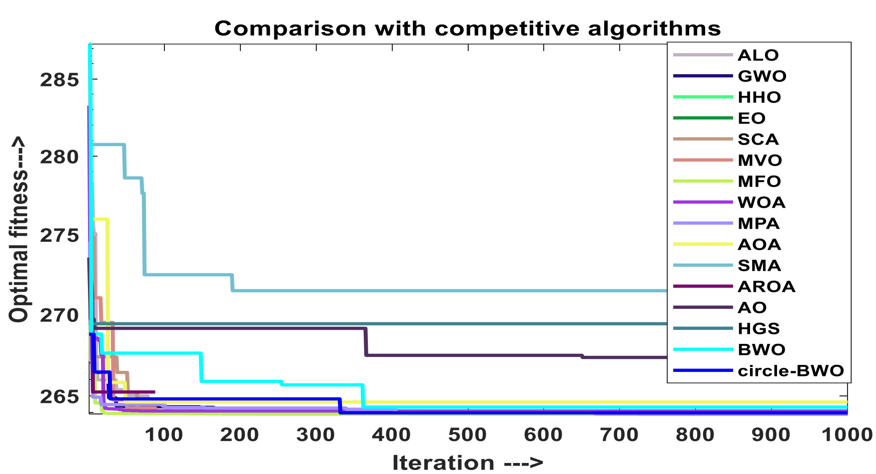

Fig. 3.15: Convergence curve for Three Truss Bar design

Table-3.19: Comparison of optimal values for variables for three truss bar engineering problem

Algorithm	Optimal Values for Variables		Optimal Weight
	a_1	**a_2**	
CBWO	0.780837	0.431131	263.9673
BWO [123]	0.788	0.410585	263.9385
ALO [135]	0.788712	0.408143	263.8958
AO [127]	0.789996	0.405413	267.6096
AOA [131]	0.785811	0.416714	263.9323
GWO [128]	0.788735	0.408079	263.896
HGS [132]	0.784879	0.425632	264.5604
HHO [130]	0.788403	0.409018	263.8959
MFO [133]	0.78851	0.408716	263.8959
MPA [129]	0.788686	0.408217	263.8958
MVO [134]	0.788696	0.408191	263.896
SCA [136]	0.793484	0.39498	263.9291
SMA [137]	0.827677	0.320319	266.1342
WOA [138]	0.791563	0.400141	263.9019

CBWO's outcomes are contrasted with other optimization techniques as shown in Table 3.19. The convergence graph is shown in Fig. 3.15. It can be shown that the recommended approach significantly enhances the goal of cost minimization as CBWO performs better than many algorithms.

3.7.2 EF2—Pressure Vessel Problem

The cylindrical pressure vessel is designed with a low cost in mind and to ensure that they are safe. The CBWO is used to save costs. Here the design factors are “inner radius, the width of the head, the length of vessel and thickness of the shell [246]. Mathematical equations for this problem are shown below.

$$s = [s_1 s_2 s_3 s_4] \tag{3.17}$$

Subject to-

$$f(s) = 0.6224 s_1 s_3 s_4 + 1.7781 s_2 s^2{}_3 + 3.1661 s^2{}_1 s_4 + 19.84 s^2{}_1 s_3; \tag{3.18}$$

$$g1(s) = -s_1 + 0.0193 s_3 \leq 0 \tag{3.19}$$

$$g2(s) = s_3 + 0.00954 s_3 \leq 0; \tag{3.20}$$

$$g3(s) = -\pi s^2{}_3 s_4 - \frac{4}{3}\pi s^3{}_3 + 1296000 \leq 0; \tag{3.21}$$

$$g4(s) = s_4 - 240 \leq 0 \tag{3.22}$$

Variable Range

$$0 \leq s_1 \leq 99,\ 0 \leq s_2 \leq 99,\ 10 \leq s_3 \leq 200,\ 10 \leq s_4 \leq 200;$$

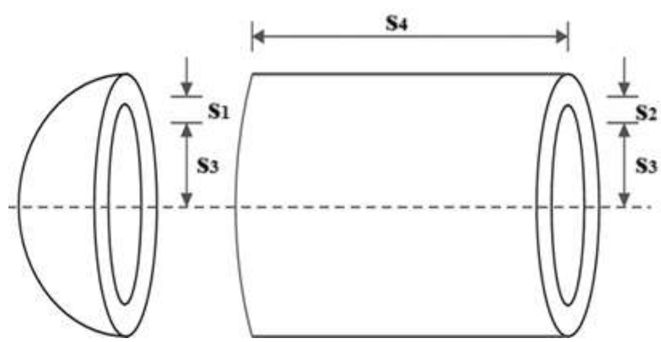

Fig. 3.16: Pressure Vessel Design

Fig. 3.17 shows the comparison graph of CBWO algorithm comparing to other existing algorithms. Table-3.20 illustrates the outcomes for optimum cost of pressure vessel design problem. It has been shown that CBWO provides cost-effective solutions of this design problems with better outcomes.

Table-3.20: Test Results for Pressure Vessel Design Problem

Algorithm	**Optimal Values for Variables**				**Optimal value**
	S_1	**S_2**	**S_3**	**S_4**	
CBWO	0.963579	0.51402	47.5895	121.8275	6781.794
BWO [123]	0.797683	0.434399	40.89814	193.9196	6136.484
ALO [135]	0.780632	0.385867	40.44723	198.235	5889.646
AO [127]	0.812393	0.403669	42.05761	182.0953	6073.207
AOA [131]	1.095769	0.931294	43.66253	164.2997	9714.165
GWO [128]	0.779219	0.385298	40.3661	199.4898	5891.493
HGS [132]	0.778169	0.384649	40.31962	200	5885.333
HHO [130]	0.789315	0.415304	40.72659	194.4112	6001.457
MFO [133]	0.778169	0.384649	40.31962	200	5885.333
MPA [129]	0.778169	0.384649	40.31962	200	5885.333
MVO [134]	0.798845	0.396439	41.27375	187.6398	5953.131
SCA [136]	0.802069	0.424988	40.37142	200	6185.009
SMA [137]	0.780631	0.385866	40.44719	198.2316	5889.555
WOA [138]	0.986644	0.486999	50.32605	95.77928	6420.357

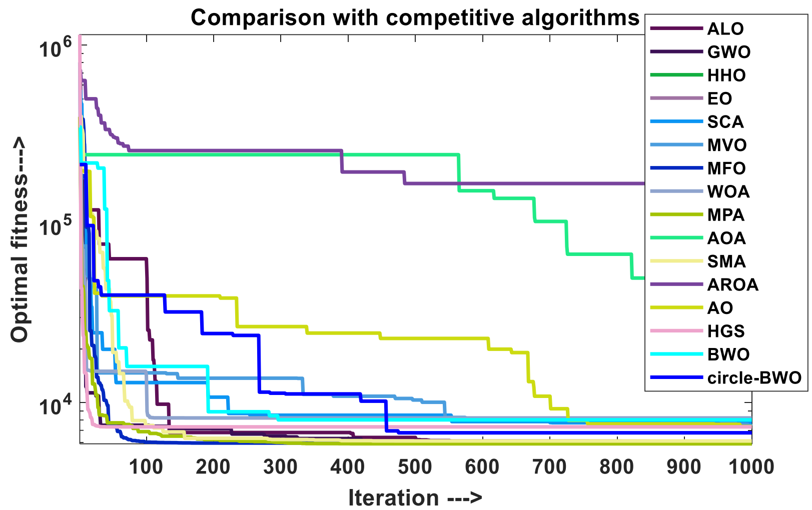

Fig.3.17: Convergence curve for Pressure Vessel Problem

3.7.3 EF3—Speed Reducer Design Problem

An engineering optimization problem known as a speed reducer design, aims to create a speed reducer that satisfies some specifications. Typically, the objective of an optimization challenge is to curtail the speed reducer's weight while meeting the required standards. The restraints of the optimization problem typically include the speed reduction ratio, the maximum torque, the maximum speed, and the strength and stiffness requirements of the speed reducer components [246].

$$f(x) = 0.7854x_{i1}x_{i2}(3.3333x^2_{i3} + 14.9334x_{i3} - 43.0934) - 1.508x_{i1}(x^2_{i6} + x^2_{i7}) + 7.4777(x^3_{i6} + x^3_{i7}) + 0.7854(x_{i4}x^2_{i6} + x_{i5}x^2_{i7}) \quad (3.23)$$

Subject to:

$$s1(x) = \frac{27}{x_{i1}x^2_{i2}x_{i3}} - 1 \le 0; \quad (3.24)$$

$$s2(x) = \frac{397.5}{x_{i1}x^2_{i2}x^2_{i3}} - 1 \le 0; \quad (3.25)$$

$$s3(x) = \frac{1.93x^{3}_{i4}}{x_{i2}x_{i3}x^{4}_{i6}} - 1 \le 0; \tag{3.26}$$

$$s4(x) = \frac{1.93x^{3}_{i5}}{x_{i2}x_{i3}x^{4}_{i7}} - 1 \le 0; \tag{3.27}$$

$$s5(x) = \frac{1}{110x^{3}_{i6}}\sqrt{(\frac{745x_{i4}}{x_{i2}x_{i3}})^{2} + 16.9\times10^{6}} - 1 \le 0; \tag{3.28}$$

$$s6(x) = \frac{1}{85x^{3}_{i7}}\sqrt{(\frac{745x_{i5}}{x_{i2}x_{i3}})^{2} + 157.9\times10^{6}} - 1 \le 0; \tag{3.29}$$

$$s7(x) = \frac{x_{i2}x_{i3}}{40} - 1 \le 0; s8(x) = \frac{5x_{i2}}{x_{i1}} - 1 \le 0 \tag{3.30}$$

$$s9(x) = \frac{x_{i1}}{12x_{i2}} - 1 \le 0; \tag{3.31}$$

$$s10(x) = \frac{1.5x_{i6} + 1.9}{12x_{i2}} - 1 \le 0; \tag{3.32}$$

$$s11(x) = \frac{1.1x_{i7} + 1.9}{x_{i5}} - 1 \le 0 \tag{3.33}$$

Where,

$$2.6 \le x_{i1} \le 3.6,\ 0.7 \le x_{i2} \le 0.8,\ 17 \le x_{i3} \le 28,\ 7.3 \le x_{i4} \le 8.3,\ 7.8 \le x_{i5} \le 8.3,\ 2.9 \le x_{i6} \le 3.9 and 5 \le x_{i7} \le 5.5.$$

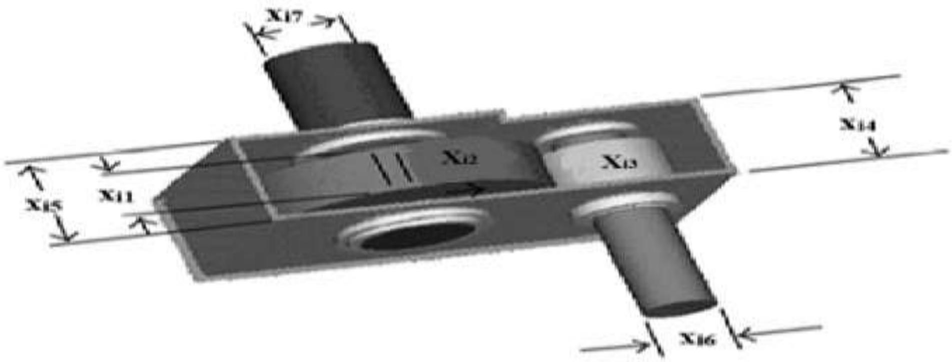

Fig. 3.18: Speed Reducer Design

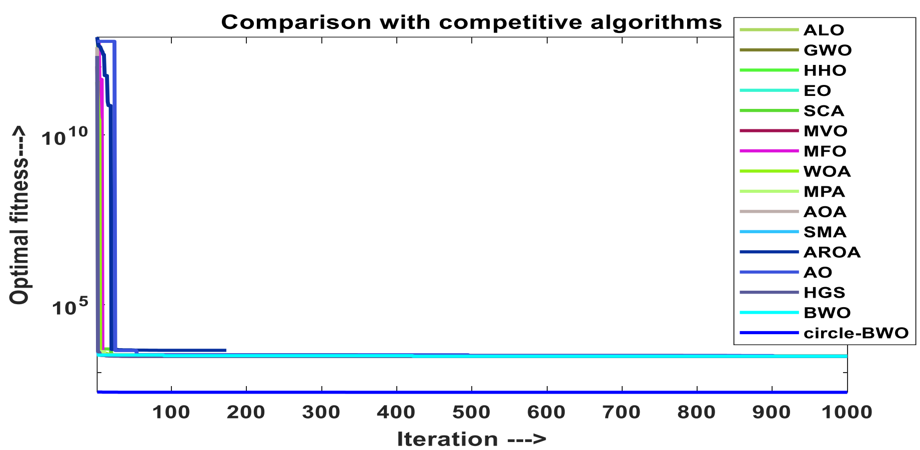

Fig.3.19: Comparison Curve for Speed Reducer Design Engineering Problem

Table 3.21 presents results for optimal values of variables for this problem and Fig. 3.19 demonstrates the graphical comparison of CBWO with other algorithms. The comparison study demonstrates that the suggested approach can manage the speed reducer problem precisely.

Table-3.21: Comparison of Results of Speed Reducer Problem with different algorithm

Algorithm	X_{i1}	X_{i2}	X_{i3}	X_{i4}	X_{i5}	X_{i6}	X_{i7}	Optimal Value
CBWO	3.522	0.7	17	7.3	8.090	3.396	5.334	3054.445
BWO [123]	3.556	0.7	17	7.3	8.202	3.368	5.292	3035.78
ALO [135]	3.5	0.7	17	7.333	7.797	3.350	5.286	2996.607
AO [127]	3.518	0.7	17	7.3	8.139	3.383	5.300	3028.545
AOA [131]	3.6	0.7	17	8.3	8.003	3.491	5.300	3096.035
GWO [128]	3.504	0.7	17	7.479	7.793	3.350	5.287	3000.194
HGS [132]	3.5	0.7	17	7.3	7.715	3.350	5.286	2994.471
HHO [130]	3.519	0.7	17	7.776	7.880	3.424	5.286	3029.515
MFO [133]	3.5	0.7	17	7.3	7.715	3.350	5.286	2994.471
MPA [129]	3.5	0.7	17	7.3	7.715	3.350	5.286	2994.471
MVO [134]	3.505	0.7	17	7.3	8.082	3.353	5.286	3005.693
SCA [136]	3.6	0.7	17	8.3	7.863	3.395	5.314	3075.251
SMA [137]	3.5	0.7	17	7.300	7.715	3.350	5.286	2994.472
WOA [138]	3.5	0.7	17	7.710	7.718	3.470	5.289	3031.756

3.7.4 EF4—Compression Spring Design

The aim of this optimization problem is typically to "minimize the weight of the spring while satisfying the specified requirements including variables like, wire diameter (y_2), active coils (y_3), and coil diameter (y_1)" [126]. Equations 3.34-3.39 provides mathematical formulation for this problem. The indicated approach is applied to address the problem of the model and the outcomes are demonstrated in Table-3.22.

$$y = [y_1 y_2 y_3] \tag{3.34}$$

Subject to-

$$f(y) = (y_3 + 2) y_2 y^2{}_1, \tag{3.35}$$

$$g1(y) = 1 - \frac{y^3{}_2 y_3}{71785 y^4{}_1} \le 0, \tag{3.36}$$

$$g2(y) = \frac{4y^2{}_2 - y_1 y_2}{12566(y_2 y^3{}_1 - y^4{}_1)} + \frac{1}{5108 y^2{}_1} \le 0, \tag{3.37}$$

$$g3(y) = 1 - \frac{140.45 y_1}{y^2{}_2 y_3} \le 0\ ; \tag{3.38}$$

$$g4(y) = \frac{y_1 + y_2}{1.5} - 1 \le 0, \tag{3.39}$$

Range-

$$0.005 \le y_1 \le 2.00,\ 0.25 \le y_2 \le 1.30,\ 2.00 \le y_3 \le 15.0;$$

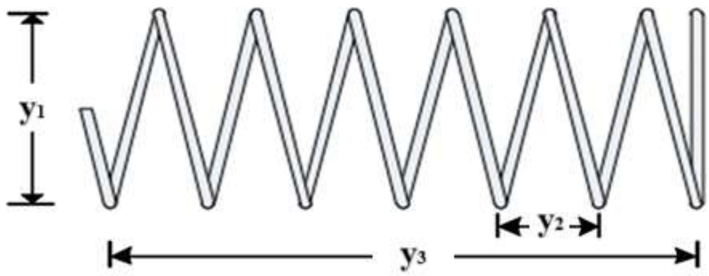

Fig.3.20: Compression Spring Design

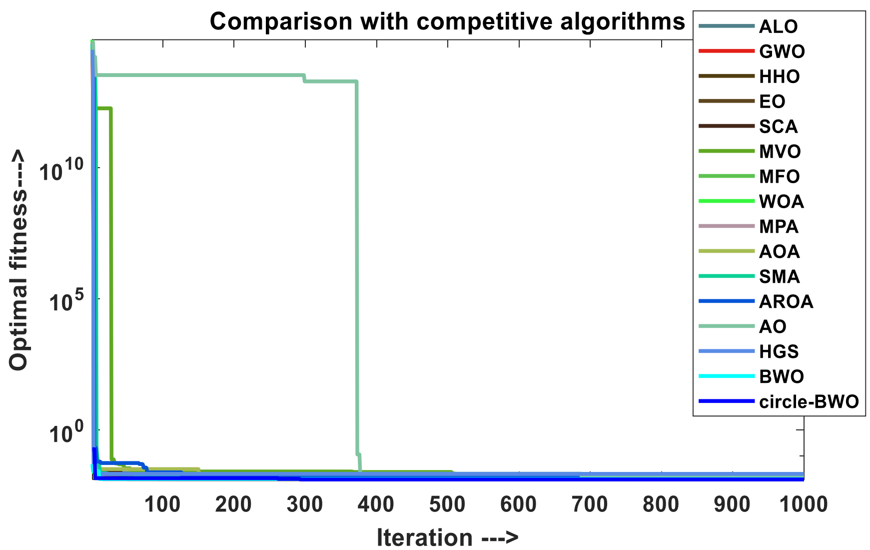

Fig.3.21: Comparison Curve for Compression Spring Design

Table 3.22 shows the optimal values of compression spring design problem. CBWO has shown better results as compared to BWO and superiority over BWO. Graph in Fig. 3.21 shows the better performance. The data makes it abundantly evident that the CBWO approach is more effective for lowering the spring weight.

Table 3.22: Optimal values of variables Comparison for Compression Spring Design Problem

Algorithm	Optimal Values for Variables			Optimum Weight
	y_1	y_2	y_3	
CBWO	0.05	0.31710	14.11225	0.012773
BWO [123]	0.05	0.31642	14.20957	0.012823
ALO [135]	0.05171	0.35723	11.25862	0.012665
AO [127]	0.05	0.31717	15	0.01348
AOA [131]	0.05	0.31044	15	0.013194
GWO [128]	0.05203	0.36508	10.81694	0.012671
HGS [132]	0.05	0.31742	14.02777	0.012719
HHO [130]	0.05403	0.41586	8.509928	0.012762
MFO [133]	0.05232	0.37215	10.43834	0.012672
MPA [129]	0.05168	0.35669	11.2903	0.012665
MVO [134]	0.05	0.31144	14.85402	0.013123
SCA [136]	0.05216	0.36781	10.72499	0.012735
SMA [137]	0.05218	0.36877	10.61588	0.01267
WOA [138]	0.05168	0.35651	11.30103	0.012665

3.7.5 EF5—Rolling Element Bearing Design

The "main objective is to enhance the dynamic load-carrying capacity of the rolling bearing element" [126], as indicated in Fig. 3.22. There are ten primary parameters that affect how much more weight a bearing can support. The ball's size, diameter pitch, number, outer curvature coefficient, and inner curvature coefficient are among these crucial variables. This design constraint is indirectly affected by the other five factors. Equations 3.40-3.48 are used to formulate the design challenge mathematically.

Maximize

$$C_D = f_c N^{2/3} D_B^{1.8}; D \leq 25.4\ mm;$$

$$CD = 3.647 f_c N^{2/3} DIM_B^{1.4}; if\ \ DIM \geq 25.4\ mm \tag{3.40}$$

Subject to-

$$a1(x) = \frac{\theta_0}{2\ sin^{-1}(\frac{D_{BS}}{D_{dm}})} - N + 1; a1(x) \geq 0; \tag{3.41}$$

$$a2(x) = 2D_{BS} - K_{D_{dm}}(D_o - d_i) \geq 0 \tag{3.42}$$

$$a3(x) = K_{D_{dm}}(D_o - d_i) \geq 0; \tag{3.43}$$

$$a4(x) = \beta B_W - D_{BS} \leq 0; a5(x) = D_{dm} - 0.5(D_o + d_i) \geq 0; \tag{3.44}$$

$$a6(x) = (0.5 + re)(D_o + d_i) \geq 0 \tag{3.45}$$

$$a7(x) = 0.5(D_o - D_{dm} - D_{BS}) - \alpha D_{BS} \geq 0; \tag{3.46}$$

$$a8(x) = f_I \geq 0.515; \tag{3.47}$$

$$a9(x) = f_0 \geq 0.515; D_o = 160,\ d_i = 90, B_W = 30,; rI = r0 = 11.033 \tag{3.48}$$

$$0.5(D_o + d_i) \leq D_{dm} \leq 0.6(D_o + d_i),$$

$$0.15(D_o - d_i) \le D_{BS} \le 0.45(D_o - d_i),\ 4 \le N_i \le 50; 0.515 \le f_I And f_0 \le 0.6$$

Table 3.23 indicates the optimal values of ten variables and comparison of CBWO algorithm with other algorithms for this problem. The graph in Fig. 3.23 shows the better performance of CBWO. By the findings shown in Table 3.23, it is evident that many suggested techniques outperform CBWO and other methods in terms of results.

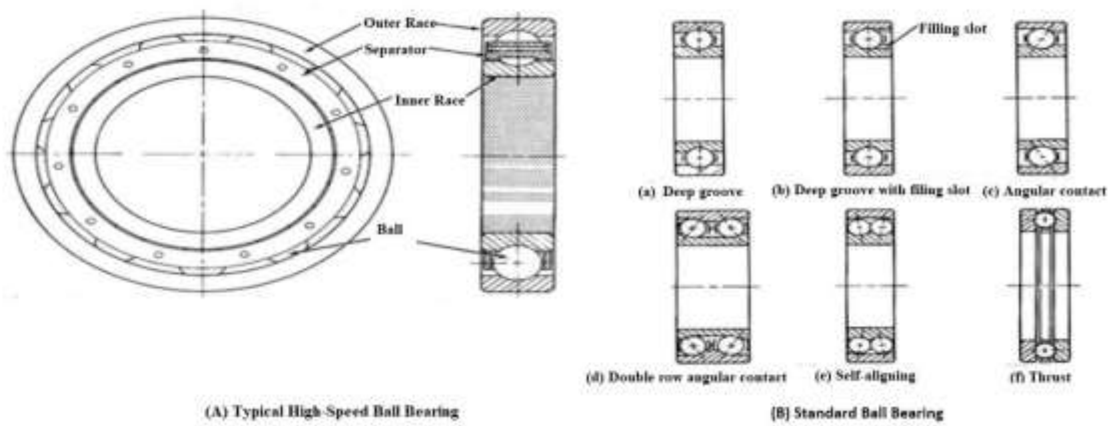

Fig.3.22: Rolling element bearing design

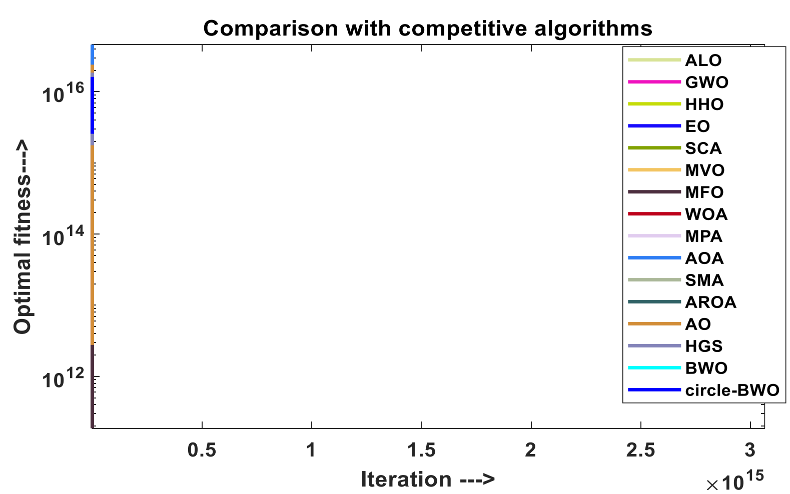

Fig.3.23: Comparison Curve for Rolling element bearing design

Table 3.23: Optimal values of variables comparisons for rolling element bearing design problem

Algorithm	r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}	Optimum fitness
CBWO	125	20.74179	11.0199	0.515	0.52615	0.44616	0.614068	0.310981	0.09935	0.6	-80855.4
BWO [123]	125	20.40766	11.23485	0.515	0.515	0.4	0.6	0.3	0.03078	0.6	-79573
ALO [135]	125.6774	21.4233	10.99752	0.515	0.515	0.400769	0.612504	0.300291	0.02097	0.60121	-85519.3
AO [127]	126.1492	21.11806	11.14601	0.515	0.515	0.475854	0.690572	0.3	0.09308	0.61536	-84133.8
AOA [131]	125	20.88604	11.09918	0.515	0.515	0.5	0.6	0.3	0.08956	0.6	-82250.2
GWO [128]	125.5831	21.41807	10.98599	0.515	0.515	0.485991	0.679063	0.300585	0.02975	0.68514	-85420.4
HGS [132]	125.7614	21.39915	11.01341	0.515	0.515	0.4	0.7	0.3	0.02	0.6008	-85433.2
HHO [130]	126.164	21.14675	11.14294	0.515	0.515	0.4	0.608508	0.3	0.06087	0.6	-84321.2
MFO [133]	125.7227	21.4233	11.00116	0.515	0.515	0.5	0.7	0.3	0.1	0.6	-85539.2
MPA [129]	125.7227	21.4233	11.00116	0.515	0.515	0.451156	0.7	0.3	0.06095	0.66790	-85539.2
MVO [134]	125.5827	21.41663	10.99113	0.515	0.51509	0.499575	0.631751	0.301605	0.05878	0.64813	-85437
SCA [136]	125	21.31616	10.5404	0.515	0.515	0.5	0.7	0.3	0.07308	0.60027	-82384.8
SMA [137]	125.7227	21.4233	11.00116	0.515	0.515	0.426265	0.662564	0.3	0.02000	0.64356	-85539.2
WOA [138]	125	21.29643	10.99108	0.515	0.515	0.450239	0.6752	0.3	0.02797	0.6	-84578.3

3.7.6 EF6—Welded Beam Design

When creating a welded beam, separate portions are fused together using molten metal. The goal is to reduce the total expense of beam by optimising four design variables while taking seven restraints into consideration. The precondition variables are shown by equations 3.49-3.57, are used to build the mathematical equations. Results of CBWO along with other algorithms are shown in Table 3.24.

$$y = [y_1 y_2 y_3 y_4] \tag{3.49}$$

Subject to-

$$f(y) = 1.10471 y^2{}_1 y_2 + 0.04811 y_3 y_4 (14.0 + y_2); \tag{3.50}$$

$$w1(y) = \tau(y) - \tau_{maxi} \leq 0, \tag{3.51}$$

$$w2(y) = \sigma(y) - \sigma_{maxi} \leq 0,; \tag{3.52}$$

$$w3(y) = \delta(y) - \delta_{maxi} \leq 0,; \tag{3.53}$$

$$w4(y) = y_1 - y_4 \leq 0, \tag{3.54}$$

$$w5(y) = P_{oi} - P_{oC}(y) \leq 0, \tag{3.55}$$

$$w6(y) = 0.125 - y_1 \leq 0, \tag{3.56}$$

$$w7(y) = 1.10471 y^2{}_1 + 0.04811 y_3 y_4 (14.0 + y_2) - 5.0 \leq 0 \tag{3.57}$$

$$0.1 \leq y_{i1} \leq 2 \;,\; 0.1 \leq y_{i2} \leq 10 \;,\; 0.3 \leq y_{i3} \leq 10 \;,\; 0.1 \leq y_{i4} \leq 2$$

$$P_{oi} = 6000 lb, L_i = 14 in; \delta_{mi} = 0.25 in, E_i = 30 \times 16 psi, G_i = 12 \times 106 psi; \tau_{mi} = 13600 psi, \sigma_{maxi} = 3000 ps$$

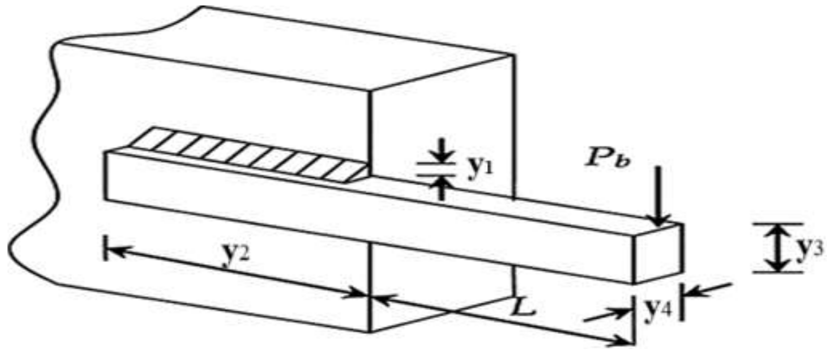

Fig.3.24: Welded beam design

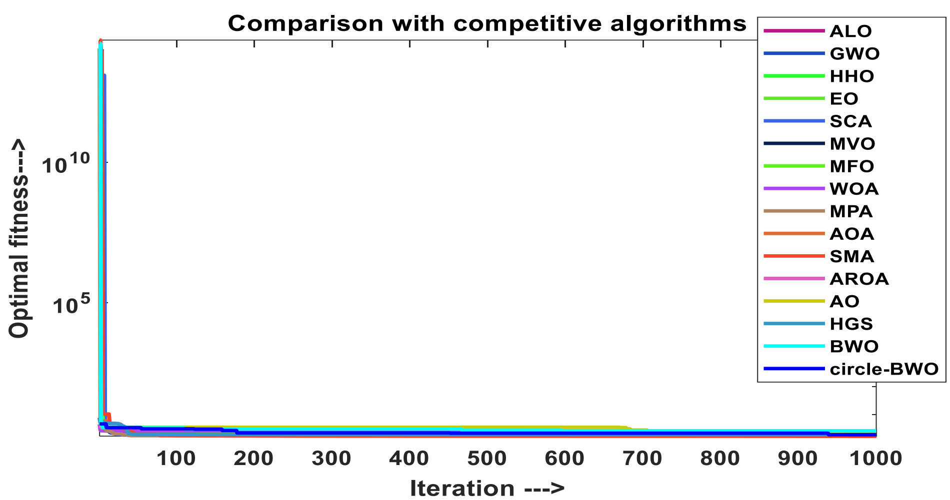

Fig.3.25: Comparison Curve for Welded beam design

Table 3.24 shows the results for optimal values of variables for welded beam design problem and Fig. 3.25 demonstrates the graphical comparison of CBWO with other algorithms. The comparison study demonstrates that the suggested method can manage the beam layout problem precisely.

Table-3.24: Optimal values of variables comparisons for welded beam design problem

Algorithm	Optimal Values for Variables				Optimal Cost
	y_1	y_2	y_3	y_4	
CBWO	0.191269	4.250316	8.553507	0.234524	1.933092
BWO [123]	0.20368	3.676839	9.034169	0.212743	1.803006
ALO [135]	0.205696	3.47119	9.036665	0.205729	1.724901
AO [127]	0.198582	4.123495	9.056711	0.205736	1.804277
AOA [131]	0.175126	4.043722	10	0.201432	1.885602
GWO [128]	0.205459	3.479894	9.036697	0.205749	1.725869
HGS [132]	0.205594	3.473418	9.036603	0.205731	1.725041
HHO [130]	0.196586	3.720833	9.016502	0.206649	1.747365
MFO [133]	0.205729	3.470505	9.036624	0.20573	1.724853
MPA [129]	0.20573	3.470489	9.036624	0.20573	1.724852
MVO [134]	0.20457	3.502387	9.035384	0.205794	1.72763
SCA [136]	0.215266	3.323734	9.009207	0.215736	1.790037
SMA [137]	0.205657	3.47207	9.036621	0.205731	1.724959
WOA [138]	0.205668	3.453472	9.084588	0.214627	1.798598

3.7.7 EF7–Multidisc Clutch Brake Design

Weight reduction is the key concern of this engineering problem. Its five parameters for design are thickness of the discs (D_h), actuation force (A_{ac}), number of friction surfaces (N_f), inner surface radius (S_{in}), and outer surface radius (F_o) as shown in Table 3.25. Equations 3.58-3.65, provides a mathematical formulation for the multi-clutch design problem. The test result of the suggested strategy is contrasted with BWO and other optimization techniques in Table 3.25.

$$f(S_{in}, F_O, N_f, D_h) = \pi D_h \gamma (F^2_O - S^2_{in})(N_f + 1)$$

SUBJECT TO

$$S_{in} \in 60-80;\ F_O \in 90-110;\ Dh \in 1,\ 1.5,..3;$$

$$Aac \in 600,\ 610,...1000;$$

$$Nf \in 2,3.....9\,;$$

$$b1 = F_O - S_{in} - \Delta S \geq 0 \tag{3.58}$$

$$b2 = L_{MAX} - (N_f + 1)(Dh + \alpha) \geq 0\,; \tag{3.59}$$

$$b3 = PM_M - PM_\pi \geq 0\,; \tag{3.60}$$

$$b4 = PM_M Y_M + PM_\pi Y_{iSR} \geq 0 \tag{3.61}$$

$$b5 = Y_{iSR\max} - Y_{iSR} \geq 0\,; \tag{3.62}$$

$$b6 = t_{i\max} - t \geq 0\,; \tag{3.63}$$

$$b7 = DC_{ih} - DC_f \geq 0\,; \tag{3.64}$$

$$b8 = t \geq 0\,; \tag{3.65}$$

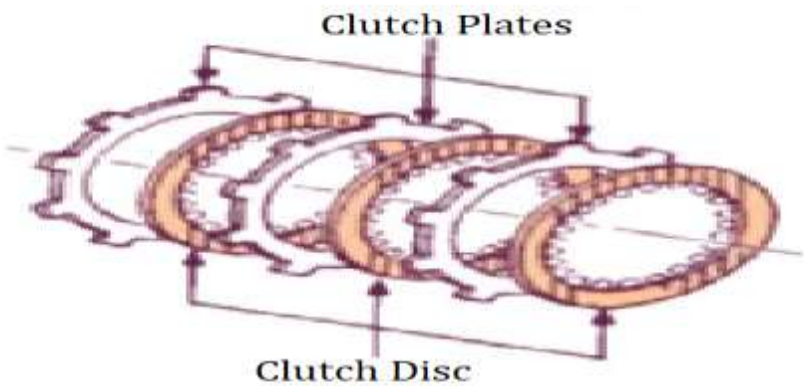

Fig.3.26: Multidisc Clutch Brake Design

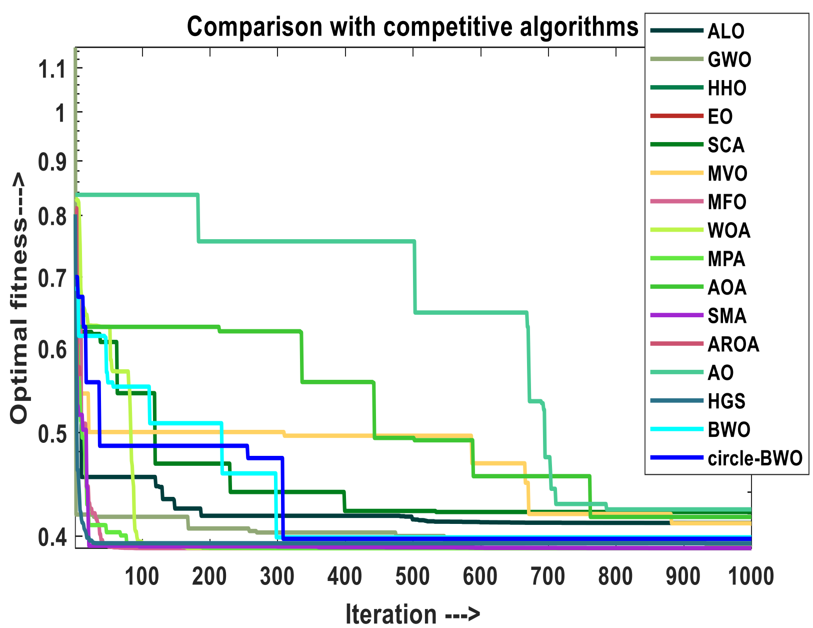

Fig.3.27: Comparison Curve for Multidisc Clutch Brake Design

Table-3.25: Optimal values of variables comparisons for multidisc clutch brake design problem

Algorithm	Fitness Variables					Optimum fitness
	S_{in}	**F_o**	**D_h**	**A_{ac}**	**N_f**	
CBWO	69.62604	90	1.5	1000	2.325857	0.397574
BWO [123]	69.79399	90	1.5	1000	2.317957	0.393774
ALO [135]	70	90	1.5	999.9967	2.31279	0.389654
AO [127]	70.021	90.06064	1.5	986.0942	2.353029	0.395371
AOA [131]	80	100.7027	1.5	1000	2.151428	0.433347
GWO [128]	69.99452	90.00115	1.5	1000	2.313668	0.389876
HGS [132]	70	90	1.5	1000	2.312782	0.389653
HHO [130]	70	90	1.5	1000	2.312782	0.389653
MFO [133]	70	90	1.5	1000	2.312782	0.389653
MPA [129]	70	90	1.5	1000	2.312782	0.389653
MVO [134]	70.00995	90.01318	1.5	1000	2.31283	0.389778
SCA [136]	69.85038	90	1.5	998.429	2.344048	0.395903
SMA [137]	70	90	1.5	1000	2.312782	0.389653
WOA [138]	70	90	1.5	1000	2.313163	0.389698

Fig. 3.27 shows the graph of CBWO algorithm comparing with other algorithms with good results. This algorithm is successfully tested on multidisc clutch design problem and in terms of cost reduction, it has been found that CBWO provides good fitness result compared to many approaches.

3.7.8 EF8–Gear Train Design

The four variables X_1, X_2, X_3 and X_4 as shown in Fig. 3.28, are reformed in this manner to reduce the scalar value & teeth ratio of gear. The conclusion making factors in the designing process are the teeth on each gear. Optimal fitness of CBWO is displayed in Table 3.26 with other techniques.

$$minf\ (X) = \left(\frac{1}{6.931} - \frac{X_3 X_2}{X_1 X_4}\right)^2; \tag{3.66}$$

$$X_1, X_2, X_3, X_4 \in (12, 13, 14, \ldots; 60);$$

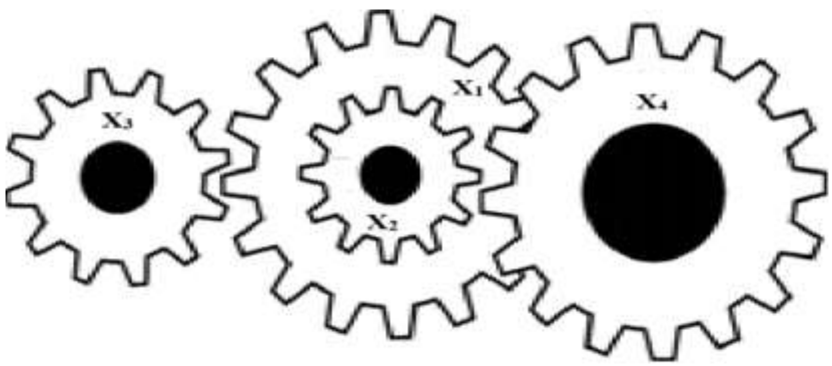

Fig.3.28: Gear Train Design

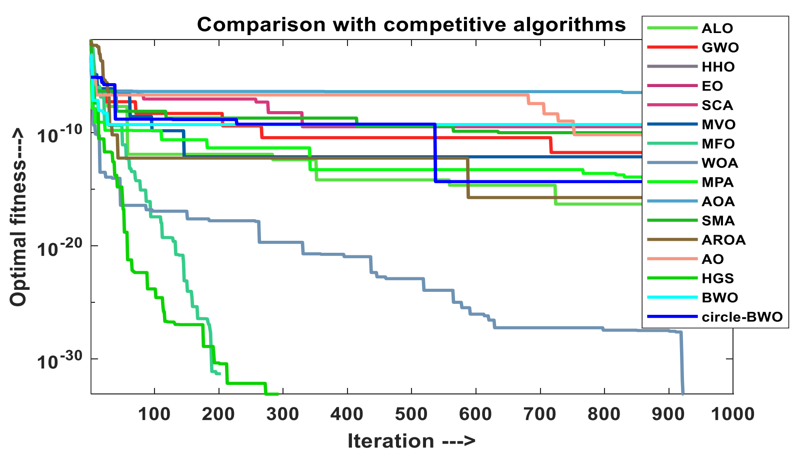

Fig.3.29: Comparison Curve for Gear Train Design

Table-3.26: Optimal values of variables comparisons for Gear Train Design Problem

Algorithm	Optimal values for variables				Optimum fitness
	X_1	X_2	X_3	X_4	
CBWO	60	12	12.27647	17.01763	4.73E-15
BWO [123]	59.64362	12	34.99424	48.79865	4.05E-13
ALO [135]	58.6288	18.7589	12.20889	27.07509	1.04E-24
AO [127]	38.42165	18.0097	13.18271	42.82844	4.96E-15
AOA [131]	49.07108	13.5169	30.0277	57.32648	2.34E-11
GWO [128]	50.23362	21.2618	14.64286	42.95643	2.31E-15
HGS [132]	58.87301	12	39.48296	55.77899	0.00E+00
HHO [130]	42.21988	12.6996	12.13988	25.3096	0.00E+00
MFO [133]	54.88092	39.5909	12	60	0.00E+00
MPA [129]	53.4367	16.4855	12.39301	26.49939	2.45E-25
MVO [134]	30.41918	12	15.3206	41.88952	2.42E-17
SCA [136]	16.63427	12	12	60	1.37E-12
SMA [137]	42.91135	14.4677	25.42703	59.4185	1.05E-17
WOA [138]	53.7102	18.8394	16.98302	41.28789	0.00E+00

CBWO has better fitness value as compared to BWO and many other algorithms. It shows the superiority on its own existing algorithm, in Table 3.26. Fig. 3.29 represents the graph of different algorithm and through which we can conclude that CBWO is performing better than many algorithms.

3.7.9 EF9-Cantilever Beam Design

The primary aim of this practical engineering challenge is to reduce the weight of beam, shown in Fig. 3.30, there are five components in a beam design: c_1, c_2, c_3, c_4 and c_5. The reduction of the beam's weight is the primary objective. Equation 3.67 serve as a mathematical representation of the design challenge. The mathematical formulas are shown as follows:

$$minf\ (c) = 0.0624(c_1 + c_2 + c_3 + c_4 + c_5) \tag{3.67}$$

Subject to-

$$g\ (C) = \frac{61}{c_1^3} + \frac{37}{c_2^3} + \frac{19}{c_3^3} + \frac{7}{c_4^3} + \frac{1}{c_5^3} - 1 \le 0.01 \le c_i \le 100 \forall I = 1, \ldots, 5;$$

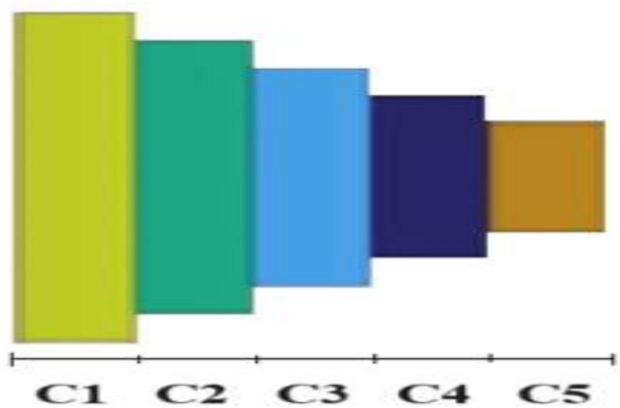

Fig.3.30: Cantilever Beam Design

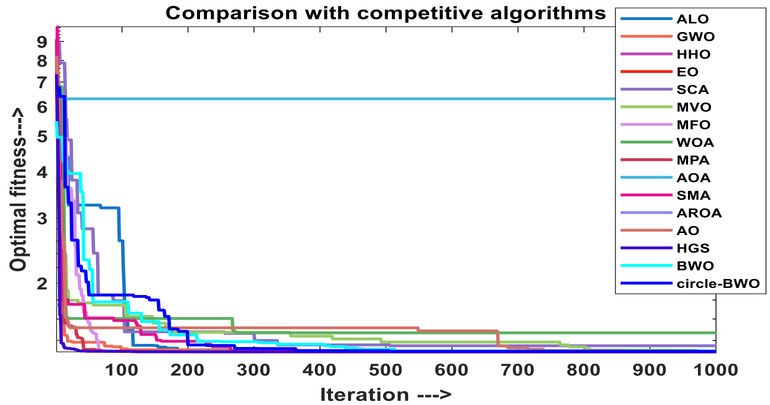

Fig.3.31: Comparison Curve for Cantilever Beam Design

Table-3.27: Optimal values of variables comparisons for cantilever beam design problem

Algorithm	Optimal Values for Variables					Optimum fitness
	C1	C2	C3	C4	C5	
CBWO	5.941881	4.93132	4.69530	3.36233	2.08629	1.303206
BWO [123]	6.011113	4.95908	4.34004	3.52864	2.15335	1.306555
ALO [135]	5.973264	4.88864	4.46159	3.47396	2.14215	1.303258
AO [127]	5.881347	4.89506	4.58927	3.43316	2.14958	1.303982
AOA [131]	5.78101	4.25323	5.54423	4.18866	2.19305	1.366802
GWO [128]	5.994714	4.87588	4.45657	3.47585	2.13630	1.303263
HGS [132]	5.969143	4.87667	4.45288	3.50730	2.13369	1.303287
HHO [130]	6.036109	4.91469	4.33450	3.51546	2.14904	1.303916
MFO [133]	5.940784	4.88629	4.47497	3.52688	2.11267	1.303406
MPA [129]	5.978223	4.87618	4.46609	3.47947	2.13914	1.303251
MVO [134]	5.98289	4.88035	4.44198	3.49232	2.14332	1.30336

SCA [136]	5.891091	5.71550	4.49117	3.53819	1.74234	1.330586
SMA [137]	5.982236	4.87529	4.46152	3.49080	2.12950	1.303267
WOA [138]	6.445122	4.80433	3.95376	3.65742	2.33860	1.319441

According to the Table-3.27, the suggested approach effectively decreases the beam's weight in comparison to AO, GWO, MPA, HHO, AOA, HGS, MFO, MVO, ALO, SCA, SMA, WOA, BWO. Optimum fitness value of CBWO is 1.303206 which is better than other algorithms. It is approx. 0.3% more efficient as compared to its older version.

3.7.10 EF10—Belleville Spring Design

The primary concern of Belleville spring design problem is to minimizing total weight while meeting different limitations. This approach calls for the optimization of four different types of suggested variables, including outer diameter, internal diameter, spring height, spring width as shown in Table 3.28. Through equation 3.68-3.74, the formulations for spring design are explained. Comparison result analysis is displayed in Table 3.28 for precision of CBWO.

$$f(x) = 0.07075\pi(DIM^{2}_{E} - DIM^{2}_{I})t$$

Subject to-

$$S1(x) = G - \frac{4P\lambda_{\max}}{(1-\delta^2)\alpha DIM_E}[\delta(S_H - \frac{\lambda_{\max}}{2}) + \mu t] \geq 0 \qquad (3.68)$$

$$S2(x) = \frac{4P}{(1-\delta^2)\alpha DIM_E}[(S_H - \frac{\lambda_{\max}}{2})(S_H - \lambda)t + t^3] - P_{MAX} \geq 0; \qquad (3.69)$$

$$S3(x) = \lambda_1 - \lambda_{\max}; S3(x) \geq 0 \qquad (3.70)$$

$$S4(x) = H - S_h - t \geq 0; \qquad (3.71)$$

$$S5(x) = DIM_{MAX} - DIM_E \geq 0; \tag{3.72}$$

$$S6(x) = DIM_E - DIM_I \geq 0 \tag{3.73}$$

$$S7(x) = 0.3 - \frac{S_h}{DIM_E - DIM_I} \geq 0; \tag{3.74}$$

$$\alpha = \frac{6}{\pi lnJ}(\frac{J_o - 1}{J_o})^2; \delta = \frac{6}{\pi lnJ_o}(\frac{J_o - 1}{lnJ_o} - 1); \mu = \frac{6}{\pi lnJ_o}(\frac{J_o - 1}{2});$$

$$P_{MAX} = 5400lb;$$

$$P = 30e06\ psi; \lambda_m = 0.2\ in; \delta_o = 0.3, G_o = 200\ Kpsi, H_o = 2\ in,\ DIM_M = 12.01\ in, J_o = \frac{DIM_E}{DIM_I}, \lambda_o = f(a_i)a_i, a_i = S_H t$$

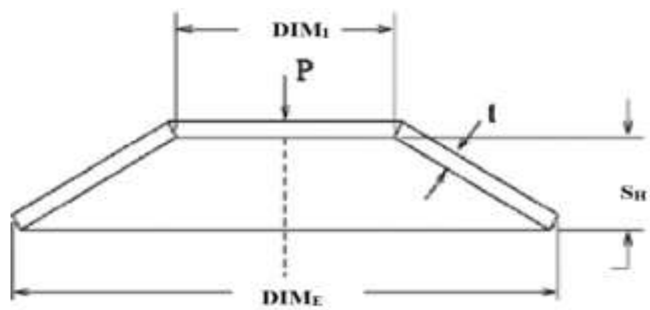

Fig.3.32: Belleville Spring Design

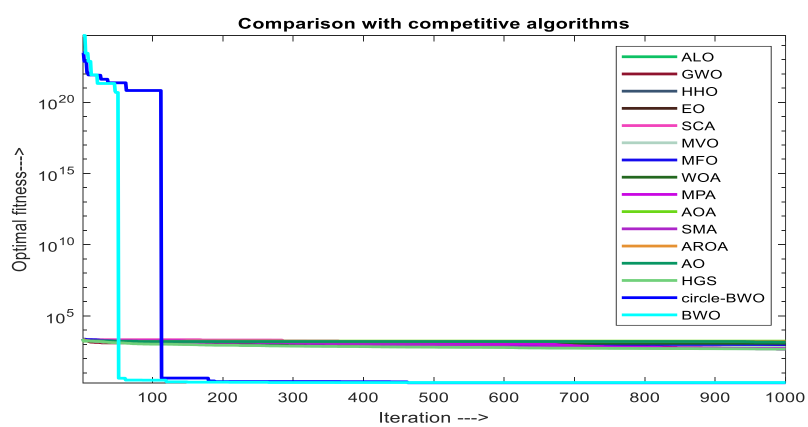

Fig.3.33: Comparison Curve for Belleville Spring Design

Table-3.28 and Fig. 3.33 show the comparative results and graph of Belleville spring design problem [128]. After comparing the results, optimum result for CBWO algorithm is 1.992514 while its previous version has more value than this hence it is more superior. GWO, HHO, MFO, MVO and WOA show better outcomes than CBWO, but overall CBWO has quite better results than many algorithms.

Table-3.28: Optimal values of variables comparisons for Belleville Spring design problem

Algorithm	Optimal Values for Variables				Optimum fitness
	DIM_E	**DIM_I**	**S_H**	**t**	
CBWO	12.01	10.02118	0.204593	0.2	1.992514
BWO [123]	12.01	10.00927	0.205341	0.201113	2.010677
ALO [135]	11.6945	9.630444	0.204714	0.2	2.002786
AO [127]	12.01	4.894993	0.412249	0.2	11.02113
AOA [131]	11.09203	8.736349	0.210299	0.2	2.183329
GWO [128]	12.00815	10.02713	0.204217	0.2	1.981422
HGS [132]	11.26173	5.188406	0.2	0.408047	4.441218
HHO [130]	12.00597	10.02522	0.204154	0.200021	1.980164
MFO [133]	12.01	10.03047	0.204143	0.2	1.979675
MPA [129]	12.01	10.03047	0.204143	0.2	1.979675
MVO [134]	12.00336	10.02043	0.20433	0.2	1.98339
SCA [136]	12.01	9.964089	0.208537	0.2	2.083804
SMA [137]	12.01	9.730961	0.2	0.2	8.54E+20
WOA [138]	12.00776	10.02763	0.204151	0.2	1.979905

3.7.11 EF11- I-Shaped Beam Design (IBD)

To reduce the weight of beam is main objective of this optimization problem while meeting the constraints. The optimal position trajectory begins with exploration, followed by a phase of exploitation to locate the answer in the practicable area.

$$min f \ X = \frac{500}{\frac{s_3(s_2 - 2s_4)^3}{12} + \frac{s_1 s_4{}^3}{6} + 2bs_4(s_2 - s_4)^2} \quad (3.75)$$

Subject To-

$$g1(X) = 2s_1 s_3 + s_3(s_2 - 2s_4) \leq 300\,; \quad (3.76)$$

$$g2(X) = \frac{18s_2 * 10^4}{s_3(s_2 - 2s_4)^3 + 2s_1 s_3(4s_4{}^2 + 3s_2(s_2 - 2s_4))} + \frac{15s_1 * 10^3}{(s_2 - 2s_4)s_3{}^2 + 2s_3 s_1{}^3} \leq 56\,;$$

(3.77)

Range- $10 \leq s_1 \leq 50; 10 \leq s_2 \leq 80; 0.9 \leq s_3 \leq 5; 0:9 \leq s_4 \leq 5$

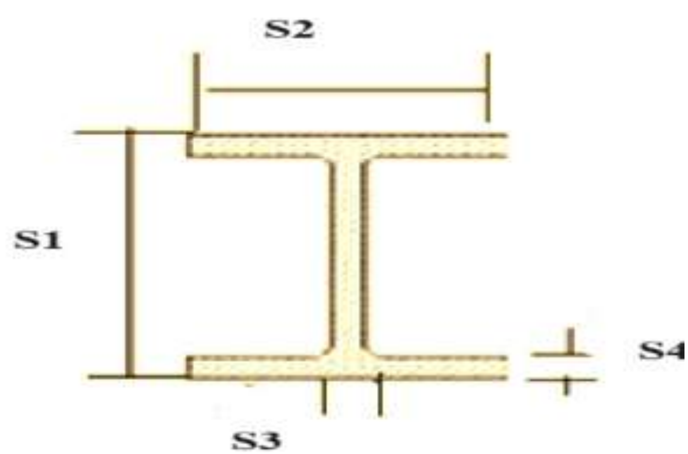

Fig.3.34: I-Shaped Beam Design

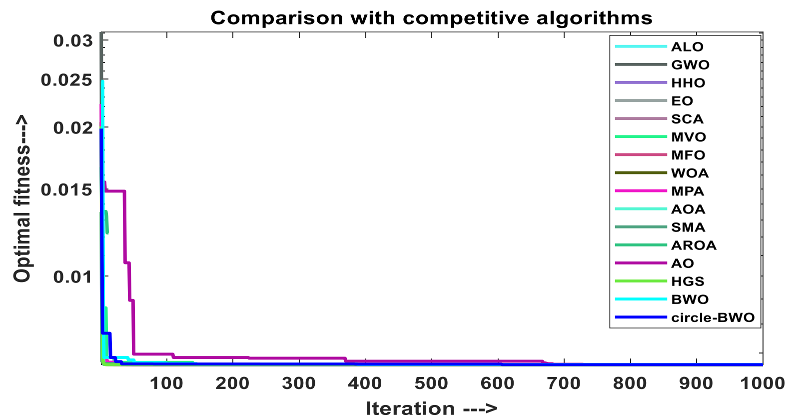

Fig.3.35: Comparison Curve for I-Shaped Beam Design

Table-3.29: Optimal values of variables comparisons for I-shape Beam Design Problem

Algorithm	S_1	S_2	S_3	S_4	Optimum fitness
CBWO	50	80	1.764391	5	0.006626
BWO [123]	50	80	1.763632	5	0.006626
ALO [135]	50	80	1.764706	5	0.006626
AO [127]	50	80	1.764186	5	0.006626
AOA [131]	50	80	1.764092	5	0.006626
GWO [128]	50	80	1.764705	5	0.006626
HGS [132]	50	80	1.764706	5	0.006626
HHO [130]	50	80	1.764706	5	0.006626
MFO [133]	50	80	1.764706	5	0.006626
MPA [129]	50	80	1.764706	5	0.006626
MVO [134]	50	80	1.764703	5	0.006626
SCA [136]	50	80	1.764497	5	0.006626
SMA [137]	50	80	1.764706	5	0.006626
WOA [138]	50	80	1.764706	5	0.006626

Table 3.29 shows the optimum results for I-shaped beam engineering design problem. Here the variables s_1, s_2, s_3, s_4 are basically the dimensions of I-shaped beam as shown in Fig. 3.34 respectively. Optimum results of all algorithms are same i.e., 0.006626, that proves the validity of CBWO algorithm which is tested here successfully with good results.

3.8 CONCLUSION

Through comparative analysis, CBWO is pitted against basic BWO and several other well-known algorithms, including AO, GWO, MPA, HHO, AOA, HGS, MFO, MVO, ALO, SCA, SMA, and WOA. The experimental findings reveal that CBWO exhibits improved convergence for the majority of benchmark functions, indicating its efficacy in achieving positive and convergent outcomes.

Furthermore, the research explores the application of CBWO to address eleven conventional engineering problems. The performance of CBWO is compared against various algorithms, as described in this chapter. The results demonstrate that CBWO outperforms most of the algorithms on these real-world tasks, showcasing its potential as a reliable solution for problems with uncertain search spaces.

The proposed Chaotic Beluga Whale Optimization (CBWO) algorithm offers a promising and trustworthy alternative for solving diverse optimization problems. Its ability to achieve enhanced convergence and superior performance on both benchmark functions and real-world engineering challenges makes it a compelling choice for various practical applications. The research findings affirm CBWO's potential as an effective optimization tool for addressing complex and challenging optimization problems in diverse domains.

Chapter-4

PRE-COVID UNIT COMMITMENT PROBLEM

4.1 INTRODUCTION

The UC problem in electric power networks prioritised generation schedule optimisation for a more stable environment, before to the disruptive pandemic of COVID-19. Prior to COVID, the main goal of UC was to maintain system stability while reducing generating costs. There was more regularity in the demand patterns, with distinct peak and off-peak times. Power system operators were able to estimate demand by using known models because of this predictability. The generating mix was dominated by fossil fuel-based generators, which are renowned for their baseload efficiency. Another important factor was nuclear power facilities, which had a large capacity and cheap marginal costs. In order to fulfil the majority of demand, the UC problem concentrated on effectively scheduling these baseload facilities, with natural gas plants serving as peaking units to manage surges [139].

Even in the case of pre-COVID, UC had considerable difficulties, power plants' ramp rate constraints made it difficult for them to swiftly alter production, therefore careful planning was required to prevent shortages or surpluses. Limitations on transmission capacity made UC even more complex since it required consideration of how to distribute produced electricity to various locations. Furthermore, it was essential to provide an enough reserve capacity in order to manage unforeseen disruptions or abrupt surges in demand.

Traditional power sources dominated the energy landscape prior to the COVID-19 pandemic, but renewable energy sources like solar and wind were progressively gaining ground. But their sporadic nature posed a further difficulty for UC because of their uncontrollable production, advanced forecasting models have to be created in order to successfully incorporate these renewables. Additionally, studies looked at ways to schedule dispatchable generators to make up for any possible deficits from wind power in order to account for the unpredictability of renewables within the UC framework [140].

4.2 UNIT COMMITMENT PROBLEM

An electric power system's ability to operate dependably and efficiently depends on a difficult decision-making process called the unit commitment problem. This crucial activity is planning the system's individual producing units' operations for a certain period of time, usually a day or a week. The objective is to minimise the total cost of generating while satisfying the constantly changing demand for power. Large amounts of electricity cannot be stored effectively. This means that generation and demand must be matched in real time. UC takes into account many kinds of power plants, each having unique features. For example, baseload production is best served by nuclear and coal facilities because of their long reaction times and high start-up costs. On the other hand, hydropower and natural gas facilities are more adaptable and can swiftly ramp up or down to meet times of peak demand.

Complex optimisation strategies that take these limits into account while minimising the overall generating cost are required to solve the UC challenge. For fossil fuel facilities, this cost usually consists of fuel expenses, variable operating and maintenance costs, and start-up costs related to turning on and off units. UC becomes much more difficult when renewable energy sources like solar and wind power become more widely used. The production of these renewable energy sources is weather-dependent and non-dispatchable, meaning it is difficult to rapidly alter to meet demand. Because of this, forecasting models must be included in the UC process in order to take renewable generation fluctuation into consideration [141].

In order to tackle these novel obstacles, UC research keeps changing. Incorporating renewable energy sources, meeting the increasing need for dispersed generation, and maintaining system resilience in the face of catastrophic weather occurrences are all being addressed by innovative strategies. Finally, it should be noted that the UCP is essential to maintaining the effective and dependable functioning of electric power systems.

At transmission level, energy management of a Virtual Power Plant (VPP) including a wind farm, energy storage systems, and a demand response program is realised, considering the cooperation between VPPs in day-ahead energy and reserve markets. The suggested method includes a noteworthy goal of trying to get VPP income as near to the producing units' operating costs as feasible. The suggested VPP restrictions, up and down reserve needs, and the network-constrained unit commitment model are applied to the goal function. This approach accounts for the unpredictability of wind farm power production, day-ahead market energy and standby prices, system and VPP demands.

The most useful techniques for managing uncertainty in renewable forecasting for power system operation and planning such that the total estimated output cost is minimised across the planning horizon are stochastic unit commitment and economic dispatch. It is almost impossible to model the vast majority of distinct scenarios using uncertain renewable resources, like solar and wind, in real time, which is necessary for an accurate estimation of the predicted production cost. The overall context envisages the expected cost 62.5% more accurately than the current state-of-the-art, on unforeseen days throughout the entire year, by decoupling the production cost estimation from the unit commitment and economic dispatch optimisation problems under uncertainty without compromising on the fidelity of the solutions [142].

The Deep Reinforcement Learning (DRL)-based UC model that is also being proposed addresses the pressing requirement to solve the UC issue in a computationally efficient way under large penetrations of renewable energy. Applying the model-free DRL framework's offline training results in high UC optimisation efficiency and significantly reduces the computing time required to find UC solutions. The state-disturbed approach is used to create a system disturbance environment impacted by real wind power output variations in order to cope with the unpredictability of wind power [143].

A multi-stage stochastic Mixed Integer Linear Program with binary recourse is used to optimise power plants' and virtual power plants' daily unit commitment. The proposed stochastic optimisation approach allows to increase the revenues of the conventional power plant by up to 13.58% and, for the combined heat and power and virtual power plant case, it permits finding a feasible and competent operational scheduling [144].

A proactive unit commitment program is suggested to improve the robustness of gearbox systems with offshore wind farms before to the onset of typhoons. In order to quantify the unpredictable effects of typhoons on transmission lines, offshore wind farms, and system states—where the random system state and offshore wind farm inertia support one other, a unique scenario is developed. When planning monthly schedules, it is important to take wind power's volatility into account. To facilitate the quick screening of overloaded power flow limitations in monthly unit commitment, a three-step watchlist creation strategy that is, a list of risk, a list of worry, and a list of interest, is presented. Significantly, in order to avoid the consequences of significant wind uncertainties, the shift factor approach is used to screen for possible overloaded restrictions resulting from the redispatch procedure [145].

A system in which renewable power generation is effectively integrated with conventional and plug-electric vehicles to meet the demand for power utilisation has been proposed in order to meet this rising demand while simultaneously taking care of the environment. Time-efficient scheduling in unit commitment problems will face significant hurdles due to the growing power grid and prohibitive computational costs and time. A time-saving and robust inference reinforcement learning strategy is presented to address the computationally costly problems in solving UCPs [146].

4.3 PROBLEM FORMULATION

The foundation of a dependable and effective electric power system is the unit commitment problem. It entails figuring out the best timetable for power plants for a certain period of time, usually a day or a week. In order to reduce the total cost of generation, this schedule details which generating units should be committed to and for how long [119].

To achieve this objective, however, a number of technical and financial considerations must be carefully taken into account, which creates a challenging optimisation challenge. Reducing the overall cost of generating is the main goal of UC. Fuel expenses for fossil fuel-based power plants, variable operating and maintenance costs, and start-up costs related to turning ON and OFF producing units are usually included in this cost [120].

4.3.1 Operating Cost

It is mathematically a quadratic, non-smooth and non-convex equation of fuel cost of each committed generator at h^{th} hour and can be represented as below:

$$FC = (\mathrm{a}_g \mathrm{P}_{g,h}^2 + \mathrm{b}_g \mathrm{P}_{g,h} + \mathrm{c}_g) \times \mathrm{U}_{g,h} + SUC \times U_{g,h} \times (1 - U_{g,(h-1)}); g = 1,....., NG; h = 1,.....H \tag{4.1}$$

where, FC is the cost associated with the g^{th} generating unit at h^{th} hour and a_g, b_g and c_g are its Fuel and Operational Cost Coefficients, Ug_h and $U_{(h-1)g}$ is the Committed Status of the g^{th} unit at h^{th} hour and $(h-1)^{th}$ hour respectively, SUC is the Start-Up Cost of g^{th} unit at h^{th} hour.

Combined Cost *(FC),* for all the Generating Units *(NG)* at a particular hour *h* can be obtained as the sum total of all the individual units' costs.

$$FC = \sum_{\mathrm{g}=1}^{NG} [(\mathrm{a}_g \mathrm{P}_{g,h}^2 + \mathrm{b}_g \mathrm{P}_{g,h} + \mathrm{c}_g) \times \mathrm{U}_{g,h} + SUC \times U_{g,h} \times (1 - U_{g,(h-1)})]; g = 1,...NG; h = 1,....H \tag{4.2}$$

Now, the total Fuel Cost FC over the given time horizon is the double summation of the costs incurred for all the generators for all the time periods considered. It can be mathematically represented as:

$$FC=\sum_{g=1}^{NG}\sum_{\mathrm{h=1}}^{H}[(\mathrm{a}_g\mathrm{P}_{g,h}^2+\mathrm{b}_g\mathrm{P}_{g,h}+\mathrm{c}_g)\times\mathrm{U}_{g,h}+SUC\times U_{g,h}\times(1-U_{g,(h-1)})];g=1,....NG;h=1,.....H \quad (4.3)$$

Start-up cost is warmth-dependent. Start-up cost is that cost which occurs while bringing the thermal generating unit online. It is expressed in terms of the time (in hours) for which the unit has been shut down. On the other hand, shut down cost is a fixed amount for each shutting unit. Mathematically, Start-Up Cost (*SUC)* can be expressed as:

$$SUC_{gh}=\begin{cases}HSC_g;\ \text{for MDT}_g\le MDT_g^{ON}\le(CSH_g+MDT_g)\\ CSC_g;\ \ \text{for } MDT_g^{ON}\ge(MDT_g+CSH_g)\end{cases}\qquad (g\in NG;\ \text{h=1,2,3....H}) \quad (4.4)$$

where, CSC_g and HSC_g are Cold Startup and Hot Start-Up Cost of gth unit respectively and *MDT* is the Minimum Down Time of gth unit, T_{gh}^{OFF} is duration for which the thermal g^{th} unit has been continuously off until hour *h*. CSH_g is the Cold Start Hour of g^{th} unit.

The start-up cost for a unit depends on its downtime. If it is longer than the related *MDT* plus its predefined *CSH*, CSC is needed to operate it. Else if the g^{th} unit down time is shorter than the mentioned duration, *HSC* is needed to operate it. The Various Constraints linked with unit commitment problem are explained below.

4.3.2 Maximum and Minimum Operating Limits of Generators

Every unit has its own maximum/minimum power level of generation, beyond and below which it cannot generate.

$$P_g^{\min}\le P_{gh}^{NG}\le P_g^{\max};g=1,.....,NG;h=1,......,H \quad (4.5)$$

4.3.3 Power Balance Constraints

The load balance or system power balance constraint requires that the sum of generation of all the committed units at h^{th} hour must be greater than or equal to the demand D_h at a particular hour *'h'*.

$$\sum_{g=1}^{NG}P_{gh}U_{gh}=P_h^{Demand};g=1,.....NG;h=1,......,H \quad (4.6)$$

Above eqn. (4.6) does not contain power loss in the system. If hourly power loss is considered, then eqn. (4.7) can be modified as:

$$\sum_{g=1}^{NG} P_{gh} U_{gh} = P_h^{Demand} + P_h^{Loss} \tag{4.7}$$

The power outputs of the gth generating units at a particular time period have to satisfy the power balance constraint and operating limit constraints.

4.3.4 Power Balance Constraint considering RES (Wind Power)

This constraint involves ensuring that the total power generated by all committed generating units at a particular time h (hour) is greater than or equal to the power demand for that same time period. Eqn. (4.9) outlines the power balance constraint that applied when RES considered in the system.

$$\sum_{g=1}^{NG} P_{gh} U_{gh} + P_h^{RES} = P_h^{Demand} + P_h^{Loss}, g = 1, \ldots.. NG; h = 1, \ldots\ldots, H \tag{4.8}$$

4.3.5 Spinning Reserve Constraints

Considering the important aspect of reliability, there is a provision of excess capacity of generation which is required to act instantly when there is a failure of already running unit or sudden increase in load demand. This excess capacity of generation is known as Spinning Reserve and mathematically given as:

$$\sum_{g=1}^{NG} P_{gh} U_{gh} \geq P_h^{Demand} + P_h^{\mathrm{Re}serve}; g = 1, \ldots.. NG; h = 1, \ldots\ldots H \tag{4.9}$$

4.3.6 Spinning Reserve Constraints Considering RES

Spinning reserve while considering the impact of COVID-19 and RES-

$$\sum_{g=1}^{NG} P_{gh} U_{gh} + P_h^{RES} \geq P_h^{Demand} + P_h^{\mathrm{Reserve}}, g = 1, \ldots.. NG; h = 1, \ldots\ldots, H \tag{4.10}$$

4.3.7 Thermal Constraints

A thermal generation unit needs to undergo gradual temperature changes and thus it takes some period of time to bring a thermal unit online. Also, the operation of a thermal unit is manually controlled. So, a crew is required to perform the operation and maintenance of any thermal unit. This leads to many restrictions on the operation of thermal unit and thus it gives rise to many constraints.

4.3.8 Minimum-up Time Constraint

Once a unit is started up, it cannot be shut-down before a minimum up-time period is met and mathematically expressed as:

$$\mathrm{T}_{gh}^{ON} \geq MUT_g ; g = 1,.....NG; h = 1,........H \tag{4.11}$$

where, T_{gh}^{ON} is duration for which g^{th} unit is continuously *ON* (in hrs) and MUT_g is its Minimum Up Time (in hrs).

4.3.9 Minimum-Down Time Constraint

Once a unit is shut down, it could not be started-up before a minimum down-time period is met and mathematically expressed as:

$$\mathrm{T}_{gh}^{OFF} \geq MDT_g ; g = 1,......NG; h = 1,........H \tag{4.12}$$

where, T_{gh}^{OFF} is duration for which g^{th} unit is continuously *OFF* (in hrs) and MDT_g is its Minimum Down Time (in hrs).

4.3.10 Crew Constraints

If a plant consists of two or more units, they could not be turned on at the same time since there are not enough crewmembers to attend all the units while starting up.

4.3.11 Initial Operating Status of Generating Units

The initial operating status of every unit must take the last day's previous schedule into account, so that every unit satisfies it's minimum up or down time.

4.4 SOLUTIONS METHODOLOGY FOR UNIT COMMITMENT PROBLEM

The UC problem has been examined by taking into account the physical limitations and system of thermal power units. This research employs hybrid versions of CBWO to address the unit commitment problem in power systems. Both stochastic and heuristic approaches are utilized to handle various operational and physical constraints associated with the unit commitment problem.

The developments for managing system constraints in UCP, including spinning reserve constraint, minimum-up and minimum-down time constraints, and deactivation of surplus power generating units, are outlined in sections 4.4.1, 4.4.2, and 4.4.3, respectively. The proposed hybrid optimization techniques for solving the unit commitment problem are discussed in the subsequent sections.

4.4.1 Repairing for Spinning Reserve Constraints

To meet the reserve capacity requirements for various power unit types, the minimum operational and non-operational periods of each power unit, along with their respective durations, have been considered.

The reserve constraints must be addressed according to the specified PSEUDO code.

Step 1: Arrange the power generators in decreasing order based on their maximum capacity to generate power.

Step 2: for g=0 to NG, if U_{gh} =0 then U_{gh} =1,

Else if $T_{g,h}^{off} \geq MDT_g$

Then $T_{g,h}^{on} \geq T_{g,h-1}^{on} + 1$

Step 3: Check the newly generated power output of the units for validation.

Step 4: if $\sum_{g=1}^{NG} P_{gh} U_{gh} \geq P_h^{demand} + P_h^{\mathrm{Re}serve}$, if the condition is not met then proceed to step 2 otherwise end the algorithm.

Step 5. If $T_{g,h}^{off} \leq MDT_g$ then do $l = h - T_{g,h}^{off} + 1$ and set U_{gh} =1.

Step 6: Calculate $T_{g,h}^{l} = T_{g,h-1}^{on} + 1$ and $T_{g,h}^{off} = 0$

Step 7: if l>h, check the power output of generator to ensure its accuracy for $\sum_{g=1}^{NG} P_{gh} U_{gh} \geq P_h^{demand} + P_h^{\mathrm{Re}serve}$

Else increase the value of *h* by 1 and go back to step 5.

Fig. 4.1- PSEUDO code for Spinning Reserve Constraint

4.4.2 Repairing for Minimum Up and Down Time Constraints

Repairing for minimum up time and down time constraints of different thermal units can be done by following process-

For *h=1 to H*

For *g=1 to NG do g=1*

If U_{gh} =1 do $U_{g,h-1}$=0, **if** $T_{g,h}^{off} < MDT_g$, do U_{gh} =0

Else U_{gh} =1

End

End

If $U_{g,h-1}$=1, **else if** U_{gh} =0 if $T_{g,h}^{off} < MDT_g$ do U_{gh} =1

Else U_{gh} =0

If *g=NG* then stop or **else** do *g=1* and follow the steps

Else

End

End.

Fig. 4.2: PSEUDO Code for Minimum Up and Down Time Constraints

4.4.3 Decommitment of the Excessive Generating Units

Surplus thermal units must be taken offline. All thermal generating units need to meet the requirements for load demand and spinning reserve. The system takes into account the minimum down and up times for each unit, as well as the duration of power unit OFF/ON periods. The algorithm allows for constraint adjustments as necessary.

For *h=1 to H*

For *g=1 to NG*

  Do *u=h(NG+1-g)* and calculate generating power

  If U_{gh} =1 then $U_{g,h-1}$ =0

  If $P_g - P_{\max} \geq P_h^{demand} + P_h^{\mathrm{Re}serve}$ then

  If $T_{g,h}^{off} > MDT_g$, $T_{g,h}^{on} = 0$ then

    Do U_{gh} =0 and $T_{g,h}^{on} = 0$

If *h==1 then*

  Do $T_{g,h}^{off} = T_{g,h-1}^{off} + 1$

Else

Do $T_{g,h}^{off} = T_{g,h-1}^{off} + 1$

End

Else

  Continue:

End

Else

  Break;

End

End

Fig. 4.3- PSEUDO code for Decommitment of the Excessive Generating Units.

4.4.4 Chaotic Beluga Whale Optimization Algorithm

The chaotic algorithm for unit commitment is created by combining the circle chaotic function with BWO's general operators. The process begins by utilizing the matching chaotic function to generate a random solution across the entire population. The subsequent steps in the recommended CBWO algorithm are outlined as follows.

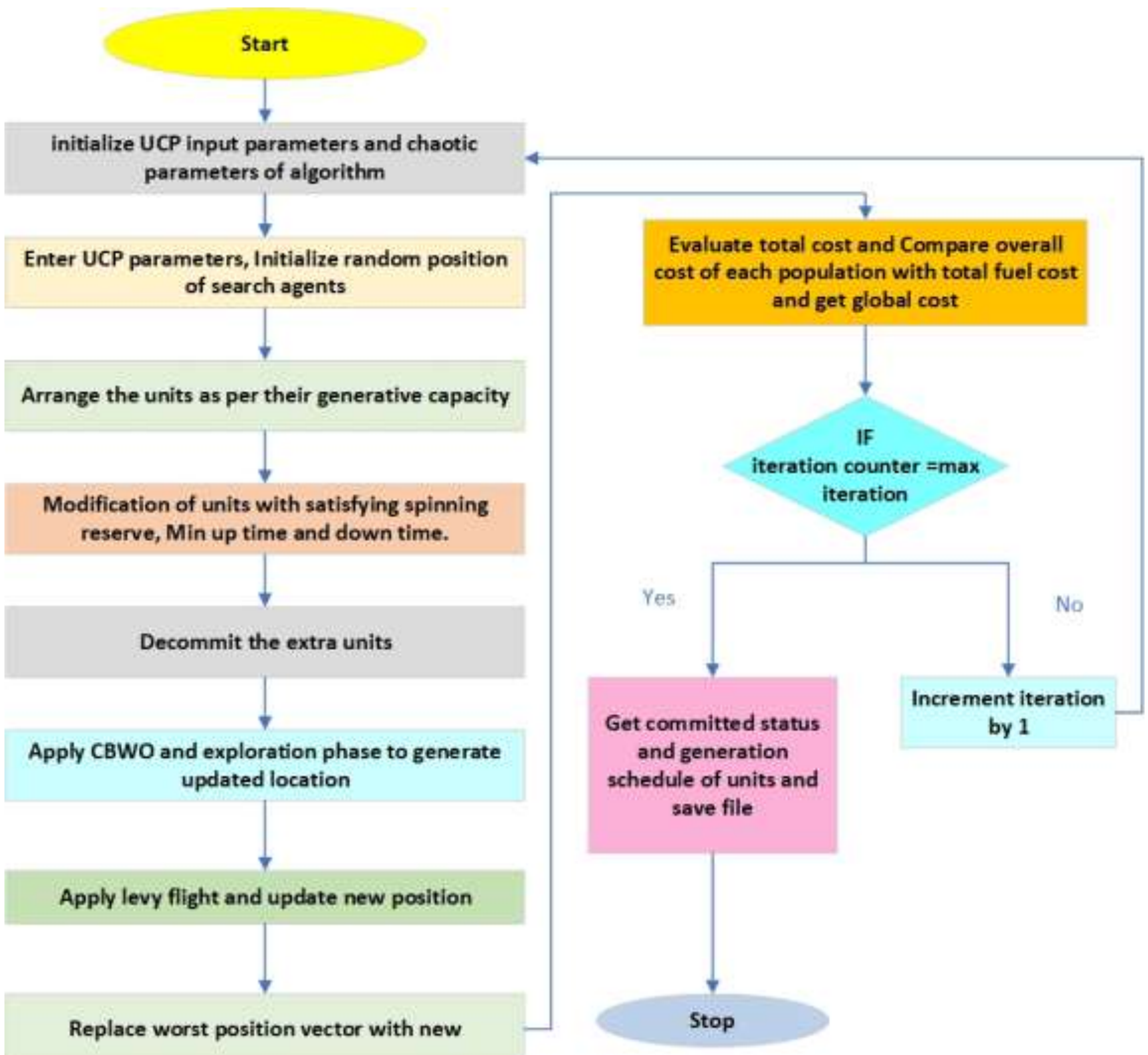

Fig. 4.4: Algorithm for CBWO

Subsequently, the optimal solution is evaluated against the BWO algorithm's outcome. In the proposed method, a chaotic search is employed to optimize a vector of units for commitment, with the aim of reducing overall costs. The procedure for solution of unit commitment using CBWO algorithm is explained below:

Step1. Enter UCP parameters and Initialize individuals in the population using equation (3.4 and 3.5) as described below:

To solve single area unit commitment problem, each individual is defined as unit's ON/OFF status modelled as 1/0, respectively. An individual represents the unit commitment schedule over the time horizon. The ON/OFF schedule of the units is stored as an integer-matrix, shown below, which is mathematically defined as:

$$U_{\kappa hg} = \begin{pmatrix} U_{11}^{\kappa} & U_{12}^{\kappa} \ldots\ldots & U_{1NG}^{\kappa} \\ U_{21}^{\kappa} & U_{22}^{\kappa} \ldots\ldots & U_{2NG}^{\kappa} \\ \vdots & \ddots & \vdots \\ U_{H1}^{\kappa} & U_{H2}^{\kappa} \ldots\ldots & U_{HNG}^{\kappa} \end{pmatrix}_{H\times NG} \qquad \left(h = 1, 2, \ldots H; g = 1, 2, \ldots, NG; \kappa = 1, 2, \ldots., NP\right)$$

Where, U_{hg} is ON/OFF status of unit g at hour h (i.e., U_{hg} =1/0 for ON/OFF)

Step-2: Generating units are prioritized according to their maximum generation capacity in descending order.

Step-3: Status of individual units is modified in the population to satisfy the spinning reserve constraints as mentioned in section-4.4.1.

Step-4: Individual units in the population are repaired for minimum up/down time violations as per section-4.4.2.

Step-5: De-commit the excessive units in the population as per section-4.4.3 to reduce excessive spinning reserve due to minimum up/down time repairing.

Step-6: Unit commitment problem is then solved and fuel cost is calculated for each hour.

Step-7: Calculate Start-up cost for each hour using equation (4.4) and overall generation cost using equation (4.3).

Step-8: Apply CBWO algorithm and perform exploration, exploitation and whale fall using equations (3.4), (3.5), (3.6) and (3.9) to generate updated target vector A_i^{T+1}.

Step-9: Verify for constraints violations using section-4.4.1, 4.4.2 and 4.4.3.

Step-10: Replace worst vector with new vector A_i^{T+1}.

Step-11: Apply levy flight using equation (3.7) and update the position.

Step-12: If iteration counter= maximum iteration then go to step 14.

Step-13: If iteration counter< maximum iteration, increase iteration by one and go back to step 3 and repeat.

Step-14: Stop and obtain the optimal solution of unit commitment problem from the individual position in the population that generated the least total generation cost.

4.4.5 Mathematical Modelling of Wind Uncertainties

Almost all ordinary activities need electrical energy to work suitably. The primary factor used by the power sectors to generate immense volumes of electricity is fossil fuels. Even though producing energy from fossil fuels is easier, the release of carbon emissions has unfavourable impacts on the environment. It becomes vigorous to pay close attention to the use of these non-conventional sources of energy in order to safeguard their elongated persistence, since the process of consuming energy if left unrestricted may lead to a rapid consumption of fossil fuels and sooner or later lead to their diminution [157].

The involvement of renewable energy sources has somewhat abridged the need for fossil fuels to meet load demand. The two main renewable energy sources that contribute to global energy production are solar and wind. The nature of wind energy is stochastic; its direction and speed alter over time. A variety of statistical methods, including the gamma function and the Weibull probability distribution function, may be used to trigger this indefinite stochastic characteristic. It is essential to comprehend how much energy is generated by various turbines at various speeds at which wind turbines operate at their rated speed [158].

Mathematical formulation

We know,

$$P = \frac{1}{2}\rho A v^3 \tag{4.13}$$

Equation (4.13) provides the wind power generated by a wind turbine at its rated Wind Velocity, or "v". The German scientist Albert Betz studied it in 1919. This threshold became known as the Power Coefficient (C_{Pmax}). Merely 59% of the energy in the wind can be captured at any one time. Similarly, wind turbines cannot operate at full capacity. The operating wind speed of the turbine determines the power coefficient. It is established that the optimal power coefficient falls between 0.35 and 0.45, even with the best-designed turbines. When several factors are considered, such the gearbox, bearings, generators, and so on, only roughly 10–30% of the wind's power can be converted into useable energy. The actual extractable power from the wind is therefore given by equation (4.14)

$$P = \frac{1}{2}\rho A v^3 . C_p \tag{4.14}$$

Wind turbine power output varies according to the cube of the rated speed. However, this is only relevant within a certain speed range. In fact, there isn't enough torque to turn the turbine at a low wind speed. The cut-in-speed is the wind speed at which the rotor begins to revolve. There is no production of electricity below cut-in speed. Usually, the cut-in speed is between 3 and 4 m/s. On the other side, because to mechanical limitations, the rotor is unable to generate significant power in severe winds. As a result, the greatest speed at which power may be generated safely is known as the "cut out-speed." Usually, the cut-out speed is around 25 m/s. Lastly, the maximum amount of power that may be generated as output power is likewise limited by electrical generators. Thus, the power is restricted to a fixed value beyond a given wind speed.

The Weibull distribution function is the most often used and developed in 1951 by Swedish researcher Waloddi Weibull. It is a variable distribution function that depends on the value of the shape parameter. For the evaluation of wind energy some functions are given below-

$$pdf(v,k,\lambda)=\frac{k}{\lambda}\left(\frac{v}{\lambda}\right)^{k-1}\exp\left[-\left(\frac{v}{k}\right)^{k}\right] \tag{4.15}$$

$$P_w=\begin{cases}0\ldots\ldots\ldots\ldots\ldots\ldots.(v^h\le v_{in}..or..v^h\ge v_{out})\\ P_{wr}\ldots\ldots\ldots\ldots\ldots.(v_r\le v^h\le v_{out})\\ \dfrac{(v-v_{in})}{v_r-v_{in}}\ldots\ldots.(v_{in}\le v^h\le v_r)\end{cases} \tag{4.16}$$

$$P_r(P_w=0)=cdf(v_{in})+[1-cdf(v_{out})] \tag{4.17}$$

$$P_w=0;.P_r=[1-\exp\left[-\left(\frac{v_{in}}{\lambda}\right)^{k}\right]+\exp\left[-\left(\frac{v_{out}}{\lambda}\right)^{k}\right] \tag{4.18}$$

$$pdf(P_w)=\frac{klv_{in}}{(P_{wr})^{\lambda}}\left[\frac{1+\left(\frac{LP_w}{P_{wr}}\right)v_{in}}{\lambda}\right]\times\exp\left[-\left(\frac{1+\left(\frac{LP_w}{P_{wr}}\right)v_{in}}{\lambda}\right)^{k}\right] \tag{4.19}$$

In the present research, Shape factor=2, Scale factor = 7, Cut-in Speed= 3 m/s, Cut-out speed = 15 m/s, Rated speed = 11-15 m/s are taken into consideration [158].

4.5 TEST SYSTEM

The UCP was successfully solved by considering the limitations of power generation units and various system sizes, including small, medium, and large-scale systems. The UCP was solved for different system sizes, namely standard 10-generating unit systems, 20-

generating unit systems, 40-generating unit systems. This part also discusses the attributes of power units with cost coefficient parameters.

4.5.1 Generation system for 10 Units

The parameters of the 10-generating unit system utilized in the experiment are displayed in Table-4.1. These specifications encompass the system's maximum and minimum Power Generation Limits (P_{max} and P_{min}), Fuel Coefficient Constraints, up and down time constraints, expenses for hot and cold start, the unit's cold start hour, and the system's initial status.

Table-4.2 illustrates the load demand of the test system. The system underwent evaluation using a 24-hour load demand pattern, with varying spinning reserve capacity of 10%. For the analysis of the proposed system, the standard IEEE 10-unit, 39-bus test system with 24 hours of data has been taken into consideration for the study.

Table 4.1.: Characteristics of the 10-Generating Unit System [158]

Generating units		**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**
Parameter	**Units**										
P_g^{max}	MW	455	455	130	130	162	80	85	55	55	55
P_g^{min}	MW	150	150	20	20	25	20	25	10	10	10
a_g	\$/hour	1000	970	700	680	450	370	480	660	665	670
b_g	\$/MWh	16.19	17.2	16.6	16.5	19.7	22.26	27.74	25.92	27.27	27.79
c_g	\$/MWh^2 (10^{-3})	0.05	0.03	0.2	0.21	0.4	0.71	0.08	0.41	0.22	0.17
MUT_g	hours	8	8	5	5	6	3	3	1	1	1
MDT_g	hours	8	8	5	5	6	3	3	1	1	1
HSC_g	\$	4500	5000	550	560	900	170	260	30	30	30
CSC_g	\$	9000	10000	1100	1120	1800	340	520	60	60	60
CSH_g	hours	5	5	4	4	4	2	2	0	0	0
INS_g	-	8	8	-5	-5	-6	-3	-3	-1	-1	-1

Table 4.2: Power demand for a system consisting of 10 generating units [158].

	Time: Hours											
Power Demand (MW)	**h_1**	**h_2**	**h_3**	**h_4**	**h_5**	**h_6**	**h_7**	**h_8**	**h_9**	**h_{10}**	**h_{11}**	**h_{12}**
	700	750	850	950	1000	1100	1150	1200	1300	1400	1450	1500
	h_{13}	**h_{14}**	**h_{15}**	**h_{16}**	**h_{17}**	**h_{18}**	**h_{19}**	**h_{20}**	**h_{21}**	**h_{22}**	**h_{23}**	**h_{24}**
	1400	1300	1200	1050	1000	1100	1200	1400	1300	1100	900	800

4.5.2 Generation system for 20 and 40 Units

To obtain the 20-unit test system, 10-unit system was duplicated and also load demand was doubled. For the 40-unit test system, 10-unit system was quadrupled and accordingly load demand was made 4-times. The problem data of 10-unit test system were scaled appropriately for the problem with 20 and 40-units test system.

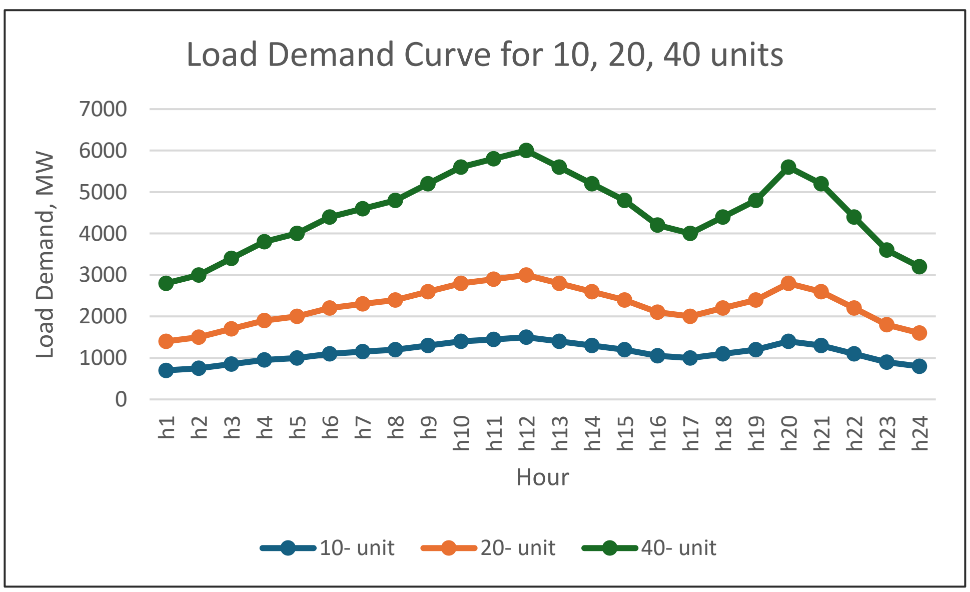

Fig. 4.5: Load Demand Curve for 10, 20, 40- unit system

4.6 RESULT AND DISCUSSION

The CBWO is a novel hybrid algorithm that combines chaotic maps with beluga whale optimization techniques. CBWO is a population-based algorithm that does not rely on gradients, which makes it suitable for a wide range of optimization problems. To determine the effectiveness of the proposed techniques for UCP, standard test systems of 10, 20, and 40 generating units were employed. The performance of the proposed algorithms was evaluated using MATLAB 2018a software on a 64-bit version of Windows 11 Home Basic, with a CPU operating at 2.10 GHz, 8 GB of RAM, and an Intel® CoreTM i5-2310M processor.

4.6.1 System of Ten Generating Units

The effectiveness of proposed algorithm CBWO is tested and used to get the optimal result for UC problem considering the several constraints. This part of theses is basically illustrating the optimal results for 10 generating units and scheduling of units. **Table 4.3** illustrates the scheduling of units for 10 units during weekend period of pre COVID-19. **Table 4.4** illustrates the scheduling of different units during weekday period of pre COVID-19. **Table 4.5** illustrates the scheduling of units for 10 units during weekend period of pre COVID-19 with wind power. **Table 4.6** also illustrates the scheduling of different units during weekday period of pre COVID-19 with wind power.

Table 4.7 display the fuel cost for 10 units during weekend period of pre COVID-19. **Table 4.8** display the fuel cost of different units during weekday period of pre COVID-19. **Table 4.9** display the fuel cost for 10 units during weekend period of pre COVID-19 with wind power. **Table 4.10** display the fuel cost of different units during weekday period of pre COVID-19 with wind power.

Table 4.3: Scheduling a 10-unit system with the help of the CBWO algorithm for UCP during Pre-COVID (For weekend); MW

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	SUC	FC
h_1	455	363	0	0	0	0	0	10	0	0	560	16661.66
h_2	455	359	0	0	0	0	0	0	0	0	0	15672.12
h_3	455	361	0	0	0	0	0	0	0	0	1330	15707.08
h_4	455	358	0	0	0	0	0	0	0	0	550	15654.63
h_5	455	372	0	0	0	0	0	0	0	0	0	15899.44
h_6	455	402	0	0	25	0	0	0	0	0	0	17369.43
h_7	455	453	0	0	25	0	0	0	0	0	0	18263.2
h_8	455	388	0	130	25	0	0	0	0	0	0	19985.02
h_9	455	404	0	130	25	0	0	0	0	0	260	20265.11
h_{10}	455	437	0	130	25	0	0	0	0	0	60	20843.29
h_{11}	455	425	0	130	25	0	0	0	0	0	0	20632.96
h_{12}	455	418	0	130	25	0	0	0	0	0	30	20510.31
h_{13}	455	322	130	130	0	0	0	0	0	0	0	20778.14
h_{14}	455	340	130	130	0	0	0	0	0	0	0	21092.52
h_{15}	455	329	130	130	0	0	0	0	0	0	900	20900.38
h_{16}	455	341	130	130	0	0	0	0	0	0	0	21109.99
h_{17}	455	365	130	130	0	20	0	0	0	0	260	22347.53
h_{18}	455	376	130	130	0	20	0	0	0	0	340	22539.92
h_{19}	455	455	0	130	89	20	0	0	0	0	0	23266.83
h_{20}	455	455	0	130	79	20	0	0	0	0	0	23063.15
h_{21}	455	455	0	130	48	0	0	0	0	0	550	21618.73
h_{22}	455	424	0	130	25	0	0	0	0	0	60	20615.44
h_{23}	455	455	0	0	53	0	0	0	0	0	0	18858.58
h_{24}	455	411	0	0	25	0	0	0	0	0	0	17527.04

Table 4.4: Scheduling a 10-unit system with the help of the CBWO algorithm for UCP during Pre-COVID (For weekday); MW

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	SUC	FC
h_1	455	384	0	0	25	0	0	0	0	0	900	17054.36
h_2	455	406	0	0	25	0	0	0	0	0	0	17439.47
h_3	455	411	0	0	25	0	0	0	0	0	0	17527.04
h_4	455	436	0	0	25	0	0	0	0	0	0	17965.1
h_5	455	351	130	0	25	0	0	0	0	0	560	19369.06
h_6	455	455	130	0	47	0	0	0	0	0	0	21629.79
h_7	455	397	130	130	25	0	0	0	0	0	1100	23034.35
h_8	455	337	130	130	25	0	0	0	0	0	0	21985.09
h_9	455	312	130	130	0	0	0	0	0	0	0	20603.58
h_{10}	455	402	0	130	0	20	0	0	0	0	0	20103.15
h_{11}	455	391	0	130	0	20	0	0	0	0	0	19910.58
h_{12}	455	401	0	130	0	20	0	0	0	0	340	20085.64
h_{13}	455	401	0	130	0	20	0	0	0	0	0	20085.64
h_{14}	455	387	0	130	0	20	0	0	0	0	0	19840.58
h_{15}	455	385	0	130	25	0	0	0	0	0	0	19932.52
h_{16}	455	438	0	130	25	0	0	0	0	0	900	20860.82
h_{17}	455	358	130	130	25	0	0	0	0	0	550	22352.08
h_{18}	455	368	130	130	25	0	0	0	0	0	0	22526.93
h_{19}	455	403	130	130	25	0	0	0	0	0	0	23139.4
h_{20}	455	439	130	130	25	0	0	0	0	0	690	23770.15
h_{21}	455	378	130	130	25	0	0	0	0	0	0	22701.84
h_{22}	455	426	0	130	25	0	0	0	0	0	0	20650.49
h_{23}	455	360	0	130	0	0	0	0	0	0	0	18550.26
h_{24}	455	304	0	130	0	0	0	0	0	0	0	17572.17

Table 4.5: Scheduling a 10-unit system with the help of the CBWO algorithm for UCP **during Pre-COVID with Wind Power Uncertainty** (For weekend); MW											
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**FC**
h_1	455	196	0	0	0	0	0	0	0	0	0	12830.69
h_2	455	188	0	0	0	0	0	0	0	0	0	12691.66
h_3	455	203	0	0	0	0	0	0	0	0	0	12952.38
h_4	455	213	0	0	0	0	0	0	0	0	0	13126.27
h_5	455	230	0	0	0	0	0	0	0	0	0	13422.02
h_6	455	290	0	0	0	0	0	0	0	0	0	14467.29
h_7	455	358	0	0	0	0	0	0	0	0	0	15654.63
h_8	455	304	0	130	0	0	0	0	0	0	1120	17572.17
h_9	455	313	0	130	0	0	0	0	0	0	0	17729.23
h_{10}	455	346	0	130	0	0	0	0	0	0	0	18305.55
h_{11}	455	333	0	130	0	0	0	0	0	0	0	18078.44
h_{12}	455	328	0	130	0	0	0	0	0	0	0	17991.11
h_{13}	455	338	0	130	0	0	0	0	0	0	0	18165.78
h_{14}	455	351	0	130	0	0	0	10	0	0	1100	19312.55
h_{15}	455	352	0	130	0	0	0	0	0	0	0	18410.41
h_{16}	455	360	0	130	0	0	0	0	0	0	0	18550.26
h_{17}	455	387	0	130	25	0	0	0	0	0	0	19967.52
h_{18}	455	410.5	0	130	25	0	0	0	0	0	0	20378.94
h_{19}	455	439.4	0	130	25	0	0	0	0	0	0	20885.36
h_{20}	455	409	0	130	25	0	0	0	0	0	860	20352.67
h_{21}	455	455	0	0	51	0	0	0	0	0	0	18818.35
h_{22}	455	417	0	0	25	0	0	0	0	0	0	17632.14
h_{23}	455	348	0	0	0	0	0	0	0	0	0	15479.84
h_{24}	455	261	0	0	0	0	0	0	0	0	0	13961.8

Table 4.6: Scheduling a 10-unit system with the help of the CBWO algorithm for UCP **during Pre-COVID with Wind Power Uncertainty** (For weekday); MW												
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**FC**
h_1	455	232	0	0	0	0	0	0	0	0	0	13456.83
h_2	455	260	0	0	0	0	0	0	0	0	1190	13944.38
h_3	455	278	0	0	0	0	0	0	0	0	1110	14258.06
h_4	455	316	0	0	0	0	0	0	0	0	0	14920.94
h_5	455	364	0	0	0	0	0	0	0	0	0	15759.54
h_6	455	345	0	130	0	20	0	0	0	0	120	19106.13
h_7	455	412	0	130	0	20	0	0	0	0	0	20278.27
h_8	455	363	0	130	0	20	0	0	0	0	0	19420.76
h_9	455	326	0	130	0	0	0	0	0	0	0	17956.19
h_{10}	455	306	0	130	0	0	0	0	0	0	0	17607.07
h_{11}	455	294	0	130	0	0	0	0	0	0	170	17397.72
h_{12}	455	411	0	0	25	0	0	0	0	0	0	17527.04
h_{13}	455	412	0	0	25	0	0	0	0	0	0	17544.55
h_{14}	455	403	0	0	25	0	0	0	0	0	120	17386.94
h_{15}	455	408	0	0	25	0	0	0	0	0	60	17474.49
h_{16}	455	455	0	0	27	0	0	0	0	0	560	18338.1
h_{17}	455	385	0	130	25	0	0	0	0	0	900	19932.52
h_{18}	455	407.5	0	130	25	0	0	0	0	0	0	20326.4
h_{19}	455	433.4	0	130	25	0	0	0	0	0	0	20780.18
h_{20}	455	449	0	130	25	0	0	0	0	0	0	21053.7
h_{21}	455	386	0	130	0	20	0	0	0	0	0	19823.08
h_{22}	455	424	0	0	0	20	0	0	0	0	0	17627.84
h_{23}	455	310	0	0	0	20	0	0	0	0	0	15634.26
h_{24}	455	259	0	0	0	0	0	0	0	0	0	13926.96

Table 4.7: Individual fuel cost for Generation of 10 Unit Test System using CBWO for UCP during Pre-COVID (Weekend); $												
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	8465.822	7276.228	0	0	0	0	0	919.613	0	0	560	16661.66
h_2	8465.822	7206.293	0	0	0	0	0	0	0	0	0	15672.12
h_3	8465.822	7241.26	0	0	0	0	0	0	0	0	1330	15707.08
h_4	8465.822	7188.811	0	0	0	0	0	0	0	0	550	15654.63
h_5	8465.822	7433.619	0	0	0	0	0	0	0	0	0	15899.44
h_6	8465.822	7958.617	0	0	944.9875	0	0	0	0	0	0	17369.43
h_7	8465.822	8852.395	0	0	944.9875	0	0	0	0	0	0	18263.2
h_8	8465.822	7713.549	0	2860.659	944.9875	0	0	0	0	0	0	19985.02
h_9	8465.822	7993.637	0	2860.659	944.9875	0	0	0	0	0	260	20265.11
h_{10}	8465.822	8571.82	0	2860.659	944.9875	0	0	0	0	0	60	20843.29
h_{11}	8465.822	8361.494	0	2860.659	944.9875	0	0	0	0	0	0	20632.96
h_{12}	8465.822	8238.844	0	2860.659	944.9875	0	0	0	0	0	30	20510.31
h_{13}	8465.822	6559.862	2891.8	2860.659	0	0	0	0	0	0	0	20778.14
h_{14}	8465.822	6874.236	2891.8	2860.659	0	0	0	0	0	0	0	21092.52
h_{15}	8465.822	6682.095	2891.8	2860.659	0	0	0	0	0	0	900	20900.38
h_{16}	8465.822	6891.707	2891.8	2860.659	0	0	0	0	0	0	0	21109.99
h_{17}	8465.822	7311.2	2891.8	2860.659	0	818.048	0	0	0	0	260	22347.53
h_{18}	8465.822	7503.587	2891.8	2860.659	0	818.048	0	0	0	0	340	22539.92
h_{19}	8465.822	8887.478	0	2860.659	2234.826	818.048	0	0	0	0	0	23266.83
h_{20}	8465.822	8887.478	0	2860.659	2031.139	818.048	0	0	0	0	0	23063.15
h_{21}	8465.822	8887.478	0	2860.659	1404.77	0	0	0	0	0	550	21618.73
h_{22}	8465.822	8343.971	0	2860.659	944.9875	0	0	0	0	0	60	20615.44
h_{23}	8465.822	8887.478	0	0	1505.28	0	0	0	0	0	0	18858.58
h_{24}	8465.822	8116.226	0	0	944.9875	0	0	0	0	0	0	17527.04

Table 4.8: Individual fuel cost for Generation of 10 Unit Test System using CBWO for UCP during Pre-COVID (Weekday); $												
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	8465.822	7643.551	0	0	944.9875	0	0	0	0	0	900	17054.36
h_2	8465.822	8028.659	0	0	944.9875	0	0	0	0	0	0	17439.47
h_3	8465.822	8116.226	0	0	944.9875	0	0	0	0	0	0	17527.04
h_4	8465.822	8554.29	0	0	944.9875	0	0	0	0	0	0	17965.1
h_5	8465.822	7066.452	2891.8	0	944.9875	0	0	0	0	0	560	19369.06
h_6	8465.822	8887.478	2891.8	0	1384.692	0	0	0	0	0	0	21629.79
h_7	8465.822	7871.079	2891.8	2860.659	944.9875	0	0	0	0	0	1100	23034.35
h_8	8465.822	6821.826	2891.8	2860.659	944.9875	0	0	0	0	0	0	21985.09
h_9	8465.822	6385.297	2891.8	2860.659	0	0	0	0	0	0	0	20603.58
h_{10}	8465.822	7958.617	0	2860.659	0	818.048	0	0	0	0	0	20103.15
h_{11}	8465.822	7766.053	0	2860.659	0	818.048	0	0	0	0	0	19910.58
h_{12}	8465.822	7941.108	0	2860.659	0	818.048	0	0	0	0	340	20085.64
h_{13}	8465.822	7941.108	0	2860.659	0	818.048	0	0	0	0	0	20085.64
h_{14}	8465.822	7696.048	0	2860.659	0	818.048	0	0	0	0	0	19840.58
h_{15}	8465.822	7661.05	0	2860.659	944.9875	0	0	0	0	0	0	19932.52
h_{16}	8465.822	8589.352	0	2860.659	944.9875	0	0	0	0	0	900	20860.82
h_{17}	8465.822	7188.811	2891.8	2860.659	944.9875	0	0	0	0	0	550	22352.08
h_{18}	8465.822	7363.661	2891.8	2860.659	944.9875	0	0	0	0	0	0	22526.93
h_{19}	8465.822	7976.127	2891.8	2860.659	944.9875	0	0	0	0	0	0	23139.4
h_{20}	8465.822	8606.884	2891.8	2860.659	944.9875	0	0	0	0	0	690	23770.15
h_{21}	8465.822	7538.574	2891.8	2860.659	944.9875	0	0	0	0	0	0	22701.84
h_{22}	8465.822	8379.018	0	2860.659	944.9875	0	0	0	0	0	0	20650.49
h_{23}	8465.822	7223.776	0	2860.659	0	0	0	0	0	0	0	18550.26
h_{24}	8465.822	6245.689	0	2860.659	0	0	0	0	0	0	0	17572.17

Table 4.9: Individual fuel cost for Generation of 10 Unit Test System using CBWO for UCP **during Pre-COVID with Wind Power Uncertainty (Weekend); $**												
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	8465.822	4364.869	0	0	0	0	0	0	0	0	0	12830.69
h_2	8465.822	4225.837	0	0	0	0	0	0	0	0	0	12691.66
h_3	8465.822	4486.555	0	0	0	0	0	0	0	0	0	12952.38
h_4	8465.822	4660.444	0	0	0	0	0	0	0	0	0	13126.27
h_5	8465.822	4956.199	0	0	0	0	0	0	0	0	0	13422.02
h_6	8465.822	6001.471	0	0	0	0	0	0	0	0	0	14467.29
h_7	8465.822	7188.811	0	0	0	0	0	0	0	0	0	15654.63
h_8	8465.822	6245.689	0	2860.659	0	0	0	0	0	0	1120	17572.17
h_9	8465.822	6402.75	0	2860.659	0	0	0	0	0	0	0	17729.23
h_{10}	8465.822	6979.072	0	2860.659	0	0	0	0	0	0	0	18305.55
h_{11}	8465.822	6751.956	0	2860.659	0	0	0	0	0	0	0	18078.44
h_{12}	8465.822	6664.631	0	2860.659	0	0	0	0	0	0	0	17991.11
h_{13}	8465.822	6839.296	0	2860.659	0	0	0	0	0	0	0	18165.78
h_{14}	8465.822	7066.452	0	2860.659	0	0	0	919.613	0	0	1100	19312.55
h_{15}	8465.822	7083.93	0	2860.659	0	0	0	0	0	0	0	18410.41
h_{16}	8465.822	7223.776	0	2860.659	0	0	0	0	0	0	0	18550.26
h_{17}	8465.822	7696.048	0	2860.659	944.9875	0	0	0	0	0	0	19967.52
h_{18}	8465.822	8107.468	0	2860.659	944.9875	0	0	0	0	0	0	20378.94
h_{19}	8465.822	8613.896	0	2860.659	944.9875	0	0	0	0	0	0	20885.36
h_{20}	8465.822	8081.197	0	2860.659	944.9875	0	0	0	0	0	860	20352.67
h_{21}	8465.822	8887.478	0	0	1465.052	0	0	0	0	0	0	18818.35
h_{22}	8465.822	8221.326	0	0	944.9875	0	0	0	0	0	0	17632.14
h_{23}	8465.822	7014.022	0	0	0	0	0	0	0	0	0	15479.84
h_{24}	8465.822	5495.978	0	0	0	0	0	0	0	0	0	13961.8

Table 4.10: Individual fuel cost for Generation of 10 Unit Test System using CBWO for UCP **during Pre-COVID with Wind Power Uncertainty (Weekday); $**												
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	8465.822	4991.005	0	0	0	0	0	0	0	0	0	13456.83
h_2	8465.822	5478.556	0	0	0	0	0	0	0	0	1190	13944.38
h_3	8465.822	5792.238	0	0	0	0	0	0	0	0	1110	14258.06
h_4	8465.822	6455.115	0	0	0	0	0	0	0	0	0	14920.94
h_5	8465.822	7293.714	0	0	0	0	0	0	0	0	0	15759.54
h_6	8465.822	6961.598	0	2860.659	0	818.048	0	0	0	0	120	19106.13
h_7	8465.822	8133.741	0	2860.659	0	818.048	0	0	0	0	0	20278.27
h_8	8465.822	7276.228	0	2860.659	0	818.048	0	0	0	0	0	19420.76
h_9	8465.822	6629.706	0	2860.659	0	0	0	0	0	0	0	17956.19
h_{10}	8465.822	6280.587	0	2860.659	0	0	0	0	0	0	0	17607.07
h_{11}	8465.822	6071.235	0	2860.659	0	0	0	0	0	0	170	17397.72
h_{12}	8465.822	8116.226	0	0	944.9875	0	0	0	0	0	0	17527.04
h_{13}	8465.822	8133.741	0	0	944.9875	0	0	0	0	0	0	17544.55
h_{14}	8465.822	7976.127	0	0	944.9875	0	0	0	0	0	120	17386.94
h_{15}	8465.822	8063.684	0	0	944.9875	0	0	0	0	0	60	17474.49
h_{16}	8465.822	8887.478	0	0	984.8014	0	0	0	0	0	560	18338.1
h_{17}	8465.822	7661.05	0	2860.659	944.9875	0	0	0	0	0	900	19932.52
h_{18}	8465.822	8054.927	0	2860.659	944.9875	0	0	0	0	0	0	20326.4
h_{19}	8465.822	8508.713	0	2860.659	944.9875	0	0	0	0	0	0	20780.18
h_{20}	8465.822	8782.236	0	2860.659	944.9875	0	0	0	0	0	0	21053.7
h_{21}	8465.822	7678.549	0	2860.659	0	818.048	0	0	0	0	0	19823.08
h_{22}	8465.822	8343.971	0	0	0	818.048	0	0	0	0	0	17627.84
h_{23}	8465.822	6350.391	0	0	0	818.048	0	0	0	0	0	15634.26
h_{24}	8465.822	5461.135	0	0	0	0	0	0	0	0	0	13926.96

4.6.2 System of 20 Generating Units

This part of chapter is basically illustrating the optimal results for 20 generating units and scheduling of units by using CBWO algorithm with 100 iteration and 30 trial runs. **Table 4.11** illustrates the scheduling of units for 20 units during weekend period of pre COVID-19. **Table 4.12** illustrates the scheduling of different units during weekday period of pre COVID-19. **Table 4.13** illustrates the scheduling of units for 20 units during weekend period of pre COVID-19 with wind power. **Table 4.14** illustrates the scheduling of different units during weekday period of pre COVID-19 with wind power.

Table 4.15 display the fuel cost for 20 units during weekend period of pre COVID-19. **Table 4.16** display the fuel cost of different units during weekday period of pre COVID-19. **Table 4.17** display the fuel cost for 20 units during weekend period of pre COVID-19 with wind power. **Table 4.18** display the fuel cost of different units during weekday period of pre COVID-19 with wind power.

Table 4.11: Scheduling a 20-unit system with the help of the CBWO algorithm for UCP during Pre-COVID (For weekend); MW																						
Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}	SUC	FC
h_1	455	366	0	0	0	0	0	0	0	0	455	366	0	0	0	0	0	0	0	0	2190	31589.0
h_2	455	351	0	0	0	0	0	0	0	0	455	351	0	0	0	0	0	0	0	0	1620	31064.5
h_3	455	340	0	0	0	0	0	0	0	0	455	340	0	0	0	0	0	0	0	0	0	30680.1
h_4	455	353	0	0	0	0	0	0	0	0	455	353	0	0	0	0	0	0	0	0	550	31134.4
h_5	455	323	0	130	0	0	0	0	0	0	455	323	0	0	0	0	0	0	0	0	580	32946.9
h_6	455	326	130	130	0	0	0	0	0	0	455	326	0	130	0	0	0	0	0	0	0	38804.1
h_7	455	411.5	130	130	25	20	0	0	0	0	455	411.	0	130	0	0	0	0	0	0	0	43557.7
h_8	455	395.5	130	130	25	20	0	0	0	0	455	395.5	0	130	0	0	0	0	0	0	120	42997.4
h_9	455	382.5	130	130	25	20	0	0	0	0	455	382.5	0	130	0	0	0	0	0	0	860	42542.4
h_{10}	455	344.5	130	0	25	0	0	0	0	0	455	344.5	130	130	0	0	0	0	0	0	0	40426.6
h_{11}	455	399.5	130	0	25	0	0	0	0	0	455	399.5	130	0	0	0	0	0	0	0	560	39489.9
h_{12}	455	381.5	130	0	25	0	0	0	0	0	455	381.5	130	0	0	0	0	0	0	0	560	38859.8
h_{13}	455	351	130	0	0	0	0	0	0	0	455	351	130	0	0	0	0	0	0	0	0	36848.1
h_{14}	455	398.5	0	0	0	0	0	0	0	0	455	398.5	130	0	25	0	0	0	0	0	0	36563.1
h_{15}	455	390.5	0	130	0	0	0	0	0	0	455	390.5	0	0	25	0	0	0	0	0	0	36251.8
h_{16}	455	361.5	0	130	0	0	0	0	0	0	455	361.5	0	130	25	0	0	0	0	0	340	38097.9
h_{17}	455	408.5	0	130	0	0	0	0	0	0	455	408.5	0	130	25	0	0	0	0	0	1100	39742.8
h_{18}	455	415.5	0	130	0	20	0	0	0	0	455	415.5	0	130	25	0	0	0	0	0	900	40806.0
h_{19}	455	384.5	130	130	0	20	0	0	0	0	455	384.5	0	130	25	0	0	0	0	0	0	42612.4
h_{20}	455	455	130	0	0	20	0	0	0	0	455	455	0	130	52	20	0	0	0	0	900	43580.3
h_{21}	455	379	130	0	0	0	0	0	0	0	455	379	130	130	0	20	0	0	0	0	0	41506.0
h_{22}	455	365	130	0	0	0	0	0	0	0	455	365	130	0	0	20	0	0	0	0	0	38155.6
h_{23}	455	323	130	0	0	0	0	0	0	0	455	323	130	0	0	0	0	0	0	0	1290	35869.8
h_{24}	455	340	0	0	0	0	0	0	0	0	455	340	130	0	0	0	0	0	0	0	520	33571.9

Table 4.12: Scheduling a 20-unit system with the help of the CBWO algorithm for UCP **during Pre-COVID (For weekday); MW**

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}	SUC	FC
h_1	455	331	0	130	0	0	0	0	0	0	455	331	0	0	0	0	0	0	0	0	2920	33226.3
h_2	455	310	0	130	0	0	0	0	0	0	455	310	0	0	0	0	0	0	0	0	1270	32493.0
h_3	455	300	0	130	0	0	0	0	0	0	455	300	0	0	0	0	0	0	0	0	0	32144.1
h_4	455	296	0	130	0	0	0	0	0	0	455	296	0	0	0	0	0	0	0	0	0	32004.5
h_5	455	305	0	130	0	0	0	0	0	0	455	305	0	0	0	0	0	0	0	0	340	32318.5
h_6	455	306	0	130	0	0	0	0	0	0	455	306	0	130	0	0	0	0	0	0	1160	35214.1
h_7	455	358	0	130	0	0	0	0	0	0	455	358	0	130	0	0	0	0	0	0	60	37030.5
h_8	455	308	130	130	0	0	0	0	0	0	455	308	130	130	0	0	0	0	0	0	60	41067.5
h_9	455	402.5	130	0	25	0	0	0	0	0	455	402.5	130	130	0	0	0	0	0	0	0	42455.6
h_{10}	455	437	130	0	25	0	0	0	0	0	455	437	130	130	25	0	0	0	0	0	30	44609.5
h_{11}	455	455	130	0	27	0	0	0	0	0	455	455	130	130	27	0	0	0	0	0	0	45320.4
h_{12}	455	455	130	0	46	0	0	0	0	0	455	455	130	130	46	0	0	0	0	0	60	46080.1
h_{13}	455	451	130	0	25	0	0	0	0	0	455	451	130	130	25	0	0	0	0	0	1740	45100.5
h_{14}	455	455	130	130	26	0	0	0	0	0	455	455	0	130	26	0	0	0	0	0	350	45249.5
h_{15}	455	444	130	130	25	0	0	0	0	0	455	444	0	130	25	0	0	0	0	0	0	44823.8
h_{16}	455	455	130	130	40	0	0	0	0	0	455	455	0	130	40	0	0	0	0	0	230	45808.4
h_{17}	455	455	130	130	55	20	0	0	0	0	455	455	0	130	55	0	0	0	0	0	60	47228.8
h_{18}	455	455	130	130	35	20	0	0	0	0	455	455	0	130	35	0	0	0	0	0	670	46426.5
h_{19}	455	384.5	130	130	25	20	0	0	0	0	455	384.5	130	130	0	0	0	0	0	0	960	45504.2
h_{20}	455	430	130	0	25	20	25	0	0	0	455	430	130	130	0	0	0	0	0	0	60	45411.1
h_{21}	455	386	130	0	25	0	25	0	0	0	455	386	130	130	0	0	0	0	0	0	60	43051.9
h_{22}	455	333	130	0	0	0	25	0	0	0	455	333.5	130	130	0	0	0	0	0	0	170	40271.2
h_{23}	455	331	130	0	0	0	0	0	0	0	455	331	130	0	0	0	0	0	0	0	0	36149.2
h_{24}	455	331	130	0	0	0	0	0	0	0	455	331	0	0	0	0	0	0	0	0	1630	33257.4

Table 4.13: Scheduling a 20-unit system with the help of the CBWO algorithm for UCP **during Pre-COVID with Wind Power Uncertainty (For weekend)**; MW

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}	SUC	FC
h_1	455	196	0	0	0	0	0	0	0	0	455	196	0	0	0	0	0	0	0	0	2520	25661.38
h_2	455	188	0	0	0	0	0	0	0	0	455	188	0	0	0	0	0	0	0	0	0	25383.32
h_3	455	203	0	0	0	0	0	0	0	0	455	203	0	0	0	0	0	0	0	0	550	25904.75
h_4	455	213	0	0	0	0	0	0	0	0	455	213	0	0	0	0	0	0	0	0	1760	26252.53
h_5	455	230	0	0	0	0	0	0	0	0	455	230	0	0	0	0	0	0	0	0	580	26844.04
h_6	455	290	0	0	0	0	0	0	0	0	455	290	0	0	0	0	0	0	0	0	0	28934.59
h_7	455	358	0	0	0	0	0	0	0	0	455	358	0	0	0	0	0	0	0	0	0	31309.27
h_8	455	304	0	130	0	0	0	0	0	0	455	304	0	130	0	0	0	0	0	0	0	35144.34
h_9	455	313	0	130	0	0	0	0	0	0	455	313	0	130	0	0	0	0	0	0	340	35458.46
h_{10}	455	346	0	130	0	0	0	0	0	0	455	346	0	130	0	0	0	0	0	0	600	36611.11
h_{11}	455	333	0	130	0	0	0	0	0	0	455	333	0	130	0	0	0	0	0	0	0	36156.87
h_{12}	455	328	0	130	0	0	0	0	0	0	455	328	0	130	0	0	0	0	0	0	0	35982.22
h_{13}	455	338	0	130	0	0	0	0	0	0	455	338	0	130	0	0	0	0	0	0	1100	36331.55
h_{14}	455	296	0	130	0	0	0	0	0	0	455	296	130	130	0	0	0	0	0	0	560	37757
h_{15}	455	352	0	130	0	0	0	0	0	0	455	352	130	0	0	0	0	0	0	0	1800	36851.96
h_{16}	455	412.5	0	0	25	0	0	0	0	0	455	412.5	130	0	0	0	0	0	0	0	1170	37053.43
h_{17}	455	399.5	130	0	25	0	0	0	0	0	455	399.5	130	0	0	0	0	0	0	0	180	39489.92
h_{18}	455	410.5	130	0	25	0	0	0	0	0	455	410.5	130	0	25	0	0	0	0	0	0	40820.16
h_{19}	455	439.4	130	0	25	0	0	0	0	0	455	439.4	130	0	25	0	0	0	0	0	950	41833.01
h_{20}	455	455	130	0	44	0	0	0	0	0	455	455	0	0	44	0	0	0	0	0	0	40247.41
h_{21}	455	416	130	0	25	0	0	0	0	0	455	416	0	0	25	0	0	0	0	0	210	38121.03
h_{22}	455	429.5	0	0	0	0	0	0	0	0	455	429.5	0	0	25	0	0	0	0	0	0	34757.34
h_{23}	455	433	0	130	0	0	0	0	0	0	0	433	0	130	25	0	0	0	0	0	290	32135.53
h_{24}	455	0	0	130	0	0	25	0	0	0	0	455	0	130	162	50	25	0	0	0	550	30669.26

Table 4.14: Scheduling a 20-unit system with the help of the CBWO algorithm for UCP **during Pre-COVID with Wind Power Uncertainty (For weekday); MW**

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}	SUC	FC
h_1	455	232	0	0	0	0	0	0	0	0	455	232	0	0	0	0	0	0	0	0	3080	26913.65
h_2	455	260	0	0	0	0	0	0	0	0	455	260	0	0	0	0	0	0	0	0	1800	27888.76
h_3	455	278	0	0	0	0	0	0	0	0	455	278	0	0	0	0	0	0	0	0	0	28516.12
h_4	455	316	0	0	0	0	0	0	0	0	455	316	0	0	0	0	0	0	0	0	120	29841.87
h_5	455	364	0	0	0	0	0	0	0	0	455	364	0	0	0	0	0	0	0	0	0	31519.07
h_6	455	417.5	0	0	25	0	0	0	0	0	455	417.5	0	130	0	0	0	0	0	0	120	37197.46
h_7	455	419.5	0	130	25	0	0	0	0	0	455	419.5	0	130	0	0	0	0	0	0	60	40128.2
h_8	455	370.5	0	130	25	0	0	0	0	0	455	370.5	0	130	0	0	0	0	0	0	0	38412.72
h_9	455	313.5	0	130	25	0	0	0	0	0	455	313.5	0	130	0	0	0	0	0	0	460	36420.9
h_{10}	455	293.5	0	130	25	0	0	0	0	0	455	293.5	0	130	0	0	0	0	0	0	0	35722.98
h_{11}	455	346.5	0	130	25	0	0	0	0	0	455	346.5	0	0	0	0	0	0	0	0	1110	34712.91
h_{12}	455	358.5	0	0	25	0	0	0	0	0	455	358.5	130	0	0	0	0	0	0	0	0	35163.54
h_{13}	455	362	0	0	0	20	0	0	0	0	455	362	130	0	0	0	0	0	0	0	1650	35158.98
h_{14}	455	353	0	0	0	20	0	0	0	0	455	353	130	0	0	0	0	0	0	0	0	34844.31
h_{15}	455	358	0	0	0	20	0	0	0	0	455	358	130	0	0	0	0	0	0	0	560	35019.11
h_{16}	455	404.5	0	0	0	0	0	0	0	0	455	404.5	130	0	25	0	0	0	0	0	1330	36773.22
h_{17}	455	397.5	0	130	0	0	0	0	0	0	455	397.5	0	130	25	0	0	0	0	0	120	39357.61
h_{18}	455	420	0	130	0	0	0	0	0	0	455	420	0	130	25	0	0	0	0	0	0	40145.72
h_{19}	455	380.9	130	130	0	0	0	0	0	0	455	380.9	0	130	25	0	0	0	0	0	260	41668.37
h_{20}	455	396.5	130	130	0	0	0	0	0	0	455	396.5	0	130	25	0	0	0	0	0	60	42214.4
h_{21}	455	328.5	130	130	0	0	0	0	0	0	455	328.5	0	130	25	0	0	0	0	0	1800	39836.48
h_{22}	455	314	130	130	0	0	0	0	0	0	455	314	0	0	0	0	0	0	0	0	0	35524.51
h_{23}	455	265	130	0	0	0	0	0	0	0	455	265	0	0	0	0	0	0	0	0	810	30954.78
h_{24}	455	258	130	0	0	0	0	0	0	0	455	0	130	0	0	0	0	0	0	0	0	28158.96

Table 4.15: Individual fuel cost for Generation of 20 Unit Test System using CBWO for UCP **during Pre-COVID (Weekend); $**

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}	SUC	FC
h_1	8466	7329	0	0	0	0	0	0	0	0	8466	7329	0	0	0	0	0	0	0	0	2190	31589
h_2	8466	7066	0	0	0	0	0	0	0	0	8466	7066	0	0	0	0	0	0	0	0	1620	31065
h_3	8466	6874	0	0	0	0	0	0	0	0	8466	6874	0	0	0	0	0	0	0	0	0	30680
h_4	8466	7101	0	0	0	0	0	0	0	0	8466	7101	0	0	0	0	0	0	0	0	550	31134
h_5	8466	6577	0	2861	0	0	0	0	0	0	8466	6577	0	0	0	0	0	0	0	0	580	32947
h_6	8466	6630	2892	2861	0	0	0	0	0	0	8466	6630	0	2861	0	0	0	0	0	0	0	38804
h_7	8466	8125	2892	2861	945	818	0	0	0	0	8466	8125	0	2861	0	0	0	0	0	0	0	43558
h_8	8466	7845	2892	2861	945	818	0	0	0	0	8466	7845	0	2861	0	0	0	0	0	0	120	42997
h_9	8466	7617	2892	2861	945	818	0	0	0	0	8466	7617	0	2861	0	0	0	0	0	0	860	42542
h_{10}	8466	6953	2892	0	945	0	0	0	0	0	8466	6953	2892	2861	0	0	0	0	0	0	0	40427
h_{11}	8466	7915	2892	0	945	0	0	0	0	0	8466	7915	2892	0	0	0	0	0	0	0	560	39490
h_{12}	8466	7600	2892	0	945	0	0	0	0	0	8466	7600	2892	0	0	0	0	0	0	0	560	38860
h_{13}	8466	7066	2892	0	0	0	0	0	0	0	8466	7066	2892	0	0	0	0	0	0	0	0	36848
h_{14}	8466	7897	0	0	0	0	0	0	0	0	8466	7897	2892	0	945	0	0	0	0	0	0	36563
h_{15}	8466	7757	0	2861	0	0	0	0	0	0	8466	7757	0	0	945	0	0	0	0	0	0	36252
h_{16}	8466	7250	0	2861	0	0	0	0	0	0	8466	7250	0	2861	945	0	0	0	0	0	340	38098
h_{17}	8466	8072	0	2861	0	0	0	0	0	0	8466	8072	0	2861	945	0	0	0	0	0	1100	39743
h_{18}	8466	8195	0	2861	0	818	0	0	0	0	8466	8195	0	2861	945	0	0	0	0	0	900	40806
h_{19}	8466	7652	2892	2861	0	818	0	0	0	0	8466	7652	0	2861	945	0	0	0	0	0	0	42612
h_{20}	8466	8887	2892	0	0	818	0	0	0	0	8466	8887	0	2861	1485	818	0	0	0	0	900	43580
h_{21}	8466	7556	2892	0	0	0	0	0	0	0	8466	7556	2892	2861	0	818	0	0	0	0	0	41506
h_{22}	8466	7311	2892	0	0	0	0	0	0	0	8466	7311	2892	0	0	818	0	0	0	0	0	38156
h_{23}	8466	6577	2892	0	0	0	0	0	0	0	8466	6577	2892	0	0	0	0	0	0	0	1290	35870
h_{24}	8466	6874	0	0	0	0	0	0	0	0	8466	6874	2892	0	0	0	0	0	0	0	520	33572

Table 4.16: Individual fuel cost for Generation of 20 Unit Test System using CBWO for UCP **during Pre-COVID (Weekday); $**

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}	SUC	FC
h_1	8466	6717	0	2861	0	0	0	0	0	0	8466	6717	0	0	0	0	0	0	0	0	2920	33226
h_2	8466	6350	0	2861	0	0	0	0	0	0	8466	6350	0	0	0	0	0	0	0	0	1270	32493
h_3	8466	6176	0	2861	0	0	0	0	0	0	8466	6176	0	0	0	0	0	0	0	0	0	32144
h_4	8466	6106	0	2861	0	0	0	0	0	0	8466	6106	0	0	0	0	0	0	0	0	0	32005
h_5	8466	6263	0	2861	0	0	0	0	0	0	8466	6263	0	0	0	0	0	0	0	0	340	32319
h_6	8466	6281	0	2861	0	0	0	0	0	0	8466	6281	0	2861	0	0	0	0	0	0	1160	35214
h_7	8466	7189	0	2861	0	0	0	0	0	0	8466	7189	0	2861	0	0	0	0	0	0	60	37031
h_8	8466	6315	2892	2861	0	0	0	0	0	0	8466	6315	2892	2861	0	0	0	0	0	0	60	41068
h_9	8466	7967	2892	0	945	0	0	0	0	0	8466	7967	2892	2861	0	0	0	0	0	0	0	42456
h_{10}	8466	8572	2892	0	945	0	0	0	0	0	8466	8572	2892	2861	945	0	0	0	0	0	30	44610
h_{11}	8466	8887	2892	0	985	0	0	0	0	0	8466	8887	2892	2861	985	0	0	0	0	0	0	45320
h_{12}	8466	8887	2892	0	1365	0	0	0	0	0	8466	8887	2892	2861	1365	0	0	0	0	0	60	46080
h_{13}	8466	8817	2892	0	945	0	0	0	0	0	8466	8817	2892	2861	945	0	0	0	0	0	1740	45101
h_{14}	8466	8887	2892	2861	965	0	0	0	0	0	8466	8887	0	2861	965	0	0	0	0	0	350	45249
h_{15}	8466	8695	2892	2861	945	0	0	0	0	0	8466	8695	0	2861	945	0	0	0	0	0	0	44824
h_{16}	8466	8887	2892	2861	1244	0	0	0	0	0	8466	8887	0	2861	1244	0	0	0	0	0	230	45808
h_{17}	8466	8887	2892	2861	1546	818	0	0	0	0	8466	8887	0	2861	1546	0	0	0	0	0	60	47229
h_{18}	8466	8887	2892	2861	1144	818	0	0	0	0	8466	8887	0	2861	1144	0	0	0	0	0	670	46427
h_{19}	8466	7652	2892	2861	945	818	0	0	0	0	8466	7652	2892	2861	0	0	0	0	0	0	960	45504
h_{20}	8466	8449	2892	0	945	818	1174	0	0	0	8466	8449	2892	2861	0	0	0	0	0	0	60	45411
h_{21}	8466	7679	2892	0	945	0	1174	0	0	0	8466	7679	2892	2861	0	0	0	0	0	0	60	43052
h_{22}	8466	6761	2892	0	0	0	1174	0	0	0	8466	6761	2892	2861	0	0	0	0	0	0	170	40271
h_{23}	8466	6717	2892	0	0	0	0	0	0	0	8466	6717	2892	0	0	0	0	0	0	0	0	36149
h_{24}	8466	6717	2892	0	0	0	0	0	0	0	8466	6717	0	0	0	0	0	0	0	0	1630	33257

Table 4.17: Individual fuel cost for Generation of 20 Unit Test System using CBWO for UCP **during Pre-COVID with Wind Power Uncertainty (Weekend); $**																						
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_{11}**	**U_{12}**	**U_{13}**	**U_{14}**	**U_{15}**	**U_{16}**	**U_{17}**	**U_{18}**	**U_{19}**	**U_{20}**	**SUC**	**FC**
h_1	8466	4365	0	0	0	0	0	0	0	0	8466	4365	0	0	0	0	0	0	0	0	2520	25661
h_2	8466	4226	0	0	0	0	0	0	0	0	8466	4226	0	0	0	0	0	0	0	0	0	25383
h_3	8466	4487	0	0	0	0	0	0	0	0	8466	4487	0	0	0	0	0	0	0	0	550	25905
h_4	8466	4660	0	0	0	0	0	0	0	0	8466	4660	0	0	0	0	0	0	0	0	1760	26253
h_5	8466	4956	0	0	0	0	0	0	0	0	8466	4956	0	0	0	0	0	0	0	0	580	26844
h_6	8466	6001	0	0	0	0	0	0	0	0	8466	6001	0	0	0	0	0	0	0	0	0	28935
h_7	8466	7189	0	0	0	0	0	0	0	0	8466	7189	0	0	0	0	0	0	0	0	0	31309
h_8	8466	6246	0	2861	0	0	0	0	0	0	8466	6246	0	2861	0	0	0	0	0	0	0	35144
h_9	8466	6403	0	2861	0	0	0	0	0	0	8466	6403	0	2861	0	0	0	0	0	0	340	35458
h_{10}	8466	6979	0	2861	0	0	0	0	0	0	8466	6979	0	2861	0	0	0	0	0	0	600	36611
h_{11}	8466	6752	0	2861	0	0	0	0	0	0	8466	6752	0	2861	0	0	0	0	0	0	0	36157
h_{12}	8466	6665	0	2861	0	0	0	0	0	0	8466	6665	0	2861	0	0	0	0	0	0	0	35982
h_{13}	8466	6839	0	2861	0	0	0	0	0	0	8466	6839	0	2861	0	0	0	0	0	0	1100	36332
h_{14}	8466	6106	0	2861	0	0	0	0	0	0	8466	6106	2892	2861	0	0	0	0	0	0	560	37757
h_{15}	8466	7084	0	2861	0	0	0	0	0	0	8466	7084	2892	0	0	0	0	0	0	0	1800	36852
h_{16}	8466	8142	0	0	945	0	0	0	0	0	8466	8142	2892	0	0	0	0	0	0	0	1170	37053
h_{17}	8466	7915	2892	0	945	0	0	0	0	0	8466	7915	2892	0	0	0	0	0	0	0	180	39490
h_{18}	8466	8107	2892	0	945	0	0	0	0	0	8466	8107	2892	0	945	0	0	0	0	0	0	40820
h_{19}	8466	8614	2892	0	945	0	0	0	0	0	8466	8614	2892	0	945	0	0	0	0	0	950	41833
h_{20}	8466	8887	2892	0	1325	0	0	0	0	0	8466	8887	0	0	1325	0	0	0	0	0	0	40247
h_{21}	8466	8204	2892	0	945	0	0	0	0	0	8466	8204	0	0	945	0	0	0	0	0	210	38121
h_{22}	8466	8440	0	0	0	0	0	0	0	0	8466	8440	0	0	945	0	0	0	0	0	0	34757
h_{23}	8466	8502	0	2861	0	0	0	0	0	0	0	8502	0	2861	945	0	0	0	0	0	290	32136
h_{24}	8466	0	0	2861	0	0	1174	0	0	0	0	8887	0	2861	3746	1501	1174	0	0	0	550	30669

Table 4.18: Individual fuel cost for Generation of 20 Unit Test System using CBWO for UCP **during Pre-COVID with Wind Power Uncertainty (Weekday); $**

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}	SUC	FC
h_1	8466	4991	0	0	0	0	0	0	0	0	8466	4991	0	0	0	0	0	0	0	0	3080	26914
h_2	8466	5479	0	0	0	0	0	0	0	0	8466	5479	0	0	0	0	0	0	0	0	1800	27889
h_3	8466	5792	0	0	0	0	0	0	0	0	8466	5792	0	0	0	0	0	0	0	0	0	28516
h_4	8466	6455	0	0	0	0	0	0	0	0	8466	6455	0	0	0	0	0	0	0	0	120	29842
h_5	8466	7294	0	0	0	0	0	0	0	0	8466	7294	0	0	0	0	0	0	0	0	0	31519
h_6	8466	8230	0	0	945	0	0	0	0	0	8466	8230	0	2861	0	0	0	0	0	0	120	37197
h_7	8466	8265	0	2861	945	0	0	0	0	0	8466	8265	0	2861	0	0	0	0	0	0	60	40128
h_8	8466	7407	0	2861	945	0	0	0	0	0	8466	7407	0	2861	0	0	0	0	0	0	0	38413
h_9	8466	6411	0	2861	945	0	0	0	0	0	8466	6411	0	2861	0	0	0	0	0	0	460	36421
h_{10}	8466	6063	0	2861	945	0	0	0	0	0	8466	6063	0	2861	0	0	0	0	0	0	0	35723
h_{11}	8466	6988	0	2861	945	0	0	0	0	0	8466	6988	0	0	0	0	0	0	0	0	1110	34713
h_{12}	8466	7198	0	0	945	0	0	0	0	0	8466	7198	2892	0	0	0	0	0	0	0	0	35164
h_{13}	8466	7259	0	0	0	818	0	0	0	0	8466	7259	2892	0	0	0	0	0	0	0	1650	35159
h_{14}	8466	7101	0	0	0	818	0	0	0	0	8466	7101	2892	0	0	0	0	0	0	0	0	34844
h_{15}	8466	7189	0	0	0	818	0	0	0	0	8466	7189	2892	0	0	0	0	0	0	0	560	35019
h_{16}	8466	8002	0	0	0	0	0	0	0	0	8466	8002	2892	0	945	0	0	0	0	0	1330	36773
h_{17}	8466	7880	0	2861	0	0	0	0	0	0	8466	7880	0	2861	945	0	0	0	0	0	120	39358
h_{18}	8466	8274	0	2861	0	0	0	0	0	0	8466	8274	0	2861	945	0	0	0	0	0	0	40146
h_{19}	8466	7589	2892	2861	0	0	0	0	0	0	8466	7589	0	2861	945	0	0	0	0	0	260	41668
h_{20}	8466	7862	2892	2861	0	0	0	0	0	0	8466	7862	0	2861	945	0	0	0	0	0	60	42214
h_{21}	8466	6673	2892	2861	0	0	0	0	0	0	8466	6673	0	2861	945	0	0	0	0	0	1800	39836
h_{22}	8466	6420	2892	2861	0	0	0	0	0	0	8466	6420	0	0	0	0	0	0	0	0	0	35525
h_{23}	8466	5566	2892	0	0	0	0	0	0	0	8466	5566	0	0	0	0	0	0	0	0	810	30955
h_{24}	8466	5444	2892	0	0	0	0	0	0	0	8466	0	2892	0	0	0	0	0	0	0	0	28159

4.6.3 System of 40 Generating Units

This part of chapter is basically illustrating the optimal results for 40 generating units and scheduling of units by using CBWO algorithm with 100 iteration and 30 trial runs. **Table 4.19 & 4.20** illustrates the scheduling of units for 40 units during weekend period of pre COVID-19. **Table 4.21 & 4.22** also illustrates the scheduling of different units during weekday period of pre COVID-19. **Table 4.23 & 4.24** illustrates the scheduling of units for 40 units during weekend period of pre COVID-19 with wind power. **Table 4.25 & 4.26** also illustrates the scheduling of different units during weekday period of pre COVID-19 with wind power.

Table 4.27 & 4.28 display the fuel cost for 40 units during weekend period of pre COVID-19. **Table 4.29 & 4.30** display the fuel cost of different units during weekday period of pre COVID-19. **Table 4.31 & 4.32** display the fuel cost for 40 units during weekend period of pre COVID-19 with wind power. **Table 4.33 & 4.34** display the fuel cost of different units during weekday period of pre COVID-19 with wind power.

Table 4.19: Scheduling a 40-unit system with the help of the CBWO algorithm for UCP **during Pre-COVID (weekend from U1- U20); MW**

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	455	363.5	0	130	0	0	0	0	0	0	455	363.5	0	0	0	0	0	0	0	0
h_2	455	342.5	0	130	0	0	0	0	0	0	455	342.5	0	0	0	0	0	0	0	0
h_3	455	332.5	0	130	0	0	0	0	0	0	455	332.5	0	0	0	0	0	0	0	0
h_4	455	328.5	0	130	0	0	0	0	0	0	455	328.5	0	0	0	0	0	0	0	0
h_5	455	337.5	0	130	0	0	0	0	0	0	455	337.5	0	0	0	0	0	0	0	0
h_6	455	338.5	0	130	0	0	0	0	0	0	455	338.5	0	130	0	0	0	0	0	0
h_7	455	358	0	130	0	0	0	0	0	0	455	358	0	130	0	0	0	0	0	0
h_8	455	340.5	130	130	0	0	0	0	0	0	455	340.5	130	130	0	0	0	0	0	0
h_9	455	343.75	130	130	25	0	0	0	0	0	455	343.75	130	130	0	0	0	0	0	0
h_{10}	455	384.5	130	130	25	0	0	0	0	0	455	384.5	130	130	0	0	0	0	0	0
h_{11}	455	404.5	130	130	25	0	0	0	0	0	455	404.5	130	130	0	0	0	0	0	0
h_{12}	455	417.25	130	130	25	0	0	0	0	0	455	417.25	130	130	25	0	0	0	0	0
h_{13}	455	424.75	130	130	25	0	0	0	0	0	455	424.75	130	130	25	0	0	0	0	0
h_{14}	455	429.75	130	130	25	0	0	0	0	0	455	429.75	130	130	25	0	0	0	0	0
h_{15}	455	417.75	130	130	25	0	0	0	0	0	455	417.75	130	130	25	0	0	0	0	0
h_{16}	455	455	130	130	40	0	0	0	0	0	455	455	130	130	40	0	0	0	0	0
h_{17}	455	455	130	130	60	20	0	0	0	0	455	455	130	130	60	0	0	0	0	0
h_{18}	455	443.75	130	130	25	20	0	0	0	0	455	443.75	130	130	25	0	0	0	0	0
h_{19}	455	422	130	130	0	20	0	0	0	0	455	422	130	130	25	0	0	0	0	0
h_{20}	455	411	130	130	0	20	0	0	0	0	455	411	130	130	0	0	0	0	0	0
h_{21}	455	395	130	0	0	0	0	0	0	0	455	395	130	0	0	0	0	0	0	0
h_{22}	455	395	130	0	0	0	0	0	0	0	455	395	130	0	0	0	0	0	0	0
h_{23}	455	359	0	0	0	0	0	0	0	0	455	359	130	0	0	0	0	0	0	0
h_{24}	455	383	0	0	0	20	0	0	0	0	455	383	130	0	0	0	0	0	0	0

Table 4.20: Scheduling a 40-unit system with the help of the CBWO algorithm for UCP during **Pre-COVID (weekend from U21- U40); MW**

Hour	U_{21}	U_{22}	U_{23}	U_{24}	U_{25}	U_{26}	U_{27}	U_{28}	U_{29}	U_{30}	U_{31}	U_{32}	U_{33}	U_{34}	U_{35}	U_{36}	U_{37}	U_{38}	U_{39}	U_{40}	SUC	FC
h_1	455	363.5	0	0	0	0	0	0	0	0	455	363.5	0	0	0	0	0	0	0	0	5260	65863.8
h_2	455	342.5	0	0	0	0	0	0	0	0	455	342.5	0	0	0	0	0	0	0	0	2360	64395.6
h_3	455	332.5	0	0	0	0	0	0	0	0	455	332.5	0	0	0	0	0	0	0	0	2560	63696.8
h_4	455	328.5	0	0	0	0	0	0	0	0	455	328.5	0	0	0	0	0	0	0	0	30	63417.4
h_5	455	337.5	0	0	0	0	0	0	0	0	455	337.5	0	0	0	0	0	0	0	0	420	64046.1
h_6	455	338.5	0	130	0	0	0	0	0	0	455	338.5	0	0	0	0	0	0	0	0	180	69837.3
h_7	455	358	0	130	0	0	0	0	0	0	455	358	0	130	0	0	0	0	0	0	350	74061.1
h_8	455	340.5	130	130	0	0	0	0	0	0	455	340.5	0	130	0	0	0	0	0	0	230	81513.2
h_9	455	343.75	130	130	0	0	0	0	0	0	455	343.75	130	130	0	0	0	0	0	0	700	85577.1
h_{10}	455	384.5	130	130	0	0	0	0	0	0	455	384.5	130	130	25	0	0	0	0	0	320	89372.3
h_{11}	455	404.5	130	130	0	0	0	0	0	0	455	404.5	130	130	25	0	0	0	0	0	180	90772.6
h_{12}	455	417.25	130	130	0	0	0	0	0	0	455	417.25	130	130	25	0	0	0	0	0	1040	92610.9
h_{13}	455	424.75	0	130	0	0	0	0	0	0	455	424.75	130	130	25	0	0	0	0	0	830	90244.7
h_{14}	455	429.75	0	130	0	0	0	0	0	0	455	429.75	130	130	25	0	0	0	0	0	290	90595.2
h_{15}	455	417.75	0	130	0	0	0	0	0	0	455	417.75	130	130	25	0	0	0	0	0	1450	89754.1
h_{16}	455	455	0	130	40	0	0	0	0	0	455	455	0	130	40	0	0	0	0	0	1660	91616.9
h_{17}	455	455	0	130	60	0	0	0	0	0	455	455	0	130	60	0	0	0	0	0	1830	94042.8
h_{18}	455	443.75	130	130	25	0	0	0	0	0	455	443.75	0	130	0	0	0	0	0	0	1270	92395.0
h_{19}	455	422	130	130	25	0	0	0	0	0	455	422	0	130	0	0	0	0	0	0	230	89925.0
h_{20}	455	411.25	130	130	25	20	0	0	0	0	455	411.25	0	130	0	20	0	0	0	0	170	89862.8
h_{21}	455	394.75	130	130	25	20	0	0	0	0	455	394.75	130	130	0	20	0	0	0	0	1430	85059.6
h_{22}	455	394.75	130	0	25	20	0	0	0	0	455	394.75	130	0	0	20	0	0	0	0	470	79338.3
h_{23}	455	358.5	130	0	0	20	0	0	0	0	455	358.5	130	0	0	0	0	0	0	0	1430	72146.9
h_{24}	455	0	130	0	0	0	0	0	0	0	455	383	130	0	25	0	0	0	0	0	1420	67179.8

Table 4.21: Scheduling a 40-unit system with the help of the CBWO algorithm for UCP during **Pre-COVID (weekday from U1- U20); MW**

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	455	340.5	0	130	0	0	0	0	0	0	455	340.5	0	0	0	0	0	0	0	0
h_2	455	326.5	0	130	0	0	0	0	0	0	455	326.5	0	0	0	0	0	0	0	0
h_3	455	328.5	0	130	0	0	0	0	0	0	455	328.5	0	0	0	0	0	0	0	0
h_4	455	325.5	0	130	0	0	0	0	0	0	455	325.5	0	0	0	0	0	0	0	0
h_5	455	339.5	0	130	0	0	0	0	0	0	455	339.5	0	0	0	0	0	0	0	0
h_6	455	362	0	130	0	0	0	0	0	0	455	362	0	130	0	0	0	0	0	0
h_7	455	348	130	130	0	0	0	0	0	0	455	348	0	130	0	0	0	0	0	0
h_8	455	348	130	130	0	0	0	0	0	0	455	348	130	130	0	0	0	0	0	0
h_9	455	331.5	130	130	0	0	0	0	0	0	455	331.5	130	130	0	0	0	0	0	0
h_{10}	455	332	130	130	0	0	0	0	0	0	455	332	130	130	0	0	0	0	0	0
h_{11}	455	346.25	130	0	25	0	0	0	0	0	455	346.25	130	130	0	0	0	0	0	0
h_{12}	455	371.75	0	0	25	0	0	0	0	0	455	371.75	130	130	0	0	0	0	0	0
h_{13}	455	407	0	0	25	0	0	0	0	0	455	407	0	130	25	0	0	0	0	0
h_{14}	455	455	0	0	47.5	0	0	0	0	0	455	455	0	0	47.5	0	0	0	0	0
h_{15}	455	455	0	0	36.5	0	0	0	0	0	455	455	0	0	36.5	0	0	0	0	0
h_{16}	455	446	0	130	25	0	0	0	0	0	455	446	0	0	25	0	0	0	0	0
h_{17}	455	455	130	130	27.5	0	0	0	0	0	455	455	0	0	27.5	0	0	0	0	0
h_{18}	455	442.25	130	130	0	0	0	0	0	0	455	442.25	130	0	25	0	0	0	0	0
h_{19}	455	416.5	130	130	0	0	0	0	0	0	455	416.5	130	130	0	20	0	0	0	0
h_{20}	455	402.75	130	130	0	20	0	0	0	0	455	402.75	130	130	0	20	0	0	0	0
h_{21}	455	390.5	130	130	0	20	0	0	0	0	455	390.5	130	130	0	20	0	0	0	0
h_{22}	455	374	130	130	0	20	0	0	0	0	455	374	130	130	0	0	0	0	0	0
h_{23}	455	394.25	0	0	0	0	25	0	0	0	455	394.25	130	130	0	0	0	0	0	0
h_{24}	455	392.25	0	0	0	0	25	0	0	0	455	392.25	0	130	0	0	0	0	0	0

Table 4.22: Scheduling a 40-unit system with the help of the CBWO algorithm for UCP during **Pre-COVID (weekend from U21- U40); MW**

Hour	U_{21}	U_{22}	U_{23}	U_{24}	U_{25}	U_{26}	U_{27}	U_{28}	U_{29}	U_{30}	U_{31}	U_{32}	U_{33}	U_{34}	U_{35}	U_{36}	U_{37}	U_{38}	U_{39}	U_{40}	SUC	FC
h_1	455	340.5	0	0	0	0	0	0	0	0	455	340.5	0	0	0	0	0	0	0	0	3110	64255.8
h_2	455	326.5	0	0	0	0	0	0	0	0	455	326.5	0	0	0	0	0	0	0	0	3130	63277.6
h_3	455	328.5	0	0	0	0	0	0	0	0	455	328.5	0	0	0	0	0	0	0	0	2280	63417.4
h_4	455	325.5	0	0	0	0	0	0	0	0	455	325.5	0	0	0	0	0	0	0	0	1490	63207.8
h_5	455	339.5	0	0	0	0	0	0	0	0	455	339.5	0	0	0	0	0	0	0	0	610	64185.9
h_6	455	362	0	0	0	0	0	0	0	0	455	362	0	0	0	0	0	0	0	0	120	68619.5
h_7	455	348	0	130	0	0	0	0	0	0	455	348	0	0	0	0	0	0	0	0	0	73393.1
h_8	455	348	130	130	0	0	0	0	0	0	455	348	0	0	0	0	0	0	0	0	320	79176.7
h_9	455	331.5	130	130	0	0	0	0	0	0	455	331.5	0	130	0	0	0	0	0	0	460	80884.3
h_{10}	455	332	130	130	0	0	0	0	0	0	455	332	130	130	0	0	0	0	0	0	810	83811.0
h_{11}	455	346.25	130	130	0	0	0	0	0	0	455	346.2	130	130	0	0	0	0	0	0	150	82891.2
h_{12}	455	371.75	130	130	0	0	0	0	0	0	455	371.7	130	130	0	0	0	0	0	0	670	81782.6
h_{13}	455	407	130	130	0	0	0	0	0	0	455	407	130	130	0	0	0	0	0	0	1230	82303.5
h_{14}	455	455	130	0	47.5	0	0	0	0	0	455	455	130	130	47.5	0	0	0	0	0	210	83636.3
h_{15}	455	455	130	0	36.5	0	0	0	0	0	455	455	130	130	36.5	0	0	0	0	0	2290	82754.8
h_{16}	455	446	130	0	25	0	0	0	0	0	455	446	130	130	25	0	0	0	0	0	1450	84066.6
h_{17}	455	455	130	0	27.5	0	0	0	0	0	455	455	130	130	27.5	0	0	0	0	0	290	87788.9
h_{18}	455	442.25	130	0	25	0	0	0	0	0	455	442.2	130	130	25	0	0	0	0	0	2800	88642.2
h_{19}	455	416.5	130	130	25	0	0	0	0	0	455	416.5	130	130	25	0	0	0	0	0	1490	92431.4
h_{20}	455	402.7	130	130	0	20	0	0	0	0	455	402.7	130	130	25	0	0	0	0	0	120	92159.2
h_{21}	455	390.5	130	130	0	20	0	0	0	0	455	390.5	0	130	0	0	0	0	0	0	1240	87464.6
h_{22}	455	374	130	130	0	20	0	0	0	0	455	374	0	0	0	0	0	0	0	0	0	82631.1
h_{23}	455	394.2	0	130	0	20	0	0	0	0	455	394.2	0	0	0	20	0	0	0	0	150	76578.2
h_{24}	455	392.2	0	0	0	0	0	0	0	0	455	392.2	0	0	0	20	0	0	0	0	1320	69867.7

Table 4.23: Scheduling a 40-unit system with the help of the CBWO algorithm for UCP **during Pre-COVID with Wind Power Uncertainty** (weekend from U1- U20); MW

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	455	261.33	0	0	0	0	0	0	0	0	455	261.33	0	0	0	0	0	0	0	0
h_2	455	250.66	0	0	0	0	0	0	0	0	455	250.66	0	0	0	0	0	0	0	0
h_3	455	270.66	0	0	0	0	0	0	0	0	455	270.66	0	0	0	0	0	0	0	0
h_4	455	284	0	0	0	0	0	0	0	0	455	284	0	0	0	0	0	0	0	0
h_5	455	306.66	0	0	0	0	0	0	0	0	455	306.66	0	0	0	0	0	0	0	0
h_6	455	343.33	0	130	0	0	0	0	0	0	455	343.33	0	0	0	0	0	0	0	0
h_7	455	304	0	130	0	0	0	0	0	0	455	304	0	130	0	0	0	0	0	0
h_8	455	353.6667	0	130	0	0	0	0	0	0	455	353.6667	0	130	25	0	0	0	0	0
h_9	455	365.6667	0	130	0	0	0	0	0	0	455	365.6667	0	130	25	0	0	0	0	0
h_{10}	455	307.25	0	130	0	0	0	0	0	0	455	307.25	0	130	25	0	0	0	0	0
h_{11}	455	326.75	0	0	0	0	0	0	0	0	455	326.75	0	130	25	0	0	0	0	0
h_{12}	455	386.75	0	0	0	0	0	0	0	0	455	386.75	0	130	25	0	0	0	0	0
h_{13}	455	396.75	0	0	0	0	0	0	0	0	455	396.75	130	130	25	0	0	0	0	0
h_{14}	455	387.25	130	0	0	0	0	0	0	0	455	387.25	130	0	25	0	0	0	0	0
h_{15}	455	378.25	130	0	0	0	0	0	0	0	455	378.25	130	0	25	0	0	0	0	0
h_{16}	455	360	130	130	0	0	0	0	0	0	455	360	130	0	0	0	0	0	0	0
h_{17}	455	347	130	130	0	0	0	0	0	0	455	347	130	0	0	0	0	0	0	0
h_{18}	455	338	130	130	0	0	0	0	0	0	455	338	130	0	0	0	0	0	0	0
h_{19}	455	334.4	130	130	0	0	0	0	0	0	455	334.4	130	130	0	0	0	0	0	0
h_{20}	455	336.5	130	130	0	0	0	0	0	0	455	336.5	130	130	0	0	0	0	0	0
h_{21}	455	343.5	0	130	0	0	0	0	0	0	455	343.5	0	130	0	0	0	0	0	0
h_{22}	455	364.333	0	130	25	0	0	0	0	0	455	364.33	0	130	0	0	0	0	0	0
h_{23}	455	369	0	130	25	0	0	0	0	0	455	369	0	130	0	0	0	0	0	0
h_{24}	455	339.666	0	0	25	0	0	0	0	0	455	339.66	0	0	0	0	0	0	0	0

Table 4.24: Scheduling a 40-unit system with the help of the CBWO algorithm for UCP **during Pre-COVID with Wind Power Uncertainty** (weekend from U21- U40); MW

Hour	U_{21}	U_{22}	U_{23}	U_{24}	U_{25}	U_{26}	U_{27}	U_{28}	U_{29}	U_{30}	U_{31}	U_{32}	U_{33}	U_{34}	U_{35}	U_{36}	U_{37}	U_{38}	U_{39}	U_{40}	SUC	FC
h_1	455	261	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	3610	50369
h_2	455	251	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	3460	49811
h_3	455	271	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	1450	50857
h_4	455	284	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	120	51554
h_5	455	307	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	1300	52740
h_6	455	343	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	640	57521
h_7	455	304	0	130	0	0	0	0	0	0	455	0	0	130	0	0	0	0	0	0	60	64043
h_8	455	354	130	130	0	0	0	0	0	0	455	0	0	130	0	0	0	0	0	0	60	70482
h_9	455	366	130	130	0	0	0	0	0	0	455	0	0	130	0	0	0	0	0	0	5670	71111
h_{10}	455	307	130	130	0	0	0	0	0	0	455	307	0	130	0	0	0	0	0	0	720	74352
h_{11}	455	327	130	130	0	0	0	0	0	0	455	327	0	130	0	0	0	0	0	0	200	72853
h_{12}	455	387	130	0	0	0	0	0	0	0	455	387	0	0	0	0	0	0	0	0	1110	71327
h_{13}	455	397	0	0	0	0	0	0	0	0	455	397	0	0	0	0	0	0	0	0	1900	72028
h_{14}	455	387	0	0	0	0	0	0	0	0	455	387	130	0	0	0	0	0	0	0	2620	74285
h_{15}	455	378	0	0	0	0	0	0	0	0	455	378	130	0	0	0	0	0	0	0	350	73655
h_{16}	455	360	0	0	0	0	0	0	0	0	455	360	130	0	0	0	0	0	0	0	260	74294
h_{17}	455	347	0	130	0	0	0	0	0	0	455	347	130	130	0	0	0	0	0	0	0	79107
h_{18}	455	338	130	130	0	0	0	0	0	0	455	338	130	130	0	0	0	0	0	0	430	81370
h_{19}	455	334	130	130	0	0	0	0	0	0	455	334	130	130	0	0	0	0	0	0	2320	83979
h_{20}	455	337	130	130	0	0	0	0	0	0	455	337	0	130	0	0	0	0	0	0	180	81234
h_{21}	455	344	130	130	0	0	0	0	0	0	455	344	0	130	0	0	0	0	0	0	1800	75939
h_{22}	455	364	130	130	0	0	0	0	0	0	455	0	0	130	0	0	0	0	0	0	990	71041
h_{23}	455	369	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	1070	62673
h_{24}	455	340	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	2510	55414

Table 4.25: Scheduling a 40-unit system with the help of the CBWO algorithm for UCP **during Pre-COVID with Wind Power Uncertainty** (weekday from U1- U20); MW

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	455	309.3	0	0	0	0	0	0	0	0	455	309.3	0	0	0	0	0	0	0	0
h_2	455	346.6	0	0	0	0	0	0	0	0	455	346.6	0	0	0	0	0	0	0	0
h_3	455	327.3	0	130	0	0	0	0	0	0	455	327.3	0	0	0	0	0	0	0	0
h_4	455	334.6	0	130	0	0	0	0	0	0	455	334.6	0	130	0	0	0	0	0	0
h_5	455	312	0	130	0	0	0	0	0	0	455	312	0	130	0	0	0	0	0	0
h_6	455	313.3	130	130	0	0	0	0	0	0	455	313.3	130	130	0	0	0	0	0	0
h_7	455	386	130	130	25	0	0	0	0	0	455	386	130	130	25	0	0	0	0	0
h_8	455	364	130	0	25	0	0	0	0	0	455	364	130	130	25	0	0	0	0	0
h_9	455	331.333	130	0	25	0	0	0	0	0	455	331.333	130	0	25	0	0	0	0	0
h_{10}	455	391.333	130	0	25	0	0	0	0	0	455	391.333	130	0	25	0	0	0	0	0
h_{11}	455	453.666	130	0	25	0	0	0	0	0	455	453.666	130	0	25	0	0	0	0	0
h_{12}	455	417.25	0	0	25	0	0	0	0	0	455	417.25	0	0	25	0	0	0	0	0
h_{13}	455	398.25	0	130	0	0	0	0	0	0	455	398.25	0	0	0	0	0	0	0	0
h_{14}	455	389.25	0	130	0	0	0	0	0	0	455	389.25	0	0	0	0	0	0	0	0
h_{15}	455	394.25	0	130	0	0	0	0	0	0	455	394.25	0	0	0	0	0	0	0	0
h_{16}	455	378.25	0	130	0	0	0	0	0	0	455	378.25	0	130	0	0	0	0	0	0
h_{17}	455	345	130	130	0	0	0	0	0	0	455	345	130	130	0	0	0	0	0	0
h_{18}	455	335	130	0	0	0	0	0	0	0	455	335	130	130	0	0	0	0	0	0
h_{19}	455	354.65	130	0	25	0	0	0	0	0	455	354.65	130	130	0	0	0	0	0	0
h_{20}	455	370.25	130	0	25	0	0	0	0	0	455	370.25	130	130	0	0	0	0	0	0
h_{21}	455	367.25	130	0	25	0	0	0	0	0	455	367.25	130	0	0	0	0	0	0	0
h_{22}	455	372.75	0	0	25	0	0	0	0	0	455	372.75	0	0	0	0	0	0	0	0
h_{23}	455	345	0	130	25	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0
h_{24}	455	293.66	0	130	25	0	0	0	0	0	455	293.66	0	0	0	0	0	0	0	0

Table 4.26: Scheduling a 40-unit system with the help of the CBWO algorithm for UCP **during Pre-COVID with Wind Power Uncertainty** (weekday from U21- U40); MW

Hour	U_{21}	U_{22}	U_{23}	U_{24}	U_{25}	U_{26}	U_{27}	U_{28}	U_{29}	U_{30}	U_{31}	U_{32}	U_{33}	U_{34}	U_{35}	U_{36}	U_{37}	U_{38}	U_{39}	U_{40}	SUC	FC
h_1	455	309	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	2730	52880
h_2	455	347	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	2010	54835
h_3	455	327	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	3000	56683
h_4	455	335	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	520	59928
h_5	455	312	0	130	0	0	0	0	0	0	455	0	0	130	0	0	0	0	0	0	340	64462
h_6	455	313	130	130	0	0	0	0	0	0	455	0	130	130	0	0	0	0	0	0	2230	76099
h_7	455	386	130	130	0	0	0	0	0	0	455	0	130	130	0	0	0	0	0	0	180	81799
h_8	455	364	130	130	0	0	0	0	0	0	455	0	130	130	0	0	0	0	0	0	0	77784
h_9	455	331	130	130	0	0	0	0	0	0	455	0	130	130	0	0	0	0	0	0	0	73210
h_{10}	455	391	130	0	0	0	0	0	0	0	455	0	130	0	0	0	0	0	0	0	1120	70636
h_{11}	455	454	0	0	0	0	0	0	0	0	455	0	0	0	25	0	0	0	0	0	1450	69074
h_{12}	455	417	0	0	0	0	0	0	0	0	455	417	0	0	25	0	0	0	0	0	820	69601
h_{13}	455	398	0	0	0	0	0	0	0	0	455	398	0	0	25	0	0	0	0	0	3310	69241
h_{14}	455	389	0	0	0	0	0	0	0	0	455	389	0	0	25	0	0	0	0	0	960	68611
h_{15}	455	394	0	0	0	0	0	0	0	0	455	394	0	0	25	0	0	0	0	0	1970	68961
h_{16}	455	378	0	130	0	0	0	0	0	0	455	378	0	0	25	0	0	0	0	0	560	73562
h_{17}	455	345	130	130	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0	520	78967
h_{18}	455	335	130	130	0	0	0	0	0	0	455	335	130	130	0	0	0	0	0	0	60	81160
h_{19}	455	355	130	130	0	0	0	0	0	0	455	355	130	130	0	0	0	0	0	0	560	83478
h_{20}	455	370	130	130	0	0	0	0	0	0	455	370	130	130	0	0	0	0	0	0	1200	84569
h_{21}	455	367	130	0	0	0	0	0	0	0	455	367	130	130	0	0	0	0	0	0	720	78638
h_{22}	455	373	0	0	0	0	0	0	0	0	455	373	130	130	0	0	0	0	0	0	1300	70348
h_{23}	455	345	0	0	0	0	0	0	0	0	455	0	130	0	0	0	0	0	0	0	550	61446
h_{24}	455	294	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	720	55865

Table 4.27: Individual fuel cost for Generation of 40 Unit Test System using CBWO for UCP **During Pre-COVID (Weekend from U1-U20); $**																				
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_{11}**	**U_{12}**	**U_{13}**	**U_{14}**	**U_{15}**	**U_{16}**	**U_{17}**	**U_{18}**	**U_{19}**	**U_{20}**
h_1	8466	7285	0	2861	0	0	0	0	0	0	8466	7285	0	0	0	0	0	0	0	0
h_2	8466	6918	0	2861	0	0	0	0	0	0	8466	6918	0	0	0	0	0	0	0	0
h_3	8466	6743	0	2861	0	0	0	0	0	0	8466	6743	0	0	0	0	0	0	0	0
h_4	8466	6673	0	2861	0	0	0	0	0	0	8466	6673	0	0	0	0	0	0	0	0
h_5	8466	6831	0	2861	0	0	0	0	0	0	8466	6831	0	0	0	0	0	0	0	0
h_6	8466	6848	0	2861	0	0	0	0	0	0	8466	6848	0	2861	0	0	0	0	0	0
h_7	8466	7189	0	2861	0	0	0	0	0	0	8466	7189	0	2861	0	0	0	0	0	0
h_8	8466	6883	2892	2861	0	0	0	0	0	0	8466	6883	2892	2861	0	0	0	0	0	0
h_9	8466	6940	2892	2861	945	0	0	0	0	0	8466	6940	2892	2861	0	0	0	0	0	0
h_{10}	8466	7652	2892	2861	945	0	0	0	0	0	8466	7652	2892	2861	0	0	0	0	0	0
h_{11}	8466	8002	2892	2861	945	0	0	0	0	0	8466	8002	2892	2861	0	0	0	0	0	0
h_{12}	8466	8226	2892	2861	945	0	0	0	0	0	8466	8226	2892	2861	945	0	0	0	0	0
h_{13}	8466	8357	2892	2861	945	0	0	0	0	0	8466	8357	2892	2861	945	0	0	0	0	0
h_{14}	8466	8445	2892	2861	945	0	0	0	0	0	8466	8445	2892	2861	945	0	0	0	0	0
h_{15}	8466	8234	2892	2861	945	0	0	0	0	0	8466	8234	2892	2861	945	0	0	0	0	0
h_{16}	8466	8887	2892	2861	1244	0	0	0	0	0	8466	8887	2892	2861	1244	0	0	0	0	0
h_{17}	8466	8887	2892	2861	1646	818	0	0	0	0	8466	8887	2892	2861	1646	0	0	0	0	0
h_{18}	8466	8690	2892	2861	945	818	0	0	0	0	8466	8690	2892	2861	945	0	0	0	0	0
h_{19}	8466	8309	2892	2861	0	818	0	0	0	0	8466	8309	2892	2861	945	0	0	0	0	0
h_{20}	8466	8121	2892	2861	0	818	0	0	0	0	8466	8121	2892	2861	0	0	0	0	0	0
h_{21}	8466	7832	2892	0	0	0	0	0	0	0	8466	7832	2892	0	0	0	0	0	0	0
h_{22}	8466	7832	2892	0	0	0	0	0	0	0	8466	7832	2892	0	0	0	0	0	0	0
h_{23}	8466	7198	0	0	0	0	0	0	0	0	8466	7198	2892	0	0	0	0	0	0	0
h_{24}	8466	7626	0	0	0	818	0	0	0	0	8466	7626	2892	0	0	0	0	0	0	0

Table 4.28: Individual fuel cost for Generation of 40 Unit Test System using CBWO for UCP **during Pre-COVID (Weekend from U21-U40); $**

Hour	U_{21}	U_{22}	U_{23}	U_{24}	U_{25}	U_{26}	U_{27}	U_{28}	U_{29}	U_{30}	U_{31}	U_{32}	U_{33}	U_{34}	U_{35}	U_{36}	U_{37}	U_{38}	U_{39}	U_{40}	SUC	FC
h_1	8466	7285	0	0	0	0	0	0	0	0	8466	7285	0	0	0	0	0	0	0	0	5260	65864
h_2	8466	6918	0	0	0	0	0	0	0	0	8466	6918	0	0	0	0	0	0	0	0	2360	64396
h_3	8466	6743	0	0	0	0	0	0	0	0	8466	6743	0	0	0	0	0	0	0	0	2560	63697
h_4	8466	6673	0	0	0	0	0	0	0	0	8466	6673	0	0	0	0	0	0	0	0	30	63417
h_5	8466	6831	0	0	0	0	0	0	0	0	8466	6831	0	0	0	0	0	0	0	0	420	64046
h_6	8466	6848	0	2861	0	0	0	0	0	0	8466	6848	0	0	0	0	0	0	0	0	180	69837
h_7	8466	7189	0	2861	0	0	0	0	0	0	8466	7189	0	2861	0	0	0	0	0	0	350	74061
h_8	8466	6883	2892	2861	0	0	0	0	0	0	8466	6883	0	2861	0	0	0	0	0	0	230	81513
h_9	8466	6940	2892	2861	0	0	0	0	0	0	8466	6940	2892	2861	0	0	0	0	0	0	700	85577
h_{10}	8466	7652	2892	2861	0	0	0	0	0	0	8466	7652	2892	2861	945	0	0	0	0	0	320	89372
h_{11}	8466	8002	2892	2861	0	0	0	0	0	0	8466	8002	2892	2861	945	0	0	0	0	0	180	90773
h_{12}	8466	8226	2892	2861	0	0	0	0	0	0	8466	8226	2892	2861	945	0	0	0	0	0	1040	92611
h_{13}	8466	8357	0	2861	0	0	0	0	0	0	8466	8357	2892	2861	945	0	0	0	0	0	830	90245
h_{14}	8466	8445	0	2861	0	0	0	0	0	0	8466	8445	2892	2861	945	0	0	0	0	0	290	90595
h_{15}	8466	8234	0	2861	0	0	0	0	0	0	8466	8234	2892	2861	945	0	0	0	0	0	1450	89754
h_{16}	8466	8887	0	2861	1244	0	0	0	0	0	8466	8887	0	2861	1244	0	0	0	0	0	1660	91617
h_{17}	8466	8887	0	2861	1646	0	0	0	0	0	8466	8887	0	2861	1646	0	0	0	0	0	1830	94043
h_{18}	8466	8690	2892	2861	945	0	0	0	0	0	8466	8690	0	2861	0	0	0	0	0	0	1270	92395
h_{19}	8466	8309	2892	2861	945	0	0	0	0	0	8466	8309	0	2861	0	0	0	0	0	0	230	89925
h_{20}	8466	8121	2892	2861	945	818	0	0	0	0	8466	8121	0	2861	0	818	0	0	0	0	170	89863
h_{21}	8466	7832	2892	2861	945	818	0	0	0	0	8466	7832	2892	2861	0	818	0	0	0	0	1430	85060
h_{22}	8466	7832	2892	0	945	818	0	0	0	0	8466	7832	2892	0	0	818	0	0	0	0	470	79338
h_{23}	8466	7198	2892	0	0	818	0	0	0	0	8466	7198	2892	0	0	0	0	0	0	0	1430	72147
h_{24}	8466	0	2892	0	0	0	0	0	0	0	8466	7626	2892	0	945	0	0	0	0	0	1420	67180

Table 4.29: Individual fuel cost for Generation of 40 Unit Test System using CBWO for UCP **during Pre-COVID (Weekday from U1-U20); $**

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	8466	6883	0	2861	0	0	0	0	0	0	8466	6883	0	0	0	0	0	0	0	0
h_2	8466	6638	0	2861	0	0	0	0	0	0	8466	6638	0	0	0	0	0	0	0	0
h_3	8466	6673	0	2861	0	0	0	0	0	0	8466	6673	0	0	0	0	0	0	0	0
h_4	8466	6621	0	2861	0	0	0	0	0	0	8466	6621	0	0	0	0	0	0	0	0
h_5	8466	6866	0	2861	0	0	0	0	0	0	8466	6866	0	0	0	0	0	0	0	0
h_6	8466	7259	0	2861	0	0	0	0	0	0	8466	7259	0	2861	0	0	0	0	0	0
h_7	8466	7014	2892	2861	0	0	0	0	0	0	8466	7014	0	2861	0	0	0	0	0	0
h_8	8466	7014	2892	2861	0	0	0	0	0	0	8466	7014	2892	2861	0	0	0	0	0	0
h_9	8466	6726	2892	2861	0	0	0	0	0	0	8466	6726	2892	2861	0	0	0	0	0	0
h_{10}	8466	6734	2892	2861	0	0	0	0	0	0	8466	6734	2892	2861	0	0	0	0	0	0
h_{11}	8466	6983	2892	0	945	0	0	0	0	0	8466	6983	2892	2861	0	0	0	0	0	0
h_{12}	8466	7429	0	0	945	0	0	0	0	0	8466	7429	2892	2861	0	0	0	0	0	0
h_{13}	8466	8046	0	0	945	0	0	0	0	0	8466	8046	0	2861	945	0	0	0	0	0
h_{14}	8466	8887	0	0	1395	0	0	0	0	0	8466	8887	0	0	1395	0	0	0	0	0
h_{15}	8466	8887	0	0	1174	0	0	0	0	0	8466	8887	0	0	1174	0	0	0	0	0
h_{16}	8466	8730	0	2861	945	0	0	0	0	0	8466	8730	0	0	945	0	0	0	0	0
h_{17}	8466	8887	2892	2861	995	0	0	0	0	0	8466	8887	0	0	995	0	0	0	0	0
h_{18}	8466	8664	2892	2861	0	0	0	0	0	0	8466	8664	2892	0	945	0	0	0	0	0
h_{19}	8466	8213	2892	2861	0	0	0	0	0	0	8466	8213	2892	2861	0	818	0	0	0	0
h_{20}	8466	7972	2892	2861	0	818	0	0	0	0	8466	7972	2892	2861	0	818	0	0	0	0
h_{21}	8466	7757	2892	2861	0	818	0	0	0	0	8466	7757	2892	2861	0	818	0	0	0	0
h_{22}	8466	7469	2892	2861	0	818	0	0	0	0	8466	7469	2892	2861	0	0	0	0	0	0
h_{23}	8466	7823	0	0	0	0	1174	0	0	0	8466	7823	2892	2861	0	0	0	0	0	0
h_{24}	8466	7788	0	0	0	0	1174	0	0	0	8466	7788	0	2861	0	0	0	0	0	0

Table 4.30: Individual fuel cost for Generation of 40 Unit Test System using CBWO for UCP **during Pre-COVID (Weekday from U21-U40); $**

Hour	U_{21}	U_{22}	U_{23}	U_{24}	U_{25}	U_{26}	U_{27}	U_{28}	U_{29}	U_{30}	U_{31}	U_{32}	U_{33}	U_{34}	U_{35}	U_{36}	U_{37}	U_{38}	U_{39}	U_{40}	SUC	FC
h_1	8466	6883	0	0	0	0	0	0	0	0	8466	6883	0	0	0	0	0	0	0	0	3110	64256
h_2	8466	6638	0	0	0	0	0	0	0	0	8466	6638	0	0	0	0	0	0	0	0	3130	63278
h_3	8466	6673	0	0	0	0	0	0	0	0	8466	6673	0	0	0	0	0	0	0	0	2280	63417
h_4	8466	6621	0	0	0	0	0	0	0	0	8466	6621	0	0	0	0	0	0	0	0	1490	63208
h_5	8466	6866	0	0	0	0	0	0	0	0	8466	6866	0	0	0	0	0	0	0	0	610	64186
h_6	8466	7259	0	0	0	0	0	0	0	0	8466	7259	0	0	0	0	0	0	0	0	120	68620
h_7	8466	7014	0	2861	0	0	0	0	0	0	8466	7014	0	0	0	0	0	0	0	0	0	73393
h_8	8466	7014	2892	2861	0	0	0	0	0	0	8466	7014	0	0	0	0	0	0	0	0	320	79177
h_9	8466	6726	2892	2861	0	0	0	0	0	0	8466	6726	0	2861	0	0	0	0	0	0	460	80884
h_{10}	8466	6734	2892	2861	0	0	0	0	0	0	8466	6734	2892	2861	0	0	0	0	0	0	810	83811
h_{11}	8466	6983	2892	2861	0	0	0	0	0	0	8466	6983	2892	2861	0	0	0	0	0	0	150	82891
h_{12}	8466	7429	2892	2861	0	0	0	0	0	0	8466	7429	2892	2861	0	0	0	0	0	0	670	81783
h_{13}	8466	8046	2892	2861	0	0	0	0	0	0	8466	8046	2892	2861	0	0	0	0	0	0	1230	82304
h_{14}	8466	8887	2892	0	1395	0	0	0	0	0	8466	8887	2892	2861	1395	0	0	0	0	0	210	83636
h_{15}	8466	8887	2892	0	1174	0	0	0	0	0	8466	8887	2892	2861	1174	0	0	0	0	0	2290	82755
h_{16}	8466	8730	2892	0	945	0	0	0	0	0	8466	8730	2892	2861	945	0	0	0	0	0	1450	84067
h_{17}	8466	8887	2892	0	995	0	0	0	0	0	8466	8887	2892	2861	995	0	0	0	0	0	290	87789
h_{18}	8466	8664	2892	0	945	0	0	0	0	0	8466	8664	2892	2861	945	0	0	0	0	0	2800	88642
h_{19}	8466	8213	2892	2861	945	0	0	0	0	0	8466	8213	2892	2861	945	0	0	0	0	0	1490	92431
h_{20}	8466	7972	2892	2861	0	818	0	0	0	0	8466	7972	2892	2861	945	0	0	0	0	0	120	92159
h_{21}	8466	7757	2892	2861	0	818	0	0	0	0	8466	7757	0	2861	0	0	0	0	0	0	1240	87465
h_{22}	8466	7469	2892	2861	0	818	0	0	0	0	8466	7469	0	0	0	0	0	0	0	0	0	82631
h_{23}	8466	7823	0	2861	0	818	0	0	0	0	8466	7823	0	0	0	818	0	0	0	0	150	76578
h_{24}	8466	7788	0	0	0	0	0	0	0	0	8466	7788	0	0	0	818	0	0	0	0	1320	69868

Table 4.31: Individual fuel cost for Generation of 40 Unit Test System using CBWO for UCP **during Pre-COVID with Wind Power Uncertainty (Weekend from U1-U20); $**																				
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_{11}**	**U_{12}**	**U_{13}**	**U_{14}**	**U_{15}**	**U_{16}**	**U_{17}**	**U_{18}**	**U_{19}**	**U_{20}**
h_1	8466	5502	0	0	0	0	0	0	0	0	8466	5502	0	0	0	0	0	0	0	0
h_2	8466	5316	0	0	0	0	0	0	0	0	8466	5316	0	0	0	0	0	0	0	0
h_3	8466	5664	0	0	0	0	0	0	0	0	8466	5664	0	0	0	0	0	0	0	0
h_4	8466	5897	0	0	0	0	0	0	0	0	8466	5897	0	0	0	0	0	0	0	0
h_5	8466	6292	0	0	0	0	0	0	0	0	8466	6292	0	0	0	0	0	0	0	0
h_6	8466	6932	0	2861	0	0	0	0	0	0	8466	6932	0	0	0	0	0	0	0	0
h_7	8466	6246	0	2861	0	0	0	0	0	0	8466	6246	0	2861	0	0	0	0	0	0
h_8	8466	7113	0	2861	0	0	0	0	0	0	8466	7113	0	2861	945	0	0	0	0	0
h_9	8466	7323	0	2861	0	0	0	0	0	0	8466	7323	0	2861	945	0	0	0	0	0
h_{10}	8466	6302	0	2861	0	0	0	0	0	0	8466	6302	0	2861	945	0	0	0	0	0
h_{11}	8466	6643	0	0	0	0	0	0	0	0	8466	6643	0	2861	945	0	0	0	0	0
h_{12}	8466	7692	0	0	0	0	0	0	0	0	8466	7692	0	2861	945	0	0	0	0	0
h_{13}	8466	7867	0	0	0	0	0	0	0	0	8466	7867	2892	2861	945	0	0	0	0	0
h_{14}	8466	7700	2892	0	0	0	0	0	0	0	8466	7700	2892	0	945	0	0	0	0	0
h_{15}	8466	7543	2892	0	0	0	0	0	0	0	8466	7543	2892	0	945	0	0	0	0	0
h_{16}	8466	7224	2892	2861	0	0	0	0	0	0	8466	7224	2892	0	0	0	0	0	0	0
h_{17}	8466	6997	2892	2861	0	0	0	0	0	0	8466	6997	2892	0	0	0	0	0	0	0
h_{18}	8466	6839	2892	2861	0	0	0	0	0	0	8466	6839	2892	0	0	0	0	0	0	0
h_{19}	8466	6776	2892	2861	0	0	0	0	0	0	8466	6776	2892	2861	0	0	0	0	0	0
h_{20}	8466	6813	2892	2861	0	0	0	0	0	0	8466	6813	2892	2861	0	0	0	0	0	0
h_{21}	8466	6935	0	2861	0	0	0	0	0	0	8466	6935	0	2861	0	0	0	0	0	0
h_{22}	8466	7300	0	2861	945	0	0	0	0	0	8466	7300	0	2861	0	0	0	0	0	0
h_{23}	8466	7381	0	2861	945	0	0	0	0	0	8466	7381	0	2861	0	0	0	0	0	0
h_{24}	8466	6868	0	0	945	0	0	0	0	0	8466	6868	0	0	0	0	0	0	0	0

Table 4.32: Individual fuel cost for Generation of 40 Unit Test System using CBWO for UCP **during Pre-COVID with Wind Power Uncertainty (Weekend from U21-U40); $**																						
Hour	**U_{21}**	**U_{22}**	**U_{23}**	**U_{24}**	**U_{25}**	**U_{26}**	**U_{27}**	**U_{28}**	**U_{29}**	**U_{30}**	**U_{31}**	**U_{32}**	**U_{33}**	**U_{34}**	**U_{35}**	**U_{36}**	**U_{37}**	**U_{38}**	**U_{39}**	**U_{40}**	**SUC**	**FC**
h_1	8466	5502	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0	3610	50369
h_2	8466	5316	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0	3460	49811
h_3	8466	5664	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0	1450	50857
h_4	8466	5897	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0	120	51554
h_5	8466	6292	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0	1300	52740
h_6	8466	6932	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0	640	57521
h_7	8466	6246	0	2861	0	0	0	0	0	0	8466	0	0	2861	0	0	0	0	0	0	60	64043
h_8	8466	7113	2892	2861	0	0	0	0	0	0	8466	0	0	2861	0	0	0	0	0	0	60	70482
h_9	8466	7323	2892	2861	0	0	0	0	0	0	8466	0	0	2861	0	0	0	0	0	0	5670	71111
h_{10}	8466	6302	2892	2861	0	0	0	0	0	0	8466	6302	0	2861	0	0	0	0	0	0	720	74352
h_{11}	8466	6643	2892	2861	0	0	0	0	0	0	8466	6643	0	2861	0	0	0	0	0	0	200	72853
h_{12}	8466	7692	2892	0	0	0	0	0	0	0	8466	7692	0	0	0	0	0	0	0	0	1110	71327
h_{13}	8466	7867	0	0	0	0	0	0	0	0	8466	7867	0	0	0	0	0	0	0	0	1900	72028
h_{14}	8466	7700	0	0	0	0	0	0	0	0	8466	7700	2892	0	0	0	0	0	0	0	2620	74285
h_{15}	8466	7543	0	0	0	0	0	0	0	0	8466	7543	2892	0	0	0	0	0	0	0	350	73655
h_{16}	8466	7224	0	0	0	0	0	0	0	0	8466	7224	2892	0	0	0	0	0	0	0	260	74294
h_{17}	8466	6997	0	2861	0	0	0	0	0	0	8466	6997	2892	2861	0	0	0	0	0	0	0	79107
h_{18}	8466	6839	2892	2861	0	0	0	0	0	0	8466	6839	2892	2861	0	0	0	0	0	0	430	81370
h_{19}	8466	6776	2892	2861	0	0	0	0	0	0	8466	6776	2892	2861	0	0	0	0	0	0	2320	83979
h_{20}	8466	6813	2892	2861	0	0	0	0	0	0	8466	6813	0	2861	0	0	0	0	0	0	180	81234
h_{21}	8466	6935	2892	2861	0	0	0	0	0	0	8466	6935	0	2861	0	0	0	0	0	0	1800	75939
h_{22}	8466	7300	2892	2861	0	0	0	0	0	0	8466	0	0	2861	0	0	0	0	0	0	990	71041
h_{23}	8466	7381	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0	1070	62673
h_{24}	8466	6868	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0	2510	55414

Table 4.33: Individual fuel cost for Generation of 40 Unit Test System using CBWO for UCP **during Pre-COVID with Wind Power Uncertainty (Weekday from U1-U20); $**

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	8466	6339	0	0	0	0	0	0	0	0	8466	6339	0	0	0	0	0	0	0	0
h_2	8466	6991	0	0	0	0	0	0	0	0	8466	6991	0	0	0	0	0	0	0	0
h_3	8466	6653	0	2861	0	0	0	0	0	0	8466	6653	0	0	0	0	0	0	0	0
h_4	8466	6781	0	2861	0	0	0	0	0	0	8466	6781	0	2861	0	0	0	0	0	0
h_5	8466	6385	0	2861	0	0	0	0	0	0	8466	6385	0	2861	0	0	0	0	0	0
h_6	8466	6409	2892	2861	0	0	0	0	0	0	8466	6409	2892	2861	0	0	0	0	0	0
h_7	8466	7679	2892	2861	945	0	0	0	0	0	8466	7679	2892	2861	945	0	0	0	0	0
h_8	8466	7294	2892	0	945	0	0	0	0	0	8466	7294	2892	2861	945	0	0	0	0	0
h_9	8466	6723	2892	0	945	0	0	0	0	0	8466	6723	2892	0	945	0	0	0	0	0
h_{10}	8466	7772	2892	0	945	0	0	0	0	0	8466	7772	2892	0	945	0	0	0	0	0
h_{11}	8466	8864	2892	0	945	0	0	0	0	0	8466	8864	2892	0	945	0	0	0	0	0
h_{12}	8466	8226	0	0	945	0	0	0	0	0	8466	8226	0	0	945	0	0	0	0	0
h_{13}	8466	7893	0	2861	0	0	0	0	0	0	8466	7893	0	0	0	0	0	0	0	0
h_{14}	8466	7735	0	2861	0	0	0	0	0	0	8466	7735	0	0	0	0	0	0	0	0
h_{15}	8466	7823	0	2861	0	0	0	0	0	0	8466	7823	0	0	0	0	0	0	0	0
h_{16}	8466	7543	0	2861	0	0	0	0	0	0	8466	7543	0	2861	0	0	0	0	0	0
h_{17}	8466	6962	2892	2861	0	0	0	0	0	0	8466	6962	2892	2861	0	0	0	0	0	0
h_{18}	8466	6787	2892	0	0	0	0	0	0	0	8466	6787	2892	2861	0	0	0	0	0	0
h_{19}	8466	7130	2892	0	945	0	0	0	0	0	8466	7130	2892	2861	0	0	0	0	0	0
h_{20}	8466	7403	2892	0	945	0	0	0	0	0	8466	7403	2892	2861	0	0	0	0	0	0
h_{21}	8466	7351	2892	0	945	0	0	0	0	0	8466	7351	2892	0	0	0	0	0	0	0
h_{22}	8466	7447	0	0	945	0	0	0	0	0	8466	7447	0	0	0	0	0	0	0	0
h_{23}	8466	6962	0	2861	945	0	0	0	0	0	8466	6962	0	0	0	0	0	0	0	0
h_{24}	8466	6065	0	2861	945	0	0	0	0	0	8466	6065	0	0	0	0	0	0	0	0

Table 4.34: Individual fuel cost for Generation of 40 Unit Test System using CBWO for UCP **during Pre-COVID with Wind Power Uncertainty (Weekday from U21-U40); $**

Hour	U_{21}	U_{22}	U_{23}	U_{24}	U_{25}	U_{26}	U_{27}	U_{28}	U_{29}	U_{30}	U_{31}	U_{32}	U_{33}	U_{34}	U_{35}	U_{36}	U_{37}	U_{38}	U_{39}	U_{40}	SUC	FC
h_1	8466	6339	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0	2730	52880
h_2	8466	6991	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0	2010	54835
h_3	8466	6653	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0	3000	56683
h_4	8466	6781	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0	520	59928
h_5	8466	6385	0	2861	0	0	0	0	0	0	8466	0	0	2861	0	0	0	0	0	0	340	64462
h_6	8466	6409	2892	2861	0	0	0	0	0	0	8466	0	2892	2861	0	0	0	0	0	0	2230	76099
h_7	8466	7679	2892	2861	0	0	0	0	0	0	8466	0	2892	2861	0	0	0	0	0	0	180	81799
h_8	8466	7294	2892	2861	0	0	0	0	0	0	8466	0	2892	2861	0	0	0	0	0	0	0	77784
h_9	8466	6723	2892	2861	0	0	0	0	0	0	8466	0	2892	2861	0	0	0	0	0	0	0	73210
h_{10}	8466	7772	2892	0	0	0	0	0	0	0	8466	0	2892	0	0	0	0	0	0	0	1120	70636
h_{11}	8466	8864	0	0	0	0	0	0	0	0	8466	0	0	0	945	0	0	0	0	0	1450	69074
h_{12}	8466	8226	0	0	0	0	0	0	0	0	8466	8226	0	0	945	0	0	0	0	0	820	69601
h_{13}	8466	7893	0	0	0	0	0	0	0	0	8466	7893	0	0	945	0	0	0	0	0	3310	69241
h_{14}	8466	7735	0	0	0	0	0	0	0	0	8466	7735	0	0	945	0	0	0	0	0	960	68611
h_{15}	8466	7823	0	0	0	0	0	0	0	0	8466	7823	0	0	945	0	0	0	0	0	1970	68961
h_{16}	8466	7543	0	2861	0	0	0	0	0	0	8466	7543	0	0	945	0	0	0	0	0	560	73562
h_{17}	8466	6962	2892	2861	0	0	0	0	0	0	8466	6962	0	0	0	0	0	0	0	0	520	78967
h_{18}	8466	6787	2892	2861	0	0	0	0	0	0	8466	6787	2892	2861	0	0	0	0	0	0	60	81160
h_{19}	8466	7130	2892	2861	0	0	0	0	0	0	8466	7130	2892	2861	0	0	0	0	0	0	560	83478
h_{20}	8466	7403	2892	2861	0	0	0	0	0	0	8466	7403	2892	2861	0	0	0	0	0	0	1200	84569
h_{21}	8466	7351	2892	0	0	0	0	0	0	0	8466	7351	2892	2861	0	0	0	0	0	0	720	78638
h_{22}	8466	7447	0	0	0	0	0	0	0	0	8466	7447	2892	2861	0	0	0	0	0	0	1300	70348
h_{23}	8466	6962	0	0	0	0	0	0	0	0	8466	0	2892	0	0	0	0	0	0	0	550	61446
h_{24}	8466	6065	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0	720	55865

Table 4.35: Average Fuel Cost Comparison of 10, 20, 40-unit system during pre-COVID ($)						
Cases	**10-Unit**		**20- Unit**		**40- Unit**	
	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday
Pre-COVID (2019)	476082.5	493730.1	919789.6	984077.7	1963436	1904969
Pre-COVID (2019) with Wind Power	409817	425711.9	828870.5	855434.6	1654870	1708666

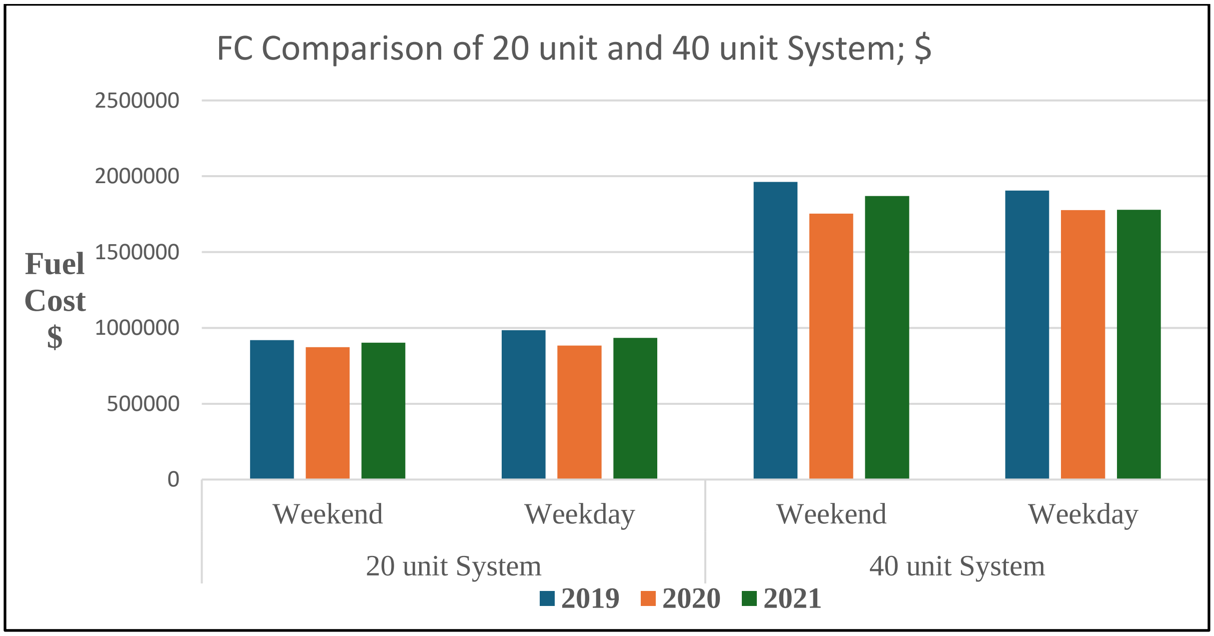

Fig. 4.6: Fuel cost comparison for 20-unit and 40-unit system.

4.6.4 Comparison of results for 10-unit system with standard load demand

To check the effectiveness of proposed algorithm CBWO, it is compared with other existing algorithms for 10-unit system in table 4.36 and 20- unit system shown in table 4.37 with standard load demand. The proposed algorithm shows better results as compared to other algorithms.

Table 4.36: Comparison of results for 10-unit system with 10% SR				
Sr. No.	**Methods**	**Total Generation Cost in $**		
		Best value	**Average value**	**Worst Value**
1	Hybrid Continuous Relaxation and Genetic Algorithm (CRGA) [203]	NA	563977	---
2	Genetic Based Method [202]	NA	623441	---
3	Continuous Relaxation and Genetic Algorithm (CRGA) [203]	---	563977	---
4	Integer Coded Genetic Algorithm (ICGA) [204]	---	566404	---
5	Lagrangian Search Genetic Algorithm (LSGA) [205]	609023.69	---	---
6	Improved Binary Particle Swarm optimization (IBPSO) [206]	599782	---	---
7	New Genetic Algorithm [207]	591715	---	---
8	PSO [208]	581450	563977	---
9	Binary Particle Swarm Optimization with bit Change Mutation (MPSO) [209]	574905	---	---
10	HPSO [210]	574153	---	---
11	LCA-PSO [211]	570006	---	---
12	Two-Stage Genetic Based Technique (TSGA) [212]	568315	---	---
13	Hybrid PSO-SQP [213]	568032.3	---	---
14	BCGA [204, 214]	567367	---	---
15	SM [215]	566686	566787	567022
16	Lagrangian Relaxation [215]	566107	566493	566817
17	GA [215]	565866	567329	571336
18	Genetic Algorithm (GA) [216]	565852	---	570032
19	Enhanced Simulated Annealing (ESA) [217]	565828	565988	566260
20	Lagrangian Relaxation (LR) [216]	565825	---	---
21	Dynamic Programming (DP) [216]	565825	---	---
22	Improved Lagrangian Relaxation (ILR) [217]	565823.23	---	---
23	LRPSO [217, 218]	565275.2	---	---
24	Lagrangian Relaxation and Genetic Algorithm (LRGA) [218]	564800	564800	---
25	Evolutionary Programming (EP) [220]	564551	565352	---
26	EP [215]	564551	565352	566231
27	Particle Swarm Optimization (PSO) [221]	564212	565103	565783
28	Ant Colony Search Algorithm (ACSA) [222]	564049	---	---

29	Hybrid Ant System/Priority List (HASP) [223]	564029	564324	564490
30	B. SMP [224]	564017.73	564121	564401
31	Annealing Genetic Algorithm (AGA) [225]	564005	---	---
32	Binary Differential Evolution [226]	5,63,997	5,63,997	5,63,997
33	Social Evolutionary Programming (SEP) [227]	563987	---	---
34	Methodological Priority List (MPL) [228]	563977.1	---	---
35	Binary PSO [234]	563977	563977	563977
36	Quantum-Inspired Binary PSO (QIBPSO) [235]	563977	563977	563977
37	IBPSO [229]	563977	564155	565312
38	Genetic Algorithm (GA) [215]	563977	564275	5665606
39	Genetic Algorithm Based on Unit Characteristics (UCC-GA) [230]	563977	---	565606
40	Enhanced Adaptive Lagrangian Relaxation (EALR) [217]	563977	---	---
41	Local Search Method (LCM) [232]	563977	---	---
42	Quantum-Inspired Binary PSO (QBPSO) [233]	563977	---	---
43	Extended Priority List (EPL) [236]	563977	---	---
44	Muller Method [237]	563977	---	---
45	Improved Particle Swarm Optimization (IPSO) [238]	563954	564162	564579
46	Advanced Fuzzy Controlled Binary PSO (AFCBPSO) [239]	563947	564285	565002
47	Hybrid PSO (HPSO) [240]	563942.3	564772	565782
48	Fuzzy Quantum Computation Based Thermal Unit Commitment (FQEA) [241]	563942	---	---
49	IQEA-UC [242]	563938	563938	563938
50	Gravitational Search Algorithm [244]	563938	564008	564241
51	QEA-UC [242]	563938	564012	564711
52	Particle Swarm-Based- Simulated Annealing (PSO-B-SA) [243]	563938	564115	564985
53	Advanced Quantum-Inspired Evolutionary Algorithm (AQEA) [242]	563938	---	---
54	Hybrid HS-Random Search algorithm [245]	563937.7	563965	563995
55	**CBWO (Proposed Method)**	**563387.68**	**564182.02**	**565107.68**

Table 4.37: Comparison of results for 20-unit system with 10% SR				
Sr. No.	**Methods**	**Total Generation Cost in $**		
		Best value	**Average value**	**Worst Value**
1	Binary Particle Swarm Optimization with bit Change Mutation [209]	1152966	...	...
2	Intelligent Mutation based Genetic Algorithm [230]	1125516	...	1128790
3	Improved Particle Swarm Optimization OPSO [238]	1125279	...	1127643
4	Improved Binary Particle Swarm optimization [206]	1196029	..	...
5	LCA-PSO [211]	1139005	..	...
6	Lagrangian Relaxation (LR) [215]	1130660	..	...
7	BCGA [214]	1130291	..	...
8	DP and Lagrangian Relaxation (DPLR) [217]	1128098	..	...
9	Enhanced Simulated Annealing (ESA) [217]	1126254	..	...
10	Genetic Algorithm (GA) [215]	1126243	..	1132059
11	Particle Swarm Optimization (PSO) [221]	1125983	..	1131054
12	Social Evolutionary Programming (SEP) [227]	1125170	..	...
13	Hybrid Continuous Relaxation and Genetic Algorithm [203]	..	1236981	...
14	Genetic Based Method [202]	..	1215066	...
15	GA [215]	1126243	1200480	...
16	New Genetic Algorithm [207]	..	1133786	...
17	GA [215]	1128876	1130160	1131565
18	LR [216]	1128362	1128395	1128444
19	SM [215]	1128192	1128213	1128403
20	Enhanced Simulated Annealing (ESA) [217]	1126251	1127955	1129112
21	Harmony Search [245]	..	1127377	...
22	Evolutionary Programming (EP) [220]	1125494	1127257	...
23	Integer Coded Genetic Algorithm [204]	..	1127244	...

24	BSMP [224]	1124838	1125102	1125283
25	HS-Random Search Algorithm [245]	1124889	1124913	1124952
26	Annealing Genetic Algorithm [225]	..	1124651	...
27	Lagrangian Relaxation and Genetic Algorithm [218]	..	1122622	...
28	**CBWO (Proposed Method)**	1123748	1124928	1130559

The suggested approach, CBWO explore search space more efficiently, so the chances to discover improved regions are higher. Rather than a random initialization, chaotic sequences may help give a more normal and varied initial distribution of candidate solutions within the search area, and hence likelier to begin with a solution near the global optimum. The proposed method has more advanced exploitation capability compared to other methods that can find the neighborhood of the good solutions. This means once it finds a promising area in the search space, it can more effectively and precisely converge to the exact optimal point within that region, leading to a slightly better objective value. This could involve a more sophisticated local search component or a more accurate convergence criterion.

4.7 CONCLUSION

This chapter shows the foundation of well-understood generation characteristics and predictable demand patterns supported the pre-COVID UC problem. The main goal was to cost-effectiveness via generation scheduling. The inherent unpredictability problem of renewable energy sources that became system more complex, the more flexible and adaptive UC solutions needed to develop. This need would be further exacerbated by the unanticipated interruptions caused by the COVID-19 epidemic. Incorporating RES with system seems to be a wise decision as it decrease fuel cost of system.

The demand for more precise and dependable technologies to ensure the best possible functioning of energy systems has grown over the last few years due to the increasing presence of unpredictable renewable energy sources in the power generating portfolio.

Chapter-5

IMPACT OF COVID-19 ON UNIT COMMITMENT PROBLEM

5.1 INTRODUCTION

The COVID-19 pandemic has significantly altered global energy consumption patterns, impacting both individuals and the environment. With many people staying at home and numerous businesses either ceasing operations or scaling back, it is essential to assess the implications of this shift on electricity demand and the electrical infrastructure. Such analyses can equip energy companies to better prepare for future pandemics and other adverse events. Policymakers have established targets for renewable energy production, and understanding power demand is vital for enhancing readiness against potential future crises [159].

The growing demand for electricity has prompted a search for alternative energy solutions, which are increasingly gaining traction. The challenges posed by climate change, habitat loss, and declining air quality necessitate a robust action plan, indicating that further efforts are required in this domain. In light of these research challenges, the objective of the proposed study is to examine the multifaceted impacts of COVID-19 on power system [160]. During the COVID-19 period, there was an increase in residential load associated with weekends, while industrial and commercial loads experienced declines. Consequently, weekend operational costs and usage rates rose from 2019 to 2020, whereas weekly operational expenses decreased [161].

The pandemic has reshaped energy sources and has had a profound effect on the environment and the broader renewable energy sector. Significant challenges have emerged for the renewable energy industry due to the pandemic, including supply chain disruptions, market instability, and revenue losses. Additionally, government support has diminished as funding has decreased during the COVID crisis [162].

5.2 UNIT COMMITMENT PROBLEM DURING COVID-19

The UCP and Economic Dispatch optimization problem is a well-researched topic in power systems, mainly aimed at decisive the most cost-efficient generator scheduling while incorporating additional loads into the system. However, the insertion of OC, EL, and Renewable Energy Sources makes the problem more intricate. In this prolonged context, the goal is not just to minimize operating costs but also to accommodate the impacts of OC and EL, as well as the variability and intermittency of RES. OC and EL introduce new dimensions of demand response, while RES contributes clean, renewable energy to the mix.

The research of Covid effects on power sector operations reveals the disease's direct influence on the energy system as well as the requirement of combining issues from both a technical and economical aspect [163]. Looked at the indirect consequences that eventually have an impact on the challenges linked to growth in the power sector and hence, power supply. Research suggests that there was a considerable spike in the demand for shelters throughout the pandemic and also the absence of investment in this area. An aggressive repeated approach was noted in effect of the pandemic on the world’s Energy System and renewables, in order to push up demand and electricity consumption [164].

In the best-case scenario, multiple countries attempt to cut their carbon emissions and adopt zero-carbon policies, resulting in low-carbon economies. Governments need to prepare ready for power production from different sources. Manufacturers have stopped down and urban pollution has reduced during the outbreak. In order to execute the recommended new renewable energy initiatives, politicians and lawmakers will need to approve imminent laws and policy changes. During the COVID-19 pandemic electricity usage plummeted by 14%, or roughly 1,267 GW [165].

The everyday demand showed a notable reduction throughout the weekend. During the week, there was a reported 18% daily drop rate, with a high of 25%. During the outbreak, greenhouse gas emissions have substantially fallen. This amounts to 40,000 tonnes of carbon dioxide and saves about $131,844. Air movement is the major method that the COVID virus spreads, therefore it is vital to figure out the effect of pandemic on Air-Conditioning Systems, Ventilation and Heating, [166].

This encompasses a number of aeration strategies, such as exhaust systems, shared ventilation for a building or numerous rooms, and individual ventilation, which is vital in minimising the risk of viral transmission and is prescribed by doctors under particular situations [167]. Government and medical groups have set guidelines concerning HVAC program and safety during COVID-19 [168].

The Consistency of Microgrids in perspective of Demand Response Program during pandemic on power and health System, seeks to reduce ENS (Energy Not Supply) and upside risk assessment in an islanded microgrid and demand response program deployment and examining the influence of Covid-19 [169]. It was shown that rise in covid induce the decrease in ENS and increase the leaked energy [170]. The impact on greenhouse gas emissions due to COVID-19, the shutdowns during the pandemic that were temporary resulted in a significant global decline in greenhouse gas emissions, indicating the importance of cutting back on the use of fossil fuels and reducing emissions from industries that have a major positive environmental impact [171].

The effect of pandemic on power consumption which reveals that fluctuations in the step of imitation have a harmful effect on the quantity of power utilised [172]. In addition to decreasing electrical loads, the COVID-19 pandemic's impacts on energy networks have led in a shift in load from industry to the private sector and from metropolitan districts to suburban areas, which has an influence on the system [173].

The overall drop in demand will be matched by a large decline in business demand during the lockdown and a surge in household demand. The Covid-19 outbreak is undoubtedly going to produce a further noticeable decline in the usage of transit as well as a steady, small growth of the demand for private transport. So, by above researches, we conclude that UCP is necessary to address when Covid-19 outbreak changes the energy transition.

5.3 PROBLEM FORMULATION

In this chapter, following cases are discussed and solved for the unit commitment problem.

Case 1: Unit Commitment Problem considering the impact of COVID-19 (During Full lockdown)

Case 2: Unit Commitment Problem considering the impact of COVID-19 (During Full lockdown) with RES (Wind)

Case 3: Unit Commitment Problem considering the impact of COVID-19 (During Partial lockdown)

Case 4: Unit Commitment Problem considering the impact of COVID-19 (During Partial lockdown) with RES (Wind).

Case 5: Unit Commitment Problem considering the impact of COVID-19 and load demand of OC.

Case 6: Unit Commitment Problem considering the impact of COVID-19 and load demand of EL.

Case 7: Unit Commitment Problem considering the impact of COVID-19 and load demand of OC and EL.

Case 8: Unit Commitment Problem considering the impact of COVID-19 and load demand of OC, EL with RES (Wind).

To successfully address the UCP with the integration of OC, EL, and RES, a range of mathematical models and constraints must be considered. These constraints include maintaining power balance, adhering to ramping limits, respecting minimum and maximum generator output levels, and ensuring voltage and stability requirements are met.

5.3.1 Objective Function of UCP Considering Impact of COVID

The main goal of the unit commitment problem is to determine the best schedule for running the available power generators in order to minimize the overall cost of generating and operating electricity. This cost includes factors such as the price of fuel, as well as the costs of starting up and shutting down generators.

$$FC = \sum_{\mathrm{g=1}}^{NG} [(\mathrm{a}_g \mathrm{P}_{g,h}^2 + \mathrm{b}_g \mathrm{P}_{g,h} + \mathrm{c}_g) \times \mathrm{U}_{g,h} + SUC \times U_{g,h} \times (1 - U_{g,(h-1)})]; g = 1,...NG; h = 1,....H \quad (5.1)$$

The above equation is to calculate the fuel cost for g^{th} unit. For power balance, the total power generated is equals to the power demand during COVID-19 and losses occur in the system. Power balance equation- and can be modified as follow:

$$\sum_{g=1}^{NG} P_{gh} U_{gh} = P_h^{Covid-19} + P_h^{Loss} \quad (5.2)$$

Spinning reserve constraints, the total power generated is always greater than and equal to the power consumed and reserve power. Equation for spinning reserve constraints, while considering the COVID-19 is described in equation 5.3.

$$\sum_{g=1}^{NG} P_{gh} U_{gh} \geq P_h^{Covid-19} + P_h^{\mathrm{Re}serve} \quad (5.3)$$

Here, $P_{gh} U_{gh}$ is the total power generated by g^{th} units for *h* hour. $P_h^{\mathrm{Re}serve}$, the reserve power for the future or any worst case. The *SUC* can be expressed as:

$$SUC_{gh} = \begin{cases} HSC_g; \text{ for } \mathrm{MDT}_g \leq MDT_g^{ON} \leq (CSH_g + MDT_g) \\ CSC_g; \text{ for } MDT_g^{ON} \geq (MDT_g + CSH_g) \end{cases} \quad \text{(g=1,2,..; h=1,2,3....H)} \quad (5.4)$$

where, CSC_g and HSH_g are Cold Startup and Hot Start-Up Cost of g^{th} unit respectively and MDT_g is the Minimum Down Time of g^{th} unit, T_{gh}^{OFF} is duration for which the thermal g^{th} unit has been continuously off until hour *h*.

5.3.2 Constraints of UCP during COVID with RES

The Unit Commitment Problem Associated with Renewable Energy Sources consists of a number of constraints that must be taken into consideration in order to guarantee an energy system that is both dependable and effective. One of the essential limitations is the power balance condition, which expects that the power supply from all sources should be equivalent to the power interest consistently. To ensure that each generating unit and transmission line operates within safe and stable parameters, it is also necessary to take into consideration the minimum and maximum operating limits. So, power balance and spinning reserve equation is-

$$\sum_{g=1}^{NG} P_{gh} U_{gh} + P_h^{RES} = P_h^{Covid-19(FL/PL)} + P_h^{Loss} \tag{5.5}$$

In the power system, maintaining power balance or load balance is the crucial constraint. This constraint involves ensuring that the total power generated by all committed generating units at a particular time h (hour) is greater than or equal to the power demand for that same time period. Equation 5.5 outlines the power balance constraint that applied when RES considered in the system.

Spinning reserve while considering the impact of COVID-19 and RES-

$$\sum_{g=1}^{NG} P_{gh} U_{gh} + P_h^{RES} \geq P_h^{Covid-19(FL/PL)} + P_h^{\mathrm{Re}serve} \tag{5.6}$$

The availability of renewable energy sources, which are affected by the weather and can change over time, is another significant constraint. To balance the intermittent nature of these sources, this necessitates the use of appropriate storage and demand response strategies as well as precise forecasting of RES output.

5.3.3 Power Balance Constraints Considering Load Demand of OC, EL and RES

The mathematical formulation for power balance constraint in the presence of oxygen concentrator is given by the equation 5.7.

$$\sum_{g=1}^{NG} P_{gh} U_{gh} = P_h^{Covid-19} + P_h^{OC} \tag{5.7}$$

In the power system, the crucial constraint is maintaining power balance or load balance. This constraint involves ensuring that the total power generated by all committed generating units at a particular time h is greater than or equal to the power demand for that same time period. Equation (5.8) outlines the power balance constraint when electrolyser is considered in the system.

$$\sum_{g=1}^{NG} P_{gh} U_{gh} = P_h^{Covid-19} + P_h^{EL} \tag{5.8}$$

Power balance equation when both oxygen concentrator and electrolyser is used is expressed by below equation.

$$\sum_{g=1}^{NG} P_{gh} U_{gh} = P_h^{Covid-19} + P_h^{OC} + P_h^{EL} \tag{5.9}$$

The power system must ensure that the total power generated at a specific hour and the power generated from renewable energy sources at the same time period meet the demand for electricity. This means that the combined electricity generated by the g^{th} unit at h time must also meet the load demand. The power balance constraints considering renewable sources is given by equation (5.10).

$$\sum_{g=1}^{NG} P_{gh} U_{gh} + P_h^{RES} = P_h^{Covid-19} + P_h^{OC} + P_h^{EL} \tag{5.10}$$

Here, P_h^{RES} is the Renewable Power at h hour, $P_h^{Covid-19}$ is the demand of power during COVID for h hour while P_h^{OC} and P_h^{EL} is the Power Demand from OC and EL for *h*-hour.

5.3.4 Spinning Reserve Constraints of UCP

The mathematical formulation for spinning reserve constraints considering OC and EL is given by equation (5.11)

$$\sum_{g=1}^{NG} P_{gh} U_{gh} \geq P_h^{Covid-19} + P_h^{\mathrm{Re}serve} + P_h^{OC} \tag{5.11}$$

$$\sum_{g=1}^{NG} P_{gh} U_{gh} \geq P_h^{Covid-19} + P_h^{\mathrm{Re}serve} + P_h^{EL} \tag{5.12}$$

Where, $P_{gh} U_{gh}$ is the Maximum Power Generation for g^{th} unit, P_h^{RES} is the Renewable Power Generation for g^{th} unit, $P_h^{Covid-19}$ is the Power Demand during the pandemic, P_h^{OC} and P_h^{EL} is Power Demand of Oxygen Concentrator and Electrolyser respectively.

$$\sum_{g=1}^{NG} P_{gh} U_{gh} + P_h^{RES} \geq P_h^{Covid-19} + P_h^{\mathrm{Re}serve} + P_h^{OC} + P_h^{EL} \tag{5.13}$$

The spinning reserve constraint for the system combine power demand of OC and EL with RES as shown in equation 5.13.

5.3.5 Minimum Up and Down Time Constraints for UCP

In the UCP process, the minimum up and down time constraint plays a significant role in regulating the amount of time that a generating unit must stay on or off before it can be turned on or off again. By carefully managing the use of generating units in adherence to these constraints, system operators can ensure the provision of dependable and cost-effective energy to fulfill the expected load, while also promoting the efficient use of resources.

$$T_{gh}^{ON} \geq MUT_h \qquad (\mathrm{g} = 1, 2, ..., G;\ \mathrm{h} = 1, 2, ..., Hour) \tag{5.14}$$

In this equation, the symbol T_{gh}^{ON} represents the time duration that a unit g^{th} remains continuously operational in h hours, while MUT_h refers to the minimum time that a particular unit must remain active before it can be shut down again, also measured in hours. Both of these parameters are relevant to the g units being considered. After a unit has been turned off, it cannot be restarted until a certain minimum duration has elapsed, known as the "down-time" period. This constraint can be expressed mathematically as follows:

$$T_{gh}^{OFF} \geq MDT_h \qquad (\mathrm{g} = 1, 2, ..., G;\ \mathrm{h} = 1, 2, ..., Hour) \tag{5.15}$$

In this context, the variable " T_{gh}^{OFF} " represents the length of time that the g^{th} unit has been continuously inactive in hours. Additionally, the parameter "MDT_h" refers to the minimum duration of inactivity required for that specific unit, also measured in hours.

5.3.6 Crew Constraints for UCP

Crew constraints play a crucial role in ensuring the safe and efficient operation and maintenance of power systems. They establish a limit on the number of workers that can work on power system equipment, ensuring that maintenance and repair tasks are carried out effectively while maintaining a reliable power system. Crew constraints are usually expressed as a maximum limit on the number of workers assigned to a specific piece of equipment or area.

5.3.7 Initial Operating Status of Generation Units

In order to ensure that every unit meets its minimum up/down time requirements, the initial operating status of each unit must consider the previous day's schedule. This means that the starting status of each unit is influenced by its previous operating state and the minimum duration it must remain in that state before it can transition to another state. By factoring in these considerations, the initial operating status of each unit can be determined in a way that promotes system reliability and efficiency.

5.4 SOLUTION METHODOLOGY FOR UCP

The UC problem has been examined by taking into account the physical limitations and system of thermal power units. This research employs hybrid versions of CBWO to address the unit commitment problem in power systems. Both stochastic and heuristic approaches are utilized to handle various operational and physical constraints associated with the unit commitment problem.

The developments for managing system constraints in UCP, including spinning reserve constraint, minimum-up and minimum-down time constraints, and deactivation of surplus power generating units, are outlined in sections 5.4.1, 5.4.2, 5.4.3 and 5.4.4 respectively. The proposed hybrid optimization techniques for solving the unit commitment problem are discussed in the subsequent sections.

5.4.1 Repairing for Spinning Reserve Constraints with RES

To meet the reserve capacity requirements for various power unit with RES, the minimum operational and non-operational periods of each power unit, along with their respective durations, have been considered. The reserve constraints must be addressed according to following procedure.

Step1: Arrange the power generation in a decreasing order based on their maximum capacity to generate power.

Step 2: If *g=1 to G*, if U_{gh} =0 then U_{gh} =1,

Else if $T_{g,h}^{off} \geq MDT_g$

Then $T_{g,h}^{on} \geq T_{g,h-1}^{on} + 1$ and $T_{g,h}^{off} = 0$

Step 3: Check the newly generated power output of the units for validation.

Step 4: If $\sum_{g=1}^{NG} P_{gh} U_{gh} + P_h^{RES} = P_h^{Covid-19} + P_h^{\mathrm{Re}serve}$ then break the process. If condition is not met then proceed to step 2, otherwise terminate the algorithm.

Step 5: If $T_{g,h}^{off} \leq MDT_g$ then do $l = h - T_{g,h}^{off} + 1$ and set U_{gh} =1.

Step 6: Calculate $T_{g,h}^{l} = T_{g,h-1}^{on} + 1$ and $T_{g,h}^{off} = 0$

Step7: If $l > h$, check the power output $\sum_{g=1}^{NG} P_{gh} U_{gh} + P_h^{RES} \geq P_h^{Covid-19} + P_h^{\mathrm{Re}serve}$ of the generator to ensure its accuracy for RES and then proceed to step 5.

Fig. 5.1- Algorithm for Spinning Reserve Constraint with RES

5.4.2 Repairing for Spinning Reserve Constraints with OC, EL and RES

To meet the reserve capacity requirements for various power unit when considering OC, EL and RES, the minimum operational and non-operational periods of each power unit, along with their respective durations, have been considered. The reserve constraints must be addressed according to following procedure.

Step1: Arrange the power generation in a decreasing order based on their maximum capacity to generate power.

Step 2: If *g=1 to G,* if U_{gh} =0 then U_{gh} =1,

Else if $T_{g,h}^{off} \geq MDT_g$

Then $T_{g,h}^{on} \geq T_{g,h-1}^{on} + 1$ and $T_{g,h}^{off} = 0$

Step 3: Check the newly generated power output of the units for validation.

Step 4: If $\sum_{g=1}^{NG} P_{gh} U_{gh} + P_h^{RES} = P_h^{Covid-19} + P_h^{\text{Re}serve} + P_h^{OC} + P_h^{EL}$ then break the process. If condition is not met then proceed to step 2, otherwise terminate the algorithm.

Step 5: If $T_{g,h}^{off} \leq MDT_g$ then do $l = h - T_{g,h}^{off} + 1$ and set U_{gh} =1.

Step 6: Calculate $T_{g,h}^{l} = T_{g,h-1}^{on} + 1$ and $T_{g,h}^{off} = 0$

Step 7: If $l > h$, check the power output $\sum_{g=1}^{NG} P_{gh} U_{gh} + P_h^{RES} \geq P_h^{Covid-19} + P_h^{\text{Re}serve} + P_h^{OC} + P_h^{EL}$ of the generator to ensure its accuracy for OC, EL and RES, then proceed to step 5.

Fig. 5.2- Algorithm for Spinning Reserve Constraint with OC, EL and RES

5.4.3 Repairing for Minimum Up and Down Time Constraints

Repairing for minimum up time and down time constraints of different thermal units can be done by following process-

Step 1: Arrange the power generation in a decreasing order based on their maximum capacity to generate power.

Step 2: for *h=1 to H* and *g=1 to G* then set *g=1*

Step 3: if U_{gh} =1 then set U_{gh-1}=1

Step 4: Check $T_{g,h}^{on} > MUT_g$ and set U_{gh} =0 or else set U_{gh} =1

Step 5: if U_{gh-1}=1, then set U_{gh} =0

Step 6: if $T_{g,h-1}^{on} > MUT_g$ then set U_{gh} =1 and stop if loop.

Step 7: if $h + MDT_g - 1 \le T$ and $T_{g,h-1}^{off} \le MUT_g$ then set U_{gh} =1 otherwise end if.

Step 8: if $h + MDT_g - 1 > T$ and $\sum_{h=1}^{H} U_{gh} > 0$ then set U_{gh} =1 and end if or else proceed to step 5.

Step 9: Modify the time period for both the committed and decommitted generation units of the g^{th} unit using the equation $T_{g,h}^{on} \ge MUT_g$ and $T_{g,h}^{off} \ge MUT_g$.

Fig. 5.3- Algorithm for Minimum Up and Down Time Constraints

5.4.4 Decommitment of the Excessive Generating Units.

Surplus thermal units must be taken offline. All thermal generating units need to meet the requirements for load demand and spinning reserve.

Step 1: Arrange the power generation in a decreasing order based on their maximum capacity to generate power.

Step2: for *h=1 to H* and g=*1 to G,* then *g=h(G+l-1) and* find out generated power, $P_g = P_{\max} \times U_{gh}{}'$ or *g=1 to G, if* U_{gh} =0 then U_{gh} =1 else if $T_{g,h}^{off} > MDT_g$

Then $T_{g,h}^{on} = T_{g,h-1}^{on} + 1$ and $T_{g,h}^{off} = 0$

$$h = 1 : H$$

$$g = 1 : G$$

$$g = h(G + 1 - g)$$

Step 3: Check the newly generated power output of the units for validation.

Step 4: If $\sum_{g=1}^{NG} P_{gh} U_{gh} + P_h^{RES} \geq P_h^{Covid-19} + P_h^{\mathrm{Re}serve} + P_h^{OC} + P_h^{EL}$ and $T_{g,h}^{off} > MDT_g$ then do U_{gh} =0, else terminate the algorithm. Or else if $T_{g,h}^{on}$ =1 do U_{gh} =0, else do the increment 1 by 1and proceed to step 2.

Step 5: If $T_{g,h}^{on}$ =0 then find out $T_{g,h}^{off} = T_{g,h-1}^{off} + 1$

Step 6: If U_{gh} =1, check the output power. Find out $\sum_{g=1}^{NG} P_{gh} U_{gh} + P_h^{RES} \geq P_h^{Covid-19} + P_h^{\mathrm{Re}serve} + P_h^{OC} + P_h^{EL}$ for OC, EL and RES, else OFF the generating unit and move to step 4.

Fig. 5.4: Algorithm for Decommitment of the Excessive Generating Units.

The minimum down and up times takes into account in system for each unit, as well as the duration of power unit OFF/ON periods. The algorithm allows for constraint adjustments as necessary.

5.4.5 Chaotic Beluga Whale Optimization Algorithm

The optimal solution is evaluated by using the CBWO algorithm. In the proposed method, a chaotic search is employed to optimize a vector of units for commitment, with the aim of reducing overall costs. The procedure for solution of unit commitment using CBWO algorithm is explained below:

Step 1: Begin by inputting the Unit Commitment Problem parameters and initializing the population of potential solutions. This initialization process for each individual is based on equations (3.4) and (3.5). For unit commitment problem, each solution candidate represents the on/off status of each generating unit over the defined time period. This status is binary, with '1' indicating the unit is online and '0' indicating it is offline. Consequently, a solution is structured as an integer matrix representing the on/off schedule of all units across the entire time horizon. This matrix can be mathematically represented as:

$$U_{\kappa hg} = \begin{pmatrix} U_{11}^{\kappa} & U_{12}^{\kappa}\ldots\ldots & U_{1NG}^{\kappa} \\ U_{21}^{\kappa} & U_{22}^{\kappa}\ldots\ldots & U_{2NG}^{\kappa} \\ \vdots & \ddots & \vdots \\ U_{H1}^{\kappa} & U_{H2}^{\kappa}\ldots\ldots & U_{HNG}^{\kappa} \end{pmatrix}_{H\times NG} \qquad \left(h=1,2,\ldots H;\, g=1,2,\ldots,NG;\, \kappa=1,2,\ldots.,NP\right)$$

Where U_{hg} denotes the on/off state of generating unit g at time period h, $\in\{0,1\}$.

Step 2: Arrange the generating units in descending order based on their maximum power generation capacity.

Step 3: Adjust the on/off status of individual units within the population to ensure that the spinning reserve requirements, as outlined in sections 5.4.1 and 5.4.2, are met.

Step 4: Correct any violations of the minimum up-time and minimum down-time constraints for the individual units within the population, following the procedures described in section 5.4.3.

Step 5: Deactivate any surplus units in the population, as detailed in section 5.4.4, to reduce excessive spinning reserve that may have resulted from the minimum up/down time constraint repairs.

Step 6: Solve the unit commitment problem for each hour and calculate the corresponding fuel cost.

Step 7: Compute the start-up cost for each hour using equation (5.4) and determine the total generation cost using equation (5.1).

Step 8: Implement the CBWO algorithm. Apply its exploration, exploitation, and whale fall phases using equations (3.4), (3.5), (3.6), and (3.9) to generate a new candidate solution vector, denoted as A_i^{T+1}.

Step 9: Evaluate the new candidate solution vector A_i^{T+1} for any constraint violations, referring to the conditions specified in sections 5.4.1, 5.4.2, 5.4.3, and 5.4.4.

Step 10: Replace the worst-performing solution vector in the current population with the newly generated vector A_i^{T+1}.

Step 11: Apply the Levy flight mechanism using equation (3.7) to update the position of a randomly selected solution vector.

Step 12: If the current iteration count equals the maximum number of iterations allowed, proceed to step 14.

Step 13: If the current iteration count is less than the maximum number of iterations, increment the iteration counter by one and return to step 3 to continue the optimization process.

Step 14: Terminate the algorithm and identify the optimal unit commitment schedule from the individual solution within the population that yielded the lowest total generation cost.

5.5 TEST SYSTEMS

The analysis of the unit commitment problem encompassed different system sizes, including standard configurations of 10, 20, and 40 generating units as presented in section 4.5.1 and 4.5.2.

The power generated by a wind turbine is proportional to the cube of its rated wind speed, although this relationship holds true only within a specific range of wind speeds as expressed in equation 4.13. At lower wind speeds, the turbine lacks sufficient torque to operate effectively. The minimum wind speed required for the rotor to begin turning is known as the cut-in speed, which generally falls between 3 to 4 m/s. The maximum wind speed at which power can be produced safely is termed the cut-out speed, typically around 25 m/s. This maximum output power, known as rated power, is usually achieved at wind speeds ranging from 12 to 17 m/s.

The Weibull distribution function developed by Swedish professor Waloddi Weibull in 1951 is the most widely used life time distribution in reliability engineering. It is a versatile distribution function, based on the value of shape parameter. The probability distribution function for the calculation of wind power can be mathematically represented in equations 4.15, 4.16, 4.17, 4.18 and 4.19 in section 4.4.5.

In table 5.1, technical specification of oxygen concentrator of two models of "AirSep" are given. Power consumption of these two models is 350 W and 410 W per hour. For this study, we use 40,000 units of each model i.e., 80,000 total. Eighty thousand units of oxygen concentrator increase the total demand by 40 MW.

Table 5.1: Oxygen Concentrator Technical Specification; Source-WHO [17]

Device Manufacturer	Min. Oxygen output (LPM)	Max. Oxygen output (LPM)	Pressure (kPa)	Electricity consumption (Watt)	Units Used
AirSep Newlife Elite	0.125	5	15-60	350	40,000
AirSep Newlife Intensity	0.125	8	135	410	40,000

Table 5.2 shows the technical specification of a type of electrolyzer in which St-Fe type of electrode with an area of 31.5 cm^2 is used. This can produce 0.16*10-3 Nm^3 of oxygen in one hour and 4.24 kW of electricity consumed. In our work, we considered twenty thousand of electrolyzer units that increased the load about 84.8 MW. This can give extra burden on our power system so it is necessary to study the load demand.

Table 5.2: Technical Specification of Electrolyzer [19]

Electrode type and Sp. Area (cm^2)	Current, (A)	Current density (A/ cm^2)	Hydrogen production, (Nm^3/h)	Oxygen production, (Nm^3/h)	Electricity consumption; (kW)	Units Used
St-Fe; 31.5	0.96	0.03	$0.33*10^{-3}$	$0.16*10^{-3}$	4.24	20,000

5.6 RESULTS and DISCUSSIONS

The CBWO is a novel hybrid algorithm that combines with chaotic maps. This algorithm is designed to address optimization problems by incorporating both exploratory and exploitative phases. CBWO is a population-based algorithm that does not rely on gradients, which makes it suitable for a wide range of optimization problems.

The CBWO algorithm is effective in the exploratory phase, where it generates a diverse set of solutions using chaotic maps. It also has a strong capability to acclimate from the exploratory phase to the exploitative phase, where it refines the solutions using arithmetic operations. Overall, CBWO is a powerful optimizer that can be applied to a variety of optimization problems. Its skill to cartel chaotic maps with whale optimization techniques makes it a capable algorithm that can effectually address complex optimization issue.

5.6.1 System of Ten Generating Units

The effectiveness of proposed algorithm CBWO is tested and used to get the optimal result for UC problem considering the several constraints. This part of theses is basically illustrating the optimal results for 10 generating units and scheduling of units. **Table 5.3** illustrates the scheduling and fuel cost for 10 units during weekend period of full lockdown (FL) in Covid-19. **Table 5.4** illustrates the scheduling and fuel cost of different units during weekday period of full lockdown in Covid-19. By analyze the result of weekend and weekday, we get almost 1.6% of rise in fuel cost during weekday.

Table 5.5 and **5.6** display the optimal scheduling and fuel cost of 10-unit system during full lockdown with wind power. Incorporating wind power with the system, a decrease of 13.6 % and 14% in fuel cost is seen in weekend and weekday respectively. **Table 5.7** and **5.8** display the optimal scheduling of units and fuel cost of 10-units during partial lockdown (PL) in country. During partial lockdown fuel cost is increased by 3.6% and 6% in weekend and weekday respectively as compared to the full lockdown period. **Table 5.9** and **5.10** shows the scheduling during PL when wind power is incorporating with system. This also shows the increment of 4.7% and 6.8% in weekend and weekday respectively.

Table 5.11 and **5.12** shows the fuel cost and scheduling of units when oxygen concentrator is incorporated. **Table 5.13** and **5.14** is also shows the scheduling of units when electrolyser is used. Fuel cost is increased by 4.6% and 9.5% by the use of OC and EL separately. **Table 5.15** and **5.16** display the scheduling when both OC and EL used during weekend and weekdays, and fuel cost increased by approximately 15%.

Table 5.3: UCP for 10 Unit Test System considering the impact of **COVID-19 FL (Weekend)** using CBWO																					
	Scheduling of 10 units										**Individual Fuel Cost**										
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	455	293	0	0	0	0	0	0	0	0	8466	6054	0	0	0	0	0	0	0	0	2010	14520
h_2	455	283	0	0	0	0	0	0	0	0	8466	5879	0	0	0	0	0	0	0	0	0	14345
h_3	455	275	0	0	0	0	0	0	0	0	8466	5740	0	0	0	0	0	0	0	0	0	14206
h_4	455	277	0	0	0	0	0	0	0	0	8466	5775	0	0	0	0	0	0	0	0	0	14241
h_5	455	291	0	0	0	0	0	0	0	0	8466	6019	0	0	0	0	0	0	0	0	0	14485
h_6	455	317	0	0	0	0	0	0	0	0	8466	6473	0	0	0	0	0	0	0	0	0	14938
h_7	455	351	0	0	0	0	0	0	0	0	8466	7066	0	0	0	0	0	0	0	0	0	15532
h_8	455	265	0	130	0	0	0	0	0	0	8466	5566	0	2861	0	0	0	0	0	0	340	16892
h_9	455	321	0	130	0	0	0	0	0	0	8466	6542	0	2861	0	0	0	0	0	0	60	17869
h_{10}	455	235	130	130	0	0	0	0	0	0	8466	5043	2892	2861	0	0	0	0	0	0	60	19262
h_{11}	455	286	130	130	0	0	0	0	0	0	8466	5932	2892	2861	0	0	0	0	0	0	0	20150
h_{12}	455	320	130	130	0	0	0	0	0	0	8466	6525	2892	2861	0	0	0	0	0	0	550	20743
h_{13}	455	319	130	130	0	0	0	0	0	0	8466	6507	2892	2861	0	0	0	0	0	0	0	20726
h_{14}	455	313	130	130	0	0	0	0	0	0	8466	6403	2892	2861	0	0	0	0	0	0	0	20621
h_{15}	455	421	0	130	25	0	0	0	0	0	8466	8291	0	2861	945	0	0	0	0	0	0	20563
h_{16}	455	449	0	130	25	0	0	0	0	0	8466	8782	0	2861	945	0	0	0	0	0	0	21054
h_{17}	455	455	0	130	43	0	0	0	0	0	8466	8887	0	2861	1304	0	0	0	0	0	900	21518
h_{18}	455	440	0	130	25	0	0	0	0	0	8466	8624	0	2861	945	0	0	0	0	0	0	20896
h_{19}	455	412	0	130	25	0	0	0	0	0	8466	8134	0	2861	945	0	0	0	0	0	0	20405
h_{20}	455	380	0	130	25	0	0	0	0	0	8466	7574	0	2861	945	0	0	0	0	0	60	19845
h_{21}	455	455	0	0	39	0	0	0	0	0	8466	8887	0	0	1224	0	0	0	0	0	0	18578
h_{22}	455	414	0	0	25	0	0	0	0	0	8466	8169	0	0	945	0	0	0	0	0	0	17580
h_{23}	455	354	0	0	25	0	0	0	0	0	8466	7119	0	0	945	0	0	0	0	0	0	16530
h_{24}	455	329	0	0	0	0	0	0	0	0	8466	6682	0	0	0	0	0	0	0	0	0	15148

Table 5.4: UCP for 10 Unit Test System considering the impact of **COVID-19 FL (Weekday)** using CBWO																						
Scheduling of 10 units											**Individual Fuel Cost**											
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	455	293	0	0	0	0	0	0	0	0	8466	6054	0	0	0	0	0	0	0	0	2010	14520
h_2	455	277	0	0	0	0	0	0	0	0	8466	5775	0	0	0	0	0	0	0	0	0	14241
h_3	455	270	0	0	0	0	0	0	0	0	8466	5653	0	0	0	0	0	0	0	0	0	14119
h_4	455	279	0	0	0	0	0	0	0	0	8466	5810	0	0	0	0	0	0	0	0	0	14275
h_5	455	316	0	0	0	0	0	0	0	0	8466	6455	0	0	0	0	0	0	0	0	0	14921
h_6	455	245	0	130	0	0	0	0	0	0	8466	5217	0	2861	0	0	0	0	0	0	0	16544
h_7	455	298	0	130	0	0	0	0	0	0	8466	6141	0	2861	0	0	0	0	0	0	0	17467
h_8	455	350	0	130	0	0	0	0	0	0	8466	7049	0	2861	0	0	0	0	0	0	0	18375
h_9	455	361	0	130	25	0	0	0	0	0	8466	7241	0	2861	945	0	0	0	0	0	0	19513
h_{10}	455	367	0	130	25	0	0	0	0	0	8466	7346	0	2861	945	0	0	0	0	0	340	19618
h_{11}	455	370	0	130	25	0	0	0	0	0	8466	7399	0	2861	945	0	0	0	0	0	0	19670
h_{12}	455	367	0	130	25	0	0	0	0	0	8466	7346	0	2861	945	0	0	0	0	0	550	19618
h_{13}	455	375	0	130	25	0	0	0	0	0	8466	7486	0	2861	945	0	0	0	0	0	0	19758
h_{14}	455	455	0	0	47	0	0	0	0	0	8466	8887	0	0	1385	0	0	0	0	0	0	18738
h_{15}	455	455	0	0	58	0	0	0	0	0	8466	8887	0	0	1606	0	0	0	0	0	560	18959
h_{16}	455	405	130	0	25	0	0	0	0	0	8466	8011	2892	0	945	0	0	0	0	0	0	20314
h_{17}	455	443	130	0	25	0	0	0	0	0	8466	8677	2892	0	945	0	0	0	0	0	0	20980
h_{18}	455	435	130	0	25	0	0	0	0	0	8466	8537	2892	0	945	0	0	0	0	0	0	20839
h_{19}	455	455	130	0	36	0	0	0	0	0	8466	8887	2892	0	1164	0	0	0	0	0	900	21409
h_{20}	455	338	130	130	0	0	0	0	0	0	8466	6839	2892	2861	0	0	0	0	0	0	0	21058
h_{21}	455	400	0	130	0	0	0	10	0	0	8466	7924	0	2861	0	0	0	920	0	0	0	20170
h_{22}	455	358	0	130	0	0	0	0	0	0	8466	7189	0	2861	0	0	0	0	0	0	0	18515
h_{23}	455	294	0	130	0	0	0	0	0	0	8466	6071	0	2861	0	0	0	0	0	0	0	17398
h_{24}	455	249	0	130	0	0	0	0	0	0	8466	5287	0	2861	0	0	0	0	0	0	0	16613

Table 5.5: UCP for 10 Unit Test System considering the impact of **COVID-19 FL (Weekend) with Wind Power** using CBWO																						
	Scheduling of 10 units										**Individual Fuel Cost**											
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	421	150	0	0	0	0	0	0	0	0	7901	3566	0	0	0	0	0	0	0	0	0	11467
h_2	417	150	0	0	0	0	0	0	0	0	7835	3566	0	0	0	0	0	0	0	0	730	11401
h_3	422	150	0	0	0	0	0	0	0	0	7918	3566	0	0	0	0	0	0	0	0	0	11484
h_4	437	150	0	0	0	0	0	0	0	0	8167	3566	0	0	0	0	0	0	0	0	0	11733
h_5	454	150	0	0	0	0	0	0	0	0	8449	3566	0	0	0	0	0	0	0	0	900	12015
h_6	455	180	0	0	0	0	0	0	0	0	8466	4087	0	0	0	0	0	0	0	0	0	12553
h_7	455	231	0	0	0	0	0	0	0	0	8466	4974	0	0	0	0	0	0	0	0	1100	13439
h_8	455	286	0	0	0	0	0	0	0	0	8466	5932	0	0	0	0	0	0	0	0	520	14398
h_9	455	335	0	0	0	0	0	0	0	0	8466	6787	0	0	0	0	0	0	0	0	0	15253
h_{10}	455	249	0	130	0	0	0	0	0	0	8466	5287	0	2861	0	0	0	0	0	0	0	16613
h_{11}	455	299	0	130	0	0	0	0	0	0	8466	6158	0	2861	0	0	0	0	0	0	0	17485
h_{12}	455	335	0	130	0	0	0	0	0	0	8466	6787	0	2861	0	0	0	0	0	0	120	18113
h_{13}	455	335	0	130	0	0	0	0	0	0	8466	6787	0	2861	0	0	0	0	0	0	560	18113
h_{14}	455	334	0	130	0	0	0	0	0	0	8466	6769	0	2861	0	0	0	0	0	0	0	18096
h_{15}	455	444	0	0	25	0	0	0	0	0	8466	8695	0	0	945	0	0	0	0	0	0	18105
h_{16}	455	455	0	0	38	0	0	0	0	0	8466	8887	0	0	1204	0	0	0	0	0	0	18558
h_{17}	455	455	0	0	60	0	0	10	0	0	8466	8887	0	0	1646	0	0	920	0	0	60	19919
h_{18}	455	455	0	0	49.5	0	0	0	0	0	8466	8887	0	0	1435	0	0	0	0	0	0	18788
h_{19}	455	442	0	0	25	0	0	0	0	0	8466	8666	0	0	945	0	0	0	0	0	0	18077
h_{20}	455	390	0	0	25	0	0	0	0	0	8466	7749	0	0	945	0	0	0	0	0	0	17159
h_{21}	455	367	0	0	0	0	0	0	0	0	8466	7346	0	0	0	0	0	0	0	0	0	15812
h_{22}	455	302	0	0	0	0	0	0	0	0	8466	6211	0	0	0	0	0	0	0	0	0	14677
h_{23}	455	219	0	0	0	0	0	0	0	0	8466	4765	0	0	0	0	0	0	0	0	0	13231
h_{24}	455	154	0	0	0	0	0	0	0	0	8466	3635	0	0	0	0	0	0	0	0	0	12101

Table 5.6: UCP for 10 Unit Test System considering the impact of **COVID-19 FL (Weekday) with Wind Power** using CBWO

	Scheduling of 10 units										**Individual Fuel Cost**											
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	421	150	0	0	0	0	0	0	0	0	7901	3566	0	0	0	0	0	0	0	0	0	11467
h_2	411	150	0	0	0	0	0	0	0	0	7735	3566	0	0	0	0	0	0	0	0	0	11301
h_3	417	150	0	0	0	0	0	0	0	0	7835	3566	0	0	0	0	0	0	0	0	1110	11401
h_4	439	150	0	0	0	0	0	0	0	0	8200	3566	0	0	0	0	0	0	0	0	0	11766
h_5	455	174	0	0	0	0	0	0	0	0	8466	3983	0	0	0	0	0	0	0	0	0	12448
h_6	455	238	0	0	0	0	0	0	0	0	8466	5095	0	0	0	0	0	0	0	0	1800	13561
h_7	455	308	0	0	0	0	0	0	0	0	8466	6315	0	0	0	0	0	0	0	0	0	14781
h_8	455	371	0	0	0	0	0	0	0	0	8466	7416	0	0	0	0	0	0	0	0	0	15882
h_9	455	270	0	130	0	0	0	0	0	0	8466	5653	0	2861	0	0	0	0	0	0	0	16979
h_{10}	455	276	0	130	0	0	0	0	0	0	8466	5757	0	2861	0	0	0	0	0	0	0	17084
h_{11}	455	278	0	130	0	0	0	0	0	0	8466	5792	0	2861	0	0	0	0	0	0	0	17119
h_{12}	455	277	0	130	0	0	0	0	0	0	8466	5775	0	2861	0	0	0	0	0	0	60	17101
h_{13}	455	286	0	130	0	0	0	0	0	0	8466	5932	0	2861	0	0	0	0	0	0	550	17258
h_{14}	455	368	0	0	25	0	0	0	0	0	8466	7364	0	0	945	0	0	0	0	0	0	16774
h_{15}	455	381	0	0	25	0	0	0	0	0	8466	7591	0	0	945	0	0	0	0	0	0	17002
h_{16}	455	424	0	0	25	0	0	0	0	0	8466	8344	0	0	945	0	0	0	0	0	0	17755
h_{17}	455	455	0	0	40	0	0	0	0	0	8466	8887	0	0	1244	0	0	0	0	0	560	18598
h_{18}	455	455	0	0	44.5	0	0	0	0	0	8466	8887	0	0	1335	0	0	0	0	0	0	18688
h_{19}	455	455	0	0	46.4	20	0	0	0	0	8466	8887	0	0	1373	818	0	0	0	0	0	19544
h_{20}	455	433	0	0	25	20	0	0	0	0	8466	8502	0	0	945	818	0	0	0	0	0	18731
h_{21}	455	393	0	0	0	20	0	0	0	0	8466	7801	0	0	0	818	0	0	0	0	0	17085
h_{22}	455	351	0	0	0	0	0	0	0	0	8466	7066	0	0	0	0	0	0	0	0	0	15532
h_{23}	455	264	0	0	0	0	0	0	0	0	8466	5548	0	0	0	0	0	0	0	0	0	14014
h_{24}	455	204	0	0	0	0	0	0	0	0	8466	4504	0	0	0	0	0	0	0	0	0	12970

Table 5.7: UCP for 10 Unit Test System considering the impact of **COVID-19 PL (Weekend)** using CBWO

Scheduling of 10 units											**Individual Fuel Cost**											
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	455	338	0	0	0	0	0	0	0	0	8466	6839	0	0	0	0	0	0	0	0	0	15305
h_2	455	305	0	0	0	0	0	0	0	0	8466	6263	0	0	0	0	0	0	0	0	0	14729
h_3	455	316	0	0	0	0	0	0	0	0	8466	6455	0	0	0	0	0	0	0	0	0	14921
h_4	455	326	0	0	0	0	0	0	0	0	8466	6630	0	0	0	0	0	0	0	0	0	15096
h_5	455	329	0	0	0	0	0	0	0	0	8466	6682	0	0	0	0	0	0	0	0	2010	15148
h_6	455	342	0	0	0	0	0	0	0	0	8466	6909	0	0	0	0	0	0	0	0	0	15375
h_7	455	380	0	0	25	0	0	0	0	0	8466	7574	0	0	945	0	0	0	0	0	520	16984
h_8	455	432	0	0	25	0	0	0	0	0	8466	8484	0	0	945	0	0	0	0	0	60	17895
h_9	455	455	0	0	40	0	0	0	0	0	8466	8887	0	0	1244	0	0	0	0	0	0	18598
h_{10}	455	393	0	130	25	0	0	0	0	0	8466	7801	0	2861	945	0	0	0	0	0	0	20073
h_{11}	455	443	0	130	25	0	0	0	0	0	8466	8677	0	2861	945	0	0	0	0	0	0	20948
h_{12}	455	448	0	130	25	0	0	0	0	0	8466	8765	0	2861	945	0	0	0	0	0	0	21036
h_{13}	455	451	0	130	25	0	0	0	0	0	8466	8817	0	2861	945	0	0	0	0	0	0	21089
h_{14}	455	451	0	130	25	0	0	0	0	0	8466	8817	0	2861	945	0	0	0	0	0	320	21089
h_{15}	455	449	0	130	25	0	0	0	0	0	8466	8782	0	2861	945	0	0	0	0	0	340	21054
h_{16}	455	455	0	130	42	0	0	0	0	0	8466	8887	0	2861	1284	0	0	0	0	0	0	21498
h_{17}	455	359	130	130	25	0	0	0	0	0	8466	7206	2892	2861	945	0	0	0	0	0	0	22370
h_{18}	455	444	130	0	25	0	0	0	0	0	8466	8695	2892	0	945	0	0	0	0	0	0	20997
h_{19}	455	430	130	0	25	0	0	0	0	0	8466	8449	2892	0	945	0	0	0	0	0	900	20752
h_{20}	455	407	130	0	25	0	0	0	0	0	8466	8046	2892	0	945	0	0	0	0	0	0	20349
h_{21}	455	389	130	0	0	0	0	10	0	0	8466	7731	2892	0	0	0	0	920	0	0	0	20008
h_{22}	455	342	130	0	0	0	0	0	0	0	8466	6909	2892	0	0	0	0	0	0	0	0	18267
h_{23}	455	273	130	0	0	0	0	0	0	0	8466	5705	2892	0	0	0	0	0	0	0	0	17063
h_{24}	455	360	0	0	0	0	0	0	0	0	8466	7224	0	0	0	0	0	0	0	0	0	15690

Table 5.8: UCP for 10 Unit Test System considering the impact of **COVID-19 PL (Weekday)** using CBWO

	Scheduling of 10 units										**Individual Fuel Cost**											
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	455	343	0	0	0	0	0	0	0	0	8466	6927	0	0	0	0	0	0	0	0	0	15392
h_2	455	324	0	0	0	0	0	0	0	0	8466	6595	0	0	0	0	0	0	0	0	0	15061
h_3	455	331	0	0	0	0	0	0	0	0	8466	6717	0	0	0	0	0	0	0	0	0	15183
h_4	455	356	0	0	0	0	0	0	0	0	8466	7154	0	0	0	0	0	0	0	0	0	15620
h_5	455	299	0	130	0	0	0	0	0	0	8466	6158	0	2861	0	0	0	0	0	0	560	17485
h_6	455	386	0	130	25	0	0	0	0	0	8466	7679	0	2861	945	0	0	0	0	0	340	19950
h_7	455	455	0	130	49	0	0	0	0	0	8466	8887	0	2861	1425	0	0	0	0	0	1100	21639
h_8	455	455	0	130	51	0	0	0	0	0	8466	8887	0	2861	1465	0	0	0	0	0	0	21679
h_9	455	439	0	130	25	0	0	0	0	0	8466	8607	0	2861	945	0	0	0	0	0	0	20878
h_{10}	455	455	0	0	83	20	0	0	0	0	8466	8887	0	0	2113	818	0	0	0	0	0	20284
h_{11}	455	455	0	0	77	20	0	0	0	0	8466	8887	0	0	1990	818	0	0	0	0	1800	20162
h_{12}	455	455	0	0	56	20	0	0	0	0	8466	8887	0	0	1566	818	0	0	0	0	0	19737
h_{13}	455	455	0	0	56	0	0	0	0	0	8466	8887	0	0	1566	0	0	0	0	0	0	18919
h_{14}	455	455	0	0	33	0	0	0	0	0	8466	8887	0	0	1104	0	0	0	0	0	0	18458
h_{15}	455	455	0	0	36	0	0	0	0	0	8466	8887	0	0	1164	0	0	0	0	0	0	18518
h_{16}	455	376	130	0	25	0	0	0	0	0	8466	7504	2892	0	945	0	0	0	0	0	560	19806
h_{17}	455	342	130	130	0	0	0	0	0	0	8466	6909	2892	2861	0	0	0	0	0	0	0	21127
h_{18}	455	347	130	130	0	0	0	0	0	0	8466	6997	2892	2861	0	0	0	0	0	0	0	21215
h_{19}	455	358	130	130	0	20	0	0	0	0	8466	7189	2892	2861	0	818	0	0	0	0	860	22225
h_{20}	455	389	130	130	0	20	0	0	0	0	8466	7731	2892	2861	0	818	0	0	0	0	0	22767
h_{21}	455	337	130	130	0	20	0	0	0	0	8466	6822	2892	2861	0	818	0	0	0	0	0	21858
h_{22}	455	282	130	130	0	0	0	0	0	0	8466	5862	2892	2861	0	0	0	0	0	0	0	20080
h_{23}	455	329	0	130	0	0	0	0	0	0	8466	6682	0	2861	0	0	0	0	0	0	0	18009
h_{24}	455	282	0	130	0	0	0	0	0	0	8466	5862	0	2861	0	0	0	0	0	0	0	17188

Table 5.9: UCP for 10 Unit Test System considering the impact of **COVID-19 PL (Weekend) with Wind Power** using CBWO

	Scheduling of 10 units										**Individual Fuel Cost**											
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	455	161	0	0	0	0	0	0	0	0	8466	3757	0	0	0	0	0	0	0	0	0	12223
h_2	439	150	0	0	0	0	0	0	0	0	8200	3566	0	0	0	0	0	0	0	0	1450	11766
h_3	455	158	0	0	0	0	0	0	0	0	8466	3705	0	0	0	0	0	0	0	0	0	12171
h_4	455	181	0	0	0	0	0	0	0	0	8466	4104	0	0	0	0	0	0	0	0	0	12570
h_5	455	187	0	0	0	0	0	0	0	0	8466	4208	0	0	0	0	0	0	0	0	0	12674
h_6	455	205	0	0	0	0	0	0	0	0	8466	4521	0	0	0	0	0	0	0	0	1120	12987
h_7	455	285	0	0	0	0	0	0	0	0	8466	5914	0	0	0	0	0	0	0	0	0	14380
h_8	455	348	0	0	0	0	0	0	0	0	8466	7014	0	0	0	0	0	0	0	0	0	15480
h_9	455	354	0	0	25	0	0	0	0	0	8466	7119	0	0	945	0	0	0	0	0	0	16530
h_{10}	455	407	0	0	25	0	0	0	0	0	8466	8046	0	0	945	0	0	0	0	0	0	17457
h_{11}	455	455	0	0	26	0	0	0	0	0	8466	8887	0	0	965	0	0	0	0	0	860	18318
h_{12}	455	455	0	0	33	0	0	0	0	0	8466	8887	0	0	1104	0	0	0	0	0	0	18458
h_{13}	455	455	0	0	37	0	0	0	0	0	8466	8887	0	0	1184	0	0	0	0	0	0	18538
h_{14}	455	455	0	0	42	0	0	0	0	0	8466	8887	0	0	1284	0	0	0	0	0	1450	18638
h_{15}	455	455	0	0	42	0	0	0	0	0	8466	8887	0	0	1284	0	0	0	0	0	0	18638
h_{16}	455	455	0	0	61	0	0	0	0	0	8466	8887	0	0	1667	0	0	0	0	0	0	19020
h_{17}	455	386	0	130	25	0	0	0	0	0	8466	7679	0	2861	945	0	0	0	0	0	0	19950
h_{18}	455	354	0	130	25	0	0	0	0	0	8466	7110	0	2861	945	0	0	0	0	0	0	19382
h_{19}	455	355	0	130	0	0	0	0	0	0	8466	7143	0	2861	0	0	0	0	0	0	0	18470
h_{20}	455	312	0	130	0	0	0	0	0	0	8466	6385	0	2861	0	0	0	0	0	0	560	17712
h_{21}	455	272	0	130	0	0	0	0	0	0	8466	5688	0	2861	0	0	0	0	0	0	0	17014
h_{22}	455	335	0	0	0	0	0	0	0	0	8466	6787	0	0	0	0	0	0	0	0	0	15253
h_{23}	455	243	0	0	0	0	0	0	0	0	8466	5182	0	0	0	0	0	0	0	0	0	13648
h_{24}	455	185	0	0	0	0	0	0	0	0	8466	4174	0	0	0	0	0	0	0	0	550	12640

Table 5.10: UCP for 10 Unit Test System considering the impact of **COVID-19 PL (Weekday) with Wind Power** using CBWO

	Scheduling of 10 units										**Individual Fuel Cost**											
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	455	293	0	0	0	0	0	0	0	0	8466	6054	0	0	0	0	0	0	0	0	2010	14520
h_2	455	283	0	0	0	0	0	0	0	0	8466	5879	0	0	0	0	0	0	0	0	0	14345
h_3	455	275	0	0	0	0	0	0	0	0	8466	5740	0	0	0	0	0	0	0	0	0	14206
h_4	455	277	0	0	0	0	0	0	0	0	8466	5775	0	0	0	0	0	0	0	0	0	14241
h_5	455	291	0	0	0	0	0	0	0	0	8466	6019	0	0	0	0	0	0	0	0	0	14485
h_6	455	317	0	0	0	0	0	0	0	0	8466	6473	0	0	0	0	0	0	0	0	0	14938
h_7	455	351	0	0	0	0	0	0	0	0	8466	7066	0	0	0	0	0	0	0	0	0	15532
h_8	455	265	0	130	0	0	0	0	0	0	8466	5566	0	2861	0	0	0	0	0	0	340	16892
h_9	455	321	0	130	0	0	0	0	0	0	8466	6542	0	2861	0	0	0	0	0	0	60	17869
h_{10}	455	235	130	130	0	0	0	0	0	0	8466	5043	2892	2861	0	0	0	0	0	0	60	19262
h_{11}	455	286	130	130	0	0	0	0	0	0	8466	5932	2892	2861	0	0	0	0	0	0	0	20150
h_{12}	455	320	130	130	0	0	0	0	0	0	8466	6525	2892	2861	0	0	0	0	0	0	550	20743
h_{13}	455	319	130	130	0	0	0	0	0	0	8466	6507	2892	2861	0	0	0	0	0	0	0	20726
h_{14}	455	313	130	130	0	0	0	0	0	0	8466	6403	2892	2861	0	0	0	0	0	0	0	20621
h_{15}	455	421	0	130	25	0	0	0	0	0	8466	8291	0	2861	945	0	0	0	0	0	0	20563
h_{16}	455	449	0	130	25	0	0	0	0	0	8466	8782	0	2861	945	0	0	0	0	0	0	21054
h_{17}	455	455	0	130	43	0	0	0	0	0	8466	8887	0	2861	1304	0	0	0	0	0	900	21518
h_{18}	455	440	0	130	25	0	0	0	0	0	8466	8624	0	2861	945	0	0	0	0	0	0	20896
h_{19}	455	412	0	130	25	0	0	0	0	0	8466	8134	0	2861	945	0	0	0	0	0	0	20405
h_{20}	455	380	0	130	25	0	0	0	0	0	8466	7574	0	2861	945	0	0	0	0	0	60	19845
h_{21}	455	455	0	0	39	0	0	0	0	0	8466	8887	0	0	1224	0	0	0	0	0	0	18578
h_{22}	455	414	0	0	25	0	0	0	0	0	8466	8169	0	0	945	0	0	0	0	0	0	17580
h_{23}	455	354	0	0	25	0	0	0	0	0	8466	7119	0	0	945	0	0	0	0	0	0	16530
h_{24}	455	329	0	0	0	0	0	0	0	0	8466	6682	0	0	0	0	0	0	0	0	0	15148

Table 5.11: UCP for 10 Unit Test System considering the impact of COVID-19 **(Weekend)** with **OC demand** using CBWO																						
	Scheduling of 10 units										**Individual Fuel Cost**											
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	455	333	0	0	0	0	0	0	0	0	8466	6752	0	0	0	0	0	0	0	0	0	15218
h_2	455	323	0	0	0	0	0	0	0	0	8466	6577	0	0	0	0	0	0	0	0	0	15043
h_3	455	315	0	0	0	0	0	0	0	0	8466	6438	0	0	0	0	0	0	0	0	2010	14903
h_4	455	317	0	0	0	0	0	0	0	0	8466	6473	0	0	0	0	0	0	0	0	0	14938
h_5	455	331	0	0	0	0	0	0	0	0	8466	6717	0	0	0	0	0	0	0	0	0	15183
h_6	455	357	0	0	0	0	0	0	0	0	8466	7171	0	0	0	0	0	0	0	0	340	15637
h_7	455	371	0	0	0	20	0	0	0	0	8466	7416	0	0	0	818	0	0	0	0	0	16700
h_8	455	415	0	0	0	20	0	0	0	0	8466	8186	0	0	0	818	0	0	0	0	0	17470
h_9	455	341	0	130	0	20	0	0	0	0	8466	6892	0	2861	0	818	0	0	0	0	0	19036
h_{10}	455	380	0	130	25	0	0	0	0	0	8466	7574	0	2861	945	0	0	0	0	0	640	19845
h_{11}	455	431	0	130	25	0	0	0	0	0	8466	8467	0	2861	945	0	0	0	0	0	0	20738
h_{12}	455	455	0	130	35	0	0	0	0	0	8466	8887	0	2861	1144	0	0	0	0	0	0	21358
h_{13}	455	455	0	130	34	0	0	0	0	0	8466	8887	0	2861	1124	0	0	0	0	0	170	21338
h_{14}	455	455	0	130	28	0	0	0	0	0	8466	8887	0	2861	1005	0	0	0	0	0	0	21219
h_{15}	455	455	0	130	31	0	0	0	0	0	8466	8887	0	2861	1065	0	0	0	0	0	0	21278
h_{16}	455	364	130	130	0	20	0	0	0	0	8466	7294	2892	2861	0	818	0	0	0	0	120	22330
h_{17}	455	388	130	130	0	20	0	0	0	0	8466	7714	2892	2861	0	818	0	0	0	0	900	22750
h_{18}	455	355	130	130	0	20	0	0	0	0	8466	7136	2892	2861	0	818	0	0	0	0	0	22173
h_{19}	455	347	130	130	0	0	0	0	0	0	8466	6997	2892	2861	0	0	0	0	0	0	0	21215
h_{20}	455	315	130	130	0	0	0	0	0	0	8466	6438	2892	2861	0	0	0	0	0	0	0	20656
h_{21}	455	394	130	0	0	0	0	0	0	10	8466	7819	2892	0	0	0	0	0	0	948	170	20124
h_{22}	455	349	130	0	0	0	0	0	0	0	8466	7031	2892	0	0	0	0	0	0	0	0	18389
h_{23}	455	409	0	0	0	0	0	10	0	0	8466	8081	0	0	0	0	0	920	0	0	0	17467
h_{24}	455	369	0	0	0	0	0	0	0	0	8466	7381	0	0	0	0	0	0	0	0	0	15847

Table 5.12: UCP for 10 Unit Test System considering the impact of COVID-19 **(Weekday)** with **OC demand** using CBWO																						
Scheduling of 10 units											**Individual Fuel Cost**											
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	455	333	0	0	0	0	0	0	0	0	8466	6752	0	0	0	0	0	0	0	0	0	15218
h_2	455	317	0	0	0	0	0	0	0	0	8466	6473	0	0	0	0	0	0	0	0	0	14938
h_3	455	310	0	0	0	0	0	0	0	0	8466	6350	0	0	0	0	0	0	0	0	0	14816
h_4	455	319	0	0	0	0	0	0	0	0	8466	6507	0	0	0	0	0	0	0	0	0	14973
h_5	455	356	0	0	0	0	0	0	0	0	8466	7154	0	0	0	0	0	0	0	0	0	15620
h_6	455	285	0	130	0	0	0	0	0	0	8466	5914	0	2861	0	0	0	0	0	0	1120	17241
h_7	455	338	0	130	0	0	0	0	0	0	8466	6839	0	2861	0	0	0	0	0	0	0	18166
h_8	455	370	0	130	0	20	0	0	0	0	8466	7399	0	2861	0	818	0	0	0	0	1800	19543
h_9	455	406	0	130	0	20	0	0	0	0	8466	8029	0	2861	0	818	0	0	0	0	0	20173
h_{10}	455	412	0	130	0	20	0	0	0	0	8466	8134	0	2861	0	818	0	0	0	0	0	20278
h_{11}	455	410	0	130	25	0	0	0	0	0	8466	8099	0	2861	945	0	0	0	0	0	0	20370
h_{12}	455	407	130	0	25	0	0	0	0	0	8466	8046	2892	0	945	0	0	0	0	0	0	20349
h_{13}	455	415	130	0	25	0	0	0	0	0	8466	8186	2892	0	945	0	0	0	0	0	0	20489
h_{14}	455	387	130	0	25	0	0	0	0	0	8466	7696	2892	0	945	0	0	0	0	0	1440	19999
h_{15}	455	398	130	0	25	0	0	0	0	0	8466	7889	2892	0	945	0	0	0	0	0	0	20191
h_{16}	455	445	130	0	25	0	0	0	0	0	8466	8712	2892	0	945	0	0	0	0	0	60	21015
h_{17}	455	353	130	130	25	0	0	0	0	0	8466	7101	2892	2861	945	0	0	0	0	0	0	22265
h_{18}	455	455	0	130	45	0	0	0	0	0	8466	8887	0	2861	1345	0	0	0	0	0	0	21559
h_{19}	455	455	0	130	66	0	0	10	0	0	8466	8887	0	2861	1768	0	0	920	0	0	520	22901
h_{20}	455	455	0	130	43	0	0	10	0	0	8466	8887	0	2861	1304	0	0	920	0	0	0	22438
h_{21}	455	425	0	130	25	0	0	0	0	0	8466	8361	0	2861	945	0	0	0	0	0	0	20633
h_{22}	455	373	0	130	25	0	0	0	0	0	8466	7451	0	2861	945	0	0	0	0	0	0	19723
h_{23}	455	439	0	0	25	0	0	0	0	0	8466	8607	0	0	945	0	0	0	0	0	0	18018
h_{24}	455	394	0	0	25	0	0	0	0	0	8466	7819	0	0	945	0	0	0	0	0	60	17229

Table 5.13: UCP for 10 Unit Test System considering the impact of COVID-19 **(Weekend)** with **EL demand** using CBWO

	Scheduling of 10 units										Individual Fuel Cost											
Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	SUC	Hourly FC
h_1	455	310	0	0	0	0	0	0	0	0	8466	6350	0	0	0	0	0	0	0	0	0	14816
h_2	455	293	0	0	0	0	0	0	0	0	8466	6054	0	0	0	0	0	0	0	0	0	14520
h_3	455	283	0	0	0	0	0	0	0	0	8466	5879	0	0	0	0	0	0	0	0	0	14345
h_4	455	275	0	0	0	0	0	0	0	0	8466	5740	0	0	0	0	0	0	0	0	1980	14206
h_5	455	277	0	0	0	0	0	0	0	0	8466	5775	0	0	0	0	0	0	0	0	550	14241
h_6	455	291	0	0	0	0	0	0	0	0	8466	6019	0	0	0	0	0	0	0	0	0	14485
h_7	455	317	0	0	0	0	0	0	0	0	8466	6473	0	0	0	0	0	0	0	0	0	14938
h_8	455	351	0	0	0	0	0	0	0	0	8466	7066	0	0	0	0	0	0	0	0	60	15532
h_9	455	265	130	0	0	0	0	0	0	0	8466	5566	2892	0	0	0	0	0	0	0	0	16923
h_{10}	455	321	130	0	0	0	0	0	0	0	8466	6542	2892	0	0	0	0	0	0	0	0	17900
h_{11}	455	235	130	130	0	0	0	0	0	0	8466	5043	2892	2861	0	0	0	0	0	0	60	19262
h_{12}	455	286	130	130	0	0	0	0	0	0	8466	5932	2892	2861	0	0	0	0	0	0	120	20150
h_{13}	455	320	130	130	0	0	0	0	0	0	8466	6525	2892	2861	0	0	0	0	0	0	0	20743
h_{14}	455	424	0	130	25	0	0	0	0	0	8466	8344	0	2861	945	0	0	0	0	0	0	20615
h_{15}	455	418	0	130	25	0	0	0	0	0	8466	8239	0	2861	945	0	0	0	0	0	0	20510
h_{16}	455	421	0	130	25	0	0	0	0	0	8466	8291	0	2861	945	0	0	0	0	0	400	20563
h_{17}	455	449	0	130	25	0	0	0	0	0	8466	8782	0	2861	945	0	0	0	0	0	520	21054
h_{18}	455	455	0	130	43	0	0	0	0	0	8466	8887	0	2861	1304	0	0	0	0	0	0	21518
h_{19}	455	440	0	130	25	0	0	0	0	0	8466	8624	0	2861	945	0	0	0	0	0	0	20896
h_{20}	455	412	0	130	25	0	0	0	0	0	8466	8134	0	2861	945	0	0	0	0	0	120	20405
h_{21}	455	380	0	130	25	0	0	0	0	0	8466	7574	0	2861	945	0	0	0	0	0	0	19845
h_{22}	455	455	0	0	39	0	0	0	0	0	8466	8887	0	0	1224	0	0	0	0	0	30	18578
h_{23}	455	419	0	0	0	20	0	0	0	0	8466	8256	0	0	0	818	0	0	0	0	0	17540
h_{24}	455	359	0	0	0	20	0	0	0	0	8466	7206	0	0	0	818	0	0	0	0	0	16490

Table 5.14: UCP for 10 Unit Test System considering the impact of COVID-19 **(Weekday)** with **EL demand** using CBWO																						
Scheduling of 10 units											**Individual Fuel Cost**											
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	455	232	0	0	0	0	0	0	0	0	8466	7360	0	0	0	0	0	0	938	0	900	16764
h_2	455	368	0	0	0	0	0	0	10	0	8466	7255	0	0	0	0	0	0	0	0	0	15721
h_3	455	362	0	0	0	0	0	0	0	0	8466	7133	0	0	0	0	0	0	0	0	1370	15599
h_4	455	355	0	0	0	0	0	0	0	0	8466	7290	0	0	0	0	0	0	0	0	0	15756
h_5	455	364	0	0	0	0	0	0	0	0	8466	7500	0	0	945	0	0	0	0	0	0	16911
h_6	455	376	0	0	25	0	0	0	0	0	8466	8533	0	0	945	0	0	0	0	0	60	17944
h_7	455	435	0	0	25	0	0	0	0	0	8466	8887	0	0	1602	0	0	0	0	0	460	18955
h_8	455	455	0	0	57.8	0	0	0	0	0	8466	8095	0	2861	945	0	0	0	0	0	0	20367
h_9	455	410	0	130	25	0	0	0	0	0	8466	8726	0	2861	945	0	0	0	0	0	30	20998
h_{10}	455	446	0	130	25	0	0	0	0	0	8466	8831	0	2861	945	0	0	0	0	0	60	21103
h_{11}	455	452	0	130	25	0	0	0	0	0	8466	8884	0	2861	945	0	0	0	0	0	0	21155
h_{12}	455	455	0	130	25	0	0	0	0	0	8466	8831	0	2861	945	0	0	0	0	0	0	21103
h_{13}	455	452	0	130	25	0	0	0	0	0	8466	8887	0	2861	1041	0	0	0	0	0	0	21255
h_{14}	455	455	0	130	29.8	0	0	0	0	0	8466	8481	0	2861	945	0	0	0	0	0	0	20752
h_{15}	455	432	0	130	25	0	0	0	0	0	8466	8674	0	2861	945	0	0	0	0	0	230	20945
h_{16}	455	443	0	130	25	0	0	0	0	0	8466	7220	2892	2861	945	0	0	0	0	0	0	22384
h_{17}	455	360	130	130	25	0	0	0	0	0	8466	7885	2892	2861	945	0	0	0	0	0	60	23048
h_{18}	455	398	130	130	25	0	0	0	0	0	8466	7745	2892	2861	945	0	0	0	0	0	0	22908
h_{19}	455	390	130	130	25	0	0	0	0	0	8466	8288	2892	2861	945	0	0	0	0	0	90	23451
h_{20}	455	421	130	130	25	0	0	0	0	0	8466	7885	2892	2861	945	0	0	0	0	0	520	23048
h_{21}	455	398	130	130	25	0	0	0	0	0	8466	6871	2892	2861	945	0	0	0	0	0	0	22034
h_{22}	455	340	130	130	25	0	0	0	0	0	8466	6399	2892	2861	0	0	0	0	0	0	170	20618
h_{23}	455	313	130	130	0	0	0	0	0	0	8466	7378	2892	0	0	0	0	920	0	0	0	19655
h_{24}	455	369	130	0	0	0	0	10	0	0	8466	6766	2892	0	0	0	0	0	0	0	60	18124

Table 5.15: UCP for 10 Unit Test System considering the impact of COVID-19 **(Weekend)** with **OC and EL demand** using CBWO																						
	Scheduling of 10 units										**Individual Fuel Cost**											
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	455	398	0	0	0	20	0	0	0	0	8466	7885	0	0	0	818	0	0	0	0	900	17169
h_2	455	388	0	0	0	20	0	0	0	0	8466	7710	0	0	0	818	0	0	0	0	1280	16994
h_3	455	380	0	0	0	20	0	0	0	0	8466	7570	0	0	0	818	0	0	0	0	0	16854
h_4	455	272	130	0	0	0	0	0	0	0	8466	5684	2892	0	0	0	0	0	0	0	0	17042
h_5	455	286	130	0	0	0	0	0	0	0	8466	5928	2892	0	0	0	0	0	0	0	520	17286
h_6	455	312	130	0	0	0	0	0	0	0	8466	6382	2892	0	0	0	0	0	0	0	60	17739
h_7	455	346	130	0	0	0	0	0	0	0	8466	6976	2892	0	0	0	0	0	0	0	0	18333
h_8	455	365	130	0	25	0	0	0	0	0	8466	7308	2892	0	945	0	0	0	0	0	170	19610
h_9	455	421	130	0	25	0	0	0	0	0	8466	8288	2892	0	945	0	0	0	0	0	60	20591
h_{10}	455	455	130	0	35	0	0	0	0	0	8466	8887	2892	0	1140	0	0	0	0	0	0	21385
h_{11}	455	386	130	130	25	0	0	0	0	0	8466	7675	2892	2861	945	0	0	0	0	0	260	22838
h_{12}	455	420	130	130	25	0	0	0	0	0	8466	8270	2892	2861	945	0	0	0	0	0	0	23434
h_{13}	455	419	130	130	25	0	0	0	0	0	8466	8253	2892	2861	945	0	0	0	0	0	0	23416
h_{14}	455	413	130	130	25	0	0	0	0	0	8466	8148	2892	2861	945	0	0	0	0	0	0	23311
h_{15}	455	416	130	130	25	0	0	0	0	0	8466	8200	2892	2861	945	0	0	0	0	0	170	23364
h_{16}	455	444	130	130	25	0	0	0	0	0	8466	8691	2892	2861	945	0	0	0	0	0	60	23854
h_{17}	455	455	130	130	38	0	0	0	0	0	8466	8887	2892	2861	1200	0	0	0	0	0	60	24306
h_{18}	455	435	130	130	25	0	0	0	0	0	8466	8533	2892	2861	945	0	0	0	0	0	0	23697
h_{19}	455	455	0	130	87	20	0	0	0	0	8466	8887	0	2861	2190	818	0	0	0	0	0	23222
h_{20}	455	455	0	130	55	20	0	0	0	0	8466	8887	0	2861	1542	818	0	0	0	0	260	22574
h_{21}	455	444	0	130	25	20	0	0	0	0	8466	8691	0	2861	945	818	0	0	0	0	120	21781
h_{22}	455	409	0	130	25	0	0	0	0	0	8466	8078	0	2861	945	0	0	0	0	0	60	20349
h_{23}	455	455	0	0	49	0	0	0	0	0	8466	8887	0	0	1421	0	0	0	0	0	0	18774
h_{24}	455	429	0	0	25	0	0	0	0	0	8466	8428	0	0	945	0	0	0	0	0	0	17839

Table 5.16: UCP for 10 Unit Test System considering the impact of COVID-19 **(Weekday)** with **OC and EL demand** using CBWO																						
	Scheduling of 10 units										**Individual Fuel Cost**											
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	455	398	0	0	0	20	0	0	0	0	8466	7885	0	0	0	818	0	0	0	0	170	17169
h_2	455	382	0	0	0	20	0	0	0	0	8466	7605	0	0	0	818	0	0	0	0	0	16889
h_3	455	375	0	0	0	20	0	0	0	0	8466	7483	0	0	0	818	0	0	0	0	0	16766
h_4	455	274	0	130	0	0	0	0	0	0	8466	5719	0	2861	0	0	0	0	0	0	550	17046
h_5	455	311	0	130	0	0	0	0	0	0	8466	6364	0	2861	0	0	0	0	0	0	0	17691
h_6	455	345	0	130	25	0	0	0	0	0	8466	6958	0	2861	945	0	0	0	0	0	60	19230
h_7	455	398	0	130	25	0	0	0	0	0	8466	7885	0	2861	945	0	0	0	0	0	1120	20157
h_8	455	450	0	130	25	0	0	0	0	0	8466	8796	0	2861	945	0	0	0	0	0	0	21068
h_9	455	356	130	130	25	0	0	0	0	0	8466	7150	2892	2861	945	0	0	0	0	0	170	22314
h_{10}	455	455	130	0	42	20	0	0	0	0	8466	8887	2892	0	1280	818	0	0	0	0	0	22344
h_{11}	455	455	130	0	45	20	0	0	0	0	8466	8887	2892	0	1341	818	0	0	0	0	0	22404
h_{12}	455	455	130	0	42	20	0	0	0	0	8466	8887	2892	0	1280	818	0	0	0	0	0	22344
h_{13}	455	455	130	0	50	20	0	0	0	0	8466	8887	2892	0	1441	818	0	0	0	0	1800	22504
h_{14}	455	455	130	0	42	0	0	0	0	0	8466	8887	2892	0	1280	0	0	0	0	0	0	21526
h_{15}	455	353	130	130	25	0	0	0	0	0	8466	7098	2892	2861	945	0	0	0	0	0	0	22261
h_{16}	455	400	130	130	25	0	0	0	0	0	8466	7920	2892	2861	945	0	0	0	0	0	520	23083
h_{17}	455	438	130	130	25	0	0	0	0	0	8466	8586	2892	2861	945	0	0	0	0	0	170	23749
h_{18}	455	430	130	130	25	0	0	0	0	0	8466	8446	2892	2861	945	0	0	0	0	0	0	23609
h_{19}	455	455	130	130	31	0	0	0	0	0	8466	8887	2892	2861	1061	0	0	0	0	0	0	24166
h_{20}	455	438	130	130	25	0	0	0	0	0	8466	8586	2892	2861	945	0	0	0	0	0	0	23749
h_{21}	455	380	130	130	25	0	0	0	0	0	8466	7570	2892	2861	945	0	0	0	0	0	0	22733
h_{22}	455	333	130	130	0	20	0	0	0	0	8466	6748	2892	2861	0	818	0	0	0	0	0	21785
h_{23}	455	399	0	130	0	20	0	0	0	0	8466	7903	0	2861	0	818	0	0	0	0	0	20047
h_{24}	455	354	0	130	0	20	0	0	0	0	8466	7115	0	2861	0	818	0	0	0	0	0	19260

Table 5.17: UCP for 10 Unit Test System considering the impact of COVID-19 **(Weekend)** with **OC, EL demand and Wind Power** using CBWO																						
Scheduling of 10 units											**Individual Fuel Cost**											
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	455	241	0	0	0	0	0	0	0	0	8466	5144	0	0	0	0	0	0	0	0	0	13610
h_2	455	237	0	0	0	0	0	0	0	0	8466	5075	0	0	0	0	0	0	0	0	0	13540
h_3	455	242	0	0	0	0	0	0	0	0	8466	5162	0	0	0	0	0	0	0	0	1170	13627
h_4	455	257	0	0	0	0	0	0	0	0	8466	5423	0	0	0	0	0	0	0	0	340	13889
h_5	455	274	0	0	0	0	0	0	0	0	8466	5719	0	0	0	0	0	0	0	0	900	14185
h_6	455	305	0	0	0	0	0	0	0	0	8466	6260	0	0	0	0	0	0	0	0	0	14725
h_7	455	356	0	0	0	0	0	0	0	0	8466	7150	0	0	0	0	0	0	0	0	60	15616
h_8	455	281	0	130	0	0	0	0	0	0	8466	5841	0	2861	0	0	0	0	0	0	0	17168
h_9	455	330	0	130	0	0	0	0	0	0	8466	6696	0	2861	0	0	0	0	0	0	0	18023
h_{10}	455	244	130	130	0	0	0	0	0	0	8466	5196	2892	2861	0	0	0	0	0	0	0	19415
h_{11}	455	294	130	130	0	0	0	0	0	0	8466	6068	2892	2861	0	0	0	0	0	0	60	20286
h_{12}	455	330	130	130	0	0	0	0	0	0	8466	6696	2892	2861	0	0	0	0	0	0	0	20914
h_{13}	455	330	130	130	0	0	0	0	0	0	8466	6696	2892	2861	0	0	0	0	0	0	550	20914
h_{14}	455	329	130	130	0	0	0	0	0	0	8466	6679	2892	2861	0	0	0	0	0	0	0	20897
h_{15}	455	334	130	130	0	0	0	0	0	0	8466	6766	2892	2861	0	0	0	0	0	0	0	20984
h_{16}	455	455	0	130	33	0	0	0	0	0	8466	8887	0	2861	1100	0	0	0	0	0	60	21314
h_{17}	455	455	0	130	55	0	0	10	0	0	8466	8887	0	2861	1542	0	0	920	0	0	0	22675
h_{18}	455	455	0	130	44	0	0	0	0	0	8466	8887	0	2861	1331	0	0	0	0	0	0	21544
h_{19}	455	437	0	130	25	0	0	0	0	0	8466	8575	0	2861	945	0	0	0	0	0	0	20847
h_{20}	455	385	0	130	25	0	0	0	0	0	8466	7658	0	2861	945	0	0	0	0	0	60	19929
h_{21}	455	455	0	0	37	0	0	0	0	0	8466	8887	0	0	1180	0	0	0	0	0	340	18534
h_{22}	455	402	0	0	25	0	0	0	0	0	8466	7955	0	0	945	0	0	0	0	0	0	17366
h_{23}	455	344	0	0	0	0	0	0	0	0	8466	6941	0	0	0	0	0	0	0	0	0	15406
h_{24}	455	279	0	0	0	0	0	0	0	0	8466	5806	0	0	0	0	0	0	0	0	0	14272

Table 5.18: UCP for 10 Unit Test System considering the impact of COVID-19 **(Weekday)** with **OC, EL demand and Wind Power** using CBWO

	Scheduling of 10 units										**Individual Fuel Cost**											
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**SUC**	**Hourly FC**
h_1	455	241	0	0	0	0	0	0	0	0	8466	5144	0	0	0	0	0	0	0	0	0	13610
h_2	455	231	0	0	0	0	0	0	0	0	8466	4970	0	0	0	0	0	0	0	0	0	13436
h_3	455	237	0	0	0	0	0	0	0	0	8466	5075	0	0	0	0	0	0	0	0	840	13540
h_4	455	259	0	0	0	0	0	0	0	0	8466	5458	0	0	0	0	0	0	0	0	560	13923
h_5	455	299	0	0	0	0	0	0	0	0	8466	6155	0	0	0	0	0	0	0	0	520	14621
h_6	455	363	0	0	0	0	0	0	0	0	8466	7273	0	0	0	0	0	0	0	0	60	15739
h_7	455	303	0	130	0	0	0	0	0	0	8466	6225	0	2861	0	0	0	0	0	0	0	17551
h_8	455	346	0	130	0	20	0	0	0	0	8466	6976	0	2861	0	818	0	0	0	0	0	19120
h_9	455	375	0	130	0	20	0	0	0	0	8466	7483	0	2861	0	818	0	0	0	0	0	19627
h_{10}	455	381	0	130	0	20	0	0	0	0	8466	7588	0	2861	0	818	0	0	0	0	0	19732
h_{11}	455	378	0	130	25	0	0	0	0	0	8466	7535	0	2861	945	0	0	0	0	0	0	19807
h_{12}	455	377	0	130	25	0	0	0	0	0	8466	7518	0	2861	945	0	0	0	0	0	260	19789
h_{13}	455	386	0	130	25	0	0	0	0	0	8466	7675	0	2861	945	0	0	0	0	0	0	19947
h_{14}	455	455	0	0	63	0	0	0	0	0	8466	8887	0	0	1703	0	0	0	0	0	0	19056
h_{15}	455	376	130	0	25	0	0	0	0	0	8466	7500	2892	0	945	0	0	0	0	0	0	19803
h_{16}	455	419	130	0	25	0	0	0	0	0	8466	8253	2892	0	945	0	0	0	0	0	0	20555
h_{17}	455	455	130	0	35	0	0	0	0	0	8466	8887	2892	0	1140	0	0	0	0	0	1800	21385
h_{18}	455	455	130	0	39	0	0	0	0	0	8466	8887	2892	0	1230	0	0	0	0	0	0	21475
h_{19}	455	361	130	130	25	0	0	0	0	0	8466	7245	2892	2861	945	0	0	0	0	0	60	22408
h_{20}	455	448	0	130	25	0	0	0	0	0	8466	8761	0	2861	945	0	0	0	0	0	0	21033
h_{21}	455	383	0	130	25	0	0	0	0	0	8466	7623	0	2861	945	0	0	0	0	0	0	19894
h_{22}	455	346	0	130	0	0	0	0	0	0	8466	6976	0	2861	0	0	0	0	0	0	0	18302
h_{23}	455	259	0	130	0	0	0	0	0	0	8466	5458	0	2861	0	0	0	0	0	0	0	16784
h_{24}	455	329	0	0	0	0	0	0	0	0	8466	6679	0	0	0	0	0	0	0	0	0	15144

Table 5.19: Statistical and hypothetical analysis of 10 Generating Unit System using CBWO Optimization Algorithm with different cases. (Weekend)

Test Case	Best	Mean	Worst	Std	Median	p-Value
UCP during covid-19 (FL)	434625.2	436447.5	438755.7	1113.967	436141.2	1.73E-06
UCP during covid-19 with wind power (FL)	372580.1	376388.8	381316	2615.44	375341.5	1.73E-06
UCP during covid-19 (PL)	450481.9	452159.3	454131.9	894.067	452078.4	1.73E-06
UCP during covid-19 with wind power (PL)	389680	392330	397880	2041.1	392090	1.73E-06
UCP with OC demand	455206.6	456685.2	459378.2	817.2608	456642	1.73E-06
UCP with EL demand	470227	471388.6	472767	605.1999	471217	1.73E-06
UCP with OC & EL demand	499741.2	501248	503471.5	804.9991	501226.7	1.73E-06
UCP with OC & EL with wind power	433221.3	435442	440763.2	1531.049	435206.3	1.73E-06

Table 5.20: Statistical and hypothetical analysis of 10 Generating Unit System using CBWO Optimization Algorithm with different cases. (Weekday)

Test Case	Best	Mean	Worst	Std	Median	p-value
UCP during covid-19 (FL)	441990.9	443469.3	445970.9	855.6401	443410.8	1.73E-06
UCP during covid-19 with wind power (FL)	378921.3	381093.9	385791.3	1315.072	381061.3	1.73E-06
UCP during covid-19 (PL)	468460.3	469344.7	470772.8	549.4721	469245.3	1.73E-06
UCP during covid-19 with wind power (PL)	405100	407290	409750	1251.3	407140	1.73E-06
UCP with OC demand	462563.9	464770.2	468721.6	1339.206	464526.6	1.73E-06
UCP with EL demand	484606.7	486260.8	487596.7	756.2914	486071.7	1.73E-06
UCP with OC & EL demand	508451.7	509898	512623.1	789.3267	509800.5	1.73E-06
UCP with OC & EL with wind power	440382.4	442432.3	444178.4	1036.38	442442.4	1.73E-06

5.6.2 System of 20 Generating Units

The effectiveness of proposed algorithm CBWO is tested and used to get the optimal result for UC problem considering the several constraints with 100 iteration and 30 trial runs. This part of chapter is illustrating the optimal results for 20 generating units and scheduling of units, individual cost of each unit. **Table 5.21 to 5.44** display the scheduling and fuel cost of each 20 units for all different cases. After incorporating wind power in system almost 13.4% of fuel cost was decreased during full lockdown and partial lockdown both.

Fuel cost is increased by using OC by 4% and 4.5% during weekend and weekday respectively and by using EL, cost increased by 9.3% and 9.5% during weekend and weekday. When both OC and EL used the fuel cost is increased by 13.5% and 14.2% during weekend and weekday respectively. Incorporating wind power is a wise decision and it decreased the fuel cost by 12.1% and 12.4% during weekend and weekday respectively when both OC and EL used. **Table 5.45 and 5.46** display the best, average and worst fuel cost of 20-unit system along with STD and median values for all cases. Wilcoxon rank t-test and p-test analyses is done to show the effectiveness.

Table 5.21: Scheduling a 20-unit system considering the impact of **COVID-19 FL (Weekend)** using CBWO																				
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_{11}**	**U_{12}**	**U_{13}**	**U_{14}**	**U_{15}**	**U_{16}**	**U_{17}**	**U_{18}**	**U_{19}**	**U_{20}**
h_1	455	293	0	0	0	0	0	0	0	0	455	293	0	0	0	0	0	0	0	0
h_2	455	283	0	0	0	0	0	0	0	0	455	283	0	0	0	0	0	0	0	0
h_3	455	275	0	0	0	0	0	0	0	0	455	275	0	0	0	0	0	0	0	0
h_4	455	277	0	0	0	0	0	0	0	0	455	277	0	0	0	0	0	0	0	0
h_5	455	291	0	0	0	0	0	0	0	0	455	291	0	0	0	0	0	0	0	0
h_6	455	317	0	0	0	0	0	0	0	0	455	317	0	0	0	0	0	0	0	0
h_7	455	351	0	0	0	0	0	0	0	0	455	351	0	0	0	0	0	0	0	0
h_8	455	330	0	130	0	0	0	0	0	0	455	330	0	0	0	0	0	0	0	0
h_9	455	321	0	130	0	0	0	0	0	0	455	321	0	130	0	0	0	0	0	0
h_{10}	455	300	0	130	0	0	0	0	0	0	455	300	130	130	0	0	0	0	0	0
h_{11}	455	351	0	130	0	0	0	0	0	0	455	351	130	130	0	0	0	0	0	0
h_{12}	455	320	130	130	0	0	0	0	0	0	455	320	130	130	0	0	0	0	0	0
h_{13}	455	319	130	130	0	0	0	0	0	0	455	319	130	130	0	0	0	0	0	0
h_{14}	455	313	130	130	0	0	0	0	0	0	455	313	130	130	0	0	0	0	0	0
h_{15}	455	423.5	130	0	25	20	0	0	0	0	455	423.5	0	130	0	0	0	0	0	0
h_{16}	455	439	130	0	25	20	0	0	0	0	455	439	0	130	25	0	0	0	0	0
h_{17}	455	455	130	0	33	20	0	0	0	0	455	455	0	130	33	0	0	0	0	0
h_{18}	455	440	130	0	25	0	0	0	0	0	455	440	0	130	25	0	0	0	0	0
h_{19}	455	455	0	0	47	0	0	0	0	0	455	455	0	130	47	0	0	0	0	0
h_{20}	455	445	0	0	25	0	0	0	0	0	455	445	0	130	25	0	0	0	0	0
h_{21}	455	416.5	0	130	0	0	0	0	0	0	455	416.5	0	0	25	0	0	0	0	0
h_{22}	455	364	0	130	0	20	0	0	0	0	455	364	0	0	0	0	0	0	0	0
h_{23}	455	304	0	130	0	20	0	0	0	0	455	304	0	0	0	0	0	0	0	0
h_{24}	455	351.5	130	130	0	20	0	0	0	0	0	351.5	130	0	0	0	0	0	0	0

Table 5.22: Individual fuel cost for Generation of 20 Unit Test System considering the impact of **COVID-19 FL (Weekday)** using CBWO																				
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_{11}**	**U_{12}**	**U_{13}**	**U_{14}**	**U_{15}**	**U_{16}**	**U_{17}**	**U_{18}**	**U_{19}**	**U_{20}**
h_1	8466	6054	0	0	0	0	0	0	0	0	8466	6054	0	0	0	0	0	0	0	0
h_2	8466	5879	0	0	0	0	0	0	0	0	8466	5879	0	0	0	0	0	0	0	0
h_3	8466	5740	0	0	0	0	0	0	0	0	8466	5740	0	0	0	0	0	0	0	0
h_4	8466	5775	0	0	0	0	0	0	0	0	8466	5775	0	0	0	0	0	0	0	0
h_5	8466	6019	0	0	0	0	0	0	0	0	8466	6019	0	0	0	0	0	0	0	0
h_6	8466	6473	0	0	0	0	0	0	0	0	8466	6473	0	0	0	0	0	0	0	0
h_7	8466	7066	0	0	0	0	0	0	0	0	8466	7066	0	0	0	0	0	0	0	0
h_8	8466	6700	0	2861	0	0	0	0	0	0	8466	6700	0	0	0	0	0	0	0	0
h_9	8466	6542	0	2861	0	0	0	0	0	0	8466	6542	0	2861	0	0	0	0	0	0
h_{10}	8466	6176	0	2861	0	0	0	0	0	0	8466	6176	2892	2861	0	0	0	0	0	0
h_{11}	8466	7066	0	2861	0	0	0	0	0	0	8466	7066	2892	2861	0	0	0	0	0	0
h_{12}	8466	6525	2892	2861	0	0	0	0	0	0	8466	6525	2892	2861	0	0	0	0	0	0
h_{13}	8466	6507	2892	2861	0	0	0	0	0	0	8466	6507	2892	2861	0	0	0	0	0	0
h_{14}	8466	6403	2892	2861	0	0	0	0	0	0	8466	6403	2892	2861	0	0	0	0	0	0
h_{15}	8466	8335	2892	0	945	818	0	0	0	0	8466	8335	0	2861	0	0	0	0	0	0
h_{16}	8466	8607	2892	0	945	818	0	0	0	0	8466	8607	0	2861	945	0	0	0	0	0
h_{17}	8466	8887	2892	0	1104	818	0	0	0	0	8466	8887	0	2861	1104	0	0	0	0	0
h_{18}	8466	8624	2892	0	945	0	0	0	0	0	8466	8624	0	2861	945	0	0	0	0	0
h_{19}	8466	8887	0	0	1385	0	0	0	0	0	8466	8887	0	2861	1385	0	0	0	0	0
h_{20}	8466	8712	0	0	945	0	0	0	0	0	8466	8712	0	2861	945	0	0	0	0	0
h_{21}	8466	8213	0	2861	0	0	0	0	0	0	8466	8213	0	0	945	0	0	0	0	0
h_{22}	8466	7294	0	2861	0	818	0	0	0	0	8466	7294	0	0	0	0	0	0	0	0
h_{23}	8466	6246	0	2861	0	818	0	0	0	0	8466	6246	0	0	0	0	0	0	0	0
h_{24}	8466	7075	2892	2861	0	818	0	0	0	0	0	7075	2892	0	0	0	0	0	0	0

Table 5.23: Scheduling a 20-unit system considering the impact of **COVID-19 PL (Weekend)** using CBWO																				
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_{11}**	**U_{12}**	**U_{13}**	**U_{14}**	**U_{15}**	**U_{16}**	**U_{17}**	**U_{18}**	**U_{19}**	**U_{20}**
h_1	455	293	0	0	0	0	0	0	0	0	455	293	0	0	0	0	0	0	0	0
h_2	455	277	0	0	0	0	0	0	0	0	455	277	0	0	0	0	0	0	0	0
h_3	455	270	0	0	0	0	0	0	0	0	455	270	0	0	0	0	0	0	0	0
h_4	455	279	0	0	0	0	0	0	0	0	455	279	0	0	0	0	0	0	0	0
h_5	455	316	0	0	0	0	0	0	0	0	455	316	0	0	0	0	0	0	0	0
h_6	455	310	0	130	0	0	0	0	0	0	455	310	0	0	0	0	0	0	0	0
h_7	455	363	0	130	0	0	0	0	0	0	455	363	0	0	0	0	0	0	0	0
h_8	455	350	0	130	0	0	0	0	0	0	455	350	0	130	0	0	0	0	0	0
h_9	455	321	130	130	0	0	0	0	0	0	455	321	0	130	0	0	0	0	0	0
h_{10}	455	327	130	130	0	0	0	0	0	0	455	327	0	130	0	0	0	0	0	0
h_{11}	455	330	130	0	0	0	0	0	0	0	455	330	130	130	0	0	0	0	0	0
h_{12}	455	327	130	0	0	0	0	0	0	0	455	327	130	130	0	0	0	0	0	0
h_{13}	455	387.5	130	0	25	0	0	0	0	0	455	387.5	130	0	0	0	0	0	0	0
h_{14}	455	359.5	130	0	25	0	0	0	0	0	455	359.5	130	0	0	0	0	0	0	0
h_{15}	455	370.5	130	0	25	0	0	0	0	0	455	370.5	130	0	0	0	0	0	0	0
h_{16}	455	352.5	130	130	25	0	0	0	0	0	455	352.5	130	0	0	0	0	0	0	0
h_{17}	455	390.5	130	130	25	0	0	0	0	0	455	390.5	130	0	0	0	0	0	0	0
h_{18}	455	382.5	130	130	25	0	0	0	0	0	455	382.5	0	130	0	0	0	0	0	0
h_{19}	455	413.5	130	130	25	0	0	0	0	0	455	413.5	0	130	0	0	0	0	0	0
h_{20}	455	390.5	130	130	25	0	0	0	0	0	455	390.5	0	130	0	0	0	0	0	0
h_{21}	455	345	130	130	0	0	0	0	0	0	455	345	0	130	0	0	0	0	0	0
h_{22}	455	358	0	130	0	0	0	0	0	0	455	358	0	130	0	0	0	0	0	0
h_{23}	455	411.5	0	0	0	0	0	0	0	0	455	411.5	0	0	25	0	0	0	0	0
h_{24}	455	366.5	0	0	0	0	0	0	0	0	455	366.5	0	0	25	0	0	0	0	0

Table 5.24: Individual fuel cost for Generation of 20 Unit Test System considering the impact of **COVID-19 PL (Weekday)** using CBWO

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	8466	6054	0	0	0	0	0	0	0	0	8466	6054	0	0	0	0	0	0	0	0
h_2	8466	5775	0	0	0	0	0	0	0	0	8466	5775	0	0	0	0	0	0	0	0
h_3	8466	5653	0	0	0	0	0	0	0	0	8466	5653	0	0	0	0	0	0	0	0
h_4	8466	5810	0	0	0	0	0	0	0	0	8466	5810	0	0	0	0	0	0	0	0
h_5	8466	6455	0	0	0	0	0	0	0	0	8466	6455	0	0	0	0	0	0	0	0
h_6	8466	6350	0	2861	0	0	0	0	0	0	8466	6350	0	0	0	0	0	0	0	0
h_7	8466	7276	0	2861	0	0	0	0	0	0	8466	7276	0	0	0	0	0	0	0	0
h_8	8466	7049	0	2861	0	0	0	0	0	0	8466	7049	0	2861	0	0	0	0	0	0
h_9	8466	6542	2892	2861	0	0	0	0	0	0	8466	6542	0	2861	0	0	0	0	0	0
h_{10}	8466	6647	2892	2861	0	0	0	0	0	0	8466	6647	0	2861	0	0	0	0	0	0
h_{11}	8466	6700	2892	0	0	0	0	0	0	0	8466	6700	2892	2861	0	0	0	0	0	0
h_{12}	8466	6647	2892	0	0	0	0	0	0	0	8466	6647	2892	2861	0	0	0	0	0	0
h_{13}	8466	7705	2892	0	945	0	0	0	0	0	8466	7705	2892	0	0	0	0	0	0	0
h_{14}	8466	7215	2892	0	945	0	0	0	0	0	8466	7215	2892	0	0	0	0	0	0	0
h_{15}	8466	7407	2892	0	945	0	0	0	0	0	8466	7407	2892	0	0	0	0	0	0	0
h_{16}	8466	7093	2892	2861	945	0	0	0	0	0	8466	7093	2892	0	0	0	0	0	0	0
h_{17}	8466	7757	2892	2861	945	0	0	0	0	0	8466	7757	2892	0	0	0	0	0	0	0
h_{18}	8466	7617	2892	2861	945	0	0	0	0	0	8466	7617	0	2861	0	0	0	0	0	0
h_{19}	8466	8160	2892	2861	945	0	0	0	0	0	8466	8160	0	2861	0	0	0	0	0	0
h_{20}	8466	7757	2892	2861	945	0	0	0	0	0	8466	7757	0	2861	0	0	0	0	0	0
h_{21}	8466	6962	2892	2861	0	0	0	0	0	0	8466	6962	0	2861	0	0	0	0	0	0
h_{22}	8466	7189	0	2861	0	0	0	0	0	0	8466	7189	0	2861	0	0	0	0	0	0
h_{23}	8466	8125	0	0	0	0	0	0	0	0	8466	8125	0	0	945	0	0	0	0	0
h_{24}	8466	7337	0	0	0	0	0	0	0	0	8466	7337	0	0	945	0	0	0	0	0

Table 5.25: Scheduling a 20-unit system considering the impact of **COVID-19 (Weekend) with wind power** using CBWO																				
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_{11}**	**U_{12}**	**U_{13}**	**U_{14}**	**U_{15}**	**U_{16}**	**U_{17}**	**U_{18}**	**U_{19}**	**U_{20}**
h_1	455	232	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0
h_2	455	224	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0
h_3	455	234	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0
h_4	455	264	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0
h_5	455	298	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0
h_6	455	230	0	130	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0
h_7	455	202	0	130	0	0	0	0	0	0	455	0	0	130	0	0	0	0	0	0
h_8	455	182	0	130	0	0	0	0	0	0	455	0	130	130	0	0	0	0	0	0
h_9	455	280	0	130	0	0	0	0	0	0	455	0	130	130	0	0	0	0	0	0
h_{10}	455	184	0	130	0	0	0	0	0	0	455	184	130	130	0	0	0	0	0	0
h_{11}	455	299	0	0	0	0	0	0	0	0	455	299	130	130	0	0	0	0	0	0
h_{12}	455	335	0	0	0	0	0	0	0	0	455	335	130	130	0	0	0	0	0	0
h_{13}	455	335	130	0	0	0	0	0	0	0	455	335	0	130	0	0	0	0	0	0
h_{14}	455	334	130	0	0	0	0	0	0	0	455	334	0	130	0	0	0	0	0	0
h_{15}	455	339	130	0	0	0	0	0	0	0	455	339	0	130	0	0	0	0	0	0
h_{16}	455	350.5	130	0	25	0	0	0	0	0	455	350.5	0	130	0	0	0	0	0	0
h_{17}	455	382.5	130	130	25	0	0	0	0	0	455	382.5	0	0	0	0	0	0	0	0
h_{18}	455	427	0	130	25	0	0	0	0	0	455	427	0	0	0	0	0	0	0	0
h_{19}	455	389.9	0	130	25	0	0	0	0	0	455	389.9	0	0	0	0	0	0	0	0
h_{20}	455	337.5	0	130	25	0	0	0	0	0	455	337.5	0	0	0	0	0	0	0	0
h_{21}	455	289.5	0	130	25	0	0	0	0	0	455	289.5	0	0	0	0	0	0	0	0
h_{22}	455	302	0	0	0	0	0	0	0	0	455	302	0	0	0	0	0	0	0	0
h_{23}	455	219	0	0	0	0	0	0	0	0	455	219	0	0	0	0	0	0	0	0
h_{24}	455	381.5	0	0	0	0	0	0	0	0	0	381.5	0	0	0	0	0	0	0	0

Table 5.26: Individual fuel cost for 20 Unit system considering the impact of COVID-19 (Weekend) with wind power using CBWO																				
Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	8466	4991	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0
h_2	8466	4852	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0
h_3	8466	5026	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0
h_4	8466	5548	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0
h_5	8466	6141	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0
h_6	8466	4956	0	2861	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0
h_7	8466	4469	0	2861	0	0	0	0	0	0	8466	0	0	2861	0	0	0	0	0	0
h_8	8466	4122	0	2861	0	0	0	0	0	0	8466	0	2892	2861	0	0	0	0	0	0
h_9	8466	5827	0	2861	0	0	0	0	0	0	8466	0	2892	2861	0	0	0	0	0	0
h_{10}	8466	4156	0	2861	0	0	0	0	0	0	8466	4156	2892	2861	0	0	0	0	0	0
h_{11}	8466	6158	0	0	0	0	0	0	0	0	8466	6158	2892	2861	0	0	0	0	0	0
h_{12}	8466	6787	0	0	0	0	0	0	0	0	8466	6787	2892	2861	0	0	0	0	0	0
h_{13}	8466	6787	2892	0	0	0	0	0	0	0	8466	6787	0	2861	0	0	0	0	0	0
h_{14}	8466	6769	2892	0	0	0	0	0	0	0	8466	6769	0	2861	0	0	0	0	0	0
h_{15}	8466	6857	2892	0	0	0	0	0	0	0	8466	6857	0	2861	0	0	0	0	0	0
h_{16}	8466	7058	2892	0	945	0	0	0	0	0	8466	7058	0	2861	0	0	0	0	0	0
h_{17}	8466	7617	2892	2861	945	0	0	0	0	0	8466	7617	0	0	0	0	0	0	0	0
h_{18}	8466	8397	0	2861	945	0	0	0	0	0	8466	8397	0	0	0	0	0	0	0	0
h_{19}	8466	7747	0	2861	945	0	0	0	0	0	8466	7747	0	0	0	0	0	0	0	0
h_{20}	8466	6831	0	2861	945	0	0	0	0	0	8466	6831	0	0	0	0	0	0	0	0
h_{21}	8466	5993	0	2861	945	0	0	0	0	0	8466	5993	0	0	0	0	0	0	0	0
h_{22}	8466	6211	0	0	0	0	0	0	0	0	8466	6211	0	0	0	0	0	0	0	0
h_{23}	8466	4765	0	0	0	0	0	0	0	0	8466	4765	0	0	0	0	0	0	0	0
h_{24}	8466	7600	0	0	0	0	0	0	0	0	0	7600	0	0	0	0	0	0	0	0

Table 5.27: Scheduling a 20-unit system considering the impact of COVID-19 (Weekday) with wind power using CBWO																				
Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	455	232	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0
h_2	455	212	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0
h_3	455	224	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0
h_4	455	268	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0
h_5	455	218	0	130	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0
h_6	455	216	0	130	0	0	0	0	0	0	455	0	0	130	0	0	0	0	0	0
h_7	455	226	130	130	0	0	0	0	0	0	455	0	0	130	0	0	0	0	0	0
h_8	455	222	130	130	0	0	0	0	0	0	455	0	130	130	0	0	0	0	0	0
h_9	455	280	130	130	0	0	0	0	0	0	455	0	130	130	0	0	0	0	0	0
h_{10}	455	211	130	0	0	0	0	0	0	0	455	211	130	130	0	0	0	0	0	0
h_{11}	455	278	130	0	0	0	0	0	0	0	455	278	130	0	0	0	0	0	0	0
h_{12}	455	342	0	0	0	0	0	0	0	0	455	342	130	0	0	0	0	0	0	0
h_{13}	455	403.5	0	0	25	0	0	0	0	0	455	403.5	0	0	0	0	0	0	0	0
h_{14}	455	380.5	0	0	25	0	0	0	0	0	455	380.5	0	0	0	0	0	0	0	0
h_{15}	455	393.5	0	0	25	0	0	0	0	0	455	393.5	0	0	0	0	0	0	0	0
h_{16}	455	371.5	0	130	25	0	0	0	0	0	455	371.5	0	0	0	0	0	0	0	0
h_{17}	455	417.5	0	130	25	0	0	0	0	0	455	417.5	0	0	0	0	0	0	0	0
h_{18}	455	422	0	130	25	0	0	0	0	0	455	422	0	0	0	0	0	0	0	0
h_{19}	455	326.4	130	130	0	0	0	0	0	0	455	326.4	0	130	0	0	0	0	0	0
h_{20}	455	283	130	130	0	0	0	0	0	0	455	283	0	130	0	0	0	0	0	0
h_{21}	455	283	130	0	0	0	0	0	0	0	455	283	0	130	0	0	0	0	0	0
h_{22}	455	0	130	0	0	0	0	0	0	0	455	287	130	130	25	0	0	0	0	0
h_{23}	455	0	111.709	0	0	0	0	0	0	0	455	150	111.709	129.582	25	0	0	0	0	0
h_{24}	455	0	0	0	0	20	0	0	0	0	455	0	130	130	108	20	0	0	0	0

Table 5.28: Individual fuel cost of 20 Unit Test System considering the impact of **COVID-19 (Weekday) with wind power** using CBWO																				
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_{11}**	**U_{12}**	**U_{13}**	**U_{14}**	**U_{15}**	**U_{16}**	**U_{17}**	**U_{18}**	**U_{19}**	**U_{20}**
h_1	8466	4991	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0
h_2	8466	4643	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0
h_3	8466	4852	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0
h_4	8466	5618	0	0	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0
h_5	8466	4747	0	2861	0	0	0	0	0	0	8466	0	0	0	0	0	0	0	0	0
h_6	8466	4713	0	2861	0	0	0	0	0	0	8466	0	0	2861	0	0	0	0	0	0
h_7	8466	4887	2892	2861	0	0	0	0	0	0	8466	0	0	2861	0	0	0	0	0	0
h_8	8466	4817	2892	2861	0	0	0	0	0	0	8466	0	2892	2861	0	0	0	0	0	0
h_9	8466	5827	2892	2861	0	0	0	0	0	0	8466	0	2892	2861	0	0	0	0	0	0
h_{10}	8466	4626	2892	0	0	0	0	0	0	0	8466	4626	2892	2861	0	0	0	0	0	0
h_{11}	8466	5792	2892	0	0	0	0	0	0	0	8466	5792	2892	0	0	0	0	0	0	0
h_{12}	8466	6909	0	0	0	0	0	0	0	0	8466	6909	2892	0	0	0	0	0	0	0
h_{13}	8466	7985	0	0	945	0	0	0	0	0	8466	7985	0	0	0	0	0	0	0	0
h_{14}	8466	7582	0	0	945	0	0	0	0	0	8466	7582	0	0	0	0	0	0	0	0
h_{15}	8466	7810	0	0	945	0	0	0	0	0	8466	7810	0	0	0	0	0	0	0	0
h_{16}	8466	7425	0	2861	945	0	0	0	0	0	8466	7425	0	0	0	0	0	0	0	0
h_{17}	8466	8230	0	2861	945	0	0	0	0	0	8466	8230	0	0	0	0	0	0	0	0
h_{18}	8466	8309	0	2861	945	0	0	0	0	0	8466	8309	0	0	0	0	0	0	0	0
h_{19}	8466	6637	2892	2861	0	0	0	0	0	0	8466	6637	0	2861	0	0	0	0	0	0
h_{20}	8466	5879	2892	2861	0	0	0	0	0	0	8466	5879	0	2861	0	0	0	0	0	0
h_{21}	8466	5879	2892	0	0	0	0	0	0	0	8466	5879	0	2861	0	0	0	0	0	0
h_{22}	8466	0	2892	0	0	0	0	0	0	0	8466	5949	2892	2861	945	0	0	0	0	0
h_{23}	8466	0	2579	0	0	0	0	0	0	0	8466	3566	2579	2854	945	0	0	0	0	0
h_{24}	8466	0	0	0	0	818	0	0	0	0	8466	0	2892	2861	2624	818	0	0	0	0

Table 5.29: Scheduling a 20-unit system considering the impact of **COVID-19 (Weekend) with OC demand** using CBWO																				
Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	455	333	0	0	0	0	0	0	0	0	455	333	0	0	0	0	0	0	0	0
h_2	455	323	0	0	0	0	0	0	0	0	455	323	0	0	0	0	0	0	0	0
h_3	455	315	0	0	0	0	0	0	0	0	455	315	0	0	0	0	0	0	0	0
h_4	455	317	0	0	0	0	0	0	0	0	455	317	0	0	0	0	0	0	0	0
h_5	455	331	0	0	0	0	0	0	0	0	455	331	0	0	0	0	0	0	0	0
h_6	455	357	0	0	0	0	0	0	0	0	455	357	0	0	0	0	0	0	0	0
h_7	455	326	0	130	0	0	0	0	0	0	455	326	0	0	0	0	0	0	0	0
h_8	455	305	0	130	0	0	0	0	0	0	455	305	0	130	0	0	0	0	0	0
h_9	455	296	130	130	0	0	0	0	0	0	455	296	0	130	0	0	0	0	0	0
h_{10}	455	340	130	130	0	0	0	0	0	0	455	340	0	130	0	0	0	0	0	0
h_{11}	455	326	130	130	0	0	0	0	0	0	455	326	130	130	0	0	0	0	0	0
h_{12}	455	347.5	130	130	25	0	0	0	0	0	455	347.5	130	130	0	0	0	0	0	0
h_{13}	455	346.5	130	130	25	0	0	0	0	0	455	346.5	130	130	0	0	0	0	0	0
h_{14}	455	405.5	0	130	25	0	0	0	0	0	455	405.5	130	130	0	0	0	0	0	0
h_{15}	455	408.5	0	130	25	0	0	0	0	0	455	408.5	130	130	0	0	0	0	0	0
h_{16}	455	424	0	130	25	0	0	0	0	0	455	424	130	130	25	0	0	0	0	0
h_{17}	455	448	0	130	25	0	0	0	0	0	455	448	130	130	25	0	0	0	0	0
h_{18}	455	455	0	0	50	0	0	0	0	0	455	455	130	130	50	0	0	0	0	0
h_{19}	455	452	130	0	25	0	0	0	0	0	455	452	130	0	25	0	0	0	0	0
h_{20}	455	420	130	0	25	0	0	0	0	0	455	420	130	0	25	0	0	0	0	0
h_{21}	455	446.5	130	0	0	20	0	0	0	0	455	446.5	0	0	25	0	0	0	0	0
h_{22}	455	394	130	0	0	20	0	0	0	0	455	394	0	0	0	20	0	0	0	0
h_{23}	455	334	130	0	0	20	0	0	0	0	455	334	0	0	0	20	0	0	0	0
h_{24}	455	359	0	0	0	0	0	0	0	0	455	359	0	0	0	20	0	0	0	0

Table 5.30: Individual fuel cost of 20 Unit Test System considering the impact of **COVID-19 (Weekend) with OC demand** using CBWO

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	8466	6752	0	0	0	0	0	0	0	0	8466	6752	0	0	0	0	0	0	0	0
h_2	8466	6577	0	0	0	0	0	0	0	0	8466	6577	0	0	0	0	0	0	0	0
h_3	8466	6438	0	0	0	0	0	0	0	0	8466	6438	0	0	0	0	0	0	0	0
h_4	8466	6473	0	0	0	0	0	0	0	0	8466	6473	0	0	0	0	0	0	0	0
h_5	8466	6717	0	0	0	0	0	0	0	0	8466	6717	0	0	0	0	0	0	0	0
h_6	8466	7171	0	0	0	0	0	0	0	0	8466	7171	0	0	0	0	0	0	0	0
h_7	8466	6630	0	2861	0	0	0	0	0	0	8466	6630	0	0	0	0	0	0	0	0
h_8	8466	6263	0	2861	0	0	0	0	0	0	8466	6263	0	2861	0	0	0	0	0	0
h_9	8466	6106	2892	2861	0	0	0	0	0	0	8466	6106	0	2861	0	0	0	0	0	0
h_{10}	8466	6874	2892	2861	0	0	0	0	0	0	8466	6874	0	2861	0	0	0	0	0	0
h_{11}	8466	6630	2892	2861	0	0	0	0	0	0	8466	6630	2892	2861	0	0	0	0	0	0
h_{12}	8466	7005	2892	2861	945	0	0	0	0	0	8466	7005	2892	2861	0	0	0	0	0	0
h_{13}	8466	6988	2892	2861	945	0	0	0	0	0	8466	6988	2892	2861	0	0	0	0	0	0
h_{14}	8466	8020	0	2861	945	0	0	0	0	0	8466	8020	2892	2861	0	0	0	0	0	0
h_{15}	8466	8072	0	2861	945	0	0	0	0	0	8466	8072	2892	2861	0	0	0	0	0	0
h_{16}	8466	8344	0	2861	945	0	0	0	0	0	8466	8344	2892	2861	945	0	0	0	0	0
h_{17}	8466	8765	0	2861	945	0	0	0	0	0	8466	8765	2892	2861	945	0	0	0	0	0
h_{18}	8466	8887	0	0	1445	0	0	0	0	0	8466	8887	2892	2861	1445	0	0	0	0	0
h_{19}	8466	8835	2892	0	945	0	0	0	0	0	8466	8835	2892	0	945	0	0	0	0	0
h_{20}	8466	8274	2892	0	945	0	0	0	0	0	8466	8274	2892	0	945	0	0	0	0	0
h_{21}	8466	8738	2892	0	0	818	0	0	0	0	8466	8738	0	0	945	0	0	0	0	0
h_{22}	8466	7819	2892	0	0	818	0	0	0	0	8466	7819	0	0	0	818	0	0	0	0
h_{23}	8466	6769	2892	0	0	818	0	0	0	0	8466	6769	0	0	0	818	0	0	0	0
h_{24}	8466	7626	0	0	0	818	0	0	0	0	8466	7626	2892	0	0	0	0	0	0	0

Table 5.31: Scheduling a 20-unit system considering the impact of **COVID-19 (Weekday) with OC demand** using CBWO

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	455	333	0	0	0	0	0	0	0	0	455	333	0	0	0	0	0	0	0	0
h_2	455	317	0	0	0	0	0	0	0	0	455	317	0	0	0	0	0	0	0	0
h_3	455	310	0	0	0	0	0	0	0	0	455	310	0	0	0	0	0	0	0	0
h_4	455	319	0	0	0	0	0	0	0	0	455	319	0	0	0	0	0	0	0	0
h_5	455	356	0	0	0	0	0	0	0	0	455	356	0	0	0	0	0	0	0	0
h_6	455	350	130	0	0	0	0	0	0	0	455	350	0	0	0	0	0	0	0	0
h_7	455	338	130	0	0	0	0	0	0	0	455	338	0	130	0	0	0	0	0	0
h_8	455	325	130	130	0	0	0	0	0	0	455	325	0	130	0	0	0	0	0	0
h_9	455	296	130	130	0	0	0	0	0	0	455	296	130	130	0	0	0	0	0	0
h_{10}	455	302	130	130	0	0	0	0	0	0	455	302	130	130	0	0	0	0	0	0
h_{11}	455	270	130	130	25	0	0	0	0	0	455	270	130	130	25	20	0	0	0	0
h_{12}	455	397	0	130	25	0	0	0	0	0	455	397	130	0	25	20	0	0	0	0
h_{13}	455	455	0	0	40	0	0	0	0	0	455	455	130	0	40	20	0	0	0	0
h_{14}	455	452	0	0	25	0	0	0	0	0	455	452	130	0	25	0	0	0	0	0
h_{15}	455	455	0	0	33	0	0	0	0	0	455	455	130	0	33	0	0	0	0	0
h_{16}	455	455	0	0	67.5	0	25	0	0	0	455	455	130	0	67.5	0	0	0	0	0
h_{17}	455	455	0	0	40.5	0	25	0	0	0	455	455	130	130	40.5	0	0	0	0	0
h_{18}	455	410	130	130	25	0	25	0	0	0	455	410	0	130	0	0	0	0	0	0
h_{19}	455	433.5	130	130	25	20	0	0	0	0	455	433.5	0	130	0	20	0	0	0	0
h_{20}	455	410.5	130	130	25	20	0	0	0	0	455	410.5	0	130	0	20	0	0	0	0
h_{21}	455	365	130	130	0	20	0	0	0	0	455	365	0	130	0	20	0	0	0	0
h_{22}	455	333	130	130	0	0	0	0	0	0	455	333	0	130	0	0	0	0	0	0
h_{23}	455	334	0	130	0	0	0	0	0	0	455	334	0	130	0	0	0	0	0	0
h_{24}	455	406.5	0	0	0	0	0	0	0	0	455	406.5	0	0	25	0	0	0	0	0

Table 5.32: Individual fuel cost of 20 Unit Test System considering the impact of **COVID-19 (Weekday) with OC demand** using CBWO

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	8466	6752	0	0	0	0	0	0	0	0	8466	6752	0	0	0	0	0	0	0	0
h_2	8466	6473	0	0	0	0	0	0	0	0	8466	6473	0	0	0	0	0	0	0	0
h_3	8466	6350	0	0	0	0	0	0	0	0	8466	6350	0	0	0	0	0	0	0	0
h_4	8466	6507	0	0	0	0	0	0	0	0	8466	6507	0	0	0	0	0	0	0	0
h_5	8466	7154	0	0	0	0	0	0	0	0	8466	7154	0	0	0	0	0	0	0	0
h_6	8466	7049	2892	0	0	0	0	0	0	0	8466	7049	0	0	0	0	0	0	0	0
h_7	8466	6839	2892	0	0	0	0	0	0	0	8466	6839	0	2861	0	0	0	0	0	0
h_8	8466	6612	2892	2861	0	0	0	0	0	0	8466	6612	0	2861	0	0	0	0	0	0
h_9	8466	6106	2892	2861	0	0	0	0	0	0	8466	6106	2892	2861	0	0	0	0	0	0
h_{10}	8466	6211	2892	2861	0	0	0	0	0	0	8466	6211	2892	2861	0	0	0	0	0	0
h_{11}	8466	5653	2892	2861	945	0	0	0	0	0	8466	5653	2892	2861	945	818	0	0	0	0
h_{12}	8466	7871	0	2861	945	0	0	0	0	0	8466	7871	2892	0	945	818	0	0	0	0
h_{13}	8466	8887	0	0	1244	0	0	0	0	0	8466	8887	2892	0	1244	818	0	0	0	0
h_{14}	8466	8835	0	0	945	0	0	0	0	0	8466	8835	2892	0	945	0	0	0	0	0
h_{15}	8466	8887	0	0	1104	0	0	0	0	0	8466	8887	2892	0	1104	0	0	0	0	0
h_{16}	8466	8887	0	0	1798	0	1174	0	0	0	8466	8887	2892	0	1798	0	0	0	0	0
h_{17}	8466	8887	0	0	1254	0	1174	0	0	0	8466	8887	2892	2861	1254	0	0	0	0	0
h_{18}	8466	8099	2892	2861	945	0	1174	0	0	0	8466	8099	0	2861	0	0	0	0	0	0
h_{19}	8466	8510	2892	2861	945	818	0	0	0	0	8466	8510	0	2861	0	818	0	0	0	0
h_{20}	8466	8107	2892	2861	945	818	0	0	0	0	8466	8107	0	2861	0	818	0	0	0	0
h_{21}	8466	7311	2892	2861	0	818	0	0	0	0	8466	7311	0	2861	0	818	0	0	0	0
h_{22}	8466	6752	2892	2861	0	0	0	0	0	0	8466	6752	0	2861	0	0	0	0	0	0
h_{23}	8466	6769	0	2861	0	0	0	0	0	0	8466	6769	0	2861	0	0	0	0	0	0
h_{24}	8466	8037	0	0	0	0	0	0	0	0	8466	8037	0	0	945	0	0	0	0	0

Table 5.33: Scheduling a 20-unit system considering the impact of **COVID-19 (Weekend) with EL demand** using CBWO																				
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_{11}**	**U_{12}**	**U_{13}**	**U_{14}**	**U_{15}**	**U_{16}**	**U_{17}**	**U_{18}**	**U_{19}**	**U_{20}**
h_1	455	312.8	0	130	0	0	0	0	0	0	455	312.8	0	0	0	0	0	0	0	0
h_2	455	302.8	0	130	0	0	0	0	0	0	455	302.8	0	0	0	0	0	0	0	0
h_3	455	294.8	0	130	0	0	0	0	0	0	455	294.8	0	0	0	0	0	0	0	0
h_4	455	296.8	0	130	0	0	0	0	0	0	455	296.8	0	0	0	0	0	0	0	0
h_5	455	310.8	0	130	0	0	0	0	0	0	455	310.8	0	0	0	0	0	0	0	0
h_6	455	336.8	0	130	0	0	0	0	0	0	455	336.8	0	0	0	0	0	0	0	0
h_7	455	305.8	130	0	0	0	0	0	0	0	455	305.8	0	130	0	0	0	0	0	0
h_8	455	349.8	130	0	0	0	0	0	0	0	455	349.8	0	130	0	0	0	0	0	0
h_9	455	340.8	130	0	0	0	0	0	0	0	455	340.8	130	130	0	0	0	0	0	0
h_{10}	455	372.3	130	0	25	0	0	0	0	0	455	372.3	130	130	0	0	0	0	0	0
h_{11}	455	410.8	130	0	25	0	0	0	0	0	455	410.8	130	130	25	0	0	0	0	0
h_{12}	455	444.8	0	130	25	0	0	0	0	0	455	444.8	130	130	25	0	0	0	0	0
h_{13}	455	433.8	0	130	25	20	0	0	0	0	455	433.8	130	130	25	0	0	0	0	0
h_{14}	455	427.8	0	130	25	20	0	0	0	0	455	427.8	130	130	25	0	0	0	0	0
h_{15}	455	430.8	0	130	25	20	0	0	0	0	455	430.8	130	130	25	0	0	0	0	0
h_{16}	455	455	0	130	38.8	0	0	0	0	0	455	455	130	130	38.8	0	0	0	0	0
h_{17}	455	427.8	130	130	25	0	0	0	0	0	455	427.8	130	130	25	0	0	0	0	0
h_{18}	455	407.3	130	130	25	0	0	0	0	0	455	407.3	130	130	0	0	0	0	0	0
h_{19}	455	434.3	130	0	25	20	0	0	0	0	455	434.3	130	130	0	0	0	0	0	0
h_{20}	455	402.3	130	0	25	20	0	0	0	0	455	402.3	130	130	0	0	0	0	0	0
h_{21}	455	373.8	130	0	0	20	0	0	0	0	455	373.8	130	130	0	0	0	0	0	0
h_{22}	455	328.8	130	0	0	0	0	0	0	0	455	328.8	130	130	0	0	0	0	0	0
h_{23}	455	388.8	0	0	0	0	0	0	0	0	455	388.8	130	0	0	20	0	0	0	0
h_{24}	455	338.8	0	130	0	0	0	0	0	0	455	338.8	0	0	0	20	0	0	0	0

Table 5.34: Individual fuel cost of 20 Unit Test System considering the impact of **COVID-19 (Weekend) with EL demand** using CBWO

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	8466	6399	0	2861	0	0	0	0	0	0	8466	6399	0	0	0	0	0	0	0	0
h_2	8466	6225	0	2861	0	0	0	0	0	0	8466	6225	0	0	0	0	0	0	0	0
h_3	8466	6085	0	2861	0	0	0	0	0	0	8466	6085	0	0	0	0	0	0	0	0
h_4	8466	6120	0	2861	0	0	0	0	0	0	8466	6120	0	0	0	0	0	0	0	0
h_5	8466	6364	0	2861	0	0	0	0	0	0	8466	6364	0	0	0	0	0	0	0	0
h_6	8466	6818	0	2861	0	0	0	0	0	0	8466	6818	0	0	0	0	0	0	0	0
h_7	8466	6277	2892	0	0	0	0	0	0	0	8466	6277	0	2861	0	0	0	0	0	0
h_8	8466	7045	2892	0	0	0	0	0	0	0	8466	7045	0	2861	0	0	0	0	0	0
h_9	8466	6888	2892	0	0	0	0	0	0	0	8466	6888	2892	2861	0	0	0	0	0	0
h_{10}	8466	7439	2892	0	945	0	0	0	0	0	8466	7439	2892	2861	0	0	0	0	0	0
h_{11}	8466	8113	2892	0	945	0	0	0	0	0	8466	8113	2892	2861	945	0	0	0	0	0
h_{12}	8466	8709	0	2861	945	0	0	0	0	0	8466	8709	2892	2861	945	0	0	0	0	0
h_{13}	8466	8516	0	2861	945	818	0	0	0	0	8466	8516	2892	2861	945	0	0	0	0	0
h_{14}	8466	8411	0	2861	945	818	0	0	0	0	8466	8411	2892	2861	945	0	0	0	0	0
h_{15}	8466	8463	0	2861	945	818	0	0	0	0	8466	8463	2892	2861	945	0	0	0	0	0
h_{16}	8466	8887	0	2861	1220	0	0	0	0	0	8466	8887	2892	2861	1220	0	0	0	0	0
h_{17}	8466	8411	2892	2861	945	0	0	0	0	0	8466	8411	2892	2861	945	0	0	0	0	0
h_{18}	8466	8051	2892	2861	945	0	0	0	0	0	8466	8051	2892	2861	0	0	0	0	0	0
h_{19}	8466	8524	2892	0	945	818	0	0	0	0	8466	8524	2892	2861	0	0	0	0	0	0
h_{20}	8466	7964	2892	0	945	818	0	0	0	0	8466	7964	2892	2861	0	0	0	0	0	0
h_{21}	8466	7465	2892	0	0	818	0	0	0	0	8466	7465	2892	2861	0	0	0	0	0	0
h_{22}	8466	6679	2892	0	0	0	0	0	0	0	8466	6679	2892	2861	0	0	0	0	0	0
h_{23}	8466	7728	0	0	0	0	0	0	0	0	8466	7728	2892	0	0	818	0	0	0	0
h_{24}	8466	6853	0	2861	0	0	0	0	0	0	8466	6853	0	0	0	818	0	0	0	0

Table 5.35: Scheduling a 20-unit system considering the impact of **COVID-19 (Weekday) with EL demand** using CBWO																				
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_{11}**	**U_{12}**	**U_{13}**	**U_{14}**	**U_{15}**	**U_{16}**	**U_{17}**	**U_{18}**	**U_{19}**	**U_{20}**
h_1	455	312.8	0	0	0	0	0	0	0	0	455	312.8	0	130	0	0	0	0	0	0
h_2	455	296.8	0	0	0	0	0	0	0	0	455	296.8	0	130	0	0	0	0	0	0
h_3	455	289.8	0	0	0	0	0	0	0	0	455	289.8	0	130	0	0	0	0	0	0
h_4	455	298.8	0	0	0	0	0	0	0	0	455	298.8	0	130	0	0	0	0	0	0
h_5	455	335.8	0	0	0	0	0	0	0	0	455	335.8	0	130	0	0	0	0	0	0
h_6	455	329.8	0	130	0	0	0	0	0	0	455	329.8	0	130	0	0	0	0	0	0
h_7	455	317.8	130	130	0	0	0	0	0	0	455	317.8	0	130	0	0	0	0	0	0
h_8	455	304.8	130	130	0	0	0	0	0	0	455	304.8	130	130	0	0	0	0	0	0
h_9	455	340.8	130	130	0	0	0	0	0	0	455	340.8	130	130	0	0	0	0	0	0
h_{10}	455	346.8	130	130	0	0	0	0	0	0	455	346.8	130	130	0	0	0	0	0	0
h_{11}	455	402.3	130	130	25	0	0	0	0	0	455	402.3	130	0	0	0	0	0	0	0
h_{12}	455	451.8	130	0	25	0	0	0	0	0	455	451.8	130	0	25	0	0	0	0	0
h_{13}	455	455	130	0	29.8	0	0	0	0	0	455	455	130	0	29.8	0	0	0	0	0
h_{14}	455	431.8	130	0	25	0	0	0	0	0	455	431.8	130	0	25	0	0	0	0	0
h_{15}	455	442.8	130	0	25	0	0	0	0	0	455	442.8	130	0	25	0	0	0	0	0
h_{16}	455	424.8	130	0	25	0	0	0	0	0	455	424.8	130	130	25	0	0	0	0	0
h_{17}	455	455	130	130	32.8	0	0	0	0	0	455	455	0	130	32.8	0	0	0	0	0
h_{18}	455	454.8	130	130	25	0	0	0	0	0	455	454.8	0	130	25	0	0	0	0	0
h_{19}	455	455	130	130	45.8	20	0	0	0	0	455	455	0	130	45.8	0	0	0	0	0
h_{20}	455	452.8	130	130	25	20	0	0	0	0	455	452.8	0	130	25	0	0	0	0	0
h_{21}	455	407.3	130	130	25	20	0	0	0	0	455	407.3	0	130	0	0	0	0	0	0
h_{22}	455	365.3	0	130	25	0	0	0	0	0	455	365.3	130	130	0	0	0	0	0	0
h_{23}	455	366.3	0	0	25	0	0	0	0	0	455	366.3	130	130	0	0	0	0	0	0
h_{24}	455	333.8	0	0	0	0	0	0	0	0	455	333.8	130	130	0	0	0	0	0	0

Table 5.36: Individual fuel cost of 20 Unit Test System considering the impact of **COVID-19 (Weekday) with EL demand** using CBWO																				
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_{11}**	**U_{12}**	**U_{13}**	**U_{14}**	**U_{15}**	**U_{16}**	**U_{17}**	**U_{18}**	**U_{19}**	**U_{20}**
h_1	8466	6399	0	0	0	0	0	0	0	0	8466	6399	0	2861	0	0	0	0	0	0
h_2	8466	6120	0	0	0	0	0	0	0	0	8466	6120	0	2861	0	0	0	0	0	0
h_3	8466	5998	0	0	0	0	0	0	0	0	8466	5998	0	2861	0	0	0	0	0	0
h_4	8466	6155	0	0	0	0	0	0	0	0	8466	6155	0	2861	0	0	0	0	0	0
h_5	8466	6801	0	0	0	0	0	0	0	0	8466	6801	0	2861	0	0	0	0	0	0
h_6	8466	6696	0	2861	0	0	0	0	0	0	8466	6696	0	2861	0	0	0	0	0	0
h_7	8466	6487	2892	2861	0	0	0	0	0	0	8466	6487	0	2861	0	0	0	0	0	0
h_8	8466	6260	2892	2861	0	0	0	0	0	0	8466	6260	2892	2861	0	0	0	0	0	0
h_9	8466	6888	2892	2861	0	0	0	0	0	0	8466	6888	2892	2861	0	0	0	0	0	0
h_{10}	8466	6993	2892	2861	0	0	0	0	0	0	8466	6993	2892	2861	0	0	0	0	0	0
h_{11}	8466	7964	2892	2861	945	0	0	0	0	0	8466	7964	2892	0	0	0	0	0	0	0
h_{12}	8466	8831	2892	0	945	0	0	0	0	0	8466	8831	2892	0	945	0	0	0	0	0
h_{13}	8466	8887	2892	0	1041	0	0	0	0	0	8466	8887	2892	0	1041	0	0	0	0	0
h_{14}	8466	8481	2892	0	945	0	0	0	0	0	8466	8481	2892	0	945	0	0	0	0	0
h_{15}	8466	8674	2892	0	945	0	0	0	0	0	8466	8674	2892	0	945	0	0	0	0	0
h_{16}	8466	8358	2892	0	945	0	0	0	0	0	8466	8358	2892	2861	945	0	0	0	0	0
h_{17}	8466	8887	2892	2861	1100	0	0	0	0	0	8466	8887	0	2861	1100	0	0	0	0	0
h_{18}	8466	8884	2892	2861	945	0	0	0	0	0	8466	8884	0	2861	945	0	0	0	0	0
h_{19}	8466	8887	2892	2861	1361	818	0	0	0	0	8466	8887	0	2861	1361	0	0	0	0	0
h_{20}	8466	8849	2892	2861	945	818	0	0	0	0	8466	8849	0	2861	945	0	0	0	0	0
h_{21}	8466	8051	2892	2861	945	818	0	0	0	0	8466	8051	0	2861	0	0	0	0	0	0
h_{22}	8466	7316	0	2861	945	0	0	0	0	0	8466	7316	2892	2861	0	0	0	0	0	0
h_{23}	8466	7334	0	0	945	0	0	0	0	0	8466	7334	2892	2861	0	0	0	0	0	0
h_{24}	8466	6766	0	0	0	0	0	0	0	0	8466	6766	2892	2861	0	0	0	0	0	0

Table 5.37: Scheduling a 20-unit system considering the impact of **COVID-19 (Weekend) with OC and EL demand** using CBWO																				
Hour	**U_1**	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**	**U_8**	**U_9**	**U_{10}**	**U_{11}**	**U_{12}**	**U_{13}**	**U_{14}**	**U_{15}**	**U_{16}**	**U_{17}**	**U_{18}**	**U_{19}**	**U_{20}**
h_1	455	352.8	0	130	0	0	0	0	0	0	455	352.8	0	0	0	0	0	0	0	0
h_2	455	342.8	0	130	0	0	0	0	0	0	455	342.8	0	0	0	0	0	0	0	0
h_3	455	334.8	0	130	0	0	0	0	0	0	455	334.8	0	0	0	0	0	0	0	0
h_4	455	336.8	0	130	0	0	0	0	0	0	455	336.8	0	0	0	0	0	0	0	0
h_5	455	350.8	0	130	0	0	0	0	0	0	455	350.8	0	0	0	0	0	0	0	0
h_6	455	311.8	130	0	0	0	0	0	0	0	455	311.8	0	130	0	0	0	0	0	0
h_7	455	345.8	130	0	0	0	0	0	0	0	455	345.8	0	130	0	0	0	0	0	0
h_8	455	324.8	130	0	0	0	0	0	0	0	455	324.8	130	130	0	0	0	0	0	0
h_9	455	368.3	130	0	25	0	0	0	0	0	455	368.3	130	130	0	0	0	0	0	0
h_{10}	455	412.3	130	0	25	0	0	0	0	0	455	412.3	130	130	0	0	0	0	0	0
h_{11}	455	398.3	130	130	25	0	0	0	0	0	455	398.3	130	130	0	0	0	0	0	0
h_{12}	455	455	130	130	44.8	0	0	0	0	0	455	455	130	0	44.8	20	0	0	0	0
h_{13}	455	455	130	130	43.8	0	0	0	0	0	455	455	130	0	43.8	20	0	0	0	0
h_{14}	455	455	130	130	37.8	0	0	0	0	0	455	455	130	0	37.8	20	0	0	0	0
h_{15}	455	455	130	130	0	20	25	0	0	0	455	455	130	0	36.6	20	0	0	0	0
h_{16}	455	455	130	130	0	20	25	0	0	0	455	455	130	0	92.6	20	0	0	0	0
h_{17}	455	455	130	130	0	20	25	0	0	0	455	455	130	130	30.6	0	0	0	0	0
h_{18}	455	455	0	130	0	20	25	10	0	0	455	455	130	130	84.6	0	0	0	0	0
h_{19}	455	455	0	130	0	20	25	0	0	0	455	455	130	130	38.6	0	0	0	0	0
h_{20}	455	432.3	0	130	0	20	0	0	0	0	455	432.3	130	130	25	20	0	0	0	0
h_{21}	455	401.3	0	130	25	0	0	0	0	0	455	401.3	130	130	0	20	0	0	0	0
h_{22}	455	411.3	0	130	25	0	0	0	0	0	455	411.3	130	0	0	20	0	0	0	0
h_{23}	455	361.3	130	0	25	0	0	0	0	0	455	361.3	130	0	0	0	0	0	0	0
h_{24}	455	376.3	130	0	25	0	0	0	0	0	455	376.3	0	0	0	0	0	0	0	0

Table 5.38: Individual fuel cost of 20 Unit Test System considering the impact of **COVID-19 (Weekend) with OC and EL demand** using CBWO

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	8466	7098	0	2861	0	0	0	0	0	0	8466	7098	0	0	0	0	0	0	0	0
h_2	8466	6923	0	2861	0	0	0	0	0	0	8466	6923	0	0	0	0	0	0	0	0
h_3	8466	6783	0	2861	0	0	0	0	0	0	8466	6783	0	0	0	0	0	0	0	0
h_4	8466	6818	0	2861	0	0	0	0	0	0	8466	6818	0	0	0	0	0	0	0	0
h_5	8466	7063	0	2861	0	0	0	0	0	0	8466	7063	0	0	0	0	0	0	0	0
h_6	8466	6382	2892	0	0	0	0	0	0	0	8466	6382	0	2861	0	0	0	0	0	0
h_7	8466	6976	2892	0	0	0	0	0	0	0	8466	6976	0	2861	0	0	0	0	0	0
h_8	8466	6609	2892	0	0	0	0	0	0	0	8466	6609	2892	2861	0	0	0	0	0	0
h_9	8466	7369	2892	0	945	0	0	0	0	0	8466	7369	2892	2861	0	0	0	0	0	0
h_{10}	8466	8139	2892	0	945	0	0	0	0	0	8466	8139	2892	2861	0	0	0	0	0	0
h_{11}	8466	7894	2892	2861	945	0	0	0	0	0	8466	7894	2892	2861	0	0	0	0	0	0
h_{12}	8466	8887	2892	2861	1341	0	0	0	0	0	8466	8887	2892	0	1341	818	0	0	0	0
h_{13}	8466	8887	2892	2861	1320	0	0	0	0	0	8466	8887	2892	0	1320	818	0	0	0	0
h_{14}	8466	8887	2892	2861	1200	0	0	0	0	0	8466	8887	2892	0	1200	818	0	0	0	0
h_{15}	8466	8887	2892	2861	0	818	1174	0	0	0	8466	8887	2892	0	1176	818	0	0	0	0
h_{16}	8466	8887	2892	2861	0	818	1174	0	0	0	8466	8887	2892	0	2308	818	0	0	0	0
h_{17}	8466	8887	2892	2861	0	818	1174	0	0	0	8466	8887	2892	2861	1057	0	0	0	0	0
h_{18}	8466	8887	0	2861	0	818	1174	920	0	0	8466	8887	2892	2861	2145	0	0	0	0	0
h_{19}	8466	8887	0	2861	0	818	1174	0	0	0	8466	8887	2892	2861	1216	0	0	0	0	0
h_{20}	8466	8489	0	2861	0	818	0	0	0	0	8466	8489	2892	2861	945	818	0	0	0	0
h_{21}	8466	7946	0	2861	945	0	0	0	0	0	8466	7946	2892	2861	0	818	0	0	0	0
h_{22}	8466	8121	0	2861	945	0	0	0	0	0	8466	8121	2892	0	0	818	0	0	0	0
h_{23}	8466	7247	2892	0	945	0	0	0	0	0	8466	7247	2892	0	0	0	0	0	0	0
h_{24}	8466	7509	2892	0	945	0	0	0	0	0	8466	7509	0	0	0	0	0	0	0	0

Table 5.39: Scheduling a 20-unit system considering the impact of **COVID-19 (Weekday) with OC and EL demand** using CBWO

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	455	352.8	0	0	0	0	0	0	0	0	455	352.8	0	130	0	0	0	0	0	0
h_2	455	336.8	0	0	0	0	0	0	0	0	455	336.8	0	130	0	0	0	0	0	0
h_3	455	329.8	0	0	0	0	0	0	0	0	455	329.8	0	130	0	0	0	0	0	0
h_4	455	338.8	0	0	0	0	0	0	0	0	455	338.8	0	130	0	0	0	0	0	0
h_5	455	310.8	0	130	0	0	0	0	0	0	455	310.8	0	130	0	0	0	0	0	0
h_6	455	304.8	130	130	0	0	0	0	0	0	455	304.8	0	130	0	0	0	0	0	0
h_7	455	345.3	130	130	0	0	0	0	0	0	455	345.3	0	130	25	0	0	0	0	0
h_8	455	397.3	130	130	0	0	0	0	0	0	455	397.3	130	0	25	0	0	0	0	0
h_9	455	420.8	130	130	25	0	0	0	0	0	455	420.8	130	0	25	0	0	0	0	0
h_{10}	455	426.8	130	130	25	0	0	0	0	0	455	426.8	130	0	25	0	0	0	0	0
h_{11}	455	429.8	130	130	25	0	0	0	0	0	455	429.8	130	0	25	0	0	0	0	0
h_{12}	455	426.8	130	130	25	0	0	0	0	0	455	426.8	130	0	25	0	0	0	0	0
h_{13}	455	382.3	130	130	25	0	0	0	0	0	455	382.3	130	130	0	0	0	0	0	0
h_{14}	455	354.3	130	130	25	0	0	0	0	0	455	354.3	130	130	0	0	0	0	0	0
h_{15}	455	420.3	130	130	25	20	0	0	0	0	455	420.3	0	130	0	0	0	0	0	0
h_{16}	455	455	130	130	29.6	20	0	0	0	0	455	455	0	130	0	20	0	0	0	0
h_{17}	455	455	130	130	80.6	20	25	0	0	0	455	455	0	130	0	20	0	0	0	0
h_{18}	455	455	130	130	64.6	20	25	0	0	0	455	455	0	130	0	20	0	0	0	0
h_{19}	455	455	130	130	73.3	20	25	0	0	0	455	455	0	130	73.3	0	0	0	0	0
h_{20}	455	455	0	130	60.3	0	25	0	0	0	455	455	130	130	60.3	0	0	0	0	0
h_{21}	455	444.8	0	130	25	0	0	0	0	0	455	444.8	130	130	25	0	0	0	0	0
h_{22}	455	405.3	0	130	0	0	0	0	0	0	455	405.3	130	130	25	0	0	0	0	0
h_{23}	455	406.3	0	130	0	0	0	0	0	0	455	406.3	130	0	25	0	0	0	0	0
h_{24}	455	361.3	0	130	0	0	0	0	0	0	455	361.3	130	0	25	0	0	0	0	0

Table 5.40: Individual fuel cost of 20 Unit Test System considering the impact of **COVID-19 (Weekday) with OC and EL demand** using CBWO

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	8466	7098	0	0	0	0	0	0	0	0	8466	7098	0	2861	0	0	0	0	0	0
h_2	8466	6818	0	0	0	0	0	0	0	0	8466	6818	0	2861	0	0	0	0	0	0
h_3	8466	6696	0	0	0	0	0	0	0	0	8466	6696	0	2861	0	0	0	0	0	0
h_4	8466	6853	0	0	0	0	0	0	0	0	8466	6853	0	2861	0	0	0	0	0	0
h_5	8466	6364	0	2861	0	0	0	0	0	0	8466	6364	0	2861	0	0	0	0	0	0
h_6	8466	6260	2892	2861	0	0	0	0	0	0	8466	6260	0	2861	0	0	0	0	0	0
h_7	8466	6967	2892	2861	0	0	0	0	0	0	8466	6967	0	2861	945	0	0	0	0	0
h_8	8466	7876	2892	2861	0	0	0	0	0	0	8466	7876	2892	0	945	0	0	0	0	0
h_9	8466	8288	2892	2861	945	0	0	0	0	0	8466	8288	2892	0	945	0	0	0	0	0
h_{10}	8466	8393	2892	2861	945	0	0	0	0	0	8466	8393	2892	0	945	0	0	0	0	0
h_{11}	8466	8446	2892	2861	945	0	0	0	0	0	8466	8446	2892	0	945	0	0	0	0	0
h_{12}	8466	8393	2892	2861	945	0	0	0	0	0	8466	8393	2892	0	945	0	0	0	0	0
h_{13}	8466	7614	2892	2861	945	0	0	0	0	0	8466	7614	2892	2861	0	0	0	0	0	0
h_{14}	8466	7124	2892	2861	945	0	0	0	0	0	8466	7124	2892	2861	0	0	0	0	0	0
h_{15}	8466	8279	2892	2861	945	818	0	0	0	0	8466	8279	0	2861	0	0	0	0	0	0
h_{16}	8466	8887	2892	2861	1037	818	0	0	0	0	8466	8887	0	2861	0	818	0	0	0	0
h_{17}	8466	8887	2892	2861	2064	818	1174	0	0	0	8466	8887	0	2861	0	818	0	0	0	0
h_{18}	8466	8887	2892	2861	1739	818	1174	0	0	0	8466	8887	0	2861	0	818	0	0	0	0
h_{19}	8466	8887	2892	2861	1915	818	1174	0	0	0	8466	8887	0	2861	1915	0	0	0	0	0
h_{20}	8466	8887	0	2861	1652	0	1174	0	0	0	8466	8887	2892	2861	1652	0	0	0	0	0
h_{21}	8466	8709	0	2861	945	0	0	0	0	0	8466	8709	2892	2861	945	0	0	0	0	0
h_{22}	8466	8016	0	2861	0	0	0	0	0	0	8466	8016	2892	2861	945	0	0	0	0	0
h_{23}	8466	8034	0	2861	0	0	0	0	0	0	8466	8034	2892	0	945	0	0	0	0	0
h_{24}	8466	7247	0	2861	0	0	0	0	0	0	8466	7247	2892	0	945	0	0	0	0	0

Table 5.41: Scheduling a 20-unit system considering the impact of **COVID-19 (Weekend) with OC, EL demand and wind power** using CBWO

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	455	221.6	0	130	0	0	0	0	0	0	455	0	0	130	0	0	0	0	0	0
h_2	455	213.6	0	130	0	0	0	0	0	0	455	0	0	130	0	0	0	0	0	0
h_3	455	223.6	0	130	0	0	0	0	0	0	455	0	0	130	0	0	0	0	0	0
h_4	455	253.6	0	130	0	0	0	0	0	0	455	0	0	130	0	0	0	0	0	0
h_5	455	287.6	0	130	0	0	0	0	0	0	455	0	0	130	0	0	0	0	0	0
h_6	455	434.6	0	0	0	20	0	0	0	0	455	0	0	130	25	0	0	0	0	0
h_7	455	406.6	130	0	0	20	0	0	0	0	455	0	0	130	25	0	0	0	0	0
h_8	455	455	130	0	0	20	0	0	0	10	455	0	0	130	76.6	0	0	0	0	0
h_9	455	382.3	130	0	0	0	0	0	0	0	455	382.3	0	0	25	0	0	0	0	0
h_{10}	455	426.3	130	0	0	0	0	0	0	0	455	426.3	0	0	25	0	0	0	0	0
h_{11}	455	411.3	130	130	0	0	0	0	0	0	455	411.3	0	0	25	0	0	0	0	0
h_{12}	455	382.3	130	130	25	0	0	0	0	0	455	382.3	130	0	0	0	0	0	0	0
h_{13}	455	434.8	0	130	25	0	25	0	0	0	455	434.8	130	0	0	0	0	0	0	0
h_{14}	455	433.8	0	130	25	0	25	0	0	0	455	433.8	130	0	0	0	0	0	0	0
h_{15}	455	438.8	0	130	25	0	25	0	0	0	455	438.8	130	0	0	0	0	0	0	0
h_{16}	455	410.3	0	130	25	0	0	0	0	0	455	410.3	130	130	0	0	0	0	0	0
h_{17}	455	455	0	130	74.6	20	0	0	10	0	455	455	0	130	0	0	25	0	0	0
h_{18}	455	455	0	0	86.8	20	0	0	0	0	455	455	0	130	86.8	0	25	0	0	0
h_{19}	455	427.2	130	0	0	20	0	0	0	0	455	427.2	0	130	25	0	25	0	0	0
h_{20}	455	397.3	130	0	0	0	0	0	0	0	455	397.3	0	130	25	0	0	0	0	0
h_{21}	455	414.3	130	0	0	0	0	0	0	0	455	414.3	0	0	25	0	0	0	0	0
h_{22}	455	349.3	130	0	0	0	0	0	0	0	455	349.3	0	0	25	0	0	0	0	0
h_{23}	455	402.6	130	0	0	0	0	0	0	0	455	0	130	0	25	0	0	0	0	0
h_{24}	455	297.6	0	130	0	0	0	0	0	0	455	0	130	0	0	0	0	0	0	0

Table 5.42: Individual fuel cost of 20 Unit Test System considering the impact of **COVID-19 (Weekend) with OC, EL demand and wind power** using CBWO

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	8466	4810	0	2861	0	0	0	0	0	0	8466	0	0	2861	0	0	0	0	0	0
h_2	8466	4671	0	2861	0	0	0	0	0	0	8466	0	0	2861	0	0	0	0	0	0
h_3	8466	4845	0	2861	0	0	0	0	0	0	8466	0	0	2861	0	0	0	0	0	0
h_4	8466	5367	0	2861	0	0	0	0	0	0	8466	0	0	2861	0	0	0	0	0	0
h_5	8466	5960	0	2861	0	0	0	0	0	0	8466	0	0	2861	0	0	0	0	0	0
h_6	8466	8530	0	0	0	818	0	0	0	0	8466	0	0	2861	945	0	0	0	0	0
h_7	8466	8039	2892	0	0	818	0	0	0	0	8466	0	0	2861	945	0	0	0	0	0
h_8	8466	8887	2892	0	0	818	0	0	0	948	8466	0	0	2861	1982	0	0	0	0	0
h_9	8466	7614	2892	0	0	0	0	0	0	0	8466	7614	0	0	945	0	0	0	0	0
h_{10}	8466	8384	2892	0	0	0	0	0	0	0	8466	8384	0	0	945	0	0	0	0	0
h_{11}	8466	8121	2892	2861	0	0	0	0	0	0	8466	8121	0	0	945	0	0	0	0	0
h_{12}	8466	7614	2892	2861	945	0	0	0	0	0	8466	7614	2892	0	0	0	0	0	0	0
h_{13}	8466	8533	0	2861	945	0	1174	0	0	0	8466	8533	2892	0	0	0	0	0	0	0
h_{14}	8466	8516	0	2861	945	0	1174	0	0	0	8466	8516	2892	0	0	0	0	0	0	0
h_{15}	8466	8603	0	2861	945	0	1174	0	0	0	8466	8603	2892	0	0	0	0	0	0	0
h_{16}	8466	8104	0	2861	945	0	0	0	0	0	8466	8104	2892	2861	0	0	0	0	0	0
h_{17}	8466	8887	0	2861	1942	818	0	0	938	0	8466	8887	0	2861	0	0	1174	0	0	0
h_{18}	8466	8887	0	0	2190	818	0	0	0	0	8466	8887	0	2861	2190	0	1174	0	0	0
h_{19}	8466	8400	2892	0	0	818	0	0	0	0	8466	8400	0	2861	945	0	1174	0	0	0
h_{20}	8466	7876	2892	0	0	0	0	0	0	0	8466	7876	0	2861	945	0	0	0	0	0
h_{21}	8466	8174	2892	0	0	0	0	0	0	0	8466	8174	0	0	945	0	0	0	0	0
h_{22}	8466	7037	2892	0	0	0	0	0	0	0	8466	7037	0	0	945	0	0	0	0	0
h_{23}	8466	7969	2892	0	0	0	0	0	0	0	8466	0	2892	0	945	0	0	0	0	0
h_{24}	8466	6134	0	2861	0	0	0	0	0	0	8466	0	2892	0	0	0	0	0	0	0

Table 5.43: Scheduling a 20-unit system considering the impact of **COVID-19 (Weekday) with OC, EL demand and wind power** using CBWO

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	455	240.8	0	0	0	0	0	0	0	0	455	240.8	0	0	0	0	0	0	0	0
h_2	455	230.8	0	0	0	0	0	0	0	0	455	230.8	0	0	0	0	0	0	0	0
h_3	455	236.8	0	0	0	0	0	0	0	0	455	236.8	0	0	0	0	0	0	0	0
h_4	455	258.8	0	0	0	0	0	0	0	0	455	258.8	0	0	0	0	0	0	0	0
h_5	455	298.8	0	0	0	0	0	0	0	0	455	298.8	0	0	0	0	0	0	0	0
h_6	455	362.8	0	0	0	0	0	0	0	0	455	362.8	0	0	0	0	0	0	0	0
h_7	455	302.8	0	130	0	0	0	0	0	0	455	302.8	0	130	0	0	0	0	0	0
h_8	455	300.8	0	130	0	0	0	0	0	0	455	300.8	130	130	0	0	0	0	0	0
h_9	455	329.8	0	130	0	0	0	0	0	0	455	329.8	130	130	0	0	0	0	0	0
h_{10}	455	335.8	0	130	0	0	0	0	0	0	455	335.8	130	130	0	0	0	0	0	0
h_{11}	455	337.8	0	130	0	0	0	0	0	0	455	337.8	130	130	0	0	0	0	0	0
h_{12}	455	336.8	130	0	0	0	0	0	0	0	455	336.8	130	130	0	0	0	0	0	0
h_{13}	455	453.3	130	0	25	20	0	0	0	0	455	453.3	0	0	0	0	0	0	0	0
h_{14}	455	430.3	130	0	25	20	0	0	0	0	455	430.3	0	0	0	0	0	0	0	0
h_{15}	455	443.3	130	0	25	20	0	0	0	0	455	443.3	0	0	0	0	0	0	0	0
h_{16}	455	455	130	0	53.8	0	0	0	0	0	455	455	0	0	53.8	0	0	0	0	0
h_{17}	455	455	130	130	34.8	0	0	0	0	0	455	455	0	0	34.8	0	0	0	0	0
h_{18}	455	455	0	130	39.3	0	0	0	0	0	455	455	0	130	39.3	0	0	0	0	0
h_{19}	455	428.7	0	130	0	20	0	0	0	0	455	428.7	130	130	25	0	0	0	0	0
h_{20}	455	385.3	0	130	0	20	0	0	0	0	455	385.3	130	130	25	0	0	0	0	0
h_{21}	455	320.3	0	130	0	20	0	0	0	0	455	320.3	130	130	25	0	0	0	0	0
h_{22}	455	345.8	0	0	0	0	0	0	0	0	455	345.8	130	130	0	0	0	0	0	0
h_{23}	455	323.8	0	0	0	0	0	0	0	0	455	323.8	130	0	0	0	0	0	0	0
h_{24}	455	328.8	0	0	0	0	0	0	0	0	455	328.8	0	0	0	0	0	0	0	0

Table 5.44: Individual fuel cost of 20 Unit Test System considering the impact of **COVID-19 (Weekday) with OC, EL demand and wind power** using CBWO

Hour	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}	U_{19}	U_{20}
h_1	8466	5144	0	0	0	0	0	0	0	0	8466	5144	0	0	0	0	0	0	0	0
h_2	8466	4970	0	0	0	0	0	0	0	0	8466	4970	0	0	0	0	0	0	0	0
h_3	8466	5075	0	0	0	0	0	0	0	0	8466	5075	0	0	0	0	0	0	0	0
h_4	8466	5458	0	0	0	0	0	0	0	0	8466	5458	0	0	0	0	0	0	0	0
h_5	8466	6155	0	0	0	0	0	0	0	0	8466	6155	0	0	0	0	0	0	0	0
h_6	8466	7273	0	0	0	0	0	0	0	0	8466	7273	0	0	0	0	0	0	0	0
h_7	8466	6225	0	2861	0	0	0	0	0	0	8466	6225	0	2861	0	0	0	0	0	0
h_8	8466	6190	0	2861	0	0	0	0	0	0	8466	6190	2892	2861	0	0	0	0	0	0
h_9	8466	6696	0	2861	0	0	0	0	0	0	8466	6696	2892	2861	0	0	0	0	0	0
h_{10}	8466	6801	0	2861	0	0	0	0	0	0	8466	6801	2892	2861	0	0	0	0	0	0
h_{11}	8466	6836	0	2861	0	0	0	0	0	0	8466	6836	2892	2861	0	0	0	0	0	0
h_{12}	8466	6818	2892	0	0	0	0	0	0	0	8466	6818	2892	2861	0	0	0	0	0	0
h_{13}	8466	8858	2892	0	945	818	0	0	0	0	8466	8858	0	0	0	0	0	0	0	0
h_{14}	8466	8454	2892	0	945	818	0	0	0	0	8466	8454	0	0	0	0	0	0	0	0
h_{15}	8466	8682	2892	0	945	818	0	0	0	0	8466	8682	0	0	0	0	0	0	0	0
h_{16}	8466	8887	2892	0	1521	0	0	0	0	0	8466	8887	0	0	1521	0	0	0	0	0
h_{17}	8466	8887	2892	2861	1140	0	0	0	0	0	8466	8887	0	0	1140	0	0	0	0	0
h_{18}	8466	8887	0	2861	1230	0	0	0	0	0	8466	8887	0	2861	1230	0	0	0	0	0
h_{19}	8466	8426	0	2861	0	818	0	0	0	0	8466	8426	2892	2861	945	0	0	0	0	0
h_{20}	8466	7666	0	2861	0	818	0	0	0	0	8466	7666	2892	2861	945	0	0	0	0	0
h_{21}	8466	6530	0	2861	0	818	0	0	0	0	8466	6530	2892	2861	945	0	0	0	0	0
h_{22}	8466	6976	0	0	0	0	0	0	0	0	8466	6976	2892	2861	0	0	0	0	0	0
h_{23}	8466	6591	0	0	0	0	0	0	0	0	8466	6591	2892	0	0	0	0	0	0	0
h_{24}	8466	6679	0	0	0	0	0	0	0	0	8466	6679	0	0	0	0	0	0	0	0

Table 5.45: Statistical and hypothetical analysis of 20 Generating Unit System using CBWO Optimization Algorithm with different cases. (Weekend)

Test Cases	Best	Avg	Worst	Std	Median	Wilcoxon Test	T-Test		Best Time	Average Time	Worst Time
						p-value	p-value	h-value			
UCP during covid-19 (FL)	873333	886069	897482	5708.9	885479	1.73E-06	2.61E-65	1	0.0156	0.0197	0.0312
UCP during covid-19 with wind power (FL)	754300	764483	775178	5828.4	765880	1.73E-06	3.44E-63	1	0.0156	0.0192	0.0312
UCP during covid-19 (PL)	903243	916906	924797	4518.55	917634	1.73E-06	1.1E-68	1	0	0.0234	0.04687
UCP during covid-19 with wind power (PL)	783124	793674	802184	4998.62	794722	1.73E-06	1.35E-65	1	0	0.0182	0.03125
UCP with OC demand	912221	923183	931916	5279.12	924672	1.73E-06	8.21E-67	1	0.0156	0.0192	0.0312
UCP with EL demand	959510	968587	978512	5045.44	969520	1.73E-06	5.49E-68	1	0	0.0166	0.0312
UCP with OC & EL demand	1001232	1006300	1010937	2441.99	1006034	1.73E-06	1.32E-77	1	0.0156	0.0197	0.0312
UCP with OC & EL with wind power	875692	883527	894434	5184.3	883703	1.73E-06	1.73E-66	1	0.0156	0.0197	0.0468

Table 5.46: Statistical and hypothetical analysis of 20 Generating Unit System using CBWO Optimization Algorithm with different cases. (Weekday)

Test Cases	Best	Avg	Worst	Std	Median	Wilcoxon Test	T-Test		Best Time	Average Time	Worst Time
						p-value	p-value	h-value			
UCP during covid-19 (FL)	883835	893721	905533	4746.46	894040.	1.73E-06	9.62E-68	1	0.01562	0.0187	0.04687
UCP during covid-19 with wind power (FL)	764970	774317	783743	5133.49	773890	1.73E-06	5.98E-65	1	0.01562	0.0192	0.04687
UCP during covid-19 (PL)	934310	939940	944440	2184.9	939960	1.73E-06	3.77E-78	1	0.01562	0.01770	0.03125
UCP during covid-19 with wind power (PL)	814051	820465	832799	4839.1	819616	1.73E-06	2.01E-66	1	0	0.02083	0.04687
UCP with OC demand	926675	934107	942618	3839.2	934538	1.73E-06	5.69E-71	1	0.0156	0.0177	0.0468
UCP with EL demand	971640	978774	985399	3269.3	978401	1.73E-06	1.39E-73	1	0.0156	0.0171	0.0312
UCP with OC & EL demand	1015190	1020083	1023947	2371.5	1020492	1.73E-06	3.79E-78	1	0.0156	0.0218	0.0312
UCP with OC & EL with wind power	883014	892926	903306	5530.5	893941	1.73E-06	8.31E-66	1	0.0156	0.0208	0.0312

5.6.3 System of 40 Generating Units

The effectiveness of proposed algorithm CBWO is tested and used to get the optimal result for UC problem considering the several constraints with 100 iteration and 30 trial runs. This part of chapter is illustrating the optimal results for 40 generating units and scheduling of units, individual cost of each unit. Details of the commitment status, optimal scheduling, and individual fuel costs of each of the 40 generating units for thermal unit during full lockdown, partial lockdown, OC, EL and Wind are presented in **Table 5.47** illustrates the statistical and hypothetical analysis of 40 Generating Unit System using CBWO optimization algorithms with different cases during weekend. **Table 5.48** illustrates the statistical and hypothetical analysis of 40 Generating Unit with the help of CBWO optimization algorithms with different cases during weekday.

Average cost is reduced by 13.7% in full lockdown compared when wind power incorporates with it. Cost is increased by 1.2% in full lockdown during weekdays compare to weekends. Almost 4.5% and 9.6% cost increment were seen when oxygen concentrator and electrolyser used during weekends. Almost 12.5% cost were saved by using wind power with thermal system when both OC and EL used. During weekdays, 13.5% fuel cost decreased in full lockdown by using wind power generation system. Almost 14% cost increased by using OC and EL both and almost 12.8% cost saved by using wind power in system.

Fig. 5.5 and Fig. 5.6 illustrates the Cost comparison of different cases for 10 units using CBWO with wind power and without wind power for weekend and weekday. **Fig. 5.7** illustrates the cost comparison chart for 20-unit system with CBWO with wind power and without wind power. **Fig. 5.8** illustrates the cost comparison chart for 40-unit system with CBWO with wind power and without wind power.

Table 5.47: Statistical and hypothetical analysis of 40 Generating Unit System using CBWO Optimization Algorithm with different cases. (Weekend)													
Test Cases	**Best**	**Avg**	**Worst**	**Std**	**Median**	**Wilcoxon Test**	**T-Test**		**Best Time**	**Average Time**	**Worst Time**	**Test Cases**
						p-value	**p-value**	**h-value**				
UCP during covid-19 (FL)	1753642	1780523	180339	13581.9	1784863	1.73E-06	3.49E-63	1	0.015625	0.019271	0.03125	1753642
UCP during covid-19 with wind power (FL)	1505390	1536425	155987	15237.7	1535628	1.73E-06	7.06E-60	1	0.01562	0.01927	0.03125	1505390
UCP during covid-19 (PL)	1869317	1897090	1913236	12188.02	1900247	1.73E-06	2.4E-65	1	0	0.022396	0.03125	1869317
UCP during covid-19 with wind power (PL)	1575666	1607335	1622193	11691.05	1609620	1.73E-06	8.79E-64	1	0	0.020833	0.03125	1575666
UCP with OC demand	1840716	1860673	1876566	8777.61	1862530	1.73E-06	3.1E-69	1	0.015625	0.019792	0.046875	1840716
UCP with EL demand	1926825	1952584	1972203	11265.6	1956085	1.73E-06	1.06E-66	1	0.015625	0.017188	0.03125	1926825
UCP with OC & EL demand	2001522	2030799	2048145	12510.19	2034918	1.73E-06	7.11E-66	1	0	0.019271	0.03125	2001522
UCP with OC & EL with wind power	1744922	1777587	1791533	9967.758	1778788	1.73E-06	4.65E-67	1	0.015625	0.018229	0.03125	1744922

Table 5.48: Statistical and hypothetical analysis of 40 Generating Unit System using CBWO Optimization Algorithm with different cases. (Weekday)													
Test Cases	**Best**	**Avg**	**Worst**	**Std**	**Median**	**Wilcoxon Test**	**T-Test**		**Best Time**	**Average Time**	**Worst Time**	**Test Cases**
						p-value	**p-value**	**h-value**				
UCP during covid-19 (FL)	1777549	1802677	1821482	12567.35	1805067	1.73E-06	2.57E-64	1	0	0.01718	0.03125	1777549
UCP during covid-19 with wind power (FL)	1535780	1558587	1583216	15020.03	1556344	1.73E-06	3.07E-60	1	0.01562	0.01666	0.04687	1535780
UCP during covid-19 (PL)	1779405	1809281	1835348	12808.43	1812101	1.73E-06	4.01E-64	1	0	0.024479	0.046875	1779405
UCP during covid-19 with wind power (PL)	1630100	1661500	1683100	15893	1662300	1.73E-06	2.47E-60	1	0.01562	0.02083	0.03125	1630100
UCP with OC demand	1845072	1881770	1897116	10478.1	1884439	1.73E-06	3.79E-67	1	0.015625	0.017708	0.046875	1845072
UCP with EL demand	1954369	1973008	1987422	8928.098	1975312	1.73E-06	9.26E-70	1	0.015625	0.020833	0.03125	1954369
UCP with OC & EL demand	2026653	2054802	2065297	11029.78	2059415	1.73E-06	1.31E-67	1	0	0.020313	0.03125	2026653
UCP with OC & EL with wind power	1765382	1791509	1810146	11617.38	1792514	1.73E-06	3.15E-65	1	0.015625	0.021875	0.03125	1765382

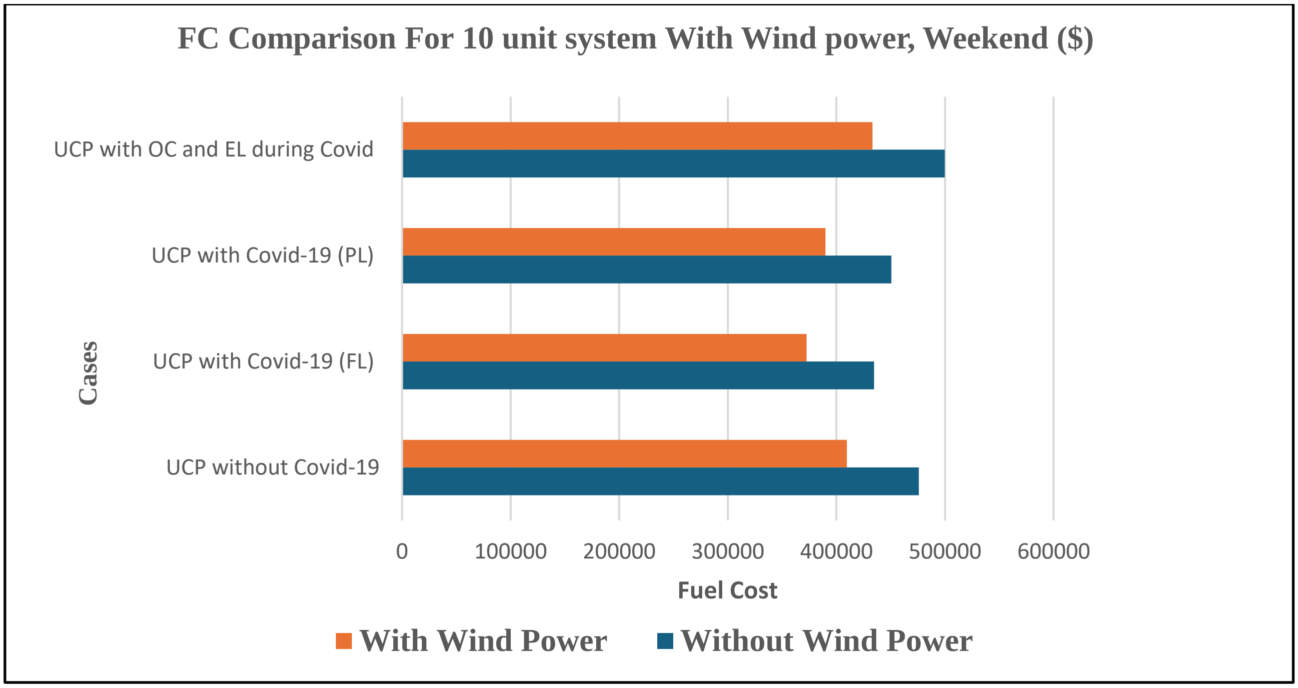

Fig. 5.5: Cost comparison of different cases for 10 units using CBWO with wind power and without wind power during Weekend

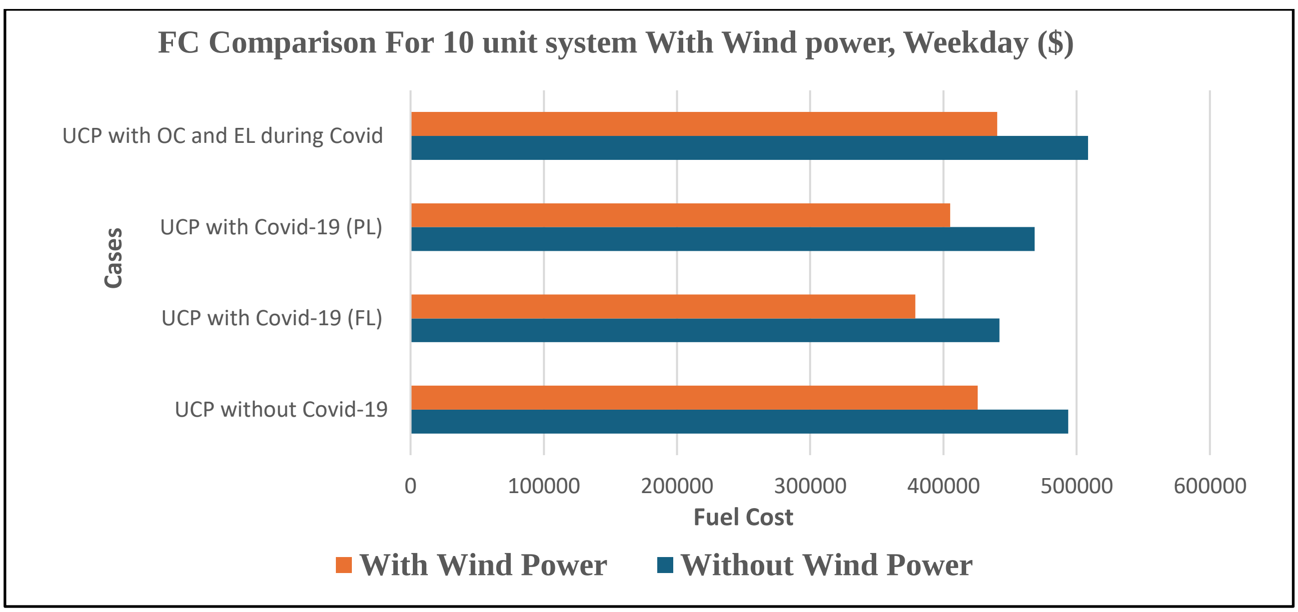

Fig. 5.6: Cost comparison of different cases for 10 units using CBWO with wind power and without wind power during Weekday

Table 5.49: Average Fuel Cost Comparison of 10, 20, 40-Unit system During COVID with OC, EL and Wind Power ($)

Cases	10-Unit		20- Unit		40- Unit	
	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday
COVID During FL (2020)	434625.2	441990.9	873332.6	883835.2	1753642	1777549
COVID During FL (2020) with Wind Power	372580.1	378921.3	754300.3	764970.2	1505390	1535780
COVID During PL (2021)	450481.9	468460.3	903242.8	934310	1869317	1779405
COVID During PL (2021) with Wind Power	389904.1	405100	783124.2	814050.9	1575666	1630100
COVID During FL (2020) With OC Demand	455206.6	462563.9	912220.5	926675	1840716	1845072
COVID During FL (2020) With EL Demand	484606.7	478301.4	959510.3	971639.9	1926825	1954369
COVID During FL (2020) With OC & EL Demand	499741.2	508451.7	1001232	1015190	2001522	2026653
COVID During FL (2020) With OC, EL Demand and Wind Power	433221.3	440382.4	875691.7	883014.4	1744922	1765382

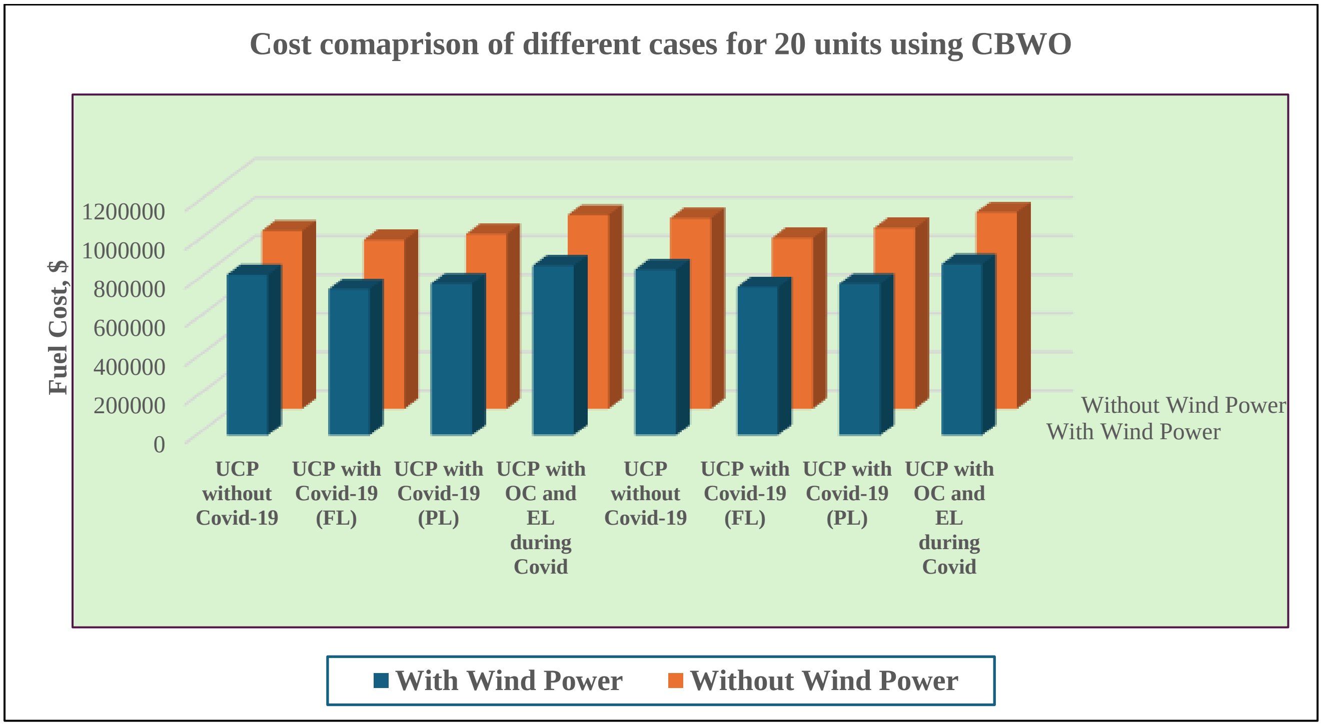

Fig. 5.7: Cost comparison of different cases for 20 units using CBWO with wind power and without wind power

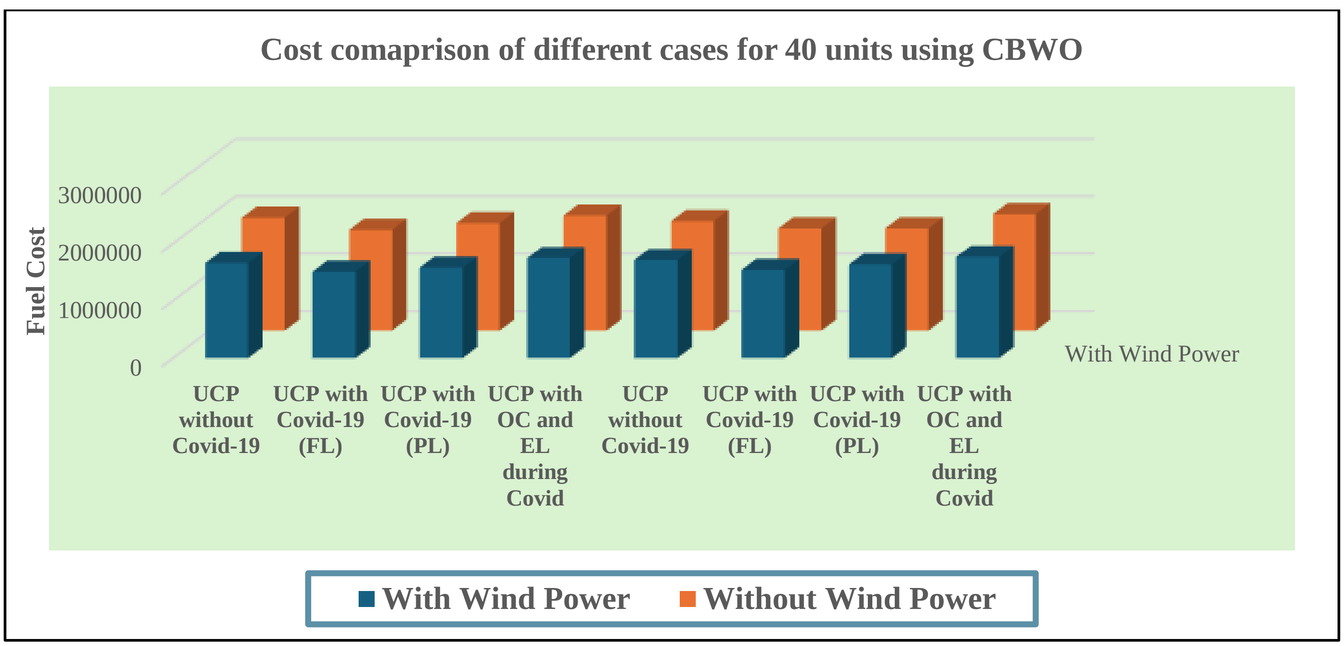

Fig. 5.8: Cost comparison of different cases for 40 units using CBWO with wind power and without wind power

5.6.4 Comparison of results for 10-unit system with standard load demand

To check the effectiveness of proposed algorithm CBWO, it is compared with other existing algorithms for 10-unit system in table 5.50 and 20- unit system shown in table 5.51 with standard load demand. The proposed algorithm shows better results as compared to other algorithms.

Table 5.50: Comparison of results for 10-unit system with 10% SR

Sr. No.	Methods	Total Generation Cost in $		
		Best value	Average value	Worst Value
1	Hybrid Continuous Relaxation and Genetic Algorithm (CRGA) [203]	NA	563977	---
2	Genetic Based Method [202]	NA	623441	---
3	Continuous Relaxation and Genetic Algorithm (CRGA) [203]	---	563977	---
4	Integer Coded Genetic Algorithm (ICGA) [204]	---	566404	---
5	Lagrangian Search Genetic Algorithm (LSGA) [205]	609023.69	---	---
6	Improved Binary Particle Swarm optimization (IBPSO) [206]	599782	---	---
7	New Genetic Algorithm [207]	591715	---	---
8	PSO [208]	581450	563977	---
9	Binary Particle Swarm Optimization with bit Change Mutation (MPSO) [209]	574905	---	---
10	HPSO [210]	574153	---	---
11	LCA-PSO [211]	570006	---	---
12	Two-Stage Genetic Based Technique (TSGA) [212]	568315	---	---
13	Hybrid PSO-SQP [213]	568032.3	---	---
14	BCGA [204, 214]	567367	---	---
15	SM [215]	566686	566787	567022
16	Lagrangian Relaxation [215]	566107	566493	566817
17	GA [215]	565866	567329	571336
18	Genetic Algorithm (GA) [216]	565852	---	570032
19	Enhanced Simulated Annealing (ESA) [217]	565828	565988	566260
20	Lagrangian Relaxation (LR) [216]	565825	---	---

21	Dynamic Programming (DP) [216]	565825	---	---
22	Improved Lagrangian Relaxation (ILR) [217]	565823.23	---	---
23	LRPSO [217, 218]	565275.2	---	---
24	Lagrangian Relaxation and Genetic Algorithm (LRGA) [218]	564800	564800	---
25	Evolutionary Programming (EP) [220]	564551	565352	---
26	EP [215]	564551	565352	566231
27	Particle Swarm Optimization (PSO) [221]	564212	565103	565783
28	Ant Colony Search Algorithm (ACSA) [222]	564049	---	---
29	Hybrid Ant System/Priority List (HASP) [223]	564029	564324	564490
30	B. SMP [224]	564017.73	564121	564401
31	Annealing Genetic Algorithm (AGA) [225]	564005	---	---
32	Binary Differential Evolution [226]	5,63,997	5,63,997	5,63,997
33	Social Evolutionary Programming (SEP) [227]	563987	---	---
34	Methodological Priority List (MPL) [228]	563977.1	---	---
35	Binary PSO [234]	563977	563977	563977
36	Quantum-Inspired Binary PSO (QIBPSO) [235]	563977	563977	563977
37	IBPSO [229]	563977	564155	565312
38	Genetic Algorithm (GA) [215]	563977	564275	5665606
39	Genetic Algorithm Based on Unit Characteristics (UCC-GA) [230]	563977	---	565606
40	Enhanced Adaptive Lagrangian Relaxation (EALR) [217]	563977	---	---
41	Local Search Method (LCM) [232]	563977	---	---
42	Quantum-Inspired Binary PSO (QBPSO) [233]	563977	---	---
43	Extended Priority List (EPL) [236]	563977	---	---
44	Muller Method [237]	563977	---	---
45	Improved Particle Swarm Optimization (IPSO) [238]	563954	564162	564579
46	Advanced Fuzzy Controlled Binary PSO (AFCBPSO) [239]	563947	564285	565002
47	Hybrid PSO (HPSO) [240]	563942.3	564772	565782

48	Fuzzy Quantum Computation Based Thermal Unit Commitment (FQEA) [241]	563942	---	---
49	IQEA-UC [242]	563938	563938	563938
50	Gravitational Search Algorithm [244]	563938	564008	564241
51	QEA-UC [242]	563938	564012	564711
52	Particle Swarm-Based- Simulated Annealing (PSO-B-SA) [243]	563938	564115	564985
53	Advanced Quantum-Inspired Evolutionary Algorithm (AQEA) [242]	563938	---	---
54	Hybrid HS-Random Search algorithm [245]	563937.7	563965	563995
55	**CBWO (Proposed Method)**	**563387.68**	**564182.02**	**565107.68**

Table 5.51: Comparison of results for 20-unit system with 10% SR

Sr. No.	**Methods**	**Total Generation Cost in $**		
		Best value	**Average value**	**Worst Value**
1	Binary Particle Swarm Optimization with bit Change Mutation [209]	1152966	...	...
2	Intelligent Mutation based Genetic Algorithm [230]	1125516	...	1128790
3	Improved Particle Swarm Optimization OPSO [238]	1125279	...	1127643
4	Improved Binary Particle Swarm optimization [206]	1196029	..	...
5	LCA-PSO [211]	1139005	..	...
6	Lagrangian Relaxation (LR) [215]	1130660	..	...
7	BCGA [214]	1130291	..	...
8	DP and Lagrangian Relaxation (DPLR) [217]	1128098	..	...
9	Enhanced Simulated Annealing (ESA) [217]	1126254	..	...
10	Genetic Algorithm (GA) [215]	1126243	..	1132059
11	Particle Swarm Optimization (PSO) [221]	1125983	..	1131054
12	Social Evolutionary Programming (SEP) [227]	1125170	..	...

13	Hybrid Continuous Relaxation and Genetic Algorithm [203]	..	1236981	...
14	Genetic Based Method [202]	..	1215066	...
15	GA [215]	1126243	1200480	...
16	New Genetic Algorithm [207]	..	1133786	...
17	GA [215]	1128876	1130160	1131565
18	LR [216]	1128362	1128395	1128444
19	SM [215]	1128192	1128213	1128403
20	Enhanced Simulated Annealing (ESA) [217]	1126251	1127955	1129112
21	Harmony Search [245]	..	1127377	...
22	Evolutionary Programming (EP) [220]	1125494	1127257	...
23	Integer Coded Genetic Algorithm [204]	..	1127244	...
24	BSMP [224]	1124838	1125102	1125283
25	HS-Random Search Algorithm [245]	1124889	1124913	1124952
26	Annealing Genetic Algorithm [225]	..	1124651	...
27	Lagrangian Relaxation and Genetic Algorithm [218]	..	1122622	...
28	**CBWO (Proposed Method)**	1123748	1124928	1130559

5.7 CONCLUSION

In this chapter, the unit commitment problem has been solved using CBWO. For result analyses, 10, 20, and 40 generating units, have been scheduled successfully and applied the suggested hybrid optimizers to minimize the cost. According to the simulation results, the recommended optimizer computes the satisfactory low-cost value with commitment scheduling in a realistic amount of time.

A powerful optimizer like this can be used to find a solution for modern power sector unit commitment. The analysis takes into account the standard deviation and median values of the profit variation's best, average, and worst values. The Wilcoxon rank sum method and the t-test are for hypothesis testing that can be used to determine the p-value and h-value. The best, average, and worst simulation times are analyzed for the computational time. The effectiveness of the hybrid CBWO optimization technique to solve UC problem with the impact of OC and EL with RES during Covid lockdown days, has been successfully presented. The standard test system, which consists of thermal units for the small, medium, and large power sectors, has been evaluated.

Chapter-6

CONCLUSION AND FUTURE SCOPE

6.1 INTRODUCTION

This section presents the key findings of the research detailed in this thesis, followed by recommendations for future research directions. The study's primary contributions include the advancement of optimization-based analysis for solving the Unit Commitment Problem incorporating oxygen concentrators, electrolyzers, and Renewable Energy Sources, i.e., wind energy. The proposed methodologies were evaluated across a diverse range of test systems, spanning small to large-scale implementations. To ensure optimal handling of the UCP, a hybrid optimization technique was employed. The efficacy of these optimization methods was validated using standard benchmark functions and established engineering design challenges. Furthermore, the feasibility of the proposed approach was demonstrated through rigorous testing on multiple test systems of varying sizes.

6.2 SIGNIFICANT CONTRIBUTION

This research focused on developing a robust and efficient optimization approach to solve the Unit Commitment Problem while considering system constraints, operational reliability, and the integration of renewable energy sources, particularly wind power. The study was motivated by the growing need to improve power system efficiency, reduce dependence on costly and environmentally harmful fossil fuels, and manage the challenges posed by uncertain renewable generation and varying demand patterns, especially during the COVID-19 pandemic.

To address the complex nature of UCP, which involves non-linearity, non-convexity, and mixed-integer variables, a novel hybrid algorithm, the Chaotic Beluga Whale Optimization algorithm, was proposed. This algorithm integrates chaotic maps to enhance the balance between exploration and exploitation phases, improving convergence speed and solution accuracy.

The problem formulation has been revised to explicitly include wind power uncertainty, ensuring that the stochastic nature of renewable generation is accurately represented in both the objective function and the constraints. This modification strengthens the real-world applicability of the model and aligns with current trends in power system operations.

The effectiveness of the proposed algorithm was thoroughly validated through:

- Benchmarking on 23 standard test functions, including unimodal, multimodal, and fixed-dimension functions.
- Application to eleven real-world engineering design problems to demonstrate broader optimization capabilities.
- Solving UCP for test systems with 10, 20, and 40 generating units, reflecting both medium- and large-scale scenarios.

The results demonstrate that CBWO consistently delivers lower fuel costs and better convergence performance compared to existing metaheuristic algorithms. Its ability to handle wind power variability, integrate auxiliary loads (oxygen concentrators, electrolysers), and manage generator scheduling under uncertain conditions was also validated. Statistical analyses, including best/worst/average values, standard deviation, and hypothesis testing (t-test and Wilcoxon rank-sum), further confirmed the robustness and reliability of the proposed method.

In conclusion, the concrete contributions of this research are:

- A novel hybrid optimization algorithm tailored to UCP under renewable energy uncertainty.
- A refined problem formulation that captures wind power variability and system constraints.
- Successful application of the algorithm to both benchmark and real-world problems, confirming its versatility and performance.

This study contributes to advancing optimization strategies in power system planning and provides a promising direction for future research, particularly in integrating additional renewable resources, storage systems, and demand response programs in next-generation UCP frameworks.

6.3 SUGGESTIONS FOR FUTURE WORK

Some potential research studies for future scope based on the proposed work are:

(i). Analysis of Deregulated Market Effects on Unit Commitment: Future research could explore the implications of deregulated market scenarios within the unit commitment problem, utilizing the methodologies suggested in this study.

(ii). Multi-Objective Optimization and Scenario Analysis in Unit Commitment: Further investigation could focus on implementing multi-objective optimization techniques and analysing various operational scenarios within the unit commitment problem.

(iii). Extension to Multi-Area Power Systems Unit Commitment: The proposed approach can be expanded to address the complexities of the multi-area power systems unit commitment problem. This extension would enable the technique to effectively manage the intricacies and challenges associated with interconnected power systems, offering potential solutions to these persistent issues.

(iv). Investigation of Advanced Metaheuristic Search Algorithms for Unit Commitment: Future research could explore the application of cutting-edge versions of metaheuristic search algorithms to enhance the solution of the unit commitment problem.

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