A COST EFFECTIVE SOLUTION STRATEGY FOR UNIT COMMITMENT PROBLEM FOR V2G OPERATION IN UNCERTAIN SUSTAINABLE ENERGY ENVIRONMENT

A Thesis Submitted for the Award of the Degree of

DOCTOR OF PHILOSOPHY

in

Electrical Engineering

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2022

DECLARATION

I declare that the work which is being presented in the thesis, entitled **"A Cost Effective Solution Strategy for Unit Commitment Problem for V2G Operation in Uncertain Sustainable Energy Environment"** in fulfillment of the requirements for the award of the degree of Doctor of Philosophy in Electrical Engineering and submitted to Lovely Professional University, Phagwara is an authentic record of my own research work under the supervision of Dr. Vikram Kumar Kamboj and Dr. Priyanka Anand. The matter embodied in this thesis has not been submitted by me for the award of any other degree of this or any other University/Institute.

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THESIS CERTIFICATE

This is to certify that the thesis entitled **"A Cost Effective Solution Strategy for Unit Commitment Problem for V2G Operation in Uncertain Sustainable Energy Environment"** submitted by **DINESH DHAWALE** to the Lovely Professional University, Punjab for the award of the degree of **Doctor of Philosophy** is a bonafide record of research work carried out by him under my supervision.

The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

In the world of technology and modernization, the demand for electric power has increased to meet the power requirements of various sectors, such as agriculture, industries, and domestic and commercial applications. A recent survey reveals that the overall energy demand of the entire world is found to have increased by around 20%. Hydro, thermal, nuclear, oil, and natural gases are the most common available energy sources. The thermal energy obtained from the fossil fuel is the major ingredient for energy production on a large scale. It is the most convenient way of generating electricity in the world. The extreme utilization of these fossils could result in their quick fading in the upcoming years. Different steps have been initiated by almost all nations for efficient energy conservation. In the modern power system, along with conventional energy sources, renewable energy plays a major role in satisfying overall power demand. There is a significant global growth in renewable energy generation. Wind and solar PV electricity generation have grown by more than 10% and 20%, respectively. The total global contribution of renewable energy is now more than 9% of the global electricity supply. The large penetration of these intermittent energy sources has further increased the complexity of the power system.

Because of the increase in renewable generation, other generation facilities, such as coal, gas, and nuclear power, have become congested. If the total hydro-power generation of 16% is included, the total renewable energy will reach 25%. Furthermore, 10% of the world’s electricity is provided by a total 440 nuclear reactors. Nuclear power and renewable energy, which are low-carbon sources, account for a major share of our electricity production. The Unit commitment problem (UCP) is an optimization problem used to determine a particular generation schedule with adequate operating reserve to satisfy a forecasted load demand. UCP is a pre-planned process of selecting an economic generation schedule for a specified time interval of 24 hours to 168 hours in order to reduce the overall operational cost. Generation companies must bear the additional cost of spinning reserve in order to ensure the reliability and security of power supply based on load demand.

The introduction of electric vehicles has accounted for a drastic change in conventional UC problems. This category of electric vehicles may be battery operated

vehicles, plug-in electric vehicles, or hybrid electric vehicles, which have bi-directional characteristics and depend upon the operation of electric vehicles under charging and discharging processes. During charging, these electric vehicles act as a load, while during discharging they feed back the stored power in their batteries to the grid and act as a source.

Due to development in power electronics and converter technology, the additional spinning reserve requirement could be waived off by utilizing renewables and V2G operations. But, this large penetration of renewables and electric vehicles may further result in system complexity. This type of energy management requires a proper selection of generating units in service in order to reduce the overall cost of generation, which includes fuel cost and operational cost and falls under the category of unit commitment problem.

Load demand keeps on varying throughout the day and never remains constant. The load demand is at its peak value throughout the day and in the evening, while it is low during the late-night hours when most of the population is asleep. Also, the electric power demand is higher during the weekdays than on the other days. Thus, a systematic and intelligent approach in selecting the proper ON/OFF generation schedule could save a lot of money for an electric utility. Though energy production from fossil fuel is simpler, it also results in harmful hazardous effects on the environment by releasing fossil emissions. If the energy consumption process continues with no alternatives, it may result in the rapid use of fossil fuels and eventually reach its end one day. It becomes necessary to pay great attention to the usage of these conventional sources. However, with the participation of renewable energy sources, it has somehow lowered the burden on fossil fuels to satisfy load demand to some extent. Wind and solar are the principal renewable energy sources contributing towards total energy production throughout the world.

This research is focused on ‘wind’ as renewable source. Wind energy is stochastic in nature meaning that its velocity and direction go on changing with time. This uncertain stochastic nature could be fixed by using various statistical techniques such as gamma function, and weibull probability distribution function, etc. To determine the economic visuals of a wind farm, it is necessary to know the estimated power and energy output of each turbine. However, with large penetration of these sustainable energy sources, unit commitment problem has become even more complex. In the contemporary research an effort has been made to develop a cost effective solution strategy for solving unit commitment problem incorporating V2G/G2V operation under uncertain renewable energy sources.

The real outcome from the prescribed substantial prospect on current electrical power scenario, sustainable energy development finds wide scope of research in discovering new methods and techniques. Energy management has now became a mix-technology wherein there should be an intelligent control of different level of penetration. Researchers are constantly working on finding most cost effective ways to provide an efficient solution to this crucial problem of energy management in complex stochastic environment. V2G looks to be the most profitable future technology which not only reduces the burden on generation companies but also helps to mitigate the environmental issues.

This thesis deals with introductory aspects of current power generation scenario and significance of unit commitment in modern integrated power system. Also, this chapter includes various possible non-conventional alternatives for minimizing dependency of modern society for energy generation and transportation sector. Further, it includes the scope of utilizing vehicle to grid operation in presence of sustainable energy environment.

Ensuring chapter explores literature review of recent optimization algorithms applied on various real world problems including the unit commitment problem. This chapter covers research work starting from 1959 to 2021 and an intense study of unit commitment problem along with benefits and hindrances has been presented in order to explore the research gap. Finally, the chapter has been concluded by exploring the scope of proposed research work.

The succeeding chapter deals with various optimization methodologies to elucidate benchmark function, real-world problems and unit commitment problem. In this chapter theoretical and mathematical calculations to solve various optimization problems has been explored. Three different algorithms have been developed using recent modern search algorithms such as Harris Hawk's optimizer (HHO) and Slime mould algorithm (SMA) and improved grey wolf optimizer (IGWO). Two chaotic variants has been developed using Harris Hawks optimizer and slime mould algorithm.

The next chapter deals with detailed description of 23 standard benchmark functions. In this chapter proposed algorithms i.e. Hybrid Harris Hawks optimizer (hHHO-IGWO), Chaotic HHO and Chaotic SMA has been used to test seven uni-modal functions, six multi-modal functions and 10 fixed dimension functions. Further, 10 practical engineering design problems are examined by applying proposed methodologies. To ensure that the suggested algorithm is effective, test results were compared to previous algorithms such as PSO, DE, GA, MVO, GWO, GSA, ACO, MFO, and others.

The next chapter deals with solution to unit commitment problem for -10, -20, -40 and 60- unit using proposed methods. The unit commitment problem for thermal units has been elucidated by hybrid Harris Hawk's optimizer, Chaotic HHO method and Chaotic SMA method for conventional UC. A Comparative analysis 10-unit system with other methods has also been performed and it is perceived that proposed methods evaluates superior results when matched to other heuristic and meta-heuristic algorithms.

The next chapter deals with solution to unit commitment problem for -10, -20, -40 and 60- unit with wind and EV using proposed methods. The unit commitment problem for thermal units has been answered by implementing hybrid Harris Hawk's optimizer, Chaotic HHO method and Chaotic SMA method for conventional UC with wind and UC with wind and electric vehicles (EV). A Comparative analysis of 10-unit system with other methods has also been performed and it is perceived that proposed methods performs better relative to other heuristic and meta-heuristic algorithms.

The last chapter encapsulates the significance and contribution of the proposed research work. A comparative result analysis including percentage cost saving for -10, -20, -40 and 60-units with wind and EV penetration has been summarized. Finally, suggestions for possible futuristic scope of proposed research work has been included.

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LIST OF PUBLICATIONS

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2. Dhawale, Dinesh, and Vikram Kumar Kamboj. *"HHHO-IGWO: A new hybrid Harris hawks optimizer for solving global optimization problems."* 2020 international conference on computation, automation and knowledge management (ICCAKM). IEEE, 2020.
3. Dhawale, Dinesh, and Vikram Kumar Kamboj. *"An Effective Solution to Unit Commitment Problem in Presence of Sustainable Energy Using Hybrid Harris Hawk's Optimizer."* 2020 International Conference on Decision Aid Sciences and Application (DASA). IEEE, 2020.

CHAPTER-1
INTRODUCTION

1.1 INTRODUCTION

In the era of technology and modernization, the demand for electric power has increased due to the necessity of electricity in various sectors such as agriculture, industries, domestic, and commercial applications. According to a recent poll, the world's overall energy demand has grown by around 20% [1]. Hydro, thermal, nuclear, oil, and natural gases are the commonly available energy sources. The thermal energy obtained by burning fossil fuels is the major ingredient for energy production on large scale. It is the most convenient way of generating electricity throughout the world. The extreme utilization of these fossils could result in their quick disappearance in the upcoming years. So, it is essential to make proper and efficient utilization of conventional energy sources for their long existence [2].

The rapid depletion of these nonrenewable energy sources was thought to be threatened by the fuel crisis of the early 1990s. Countries throughout the world are now become aware of this energy crisis issue and have developed a number of measures to use the conventional fuels that are now accessible for a long time [3]. The tracking and documentation of all information pertaining to the residual stock availability of the fuel sources is currently highly prioritized in the power industry. In the contemporary power system, the contribution of renewable power plays a vital role in meeting the overall power demand in addition to power generation from thermal energy [4].

In recent years, the liability on conventional power sources has been reduced to some extent due to the integration of renewable power with utility grids. Wind and Solar energy are the major non-conventional sources for renewable energy production, but these renewable sources are intermittent and cannot provide constant output power. However, due to advancements in control systems and power electronic convertor technology, an efficient storage system could now be possible. These energy storage systems could be further modified to improve their efficiency and reliability. Large penetration of these intermittent energy sources has further increased the power system complexity. There is significant global growth in sustainable energy generation. Wind and solar Photo Voltaic (PV) electricity generation has grown by more than 10% and 20% respectively. Now total global contribution of renewable energy is more than 9% of the global electricity supply [5].

The rise in renewable generation resulted in congestion on other generation facilities, namely coal, gas, and nuclear power. If the total hydro-power generation of 16% is included, the total renewable power accounts around 25 %. Around 10% of the world's electricity is provided by a total of 440 nuclear reactors. Nuclear and renewables which are the low-carbon sources account for a major share of electricity production. Further, the introduction of electric vehicles has accounted for the drastic change in a conventional power grid. In the modern power grid, electric vehicles can be utilized as another source of energy.

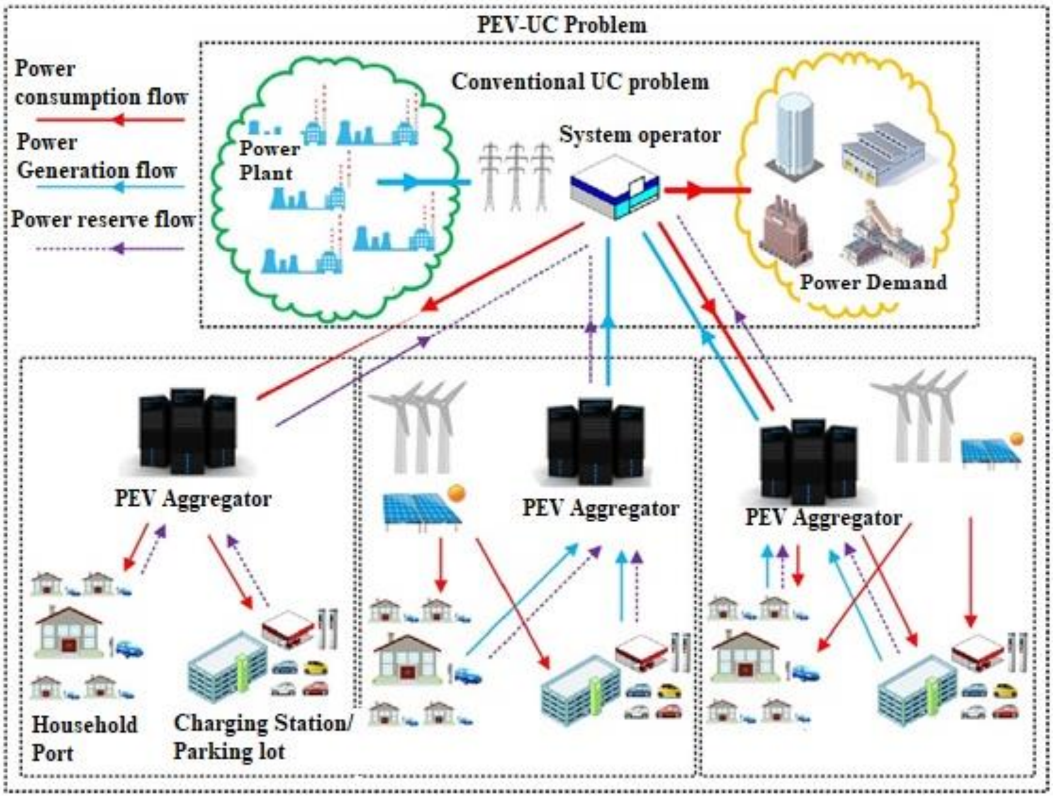


Fig.1.1: Integrated Power System[6]

The electric vehicles may be battery-operated vehicles, plug-in electric vehicles, or hybrid electric vehicles. The characteristics of EVs depends upon the operation of electric vehicles under the charging and discharging process. During charging, these electric vehicles act as load, while during discharging drive back the stored power in batteries to the grid and act as a source. Now, the present power system is an integrated system constituting different sources such as conventional, renewable, and electric vehicles as shown in fig.1.1 [7].

1.2 GENERATION SCHEDULING

Today's modern world rely on electrical energy to fulfill the human amenities. It now becomes essential to utilize available power generation sources more intelligently for the long existence of conventional energy sources. Power cannot be generated instantly as per wish. It requires appropriate planning and time duration to set a required number of generating units online or offline as per the load requirement. Further, the forecasted load never remains constant but keeps on varying every hour throughout the day. So, it is required to monitor the current load profile and accordingly turn on or turn off a particular generating unit with the adequate spinning reserve under unpredicted emergencies. This planned generation scheduling is referred to as Unit Commitment (UC) [8].

The generation scheduling plays a vital role in determining commitment status and load allocation for a specific time interval. The major objective of generation scheduling is identifying the most deserving combination of units and distributing the forecasted load to the number of committed units. Selection of an appropriate generation schedule could be beneficial in reducing the total fuel cost. Thus, the selection of a proper generation schedule not only decreases fuel cost amount but also results in an appreciable saving of money per year for power companies. Optimal generation scheduling is the major requirement of a power system considering technical and economic constraints over a scheduled time. Further, the introduction of electric vehicles has accounted for drastic change in conventional UC and generation scheduling [9].

Generation scheduling may be short-term or long-term. The short-term and long-term scheduling has different operating constraints and thus subjected to certain limitations. Generation scheduling is the process of selecting the most economical unit for meeting the load demand. There may be a possibility of sudden failure of some generating units or intentional shut down for some maintenance purpose. For such situations, it is necessary to keep equipped a 5% or 10 % additional generation facility. This excess generation facility is called as 'Spinning Reserve'. It is a waste of power and energy, because even if these units are not online, they keep on continuously spinning and thus termed as spinning reserve [10].

In order to facilitate reliability and security of power supply as per the load demand, generation companies have to bear this additional cost of spinning reserve. Due to advancements in power electronics and converter technology, this additional spinning reserve requirement could be compensated by utilizing renewables and V2G power flow. But, the large penetration of renewables and electric vehicles may further result in system complexity. For this type of energy management, requires a proper selection of generating units in service to moderate the overall generation charge, which includes fuel price and operating charge, and falls under the category of unit commitment problem (UCP)[11].

1.3 UNIT COMMITMENT PROBLEM

Unit commitment is the optimization problem used to regulate generation schedule with sufficient spinning reserve subjected to different system and environment conditions. Though it is an old concept of selection of a particular combination of generating units, still plays a vital role in predicting the most appropriate solution for the economic operation of the power system. The unit commitment problem is an optimization issue to govern a particular generation scheduling with adequate operating reserve to meet a forecasted load demand. UCP is a pre-planned process of selecting an economic generation schedule for a specified time interval of 24 hours to 168 hours to reduce the overall operational cost [12].

The need for an economic power schedule is subjected to the constraint of committing enough generating units online to prevent any unavailability of power supply to the consumers, which are referred to as the 'Unit commitment problem'. On the other hand, Economic Dispatch (ED) explores the progression of generation allocation of units within their minimum and maximum limits under different constraints and environmental conditions. UCP is a more critical and complex process than economic dispatch, where the decisions of committing or de-committing a generator have to be taken. The complexity associated with UCP is due to the presence of binary decision variables on the generating units ON/OFF status.

UCP is a non-convex, non-linear optimization problem subjected to an extensive range of time-varying constraints. It contains load balancing, reserve constraints, unit limitations such as up/down ramp rates, timings, and generating limits. Beside these complexities demand fluctuates throughout the day and is never constant. It is illustrious that load demand is at peak value throughout the day and in the evening, while it is low during the late-night time when the record of the public is in sleep. Also, the electric power demand is higher on weekdays. Thus, a systematic intelligent approach for selecting a proper generation schedule could save a lot of money for an electric utility [13].

1.4 VEHICLE TO GRID TECHNOLOGIES

This section presents a brief overview of the historical background, benefits of electric vehicles, and detailed vehicle-to-grid operation. Vehicle to grid (V2G) is an emerging technology that allows to feed surplus power stored in the battery to the power grid. Presently, V2G is in the most advancing phase and falls under developing technologies. In the future, this technology can play a crucial role in reducing overall generation cost.

1.4.1 Historical Background of Electrical Vehicles

Nowadays all global countries throughout the world are getting more and more attracted to search new alternatives for energy sources after being acknowledged the threat of the fade of limited fossil fuels and environmental issues. A sufficient amount of coordinated Electric Vehicle (EVs) utilization for transportation could be a possible solution for minimizing emissions released from the conventional vehicle by combustion of fossil fuels. Although electric vehicles seem to get more popularized these days, it has a surprising historical background. In 1834 Thomas Davenport developed the first non-rechargeable battery-operated EV in tricycle form. After the invention of lead-Acid batteries in 1874, David Salomon was successful in developing an electric vehicle with a rechargeable battery. In 1884, a famous electric vehicle known as ‘Electrobat’ was introduced by Electric Carriage and Wagon Company. This development led to the construction of commercial EVs in late 1886 by many companies [14].

One of the examples is electric trolley developed by Frank Spraque in 1886. ‘Victoria’ EV designed by Riker Electric Motor in 1887 which became the house name during that period. Between 1899 and 1906, Bouquet, Gracin, and Schivre (BGS) manufactured a large variety of cars, buses, etc. They invented an EV named ‘Jamais Contente’ in 1899, which performed a record run of 110 Km/Hr. All these developments were the major benchmarks for the popularization of electric vehicles. Historical data reveals that in 1900, out of 4200 vehicles sold in the USA, 38 % were EVs. A large number of companies in the US, England, and France were the leading countries, that started manufacturing EVs in 1900. Around 34000 registered EVs were used for transport in 1912. Eventually, EVs became the major mode of transport. The introduction of low-cost Internal Combustion engines (ICE) by Henry Ford and automobile starters by Charles Keetering [15]. These two developments made ICE vehicles more user-friendly and economical. Eventually, EVs got suddenly disappeared in the 1930s. After a gap of around 40 years in the 1970s, again resurgence was noted in the evolution of EVs because of two major circumstances. The first one was a search for alternative fuels by global countries due to the oil shortage faced by Arabian countries. Secondly, from the 1950s onwards many western countries, witnessed the worst type of Smog in nature. This captured the attention of governing bodies of these countries to frame strict restrictions and regulations to mitigate the impact of Smog on environmental issues. In 1990, famous regulation known as “California Air Resolution Board (CARB) was devised with a compulsion of 2 % EV sale annually out of total vehicles on the road [16].

Many new schemes offering opportunities and subsidiaries to the customers were introduced for promoting the participation of EVs in transportation. Due to strict regulations and opportunities for getting subsidies, many automakers in the US, Japan, and Europe started manufacturing more and more EVs. Some of the major companies included as follows:

General Motors introduced three series of EVs; Electrovair in 1966, Electrovan in 1968, and Electrovette in 1979. These vehicles were based on conventional separately excited dc motors with an SCR-based inverter since conventional IGBT-based VSI was not available at that time. Ford EV projects resulted in Fiesta EV, Escort EV, Arostar, Ecostar, etc. in the 1970s. Nissan designed EV-4, EV-Resort, President EV, and Credric-EV in the late 1970's /'80s. Toyota introduced a series of EVs named EV-10 to EV-40 in the 1980s. Fiat introduced X123, Y10 in the 1980s, and Electra in the 90s. BMW produced EV series such as E30E, E36E in the early 90s, and E1 in the mid-90s. During 1990-2000 many companies were liable to launch their own EVs. These vehicles were marked to have ratings in terms of performance and efficiency [17]. In the current scenario, EVs are extremely popular and can compete with conventional ICE. Some examples are; Tesla Road star (2007) and Model-S (2012). Also, some luxurious sedans are available such as Ford Fusion Hybrid, Lexus RX 450h, Volvo XC 60 T8, BMW 740e XDrive, etc [18].

1.4.2 Benefits of Electrical Vehicles

The current global population is around 6 Billion. If the increase in population follows the same trends, then it may become 10 Billion by 2050, and vehicles on road would be around 2.5 Billion by 2050. Subsequently, if all the vehicles are ICEs, then all cities may be covered with permanent smog with extreme air pollution. It was reported by the Air research board (ARB) that around 9000 death every year due to fine particle matters in California. This calls up the necessity of identifying the most promising solution. Sustainable transportation could be an immediate solution to reduce the harness of air pollution. Sustainable transportation means making utilization of renewable energy sources for charging zero-emission vehicles. This also allows in reducing dependency on fossil fuels for charging these EVs. Thus, in short, the benefits of EVs can be summarized as (i) alternative energy sources (ii) allowing energy diversification (iii) minimizing pollution (iv) enabling improved performance [19].

1.4.3 Vehicle to Grid operation

V2G is an emerging technology composed of grid-able EVs, utility system and information technology. The EV batteries can store energy and may act as energy storage device. Thus, if there is an adequate facility to make these EVs grid-able and also bi-directional information exchange between grid and EV owners, it could be possible to use these batteries as power on-wheel generators. With the advancement in technology and improved power converter, it now became possible to fed back additional energy stored in batteries to the grid. This process of feeding power back to the utility from vehicles is termed as ‘Vehicle to Grid’[20] .

In hybrid Electric vehicles categories, PHEV and HEV are grid-able means they can be connected to exchange energy with the grid. On the other hand, Electric vehicles charged their batteries from the grid supply. However, with an adequate energy exchange facility, it could be possible to have a bi-directional flow of energy; either from Grid to vehicle or Vehicle to grid [21].These days V2G is emerging as a new business model in power industry. In an average EVs can store or generate 4 kWh to 80 kWh. So, if a properly coordinated system is available, it could be possible to make mass use of these EVs. The un-coordinated charging/discharging of such a huge number of EVs may cause disturbance in power system dynamics and stability. A typical V2G operation is depicted in Fig.1.2.

Fig.1.2: A typical V2G Scenario[22]

It requires communication of EVs with grid operators such that the operator not only control the energy flow from battery to grid but also control the charging rate of batteries. Thus, it may be noticed that all these batteries if connected to grid, while vehicles are parked, each EV can typically provide energy between 4 kWh to 80 kWh [23].

It is required that the power aggregator should have a quick watch such that a sufficient number of vehicles could participate in the V2G operation. This coordinated V2G participation could account for an appreciable amount of power contribution and would play a potential role in reducing greenhouse emissions. Assuming that in a huge building, there may possibility of large Electric vehicles say for 200 to 300 vehicles on an average, parked 90 percent of the total life span or some vehicles to homes located at a small distance may be connected to a common aggregator and having capabilities of V2V, V2B, V2H such that the efficiency of energy transfer is maximum[24].

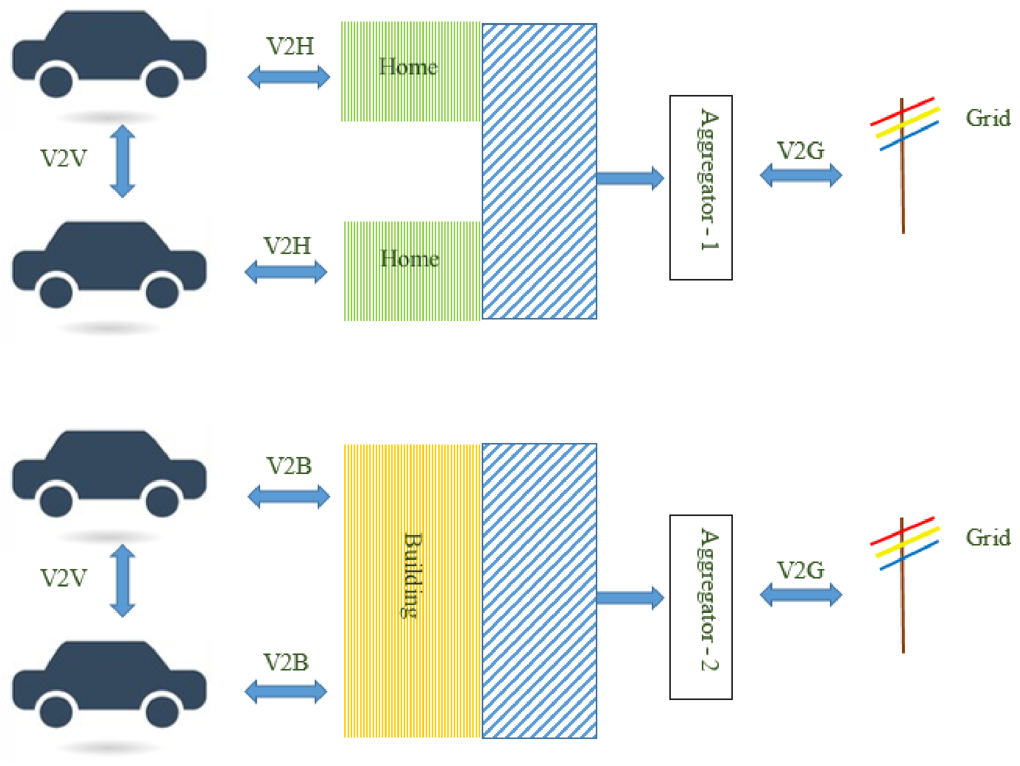


Fig.1.3: Different V2G Scenarios[25]

On the other hand, this power should have enough security to optimize voltage deviation if at any point of common coupling between the aggregator and utility grid Thus, the following are the schemes under which V2G operation can be implemented [26]. Fig.1.3 illustrates a simple model which explains different operations that comes under V2G operation. If there are many homes which are isolated but located nearby in a locality, they can be connected to a common aggregator. The aggregator will monitor the dynamics and energy flow within this pool of homes and vehicles. It is also possible to have similar situations when we have a common building. Nowadays in urban areas, very huge buildings are constructed with two or three basements for parking. So, it has a high pool of vehicles located or parked in the basement. Thus, similar things can also be done with the vehicles in the parking [20].

In addition to that, V2G Technology has a lot of applications for the power system. Thus, if there are a lot of aggregators connected to the grid, it will act as a power generator system, capable of taking energy, storing energy, and capable of delivering energy. If such a system is linked to a utility grid, it can support the power system in many ways. The power generation always tries to match the load demand but there will be a lot of fluctuations between the peak hours during the day and off-peak hours at the night. The V2G operation can help the grid by energy generation during the daytime and support the peak load demand, which is called peak shaving. It can also support the regulation of grid voltage [27].

EVs under V2G can support this by quickly supporting the peak demand in a very dynamic fashion. Secondly, it will not be an additional burden on the power system and will be correspondingly less expensive. It is possible to use the reactive power capability of EVs and help the grid with reactive power compensation. A lot of renewable power is getting added to the grid through wind and solar. But, these sources of energy are intermittent and depend on solar irradiance or wind availability. Thus, V2G and support of EVs could be utilized, such that these transients can be minimized in a highly dynamic fashion [26].

1.5 SUSTAINABLE ENERGY ENVIRONMENT

Electrical energy is the primary requirement for the functioning of almost all routine activities. With the development and advancement of modern civilised environments, the demand for energy for the fulfilment of requirements has increased enormously. Fossil fuels are the major ingredient for power industries to produce a large bulk of power. Though energy production from fossil fuels is simpler, it results in harmful and hazardous effects on the environment by releasing gaseous emissions. If the process of energy usage continues to stay with no alternatives, it may result in the fast usage of fossil fuels and ultimately reach an end one day. It becomes necessary to pay great attention to the usage of these conventional sources for their long existence. Nevertheless, the participation of sustainable energy sources has somehow lowered the burden on fossil fuels to satisfy load demand to some extent.

The Per capita energy consumption reflects the prosperity of the population in any nation. Experts have an opinion that there is an urgent need for additional power generation capacity to retain sustained economic development. The Central Electricity Authority (CEA) has reported that with this generation level of about 2, 37,742.94 MW and leaving a gap of about 35,661 MW and it would be 85% only in the total installed capacity. Hence, the Indian power sector needs to cope with demand and supply. As per the CEA report, around 68% of power is contributed by the thermal power plant. Thus, it suggests that there is an immediate need of sustainable energy growth. Now, the scheme under 'Power for all' is encouraging the growth and development of renewable and sustainable energy sources such as biomass, wind, hydro, solar photo-voltaic, etc [28].

The governing authorities are now very much concerned about low-cost generation, utilization of available resources, optimization of generation possibilities such as fuel-mix technology, and promoting extensive usage of renewables and V2G technology. This suggests that there is a lot of scope for sustainable renewable energy sources in power production sector, to reduce greenhouse gases and climate change. Among list of renewable energy possibilities, wind energy is rapidly growing and seems to be one of the most promising sources of power generation in the future. The Global Wind Energy Council (GWEC) says that global wind energy generation is about 318.14GW worldwide and contributes around 19% of the total power generation. China is at the top, with the highest installed capacity of about 91.42 GW, followed by the USA, Germany, Spain, and India. Globally, India ranks 5th with an installed capacity of about 20.15 GW. The United States and China have 3% and 2% integration with the existing power system, while India is ahead with 3 to 4% penetration, respectively [29].

1.6 OUTLINES OF THE DISSERTATION

In contemporary work, a cost-effective solution strategy is explored for solving UCP incorporating V2G/G2V operation under uncertain renewable energy sources. Three different optimization strategies have been developed to investigate the optimum solution strategy for the economic operation of a single-area multi-objective framework. Furthermore, to check the proficiency of global and local search capabilities, developed strategies have been applied to standard test functions and real-life design challenges. One hybrid algorithm and two chaotic algorithms have been tested to discover the optimal solution for UCP under different scenarios. The effectiveness of the suggested work has been validated by testing different IEEE test systems consisting of small, medium, and large systems. The detailed research work has been organized chapter-wise in the thesis as follows:

Chapter-1 deals with introductory aspects of the current power generation scenario and presents the various adverse effects of the utilization of conventional fossil-based fuels on living organisms and the environment. This chapter also presents various possible non-conventional alternatives for minimizing the dependency of modern society on energy generation and the transportation sector. Furthermore, it outlines the benefits and scope of V2G technology in reducing the excessive burden on grids to satisfy the tremendous increase in load power demand.

Chapter-2 comprises a literature review of numerous techniques effectively applied to various numerical and computational problems along with unit commitment problems. The chapter includes a general review of the related research papers starting from 1959 to 2021 and an intense review of UCP employing different optimization methods along with advantages and disadvantages. These have been worked out to explore the research gap. The literature review is divided into three sections based on conventional unit commitment, unit commitment incorporating renewable sources, and unit commitment with V2G under sustainable energy sources. Furthermore, five research objectives have been formulated to accomplish the proposed research work. Finally, the chapter has been concluded by exploring the scope of the proposed research work.

Chapter-3 explores various optimization methodologies to elucidate benchmark functions, real-world problems, and unit commitment problems. In this chapter, the initial theoretical and mathematical necessities to solve various optimization problems, such as constrained, unconstrained, uni-modal, multi-modal, deterministic, stochastic, linear, nonlinear, convex, non-convex, etc., are presented. This chapter presents three novel optimization methods to accomplish the proposed research objectives. One hybrid algorithm has been developed by integrating the Harris Hawks optimizer with an improved Grey Wolf optimizer. Two chaotic variants are developed using the Harris Hawks optimizer and the slime mould algorithm.

Chapter-4 deals with a detailed description of 23 standard test functions and 10 practical design problems. Furthermore, this chapter deals with the testing of 23 benchmark functions and 10 practical design problems using three different methodologies. The proposed algorithms are applied to test seven unimodal functions, six multi-modal functions, and 10 fixed dimension functions. To corroborate the usefulness of the proposed algorithm, test results were compared with recent algorithms such as PSO, ACO, DE, GA, MVO, GSA, GWO, MFO, etc. It is seen that simulation results of proposed algorithms outperform in comparison with other methods and give more efficient results.

Chapter-5 deals with the solution to the unit commitment Problem incorporating 10, 20, 40, and 60 units using proposed hHHO-IGWO, CHHO, and CSMA methodologies. Experimental results for 10 unit system were authenticated by performing comparative analysis with other universally accepted evolutionary, heuristic, and meta-heuristic optimization techniques.

Chapter-6 deals with the unit commitment problem tackled by proposed methods for with wind and, wind & electric vehicles. Finally, comparative analysis has been performed for all three methods. Also, results for 10 unit system has been validated by comparing simulation results with other competitive algorithms and it is perceived that proposed methods accomplishes better results in comparison to other heuristic and meta-heuristic algorithms.

Chapter-7 deals with the conclusion of the proposed research accomplished to develop a cost-effective solution strategy for unit commitment problem incorporating V2G/G2V operation under uncertain renewable energy sources. Further, suggestions for future work have also been included.

CHAPTER-2
LITERATURE SURVEY

2.1 INTRODUCTION

Unit commitment is the process of determining ON/OFF schedule of generating unit in order to fulfill load demand with adequate reserve margin within certain constraints. The objective of unit commitment problem is to minimize the overall operating cost. The overall operating cost includes fuel cost ($F_{\cos t}$), startup cost (STC_i) and shunt down cost. In general the fuel cost is characterized by second order quadratic equation given as,

$$F_{\cos t} = \sum_{i=1}^{N} [\left(a_i\, P_{i,h}^2 + b_i\, P_{i,h} + c_i\right)]$$

Where, $a_i\, b_i and\, c_i$ are the fuel cost function expressed in $\$/\mathrm{h}, \$/MWh, and\ \$/MWh^2$ respectively.

The startup cost is related to the boiler temperature and mathematically, startup cost STC_i can be expressed in terms of hot start-up cost $(HSch)$ and cold startup (CSc) of i[th] unit respectively.

$$STC_i = \begin{cases} HSc_{i,h}; & MDt_i \le T_{i.h}^{OFF} \le (MDt_i + CSh_i) \\ CSc_{i,h}; & T_{i,h}^{OFF} > \left(MDt_i + CSh_i\right) \end{cases} \quad (i = N; h = 1,2,3,.....,\mathrm{H})$$

Where, MDt_i is the minimum down time of unit 'i', $T_{i.h}^{OFF}$ is the duration for which unit 'i' is continuously OFF and CSh_i is the cold start-up hours.

Shut down cost is constant and taken as zero in standard systems. Now, the total operating cost F_T is determined by summing up the generation cost of each unit and the start-up cost for a defined time interval. It can be mathematically represented as:

$$F_T = \sum_{h=1}^{H} (\sum_{i=1}^{N} [\left(a_i\, P_{i,h}^2 + b_i\, P_{i,h} + c_i\right) U_{i,h} + STC_i (1 - U_{\mathrm{i}(h-1)}) U_{i,h}]\ \$/\mathrm{hr}$$

Unit commitment problem is restricted with large number of unit and system constraints. These operational and environmental constraints are explored in details in separate chapter.

Unit commitment is the process of determining optimum generation schedule within system operating constraints and environmental factors. The task of selection and allocation of generation scheduling under adequate spinning for the predicted load forecasting is the basic requirement of unit commitment problem. It is very simple and easy to implement a desired scheduling for conventional unit commitment problem based on priority list. However, the involvement of renewable energy sources and electric vehicles introduces increased complexities in determining the unit commitment problem with large number of constrictions. An appropriate solution strategy is necessary to fix the uncertainties associated with renewable energy sources and match charging / discharging behavior of electric vehicles. A large number of research endeavors have deeply explored the conventional unit commitment problem by applying different methods. Researchers are continuously giving their hard efforts to discover new advanced techniques and methodologies. The major objective intricate in these studies is to minimize the overall operating cost by applying different optimization techniques. The following section presents literature review relevant to proposed research work.

2.2 REVIEW OF LITERATURES

Power system optimization is a vast research area where research endeavors tend to apply different optimization algorithms. The researchers are trying to discover advanced optimization methods for solving various problems. Plenty of research effort is going on to discover new processes and build modified, hybrid and chaotic strategies to improve the solution efficiency of existing techniques. The successfully implemented methods on real-world problems including unit commitment problem, falls into two categories; viz conventional methods and non-conventional methods. The conventional methods such as Priority list method [30]–[32], De-commitment method [33], Dynamic programming method [34]–[37], Branch and Bound method [38], Integer and Mixed Integer programming [39]–[41], Lagrangian relaxation (LR) method [42]–[45], Simulated annealing method [46]–[50], Expert system[34], [51]–[53], The non-conventional methods; viz Genetic algorithm [54]–[56], Tabu Search [57], [58], Artificial Neural Network (ANN) [59]–[62], Memetic algorithm [63]–[66], Differential evolution (DE)[67]–[69], Harmony search algorithm (HSA) [70]–[74], Shuffled frog leaping algorithm (SFLA)[75]–[77], Biogeography based optimization (BBO) [78]–[83], Particle swarm optimization (PSO)[84], [85], Fuzzy Logic method [86]–[88], Evolutionary programming (EP)[89]–[91], Ant Colony Optimization (ACO) [92]–[98], Grey Wolf Optimizer (GWO) [99]–[103], Slime Mould Algorithm (SMA) [104]–[106], Hybrid methods [90], [107]–[112]. Baldwin was the first to publish research article on unit commitment problem in the year 1959 [113]. Thereafter, an appreciable research innovation has been carried out by many researchers in the area of a single area of unit commitment problem.

This subsequent section presents literature assessment of various optimization techniques pragmatic on various real-world problems along with unit commitment problem. A concise review for the study has been divided into three sections; viz (i) Classical UC (ii) UC incorporating wind as renewable energy and (iii) UC incorporating renewables and Electric vehicles.

2.2.1 Review of literatures on Unit Commitment Problem

Sheble *et al*. [114] presented a list of methods for solving unit commitment problem**.** Each classical approach for treating unit commitment problem has been elaborated to provide basic information. In this review paper, a large number of techniques and knowledge-based systems were explored systematically to provide different perspective of unit commitment problem. Lowery *et al*. [115] in 1966 presented novel dynamic programming to reduce the computation time required for evaluating the economic generation schedule. It was noted that an IBM computer generates an economic generation schedule for 14 unit system in just six minutes which would rather take six hours to evaluate the same combination by manual calculation.

Guy *et al*. [116] have focused on security constraint for ensuring reliability of ample generation in the event some faults or maintenance of any committed unit. A prediction model based on load curve information was suggested to fulfill criterion of reliability in operation and economic dispatch. Dillon *et al*. [117] have modified the branch and bound approach by integer programming to provide cost effective solution with sufficient reserve margin. Shoults *et al*. [118] have applied a modified priority list method for power dispatch for a multi-area import/export system. It has been observed that the proposed study provides an excellent solution for multi-area, multi-objective problems. Cohen *et al*. [38] proposed a modified version of the branch and bound method for handling constraints to solve the unit commitment problem. Chen *et al*. [119] used the branch and bound method to appraise unit commitment problem involving a large number of units. In this work, the commitment problem for 10 units with 24 hours and 20 units with 36 hours was resolved with improved performance.

Senjyu *et al*. [30] adopted an extended priority list method to tackle systems involving large units. The unit selection involves two steps for categorizing similar and dissimilar units. In the first step, units are randomly selected in order of priority and the solutions obtained in the first step are modified by applying the heuristic approach. The same author has also worked on unit commitment problem using stochastic approach [120]. In this work, SPL was experimentally tested for different systems involving up to 100 units. The key objective identified in this method is to avoid repeated calculations and reduce ELD calculations by the protected sign vector method.

Kadam *et al*. [121] introduced a hybrid approach for tackling unit commitment problem which is highly non-linear, multi-constrained optimization problems. Daneshi *et al*. [35] incorporated a fuzzy dynamic programming-based technique. This method was found to be effective to solve UC in lesser time and reduced dimensions of neural networks by applying gray code. Chen *et al*. [36] have combined fuzzy iteration at the initial stage of dynamic programming. It was noticed that proposed technique permits conventional dynamic programming to evaluate the decision process more appropriately for solving multi-objective problems.

Senthil Kumar *et al*. [37] used Hopfield neural network method by incorporating formulation computation instead of weighted factors. The authors have analyzed a case study comprising three units at Neyveli Thermal Power Station (NTPS), India, and also performed the analysis of a system consisting of 10 units. The main focus behind this work was to provide an efficient solution economic dispatch problem while considering ramp rate and security constraints.

Mokhtari *et al*. [51] utilized the Expert System (ES) based rule base for solving UC problem and observed that ES is more efficient than the knowledge rule base. Padhy et al. [34] presented an expert system to resolve UC problems by developing a new fuzzy train operator tool. The suggested scheme is found resourceful in solving the UC problem compared to classical methods.

Neiva *et al*. [42] utilized the Lagrangian method to reduce the number of iterations in successive approximation. The program code was tested using FORTRAN on a vax-11/780 computing system. Large - scale unit commitment problem was tested and analyzed by implementing dynamic programming with the lagrangian relaxation method (DP-LR) and relaxed DP-LR approaches. Zhuang *et al*. [43] have applied Lagrangian method in three phases to resolute dispatch for a 100 unit system scheduled over a time duration of 168 hours. In the first phase maximization of dual function occurred. Reserve feasibility search incurred in second phase and at last economic dispatch problem was solved using proposed method.

Li *et al*. [122] presented a price-based unit commitment solution for a modified 118 IEEE system with 54- thermal units, 7 cascaded-hydro and 3 pumped storage units. A comparative analysis was performed between the proposed mixed-integer approach and the classical Lagrangian method. It was noticed that mixed-integer programming performs better in solving UCP for small cascaded-hydro and pumped storage units. Takriti *et al*. [41] introduced an improved mixed-integer program (MIP) by applying Lagrangian method. The programing was performed by writing codes in C language.

Guan *et al*. [39] have shown comparison between general integer programming and Lagrangian method. Test results for 10 and 24 units had been compared. Lagrangian method performs more efficiently in solving unit commitment problem compared to MIP. Damousis *et al*. [40] formulated a new integer-coded genetic algorithm. It was witnessed that the proposed method has the inherent ability to reduce the number of chromosome sizes compared to usual binary coding. Simulation results revealed that the LR gives a more robust performance in less period compared to other methods.

Zhuang *et al*. [46] in 1990 introduced the simulated annealing (SA) method to solve the unit commitment problem by utilizing the process of formation of annealing during the cooling process. The SA method was applied for up to 100 unit test systems. It was noted that SA effectively solves the UC problem more precisely due to its inherent characteristics of separating ‘easy’ and ‘difficult’ constraints. Mantawy *et al*. [49] have applied SA algorithm for solving combinatorial optimization problems and a quadratic programming routine for handling non-linear programming problems. Simulation results revealed that the algorithm outperforms over LR and IP implemented for solving three different cases.

In 1999, Mantawy elaborated a hybrid version of SA by incorporating Tabu Search (TS) and Genetic Algorithm (GA). In this work, Tabu search was applied to generate a new population, and simulating annealing was programmed to improve the convergence rate by exploring annealing’s properties. The applicability of the proposed hybrid algorithm was validated by equating simulation results with conventional approaches such as LR, IP, GA, and SA[50]. Wong *et al*. [47] introduced an enhanced Simulated Annealing method by adopting the characteristics of the annealing formation process. Simulation results for 2 test systems containing of 13 and 32 generator units were compared with the dynamic programming method. Venkatesan *et al*. [48] have performed similar research. This method was effective in maintaining reliability and security by exchange of power between four different areas. Generation cost optimization with adequate reliability and security was the major objective achieved in this method.

Ma *et al*. [54] have carried out extensive study of mutation control variables for solving non-convex combinatorial unit commitment problem. In this work, two different GA coding systems were applied on 10-unit generating system in FORTRAN 77. The experiment was performed for different populations of 150, 250, 350, 450, and 500. It was illustrated that GA explores the search more intensively to reach an optimal unit commitment solution. Kazarlis *et al*. [123] implemented varying search operators to search optimal solution for UCP. A 100-unit system was tested by applying the genetic algorithm. Simulation results were compared with LR and DP. It was noted that stochastic nature creates deterrents and thus optimal solution cannot be guaranteed.

Orero *et al*. [56] have applied a genetic algorithm with sequential decomposition logic. The proposed method was found to be capable of exploring a good solution for a medium-sized system. The method guarantees a good solution for UCP without violating system or unit constraints. Huang *et al*. [124] applied a combination of genetic programming and dynamic programming to find an enhanced solution to UCP. The proposed method was tested for 43 thermal units of the Taiwan power system. Initially, a feasible generation schedule was obtained by genetic algorithm and then the pre-committed solutions were enhanced by implementing a dynamic programming method.

Mantawy *et al*. [57] presented the Tabu search method for enhancing the local search capability. This method generates memory structures to solve non-linearity and combinatorial optimization problems involved in unit commitment problem. Borghetti *et al*. [58] have accounted operating constraints and physical characteristics while solving short-term unit commitment optimization problems. However, after a concise comparison between LR and TS, for the more feasible solution, it was suggested to opt for the hybrid version of LR and TS.

Sasaki *et al*. [59] developed a Hopfield neural network (HNN) to resolve the scheduling problem of a 30-unit system. In the beginning, generator initialization at each duration was resolute by the neural network and final solution was obtained by conventional algorithm. Similar work was demonstrated for anticipating mixed integer programming problem in identifying number of equality and inequality constraint [60]. Swarup *et al*. [62] anticipated the discrete and continuous conditions required to compute solutions for UC and ED using conventional methods. Initially, HNN was applied to get unit commitment outputs in discrete form, and then these Unit commitment solutions were applied for continuous HNN form to solve the economic dispatch problem. Different test systems with varying load patterns for a duration of 24 to 168 hours were simulated in MATLAB on a P-IV system.

Padhy *et al*. [61] have analyzed unit commitment problem of practical system at Tamil Nadu for different load profiles. In the initial step, designing of non-linear fuzzy membership was evaluated while second step involves adjustment of generation schedule by using rule-base and inference mechanism of expert system. The results of this method were found be progressive and encouraging in solving real-time optimization of power system.

Valenzuela *et al*. [63] integrated genetic algorithm with lagrangian relaxation method to explore unit commitment problem with more enhanced performance compared GA, MA, DP and LR. It was proven that the seeded memetic GA-LR method gave better results compared with general methods. Sanusi *et al*. [64] performed a comparative analysis between the genetic algorithm and memetic algorithm applied to solve Knapsack Problem. It was observed that Roulette-Wheel selection excels over the Ranking and scaling method in terms of accuracy and optimality. Furthermore, it was also figured that the memetic algorithm outperforms over genetic algorithm when compared to Roulette-Wheel selection scale. Vaisakh *et al*. [125] utilized a genetic algorithm for finding optimal parameters for ACO and the optimum generation schedule for a system consisting of 4 and 10 units was recorded. The comparative results of these test systems with conventional methods such as DP, BB, and ACS show that the proposed method gave a more efficient operation.

Mafteiu Scai *et al*. [65] applied the memetic approach to explore more optimal solution by exploiting global and local more intensively. Dual optimization was applied in the initial phase of the run process. The system was again subjected to the iterative method for extracting better results compared to the gradient and constraint optimization method. Li *et al*. [126] adopted memetic approach for solving multi-objective unit commitment problem. Simultaneously economic dispatch and emission from generation issues were handled by combining non-dominated sorted genetic algorithm with a local search algorithm. The memetic algorithm was applied to 10 and 100-units to resolute the approximation of the offered scheme.

Thomsen *et al*. [69] incorporated crowded scheme with differential evolution algorithm to explore more optima points that enables to extended performance with the high-quality solution for multi-modal optimization problems. Karaboga *et al*. [127] presented a more simplified method to solve the global optimization problem. The differential evolution method was applied to solve five benchmark functions with fine-tuning of selection parameters. Keles *et al*. [128] implemented DE for solving standard benchmarks and also on a real-world dataset of a Turkish interconnected power network. This was very simple research and further modified to enhance the performance. Muelas *et al*. [68] have presented a memetic differential evolution strategy for solving low or high-dimensional problems. A heuristic approach was adopted to intensify the exploration and exploitation phase. It was shown that the DE gave excellent local search results which allow the proposed method to deal with problems of different dimensionality.

Omran *et al*. [129] incorporated swarm intelligence with the improvisation process of harmony search to find a global-best position. The effect of noise using Harmony search (HS) variants have been tested and results were compared with HS and improved Harmony search (HIS). It was noticed that the global best harmony search method outperforms in searching global-best position more precisely for even extremely small value of PAR. Wang *et al*. [71] also utilized musical improvisation and also included low-discrepancy sequence during initialization process for finding global optima. Coelho *et al*. [70] included exponential distribution in the Harmony search method to improve performance. The cost of generation for a 13-unit system was found to be minimized by the proposed method.

Paqaleh *et al*. [130] attempted to solve the unit commitment problem for two case studies by using HSA. A 10 and 26-unit system was experimented and outcomes were correlated with competitive algorithms such as EP, GA, improved lagrangian relaxation (ILR), and improved priority list method with augmented Lagrange Hopfield (IPL-ALH). Arul *et al*. [73] presented the applicability of HSA to workout exceptional load allocation considering line losses under capricious load forms. The algorithm was applied to the six-bus system, IEEE-14 & 30 bus system under an experimental load pattern. It was observed that the proposed method gave more optimized results compared to IFEP and PSO.

Xue-hui *et al*. [75] introduced the SFLA method to rectify the errors in the original Travelling salesman problem (TSP) for managing tours of cities with accuracy. SFLA improves local exploration for small TSP with 51 cities. The algorithm finds six tours earlier compared to the optimal tour provided by TSP. Reddy *et al*. [131] modified

SFLA by introducing an accelerating factor, resolute power dispatching. The modified scheme was introduced to a standard IEEE bus system and results were compared with other competitive algorithms. It is noticed that this method gave more excellent and convergent results compared to other techniques.

Simon *et al*. [78] introduced biogeography based optimization (BBO) algorithm based on the acquired experience from the mathematics applied to other biology-based algorithms such as genetic algorithm and artificial neural networks. The algorithm was tested for 13 benchmark functions and results were compared with seven competitive algorithms. Rarick *et al*. [132] applied BBO algorithm to solve optimal power flow problem for a 30-bus system. Authors revealed that BBO outperforms over GA in evaluating optimal power flow solution. It was reported that BBO method generated more feasible and economical solution compared to Lagrange multiplier and particle swarm optimizer.

Eberhart and Kennedy in 1995 introduced a simple and easily accessible algorithm by mimicking the behavior of bird flock or fish school. The procedure was tested for exploring global and local optima's with reduced errors [133], [134]. Shi *et al*. [85] introduced initial weight and maximum velocity parameters, and provided guidelines for tuning these parameters. For getting more improved performance, time varying inertia weight was also employed. Ting *et al*. [135] used visual basic language for simulating a 10-unit system. The hybrid PSO method was applied to find cost effective solution with least possible errors. Zhao *et al*. [136] proposed a hybrid PSO algorithm by integrating the interior point method with PSO for retrieving the economic dispatch of a system incorporating wind energy and V2G operation. This study also provides detailed modeling of uncertainties associated with wind and electric vehicles under different constraints and limitations.

Zhao *et al*. [137] incorporated IPSO for resolving the UC problem. In this work, enhanced information of particles was incubated to control the mutation operation. It also provides a stratagem for choosing constraints and orthogonal design. The algorithm was tested for 10 to 100 unit systems, and results were authenticated with competitive algorithms such as EP and GA in terms of exploitation properties.

Pandian *et al*. [86] introduced a new methodology using the Fuzzy logic rule for investigating scheduling problem. Linguistic fuzzy control rules were employed for establishing relationships between inputs/outputs. The algorithm was tested for 10, 26, and 34 generating units of the power system. Numerical results show that proposed method gave the best cost solutions. Chen *et al*. [36] developed a modified algorithm by combing fuzzy iteration and dynamic programming model for solving multi-objective optimization problems. The rule-base was framed in such a manner that, a new iteration generates decision operators for solving the specified problem. Saber *et al*. [88] used enhanced fuzzy model along with linguistic fuzzy control. The adapted algorithm was effectively applied to examine economic dispatch for systems consisting of 10 to 100 units. Finally, it was concluded that the proposed method furnished superior performance with a good solution and faster response.

Christober *et al*. [89] developed a new Tabu-search-based evolutionary programming method for solving scheduling problems. It was tested for systems entailing 10, 26, and 34 units. The results of the test system were compared to Tabu search, dynamic programming, simulated annealing, and the Lagrangian method. It was noticed that the proposed method gave more promising results in evaluating the optimal generation schedule. Bavafa *et al*. [91] applied a hybrid combination of Lagrangian, evolutionary and quadratic programming to tackle the economic dispatch problem of a 26-unit IEEE system. It is noticed that the hybrid method gave superior search results within a short time. Selvi *et al*. [90] demonstrated the applicability of evolutionary programming with dynamic programming to rectify generation allocation problems for a multi-area system consisting of four area interconnected networks. A cost-centric comparison between EP, DP, and PSO also was acknowledged to authenticate the value of the proposed method.

Sisworahardjo *et al*. [94] implemented an ant colony search method for evaluating the UC problem of a ten-unit system. The generation schedule was determined from the inherent searching characteristics of ants. The outcomes of proposed method were compared with meta-heuristic methods such as LR, DP, GA, and MA. Shi *et al*. [95] developed a stochastic mechanism by incorporating random perturbation behavior with an ant colony algorithm for solving UC problem. Adequate efforts had taken by the authors to take care of reliability, security, and spinning reserve constraints. Saber *et al*. [138] formulated a modified memory-bounded algorithm by combing a local search heuristic approach to exclude possibilities of local entrapment and the probabilistic nearest neighbor method to intensify the search forgotten value. The algorithm was simulated for handling unit commitment to systems consisting of 10-100 units. It was noted that the proposed methods gave more cost-effective solutions for unit commitment problems compared to competitive methods such as integer-coded GA, LRGA, GA, LR, and DP.

Venkatesan *et al*. [139] applied an ant colony optimization algorithm to select a combination of generating units with efficient operation. A case study was carried out considering 26 units under different load patterns. Based on information gathered from a case study, algorithm was accomplished in Matlab for a 24 hours' time cycle. Chitra *et al*. [97] presented voltage frequency control and harmonic analysis for power quality improvement using ant colony optimization algorithm. Experiments were performed in matlab simulink environment for a 50 kW load under switching and sampling frequency of 10 kHz and 500 kHz.

Singh *et al*. [117] developed upgraded GWO for solving power dispatch problem for systems consisting of 38, and 40 units with different parameter settings. FORTRAN software language was implemented to find the economic dispatch problem. The test outcomes revealed that the proposed technique was found to be generating an optimal generation schedule compared with other competing methods such as BBO, DE, PSO, etc. Yadav *et al*. [108] have developed a hybrid method by integrating PSO with DE for determining dispatch problem and economic emissions. The hybrid model was utilized to minimize overall generation costs and emission costs. The algorithm experimented on three separate bus systems, and the results were compared with basic methods and a recently developed hybrid model of PSO and DE.

Fang *et al*. [109] used a combined-cycle gas turbines model considering minimum online/offline time and ramp rates without involving any additional binary variables in UC formulation compared to independent system operators. Chen *et al*. [140] provided a unique method for eliminating the difficulties involved in using the penalty function method. It was observed that this method sometimes fails in determining optimal penalty coefficients during economic load dispatch calculation. This problem was resolved by implementing a two-stage strategy using an artificial bee colony algorithm. Kein *et al*. [141] used a social spider optimization algorithm to find the most feasible least-cost generation scheduling for systems consisting of 6 to 20 units.

Kamboj et al. [142] implemented harmony search algorithm to resolute the UC problem. The proposed method was applied to 4, 10, 20, and 40 units. The simulation outcomes were equated with other methods such as GA, EP, PSO, IPSO, DPLR, etc. Results revealed that the algorithm gave better outcomes related to other algorithms. The same author has employed DE-random search method on similar grounds and solved unit commitment problem very precisely [143].

2.2.2 Review of literatures on UCP with Renewable Energy Source

Chao *et al*. [144] estimated a co-relation between historical wind speed with a simulation-based method such as Weibull parameters of hourly wind speed and the lag-one autocorrelation of hourly wind speed values. A comparison was made on parameters such as wind power histograms, autocorrelation function, and mean persistence and recorded good resemble with simulated and actual data for a sample of six different wind turbines in three regional arrays. Billinton *et al*. [144] executed a similar study. The results were validated by F-criterion and Q-test. The simulated results were compared with the actual wind speeds. Giorsetto *et al*. [145] proposed cumulative distribution function to check the influence of wind generation on system reliability. This method was found useful in determining effective load carrying capability and contribution in overall power generation.

Pappala *et al*. [146] applied particle swarm optimization for influential scheduling of a wind power system by employing a stochastic approach instead deterministic model. Methaprayoon *et al*. [147] introduced an artificial neural network-based wind power forecaster to take account of probable wind uncertainties while performing UC scheduling planning. Soman *et al*. [148] have presented an insight review on existing wind power prediction studies. This study covers various wind power forecasting methods such as numeric, statistical, artificial networks, and hybrid techniques. Siahkali *et al*. [149] implemented a stochastic probabilistic model considering wind power uncertainties.

Kamalinia *et al*. [150] incorporated mixed-integer programming and develop a novel approach for solving security-constrained based unit commitment problem to avoid ramping requirements due to the uncertainty of WG. Osorio et al. [151] have applied the priority list method to solve probabilistic unit commitment for acquiring a cost-effective and consistent solution. Umamaheswaran *et al*. [152] have elaborated various reliability, financial constraints, and limitations for large-scale renewable participation in the Indian power sector. Foley *et al*. [153] reviewed historical and current wind power generation methods based on wind speed and weather forecasting. A large number of statistical, theoretical, and analytical methods have been studied to explore wind power generation complexities.

Singh *et al*. [154] implemented forward-reduction algorithm and applied a bidding strategy to maximize profit. Wind uncertainties were modeled by adopting an overestimation and underestimation cost function. Zhao *et al*. [155] incorporated wind output and demand response by utilizing the properties of the cutting plane method to determine the optimum power flow solution. It is concluded that the robust unit commitment model reduces the total operational cost and computation time compared with traditional Benders decomposition.

Li *et al*. [156] presented different techniques for wind power prediction along with their advantages and disadvantages. Further, characteristics of various methods for wind power generation were discussed. Hetzer *et al*. [157] introduced wind energy transfiguration system. In this work, the Weibull probability density function is utilized to find speed-power characteristics. Reserve and cost penalty factors were also incorporated to a keep a balance between under-estimation and over-estimation of wind power. Purwadi *et al*. [158] elaborately described the determination of wind speed by measuring the output power of the turbine from voltage and current data. It enables the users not only to eliminate measurement errors but also allows them to measure wind speed directly as a function of output power.

Yu *et al*. [159] formulated an integrated hybrid model by combing the Markov strategy and interval optimization approach to locate various nodes corresponding to wind energy. Mahari *et al*. [160] have applied modified Imperialistic Competition Algorithm (MICA) method to determine an optimal generation schedule for a hybrid system incorporating wind energy. The proposed technique was validated by applying MICA to various combinations of generating units at different wind penetration. Shahriar *et al*. [161] used fuzzy technique for incorporating uncertainty of wind power penetration. A system consisting of three units and one wind power generation unit was tested using the CPLEX optimizer. The fuzzy base-rule trained program was found to be effective in minimizing cost of generation.

Ban *et al*. [162] used mixed-integer linear programming with the benders decomposition technique. The uncertain wind power penetration had compensated by converting the excess wind power into hydrogen gas using an electrolyzer. Abujarad *et al*. [32] utilized the priority list method to solve the UC problem by incorporating solar and wind for a 10-unit system. The cost comparison was also provided for conventional UC, UC with solar, and UC with wind. Shao *et al*. [163] developed a robust security constraint method for mitigating the effect of hourly wind power uncertainties and also accounted for any disturbances due to any wind spillage. Azizipanah-Abarghooee *et al*. [164] applied an improved Jaya system to solve probabilistic power distribution problem of a 10 unit, 118-bus system.

Saravanan *et al*. [165] applied the firefly algorithm for determining a cost-effective solution for a hybrid system consisting of 30 thermal generating units and 4 wind farms for five different population size. From the compared results, it was noted that as the population size decreases, the cost of generation also decreases. Esmaeeli *et al*. [166] introduced the Monte Carlo simulation approach to anticipate unseen forecasted weather uncertainties. A mixed-integer program was used to generate an appropriate spinning reserve requirement. Bhadoria *et al*. [167] incorporated BMFA to solve the numerical optimization problem for 23 standard benchmark functions. Further, the algorithm was applied to determine the optimum scheduling of systems consisting of small and medium-size with 5,7,10, 20, and 40 units.

Ji *et al*. [168] adopted the scenario generation and reduction technique and applied GSA to solve the UCW problem. In this method, GSA explores local search intensively to reduce losses and improve reliability and security. Shilaja *et al*. [169] elaborated a new hybrid approach by integrating Moth swarm algorithm and gravitational search algorithm (MSA–GSA) method for determining optimal power flow for power systems with wind energy sources.

Lakshmi *et al*. [170] have used an Artificial Immune System approach for determining optimal generation scheduling for wind–thermal systems. The proficiency of the method was analyzed by applying the suggested algorithm to a scheme consisting of 10 thermal units with two wind farms.

2.2.3 Review of literatures on UCP with RES and electric vehicles

Saber *et al*. [3] introduced the PSO algorithm for charging /discharging patterns to discover the most economical cost and emission system. The research presents a cost and emission solution for a 10-unit system with a wind farm having 25.5 MW power capacity provided by 17 wind turbines (each 1.5 MW) and 50000 registered grid-able vehicles. The simulation results with RES and EVs revealed that the proposed method was effective in reducing total grid operational cost and emission for the suggested system. Khodayar *et al*. [171] included various constraints associated with the intermittent nature of wind power and charging/discharging characteristics.V2G operating costs and additional constraints that arose due to distributed storage were also addressed. The impact of integration PEV on the generation schedule was analyzed using mixed-integer programming.

Yu *et al*. [172] utilized chemical reaction algorithm for efficient utilization of energy stored in batteries through V2G operation. The major contribution of this research is to generate an optimal generation schedule by considering some part of energy via effective V2G operation. The simulation results of 10, 20, and 40 units systems were compared with competitive methods such as evolutionary programming and simulated annealing. It was noted that the proposed method explored excellent results over other methods. Chandrashekar *et al*. [173] introduced rolling horizon search algorithm for providing controlled PEV operation to mitigate additional reserve cost requirements because of uncertain wind availability.

Ghofrani *et al*. [174] integrated genetic algorithm with Monte Carlo simulation for optimizing the charging/discharging patterns of electric vehicles. In this work, a synergized control model is used to balance the cost penalty associated with the uncertain wind power penetration. Separate wind prediction and EV clustering models were provided to develop a collaborative strategy to benefit wind participants and EV owners. Gao *et al*. [175] developed a controlled stochastic optimization algorithm for the effective V2G operation in presence of intermittent wind power. Different controlled and uncontrolled charging/discharging strategies were demonstrated for mitigating fluctuations in wind power penetration by optimized V2G Control.

Zhang *et al*. [176] introduced a fuzzy chance constraint program for anticipating the problems of time mismatch between supply and load demand by using Demand Response (DR) and Electric Vehicle (EV) reserve during wind power fluctuations. A 10-unit system with wind, DR, and EV was examined in MATLAB software under five scenarios using particle swarm optimization. Reddy *et al*. [19] investigated the performance of different systems consisting of 10, 20, 40, 60, and 100 units incorporating electric vehicles and renewable energy sources such as wind and solar by implementing modified firework algorithm. The results of the proposed algorithm were compared for different units with classical and modern methods such as LR, GA, EP, memetic algorithm (MA), Greedy randomized adaptive search procedure (GRASP), LRPSO, PSO, and IBPSO. It was observed that the proposed Binary firework algorithm (BFWA) method gave more precise results in comparison with other methods.

Zhang *et al*. [177] have proposed a highly coordinated scheme using multiple group optimization based on multi-objective decomposition by incorporating uncertainties of PEVs and wind power. The comparative assessment revealed that the proposed method is efficient in evaluating economic dispatch with superior convergence. Pal *et al*. [26] introduced a centralized system that allows various options of energy transfer for consumers profit. In this work, vehicle to home and vehicle to grid operations were explored systematically using mixed-integer programming.

Clement-Nyns *et al.* [178] used Quadratic programming and dynamic programming to explore a coordinated charging of PHEVs for maintaining voltage profile and grid supply reliability. The uncertainties caused due to the stochastic nature of the charging/discharging pattern were retrieved by the probability density function. The impact of un-coordinated penetration of PHEVs is analyzed to explore the most economical solution. Su *et al.* [179] performed a survey to explore various opportunities and challenges for vehicle electrification and V2G technology. This research explores various aspects of battery technology, battery charging/discharging pattern, energy management, and V2G technologies infrastructure.

Fernandez *et al.* [23] demonstrated possibilities of increased cost and distribution losses with three different levels of PEV penetration. The impact of tremendous penetration of PEV in two distribution areas was analyzed considering a probable percentage of PEV. This work explores different scenarios which support the probability of increased cost due to the large penetration of PEV. Ma *et al.* [180] tested an IEEE-30 bus system incorporating V2G operation for rectifying any flaws in supplying wind power that might occur due to probable uncertainties. In this work, various battery constraints concerning ratings, state of charge, real-time, extend of charge/discharge, the impact of EV penetration, and the cost is evaluated to know various terminologies and challenges associated with V2G operation.

Yao *et al.* [136] presented a hierarchical decomposition approach to provide a coordinated charging/ discharging EV interpretation for maintaining power security and reliability. The proposed method was applied to a 118 bus system with 6 Electric vehicle Aggregators (EVA) with two level-model coordinated charging/discharging schedules. The simulation results suggest that a coordinated EV participation gave much cost-effective solution without any adverse effect on the security and economic operation of the power system. Darabi *et al.* [181] estimated various constraints and limitations that might occur while charging a large fleet of electric vehicles from the utility grid. The proposed method is experimented to evaluate the percentage of PHEVs that may be allowed to charge and the chances of the grid not to provide power for charging EVs. Two cases with 2-level charging were simulated based on various scenarios and also on the information related to arrival- time, charging duration, wait-time, and time of give-up.

Wang *et al*. [182] investigated the impact of V2G penetration to mitigate the imbalance in power distribution during peak shaving due to uncertainties associated with wind availability and solar irradiance. Cross-entropy (CE) algorithm was tested to determine results for a 33-node system for anticipating the unavailability of renewable power by energy transfer through V2G operation. Peng *et al*. [22] developed a novel dispatching strategy for V2G aggregators aimed to participate in regulating power, load frequency, and demand management. Ansari *et al*. [183] presented a fuzzy set theory for accounting uncertainties in market value and initiated efforts to maximize the profit of electric owners and aggregator service providers.

Shekari *et al*. [184] applied multi-objective linear programming to maintain a proper balance between active and reactive power by incorporating a fleet of electric vehicles in a micro-grid. The results were analyzed in terms of voltage profile, generating units dispatch capacity, operation of under-load tap changers (ULTCs), and operational cost minimization of microgrid. Andervazh *et al*. [185] utilized a learning-based approach for solving power dispatch and transportation emissions. Uncertainties associated with load, renewables, and plug-in-vehicles were addressed and modeled using specific techniques such as Monte-Carlo-based simulation, Weibull probability density function, and normal distribution function.

2.3 RESEARCH FINDINGS & SCOPE OF RESEARCH

The survey of the literature suggests that several optimization strategies have been used to address the unit commitment and economic dispatch problems. The following are a few techniques: Priority list, Differential Evolution, Genetic Algorithm, Particle Swarm Optimization, Bird Swarm Algorithm, gbest-Guided Search Algorithm, Binary Bat Algorithm, Binary Gravitational Search Algorithm, Flower Pollination Algorithm, Grey Wolf Optimization, Random Walk Grey Wolf Optimizer, Simulated Annealing, Teaching-Learning-Based Optimization, and Water Cycle Algorithm. From the reviewed literature, key findings related to unit commitment problem and economic load dispatch are discussed in the subsequent section.

Classical UC problems with fewer generating units employ traditional methods such as PL, Lagrangian method, DP, and branch and bound algorithm. Tabu search (TS) is a local search used to elucidate combinational optimization problems. It provides a flexible memory system to solve optimization problems. The major issue associated with TS is its inability to provide an effective solution for large problems of dimension. For the n–unit system, the classical numerical approach employs a 2N-1 combination. It slows down the evaluation process and makes calculations complex for large dimensions. The dynamic programming method has the inherent capability to provide feasible solutions with reduced dimensionality. But, it requires more computation time.

Genetic algorithm is capable of handling constraint and unconstrained optimization with less computational time but fails to explore global optima. DE has ability to explore global optima. It does not require initial control parameters. However, tends to get struck in local minima due to premature convergence and computational time is high. SA has superior local search capability but requires more time to find global optimal. GSA has excellent exploration capability but fails to explore local search. UCP is a complex non-linear problem due to the involvement of large number of constraints. A major weakness of these heuristic and meta-heuristic methods is poor exploration and exploitation capability and thus fails to tackle unit commitment problem with precision and accuracy.

The foremost objective of UCP is to minimize overall generation costs by selecting the most economical combination of generating units. Various environmental issues, such as global warming and air pollution, have raised concerns in the search for alternative energy sources for transportation and power generation. In this regard, renewable resources and vehicles on the grid appears to be a prominent solution to these issues. However, because of the uncertainties associated with renewables, such as wind unavailability, solar irradiance, and V2G limitations, the addition of RERs and PHEVs to power systems increases system complexities. This research work, wind power penetration, is considered for renewable energy. It is the cleanest and most economical energy source, whose output power depends on wind speed. However, it does not produce constant output power and causes uncertainty in the scheduling and satisfaction of forecasted load demand. Similarly, several uncertain factors are associated with the V2G operation. For example, the variation in the driving pattern of owners, start time, state of charge, and technical specifications of the vehicles. The penetration of PHEVs into the power system also introduces substantial levels of uncertainty in the existing power system.

A wide range of research is in continuous progress to invent new and advanced methods for reducing problems associated with UCP by implementing various classical, heuristic, and meta-heuristic approaches. The literature review reveals that V2G is an emerging technology and is still in its development phase. Among all the reviewed research, the unit commitment problem involving renewables and V2G operation is tested only for small micro-grids or small systems with many assumptions and constraints. The key objective of all these methods is to determine an optimal solution for the unit commitment problem.

It is observed that there is a wide scope of research in the area of unit commitment for V2G operation under uncertain stochastic environment. In most of the studied literature, the problem of economic dispatch was tackled for small system mostly consisting of 10-units. It could be possible to apply different algorithms to various small systems consisting 10-units, medium systems consisting of 20 and 40 -units and large system consisting of 60-units. A specific system with a particular number of generating units could be tested to determine optimal for different conditions such as Classical Unit commitment (UC), UC with renewables, UC with V2G, and combined system with UC, renewables and V2G operation. The work is therefore justified in presenting the proposed study. The research proposal therefore presents, “A Cost Effective Solution Strategy for Unit Commitment Problem for V2G operation in uncertain Sustainable Energy Environment” for electric power system.

2.4 RESEARCH OBJECTIVES

The proposed study aims to develop a solution strategy for the unit-commitment problem in the presence of renewables and electric vehicles. The following are the objectives of the proposed research work:

(1) To develop a hybrid optimization algorithm by combing local search algorithm with modern global search algorithm for constrained optimization problem using memetic algorithm approach.
(2) To evaluate performance analysis of standard uni-modal, multi- model, fixed dimension and engineering benchmark problems.
(3) To tackle the unit commitment problem of electric power system with due consideration of Vehicle to Grid operation in stochastic sustainable environment using proposed hybrid meta-heuristics search algorithm.
(4) Testing the performance of the proposed algorithm for various IEEE benchmarks problems with incorporation of V2G operations in stochastic sustainable environment.
(5) Analysis and Validation of results and publication of research work

2.5 CONCLUSION

This chapter deals with a specific review of literature related to the proposed work. The survey of literature has been explored in three sections. The first section includes a review of literature corresponding to convention unit commitment methodologies implemented to minimize overall generation cost. The second section covers the survey of literature corresponding to renewable energy penetration. It covers a review of optimization techniques incorporating wind energy considering wind uncertainties. The last section includes literature concerned with the unit commitment problem due to the penetration of renewables and electric vehicles. This section also presents optimization techniques promoting the advantages of coordinated V2G operation in the presence of sustainable energy sources. The extensive review reveals that there is a scope for research in solving unit commitment problems involving renewable and V2G penetration.

CHAPTER-3
OPTIMIZATION METHODOLOGIES

3.1 INTRODUCTION

An optimization is process of determining different possibilities to discover the most precise solution. Optimization provides an appropriate solution for any simple or complex problem. It is an effective way to provide systematic and efficient ways to create new design solutions to achieve an optimal design. There are many real-world and practical examples where we can recognize the application of optimization. It is difficult to solve complex optimization problems analytically due to certain uncertainties. The advancement in computing techniques enables us to solve complex optimization problems more efficiently by selecting specific optimization tools. Optimization is the process of finding a better and more improvised solution in almost all fields, including science, technology, and engineering design problems.

Optimal control and machine learning are two fields where optimization plays a crucial role. Wing design, pressure vessel design, truss design, structural design, economic dispatch, beam design, mechanism design, gear train design, multi-cultch design, chemical process control, photo-voltaic storage design, and medicine manufacturing are only a few of the examples, where optimization acts as a key ingredient for achieving excellent performance and improved outcomes.

All the above design issues involve either minimization or maximization (collectively known as optimization) of an objective function. Certain specifications, such as initial design idea, conceptual review, market analysis, method/strategy opted, feasibility, efficiency, reliability, cost consideration, minimization of losses, and maximization of profits, needed for the successful implementation of any innovative realization. For understanding the difference between conventional and design optimization methods, a conceptual idea has been formulated in Fig.3.1. The manual optimization process is shown in Fig.3.1 (a).

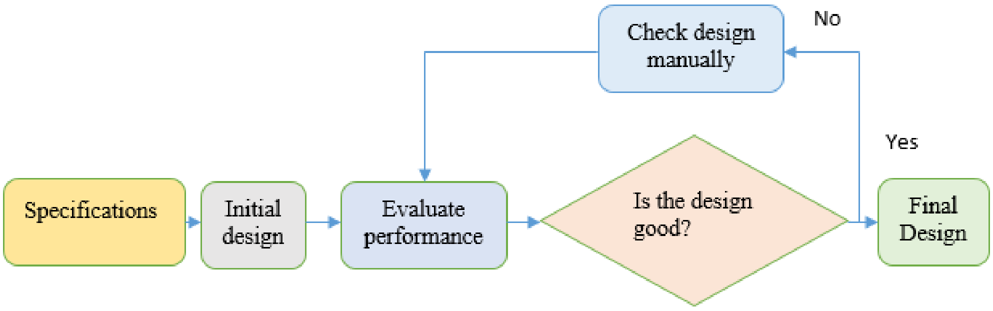


Fig.3.1: (a) Manual optimization process

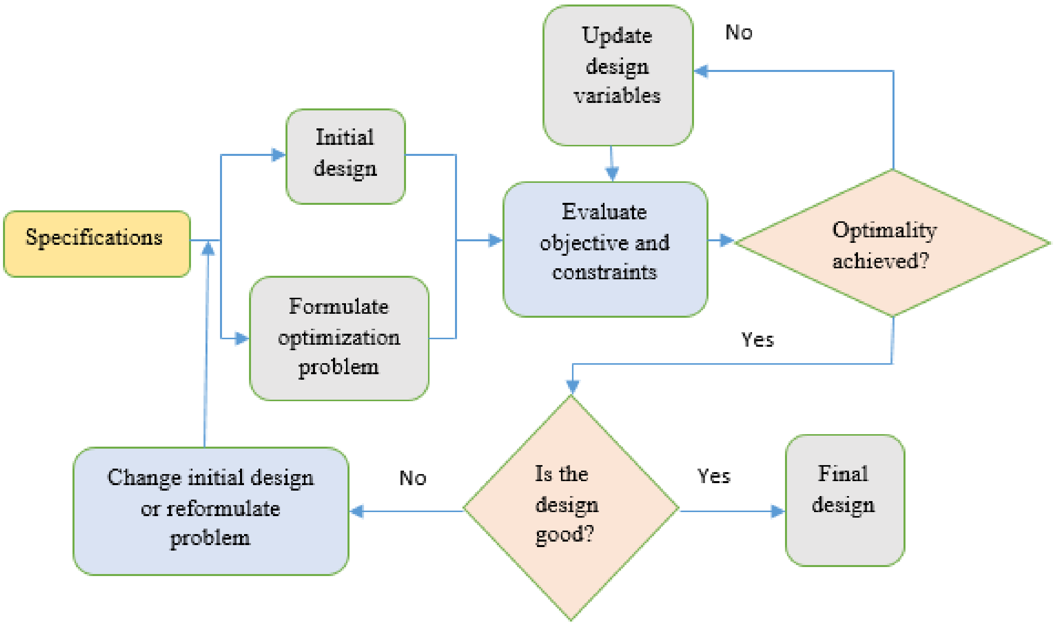


Fig.3.1 (b) Optimization process through software

From the gathered data, the problem is executed, and then the solution is verified by comparison with the previous analysis. If the solution obtained is found to be better than the previous experience, then that design is to be concluded as the final design. But, if it reaches an acceptable level, further iteration is repeated manually. In Fig.3.1 (b), a flowchart for the optimization process through software is explored. In the case of design optimization, initial specification and data processing are similar to those of a conventional method. However, optimization involves problem formulation, variable design, and the desired objective under certain constraints and limitations.

The optimization process generates the most feasible solution and allows the same program to perform different tasks by changing the design variables and related constraints. The optimization algorithm uses stored information to generate a new optimized solution for the same problem. The process is repeated as per programmed command until the design reaches a satisfactory level. It allows automatic variations of programmed commands and keeps running the information in cycle form till the desired outcome. Due to the availability and capability of high-speed computers, optimization algorithms are progressively widespread in engineering design activities.

Despite the numerous advantages of computational techniques such as accuracy, efficiency, and reliability, they introduce some non-linear constraints while solving optimization problems. Differentiability or convexity is the adverse result of riotous computation due to increased problem size or constraint violation. These problems are common even in the real world. Newton developed the gradient method for solving optimization problems involving real-valued continuous parameters. This development of Newton, also known as the steepest descent algorithm, was found to be capable of solving only problems involving continuously differentiable functions. But in real-world applications, the problem may be a discontinuous function with an incomplete definition. The designer has to adopt other search algorithms to solve the problem[186]–[189].

In most real-world optimization problems are not isolated but interrelated with each other. Such optimization problems are called multiple objective design problems (MOD). Management terminology uses multiple criterion decision-making (MCDM) problems for such search and optimization problems.

There is a possibility of having conflicting scenarios while solving a particular type of optimization problem. For instance, cost minimization and profit maximization are the two conflicting issues, and it is difficult to achieve both objectives simultaneously. The process of optimization proceeds with the initialization of the problem formulation and continues till an optimum or desired solution is generated [190]–[192].

3.2 OPTIMIZATION PROBLEM FORMULATION

The most important aspect of developing an optimal design process is converting an idea or intention into a mathematical format that an optimization algorithm can analyze. This mathematical format helps the designer to understand the design problem more deeply. The problem statement should be defined more precisely to avoid any intrinsic weakness that may cause the optimization to congregate to undesirable or unrealistic optima. Fig.3.2. illustrates the procedure to formulate optimization problems.

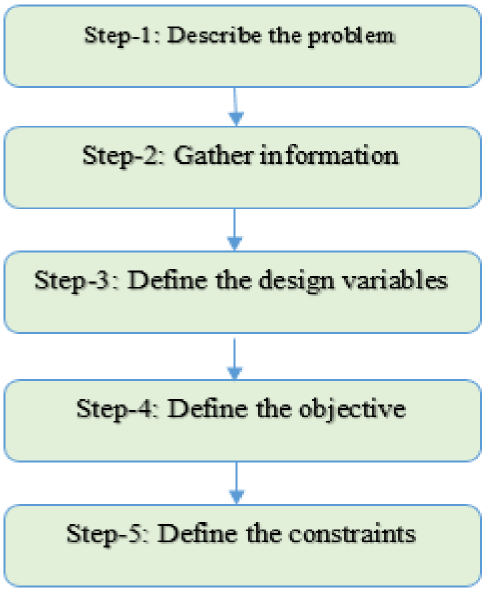


Fig.3.2: Steps in optimization problem formulation

In the first step, description of system, statement of goals and requirements are written a design format. In the next step, all possible data and information about the problem is collected relevant to performance requirements and expectations. Adequate measures are needed to identify, gather and analyze all input and outputs to develop a sound formulation. The three crucial and necessary entities are elaborated as follows:

(i) **Design Variables**: The highly sensitive parameters with inherent ability for proper working of desired strategy are known as decision or design variables. A specific example of design variables can be represented by a column vector as shown in eqn. (3.2).

$$x = [x_1, x_2, ..., x_{nx}] \tag{3.2}$$

The problem dimensionality depends upon the number of x design variables corresponding to different designs. The design variables should have specific identities such that the optimizer can select the elements of x independently. These decision variables should be fixed parameters throughout the optimization process. Nevertheless, despite all possible precautions, there is a chance of having a linear combination of design variables. It could result in an infinite number of variables with a similar design. It is possible to define parameters of the same system with different units without changing the functional form of the problem.

(ii) Objective function: The objective function is to execute the performance of the optimization problem for defined design variables. It is the task for formulating any optimization problem. There may be different objective functions associated with a particular design problem. Some functions may be designed for minimization while others may require maximization. In such cases, the principle of duality is applied which permits the same algorithm to accomplish both the task using non-linear programming [193]–[195].

(iii) Constraints: After choosing a specific objective function, the next step is to frame constraints associated with the design problem. These constraints may be those of equality or inequality, depending on the circumstances. The practical requirement is to apply constraints to minimize or maximize the objective function. Some functions need to be restricted to a fixed equality constraint. Although, for having a flexible range for a certain objective function, an inequality constraint is introduced by applying "less or equal" or "greater or equal" conventions. A generalized mathematical statement for a single-objective optimization problem can be written using eqn. 3.3 (a) & (b) given below.

$$minimize \;\; f(x)$$

$$By\ varying \quad x_i^{min} \leq x_i \leq {}_i^{max} \quad i = 1,......,n_x \tag{3.3a}$$

$$Subjected\ to \quad \begin{matrix} g_j(x) \leq 0 & j = 1,.......,n_g \\ h_l(x) = 0 & l = 1,.......,n_h \end{matrix} \tag{3.3b}$$

The above mathematical statement articulates that minimizing the objective function for the given set of defined decision variables within the minimum and maximum bounds is related to inequality and equality constraints. It is required to classify optimization problems for checking and choosing an appropriate optimization algorithm for solving a particular design [6]. As no single algorithm is proficient in solving all types of optimization problems, it is necessary to define an optimization problem. In general prospect, an optimization problem is classified based on three main traits: the problem preparation, the features of the objective, and restriction functions, as shown in Fig.3. 3.

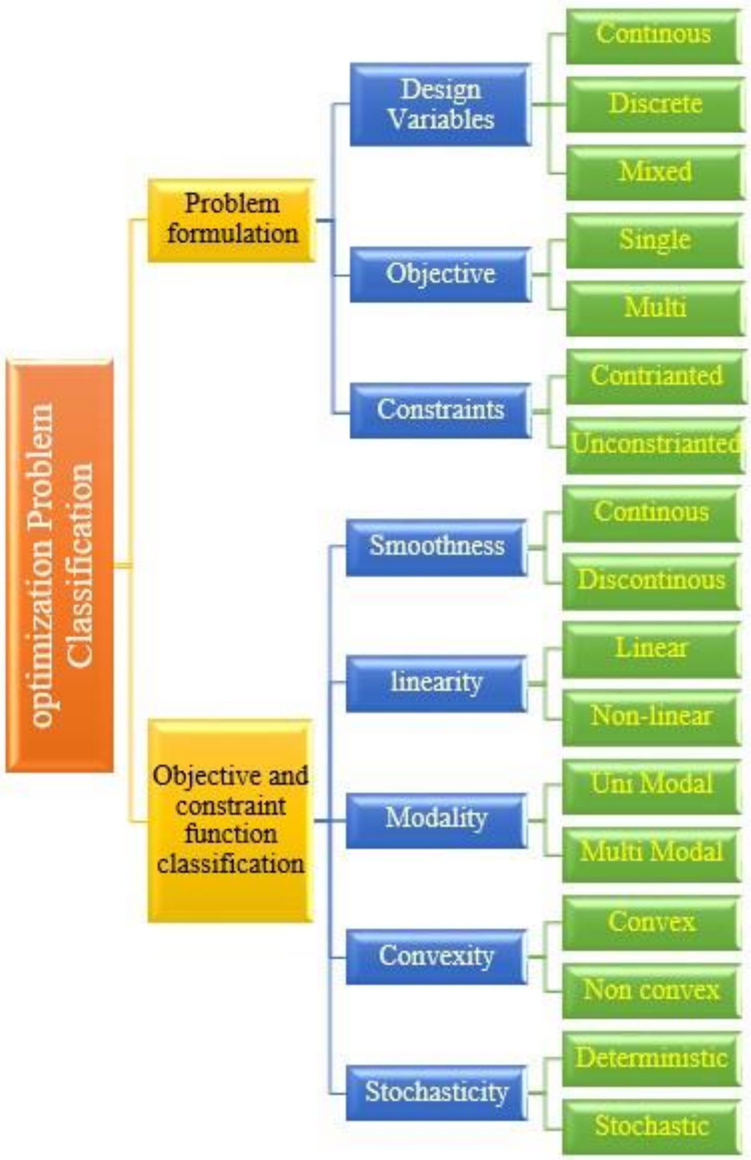


Fig.3.3: Optimization Problem Classification

Fig.3.3 explores the detailed classification of the optimization problem. The design variables may be continuous, discrete, or mixed. The Objectives may be single-objective or multi-objective. Problems may be constrained or unconstrained. Objective and constrained may be further classified depending on smoothness, linearity, modality, convexity, and stochasticity. Thus, the objective functions may be continuous, discontinuous, linear or nonlinear, unimodal or multi-modal, convex or non-convex. It may also be stochastic or deterministic. For the same initial conditions, a deterministic optimization algorithm assesses the same points and converges to the same outcome, but a stochastic optimization algorithm evaluates a new set of points from the same initial conditions, even if performed numerous times [191]. Thus, stochastic algorithms are gaining more popularity than the deterministic approach and are more suitable for optimization problems [149] . Fig.3.4 illustrates the detailed classification of different optimization algorithms.

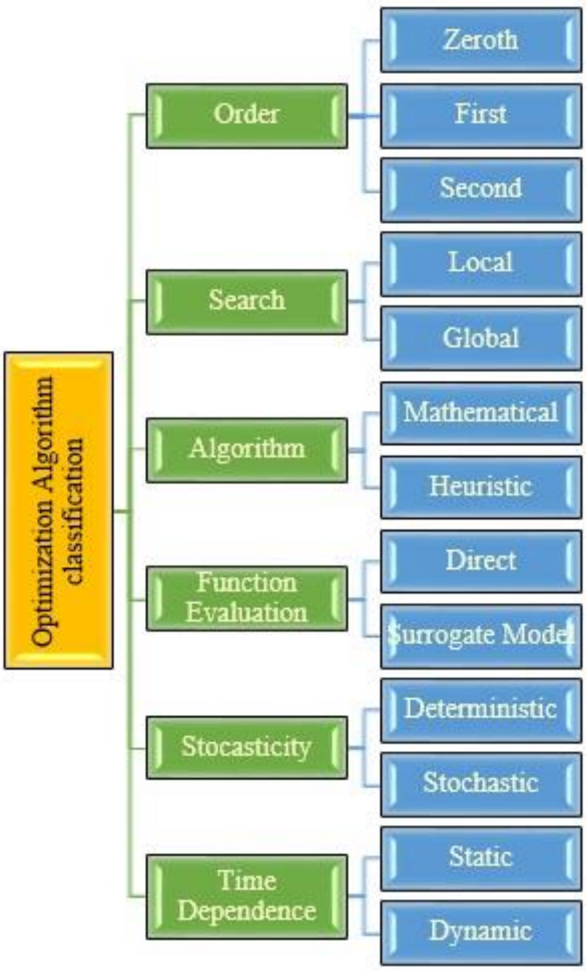


Fig.3.4: Classification of optimization algorithms

The optimization algorithms are classified based on order, search process, algorithm employed, function, type of stochasticity, and run time of the algorithm. The order may be zero, first, and second. The search may be local or global type depending upon the type of algorithm employed for the evaluation of a particular objective function to accomplish a prior defined optimization problem [196]–[198].

3.3 OPTIMIZATION METHODOLOGIES

Discrete optimization algorithms are proficient in solving simple engineering design problems by employing basic techniques with the accessibility and affordability of high-speed computation facilities. These algorithms are gradient-based techniques based on linear and non-linear programming methods, which search for an optimal solution near the initial starting point and require more gradient information. Gradient search algorithm generates worst results for more than one local optima and fails to find a global optimum. The computational drawbacks of prevailing linear and non-linear approaches have motivated researchers to opt for simulation-based meta-heuristic algorithms for solving multi-disciplinary engineering design problems. These meta-heuristic algorithms are simple, easy to implement, and efficient for solving continuous, discrete, constrained, or unconstrained problems. Meta-heuristic algorithms may be single-solution or population-based and evolve a set of solutions during each iteration. These meta-heuristic algorithms are mainly categorized into four main groups and tabulated in Table-3.1 as Evolutionary, Physics-based, Human-based, and Swarm Intelligence type algorithms.

Table-3.1: Advantages and Disadvantages of Meta-heuristic algorithms

Algorithm	Inspiration/Technique	Advantages	Disadvantages
Genetic algorithm (GA) [199]	This algorithm is based on Darwinian theory of evolution.	It is capable in handling constraint and unconstrained optimization with less computational time.	Faces difficulty in obtaining global solution with optimal result.
Differential evolution (DE)[200]	This is also an evolutionary algorithm and starts search with a randomly generated population.	It has ability to explore global minima. It does not require initial control parameters. Requires only few control parameters.	It tends to get struck in local minima due to premature convergence and computational time is high.
Branch and bound(BB)[201]	This algorithm is developed from the inspiration of branches of tree.	It employs linear function to objective function within upper and lower bounds.	Requires large execution time for systems with large size.
Simulated Annealing[202]	Based on Annealing process in metallurgy	It has superior local search capability with less computational time	It takes much time to explore global minima.
Biogeography Based optimization (BBO)[78]	This algorithm is based on bio geographical process	Better global and local search capability and computational efficiency is high	Poor convergence for medium and large scale systems

Table-3.1: Advantages and Disadvantages of Meta-heuristic algorithms *(Continued.)*

Algorithm	Inspiration/Technique	Advantages	Disadvantages
Gravitational search algorithm (GSA) [203]	This method is based on Law of gravity and fitness function of masses.	It has excellent exploration capability.	It has poor exploitation capability due to close proximity in the neighboring masses progress of iterations.
Harmony Search algorithm(HAS)[70]	This algorithm is inspired from searching of a perfect musical harmony.	It is a divergence free method. It does not require any information regarding differential gradient and setting of variables.	Lower exploitation in end search space results in slow convergence.
Sine-Cosine algorithm (SCA)[204]	It is random search population based technique which involves Sine cosine function.	It has simple structure and fewer parameters and capable of determining optimal solution based on sine cosine function.	It losses population diversity due to loss of control parameters in the successive runs of the algorithm.
Tabu search (TS)[205]	It is based on evaluation of neighborhood solution.	It has a flexible memory system which enables search agents to explore search space efficiently	Poor sensitivity for parameter selection. Computation time is high.
Teaching learning Based Optimization (TLBO)[206]	It is based on teaching learning behavior in classroom	It requires less controlling parameters such as population size and number of generations	Fails to explore search space efficiently for complex problems involving large matrix size.
Particle Swarm Optimization (PSO) [207]	This algorithm is a population based inspired from particles moving in search space	It is simple, easy to implement and robust method. It is also insensitive to initial parameters and require less control parameters.	It has a tendency to fall in local minima entrapment and results in inferior convergence.
Ant Colony Optimization (ACO) [208]	This algorithm is based on foraging strategy of real ants for food.	It does not much parameter setting and hence provides optimal global solutions for complex problems involving large constraints.	It has premature convergence and generates stagnating output.
Artificial Bee Colony (ABC) [209]	It is based on Bees ability to form colonies	It is simple, easy to implement and possess good exploration capability	It is inefficient to provide optimal solution for complicated optimization problems.
Bat-inspired Algorithm (BA)[210]	It is based on Echolocation characteristics of Micro-bats.	High convergence rate due to proper balance between exploration and exploitation.	It has tendency to get capture in local search if loudness and pulse rate are not properly tuned
Grey Wolf Optimization (GWO) [99]	It is based on chasing, encircling and hunting strategy of grey wolves in a group.	It is gradient free, simple, and scalable algorithm. Requires less parameter adjustment.	It fails to exploit search space at the end of search space and results in early convergence.

Table-3.1: Advantages and Disadvantages of Meta-heuristic algorithms *(Continued.)*

Algorithm	Inspiration/Technique	Advantages	Disadvantages
Moth Flame Optimization (MFO)[211]	It is based on inclination of moths in a particular direction of flame	It is simple method and has improved computational efficiency	It has tendency to get entrap in diverse spiral path and thus convergent rate is slow.
Whale optimizer algorithm(WOA)[212]	This algorithm is based on cooperative behavior of humpback whales.	It has better convergence rate due to randomized operator.	Immature convergence due wide local area stagnation.
Grasshopper Optimization Algorithm [41]	This algorithm is based on behavior of grasshopper swarms in nature	It has high local optima avoidance due to high repulsion rate.	Gravity force on the updated position results in poor convergence.
Harris Hawks Optimizer(HHO)[213]	This algorithm is based on chasing, encircling and hunting strategy of Hawks for their survival	It is simple, able to escape safely from local minima, provides flexibility and ease of adoption	The major limitations are possibility of being trapped in local minima while solving large multimodal and composition optimization problems.
Slime Mould Algorithm(SMA) [214]	This algorithm is based on foraging strategy of moulds for food	It is simple and easily adoptable to compute complex structural problems.	It tends to fall easily in local optima due to improper transfer of exploration to exploitation phase.

Although these optimizations compute various design and engineering problems with precision, local area stagnation is a crucial problem. This local stagnation forces the optimizer to get entrapped in nearby local minima points and resist the algorithm to search for the most feasible solution. It also reduces the proficiency of the optimizer to explore and exploit the search space accurately. Researchers are continuously contributing their efforts to develop advanced hybrid and chaotic methods to augment the local search fitness to find more efficient solutions to optimization problems

In the present research work, three hybrid optimization algorithms are developed to solve different optimization problems. The suggested algorithms are applied to solve complex unit commitment problems involving wind and V2G penetration. The following section presents the detailed theory and mathematics of the optimization methodologies employed for solving engineering design problems and economic scheduling problems in a stochastic sustainable environment.

3.3.1 Harris Hawks Optimizer

Harris Hawks are intelligent hunting birds residing in the United States and Mexico. For their survival, hawks used to hunt in groups. The hunting process begins with group members utilizing their ability to communicate, encircle the target, and attack by making soft and hard besieges. Meanwhile, if the target succeeds in escaping, the hawks again organize themselves for another attack by exchanging their positions. Finally, the exhausted prey loses its all energy and gets caught by the hawk's group members [215]. Harris Hawks optimizer (HHO) developed by Heidari et al. [213] is a meta-heuristic algorithm search algorithm, based on the chasing strategy of Hawks to capture the escaping prey, most probably a rabbit.

HHO is a simple and easily adaptable method and finds wide applications in meta-heuristic and hybrid variants of HHO developed by the researchers to fix different classes of stochastic complexities. Some of the examples where HHO was utilized are data-mining[216], environmental issues [217], medicine and drugs, materials [218], engineering design [219], image segmentation [220], power flow [221], solar PV modules [222], feature selection [223] and other variants [224]. HHO has the inherent capability of pursuing a proper balance between intensification and diversification. Studies reveal that slow convergence gives rise to reduced computational efficiency. The HHO algorithm does not require initial values for decision variables and instead employs stochastic indiscriminate search rather than gradient search.

The main feature of HHO is to mimic collective hunting by adopting four strategies. These are encircling, surprise pouch, soft besiege, and hard besiege. It is a fast and efficient method to solve multifarious optimization problems, including discrete, incessant, constrained, and unconstraint issues. The advantages of HHO are simplicity in methodology, the ability to escape safely from local minima stagnation, flexibility in operation, improved performance, and ease of adoption. The mathematical formulation of the HHO algorithm is based on the 'seven kill strategy' of hawks and the escaping energy of rabbits. A successful hunting process involves soft besiege, hard besiege, soft-besiege with hard bounds, and hard besiege with hard bound, as depicted in Fig.3.5

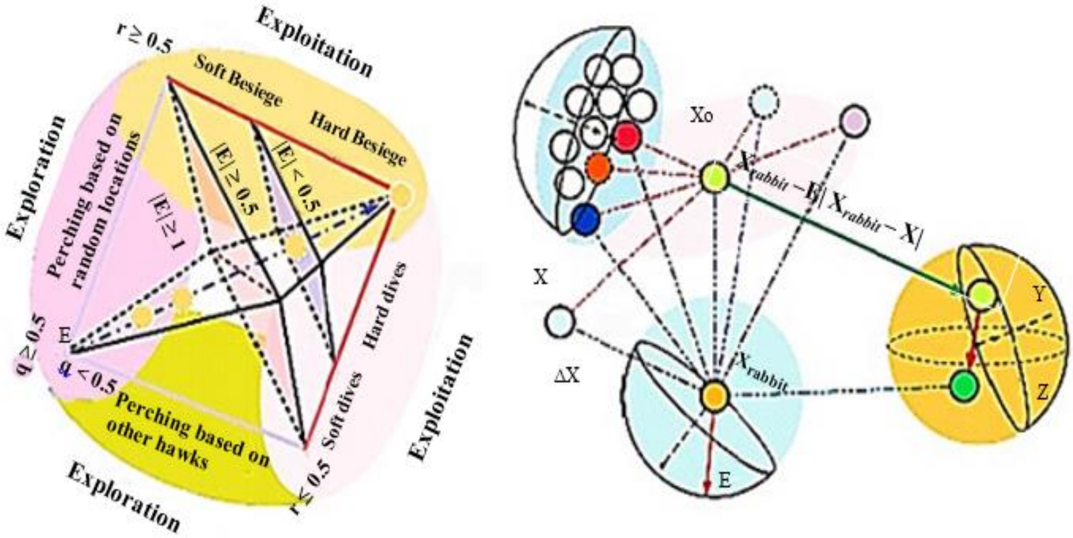


Fig.3.5: Searching phases of HHO[213]

The mathematical equations are developed based on the behavior of Harris hawks and chaotic strategy. This section includes the methodology for capturing the prey. The typical chasing technique of Harris birds is where they recognize the food and chase it by using their sharp judgments while the victim does not know about the hunters' plan. Let q be the probability for each equalizing attempt which depends on the position of the other family members close enough to them, which is modeled in eqn. (3.4a), when $q \geq 0.5$ or perch on randomly on tall trees and modeled as in eqn. (3.4b) for $q < 0.5$.

$$X(itn+1) = \{ X_{rand}(itn) - r_1 \times abs(X_{rand}(itn) - 2 \times r_2 \times X(itn)); \quad q \geq 0.5 \tag{3.4a}$$

$$X(itn+1) = \{ (X_{prey}(itn) - X_m(itn)) - r_3 \times (Lb + r_4 \times (Ub - Lb)); \quad q < 0.5 \tag{3.4b}$$

Where, $X(itn+1)$ represents the hawks position in next iteration (itn) , $X_{rand}(itn)$ represents randomly selected hawks , corresponding to the vectors r_1, r_2, r_3, r_4 and q are random values in between (0, 1) and these are modified in each iteration between upper bound (Ub) and lower bound (Lb) . $X_{prey}(itn)$ denotes the position of prey. $X_m(itn)$ represents the mean position of Hawks which is determined by eqn. (3.5).

$$X_m(itn) = \frac{1}{N}\left(\sum_{i=1}^{N} X_i(itn)\right) \tag{3.5}$$

Where, $X(itn)$ is the hawk location in each iteration and N denotes total number of hawks.

Transition from Exploration to exploitation phase depends upon the absconding energy of the victim and is evaluated using eqn. (3.6)

$$E_A = 2\times E_0 \times \left(1-\frac{itn}{itn_{\max}}\right) \tag{3.6}$$

Where, E_A is avoidance energy of the prey, E_0 is the initial energy of the prey changing randomly between (-1, 1) and $itn_{\max}$ is maximum iterations eqn. (3.6) is used to determine the upgraded position of hawks. The successful capture relies on attacking strategies of Hawks depending upon escaping energy and change of escape (r). Hawks will first encircle and then surprise pounce is performed. Modeled in eqn. (3.7) & eqn. (3.8). Hawks perform a soft besiege for $r \geq 0.5\, \& |E| \geq 0.5$.

$$X(itn+1) = \Delta X(itn) - E_A \times abs(J\times X_{prey}(itn) - X(itn)) \tag{3.7}$$

$$\Delta X(itn) = \left(X_{prey}(itn) - X(itn)\right) \tag{3.8}$$

Where, $\Delta X(itn)$ is the variance between current location of prey and locality of Hawks at iteration itn. $J = 2(1-r_5)$ is the Jump energy which alters randomly in every iteration. r_5 is the random numeral in the range (0, 1). The exhausted prey fails to escape and Hawks perform hard besiege as modeled in eqn. (3.9). Hawks perform a hard Besiege for $r \geq 0.5\, \& |E| < 0.5$.

$$X(itn+1) = Xprey(itn) - E_A \times abs(\Delta X(itn)) \tag{3.9}$$

$$Y = Xprey(itn) - E\times abs(JXprey(itn) - X(itn)) \tag{3.10}$$

$$Z = Y + S\times L_F(D) \tag{3.11}$$

Where, D = Problem's dimension, S = Range of fractal flight path by size $(1\times D)$

The L_F (D) based designs which follow the certain rule in eqn. (3.12) and eqn. (3.13)

$$L_F(x) = 0.01\left(\frac{\mu\times\sigma}{|v|^{\frac{1}{\beta}}}\right) \tag{3.12}$$

$$\sigma = \left(\frac{\Gamma(1+\beta)\times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right)\times\beta\times 2\left(\frac{\beta-1}{2}\right)}\right)^{\frac{1}{\beta}} \tag{3.13}$$

Where, μ,σ are signified as particular type of random value between (0, 1) and β is default constant fixed to 1.5.

At this stage the prey has enough energy and besiege during this phase depends on levy flight (LF) concept as modeled in eqn. (3.12). Hawks perform a soft besiege through rapid dives for $|E| \geq 0.5$ & $r < 0.5$.

$$X(itn+1) = \begin{cases} Y; & if \quad F(Y) < F(X(itn)) \\ Z; & if \quad F(Z) < F(X(itn)) \end{cases} \tag{3.14}$$

Where, Y and Z are the positions based on soft besiege.

$$Y^{'} = Xprey(itn) - E \times abs(JXprey(itn) - X_m(itn)) \tag{3.15}$$

$$Z^{'} = Y^{'} + S \times L_F(D) \tag{3.16}$$

The Hawks are very close to prey and perform hard besiege as modeled in eqn. (3.17). Hawks perform hard besiege through rapid dives for $|E| < 0.5$ & $r < 0.5$.

$$X(itn+1) = \begin{cases} Y^{'}; & if \quad F(Y^{'}) < F(X(itn)) \\ Z^{'}; & if \quad F(Z^{'}) < F(X(itn)) \end{cases} \tag{3.17}$$

Where, $Y^{'}$ and $Z^{'}$ are the positions based on hard besiege.

3.3.2 Improved Grey wolf optimizer Algorithm

Grey wolf optimizer (GWO) is a newly proposed meta-heuristic algorithm developed by Mirjalili *et al*. [99] in 2014. The grey wolves stay in groups of 5–12 on average during hunting process with their inherent encircling and attacking strategies. The GWO algorithm adopts the wolf hierarchy and has different roles in the wolf pack. The Wolfs are divided into four groups based on their role during the hunting process. The four groups are alpha, beta, delta, and omega. Alpha represents the best solution found for hunting and is at the apex. A typical social dominant hierarchy is as shown in Fig. 3.6.

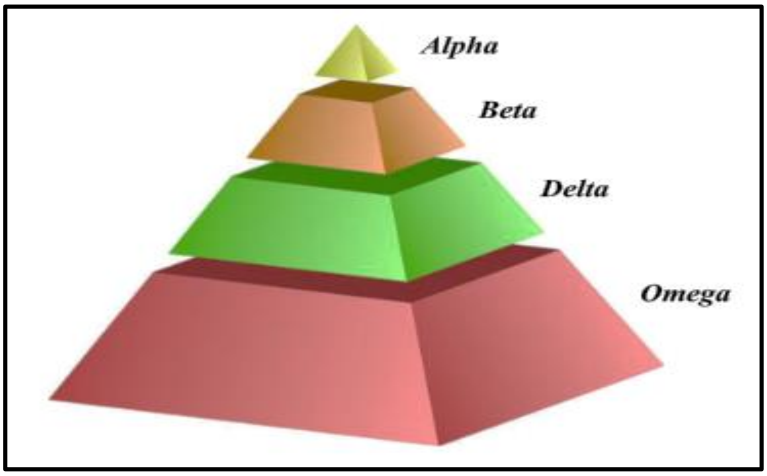


Fig.3.6: Social dominant hierarchy of grey wolves [99]

The alphas may be male or female and responsible for making decisions and performing the dominant role of the wolf pack. The beta wolfs assisted the alphas in decision-making and initiating pack activities. Delta wolves follow the commands of alphas and betas, but they govern the omega wolves. The hunting process with mathematical steps is depicted in Fig.3.7.

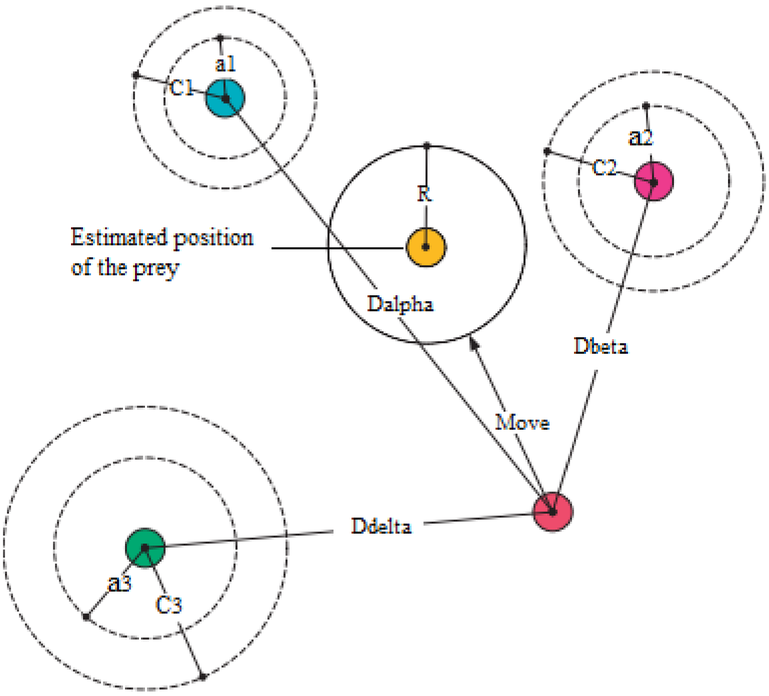


Fig.3.7: Hunting process of GWO [99]

In IGWO, a weighted average of alpha, beta and delta wolfs is evaluated and then best individual is assigned a weight obtained by multiplying its corresponding A and C. The IGWO optimization algorithm is used to update the positions of alpha $(\overrightarrow{W_\alpha})$, beta

$(\overrightarrow{W_\beta})$, and delta wolves $(\overrightarrow{W_\delta})$ during the hunting process involving searching, encircling, and attacking the target prey. The best fitness value of grey wolves depends upon the fitness value evaluated as 'a' shown in eqn. (3.18). Mathematically, $(\overrightarrow{G_w})$ & $\vec{W}_{G(itn+1)}$ vectors are defined through eqn. (3.19) and eqn. (3.20).

$$a = 2 - t \times \left(\frac{2}{itn_{\max}} \right) \tag{3.18}$$

$$\overrightarrow{G_W} = \left| C \times W_{prey}(itn) - W_G(itn) \right| \tag{3.19}$$

$$W_G(itn+1) = W_{Prey}(itn) - \vec{A} \times G_W \tag{3.20}$$

Where, $\vec{A} = 2 \times \vec{a} \times \vec{r}_1 - \vec{a}$ And, $\vec{C} = 2 \times \vec{r}_2$

Here, $\vec{r}_1, \vec{r}_2 \in rand(0,1) and\ \vec{a}$ reduces linearly from 2 to 0.The extreme search process takes place and various fitness values for $(\overrightarrow{W_\alpha})$, $(\overrightarrow{W_\beta})$ and $(\overrightarrow{W_\delta})$ are updated using eqn.(3.21), (3.23) and eqn.(3.25).The final position for capturing the prey is evaluated by eqn. (3.27).

$$G_\alpha = abs\left(\vec{C}_1 . \vec{W}_\alpha - \overrightarrow{W_G} \right) \tag{3.21}$$

$$\overrightarrow{W_1} = \overrightarrow{W_\alpha} - \vec{A}_1 . \overrightarrow{G_\alpha} \tag{3.22}$$

$$G_\beta = abs\left(\vec{C}_2 . \vec{W}_\beta - \overrightarrow{W_G} \right) \tag{3.23}$$

$$\overrightarrow{W_2} = \overrightarrow{W_\beta} - \vec{A}_2 . \overrightarrow{G_\beta} \tag{3.24}$$

$$G_\delta = abs\left(\vec{C}_3 . \vec{W}_\delta - \overrightarrow{W_G} \right) \tag{3.25}$$

$$\overrightarrow{W_3} = \overrightarrow{W_\delta} - \vec{A}_3 . \overrightarrow{G_\delta} \tag{3.26}$$

$$\vec{W}_{(itn)} = \left(\frac{\vec{W}_1 + \vec{W}_2 + \vec{W}_3}{3} \right) \tag{3.27}$$

3.3.3 Hybrid Harris Hawks Optimizer Algorithm

The detailed mathematical formulation for Harris Hawk's optimizer has discussed in section 3.3.2. However, the local search of the basic HHO algorithm is slow due to its poor exploitation capability. The major flaws are the possibility of being trapped in local minima while dealing with multimodal and composition optimization problems, an improper balance between global and a local search, and sluggish performance in handling the multi-dimensional issue [224].

From the vast HHO variants, some of the specific work has been selected for comparison and fair interpretation. Yildiz *et al*. [225] developed an effective hybrid algorithm by combining HHO, GOA and MVO for solving manufacturing optimization problems. Abbasi *et al*. [219] provided prominent solution in lowering entropy generation by adopting HHO to explore more intensively micro channel for definite velocity and temperature. Moayedi *et al*. [226] incorporated HHO-ANN method to find stability of soil slopes with better fitted structure related to civil engineering problem. Chen *et al*. [227] have combined chaos maps with HHO to improve local search capability of basic HHO by adopting multi-population approach and differential strategy using logistic chaotic mapping.

Firouzi *et al*. [228] have developed hybrid algorithms for solving complications associated with cracks in cantilever beam design for explored location and depth of crack for Euler–Bernoulli beam. Chiwen *et al*. [229] formulated improved HHO by information exchange between search agents and tested nine benchmark problems and seven engineering design problems. Elkadeem *et al*. [230] used hybrid HHO-PSO method for analyzing economic dispatch problem considering renewables and distributed generator. All these studies were attempted to optimize certain objective by modifying classical HHO.

In the present work, the global and local search phases of HHO is enhanced by combining the Harris Hawk optimizer with the improved Grey Wolf optimizer (IGWO). The resultant algorithm is abbreviated as hybrid Harris Hawk's optimizer (hHHO-IGWO). IGWO assists HHO in exploring the search space more intensively and prevents the algorithm from local minima stagnation or immature convergence. The steps of the HHO-IGWO method are as follows.

$$minimize \;\; f(X) \qquad 3.28)$$

Subjected to $x_i^{min} \le x_i \le x_i^{max} \qquad (i = 1,2,.....,N)$ (3.29)

Where, $X = [x_1, x_2, ..., x_N]^T$ is the set of design variables and N is the number of decision or design variables.

Algorithm

The optimization procedure for the hHHO-IGWO method comprises of the subsequent ten steps:

Step-1: Define algorithm parameters.

Specify the input parameters required by the HHO and IGWO algorithms to solve the optimization problem defined by Eqn. (3.2), such as the number of solution vectors in HHO and IGWO. Position of Rabbits, Hawks, and Wolf Variables and parameter adjustments associated with hunting strategy.

Notations are specified as Updated position $X(itn+1)$, number of iteration (itn), random iteration $X_{rand}(itn)$, random variables r_1, r_2, r_3, r_4, mean position of Hawks $X_m(itn)$, upper bound and lower bound (Ub), (Lb).

Step-2: Initialization of stochastic population $X_i(i = 1, 2, 3......., N)$ and maximum iteration is itn

Step-3: Initialization of exploration phase for each chance q, with condition $q \geq 0.5$ and $q < 0.5$,

$$X(itn+1) = \{X_{rand}(itn) - r_1 \times abs(X_{rand}(itn) - 2 \times r_2 \times X(itn)); \quad q \geq 0.5$$

$$X(itn+1) = \{(X_{prey}(itn) - X_m(itn)) - r_3 \times (\mathrm{L}b + r_4 \times (Ub - Lb)); \quad q < 0.5$$

The mean position of Hawks which is determined by following equation.

$$X_m(itn) = \frac{1}{N}\left(\sum_{i=1}^{N} X_i(itn)\right)$$

Step-4: Exploration to exploitation phase depends upon the Escaping energy (E)

$$E = 2 \times E_0 \times \left(1 - \frac{itn}{itn_{\max}}\right)$$

Step-5: For $|E| < 1$, exploration phase is completed and the new position vector is determined .The difference between current and updated position of prey and hawks is evaluated for each jump energy J in each iteration within the range of (0, 1).

$$X(itn+1) = \Delta X(itn) - E \times abs(JX_{prey}(itn) - X(itn))$$

$$\Delta X(itn) = \left(X_{prey}(itn) - X(itn)\right)$$

Step-6: At this stage hawks execute a hard Besiege for $r \geq 0.5 \,\&\, |E| < 0.5$.

$$X(itn+1) = Xprey(itn) - E_A \times abs(\Delta X(itn))$$

$$X(itn+1) = Xprey(itn) - E_A \times abs(\Delta X(itn))$$

$$Y = Xprey(itn) - E \times abs(JXprey(itn) - X(itn))$$

$$Z = Y + S \times L_F(D)$$

Step-7: Hawks execute a soft besiege via rapid dives for $|E| \geq 0.5$ & $r < 0.5$.

$$X(itn+1) = \begin{cases} Y; & if \quad F(Y) < F(X(itn)) \\ Z; & if \quad F(Z) < F(X(itn)) \end{cases}$$

$$Y = Xprey(itn) - E \times abs(JXprey(itn) - X_m(itn))$$

$$Z = Y + S \times L_F(D)$$

Step-8: When hawks are very close to prey and perform hard besiege. Modeled in Eqn. (15). Hawks perform hard Besiege via rapid dives for $|E| < 0.5$ & $r < 0.5$.

$$X(itn+1) = \begin{cases} Y'; & if \quad F(Y') < F(X(itn)) \\ Z'; & if \quad F(Z') < F(X(itn)) \end{cases}$$

Step-9: Initialization of the grey wolf population $\overrightarrow{G_w}, \vec{C}$ *and* $\vec{A}$. After this, calculating the best fitness value search agents whose value is determined as follows

$$a = 2 - t \times \left(\frac{2}{i_{ter\_max}} \right)$$

$$\overrightarrow{G_W} = \left| C.W_{prey}(itn) - W_G(itn) \right|$$

$$W_G(itn+1) = W_{Prey}(itn) - \vec{A}.G_W$$

Where, $\vec{A} = 2 \times \vec{a} \times \vec{r_1} - \vec{a}$ And, $\vec{C} = 2 \times \vec{r_2}$

Step-10: Allotting best fitness values to search agents $\alpha_w, \beta_w)$ *and* δ_w. Here, $\vec{r_1}, \vec{r_2} \in rand(0,1)$ *and* $\vec{a}$ reduces linearly from 2 to 0. In this this updated position vectors are determined by multiplying weighted position vectors with the global best values and final position is evaluated as follows.

$$\overrightarrow{W}_{(itn)} = \left(\frac{\overrightarrow{W_1} + \overrightarrow{W_2} + \overrightarrow{W_3}}{3} \right)$$

3.3.4 Chaotic Harris Hawks Optimizer

The detailed mathematical formulation for HHO along with its merits and demerits has been discussed in section 3.3.2. According to research, meta-heuristic approaches face the issue of poor exploitation in some uni-modal and multi-modal benchmark functions. Researchers have developed many hybrid and chaotic algorithms. Such chaotic behavior has been utilized by researchers in algorithms like genetic algorithms[231], chaotic Krill Herd search [232], SCA [233], BA [234], GWO [235], PSO [236] ,WOA [237]. Slow convergence and the tendency to get trapped in local optima is the most commonly reported problem by many researchers[224].

Specific work on recent HHO variants and different chaotic strategies has been investigated to find limitations and scope. Some examples of hybrid and chaotic variants of HHO are Chaotic Multi-Verse Harris Hawks Enhancement [238]**,** SCA-HHO Algorithm [239]**,** Boosted Harris Hawk's Optimization (BHHO) [240]**,** Improved Harris's Hawks Optimization(IHHO) [241]**,** Enhanced Harris Hawks Optimization (EHHO) [242]**,** Quasi-reflected Harris hawks optimization algorithm [243]**,** HHO-ANN [222]**,** Chaotic HHO [244]**,** CHHO – QWSC [245]**,** ANFIS-HHO [246], etc.

The literature survey reveals that different hybrid and chaotic variants of HHO have been developed by the researchers to fix various kinds of stochastic complexities. The solution accuracy of these algorithms depends on a proper balance between intensification and diversification. Studies reveal that slow convergence is the common problem of most heuristic algorithms and results in reduced sluggish convergence.

Thus, to improve the performance, chaotic approaches are emerging widely. The ultimate aim of these techniques is to solve a pre-defined problem more precisely. Recently, a chaotic variant of HHO using the "logistic function" was implemented by Chen *et al*. [247] to estimate PV parameters. Current-Voltage characteristics of PV modules were upgraded by exploiting chaos periodicity and sensing temperature difference and irradiation variance.

Ewes *et al*. [238] incorporated HHO for enhancing exploration phase of MVO and parameters were tuned by chaotic maps. Gao *et al*. [248] have applied Tent Chaotic function to enhance the local search capability of HHO. The benchmark functions were not searched to an appreciable level. Also, the results have not justified by any comparative analysis. However, the No Free Lunch theorem permits researchers to invent new optimization techniques for achieving good solution efficiency. Therefore, this research study intends to offer a novel chaotic HHO algorithm (CHHO).

Table- 3.2: Chaotic Functions [249]

Sr. No	Chaotic Name	Mathematical Description
1	Chebyshev	$x_{i+1} = \cos\left(\cos^{-1}\left(x_i\right)\right)$
2	Iterative	$x_{i+1} = Sin\left(\frac{a\pi}{x_i}\right), a = 0.7$
3	Sinusoidal	$x_{i+1} = a x_i \, Sin\left(\pi xi\right); a = 2.3$
4	Sine	$x_{i+1} = \frac{a}{4} \, Sin\left(\pi xi\right), a = 4$
5	Circle	$x_{i+1} = \mathrm{mod}(x_i + b - \left(\frac{a}{2\pi}\right) Sin\left(2\pi x_i\right), 1); a = 0.5, b = 0.2$
6	Piecewise	$\begin{cases} \frac{x_i}{p} & 0 \le x_i < p \\ \frac{(x_i - p)}{(0.5 - p)} & p \le y_i < 0.5 \\ \frac{(1 - p - x_i)}{(0.5 - p)} & 0.5 \le x_i < 1 - p \\ \frac{(1 - x_i)}{p} & 1 - p \le x_i < 1 \end{cases}, p = 0.4$
7	Gauss/ Mouse	$\begin{cases} 1, & x_i = 0 \\ \frac{1}{\mathrm{mod}\left(y_i, 1\right)} & otherwise \end{cases}$
8	Singer	$x_{i+1} = \mu\left(7.86 y_i - 23.3 x_i^2 + 28.75 x_i^3 - 13.301875 x_i^4\right), \mu = 1.07$
9	Logistic	$x_{i+1} = a x_i \left(1 - x_i\right), a = 4$
10	Tent	$x_{i+1} = \begin{cases} \left(x_i / 0.7\right), & x_i < 0.7 \\ (10/3)\left(1 - x\right), & x_i \ge 0.7 \end{cases}$

In the proposed research, out of the 10 most commonly used chaotic strategies depicted in Table 3. 2, the Tent chaotic function has been combined with the basic HHO algorithm to search the space more intensively. To speed up the Harris Hawks search process and exploit the nearby search space of the Harris Hawks optimizer, a chaotic local search and abbreviated as *Chaotic Harris Hawks-Optimizer (CHHO).* The strategy is shown briefly in Fig.3.8.

The concept of probability distribution has been introduced in many meta-heuristics algorithms to gain randomness. Chaotic maps could be beneficial if randomness due to ergodicity and idleness are utilized properly. These chaotic criteria are satisfied by eqn.3.30.

$$O_{k+1} = f(O_k) \tag{3.30}$$

In eqn. (3. 30) O_{k+1} & O_k are the $(k+1)^{th}$ & k^{th} chaotic number, respectively.

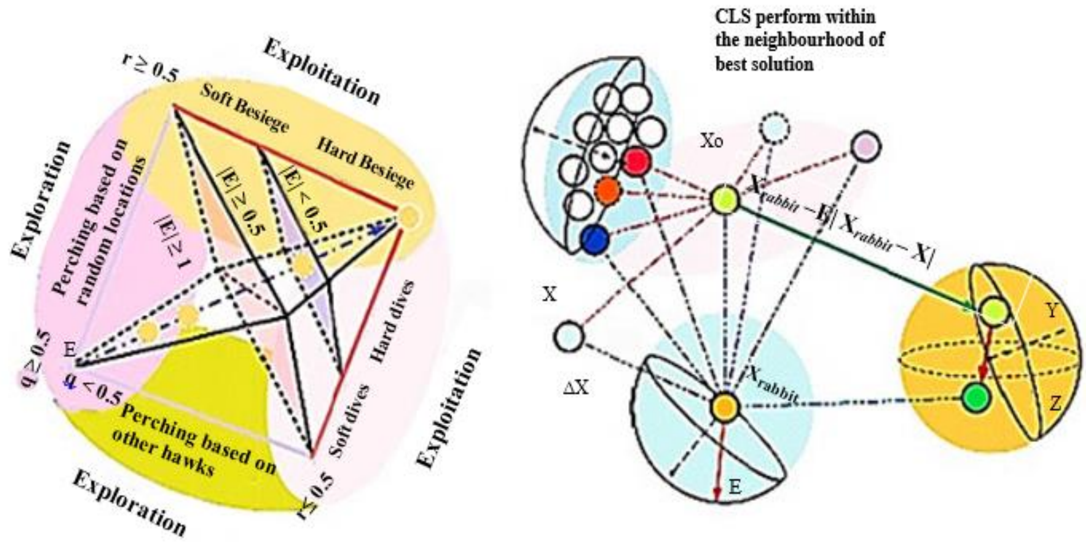


Fig.3.8: Improved Exploitation phase of HHO with Chaotic local search strategy

The basic HHO is upgraded by combining the chaotic approach to further enhance the search accuracy. The Pseudo-code for proposed method is presented in Appendix-A (i).

3.3.5 Slime Mould Algorithm

Slime mould algorithm (SMA) is the meta-heuristic algorithm developed by Chen et al. [104] for solving stochastic optimization problems. The algorithm is formatted by imitating the behavior of slime moulds and their ability to search, approach, wrap, and grab food. The foraging behavior of pysarum polycephalum, commonly known as "slime mould," to search for food sites has been efficiently adopted by researchers to develop new algorithms with different objectives. A few examples of such analogical approaches are discussed below.

The inherent ability of slime moulds to navigate through dissimilar channels and reach rich food sources via shortest path have been identified by Adamatzky *et al.* [250]. Andrew Adamatzky and Jeff Jones effectively developed a method for reconfiguring transport networks by implementing the foraging capability moulds to search for optimal routes through transport networks [251]. An intensive study on ability of moulds for choosing optimal path was carried out by Beekman *et al*. [252]. Burgin et al. [253] designed structural machines modal by exploiting the intrinsic capacity of moulds to sense cell information to solve complex computational problems.

Houbraken *et al*. have formulated an extended fault-tolerant algorithm to rectify the fault signals in the telecommunication [254]. Kouadri *et al*. have implemented SMA to solve the optimal power flow problem of a hybrid renewable with the thermal-wind system [255]. Kropat *et al*. incorporated a deterministic method for solving single-path and multi-path optimization problems under uncertainty to avoid emergencies and disasters [256]. Davut *et al*. utilized search capability of SMA and develop a PID-controlled DC motor and AVR system [257].

It was found that the organism's behavior has been adopted and statistically modeled to solve unconstrained and non-convex mathematics. Slime molds have acknowledged ample interest in recent years. Typically, the plasmodium creates a protoplasmic tube linking the masses of protoplasm to the food sources [250]. Moulds use their venous for searching vast food sources by secreting enzymes to encircle the food centers. Moulds may even foster more than nine hundred cm2 when there is adequate food in the environment [256]. In the case of food scarcity, the slime mould even flows vibrantly, which helps to understand how slime mould search, moves, and connect food in the changing environment. When a secretion approaches the target, slime can judge the positive and negative feedback and find the ultimate route to grasp food in a better way. This suggests that slime mould can construct a concrete path subject to the level of food concentration as shown in Fig.3.9.

Moulds prefers to select the region of high food concentration. Depending upon the food concentration and environmental risk, the mould weighs the speed and decides to leave the old location, and begins its new search during foraging. Slime mould adopts empirical rules based on currently available insufficient data to initialize new search and exit present location while foraging. It may dynamically adjust their search patterns as per the quality of food stock. The mathematics involve in searching the best food location by moulds is as shown in Fig.3.11 given below.

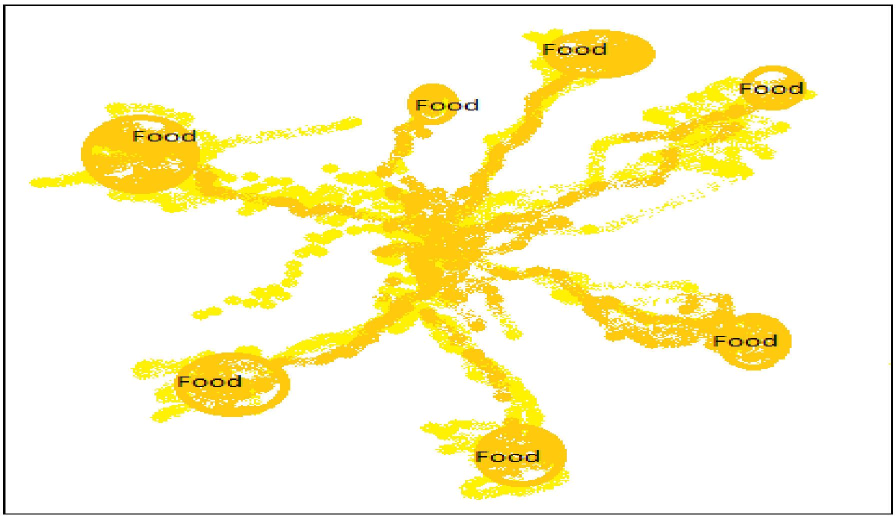


Fig.3.9: Searching structure of Slime Mould

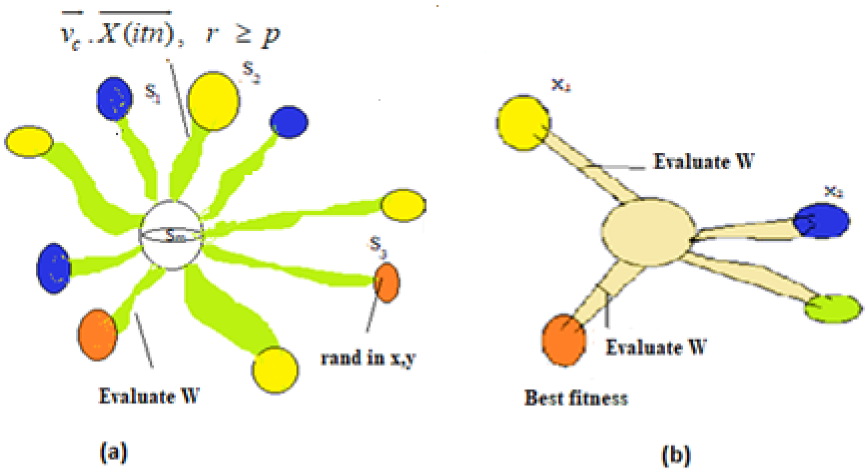


Fig.3.10: (a) possible position of moulds (b) Fitness evaluation

Following steps are involved during food searching process

Step-1: In this step mathematics for the slime moulds behavior is formed and following rule is assigned to find updated position during search for food. The criteria for this depends upon r and p. This is the contraction mode of mould.

$$\overrightarrow{X(itn+1)} = \begin{cases} \overrightarrow{X_b(itn)} + \overrightarrow{v_b}.(\overrightarrow{\mathrm{W}}.\overrightarrow{X_{\mathrm{A}}(\mathrm{t})} - \overrightarrow{X_B(itn)}\ ), r < p \\ \overrightarrow{v_c}.\overrightarrow{X(itn)},\quad r \geq p \end{cases} \tag{3.31}$$

Where, $\overrightarrow{v_b}$ is a parameter with a range of $[-a, a]$, $\overrightarrow{v_c}$ is the parameter which approaches linearly toward zero. itn is the current iteration, $\overrightarrow{X_b}$ is the location of each particle in region where odor is maximum, $\vec{X}$ is the mould's location, $\overrightarrow{X_A}$ and $\overrightarrow{X_B}$ are the randomly selected variables from the swarm, $\vec{W}$ is the measure of weighs of masses. The maximum limit of 'p' is as follows:

$$p = \tanh|S(i) - DF| \tag{3.32}$$

Where, $i \in 1, 2, ..., n$, $S(i)$ = fitness of $\vec{X}$, DF = overall fitness from all steps.

The eqn. of $\overrightarrow{v_b}$ is as follows:

$$\overrightarrow{v_b} = [-a, a] \tag{3.33}$$

Where, $$a = \operatorname{arctanh}\left(-\left(\frac{itn}{itn_{\max}}\right) + 1\right) \tag{3.34}$$

The eqn. of $\vec{W}$ is listed as follows:

$$\overrightarrow{W(\text{smell index(i)})} = \begin{cases} 1 + r.\log\left(\dfrac{bF - S(i)}{bF - wF} + 1\right), condition \\ 1 - r.\log\left(\dfrac{bF - S(i)}{bF - wF} + 1\right), \; others \end{cases} \tag{3.35}$$

$$Smell\ Index = sort(\text{S}) \tag{3.36}$$

Where, $S(i)$ ranks first half of the population, r = random value in the interval of $[0,1]$, bF = optimal fitness obtained in the current iterative process, wF = worst fitness value obtained in the iterative process, Sort (s) function sorts fitness values.

Step-2: The eqn. for upgrading the positions of agents (i.e. to wrap food) is given as:

$$\overrightarrow{X^*} = \begin{cases} rand.(UB - LB) + LB, rand < z \\ \overrightarrow{X_b(itn)} + \overrightarrow{v_b} \times (\text{W}.\overrightarrow{X_A(itn)} - \overrightarrow{X_B} \times (itn), r < p \\ \overrightarrow{v_c} \times \overrightarrow{X(itn)}, r \geq p \end{cases} \tag{3.37}$$

Where, LB and UB are the search limits, $rand$ and r denote the random value

Step-3: With the up gradation in the search process, the value of $\overrightarrow{v_b}$ vibrantly changes between $[-a, a]$ and $\overrightarrow{v_c}$ varies between $[-1,1]$ and at last shrinks to zero. This is known to be as 'grabbling of food'

3.3.6 Chaotic Slime Mould Algorithm

The detailed mathematical formulation for the slime mould algorithm along with its merits and demerits has been discussed in section 3.3.5. From the reviewed survey, it is seen that meta-heuristic approaches face the issue of poor exploitation in some uni-modal and multi-modal benchmark functions. To resolve this problem, researchers have developed many hybrid and chaotic algorithms like genetic algorithms [231], chaotic Krill Herd search [232], SCA [233], BA [234], GWO [235], PSO [236] ,WOA [237].

From the literature studies, it has been noticed that various variants of SMA have been developed by the researchers to fix different kinds of stochastic complexities. The ultimate aim of these techniques is to solve a pre-defined problem more precisely. Recently, a chaotic variant of SMA using “Chebyshev function” was developed by Zhao *et al*. [74]. In this work, 100 Monte Carlo trials were performed by using SMA and Chebyshev mapping. Only the “Sargan and sine wave function” were tested for unimodal function for 100 iterations. It was noticed that the results given by Chebyshev and sine wave function were not efficient in exploring search space precisely. Moreover, methodologies remain same, selection of chaos map makes a large difference in solution efficiency. In the projected research the exploration and exploitation phase of basic SMA has been boosted using “sinusoidal chaotic function”. It is observed that chaotic SMA helps to exploit the search space with superior convergence. Fig.3.11 illustrates 2D view of chaotic SMA along with fitness.

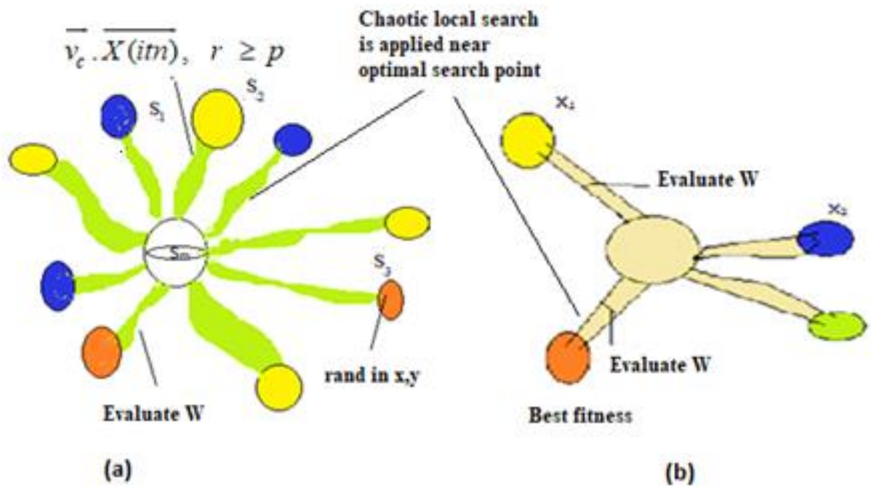


Fig.3.11: (a) 2D View of possible position with chaotic search (b) Assessment of Fitness

Algorithm

The optimization procedure for the CSMA comprises of the ensuing eight steps:

Step-1: Define algorithm parameters.

Specify the parameters required by SMA and random chaotic function to solve the optimization problem defined by eqn. (3.30) such as; solution vectors in SMA. Moulds position. population size, Maximum iteration and smell index associated food searching., random iteration, random variables r, mean position of moulds , upper bound and lower bound (Ub), (Lb).

Step-2: Nomination of stochastic populace $X_i (i = 1, 2, 3......., N)$ and maximum iteration number is taken as $itn_{\max}$

Step-3: Calculate the fitness of all slime mould and estimating the updated position of moulds.

$$\overrightarrow{X(itn+1)} = \begin{cases} \overrightarrow{X_b\,(itn)} + \overrightarrow{v_b}.(\overrightarrow{\mathrm{W}}.\overrightarrow{X_{\mathrm{A}}(\mathrm{t})} - \overrightarrow{X_B\left(itn\right)}\ \ ), r < p \\ \overrightarrow{v_c}.\overrightarrow{X(itn)},\ \ r \geq p \end{cases}$$

Step-4: Enhancing the search process by clubbing chaotic strategy

Step-5: Calculating the $\overrightarrow{\mathrm{W(smell\,index(i))}} = \begin{cases} 1 + r.\log\left(\dfrac{bF - S(i)}{bF - wF} + 1\right), condition \\ 1 - r.\log\left(\dfrac{bF - S(i)}{bF - wF} + 1\right),\ others \end{cases}$

Step-6: For each search iteration, the positions of p, vb, vc are updated.

$$\begin{aligned} &r_o = rand; \\ &r_o(itn+1) = 2.3 \times r_0^2 \times Sin\ (Pi.r_0) \\ &r_1 = r_0(itn+1); \end{aligned}$$

Step-7: The eqn. for upgrading the positions of agents (i.e. to wrap food) is given as:

$$\overrightarrow{X^*} = \begin{cases} rand.\left(UB - LB\right) + LB, rand < z \\ \overrightarrow{X_b(itn)} + \overrightarrow{v_b} \times (\mathrm{W}.\overrightarrow{X_A(itn)} - \overrightarrow{X_B \times (itn)}, r < p \\ \overrightarrow{v_c} \times \overrightarrow{X(itn)}, r \geq p \end{cases}$$

Step-8: With the up gradation in the search process, the value of $\overrightarrow{v_b}$ vibrantly changes between $\left[-a, a\right]$ and $\overrightarrow{v_c}$ varies between $\left[-1,1\right]$ and at last shrinks to zero. This is known to be as ‘grabbling of food’.

The Pseudo-code for Chaotic SMA is presented in Appendix-A (ii)

3.4 CONCLUSION

This chapter deals with exploring detailed information about different recent optimization methodologies for solving complex design problems. Basic steps involve the problem formulation for adopting specific optimization problem are explored in the earlier section. Finally, methodologies employed in the proposed research work were explained in detailed in separate sub-sections. Three different hybrid algorithms are developed using recent modern search algorithms such as Harris hawk's optimizer, improved grey wolf and Slime mould algorithm. In the proposed work, one hybrid algorithm and two chaotic algorithms are developed as follows.

(i) Hybrid Harris hawk's optimizer by combing basic HHO with improved grey wolf optimizer. This new hybrid algorithm is abbreviated as hHHO-IGWO.

(ii) Chaotic Harris Hawk optimizer (CHHO) algorithm by incorporating Tent chaotic function.

(iii) Chaotic Slime Mould Algorithm (CSMA) by incorporating sinusoidal chaotic function.

CHAPTER-4

BENCHMARK AND ENGINEERING OPTIMIZATION PROBLEM

4.1 INTRODUCTION

This chapter deals with testing of 23 commonly used benchmark functions corresponding to CEC-2005. These benchmark functions are categorize into three groups. The unimodal bench functions are from F1 to F7, multi-modal from F8 to F13, and fixed from F14 to F23. F32 to F43 comes under special benchmark functions noted as "Engineering Benchmark Functions." Three distinct algorithms have been tested for unimodal, multi-modal, and fixed-dimension in terms of average, mean, standard deviation, and worst value. Statistical non-parametric Wilcoxon is also performed to check the significance of the offered methods. The characteristics of benchmark functions differ from each other. Some functions show better performance in exploring local search, while a few functions are found to be excellent in determining global optima. These test functions have different global and local search capacities.

Out of these benchmark functions, Griewank, Levy, Ackley, Rastrigin, Schwefel functions, and sphere functions are noted to have many local minima points, while sum square function and Zakharov have global minima points. Furthermore, the effectiveness of the proposed methods has been tested by independent trial runs for each benchmark function. All the experiments have been executed in the Matlab environment. Firstly, hHHO-IGWO algorithm is tested for benchmark and engineering design problems. Then testing of the chaotic variant of HHO using the Tent chaotic function was executed, and finally testing of the Sinusoidal chaotic variant Slime Mould algorithm has been accomplished. The potentiality and feasibility of these methods have been analyzed by comparing the test results for each benchmark function with other methods such as BA [258], BDA [259], MFO [211], GWO [99], GSA [203], BPSO [260], FEP [261], GOA [262], ALO [263], WOA [212], CS[264], GA [265], MVO [266], DA [259], BGSA [267], SCA [268], SSA [269], FEP [261].

4.2 STANDARD BENCHMARK FUNCTIONS

In this section, 23 standard benchmark problems were analyzed in terms of average, standard deviation, median, and worst value by implementing proposed hybrid and chaotic optimization methodologies. These standard benchmark function are characterized by their objective fitness in parameter space within a particular dimension (Dim), range, and optimal value $\left(f_{\min}\right)$.

4.2.1 Unimodal Benchmark Function

In this section, seven unimodal benchmark function along with their fitness characteristics are elaborated. Unimodal benchmark functions are Sphere Function, Schwefel Absolute Function, Schwefel Double Sum Function, Schwefel max. Function, Rosenbrock Function, Step Function and Quartic Random Function. Each function has a dimension of 30 and optimum value $\left(f_{\min}\right)$.

F1, F3, F4 and F6 has a range of -100 to 100, F2 has range of -10 to 10, and F5 has range of 30 to 30, while F7 has range of 1.28 to 1.28. Fig.4.1 shows 3D view for unimodal benchmark function. The performance of any benchmark function depends upon its ability to explore the search space more accurately. The accuracy of any benchmark function can be examined from its convergence characteristics. The mathematical formulation for each function along with their range and optimal fitness value from F1 to F7 are illustrated in Table-4.1.

Table-4.1: Unimodal Benchmark Function

Uni-modal Test Function	Dim	Range	$f_{\min}$
$f_1(y)=\sum_{i=1}^{n} y_i^2$	30	[-100 , 100]	0
$f_2(y)=\sum_{i=1}^{n} \lvert y\rvert+\prod_{i=1}^{n}\lvert y_i\rvert$	30	[-10 ,10]	0
$f_3(y)=\sum_{i=1}^{n}\left(\sum_{j=1}^{i} y_j\right)^2$	30	[-100 , 100]	0
$f_4(y)=\max_i\left\{\lvert y_i\rvert, 1\le i\le n\right\}$	30	[-100 , 100]	0

Table-4.1: Unimodal Benchmark Function *(Continued.)*

Uni-modal Test Function	**Dim**	**Range**	$f_{\min}$
$f_5(y)=\sum_{i=1}^{n-1}\left[100(y_{i+1}-y_i^2)^2+(y_i-1)^2\right]$	30	[-30 ,30]	0
$f_6(y)=\sum_{i=1}^{n}\left(\left[y_i+0.5\right]\right)^2$	30	[-100 , 100]	0
$f_7(y)=\sum_{i=1}^{n} y_i^4+random\left[0,1\right]$	30	[-1.28, 1.28]	0

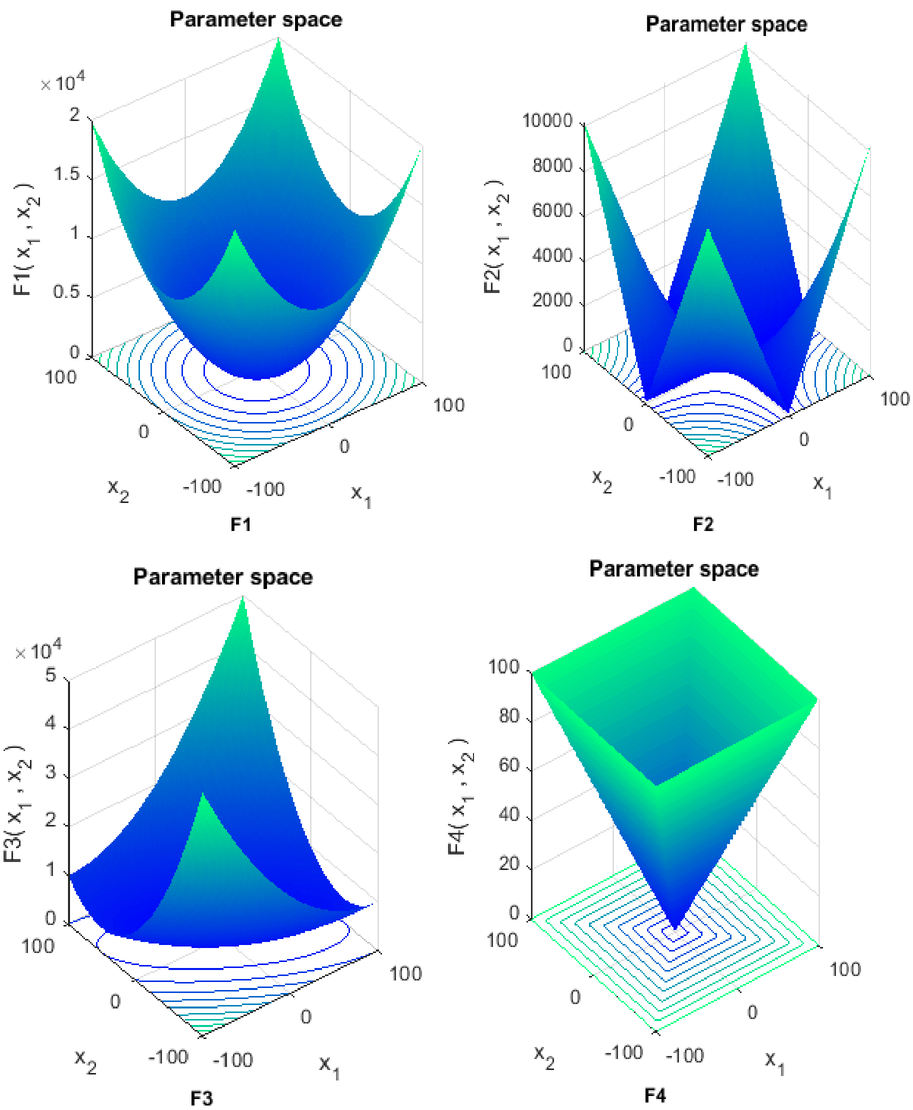


Fig.4.1: 3D projection of UM function

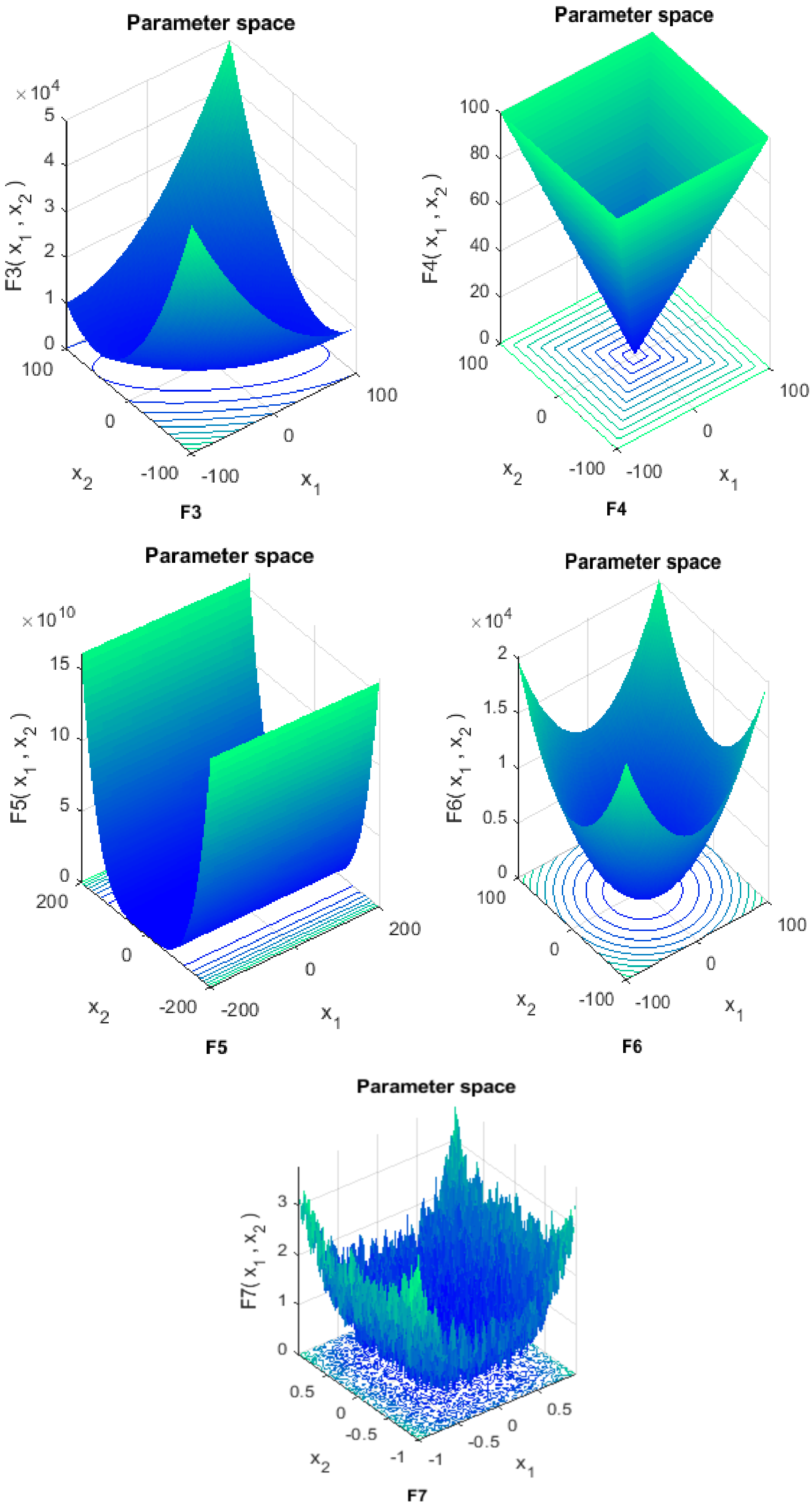


Fig.4.1: 3D projection of UM function *(Continued)*

4.2.2 Multi-modal Benchmark Function

Multi-modal benchmark functions are Schwefel Sine Function, Rastrigin Function, Ackley Function, Griewank Function, Pendlized Penalty#1 Function and Levi N. 13 function and represented as F8 to F13 as Shown in Table- 4.2. Each function has a dimension of 30 and optimum value ($f_{\min}$) as zero in most of the cases. Multi-modal function has variable range corresponding to each function. Fig.4.2 shows 3D view for Multi-modal benchmark function.

Table-4.2: Multi-modal benchmark Function

Multi-modal Test Function	**Dim**	**Range**	$f_{\min}$
$f_8(\mathrm{y}) = \sum_{i=1}^{n} -y_i \sin(\sqrt{\lvert y_i \rvert})$	30	[-500, 500]	-418.98295
$f_9(\mathrm{y}) = \sum_{i=1}^{n} [\mathrm{y}_i^2 - 10\cos(2\pi y_i) + 10]$	30	[-5.12, 5.12]	0
$f_{10}(\mathrm{y}) = -20\exp(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} y_i^2}) - \exp(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi y_i) + 20 + c$	30	[-32, 32]	0
$f_{11}(\mathrm{y}) = 1 + \sum_{i=1}^{n} \frac{y_i^2}{4000} - \Pi_{i=1}^{n} \cos\frac{(\mathrm{y}_i)}{\sqrt{i}}$	30	[-600, 600]	0
$f_{12}(\mathrm{y}) = \frac{\pi}{n}\left\{10\sin(\pi y_1) + \sum_{i=1}^{n-1}(y_i-1)^2[1+10\sin^2(\pi \mathrm{z}_{i+1})] + (\mathrm{z}_n-1)^2\right\}$ $+\sum_{i=1}^{n} u(\mathrm{y}_i, 10, 100, 4)$ $\mathrm{z}_1 = 1 + \frac{y_i+1}{4}$, $u(y_{i,} a, k, m) = \begin{cases} k(y_i-a)^n & y_i > a \\ 0 & -a < y_i < a \\ k(-y_i-a)^n & y_i < -a \end{cases}$	30	[-50,50]	0
$f_{13}(y) = 0.1\left\{\begin{array}{c}\sin^2(3\pi y_1) + \sum_{i=1}^{n}(y_i-1)^2\left[1+\sin^2(3\pi y_i+1)\right] + \\ (x_n-1)^2\left[1+\sin^2(2\pi x_n)\right]\end{array}\right\} +$ $\sum_{i=1}^{n} u(y_i, 5, 100, 4)$	30	[-50,50]	0

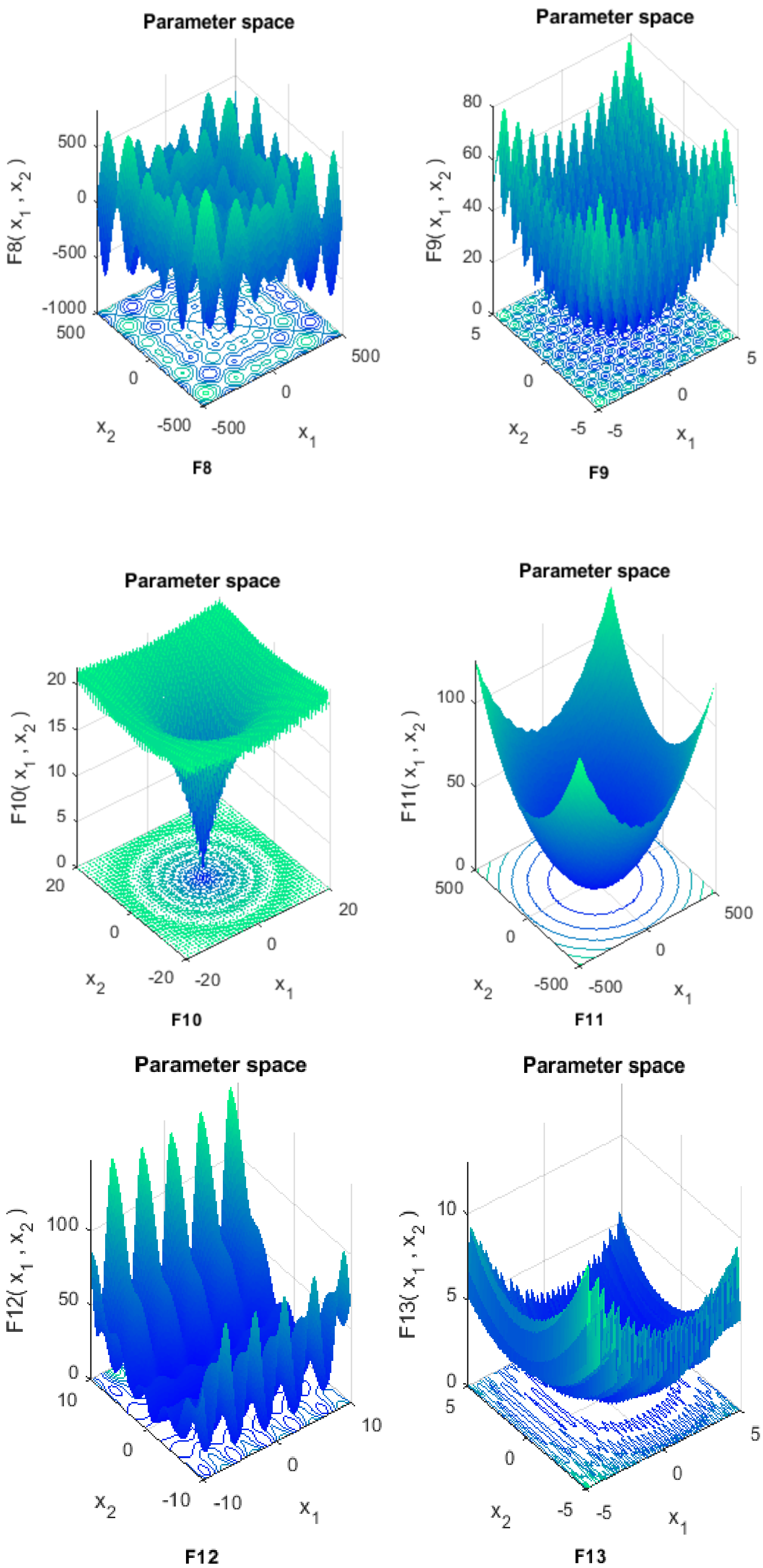


Fig. 4.2: 3D projection of MM function

4.2.3 Fixed Dimension Benchmark Function

Table- 4.3: Fixed Dimension Benchmark Function

FD Test Function	Dim	*Range*	*fmin*
$f_{14}(y) = \left[\frac{1}{500} + \sum_{j=1}^{2} 5 \frac{1}{j + \sum_{i=1}^{n} (y_i - a_{ij})^6} \right]^{-1}$	2	[-65.536, 65.536]	1
$f_{15}(y) = \sum_{i=1}^{11} \left[a_i - \frac{y_1 \left(b_i^2 + b_i y_2 \right)}{b_i^2 + b_i y_3 + y_4} \right]^2$	4	[-5, 5]	0.00030
$f_{16}(y) = 4y_1^2 - 2.1y_1^4 + \frac{1}{3} y_1^6 + y_1 y_2 - 4y_2^2 + 4y_2^4$	2	[-5, 5]	-1.0316
$f_{17}(y) = \left(y_2 - \frac{5.1}{4\pi^2} y_1^2 + \frac{5}{\pi} y_1 - 6 \right)^2 + 10 \left(1 - \frac{1}{8\pi} \right) \cos y_1 + 10$	2	[-5, 5]	0.398
$f_{18}(y) = \left[\begin{matrix} 1 + (y_1 + y_2 + 1)^2 \\ \left(19 - 14y_1 + 3y_1^2 - 14y_2 + 6y_1 y_2 + 3y_2^2 \right) \end{matrix} \right] \times \left[\begin{matrix} 30 + \left(2y_1 - 3y_2 \right)^2 \times \\ \left(\begin{matrix} 18 - 32y_1 + 12y_1^2 + 48y_2 \\ -36y_1 y_2 + 27y_2^2 \end{matrix} \right) \end{matrix} \right]$	2	[-2,2]	3
$f_{19}(y) = -\sum_{i=1}^{4} c_i \exp \left(-\sum_{j=1}^{3} a_{ij} (y_j - q_{ij})^2 \right)$	3	[1, 3]	-3.32
$f_{20}(y) = -\sum_{i=1}^{4} c_i \exp \left(-\sum_{j=1}^{6} a_{ij} (y_j - q_{ij})^2 \right)$	6	[0, 1]	-3.32
$f_{21}(y) = -\sum_{i=1}^{5} \left[\begin{matrix} (y - a_i) \\ (y - a_i)^T + d_i \end{matrix} \right]^{-1}$	4	[0,10]	-10.1532
$f_{22}(y) = -\sum_{i=1}^{7} \left[\begin{matrix} (y - a_i) \\ (y - a_i)^T + d_i \end{matrix} \right]^{-1}$	4	[0, 10]	-10.4028
$f_{23}(y) = -\sum_{i=1}^{10} \left[\begin{matrix} (y - a_i) \\ (y - a_i)^T + d_i \end{matrix} \right]^{-1}$	4	[0, 10]	-10.5363

Fixed Dimension (FD) functions are Shekel Foxhole Function, Brad Function, Camel Function – Six Hump, Branin RCOS Function, Goldstein-Price Function, Hartman 3 Function, Hartman 6 Function, Hybrid Composition Function #1, Hybrid Composition

Function #2 and Hybrid Composition Function #3 and represented as F14 to F23 as shown in Table- 4.3. Each function have fixed dimension, optimum value ($f_{\min}$) and variable range corresponding to each function. Fig.4.3 shows 3D view for FD benchmark function.

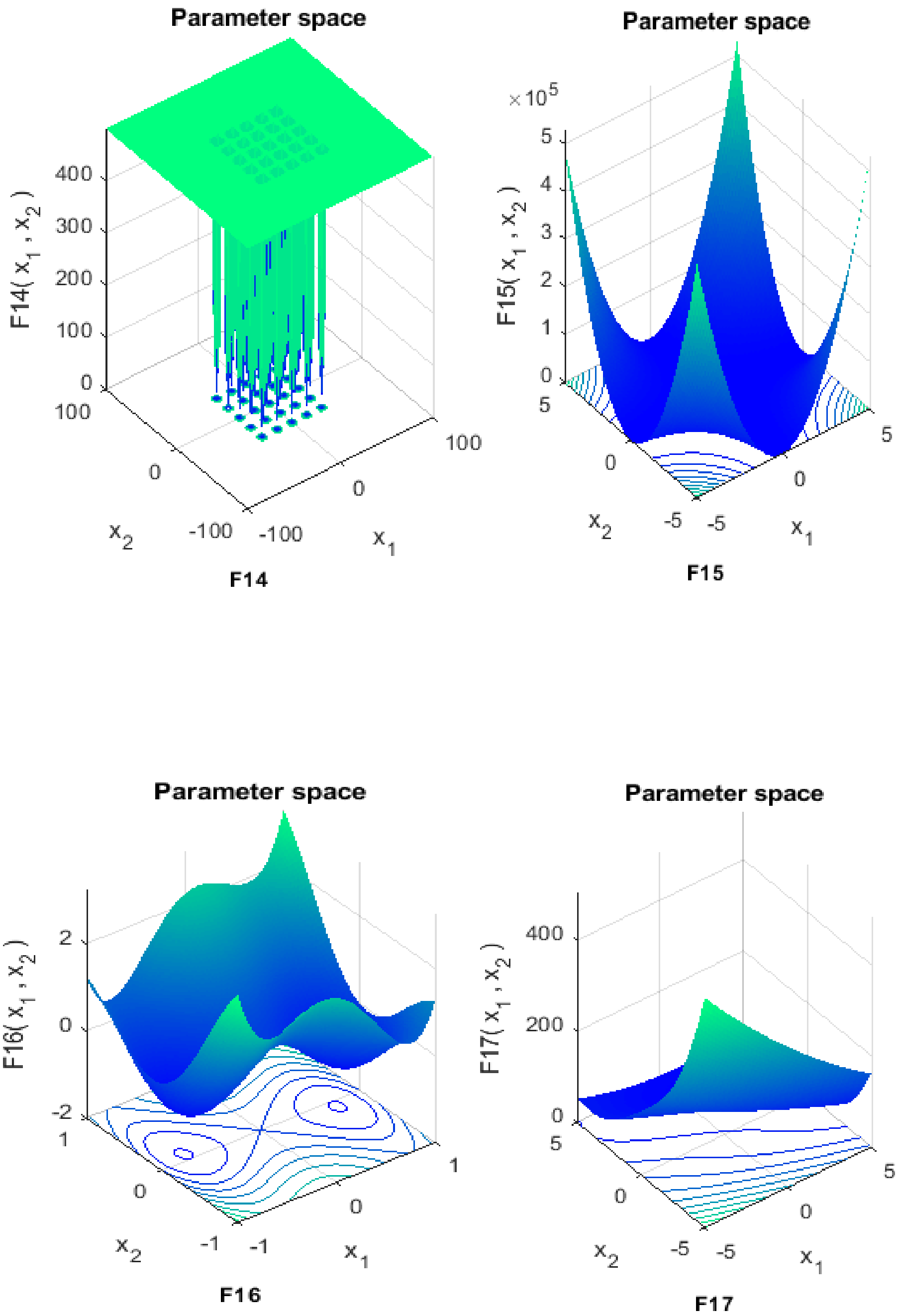


Fig. 4.3: 3D projection of FD function

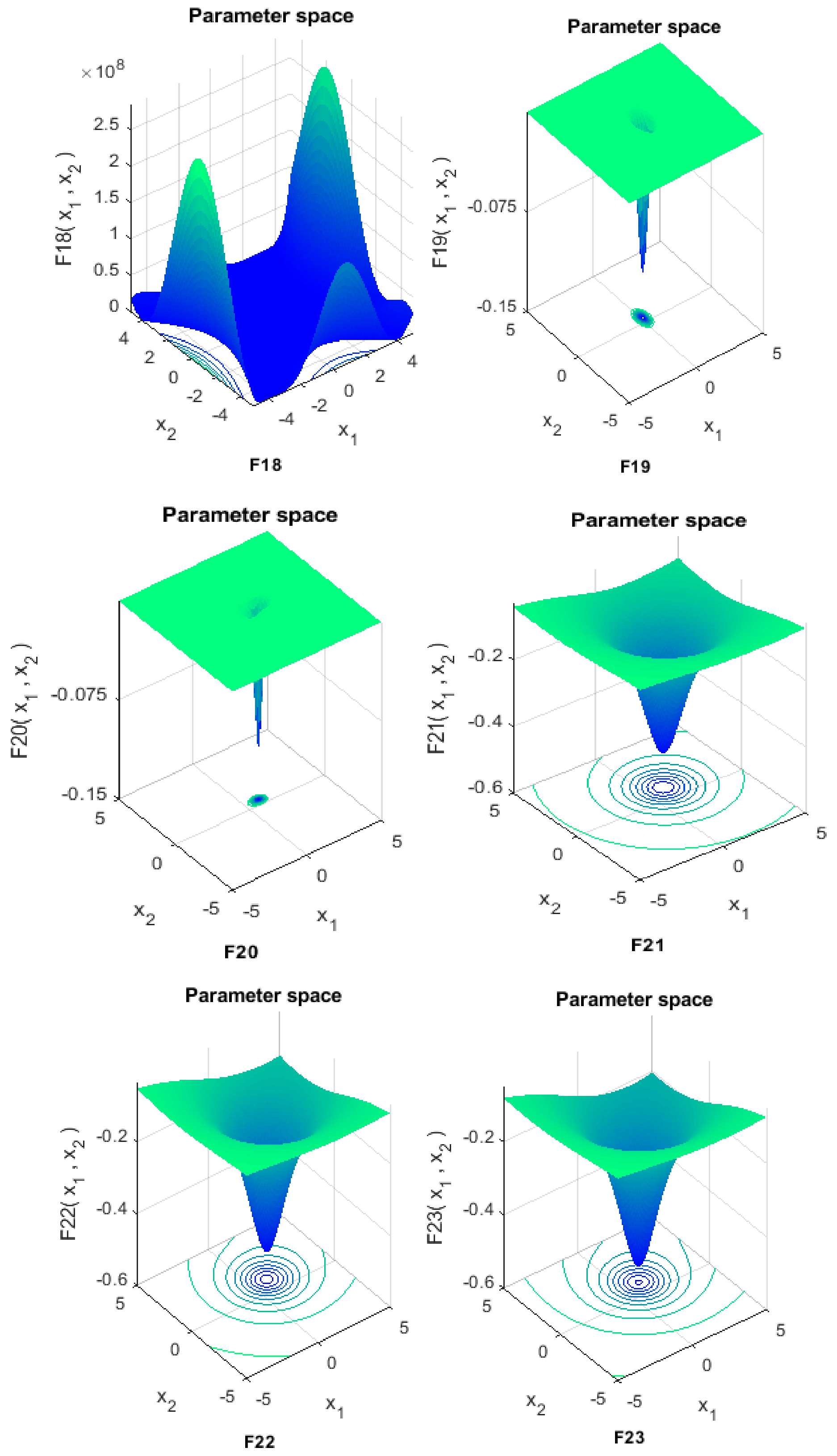


Fig. 4.3: 3D projection of FD function *(Continued)*

4.3 ENGINEERING DESIGN OPTIMIZATION

In this section, ten real-world design problems are tested, which include "3-bar truss problem; pressure vessel design; compression design; welded beam; cantilever beam design; gear train design problem; speed reducer problem; belleville spring problem; rolling element problem; and multidisc clutch brake problem" [270]. The abbreviations used for various multidisciplinary Engineering Function (EF) are shown in Table-4.4. Each design problem is tested by applying the proposed hybrid and chaotic algorithm.

Table -4.4: Abbreviations for 10 types of design problems

EF	Type of problem
EF1	3-bar truss problem
EF2	Pressure- Vessel
EF3	Compression Design
EF4	Welded Beam
EF5	Cantilever Beam Design
EF6	Gear Train
EF7	Speed Reducer problem
EF8	Belleville Spring
EF9	Rolling Element Bearing
EF10	Multiple Disk Clutch variables

In this section, the theoretical description of each design problem has been elaborated. In addition, the mathematical analysis of each design problem along with associated constraints and optimization problems are deeply explored. The following are detailed descriptions of ten engineering design problems:

4.3.1 Truss Design Problem

Truss design as shown in Fig.4.4 [271]-[272] is tested by applying proposed methodologies. The main focus of truss design problem is to minimize weight. The various constraints involved in truss bar design problem are warping, deflection and stress. These constraints are optimized to achieve the desired objective. The mathematical modelling for 3-Bar Truss are illustrated through eqn. (4.1) to eqn.4.1 (d) subject to various constraints. It is seen that the suggested method appreciably improves the objective of cost minimization. The design problem is modeled as shown below:

Consider,

$$\vec{y} = [y_1, y_2] = [A_1, A_2] \tag{4.1}$$

Minimize,

$$f(\vec{y}) = \left(2\sqrt{2}y_1 + y_2\right) * l \tag{4.1a}$$

Subjected to:

$$g_1(\vec{y}) = \frac{\sqrt{2}y_1 + y_2}{\sqrt{2}y_1^2 + 2y_1y_2} P - \sigma \le 0 \tag{4.1b}$$

$$g_2(\vec{y}) = \frac{y_2}{\sqrt{2}y_1^2 + 2y_1y_2} P - \sigma \le 0 \tag{4.1c}$$

$$g_3(\vec{y}) = \frac{1}{\sqrt{2}y_2 + y_1} P - \sigma \le 0 \tag{4.1d}$$

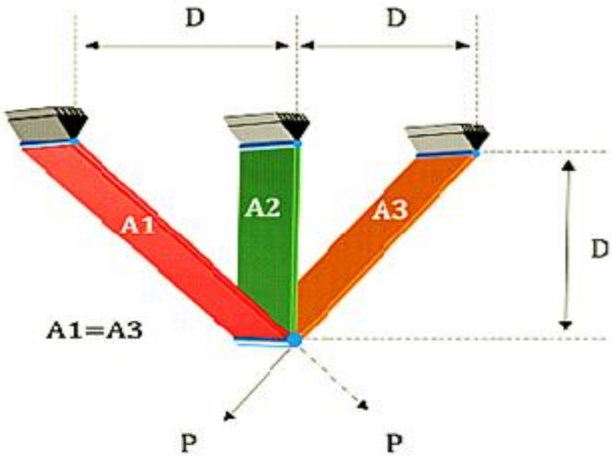


Fig. 4.4: Truss Design

4.3.2 Pressure Vessel Design

The design specification for such kind of engineering problem as illustrated in Fig.4.5 [271], [272]. All proposed three methodologies are applied to minimize overall cost, which includes the material and welding cost to form the pressure vessel in cylindrical form. The four variables for designing the vessel are: (i) shell thickness (Ts) (ii) head thickness (Th) (iii) length of cylindrical unit (Lh). These four variables are modelled as y1 to y4. The mathematical formulations are given in equations (4.2) to 4.2(e).

Consider:

$$\vec{y} = [y_1 y_2 y_3 y_4] = [T_s T_h R L_h] \tag{4.2}$$

Minimize;

$$f(\vec{y}) = 0.6224 y_1 y_3 y_4 + 1.7781 y_2 y_3^2 + 3.1661 y_1^2 y_4 + 19.84 y_1^2 y_3 \tag{4.2(a)}$$

Subject to:

$$g_1(\vec{y}) = -y_1 + 0.0193 y_3 \le 0 \tag{4.2b}$$

$$g_2(\vec{y}) = y_3 + 0.00954 y_3 \le 0 \tag{4.2c}$$

$$g_3(\vec{y}) = -\pi y_3^2 y_4 - \frac{4}{3}\pi y_3^3 + 1296000 \le 0 \tag{4.2d}$$

$$g_4(\vec{y}) = y_4 - 240 \le 0 \tag{4.2e}$$

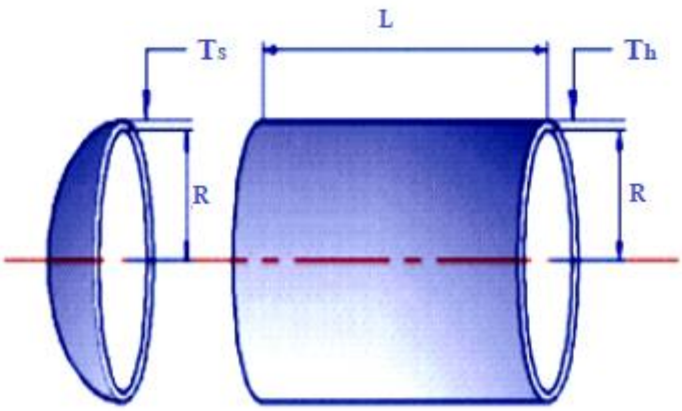


Fig.4.5: Pressure Vessel Design

4.3.3 Compression Spring Design

The design of compression spring is a mechanical engineering problem [271], [272] as depicted in Fig.4.6. The major objective is to minimize spring weight. There are three design dimensions :-(i) No. of active coils (Nc) (ii) wire diameter (dr) and (iii) mean coil diameter (Dm).The design problem is formulated through eqn. (4.3) to eqn. 4.3(f). The proposed method is applied to test compression spring engineering design problem and validated by comparing results with other competitive methods.

Consider; $\vec{y} = [y_1 y_2 y_3] = [drDmNc]$ (4.3)

Minimize

$$f(\vec{y}) = (y_3 + 2) y_2 y_1^2 \tag{4.3(a)}$$

Subject to:

$$g_1(\vec{y}) = 1 - \frac{y_2^3 y_3}{71785 y_1^4} \le 0, \tag{4.3(b)}$$

$$g_2(\vec{y}) = \frac{4y_2^2 - y_1 y_2}{12566\left(y_2 y_1^3 - y_1^4\right)} + \frac{1}{5108 y_1^2} \le 0, \tag{4.3 (c)}$$

$$g_2(\vec{y}) = \frac{4y_2^2 - y_1 y_2}{12566\left(y_2 y_1^3 - y_1^4\right)} + \frac{1}{5108 y_1^2} \le 0 \tag{4.3(d)}$$

$$g_3(\vec{y}) = 1 - \frac{140.45 y_1}{y_2^2 y_3} \le 0, \tag{4.3(e)}$$

$$g_4(\vec{y}) = \frac{y_1 + y_2}{1.5} - 1 \le 0, \tag{4.3(f)}$$

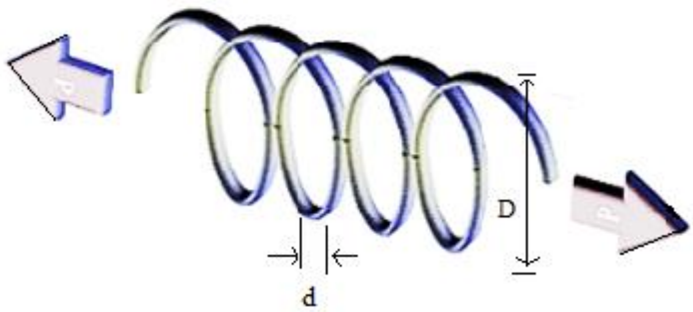


Fig.4.6: Compression Spring Design

4.3.4 Welded Beam Design

In this process, welding is carried out by fusing different sections of molten metal as shown in Fig.4.7 [271]. The main focus is minimization for overall cost of the welded beam. The four constraints are (i)bar thickness (b) is specified by y_1, (ii)bar length (l) is specified by y_2, (iii) weld thickness (h) is specified by y_3 and (iv) the bar height (h) is specified by y4. The structure is modeled through eqn. (4.4) to 4.4(m). The proposed method is applied to solve welded design problem and noted that proposed method gives more precise results compared to other algorithms.

Consider; $\vec{y} = [y_1 y_2 y_3 y_4] = [hltb]$ (4.4)

Minimize,

$$f(\vec{y}) = 1.10471 y_1^2 y_2 + 0.04811 y_3 y_4 \left(14.0 + y_2\right) \qquad 4.4(a)$$

Subject to

$$g_1(\vec{y}) = \tau(\vec{y}) - \tau_{\text{maxi}} \le 0, \qquad 4.4(b)$$

$$g_2(\vec{y}) = \sigma(\vec{y}) - \sigma_{\text{maxi}} \le 0, \qquad 4.4(c)$$

$$g_3(\vec{y}) = \delta(\vec{y}) - \delta_{\text{maxi}} \le 0, \qquad 4.4(d)$$

$$g_4(\vec{y}) = y_1 - y_4 \le 0, \qquad 4.4(e)$$

$$g_5(\vec{y}) = P_i - P_c(\vec{y}) \le 0, \qquad 4.4(f)$$

$$g_6(\vec{y}) = 0.125 - y_1 \le 0, \qquad 4.4(f)$$

$$g_7(\vec{y}) = 1.10471 y_1^2 + 0.04811 y_3 y_4 (14.0 + y_2) - 5.0 \le 0 \qquad 4.4(g)$$

Variable range $0.1 \le y_1 \le 2$, $0.1 \le y_2 \le 10$, $0.1 \le y_3 \le 10$, $0.1 \le y_4 \le 2$,

Where,

$$\tau(\vec{y}) = \sqrt{(\tau^{/})^2 + 2\tau^{/}\tau^{//}\frac{y_2}{2R} + (\tau^{//})^2}, \qquad 4.4(h)$$

$$\tau^{/} = \frac{P_i}{\sqrt{2} y_1 y_2}, \tau^{//} = \frac{MR}{J}, M = P_i\left(L + \frac{y_2}{2}\right), \qquad 4.4(i)$$

$$R = \sqrt{\frac{y_2^2}{4} + \left(\frac{y_1 + y_3}{2}\right)^2}, \qquad 4.4(j)$$

$$J = 2\left\{\sqrt{2} y_1 y_2 \left[\frac{y_2^2}{4} + \left(\frac{y_1 + y_3}{2}\right)^2\right]\right\}, \qquad 4.4(k)$$

$$\sigma(\vec{y}) = \frac{6P_i L}{y_4 y_3^2}, \delta(\vec{y}) = \frac{6P_i L^3}{E y_2^2 y_4}, \qquad 4.4(l)$$

$$P_c(\vec{y}) = \frac{4.013E\dfrac{\sqrt{y_3^2 y_4^6}}{36}}{L^2}\left(1 - \frac{y_3}{2L}\sqrt{\frac{E}{4G}}\right), \qquad 4.4(m)$$

$P_i = 6000lb, L = 14in, \delta_{\max i} = 0.25in, E = 30 \times 1^6\, psi, G = 12 \times 10^6\, psi,$
$\tau_{\text{maxi}} = 13600\, psi, \sigma_{\text{maxi}} = 3000\, psi$

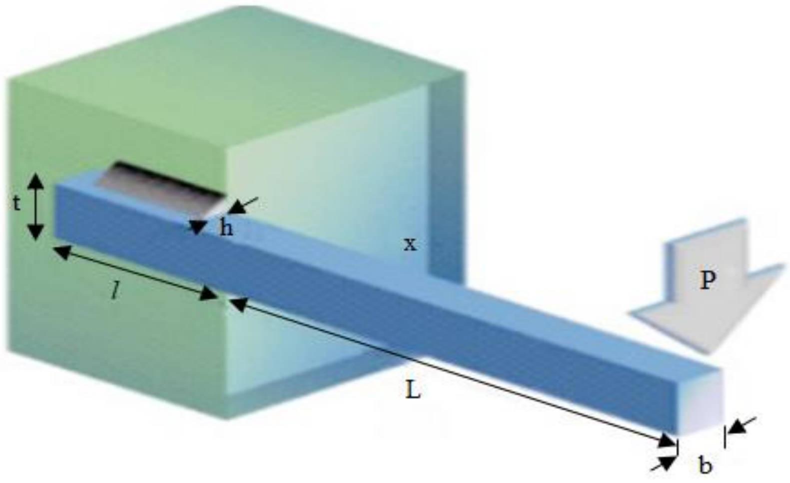


Fig.4.7: Welded Beam Design

4.3.5 Cantilever Beam Design

This is civil engineering problem concerned with minimization of beam weight as shown in Fig.4.8. In beam design there are five elements $l_1, l_2, l_3, l_4 and\, l_5$ [272]. The main aim is weight minimization of the beam. Taking care that displacement of vertical constraint not to disturb during finishing process of the beam. The final optimal solution is estimated by using eqn. (4.5) to 4.5(b) as shown below:

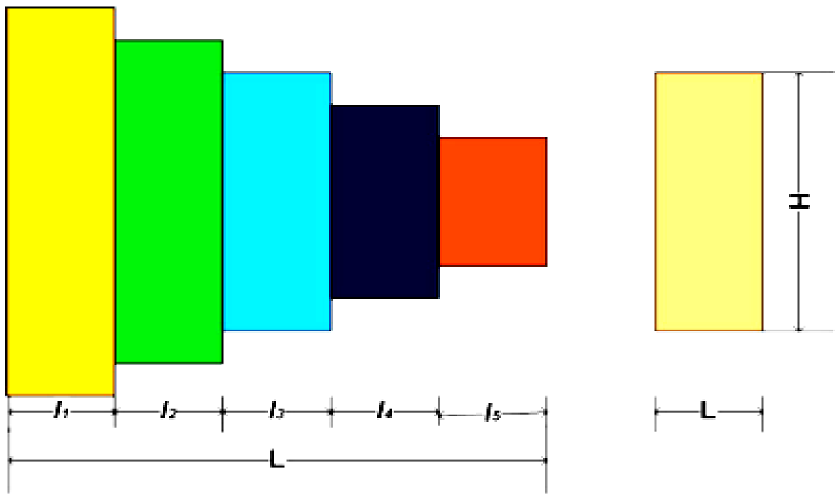


Fig.4.8: Cantilever Beam Design

Consider; $\vec{x} = [l_1 l_2 l_3 l_4 l_5]$, (4.5)

Minimize,

$$f(\vec{x}) = 0.6224(l_1 + l_2 + l_3 + l_4 + l_5), \quad 4.5(a)$$

Subject to

$$g(\vec{x}) = \frac{61}{l_1^3} + \frac{37}{l_2^3} + \frac{19}{l_3^3} + \frac{7}{l_4^3} + \frac{1}{l_5^3} \leq 1 \quad 4.5(b)$$

4.3.6 Gear Train Design

In this method the four variables $g_1, g_2, g_3, and\ g_4$ are estimated as shown in Fig.4.9 [271]. Teeth's on each gear are the decision variables in designing process. The gear train design problem is formulated through eqn. 4.6(a) to 4.6(b). From the analysis of test results, it is seen that proposed methods effectively evaluates the gear train ratio.

Let, considering;

$$\vec{g} = [g_1 g_2 g_3 g_4] = [M_A M_B M_C M_D] \quad 4.6(a)$$

Minimizing;

$$f(\vec{g}) = \left(\frac{1}{6.931} - \frac{g_3 g_4}{g_1 g_4} \right)^2 \quad 4.6(b)$$

Subject to: $12 \leq g_1, g_2, g_3, g_4 \leq 60$

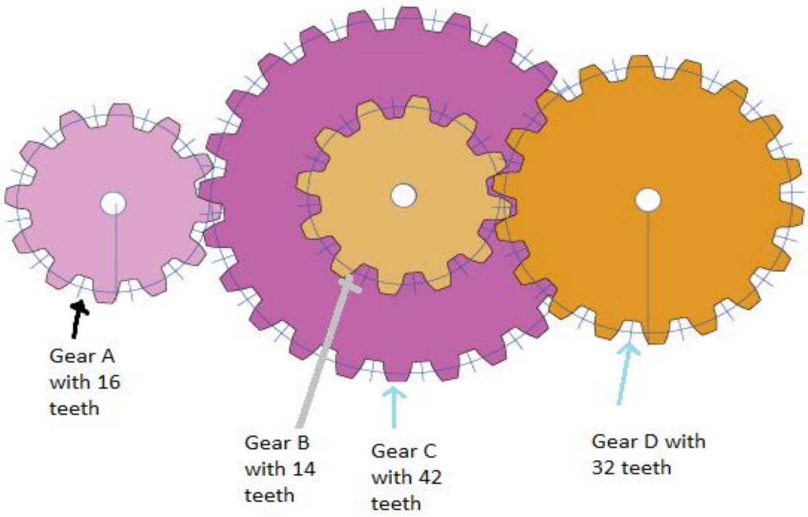


Fig.4.9: Gear Train Design

4.3.7 Speed Reducer Design Problem

The main concern in this design problem is to minimize the weight of the speed reducer. This type of design problem seven design variables are involved as shown in Fig.4.10 [271]. The seven variables are face width (x_1), teeth module (x_2), pinion teeth (x_3), first shaft length (x_4), second shaft length (x_5), the first shaft diameter (x_6) and second shaft diameter (x_7). The mathematical equations are formulated as given below:

Minimizing;

$$f(\vec{x}) = 0.7854x_1x_2(3.3333x_3^2 + 14.9334x_3 - 43.0934) - 1.508x_1(x_6^2 + x_7^2) + 7.4777(x_6^3 + x_7^3) + 0.7854(x_4 x_6^2 + x_5 x_7^2) \quad (4.7)$$

Subject to;

$$g_1(\vec{x}) = \frac{27}{x_1x_2^2x_3} - 1 \le 0 \quad 4.7(a)$$

$$g_2(\vec{x}) = \frac{397.5}{x_1x_2^2x_3^2} - 1 \le 0 \quad 4.7(b)$$

$$g_3(\vec{x}) = \frac{1.93x_4^3}{x_2x_3x_6^4} - 1 \le 0 \quad 4.7(c)$$

$$g_4(\vec{x}) = \frac{1.93x_5^3}{x_2x_3x_7^4} - 1 \le 0 \quad 4.7(d)$$

$$g_5(\vec{x}) = \frac{1}{110x_6^3}\sqrt{\left(\frac{745.0x_4}{x_2x_3}\right)^2 + 16.9\times10^6} - 1 \le 0 \quad 4.7(e)$$

$$g_6(\vec{x}) = \frac{1}{85x_7^3}\sqrt{\left(\frac{745.0x_5}{x_2x_3}\right)^2 + 157.5\times10^6} - 1 \le 0 \quad 4.7(f)$$

$$g_7(\vec{x}) = \frac{x_2x_3}{40} - 1 \le 0 \quad 4.7(g)$$

$$g_8(\vec{x}) = \frac{5x_2}{x_1} - 1 \le 0 \quad 4.7(h)$$

$$g_9(\vec{x}) = \frac{x_1}{12x_2} - 1 \le 0 \quad 4.7(i)$$

$$g_{10}(\vec{x}) = \frac{1.5x_6 + 1.9}{12x_2} - 1 \le 0 \quad 4.7(j)$$

$$g_{11}(\vec{x}) = \frac{1.1x_7 + 1.9}{x_5} - 1 \le 0 \quad 4.7(k)$$

Where $2.6 \le x_1 \le 3.6, 0.7 \le x_2 \le 0.8, 17 \le x_3 \le 28, 7.3 \le x_4 \le 8.3, 7.8 \le x_5 \le 8.3, 2.9 \le x_6 \le 3.9 \, and \, 5 \le x_7 \le 5.5$

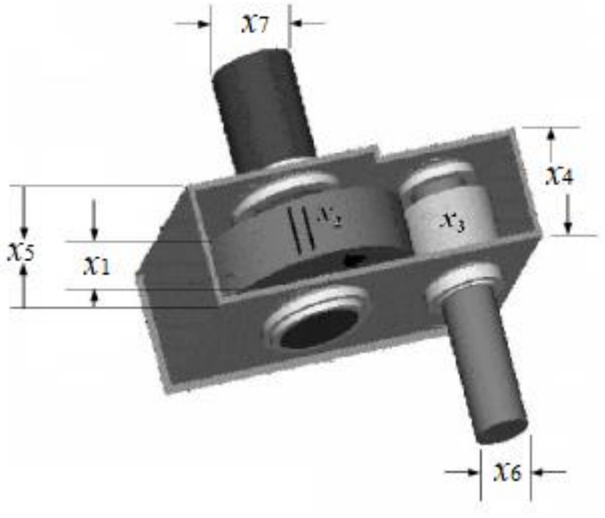


Fig.4.10: Speed reducer design

4.3.8 Belleville Spring Design

In this kind of design problem design parameters are selected according to variable ratio as shown in Fig.4.11 [271]. The major objective is to minimize weight within certain constraints. The designed variables are internal diameter of the spring (DIMI), external diameter of the spring (DIME), spring height (SH) and spring thickness (ST). The mathematical expressions are formulated through eqn. 4.8(a) to eqn.4.8 (i).

Minimizing;

$$f(x) = 0.07075\pi(DIM_E^2 - DIM_I^2)t \qquad 4.8(a)$$

Subject to:

$$b_1(x) = G - \frac{4P\lambda_{max}}{(1-\delta^2)\alpha DIM_E}\left[\delta(S_H - \frac{\lambda \max}{2}) + \mu t\right] \geq 0 \qquad 4.8(b)$$

$$b_2(x) = (\frac{4P\lambda_{max}}{(1-\delta^2)\alpha DIM_E}\left[(S_H - \frac{\lambda}{2})(S_H - \lambda)t + t^3)\right] \lambda_{max} - P_{MAX} \geq 0 \qquad 4.8(c)$$

$$b_3(x) = \lambda_1 - \lambda_{max} \geq 0 \qquad 4.8(d)$$

$$b_4(x) = H - S_H - t \geq 0 \qquad 4.8(f)$$

$$b_5(x) = DIM_{MAX} - DIM_E \geq 0 \qquad 4.8(g)$$

$$b_6(x) = DIM_E - DIM_I \geq 0 \qquad 4.8(h)$$

$$b_7(x) = 0.3 - \frac{S_H}{DIM_E - DIM_I} \geq 0 \qquad 4.8(i)$$

Where, $\alpha = \frac{6}{\pi \ln J}(\frac{J-1}{J})^2$ $\delta = \frac{6}{\pi \ln J}(\frac{J-1}{\ln J} - 1)$, $\mu = \frac{6}{\pi \ln J}(\frac{J-1}{2})$

$P_{MAX} = 5400lb, P = 30e6\,psi, \lambda_{\max} = 0.2in, \delta = 0.3, G = 200Kpsi,$

$H = 2in, DIM_{MAX} = 12.01in, J = \frac{DIM_E}{DIM_I}, \lambda_1 = f(a)a, a = \frac{S_H}{t}$

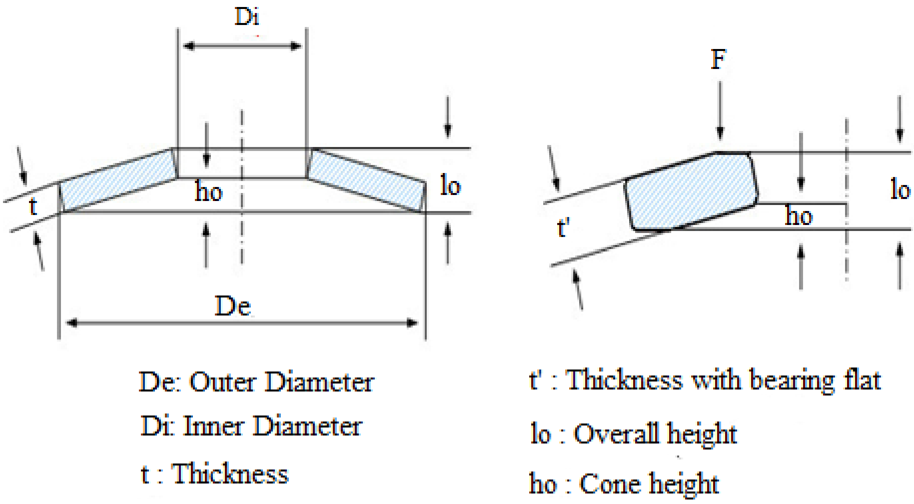


Fig.4.11: Belleville Spring Design

4.3.9 Rolling Element Bearing Design

In rolling bearing design, dynamic load carrying capacity of rolling element is major concern as illustrated in Fig.4.12 [89].

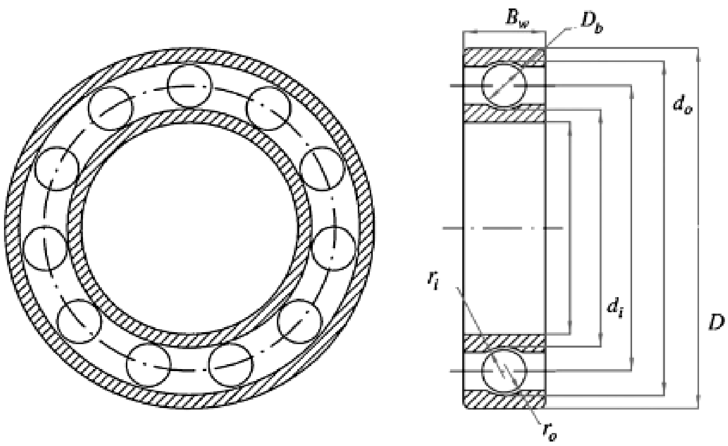


Fig.4.12: Rolling element bearing design

Five out of ten variables plays major role in the optimum design of bearing with greater load bearing capacity. These major variables are (a) diameter of the ball (DIMB), (b) diameter pitch (DIMP), (c) ball numbers (Nb), (d) Outer curvature coefficient and (e) inner curvature coefficient. Remaining five variables only disturb meanderingly to the inner part of the structure. The design equations are modeled through eqn. 4.9(a) to eqn.4.9 (k) as given below:

Maximizing;

$$C_D = f_c N^{2/3} DIM_B^{1.8} \tag{4.9(a)}$$

$if \;\; DIM \le 25.4mm$

$$C_D = 3.647 f_C N^{2/3} DIM_B^{1.4} \tag{4.9(b)}$$

$if \;\; DIM \ge 25.4mm$

Subjected to;

$$r_1(x) = \frac{\theta_0}{2\sin^{-1}\left(\dfrac{DIM_B}{DIM_{MAX}}\right)} - N + 1 \ge 0 \tag{4.9(c)}$$

$$r_2(x) = 2DIM_B - K_{DIM_{MIN}}(DIM - \dim) \ge 0 \tag{4. 9(d)}$$

$$r_3(x) = K_{DIM_{MAX}}(DIM - \dim) \ge 0 \tag{4.9(e)}$$

$$r_4(x) = \beta B_W - DIM_B \le 0 \tag{4. 9(f)}$$

$$r_5(x) = DIM_{MAX} - 0.5(DIM + \dim) \ge 0 \tag{4. 9(g)}$$

$$r_6(x) = (0.5 + re)(DIM + \dim) \ge 0 \tag{4.9(h)}$$

$$r_7(x) = 0.5(DIM - DIM_{MAX} - DIM_B) - \alpha DIM_B \ge 0 \tag{4. 9(i)}$$

$$r_8(x) = f_I \ge 0.515 \tag{4.9(j)}$$

$$r_9(x) = f_0 \ge 0.515 \tag{4. 9(k)}$$

Where,

$$f_c = 37.91\left[1 + \left\{1.04\left(\frac{1-\varepsilon}{1+\varepsilon}\right)^{1.72}\left(\frac{f_I\left(2f_0 - 1\right)}{f_0\left(2f_I - 1\right)}\right)^{0.41}\right\}^{10/3}\right]^{-0.3} \times \left[\frac{\varepsilon^{0.3}\left(1-\varepsilon\right)^{1.39}}{\left(1+\varepsilon\right)^{1/3}}\right]\left[\frac{2f_I}{2f_I - 1}\right]^{0.41}$$

$$\theta_0 = 2\pi - 2\cos^{-1}\left(\frac{\left[\{(DIM - \dim)/2 - 3(t/4)\}^2 + \left(DIM/2 - t/4 - DIM_B\right)^2 - \{\dim/2 + t/4\}^2\right]}{2\{(DIM - \dim)/2 - 3(t/4)\}\{D/2 - t/4 - DIM_B\}}\right)$$

$$\varepsilon = \frac{DIM_B}{DIM_{MAX}},\ f_I = \frac{R_I}{DIM_B},\ f_0 = \frac{R_0}{DIM_B},\ t = DIM - \dim - 2DIM_B$$

$$DIM = 160, \dim = 90, B_W = 30, R_I = R_0 = 11.033$$

$$0.5(DIM + \dim) \le DIM_{MAX} \le 0.6(DIM + \dim), 0.15(DIM - \dim) \le DIM_B \le 0.45(DIM - \dim),$$

$$4 \le N \le 50$$

$$0.515 \le f_I \text{ and } f_0 \le 0.6$$

$$0.4 \le K_{DIM_{MIN}} \le 0.5, 0.6 \le K_{DIM_{MAX}} \le 0.7, 0.3 \le re \le 0.1, 0.02 \le re \le 0.1, 0.6 \le \beta \le 0.85$$

4.3.10 Multi disc-clutch Design

Multi disc-clutch design is the most crucial problem in engineering as illustrated in Fig.4.13 [273]. The structure is mainly fabricated to abate the overall weight. The five variables are (a) inner surface radius (Rin), (b) outer surface radius (Ro), (c) thickness of disc's (Th), (d) actuating force (Fac) and count friction surface (Sf). The equations for design problem are illustrated through eqn.4.10 to 4.10(h).

Minimizing;

$$f\left(R_{in}, R_O, S_f, Th\right) = \pi Th\gamma\left(R_0^2 - R_{in}^2\right)\left(S_f + 1\right) \tag{4.10}$$

Where,

$$R_{in} \in 60, 61, 62....80; R_o \in 90, 91, ...110; Th \in 1, 1.5, 2, 2.5, 3; F_{ac} \in 600, 610, 620, 1000; S_f \in 2, 3, 4, 5, 6, 7, 8, 9$$

Subject to:

$$m_1 = R_0 - R_{in} - \Delta R \ge 0 \quad 4.10(a)$$

$$m_2 = L_{MAX} - (S_f + 1)(Th + \alpha) \ge 0 \quad 4.10(a)$$

$$m_3 = PM_{MAX} - PM_\pi \ge 0 \quad 4.10(c)$$

$$m_4 = PM_{MAX} Y_{MAX} + PM_\pi Y_{SR} \ge 0 \quad 4.10(d)$$

$$m_5 = Y_{SR_{MAX}} - Y_{SR} \ge 0 \quad 4.10(e)$$

$$m_6 = t_{MAX} - t \ge 0 \quad 4.10(f)$$

$$m_7 = DC_h - DC_f \ge 0 \quad 4.10(g)$$

$$m_8 = t \ge 0 \quad 4.10(h)$$

Where, $PM_{\pi} = \dfrac{F_{ac}}{\Pi\left(R_0^2 - R_{in}^2\right)}$, $Y_{SR} = \dfrac{2\pi n\left(R_0^3 - R_{in}^3\right)}{90\left(R_0^2 - R_{in}^2\right)}$

$$t = \frac{i_x \pi n}{30\left(DC_h + DC_f\right)}$$

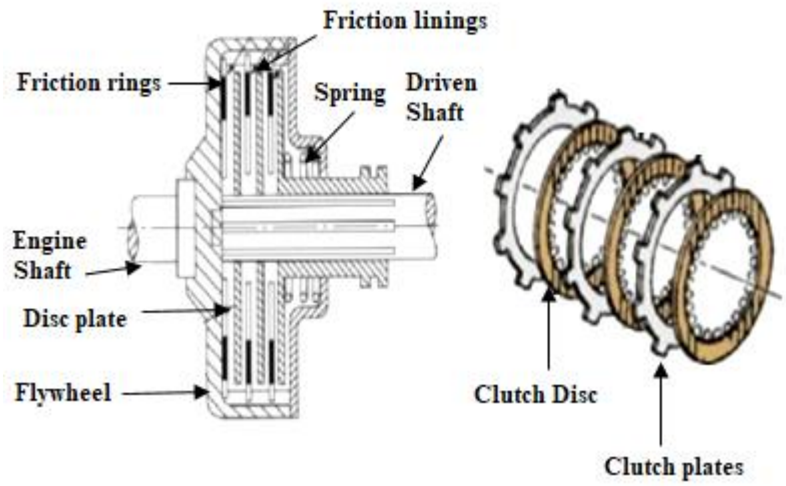


Fig.4.13: Multidisc clutch break design

4.4 RESULTS AND DISCUSSION

In this section, test results of benchmark and engineering design problems are discussed. Twenty-three benchmark functions are tested by implementing the hHHO-IGWO, CHHO, and CSMA methods. Also, 10 multidisciplinary engineering design problems have been tested. To authenticate the feasibility of the proposed methodologies, simulation results were compared with standard existing trends.

4.4.1 Testing of benchmark problems using hHHO-IGWO, CHHO and CSMA

The benchmark problems were simulated in MATLAB 2018a Windows 10, CPU@2.10Ghz-4GB RAM Core i5. Test results for benchmark functions were recorded with their average, worst, best, median, standard deviation. The stochastic complexity of the proposed algorithms are investigated and justified by running the algorithm for 30 trial runs and 500 iterations. On similar grounds, results are compared with other competitive methods.

4.4.2 Test Results for hHHO-IGWO method

(a) Test Results for UM function

Table-4.5 presents the simulation results of UM function in terms of mean, standard deviation, best, worst, median and p-value.

Table-4.5: Test results of UM function using hHHO-IGWO method

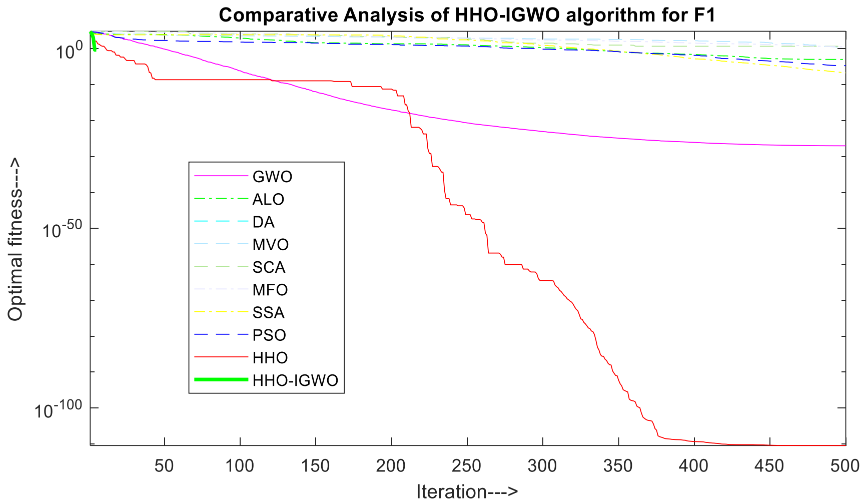
Functions	Mean	SD	Best	Worst	Median	p-Value
F1	4.17E-98	1.43E-97	2.2E-113	7.31E-97	2.7E-103	1.73E-06
F2	1.26E-50	5.39E-50	2.72E-59	2.95E-49	7.68E-53	1.73E-06
F3	2.68E-67	1.47E-66	2.2E-110	8.04E-66	3.34E-88	1.73E-06
F4	1.43E-48	6.87E-48	4.17E-57	3.77E-47	3.36E-51	1.73E-06
F5	0.011138	0.010195	4.06E-06	0.040574	0.008431	1.73E-06
F6	0.000212	0.000368	2.76E-07	0.001957	0.000105	1.73E-06
F7	0.000104	0.000107	1.72E-06	0.000403	6.56E-05	1.73E-06

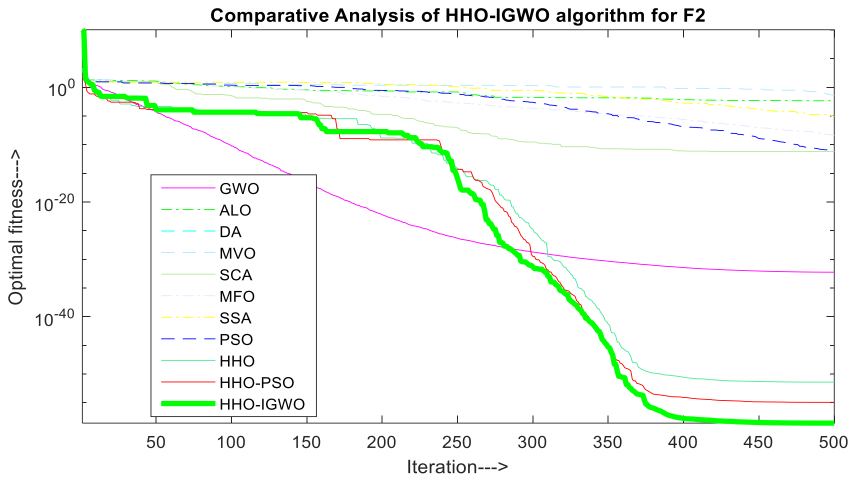
The p-value in table -4.5, 4.11 and 4.17 are the results of Wilcoxon rank-sum test. In proposed research, Wilcoxon rank-sum test has been used as a hypothesis test at 5% significance level to test the null hypothesis and alternative hypothesis. Null hypothesis indicates significant difference between compared algorithms; whereas, alternative hypothesis shows no significant difference between algorithms. If p-value is less than 0.05, null hypothesis is accepted. If p-value is equal to or greater than 0.05, alternative hypothesis is accepted.

In order to inspect the feasibility of the estimated method, test outcomes are cross examined with other meta-heuristic approaches such as BA [258],BDA [259], MFO [211],GWO [99], GSA [203], BPSO [260], FEP [261], GOA [262], ALO [263], WOA [212], CS[264], GA [265], MVO [266], DA [259], BGSA [267], SCA [268], SSA [269], FEP [261] as shown in Table-4.6. The convergence curve of hHHO-IGWO compared with competence methodologies are shown in Fig.4.14 and the experimental runs for UM benchmark functions are shown in Fig.4.15.

Table-4.6: Comparison of UM test results of hHHO-IGWO with other methods

Algorithms	Parameters	UM test functions						
		F1	F2	F3	F4	F5	F6	F7
GWO [99]	Mean	0.000	0.000	0.000	0.000	26.813	0.817	-6120.000
	SD	0.000	0.029	79.150	1.315	69.905	0.000	-4090.000
ALO [263]	Mean	0.000	0.000	0.000	0.000	0.347	0.000	-1610.000
	SD	0.000	0.000	0.000	0.000	0.110	0.000	314.000
GSA [203]	Mean	0.000	0.056	896.535	7.355	67.543	0.000	-2820.000
	SD	0.000	0.194	318.956	1.741	62.225	0.000	493.000
GA [265]	Mean	0.119	0.145	0.139	0.158	0.714	0.168	-2090.000
	SD	0.126	0.053	0.121	0.862	0.973	0.869	2.470
GOA [262]	Mean	0.000	0.002	0.001	0.000	0.000	0.000	1.000
	SD	0.000	0.001	0.020	0.000	0.000	0.000	0.000
MFO [211]	Mean	0.000	0.001	696.731	70.68	139.14	0.000	-8500.000
	SD	0.000	0.001	188.528	5.275	120.26	0.000	726.000
MVO [266]	Mean	2.086	15.92	453.200	3.123	1272.1	2.295	-11700.000
	SD	0.649	44.74	177.097	1.583	1479.4	0.631	937.000
DA [259]	Mean	0.000	0.000	0.000	0.001	7.600	0.000	-2860.000
	SD	0.000	0.000	0.000	0.003	6.790	0.000	384.000
BPSO [260]	Mean	5.590	0.196	15.500	1.900	86.400	6.980	-989.000
	SD	1.980	0.053	13.700	0.484	65.800	3.850	16.700
BGSA [267]	Mean	83.000	1.190	456.000	7.370	3100.0	107.00	-861.000
	SD	49.800	0.228	272.000	2.210	2930.0	77.500	80.600
SCA [268]	Mean	0.000	0.000	0.037	0.097	0.001	0.000	1.000
	SD	0.000	0.000	0.137	0.582	0.002	0.000	0.004
SSA [269]	Mean	0.000	0.227	0.000	0.000	0.000	0.000	0.056
	SD	0.000	1.000	0.000	0.656	0.000	0.000	0.809
WOA [212]	Mean	0.000	0.000	0.000	0.073	27.866	3.116	-5080.000
	SD	0.000	0.000	0.000	0.397	0.764	0.532	696.000
hHHO-PSO	Mean	0.000	0.000	0.000	0.000	0.007	0.000	0.000
	SD	0.000	0.000	0.000	0.000	0.009	0.000	0.000174
hHHO-IGWO	**Mean**	**4.17E-98**	**1.26E-50**	**2.68E-67**	**1.43E-48**	**0.011138**	**0.000212**	**0.000104**
	SD	**1.43E-97**	**5.39E-50**	**1.47E-66**	**6.87E-48**	**0.010195**	**0.000368**	**0.000107**





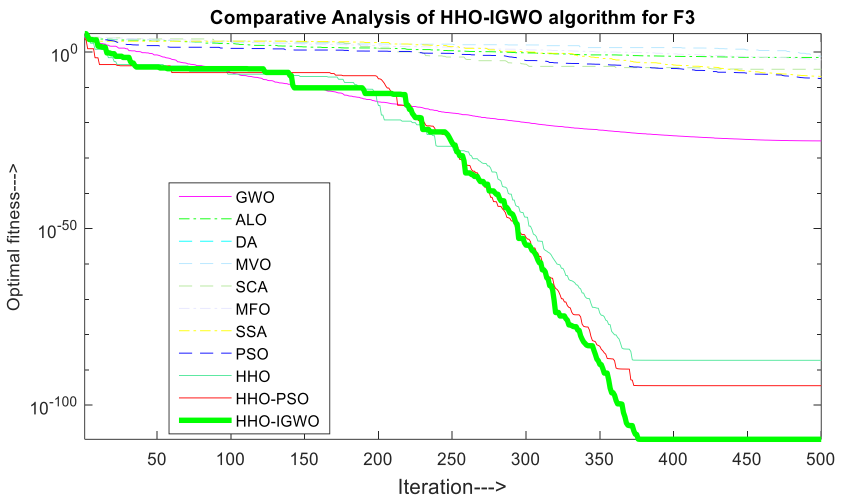
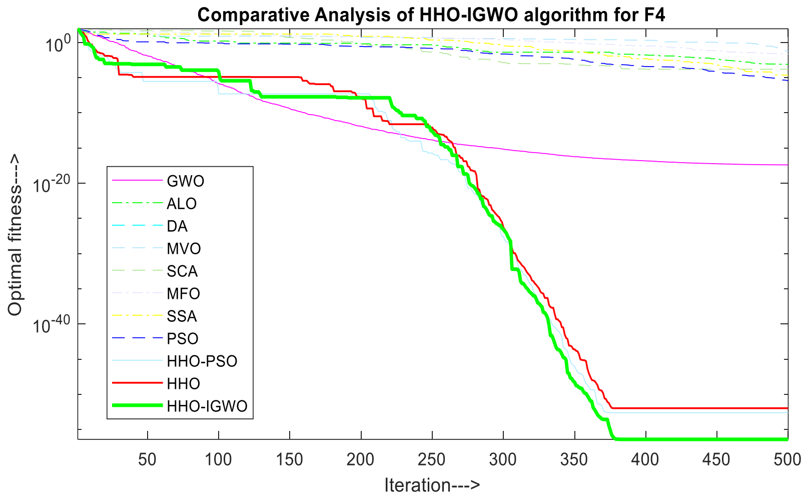
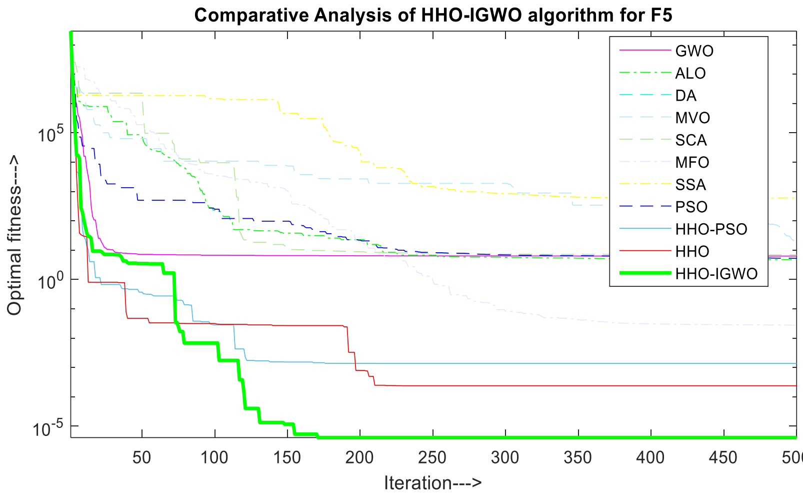


Fig.4.14: Assessment of convergence of UM with other methods





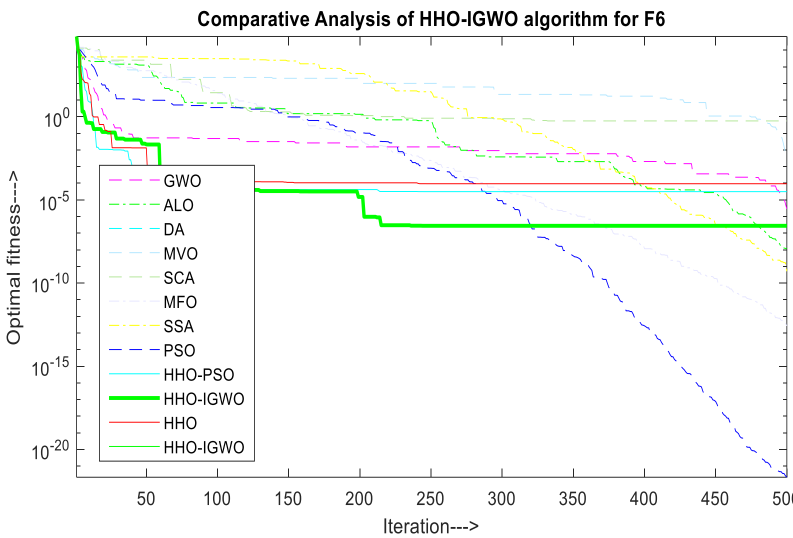


Fig.4.14: Assessment of convergence for UM with other methods *(Continued)*

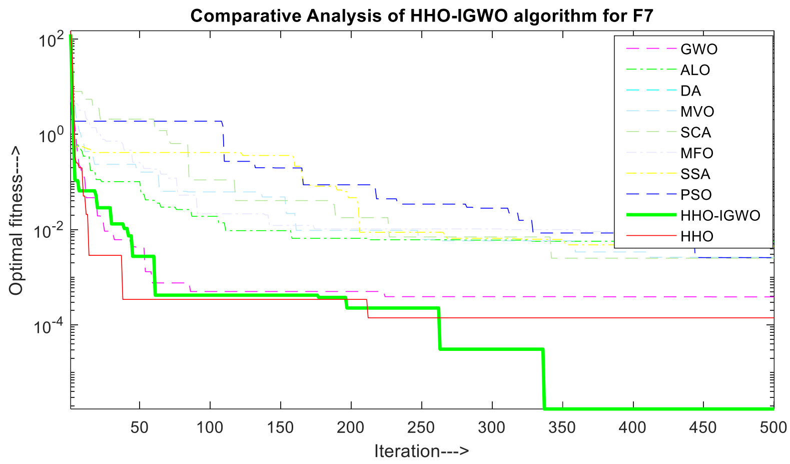


Fig.4.14: Assessment of convergence for UM with other methods *(Continued)*

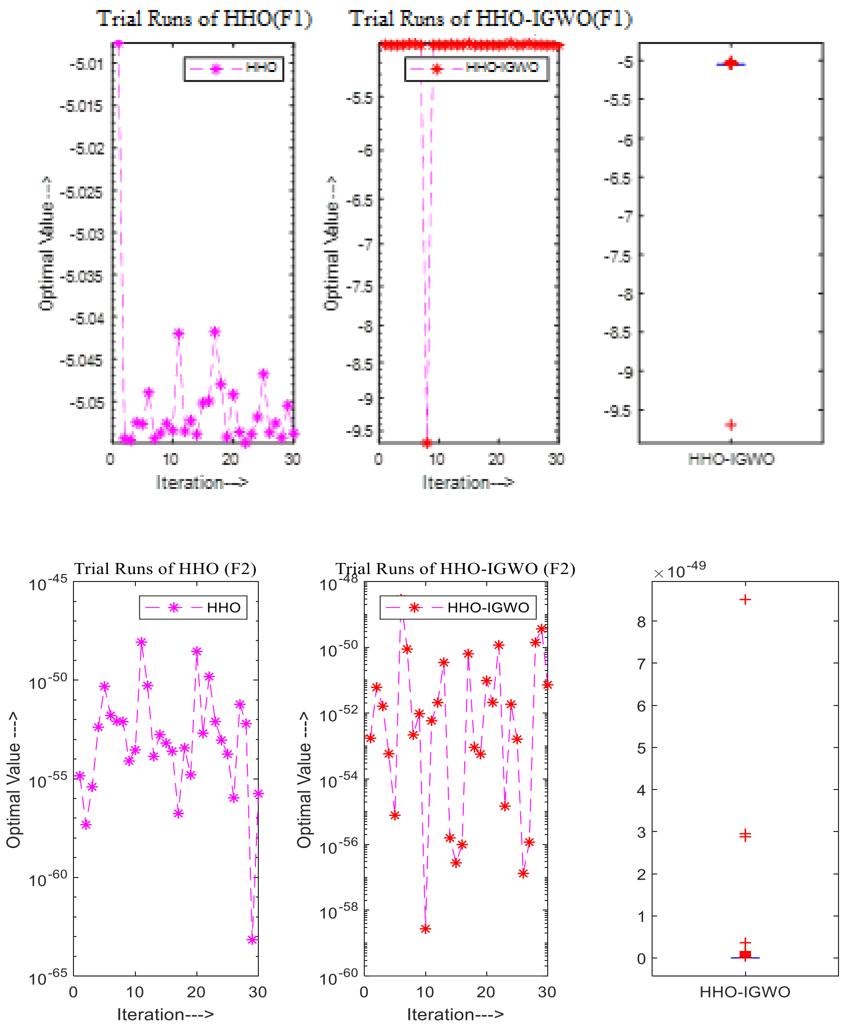


Fig.4.15: Trials of UM function for hHHO-IGWO

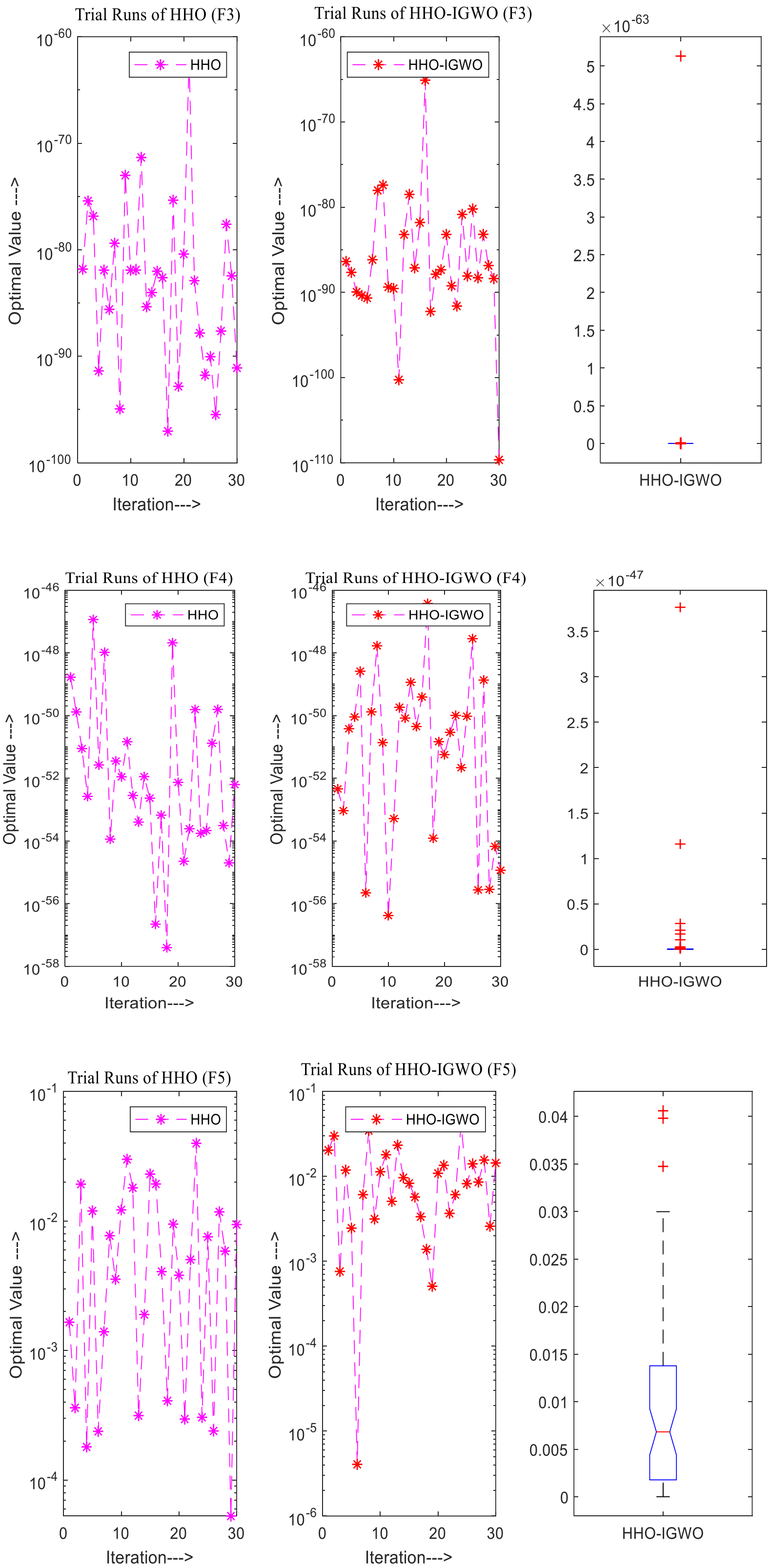


Fig.4.15: Trials of UM function for hHHO-IGWO *(Continued)*

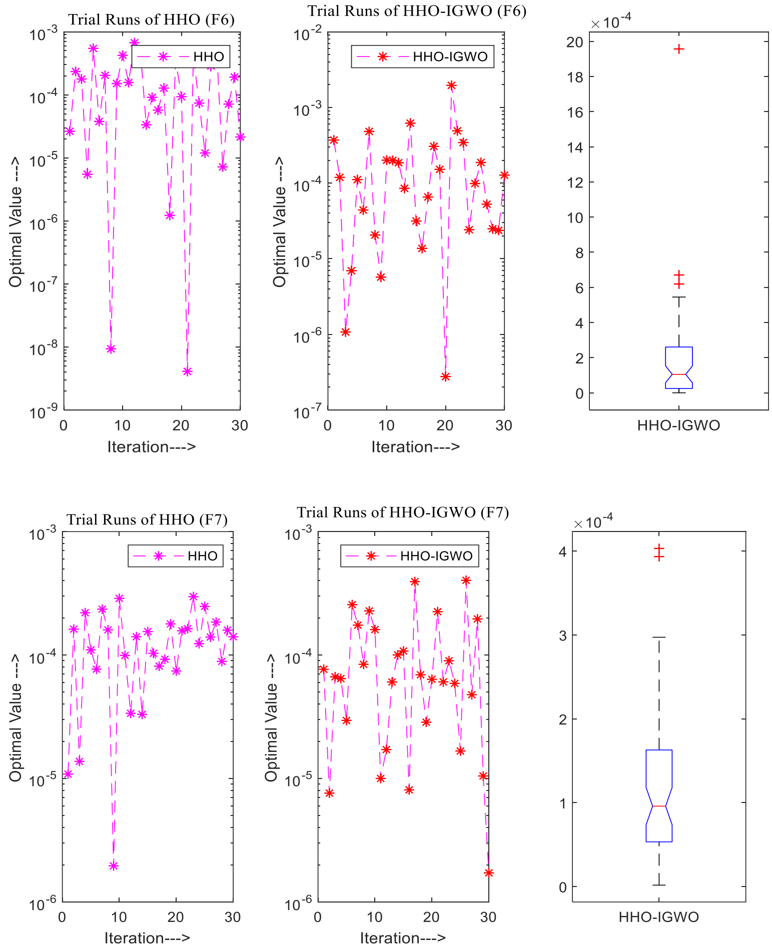


Fig.4.15: Trials of UM function for hHHO-IGWO *(Continued)*

The quality of the solution is high, if average (mean) values are small, and for small standard deviation values, the algorithm is more stable. Table 4.6 presents the average and standard deviation of all test algorithms. It can be seen that the average and standard deviation values of hHHO-IGWO are much less than other techniques. This suggests that hHHO-IGWO can provide a high-quality solution with more stability. Fig. 4.14 inferred that hHHO-IGWO rapidly convergences towards an optimum due to better exploitation. In Fig.4.14, F2, F3, and F4 have better convergence, while other algorithms seem to enter into local optimum. In the latter stages of iterations, F5 and F7 initially converge slowly but precisely converges to the global optimum. The above analysis reveals that hHHO-IGWO is capable in testing unimodal test functions.

(b) Test Results for MM function

Table-4.7 displays the simulation results of MM function using hHHO-IGWO

Table-4.7: Test results of MM benchmark function using hHHO-IGWO

Functions	Mean	SD	Best	Worst	Median	p-Value
F8	-12471	390.075	-12569.5	-10655.6	-12569.3	1.73E-06
F9	0	0	0	0	0	1
F10	8.88E-16	0	8.88E-16	8.88E-16	8.88E-16	4.32E-08
F11	0	0	0	0	0	1
F12	0	0	0	0	0	0
F13	0	0	0	0	0	0

The test results for MM benchmark function illustrated in Table-4.8 are compared with others meta-heuristics methods such as GWO [99], GSA [203], FEP [261], ALO [263], GA [265], GOA [262], MFO [211], BA [258], MVO [266], DA [259], BDA [259], BPSO [260], BGSA [267], SCA [268] , SSA [269], FEP [261] and WOA [212]. In Table 4.7, p-values for F8 and F10 are less than 0.005 and thus F8 and F10 are statistically significant. F9 and F11 shows values greater than 0.05 and null hypothesis is rejected.

Table-4.8: Comparison of MM test results of hHHO-IGWO with other methods

Algorithm	Parameters	Multi modal Benchmark functions					
		F8	**F9**	**F10**	**F11**	**F12**	**F13**
GWO [99]	Mean	-6.123E+224	0.31052	1.06E-13	0.00448	0.053438	0.654464
	SD	-4087.44	47.3561	0.077835	0.00665	0.654464	0.004474
PSO	Mean	-4841.29	46.7042	0.276015	0.00921	0.006917	0.006675
	SD	1152.814	11.6293	0.50901	0.00772	0.026301	0.008907
GSA [203]	Mean	-2821.07	25.97	0.06	27.70	1.80	8.90
	SD	493.04	7.47	0.24	5.04	0.95	7.13
DE[200]	Mean	-11080.10	69.20	0.00	0.00	0.00	0.00
	SD	574.70	38.80	0.000	0.000	0.00	0.00
FEP [261]	Mean	-12554.50	0.05	0.02	0.02	0.00	0.00
	SD	52.60	0.01	0.00	0.02	0.00	0.00
hHHO-PSO	Mean	-12568.8115	0.00	8.88178E-16	0.00	1.12558E-05	0.000113306
	SD	0.946744548	0.00	0.00	0.00	1.49725E-05	0.000166039
hHHO-IGWO	**Mean**	**-12471**	**0**	**8.88E-16**	**0**	**0**	**0**
	SD	**390.075**	**0**	**0**	**0**	**0**	**0**

The comparison of the hHHO-IGWO Convergence curves with other competing methods are shown in Fig.4.16. Figure 4.17 shows the 30 iterative runs for the MM functions. Since the multimodal have large number of local minima, the results shown in Table 4.8 reveals that hHHO-IGWO gives better exploration compared to other techniques. The Convergence curves reflects closeness in most of the test functions.

The above analysis reveals that hHHO-IGWO is competent in testing multimodal test functions.

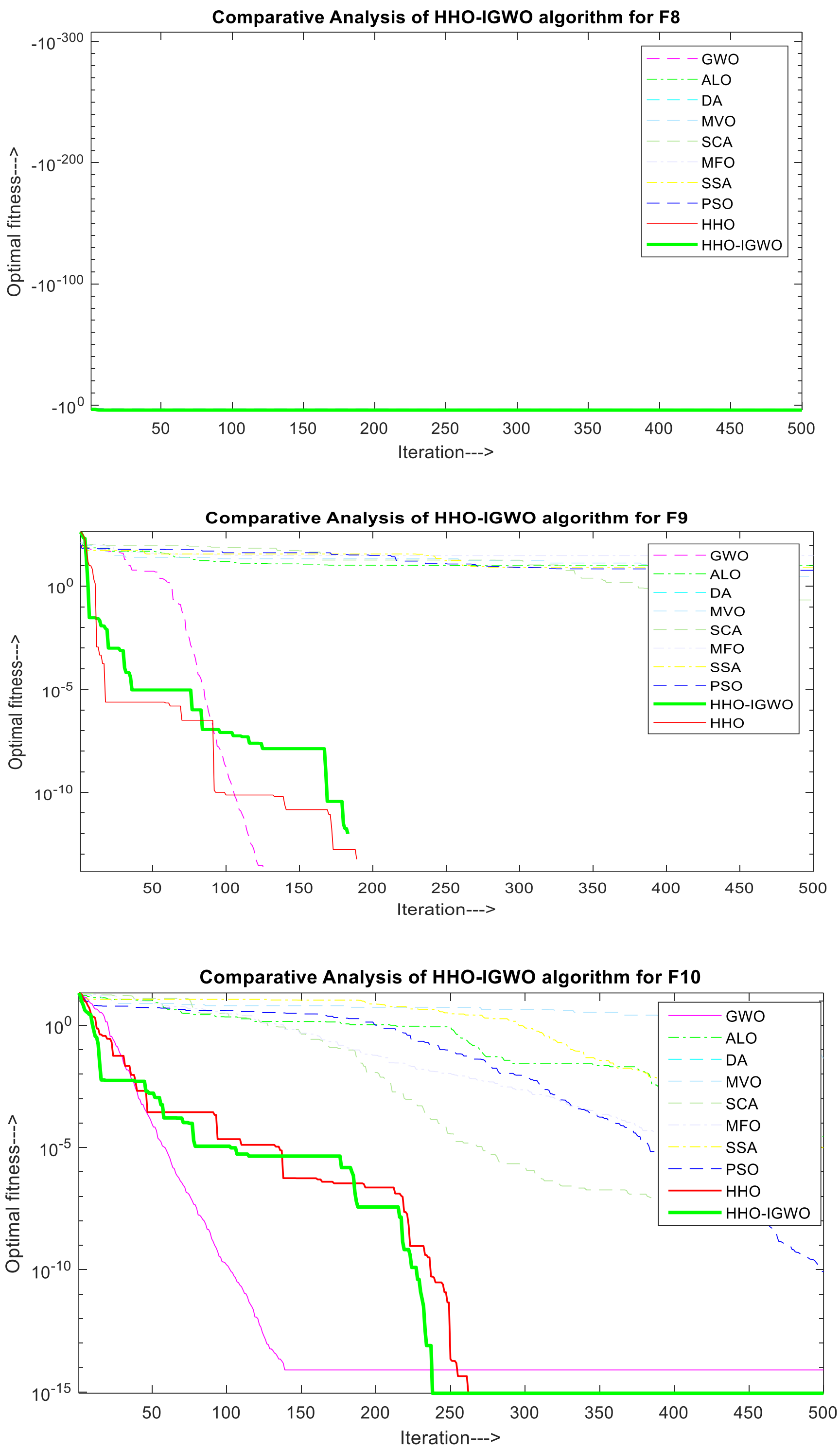


Fig.4.16: Assessment of convergence for MM with other methods

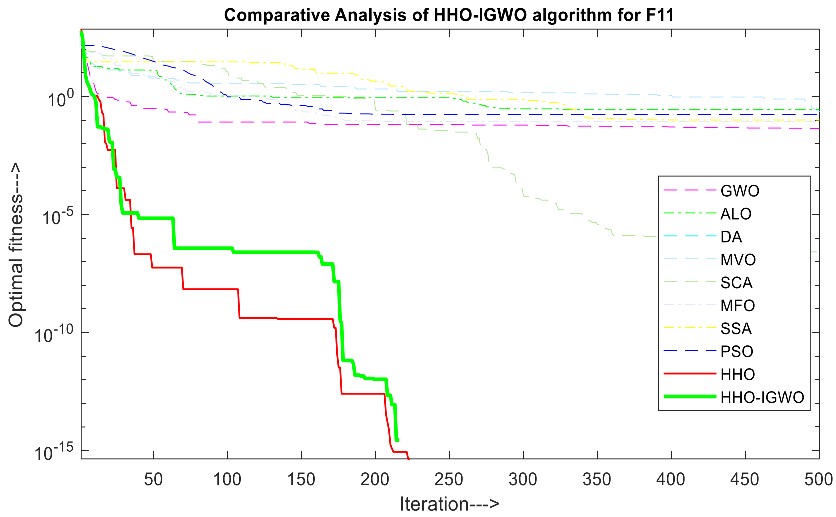


Fig.4.16: Assessment of convergence for MM with other methods *(Continued)*

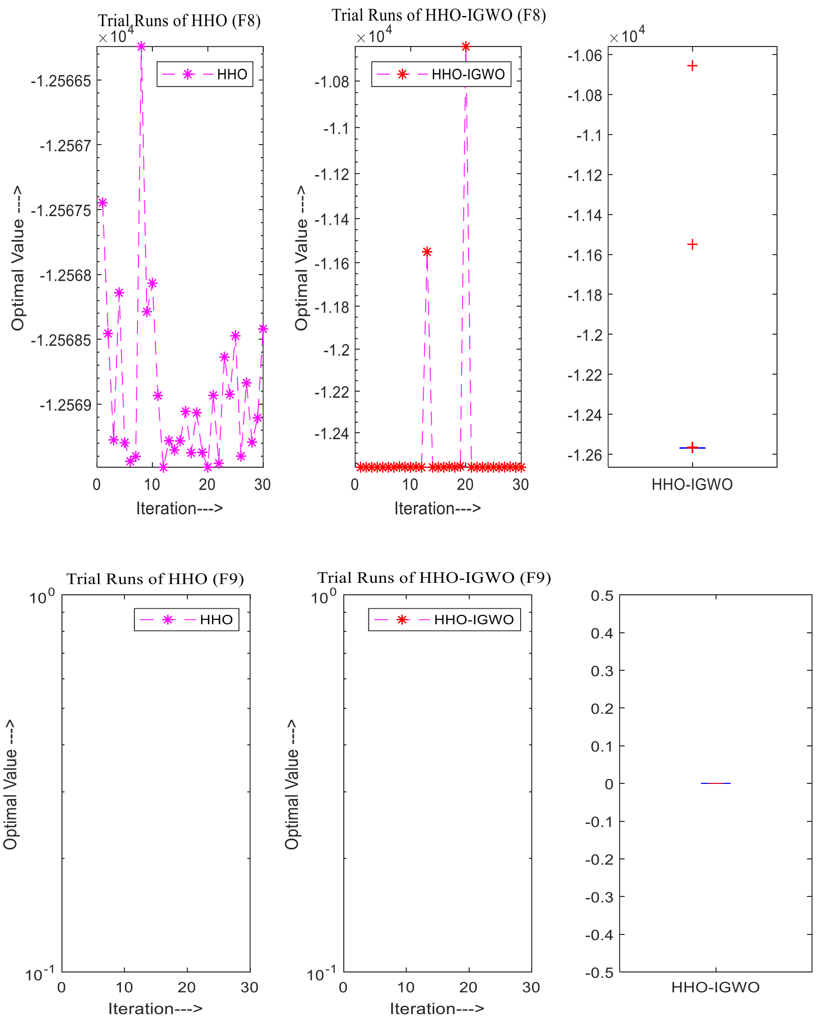


Fig.4. 17: Trials of MM function for hHHO-IGWO

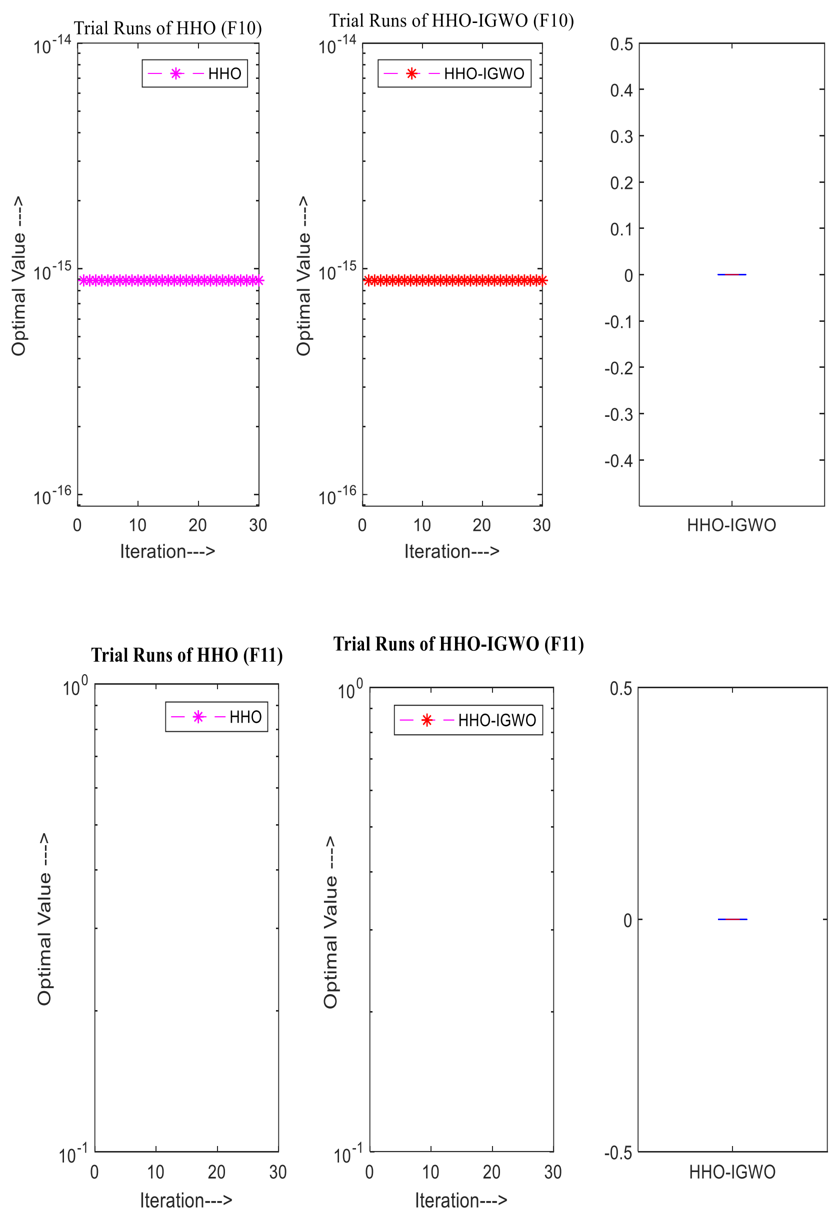


Fig.4. 17: Trials of MM function for hHHO-IGWO *(Continued)*

(c) Test Results for FD function

Table- 4.9 illustrates the simulation results of FD function in terms of mean, standard deviation, best, worst, median and p-value. The p-value in Table 4.9 are the results of Wilcoxon rank-sum test. The values less than 5% significance justifies the null hypothesis As the p-value for all test functions are less than 0.05, the proposed algorithm is statistically significant.

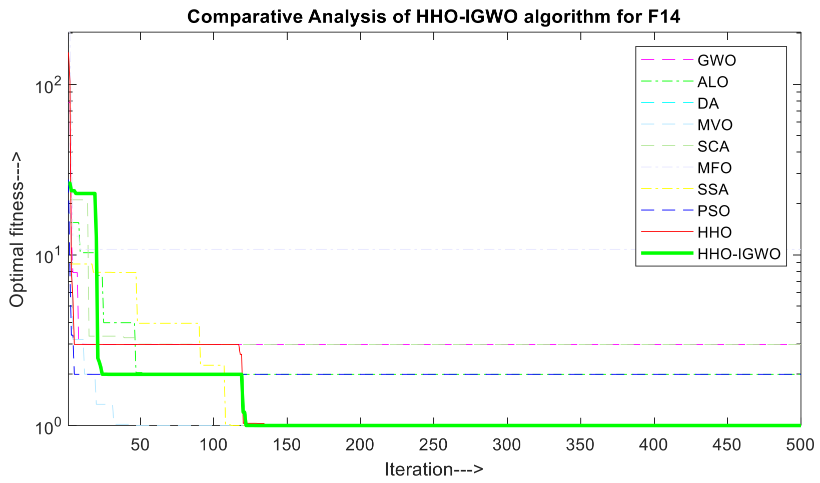
Table-4.9: Test results for FD functions using hHHO-IGWO

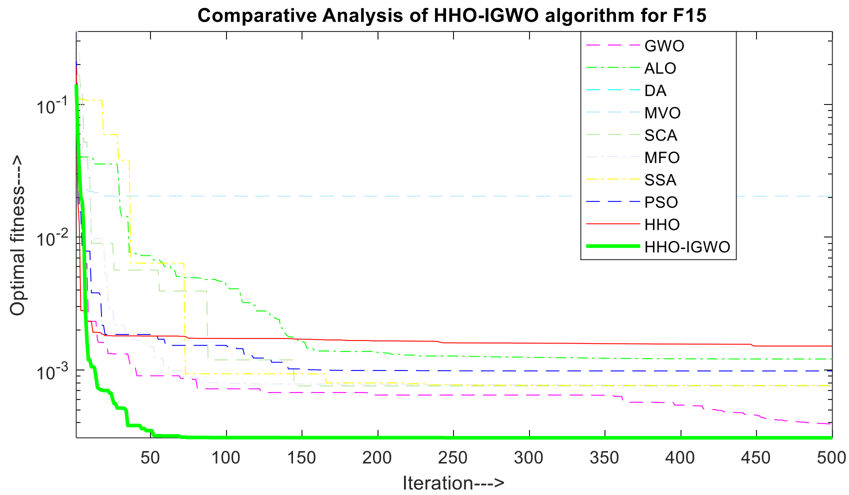
Functions	Mean	SD	Best	Worst	Median	p-Value
F14	1.75603	1.503635	0.998004	5.928845	0.998004	1.73E-06
F15	0.000442	0.000315	0.000308	0.001547	0.000332	1.73E-06
F16	-1.03163	1.08E-09	-1.03163	-1.03163	-1.03163	1.73E-06
F17	0.397896	2.85E-05	0.397887	0.398041	0.397887	1.73E-06
F18	3	8.75E-07	3	3.000004	3	1.73E-06
F19	-3.86117	0.001996	-3.86278	-3.85506	-3.86214	1.73E-06
F20	-3.08494	0.116906	-3.28159	-2.8059	-3.09637	1.73E-06
F21	-5.20509	0.846908	-9.68909	-5.03506	-5.0521	1.73E-06
F22	-5.00365	0.428369	-5.08767	-2.73596	-5.08399	1.73E-06
F23	-5.2967	0.949332	-10.323	-5.09797	-5.12472	1.73E-06

Table-4.10 illustrates comparative assessment with other similar approaches such as GWO [99], GSA [203], DE [200], FEP [261], ALO [263], GA [265], GOA [262], MFO [211], BA [258], MVO [266], DA [259], SCA [268], SSA [269], FEP [261] and WOA [212]. Fig.4.18 illustrates convergence curves of hHHO-IGWO with other methodologies and iterative attempts are depicted in Fig.4.19.

Table-4.10: Assessment of FD test results of hHHO-IGWO with other methods

Algorithm	Parameters	F14	F15	F16	F17	F18	F19	F20	F21	F22	F23
GWO [99]	Mean	4.04	0.00	-1.03	0.40	3.00	-3.86	-3.29	-10.15	-10.40	-10.53
	SD	4.25	0.00	-1.03	0.40	3.00	-3.86	-3.25	-9.14	-8.58	-8.56
PSO[274]	Mean	3.63	0.00	-1.03	0.40	3.00	-3.86	-3.27	-6.87	-8.46	-9.95
	SD	2.56	0.00	0.00	0.00	0.00	0.00	0.06	3.02	3.09	1.78
GSA [203]	Mean	5.86	0.00	-1.03	0.40	3.00	-3.86	-3.32	-5.96	-9.68	-10.54
	SD	3.83	0.00	0.00	0.00	0.00	0.00	0.02	3.74	2.01	0.00
DE[200]	Mean	1.00	0.00	-1.03	0.40	3.00	N/A	N/A	-10.15	-10.40	-10.54
	SD	0.00	0.00	0.00	0.00	0.00	N/A	N/A	0.00	0.00	0.00
FEP [261]	Mean	1.22	0.00	-1.03	0.40	3.02	-3.86	-3.27	-5.52	-5.53	-6.57
	SD	0.56	0.00	0.00	0.00	0.11	0.00	0.06	1.59	2.12	3.14
hHHO-PSO	Mean	1.3598 60	0.0003 94	-1.03	0.3979 04	3.0000 00	- 3.86123 297	- 3.0950 84	- 5.04939 692	- 5.08332 488	- 5.122724 70
	SD	1.2551 448	0.0002 177	4.8034 3E-09	3.4902 1E-05	5.2791 2E-07	0.00341 0542	0.1032 207	0.00660 4414	0.00411 6707	0.005765 656
hHHO-IGWO	**Mean**	**1.7560 3**	**0.0004 42**	**- 1.0316 3**	**0.3978 96**	**3**	**-3.86117**	**-3.0849**	**-5.20509**	**-5.00365**	**-5.2967**
	SD	**1.5036 35**	**0.0003 15**	**1.08E- 09**	**2.85E- 05**	**8.75E- 07**	**0.00199 6**	**- 3.2815 9**	**0.84690 8**	**0.42836 9**	**0.949332**





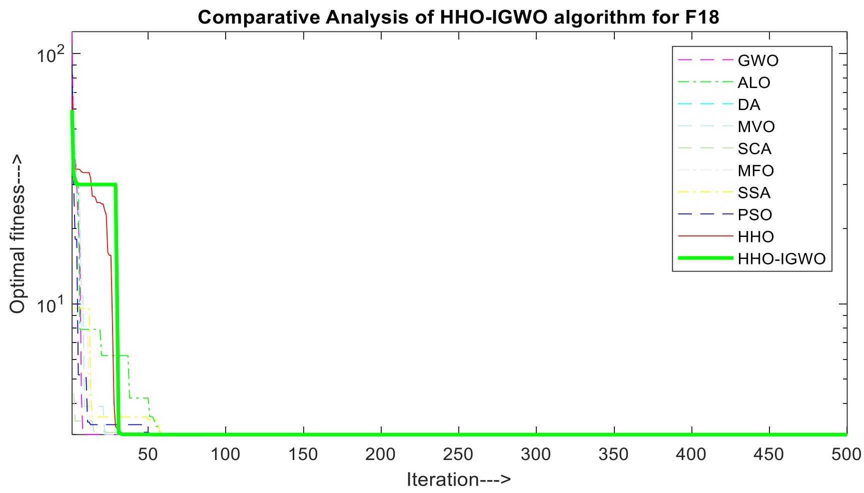
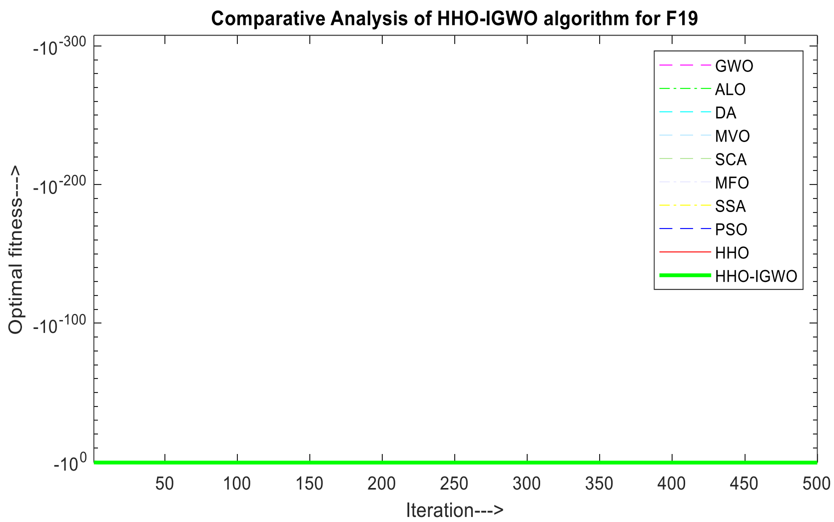
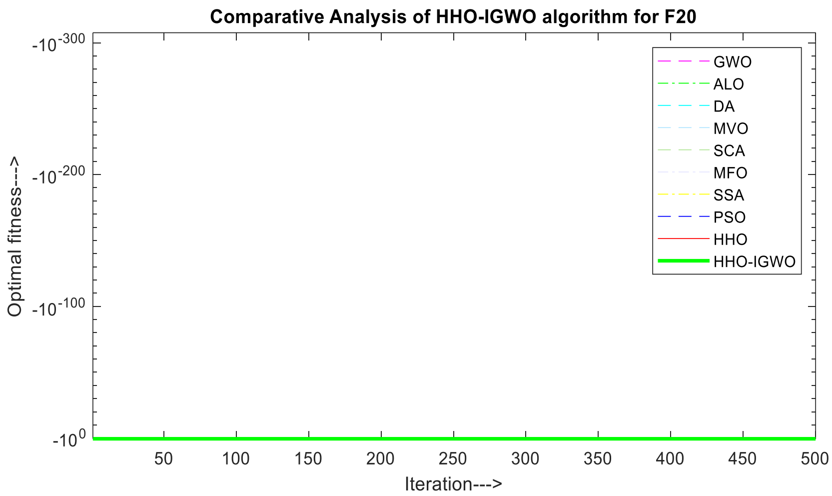


Fig.4.18: Assessment of convergence for FD function with other methods





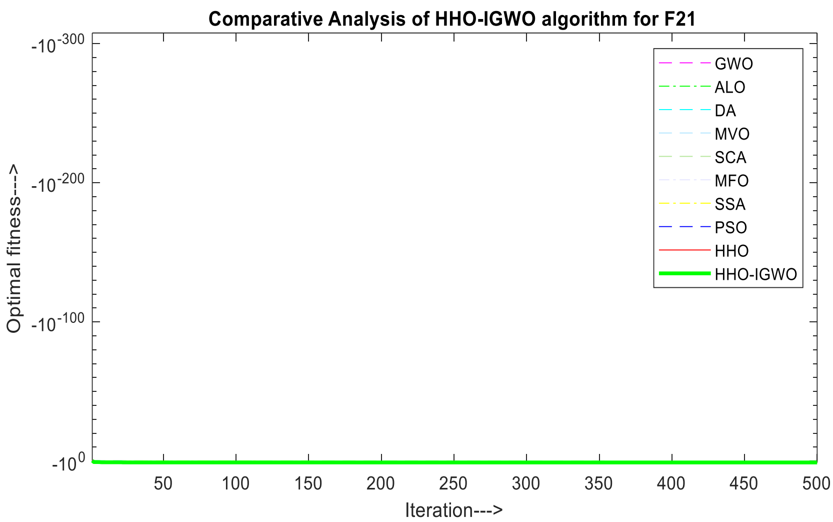
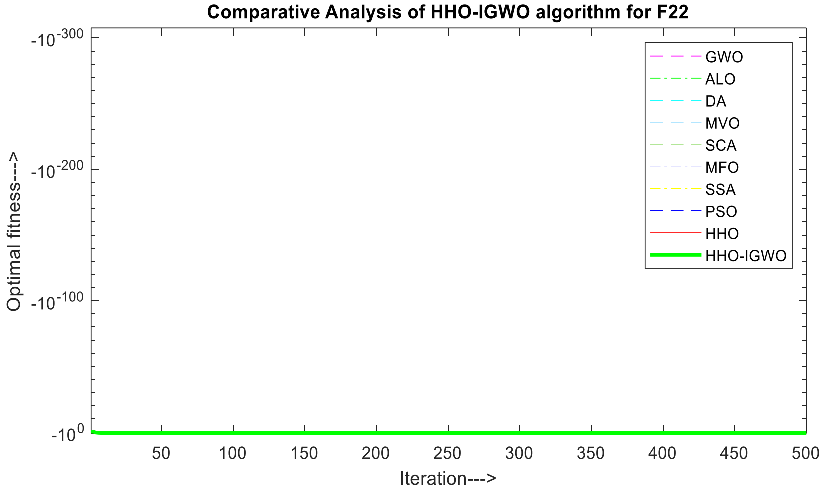


Fig.4.18: Assessment of convergence for FD function with other methods *(continued)*



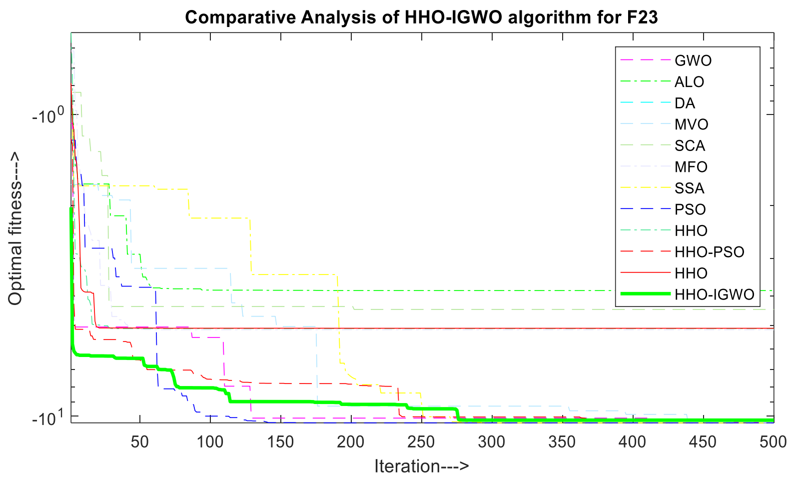


Fig.4.18: Assessment of convergence for FD function with other methods *(Continued)*

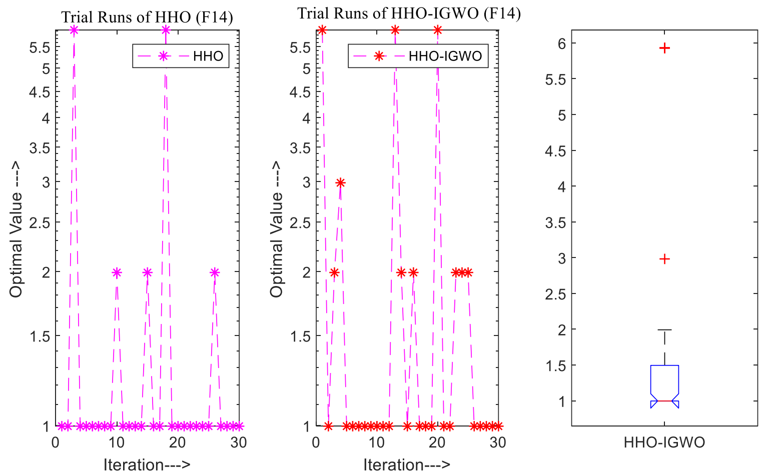


Fig.4.19: Trials of FD function for hHHO-IGWO

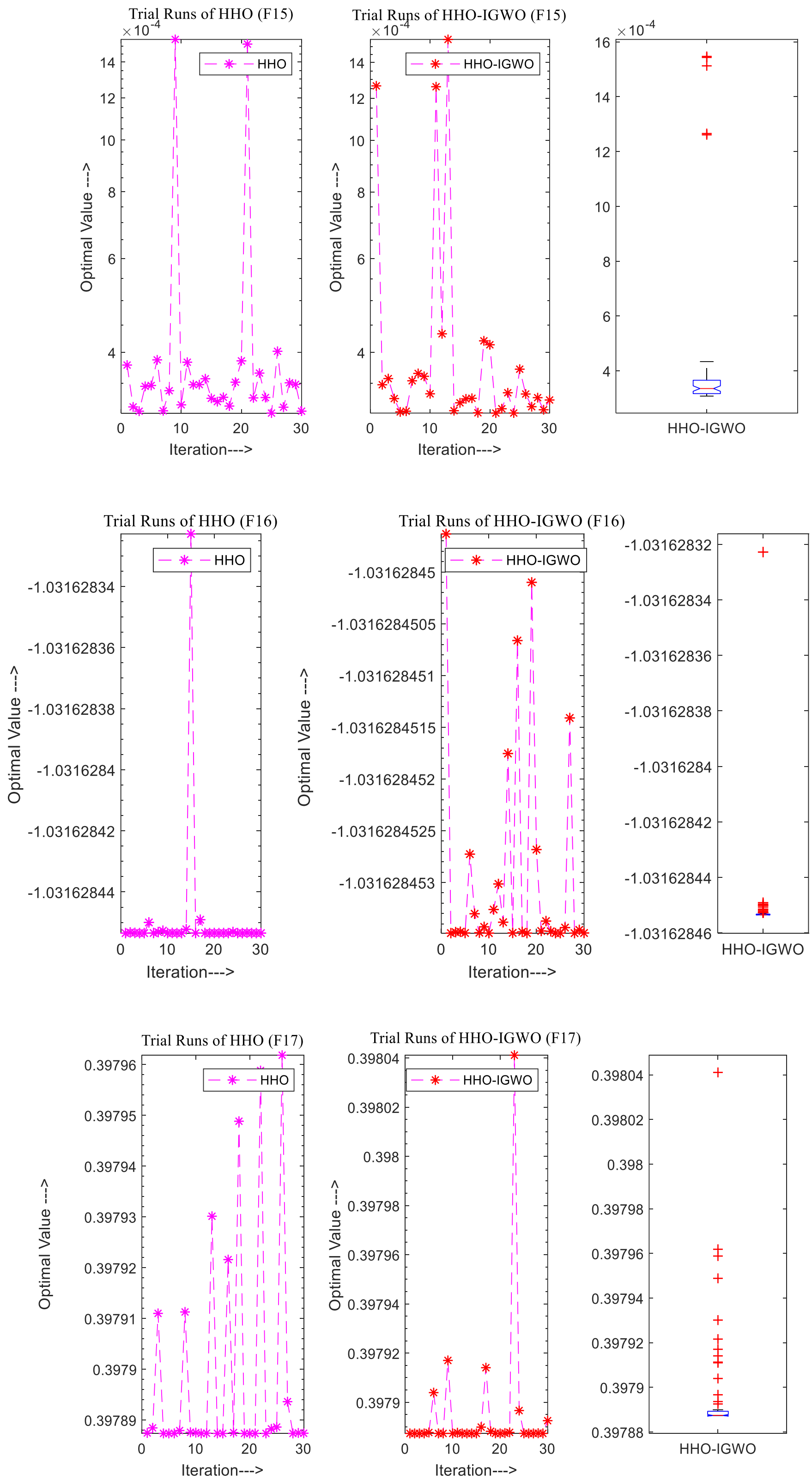


Fig.4.19: Trials of FD function for hHHO-IGWO *(Continued)*

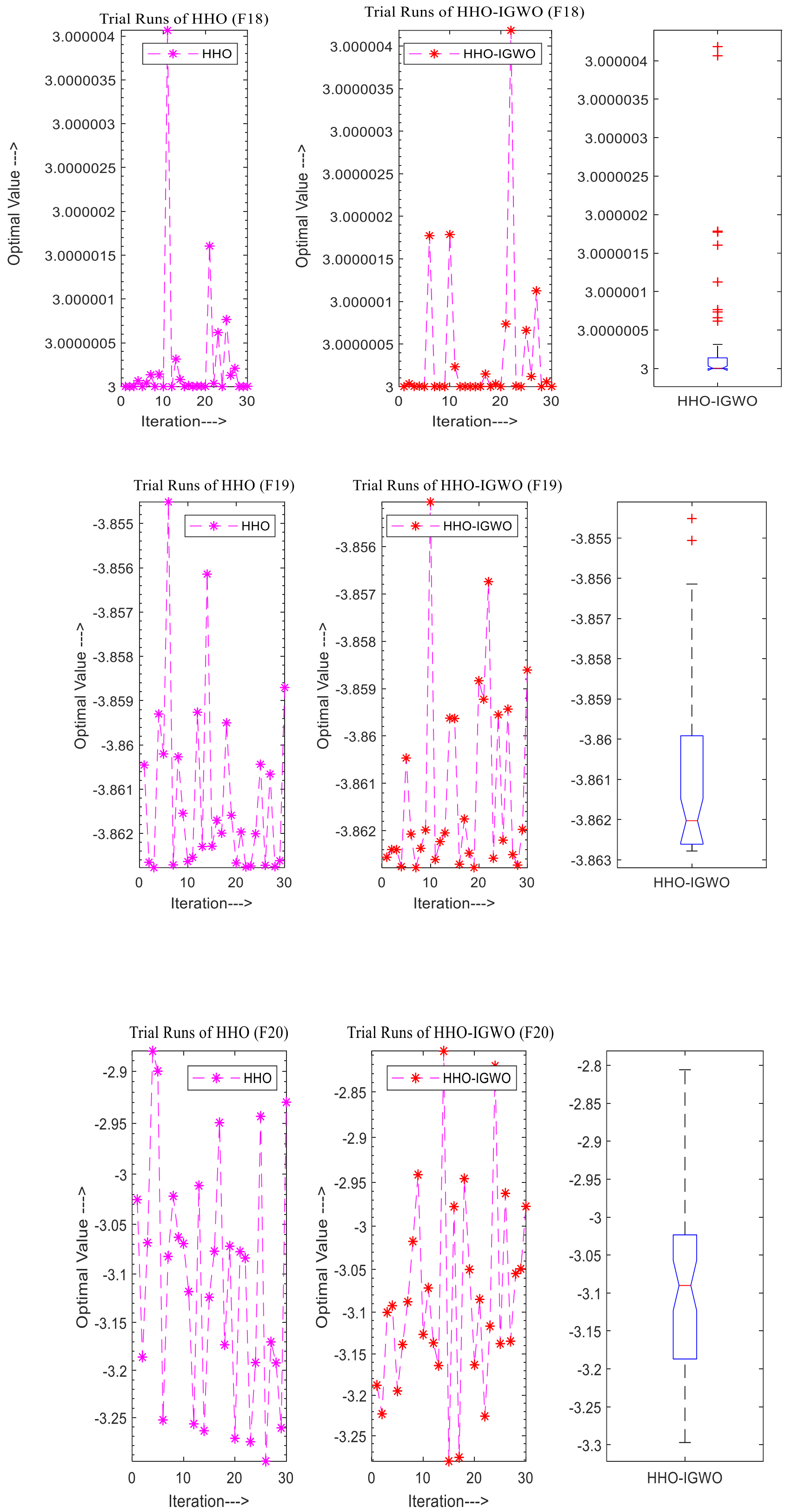


Fig.4.19: Trials of FD function for hHHO-IGWO *(Continued)*

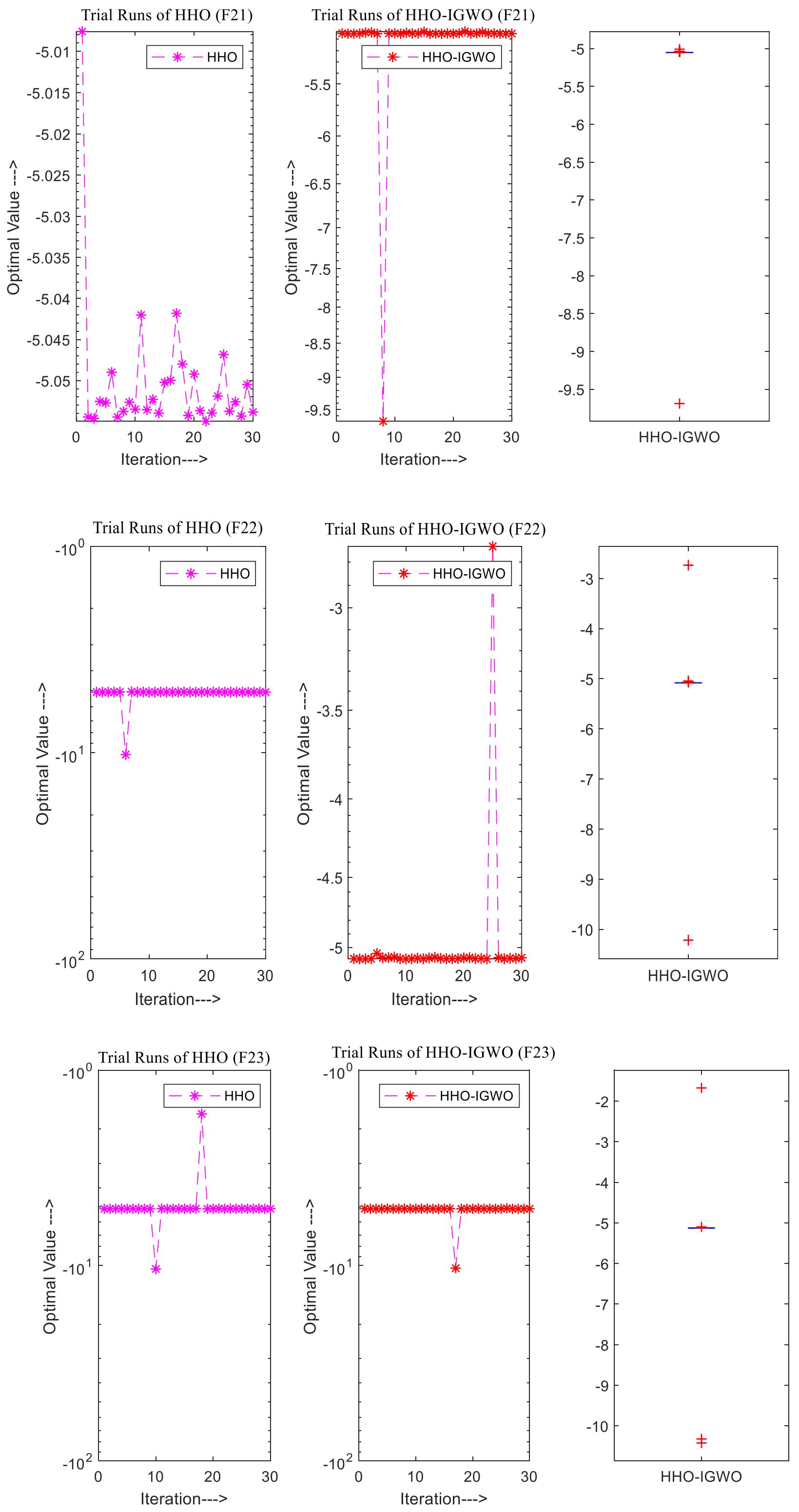


Fig.4.19: Trials of FD function for hHHO-IGWO method *(Continued)*

Table 4.10 presents average and standard deviation values of hHHO-IGWO and other methods for FD test function. These values are smaller compared to GWO, PSO, and GSA. Thus, the proposed method gives high quality solution as compared to other methods in case of F14, F15, F18, and F23.The results are consistent in case of F19, F20, F18, and F23. It can be seen that F14, F15, F18, and F23 shows better convergence, while other methods are trapped in local optimum. It is also noted that F15 and F23 have better convergence speed and settles to optimal value with less iterations. The above analysis reveals that hHHO-IGWO is capable in testing fixed dimension test functions.

4.4.3 Test Results for benchmark function using CHHO method

(a)Test Results for UM benchmark function using CHHO method

Table-4.11 illustrates simulation results of UM benchmark function from F1 to F7. Simulation time for UM test function using Chaotic HHO algorithm are shown in Table-4.12.

Table-4.11: Test results of UM benchmark functions using CHHO method

Function	Objective Function fitness					Wilcoxon rank Sum Test	T-Test	
	Mean	STD	Best	Worst	median	p-value	t-value	h-value
F1	2.29E-96	1.18E-95	1.5E-119	6.49E-95	2E-104	1.7344E-06	0.299955	0
F2	1.08E-48	5.77E-48	2.12E-60	3.16E-47	4.43E-54	1.7344E-06	0.157795	0
F3	1.54E-69	7.74E-69	7.32E-98	4.24E-68	1.56E-84	1.7344E-06	0.318537	0
F4	1.4E-48	6.39E-48	2.94E-55	3.48E-47	2.68E-52	1.7344E-06	0.237638	0
F5	0.013086	0.01999	1.59E-06	0.08431	0.003289	1.7344E-06	0.000232	1
F6	0.00016	0.000299	1.99E-08	0.001119	5.94E-05	1.7344E-06	0.000957	1
F7	0.00015	0.000159	2.54E-06	0.00069	9.11E-05	1.7344E-06	3.58E-06	1

Table-4.12: Simulation time for UM test function using CHHO method

Functions	Mean Time	Best Time	Worst Time
F1	0.264583333	0.21875	0.71875
F2	0.277604167	0.234375	0.828125
F3	0.466145833	0.390625	1.125
F4	0.315104167	0.25	0.828125
F5	0.469791667	0.390625	1.15625
F6	0.358854167	0.3125	0.859375
F7	0.43125	0.375	1.0625

Table-4.13 illustrates CHHO results authenticated with techniques like PSO [275], GWO [99], GSA [276], BA [277], FA [278], GA [55], MFO [279], MVO[266], SMS[280], DE[281], ALO[263], WOA[212], etc. in terms of standard and mean deviation. The algorithm is tested for 30 trial runs and 500 iterations as presented in Fig.4.21. The test outcomes of UM have some raised points with increased convergence using CHHO reveals the effectiveness of CHHO algorithm.

Table-4.13: Comparison of UM test results of CHHO with other methods

Algorithm	Para-meter	UM test function						
		F1	F2	F3	F4	F5	F6	F7
GWO [99]	STD	6.3400E-07	0.02901	7.9.1495E +01	1.31508	69.9049	0.00012	0.10028
	Mean	6.590E-29	7.180E-18	3.20E-07	5.610E-08	26.8125	0.81657	0.00221
PSO [207]	STD	0.0002.0E-04	0.04542	2.1192E+01	3.1703E+01	6.01155E+01	8.28E-05	0.04495
	Mean	1.3E-04	0.04214	7.01256E +01	1.08648	96.7183	0.00010	0.12285
MFO [211]	STD	0.00015	0.00087	188.527	5.27505	120.2607	9.87E-05	0.04642
	Mean	0.00011	0.00063	696.730	70.6864	139.1487	0.000113	0.091155
SCA [268]	STD	0.000	0.0001	0.1372	0.5823	0.0017	0.0001	0.0014
	Mean	0.000	0.000	0.0371	0.0965	0.0005	0.0002	0.000
MVO [266]	STD	0.64865	44.7459	177.0973	1.58291	1479.47	0.63081	0.02961
	Mean	2.08583	15.9247	453.200	3.12301	1272.13	2.29495	0.05199
SSA [269]	STD	0.000	1.000	0.000	0.6556	0.000	0.000	0.007
	Mean	0.000	0.2272	0.000	0.000	0.000	0.000	0.0028
TENT_CHHO	**STD**	**1.18E-95**	**5.77E-48**	**7.74E-69**	**6.39E-48**	**0.01999**	**0.000299**	**0.00015**
	Mean	**2.29E-96**	**1.08E-48**	**1.54E-69**	**1.4E-48**	**0.013086**	**0.00016**	**0.00015**

Table 4.13 presents the average and standard deviation of all test algorithms. It can be seen that the average and standard deviation values of CHHO are much less than other techniques. This suggests that CHHO can provide a high-quality solution with more stability. In Fig.4.20, F5, F6, and F7 shows better convergence, while other algorithms are seem to be trapped in local optimum. However, unimodal involves only one global optimum, F1, F2, F3, and F4 shows inferior convergence compared to ALO, GWO, MFO and ALO. The above analysis reveals that CHHO is competent in testing unimodal test functions.

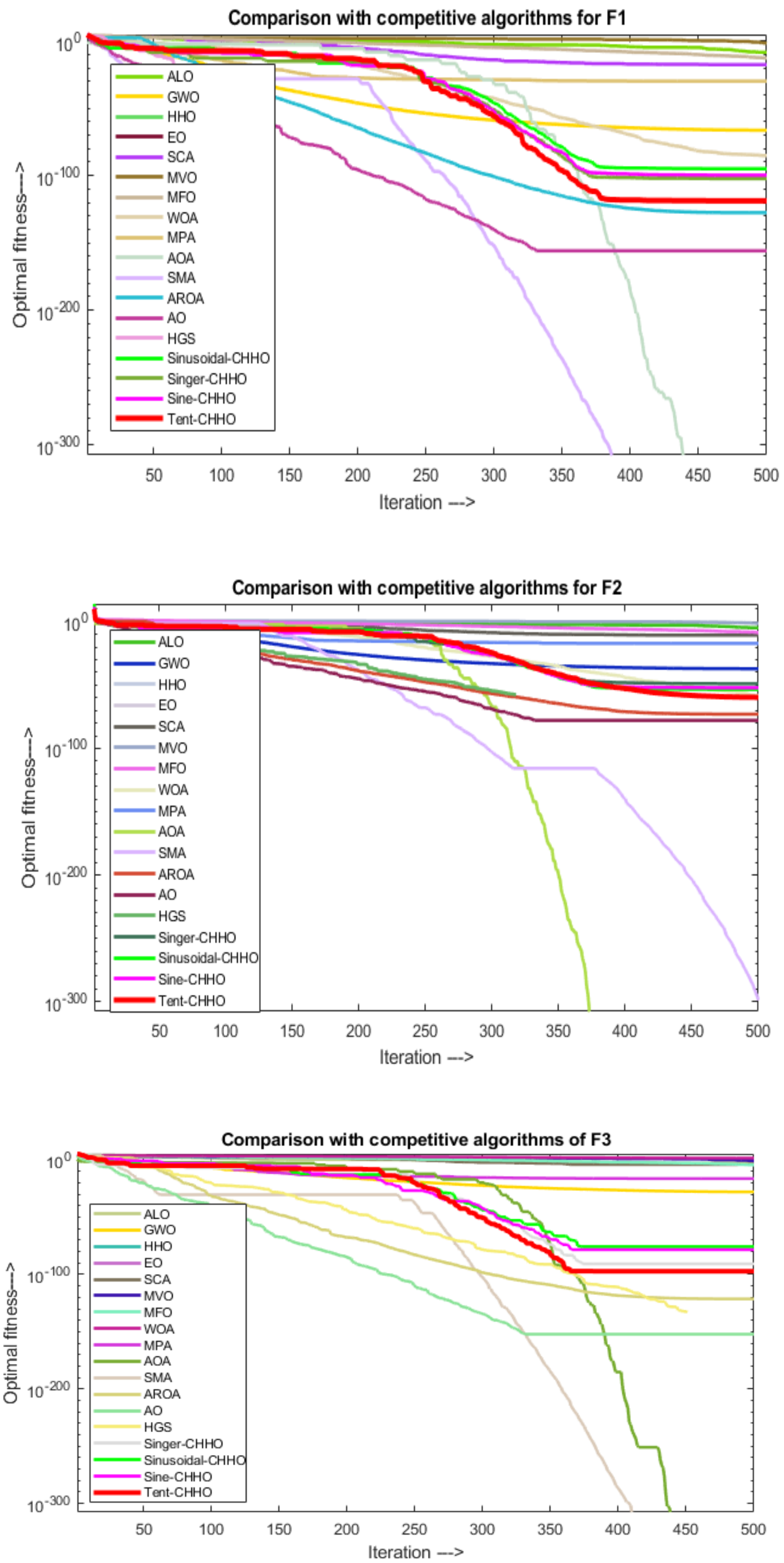


Fig.4.20: Assessment of convergence of CHHO with other algorithms for UM test function

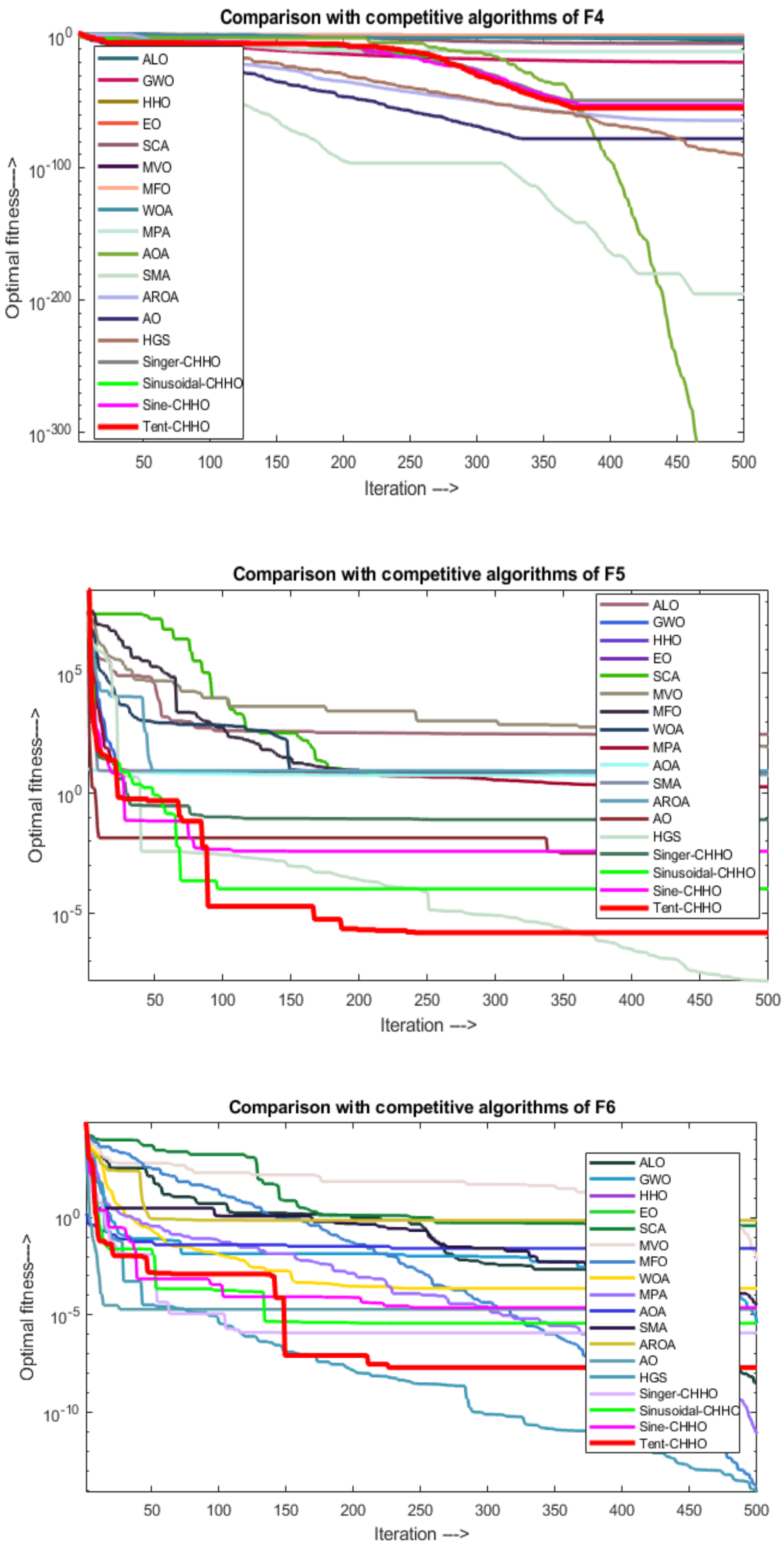


Fig.4.20: Comparison of convergence of CHHO with other algorithms for UM test function *(Continued)*

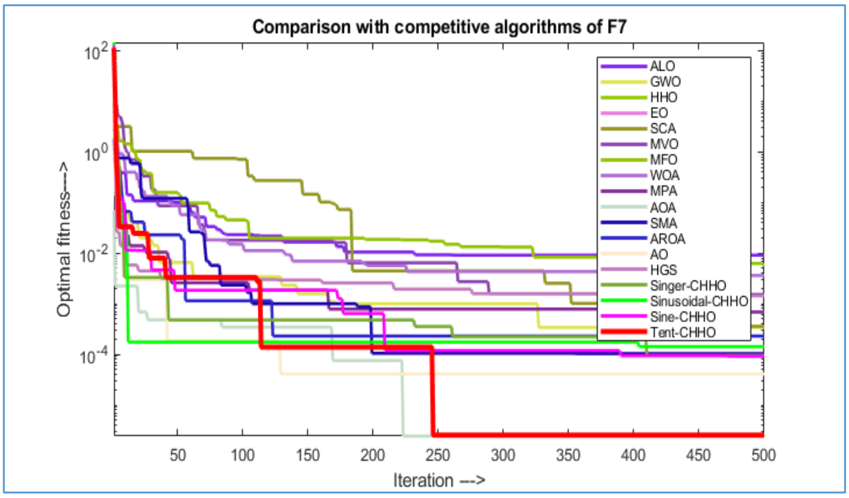


Fig.4.20: Assessment of convergence of CHHO with other algorithms for UM test function *(Continued)*

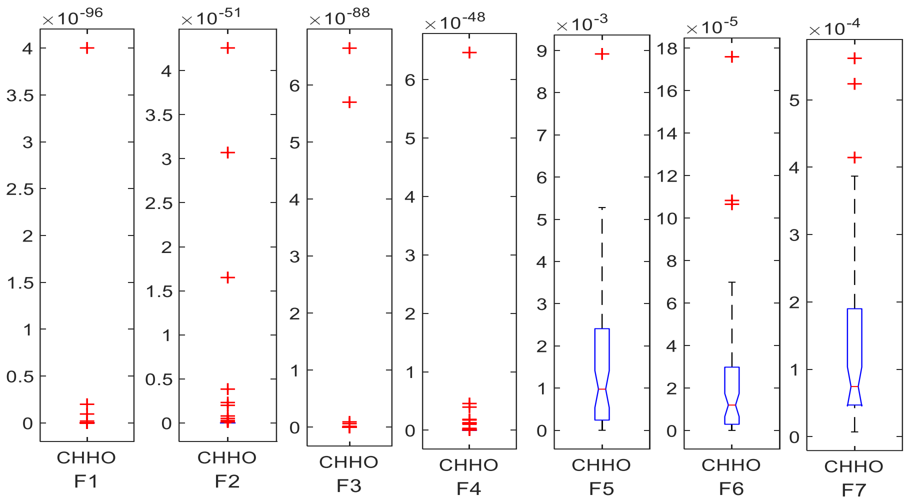


Fig.4.21: Trial runs of UM Benchmark function for CHHO

(b)Test Results for Multi-Modal (MM) benchmark function using CHHO method

Table-4.14 illustrates simulation results of multi-modal (MM) benchmark function. Simulation time for MM Benchmark Problems with best, mean and worst utilizing CHHO are shown in Table-4.15. Table-4.16 summarizes compared results with other meta-heuristics search algorithms like PSO [275], GWO [99], GSA [276], BA [277], FA [278], GA [55], BDA [259], BPSO [282], MFO [279], MVO [266], SMS [280], DE [281], ALO [263], etc.

Table-4.14: Test results of MM benchmark functions using CHHO method

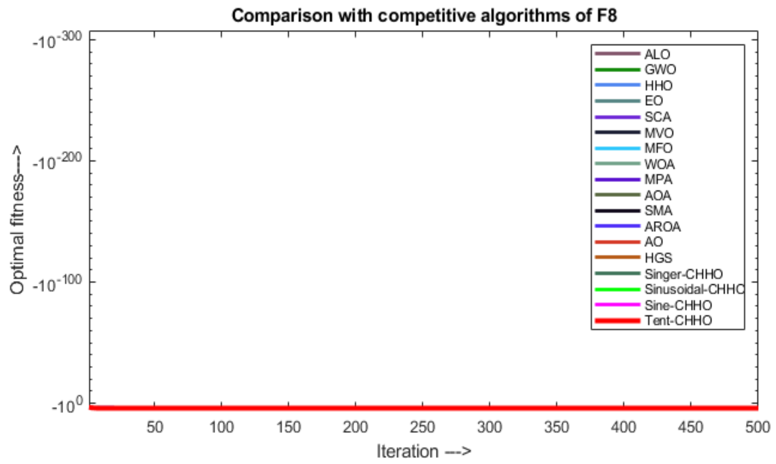
Function	Objective Function fitness					Wilcoxon rank Sum Test	T-Test	
	Mean	STD	Best	Worst	median	p-value	t-value	h-value
F8	-12569.1	0.661731	-12569.5	-12566.1	-12569.3	1.7344E-06	2.05E-28	1
F9	0	0	0	0	0	1	0.0	1
F10	8.88E-16	0	8.88E-16	8.88E-16	8.88E-16	4.320460E-09	0.0	1
F11	0	0	0	0	0	1	0.0	1
F12	5.78E-06	5.92E-06	1.41E-09	1.86E-05	3.38E-06	1.7344E-06	0.00057	1
F13	8.42E-05	9.09E-05	3.99E-08	0.000374	5.94E-05	1.7344E-06	0.00062	1

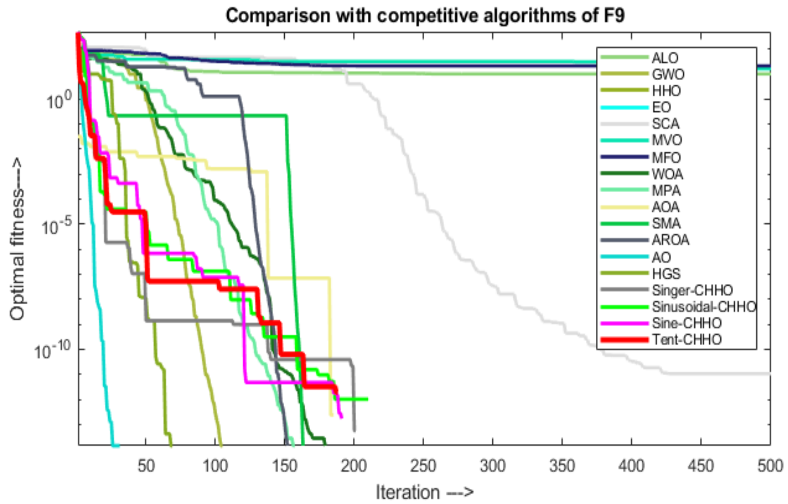
Table- 4.15: Simulation time for MM benchmark function using CHHO

Functions	Mean Time	Best Time	Worst Time
F8	0.457	0.375	1.140
F9	0.395	0.343	1.031
F10	0.409	0.359	1.015
F11	0.515	0.453	1.234
F12	0.968	0.890	1.687
F13	0.959	0.890	1.703

Table-4.16: Assessment of MM test of CHHO with competent methods

Algorithms	Parameter	Multi- Modal test function					
		F8	F9	F10	F11	F12	F13
GWO [99]	STD	-4.0900E+02	4.740E+01	7.7800E-03	6.6600E-04	2.0700E-03	4.470E-03
	Mean	-6.1200E+02	3.1100E-02	1.0600E-14	4.4900E-04	5.3400E-03	6.5400E-02
PSO [207]	STD	1.1500E+04	1.160E+01	5.090E-01	7.7200E-04	2.6300E-03	8.9100E-04
	Mean	-4.8400E+04	4.670E+01	2.760E-01	9.2200E-04	6.9200E-04	6.6800E-04
GSA [203]	STD	4.930E+02	7.470E+00	2.360E-01	5.040E+00	9.510E-01	7.130E+00
	Mean	-2.820E+03	2.600E+01	6.210E-02	2.770E+01	1.800E+00	8.900E+00
MFO [211]	STD	7.260E+02	1.620E+01	7.300E-01	2.170E-02	8.810E-01	1.930E-01
	Mean	-8.500E+03	8.460E+01	1.260E+00	1.910E-02	8.940E-01	1.160E-01
ALO [263]	STD	3.14E+02	8.45E-06	1.50E-15	9.55E-03	9.33E-12	1.13E-11
	Mean	-1.61E+03	7.71E-06	3.73E-15	1.86E-02	9.75E-12	2.00E-11
GA [265]	STD	2.470E+00	8.160E-01	8.080E-01	2.180E-01	2.150E-03	6.890E-02
	Mean	-2.090E+03	6.590E-01	9.560E-01	4.880E-01	1.110E-01	1.290E-01
MVO [266]	STD	9.370E+02	3.930E+01	5.500E+00	6.000E-02	7.900E-01	9.000E-02
	Mean	-1.170E+04	1.180E+02	4.070E+00	9.400E-01	2.460E+00	2.200E-01
SCA [268]	STD	3.600E-03	7.300E-01	1.000E+00	5.100E-03	0.000E+00	0.000E+00
	Mean	1.000E+00	0.000E+00	3.800E-01	0.000E+00	0.000E+00	0.000E+00
DA [259]	STD	3.840E+02	9.480E+00	4.870E-01	7.350E-02	9.830E-02	4.630E-03
	Mean	-2.860E+03	1.600E+01	2.310E-01	1.930E-01	3.110E-02	2.200E-03
SSA [269]	STD	8.090E-01	0.000E+00	1.530E-01	6.510E-02	5.570E-01	7.060E-01
	Mean	5.570E-02	0.000E+00	1.950E-01	0.000E+00	1.420E-01	8.320E-02
TENT_CHHO	STD	0.661731	0	0	0	5.92E-06	9.09E-05
	Mean	-12569.1	0	8.88E-16	0	5.78E-06	8.42E-05





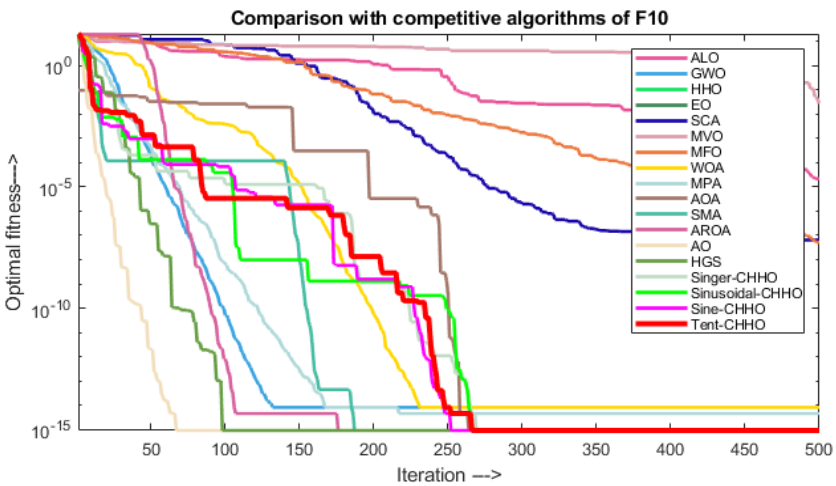
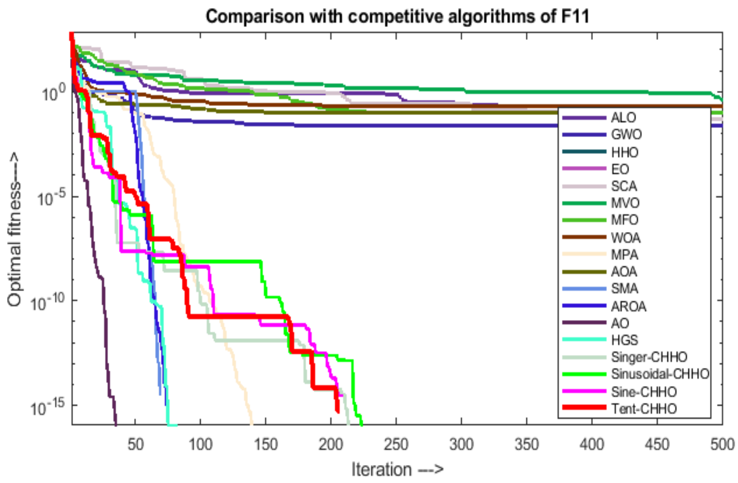
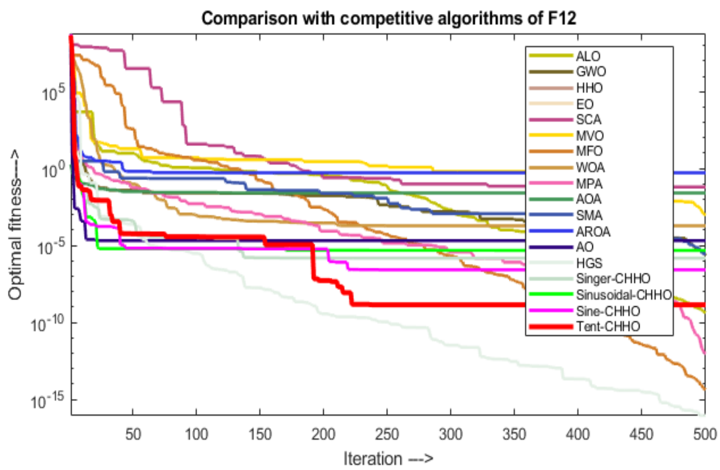


Fig.4.22: Assessment of convergence of CHHO with other algorithms for MM test function





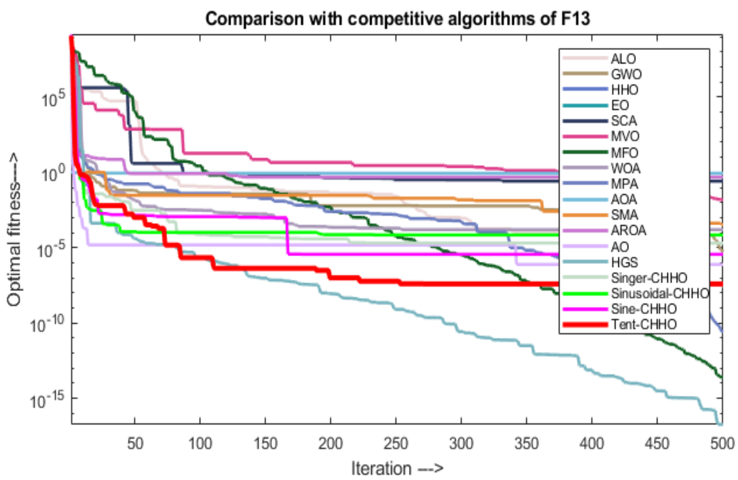


Fig.4.22: Assessment of convergence of CHHO with other algorithms for MM test function *(Continued)*

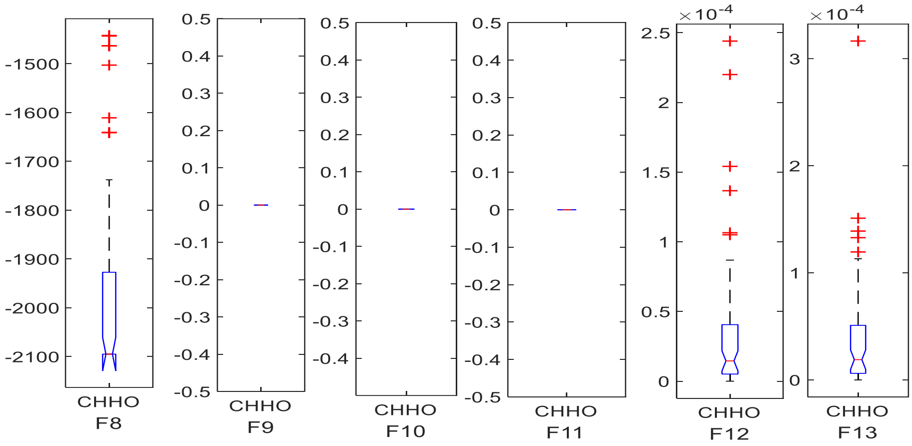


Fig.4.23: Trial runs of MM benchmark function for CHHO method

The comparison of the CHHO convergence curves with other competing methods are shown in Fig.4.22. Figure 4.23 shows the 30 iterative runs for the MM functions. Since the multimodal have large number of local optimum, the results shown in Table 4.16 reveals that CHHO gives better exploration compared to other techniques. The convergence curves reflects resemblance in most of the test functions. The above analysis reveals that CHHO is competent in testing multimodal test functions.

(c)Test Results for FD benchmark function using CHHO

The simulation results for FD test functions are illustrated in Table-4.17. Simulation time for FD Benchmark Problems utilizing CHHO is shown in Table-4.18.

Table-4.17: Test results of FD benchmark functions using CHHO method

Function	Objective Function fitness					Wilcoxon rank Sum Test	T-Test	
	Mean	STD	Best	Worst	median	p-value	t-value	h-value
F14	1.590491	1.501409	0.998004	5.928845	0.998004	1.7344E-06	6.42E-07	1
F15	0.000368	0.00019	0.000308	0.001364	0.000327	1.7344E-06	2E-10	1
F16	-1.03163	1.38E-09	-1.03163	-1.03163	-1.03163	1.7344E-06	2.1E-260	1
F17	0.397892	1E-05	0.397887	0.397929	0.397888	0	0	0
F18	3	7.27E-08	3	3	3	1.7344E-06	1.2E-191	1
F19	-3.85926	0.006377	-3.86278	-3.83785	-3.86186	1.7344E-06	4.68E-89	1
F20	-3.11029	0.126286	-3.28658	-2.7957	-3.13992	1.7344E-06	8.66E-45	1
F21	-5.21858	0.912798	-10.0515	-5.04081	-5.05327	1.7344E-06	2.49E-21	1
F22	-4.97575	0.593354	-5.08766	-1.83423	-5.08605	1.7344E-06	3.45E-18	1
F23	-5.1241	0.00409	-5.12839	-5.11147	-5.12541	1.7344E-06	3.84E-24	1

Table-4.18: Simulation time of FD benchmark function using CHHO

Functions	Mean Time	Best Time	Worst Time
F14	2.5083333	2.39062	3.2343
F15	0.3911458	0.32812	1
F16	0.3744791	0.32812	0.96875
F17	0.00	0.00	0.00
F18	0.3322916	0.28125	0.875
F19	0.4453125	0.375	1.10937
F20	0.4442708	0.39062	1.0625
F21	1.0484375	0.95312	1.79687
F22	1.2630208	1.1875	2
F23	1.6984375	1.48437	2.59375

Table-4.19: Comparison of FD test results of CHHO with other methods

Algorithms	**Parameters**	**FD benchmark function**									
		F14	**F15**	**F16**	**F17**	**F18**	**F19**	**F20**	**F21**	**F22**	**F23**
GSA [203]	STD	3.83	0.00	0.00	0.00	0.00	0.00	0.02	3.74	2.01	0.00
	Mean	5.86	0.00	-1.03	0.40	3.00	-3.86	-3.32	-5.96	-9.68	-10.54
GWO [99]	STD	4.25	0.00	-1.03	0.40	3.00	-3.86	-3.25	-9.14	-8.58	-8.56
	Mean	4.04	0.00	-1.03	0.40	3.00	-3.86	-3.29	-10.15	-10.40	-10.53
PSO	STD	2.56	0.00	0.00	0.00	0.00	0.00	0.06	3.02	3.09	1.78
	Mean	3.63	0.00	-1.03	0.40	3.00	-3.86	-3.27	-6.87	-8.46	-9.95
DE[200]	STD	0.00	0.00	0.00	0.00	0.00	N/A	N/A	0.00	0.00	0.00
	Mean	1.00	0.00	-1.03	0.40	3.00	N/A	N/A	-10.15	-10.40	-10.54
CSMA[283]	STD	9.26E-13	0.000244	1.51E-09	6.82E-08	8.43E-12	4.21E-07	0.060654	0.000274	0.000208	0.000299
	Mean	0.998004	0.00055	-1.03163	0.397887	3	-3.86278	-3.25824	-10.1528	-10.4026	-10.536
TENT_CHHO	**STD**	**1.501409**	**0.00019**	**1.38E-09**	**1.00E-05**	**7.27E-08**	**0.006377**	**0.126286**	**0.912798**	**0.593354**	**0.00409**
	Mean	**1.590491**	**0.000368**	**-1.03163**	**0.397892**	**3**	**-3.85926**	**-3.11029**	**-5.21858**	**-4.97575**	**-5.1241**

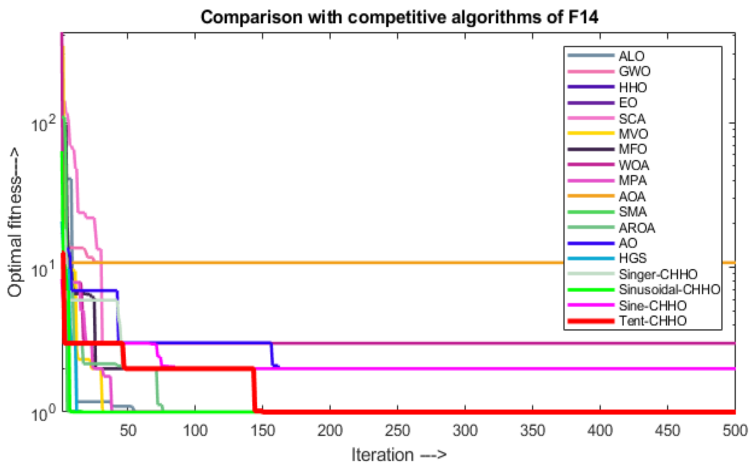


Fig.4.24: Assessment of convergence of CHHO with other algorithms for FD test function

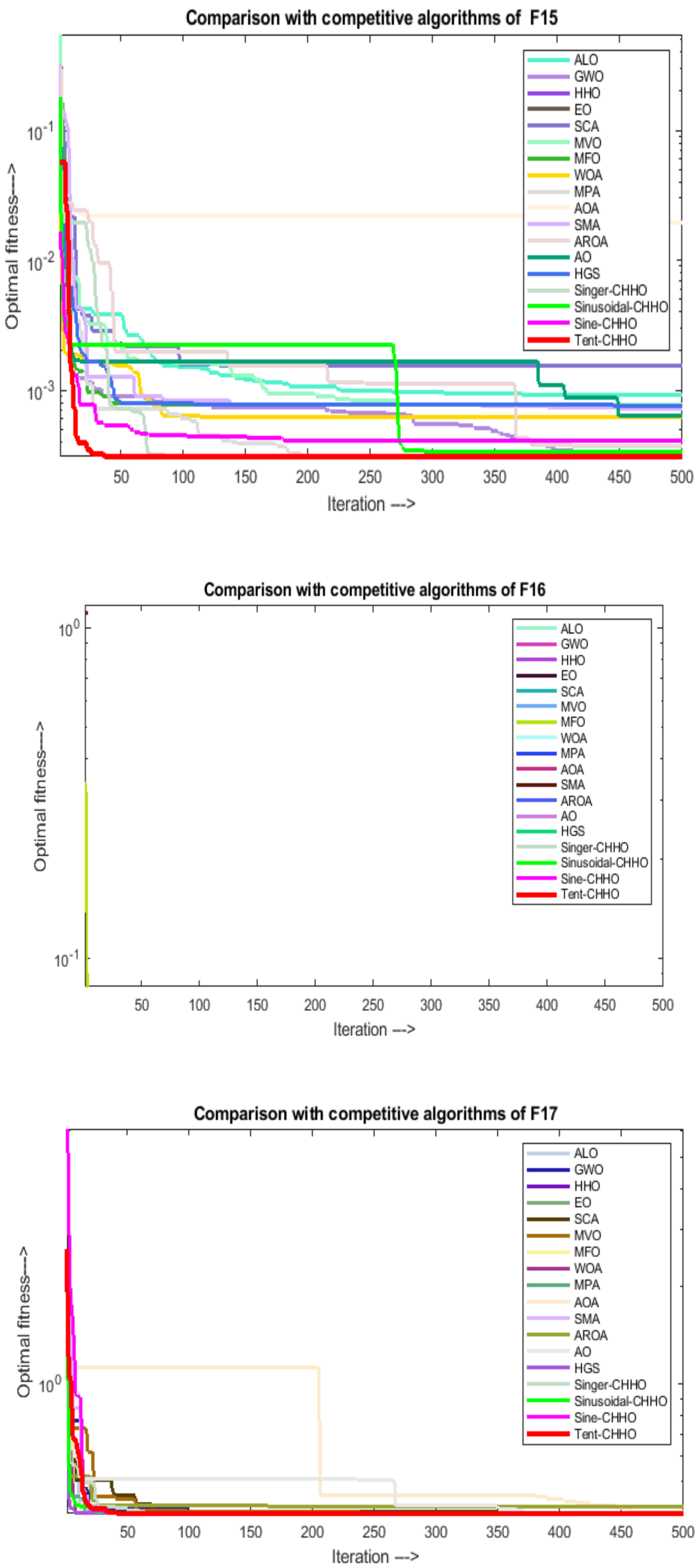
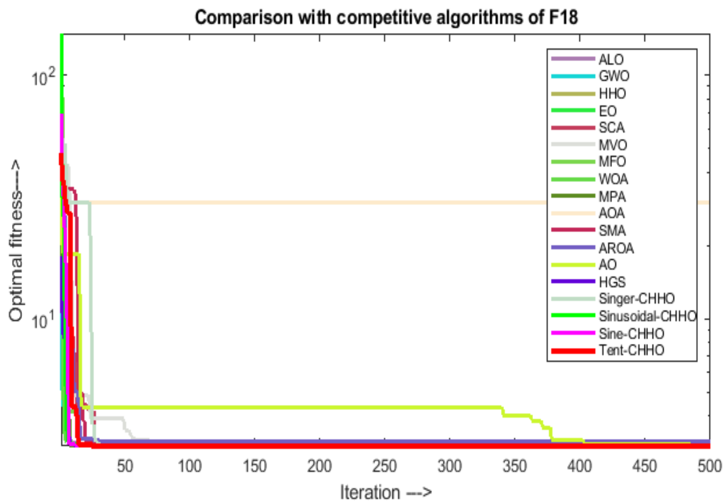
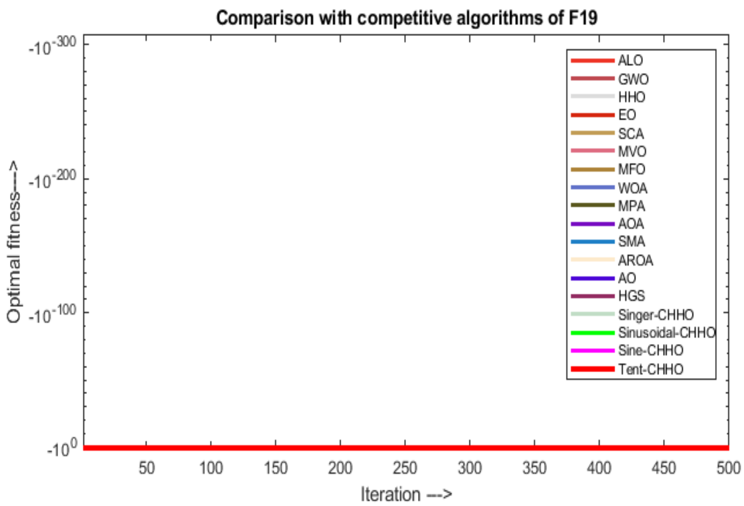


Fig.4.24: Assessment of convergence of CHHO with other algorithms for FD test function *(Continued)*





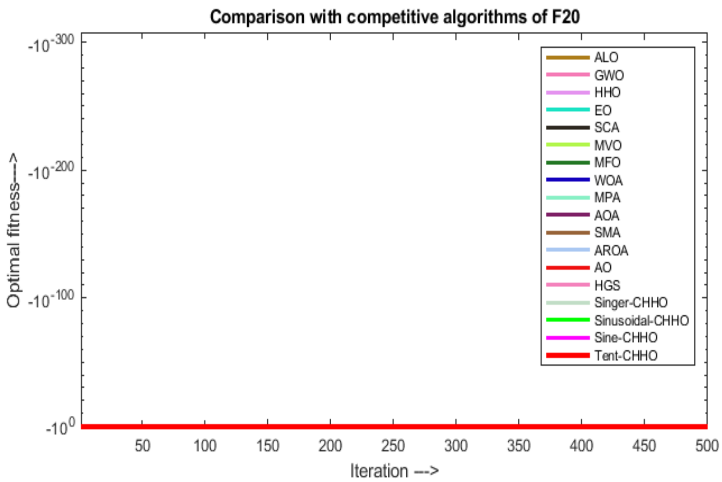


Fig.4.24: Assessment of convergence of CHHO with other algorithms for FD test function *(Continued)*

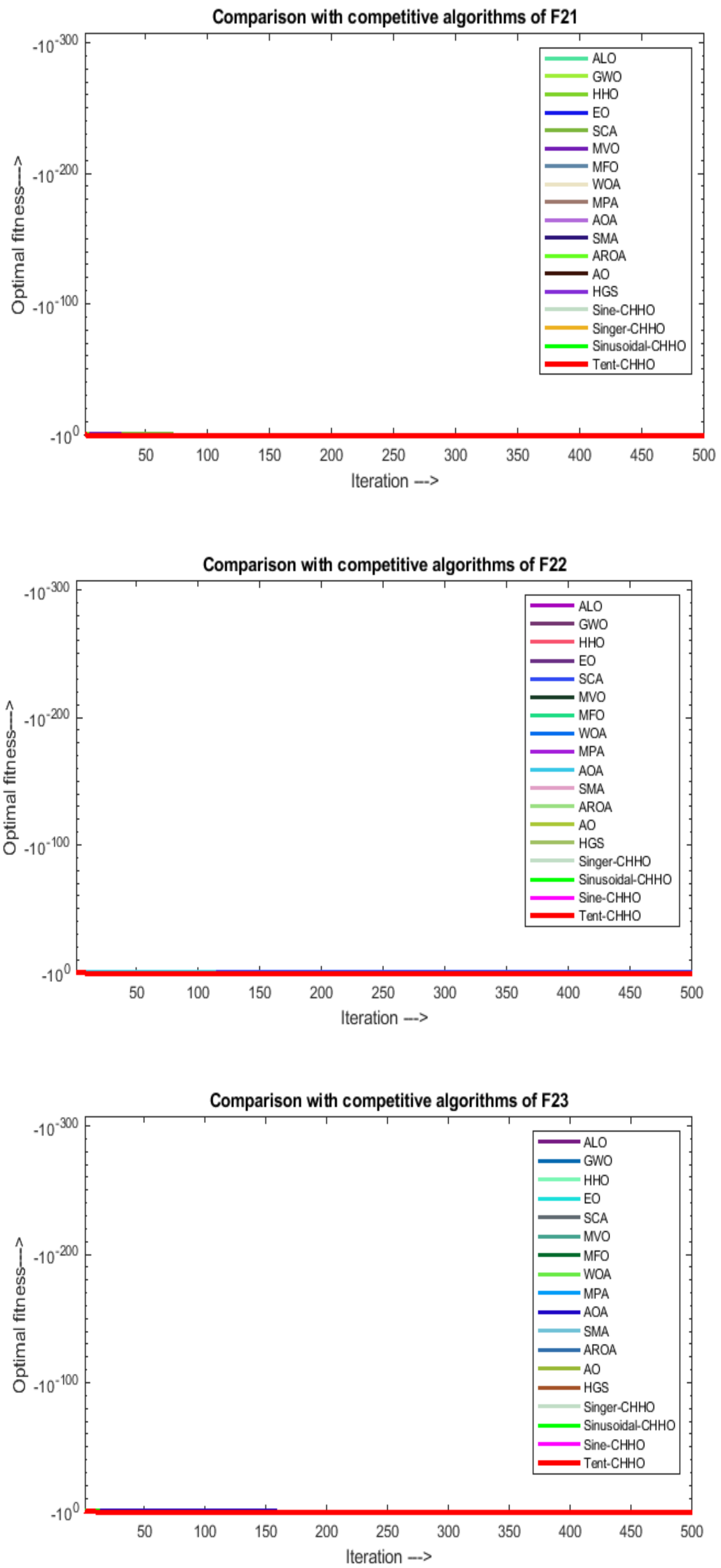


Fig.4.24: Assessment of convergence of CHHO with other algorithms for FD test function *(Continued)*

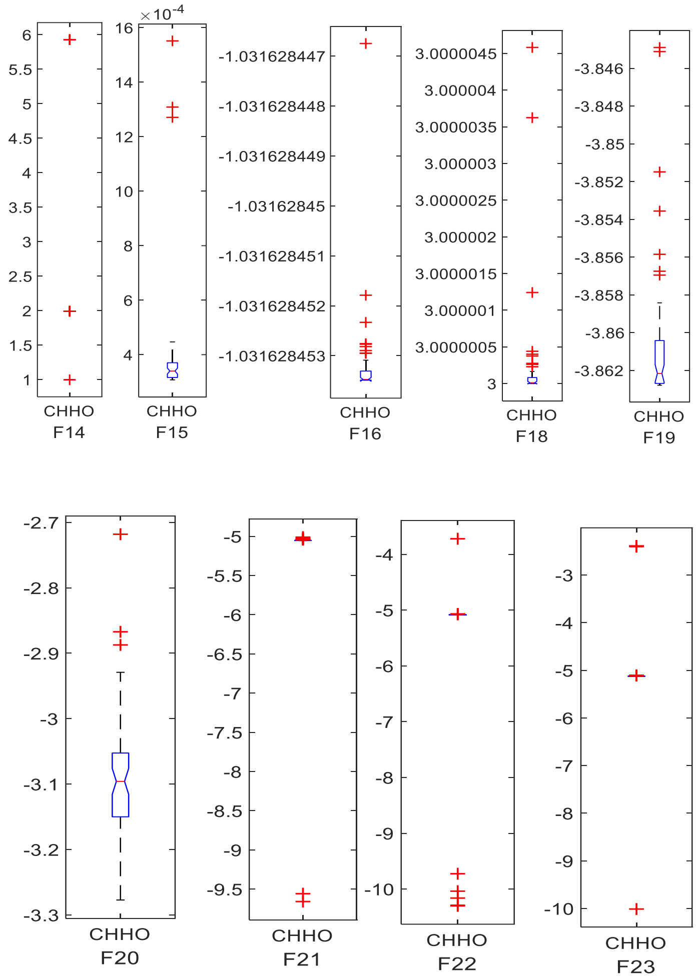


Fig.4.25: Trial run of FD test function for CHHO method

The results are compared with others methods such as, GWO [99], PSO [207], GSA [203], DE [200], ALO [263], BA[284], GA [265] , SSA [269], DE [285], etc. in terms of Mean & standard deviation. Fig.4.25 shows the trial runs for fixed dimension function for CHHO method. Table 4.19 presents average and standard deviation values of CHHO and other methods. These values are smaller compared to GWO, PSO, and GSA. Thus, the proposed method gives high quality solution as compared to other methods in case of F15, F17, F18.The results are consistent in case of F14, F19, F20, F21, and F22. It is also noted that F15 and F28 have better convergence speed and settles to optimal value with less iterations. The above analysis reveals that CHHO is capable in testing fixed dimension test functions.

4.4.4 Test Results for benchmark function using CSMA method

(a)Test Results for UM benchmark function using CSMA method

Table-4.20 illustrates simulation results of unimodal (UM) benchmark function using CSMA. Simulation time for F1 to F7 using CSMA method is shown in Table-4.21. Table-4.22 shows the comparison of the CSMA method with other techniques such as PSO [275], GWO [99], GSA [276], BA [277], FA [278], GA [55], BDA [259], BPSO [282], MFO [279], MVO [266], BGSA [267], SMS [280], DE [281], ALO [263], WOA [212], etc. Trial runs of unimodal benchmark function for CSMA method are shown in Fig.4.27.

Table-4.20: Test results of UM benchmark functions using CSMA method

Functions	Average Value	STD	Best value	Worst value	Median value	p-Value
F1	1.2E-280	0	0	3.5E-279	0	0.5
F2	3.4E-156	1.7E-155	3E-258	9.4E-155	1.3E-188	1.7344E-06
F3	0	0	0	0	0	1
F4	5.1E-134	2.8E-133	1.5E-269	1.5E-132	2.7E-190	1.7344E-06
F5	5.035453	9.27916	0.044388	28.19006	1.219173	1.7344E-06
F6	0.004431	0.003059	2.06E-05	0.016714	0.004434	1.7344E-06
F7	0.0003	0.000211	2.17E-05	0.000935	0.000274	1.7344E-06

Table-4.21: Simulation time for UM test function using CSMA method

Functions	Best Time(sec)	Mean Time(sec)	Worst Time(sec)
F1	2.71875	2.915625	3.453125
F2	2.78125	2.890625	3.375
F3	2.984375	3.295313	4.078125
F4	2.84375	3.039583	3.875
F5	2.84375	2.991667	3.578125
F6	2.8125	2.955208	3.453125
F7	2.9375	3.077604	3.59375

Table 4.22 presents the average and standard deviation of all test algorithms. It can be seen that the average and standard deviation values of CSMA are much less than other techniques. This suggests that CSMA can provide a high-quality solution with more stability. In Fig.4.26, F5, F6, and F7 have better convergence, while other algorithms seem to be trapped in local optimum. However, unimodal involves only one global optimum, F1, F2, F3, and F4 shows earlier convergence compared to ALO, GWO, MFO and ALO. The above analysis reveals that CSMA is capable in testing unimodal test functions.

Table-4.22: Comparison of UM test results of CSMA with other methods

Algorithm	Parameters	UM Test Function						
		F1	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**
PSO [275]	AVG	1.3E-04	0.04214	7.016E+01	1.08648	96.7183	0.00010	0.1228
	SD	0.02.0E-06	0.04542	2.119E+01	3.17E+01	6.0115E+01	8.28E-05	0.0449
GWO [99]	AVG	6.590E-29	7.180E-18	3.20E-07	5.610E-08	26.8125	0.81657	0.0022
	SD	6.3400E-07	0.02901	7.9.5E+01	1.31508	69.9049	0.00012	0.1002
GSA [203]	AVG	2.530E-17	0.05565	896.534	7.35487	6.7543E+01	2.50E-17	0.0894
	SD	9.670E-18	0.19407	318.955	1.741452	6.2225E+01	1.740E-17	0.0433
DE [200]	AVG	8.200E-15	1.50E-09	6.80E-11	0.00	0.00	0.00	0.0046
	SD	5.900E-15	9.900E-11	7.40E-11	0.00	0.00	0.00	0.0012
ALO [263]	AVG	2.59E-10	1.84E-06	6.07E-10	1.36E-08	0.3467724	2.56E-10	0.004292
	SD	1.65E-10	6.58E-07	6.34E-10	1.81E-09	0.10958	1.09E-10	0.00508
BA[210]	AVG	0.77362	0.33458	0.11530	0.19218	0.33407	0.77884	0.13748
	SD	0.52813	3.81602	0.76603	0.890266	0.30003	0.67392	0.11267
CS [286]	AVG	0.0065	0.212	0.247	1.120E-06	0.00719	5.95E-06	0.00132
	SD	0.00020	0.0398	0.0214	8.250E-07	0.00722	1.08E-07	0.00072
MFO [211]	AVG	0.00011	0.00063	696.730	70.6864	139.1487	0.000113	0.091155
	SD	0.00015	0.00087	188.527	5.27505	120.2607	9.87E-05	0.04642
SCA [268]	AVG	0.000	0.000	0.0371	0.0965	0.0005	0.0002	0.000
	SD	0.000	0.0001	0.1372	0.5823	0.0017	0.0001	0.0014
SSA [269]	AVG	0.000	0.2272	0.000	0.000	0.000	0.000	0.0028
	SD	0.000	1.000	0.000	0.6556	0.000	0.000	0.007
WOA [212]	AVG	1.410E-31	1.060E-22	5.390E-08	7.258E-02	27.8655	3.11626	0.00142
	SD	4.910E-31	2.390E-22	2.930E-07	3.9747E-01	7.6362E-01	0.53242	0.00114
CSMA	AVG	**1.2E-280**	**3.4E-156**	**0**	**5.1E-134**	**5.035453**	**0.00443**	**0.0003**
	SD	**0**	**1.7E-155**	**0**	**2.8E-133**	**9.27916**	**0.003059**	**0.00021**

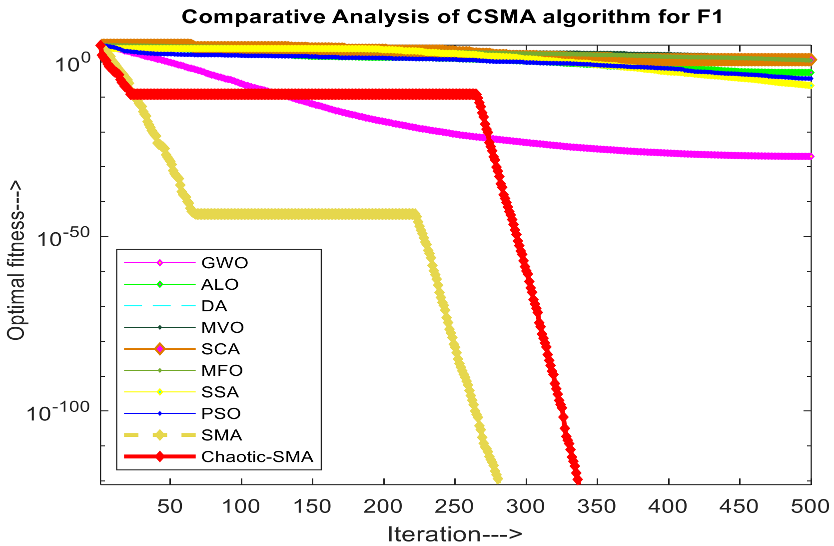
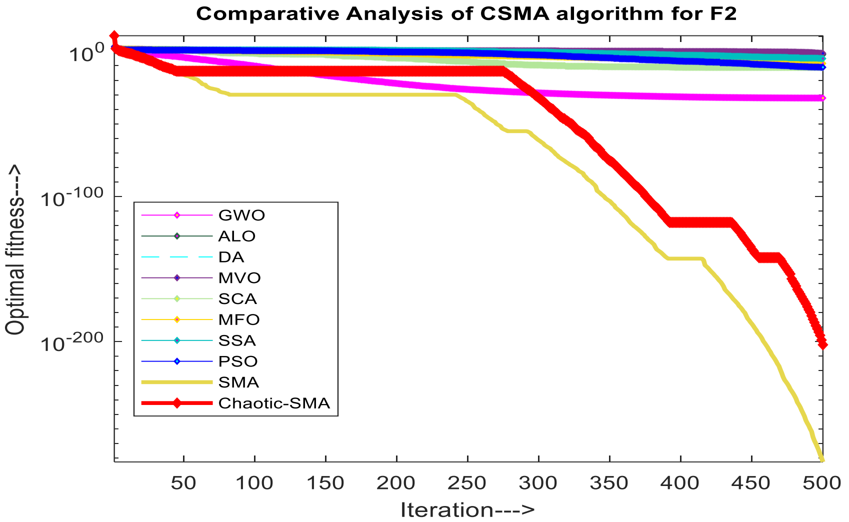
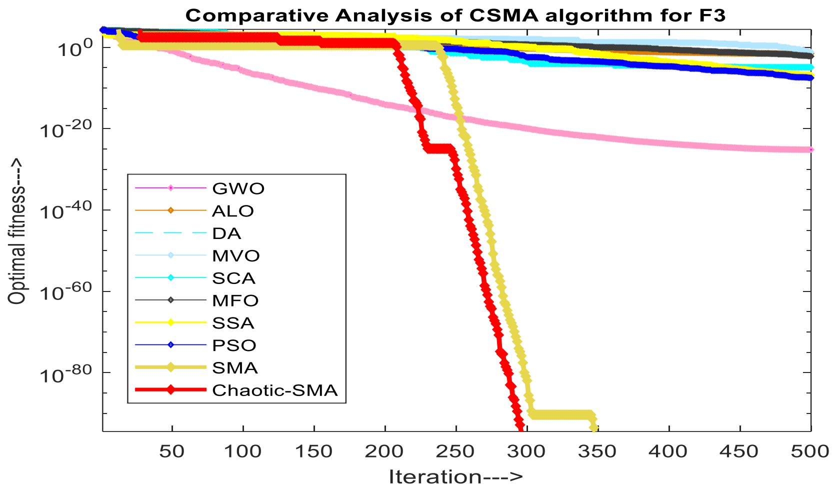


Fig.4.26: Assessment of convergence of CSMA with other algorithms for UM test function





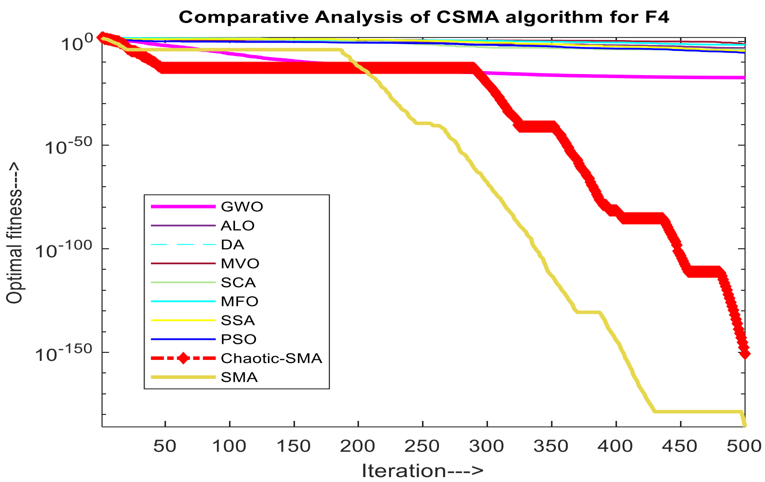
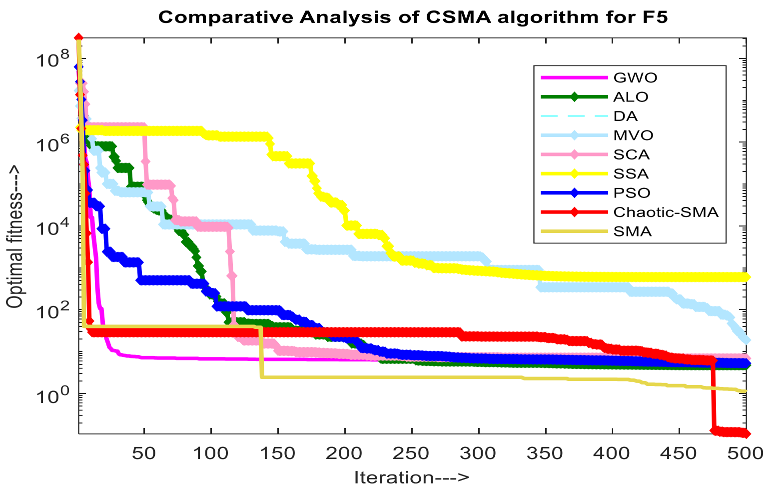
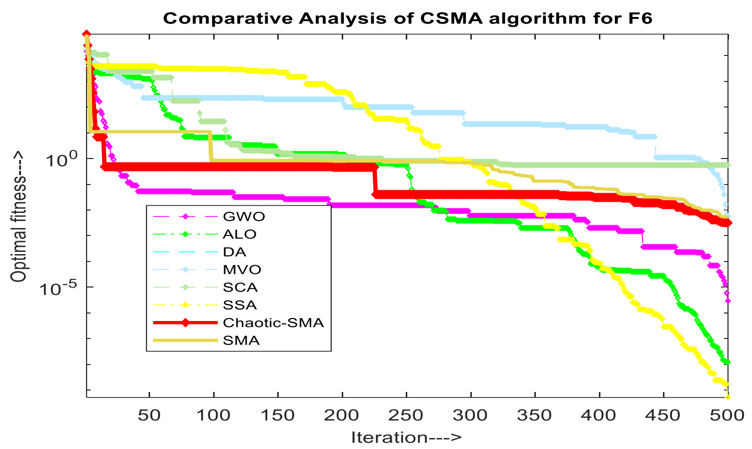


Fig.4.26: Assessment of convergence of CSMA with other algorithms for UM test function *(Continued)*





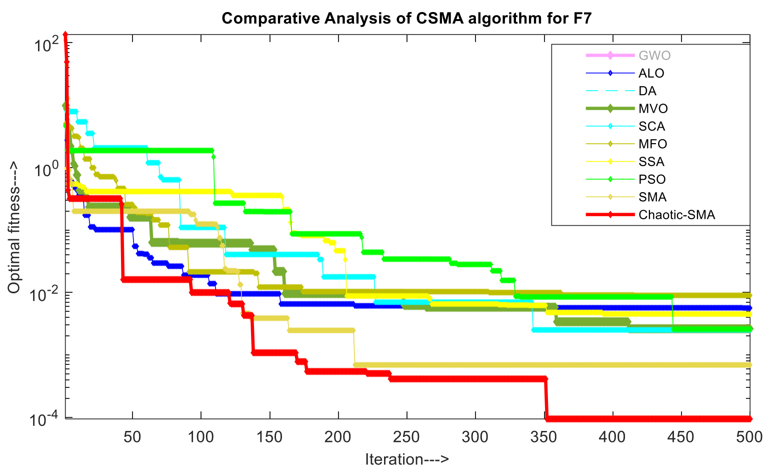


Fig.4.26: Assessment of convergence of CSMA with other algorithms for UM test function *(Continued)*

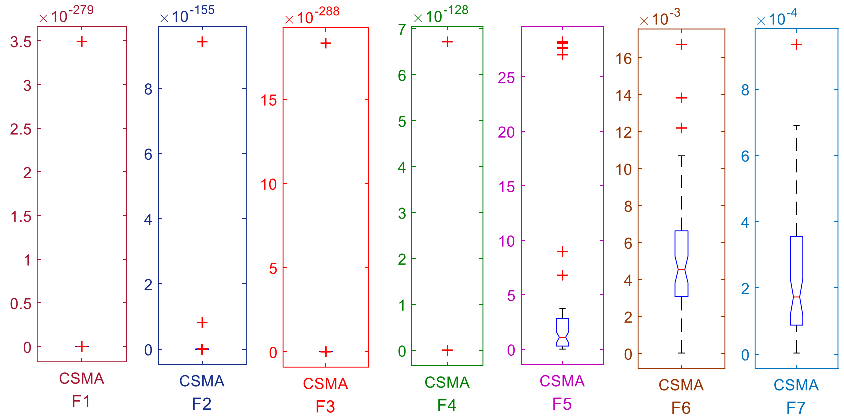


Fig.4.27: Trial run of UM test function for CSMA method

(b)Test Results for MM benchmark function using CSMA method

Table-4.23 illustrates simulation results of Multi-modal benchmark function from F8 to F13.Simulation time for multi-modal (MM) Benchmark Problems with best, mean and worst utilizing CHHO are shown in Table-4.24. The convergence curve of SMA and CSMA are indicated by yellow and red curve respectively

Table-4.23: Test results of MM benchmark functions using CSMA method

Functions	Average Value	STD	Best value	Worst value	Median value	p-Value
F8	-12569.1	0.319584	-12569.5	-12568.1	-12569.2	1.7344E-06
F9	0	0	0	0	0	1
F10	8.88E-16	0	8.88E-16	8.88E-16	8.88E-16	4.32046E-08
F11	0	0	0	0	0	1
F12	0.003937	0.006237	5.64E-07	0.032017	0.002066	1.7344E-06
F13	0.00664	0.00989	7.428E-05	0.05034892	0.00270	1.7344E-06

Table-4.24: Simulation time for MM test function using CSMA method

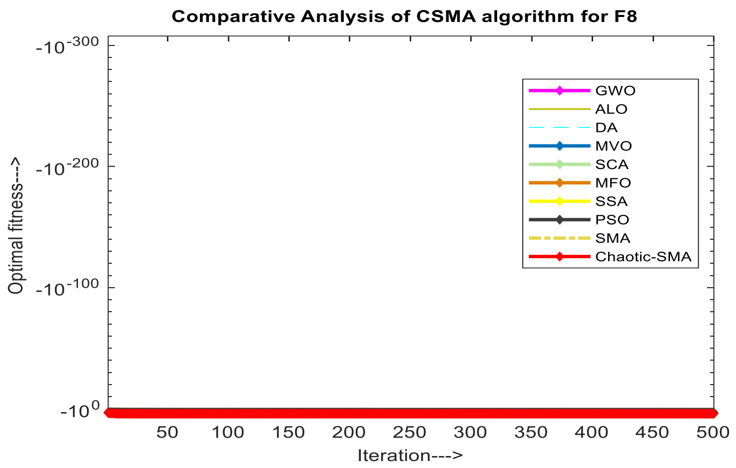
Functions	Best Time	Mean Time	Worst Time
F8	2.796875	2.929167	3.421875
F9	2.765625	2.911458	3.546875
F10	2.828125	2.948438	3.40625
F11	2.84375	2.996875	3.6875
F12	3.09375	3.206771	3.765625
F13	3.09375	3.198958	3.765625

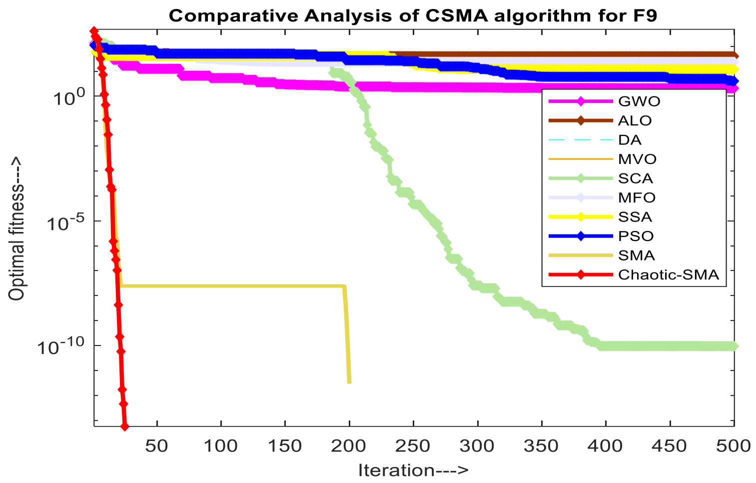
Table-4.25 illustrates results compared with other meta-heuristics search algorithms like PSO [275], GWO [99], GSA [276], BA [277], FA [278], GA [55], BDA [259],

BPSO [282], MFO [279], MVO [266], BGSA [267], SMS [280], DE [281], ALO [263], WOA [212], etc. in terms of average value and std. deviation. The comparison of the CHHO convergence curves with other competing methods are shown in Fig.4.28. Figure 4.29 shows the 30 iterative runs for the MM functions. Since the multimodal have large number of local optimum, the results shown in Table 4.8 reveals that CSMA gives better exploration compared to other techniques. The convergence curves reflects closeness in most of the test functions. The above analysis reveals that CSMA is capable in testing multimodal test functions.

Table-4.25: Comparison of MM test results of CSMA with other methods

Algorithm	Parameter	MM benchmark function					
		F8	F9	F10	F11	F12	F13
PSO [207]	AVG	-4.8400E+04	4.670E+01	2.760E-01	9.2200E-04	6.9200E-04	6.6800E-04
	SD	1.1500E+04	1.160E+01	5.090E-01	7.7200E-04	2.6300E-03	8.9100E-04
GWO [99]	AVG	-6.1200E+02	3.1100E-02	1.0600E-14	4.4900E-04	5.3400E-03	6.5400E-02
	SD	-4.0900E+02	4.740E+01	7.7800E-03	6.6600E-04	2.0700E-03	4.470E-03
GSA [203]	AVG	-2.820E+03	2.600E+01	6.210E-02	2.770E+01	1.800E+00	8.900E+00
	SD	4.930E+02	7.470E+00	2.360E-01	5.040E+00	9.510E-01	7.130E+00
DE [200]	AVG	-1.110E+04	6.920E+01	9.700E-08	0.000E+00	7.900E-15	5.100E-14
	SD	5.750E+02	3.880E+01	4.200E-08	0.000E+00	8.000E-15	4.800E-14
ALO [263]	AVG	-1.61E+03	7.71E-06	3.73E-15	1.86E-02	9.75E-12	2.00E-11
	SD	3.14E+02	8.45E-06	1.50E-15	9.55E-03	9.33E-12	1.13E-11
BA [210]	AVG	-1.070E+03	1.230E+00	1.290E-01	1.450E+00	3.960E-01	3.870E-01
	SD	8.580E+02	6.860E-01	4.330E-02	5.700E-01	9.930E-01	1.220E-01
CS[278]	AVG	-2.090E+03	1.270E-01	8.160E-09	1.230E-01	5.600E-09	4.880E-06
	SD	7.620E-03	2.660E-03	1.630E-08	4.970E-02	1.580E-10	6.090E-07
GA [265]	AVG	-2.090E+03	6.590E-01	9.560E-01	4.880E-01	1.110E-01	1.290E-01
	SD	2.470E+00	8.160E-01	8.080E-01	2.180E-01	2.150E-03	6.890E-02
MFO [211]	AVG	-8.500E+03	8.460E+01	1.260E+00	1.910E-02	8.940E-01	1.160E-01
	SD	7.260E+02	1.620E+01	7.300E-01	2.170E-02	8.810E-01	1.930E-01
MVO [266]	AVG	-1.170E+04	1.180E+02	4.070E+00	9.400E-01	2.460E+00	2.200E-01
	SD	9.370E+02	3.930E+01	5.500E+00	6.000E-02	7.900E-01	9.000E-02
DA [259]	AVG	-2.860E+03	1.600E+01	2.310E-01	1.930E-01	3.110E-02	2.200E-03
	SD	3.840E+02	9.480E+00	4.870E-01	7.350E-02	9.830E-02	4.630E-03
BPSO [260]	AVG	-9.890E+02	4.830E+00	2.150E+00	4.770E-01	4.070E-01	3.070E-01
	SD	1.670E+01	1.550E+00	5.410E-01	1.290E-01	2.310E-01	2.420E-01
SCA [268]	AVG	1.000E+00	0.000E+00	3.800E-01	0.000E+00	0.000E+00	0.000E+00
	SD	3.600E-03	7.300E-01	1.000E+00	5.100E-03	0.000E+00	0.000E+00
CSMA	**AVG**	**-12569.1**	**0**	**8.88E-16**	**0**	**0.003937**	**0.00664**
	SD	**0.319584**	**0**	**0**	**0**	**0.006237**	**0.00989**





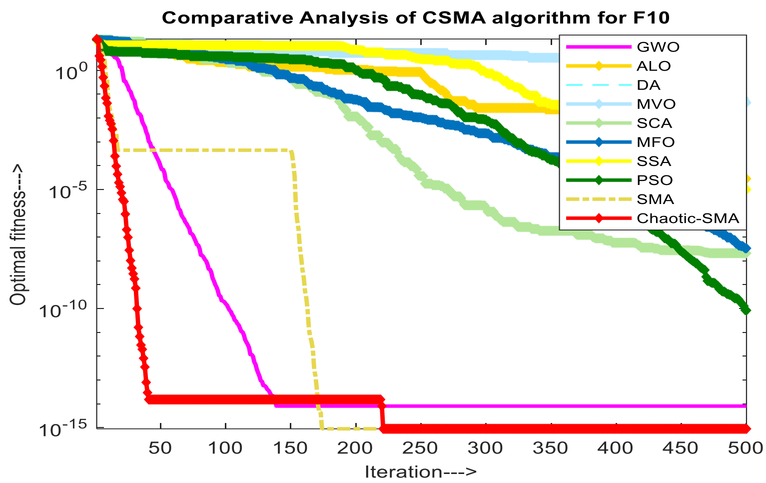


Fig.4.28: Assessment of convergence of CSMA with other algorithms for MM test function

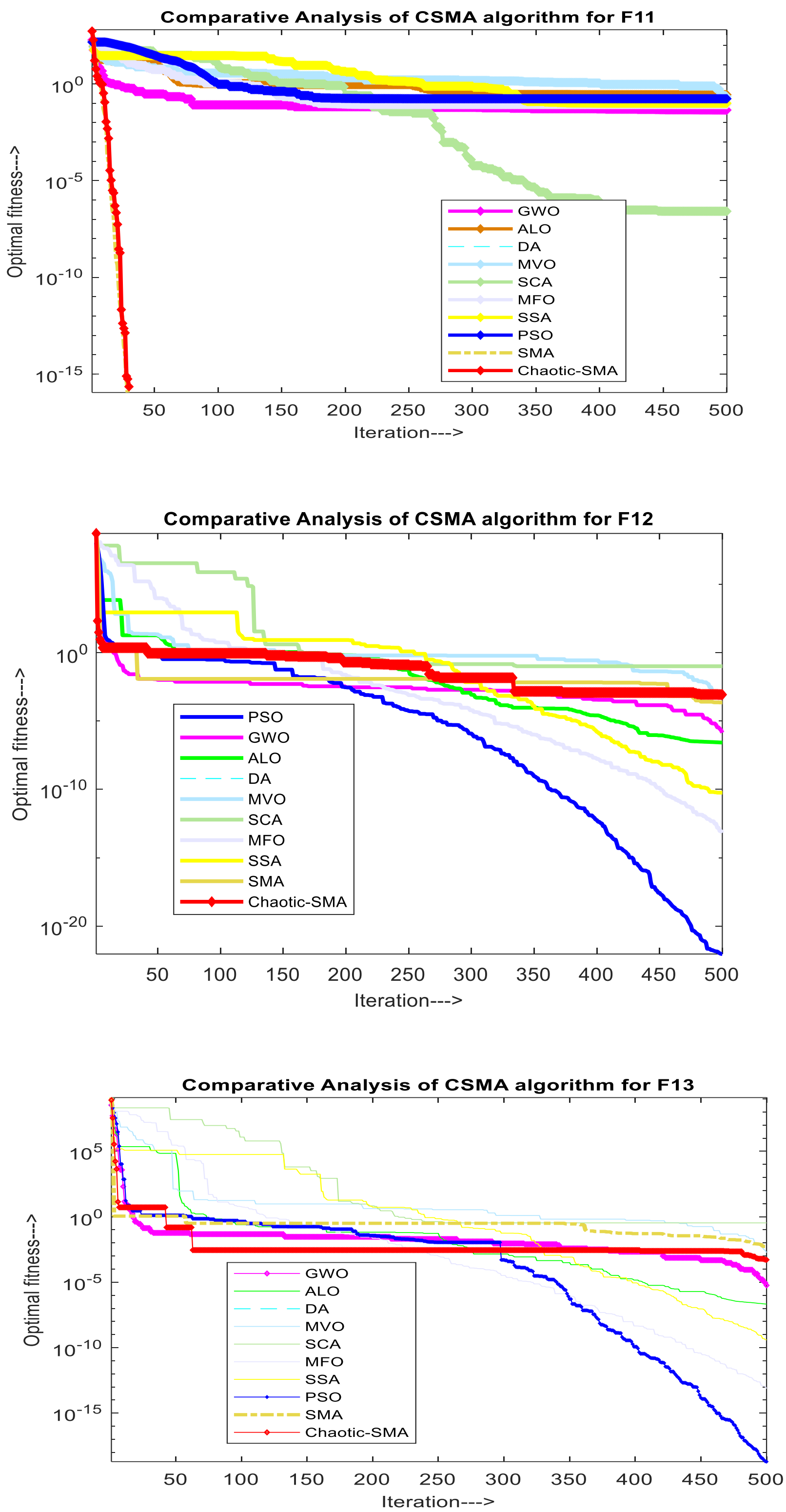


Fig.4.28: Assessment of convergence of CSMA with other algorithms for MM test function *(Continued)*

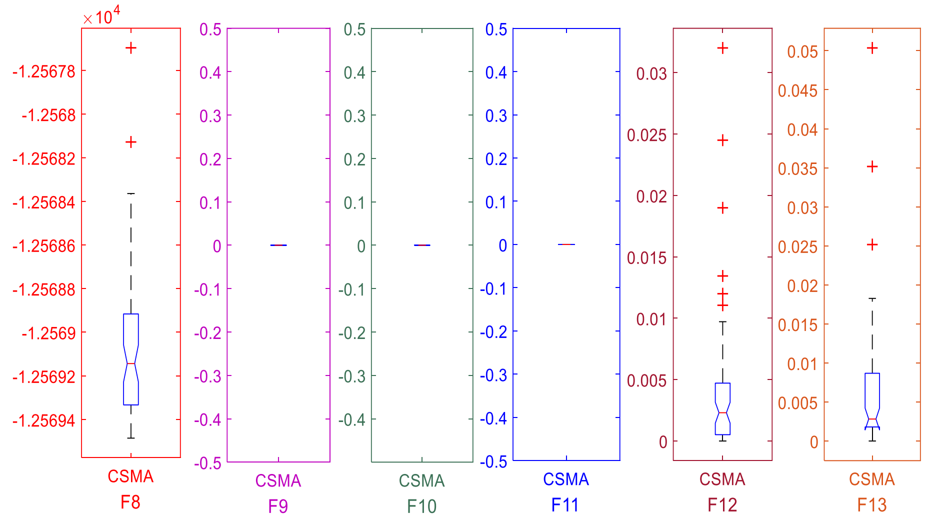


Fig.4.29: Trial run of MM test function for CSMA method

(c) Test Results for Fixed dimension (FD) benchmark function using CSMA method

The simulation outcomes for fixed dimension (FD) test functions has been illustrated in Table-4.26. Simulation time for FD Benchmark Problems utilizing CSMA is shown in Table-4.27.

Table-4.26: Test outcomes of FD functions using CSMA method

Functions	AVG	SD	Best value	Worst value	Median value	p-Value
F14	0.998004	9.26E-13	0.998004	0.998004	0.998004	1.7344E-06
F15	0.00055	0.000244	0.00031	0.001223	0.000469	1.7344E-06
F16	-1.03163	1.51E-09	-1.03163	-1.03163	-1.03163	1.7344E-06
F17	0.397887	6.82E-08	0.397887	0.397888	0.397887	1.7344E-06
F18	3	8.43E-12	3	3	3	1.7344E-06
F19	-3.86278	4.21E-07	-3.86278	-3.86278	-3.86278	1.7344E-06
F20	-3.25824	0.060654	-3.32199	-3.20008	-3.20309	1.7344E-06
F21	-10.1528	0.000274	-10.1532	-10.1519	-10.1529	1.7344E-06
F22	-10.4026	0.000208	-10.4029	-10.4021	-10.4027	1.7344E-06
F23	-10.536	0.000299	-10.5364	-10.5354	-10.5361	1.7344E-06

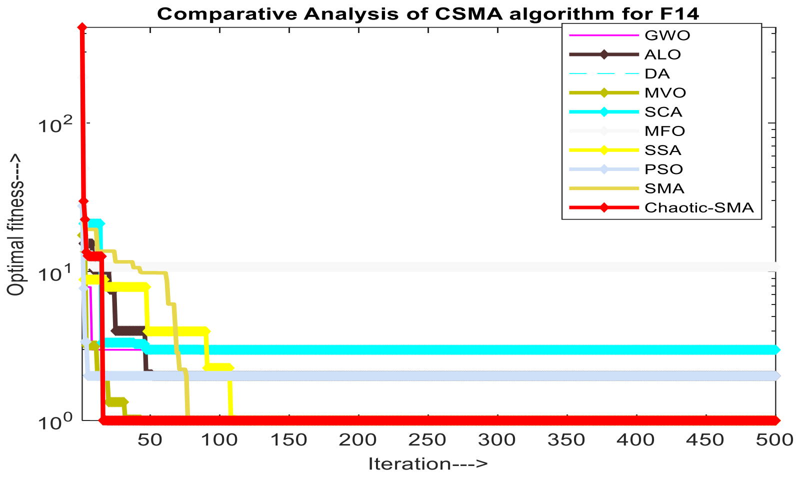
Table-4.27: Simulation time for FD test function using CSMA method

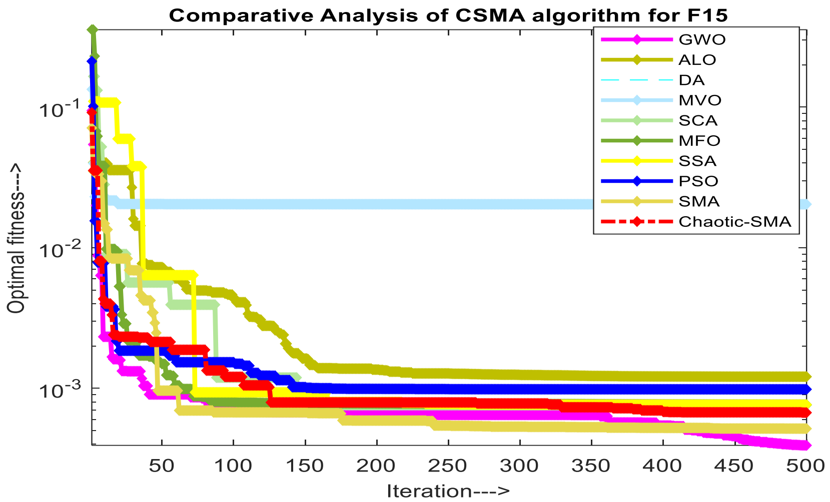
Functions	**Best Time**	**Mean Time**	**Worst Time**
F14	1.140625	1.215104	1.921875
F15	0.671875	0.788021	1.34375
F16	0.53125	0.623438	1.171875
F17	0.5	0.582813	1.21875
F18	0.5	0.595313	1.125
F19	0.59375	0.680729	1.265625
F20	0.859375	0.971354	1.46875
F21	0.8125	0.941146	1.4375
F22	0.859375	0.972917	1.40625
F23	0.9375	1.065104	1.59375

Table-4.28 illustrates CSMA results compared with others variants such as GWO [99], PSO [207], GSA [203], DE [200], FEP [261] in terms of average(AVG) & standard deviation (SD). From the compared convergence curves shown in Fig.4.30, it is observed that proposed CSMA gives more superior results in terms of convergence. Fig.4.31 shows the trial runs for fixed dimension function.

Table-4.28: Comparison of FD test results of CSMA with other methods

Algorithm	**Parameter**	**FD Test Function**									
		F14	**F15**	**F16**	**F17**	**F18**	**F19**	**F20**	**F21**	**F22**	**F23**
GWO [99]	**AVG**	4.04	0.00	-1.03	0.40	3.00	-3.86	-3.29	-10.15	-10.40	-10.53
	SD	4.25	0.00	-1.03	0.40	3.00	-3.86	-3.25	-9.14	-8.58	-8.56
PSO[287]	**AVG**	3.63	0.00	-1.03	0.40	3.00	-3.86	-3.27	-6.87	-8.46	-9.95
	SD	2.56	0.00	0.00	0.00	0.00	0.00	0.06	3.02	3.09	1.78
GSA [203]	**AVG**	5.86	0.00	-1.03	0.40	3.00	-3.86	-3.32	-5.96	-9.68	-10.54
	SD	3.83	0.00	0.00	0.00	0.00	0.00	0.02	3.74	2.01	0.00
DE[200]	**AVG**	1.00	0.00	-1.03	0.40	3.00	N/A	N/A	-10.15	-10.40	-10.54
	SD	0.00	0.00	0.00	0.00	0.00	N/A	N/A	0.00	0.00	0.00
FEP [261]	**AVG**	1.22	0.00	-1.03	0.40	3.02	-3.86	-3.27	-5.52	-5.53	-6.57
	SD	0.56	0.00	0.00	0.00	0.11	0.00	0.06	1.59	2.12	3.14
CSMA(Proposed Method)	**AVG**	**0.998004**	**0.00055**	**-1.03163**	**0.397887**	**3**	**-3.86278**	**-3.25824**	**-10.1528**	**-10.4026**	**-10.536**
	SD	**9.26E-13**	**0.000244**	**1.51E-09**	**6.82E-08**	**8.43E-12**	**4.21E-07**	**0.060654**	**0.000274**	**0.000208**	**0.000299**





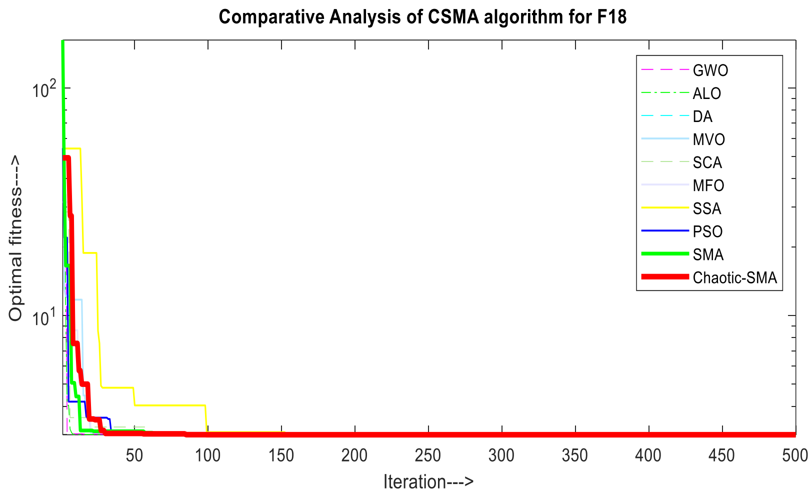


Fig.4.30: Assessment of CSMA with other algorithms for FD test function

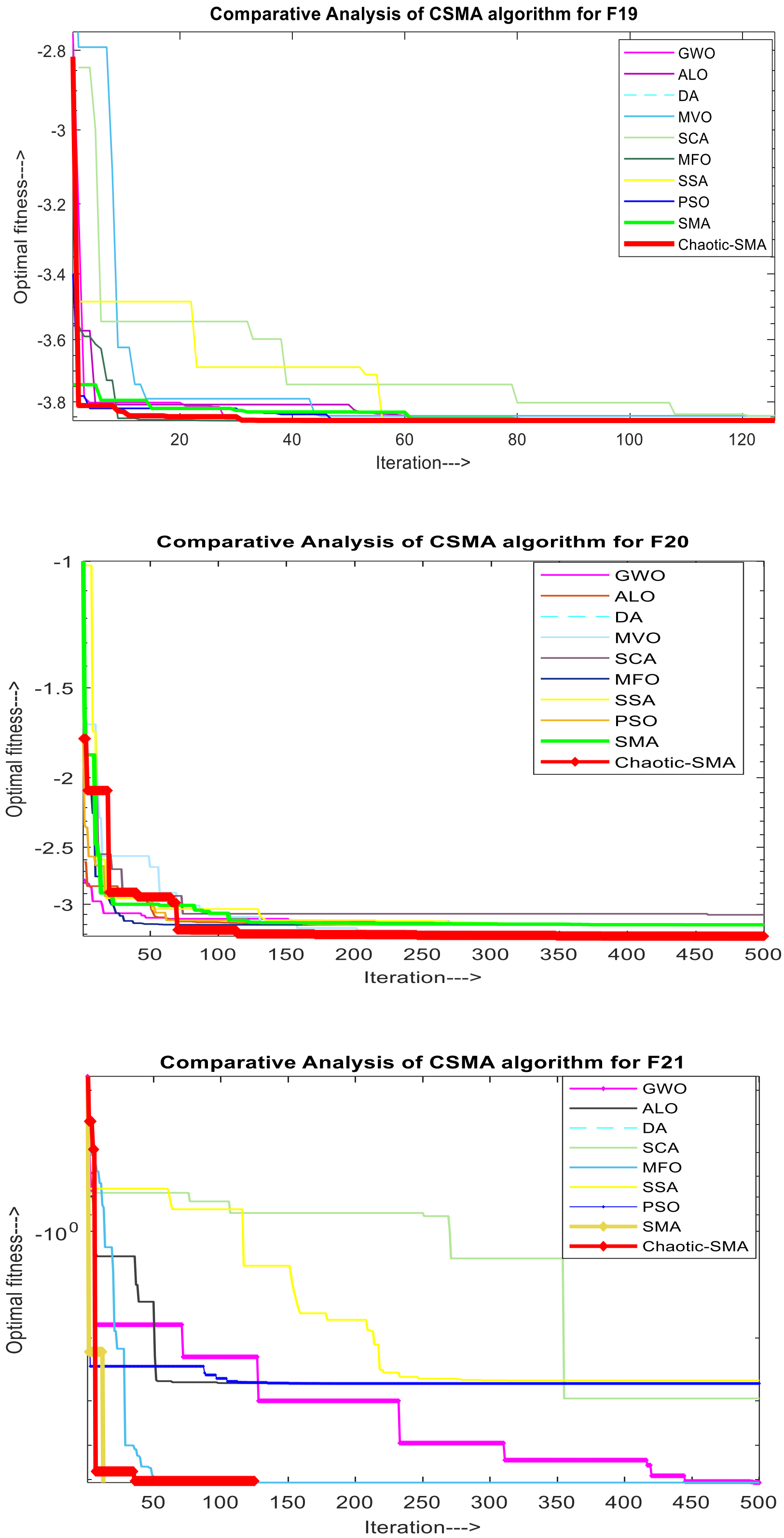
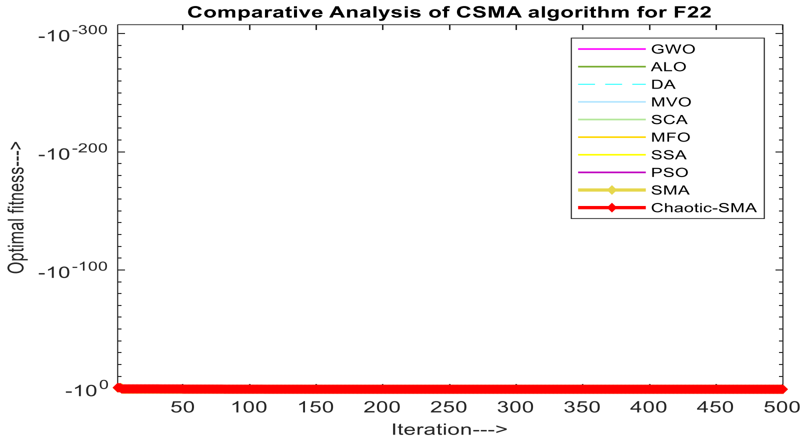


Fig.4.30: Assessment of CSMA with other algorithms for FD test function

(Continued)



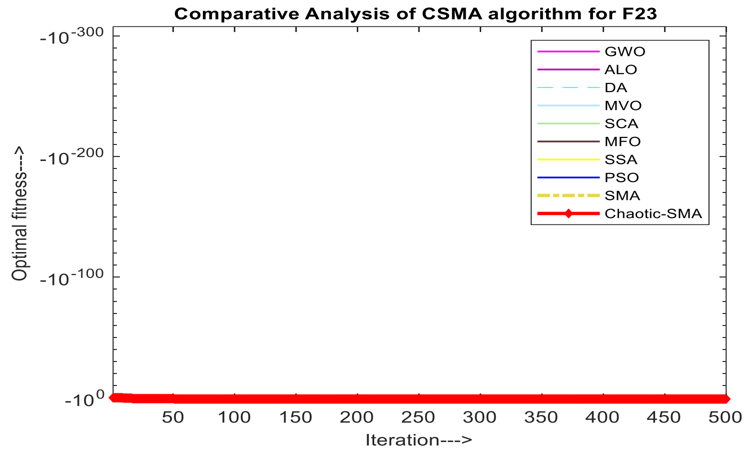


Fig.4.30: Assessment of CSMA with other algorithms for FD test function *(Continued)*

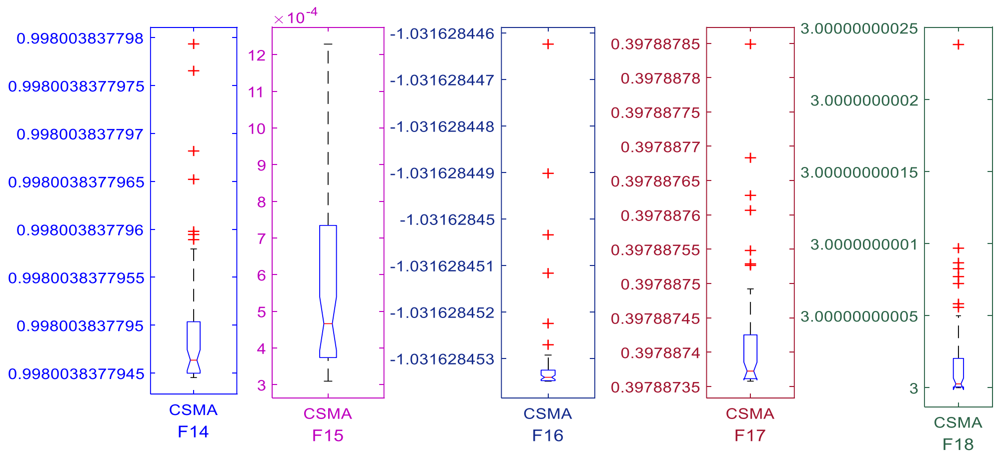


Fig.4.31: Trial run of FD test function for CSMA method

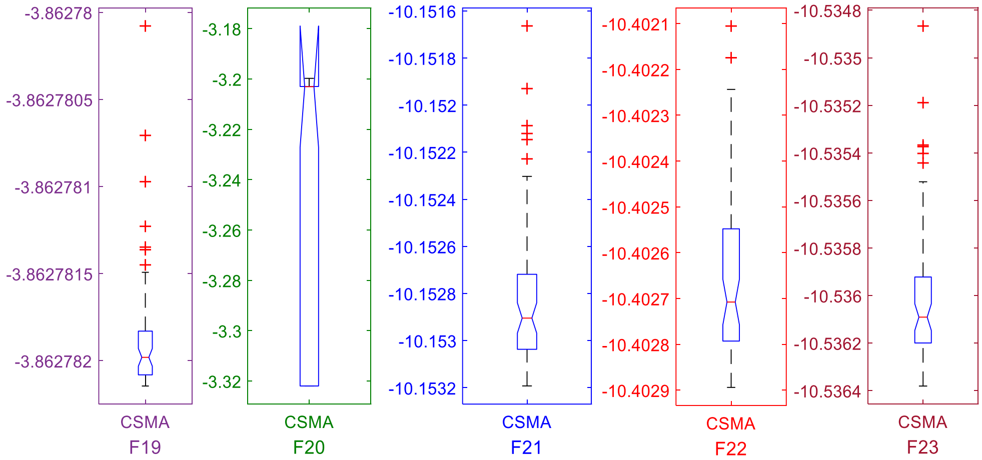


Fig.4.31: Trial run of FD test function for CSMA method *(continued)*

Table 4.28 presents average and standard deviation values of CSMA and other methods. These values are smaller compared to GWO, PSO, and GSA. Thus, the proposed method gives high quality solution as compared to other methods in case of F14, F15, F18, and F23.The results are consistent in case of F19, F20, F18, and F23. It can be seen that F14, F15, F18, and F23 shows better convergence, while other methods are trapped in local optimum. It is also noted that F15 and F23 have better convergence speed and settles to optimal value with less iterations. The above analysis reveals that CSMA is capable in testing fixed dimension test functions.

4.5 RESULTS AND DISCUSSION FOR ENGINEERING DESIGN PROBLEMS

Table-4.29 illustrates test results of ten engineering problems. In Table-4.30 illustrates simulation time in term of mean, best and mean value for corresponding design problems.

Table-4.29: Test Results for Engineering Design Problems by using hHHO-IGWO, CHHO and CSMA

Engineering Functions(EF)	Mean	STD value	Best value	Worst value	Median value	p-Value
EF1(hHHO-IGWO)	264.0243	0.149207	263.8959	264.4953	263.9697	1.73E-06
EF1(CHHO)	264.00	0.3.19	264.00	265.00	264.00	1.73E-06
EF1(CSMA)	270.7824	1.791805	265.4599	273.3948	271.2534	1.7344E-06
EF2(hHHO-IGWO)	3694.179	628.0672	3002.04	5241.398	3483.753	1.73E-06
EF2(CHHO)	3750.00	737.00	3010.00	5260.00	3360.00	1.73E-06

Table-4.29: Test Results for Engineering Design Problems by using hHHO-IGWO, CHHO and CSMA *(Continued)*

Engineering Functions(EF)	Mean	STD value	Best value	Worst value	Median value	p-Value
EF2(CSMA)	2994.48	0.005837	2994.474	2994.495	2994.479	1.7344E-06
EF3(hHHO-IGWO)	9010.828	12492.69	6086.874	75122.61	6730.517	1.73E-06
EF3(CHHO)	7020.00	363.00	6290.00	7710.00	7090.00	1.73E-06
EF3(CSMA)	6427.41	531.9222	5885.341	7318.996	6195.263	1.7344E-06
EF4(hHHO-IGWO)	0.013457	0.000997	0.012666	0.017775	0.013238	1.73E-06
EF4(CHHO)	1.40E-02	1.38E-03	1.27E-02	1.78E-02	1.33E-02	1.73E-06
EF4(CSMA)	3.34E-11	6.46E-11	4.82E-14	2.91E-10	7.56E-12	1.7344E-06
EF5(hHHO-IGWO)	2.147051	0.408326	1.770391	3.440706	1.952591	1.73E-06
EF5(CHHO)	2.140E+00	3.610E-01	1.740E+00	3.490E+00	2.040E+00	1.73E-06
EF5(CSMA)	1.740409	0.052373	1.724899	2.00749	1.726646	1.7344E-06
EF6(hHHO-IGWO)	-70571.6	15121.97	-83014	-42057	-80687.1	1.73E-06
EF6(CHHO)	-6.740E+04	1.630E+04	-8.410E+04	-4.240E+04	-7.370E+04	1.73E-06
EF6(CSMA)	-85534.4	10.61208	-85539.2	-85498.2	-85538.7	1.7344E-06
EF7(hHHO-IGWO)	0.444596	0.052704	0.389663	0.563677	0.432178	1.73E-06
EF7(CHHO)	4.47E-01	4.64E-02	3.90E-01	5.71E-01	4.42E-01	1.73E-06
EF7(CSMA)	0.392818	0.005457	0.389654	0.404654	0.389664	1.7344E-06
EF8(hHHO-IGWO)	0	0	0	0	0	1
EF8(CHHO)	0	0	0	0	0	1
EF8(CSMA)	0.014245	0.001415	0.012715	0.017524	0.013955	1.7344E-06
EF9(hHHO-IGWO)	2.65E+22	2.7E+22	1.981265	5.3E+22	2.65E+22	1.44E-06
EF9(CHHO)	2.65E+22	2.70E+22	1.98E+00	5.30E+22	2.65E+22	1.29E-06
EF9(CSMA)	5.24E+22	5.87E+22	1.57E+21	1.79E+23	1.21E+22	1.7344E-06
EF10(hHHO-GWO)	1.31E+00	1.68E-03	1.30E+00	1.31E+00	1.31E+00	1.73E-06
EF10(CHHO)	1.31E+00	1.68E-03	1.30E+00	1.31E+00	1.31E+00	1.73E-06
EF10(CSMA)	1.303713	0.000368	1.303281	1.30519	1.303612	1.7344E-06

Table-4.30: Computation time for EF1 to EF10 using hHHO-IGWO, CHHO and CSMA method

Functions	Best Time	Mean Time	Worst Time
EF1(hHHO-IGWO)	0.421875	0.494271	1.3125
EF1(CHHO)	0.328125	0.388541667	0.96875
EF1(CSMA)	0.5	0.584896	1.390625
EF2(hHHO-IGWO)	0.59375	0.665104	1.6875
EF2(CHHO)	0.40625	0.566145833	1.34375
EF2(CSMA)	0.984375	1.063021	1.453125
EF3(hHHO-IGWO)	0.453125	0.513021	1.3125
EF3(CHHO)	0.3125	0.4203125	0.953125
EF3(CSMA)	0.671875	0.814063	1.359375
EF4(hHHO-IGWO)	0.46875	0.529167	1.40625
EF4(CHHO)	0.359375	0.463020833	1.015625
EF4(CSMA)	0.578125	0.663542	1.3125
EF5(hHHO-IGWO)	0.53125	0.595833	1.54687
EF5(CHHO)	0.3125	0.4203125	0.953125

Table-4.30: Computation time for EF1 to EF10 using hHHO-IGWO, CHHO and CSMA method *(Continued)*

Functions	Best Time	Mean Time	Worst Time
EF5(CSMA)	0.671875	0.829167	1.515625
EF6(hHHO-IGWO)	0.8125	0.891146	2.15625
EF6(CHHO)	0.296875	0.510416667	1.109375
EF6(CSMA)	1.21875	1.301042	1.796875
EF7(hHHO-IGWO)	0.515625	0.61875	1.46875
EF7(CHHO)	0.578125	0.7828125	1.640625
EF7(CSMA)	0.734375	0.829688	1.28125
EF8(hHHO-IGWO)	0.359375	0.429688	1.09375
EF8(CHHO)	0.375	0.484375	1.234375
EF8(CSMA)	0.6875	0.784375	1.5
EF9(hHHO-IGWO)	0.46875	0.579167	1.34375
EF9(CHHO)	0.265625	0.35	0.796875
EF9(CSMA)	0.671875	0.782813	1.359375
EF10(hHHO-IGWO)	0.328125	0.449479167	1.236
EF10(CHHO)	0.3125	0.492708333	1.078125
EF10(CSMA)	0.75	0.833333	1.359375

4.5.1 Analysis of Truss design problem using hHHO-IGWO, CHHO and CSMA method

Table-4.31 shows the comparative analysis of results for hHHO-IGWO, CHHO and CSMA, HHO, CS, Ray and Sain and TSA method for 3-bar truss Design.

Table - 4.31: hHHO-IGWO, CHHO and CSMA results compared with other methods for 3-bar truss Design

Algorithm		**hHHO-IGWO**	CHHO	**CSMA**	**HHO**	**CS** [288]	**Ray and Sain** [289]	**TSA** [195]
Optimal values for variables	*y*1	0.786672	0.763	0.766	0.7886	0.789	0.795	0.788
	y2	0.413943	0.494	0.494	0.4082	0.409	0.395	0.408
Optimal weight		263.891	263.898	263.45	263.899	263.972	264.3	263.68

Table 4.31 presents results of hHHO-IGWO, CHHO and CSMA compared with other methods for 3-bar truss design. It is inferred that results of proposed methods are very close to those of CS, Ray and sain and TSA. It is evident from results that CSMA outperforms other methods in cost minimization of 3-bar truss design.

4.5.2 Analysis of speed reducer problems Using hHHO-IGWO, CHHO and CSMA method

Table-4.32 shows the comparative analysis of hHHO-IGWO, CHHO and CSMA results compared with HHO, MDE, PSO-DE and MBA method for speed reducer problem.

Table -4.32: Comparison of results for speed reducer problem with other methods

Method		hHHO-IGWO	CHHO	CSMA	HHO	MDE [290]	PSO-DE[291]	MBA[271]
Fitness values for variables	z_1	3.5074	3.5	3.5	3.56	3.50001	3.50	3.5
	z_2	0.7	0.7	0.7	0.7	0.7	0.7	0.7
	z_3	17	17	17	17	17	17	17
	z_4	7.3	7.3	7.3	8.0186	7.300156	7.3	7.300033
	z_5	7.759	7.71541	7.715418	8.01891	7.800027	7.8	7.715772
	z_6	3.35065	3.35021	3.350215	3.4948	3.350221	3.3502	3.350218
	z_7	5.2922	5.28665	5.286655	5.2867	5.286685	5.2866	5.286654
Optimum Cost		3002.0401	2994.473	2993.4738	3060.37	2996.3566	2996.3	2994.482

It can be seen from the comparative analysis that CHHO and CSMA gives 2994.473 and 2993.4738 respectively. The results reveals that CSMA gives least optimum cost compared to other techniques. It is evidence from the compared results that CSMA is more effective in cost minimization due to better exploitation.

4.5.3 Analysis of Pressure Vessel Design problems Using hHHO-IGWO, CHHO and CSMA method

Table-4.33 shows the comparative analysis of hHHO-IGWO, CHHO and CSMA with PSO, GA, HHO, ACO, GWO, GSA, DE, and branch &bound method for pressure vessel design problem.

Table-4.33: Comparative analysis of hHHO-IGWO, CHHO and CSMA with classical heuristic algorithms for Pressure Vessel Design

Algorithm		hHHO-IGWO	CHHO	CSMA	HHO	GWO [103]	GSA [276]	PSO [213]	GA [292]	DE [293]	Branch-bound [212]
Optimum Value	Ts	0.86996	0.88649	0.77817	0.81758	0.84806	1.125	0.8125	0.812	0.812	1.125
	Th	0.42783	0.48604	0.3846	0.4312	0.4345	0.625	0.4375	0.434	0.437	0.625
	R	44.7916	45.8502	40.38	42.0917	42.8279	55.98	42.091	40.32	42.09	47.7
	L	145.896	135.125	199.99	167.836	176.758	84.454	176.74	200	176.63	117.701
Optimum Cost		6086.87	6193.94	5885.34	6286.33	7016.96	6051.5	8538.8	6061.0	6059.7	7198.04

The comparative assessment presented in Table 4.33 suggests that hHHO-IGWO, CHHO and CSMA methods are efficient in handling pressure vessel design problem. It can be seen that CSMA most gives most cost effective solution compared with other methods.

4.5.4 Analysis of Cantilever beam design problem using hHHO-IGWO, CHHO and CSMA method

Table-4.34 shows the comparative analysis of hHHO-IGWO, CHHO and CSMA results compared with HHO, CS, ALO, SOS, MMA and GCA_I method for cantilever beam design problem.

Table-4.34: Comparison of results for Cantilever beam design problem with other methods

Method		**hHHO-IGWO**	**CHHO**	**CSMA**	**HHO**	**CS** [288]	**ALO** [263]	**SOS** [294]	**MMA** [295]	**GCA_I** [295]
variables	l_1	5.97504	6.048512	5.970	5.977	6.0089	6.0181	6.0188	6.01	6.01
	l_2	4.848219	4.838525	4.8841	5.000	5.3049	5.3114	5.3034	5.3	5.304
	l_3	4.485641	4.460903	4.4544	4.479	4.5023	4.4884	4.4959	4.49	4.49
	l_4	3.456451	3.471295	3.4738	3.361	3.5077	3.4975	3.499	3.49	3.498
	l_5	2.175804	2.113283	2.1571	2.134	2.1504	2.1583	2.1556	2.15	2.15
Optimum weight		1.30337	1.30328	1.3031	1.304	1.3399	1.3399	1.33995	1.3399	1.34

The results shown in Table 4.34 suggest all three methods outperforms other methods in handling cantilever beam design problem. The optimal value evaluated by hHHO-IGWO and CSMA are 1.30337 and 1.3031. It can be seen from above table that CSMA gives more precise results as compared to HHO, CS, ALO, SOS, and GCA_I due to better exploitation and local minima avoidance.

4.5.5 Analysis of Spring design problem using hHHO-IGWO, CHHO and CSMA method

Table-4.35 presents the comparative analysis of hHHO-IGWO, CHHO and CSMA results compared with HHO, GWO, GSA, CPSO, ES, GA, HS and DE method for spring design problem.

Table-4.35: Comparison of hHHO-IGWO, CHHO and CSMA with other methods for Compression Spring Design Problem

Method		hHHO-IGWO	CHHO	CSMA	HHO	GWO [296]	GSA [276]	CPSO [297]	ES [196]	GA [298]	HS [299]	DE [300]
Variable	'd'	0.05187	0.05170	0.05	0.05179	0.0516	0.0503	0.0517	0.052	0.0515	0.0512	0.0516
	'D'	0.36127	0.35712	0.3174	0.35930	0.3567	0.3237	0.3576	0.364	0.3517	0.3499	0.3547
	'N'	11.0267	11.2652	11.2889	11.1388	11.2889	13.5254	11.2445	10.890	11.632	12.076	11.4108
Optimum weight		**0.01266**	0.01266	0.01267	0.01269	0.01195	0.01267	0.0127	0.0126	0.0126	0.0127	0.01267

The results shown in Table 4.35 reveals that hHHO-IGWO, CHHO and CSMA are effective in determining optimum cost for spring design problem. Results of proposed methods are very close to GSA, CPSO, ES, GA, HS and DE.

4.5.6 Analysis of rolling design problems Using hHHO-IGWO, CHHO and CSMA method

Table-4.36: Comparison of hHHO-IGWO, CHHO and CSMA with other methods for rolling design problem

Method		hHHO-IGWO	CHHO	CSMA	HHO	WCA [301]	SCA [302]	MFO [279]	**MVO** [266]
Values for variables	r_1	125	125.7227	125.7227	125	125.72	125	125	125.6002
	r_2	21	21.4233	21.4233	20.99292	21.42300	21.0328	21.0328	21.32250
	r_3	11.092500	11.00146	11.00116	11.10833	10.01030	10.9657	10.9657	10.97338
	r_4	0.515	0.515	0.515	0.515	0.515000	0.515	0.515	0.515
	r_5	0.515	0.51500	0.515	0.515	0.515000	0.515	0.51500	0.515000
	r_6	0.4	0.4954	0.4944	0.4	0.401514	0.5	0.5	0.5
	r_7	0.6	0.6996	0.6986	0.6	0.659047	0.7	0.67584	0.68782
	r_8	0.3	0.3	0.3	0.3	0.300032	0.3	0.30021	0.301348
	r_9	0.0648640	0.03398	0.03346	0.057948	0.040045	0.02778	0.02397	0.03617
	r_{10}	0.6	0.60034	0.60049	0.6	0.600000	0.62912	0.61001	0.61061
Optimum fitness		83014.012	83455.82	85534.16	83043.30	85538.48	83431.1	84002.5	84491.266

Table-4.36 shows the comparative analysis of hHHO-IGWO, CHHO and CSMA results compared with HHO, WCA, SCA, MFO and MVO method for rolling design problem.It is noticed from the analysis that the proposed method gives competitive results to other stochastic techniques. It can be seen that hHHO-IGWO excels in achieving optimal fitness compared to CHHO, CSMA and other techniques.

4.5.7 Analysis of welded beam design problems Using hHHO-IGWO , CHHO and CSMA method

Table-4.37 shows the comparative analysis of hHHO-IGWO, CHHO and CSMA results compared with HHO, GSA, HS and GA, Random, Simplex, and Approx. It is revealed from the comparative analysis that the proposed method gives more precise results compared to other methods. It can be seen that CSMA is more effective in evaluating optimal cost for welded beam design due to randomness introduced by chaotic function.

Table-4.37: Relative analysis of welded beam design problem with other methods

Method		**hHHO-IGWO**	**CHHO**	**CSMA**	**HHO**	**GSA** [212]	**HS** [303]	**GA** [298]	**Random** [304]	**Simplex** [304]	**APPROX** [304]
Optimum Variables	**h**	0.19655	0.2028	0.2057	0.2040	0.244	0.182	0.2489	0.4575	0.2792	0.2444
	l	3.68507	3.5452	3.4710	3.5310	6.223	3.857	6.173	4.7313	5.6256	6.2189
	t	9.02302	9.0050	9.0366	9.0274	8.291	10	8.1789	5.0853	7.7512	8.2915
	b	0.21012	0.2073	0.2057	0.2061	0.244	0.202	0.2533	0.66	0.2796	0.2444
Optimal Cost		1.77039	1.7369	1.7248	1.8112	1.88	2.380	2.4331	4.1185	2.5307	2.3815

4.5.8 Analysis of Belleville spring design problems using hHHO-IGWO, CHHO and CSMA method

Table-4.38 shows the comparative analysis of hHHO-IGWO, CHHO and CSMA results compared with HHO, TLBO, and MBA method for Belleville spring design problem.

Table-4.38: Relative analysis of design variables with other algorithms for Belleville Spring Design

Method		**hHHO-IGWO**	**CHHO**	**CSMA**	**HHO**	**TLBO**[206]	**MBA**[271]
Variables	$x1$	11.99338	11.98694	8.83686	11.93789	12.01	12.01
	$x2$	10.00925	10.00147	4.81595	9.939825	10.0304	10.0304
	$x3$	0.204184	0.204191	0.2	0.204267	0.20414	0.20414
	$x4$	0.200003	0.2	0.2	0.2	0.2	0.2
Optimal Cost		1.98126	1.9798	0.0572	1.98465	1.98966	1.98965

The comparative analysis presented in Table 4.38 reveals that the hHHO-IGWO, CHHO and CSMA gives precise results compared with other techniques. The optimal value evaluated by CHHO and CSMA are 1.9798 and 0.0572. It can be seen that CSMA has better search capability compared to hHHO, CHHO and other methods.

4.5.9 Analysis of Gear Train Design problem using hHHO-IGWO , CHHO and CSMA method

Table-4.39 shows the comparative analysis of hHHO-IGWO, CHHO and CSMA results compared with HHO, GeneAS, Kannan and Kramer and Sandgren method for Gear Train design problem.

Table-:4.39: Relative analysis of Gear Train problem with other methods

Method		**hHHO-IGWO**	**CHHO**	**CSMA**	**HHO**	**GeneAS** [292]	**Kannan and Kramer** [292]	**Sandgren** [292]
Optimal values for variables	$g1$	41	41	41	56	50	41	60
	$g2$	47	46	33	58	33	33	45
	$g3$	16	16	15	22	14	15	22
	$g4$	17	15	13	21	17	13	18
Optimum fitness		0.1434	0.14423	0.144124	0.14563	0.144242	0.144242	0.144124

The comparative analysis reveals that the proposed methods gives competitive results with other techniques. It is also worth noticing that gear ratio variables are different. This suggests that proposed methods finds a new optimal design for this problem. The optimal fitness evaluated by CHHO and CSMA are 0.1434 and 0.144124. It can be seen that CSMA is effective in evaluating optimal fitness for Gear Train due to randomness introduced by chaotic function.

4.5.10 Analysis of multiple disc clutch brake design using hHHO-IGWO, CHHO and CSMA method

Table-4.40 presents the comparative analysis of hHHO-IGWO, CHHO, CSMA HHO, WCA, TLBO and PVS for multi disc clutch design problem.

Table-4.40: Relative analysis for multiple disc clutch brake design with other algorithms

Method		**hHHO-IGWO**	**CHHO**	**CSMA**	**HHO**	**WCA** [305]	**TL-BO**[306]	**PVS** [307]
Fitness variables	x_1	69.99998	69.9991	69.99	70	70	70	70.00
	x_2	90	90	90	90	90	90	90
	x_3	2.31286	2.31812	2.312	2.32929	3	3	3
	x_4	1.5	1.5	1.5	1.5	1	1	1
	x_5	999.9671	997.702	1000	992.915	910	810	880
Optimum fitness		0.3896	0.24697	0.38965	0.39159	0.3166	0.31365	0.32365

It is observed that results of proposed methodologies are very close to other algorithms. The optimal fitness evaluated by CHHO and CSMA are 0.24697 and 0.38965. It can be seen that CHHO is more effective in evaluating optimal fitness for said problem due to randomness introduced by chaotic property.

4.6 Conclusion

This chapter deals with the testing of 23 test functions and 10 real-world engineering design problems. Three different algorithms are developed using recent modern search algorithms such as Harris Hawk's optimizer and Slime mould algorithm. One hybrid and two chaotic algorithms are applied to test benchmark and design complications. To check the accurateness of the proposed methods, test results were equated with recent algorithms such as PSO, DE, GA, MVO, GWO, GSA, ACO, MFO, etc. It is seen that simulation results of proposed algorithms outperform other methods in testing benchmark and engineering design problems.

CHAPTER-5

UNIT COMMITMENT PROBLEM WITH THERMAL GENERATING UNIT

5.1 INTRODUCTION

Unit commitment is the process used to determine the ON/OFF status of generating units to meet forecasted load demand with sufficient reserve margin. In a unit commitment problem, it is desirable to have economic generation by selecting a particular combination of generation units. From the available number of generating units, the units with the lowest operating costs should be given first priority to be turned on, and the units with the highest operating costs will be given the least priority. In today's smart grid power system, besides the main coal-fired generation, a large number of power sources are integrated.

To address this complex unit commitment problem, the contribution of electricity by a large number of renewables participation and a significant quantity of V2G in the current grid has a broad scope in reducing our dependence on fossil-based fuels for energy production and transportation. However, the high penetration of renewable energy and the unregulated structure of the electricity grid, unit commitment has become a more challenging and complicated task. This huge penetration of sustainable sources has rather made the unit commitment problem more complex. This creates a necessity for immediate attention to developing new advanced optimization topologies to resolve commitment problems with great precision and approximations. Thus, optimization of power systems has gained great importance in modern power systems to cope with the economic dispatch problem.

In the traditional power system network, power is generated by a variety of generating stations, including thermal, hydro, nuclear, and others. Hydro and nuclear units are classified as base load plants and must be maintained operational at all times. Thermal units cannot be started immediately and must wait six to eight hours before they can be used. Furthermore, the load demand changes throughout the day and reaches various peak levels. The classical unit commitment problem in electric power systems focuses on developing optimum methods for assigning available power generation optimally to various generating units in order to maintain power balance with adequate reserve capacity under various constraints.

As a precautionary measure, there should be an adequate reserve margin to avoid any malfunction in the event of a fault in the generating or transmission lines or a sudden increase in load demand. Such units are to be kept ready for any emergency and keep spinning all the time, even if they are not connected to the grid, and are termed "Spinning Reserve". It is known that a definite cost is associated with starting and switching off any generating unit. For an economical operation, a proper generation allocation is needed. So, it is necessary to fulfill the forecasted load demand by selecting low-cost units in operation and putting off the units with higher costs.

The units that are connected to the utility are termed "committed units," while the units that are disconnected are called "de-committed units." The complete process of selecting the most feasible generation schedule and load allocation comes under the economic operation of a power system. Unit commitment is the task of identifying most economical generation schedule subjected to operational constraints such that (i) generated power should be equal to demand and losses (ii) there should be sufficient reserve margin, (iii) the generator should be loaded to maximum capacity and (iv) operation time of each unit must be realistic for proper service operation [308] , [274].

In recent years, many traditional methods have been applied to handle unit commitment problems. For efficient implementation of these methods, there is a need for an exact mathematical model and an adequate formulation. Moreover, despite all the possible cautions taken during problem formulation while designing a particular algorithm, there may be a chance of being trapped in local minima. This may prevent the optimizer from giving a desirable performance in determining global search points. [296], [309].

Over the last two decades, a significant research effort has been made to improve the current UC problems. The primary scalability factors for measuring the performance of any optimizing technique are computational ability, memory allocation requirements, and computational time. Based on these measuring factors, some flaws are seen in the existing conventional optimization methods for solving the UC problem.

Numerical techniques [310] and dynamic programming method [115], [311] has limited estimation of the problem, requires huge time. The MIP method [312], [313] faces problems in handling the economic power dispatch particularly when subjected to the increased number of units and produce computational delays due to requirement of large memory size. Gradient descent method is found to be unfocused in selecting units. The lagrangian relaxation [42] obsolete to explore feasible solutions and creates problems for systems with large number of units. The BB method [38], [119] is subjected to exponential time growth to execute problems with large systems. An expert system [51] is efficient in solving complex calculations in less computational time. But, inefficient in solving problems with new schedule.

The fuzzy theory [314] fuzzy set are used to determine the schedules error, but produces more complexities. Gravitational search algorithm has inherent ability to discover search space optimally. But, with the progress of subsequent iterations masses gets heavier and remains in close proximity and restrict algorithm to exploit search space with optimal fitness [276], [315].

One of the major observations from the above discussion is that some algorithms give better performance in solving a particular parameter but fail to give an optimal solution at the other end. It may be simple but optimal, and the other one may be complex but precise. [316]–[318]. So, in order to anticipate these complications, a trend of developing hybrid algorithms is advancing to evolve more efficient solutions [319], [320].

Chen *et al*. [36] have combined fuzzy iteration at the initial stage of dynamic programming. It was noticed that this fuzzy-based technique permits conventional dynamic programming to evaluate decision process more appropriately for solving multi-objective problems. Valenzuela *et al*. [63] integrated genetic algorithm with Lagrangian relaxation method to explore unit commitment problem with more enhanced performance compared GA, MA, DP and LR. It was proven that the seeded memetic GA-LR method gave better results compared with general methods.

Omran et al. [129] incorporated swarm intelligence with improvisation process of harmony search to find global-best position. The effect of noise on three Harmony search (HS) variants had been tested and results were compared with HS and improved Harmony search (IHS). It was noticed that global best harmony search method outperforms in searching global-best position precisely for even extremely small value of PAR.

Bavafa *et al*. [91] applied a hybrid combination of Lagrangian, evolutionary and quadratic programming to resolute UC problem of a 26 unit IEEE system. The advantages of both methods were integrated to provide superior search results within a short time. Yadav *et al*. [108] have developed a hybrid method by assimilating PSO with DE for solving dispatch and economic emissions. The hybrid model was utilized to minimize overall generation costs and emission costs. Now, after getting familiar with sufficient literature corresponding to the classical unit commitment problem, the following section presents the unit commitment problem formulation.

5.2 UNIT COMMITMENT PROBLEM FORMULATION

Unit commitment is a mixed-integer non-linear optimization problem due to the involvement of a large number of unit and system constraints. Classical UCP is subjected to various equality and inequality constraints. The objective of cost minimization can be brought into realization by selecting a particular combination of generating units for scheduling. The following section includes the UCP formulation for conventional power systems.

5.2.1 Unit commitment problem formulation for conventional power system

Electricity is generated primarily from thermal energy derived from the combustion of expensive fossil fuels. Fuel cost depends upon cost coefficients associated with each individual generator's characteristics. In a more broad sense, these generating units need a specific cost to start up before being available for service, and this cost is termed the "start-up cost". Once a generating unit is put online and connected with the system, it should be kept connected, as turning off a unit also has some associated costs. This cost is known as the "shut-down cost". So, the total cost of power generation is the algebraic addition of fuel cost, shut-down cost, and startup cost. The system and unit constraints are discussed in detail as follows:

5.2.1.1 Operating Cost

In general the fuel cost is characterized by second order quadratic equation given as,

$$F_{\cos t}=\sum_{i=1}^{N}[\left(a_i\,P_{i,h}^2+b_i\,P_{i,h}+c_i\right)] \tag{5.1}$$

Where, $a_i\,b_i and\,c_i$ are the fuel cost function expressed in $\$/\mathrm{h},\$/MWh, and\ \$/MWh^2$ respectively.

The startup cost is related to the boiler temperature and mathematically, startup cost STC_i can be expressed in terms of hot start-up cost $(HSch)$ and cold startup (CSc) of i[th] unit respectively.

$$STC_i=\begin{cases}HSc_{i,h}; & MDt_i\le T_{i.h}^{OFF}\le(MDt_i+CSh_i)\\ CSc_{i,h}; & T_{i,h}^{OFF}>\left(MDt_i+CSh_i\right)\end{cases}\ (i=N;h=1,2,3,.....,\mathrm{H}) \tag{5.2}$$

Where, MDt_i is the minimum down time of unit 'i', $T_{i.h}^{OFF}$ is the duration for which unit 'i' is continuously OFF and CSh_i is the cold start-up hours.

Shut down cost is constant and taken as zero in standard systems. Now, the total operating cost F_T is determined by summing up the generation cost of each unit and the start-up cost for a defined time interval. It can be mathematically represented as:

$$F_T=\sum_{h=1}^{H}(\sum_{i=1}^{N}[\left(a_i\,P_{i,h}^2+b_i\,P_{i,h}+c_i\right)U_{i,h}+STC_i(1-U_{\mathrm{i}(h-1)})U_{i,h}]\ \$/\mathrm{hr} \tag{5.3}$$

Unit commitment problem needs to provide optimum solution within certain constraints. The major constraints involved in UC problem are:

5.2.1.2 Operating Limits Constraints

This constraint deals with the maximum and minimum power generation. There is a limit below which power generation is not economical due to some technical limitations. Similarly, power generation should not be more maximum power generation limit. These power generation limits for a particular unit are calculated from the heat rate curve and fuel cost coefficient limits.

$$PG_i^{\min}\le PG\le PG_i^{\max}\ (i=1,2,....,N\ ;\ h=1,2,....,H) \tag{5.4}$$

5.2.1.3 Load Balance Constraints

The load demand never remains constant and continuously changes over the entire span of the time interval. It is desired that the overall power produced by all the committed units (N) for a particular duration (h) should always satisfy the connected load demand (D_L). Therefore, at any instant of time, the power supplied by thermal unit should always be equal to power demand.

$$\sum_{i=1}^{N} PG_i .U_{i,h} = D_L \qquad (i = 1,2,........,N; h = 1,2,3....,H) \tag{5.5}$$

5.2.1.4 Spinning Reserve Constraints

The additional generation capacity is referred to as Spinning Reserve. At any instant, the generated power should be equal to load demand and spinning reserve.

Mathematically,

$$\sum_{i=1}^{N} PG_i .U_{i,h} \geq D_{L(h)} + SR_{(h)} \qquad (i = 1,2,........,N; h = 1,2,3....,H) \tag{5.6}$$

5.2.1.5 Thermal Constraints

A generating unit cannot be instantly turned on and produce power. Before putting a particular generating unit online, it should meet certain thermal constraints.

5.2.1.6 Minimum Up-time Constraints

This constraint gives the minimum time to put a generating unit online after it has already been shut down.

Mathematically expressed as:

$$T_{i,h}^{ON} \geq MUT_i \tag{5.7}$$

5.2.1.7 Minimum down time Constraints

This constraint gives the minimum amount of time for which a particular unit should be kept in off condition before putting it online.

Mathematically expressed as:

$$T_{i,h}^{OFF} \geq MDT_i \tag{5.8}$$

5.2.1.8 Crew Constraints

This constraint is related to the probability of unavailability of sufficient crew members to monitor all units at the same time during the start-up process.

5.2.1.9 Initial States of units

It gives information related to the unit on-line/off-line status of each unit and helps to select minimum up /downtime based on data of the previous day's schedule. The initial state is indicated by either plus or minus signs. A '+' sign is for online status and a '-' sign is for offline status for a particular generating unit.

5.3 SOLUTION METHODOLOGIES FOR UNIT COMMITMENT PROBLEM

In this section, UC problem has been resolved by applying hHHO-IGWO, CHHO and CSMA. Subsequent section present various steps for spinning reserve and minimum up/down constraints repairing to minimize the overall generation cost.

5.3.1 Spinning Reserve Constraint Repairing

In order to update spinning reserve requirement of various thermal generating units, Minimum down time (MDT_i) of each generating unit along with duration for which i[th] generating unit is continuously OFF $(T_{i,h}^{OFF})$ is taken into consideration. Spinning reserve constraint is repaired as per code mentioned below and flow chart for spinning reserve repair mechanism is shown in Fig.5.1.

Step1: list the units in descending as per maximum generation.

Step2: *for* i = 1 to N
if $u_{i,h} = 0$
then $u_{i,h} = 1$
else if $T_{i,h}^{OFF} > MDT_i$
then $T_{i,h}^{ON} = T_{i,h-1}^{ON} + 1$ and $T_{i,h}^{OFF} = 0$
end if
end for

Step-3: Verify new generating power of units.

Step-4: if $\sum_{j=1}^{N} P_{j,\max} u_{j,h} \geq D_{Lh} + SR_h$ then stop the algorithm, else go to step-2.

Step-5: if $T_{i,h}^{OFF} < MDT_i$ then do $l = h - T_{i,h}^{OFF} + 1$ and set $u_{i,h} = 1$

Step-6: Calculate $T_i^l = T_{l-1,i}^{ON} + 1$ and $T_{i,h}^{OFF} = 0$

Step-7: if l >h, Verify generator output power for $\sum_{j=1}^{N} P_{\mathrm{j,max}} u_{h,j} \geq D_h + R_h$, else increment l by 1 and go to step-5.

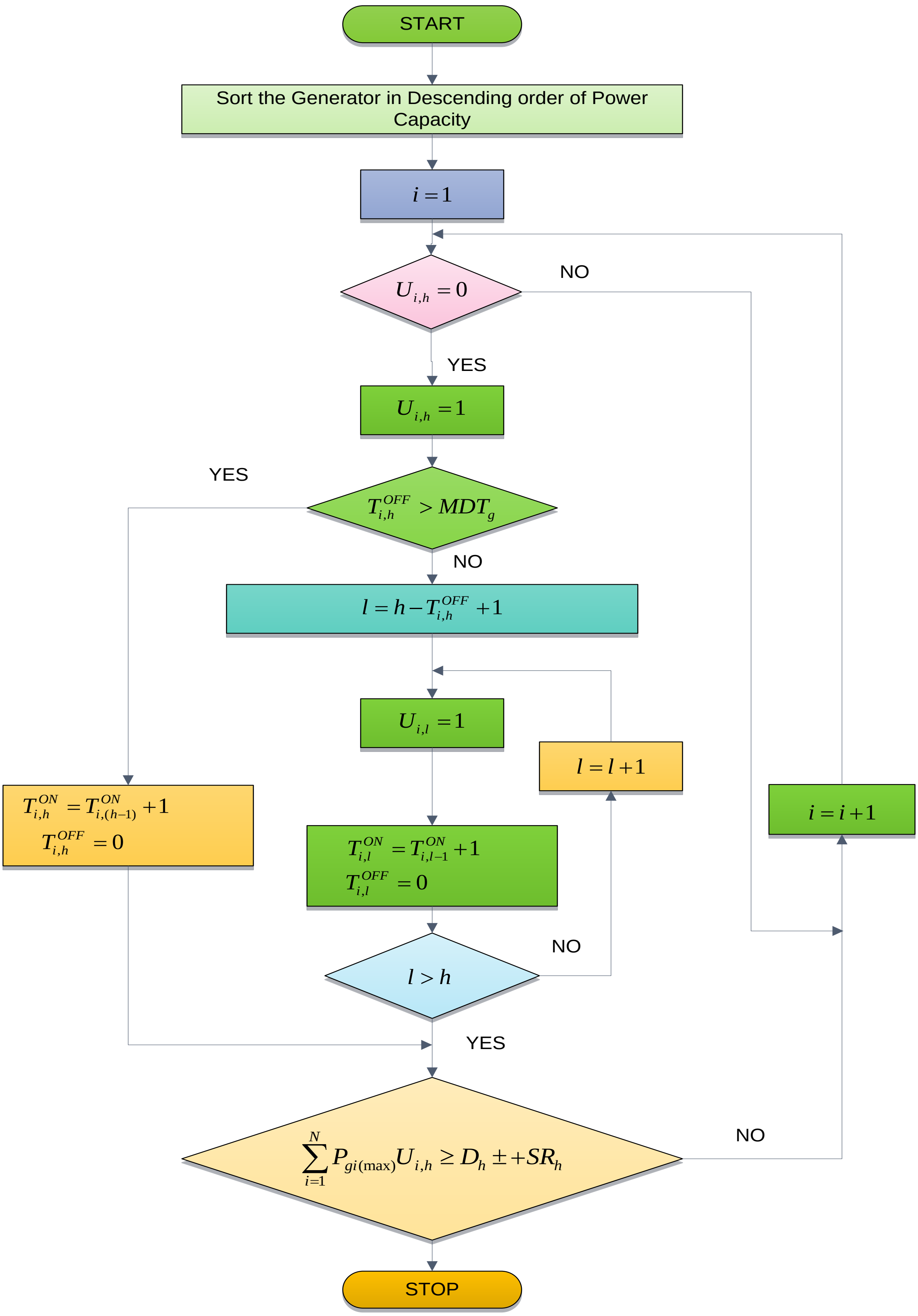


Fig.5.1: Spinning reserve repairing

5.3.2 Minimum Up/Down constraints repairing

To satisfy Minimum up/down time requirement of generating units, following repairing mechanism is adopted as follows.

for *h*=1 to H
if h==1
Compute $T_h^{ON} = T_{h_0}^{ON}\ U_{i,h} + U_{i,h}\,'$
Compute $T_h^{OFF} = (T_{h_0}^{OFF})'\ \bar{T}_h^{ON} + \bar{T}_h^{ON}$
else
Compute $T_h^{ON} = T_{h-1}^{ON}\ U_{i,h}\,' + U_{i,h}\,'$
Compute $T_h^{OFF} = T_{h-1}^{OFF}\ \bar{T}_h^{ON} + \bar{T}_h^{ON}$
end
end
where,
$U_{i,h} = U_{i,(h-1)}F + U_{i,h}\bar{F}$ and $F = [T_{h-1}^{OFF} == 0\ \&\ T_{h-1}^{ON} < MUT\,')\,|\,(T_{h-1}^{ON} == 0\ \&\ T_{h-1}^{OFF} < MDT\,']^T$

5.3.3 De-commitment of excessive generating units

In unit commitment problem, it is beneficial to shut-down the excessive units to avoid power wastage. In order to de-commit excessive generating units for which i[th] generating unit is continuously OFF is taken into consideration and constraint is repaired as represented in Fig.5.2 (a) and process is illustrated in Fig.5.2 (b)

for h=1: H
for i=1: N
do $i = h(N+1-i)$ and calculate generating power $P1 = P_{i(\max)} \times (U_{i,h})'$
if $u_{i,h} = 1$ **then**
if $P1 - P_{\max(i)} \geq D_h + SR_h$ **then**
if $(T_{i,h}^{ON} > MUT_i)\,|\,(T_{i,h}^{ON} = 1)$ **then**
do $u_{hi} = 0$ and $T_{i,h}^{ON} = 0$
if h==1 **then**
do $T_{i,h}^{OFF} = T_{i,h_0}^{OFF} + 1$
else
do $T_{i,h}^{OFF} = T_{i,h-1}^{OFF} + 1$
end
else
continue;
end
else
break;
end
end

Fig.5.2 (a): De-commitment of excessive generative units

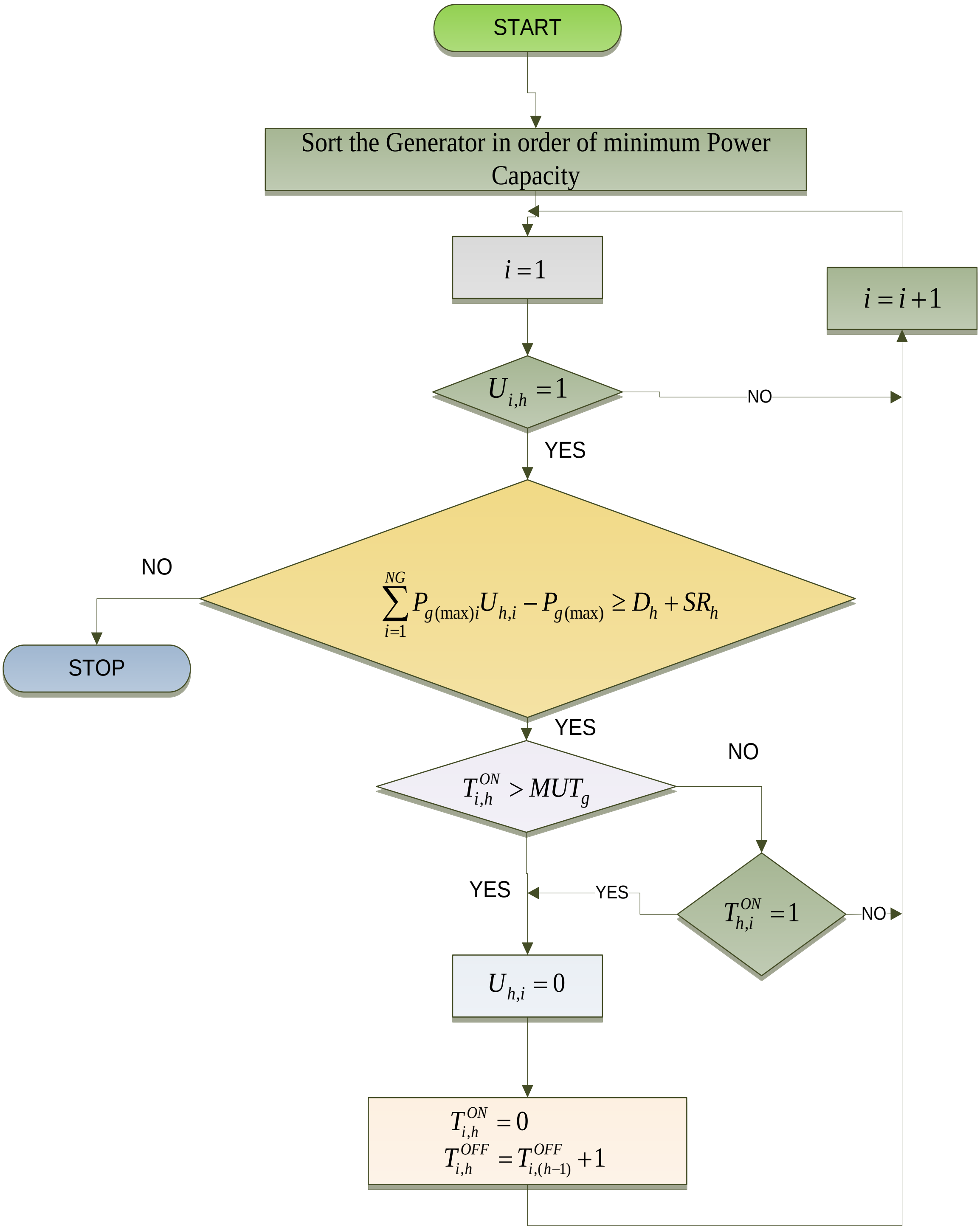


Fig.5.2 (b): De-commitment procedure of disproportionate generative units

5.4 HYBRID HARRIS HAWKS OPTIMIZER

In order to implement Hybrid Harris Hawks optimizer (hHHO-IGWO), the general operators of HHO algorithm and IGWO algorithm are integrated.

The optimization procedure for the hHHO-IGWO algorithm shown in Fig.5.3.consists of the following ten steps:

Step-1: As indicated below, configure UCP parameters and individuals in the population:

The unit's ON/OFF schedule is saved as an integer-matrix, which is technically described as:

$$U_{\kappa hi} = \begin{bmatrix} u_{11}^{\kappa} & u_{12}^{\kappa} & \cdots & u_{1NG}^{\kappa} \\ u_{21}^{\kappa} & u_{22}^{\kappa} & \cdots & u_{2NG}^{\kappa} \\ \vdots & \vdots & \vdots & \vdots \\ u_{H1}^{\kappa} & u_{H2}^{\kappa} & \cdots & u_{HNG}^{\kappa} \end{bmatrix}_{H \times NG}$$

Step-2: Reconfigure the schedule.

Step-3: Change the individual status.

Step-4: Repair unit status for minimum up/down time defilements.

Step-5: De-commit the population's extra units

Step-6: The problem of cost-effective load dispatch is then solved, and fuel costs for each hour are determined.

Step-7: Apply HHO and perform exploration phase to generate updated target vector $X(itn+1)$.

Step-8: Apply Levy flight to further update to generate $X(itn+1)^{new}$.

Step-9: Replace worst positions vector $X(itn+1)^{worst}$ with $X(itn+1)^{new}$

Step-10: Determine overall generation cost for (it^n)

Step-11: If $it^n = it_{\max}^n$, then go to step 13.

Step-12: If $it^n < it_{\max}^n$, increase it^n by one and return to step 3 and repeat.

Step-13: Stop and evaluate best solution in the population

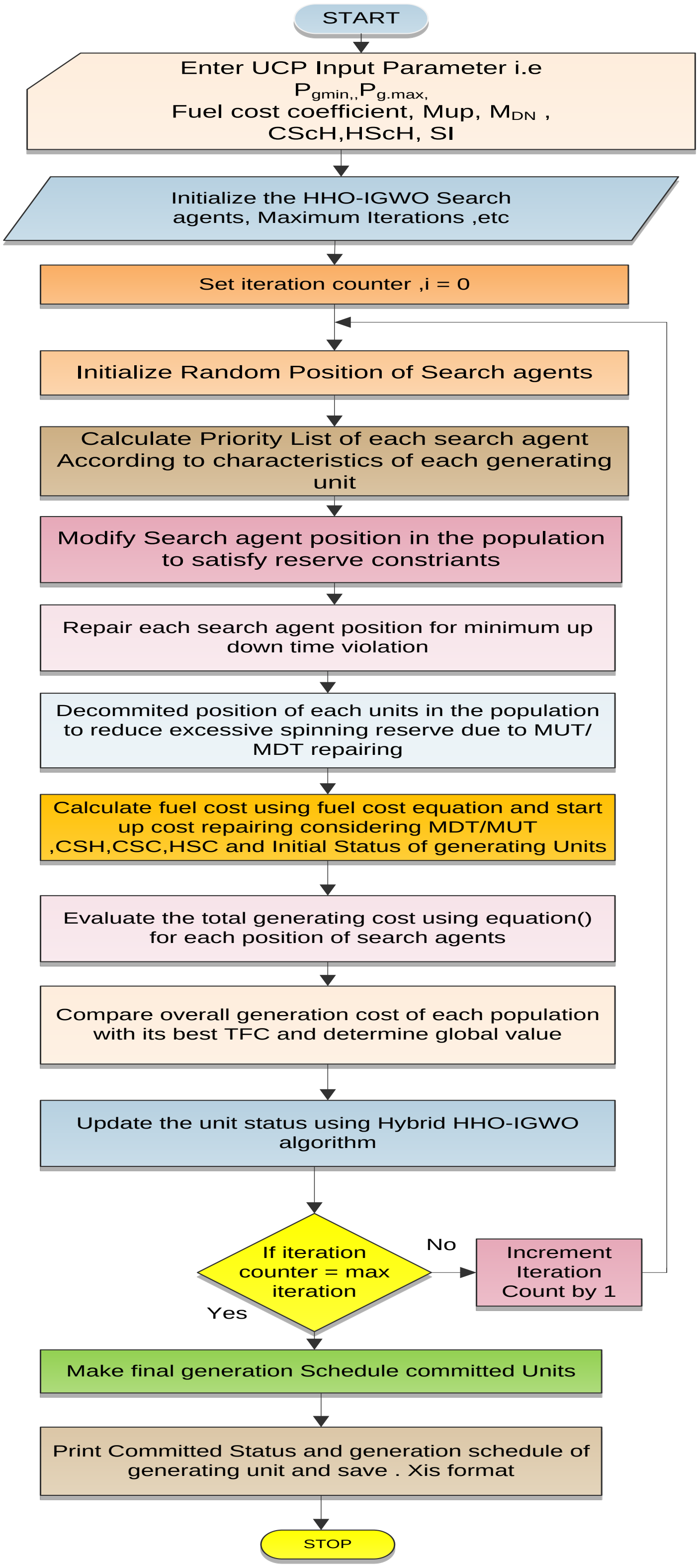


Fig.5.3: Flowchart of UC process using Hybrid HHO-IGWO

5.5 CHAOTIC HARRIS HAWKS OPTIMIZER

In order to utilize the chaotic algorithm for unit commitment issue, the general operators of Harris Hawks are integrated with Tent chaotic function. Initially, a random solution is generated within the entire population by clubbing corresponding chaotic function. This best solution is then compared with the solution obtained by HHO algorithm. In proposed algorithm, chaotic search is applied to optimize a group of units to be committed for mininizing the overall cost. The succeeding steps in the proposed CHHO algorithm are:

Step-1: Initialization of UCP and Chaotic parameters of the algorithm.

Step-2: Enter UCP input parameters and generate random vectors as many Hawks position using eqn.(5.1).Each random vector is defined as generating unit ON/OFF (or 1/0) status, defined as:

$$U_{\kappa hi} = \begin{bmatrix} u_{11}^{\kappa} & u_{12}^{\kappa} & \cdots & u_{1NG}^{\kappa} \\ u_{21}^{\kappa} & u_{22}^{\kappa} & \cdots & u_{2NG}^{\kappa} \\ \vdots & \vdots & \vdots & \vdots \\ u_{H1}^{\kappa} & u_{H2}^{\kappa} & \cdots & u_{HNG}^{\kappa} \end{bmatrix}_{H\times NG}$$

Step-3: Arrange the generating units in descending order according to their maximum generation capability.

Step-4: Modification of units' status of every entities in the population obeying reserve restrictions as mentioned in 5.3.1.

Step-5: Repair unit status for minimum up/down time defilements as per section 5.3.2.

Step-6: De-commit the population's extra units

Step-7: Apply HHO and perform exploration phase to generate updated target vector $X(itn+1)$.

Step-8: Apply Levy flight to further update $X(itn+1)$ to generate $X(itn+1)^{new}$.

Step-9: Replace worst positions vector $X(itn+1)^{worst}$ with $X(itn+1)^{new}$ using eqn. (2.13)

Step-10: Determine overall generation cost for (it^n) .

Step-11: If $it^n = it_{\max}^n$, then go to step 13.

Step-12: If $it^n < it^n_{\max}$, increase it^n by one and return to step 3 and repeat.

Step-13: Break and figure out the most profitable solution to the unit commitment dilemma.

5.6 CHAOTIC SLIME MOULD ALGORITHM

The detailed theoretical and mathematical aspects of CSMA has been already discussed in chapter 3. In proposed algorithm, chaotic search is applied to optimize a vector U_{NP} of units to be committed for mininizing the overall cost. The various steps for the proposed CHHO algorithm are mentioned below:

Step-1: Initialization of UCP and Chaotic parameters of the algorithm

Step-2: Enter UCP input parameters and generate random vectors as many Slime mould position using eqn (5.1).

Step-3: Display the generating units in descending order according to their maximum generation capability.

Step-4: Modification of units' status of every individuals in the population

Step-5: Repair individual unit status time defilements

Step-6: De-commit the population's extra units for reducing spinning reserve

Step-7: Apply SMA and perform exploration to generate updated target vector $X(itn+1)$

.**Step-8:** Apply Chaotic strategy further update $X(itn+1)$ using smell index generate $X(itn+1)^{new}$.

Step-9: Replace worst positions vector $X(itn+1)^{worst}$ with $X(itn+1)^{new}$

Step-10: Determine overall generation cost for (it^n)

Step-11: If $it^n = it^n_{\max}$, then go to step 13.

Step-12: If $it^n < it^n_{\max}$, increase it^n by one and return to step 3 and repeat.

Step-13: End and figure out the most profitable solution to the unit commitment dilemma.

5.7 SYSTEM DATA

In this research work, to resolute unit commitment problem for small, medium and large system, standard IEEE system data consisting of 10, 20, 40 and 60 units has been analyzed by implementing proposed algorithms. The system data used in the proposed study are load demand, fuel cost coefficients of each generating unit, MUT, MDT and Initial State (IS).

5.7.1 Ten Unit System

The test data for 10- unit system is specified in Table-5.1 and fuel cost coefficients for corresponding units are given in Table-5.2. The load demand profile for 24-hours is presented in Table-5.3.

Table-5.1: Test data for 10-unit system

Unit No.	Pmax (MW)	Pmin (MW)	Minimum Up-Down Time (h)		Start-up Costs ($)		CSH (h)	IS
			MUT	MDT	HSC	CSC		
U1	455	150	8	8	4500	9000	5	8
U2	455	150	8	8	5000	10000	5	8
U3	130	20	5	5	550	1100	4	-5
U4	130	20	5	5	560	1120	4	-5
U5	162	25	6	6	900	1800	4	-6
U6	80	20	3	3	170	340	2	-3
U7	85	25	3	3	260	520	2	-3
U8	55	10	1	1	30	60	0	-1
U9	55	10	1	1	30	60	0	-1
U10	55	10	1	1	30	60	0	-1

Table-5.2: Fuel cost coefficients for 10-generating units

Unit No.	Fuel Cost Coefficients		
	a ($/MW^{2}h)	b ($/MWh)	c ($/h)
U1	1000	16.19	0.00048
U2	970	17.26	0.00031
U3	700	16.6	0.002
U4	680	16.5	0.00211
U5	450	19.7	0.00398
U6	370	22.26	0.00712
U7	480	27.74	0.00079
U8	660	25.92	0.00413
U9	665	27.27	0.00222
U10	670	27.79	0.00173

Table-5.3: Demand for 10, 20, 40 and 60 units for 24-hours

Hour	10-Units	20-Units	40-units	60-Units
h1	700	1400	2800	4200
h2	750	1500	3000	4500
h3	850	1700	3400	5100
h4	950	1900	3800	5700
h5	1000	2000	4000	6000
h6	1100	2200	4400	6600
h7	1150	2300	4600	6900
h8	1200	2400	4800	7200
h9	1300	2600	5200	7800
h10	1400	2800	5600	8400
h11	1450	2900	5800	8700
h12	1500	3000	6000	9000
h13	1400	2800	5600	8400
h14	1300	2600	5200	7800
h15	1200	2400	4800	7200
h16	1050	2100	4200	6300
h17	1000	2000	4000	6000
h18	1100	2200	4400	6600
h19	1200	2400	4800	7200
h20	1400	2800	5600	8400
h21	1300	2600	5200	7800
h22	1100	2200	4400	6600
h23	900	1800	3600	5400
h24	800	1600	3200	4800

5.8 RESULTS AND DISCUSSION

This section presents UC problem resolved by proposed hybrid and chaotic algorithms such as hHHO-IGWO, CHHO and CSMA. The solution for standard test systems entailing of 10, 20, 40 and 60 generating units has been discussed. The proposed algorithms have been simulated in MATLAB 2018a Windows 10, CPU@2.10Ghz-4GB RAM Core i5.

5.8.1 Testing of unit commitment problem by using hHHO-IGWO method

The hHHO-IGWO is applied to systems entailing 10, 20, 40 and 60 units and simulation results are recorded for corresponding thermal units. Due to stochastic nature of hHHO-

IGWO algorithm, program is simulated for 30 trials runs and 500 iterations for better solution efficiency.

(a) Testing of 10 -unit system using hHHO-IGWO

The proposed algorithm is applied to standard test systems of 10-units with 10% SR. The simulation results for Classical UC consisting of conventional thermal units has been recorded. Due to stochastic nature of hHHO-IGWO algorithm, program is simulated for 30 trials runs and 500 iterations for better solution efficiency.

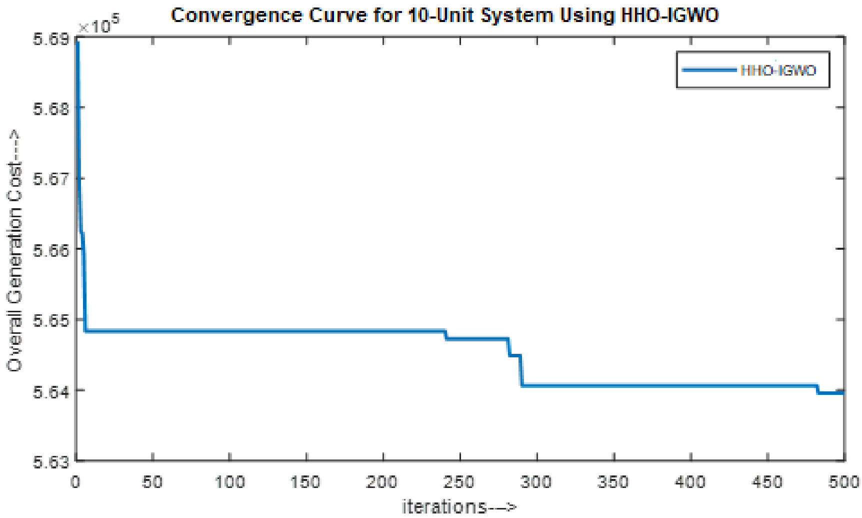


Fig.5.4: Convergence for 10 unit system using hHHO-IGWO

Referring Table 5.4 , U1 and U2 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load deamd. During the peak hours, U3 to U9 units contribute their power to meet the corresponding load demand.At 12th hour , load is at Peak demand and thus all the units are in ON state. U10 act as the reserve unit and runs only during the peak demand.Start-up cost depends upon the operating temperature of particular unit.The total operating cost is the sum of start-up cost and generation cost of units for a 24 hour duration. The simulation results for HHO-IGWO algorithm for 10 units with 10% SR shows that total cost of generation with UC is **$ 563435.9964**. Fig. 5.4 shows that evaluaion for 10 units using hHHO-IGWO convergences effciently towards best fitness.The results shows that proposed algorithm effeciently selects a particular combination of units to meet the hourly load demand and evaluates a cost effective solution to unit commitment problem.

Table-5.4: Scheduling for 10 units using hHHO-IGWO

Time (h)	Generation scheduling										Power (MW)	Start-Up Cost	Hourly Fuel Cost
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10			
1	455	245	0	0	0	0	0	0	0	0	700	1020	13683
2	455	295	0	0	0	0	0	0	0	0	750	550	14554
3	455	370	0	0	25	0	0	0	0	0	850	900	16809
4	455	455	0	0	40	0	0	0	0	0	950	0	18598
5	455	390	0	130	25	0	0	0	0	0	1000	0	20020
6	455	360	130	130	25	0	0	0	0	0	1100	0	22387
7	455	410	130	130	25	0	0	0	0	0	1150	0	23262
8	455	455	130	130	30	0	0	0	0	0	1200	0	24150
9	455	455	130	130	85	20	25	0	0	0	1300	430	27251
10	455	455	130	130	162	33	25	0	10	0	1400	60	30076
11	455	455	130	130	162	73	25	10	10	0	1450	60	31916
12	455	455	130	130	162	80	25	43	10	10	1500	60	33890
13	455	455	130	130	162	33	25	10	0	0	1400	0	30058
14	455	455	130	130	85	20	25	0	0	0	1300	0	27251
15	455	455	130	130	30	0	0	0	0	0	1200	0	24150
16	455	310	130	130	25	0	0	0	0	0	1050	0	21514
17	455	260	130	130	25	0	0	0	0	0	1000	0	20642
18	455	360	130	130	25	0	0	0	0	0	1100	0	22387
19	455	455	130	130	30	0	0	0	0	0	1200	0	24150
20	455	455	130	130	162	33	25	10	0	0	1400	490	30058
21	455	455	130	130	85	20	25	0	0	0	1300	0	27251
22	455	455	0	0	145	20	25	0	0	0	1100	0	22736
23	455	425	0	0	0	20	0	0	0	0	900	0	17645
24	455	345	0	0	0	0	0	0	0	0	800	0	15427
Worst Cost($)=565425.50222				**Best Cost($)=563435.9964**				**Mean Cost($)=564452.7594**					**Total= 563435.9964($)**
Worst Time(Sec.)= 0.0625				**Best Time(Sec.)= 0.03125**				**Mean Time(Sec.)= 0.04895**					

(b) Testing of 20 -unit system using hHHO-IGWO

For 20-unit test system, the data from the 10-unit system was copied and multiplied by two. For all 30 trial runs with 500 iterations, the population size is set to 80, and simulation results for corresponding thermal units are recorded.

Optimal solution of 20-unit test system using hHHO-IGWO is illustrated in Table-5.5. Referring Table 5.5, U1, U2, U11 and U12 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load demand. During the peak hours, U3 to U19 units contribute their power to meet the corresponding load demand. At 12th hour, load is at maximum and thus all the units are in ON state. U10 and U20 act as the reserve unit and runs only during the peak demand.

Table-5.5: Scheduling of 20-units using hHHO-IGWO

Time (h)	Scheduling for 20-unit																				Hourly Fuel Cost
	U1	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**	**U8**	**U9**	**U10**	**U11**	**U12**	**U13**	**U14**	**U15**	**U16**	**U17**	**U18**	**U19**	**U20**	
1	455	245	0	0	0	0	0	0	0	0	455	245	0	0	0	0	0	0	0	0	27366
2	455	295	0	0	0	0	0	0	0	0	455	295	0	0	0	0	0	0	0	0	29109
3	455	382	0	0	25	0	0	0	0	0	455	382	0	0	0	0	0	0	0	0	33111
4	455	418	0	130	25	0	0	0	0	0	455	418	0	0	0	0	0	0	0	0	37197
5	455	403	0	130	25	0	0	0	0	0	455	403	0	130	0	0	0	0	0	0	39533
6	455	372	130	130	25	0	0	0	0	0	455	372	130	130	0	0	0	0	0	0	44266
7	455	410	130	130	25	0	0	0	0	0	455	410	130	130	25	0	0	0	0	0	46524
8	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	48301
9	455	455	130	130	98	20	25	0	0	0	455	455	130	130	98	20	0	0	0	0	53839
10	455	455	130	130	162	33	25	10	0	10	455	455	130	130	162	33	25	0	0	0	60144
11	455	455	130	130	162	73	25	10	10	0	455	455	130	130	162	73	25	10	10	0	63832
12	455	455	130	130	162	80	25	43	10	10	455	455	130	130	162	80	25	43	10	10	67780
13	455	455	130	130	162	33	25	10	10	0	455	455	130	130	162	33	25	0	0	0	60133
14	455	455	130	130	98	20	25	0	0	0	455	455	130	130	98	20	0	0	0	0	53839
15	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	48301
16	455	310	130	130	25	0	0	0	0	0	455	310	130	130	25	0	0	0	0	0	43027
17	455	260	130	130	25	0	0	0	0	0	455	260	130	130	25	0	0	0	0	0	41284
18	455	350	130	130	25	20	0	0	0	0	455	350	130	130	25	0	0	0	0	0	45243
19	455	450	130	130	25	20	0	0	0	0	455	450	130	130	25	0	0	0	0	0	48744
20	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	0	10	0	60133
21	455	455	130	130	95	0	25	0	0	0	455	455	130	130	95	20	25	0	0	0	54092
22	455	455	0	130	50	0	25	0	0	0	455	455	0	130	0	20	25	0	0	0	45039
23	455	315	0	130	0	0	0	0	0	0	455	315	0	130	0	0	0	0	0	0	35528
24	455	345	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0	30855
																Overall Cost of Generation =**1124860.6904($)**					

The convergence curves with for 20-unit system is shown in Fig.5.5. The simulation results for Hybrid Harris Hawks algorithm shows that total cost of generation with thermal units is **$ 1124860.6904**.

The results shows that proposed algorithm efficiently selects a particular combination of units to meet the hourly load demand and evaluates a cost effective solution to unit commitment problem.

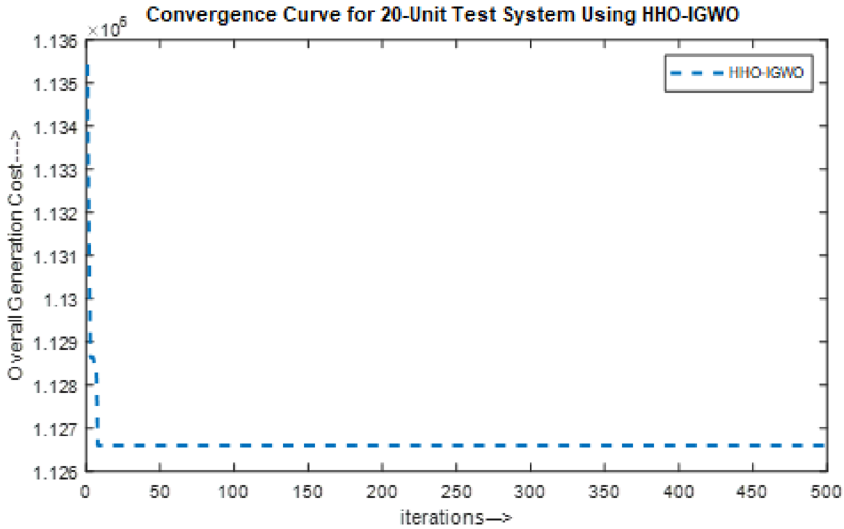


Fig.5.5: Convergence for 20-units using hHHO-IGWO

(c) Testing of 40 -unit system using hHHO-IGWO

The hHHO-IGWO method is tested for solving unit commitment problem 40-unit system. The data of 10-unit system was replicated and load demand is multiplied by 4 for forty units. Population size of 80 is taken into consideration for all trial solutions. Table-5.6(a) and 5.6(b) illustrates optimal dispatch for 40-unit system. The convergence curve for 40-unit system is shown in Fig.5.6.

Referring Table 5.6(a) and 5.6(b), U1, U2, U11, U12,U21,U22,U31 and U32 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load demand. For rest of hours, U3 to U9, U13 to U19, U23 to U29 and U33 to U39 contributes their power meet the corresponding load demand. At 12th hour, load is at maximum and thus all the units are in ON state. U10, U20, U30 and U40 act as the reserve unit and runs only during the peak demand. The total operating cost is the sum of start-up cost and generation cost of units for a 24 hour duration.

Table-5.6(a): Scheduling of 1 to 20 for 40 units using hHHO-IGWO

Time (h)	Scheduling for 1 to 20 units																			
	U1	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**	**U8**	**U9**	**U10**	**U11**	**U12**	**U13**	**U14**	**U15**	**U16**	**U17**	**U18**	**U19**	**U20**
1	455	245	0	0	0	0	0	0	0	0	455	245	0	0	0	0	0	0	0	0
2	455	295	0	0	0	0	0	0	0	0	455	295	0	0	0	0	0	0	0	0
3	455	363	0	0	0	0	0	0	0	0	455	363	0	0	0	0	0	0	0	0
4	455	363	0	130	0	0	0	0	0	0	455	363	0	130	0	0	0	0	10	0
5	455	350	130	130	0	0	0	0	0	0	455	350	130	130	0	0	0	0	0	0
6	455	379	130	130	25	0	0	0	0	0	455	379	130	130	0	0	0	0	0	0
7	455	416	130	130	25	0	25	0	0	0	455	416	130	130	25	0	0	0	0	0
8	455	454	130	130	25	0	25	0	0	0	455	454	130	130	25	0	25	0	0	0
9	455	455	130	130	103	20	25	0	0	0	455	455	130	130	103	20	25	0	0	0
10	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0
11	455	455	130	130	162	73	25	10	10	0	455	455	130	130	162	73	25	10	10	0
12	455	455	130	130	162	80	25	43	10	10	455	455	130	130	162	80	25	43	10	10
13	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0
14	455	455	130	130	104	20	25	0	0	0	455	455	130	130	104	20	0	0	0	0
15	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0
16	455	310	130	130	25	0	0	0	0	0	455	310	130	130	25	0	0	0	0	0
17	455	260	130	130	25	0	0	0	0	0	455	260	130	130	25	0	0	0	0	0
18	455	360	130	130	25	0	0	0	0	0	455	360	130	130	25	0	0	0	0	0
19	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0
20	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0
21	455	455	130	130	113	20	25	0	0	0	455	455	130	130	113	20	25	0	0	0
22	455	438	130	130	0	20	25	0	0	0	455	438	0	130	0	20	25	0	0	0
23	455	348	0	130	0	0	0	0	0	0	455	348	0	130	0	0	0	0	0	0
24	455	345	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0

Table-5.6(b): Scheduling of 21-40 units for 40 units using hHHO-IGWO

Time (h)	Scheduling for 21 to 40-Units																				Hourly Fuel Cost
	U21	**U22**	**U23**	**U24**	**U25**	**U26**	**U27**	**U28**	**U29**	**U30**	**U31**	**U32**	**U33**	**U34**	**U35**	**U36**	**U37**	**U38**	**U39**	**U40**	
1	455	245	0	0	0	0	0	0	0	0	455	245	0	0	0	0	0	0	0	0	54733
2	455	295	0	0	0	0	0	0	0	0	455	295	0	0	0	0	0	0	0	0	58218
3	455	363	0	0	0	0	0	0	0	0	455	363	0	130	0	0	0	0	0	0	65794
4	455	363	0	130	0	0	0	0	0	0	455	363	0	130	0	0	0	0	0	0	75314
5	455	350	0	130	0	0	0	0	0	0	455	350	0	130	0	0	0	0	0	0	79285
6	455	379	130	130	0	0	0	0	0	0	455	379	130	130	0	0	0	0	0	0	88025
7	455	416	130	130	0	0	0	0	0	0	455	416	130	130	0	0	0	0	0	0	92770
8	455	454	130	130	25	0	0	0	0	0	455	454	130	130	0	0	0	0	0	0	97518
9	455	455	130	130	103	20	0	0	0	0	455	455	130	130	103	0	0	0	0	0	107269
10	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0	120230
11	455	455	130	130	162	73	25	10	10	0	455	455	130	130	162	73	25	10	10	0	127664
12	455	455	130	130	162	80	25	43	10	10	455	455	130	130	162	80	25	43	10	10	135561
13	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0	120230
14	455	455	130	130	104	20	0	0	0	0	455	455	130	130	104	20	0	0	0	0	107016
15	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	96601
16	455	310	130	130	25	0	0	0	0	0	455	310	130	130	25	0	0	0	0	0	86055
17	455	260	130	130	25	0	0	0	0	0	455	260	130	130	25	0	0	0	0	0	82567
18	455	360	130	130	25	0	0	0	0	0	455	360	130	130	25	0	0	0	0	0	89548
19	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	96601
20	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0	120230
21	455	455	130	130	113	20	25	0	0	0	455	455	130	130	0	20	25	0	0	0	108593
22	455	438	0	130	0	20	25	0	0	0	455	438	0	130	0	20	25	0	0	0	90488
23	455	348	0	130	0	0	0	0	0	0	455	348	0	0	0	0	0	0	0	0	70466
24	455	345	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0	61710
																Overall Cost of Generation =**2249657.3623($)**					

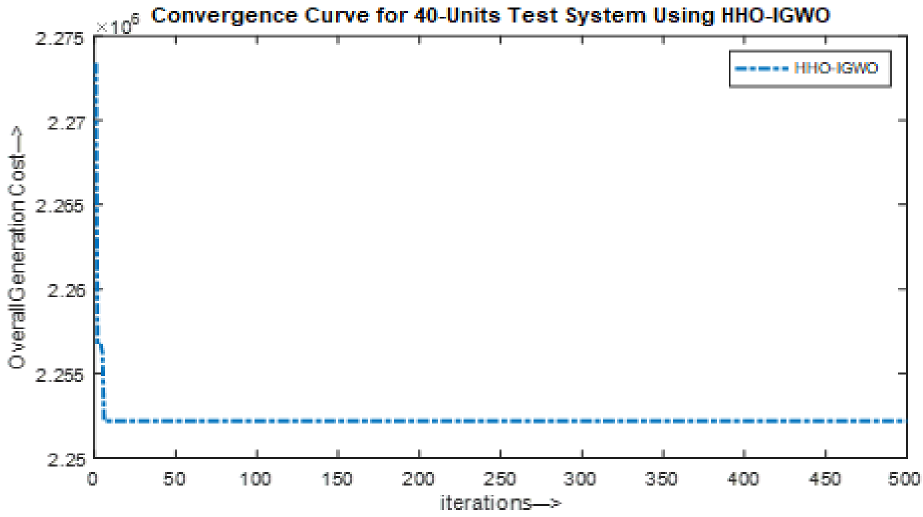


Fig.5.6: Convergence Curve for 40-unit system using hHHO-IGWO

The simulation results for hHHO-IGWO method for 40 units shown in above results shows that total cost of generation with thermal units is **$ 2249657.3623**. The results shows that proposed algorithm efficiently selects a particular combination of units to meet the hourly load demand and evaluates a cost effective solution to unit commitment problem.

(d) Testing of 60-unit system using hHHO-IGWO

The hHHO-IGWO method is tested for solving unit commitment problem for 60-units. The statistics of 10-unit system was replicated and multiplied by 6 for sixty units. Table-5.7 (a), 5.7(b) and 5.7(c) illustrates optimal dispatch for 60-unit system. The convergence curve for 60-unit system is shown in Fig.5.7.

In Table 5.7(a), 5.7(b) and 5.7(c), U1, U2, U11, U12, U21, U22, U31, U32, U41, U42, U51 and U52 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load demand. For rest of hours, U3 to U9, U13 to U19, U23 to U29, U33 to U39, U43 to U49 and U53 to U59 contributes their power to meet the corresponding load demand. At 12th hour, load is at peak demand and thus all the units are in ON state. U10, U20, U30, U40, U50 and U60 act as the reserve unit and runs only during the peak demand. The total operating cost is the sum of start-up cost and generation cost of units for a 24 hour duration.

Table-5.7(a): Scheduling of 1 to 20 for 60 units using hHHO-IGWO

Time (h)	Scheduling for 1 to 20 units																			
	U1	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**	**U8**	**U9**	**U10**	**U11**	**U12**	**U13**	**U14**	**U15**	**U16**	**U17**	**U18**	**U19**	**U20**
1	455	223	0	0	0	0	0	0	0	0	455	223	130	0	0	0	0	0	0	0
2	455	273	0	0	0	0	0	0	0	0	455	273	130	0	0	0	0	0	0	0
3	455	352	0	130	0	0	0	0	0	0	455	352	130	0	0	0	0	0	0	0
4	455	363	0	130	0	0	0	0	0	0	455	363	130	130	0	0	0	0	0	0
5	455	350	130	130	0	0	0	0	0	0	455	350	130	130	0	0	0	0	0	0
6	455	377	130	130	25	0	0	0	0	0	455	377	130	130	25	0	0	0	0	0
7	455	418	130	130	25	0	0	0	0	0	455	418	130	130	25	0	0	0	0	0
8	455	455	130	130	29	0	0	0	0	0	455	455	130	130	29	0	0	0	0	0
9	455	455	130	130	102	20	25	0	0	0	455	455	130	130	102	20	0	0	0	0
10	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	10	0	0
11	455	455	130	130	162	75	25	10	10	10	455	455	130	130	162	75	25	10	10	0
12	455	455	130	130	162	80	25	45	10	10	455	455	130	130	162	80	25	45	10	10
13	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	10	0	0
14	455	455	130	130	102	20	25	0	0	0	455	455	130	130	102	20	0	0	0	0
15	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0
16	455	310	130	130	25	0	0	0	0	0	455	310	130	130	25	0	0	0	0	0
17	455	260	130	130	25	0	0	0	0	0	455	260	130	130	25	0	0	0	0	0
18	455	356	130	130	25	0	0	0	0	0	455	356	130	130	25	0	0	0	0	0
19	455	455	130	130	26	0	0	0	0	0	455	455	130	130	26	0	0	0	0	0
20	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	10	0	0
21	455	455	130	130	131	20	25	0	0	0	455	455	130	130	131	20	25	0	10	0
22	455	453	0	130	0	20	25	0	0	0	455	453	0	130	0	20	25	0	0	0
23	455	377	0	130	0	0	0	0	0	0	455	377	0	130	0	0	0	0	0	0
24	455	345	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0

Table-5.7(b): Scheduling of 21 to 40 units for 60 units using hHHO-IGWO

Time (h)	Scheduling for 21 to 40 units																			
	U21	**U22**	**U23**	**U24**	**U25**	**U26**	**U27**	**U28**	**U29**	**U30**	**U31**	**U32**	**U33**	**U34**	**U35**	**U36**	**U37**	**U38**	**U39**	**U40**
1	455	223	0	0	0	0	0	0	0	0	455	223	130	0	0	0	0	0	0	0
2	455	273	0	0	0	0	0	0	0	0	455	273	130	0	0	0	0	0	0	0
3	455	352	0	130	0	0	0	0	0	0	455	352	130	0	0	0	0	0	0	0
4	455	363	0	130	0	0	0	0	0	0	455	363	130	130	0	0	0	0	0	0
5	455	350	130	130	0	0	0	0	0	0	455	350	130	130	0	0	0	0	0	0
6	455	377	130	130	25	0	0	0	0	0	455	377	130	130	25	0	0	0	0	0
7	455	418	130	130	25	0	0	0	0	0	455	418	130	130	25	0	0	0	0	0
8	455	455	130	130	29	0	0	0	0	0	455	455	130	130	29	0	0	0	0	0
9	455	455	130	130	102	20	25	0	0	0	455	455	130	130	102	20	0	0	0	0
10	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	10	0	0
11	455	455	130	130	162	75	25	10	10	10	455	455	130	130	162	75	25	10	10	0
12	455	455	130	130	162	80	25	45	10	10	455	455	130	130	162	80	25	45	10	10
13	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	10	0	0
14	455	455	130	130	102	20	25	0	0	0	455	455	130	130	102	20	0	0	0	0
15	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0
16	455	310	130	130	25	0	0	0	0	0	455	310	130	130	25	0	0	0	0	0
17	455	260	130	130	25	0	0	0	0	0	455	260	130	130	25	0	0	0	0	0
18	455	356	130	130	25	0	0	0	0	0	455	356	130	130	25	0	0	0	0	0
19	455	455	130	130	26	0	0	0	0	0	455	455	130	130	26	0	0	0	0	0
20	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	10	0	0
21	455	455	130	130	131	20	25	0	0	0	455	455	130	130	131	20	25	0	10	0
22	455	453	0	130	0	20	25	0	0	0	455	453	0	130	0	20	25	0	0	0
23	455	377	0	130	0	0	0	0	0	0	455	377	0	130	0	0	0	0	0	0
24	455	345	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0

Table-5.7(c): Scheduling of 41 to 60 for 60 units using hHHO-IGWO

Time (h)	Scheduling for 41 to 60 units																				Hourly Fuel Cost
	U41	**U42**	**U43**	**U44**	**U45**	**U46**	**U47**	**U48**	**U49**	**U50**	**U51**	**U52**	**U53**	**U54**	**U55**	**U56**	**U57**	**U58**	**U59**	**U60**	
1	455	223	0	0	0	0	0	0	0	0	455	223	0	0	0	0	0	0	0	0	82728
2	455	273	0	0	0	0	0	0	0	0	455	273	0	0	0	0	0	0	0	0	87952
3	455	352	0	0	0	0	0	0	0	0	455	352	0	0	0	0	0	0	0	0	99016
4	455	363	0	130	0	0	0	0	10	0	455	363	0	0	0	0	0	0	0	0	112620
5	455	350	0	130	0	0	0	0	0	0	455	350	0	130	0	0	0	0	0	0	118928
6	455	377	130	130	0	0	0	0	0	0	455	377	130	130	0	0	0	0	0	0	132291
7	455	418	130	130	0	0	25	0	0	0	455	418	130	130	0	0	0	0	0	0	138787
8	455	455	130	130	29	0	25	0	0	0	455	455	130	130	0	0	0	0	0	0	145851
9	455	455	130	130	102	20	25	0	0	0	455	455	130	130	102	20	0	0	0	0	160855
10	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	0	0	0	179653
11	455	455	130	130	162	75	25	10	0	0	455	455	130	130	162	75	25	10	0	0	190802
12	455	455	130	130	162	80	25	45	10	10	455	455	130	130	162	80	25	45	10	0	202656
13	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	0	0	0	179653
14	455	455	130	130	102	20	0	0	0	0	455	455	130	130	102	20	0	0	0	0	160855
15	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	144902
16	455	310	130	130	25	0	0	0	0	0	455	310	130	130	25	0	0	0	0	0	129082
17	455	260	130	130	25	0	0	0	0	0	455	260	130	130	25	0	0	0	0	0	123851
18	455	356	130	130	25	0	0	0	0	0	455	356	130	130	25	0	0	0	0	0	135059
19	455	455	130	130	26	0	0	0	0	0	455	455	130	130	26	0	0	0	0	0	145578
20	455	455	130	130	162	35	25	0	0	0	455	455	130	130	162	35	25	10	0	0	179653
21	455	455	130	130	0	20	25	0	0	0	455	455	130	130	0	20	25	0	0	0	162767
22	455	453	0	130	0	20	25	0	0	0	455	453	0	130	0	20	25	0	0	0	134691
23	455	377	0	0	0	0	0	0	10	0	455	377	0	0	0	0	0	0	10	0	106344
24	455	345	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0	92565
																Overall Cost of Generation = **3374668.8771($)**					

The simulation results for hHHO method for 60 unit system shows that total cost of generation with thermal units is **$ 3374668.8771.** Fig. 5.7 shows that Convergence Curve for 60 unit system using hHHO-IGWO convergences efficiently towards best fitness.

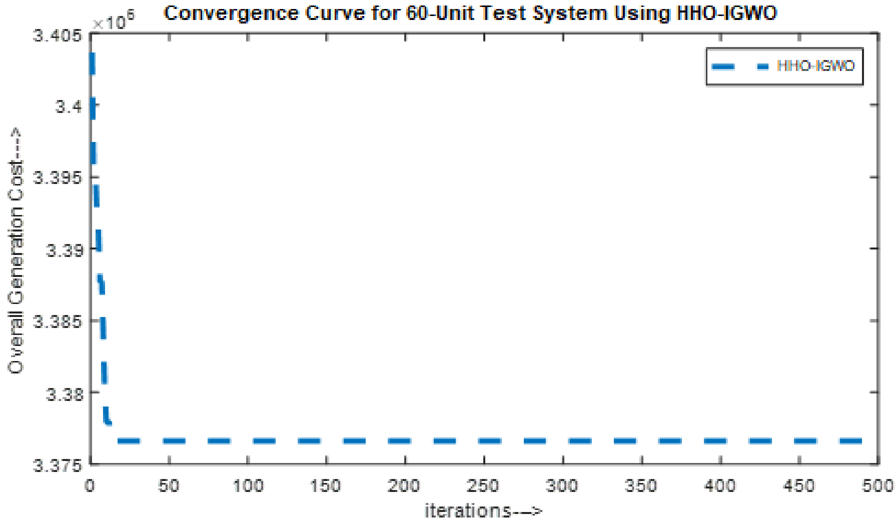


Fig.5.7: Convergence curve for 60-units using hHHO-IGWO method

The analysis revealed that the suggested algorithm generates a specific combination of units to match the hourly load requirement and evaluates a cost-effective solution to the unit commitment problem.

5.8.2 Testing of Unit Commitment Problem by CHHO method

The propose algorithm is applied to standard test systems consisting of 10,20, 40 and 60-units and simulation results are recorded for Classical UC consisting of conventional thermal. Each run begins with a new set of population. For all runs, the population size is set to 40 for the 10-units. The population size for the 20-units is set at 80, while the population size for the 40-unit test system is set at 160.

(a) Testing of 10 -unit system using CHHO

The CHHO is applied to 10-unit system with 10% SR and simulation results are recorded for corresponding thermal units. Due to stochastic nature of CHHO algorithm, program is simulated for 30 trials runs and 500 iterations for better solution efficiency. Table-5.8 illustrates their corresponding power dispatch. The convergence curves for 10-unit system is shown in Fig.5.8.

Table-5.8: Scheduling of 10-units using CHHO method

Time (h)	Scheduling for 10 units										Power (MW)	Start-Up Cost	Hourly Fuel Cost
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10			
1	405	150	0	0	0	0	0	0	0	0	555	0	11208
2	450	150	0	0	0	0	0	0	0	0	601	1070	11957
3	455	258	0	0	0	0	0	0	0	0	713	560	13914
4	455	367	0	0	25	0	0	0	0	0	847	0	16763
5	455	401	0	0	25	0	0	0	0	0	881	1070	17352
6	455	392	0	130	25	0	0	0	0	0	1002	0	20059
7	455	434	0	130	25	0	0	0	0	0	1044	0	20783
8	455	355	130	130	25	0	0	0	0	0	1095	0	22294
9	455	397	130	130	25	0	0	0	0	0	1137	0	23039
10	455	455	130	130	44	0	25	0	0	0	1239	170	25595
11	455	455	130	130	85	20	25	0	0	0	1300	60	27246
12	455	455	130	130	121	20	25	0	0	0	1336	260	27995
13	455	455	130	130	49	20	0	0	0	0	1239	0	25354
14	455	449	130	130	25	0	0	0	0	0	1189	60	23937
15	455	382	130	130	25	0	0	0	0	0	1122	120	22772
16	455	206	130	130	25	0	0	0	0	0	946	0	19699
17	455	192	130	130	25	0	0	0	0	0	932	0	19455
18	455	310	130	130	25	0	0	0	0	0	1050	0	21515
19	455	402	130	130	25	0	0	0	0	0	1142	0	23115
20	455	455	130	130	53	0	0	10	0	0	1233	340	25531
21	455	416	130	130	25	0	0	0	0	0	1156	60	23374
22	455	331	130	0	0	0	0	0	0	0	916	0	18067
23	455	249	0	0	0	0	0	0	0	0	704	0	13754
24	431	150	0	0	0	0	0	0	0	0	581	0	11626
Worst Cost($)=492502.5759				**Best Cost($)=490174.8291**			**Mean Cost($)=491308.0262**						**Total=490174.8291($)**
Worst Time(Sec.)= 0.046875				**Best Time(Sec.)= 0.015625**			**Mean Time(Sec.)= 0.0291**						

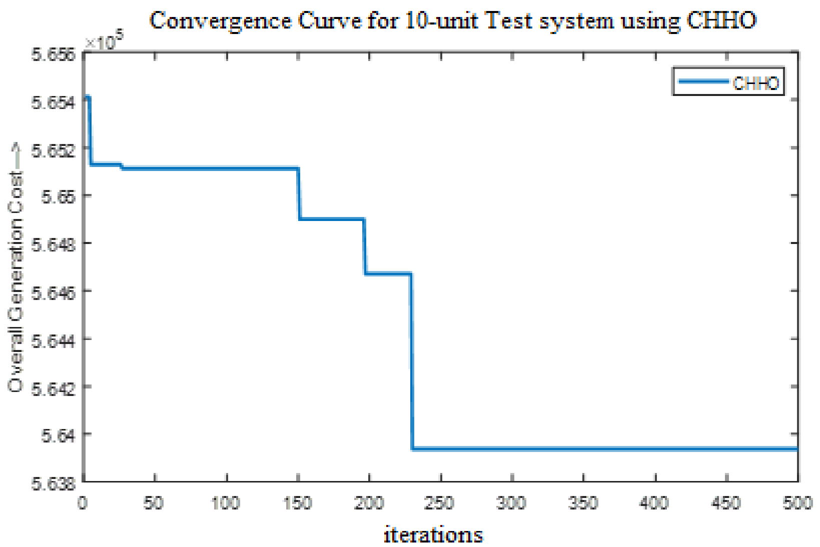


Fig.5.8: Convergence Curve 10 unit system using CHHO method

Referring Table 5.8 , U1 and U2 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load deamd. During the peak hours, U3 to U9 units contribute their power meet the corresponding load demand.At 12^{th} hour , load is at maximum and thus all the units are in ON state. U10 act as the reserve unit and runs only during the peak demandd. Start-up cost depends upon the operating temperature of particular unit.The total operating cost is the sum of start-up cost and generation cost of units for a 24 hour duration. The simulation results for CHHO algorithm for 10 units with 10% SR shown in above results shows that total cost of generation with UC is **\$ 563387.6874**.The results reveals that proposed algorithm selects a particular combination of units to fulfill the hourly load demand and estimates a superior solution to unit commitment problem.

(b) Testing of 20 units using CHHO

The CHHO method is applied to standard test system of 20-units with 10% SR. The data of 10-units was replicated and is multiplied by 2 for obtaining the results of 20-units test system. Population size is taken as 80 for all 30 trial runs with 500 iterations and simulation results are recorded for conventional thermal units. Table-5.9 illustrates optimal status of committed generators. The convergence plot of 10-unit system is illustrated in Fig.5.9.

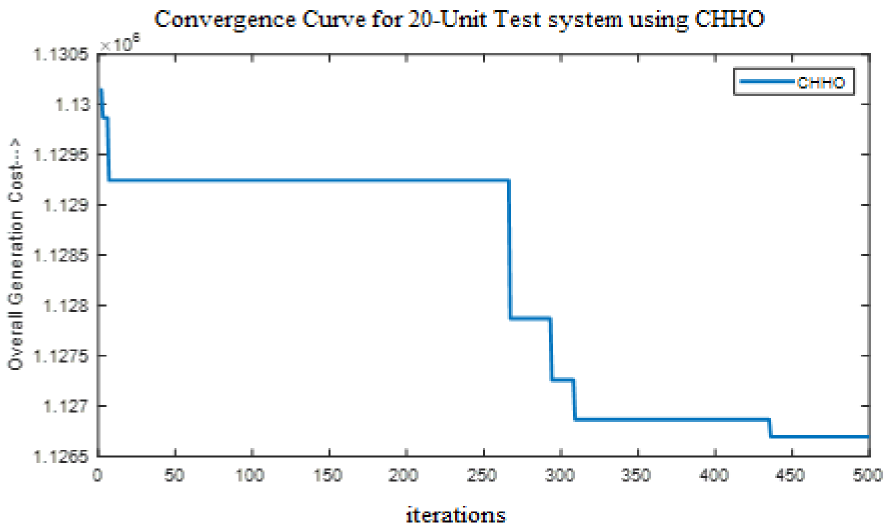


Fig. 5.9: Convergence Curve for 20 units using CHHO method

Table-5.9: Scheduling of 20-units using CHHO

Time (h)	**Scheduling for 20-unit**																				**Hourly Cost**
	U1	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**	**U8**	**U9**	**U10**	**U11**	**U12**	**U13**	**U14**	**U15**	**U16**	**U17**	**U18**	**U19**	**U20**	
1	455	245	0	0	0	0	0	0	0	0	455	245	0	0	0	0	0	0	0	0	27366
2	455	295	0	0	0	0	0	0	0	0	455	295	0	0	0	0	0	0	0	0	29109
3	455	330	0	130	0	0	0	0	0	0	455	330	0	0	0	0	0	0	0	0	33191
4	455	300	0	130	0	0	0	0	0	0	455	300	130	130	0	0	0	0	0	0	37197
5	455	350	0	130	0	0	0	0	0	0	455	350	130	130	0	0	0	0	0	0	39457
6	455	425	0	130	25	0	0	0	0	0	455	425	130	130	25	0	0	0	0	0	44158
7	455	455	0	130	45	0	0	0	0	0	455	455	130	130	45	0	0	0	0	0	46009
8	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	48301
9	455	455	130	130	103	0	0	0	0	0	455	455	130	130	103	20	25	0	10	0	53920
10	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0	60115
11	455	455	130	130	162	73	25	10	10	0	455	455	130	130	162	73	25	10	10	0	63832
12	455	455	130	130	162	80	25	43	10	10	455	455	130	130	162	80	25	43	10	10	67780
13	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0	60115
14	455	455	130	130	105	20	0	0	0	0	455	455	130	130	105	20	0	0	0	10	53839
15	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	48301
16	455	310	130	130	25	0	0	0	0	0	455	310	130	130	25	0	0	0	0	0	43027
17	455	260	130	130	25	0	0	0	0	0	455	260	130	130	25	0	0	0	0	0	41284
18	455	360	130	130	25	0	0	0	0	0	455	360	130	130	25	0	0	0	0	0	44774
19	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	48301
20	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	0	10	0	60115
21	455	455	0	130	150	20	25	0	0	0	455	455	130	130	150	20	25	0	0	0	54293
22	455	455	0	130	0	20	25	0	0	0	455	455	0	0	160	20	25	0	0	0	45255
23	455	433	0	0	0	0	0	0	0	0	455	433	0	0	25	0	0	0	0	0	35447
24	455	345	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0	30855
																Overall Cost of Generation = **1124685.2088 ($)**					

Referring Table 5.9, U1, U2, U11 and U12 are the most cost economical units and thus run for total 24 hours duration to match the corresponding load demand. During the peak hours, U3 to U19 units supplies power to meet the corresponding load demand. At 12th hour, load is at maximum and almost all units are in ON state. U10 and U20 act as the reserve unit and runs only during the peak demand. The total operating cost is the sum of start-up cost and generation cost of units for a 24 hour duration. The simulation results for CHHO shows that total cost of generation with thermal units is **$ 1124685.2088**.

The convergence curves with only UC for 20-unit system is shown in Fig.5.9. It shows that proposed algorithm selects a particular combination of units from 20 units satisfying all system and unit constraints to meet the hourly load demand with superior convergence.

(c) Testing of 40-unit system using CHHO

The CHHO method is tested for solving unit commitment problem of 40-unit system. Population size of 80 is taken into consideration for all trial solutions.Table-5.10(a) and (b) illustrates optimal dispatch for 40-unit system. The convergence curve for 40-unit system is depicted in Fig.5.10.

Table 5.10(a) and 5.10(b) illustrates that U1, U2, U11, U12, U21, U22, U31 and U32 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load demand. For rest of hours, U3 to U9, U13 to U19, and U23 to U29 and U33 to U39 contributes their power meet the corresponding load demand.

During 12th hour, load is at peak and thus most of the units are in ON state. U10, U20, U30 and U40 act as the reserve unit and runs only during the peak demand. The total operating cost is the sum of start-up cost and generation cost of units for a 24 hour duration.

The simulation results for CHHO method for 40 units shown in Table-5.10(a) and 5.10(b) results shows that total cost of generation with thermal units is **$ 2257230.8455**. It shows that proposed chaotic algorithm efficiently picks a specific combination of units from 40-units to meet the forecasted load demand and determines a unique solution to unit commitment problem.

Table-5.10(a): Scheduling of 1 to 20 for 40 units using CHHO

Time	Scheduling for 1 to 20 units																			
(h)	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13	U14	U15	U16	U17	U18	U19	U20
1	455	245	0	0	0	0	0	0	0	0	455	245	0	0	0	0	0	0	0	0
2	455	289	0	0	0	0	0	0	0	0	455	289	0	0	0	0	0	0	0	0
3	455	318	0	0	0	0	0	0	0	0	455	318	130	0	25	0	0	0	0	0
4	455	418	0	0	0	0	0	0	0	0	455	418	130	0	25	0	0	0	0	0
5	455	429	130	0	0	0	0	0	0	0	455	429	130	0	25	0	0	0	0	0
6	455	431	130	130	0	0	0	0	0	0	455	431	130	130	25	0	0	0	0	0
7	455	444	130	130	0	0	0	0	0	0	455	444	130	130	25	0	0	0	0	0
8	455	455	130	130	0	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0
9	455	455	130	130	104	20	0	0	0	0	455	455	130	130	104	20	0	0	0	0
10	455	455	130	130	162	33	25	10	10	0	455	455	130	130	162	33	25	0	0	0
11	455	455	130	130	162	73	25	10	10	0	455	455	130	130	162	73	25	10	10	0
12	455	455	130	130	162	80	25	43	10	10	455	455	130	130	162	80	25	43	10	10
13	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	10	0
14	455	455	130	130	104	20	25	0	0	0	455	455	130	130	104	20	0	0	0	0
15	455	450	130	130	25	20	0	0	0	0	455	450	130	130	25	0	0	0	0	0
16	455	300	130	130	25	0	0	0	0	0	455	300	130	130	25	0	0	0	0	10
17	455	260	130	130	25	0	0	0	0	0	455	260	130	130	25	0	0	0	0	0
18	455	348	130	130	25	0	0	0	0	0	455	348	130	130	25	0	0	0	0	0
19	455	429	130	130	25	0	0	0	0	0	455	429	130	130	25	20	25	0	0	0
20	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0
21	455	455	130	130	123	20	25	0	0	0	455	455	130	130	123	20	25	0	0	0
22	455	450	130	130	0	20	25	0	0	0	455	450	0	130	25	20	0	0	0	0
23	455	348	0	130	0	0	0	0	0	0	455	348	0	130	0	0	0	0	0	0
24	455	345	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0

Table-5.10(b): Scheduling of 21 to 40 for 40 units using CHHO

Time (h)	Scheduling for 21 to 40-Units																				Hourly Fuel Cost
	U21	**U22**	**U23**	**U24**	**U25**	**U26**	**U27**	**U28**	**U29**	**U30**	**U31**	**U32**	**U33**	**U34**	**U35**	**U36**	**U37**	**U38**	**U39**	**U40**	
1	455	245	0	0	0	0	0	0	0	0	455	245	0	0	0	0	0	0	0	0	54733
2	455	289	0	0	25	0	0	0	0	0	455	289	0	0	0	0	0	0	0	0	58727
3	455	318	0	130	25	0	0	0	0	0	455	318	0	0	0	0	0	0	0	0	67431
4	455	418	0	130	25	0	0	0	0	0	455	418	0	0	0	0	0	0	0	0	74426
5	455	429	0	130	25	0	0	0	0	0	455	429	0	0	25	0	0	0	0	0	79051
6	455	431	130	130	25	0	0	0	0	0	455	431	0	0	25	0	0	0	0	0	87840
7	455	444	130	130	25	0	0	0	0	0	455	444	130	0	25	20	0	0	0	0	92426
8	455	455	130	130	30	0	0	10	0	0	455	455	130	130	30	20	0	0	0	0	97294
9	455	455	130	130	104	20	25	0	0	0	455	455	130	130	104	20	0	0	0	0	107016
10	455	455	130	130	162	33	25	10	10	0	455	455	130	130	162	33	25	0	0	0	120267
11	455	455	130	130	162	73	25	10	10	0	455	455	130	130	162	73	25	10	10	0	127664
12	455	455	130	130	162	80	25	43	10	10	455	455	130	130	162	80	25	43	10	10	135561
13	455	455	130	130	162	33	25	0	10	0	455	455	130	130	162	33	25	0	0	0	120267
14	455	455	130	130	104	20	0	10	0	0	455	455	130	130	104	0	0	0	0	10	108066
15	455	450	130	130	25	20	0	0	0	0	455	450	130	130	25	0	0	0	0	0	97488
16	455	300	130	130	25	20	0	0	0	0	455	300	130	130	25	0	0	0	0	10	88071
17	455	260	130	130	25	0	0	0	0	0	455	260	130	130	25	0	0	0	0	0	82567
18	455	348	130	130	25	0	25	0	0	0	455	348	130	130	25	0	25	0	0	0	91022
19	455	429	130	130	25	0	25	0	0	0	455	429	130	130	25	20	25	0	10	0	100458
20	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0	120230
21	455	455	130	130	123	20	0	0	0	0	455	455	130	130	0	20	0	10	0	10	108732
22	455	450	0	130	0	20	0	0	0	0	455	450	0	130	0	20	0	0	0	0	88788
23	455	348	0	130	0	0	0	0	0	0	455	348	0	0	0	0	0	0	0	0	70466
24	455	345	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0	61710
																Overall Cost of Generation = **2257230.8455 ($)**					

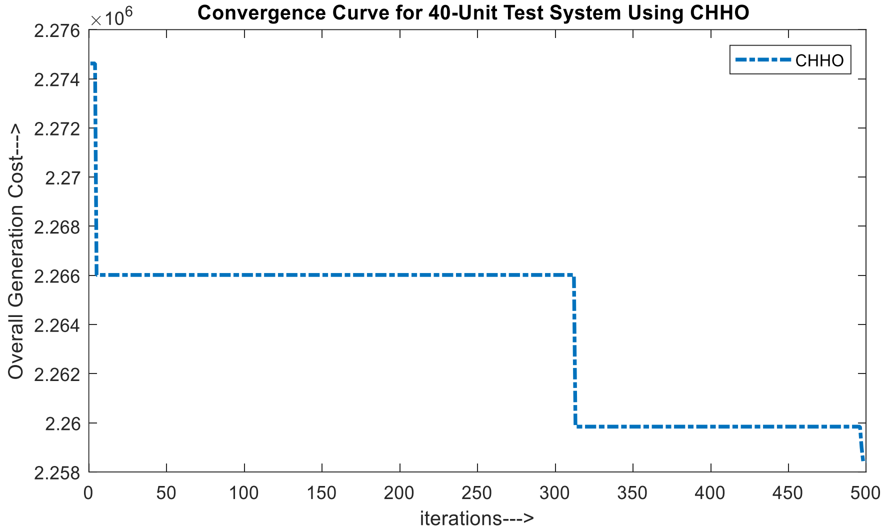


Fig.5.10: Convergence Curve for 40 units using CHHO method

(d) Testing of 60-unit system using CHHO

The CHHO method is tested for solving unit commitment problem for 60-unit system. The statistics of 10-unit system was replicated and multiplied by 6 for sixty units. Table-5.11 (a), 5.11(b) and 5.11(c) illustrates optimal dispatch for 60-unit system. The convergence curve for 60-unit system is shown in Fig.5.11.

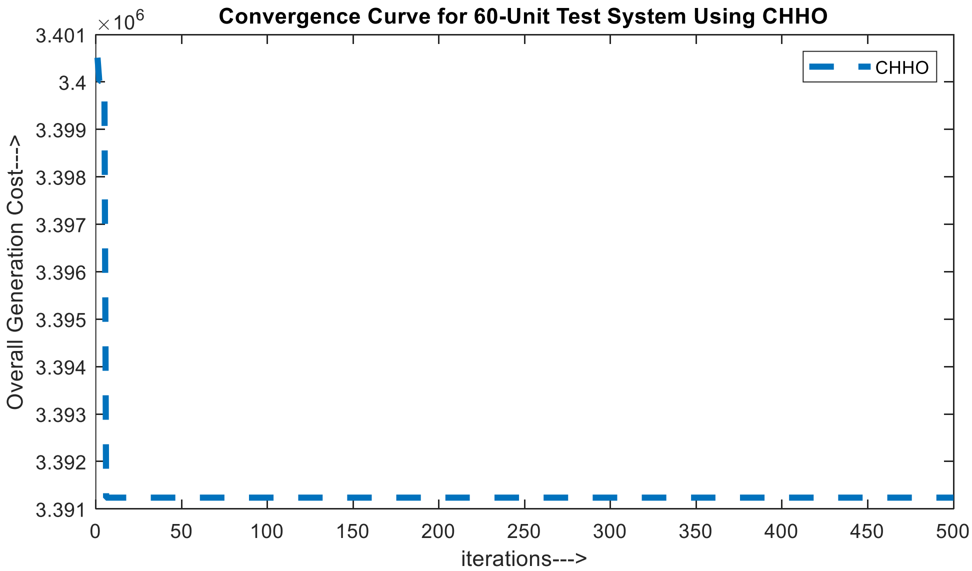


Fig. 5.11: Convergence curve for 60-units using CHHO method

Table-5.11(a): Scheduling of 1 to 20 units for 60 unit system using CHHO

Time (h)	Scheduling for 1 to 20 units																			
	U1	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**	**U8**	**U9**	**U10**	**U11**	**U12**	**U13**	**U14**	**U15**	**U16**	**U17**	**U18**	**U19**	**U20**
1	455	294	0	0	0	0	0	0	0	0	455	294	0	0	0	0	0	0	0	0
2	455	354	0	0	0	0	0	0	0	0	455	354	0	0	0	0	0	0	0	0
3	455	344	0	130	0	0	0	0	0	0	455	344	0	130	0	0	0	0	0	0
4	455	334	130	130	0	0	0	0	0	0	455	334	130	130	0	0	0	0	0	0
5	455	337	130	130	25	0	0	0	0	0	455	337	130	130	0	0	0	0	0	0
6	455	437	130	130	25	0	0	0	0	0	455	437	130	130	25	0	0	0	0	0
7	455	455	130	130	53	20	0	0	0	0	455	455	130	130	53	0	0	0	0	0
8	455	455	130	130	89	20	0	0	0	0	455	455	130	130	89	20	0	0	0	0
9	455	455	130	130	102	20	25	0	0	0	455	455	130	130	102	20	25	0	0	0
10	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	10	0	0
11	455	455	130	130	162	75	25	10	0	10	455	455	130	130	162	75	25	10	0	10
12	455	455	130	130	162	80	25	45	10	10	455	455	130	130	162	80	25	45	10	10
13	455	455	130	130	162	35	25	0	0	0	455	455	130	130	162	35	25	10	10	0
14	455	455	130	130	0	20	25	10	0	0	455	455	130	130	117	0	25	10	0	0
15	455	455	130	130	0	20	0	0	0	0	455	455	130	130	28	0	0	0	0	0
16	455	314	130	130	0	0	0	0	0	0	455	314	130	130	25	0	0	0	0	0
17	455	264	130	130	0	0	0	0	0	0	455	264	130	130	25	0	0	0	0	0
18	455	338	130	130	0	0	25	0	0	0	455	338	130	130	25	20	25	0	0	0
19	455	425	130	130	0	0	25	10	0	0	455	425	130	130	25	20	25	0	0	0
20	455	455	130	130	162	35	25	10	0	10	455	455	130	130	162	35	25	0	0	0
21	455	455	130	130	135	20	25	10	0	0	455	455	130	130	135	20	0	0	0	0
22	455	455	130	0	102	20	0	10	0	0	455	455	130	0	0	20	0	0	0	0
23	455	455	130	0	27	0	0	0	0	0	455	455	0	0	0	0	0	0	0	0
24	455	383	0	0	25	0	0	0	0	0	455	383	0	0	0	0	0	0	0	0

Table-5.11(b): Scheduling of 21 to 40 units for 60 units using CHHO

Time (h)	**Scheduling for 21 to 40 units**																			
	U21	**U22**	**U23**	**U24**	**U25**	**U26**	**U27**	**U28**	**U29**	**U30**	**U31**	**U32**	**U33**	**U34**	**U35**	**U36**	**U37**	**U38**	**U39**	**U40**
1	455	294	0	0	0	0	0	0	0	0	455	294	0	0	0	0	0	0	0	0
2	455	354	0	0	0	0	0	0	0	0	455	354	0	0	0	0	0	0	0	0
3	455	344	0	130	0	0	0	0	0	0	455	344	0	130	0	0	0	0	0	0
4	455	334	0	130	0	0	0	0	0	0	455	334	130	130	0	0	0	0	0	0
5	455	337	130	130	0	0	0	0	0	0	455	337	130	130	0	0	0	0	0	0
6	455	437	130	130	25	0	0	0	0	0	455	437	130	130	25	0	0	0	0	0
7	455	455	130	130	53	0	0	0	0	0	455	455	130	130	53	0	0	0	0	0
8	455	455	130	130	89	20	0	0	0	0	455	455	130	130	89	20	0	0	0	0
9	455	455	130	130	102	20	0	0	0	0	455	455	130	130	102	20	0	0	0	0
10	455	455	130	130	162	35	25	0	0	0	455	455	130	130	162	35	25	10	0	0
11	455	455	130	130	162	75	25	10	10	0	455	455	130	130	162	75	25	10	0	0
12	455	455	130	130	162	80	25	45	10	10	455	455	130	130	162	80	25	45	10	10
13	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	10	0	0
14	455	455	130	130	117	20	0	0	0	0	455	455	130	130	117	20	25	0	0	0
15	455	455	130	130	28	20	0	0	0	0	455	455	130	130	28	0	0	0	0	0
16	455	314	130	130	25	0	0	0	0	0	455	314	130	130	25	0	0	0	0	0
17	455	264	130	130	25	0	0	0	0	0	455	264	130	130	25	0	0	0	0	0
18	455	338	130	130	25	0	25	0	0	0	455	338	130	130	25	20	25	0	0	0
19	455	425	130	130	25	20	25	0	0	0	455	425	130	130	25	20	25	0	0	0
20	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	0	0	0
21	455	455	130	130	135	20	25	0	0	0	455	455	130	130	0	0	25	0	0	0
22	455	455	0	130	102	20	25	0	0	0	455	455	0	0	0	0	0	0	0	0
23	455	455	0	0	27	0	0	10	0	0	455	455	0	0	0	0	0	0	0	0
24	455	383	0	0	0	0	0	0	0	0	455	383	0	0	0	0	0	0	0	0

Table-5.11(c): Scheduling of 21 to 40 units for 60 unit system using CHHO

Time (h)	Scheduling 41 to 60 units																				Hourly Fuel Cost
	U41	**U42**	**U43**	**U44**	**U45**	**U46**	**U47**	**U48**	**U49**	**U50**	**U51**	**U52**	**U53**	**U54**	**U55**	**U56**	**U57**	**U58**	**U59**	**U60**	
1	455	294	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	81151
2	455	354	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	86389
3	455	344	0	130	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	99819
4	455	334	130	130	0	0	0	0	0	0	455	0	0	130	0	0	0	0	0	0	113373
5	455	337	130	130	0	0	0	0	0	0	455	0	130	130	0	0	0	0	0	0	120364
6	455	437	130	130	25	0	0	0	0	0	455	0	130	130	0	0	0	0	0	0	132894
7	455	455	130	130	53	0	0	0	0	0	455	0	130	130	53	0	0	0	0	0	139536
8	455	455	130	130	89	20	0	0	0	0	455	0	130	130	89	0	0	0	0	0	147267
9	455	455	130	130	102	20	0	0	0	0	455	455	130	130	102	20	0	0	0	0	160855
10	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	10	0	0	179653
11	455	455	130	130	162	75	25	10	10	0	455	455	130	130	162	75	25	10	10	0	190812
12	455	455	130	130	162	80	25	45	10	10	455	455	130	130	162	80	25	45	10	0	202656
13	455	455	130	130	162	35	25	0	0	0	455	455	130	130	162	35	25	10	0	0	179671
14	455	455	130	130	117	20	0	0	0	0	455	455	130	130	117	20	0	0	0	0	162133
15	455	455	130	130	28	0	0	0	0	0	455	455	130	130	28	0	0	0	0	0	145294
16	455	314	130	130	25	0	0	0	0	0	455	314	130	130	25	0	0	0	0	0	128573
17	455	264	130	130	25	0	0	0	0	0	455	264	130	130	25	0	0	0	0	0	123342
18	455	338	130	130	25	0	0	0	0	0	455	338	130	130	25	20	0	0	0	0	138168
19	455	425	130	130	25	20	0	0	0	0	455	425	130	130	25	20	25	0	0	0	151083
20	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	0	0	10	179710
21	455	455	130	130	135	20	25	0	0	0	455	455	0	130	135	20	25	0	0	0	162533
22	455	455	130	0	0	20	25	0	0	0	455	455	0	130	102	20	25	0	0	0	134530
23	455	455	0	0	0	0	25	0	0	0	455	0	0	130	27	20	0	0	0	0	106831
24	455	383	0	0	0	0	0	0	0	0	455	0	0	130	0	0	0	0	0	0	92731
																Overall Cost of Generation = **3386078.2574 ($)**					

From Table 5.11(a), 5.11(b) and 5.11(c), it can be seen that U1, U2, U11, U12, U21, U22, U31, U32, U41, U42, U51 and U52 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load demand. For rest of hours, U3 to U9, U13 to U19, U23 to U29, U33 to U39, U43 to U49 and U53 to U59 contributes their power meet the corresponding load demand. At 12th hour, load is at peak and thus most of the units are in ON state. U10, U20, U30, U40, U50 and U60 act as the reserve unit and runs only during the peak demand. The simulation results for CHHO method for 60 units evaluates **$ 3386078.2574** total cost of generation. The analysis reveals that proposed algorithm is effective in solving unit commitment problem.

5.8.3 Testing of Unit Commitment Problem by CSMA method

The proposed algorithm is applied to standard test systems consisting of 10, 20, 40 and 60 units and simulation results are recorded for corresponding systems consisting of conventional thermal units.

(a) Testing of 10-unit system using CSMA

The proposed algorithm is applied to 10-unit system with 10% SR and simulation results are recorded for classical UC consisting of conventional thermal units.Table-5.12 represents their corresponding power dispatch. The convergence curves for 10-unit system is depicted in Fig.5.12.

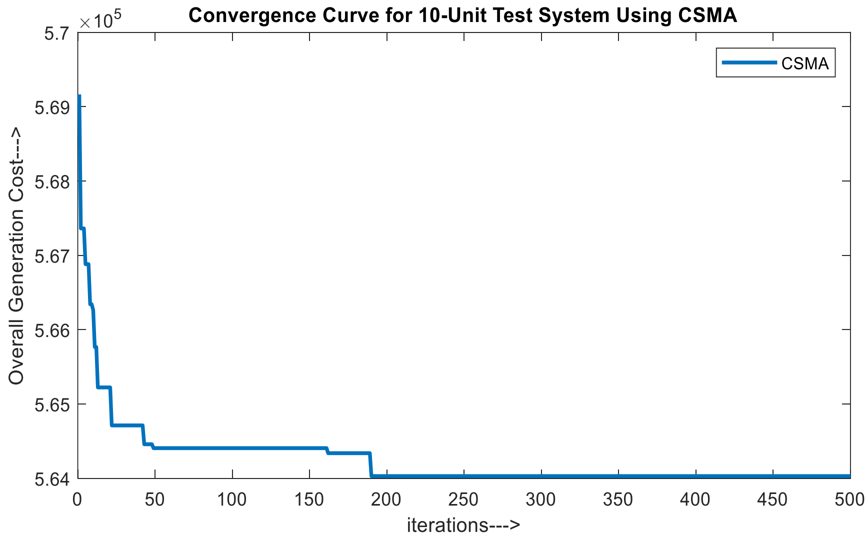


Fig.5.12: Convergence Curve for 10-unit using CSMA method

Table-5.12: Scheduling for 10 units using CSMA method

Time (h)	Optimal scheduling										Power (MW)	Start-Up Cost	Hourly Fuel Cost
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10			
1	455	245	0	0	0	0	0	0	0	0	700	1620	13683
2	455	295	0	0	0	0	0	0	0	0	750	0	14554
3	455	370	0	0	25	0	0	0	0	0	850	560	16809
4	455	455	0	0	40	0	0	0	0	0	950	0	18598
5	455	390	130	0	25	0	0	0	0	0	1000	0	20051
6	455	360	130	130	25	0	0	0	0	0	1100	520	22387
7	455	410	130	130	25	0	0	0	0	0	1150	0	23262
8	455	455	130	130	30	0	0	0	0	0	1200	170	24150
9	455	455	130	130	85	20	25	0	0	0	1300	180	27251
10	455	455	130	130	162	33	25	10	0	0	1400	0	30058
11	455	455	130	130	162	73	25	10	10	0	1450	60	31916
12	455	455	130	130	162	80	25	43	10	10	1500	30	33890
13	455	455	130	130	162	33	25	10	0	0	1400	0	30058
14	455	455	130	130	85	20	25	0	0	0	1300	0	27251
15	455	455	130	130	30	0	0	0	0	0	1200	0	24150
16	455	310	130	130	25	0	0	0	0	0	1050	0	21514
17	455	260	130	130	25	0	0	0	0	0	1000	120	20642
18	455	360	130	130	25	0	0	0	0	0	1100	60	22387
19	455	455	130	130	30	0	0	0	0	0	1200	430	24150
20	455	455	130	130	162	33	25	10	0	0	1400	30	30058
21	455	455	130	130	85	20	25	0	0	0	1300	0	27251
22	455	455	0	0	145	20	25	0	0	0	1100	0	22736
23	455	420	0	0	25	0	0	0	0	0	900	0	17685
24	455	345	0	0	0	0	0	0	0	0	800	0	15427
Worst Cost($)=565398.9054				**Best Cost($)=563698.15824**				**Mean Cost($)=564310.5195**					**Total= 563698.15824**
Worst Time(Sec.)= 0.04687				**Best Time(Sec.)= 0.015625**				**Mean Time(Sec.)= 0.0307291**					

Referring Table 5.12 , U1 and U2 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load deamd. During the peak hours, U3 to U9 units contribute their power meet the corresponding load demand.

At 12th hour , load is at maximum and thus all the units are in ON state. U10 act as the reserve unit and runs only during the peak deamd.Start-up cost depends upon the operating temperature of particular unit.The total operating cost is the sum of start-up cost and generation cost of units for a 24 hour duration. The simulation results for CSMA algorithm for 10 units with 10% SR shows that total cost of generation with UC is **$ 563698.15824**. Fig. 5.12 shows that evaluaion for 10 units using CSMA convergences effciently towards best fitness.

(b) Testing of 20-unit system using CSMA

The CSMA method is applied to standard test systems of 20-units with 10% SR. Population size is taken as 80 for all 30 trial runs with 500 iterations and simulation results are recorded for classical UC consisting of conventional thermal units. Table-5.13 illustrates optimal generation of committed generators.

In Table 5.13, U1, U2, U11 and U12 are the most cost efficient units and thus remains ON for total time duration to meet the load demand. During the peak hours, U3 to U19 units contribute their power meet the corresponding load demand. At 12th hour, load is at maximum and thus maximum units are in ON state. U10 and U20 act as the reserve unit and runs only during the peak demand.

The simulation results for CSMA shows that total cost of generation with thermal units is **$ 1124242.1047**.The results shows that CSMA efficiently selects a particular combination from available 20 units to meet corresponding demand and evaluates a cost effective solution to unit commitment problem. The convergence curve in Fig.5.13 illustrates that CSMA is efficient in evaluating UC problem.

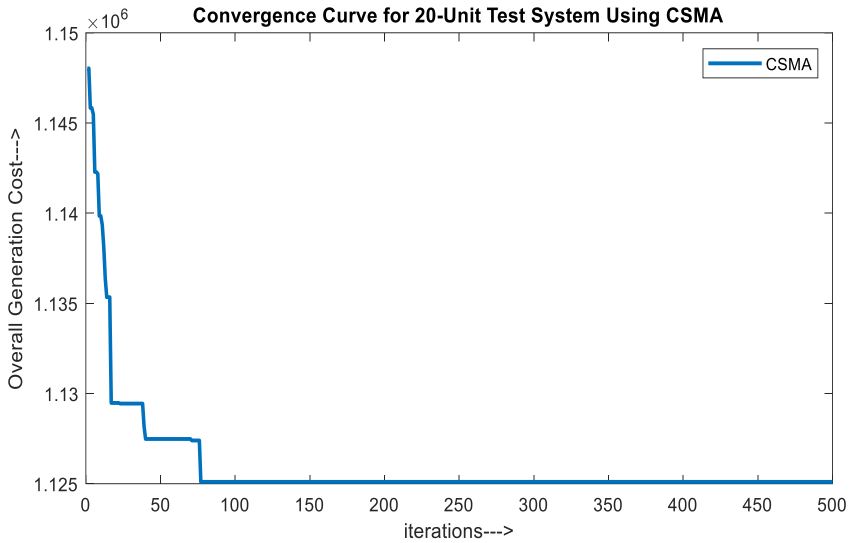


Fig. 5.13: Convergence Curve for 20 unit system using CSMA method

Table-5.13: Scheduling of 20-units using CSMA method

Time (h)	**Scheduling for 20 units**																				Hourly Cost
	U1	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**	**U8**	**U9**	**U10**	**U11**	**U12**	**U13**	**U14**	**U15**	**U16**	**U17**	**U18**	**U19**	**U20**	
1	455	245	0	0	0	0	0	0	0	0	455	245	0	0	0	0	0	0	0	0	27366
2	455	295	0	0	0	0	0	0	0	0	455	295	0	0	0	0	0	0	0	0	29109
3	455	330	0	0	0	0	0	0	0	0	455	330	0	130	0	0	0	0	0	0	33191
4	455	418	0	0	0	0	0	0	0	0	455	418	0	130	25	0	0	0	0	0	37197
5	455	455	0	0	25	0	0	0	0	0	455	455	0	130	25	0	0	0	0	0	39457
6	455	425	130	130	25	0	0	0	0	0	455	425	0	130	25	0	0	0	0	0	44158
7	455	455	130	130	45	0	0	0	0	0	455	455	0	130	45	0	0	0	0	0	46009
8	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	48301
9	455	455	130	130	105	20	0	0	0	0	455	455	130	130	105	20	0	0	0	10	53920
10	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0	60115
11	455	455	130	130	162	73	25	10	10	0	455	455	130	130	162	73	25	10	10	0	63832
12	455	455	130	130	162	80	25	43	10	10	455	455	130	130	162	80	25	43	10	10	67780
13	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0	60115
14	455	455	130	130	98	20	25	0	0	0	455	455	130	130	98	20	0	0	0	0	53839
15	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	48301
16	455	310	130	130	25	0	0	0	0	0	455	310	130	130	25	0	0	0	0	0	43027
17	455	260	130	130	25	0	0	0	0	0	455	260	130	130	25	0	0	0	0	0	41284
18	455	360	130	130	25	0	0	0	0	0	455	360	130	130	25	0	0	0	0	0	44774
19	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	48301
20	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0	60115
21	455	455	130	130	150	20	25	0	0	0	455	455	0	130	150	20	25	0	0	0	54293
22	455	455	0	130	0	20	25	0	0	0	455	455	0	0	160	20	25	0	0	0	45255
23	455	367	0	130	0	0	0	0	0	0	455	367	0	0	25	0	0	0	0	0	35447
24	455	345	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0	30855
															Overall Cost of Generation = **1124242.1047($)**						

(c) Testing of 40-unit system using CSMA

The CSMA method is tested for solving unit commitment problem 40 units. The data of 10-unit system is multiplied by 4 for obtaining the results of 40-units test system. Population size of 80 is taken into consideration for all trial solutions. Table-5.14 (a) and 5.14(b) illustrates optimal dispatch for 40-unit system. The convergence curve for 40-unit system is shown in Fig.5.14.

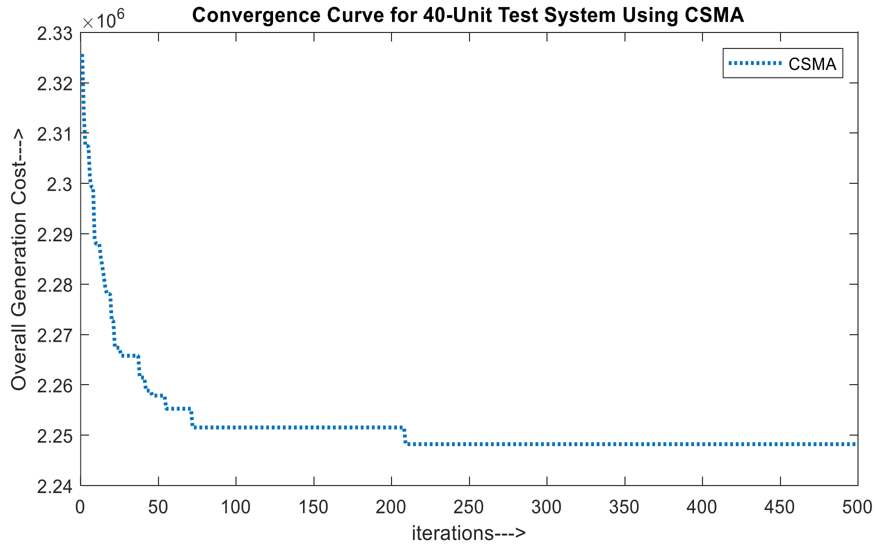


Fig.5.14: Convergence Curve for 40-unit system using CSMA method

Referring Table 5.14(a) and 5.14(b), U1, U2, U11, U12, U21, U22, U31 and U32 are the most economical units and thus for most of the hours to meet the corresponding load demand. For rest of hours, U3 to U9, U13 to U19, and U23 to U29 and U33 to U39 contributes their power to meet the corresponding load demand.

At 12th hour, load is at maximum and thus maximum units are in ON state. U10, U20, U30 and U40 act as the reserve unit and runs only during the peak demand. The total operating cost is the sum of start-up cost and generation cost of units for a 24 hour duration.

The simulation results for CSMA method for 40 unit shows that total cost of generation with thermal units is **$ 2246297.7597**. The convergence curve illustrated in Fig.5.14 reveals that it converges sharply up to 50 iteration, and then settles to final value after 200 iterations. The analysis shows that CSMA is effective in effective in solving UC problems for large system.

Table-5.14(a): Scheduling of 1 to 20 units for 40 unit system using CSMA

Time (h)	Scheduling for 1 to 20 units																		
	U1	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**	**U8**	**U9**	**U10**	**U11**	**U12**	**U13**	**U14**	**U15**	**U16**	**U17**	**U18**	**U19**	**U20**
1	455	245	0	0	0	0	0	0	0	0	455	245	0	0	0	0	0	0	0	0
2	455	295	0	0	0	0	0	0	0	0	455	295	0	0	0	0	0	0	0	0
3	455	363	0	0	0	0	0	0	0	0	455	363	0	0	0	0	0	0	0	0
4	455	391	0	0	0	0	0	0	0	0	455	391	130	0	25	0	0	0	0	0
5	455	403	0	0	0	0	0	0	0	0	455	403	130	0	25	0	0	0	0	0
6	455	405	130	130	0	0	0	0	0	0	455	405	130	130	25	0	0	0	0	0
7	455	444	130	130	25	0	0	0	0	0	455	444	130	130	25	20	0	0	0	0
8	455	455	130	130	62	0	0	0	0	0	455	455	130	130	62	20	0	0	0	0
9	455	455	130	130	103	20	0	0	0	0	455	455	130	130	103	20	0	0	0	0
10	455	455	130	130	162	33	25	10	0	10	455	455	130	130	162	33	25	10	0	0
11	455	455	130	130	162	73	25	10	10	10	455	455	130	130	162	73	25	10	10	0
12	455	455	130	130	162	80	25	43	10	10	455	455	130	130	162	80	25	43	10	10
13	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0
14	455	455	130	130	104	20	25	0	0	0	455	455	130	130	104	20	0	0	0	0
15	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0
16	455	310	130	130	25	0	0	0	0	0	455	310	130	130	25	0	0	0	0	0
17	455	260	130	130	25	0	0	0	0	0	455	260	130	130	25	0	0	0	0	0
18	455	360	130	130	25	0	0	0	0	0	455	360	130	130	25	0	0	0	0	0
19	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0
20	455	455	130	130	162	37	25	0	10	0	455	455	130	130	162	37	25	10	0	10
21	455	455	130	130	122	20	25	0	0	0	455	455	130	130	122	20	25	0	0	0
22	455	444	130	130	0	20	25	0	0	0	455	444	0	130	0	20	25	0	0	0
23	455	348	0	0	0	0	0	0	0	0	455	348	0	130	0	0	0	0	0	0
24	455	345	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0

Table-5.14(b): Scheduling of 21 to 40 units for 40 unit system using CSMA

Time (h)	**Scheduling for 21 to 40 Units**																				**Hourly Fuel Cost**
	U21	**U22**	**U23**	**U24**	**U25**	**U26**	**U27**	**U28**	**U29**	**U30**	**U31**	**U32**	**U33**	**U34**	**U35**	**U36**	**U37**	**U38**	**U39**	**U40**	
1	455	245	0	0	0	0	0	0	0	0	455	245	0	0	0	0	0	0	0	0	54733
2	455	295	0	0	0	0	0	0	0	0	455	295	0	0	0	0	0	0	0	0	58218
3	455	363	0	130	0	0	0	0	0	0	455	363	0	0	0	0	0	0	0	0	65794
4	455	391	0	130	0	0	0	0	0	0	455	391	130	0	0	0	0	0	0	0	74534
5	455	403	0	130	0	0	0	0	0	0	455	403	130	130	25	0	0	0	0	0	79128
6	455	405	0	130	0	0	0	0	0	0	455	405	130	130	25	0	0	0	0	0	87916
7	455	444	0	130	0	0	0	0	0	0	455	444	130	130	25	0	0	0	0	0	92395
8	455	455	0	130	0	20	25	0	0	0	455	455	130	130	62	0	0	0	0	0	97381
9	455	455	130	130	103	20	25	0	0	0	455	455	130	130	103	0	25	0	0	0	107269
10	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	0	0	0	120259
11	455	455	130	130	162	73	25	10	0	0	455	455	130	130	162	73	25	10	10	0	127674
12	455	455	130	130	162	80	25	43	10	10	455	455	130	130	162	80	25	43	10	10	135561
13	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0	120230
14	455	455	130	130	104	20	0	0	0	0	455	455	130	130	104	20	0	0	0	0	107016
15	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	96601
16	455	310	130	130	25	0	0	0	0	0	455	310	130	130	25	0	0	0	0	0	86055
17	455	260	130	130	25	0	0	0	0	0	455	260	130	130	25	0	0	0	0	0	82567
18	455	360	130	130	25	0	0	0	0	0	455	360	130	130	25	0	0	0	0	0	89548
19	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	96601
20	455	455	130	130	162	37	25	10	0	0	455	455	130	130	162	37	0	10	0	0	120364
21	455	455	130	130	122	20	25	0	0	0	455	455	130	130	0	20	0	0	0	0	107934
22	455	444	0	130	0	20	25	0	0	0	455	444	0	130	0	20	0	0	0	0	89753
23	455	348	0	130	0	0	0	0	0	0	455	348	0	130	0	0	0	0	0	0	70466
24	455	345	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0	61710
															Overall Cost of Generation = **2246297.7597($)**						

(d) Testing of 60-unit system using CSMA

The CSMA method is tested for solving unit commitment problem for 60-unit test system. The statistics of 10-unit system was replicated and multiplied by 6 for sixty units. Table-5.15 (a), 5.15(b) and 5.15(c) illustrates optimal dispatch for 60-unit system. The convergence curve for 60-unit system is Fig.5.15.

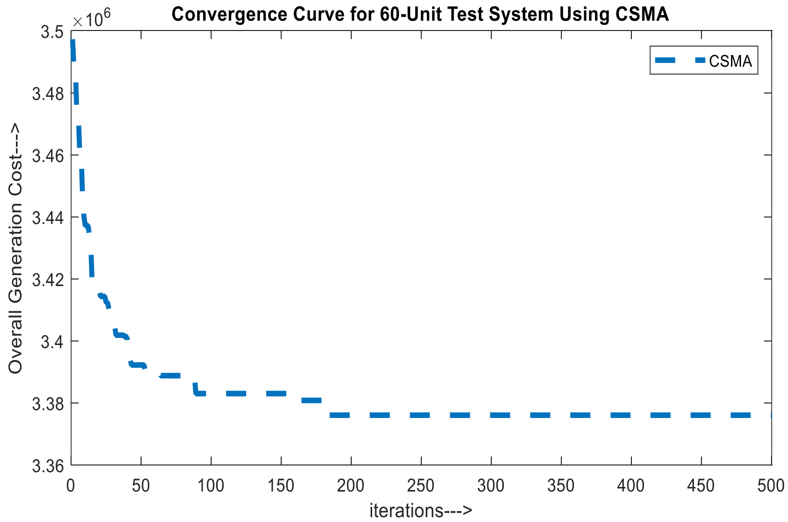


Fig.5.15: Convergence Curve for 60-unit system using CSMA method

Referring Table 5.15(a), 5.15(b) and 5.15(c), U1, U2, U11, U12, U21, U22, U31, U32, U41, U42, U51 and U52 are the most appropriate units and thus remains in ON state for maximum time duration. For rest of hours, U3 to U9, U13 to U19, U23 to U29, U33 to U39, U43 to U49 and U53 to U59 contributes power to meet the predicted load demand. During 12th hour, load is at peak and thus most of the units are in ON state. U10, U20, U30, U40, U50 and U60 act as the reserve units.

The simulation results for CSMA method for 60 units shown in above results shows that total cost of generation with thermal units is **$ 3375159.0917.** Fig. 5.15 shows that Convergence Curve for 60 unit system using CSMA convergences efficiently towards best fitness. It shows that the curve converges steeply till 200 iterations and then settles to optimum value. Thus, it reveals that proposed CSMA method is effective in estimating UC problem.

Table-5.15(a): Scheduling of 1 to 20 units for 60 unit system using CSMA

Time	Scheduling for 1 to 20 units																			
(h)	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13	U14	U15	U16	U17	U18	U19	U20
1	455	245	0	0	0	0	0	0	0	0	455	245	0	0	0	0	0	0	0	0
2	455	295	0	0	0	0	0	0	0	0	455	295	0	0	0	0	0	0	0	0
3	455	358	0	130	0	0	0	0	0	0	455	358	0	0	0	20	0	0	10	0
4	455	436	0	130	0	0	0	0	0	0	455	436	130	0	0	20	0	0	0	0
5	455	421	0	130	0	0	0	0	0	0	455	421	130	0	0	20	0	0	0	0
6	455	455	0	130	40	0	0	0	0	0	455	455	130	130	0	20	25	0	0	0
7	455	455	0	130	44	0	0	0	0	0	455	455	130	130	0	0	25	0	0	0
8	455	455	0	130	40	0	0	0	0	0	455	455	130	130	40	0	25	0	0	0
9	455	455	130	130	102	0	0	0	0	0	455	455	130	130	102	0	25	0	0	0
10	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	10	0	0
11	455	455	130	130	162	75	25	10	10	0	455	455	130	130	162	75	25	10	10	0
12	455	455	130	130	162	80	25	45	10	10	455	455	130	130	162	80	25	45	10	10
13	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	10	0	0
14	455	455	130	130	103	20	25	0	0	0	455	455	130	130	103	20	0	0	0	0
15	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0
16	455	310	130	130	25	0	0	0	0	0	455	310	130	130	25	0	0	0	0	0
17	455	260	130	130	25	0	0	0	0	0	455	260	130	130	25	0	0	0	0	0
18	455	360	130	130	25	0	0	0	0	0	455	360	130	130	25	0	0	0	0	0
19	455	453	130	130	25	0	0	0	0	0	455	453	130	130	25	0	25	0	0	0
20	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	10	0	0
21	455	455	130	130	128	20	25	0	0	0	455	455	130	130	128	20	25	0	0	0
22	455	453	0	130	0	20	25	0	0	0	455	453	0	130	0	20	0	0	0	0
23	455	358	0	130	0	0	0	0	0	0	455	358	0	130	0	0	0	0	0	0
24	455	345	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0

Table-5.15(b): Scheduling of 21 to 40 units for 60 unit system using CSMA

Time	Scheduling for 21 to 40 units																			
(h)	U21	U22	U23	U24	U25	U26	U27	U28	U29	U30	U31	U32	U33	U34	U35	U36	U37	U38	U39	U40
1	455	245	0	0	0	0	0	0	0	0	455	245	0	0	0	0	0	0	0	0
2	455	295	0	0	0	0	0	0	0	0	455	295	0	0	0	0	0	0	0	0
3	455	358	0	0	25	0	0	0	0	0	455	358	0	0	25	0	0	0	0	0
4	455	436	0	0	25	0	0	0	0	0	455	436	0	0	25	0	0	0	0	0
5	455	421	130	0	25	0	0	0	0	0	455	421	0	130	25	0	0	0	0	0
6	455	455	130	0	40	0	0	0	0	0	455	455	0	130	40	0	0	0	0	0
7	455	455	130	0	44	0	0	0	0	0	455	455	130	130	44	0	0	0	0	0
8	455	455	130	130	40	20	0	0	0	0	455	455	130	130	40	0	0	0	0	0
9	455	455	130	130	102	20	0	0	0	0	455	455	130	130	102	20	25	0	0	0
10	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	10	0	0
11	455	455	130	130	162	75	25	10	10	0	455	455	130	130	162	75	25	10	10	0
12	455	455	130	130	162	80	25	45	10	10	455	455	130	130	162	80	25	45	10	10
13	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	10	0	0
14	455	455	130	130	103	20	0	0	0	0	455	455	130	130	103	20	25	0	0	0
15	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0
16	455	310	130	130	25	0	0	0	0	0	455	310	130	130	25	0	0	0	0	0
17	455	260	130	130	25	0	0	0	0	0	455	260	130	130	25	0	0	0	0	0
18	455	360	130	130	25	0	0	0	0	0	455	360	130	130	25	0	0	0	0	0
19	455	453	130	130	25	0	0	0	0	0	455	453	130	130	25	0	0	0	0	0
20	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	10	0	10
21	455	455	130	130	128	20	25	0	0	0	455	455	130	130	128	20	25	0	0	0
22	455	453	130	130	0	20	25	0	0	0	455	453	0	130	0	20	25	0	0	0
23	455	358	0	130	0	0	0	0	0	0	455	358	0	130	0	0	0	0	0	0
24	455	345	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0

Table-5.15(c): Scheduling of 41 to 60 units for 60 unit system using CSMA

Time (h)	**Scheduling for 41 to 60 units**																				**Hourly Fuel Cost**
	U41	**U42**	**U43**	**U44**	**U45**	**U46**	**U47**	**U48**	**U49**	**U50**	**U51**	**U52**	**U53**	**U54**	**U55**	**U56**	**U57**	**U58**	**U59**	**U60**	
1	455	245	0	0	0	0	0	0	0	0	455	245	0	0	0	0	0	0	0	0	82099
2	455	295	0	0	0	0	0	0	0	0	455	295	0	0	0	0	0	0	0	0	87327
3	455	358	0	0	0	0	0	0	0	10	455	358	0	0	0	0	0	0	0	0	101417
4	455	436	0	0	0	0	0	0	0	0	455	436	0	0	25	0	0	0	0	0	111509
5	455	421	0	0	0	0	0	0	0	0	455	421	0	130	25	0	0	0	0	0	118544
6	455	455	0	130	0	0	25	0	0	0	455	455	0	130	40	0	0	0	0	0	132350
7	455	455	130	130	44	0	25	0	0	0	455	455	0	130	44	0	0	0	0	0	138961
8	455	455	130	130	40	0	25	0	0	0	455	455	130	130	40	0	0	0	0	0	146375
9	455	455	130	130	102	0	25	10	0	0	455	455	130	130	102	20	25	0	0	0	161668
10	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	0	0	0	179653
11	455	455	130	130	162	75	25	10	10	0	455	455	130	130	162	75	25	10	0	0	190792
12	455	455	130	130	162	80	25	45	10	10	455	455	130	130	162	80	25	45	10	0	202656
13	455	455	130	130	162	35	25	10	0	0	455	455	130	130	162	35	25	0	0	0	179653
14	455	455	130	130	103	20	0	0	0	10	455	455	130	130	103	0	0	0	0	0	161190
15	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	144902
16	455	310	130	130	25	0	0	0	0	0	455	310	130	130	25	0	0	0	0	0	129082
17	455	260	130	130	25	0	0	0	0	0	455	260	130	130	25	0	0	0	0	0	123851
18	455	360	130	130	25	0	0	0	0	0	455	360	130	130	25	0	0	0	0	0	134322
19	455	453	130	130	25	0	0	0	0	0	455	453	130	130	25	20	0	0	0	0	146033
20	455	455	130	130	162	35	25	0	0	0	455	455	130	130	162	35	25	0	0	0	179682
21	455	455	130	130	0	20	25	0	0	0	455	455	130	130	0	20	25	0	0	0	162693
22	455	453	0	130	0	20	25	0	0	0	455	453	0	130	0	20	25	0	0	0	134691
23	455	358	0	0	0	0	0	0	0	0	455	358	0	0	0	0	0	0	0	0	105405
24	455	345	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0	92565
																Overall Cost of Generation = **3375159.0917($)**					

Table 5.16: Cost comparison for 10, 20, 40 and 60 unit system with best, mean and worst values

Units	Method	Best Cost ($/day)	Mean Cost($/day)	Worst Cost($/day)	Time (s)
10	hHHO-IGWO	563435.9964	564452.7594	565425.30224	0.03628
	CHHO	563387.6874	564379.5791	565305.50224	0.015625
	CSMA	563698.1582	564310.5195	565398.9054	0.030729
20	hHHO-IGWO	1124860.6904	112615.1648	1128872.8693	0.054688
	CHHO	1124685.2088	1126291.9476	1128859.9733	0.029688
	CSMA	1124242.1047	1125317.9113	112622.1086	0.046875
40	hHHO-IGWO	2249657.3623	2252698.0896	2256317.4070	0.078125
	CHHO	2257230.0455	2260310.6018	2264045.7170	0.046875
	CSMA	2246297.7597	2249497.0688	2252324.6943	0.06657
60	hHHO-IGWO	3374668.8771	3378103.0758	3381703.9070	0.096875
	CHHO	3386078.2574	3392629.3063	3402247.3615	0.086834
	CSMA	3375159.0917	3377469.9456	3378854.9012	0.076875

Table 5.16 illustrates cost comparison for 10, 20, 40 and 60 unit system with best, mean and worst values for the proposed hybrid and chaotic methods. As the stochastic meta-heuristic methods have a tendency to get entrap in local minima, algorithms perform differently for a particular unit system. It can be seen from table that CHHO gives better result compared to hHHO-IGWO and CSMA for 10 unit system. CSMA is found to be efficient in handling 20 and 40 units, whereas hHHO-IGWO method shows better performance in handling 60 unit system.

The results have been compared with other heuristic and meta-heuristic methods such as SM, GA, ESA, PSO, EP, BPSO, BGSA, HPSO, BF, SGA, hGWO-RES, EACO, etc. Table-5.17 illustrates comparison of 10-unit system (10% SR) for UC problem using hHHO-IGWO, CHHO and CSMA with competent algorithms. From the comparative table, it is observed that proposed methods gives superior performance compared to other methods.

Table-5.17: Cost comparison for 10- unit system with other methods

Method	Overall Generation Cost ($)			Average Time(Sec.)
	Best	Average	Worst	
SM[12]	566686	566787	567022	---
LR[12]	566107	566493	566817	---
GA [12]	565866	567329	571336	---
ESA [252]	565828	565988	566260	3.35
LRGA [321]	564800	564800	---	518
EP [310]	564551	565352	---	5.61
Evolutionary Programming [12]	564551	565352	566231	100
PSO [262]	564212	565103	565783	---
BDE [322]	563,997	563,997	563,997	---
Ant Colony Search Algorithm (ACSA) [94]	564049	---	---	---
Particle Swarm-Based- Simulated Annealing (PSO-B-SA)[323]	563938	564115	564985	---
Quantum-Inspired Binary PSO (QIBPSO)[324]	563977	563977	563977	---
Hybrid Ant System/Priority List (HASP[44]	564029	564324	564490	---
B. SMP[325]	564,017.73	564121.46	564401.08	---
(AGA)[326]	564005	---	---	---
GA [327]	563977	564275	5665606	221
IBPSO[323]	563977	564155	565312	---
IQEA-UC[328]	563938	563938	563938	
Binary PSO[278]	563977	563977	563977	---
IPSO [262]	563954	564162	564579	---
Advanced Fuzzy Controlled Binary PSO(AFCBPSO)[329]	563947	564285	565002	5.54
Hybrid PSO(HPSO)[330]	563942.3	564772.3	565782.3	---
QEA-UC[263]	563938	564012	564711	
GSA[2]	563938	564008	564241	2.89
HSA[331]	563977	564168.6	---	3
Integrated DE-HS algorithm [272]	565089.6	565509.90	565681.27	133.7055
Hybrid HS- Random Search algorithm [142]	563937.7	563965.30	563995.33	16.8312
Hybrid DE-Random Search algorithm [143]	563937.7	563958.28	563994.82	186.6578
Harmony Search Algorithm (HAS)[331]	563977	564168.6	---	3
Hybrid HHO-IGWO(Proposed Method)	563435.9964	564452.7594	565425.30224	0.03628
Chaotic HHO(Proposed Method)	563387.6874	564379.5791	565305.50224	0.015625
Chaotic SMA(Proposed Method)	563698.1582	564310.5195	565398.9054	0.030729

Table 5.18 illustrates results of proposed methods for 20-unit system compared with other methods in terms of best, average and worst. The comparative analysis revealed that CSMA method is more cost effective compared to other methods.

Table-5.18: Cost comparison for 20-unit system with other methods

Method	Overall Generation Cost ($)			Average Time(Sec.)
	Best	**Average**	**Worst**	
GA[332]	1128876	1130160	1131565	-
SM[332]	1128192	1128213	1128444	-
LR[332]	1128362	1128395	1128444	-
Enhanced Simulated Annealing[47]	1126251	1127955	1129112	16.8
Particle swarm optimization[137]	1125983	-	1131054	-
Evolutionary Programming (EP)[310]	1125494	1127257	-	340
Improved PSO[333]	1125279	-	1127643	-
B.SMP[324]	1124839	1125102	1125283	-
Hybrid HS-Random Search[142]	1124889.39	1124912.84	1124951.55	35.01
Hybrid HHO-IGWO(Proposed Method)	1124860.6904	112615.1648	1128872.8693	0.054688
Chaotic HHO(Proposed Method)	1124685.2088	1126291.9476	1128859.9733	0.029688
Chaotic SMA(Proposed Method)	1124242.1047	1125317.9113	112622.1086	0.046875

Table 5.19 illustrates results of proposed methods for 40-unit system with other methods in terms of best, average and worst. The comparative analysis revealed that CSMA method is more cost effective compared to other methods.

Table-5.19: Cost comparison for 40- unit system with other methods

Method	Overall Generation Cost ($)			Average Time(Sec.)
	Best	**Average**	**Worst**	
GA[332]	2249715	-	2256824	2697-
SM[332]	2249589	2249589	2249589	-
LR[332]	2250223	2250223	2250223	-
Enhanced Simulated Annealing[47]	2255864	2256971	2258897	199.55
Particle swarm optimization[137]	2250012	-	2257146	-
Evolutionary Programming (EP)	2249093	2252612	-	1176
Improved PSO[333]	2401728	-	-	316.86
Harmony Search[334]	-	2250968	-	467
Hybrid HS-Random Search[142]	2248508	2248652.78	2248.757	179.66
Hybrid HHO-IGWO(Proposed Method)	2249657.3623	2252698.0896	2256317.4070	0.078125
Chaotic HHO(Proposed Method)	2257230.0455	2260310.6018	2264045.7170	0.046875
Chaotic SMA(Proposed Method)	2246297.7597	2249497.0688	2252324.6943	0.06657

Table 5.18 illustrates results of proposed methods for 40-unit system compared with other methods in terms of best, average and worst. The comparative analysis revealed that hHHO-IGWO method is more cost effective compared to CHHO, CSMA and other methodologies.

Table-5.20: Cost comparison for 60- unit system with other methods

Method	**Overall Generation Cost ($)**			**Average Time(Sec.)**
	Best	**Average**	**Worst**	
GA[310]	3376625	-	3384252	5840
MINLP	3392140	-	-	69.721
IBPSO[333]	3367865	3368278	3368779	172
Evolutionary Programming (EP)[55]	3371611	3376255	3381012	2267
Improved PSO[137]	3370979	-	3379125	-
Hybrid HHO-IGWO(Proposed Method)	3374668.8771	3378103.0758	3381703.9070	0.096875
Chaotic HHO(Proposed Method)	3386078.2574	3392629.3063	3402247.3615	0.086834
Chaotic SMA(Proposed Method)	3375159.0917	3377469.9456	3378854.9012	0.076875

5.9 CONCLUSION

This chapter comprises solution to unit commitment problem by implementing proposed hHHO-IGWO, CHHO and CSMA method. Each method has been employed to solve UC problem for 10, 20, 40 and 60 unit system. The simulation outcomes for the test systems are recorded in terms of best, worst and average value. In order to inspect validity of proposed method, final outcomes were authenticated with other competitive algorithms such as SM, GA, ESA, LRGA, EP, PSO, IBPSO, binary PSO, GSA, HSA, etc. It is observed that proposed method is effective in handling unit commitment problem meritoriously with improved convergence.

CHAPTER-6

UNIT COMMITMENT PROBLEM WITH RENEWABLE SOURCE AND ELECTRIC VEHICLES

6.1 INTRODUCTION

A contemporary electrical power system is associated with a wide range of conventional and non-conventional energy sources. Since conventional energy sources are increasingly depleting, they must be used wisely. Renewable energy sources are inherently intermittent and do not deliver steady output power. The process of deciding the ON/OFF status of a generating unit in order to minimize total operating costs is known as unit commitment. Due to the large penetration of renewables, the UC problem has become even more complex. Furthermore, as battery technology, storage capacity, and energy policies have advanced, a large number of EVs have been introduced in recent years. As these EVs are charged from the existing grid, it may result in additional power demand. However, the energy stored in EVs could be fed back to the grid through V2G operation. It requires a coordinated charging and discharging schedule of PEVs in accordance with the system operator. An intelligent scheduling of generating units with significant V2G power would result in significant power generation savings.

Some research-related work is explored for better disclosure of problems concerned with wind and EV. Saber *et al*. [3] utilized the PSO method for selecting charging and discharging patterns in order to achieve the most economical operation and reduce emissions. A 10 unit system with a wind farm has a total output power of 25.5 MW from 17 wind turbines (each 1.5 MW) and 50,000 registered vehicles. The proposed method was found to be operative in reducing total operational costs. Khodayar *et al*. [171] explored various constraints associated with the intermittent nature of wind power. Furthermore, charging and discharging characteristics, V2G operating costs, and additional constraints due to storage are also included. In this work, uncertainties related to the vehicle to grid operation and wind power penetration were modeled by applying mixed-integer programming.

Yu *et al*. [172] used a chemical reaction algorithm for the utilization of energy stored in batteries via V2G. The major influence of this work is to provide an optimal generation schedule by diverting some part of energy via effective V2G operation. It was observed that the proposed method explored excellent results over other competitive algorithms. Chandrashekar *et al*. [173] incorporated rolling horizon search algorithm for controlled PEV operation to compensate for additional reserve cost requirements occurring due to uncertain wind availability.

Ghofrani *et al*. [174] integrated genetic algorithm with Monte Carlo simulation for getting optimal charging and discharging patterns of EVs. A control model was designed to balance the cost penalty with the uncertain wind power penetration. Gao *et al*. [175] introduced a controlled stochastic optimization technique for the effective V2G operation in the presence of intermittent wind power. The uncertainties associated with renewable penetration were compensated for by optimizing V2G control.

Zhang *et al*. [176] employed a fuzzy chance-constraint based program to solve problems of time mismatch between supply and load demand by using particle swarm optimization. Reddy *et al*. [19] explored the performance of different systems consisting of 10, 20, 40, 60, and 100 units in the presence of electric vehicles and renewable energy sources by implementing a modified firework algorithm. It was reported that the proposed Binary Firework Algorithm (BFWA) method gave more precise results when compared with other methods. Zhang *et al*. [177] developed a highly coordinated scheme using multiple group optimization based on multi-objective decomposition for eliminating uncertainties associated with PEVs and wind power. Pal *et al*. [26] proposed a centralized system modes of power transfer for direct benefit to consumers involved in vehicle to home and vehicle to grid operations using mixed integer programming.

Clement-Nyns *et al*. [178] incorporated quadratic programming and dynamic programming and introduced coordinated charging of PHEVs for maintaining a constant voltage profile and reliability. The stochastic nature of charging and discharging was mitigated by applying a probability density function. Su *et al*. [179] surveyed various opportunities and challenges for electrification of vehicles and V2G operation. Fernandez *et al*. [23] suggested methods to reduce different possibilities of increased cost and distribution losses with variable PEV penetration. This work explores different scenarios of increased cost due to large penetration of PEV. Ma *et al*. [180] investigated V2G operation for an IEEE-30 bus system and predicted problems in energy supply to customers in the case of wind power unavailability owing to likely uncertainties. Yao *et al*. [136] introduced a hierarchical decomposition approach by applying a coordinated charging/ discharging EV interpretation in order to maintain power supply security and reliability.

Darabi *et al*. [181] investigated various constraints and limitations while charging a large fleet of electric vehicles from the supply system. The proposed method was tested to determine percentage of PHEV allowed to charged, uncharged. Wang *et al*. [182] elaborated the impact of large V2G operation in existing grid. In order to minimize the power imbalance in distribution network during peak shaving, cross-entropy (CE) algorithm was tested for a 33-node system. Peng *et al*. [22] proposed a novel dispatching strategy for V2G aggregators to participate in power regulation, load frequency and load demand fulfillment.

Shekari *et al*. [184] applied linear programming to regulate the balance between active and reactive power by connecting a fleet of EVs in a micro-grid. The results were analyzed in terms of voltage profile, generating unit dispatch capacity, and operational cost minimization of the micro grid. Andervazh *et al*. [185] used the Weibull probability density function and the normal distribution function to revive uncertainties related with demand, renewables, and plug-in vehicles. Zhao *et al*. [335] devised a hybrid PSO algorithm by combining interior point method with PSO for solving economic dispatch involving wind and V2G penetration. This study also provides detailed modeling of uncertainties associated with wind and electric vehicles under diverse constraints and restrictions.

This chapter is committed to explore Unit commitment problem with thermal and wind (UC+W) and thermal with wind and electric vehicles (UC+W+EV). Unit commitment problem with wind and EV for -10, -20, -40 and -60 units has been tackled by incorporating one hybrid algorithm i.e. hHHO-IGWO and two chaotic variants i.e. CHHO and CSMA.

6.2 PROBLEM FORMULATION

The total generation cost is associated with cost for starting and shut down units, minimum up/down time, IS, SR and other system and environmental constraints. In general, the fuel cost is characterized by second order quadratic equation given as,

$$F_{\cos t} = \sum_{i=1}^{N} [\left(a_i P_{i,h}^2 + b_i P_{i,h} + c_i\right)] \tag{6.1}$$

Where, $a_i\, b_i and\, c_i$ are the fuel cost function expressed in $\$/\mathrm{h}, \$/MWh, and\ \$/MWh^2$ respectively.

The startup cost is related to the boiler temperature and mathematically, startup cost STC_i can be expressed in terms of hot start-up cost $(HSch)$ and cold startup (CSc) of i[th] unit respectively.

$$STC_i = \begin{cases} HSc_{i,h}; & MDt_i \le T_{i.h}^{OFF} \le (MDt_i + CSh_i) \\ CSc_{i,h}; & T_{i,h}^{OFF} > \left(MDt_i + CSh_i\right) \end{cases} \quad (i = N; h = 1,2,3,.....,\mathrm{H}) \tag{6.2}$$

Where, MDt_i is the minimum down time of unit 'i', $T_{i.h}^{OFF}$ is the duration for which unit 'i' is continuously OFF and CSh_i is the cold start-up hours.

Now, the total operating cost F_T is determined by summing up the generation cost of each unit and the start-up cost for a defined time interval. It can be mathematically represented as:

$$F_T = \sum_{h=1}^{H} (\sum_{i=1}^{N} [\left(a_i P_{i,h}^2 + b_i P_{i,h} + c_i\right) U_{i,h} + STC_i (1 - U_{\mathrm{i}(h-1)}) U_{i,h}]\ \$/\mathrm{hr} \tag{6.3}$$

The UC is associated with following system and unit constraints.

6.2.1 Operating Limits Constraints

These generation limits for a particular unit are calculated from the heat rate curve and fuel cost coefficient limits. Each generator is limited to maximum and minimum generation limit

$$PG_i^{\min} \le PG \le PG_i^{\max} \quad (i = 1, 2, ..., N \ ; \ h = 1, 2, ..., H) \tag{6.4}$$

6.2.1.1 Load Balance Constraints

To maintain reliability and security of power supply, total power demand should always meet the forecasted load demand.

$$\sum_{i=1}^{N} PG_i . U_{i,h} = D_L \qquad (i = 1,2,........,N; h = 1,2,3....,H) \qquad (6.5)$$

6.2.1.2 Spinning Reserve Constraints

It is the additional generation capacity to satisfy the demand with sufficient reserve margin should always be available. Mathematically, Spinning Reserve is given as:

$$\sum_{i=1}^{N} PG_i . U_{i,h} \geq D_{L(h)} + SR_{(h)} \qquad (i = 1,2,........,N; h = 1,2,3....,H) \qquad (6.6)$$

6.2.1.3 Minimum Up-time Constraints

This constraint gives the minimum time to put a generating unit online after it has already been shut down.

Mathematically expressed as:

$$T_{i,h}^{ON} \geq MUT_i \qquad (6.7)$$

6.2.1.4 Minimum down time Constraints

This constraint gives the minimum amount of time for which a particular unit should be kept in off condition before putting it online.

Mathematically expressed as:

$$T_{i,h}^{OFF} \geq MDT_i \qquad (6.8)$$

6.2.2 Mathematical modeling of Wind Uncertainties

Electrical energy is the primary requirement for the functioning of almost all day-to-day activities. Fossil fuels are the major ingredient for power industries to produce a large amount of power. Though energy production from fossil fuel is simpler, it also results in harmful hazardous effects on the environment by releasing fossil emissions. If the process of energy usage continues to stay with no alternatives, it may result in the fast usage of fossil fuels and ultimately reach its end one day. It becomes necessary to pay great attention towards the usage of these non-conventional sources for their long existence. The participation of renewable energy sources has lowered the burden on fossil fuels to satisfy load demand to some extent. Wind and solar are the principal renewable energy sources contributing towards total energy production throughout the world. Wind energy is stochastic in nature, with its velocity and direction changing over time. This uncertain stochastic nature could be revive by using various statistical techniques, such as the gamma function and the weibull probability distribution function, etc. It is necessary to understand the amount of energy produced by various turbines at various speeds

Mathematical formulation

We know, $P = \frac{1}{2}\rho A v^3$ (6.9)

Equation (6.9) determines the wind power produced by wind turbine at rated wind velocity 'V'. There is a limit for maximum produced by wind at any velocity 'V' investigated by German physicist Albert Betz in 1919. This limit turned to as power coefficient (CP max). At any instant, only 59% energy can be extracted from wind. Wind turbines, too, are unable to function at this maximum capacity. The power coefficient is a function of the turbine's operational wind speed. Even with the finest-designed turbines, the best power coefficient is determined to be between 0.35-0.45. Only about 10-30% of the wind's power can be transformed into useful electricity when numerous elements are taken into account, such as the gearbox, bearings, generators, and so on. As a result, the power coefficient element in eqn. (6.9) must be included, and the real extractable power from the wind is provided by,

$$P = \frac{1}{2}\rho A v^3 .Cp \qquad (6.10)$$

The power produced by wind turbines varies to cube of the rated speed. This however is applicable for certain range of speed. Indeed, for a small wind speed, there is not enough torque to rotate the turbine. The wind speed at which the rotor start to rotate is called the cut-in-speed. Below cut-in-speed, no power is produced. The cut-in-speed is typically around 3 to 4 m/s. On the other hand, if the wind is strong, the rotor cannot produce large power because of mechanical constraints. Therefore, the so called cut-out-speed is the maximum speed at which power can be safely produced. The cut-out-speed lies typically around 15 m/s. Finally, electrical generator also imposes a limit on the power that can be produced as output power. Thus, beyond a certain wind speed, the power is limited to a constant value.

The most often used distribution in reliability engineering is the Weibull distribution function, which was devised by Swedish academic Waloddi Weibull in 1951. It is a flexible distribution function dependent on the shape and scale factor. The function for the evaluation of wind energy is,

$$pdk(v;k,\lambda)=\frac{k}{\lambda}\left(\frac{v}{\lambda}\right)^{k-1}\exp\left[-\left(\frac{v}{k}\right)^{k}\right] \tag{6.11}$$

$$Pw=\begin{cases} 0 & (v^h \le v_{in} \ or \ v^h \ge v_{out}) \\ Pwr & (v_r \le v^h \le v_{out}) \\ \dfrac{(v-vin)}{v_r - vin} & (v_{in} \le v^h \le v_r) \end{cases} \tag{6.12}$$

Pr (Pw=0) = $cdf(v_{in})+\left[1-cdf(v_{out})\right]$ (6.13)

For Pw=0, Pr = $\left[1-\exp\left[-\left(\frac{v_{in}}{\lambda}\right)^{k}\right]+\exp\left[-\left(\frac{v_{out}}{\lambda}\right)^{k}\right]\right]$ (6.14)

$$pdf(PW)=\frac{KLv_{in}}{(P_{wr})^{\lambda}}\left[\frac{1+\left(LP_w/P_{WR}\right)v_{in}}{\lambda}\right]\times\exp\left[-\left(\frac{1+\left(LP_W/P_{WR}\right)v_{in}}{\lambda}\right)^{k}\right] \tag{6.15}$$

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.

6.2.3 Unit commitment problem formulation for integrated system consisting of thermal units and wind as renewable source

Case-1: UCP with RES

The power balance is achieved when overall generation meets the allocated load as,

$$\sum_{i=1}^{N} PG_i .U_{i,h} + P_g^w = D_L \qquad \left(i=1,2,........,N; h=1,2,3....,H\right) \tag{6.16}$$

For arbitrary free unit power outputs Phi, within minimum and maximum power limit.

$P_{g\,\mathrm{min(i)}} \le P_{g(i)} \le P_{g\,\mathrm{max)(i)}}$ $(i \in 1,2,...., N \ ; \ h \in 1,2,...., H)$.

It is assumed that the Rth reference unit power output is constrained by the power balance eqn. as:

$$P_{hR} = D_L - \sum_{\substack{i=1\\ i\ne R}}^{NG} (P_{g(i)}U_{i,\mathrm{h}} + P_g^w) \qquad (h=1,2,...,H) \tag{6.17}$$

Case-2: UCP with RES and EVs

In this section, unit commitment problem formulation for an integrated system consisting of thermal units, wind as a renewable source, and electric vehicles.

It is assumed that there is a fleet of 40,000 registered vehicles. As all the EVs cannot be charged and discharged simultaneously, only 20 % of the vehicles are involved in G2V/V2G operation. The battery capacity of each vehicle is 15 KW, the departure state of charge (δ) = 0.50% and efficiency (η). Thus, only 8000 vehicles can participate returning back a net power of 51 MW for a typical charging/discharging pattern as depicted in Table .6.1 given below. During charging, these electric vehicles act as load and consumes energy, while during discharging they perform V2G operation and fed back stored energy in batteries to the grid. A typical charging/discharging is considered for G2V and V2G operation.

Table-6.1: A typical charging/ discharging scenario

Time(H)	Number of EVs	P_{G2V} (MW)	P_{V2G} (MW)
1	5096	32.4	0
2	3378	21.5	0
3	3646	21.24	0
4	6643	42.35	0
5	1918	22.99	0
6	6155	39.24	0
7	3633	13.54	0
8	577	3.67	0
9	7335	0	46.76
10	7134	0	45.48
11	5213	0	33.23
12	7541	0	48.73
13	7330	0	46.73
14	388	0	2.47
15	4552	29.02	0
16	1069	6.81	0
17	5460	34.8	0
18	6363	40.56	0
19	4426	41.21	0
20	7367	0	46.96
21	2606	0	16.58
22	7442	0	47.44
23	5635	0	35.92
24	6967	0	44.41

Condition-1: During Charging of Vehicle (Grid to Vehicle)

$$\sum_{i=1}^{N} P_{g(i)} U_{i,h} + P_g^w = D_L + D_h^V \qquad (i = 1, 2, ..., N) \tag{6.18}$$

Condition-2: During Discharging (Vehicle to Grid)

$$\sum_{i=1}^{N} P_{g(i)} U_{i,h} + P_g^w + D_h^V = D_L \qquad (i = 1, 2, ..., N) \tag{6.19}$$

. For arbitrary free unit power outputs *Phi*, (i=1, 2, NG), it is implicit that the Rth reference output is controlled by the power balance eqn. as:

$$P_{Rh} = D_L - \sum_{i=1}^{N} P_{g(i)} U_{i,h} + P_g^w \qquad (i = 1, 2, ..., N) \tag{6.20}$$

Condition-3: During Charging of Vehicle

$$P_{Rh} = (D_L - \sum_{i=1}^{N} (P_{g(i)} \; U_{i,h} \; + \; P_g^w - \; D_h^V) \qquad (i = 1, 2, ..., N) \tag{6.21}$$

Condition-4: During Discharging

$$P_{Rh} = (D_L - \sum_{i=1}^{N} (P_{g(i)} U_{i,h} + P_g^w + D_h^V) \qquad (i = 1, 2, ..., N) \tag{6.22}$$

V2G Constraint: V2G technology enables a fixed number of registered vehicle to participate in UC. Electric vehicles are assumed to be charged during off-load period by utility grid or from renewable energy sources. Charging- discharging duration depends upon battery size and charging facilities. It is assumed that all vehicles charged by stand-alone system available at the parking slot. It is also assumed that only β% of total vehicles can participate in V2G operation

$$\sum_{t=1}^{H} N_{V2G}(t) = \beta \% N_{V2G}^{Max}(t) \tag{6.23}$$

6.3 SOLUTION METHODOLOGIES FOR UNIT COMMITMENT PROBLEM

In this section UCP is tested by applying hybrid Harris hawks algorithm, Chaotic Harris Hawks algorithm and Chaotic Slime Mould Algorithm. Subsequent section presents various spinning reserve and minimum up/down constraints.

6.3.1 Spinning Reserve Constraint Repairing

Spinning reserve constraint is repaired as per code illustrated in appendix-A (iii) and flow chart for spinning reserve repair mechanism as shown in Fig.6.1.

Step1: Align the generators in order of generating capacity in descending order.

Step2: *for* i = 1 to N

if $u_{i,h} = 0$

then $u_{i,h} = 1$

else if $T_{i,h}^{OFF} > MDT_i$

then $T_{i,h}^{ON} = T_{i,h-1}^{ON} + 1$ and $T_{i,h}^{OFF} = 0$

end if

end for

Step-3: Verify new generating power of units.

Step-4: if $\sum_{i=1}^{N} P_{gi(\max)} U_{i,h} - P_h^{RES} \geq D_h \pm D_h^v + R_h$ then stop the iterations, else go to step-2.

Step-5: if $T_{i,h}^{OFF} > MDT_i$ then do $l = h - T_{i,h}^{OFF} + 1$ and set $u_{i,h} = 1$

Step-6: Calculate $T_i^l = T_{l-1,i}^{ON} + 1$ and $T_{i,h}^{OFF} = 0$

Step-7: if l >h, Verify generator output power for $\sum_{i=1}^{N} P_{gi(\max)} U_{i,h} - P_h^{RES} \geq D_h \pm D_h^v + R_h$, else increment l by 1 and go to step-5.

6.3.2 Minimum Up/Down constraints repairing

To satisfy Minimum up/down time requirement of generating units, repairing mechanism is presented in Appendix-A (iii)

6.3.3 De-commitment of Excessive Generating Units

In order to update spinning reserve requirement of various thermal generating units, Minimum down time (MDT_i) of each generating unit along with duration for which i^th^ generating unit is continuously OFF $(T_{i,h}^{OFF})$ is taken into consideration and constraint is repaired as presented in Appendix-A (iv). The flow chart is illustrated in Fig.6.2.

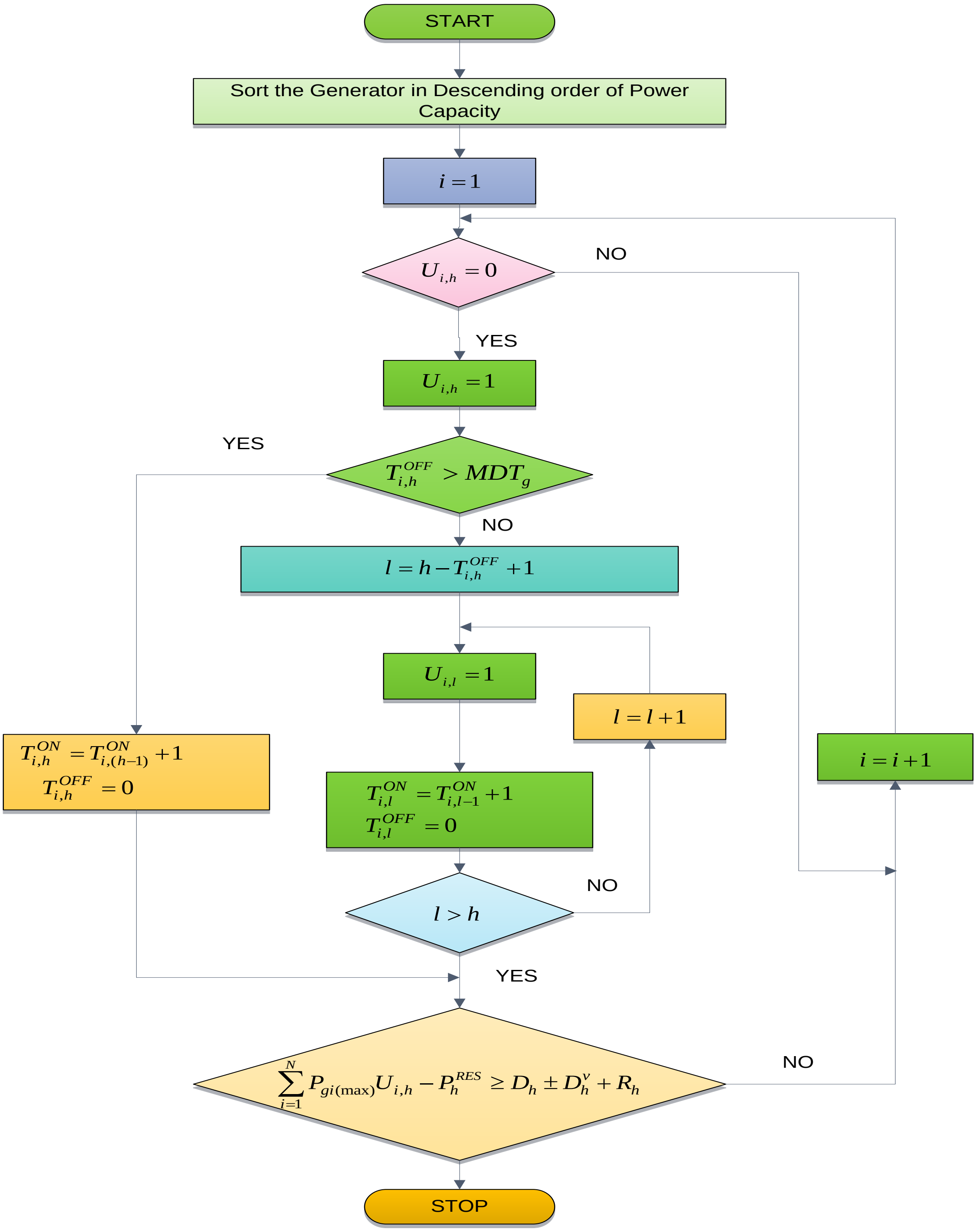


Fig. 6.1: Spinning reserve repairing in presence RES and EV

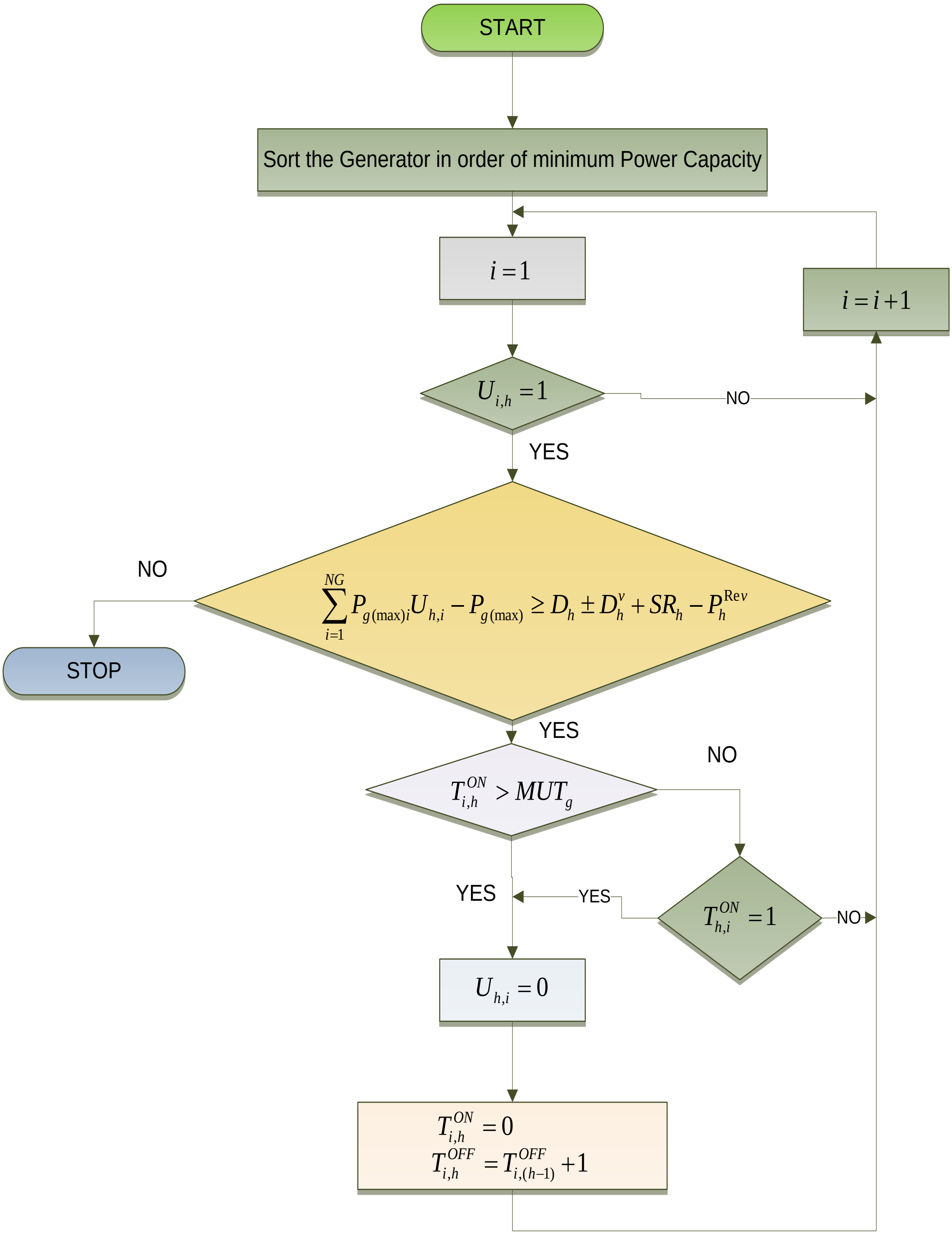


Fig.6.2: Flow chart for de-commitment of excessive generative units

6.4 HYBRID HARRIS HAWKS OPTIMIZER

In order to develop Hybrid Harris Hawks optimizer (hHHO-IGWO), the general operators of HHO algorithm and IGWO algorithm are integrated. The procedure for unit commitment using hHHO-IGWO algorithm is explained below.

The optimization procedure for the hHHO-IGWO algorithm consists of the following 13 steps:

Step-1: As indicated below, configure UCP parameters and individuals in the population: The unit's ON/OFF schedule is saved as an integer-matrix, which is technically described as:

$$U_{\kappa hi} = \begin{bmatrix} u_{11}^{\kappa} & u_{12}^{\kappa} & \cdots & u_{1NG}^{\kappa} \\ u_{21}^{\kappa} & u_{22}^{\kappa} & \cdots & u_{2NG}^{\kappa} \\ \vdots & \vdots & \vdots & \vdots \\ u_{H1}^{\kappa} & u_{H2}^{\kappa} & \cdots & u_{HNG}^{\kappa} \end{bmatrix}_{H \times NG} \quad (h = 1, 2, ..., H; \quad i = 1, 2, ..., N; \quad \kappa = 1, 2, ..., NP)$$

Step-2: In descending order, generating units are prioritized based on their greatest generation capacity.

Step-3: Individual unit status is changed to meet the spinning reserve constrictions.

Step-4: Repair unit status for minimum time defilements.

Step-5: De-commit the population's extra units to reduce reserve requirement

Step-6: The problem of UC is solved, and fuel costs for each hour are determined.

Step-7: Apply HHO and perform exploration phase to generate updated target vector $X(itn+1)$.

Step-8: Apply Levy flight to further update to generate $X(itn+1)^{new}$.

Step-9: Replace worst positions vector $X(itn+1)^{worst}$ with $X(itn+1)^{new}$

Step-10: Determine overall generation cost for (it^n)

Step-11: If $it^n = it_{\max}^n$, then go to step 13.

Step-12: If $it^n < it_{\max}^n$, increase it^n by one and return to step 3 and repeat.

Step-13: Stop and determine best solution for UC.

6.5 CHAOTIC HARRIS HAWKS OPTIMIZER

In order to develop the chaotic algorithm for solving unit commitment problem, the general operators of Harris Hawks are integrated Tent chaotic function. Initially, a random solution is generated within the entire population by clubbing corresponding chaotic function. In proposed algorithm, chaotic search is applied to optimize a vector of units to be committed for mininizing the overall cost. The following are the various steps in the proposed CHHO algorithm:

Step-1: Initialization of UCP and Chaotic parameters of the algorithm.

Step-2: Enter UCP input parameters and generate random vectors as many Hawks position using eqn.(6.1).Each random vector is defined as generating unit ON/OFF (or 1/0) status, defined as:

$$U_{\kappa hi} = \begin{bmatrix} u_{11}^{\kappa} & u_{12}^{\kappa} & \cdots & u_{1NG}^{\kappa} \\ u_{21}^{\kappa} & u_{22}^{\kappa} & \cdots & u_{2NG}^{\kappa} \\ \vdots & \vdots & \vdots & \vdots \\ u_{H1}^{\kappa} & u_{H2}^{\kappa} & \cdots & u_{HNG}^{\kappa} \end{bmatrix}_{H\times NG} \qquad (h=1,2,...,H; \quad i=1,2,...,N; \quad \kappa=1,2,...,H)$$

Where, u_{hi} is unit ON/OFF status of ith unit at hour h (i.e. u_{hi} =1/0 for ON/OFF).

Step-3: Arrange the generating units in descending order according to their maximum generation capability.

Step-4: Modification of units' status of every entities in the population obeying reserve restrictions as mentioned in section -5.3.1.

Step-5: Repair individual unit status for minimum up/down time defilements as per section -5.3.2.

Step-6: De-commit the population's extra units to reduce spinning reserve due to less up/down time mending.

Step-7: Apply HHO and perform exploration phase to generate updated target vector $X(itn+1)$.

Step-8: Apply Levy flight to further update $X(itn+1)$ to generate $X(itn+1)^{new}$.

Step-9: Replace worst positions vector $X(itn+1)^{worst}$ with $X(itn+1)^{new}$ using eqn. (2.13)

Step-10: Determine overall generation cost for (it^{n}) .

Step-11: If $it^n = it^n_{\max}$, then go to step 13.

Step-12: If $it^n < it^n_{\max}$, increase it^n by one and return to step 3 and repeat.

Step-13: Stop and figure out the most profitable solution to the unit commitment dilemma.

6.6 CHAOTIC SLIME MOULD ALGORITHM

The detailed theoretical and mathematical aspects of CSMA has been already discussed in chapter 3. In proposed algorithm, chaotic search is applied to optimize a vector U_{NP} of units to be committed for mininizing the overall cost. The various steps for the proposed CHHO algorithm are mentioned below:

Step-1: Initialization of UCP and Chaotic parameters of the algorithm

Step-2: Enter UCP input parameters and generate random vectors as many Slime mould position using eqn (6.1).

Step-3: Display the generating units in descending order according to their maximum generation capability.

Step-4: Modification of units' status of every individuals in the population

Step-5: Repair individual unit status for minimum up/down time defilements

Step-6: De-commit the population's extra units to reduce spinning reserve due to less up/down time mending.

Step-7: Apply SMA and perform exploration to generate updated target vector $X(itn+1)$

Step-8: Apply Chaotic strategy further update $X(itn+1)$ using smell index generate $X(itn+1)^{new}$.

Step-9: Replace worst positions vector $X(itn+1)^{worst}$ with $X(itn+1)^{new}$

Step-10: Determine overall generation cost for (it^n)

Step-11: If $it^n = it^n_{\max}$, then go to step 13.

Step-12: If $it^n < it^n_{\max}$, increase it^n by one and return to step 3 and repeat.

Step-13: Stop and figure out the most profitable solution to the unit commitment dilemma.

6.7 Testing of Unit Commitment Problem with RES and EV

Standard IEEE system data consisting of 10, 20, 40 and 60 units has been analysed by implementing three proposed algorithms. The system data used in the proposed study are load demand, fuel cost coefficients of each generating unit, MUT, MDT and Initial State (IS).

6.7.1 Testing of Unit Commitment Problem with RES and EV by Hybrid Harris Hawks Algorithm

The proposed algorithm is applied to standard test systems consisting of 10, 20, 40 and 60 units and simulation results are recorded for UC with wind as renewable energy source and UC with wind and Electric vehicle. Each run is performed starting with different initial population size.

(a)Testing of 10-unit system using hHHO-IGWO

The hHHO-IGWO algorithm is applied to standard test systems consisting of 10-units with 10% SR and simulation results are recorded for wind and wind & EV. Table-6.2 represents their corresponding power dispatch for each unit with wind penetration. Table-6.3 shows corresponding power dispatch with wind & EV penetration. The convergence curves with wind and with wind & EV for 10-unit system are demonstrated in Fig.6.3 and Fig.6.4 separately.

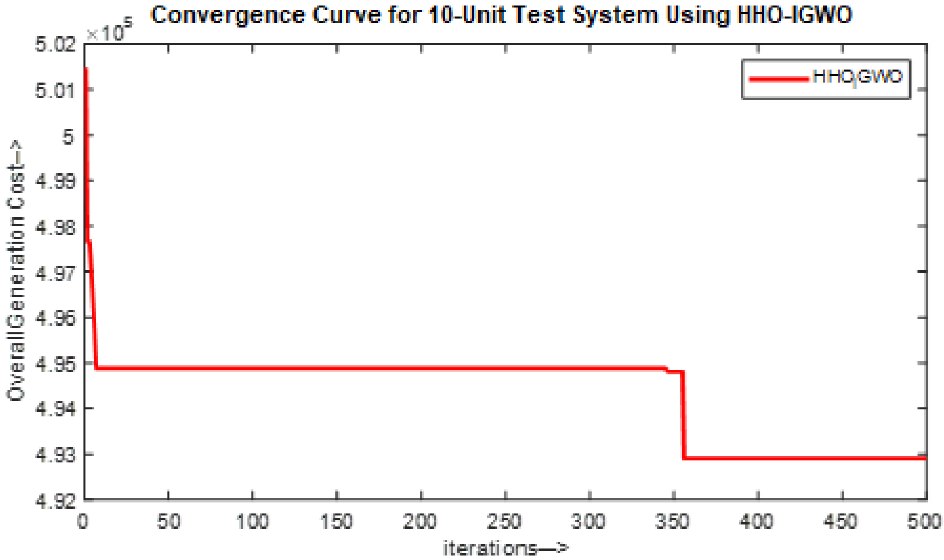


Fig.6.3: Convergence Curve 10 unit system with wind using hHHO-IGWO

Table-6.2: Scheduling of 10-unit system with wind

Time (h)	**Scheduling of 10 units**										**Generated Power (MW)**	**Start-Up Cost**	**Hourly Fuel Cost**
	U1	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**	**U8**	**U9**	**U10**			
1	373	150	0	0	0	0	0	0	0	0	523	550	10672
2	429	150	0	0	0	0	0	0	0	0	579	260	11600
3	455	237	0	0	0	0	0	0	0	0	692	560	13544
4	455	350	0	0	0	0	0	0	0	0	805	400	15515
5	455	378	0	0	25	0	0	0	0	0	858	900	16949
6	455	455	0	0	53	0	0	0	0	0	963	0	18859
7	455	420	130	0	25	0	0	0	0	0	1030	0	20576
8	455	455	130	0	51	0	0	0	0	0	1091	0	21710
9	455	444	130	130	25	0	0	0	0	0	1184	0	23858
10	455	455	130	130	89	0	25	0	0	0	1284	260	26515
11	455	455	130	130	118	20	25	0	0	0	1333	170	27928
12	455	455	130	130	160	20	25	10	0	0	1385	60	29721
13	455	455	130	130	71	20	25	0	0	0	1286	60	26967
14	455	451	130	130	25	0	0	0	0	0	1191	90	23981
15	455	353	130	130	25	0	0	0	0	0	1093	0	22265
16	455	199	130	130	25	0	0	0	0	0	939	0	19580
17	455	157	130	130	25	0	0	0	0	0	897	0	18851
18	455	250	130	130	25	20	0	0	0	0	1010	0	21277
19	455	340	130	130	25	20	0	0	0	0	1100	60	22863
20	455	455	130	130	90	20	0	0	0	0	1280	340	26179
21	455	433	130	130	25	0	0	0	0	0	1173	0	23665
22	455	455	0	0	53	0	0	0	0	0	963	0	18859
23	455	285	0	0	0	0	0	0	0	0	740	0	14380
24	455	170	0	0	0	0	0	0	0	0	625	0	12379
Worst Cost($)=495978.9707				**Best Cost($)=492400.2699**				**Mean Cost($)=494231.2616**					**Total= 492400.2699($)**
Worst Time(Sec.)= 0.09375				**Best Time(Sec.)= 0.03125**				**Mean Time(Sec.)= 0.0526**					

Referring Table 6.1 , U1 and U2 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load demand. Start-up cost depends upon the operating temperature of particular unit and initial state. At 9th to 13th hour , load is at peak demand and thus units U1 to U7 are in ON state. U8 to U10 act as the reserve unit and runs only during the peak load.The total operating cost is the sum of start-up cost and generation cost of units for a 24 hour duration.

In Table 6.2 , U1 and U2 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load deamd. During the peak hours, U3 to U5 units contribute their power meet the corresponding load demand. During 9th to 13th hour , load is at peak demand and thus units U1 to U7 are in ON state. U8 to U10 act as the reserve unit and runs only during the peak demand.

The simulation results for HHO-IGWO algorithm for 10 unit shows total cost of UC, UC+W and UC+W+EV are **$ 563435.9964, $ 492400.2699** and **$ 489514.5979** respectively. The results shows that there is cost saving of **$ 73921.3985** with coordinated charging/discharging of EV for V2G operation.Thus, the proposed method is cost effective in dealing unit commitment problem under uncertain sustainable environment.

Table-6.3: Scheduling of 10 units with wind & EV using hHHO-IGWO method

Time (h)	Generation scheduling										Power (MW)	Start-Up Cost	Hourly Fuel Cost
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10			
1	405	150	0	0	0	0	0	0	0	0	555	0	11208
2	450	150	0	0	0	0	0	0	0	0	601	960	11957
3	455	258	0	0	0	0	0	0	0	0	713	820	13914
4	455	367	0	0	25	0	0	0	0	0	847	90	16763
5	455	401	0	0	25	0	0	0	0	0	881	550	17352
6	455	392	130	0	25	0	0	0	0	0	1002	0	20090
7	455	434	130	0	25	0	0	0	0	0	1044	0	20814
8	455	355	130	130	25	0	0	0	0	0	1095	60	22294
9	455	397	130	130	25	0	0	0	0	0	1137	0	23039
10	455	455	130	130	44	0	25	0	0	0	1239	600	25595
11	455	455	130	130	85	20	25	0	0	0	1300	120	27246
12	455	455	130	130	121	20	25	0	0	0	1336	0	27995
13	455	455	130	130	49	20	0	0	0	0	1239	0	25354
14	455	449	130	130	25	0	0	0	0	0	1189	0	23937
15	455	382	130	130	25	0	0	0	0	0	1122	60	22772
16	455	336	0	130	25	0	0	0	0	0	946	0	19073
17	455	322	0	130	25	0	0	0	0	0	932	320	18828
18	455	440	0	130	25	0	0	0	0	0	1050	0	20897
19	455	455	0	130	82	20	0	0	0	0	1142	170	23116
20	455	455	0	130	153	20	0	0	10	10	1233	120	26476
21	455	455	0	130	96	20	0	0	0	0	1156	30	23418
22	455	331	0	130	0	0	0	0	0	0	916	60	18036
23	455	249	0	0	0	0	0	0	0	0	704	0	13754
24	431	150	0	0	0	0	0	0	0	0	581	0	11626
Worst Cost($)=492893.0072			**Best Cost($)=489514.5979**			**Mean Cost($)=491394.7670**							**Total= 489514.5979($)**
Worst Time(Sec.)= 0.0625			**Best Time(Sec.)= 0.046875**			**Mean Time(Sec.)= 0.05**							

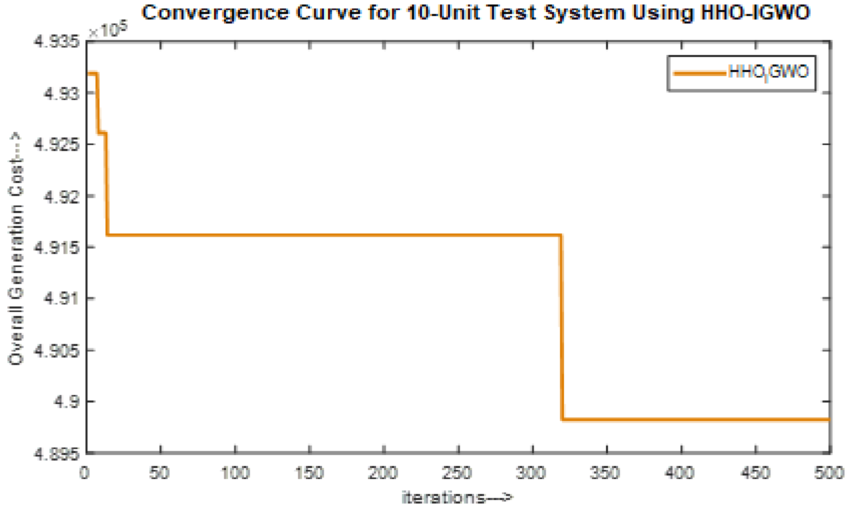


Fig.6.4: Convergence Curve 10 unit system with wind and EV using hHHO-IGWO

(b) Testing of 20-unit system using hHHO-IGWO

Population size is taken as 80 for all 30 trial runs with 500 iterations and simulation results are recorded for UC with wind and UC with wind & EV. Table-6.4 illustrates optimal status of committed generators with wind. Table-6.5 shows their corresponding power dispatch with wind & EV penetration. The convergence curves with (UC + W) and (UC +W+EV) for 20-unit system are demonstrated in Fig.6.5 and Fig.6.6.

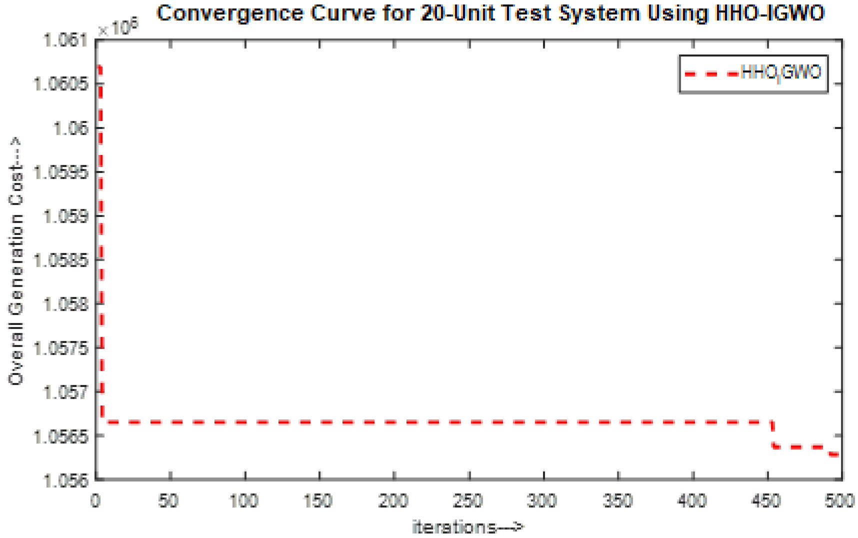


Fig.6.5: Convergence Curve for 20-unit system with wind using hHHO-IGWO

Table-6.4: Scheduling of 20 units with wind using hHHO-IGWO

Time (h)	**Scheduling for 20 unit**																				**Hourly Fuel Cost**
	U1	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**	**U8**	**U9**	**U10**	**U11**	**U12**	**U13**	**U14**	**U15**	**U16**	**U17**	**U18**	**U19**	**U20**	
1	455	157	0	0	0	0	0	0	0	0	455	157	0	0	0	0	0	0	0	0	24289
2	455	197	0	0	25	0	0	0	0	0	455	197	0	0	0	0	0	0	0	0	26641
3	455	304	0	0	25	0	0	0	0	0	455	304	0	0	0	0	0	0	0	0	30351
4	455	410	0	0	25	0	0	0	0	0	455	410	0	0	0	0	0	0	0	0	34074
5	455	397	130	0	25	0	0	0	0	0	455	397	0	0	0	0	0	0	0	0	36493
6	455	369	130	0	25	0	0	0	0	0	455	369	130	130	0	0	0	0	0	0	41283
7	455	363	130	130	25	0	0	0	0	0	455	363	130	130	0	0	0	0	0	0	43917
8	455	406	130	130	25	0	0	0	0	0	455	406	130	130	25	0	0	0	0	0	46366
9	455	455	130	130	59	0	25	0	0	0	455	455	130	130	59	0	0	0	0	0	50658
10	455	455	130	130	134	20	25	0	0	0	455	455	130	130	134	20	0	10	0	0	56285
11	455	455	130	130	162	32	25	10	0	10	455	455	130	130	162	32	0	10	0	0	59844
12	455	455	130	130	162	65	25	10	10	0	455	455	130	130	162	65	25	10	10	0	63483
13	455	455	130	130	128	20	25	0	0	0	455	455	130	130	128	20	25	0	0	0	56269
14	455	455	130	130	63	0	0	0	0	0	455	455	130	130	63	0	25	0	0	0	50799
15	455	407	130	130	25	0	0	0	0	0	455	407	130	130	25	0	0	0	0	0	46401
16	455	254	130	130	25	0	0	0	0	0	455	254	130	130	25	0	0	0	0	0	41092
17	455	209	130	130	25	0	0	0	0	0	455	209	130	130	25	0	0	0	0	0	39491
18	455	302	130	130	25	0	25	0	0	0	455	302	130	130	25	0	0	0	0	0	43931
19	455	398	130	130	25	0	25	0	0	0	455	398	130	130	25	0	0	0	0	0	47267
20	455	455	130	130	132	20	25	0	0	0	455	455	130	130	132	20	0	10	0	0	56201
21	455	455	130	130	99	20	25	0	0	0	455	455	130	0	99	20	0	0	0	0	51040
22	455	455	130	0	0	20	0	0	0	0	455	455	0	0	73	20	0	0	0	0	41144
23	455	365	0	0	0	0	0	0	0	0	455	365	0	0	0	0	0	0	0	0	31554
24	455	258	0	0	0	0	0	0	0	0	455	258	0	0	0	0	0	0	0	0	27802
															Overall Cost of Generation =**1052906.5262($)**						

Table-6.5: Scheduling of 20 units with Wind and EV using hHHO-IGWO

Time (h)	**Scheduling for 20 units**																				**Hourly Fuel Cost**
	U1	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**	**U8**	**U9**	**U10**	**U11**	**U12**	**U13**	**U14**	**U15**	**U16**	**U17**	**U18**	**U19**	**U20**	
1	445	150	0	0	0	0	0	0	0	0	445	150	0	0	0	0	0	0	0	0	23741
2	455	199	0	0	0	0	0	0	0	0	455	199	0	0	0	0	0	0	0	0	25757
3	455	305	0	0	0	0	0	0	0	0	455	305	0	0	0	0	0	0	0	0	29471
4	455	389	0	0	25	0	0	0	0	0	455	389	0	0	0	0	0	0	0	0	33333
5	455	440	0	0	25	20	0	0	0	0	455	440	0	0	0	0	0	0	0	0	35944
6	455	455	0	0	27	20	0	0	0	0	455	455	0	130	27	0	0	0	0	0	40350
7	455	455	0	130	33	20	0	0	0	0	455	455	0	130	33	0	0	0	0	0	43464
8	455	455	0	130	29	20	0	0	0	0	455	455	130	130	29	0	0	0	0	0	46174
9	455	455	130	130	80	20	0	0	0	0	455	455	130	130	80	0	0	0	10	0	52086
10	455	455	130	130	145	20	25	10	0	0	455	455	130	130	145	20	25	0	0	0	57885
11	455	455	130	130	162	41	25	10	0	0	455	455	130	130	162	41	25	0	10	0	60503
12	455	455	130	130	162	80	25	15	10	10	455	455	130	130	162	80	25	15	10	0	65360
13	455	455	130	130	146	20	25	10	0	0	455	455	130	130	146	20	25	0	0	0	57953
14	455	455	130	130	88	20	0	0	0	0	455	455	130	130	0	20	25	0	0	0	51246
15	455	404	130	130	25	0	0	0	0	0	455	404	130	130	0	0	0	0	0	0	45386
16	455	264	130	130	25	0	0	0	0	0	455	264	130	130	0	0	0	0	0	0	40464
17	455	204	130	130	25	0	0	0	0	0	455	204	130	130	0	0	0	0	0	0	38376
18	455	307	130	130	25	0	0	0	0	0	455	307	130	130	0	0	0	0	0	0	41977
19	455	402	130	130	25	0	0	0	0	0	455	402	130	130	0	0	0	0	0	0	45302
20	455	455	130	130	151	20	0	0	10	0	455	455	130	130	151	20	25	0	10	0	57928
21	455	455	130	0	107	20	0	0	0	0	455	455	130	130	107	20	25	0	0	0	51380
22	455	455	0	0	0	20	0	0	0	0	455	455	0	130	95	20	25	0	0	0	42744
23	455	370	0	0	0	0	0	0	0	0	455	370	0	0	25	0	0	0	0	0	32690
24	455	267	0	0	0	0	0	0	0	0	455	267	0	0	25	0	0	0	0	0	29085
																Overall Cost of Generation = **1057895.7527($)**					

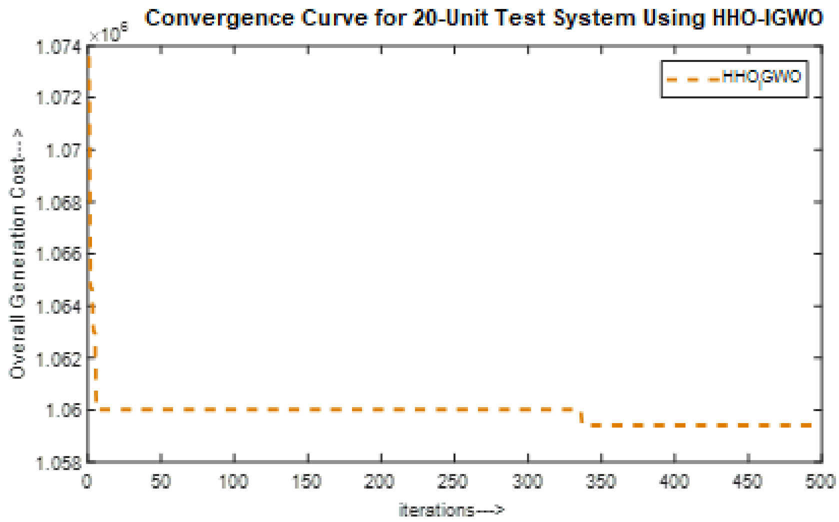


Fig.6.6: Convergence Curve for 20-unit system with wind &EV using hHHO-IGWO

Referring Table 6.4, U1, U2, U11 and U12 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load demand. At 8th to 10th hour, load is at peak demand and thus units U1 to U6 and U11 to U16 are in ON state. U7 to U10 and U17 to U20 act as the reserve unit and runs only during the peak demand.

Referring Table 6.5, U1, U2, U11 and U12 are the economical units and thus run for total 24 hours to meet the corresponding load demand. At 10th to 13th hour, load is at peak demand and thus units U1 to U6 and U11 to U16 are in ON state. U7 to U10 and U17 to U19 act as the reserve unit and runs only during the peak demand.

The simulation results for HHO-IGWO algorithm for 20 unit system shows total cost of UC, UC+W and UC+W+EV are **$ 1124860.6904, $ 1052906.5262** and **$ 1057895.7527** respectively.

The results shows that there is cost saving of **$ 66964.9377** with coordinated charging/discharging of EV for V2G operation.It can be seen from Fig.6.5 and Fig.6.5 that the curves converges smothly to an optimal value.Thus, the proposed method is cost effective in dealing unit commitment problem under uncertain sustainable environment.

(c) Testing of 40-unit system using hHHO-IGWO

The hHHO-IGWO method is tested for solving unit commitment problem for 40-unit system with wind and EV. Table-6.6 (a) and 6.6(b) illustrates optimal dispatch for 40-unit system with wind. Table-6.7 (a) and 6.7(b) illustrates optimal dispatch for 40-unit system with wind & EV. The convergence curves with wind and wind & EV for 40-unit system are demonstrated in Fig.6.7 and Fig.6.8.

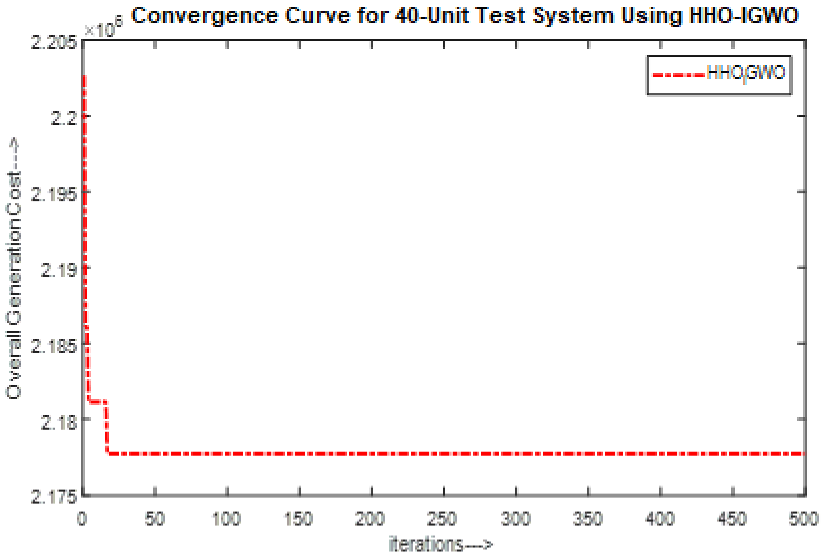


Fig.6.7: Convergence Curve for 40-units with wind using hHHO-IGWO

Referring Table 6.6(a) and 6.6(b), U1, U2, U11, U12,U21,U22,U31 and U32 are the most cost efficient units and thus remains ON for maximum hours to meet the corresponding power demand. For rest of hours, U3 to U9, U13 to U19, U23 to U29 and U33 to U39 contributes their power meet the corresponding power demand. At 12th hour, load is at peak and thus all the units are in ON state. U10, U20, U30 and U40 act as the reserve unit and runs only during the peak demand.

Referring Table 6.7(a) and 6.7(b), U1, U2, U11, U12,U21,U22,U31 and U32 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load demand. For rest of hours, U3 to U9, U13 to U19, U23 to U29 and U33 to U39 contributes their power meet the corresponding load demand. During 12th hour, load is at maximum demand and thus most of the units are in ON state. U10, U20, U30 and U40 act as the reserve unit and runs only during the peak demand.

Table-6.6(a): Scheduling of 1 to 20 units for 40 units system with wind using hHHO-IGWO

Time (h)	Scheduling for 1 to 20 units																			
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13	U14	U15	U16	U17	U18	U19	U20
1	455	201	0	0	0	0	0	0	0	0	455	201	0	0	0	0	0	0	0	0
2	455	252	0	0	0	0	0	0	0	0	455	252	0	0	0	0	0	0	0	0
3	455	356	0	0	0	0	0	0	0	0	455	356	0	0	0	0	0	0	0	0
4	455	441	0	0	0	0	0	0	0	0	455	441	0	0	0	0	0	0	0	0
5	455	455	0	130	0	0	0	0	0	0	455	455	0	0	0	0	0	0	0	0
6	455	431	0	130	0	0	0	0	0	0	455	431	130	130	0	0	0	0	0	0
7	455	414	130	130	25	0	0	0	0	0	455	414	130	130	0	0	0	0	0	0
8	455	434	130	130	25	0	0	0	0	0	455	434	130	130	0	0	0	0	0	0
9	455	455	130	130	81	20	0	0	0	0	455	455	130	130	81	20	0	0	0	0
10	455	455	130	130	154	20	25	10	0	0	455	455	130	130	154	20	25	0	0	0
11	455	455	130	130	162	51	25	10	0	0	455	455	130	130	162	51	25	10	0	0
12	455	455	130	130	162	80	25	22	10	10	455	455	130	130	162	80	25	22	10	0
13	455	455	130	130	154	20	25	0	0	0	455	455	130	130	154	20	25	10	0	0
14	455	455	130	130	83	20	0	0	0	0	455	455	130	130	83	20	0	0	0	0
15	455	433	130	130	25	0	0	0	0	0	455	433	130	130	25	0	0	0	0	0
16	455	282	130	130	25	0	0	0	0	0	455	282	130	130	25	0	0	0	0	0
17	455	234	130	130	25	0	0	0	0	0	455	234	130	130	25	0	0	0	0	0
18	455	332	130	130	25	0	0	0	0	0	455	332	130	130	25	20	0	0	0	0
19	455	421	130	130	25	0	0	0	0	0	455	421	130	130	25	20	0	0	0	10
20	455	455	130	130	153	20	25	10	0	0	455	455	130	130	153	20	25	0	0	0
21	455	455	130	130	117	20	25	0	0	0	455	455	130	130	117	0	25	0	0	0
22	455	455	0	130	88	20	25	0	0	0	455	455	0	130	0	0	25	0	10	0
23	455	399	0	0	25	0	0	0	0	0	455	399	0	0	0	0	0	0	0	0
24	455	301	0	0	0	0	0	0	0	0	455	301	0	0	0	0	0	0	0	0

Table-6.6(b): Scheduling of 21 to 40 units for 40 unit system with wind using hHHO-IGWO

Time (h)	Scheduling for 21-40 Units																				Hourly Fuel Cost
	U21	U22	U23	U24	U25	U26	U27	U28	U29	U30	U31	U32	U33	U34	U35	U36	U37	U38	U39	U40	
1	455	201	0	0	0	0	0	0	0	0	455	201	0	0	0	0	0	0	0	0	51653
2	455	252	0	0	0	0	0	0	0	0	455	252	0	0	0	0	0	0	0	0	55238
3	455	356	0	0	0	0	0	0	0	0	455	356	0	0	0	0	0	0	0	0	62444
4	455	441	0	0	25	0	0	0	0	0	455	441	0	0	25	20	0	0	0	0	71157
5	455	455	0	0	25	0	0	0	0	10	455	455	0	0	25	20	0	0	0	10	76843
6	455	431	0	130	25	0	0	0	0	0	455	431	0	130	25	20	0	0	0	0	84755
7	455	414	130	130	25	0	0	0	0	0	455	414	0	130	25	20	0	0	0	0	90292
8	455	434	130	130	25	0	0	0	0	0	455	434	130	130	25	20	0	0	0	0	94603
9	455	455	130	130	81	20	0	0	0	0	455	455	130	130	81	20	0	0	0	0	103982
10	455	455	130	130	154	20	25	0	0	0	455	455	130	130	154	20	25	0	0	0	115582
11	455	455	130	130	162	51	25	10	10	0	455	455	130	130	162	51	25	10	0	0	122837
12	455	455	130	130	162	80	25	22	10	0	455	455	130	130	162	80	25	22	10	0	130491
13	455	455	130	130	154	20	25	0	0	0	455	455	130	130	154	20	25	0	0	0	115624
14	455	455	130	130	83	20	0	0	0	0	455	455	130	130	83	20	0	0	0	0	104125
15	455	433	130	130	25	0	0	0	0	0	455	433	130	130	25	0	0	0	0	0	94677
16	455	282	130	130	25	0	0	0	0	0	455	282	130	130	25	0	0	0	0	0	84118
17	455	234	130	130	25	0	0	0	0	0	455	234	130	130	25	0	0	0	0	0	80774
18	455	332	130	130	25	0	0	0	0	0	455	332	130	130	25	0	0	0	0	0	88435
19	455	421	130	130	25	0	25	0	0	0	455	421	130	130	25	0	0	0	0	0	96783
20	455	455	130	130	153	20	25	0	0	0	455	455	130	130	153	20	25	0	0	0	115498
21	455	455	130	130	0	20	25	0	0	0	455	455	130	130	0	20	25	0	0	0	105171
22	455	455	0	130	0	20	0	0	0	0	455	455	0	0	0	20	25	0	0	0	87124
23	455	399	0	0	0	0	0	0	0	0	455	399	0	0	0	0	0	0	0	0	66415
24	455	301	0	0	0	0	0	0	0	0	455	301	0	0	0	0	0	0	0	0	58654
																Overall Cost of Generation = **2172364.1608($)**					

Table-6.7(a): Scheduling of 1 to 20 units for 40 unit system with wind and EV using hHHO-IGWO

Time (h)	Scheduling for 1 to 20 units																			
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13	U14	U15	U16	U17	U18	U19	U20
1	455	193	0	0	0	0	0	0	0	0	455	193	0	0	0	0	0	0	0	0
2	455	247	0	0	0	0	0	0	0	0	455	247	0	0	0	0	0	0	0	0
3	455	350	0	0	0	0	0	0	0	0	455	350	0	0	0	0	0	0	0	0
4	455	403	0	130	25	0	0	0	0	0	455	403	0	0	0	0	0	0	0	0
5	455	426	0	130	25	0	0	0	0	0	455	426	0	130	0	0	0	0	0	0
6	455	393	130	130	25	0	0	0	0	0	455	393	130	130	0	0	0	0	0	0
7	455	419	130	130	25	0	0	0	0	0	455	419	130	130	0	0	0	0	0	0
8	455	438	130	130	25	0	0	0	0	0	455	438	130	130	25	0	0	0	0	0
9	455	455	130	130	93	20	0	0	0	0	455	455	130	130	93	20	0	0	0	0
10	455	455	130	130	162	20	25	10	0	0	455	455	130	130	162	20	25	10	0	0
11	455	455	130	130	162	57	25	10	10	0	455	455	130	130	162	57	25	10	0	0
12	455	455	130	130	162	80	25	31	10	10	455	455	130	130	162	80	25	31	10	10
13	455	455	130	130	162	21	25	10	0	0	455	455	130	130	162	21	25	0	0	0
14	455	455	130	130	86	20	0	0	10	0	455	455	130	130	86	20	0	0	0	0
15	455	426	130	130	25	0	0	0	0	0	455	426	130	130	25	0	0	0	0	0
16	455	281	130	130	25	0	0	0	0	0	455	281	130	130	25	0	0	0	0	0
17	455	226	130	130	25	0	0	0	0	0	455	226	130	130	25	0	0	0	0	0
18	455	321	130	130	25	0	0	0	0	0	455	321	130	130	25	0	0	0	0	0
19	455	416	130	130	25	0	0	0	10	0	455	416	130	130	25	0	0	0	0	0
20	455	455	130	130	162	20	25	0	0	10	455	455	130	130	162	20	25	0	0	0
21	455	455	130	130	122	20	25	10	0	0	455	455	130	130	122	20	25	0	0	0
22	455	451	0	130	0	20	25	0	0	0	455	451	0	130	0	20	25	0	0	0
23	455	349	0	130	0	0	0	0	0	0	455	349	0	130	0	0	0	0	0	0
24	455	312	0	0	0	0	0	0	0	0	455	312	0	0	0	0	0	0	0	0

Table-6.7(b): Scheduling of 21 to 40 units for 40 unit system with wind and EV using hHHO-IGWO

Time (h)	Scheduling for 21 to 40 Units																				Hourly Fuel Cost
	U21	**U22**	**U23**	**U24**	**U25**	**U26**	**U27**	**U28**	**U29**	**U30**	**U31**	**U32**	**U33**	**U34**	**U35**	**U36**	**U37**	**U38**	**U39**	**U40**	
1	455	193	0	0	0	0	0	0	0	0	455	193	0	0	0	0	0	0	0	0	51090
2	455	247	0	0	0	0	0	0	0	0	455	247	0	0	0	0	0	0	0	0	54863
3	455	350	0	0	0	0	0	0	0	0	455	350	0	0	0	0	0	0	0	0	62072
4	455	403	0	0	0	0	0	0	0	0	455	403	0	0	25	0	0	0	0	0	70530
5	455	426	0	0	0	0	0	0	0	0	455	426	0	0	25	0	0	0	0	0	75008
6	455	393	0	130	0	0	0	0	0	0	455	393	0	130	25	0	0	0	0	0	84215
7	455	419	130	130	0	0	0	0	0	0	455	419	0	130	25	0	0	0	10	0	89843
8	455	438	130	130	0	0	0	0	0	0	455	438	130	130	25	0	0	0	0	0	94071
9	455	455	130	130	93	20	0	0	0	0	455	455	130	130	93	20	0	0	0	0	104936
10	455	455	130	130	162	20	25	0	0	0	455	455	130	130	162	20	25	0	0	0	117247
11	455	455	130	130	162	57	25	10	10	0	455	455	130	130	162	57	25	10	0	0	124310
12	455	455	130	130	162	80	25	31	10	0	455	455	130	130	162	80	25	31	10	0	132451
13	455	455	130	130	162	21	25	0	0	0	455	455	130	130	162	21	25	10	0	0	117321
14	455	455	130	130	86	0	0	0	0	0	455	455	130	130	86	20	0	0	0	0	104499
15	455	426	130	130	25	0	0	0	0	0	455	426	130	130	25	0	0	0	0	0	94169
16	455	281	130	130	25	0	0	0	0	0	455	281	130	130	25	0	0	0	0	0	84000
17	455	226	130	130	25	0	0	0	0	0	455	226	130	130	25	0	0	0	0	0	80168
18	455	321	130	130	25	0	0	0	0	0	455	321	130	130	25	0	25	0	0	0	87996
19	455	416	130	130	25	0	0	0	0	0	455	416	130	130	25	0	25	0	0	0	95584
20	455	455	130	130	162	20	25	0	10	0	455	455	130	130	162	20	25	0	0	0	117239
21	455	455	130	130	0	20	25	0	0	0	455	455	130	130	0	20	0	0	0	0	105974
22	455	451	130	130	0	20	25	0	0	0	455	451	0	0	0	20	0	0	10	0	88364
23	455	349	0	0	0	0	0	0	0	0	455	349	0	0	0	0	0	0	0	0	67709
24	455	312	0	0	0	0	0	0	0	0	455	312	0	0	0	0	0	0	0	0	59429
																Overall Cost of Generation = **2179556.0791 ($)**					

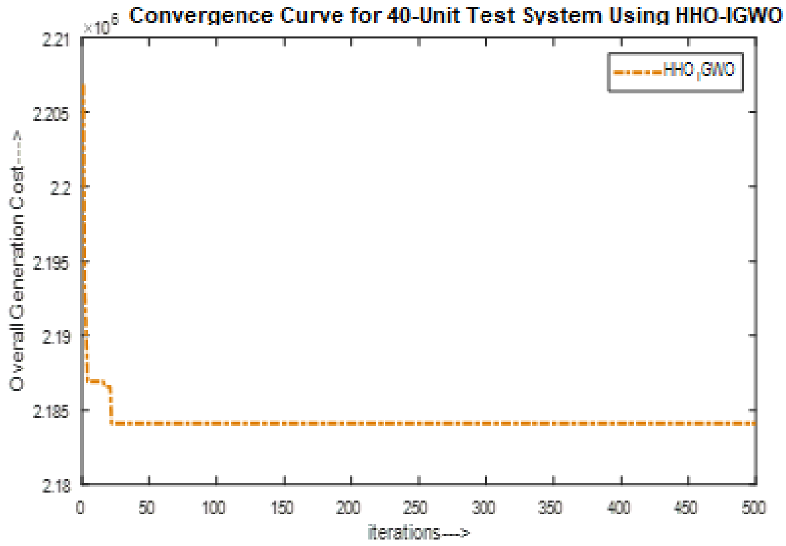


Fig.6.8: Convergence Curve for 40-units with wind and EV using hHHO-IGWO

The simulation results for Hybrid Harris Hawks algorithm for 40 unit system shows that total cost of generation with thermal with UC, UC+W and UC+W+EV are is **$ 2249657.3623, $ 2172364.16**08 and **$ 2179556.0791** respectively. The results shows that there is cost saving of **$ 2030101.2832** with coordinated charging/discharging of EV for V2G operation. Thus, the proposed method is cost effective in dealing unit commitment problem in presence of renewable and EV.

(d) Testing of 60-unit system using hHHO-IGWO

The hHHO-IGWO method is tested for solving unit commitment problem for 60-unit system. Table-6.8 (a), 6.8(b) and 6.8(c) illustrates optimal dispatch for 60-unit system with wind. Table-6.9 (a), 6.9(b) and 6.9(c) illustrates optimal dispatch for 60-unit system with wind & EV. The convergence curve for 60-unit system with wind and with wind & EV are depicted in Fig.6.9 and Fig.6.10.

Referring Table 6.8(a), 6.8(b) and 6.8(c), U1, U2, U11, U12, U21, U22, U31, U32, U41, U42, U51 and U52 are the most economical units and thus run for maximum hours duration to meet the forecasted load demand. For rest of hours, U3 to U9, U13 to U19, U23 to U29, U33 to U39, U43 to U49 and U53 to U59 contributes their power meet the corresponding load demand. At 12th hour, load is at peak demand and thus all the units are in ON state. U10, U20, U30, U40, U50 and U60 act as the reserve unit and runs only during the peak demand.

Table-6.8(a): Scheduling of 1 to 20 for 60 unit system with wind using hHHO-IGWO

Time (h)	Scheduling for 1 to 20 units																			
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13	U14	U15	U16	U17	U18	U19	U20
1	455	216	0	0	0	0	0	0	0	0	455	216	0	0	0	0	0	0	0	0
2	455	258	0	0	0	0	0	0	0	0	455	258	0	0	0	0	0	0	0	0
3	455	357	0	0	0	0	0	0	0	10	455	357	0	0	0	0	0	0	0	0
4	455	453	0	0	0	0	0	0	0	0	455	453	0	0	25	0	0	0	0	0
5	455	440	0	130	0	0	0	0	0	0	455	440	0	130	25	0	0	0	0	0
6	455	455	0	130	0	0	0	0	0	0	455	455	0	130	39	20	0	0	0	0
7	455	452	130	130	0	0	0	0	0	0	455	452	130	130	25	20	0	0	0	0
8	455	435	130	130	25	0	0	0	0	0	455	435	130	130	25	20	0	0	0	0
9	455	455	130	130	86	20	0	0	0	0	455	455	130	130	86	20	0	0	0	0
10	455	455	130	130	161	20	25	10	0	0	455	455	130	130	161	20	25	10	0	10
11	455	455	130	130	162	59	25	10	10	0	455	455	130	130	162	59	25	10	10	0
12	455	455	130	130	162	80	25	29	10	10	455	455	130	130	162	80	25	29	10	10
13	455	455	130	130	161	20	25	10	0	0	455	455	130	130	161	20	25	10	0	0
14	455	455	130	130	92	20	0	0	0	0	455	455	130	130	92	20	0	0	0	0
15	455	442	130	130	25	0	0	0	0	0	455	442	130	130	25	0	0	0	0	0
16	455	290	130	130	25	0	0	0	0	0	455	290	130	130	25	0	0	0	0	0
17	455	243	130	130	25	0	0	0	0	0	455	243	130	130	25	0	0	0	0	0
18	455	345	130	130	25	0	0	0	0	0	455	345	130	130	25	0	0	0	0	0
19	455	443	130	130	25	0	0	0	0	0	455	443	130	130	25	0	0	0	0	0
20	455	455	130	130	160	20	25	10	0	0	455	455	130	130	160	20	25	10	0	0
21	455	455	130	130	128	20	25	0	0	0	455	455	130	130	128	20	25	0	0	0
22	455	455	0	130	0	32	25	0	0	0	455	455	0	130	0	32	25	10	0	0
23	455	371	0	130	0	0	0	0	0	0	455	371	0	130	0	0	25	0	0	0
24	455	316	0	0	0	0	0	0	0	0	455	316	0	0	0	0	0	0	0	0

Table-6.8(b): Scheduling of 21 to 40 for 60 unit system with wind using hHHO-IGWO

Time (h)	Scheduling for 21 to 40 units																			
	U21	U22	U23	U24	U25	U26	U27	U28	U29	U30	U31	U32	U33	U34	U35	U36	U37	U38	U39	U40
1	455	216	0	0	0	0	0	0	0	0	455	216	0	0	0	0	0	0	0	0
2	455	241	0	0	0	0	0	0	0	0	455	241	0	0	0	0	0	0	0	0
3	455	317	0	0	25	0	0	0	0	0	455	317	0	0	0	0	0	0	0	0
4	455	396	0	0	25	0	0	0	0	0	455	396	0	0	0	0	0	0	0	0
5	455	388	130	0	25	0	25	0	0	0	455	388	0	0	0	0	0	0	0	0
6	455	455	130	0	38	0	25	0	0	0	455	455	130	0	0	0	0	0	0	0
7	455	448	130	130	25	20	25	0	0	0	455	448	130	130	0	0	0	0	0	0
8	455	455	130	130	39	20	25	0	0	0	455	455	130	130	0	0	0	0	0	0
9	455	455	130	130	96	20	25	0	0	0	455	455	130	130	0	0	0	0	0	0
10	455	455	130	130	161	20	25	10	0	0	455	455	130	130	161	20	25	0	0	0
11	455	455	130	130	162	58	25	10	0	0	455	455	130	130	162	58	25	10	0	0
12	455	455	130	130	162	80	25	29	10	10	455	455	130	130	162	80	25	29	10	0
13	455	455	130	130	161	20	25	0	0	0	455	455	130	130	161	20	25	0	0	0
14	455	455	130	130	92	20	0	0	0	0	455	455	130	130	92	20	0	0	0	0
15	455	429	130	130	25	0	0	0	0	0	455	429	130	130	25	20	0	0	0	0
16	455	290	130	130	25	0	0	0	0	0	455	290	130	130	25	0	0	0	0	0
17	455	231	130	130	25	0	0	0	10	0	455	231	130	130	25	0	25	0	0	0
18	455	331	130	130	25	0	0	10	0	0	455	331	130	130	25	0	25	0	0	0
19	455	428	130	130	25	20	0	0	0	0	455	428	130	130	25	0	25	0	0	0
20	455	455	130	130	160	20	25	10	0	0	455	455	130	130	160	20	25	0	0	0
21	455	455	130	130	0	20	25	0	0	0	455	455	130	130	133	20	25	0	0	0
22	455	455	0	130	0	0	25	0	0	0	455	455	0	0	38	20	0	0	0	0
23	455	387	0	0	0	0	0	0	0	0	455	387	0	0	0	0	0	0	0	0
24	455	375	0	0	0	0	0	0	0	0	455	375	0	0	0	0	0	10	0	0

Table-6.8(c): Scheduling of 41 to 60 for 60 unit system with wind using hHHO-IGWO

Time (h)	**Scheduling for 41 to 60 units**																				**Hourly Fuel Cost**
	U41	**U42**	**U43**	**U44**	**U45**	**U46**	**U47**	**U48**	**U49**	**U50**	**U51**	**U52**	**U53**	**U54**	**U55**	**U56**	**U57**	**U58**	**U59**	**U60**	
1	455	216	0	0	0	0	0	0	0	0	455	216	0	0	0	0	0	0	0	0	79018
2	455	258	0	0	0	0	0	0	0	0	455	258	0	0	0	0	0	0	0	0	85365
3	455	357	0	0	0	0	0	0	0	0	455	357	0	0	0	0	0	0	0	0	97581
4	455	453	0	0	0	0	0	0	0	0	455	453	0	0	25	0	0	10	0	0	108556
5	455	440	0	0	0	0	0	0	0	0	455	440	0	0	25	0	0	0	0	0	114868
6	455	455	0	130	0	0	0	0	0	0	455	455	0	130	39	0	25	0	0	0	129031
7	455	452	0	130	0	0	0	0	0	0	455	452	0	130	25	0	25	0	0	0	136286
8	455	435	130	130	0	0	0	0	0	0	455	435	130	130	25	0	25	0	0	0	144083
9	455	455	130	130	86	20	0	0	0	0	455	455	130	130	86	20	25	0	0	0	157820
10	455	455	130	130	161	20	25	0	0	0	455	455	130	130	161	20	25	0	0	0	175681
11	455	455	130	130	162	59	25	10	0	0	455	455	130	130	162	59	25	10	0	0	186665
12	455	455	130	130	162	80	25	29	10	0	455	455	130	130	162	80	25	29	10	0	198268
13	455	455	130	130	161	20	25	0	0	0	455	455	130	130	161	20	25	0	0	0	175695
14	455	455	130	130	92	20	0	0	0	0	455	455	130	130	92	20	0	0	0	0	157299
15	455	442	130	130	25	0	0	0	0	0	455	442	130	130	25	0	0	0	0	0	142954
16	455	290	130	130	25	0	0	0	0	0	455	290	130	130	25	0	0	10	0	0	127891
17	455	243	130	130	25	0	0	0	0	0	455	243	130	130	25	0	0	0	0	0	122057
18	455	345	130	130	25	0	0	0	0	0	455	345	130	130	25	0	0	0	0	0	132740
19	455	443	130	130	25	0	0	0	0	0	455	443	130	130	25	0	0	0	0	0	143084
20	455	455	130	130	160	20	25	0	0	0	455	455	130	130	160	20	25	0	0	0	175597
21	455	455	130	130	128	20	25	0	0	0	455	455	130	130	0	20	25	0	0	0	159677
22	455	455	0	130	0	32	25	0	0	0	455	455	0	0	0	32	25	0	0	0	132947
23	455	371	0	0	0	0	0	0	0	0	455	371	0	0	0	0	0	0	0	0	102170
24	455	316	0	0	0	0	0	0	0	0	455	316	0	0	0	0	0	0	0	0	89508
																Overall Cost of Generation = **3299960.8457($)**					

Table-6.9(a): Scheduling of 1 to 20 for 60 unit system with wind and EV using hHHO-IGWO

Time	Scheduling for 1 to 20 units																			
(h)	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13	U14	U15	U16	U17	U18	U19	U20
1	455	210	0	0	0	0	0	0	0	0	455	210	0	0	0	0	0	0	0	0
2	455	255	0	0	25	0	0	0	0	0	455	255	0	0	0	0	0	0	0	0
3	455	335	130	0	25	0	0	0	0	0	455	335	0	0	0	0	0	0	0	0
4	455	426	130	0	25	0	0	0	0	0	455	426	0	0	0	0	25	0	0	0
5	455	433	130	130	25	0	0	0	0	0	455	433	0	130	0	0	25	0	0	0
6	455	441	130	130	25	0	0	0	0	0	455	441	0	130	0	0	25	0	0	0
7	455	415	130	130	25	0	0	0	0	0	455	415	130	130	0	0	0	0	0	0
8	455	439	130	130	25	0	0	0	0	0	455	439	130	130	25	0	0	0	0	0
9	455	455	130	130	96	20	0	0	0	0	455	455	130	130	96	20	0	0	10	0
10	455	455	130	130	162	25	25	10	0	0	455	455	130	130	162	25	25	10	10	0
11	455	455	130	130	162	62	25	10	10	0	455	455	130	130	162	62	25	10	10	0
12	455	455	130	130	162	80	25	35	10	10	455	455	130	130	162	80	25	35	10	10
13	455	455	130	130	162	25	25	10	0	0	455	455	130	130	162	25	25	10	0	0
14	455	455	130	130	91	20	0	0	0	0	455	455	130	130	91	20	0	0	0	0
15	455	430	130	130	25	0	0	0	0	0	455	430	130	130	25	0	0	0	0	0
16	455	289	130	130	25	0	0	0	0	10	455	289	130	130	25	0	0	0	0	0
17	455	237	130	130	25	0	0	0	0	0	455	237	130	130	25	0	0	0	0	0
18	455	335	130	130	25	0	0	0	10	0	455	335	130	130	25	0	0	0	0	0
19	455	437	130	130	25	0	0	0	0	0	455	437	130	130	25	0	0	0	0	0
20	455	455	130	130	162	27	25	0	10	0	455	455	130	130	162	27	25	10	0	0
21	455	455	130	130	138	20	25	0	0	0	455	455	130	130	138	20	25	10	0	0
22	455	455	130	130	0	20	25	0	0	0	455	455	0	130	0	20	25	0	0	0
23	455	377	130	0	0	0	0	0	0	0	455	377	0	0	0	0	0	0	0	0
24	455	323	0	0	0	0	0	0	0	0	455	323	0	0	0	0	0	0	0	0

Table-6.9(b): Scheduling of 21 to 40 for 60 unit system with wind and EV using hHHO-IGWO

Time (h)	Scheduling for 21 to 40 units																			
	U21	U22	U23	U24	U25	U26	U27	U28	U29	U30	U31	U32	U33	U34	U35	U36	U37	U38	U39	U40
1	455	216	0	0	0	0	0	0	0	0	455	216	0	0	0	0	0	0	0	0
2	455	241	0	0	0	0	0	0	0	0	455	241	0	0	0	0	0	0	0	0
3	455	317	0	0	25	0	0	0	0	0	455	317	0	0	0	0	0	0	0	0
4	455	396	0	0	25	0	0	0	0	0	455	396	0	0	0	0	0	0	0	0
5	455	388	130	0	25	0	25	0	0	0	455	388	0	0	0	0	0	0	0	0
6	455	455	130	0	38	0	25	0	0	0	455	455	130	0	0	0	0	0	0	0
7	455	448	130	130	25	20	25	0	0	0	455	448	130	130	0	0	0	0	0	0
8	455	455	130	130	39	20	25	0	0	0	455	455	130	130	0	0	0	0	0	0
9	455	455	130	130	96	20	25	0	0	0	455	455	130	130	0	0	0	0	0	0
10	455	455	130	130	161	20	25	10	0	0	455	455	130	130	161	20	25	0	0	0
11	455	455	130	130	162	58	25	10	0	0	455	455	130	130	162	58	25	10	0	0
12	455	455	130	130	162	80	25	29	10	10	455	455	130	130	162	80	25	29	10	0
13	455	455	130	130	161	20	25	0	0	0	455	455	130	130	161	20	25	0	0	0
14	455	455	130	130	92	20	0	0	0	0	455	455	130	130	92	20	0	0	0	0
15	455	429	130	130	25	0	0	0	0	0	455	429	130	130	25	20	0	0	0	0
16	455	290	130	130	25	0	0	0	0	0	455	290	130	130	25	0	0	0	0	0
17	455	231	130	130	25	0	0	0	10	0	455	231	130	130	25	0	25	0	0	0
18	455	331	130	130	25	0	0	10	0	0	455	331	130	130	25	0	25	0	0	0
19	455	428	130	130	25	20	0	0	0	0	455	428	130	130	25	0	25	0	0	0
20	455	455	130	130	160	20	25	10	0	0	455	455	130	130	160	20	25	0	0	0
21	455	455	130	130	0	20	25	0	0	0	455	455	130	130	133	20	25	0	0	0
22	455	455	0	130	0	0	25	0	0	0	455	455	0	0	38	20	0	0	0	0
23	455	387	0	0	0	0	0	0	0	0	455	387	0	0	0	0	0	0	0	0
24	455	375	0	0	0	0	0	0	0	0	455	375	0	0	0	0	0	10	0	0

Table-6.9 (c): Scheduling of 41 to 60 for 60 unit system with wind and EV using hHHO-IGWO

Time (h)	**Scheduling for 41 to 60 units**																				**Hourly Fuel Cost**
	U41	**U42**	**U43**	**U44**	**U45**	**U46**	**U47**	**U48**	**U49**	**U50**	**U51**	**U52**	**U53**	**U54**	**U55**	**U56**	**U57**	**U58**	**U59**	**U60**	
1	455	210	0	0	0	0	0	0	0	0	455	210	0	0	0	0	0	0	0	0	78455
2	455	255	0	0	0	0	0	0	0	0	455	255	0	0	0	0	0	0	0	0	84990
3	455	335	0	0	0	0	0	0	0	0	455	335	0	0	0	0	0	0	0	0	96311
4	455	426	0	0	0	0	0	0	0	0	455	426	0	0	0	0	0	0	0	0	107872
5	455	433	0	0	0	0	0	0	0	0	455	433	0	0	0	0	0	0	0	0	115154
6	455	441	0	130	0	0	0	0	0	0	455	441	0	130	0	0	0	0	0	0	128308
7	455	415	130	130	0	0	0	0	0	0	455	415	0	130	0	0	0	0	0	0	136032
8	455	439	130	130	25	0	0	0	0	0	455	439	130	130	0	0	0	0	0	0	143283
9	455	455	130	130	96	20	0	0	0	0	455	455	130	130	96	0	0	0	0	0	159099
10	455	455	130	130	162	25	25	0	0	0	455	455	130	130	162	25	25	0	0	0	177379
11	455	455	130	130	162	62	25	10	0	0	455	455	130	130	162	62	25	10	0	0	188140
12	455	455	130	130	162	80	25	35	10	0	455	455	130	130	162	80	25	35	10	0	200231
13	455	455	130	130	162	25	25	0	0	0	455	455	130	130	162	25	25	0	0	0	177463
14	455	455	130	130	91	20	0	0	0	0	455	455	130	130	91	0	25	0	0	0	157603
15	455	430	130	130	25	0	0	0	0	0	455	430	130	130	25	0	25	0	0	0	143648
16	455	289	130	130	25	0	0	0	0	0	455	289	130	130	25	0	0	0	0	0	127800
17	455	237	130	130	25	0	0	0	0	0	455	237	130	130	25	0	0	0	0	0	121451
18	455	335	130	130	25	0	0	0	0	0	455	335	130	130	25	0	0	10	0	0	133540
19	455	437	130	130	25	0	0	0	0	0	455	437	130	130	25	0	0	0	0	0	142361
20	455	455	130	130	162	27	25	0	10	10	455	455	130	130	162	27	0	0	0	0	177472
21	455	455	130	130	0	20	25	0	0	0	455	455	130	130	0	20	0	0	0	0	160078
22	455	455	0	0	0	20	25	0	0	0	455	455	0	0	0	20	0	0	0	0	132841
23	455	377	0	0	0	0	0	0	0	0	455	377	0	0	0	0	0	0	0	0	102600
24	455	323	0	0	0	0	0	0	0	0	455	323	0	0	0	0	0	0	0	0	90283
																Overall Cost of Generation = **3309624.5229($)**					

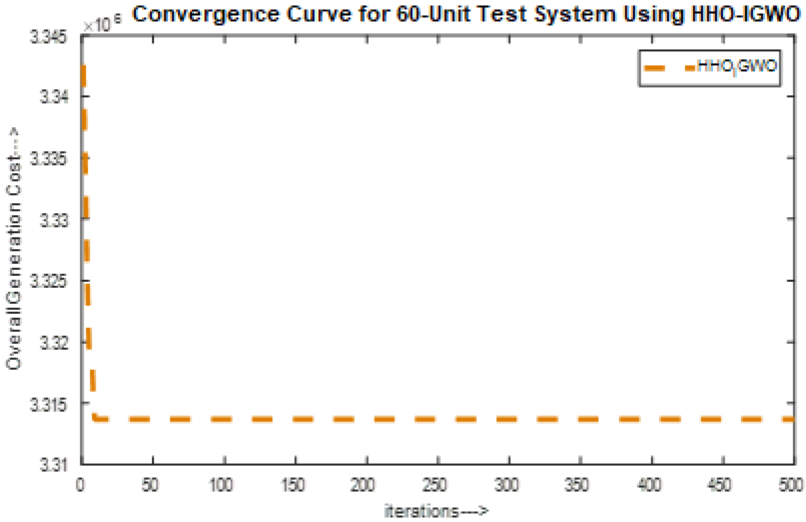


Fig.6.9: Convergence curve for 60-units with wind using hHHO-IGWO method

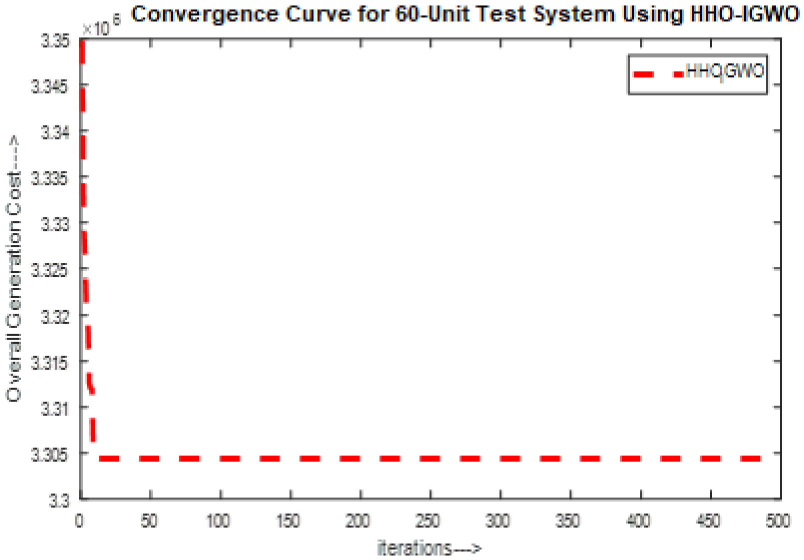


Fig.6.10: Convergence curve for 60-units with wind & EV Using hHHO-IGWO

Referring Table 6.9(a), 6.9(b) and 6.9(c), U1, U2, U11, U12, U21, U22, U31, U32, U41, U42, U51 and U52 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load demand. For rest of hours, U6 to U8, U15 to U18, U25 to U29, U36 to U39, U45 to U49 and U59 to U59 contributes their power meet the corresponding load demand. At 12th hour, load is at peak demand and thus all the units are in ON state. U10, U20, U30, U40, U50 and U60 act as the reserve unit and runs only during the peak demand. The simulation results for hHHO-IGWO for 60 unit system illustrates that total cost of generation with thermal, wind and thermal and wind

& EV are **$ 3374668.8771** **$ 3299960.8457** and **$ 3309624.5229** respectively. The results shows that there is cost saving of **$ 65044.3542** with coordinated charging/discharging of EV for V2G operation. Thus, the proposed hHHO-IGWO method is effective in dealing unit commitment problem under uncertain sustainable environment.

6.7.2 Testing of Unit Commitment Problem with RES and EV by CHHO

The CHHO algorithm is applied to standard test systems consisting of 10, 20, 40 and 60-units and simulation results are recorded for UC with wind and with wind and EV.

(a) Testing of 10-unit system using CHHO

The CHHO algorithm is applied to standard test systems consisting of 10-units with 10% SR and simulation results are recorded for UC with wind and wind & EV.

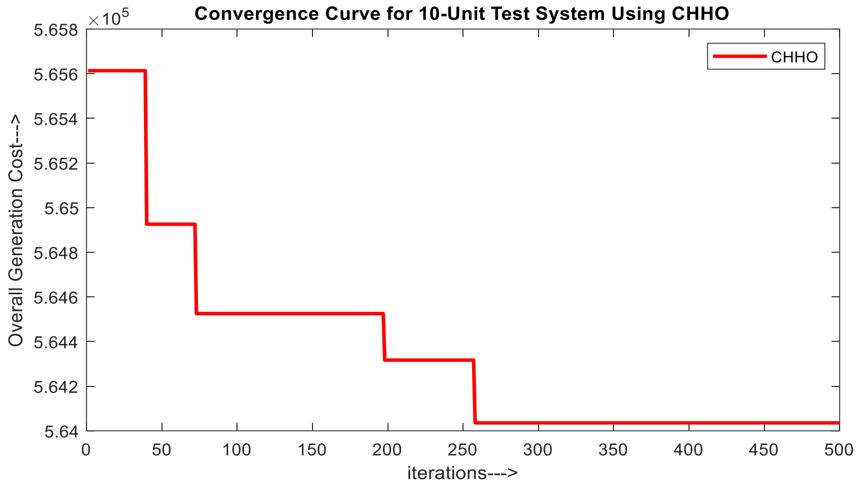


Fig.6.11: Convergence Curve 10 unit system with wind using CHHO method

Table-6.10 represents their corresponding power dispatch for each unit with wind penetration. Table-6.11 shows corresponding power dispatch with wind & EV penetration. The convergence curves with wind and with wind & EV for 10-unit system are described in Fig.6.11 and Fig.6.12.

Referring Table 6.10, U1 and U2 are the most appropriate units and thus remains online for total 24 hours duration to meet the load demand. Start-up cost depends upon the operating temperature of particular unit and initial state. During 10th to 13th hour, load is at peak demand and thus units U3 to U5 are in ON state. U6 to U9 act as the reserve unit and runs only during the peak demand. Referring Table 6.11, U1 and U2 are the most economical units and thus remains ON for maximum duration to satisfy the corresponding load demand. During the peak hours, U3 to U5 units contribute their power meet the corresponding load demand

Table-6.10: Scheduling of 10-units with wind using CHHO

Time (h)	Scheduling of 10 units										Power (MW)	Start-Up Cost	Hourly Fuel Cost
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10			
1	373	150	0	0	0	0	0	0	0	0	523	0	10672
2	429	150	0	0	0	0	0	0	0	0	579	730	11600
3	455	237	0	0	0	0	0	0	0	0	692	550	13544
4	455	350	0	0	0	0	0	0	0	0	805	900	15515
5	455	378	0	0	25	0	0	0	0	0	858	0	16949
6	455	455	0	0	53	0	0	0	0	0	963	0	18859
7	455	420	0	130	25	0	0	0	0	0	1030	0	20545
8	455	455	0	130	51	0	0	0	0	0	1091	0	21679
9	455	444	130	130	25	0	0	0	0	0	1184	690	23858
10	455	455	130	130	69	20	25	0	0	0	1284	60	26926
11	455	455	130	130	118	20	25	0	0	0	1333	0	27928
12	455	455	130	130	160	20	25	10	0	0	1385	90	29721
13	455	455	130	130	86	20	0	10	0	0	1286	0	27017
14	455	451	130	130	25	0	0	0	0	0	1191	0	23981
15	455	353	130	130	25	0	0	0	0	0	1093	0	22265
16	455	199	130	130	25	0	0	0	0	0	939	0	19580
17	455	157	130	130	25	0	0	0	0	0	897	170	18851
18	455	270	130	130	25	0	0	0	0	0	1010	180	20807
19	455	360	130	130	25	0	0	0	0	0	1100	0	22394
20	455	455	130	130	90	20	0	0	0	0	1280	30	26179
21	455	413	130	130	25	20	0	0	0	0	1173	0	24133
22	455	455	0	0	33	20	0	0	0	0	963	30	19276
23	455	285	0	0	0	0	0	0	0	0	740	0	14380
24	455	170	0	0	0	0	0	0	0	0	625	0	12379
Worst Cost($)=494816.9018				**Best Cost($)=492466.6232**				**Mean Cost($)=493656.7593**					**Total=492466.6232($)**
Worst Time(Sec.)= 0.0625				**Best Time(Sec.)= 0.03125**				**Mean Time(Sec.)= 0.03802**					

During 9th to 13th hour , load is at peak demand and thus units U6 to U8 are in ON state to balance load demand.It can be seen that U9 and U10 remains in OFF state thus saving an appreciable cost. The simulation results for CHHO algorithm for 10 unit shows total cost of UC, UC+W and UC+W+EV are **$ 563387.6874 ,** $**492466.6232** and $ **490174.8291** respectively. The results shows that there is cost saving of **$ 514212.8583** with coordinated discharging of EV for V2G operation. It can be seen from Fig.6.12 that the curve converges to optimum within 50 iterations. Thus, the proposed method is efficient in solving unit commitment problem under uncertain sustainable environment.

Table-6.11: Scheduling of 10 units with wind & EV using CHHO method

Time (h)	Scheduling of 10 units										Power (MW)	Start-Up Cost	Hourly Fuel Cost
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10			
1	405	150	0	0	0	0	0	0	0	0	555	0	11208
2	450	150	0	0	0	0	0	0	0	0	601	1070	11957
3	455	258	0	0	0	0	0	0	0	0	713	560	13914
4	455	367	0	0	25	0	0	0	0	0	847	0	16763
5	455	401	0	0	25	0	0	0	0	0	881	1070	17352
6	455	392	0	130	25	0	0	0	0	0	1002	0	20059
7	455	434	0	130	25	0	0	0	0	0	1044	0	20783
8	455	355	130	130	25	0	0	0	0	0	1095	0	22294
9	455	397	130	130	25	0	0	0	0	0	1137	0	23039
10	455	455	130	130	44	0	25	0	0	0	1239	170	25595
11	455	455	130	130	85	20	25	0	0	0	1300	60	27246
12	455	455	130	130	121	20	25	0	0	0	1336	260	27995
13	455	455	130	130	49	20	0	0	0	0	1239	0	25354
14	455	449	130	130	25	0	0	0	0	0	1189	60	23937
15	455	382	130	130	25	0	0	0	0	0	1122	120	22772
16	455	206	130	130	25	0	0	0	0	0	946	0	19699
17	455	192	130	130	25	0	0	0	0	0	932	0	19455
18	455	310	130	130	25	0	0	0	0	0	1050	0	21515
19	455	402	130	130	25	0	0	0	0	0	1142	0	23115
20	455	455	130	130	53	0	0	10	0	0	1233	340	25531
21	455	416	130	130	25	0	0	0	0	0	1156	60	23374
22	455	331	130	0	0	0	0	0	0	0	916	0	18067
23	455	249	0	0	0	0	0	0	0	0	704	0	13754
24	431	150	0	0	0	0	0	0	0	0	581	0	11626
Worst Cost($)=492502.5759				**Best Cost($)=490174.8291**				**Mean Cost($)=491308.0262**					**Total=490 174.8291($)**
Worst Time(Sec.)= 0.046875				**Best Time(Sec.)= 0.015625**				**Mean Time(Sec.)= 0.0291**					

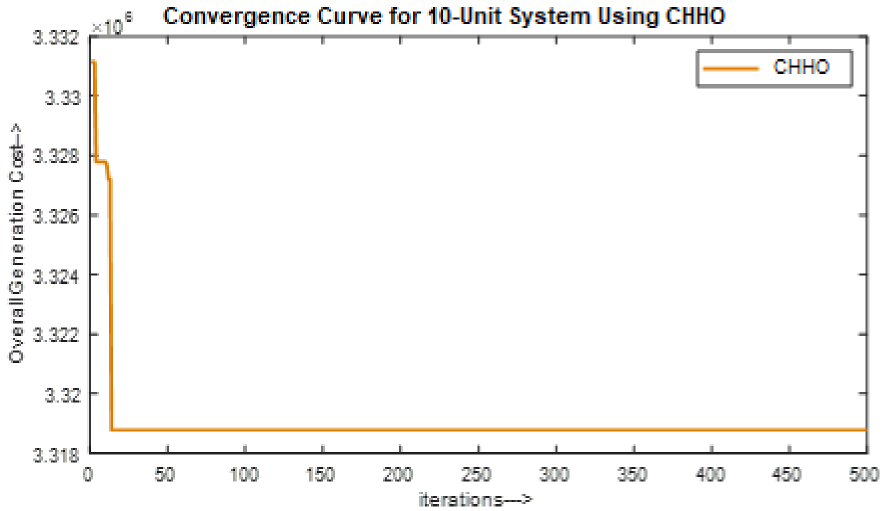


Fig.6.12: Convergence Curve 10 unit system with wind and EV using CHHO method

(b) Testing of 20 units using CHHO

Population size is taken as 80 for all 30 trial runs with 500 iterations and simulation results are recorded for UC with wind and UC with wind & EV. Table-6.12 illustrates optimal status of committed generators with wind. Table-6.13 shows their corresponding power dispatch with wind & EV penetration. The convergence curves with UC + W and UC +W+EV for 20-unit system are depicted in Fig.6.13 and Fig.6.14.

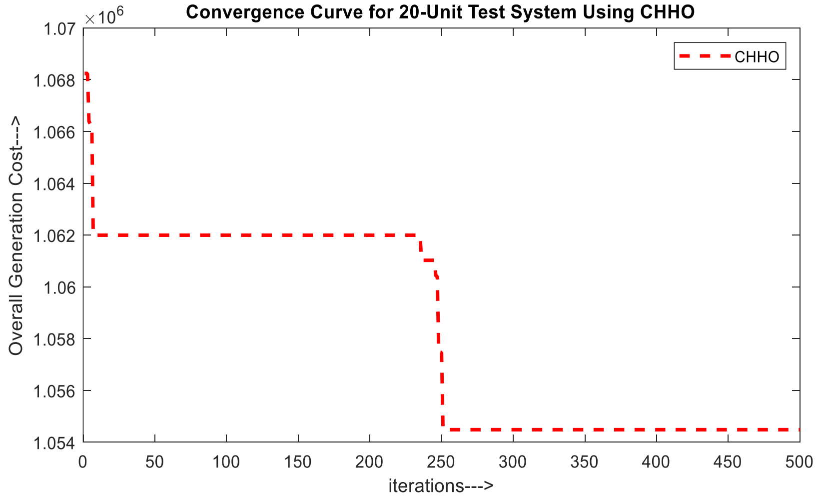


Fig.6.13: Convergence Curve for 20 units with wind using CHHO method

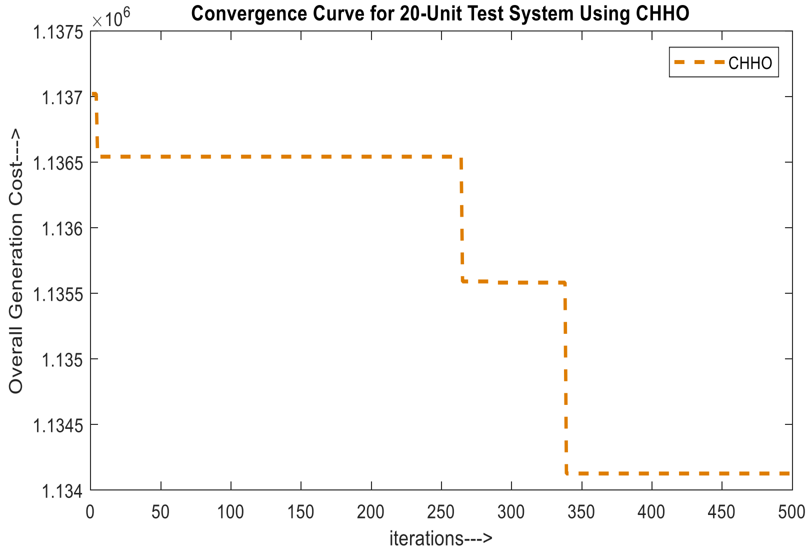


Fig. 6.14: Convergence Curve for 20 units with wind and EV using CHHO method

Table-6.12: Scheduling of 20 units with wind using CHHO

Time (h)	Scheduling for 20 units																				Hourly Fuel Cost
	U1	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**	**U8**	**U9**	**U10**	**U11**	**U12**	**U13**	**U14**	**U15**	**U16**	**U17**	**U18**	**U19**	**U20**	
1	455	157	0	0	0	0	0	0	0	0	455	157	0	0	0	0	0	0	0	0	1880
2	455	210	0	0	0	0	0	0	0	0	455	210	0	0	0	0	0	0	0	0	900
3	455	316	0	0	0	0	0	0	0	0	455	316	0	0	0	0	0	0	0	0	620
4	455	358	0	130	0	0	0	0	0	0	455	358	0	0	0	0	0	0	0	0	560
5	455	344	0	130	0	0	0	0	0	0	455	344	130	0	0	0	0	0	0	0	0
6	455	422	0	130	25	0	0	0	0	0	455	422	130	0	25	0	0	0	0	0	0
7	455	455	0	130	50	0	0	0	0	0	455	455	130	0	50	0	0	0	0	0	0
8	455	455	0	130	41	0	0	0	0	0	455	455	130	130	41	0	0	0	0	0	1360
9	455	455	130	130	62	20	0	0	0	0	455	455	130	130	62	0	0	0	0	0	0
10	455	455	130	130	134	20	0	0	0	0	455	455	130	130	134	20	25	0	10	0	1200
11	455	455	130	130	162	25	25	10	0	0	455	455	130	130	162	25	25	10	0	0	120
12	455	455	130	130	162	65	25	10	10	0	455	455	130	130	162	65	25	10	10	0	120
13	455	455	130	130	135	20	25	0	0	0	455	455	130	130	135	20	0	10	0	0	0
14	455	455	130	130	65	20	0	0	0	0	455	455	130	130	65	0	0	0	0	0	0
15	455	407	130	130	25	0	0	0	0	0	455	407	130	130	25	0	0	0	0	0	30
16	455	254	130	130	25	0	0	0	0	0	455	254	130	130	25	0	0	0	0	0	0
17	455	204	130	130	25	0	0	0	0	0	455	204	130	130	25	0	0	0	0	10	0
18	455	315	130	130	25	0	0	0	0	0	455	315	130	130	25	0	0	0	0	0	690
19	455	400	130	130	25	20	0	0	0	0	455	400	130	130	25	0	0	0	0	0	0
20	455	455	130	130	132	20	25	10	0	0	455	455	130	130	132	20	0	0	0	0	340
21	455	455	130	130	68	20	25	0	0	0	455	455	130	130	0	20	0	0	0	0	60
22	455	359	130	130	0	0	25	0	0	0	455	359	0	130	0	20	0	0	0	0	0
23	455	365	0	0	0	0	0	0	0	0	455	365	0	0	0	0	0	0	0	0	0
24	455	258	0	0	0	0	0	0	0	0	455	258	0	0	0	0	0	0	0	0	0
																Overall Cost of Generation = **1052294.5319 ($)**					

Table-6.13: Scheduling of 20 units with wind and EV using CHHO

Time (h)	Scheduling for 20-unit																				Hourly Fuel Cost
	U1	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**	**U8**	**U9**	**U10**	**U11**	**U12**	**U13**	**U14**	**U15**	**U16**	**U17**	**U18**	**U19**	**U20**	
1	445	150	0	0	0	0	0	0	0	0	445	150	0	0	0	0	0	0	0	0	23741
2	455	199	0	0	0	0	0	0	0	0	455	199	0	0	0	0	0	0	0	0	25757
3	455	305	0	0	0	0	0	0	0	0	455	305	0	0	0	0	0	0	0	0	29471
4	455	389	0	0	0	0	0	0	0	0	455	389	0	0	25	0	0	0	0	0	33333
5	455	438	0	0	25	0	0	0	0	0	455	438	0	0	25	0	0	0	0	0	35983
6	455	455	130	0	37	0	0	0	0	0	455	455	0	0	37	0	0	0	0	0	39962
7	455	455	130	0	43	0	0	0	0	0	455	455	130	0	43	0	0	0	0	0	43108
8	455	455	130	0	39	0	0	0	0	0	455	455	130	130	39	0	0	0	0	0	45786
9	455	455	130	130	75	20	0	0	0	0	455	455	130	130	75	20	0	0	0	0	51763
10	455	455	130	130	145	20	25	10	0	0	455	455	130	130	145	20	25	0	0	0	57885
11	455	455	130	130	162	41	25	10	0	0	455	455	130	130	162	41	25	10	0	0	60485
12	455	455	130	130	162	80	25	15	10	10	455	455	130	130	162	80	25	15	10	0	65360
13	455	455	130	130	146	20	25	10	0	0	455	455	130	130	146	20	25	0	0	0	57953
14	455	455	130	130	67	20	0	0	0	0	455	455	130	130	67	0	0	0	0	0	50594
15	455	392	130	130	25	0	0	0	0	0	455	392	130	130	25	0	0	0	0	0	45893
16	455	251	130	130	25	0	0	0	0	0	455	251	130	130	25	0	0	0	0	0	40973
17	455	191	130	130	25	0	0	0	0	0	455	191	130	130	25	0	0	0	0	0	38886
18	455	294	130	130	25	0	0	0	0	0	455	294	130	130	25	0	0	0	0	0	42485
19	455	390	130	130	25	0	0	0	0	0	455	390	130	130	25	0	0	0	0	0	45809
20	455	455	130	130	151	20	25	0	10	0	455	455	130	130	151	20	0	10	0	0	57909
21	455	455	130	130	85	20	25	0	0	0	455	455	130	130	0	20	0	0	0	0	51166
22	455	438	0	130	0	20	25	0	0	0	455	438	0	130	0	20	0	0	0	0	42632
23	455	318	0	130	0	0	0	0	0	0	455	318	0	0	0	0	0	0	0	0	32771
24	455	280	0	0	0	0	0	0	0	0	455	280	0	0	0	0	0	0	0	0	28576
															Overall Cost of Generation = **1056942.8444 ($)**						

In Table 6.12, U1, U2, U11 and U12 are the most economical units and thus run for total 24 hours duration to meet the corresponding load demand. At 8th to 10th hour, load is at peak demand and thus units U1 to U6 and U11 to U16 are in ON state. U7 to U10 and U17 to U20 act as the reserve unit and runs only during the peak demand. Referring Table 6.13, U1, U2, U11 and U12 are the most cost efficient units and remains online for maximum duration. At 10th to 13th hour, load is at peak value and thus units U1 to U6 and U11 to U16 are in ON state. U7 to U10 and U17 to U19 act as the reserve unit and supplies power only during the peak demand. The simulation results for CHHO algorithm for 20 unit system shows total cost of UC, UC+W and UC+W+EV are **$ 1124685.2088,, $1052294.5319** and $**1056942.8444** respectively. The results shows that there is cost saving of **$ 67742.3644** with coordinated charging/discharging of EV for V2G operation. Thus, the proposed method is effective in dealing UCP under uncertain sustainable environment.

(c) Testing of 40-unit system using CHHO

The CHHO method is tested for solving unit commitment problem for 40-unit system with wind and EV. Table-6.14 (a) and 6.14(b) illustrates optimal dispatch for 40-unit system with wind. Table-6.15 (a) and 6.15(b) illustrates optimal dispatch for 40-unit system with wind & EV. The convergence curves with wind and wind & EV for 40-unit system are presented in Fig.6.15 and Fig.6.16.

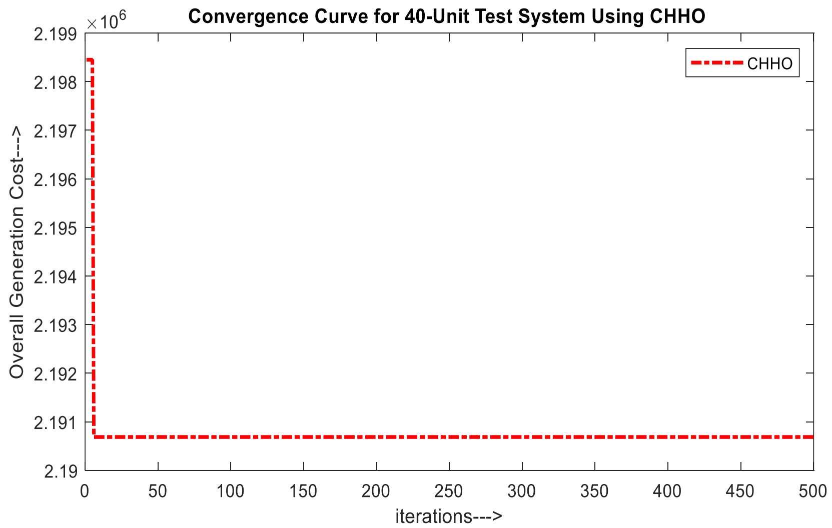


Fig.6.15: Convergence Curve for 40 units with wind using CHHO method

Table-6.14(a): Scheduling of 1 to 20 units for 40 unit system with wind using CHHO

Time (h)	Scheduling for 1 to 20 units																			
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13	U14	U15	U16	U17	U18	U19	U20
1	455	210	0	0	0	0	0	0	0	0	455	210	0	0	0	0	0	0	0	0
2	455	255	0	0	25	0	0	0	0	0	455	255	0	0	0	0	0	0	0	0
3	455	335	130	0	25	0	0	0	0	0	455	335	0	0	0	0	0	0	0	0
4	455	426	130	0	25	0	0	0	0	0	455	426	0	0	0	0	25	0	0	0
5	455	433	130	130	25	0	0	0	0	0	455	433	0	130	0	0	25	0	0	0
6	455	441	130	130	25	0	0	0	0	0	455	441	0	130	0	0	25	0	0	0
7	455	415	130	130	25	0	0	0	0	0	455	415	130	130	0	0	0	0	0	0
8	455	439	130	130	25	0	0	0	0	0	455	439	130	130	25	0	0	0	0	0
9	455	455	130	130	96	20	0	0	0	0	455	455	130	130	96	20	0	0	10	0
10	455	455	130	130	162	25	25	10	0	0	455	455	130	130	162	25	25	10	10	0
11	455	455	130	130	162	62	25	10	10	0	455	455	130	130	162	62	25	10	10	0
12	455	455	130	130	162	80	25	35	10	10	455	455	130	130	162	80	25	35	10	10
13	455	455	130	130	162	25	25	10	0	0	455	455	130	130	162	25	25	10	0	0
14	455	455	130	130	91	20	0	0	0	0	455	455	130	130	91	20	0	0	0	0
15	455	430	130	130	25	0	0	0	0	0	455	430	130	130	25	0	0	0	0	0
16	455	289	130	130	25	0	0	0	0	10	455	289	130	130	25	0	0	0	0	0
17	455	237	130	130	25	0	0	0	0	0	455	237	130	130	25	0	0	0	0	0
18	455	335	130	130	25	0	0	0	10	0	455	335	130	130	25	0	0	0	0	0
19	455	437	130	130	25	0	0	0	0	0	455	437	130	130	25	0	0	0	0	0
20	455	455	130	130	162	27	25	0	10	0	455	455	130	130	162	27	25	10	0	0
21	455	455	130	130	138	20	25	0	0	0	455	455	130	130	138	20	25	10	0	0
22	455	455	130	130	0	20	25	0	0	0	455	455	0	130	0	20	25	0	0	0
23	455	377	130	0	0	0	0	0	0	0	455	377	0	0	0	0	0	0	0	0
24	455	323	0	0	0	0	0	0	0	0	455	323	0	0	0	0	0	0	0	0

Table-6.14(b): Scheduling of 21 to 20 units for 40 unit system with wind using CHHO

Time (h)	**Scheduling for 21 to 40 Units**																				**Hourly Fuel Cost**
	U21	**U22**	**U23**	**U24**	**U25**	**U26**	**U27**	**U28**	**U29**	**U30**	**U31**	**U32**	**U33**	**U34**	**U35**	**U36**	**U37**	**U38**	**U39**	**U40**	
1	455	268	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	50700
2	455	336	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	54294
3	455	344	0	130	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	63278
4	455	308	130	130	0	0	0	0	0	0	455	0	0	130	0	0	0	0	0	0	72945
5	455	324	130	130	0	0	0	0	0	0	455	0	130	130	0	0	0	0	0	0	77620
6	455	443	130	130	25	0	0	0	0	0	455	0	130	130	0	0	0	0	0	0	85722
7	455	455	130	130	59	20	0	0	0	0	455	0	130	130	59	0	0	0	0	0	90838
8	455	455	130	130	94	20	0	0	0	0	455	0	130	130	94	20	25	0	0	0	96868
9	455	455	130	130	79	20	0	0	0	0	455	455	130	130	79	20	25	0	0	0	104491
10	455	455	130	130	158	20	0	10	10	0	455	455	130	130	158	20	25	0	0	0	116430
11	455	455	130	130	162	51	25	10	0	0	455	455	130	130	162	51	25	10	0	0	122847
12	455	455	130	130	162	80	25	22	0	0	455	455	130	130	162	80	25	22	10	0	130501
13	455	455	130	130	154	20	25	0	0	10	455	455	130	130	154	20	25	0	10	0	116710
14	455	455	130	130	100	0	25	0	10	0	455	455	130	130	100	0	0	0	0	0	106732
15	455	440	130	130	25	0	0	0	0	0	455	440	130	130	25	0	0	0	0	0	94171
16	455	289	130	130	25	0	0	0	0	0	455	289	130	130	25	0	0	0	0	0	83609
17	455	241	130	130	25	0	0	0	0	0	455	241	130	130	25	0	0	0	0	0	80264
18	455	327	130	130	25	0	0	0	0	0	455	327	130	130	25	20	0	0	0	0	89133
19	455	415	130	130	25	20	0	0	0	0	455	415	130	130	25	20	0	0	0	0	96906
20	455	455	130	130	153	20	25	0	0	0	455	455	130	130	153	20	25	0	0	0	115498
21	455	455	130	130	0	20	25	0	0	0	455	455	130	130	0	0	25	10	0	0	106192
22	455	455	0	0	0	0	25	10	0	0	455	455	0	130	0	0	25	0	0	0	87044
23	455	399	0	0	0	0	0	0	0	0	455	399	0	0	0	0	0	0	0	0	66415
24	455	393	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	58229
																Overall Cost of Generation = **2172364.1608 ($)**					

Table-6.15(a): Scheduling of 1 to 20 units for 40 unit system with wind and EV using CHHO

Time (h)	Scheduling for 1 to 20 units																			
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13	U14	U15	U16	U17	U18	U19	U20
1	455	210	0	0	0	0	0	0	0	0	455	210	0	0	0	0	0	0	0	0
2	455	255	0	0	25	0	0	0	0	0	455	255	0	0	0	0	0	0	0	0
3	455	335	130	0	25	0	0	0	0	0	455	335	0	0	0	0	0	0	0	0
4	455	426	130	0	25	0	0	0	0	0	455	426	0	0	0	0	25	0	0	0
5	455	433	130	130	25	0	0	0	0	0	455	433	0	130	0	0	25	0	0	0
6	455	441	130	130	25	0	0	0	0	0	455	441	0	130	0	0	25	0	0	0
7	455	415	130	130	25	0	0	0	0	0	455	415	130	130	0	0	0	0	0	0
8	455	439	130	130	25	0	0	0	0	0	455	439	130	130	25	0	0	0	0	0
9	455	455	130	130	96	20	0	0	0	0	455	455	130	130	96	20	0	0	10	0
10	455	455	130	130	162	25	25	10	0	0	455	455	130	130	162	25	25	10	10	0
11	455	455	130	130	162	62	25	10	10	0	455	455	130	130	162	62	25	10	10	0
12	455	455	130	130	162	80	25	35	10	10	455	455	130	130	162	80	25	35	10	10
13	455	455	130	130	162	25	25	10	0	0	455	455	130	130	162	25	25	10	0	0
14	455	455	130	130	91	20	0	0	0	0	455	455	130	130	91	20	0	0	0	0
15	455	430	130	130	25	0	0	0	0	0	455	430	130	130	25	0	0	0	0	0
16	455	289	130	130	25	0	0	0	0	10	455	289	130	130	25	0	0	0	0	0
17	455	237	130	130	25	0	0	0	0	0	455	237	130	130	25	0	0	0	0	0
18	455	335	130	130	25	0	0	0	10	0	455	335	130	130	25	0	0	0	0	0
19	455	437	130	130	25	0	0	0	0	0	455	437	130	130	25	0	0	0	0	0
20	455	455	130	130	162	27	25	0	10	0	455	455	130	130	162	27	25	10	0	0
21	455	455	130	130	138	20	25	0	0	0	455	455	130	130	138	20	25	10	0	0
22	455	455	130	130	0	20	25	0	0	0	455	455	0	130	0	20	25	0	0	0
23	455	377	130	0	0	0	0	0	0	0	455	377	0	0	0	0	0	0	0	0
24	455	323	0	0	0	0	0	0	0	0	455	323	0	0	0	0	0	0	0	0

Table-6.15(b): Scheduling of 21 to 40 units for 40 unit system with wind and EV using CHHO

Time (h)	Scheduling for 21 to 40 Units																				Hourly Fuel Cost
	U21	U22	U23	U24	U25	U26	U27	U28	U29	U30	U31	U32	U33	U34	U35	U36	U37	U38	U39	U40	
1	455	257	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	50135
2	455	329	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	53918
3	455	372	0	0	0	0	0	0	0	0	455	0	0	0	25	0	0	0	0	0	62826
4	455	373	130	0	0	0	0	0	0	0	455	0	130	0	25	0	0	0	0	0	71535
5	455	360	130	130	0	0	0	0	0	0	455	0	130	130	25	0	0	0	0	0	76598
6	455	430	130	130	25	0	0	0	0	0	455	0	130	130	25	0	0	0	0	0	85034
7	455	455	130	130	55	0	0	0	0	0	455	0	130	130	55	0	0	0	0	0	90565
8	455	455	130	130	96	20	0	0	0	0	455	0	130	130	96	20	0	0	0	0	96285
9	455	455	130	130	93	20	0	0	0	0	455	455	130	130	93	20	0	0	0	0	104936
10	455	455	130	130	162	20	25	0	0	0	455	455	130	130	162	20	25	10	0	0	117266
11	455	455	130	130	162	57	25	10	0	0	455	455	130	130	162	57	25	10	0	0	124310
12	455	455	130	130	162	80	25	31	10	10	455	455	130	130	162	80	25	31	10	10	132461
13	455	455	130	130	162	22	0	10	0	0	455	455	130	130	162	22	25	10	0	0	118117
14	455	455	130	130	82	20	0	0	0	0	455	455	130	130	82	20	0	0	0	0	104429
15	455	426	130	130	25	0	0	0	0	0	455	426	130	130	25	0	0	0	0	0	94169
16	455	281	130	130	25	0	0	0	0	0	455	281	130	130	25	0	0	0	0	0	84000
17	455	226	130	130	25	0	0	0	0	0	455	226	130	130	25	0	0	0	0	0	80168
18	455	305	130	130	25	0	0	0	0	0	455	305	130	130	25	20	25	0	0	0	89671
19	455	402	130	130	25	0	0	0	0	0	455	402	130	130	25	20	25	0	0	0	96492
20	455	455	130	130	162	20	25	0	0	0	455	455	130	130	162	20	25	0	0	0	117210
21	455	455	130	130	0	20	25	0	0	0	455	455	130	130	115	20	25	0	0	0	105919
22	455	431	130	0	0	20	25	0	0	0	455	431	130	0	0	0	0	0	0	0	87112
23	455	375	0	0	0	0	0	0	0	0	455	375	0	0	0	0	0	0	0	0	67661
24	455	312	0	0	0	0	0	0	0	0	455	312	0	0	0	0	0	0	0	0	59429
																Overall Cost of Generation = **2185806.0424 ($)**					

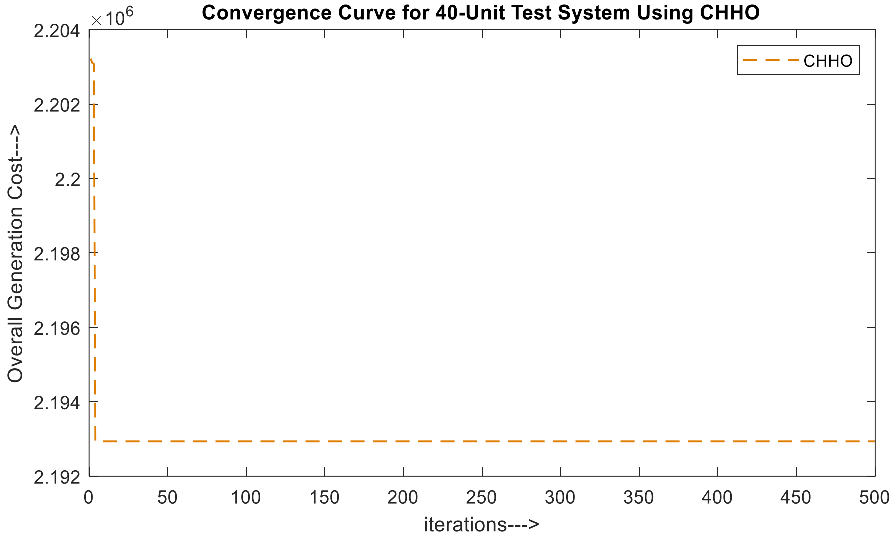


Fig.6.16: Convergence Curve for 40 units with wind and EV using CHHO method

Referring Table 6.14(a) and 6.14(b), U1, U2, U11, U12,U21,U22,U31 and U32 are the most cost efficient units and thus run for maximum duration to fulfill the load demand. For rest of hours, U3 to U9, U13 to U19, U23 to U29 and U33 to U39 contributes their power match the forecasted load demand. During 12th hour, load is at peak and thus all the units are in ON state. U10, U20, U30 and U40 act as the reserve unit and runs only during the peak demand.

In Table 6.15(a) and 6.15(b), U1, U2, U11, U12,U21,U22,U31 and U32 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load demand. For rest of hours, U3 to U9, U13 to U19, U23 to U29 and U33 to U39 contributes their power meet the corresponding load demand. At 12th hour, load is at peak demand and thus all the units are in ON state. U10, U20, U30 and U40 act as the reserve unit and runs only during the peak demand. The simulation results for CHHO algorithm for 40 unit system shows that total cost of generation with thermal with UC, UC+W and UC+W+EV are is **$ 2257230.8455, $ 2172364.1608**and **$ 2185806.0424** respectively. The results shows that there is cost saving of **$ 71424.8031** with coordinated discharging of EV for V2G operation. It can be seen from Fig.6.16 that the curve converges to optimum within 50 iterations. Thus, the proposed method is effective in handling unit commitment problem in presence of wind and EV.

(d) Testing of 60-unit system using CHHO

The CHHO method is tested for solving unit commitment problem for 60-unit system. Table-6.16 (a), 6.16(b) and 6.16(c) illustrates optimal dispatch for 60-unit system with wind. Table-6.17 (a), 6.17(b) and 6.17(c) illustrates optimal dispatch for 60-unit system with wind & EV. The convergence curve for 60-unit system with wind and with wind & EV are presented in Fig.6.17 and Fig.6.18.

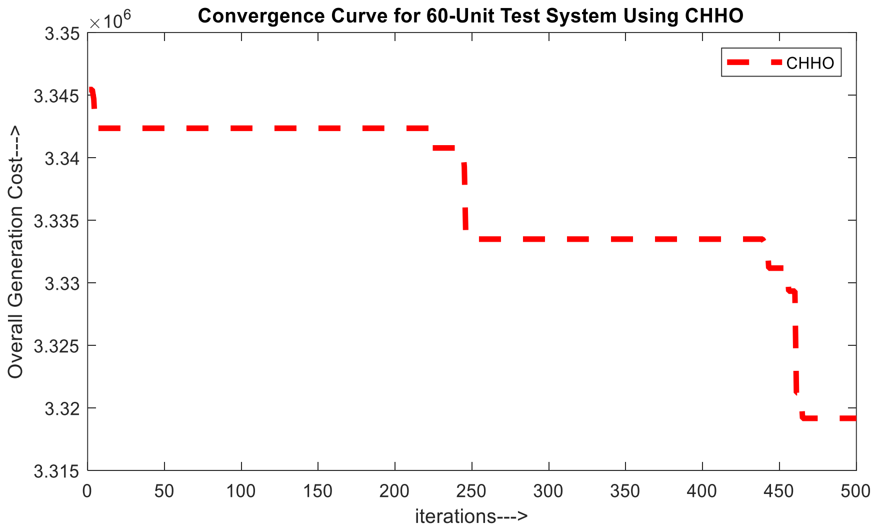


Fig.6.17: Convergence curve for 60-units with wind using CHHO method

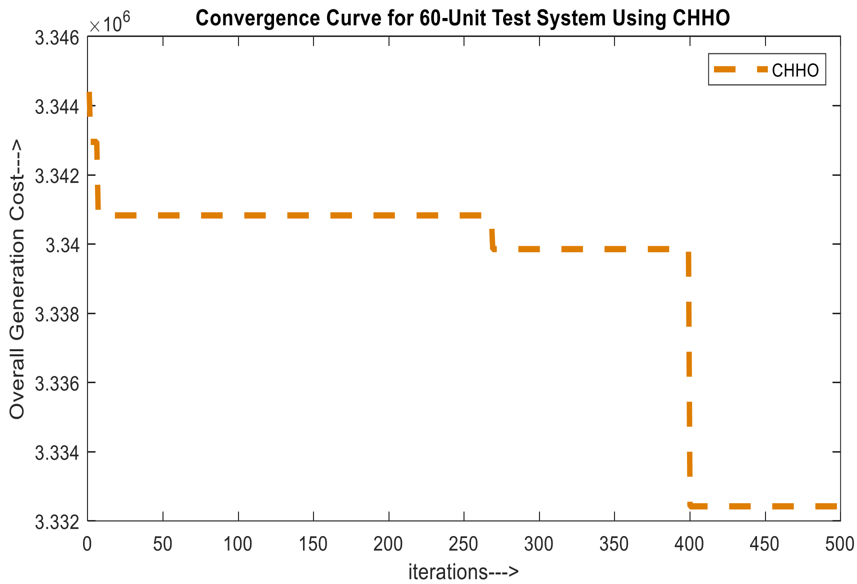


Fig.6.18: Convergence curve for 60-units with wind and EV using CHHO method

Table-6.16(a): Scheduling of 1 to 20 units for 60 unit system with wind using CHHO

Time (h)	Scheduling for 1 to 20 units																			
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13	U14	U15	U16	U17	U18	U19	U20
1	455	216	0	0	0	0	0	0	0	0	455	216	0	0	0	0	0	0	0	0
2	455	241	0	0	0	0	0	0	0	0	455	241	0	130	0	0	0	0	0	0
3	455	317	0	0	0	0	0	0	0	0	455	317	0	130	0	0	0	0	0	0
4	455	396	0	130	0	0	0	0	0	0	455	396	0	130	0	0	0	0	0	0
5	455	388	0	130	25	0	25	0	0	0	455	388	0	130	25	0	0	0	0	0
6	455	455	0	130	38	0	25	0	0	0	455	455	0	130	38	20	0	0	0	0
7	455	448	130	130	25	0	25	0	0	0	455	448	0	130	25	20	0	0	0	0
8	455	455	130	130	39	0	25	0	0	0	455	455	130	130	39	20	0	0	0	0
9	455	455	130	130	96	20	25	0	0	0	455	455	130	130	96	20	0	0	0	0
10	455	455	130	130	161	20	25	10	0	0	455	455	130	130	161	20	25	10	0	0
11	455	455	130	130	162	58	25	10	10	0	455	455	130	130	162	58	25	10	0	0
12	455	455	130	130	162	80	25	29	10	10	455	455	130	130	162	80	25	29	10	10
13	455	455	130	130	161	20	25	10	0	0	455	455	130	130	161	20	25	10	0	0
14	455	455	130	130	92	20	0	0	0	0	455	455	130	130	92	20	0	0	0	0
15	455	429	130	130	25	20	0	0	0	0	455	429	130	130	25	20	0	0	0	0
16	455	290	130	130	25	0	0	0	0	0	455	290	130	130	25	0	0	0	0	0
17	455	231	130	130	25	0	25	0	0	0	455	231	130	130	25	0	0	0	10	0
18	455	331	130	130	25	0	25	0	0	0	455	331	130	130	25	0	25	0	0	0
19	455	428	130	130	25	0	25	0	0	0	455	428	130	130	25	0	25	0	0	0
20	455	455	130	130	160	20	25	10	0	0	455	455	130	130	160	20	25	0	10	0
21	455	455	130	130	133	20	0	0	0	0	455	455	130	130	133	20	25	0	10	0
22	455	455	0	130	0	20	0	10	0	0	455	455	130	130	0	20	0	0	0	0
23	455	387	0	0	0	20	0	0	0	0	455	387	0	130	0	20	0	0	0	0
24	455	375	0	0	0	0	0	10	0	0	455	375	0	0	0	0	0	0	0	0

Table-6.16(b): Scheduling of 21 to 40 units for 60 unit system with wind using CHHO

Time (h)	Scheduling for 21 to 40 units																			
	U21	U22	U23	U24	U25	U26	U27	U28	U29	U30	U31	U32	U33	U34	U35	U36	U37	U38	U39	U40
1	455	216	0	0	0	0	0	0	0	0	455	216	0	0	0	0	0	0	0	0
2	455	241	0	0	0	0	0	0	0	0	455	241	0	0	0	0	0	0	0	0
3	455	317	0	0	25	0	0	0	0	0	455	317	0	0	0	0	0	0	0	0
4	455	396	0	0	25	0	0	0	0	0	455	396	0	0	0	0	0	0	0	0
5	455	388	130	0	25	0	25	0	0	0	455	388	0	0	0	0	0	0	0	0
6	455	455	130	0	38	0	25	0	0	0	455	455	130	0	0	0	0	0	0	0
7	455	448	130	130	25	20	25	0	0	0	455	448	130	130	0	0	0	0	0	0
8	455	455	130	130	39	20	25	0	0	0	455	455	130	130	0	0	0	0	0	0
9	455	455	130	130	96	20	25	0	0	0	455	455	130	130	0	0	0	0	0	0
10	455	455	130	130	161	20	25	10	0	0	455	455	130	130	161	20	25	0	0	0
11	455	455	130	130	162	58	25	10	0	0	455	455	130	130	162	58	25	10	0	0
12	455	455	130	130	162	80	25	29	10	10	455	455	130	130	162	80	25	29	10	0
13	455	455	130	130	161	20	25	0	0	0	455	455	130	130	161	20	25	0	0	0
14	455	455	130	130	92	20	0	0	0	0	455	455	130	130	92	20	0	0	0	0
15	455	429	130	130	25	0	0	0	0	0	455	429	130	130	25	20	0	0	0	0
16	455	290	130	130	25	0	0	0	0	0	455	290	130	130	25	0	0	0	0	0
17	455	231	130	130	25	0	0	0	10	0	455	231	130	130	25	0	25	0	0	0
18	455	331	130	130	25	0	0	10	0	0	455	331	130	130	25	0	25	0	0	0
19	455	428	130	130	25	20	0	0	0	0	455	428	130	130	25	0	25	0	0	0
20	455	455	130	130	160	20	25	10	0	0	455	455	130	130	160	20	25	0	0	0
21	455	455	130	130	0	20	25	0	0	0	455	455	130	130	133	20	25	0	0	0
22	455	455	0	130	0	0	25	0	0	0	455	455	0	0	38	20	0	0	0	0
23	455	387	0	0	0	0	0	0	0	0	455	387	0	0	0	0	0	0	0	0
24	455	375	0	0	0	0	0	0	0	0	455	375	0	0	0	0	0	10	0	0

Table-6.16(c): Scheduling of 41 to 60 units with for 60 units with wind using CHHO

Time (h)	**Scheduling for 41 to 60 Units**																				**Hourly Cost**
	U41	**U42**	**U43**	**U44**	**U45**	**U46**	**U47**	**U48**	**U49**	**U50**	**U51**	**U52**	**U53**	**U54**	**U55**	**U56**	**U57**	**U58**	**U59**	**U60**	
1	455	216	0	0	0	0	0	0	0	0	455	216	0	0	0	0	0	0	0	0	79018
2	455	241	0	0	0	0	0	0	0	0	455	241	0	0	0	0	25	0	0	0	85681
3	455	317	0	0	0	0	0	0	0	0	455	317	130	0	0	0	25	0	0	0	97502
4	455	396	0	0	0	0	0	10	0	0	455	396	130	0	0	0	25	0	0	0	109551
5	455	388	0	0	25	0	0	0	0	0	455	388	130	130	0	0	0	0	0	0	117570
6	455	455	0	0	38	0	0	0	0	0	455	455	130	130	0	0	0	0	0	0	129381
7	455	448	0	0	25	0	0	0	0	0	455	448	130	130	0	0	0	0	0	0	137053
8	455	455	0	0	39	0	0	0	0	0	455	455	130	130	39	20	25	0	0	0	145000
9	455	455	130	130	96	20	0	10	0	0	455	455	130	130	96	20	25	0	0	0	159035
10	455	455	130	130	161	20	25	0	0	0	455	455	130	130	161	20	25	0	0	0	175653
11	455	455	130	130	162	58	25	10	10	0	455	455	130	130	162	58	25	10	0	10	186675
12	455	455	130	130	162	80	25	29	10	0	455	455	130	130	162	80	25	29	10	0	198268
13	455	455	130	130	161	20	25	0	0	0	455	455	130	130	161	20	25	0	10	0	175713
14	455	455	130	130	92	20	0	0	0	0	455	455	130	130	92	20	0	0	0	0	157299
15	455	429	130	130	25	20	0	0	0	0	455	429	130	130	25	0	0	0	0	0	144824
16	455	290	130	130	25	0	0	0	0	0	455	290	130	130	25	0	0	10	0	0	127891
17	455	231	130	130	25	0	0	0	0	0	455	231	130	130	25	0	0	0	0	0	125062
18	455	331	130	130	25	0	0	0	0	0	455	331	130	130	25	0	0	0	0	0	135697
19	455	428	130	130	25	0	0	0	0	0	455	428	130	130	25	0	0	0	0	0	145758
20	455	455	130	130	160	20	25	0	0	0	455	455	130	130	160	20	25	0	0	0	175587
21	455	455	130	130	0	20	25	0	0	0	455	455	130	130	0	20	25	0	0	0	159751
22	455	455	0	130	0	20	25	0	0	0	455	455	0	130	0	20	25	0	0	0	131051
23	455	387	0	0	0	0	0	0	0	0	455	387	0	0	0	20	0	0	0	0	102251
24	455	0	0	0	0	0	0	0	0	0	455	375	0	0	0	0	0	0	0	0	90065
																Overall Cost of Generation = **3316505.9939 ($)**					

Table-6.17(a): Scheduling of 1 to 20 units for 60 unit system with wind and EV using CHHO

Time	Scheduling for 1 to 20 units																			
(h)	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13	U14	U15	U16	U17	U18	U19	U20
1	455	210	0	0	0	0	0	0	0	0	455	210	0	0	0	0	0	0	0	0
2	455	204	0	130	0	0	0	0	0	0	455	204	0	0	0	0	0	10	0	0
3	455	263	0	130	0	0	0	0	0	0	455	263	0	0	0	0	0	0	0	0
4	455	337	0	130	0	20	0	0	0	0	455	337	0	0	0	0	0	0	0	0
5	455	348	0	130	0	20	0	0	0	0	455	348	0	0	0	20	0	0	0	0
6	455	402	130	130	0	20	0	0	0	0	455	402	130	0	0	20	0	0	0	0
7	455	411	130	130	25	0	0	0	0	0	455	411	130	0	0	20	25	0	0	0
8	455	435	130	130	25	0	0	0	0	0	455	435	130	130	0	20	25	0	0	0
9	455	455	130	130	90	0	0	0	0	0	455	455	130	130	90	20	25	0	0	0
10	455	455	130	130	162	25	25	10	0	0	455	455	130	130	162	25	25	10	0	0
11	455	455	130	130	162	62	25	10	10	0	455	455	130	130	162	62	25	10	10	0
12	455	455	130	130	162	80	25	35	10	10	455	455	130	130	162	80	25	35	10	10
13	455	455	130	130	162	25	25	10	10	0	455	455	130	130	162	25	25	10	0	0
14	455	455	130	130	91	20	25	0	0	0	455	455	130	130	91	20	0	0	0	0
15	455	434	130	130	25	0	0	0	0	0	455	434	130	130	25	0	0	0	0	0
16	455	287	130	130	25	0	0	0	0	0	455	287	130	130	25	0	0	0	0	0
17	455	234	130	130	25	0	0	0	0	0	455	234	130	130	25	0	0	0	0	0
18	455	333	130	130	25	0	0	0	0	0	455	333	130	130	25	0	0	0	0	0
19	455	424	130	130	25	20	0	10	0	0	455	424	130	130	25	0	25	0	0	0
20	455	455	130	130	162	24	25	10	0	0	455	455	130	130	162	24	25	10	0	0
21	455	455	130	130	137	20	25	0	0	0	455	455	130	130	137	20	25	0	0	10
22	455	455	0	130	0	0	25	0	0	0	455	455	0	130	55	20	0	0	0	0
23	455	376	0	130	0	0	0	0	0	0	455	376	0	0	0	20	0	0	0	0
24	455	360	0	130	0	0	0	0	10	0	455	360	0	0	0	0	0	0	0	0

Table-6.17(b): Scheduling of 21 to 40 units for 60 unit system with wind and EV using CHHO

Time (h)	Scheduling for 21 to 40 units																			
	U21	U22	U23	U24	U25	U26	U27	U28	U29	U30	U31	U32	U33	U34	U35	U36	U37	U38	U39	U40
1	455	216	0	0	0	0	0	0	0	0	455	216	0	0	0	0	0	0	0	0
2	455	241	0	0	0	0	0	0	0	0	455	241	0	0	0	0	0	0	0	0
3	455	317	0	0	25	0	0	0	0	0	455	317	0	0	0	0	0	0	0	0
4	455	396	0	0	25	0	0	0	0	0	455	396	0	0	0	0	0	0	0	0
5	455	388	130	0	25	0	25	0	0	0	455	388	0	0	0	0	0	0	0	0
6	455	455	130	0	38	0	25	0	0	0	455	455	130	0	0	0	0	0	0	0
7	455	448	130	130	25	20	25	0	0	0	455	448	130	130	0	0	0	0	0	0
8	455	455	130	130	39	20	25	0	0	0	455	455	130	130	0	0	0	0	0	0
9	455	455	130	130	96	20	25	0	0	0	455	455	130	130	0	0	0	0	0	0
10	455	455	130	130	161	20	25	10	0	0	455	455	130	130	161	20	25	0	0	0
11	455	455	130	130	162	58	25	10	0	0	455	455	130	130	162	58	25	10	0	0
12	455	455	130	130	162	80	25	29	10	10	455	455	130	130	162	80	25	29	10	0
13	455	455	130	130	161	20	25	0	0	0	455	455	130	130	161	20	25	0	0	0
14	455	455	130	130	92	20	0	0	0	0	455	455	130	130	92	20	0	0	0	0
15	455	429	130	130	25	0	0	0	0	0	455	429	130	130	25	20	0	0	0	0
16	455	290	130	130	25	0	0	0	0	0	455	290	130	130	25	0	0	0	0	0
17	455	231	130	130	25	0	0	0	10	0	455	231	130	130	25	0	25	0	0	0
18	455	331	130	130	25	0	0	10	0	0	455	331	130	130	25	0	25	0	0	0
19	455	428	130	130	25	20	0	0	0	0	455	428	130	130	25	0	25	0	0	0
20	455	455	130	130	160	20	25	10	0	0	455	455	130	130	160	20	25	0	0	0
21	455	455	130	130	0	20	25	0	0	0	455	455	130	130	133	20	25	0	0	0
22	455	455	0	130	0	0	25	0	0	0	455	455	0	0	38	20	0	0	0	0
23	455	387	0	0	0	0	0	0	0	0	455	387	0	0	0	0	0	0	0	0
24	455	375	0	0	0	0	0	0	0	0	455	375	0	0	0	0	0	10	0	0

Table-6.17(c): Scheduling of 41 to 60 units for 60 unit system with wind and EV using CHHO

Time	**Scheduling for 41 to 60 Units**																				**Hourly**
(h)	**U41**	**U42**	**U43**	**U44**	**U45**	**U46**	**U47**	**U48**	**U49**	**U50**	**U51**	**U52**	**U53**	**U54**	**U55**	**U56**	**U57**	**U58**	**U59**	**U60**	**Cost**
1	455	210	0	0	0	0	0	0	0	0	455	210	0	0	0	0	0	0	0	0	78455
2	455	204	0	0	0	20	0	10	0	0	455	204	130	0	0	0	0	0	0	0	89114
3	455	263	0	0	25	20	0	0	0	0	455	263	130	0	0	0	0	0	0	0	99319
4	455	337	0	130	25	20	0	0	0	0	455	337	130	0	0	0	0	0	0	0	110707
5	455	348	0	130	25	0	0	0	0	0	455	348	130	130	25	0	0	0	0	0	117289
6	455	402	0	130	25	0	0	0	0	0	455	402	130	130	25	0	0	0	0	0	128823
7	455	411	130	130	25	0	0	0	0	0	455	411	130	130	25	0	0	0	0	0	136799
8	455	435	130	130	25	20	0	0	0	0	455	435	130	130	25	0	0	0	0	0	143979
9	455	455	130	130	90	20	0	0	10	0	455	455	130	130	90	20	0	0	0	0	160477
10	455	455	130	130	162	25	25	0	10	0	455	455	130	130	162	25	25	0	0	10	177408
11	455	455	130	130	162	62	25	10	0	10	455	455	130	130	162	62	25	10	0	0	188150
12	455	455	130	130	162	80	25	35	10	0	455	455	130	130	162	80	25	35	10	0	200231
13	455	455	130	130	162	25	25	0	0	0	455	455	130	130	162	25	25	0	0	0	177453
14	455	455	130	130	91	0	0	0	0	0	455	455	130	130	91	0	25	0	0	0	157857
15	455	434	130	130	25	0	0	0	0	0	455	434	130	130	25	0	0	0	0	10	143991
16	455	287	130	130	25	0	0	0	0	0	455	287	130	130	25	0	0	0	0	10	128574
17	455	234	130	130	25	20	0	0	0	0	455	234	130	130	25	0	0	0	0	0	121921
18	455	333	130	130	25	20	0	0	0	0	455	333	130	130	25	0	0	0	0	10	133274
19	455	424	130	130	25	20	0	0	0	0	455	424	130	130	25	0	0	0	0	0	144776
20	455	455	130	130	162	24	25	0	0	10	455	455	130	130	162	24	25	10	0	0	177332
21	455	455	130	130	0	0	25	0	0	0	455	455	130	130	0	20	25	0	0	0	160358
22	455	455	0	130	0	0	25	0	0	0	455	455	0	130	0	20	25	0	0	0	132918
23	455	376	0	0	0	0	0	0	0	0	455	376	0	130	0	0	0	0	0	0	103274
24	455	360	0	0	0	0	0	0	0	0	455	0	0	0	0	0	0	0	0	0	90702
															Overall Cost of Generation = **3328971.6499 ($)**						

Referring Table 6.16(a), 6.16(b) and 6.16(c), U1, U2, U11, U12, U21, U22, U31, U32, U41, U42, U51 and U52 are the most cost efficient units and thus run for maximum hours to meet the corresponding demand. For rest of hours, U3 to U9, U13 to U19, U23 to U29, U33 to U39, U43 to U49 and U53 to U59 contributes their power meet the corresponding load demand. During 12th hour, load is at peak demand and thus all the units are in ON state. U10, U20, U30, U40, U50 and U60 act as the reserve unit and runs only during the peak demand.

In Table 6.17(a), 6.17(b) and 6.17(c), U1, U2, U11, U12, U21, U22, U31, U32, U41, U42, U51 and U52 are the most economical units and thus run for total 24 hours duration to meet the corresponding power demand. For rest of hours, U6 to U8, U15 to U18, U25 to U29, U36 to U39, U45 to U49 and U59 to U59 contributes their power meet the corresponding load demand. At 12th hour, load is at peak and thus most of the units are in ON state. U10, U20, U30, U40, U50 and U60 act as the reserve unit and runs only during the peak demand.

The simulation results for CHHO method for 60 unit system illustrates that total cost of generation with thermal, wind and thermal and wind & EV are **$ 3386078.2574, $** $**3316505.9939** and **$3328971.6499** respectively. The results shows that there is cost saving of **$ 57106.6075** with coordinated charging/discharging of EV for V2G operation. Thus, the proposed method is efficient in solving unit commitment problem under uncertain sustainable environment.

6.7.3 Testing of Unit Commitment Problem with RES and EV by CSMA

The CHHO algorithm is applied to test systems consisting of 10, 20, 40 and 60-units and simulation results are recorded for UC with wind and with wind and EV.

(a) Testing of 10-unit system using CSMA

The CSMA method is applied to standard test systems consisting of 10-units with 10% SR and simulation results are recorded for with wind and with wind & EV. Table-6.18 represents their corresponding power dispatch for each unit with wind penetration. Table-6.19 shows corresponding power dispatch with wind & EV penetration. The convergence curves with wind and with wind & EV for 10-unit system are described in Fig.6.19 and Fig.6.20.

Table-6.18: Scheduling of 10 units with wind using CSMA

Time (h)	Generation scheduling										Power (MW)	Start-Up Cost	Hourly Fuel Cost
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10			
1	455	245	0	0	0	0	0	0	0	0	700	1620	13683
2	455	295	0	0	0	0	0	0	0	0	750	0	14554
3	455	370	0	0	25	0	0	0	0	0	850	560	16809
4	455	455	0	0	40	0	0	0	0	0	950	0	18598
5	455	390	130	0	25	0	0	0	0	0	1000	0	20051
6	455	360	130	130	25	0	0	0	0	0	1100	520	22387
7	455	410	130	130	25	0	0	0	0	0	1150	0	23262
8	455	455	130	130	30	0	0	0	0	0	1200	170	24150
9	455	455	130	130	85	20	25	0	0	0	1300	180	27251
10	455	455	130	130	162	33	25	10	0	0	1400	0	30058
11	455	455	130	130	162	73	25	10	10	0	1450	60	31916
12	455	455	130	130	162	80	25	43	10	10	1500	30	33890
13	455	455	130	130	162	33	25	10	0	0	1400	0	30058
14	455	455	130	130	85	20	25	0	0	0	1300	0	27251
15	455	455	130	130	30	0	0	0	0	0	1200	0	24150
16	455	310	130	130	25	0	0	0	0	0	1050	0	21514
17	455	260	130	130	25	0	0	0	0	0	1000	120	20642
18	455	360	130	130	25	0	0	0	0	0	1100	60	22387
19	455	455	130	130	30	0	0	0	0	0	1200	430	24150
20	455	455	130	130	162	33	25	10	0	0	1400	30	30058
21	455	455	130	130	85	20	25	0	0	0	1300	0	27251
22	455	455	0	0	145	20	25	0	0	0	1100	0	22736
23	455	420	0	0	25	0	0	0	0	0	900	0	17685
24	455	345	0	0	0	0	0	0	0	0	800	0	15427
Worst Cost($)=494987.2356				**Best Cost($)=492522.21780**				**Mean Cost($)=493701.8040**					**Total= 492522.21780**
Worst Time(Sec.)= 0.046875				**Best Time(Sec.)= 0.015625**				**Mean Time(Sec.)= 0.02916**					

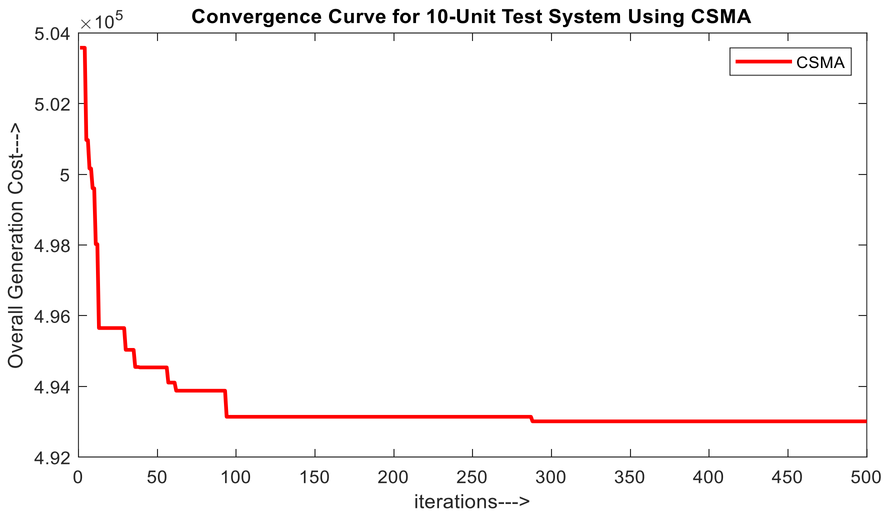


Fig.6.19: Convergence Curve for 10-unit with Wind using CSMA method

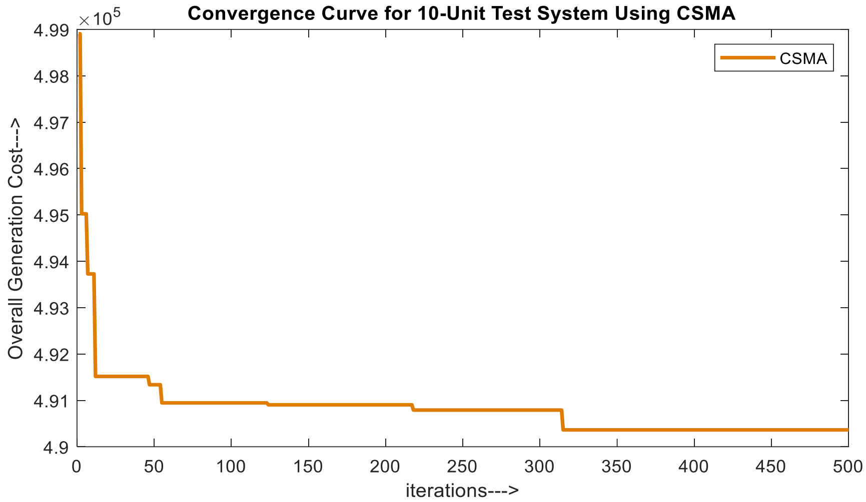


Fig.6.20: Convergence Curve for 10-unit with Wind and EV using CSMA method

Table-6.19: Scheduling of 10 units with wind and EV using CSMA method

Time (h)	**Scheduling of 10 units**										**Power (MW)**	**Start-Up Cost**	**Hourly Fuel Cost**
	U1	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**	**U8**	**U9**	**U10**			
1	405	150	0	0	0	0	0	0	0	0	555	1450	11208
2	450	150	0	0	0	0	0	0	0	0	601	0	11957
3	455	258	0	0	0	0	0	0	0	0	713	170	13914
4	455	367	0	0	25	0	0	0	0	0	847	560	16763
5	455	401	0	0	25	0	0	0	0	0	881	60	17352
6	455	392	0	130	25	0	0	0	0	0	1002	0	20059
7	455	434	0	130	25	0	0	0	0	0	1044	0	20783
8	455	355	130	130	25	0	0	0	0	0	1095	60	22294
9	455	397	130	130	25	0	0	0	0	0	1137	750	23039
10	455	455	130	130	49	20	0	0	0	0	1239	30	25339
11	455	455	130	130	85	20	25	0	0	0	1300	60	27246
12	455	455	130	130	121	20	25	0	0	0	1336	0	27995
13	455	455	130	130	44	0	25	0	0	0	1239	0	25610
14	455	449	130	130	25	0	0	0	0	0	1189	0	23937
15	455	382	130	130	25	0	0	0	0	0	1122	60	22772
16	455	206	130	130	25	0	0	0	0	0	946	260	19699
17	455	192	130	130	25	0	0	0	0	0	932	170	19455
18	455	310	130	130	25	0	0	0	0	0	1050	0	21515
19	455	402	130	130	25	0	0	0	0	0	1142	60	23115
20	455	455	130	130	53	0	0	0	0	10	1233	0	25560
21	455	416	130	130	25	0	0	0	0	0	1156	0	23374
22	455	436	0	0	25	0	0	0	0	0	916	0	17957
23	455	249	0	0	0	0	0	0	0	0	704	0	13754
24	431	150	0	0	0	0	0	0	0	0	581	0	11626
Worst Cost($)=492676.0864				**Best Cost($)=490013.6840**				**Mean Cost($)=491389.1473**					**Total= 490013.6840**
Worst Time(Sec.)= 0.0625				**Best Time(Sec.)= 0.015625**				**Mean Time(Sec.)= 0.03125**					

Referring Table 6.18 , U1 and U2 are the most economical units and thus run for total 24 hours duration to meet the corresponding load demand. Start-up cost depends upon the operating temperature of particular unit and initial state. At 9th to 13th hour , load is at peak demand and thus units U1 to U7 are in ON state. U8 to U10 act as the reserve unit and runs only during the peak demand..The total operating cost is the sum of start-up cost and generation cost of units for a 24 hour duration.

In Table 6.19 , U1 and U2 are the most cost efficient units and thus runs for maximum hours to meet the corresponding load deamd. During the peak hours, U3 to U5 units contribute their power meet the corresponding load demand. During 9th to 13th hour , load is at peak demand and thus units U1 to U8 are in ON state. U9 to U10 act as the reserve unit and runs only during the peak demand. The simulation results for CSMA algorithm for 10 unit shows total cost of UC, UC+W and UC+W+EV are **$ 563698.1582,** $**492522.21780** and $**490013.6840** respectively.

The results shows that there is cost saving of **$ 73684.4742** with coordinated discharging of EV for V2G operation.Thus, the proposed method is efficient in solving unit commitment problem under uncertain sustainable environment.

(b) Testing of 20-unit system using CSMA

The CSMA method is applied to standard test system of 20-units with 10% SR. The data of 10-units was replicated and is multiplied by 2 for obtaining the results of 20-units test system.

Table-6.20 illustrates optimal status of committed generators with wind. Table-6.21 shows their corresponding power dispatch with wind & EV penetration. The convergence curves with UC + W and UC +W+EV for 20-unit system are presented in Fig.6.21 and Fig.6.22.

Referring Table 6.20, U1, U2, U11 and U12 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load demand. At 8th to 10th hour, load is at peak demand and thus units U1 to U6 and U11 to U16 are in ON state. U7 to U10 and U17 to U20 act as the reserve unit and runs only during the peak demand.

Table-6.20: Scheduling of 20-units with wind using CSMA method

Time	Scheduling for 20 Units																				Hourly
(h)	**U1**	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**	**U8**	**U9**	**U10**	**U11**	**U12**	**U13**	**U14**	**U15**	**U16**	**U17**	**U18**	**U19**	**U20**	**Cost**
1	455	245	0	0	0	0	0	0	0	0	455	245	0	0	0	0	0	0	0	0	27366
2	455	295	0	0	0	0	0	0	0	0	455	295	0	0	0	0	0	0	0	0	29109
3	455	330	0	0	0	0	0	0	0	0	455	330	0	130	0	0	0	0	0	0	33191
4	455	418	0	0	0	0	0	0	0	0	455	418	0	130	25	0	0	0	0	0	37197
5	455	455	0	0	25	0	0	0	0	0	455	455	0	130	25	0	0	0	0	0	39457
6	455	425	130	130	25	0	0	0	0	0	455	425	0	130	25	0	0	0	0	0	44158
7	455	455	130	130	45	0	0	0	0	0	455	455	0	130	45	0	0	0	0	0	46009
8	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	48301
9	455	455	130	130	105	20	0	0	0	0	455	455	130	130	105	20	0	0	0	10	53920
10	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0	60115
11	455	455	130	130	162	73	25	10	10	0	455	455	130	130	162	73	25	10	10	0	63832
12	455	455	130	130	162	80	25	43	10	10	455	455	130	130	162	80	25	43	10	10	67780
13	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0	60115
14	455	455	130	130	98	20	25	0	0	0	455	455	130	130	98	20	0	0	0	0	53839
15	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	48301
16	455	310	130	130	25	0	0	0	0	0	455	310	130	130	25	0	0	0	0	0	43027
17	455	260	130	130	25	0	0	0	0	0	455	260	130	130	25	0	0	0	0	0	41284
18	455	360	130	130	25	0	0	0	0	0	455	360	130	130	25	0	0	0	0	0	44774
19	455	455	130	130	30	0	0	0	0	0	455	455	130	130	30	0	0	0	0	0	48301
20	455	455	130	130	162	33	25	10	0	0	455	455	130	130	162	33	25	10	0	0	60115
21	455	455	130	130	150	20	25	0	0	0	455	455	0	130	150	20	25	0	0	0	54293
22	455	455	0	130	0	20	25	0	0	0	455	455	0	0	160	20	25	0	0	0	45255
23	455	367	0	130	0	0	0	0	0	0	455	367	0	0	25	0	0	0	0	0	35447
24	455	345	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0	30855
															Overall Cost of Generation = **1052668.6335 ($)**						

Table-6.21: Scheduling of 20 units with wind and EV using CSMA method

Time	Scheduling for 20 units																				Hourly
(h)	**U1**	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**	**U8**	**U9**	**U10**	**U11**	**U12**	**U13**	**U14**	**U15**	**U16**	**U17**	**U18**	**U19**	**U20**	**Cost**
1	445	150	0	0	0	0	0	0	0	0	445	150	0	0	0	0	0	0	0	0	23741
2	455	199	0	0	0	0	0	0	0	0	455	199	0	0	0	0	0	0	0	0	25757
3	455	305	0	0	0	0	0	0	0	0	455	305	0	0	0	0	0	0	0	0	29471
4	455	336	0	0	0	0	0	0	0	0	455	336	130	0	0	0	0	0	0	0	33444
5	455	333	0	0	0	0	0	0	0	0	455	333	130	130	0	0	0	0	0	0	36171
6	455	414	0	0	25	0	0	0	0	0	455	414	130	130	0	0	0	0	0	0	39980
7	455	408	0	130	25	0	0	0	0	0	455	408	130	130	25	0	0	0	0	0	43570
8	455	455	0	130	39	0	0	0	0	0	455	455	130	130	39	0	0	0	0	0	45755
9	455	455	130	130	80	20	0	0	0	0	455	455	130	130	80	0	0	10	0	0	52068
10	455	455	130	130	145	20	25	10	0	0	455	455	130	130	145	20	25	0	0	0	57885
11	455	455	130	130	162	41	25	10	0	0	455	455	130	130	162	41	25	10	0	0	60485
12	455	455	130	130	162	80	25	15	10	10	455	455	130	130	162	80	25	15	10	0	65360
13	455	455	130	130	146	20	25	0	0	0	455	455	130	130	146	20	25	10	0	0	57953
14	455	455	130	130	67	20	0	0	0	0	455	455	130	130	67	0	0	0	0	0	50594
15	455	455	130	130	27	0	0	0	0	0	455	455	0	130	27	0	0	0	0	0	45289
16	455	316	130	130	25	0	0	0	0	0	455	316	0	130	25	0	0	0	0	0	40348
17	455	256	130	130	25	0	0	0	0	0	455	256	0	130	25	0	0	0	0	0	38256
18	455	347	130	130	25	0	0	0	0	0	455	347	0	130	25	0	25	0	0	0	42601
19	455	432	130	130	25	0	0	0	0	0	455	432	0	130	25	20	25	0	0	0	46398
20	455	455	130	130	143	20	25	0	0	0	455	455	130	130	143	20	25	0	10	0	57851
21	455	455	130	130	85	20	25	0	0	0	455	455	130	130	0	20	0	0	0	0	51166
22	455	383	0	130	0	20	25	0	0	0	455	383	130	130	0	0	0	0	0	0	42779
23	455	318	0	0	0	0	0	0	0	0	455	318	130	0	0	0	0	0	0	0	32802
24	455	215	0	0	0	0	0	0	0	0	455	215	130	0	0	0	0	0	0	0	29204
																Overall Cost of Generation = **1057617.1687($)**					

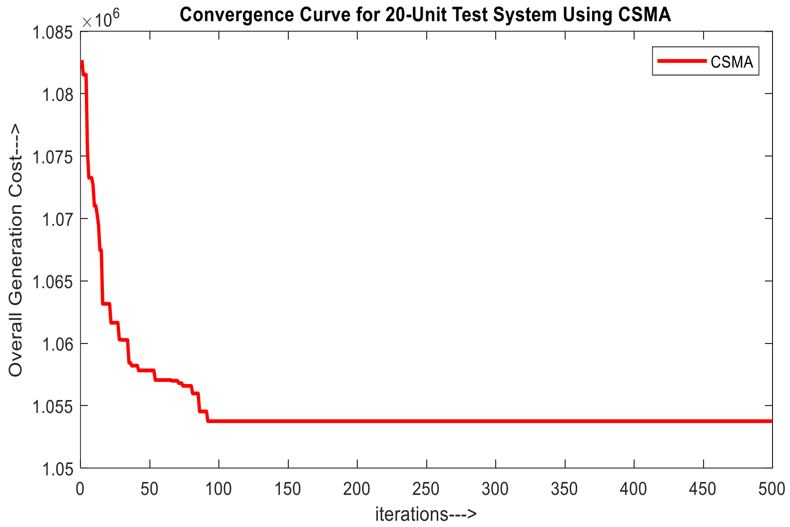


Fig.6.21: Convergence Curve for 20 unit system with Wind using CSMA method

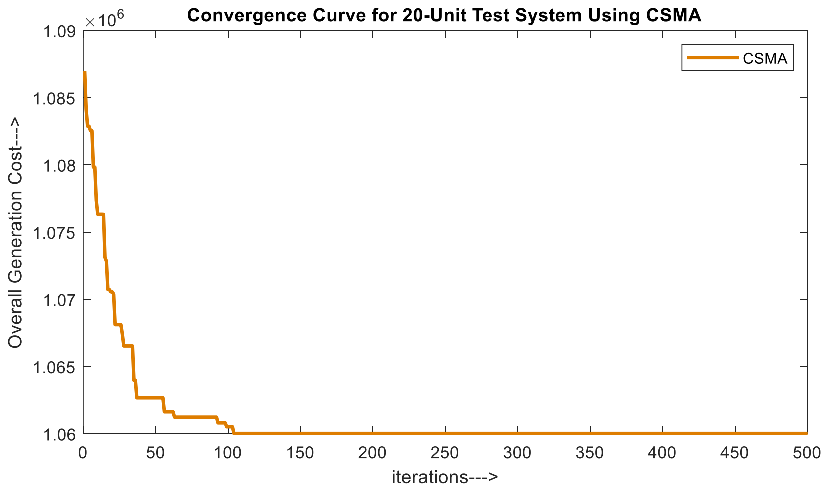


Fig.6.22: Convergence Curve for 20 unit system with wind and EV using CSMA

Referring Table 6.21, U1, U2, U11 and U12 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load demand. At 10th to 13th hour, load is at peak demand and thus units U1 to U6 and U11 to U16 are in ON state. U7 to U10 and U17 to U19 act as the reserve unit and runs only during the peak demand. The simulation results for CHHO algorithm for 20 unit system shows total cost of UC, UC+W and UC+W+EV are **$1124242.1047,** $**1052668.6335** and $**1057617.1687** respectively. The results shows that there is cost saving of **$ 66624.936** with coordinated charging/discharging of EV for V2G operation. Thus, the proposed method is cost effective in solving unit commitment problem under uncertain sustainable environment.

(c) Testing of 40-unit system using CSMA

The CSMA method is tested for solving unit commitment problem for 40-unit system with wind and EV. Table-6.22 (a) and 6.22(b) illustrates optimal dispatch for 40-unit system with wind. Table-6.23 (a) and 6.23(b) illustrates optimal dispatch for 40-unit system with wind & EV. The convergence curves with wind and wind & EV for 40-unit system are explored in Fig.6.23 and Fig.6.24.

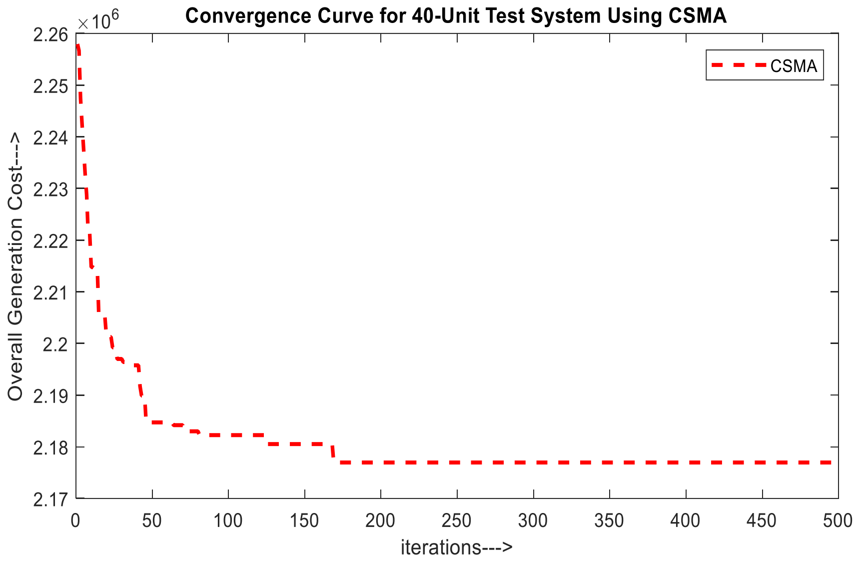


Fig.6.23: Convergence curve for 40-unit system with wind using CSMA method

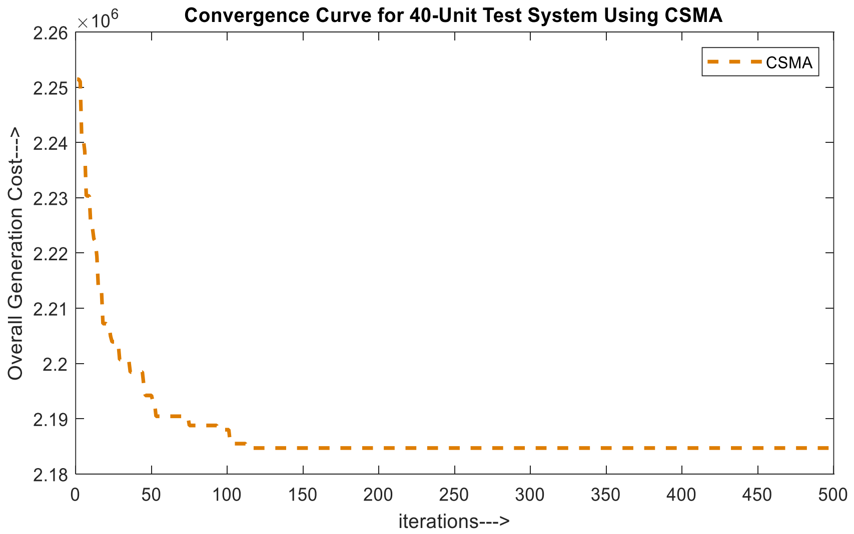


Fig.6.24: Convergence curve for 40-unit system with wind and EV using CSMA

Table-6.22(a): Scheduling of 1 to 20 units for 40 unit system with wind using CSMA method

Time	Scheduling for 1 to 20 units																			
(h)	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13	U14	U15	U16	U17	U18	U19	U20
1	455	201	0	0	0	0	0	0	0	0	455	201	0	0	0	0	0	0	0	0
2	455	252	0	0	0	0	0	0	0	0	455	252	0	0	0	0	0	0	0	0
3	455	356	0	0	0	0	0	0	0	0	455	356	0	0	0	0	0	0	0	0
4	455	388	0	0	25	0	0	0	0	0	455	388	130	0	0	0	0	0	0	0
5	455	400	130	0	25	0	0	0	0	0	455	400	130	0	25	0	0	0	0	0
6	455	431	130	130	25	0	0	0	0	0	455	431	130	130	25	0	0	0	0	0
7	455	420	130	130	25	0	0	0	0	0	455	420	130	130	25	0	0	0	0	0
8	455	435	130	130	25	20	0	0	0	0	455	435	130	130	25	0	0	0	0	0
9	455	455	130	130	80	20	0	0	0	0	455	455	130	130	80	20	25	0	0	0
10	455	455	130	130	154	20	25	0	0	0	455	455	130	130	154	20	25	0	0	0
11	455	455	130	130	162	51	25	10	10	0	455	455	130	130	162	51	25	10	0	0
12	455	455	130	130	162	80	25	22	10	10	455	455	130	130	162	80	25	22	10	0
13	455	455	130	130	154	20	25	10	0	0	455	455	130	130	154	20	25	0	0	0
14	455	455	130	130	82	20	0	0	0	0	455	455	130	130	82	20	25	0	0	0
15	455	433	130	130	25	0	0	0	0	0	455	433	130	130	25	0	0	0	0	0
16	455	282	130	130	25	0	0	0	0	0	455	282	130	130	25	0	0	0	0	0
17	455	234	130	130	25	0	0	0	0	0	455	234	130	130	25	0	0	0	0	0
18	455	332	130	130	25	0	0	10	0	0	455	332	130	130	25	0	0	0	0	0
19	455	430	130	130	25	0	0	0	0	0	455	430	130	130	25	0	0	0	0	0
20	455	455	130	130	153	20	25	0	0	0	455	455	130	130	153	20	25	0	10	0
21	455	455	130	130	107	20	25	0	0	0	455	455	130	130	107	20	25	0	0	0
22	455	441	130	130	0	20	25	0	0	0	455	441	0	130	0	20	25	0	0	0
23	455	393	0	0	0	0	0	0	0	0	455	393	0	0	0	0	25	0	0	0
24	455	301	0	0	0	0	0	0	0	0	455	301	0	0	0	0	0	0	0	0

Table-6.22(b): Scheduling of 21 to 40 units for 40 unit system with wind using CSMA method

Time (h)	**Scheduling for 21 to 40 Units**																				**Hourly Fuel Cost**
	U21	**U22**	**U23**	**U24**	**U25**	**U26**	**U27**	**U28**	**U29**	**U30**	**U31**	**U32**	**U33**	**U34**	**U35**	**U36**	**U37**	**U38**	**U39**	**U40**	
1	455	201	0	0	0	0	0	0	0	0	455	201	0	0	0	0	0	0	0	0	51653
2	455	252	0	0	0	0	0	0	0	0	455	252	0	0	0	0	0	0	0	0	55238
3	455	356	0	0	0	0	0	0	0	0	455	356	0	0	0	0	0	0	0	0	62444
4	455	388	0	0	0	0	0	0	0	0	455	388	130	0	0	0	0	0	0	0	71411
5	455	400	0	0	0	0	0	0	0	0	455	400	130	0	0	0	0	0	0	0	76088
6	455	431	0	0	0	20	0	0	0	0	455	431	130	0	0	0	0	0	0	0	84817
7	455	420	130	0	0	20	0	0	0	0	455	420	130	130	0	0	0	0	0	0	89816
8	455	435	130	130	0	20	0	0	0	0	455	435	130	130	0	0	0	0	0	0	94564
9	455	455	130	130	80	20	0	0	0	0	455	455	130	130	80	0	0	0	0	0	104237
10	455	455	130	130	154	20	25	10	0	0	455	455	130	130	154	20	25	0	0	0	115582
11	455	455	130	130	162	51	25	10	0	0	455	455	130	130	162	51	25	10	0	0	122837
12	455	455	130	130	162	80	25	22	10	0	455	455	130	130	162	80	25	22	10	0	130491
13	455	455	130	130	154	20	25	0	0	0	455	455	130	130	154	20	25	0	0	0	115624
14	455	455	130	130	82	0	0	0	0	0	455	455	130	130	82	20	0	0	0	0	104379
15	455	433	130	130	25	0	0	0	0	0	455	433	130	130	25	0	0	0	0	0	94677
16	455	282	130	130	25	0	0	0	0	0	455	282	130	130	25	0	0	0	0	0	84118
17	455	234	130	130	25	0	0	0	0	0	455	234	130	130	25	0	0	0	0	0	80774
18	455	332	130	130	25	0	0	0	0	10	455	332	130	130	25	0	0	0	0	0	89485
19	455	430	130	130	25	20	0	0	0	0	455	430	130	130	25	0	0	0	0	0	95275
20	455	455	130	130	153	20	25	0	0	0	455	455	130	130	153	20	25	0	0	0	115516
21	455	455	130	130	0	20	25	0	0	0	455	455	130	130	0	20	25	0	0	0	105578
22	455	441	0	130	0	0	25	0	0	0	455	441	0	0	0	20	25	0	0	0	87037
23	455	393	0	0	0	0	0	0	0	0	455	393	0	0	0	0	25	0	0	0	67381
24	455	301	0	0	0	0	0	0	0	0	455	301	0	0	0	0	0	0	0	0	58654
																Overall Cost of Generation = **2172364.1608($)**					

Table-6.23(a): Scheduling of 1 to 20 units for 40 unit system with wind and EV using CSMA method

Time (h)	Scheduling for 1 to 20 units																			
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13	U14	U15	U16	U17	U18	U19	U20
1	455	193	0	0	0	0	0	0	0	0	455	193	0	0	0	0	0	0	0	0
2	455	247	0	0	0	0	0	0	0	0	455	247	0	0	0	0	0	0	0	0
3	455	350	0	0	0	0	0	0	0	0	455	350	0	0	0	0	0	0	0	0
4	455	403	0	0	0	0	0	0	0	0	455	403	0	130	25	0	0	0	0	0
5	455	394	130	0	0	0	0	0	0	0	455	394	0	130	25	0	0	0	0	0
6	455	455	130	0	51	0	0	0	0	0	455	455	0	130	51	20	0	0	0	0
7	455	438	130	130	25	0	0	0	0	0	455	438	130	130	25	20	0	0	0	0
8	455	455	130	130	32	0	0	0	0	0	455	455	130	130	32	20	0	0	0	0
9	455	455	130	130	85	0	25	0	0	0	455	455	130	130	85	20	0	0	0	0
10	455	455	130	130	162	20	25	10	0	0	455	455	130	130	162	20	25	10	0	0
11	455	455	130	130	162	57	25	10	10	0	455	455	130	130	162	57	25	10	10	0
12	455	455	130	130	162	80	25	31	10	10	455	455	130	130	162	80	25	31	10	10
13	455	455	130	130	162	21	25	10	0	0	455	455	130	130	162	21	25	10	0	0
14	455	455	130	130	86	0	0	0	0	0	455	455	130	130	86	20	0	10	0	0
15	455	426	130	130	25	0	0	0	0	0	455	426	130	130	25	0	0	0	0	0
16	455	281	130	130	25	0	0	0	0	0	455	281	130	130	25	0	0	0	0	0
17	455	226	130	130	25	0	0	0	0	0	455	226	130	130	25	0	0	0	0	0
18	455	325	130	130	25	0	0	0	0	0	455	325	130	130	25	0	0	0	0	10
19	455	425	130	130	25	0	0	0	0	0	455	425	130	130	25	0	0	0	0	0
20	455	455	130	130	162	20	25	10	0	0	455	455	130	130	162	20	25	10	0	0
21	455	455	130	130	162	32	25	0	0	10	455	455	130	130	0	32	25	0	0	0
22	455	448	130	130	0	20	25	0	0	0	455	448	0	130	0	20	25	0	0	0
23	455	379	0	130	0	0	0	0	0	0	455	379	0	0	0	0	0	0	0	0
24	455	312	0	0	0	0	0	0	0	0	455	312	0	0	0	0	0	0	0	0

Table-6.23(b): Scheduling of 21 to 40 units for 40 unit system with wind and EV using CSMA method

Time (h)	Scheduling for 21 to 40 Units																				Hourly Fuel Cost
	U21	U22	U23	U24	U25	U26	U27	U28	U29	U30	U31	U32	U33	U34	U35	U36	U37	U38	U39	U40	
1	455	193	0	0	0	0	0	0	0	0	455	193	0	0	0	0	0	0	0	0	51090
2	455	247	0	0	0	0	0	0	0	0	455	247	0	0	0	0	0	0	0	0	54863
3	455	350	0	0	0	0	0	0	0	0	455	350	0	0	0	0	0	0	0	0	62072
4	455	403	0	0	0	0	0	0	0	0	455	403	0	0	25	0	0	0	0	0	70530
5	455	394	0	0	0	0	0	0	0	0	455	394	130	0	25	0	0	0	0	0	75654
6	455	455	0	0	0	0	0	0	0	0	455	455	130	0	51	20	0	0	0	0	84104
7	455	438	0	130	0	0	0	0	0	0	455	438	130	0	25	20	0	0	0	0	89940
8	455	455	0	130	0	0	0	0	0	0	455	455	130	130	32	20	0	0	0	0	94447
9	455	455	130	130	85	20	25	0	0	0	455	455	130	130	85	20	0	0	0	0	105854
10	455	455	130	130	162	20	25	0	0	0	455	455	130	130	162	20	25	0	0	0	117247
11	455	455	130	130	162	57	25	10	0	0	455	455	130	130	162	57	25	10	0	0	124310
12	455	455	130	130	162	80	25	31	10	0	455	455	130	130	162	80	25	31	10	0	132451
13	455	455	130	130	162	21	25	0	0	0	455	455	130	130	162	21	25	0	0	0	117321
14	455	455	130	130	86	20	0	0	0	0	455	455	130	130	86	20	0	0	0	0	104481
15	455	426	130	130	25	0	0	0	0	0	455	426	130	130	25	0	0	0	0	0	94169
16	455	281	130	130	25	0	0	0	0	0	455	281	130	130	25	0	0	0	0	0	84000
17	455	226	130	130	25	0	0	0	0	0	455	226	130	130	25	0	0	0	0	0	80168
18	455	325	130	130	25	0	0	0	0	0	455	325	130	130	25	0	0	0	0	0	88032
19	455	425	130	130	25	0	0	0	0	0	455	425	130	130	25	0	0	0	0	0	94085
20	455	455	130	130	162	20	25	0	0	0	455	455	130	130	162	20	25	0	0	0	117192
21	455	455	130	130	0	32	25	0	0	0	455	455	130	130	0	32	25	0	10	0	107100
22	455	448	0	130	0	20	25	0	0	0	455	448	0	0	0	20	25	0	0	0	88337
23	455	379	0	0	0	0	0	10	0	0	455	379	0	0	0	0	0	0	0	0	67866
24	455	312	0	0	0	0	0	0	0	0	455	312	0	0	0	0	0	0	0	0	59429
																Overall Cost of Generation = **2181710.3802($)**					

Referring Table 6.22(a) and 6.22(b), U1, U2, U11, U12,U21,U22,U31 and U32 are the most cost efficient units and thus provides power for maximum duration to meet the corresponding power demand. For rest of hours, U3 to U9, U13 to U19, U23 to U29 and U33 to U39 contributes their power meet the corresponding power demand. At 12th hour, load is at maximum and thus all the units are in ON state. U10, U20, U30 and U40 act as the reserve unit and runs only during the peak demand.

In Table 6.23(a) and 6.23(b), U1, U2, U11, U12,U21,U22,U31 and U32 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load demand. For rest of hours, U3 to U9, U13 to U19, U23 to U29 and U33 to U39 contributes their power meet the corresponding load demand. During 12th hour, load is at peak demand and thus all the units are in ON state. U10, U20, U30 and U40 act as the reserve unit and runs only during the peak demand.

The simulation results for CSMA algorithm for 40 unit system shows that total cost of generation with thermal with UC, UC+W and UC+W+EV are is **$ 2246297.7597, $ 2162363.1908** and **$ 218170.3802** respectively. The results shows that there is cost saving of **$ 2028127.3795** with coordinated charging/discharging of EV for V2G operation. Thus, the proposed method is cost effective in dealing unit commitment problem in presence of wind and EV.

(d) Testing of 60-unit system using CSMA

The CSMA method is tested for solving unit commitment problem for 60-unit system with wind and EV penetration. Table-6.24 (a), 6.24(b) and 6.24(c) illustrates optimal dispatch for 60-unit system with wind. Table-6.25(a), 6.25(b) and 6.25(c) illustrates optimal dispatch for 60-unit system with wind & EV. The convergence curve for 60-unit system with wind and with wind & EV are illustrated in Fig.6.25 and Fig.6.26.

Referring Table 6.24(a), 6.24(b) and 6.24(c), U1, U2, U11, U12, U21, U22, U31, U32, U41, U42, U51 and U52 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding load demand. For rest of hours, U3 to U9, U13 to U19, U23 to U29, U33 to U39, U43 to U49 and U53 to U59 contributes their power meet the corresponding load demand.

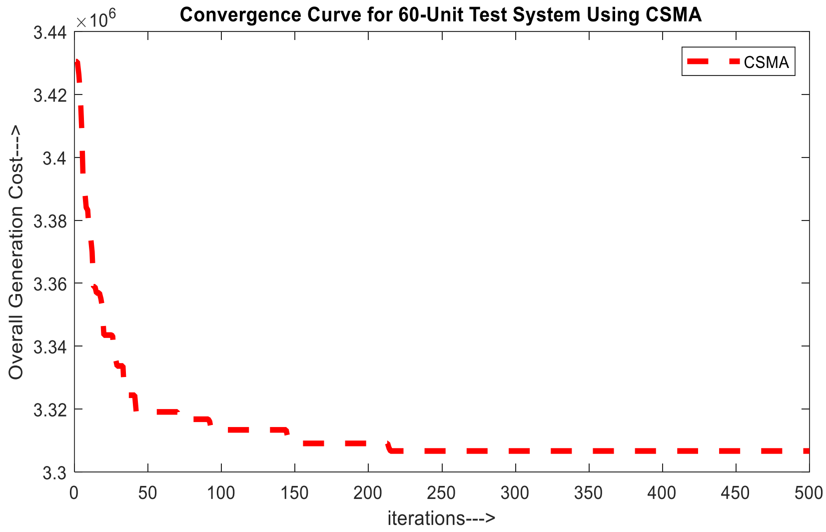


Fig.6.25: Convergence Curve for 60-units system with Wind using CSMA method

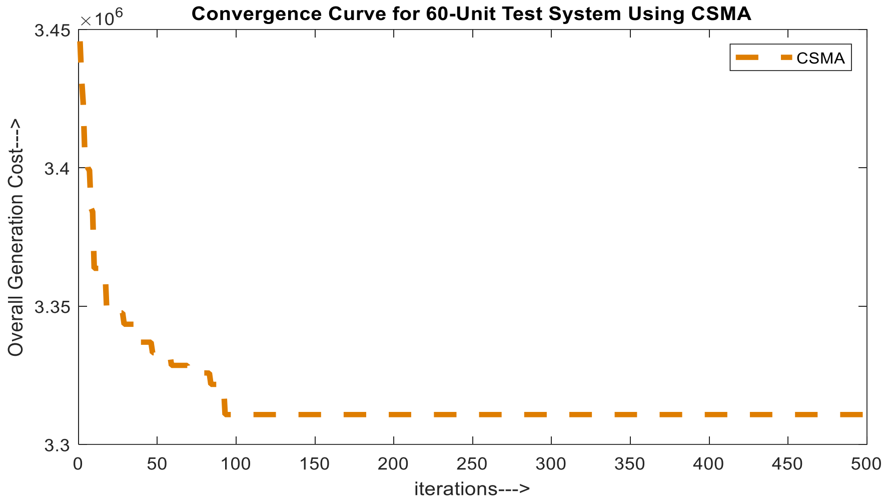


Fig.6.26: Convergence Curve for 60-units system with Wind and EV using CSMA

During 12th hour, load is at peak demand and thus most of the units are in on state. U10, U20, U30, U40, U50 and U60 act as the reserve unit and runs only during the peak demand.

Referring Table 6.25(a), 6.25(b) and 6.25(c), U1, U2, U11, U12, U21, U22, U31, U32, U41, U42, U51 and U52 are the most cost efficient units and thus run for total 24 hours duration to meet the corresponding power demand. For rest of hours, U6 to U8, U15 to U18, U25 to U29, U36 to U39, U45 to U49 and U59 to U59 contributes their power meet the corresponding load demand. At 12th hour, load is at peak demand and thus all the units are in ON state. U10, U20, U30, U40, U50 and U60 act as the reserve unit and runs only during the peak load.

Table-6.24(a): Scheduling of 1 to 20 units for 60 units with wind using CSMA method

Time (h)	Scheduling for 1 to 20 units																			
	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12	U13	U14	U15	U16	U17	U18	U19	U20
1	455	216	0	0	0	0	0	0	0	0	455	216	0	0	0	0	0	0	0	0
2	455	267	0	0	0	0	0	0	0	0	455	267	0	0	0	0	0	0	0	0
3	455	335	0	0	0	0	25	0	0	0	455	335	0	0	0	0	0	0	0	0
4	455	412	0	0	0	0	25	0	0	0	455	412	0	0	0	0	0	0	0	0
5	455	436	130	0	25	0	25	0	0	0	455	436	0	0	0	0	0	0	0	0
6	455	455	130	0	41	0	0	0	0	0	455	455	130	130	0	20	0	0	0	0
7	455	455	130	0	26	0	0	0	0	0	455	455	130	130	0	20	0	0	0	0
8	455	455	130	0	52	0	0	0	0	0	455	455	130	130	52	20	0	0	0	0
9	455	455	130	130	91	20	0	0	0	0	455	455	130	130	91	20	0	10	0	0
10	455	455	130	130	161	20	25	10	0	0	455	455	130	130	161	20	25	10	0	0
11	455	455	130	130	162	59	25	10	10	0	455	455	130	130	162	59	25	10	10	0
12	455	455	130	130	162	80	25	29	10	10	455	455	130	130	162	80	25	29	0	10
13	455	455	130	130	161	20	25	10	0	0	455	455	130	130	161	20	25	10	0	0
14	455	455	130	130	92	20	0	0	0	0	455	455	130	130	92	20	0	0	0	0
15	455	437	130	130	25	0	0	0	0	0	455	437	130	130	25	20	0	0	0	10
16	455	290	130	130	25	0	0	10	0	0	455	290	130	130	25	0	0	0	0	0
17	455	243	130	130	25	0	0	0	0	0	455	243	130	130	25	0	0	0	0	0
18	455	337	130	130	25	0	0	0	0	0	455	337	130	130	25	0	25	0	0	0
19	455	436	130	130	25	0	0	0	0	0	455	436	130	130	25	0	25	0	0	0
20	455	455	130	130	160	20	25	10	0	0	455	455	130	130	160	20	25	10	0	10
21	455	455	130	130	128	20	25	0	0	0	455	455	130	130	0	20	25	0	0	0
22	455	453	130	130	0	20	25	0	0	0	455	453	0	130	0	20	0	0	0	0
23	455	373	130	130	0	0	0	0	0	0	455	373	0	0	0	0	0	0	0	10
24	455	316	0	0	0	0	0	0	0	0	455	316	0	0	0	0	0	0	0	0

Table-6.24(b): Scheduling of 21 to 40 units for 60 units with wind using CSMA method

Time (h)	Scheduling for 21 to 40 units																			
	U21	U22	U23	U24	U25	U26	U27	U28	U29	U30	U31	U32	U33	U34	U35	U36	U37	U38	U39	U40
1	455	216	0	0	0	0	0	0	0	0	455	216	0	0	0	0	0	0	0	0
2	455	267	0	0	0	0	0	0	0	0	455	267	0	0	0	0	0	0	0	0
3	455	335	0	0	0	20	0	0	0	0	455	335	0	0	0	0	0	0	0	0
4	455	412	0	0	0	20	0	0	0	0	455	412	0	0	25	0	0	0	0	0
5	455	436	0	0	0	20	0	0	0	0	455	436	0	0	25	0	0	0	0	0
6	455	455	0	0	41	0	0	0	0	0	455	455	0	0	41	0	0	0	0	0
7	455	455	130	0	26	0	0	0	0	0	455	455	130	0	26	0	0	0	0	0
8	455	455	130	130	52	0	0	0	0	0	455	455	130	0	52	0	0	0	0	0
9	455	455	130	130	91	20	25	0	0	0	455	455	130	130	91	0	0	0	0	0
10	455	455	130	130	161	20	25	0	10	0	455	455	130	130	161	20	25	0	0	0
11	455	455	130	130	162	59	25	10	10	0	455	455	130	130	162	59	25	10	0	0
12	455	455	130	130	162	80	25	29	10	10	455	455	130	130	162	80	25	29	10	0
13	455	455	130	130	161	20	25	10	0	0	455	455	130	130	161	20	25	0	0	0
14	455	455	130	130	92	20	0	0	0	0	455	455	130	130	92	20	0	0	10	0
15	455	437	130	130	25	0	0	0	0	0	455	437	130	130	25	0	0	0	0	0
16	455	290	130	130	25	0	0	0	0	0	455	290	130	130	25	0	0	0	0	0
17	455	243	130	130	25	0	0	0	0	0	455	243	130	130	25	0	0	0	0	0
18	455	337	130	130	25	20	0	0	0	0	455	337	130	130	25	0	0	0	0	0
19	455	436	130	130	25	20	0	0	0	0	455	436	130	130	25	0	0	0	0	0
20	455	455	130	130	160	20	25	0	0	0	455	455	130	130	160	20	25	0	0	0
21	455	455	130	130	128	20	25	0	0	0	455	455	130	130	0	20	25	0	0	0
22	455	453	0	130	0	0	25	0	0	0	455	453	0	130	0	20	25	0	0	0
23	455	373	0	0	0	0	0	0	0	0	455	373	0	0	0	0	0	0	0	0
24	455	316	0	0	0	0	0	0	0	0	455	316	0	0	0	0	0	0	0	0

Table-6.24(c): Scheduling of 41 to 60 units for 60 units with wind using CSMA method

Time (h)	Scheduling for 41 to 60 Units																				Hourly Fuel Cost
	U41	**U42**	**U43**	**U44**	**U45**	**U46**	**U47**	**U48**	**U49**	**U50**	**U51**	**U52**	**U53**	**U54**	**U55**	**U56**	**U57**	**U58**	**U59**	**U60**	
1	455	216	0	0	0	0	0	0	0	0	455	216	0	0	0	0	0	0	0	0	79018
2	455	267	0	0	0	0	0	0	0	0	455	267	0	0	0	0	0	0	0	0	84346
3	455	335	0	130	25	0	0	0	0	0	455	335	0	0	0	0	0	0	0	0	97349
4	455	412	0	130	25	0	0	0	0	0	455	412	0	130	0	0	0	0	0	0	109166
5	455	436	0	130	25	0	0	0	0	0	455	436	0	130	0	0	0	0	0	0	115596
6	455	455	0	130	41	0	0	0	0	0	455	455	130	130	41	0	0	0	0	0	128477
7	455	455	130	130	26	0	0	0	0	0	455	455	130	130	26	0	0	0	0	0	135695
8	455	455	130	130	52	0	0	0	0	0	455	455	130	130	52	0	0	0	0	0	142622
9	455	455	130	130	91	0	25	0	0	0	455	455	130	130	91	0	0	0	0	0	157969
10	455	455	130	130	161	20	25	0	0	0	455	455	130	130	161	20	25	0	0	0	175671
11	455	455	130	130	162	59	25	10	0	0	455	455	130	130	162	59	25	10	0	0	186665
12	455	455	130	130	162	80	25	29	10	10	455	455	130	130	162	80	25	29	10	0	198278
13	455	455	130	130	161	20	25	0	0	0	455	455	130	130	161	20	25	0	0	0	175695
14	455	455	130	130	92	0	0	10	0	0	455	455	130	130	92	20	0	0	0	0	158338
15	455	437	130	130	25	0	0	0	0	0	455	437	130	130	25	0	0	0	0	0	144194
16	455	290	130	130	25	0	0	0	0	0	455	290	130	130	25	0	0	0	0	0	127891
17	455	243	130	130	25	0	0	0	0	0	455	243	130	130	25	0	0	0	0	0	122057
18	455	337	130	130	25	0	0	0	0	0	455	337	130	130	25	0	0	0	0	0	133946
19	455	436	130	130	25	0	0	0	0	0	455	436	130	130	25	0	0	0	0	0	144287
20	455	455	130	130	160	20	25	0	0	0	455	455	130	130	160	20	25	0	0	0	175597
21	455	455	130	130	0	20	25	0	0	0	455	455	130	130	128	20	25	0	0	0	159677
22	455	453	0	0	0	20	25	10	0	0	455	453	0	130	0	20	25	0	0	0	131984
23	455	373	0	0	0	0	0	0	0	0	455	373	0	0	0	0	0	0	0	0	102237
24	455	316	0	0	0	0	0	0	0	0	455	316	0	0	0	0	0	0	0	0	89508
																Overall Cost of Generation = **3303824.3855($)**					

Table-6.25(a): Scheduling of 1 to 20 units for 60 units with wind and EV using CSMA method

Time (h)	Scheduling for 1 to 20 units																			
	U1	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**	**U8**	**U9**	**U10**	**U11**	**U12**	**U13**	**U14**	**U15**	**U16**	**U17**	**U18**	**U19**	**U20**
1	455	210	0	0	0	0	0	0	0	0	455	210	0	0	0	0	0	0	0	0
2	455	263	0	0	0	0	0	0	0	0	455	263	0	0	0	0	0	0	0	0
3	455	318	0	0	0	0	0	0	0	0	455	318	0	130	25	0	0	0	0	0
4	455	390	130	0	25	0	0	0	0	0	455	390	0	130	25	0	0	0	0	0
5	455	388	130	0	25	0	0	0	0	0	455	388	0	130	25	0	0	0	0	0
6	455	455	130	0	33	0	0	0	0	0	455	455	0	130	33	0	0	0	0	0
7	455	455	130	0	41	0	0	0	0	0	455	455	130	130	41	0	0	0	0	0
8	455	455	130	130	51	0	0	0	0	0	455	455	130	130	51	0	0	0	0	0
9	455	455	130	130	92	0	25	0	0	0	455	455	130	130	92	20	25	0	0	0
10	455	455	130	130	162	25	25	10	0	0	455	455	130	130	162	25	25	10	0	0
11	455	455	130	130	162	62	25	10	10	0	455	455	130	130	162	62	25	10	10	0
12	455	455	130	130	162	80	25	35	10	10	455	455	130	130	162	80	25	35	10	10
13	455	455	130	130	162	25	25	10	0	0	455	455	130	130	162	25	25	10	0	0
14	455	455	130	130	92	20	0	0	0	0	455	455	130	130	92	20	0	0	0	0
15	455	432	130	130	25	0	0	0	0	0	455	432	130	130	25	0	0	0	0	0
16	455	290	130	130	25	0	0	0	0	0	455	290	130	130	25	0	0	0	0	0
17	455	237	130	130	25	0	0	0	0	0	455	237	130	130	25	0	0	0	0	0
18	455	335	130	130	25	20	0	0	0	0	455	335	130	130	25	0	0	0	0	0
19	455	432	130	130	25	20	0	0	0	0	455	432	130	130	25	0	0	0	0	0
20	455	455	130	130	162	24	25	10	0	0	455	455	130	130	162	24	25	10	0	0
21	455	455	130	130	137	0	25	0	0	0	455	455	130	130	137	20	25	0	0	0
22	455	455	0	130	0	0	25	0	0	0	455	455	130	130	0	22	25	0	0	10
23	455	393	0	130	0	0	0	10	0	0	455	393	0	0	0	0	25	0	10	0
24	455	323	0	0	0	0	0	0	0	0	455	323	0	0	0	0	0	0	0	0

Table-6.25(b): Scheduling of 21 to 40 units for 60 units with wind and EV using CSMA method

Time (h)	Scheduling for 21 to 40 units																			
	U21	U22	U23	U24	U25	U26	U27	U28	U29	U30	U31	U32	U33	U34	U35	U36	U37	U38	U39	U40
1	455	216	0	0	0	0	0	0	0	0	455	216	0	0	0	0	0	0	0	0
2	455	241	0	0	0	0	0	0	0	0	455	241	0	0	0	0	0	0	0	0
3	455	317	0	0	25	0	0	0	0	0	455	317	0	0	0	0	0	0	0	0
4	455	396	0	0	25	0	0	0	0	0	455	396	0	0	0	0	0	0	0	0
5	455	388	130	0	25	0	25	0	0	0	455	388	0	0	0	0	0	0	0	0
6	455	455	130	0	38	0	25	0	0	0	455	455	130	0	0	0	0	0	0	0
7	455	448	130	130	25	20	25	0	0	0	455	448	130	130	0	0	0	0	0	0
8	455	455	130	130	39	20	25	0	0	0	455	455	130	130	0	0	0	0	0	0
9	455	455	130	130	96	20	25	0	0	0	455	455	130	130	0	0	0	0	0	0
10	455	455	130	130	161	20	25	10	0	0	455	455	130	130	161	20	25	0	0	0
11	455	455	130	130	162	58	25	10	0	0	455	455	130	130	162	58	25	10	0	0
12	455	455	130	130	162	80	25	29	10	10	455	455	130	130	162	80	25	29	10	0
13	455	455	130	130	161	20	25	0	0	0	455	455	130	130	161	20	25	0	0	0
14	455	455	130	130	92	20	0	0	0	0	455	455	130	130	92	20	0	0	0	0
15	455	429	130	130	25	0	0	0	0	0	455	429	130	130	25	20	0	0	0	0
16	455	290	130	130	25	0	0	0	0	0	455	290	130	130	25	0	0	0	0	0
17	455	231	130	130	25	0	0	0	10	0	455	231	130	130	25	0	25	0	0	0
18	455	331	130	130	25	0	0	10	0	0	455	331	130	130	25	0	25	0	0	0
19	455	428	130	130	25	20	0	0	0	0	455	428	130	130	25	0	25	0	0	0
20	455	455	130	130	160	20	25	10	0	0	455	455	130	130	160	20	25	0	0	0
21	455	455	130	130	0	20	25	0	0	0	455	455	130	130	133	20	25	0	0	0
22	455	455	0	130	0	0	25	0	0	0	455	455	0	0	38	20	0	0	0	0
23	455	387	0	0	0	0	0	0	0	0	455	387	0	0	0	0	0	0	0	0
24	455	375	0	0	0	0	0	0	0	0	455	375	0	0	0	0	0	10	0	0

Table-6.25(c): Scheduling of 41 to 60 units for 60 units with wind and EV using CSMA method

Time (h)	Scheduling for 41 to 60 Units																				Hourly Fuel Cost
	U41	U42	U43	U44	U45	U46	U47	U48	U49	U50	U51	U52	U53	U54	U55	U56	U57	U58	U59	U60	
1	455	210	0	0	0	0	0	0	0	0	455	210	0	0	0	0	0	0	0	0	78455
2	455	263	0	0	0	0	0	0	0	0	455	263	0	0	0	0	0	0	0	0	83971
3	455	318	0	0	0	0	0	0	0	0	455	318	0	0	0	0	0	0	0	0	96362
4	455	390	0	0	0	0	0	0	0	0	455	390	0	0	0	0	0	0	0	0	107836
5	455	388	130	130	25	0	0	0	0	0	455	388	0	0	25	0	0	0	0	0	116202
6	455	455	130	130	33	0	0	0	0	0	455	455	0	0	33	0	0	0	0	0	127693
7	455	455	130	130	41	0	0	0	0	0	455	455	130	0	41	0	0	0	0	0	135574
8	455	455	130	130	51	0	0	0	0	0	455	455	130	0	51	0	0	0	0	0	142548
9	455	455	130	130	92	0	25	0	0	0	455	455	130	130	92	20	25	0	0	0	159536
10	455	455	130	130	162	25	25	0	0	0	455	455	130	130	162	25	25	0	0	0	177389
11	455	455	130	130	162	62	25	10	0	0	455	455	130	130	162	62	25	10	0	0	188140
12	455	455	130	130	162	80	25	35	10	0	455	455	130	130	162	80	25	35	10	0	200231
13	455	455	130	130	162	25	25	0	0	0	455	455	130	130	162	25	25	0	0	0	177434
14	455	455	130	130	92	20	0	0	0	0	455	455	130	130	92	20	0	0	0	0	157349
15	455	432	130	130	25	0	0	0	0	10	455	432	130	130	25	0	0	0	0	0	143685
16	455	290	130	130	25	0	0	0	0	0	455	290	130	130	25	0	0	0	0	0	127027
17	455	237	130	130	25	0	0	0	0	0	455	237	130	130	25	0	0	0	0	0	121451
18	455	335	130	130	25	0	0	0	0	0	455	335	130	130	25	0	0	0	0	0	132500
19	455	432	130	130	25	0	0	0	0	0	455	432	130	130	25	0	0	0	0	0	143591
20	455	455	130	130	162	24	25	0	0	0	455	455	130	130	162	24	25	0	0	0	177304
21	455	455	130	130	0	20	25	0	0	0	455	455	130	130	0	20	25	10	0	0	160330
22	455	455	0	0	0	22	25	0	0	0	455	455	0	130	0	22	25	0	0	0	133633
23	455	393	0	0	0	0	0	0	0	0	455	393	0	0	0	0	0	0	0	0	104464
24	455	323	0	0	0	0	0	0	0	0	455	323	0	0	0	0	0	0	0	0	90283
																Overall Cost of Generation = **3309829.4010 ($)**					

The simulation results for CSMA method for 60 unit system illustrates that total cost of generation with thermal, wind and thermal and wind & EV are **$ 3375159.0917,** $ **3303824.3855** and **$ 3309829.4010** respectively. The results shows that there is cost saving of **$ 65329.6907** with coordinated charging/discharging of EV for V2G operation. Thus, the proposed method is cost effective in dealing unit commitment problem under uncertain sustainable environment.

6.8 COMPARISON OF RESULTS

Table-6.26 illustrates comparison of Results for 10, 20, 40 and 60 unit for UC, UC+W and UC+W+EV using hHHO-IGWO method. The results of total cost of generation are presented in terms of best, average and worst values along with best execution time for each system. Cost comparison statistics for 10, 20, 40 and 60-units using hHHO-IGWO method are shown in Fig.6.27, Fig.6.28, Fig.6.29 and Fig.6.30. It is observed that cost of generation has been reduced to an appreciable level in almost all systems with wind and EV penetration.

Table-6.26: Comparison of Results for 10, 20, 40 and 60 unit using hHHO-IGWO method

Unit	Test System	Best	Mean	Worst	Time
10	UC	563435.9964	564452.7594	565425.30224	0.03628
	UC+Wind	492400.2699	494231.2616	495978.9707	0.05204
	UC+Wind+EV	489514.5979	491394.7670	492893.0072	0.05625
20	UC	1124860.6904	112615.1648	1128872.8693	0.054688
	UC+Wind	1052906.5262	1055303.1323	1058600.3826	0.062083
	UC+Wind+EV	1057895.7527	1057895.10060	1062786.4854	0.066875
40	UC	2249657.3623	2252698.0896	2256317.4070	0.078125
	UC+Wind	2172364.1608	2178985.5088	2181325.2861	0.0725
	UC+Wind+EV	2179556.0791	2185560.2438	2189993.7649	0.09375
60	UC	3374668.8771	3378103.0758	3381703.9070	0.096875
	UC+Wind	3299960.8457	3303839.6671	3306076.762979	0.098126
	UC+Wind+EV	3309624.5229	3314324.769	331985.2642	0.098257

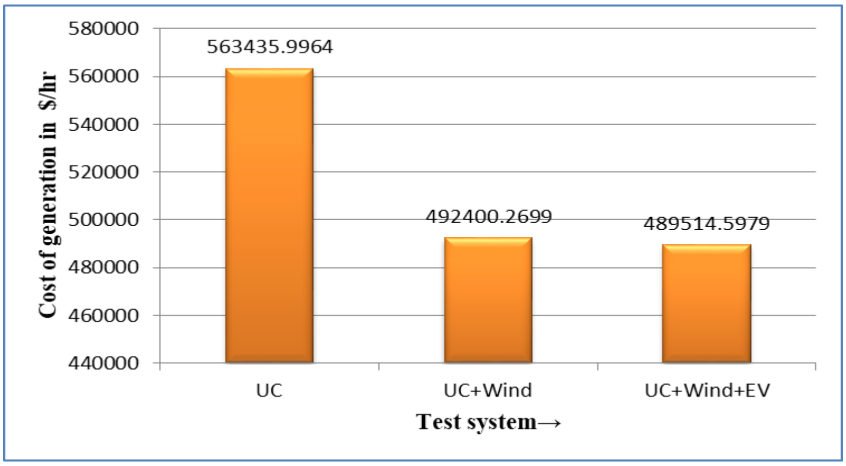


Fig.6.27: Cost comparison for 10-units system using hHHO-IGWO

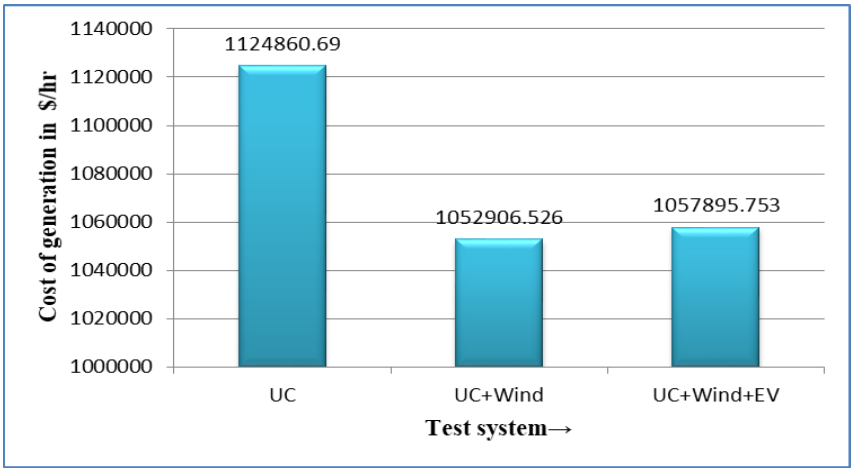


Fig.6.28: Cost comparison for 20-units system using hHHO-IGWO

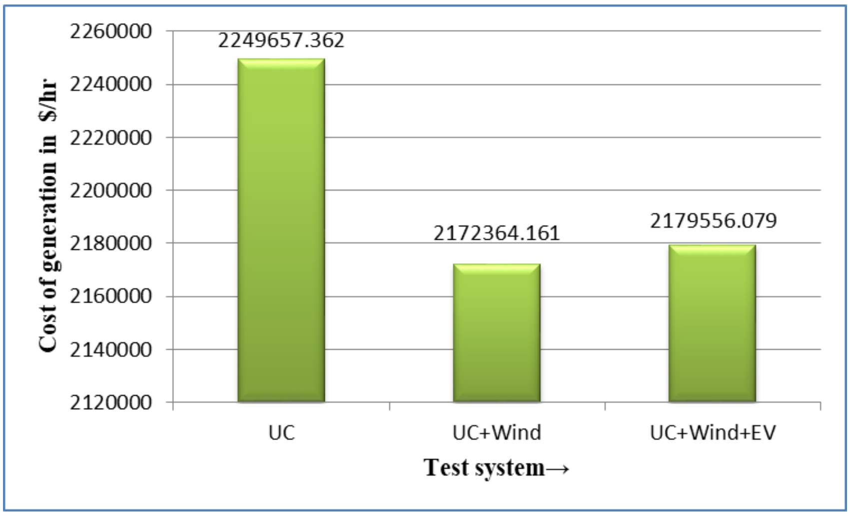


Fig.6.29: Cost Comparison for 40-units system using hHHO-IGWO

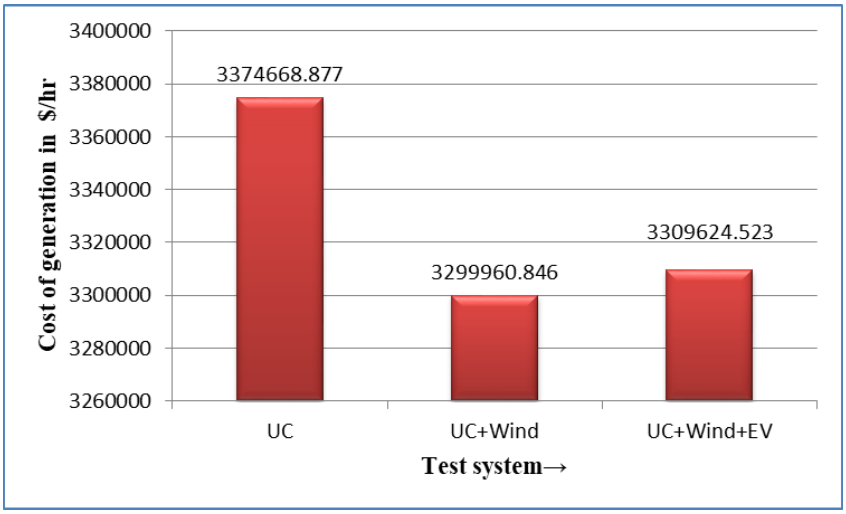


Fig.6.30: Cost Comparison for 60-units system using hHHO-IGWO

Table-6.27 illustrates Comparison of Results for 10, 20, 40 and 60 unit for Classical UC, UC+W and UC+W+EV for CHHO method. The results of total cost of generation are presented in terms of best, average and worst values along with best execution time for each system. Cost Comparison Curves for 10, 20, 40 and 60 -units using hHHO-IGWO method are shown in Fig.6.31, Fig.6.32, Fig.6.33 and Fig.6.34. It is observed that cost of generation has reduced to an appreciable level in almost all systems with wind and EV penetration.

Table-6.27: Comparison of Results for 10, 20, 40 and 60 unit using CHHO method

Unit		Best	Mean	Worst	Time
10	UC	563387.6874	564379.5791	565305.50224	0.015625
	UC+Wind	492466.6232	493656.7593	494816.90	0.03168
	UC+Wind+EV	490174.8291	491308.0262	492502.5759	0.039167
20	UC	1124685.2088	1126291.9476	1128859.9733	0.029688
	UC+Wind	1052294.5319	1056184.5351	1058983.5529	0.030208
	UC+Wind+EV	1056942.8444	1061277.7213	1066429.9377	0.03689
40	UC	2257230.0455	2260310.6018	2264045.7170	0.046875
	UC+Wind	2185306.3264	2188505.8828	2196914.7090	0.056865
	UC+Wind+EV	2185806.0424	2192999.6662	2194941.8292	0.070625
60	UC	3386078.2574	3392629.3063	3402247.3615	0.086834
	UC+Wind	3316505.9939	3326614.6644	3333139.78003	0.090625
	UC+Wind+EV	3328971.6499	3332280.3385	3334514.6621	0.09826

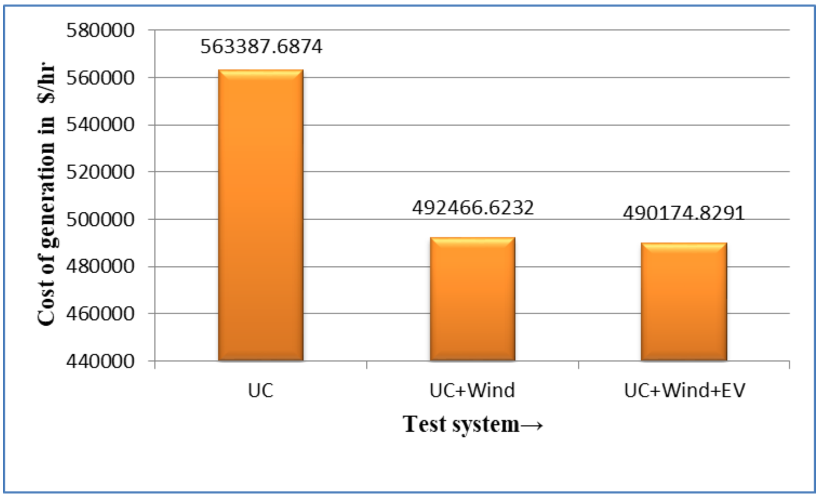


Fig.6.31: Cost Comparison for 10-units system using CHHO

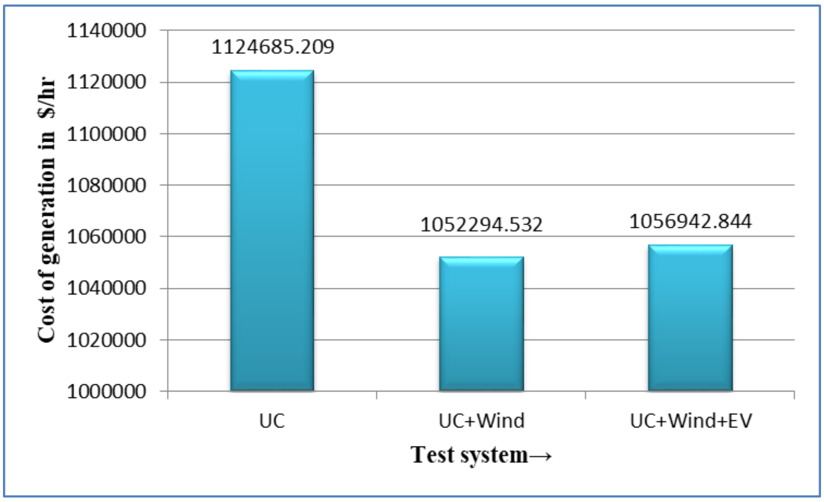


Fig.6.32: Cost Comparison for 20-units system using CHHO

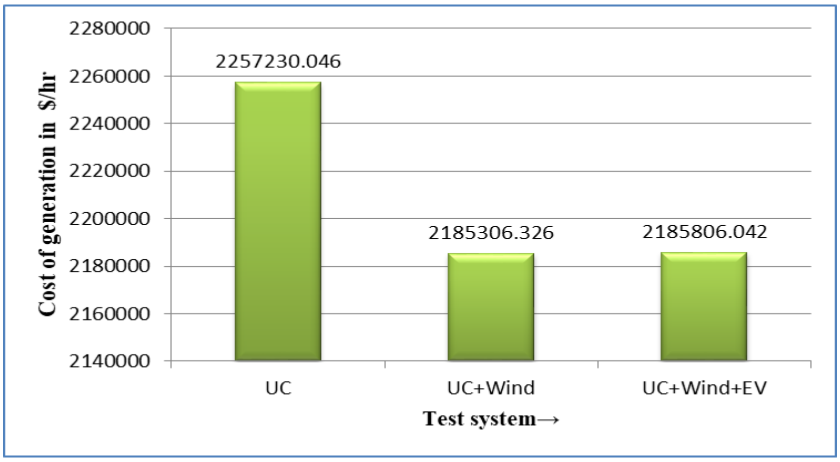


Fig.6.33: Cost comparison for 40-units system using CHHO

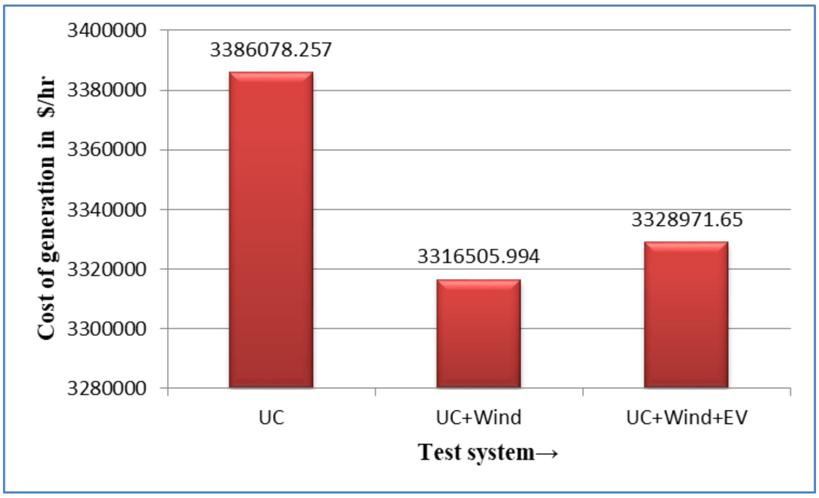


Fig.6.34: Cost Comparison for 60-units system using CHHO

Table-6.28 illustrates comparison of results for 10, 20, 40 and 60 unit for Classical UC, UC+W and UC+W+EV for CHHO method. The results of total cost of generation are presented in terms of best, average and worst values along with best execution time for each system. Cost Comparison Curves for 10, 20, 40 and 60 -units using hHHO-IGWO method are shown in Fig.6.35, Fig.6.36, Fig.6.37 and Fig.6.38. It is observed that cost of generation has reduced to an appreciable level in almost all systems with wind and EV penetration.

Table-6.28: Comparison of Results for 10, 20, 40 and 60 unit using CSMA Method

Unit	Test System	Best	Mean Cost	Worst Cost	Time
10	UC	563698.1582	564310.5195	565398.9054	0.030729
	UC+Wind	492522.21780	493701.8040	494987.2356	0.035625
	UC+Wind+EV	490013.6840	491389.1473	492676.0864	0.045625
20	UC	1124242.1047	1125317.9113	112622.1086	0.046875
	UC+Wind	1052668.6335	1053792.1979	104989.191	0.0754389
	UC+Wind+EV	1057617.1687	106050.3888	10605924.4393	0.076876
40	UC	2246297.75978	2249497.06888	2252324.6943	0.06657
	UC+Wind	2175383.9024	2176205.2983	2177753.5051	0.06783
	UC+Wind+EV	2181710.3802	225070.6386	227366.6806	0.06832
60	UC	3375159.0917	3377469.9456	3378854.9012	0.076875
	UC+Wind	3303824.3855	3304168.7654	3304510.1825	0.086838
	UC+Wind+EV	3309829.4010	3332280.3385	3334514.6621	0.08964

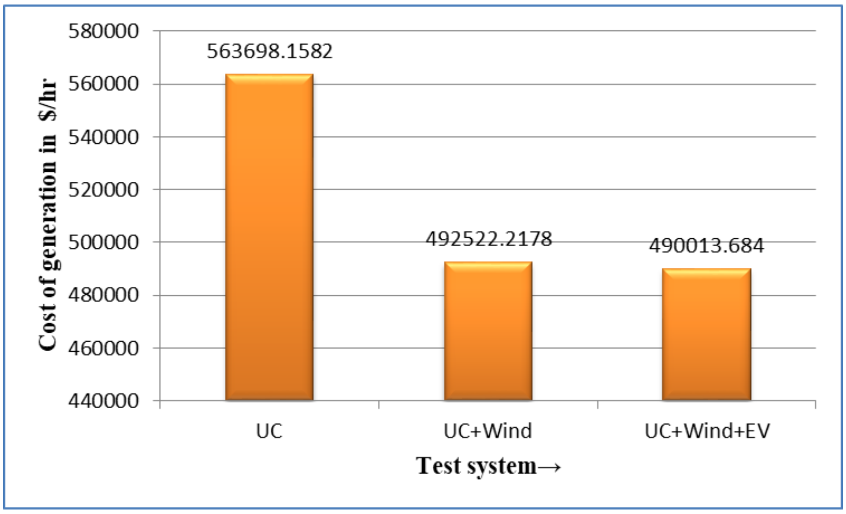


Fig.6.35: Cost comparison for 10-units system using CSMA

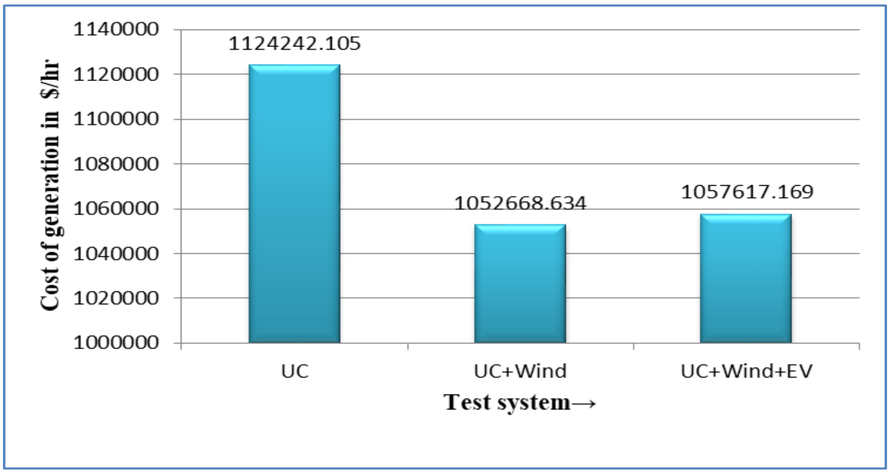


Fig.6.36: Cost comparison for 20-units system using CSMA

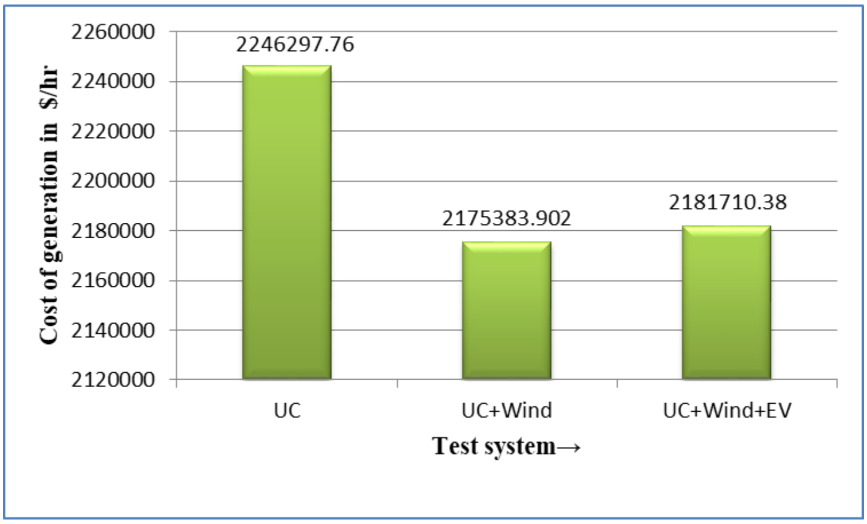


Fig.6.37: Cost comparison for 40-units system using CSMA

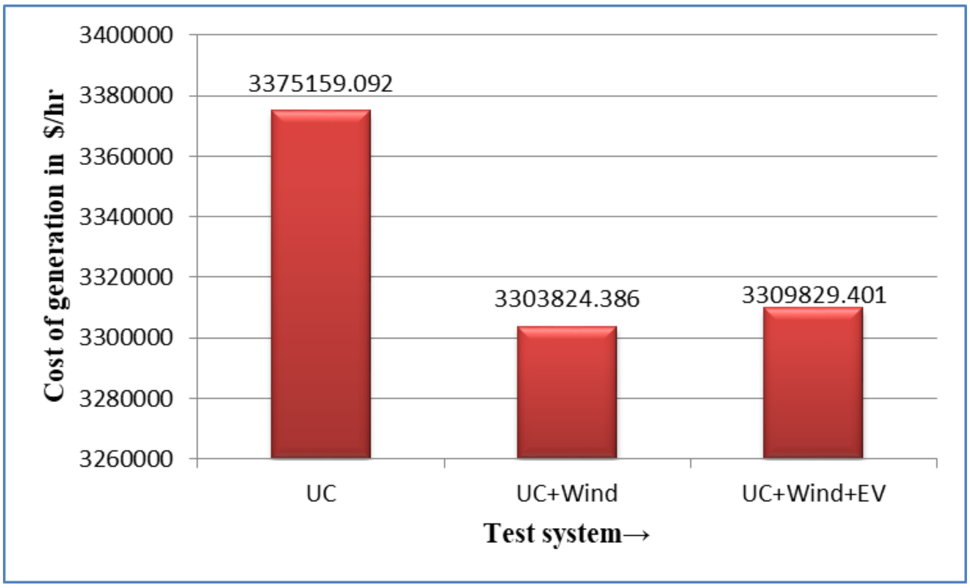


Fig.6.38: Cost comparison for 60-units system using CSMA

Fig.6.39, Fig.6.40, Fig.6.41 and Fig.6.42 illustrates the comparative analysis for 10, 20, 40 and 60 units using hHHO-IGWO, CHHO and CSMA method with UC, UC-Wind and UC with wind and EV

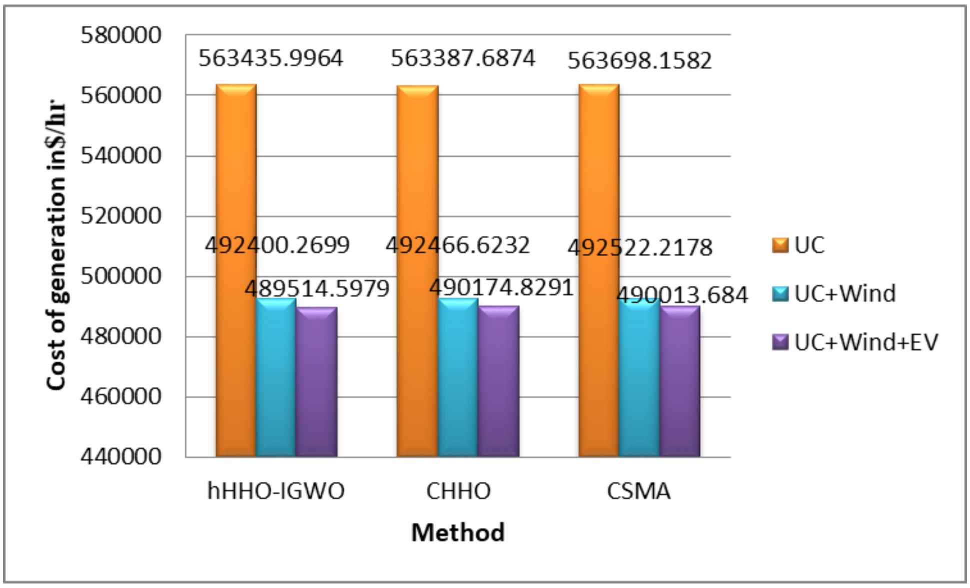


Fig.6.39: Cost comparison UC with wind, and UC with wind & EV using proposed methods for 10-units system

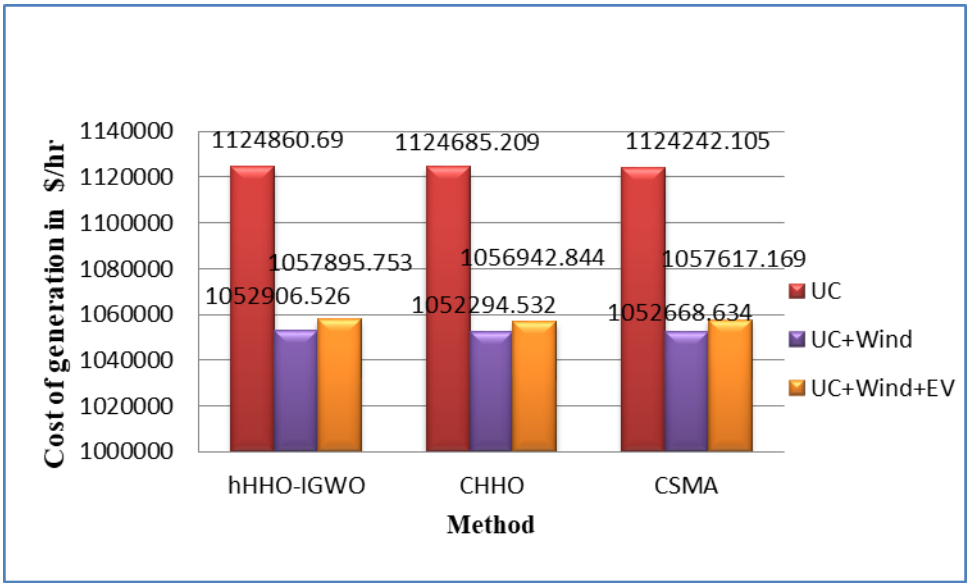


Fig.6.40: Cost comparison with UC, UC with Wind and EV using proposed methods for 20-units system

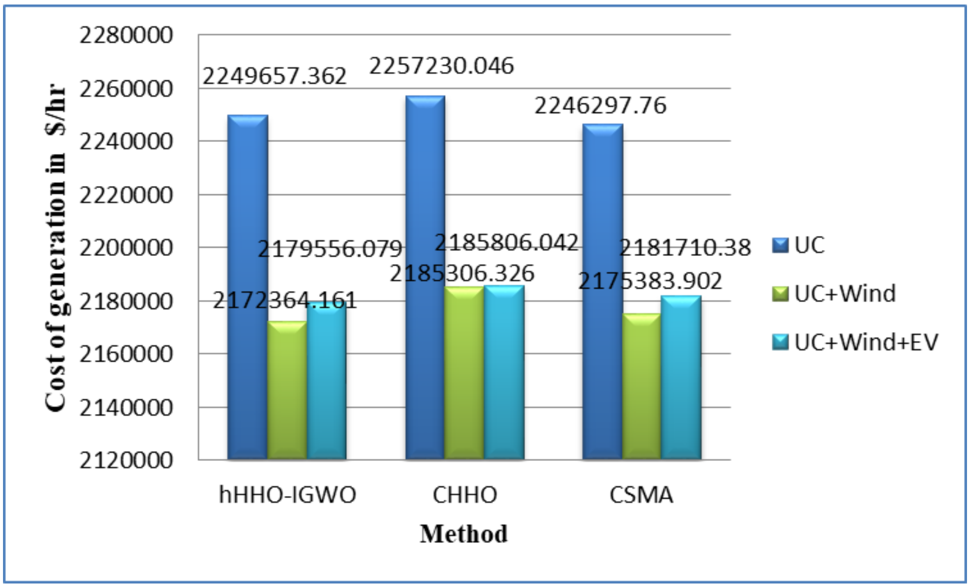


Fig.6.41: Cost comparison with UC, UC with Wind and EV using proposed methods for 40-units system

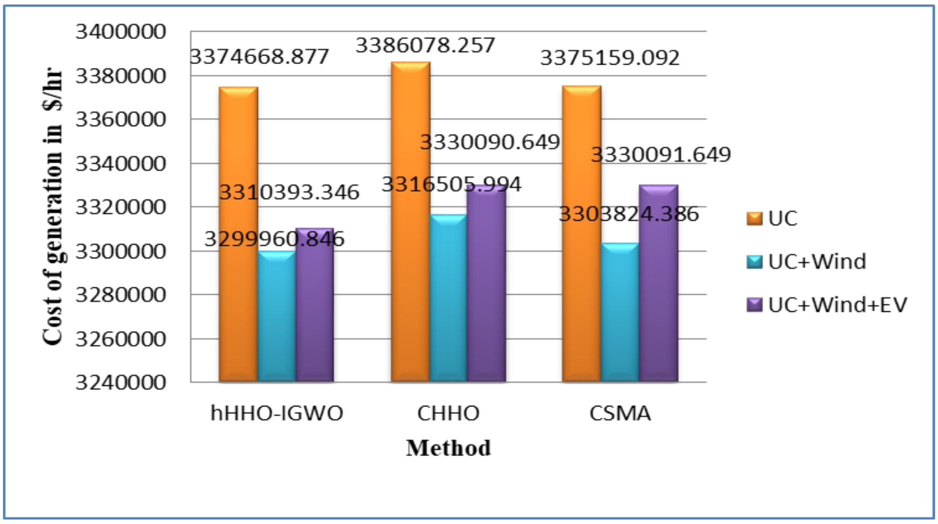


Fig.6.42: Cost comparison for UC, UC with Wind and EV using proposed methods for 60-units system

Percentage Cost saving for 10, 20, 40 and 60 units for hHHO-IGWO, CHHO and CSMA are illustrated in shown in Table-6.29, 6.30 and 6.31 given below

Table- 6.29: Percentage Cost saving for hHHO-IGWO method

Unit	UC	UC with Wind and EV	Cost of generation	% Cost Saving
10	563435.7594	UC+W	492400.2699	12.60%
		UC+W+EV	489514.5979	13.75%
20	1124860.6904	UC+W	1052906.5262	6.39%
		UC+W+EV	1057895.7527	5.95%
40	2249657.3623	UC+W	2172364.1608	3.16%
		UC+W+EV	2179556.0791	2.27%
60	3374668.8771	UC+W	3209960.8457	0.49%
		UC+W+EV	3309624.5229	1.34%

Table- 6.30: Percentage Cost saving for CHHO method

Unit	UC	UC with Wind and EV	Cost of generation	% Cost Saving
10	563387.6874	UC+W	492466.6232	12.58%
		UC+W+EV	490174.8291	12.85%
20	1124685.2088	UC+W	1052294.5319	6.43%
		UC+W+EV	1056942.8444	6.02%
40	2257230.8455	UC+W	2172364.1608	3.75%
		UC+W+EV	2185806.0424	3.16%
60	3386078.2574	UC+W	3316505.9939	2.05%
		UC+W+EV	3328971.6499	1.71%

Table- 6.31: Percentage Cost saving for CSMA method

Unit	UC	UC with Wind and EV	Cost of generation	% Cost Saving
10	564310.5195	UC+W	492522.21780	12.72%
		UC+W+EV	490013.6840	13.16%
20	1124242.1047	UC+W	1052668.6335	6.36%
		UC+W+EV	1057617.1687	5.92%
40	2246297.7597	UC+W	2162363.1908	3.29%
		UC+W+EV	2181710.3802	2.87%
60	3375159.092	UC+W	3303824.386	2.11%
		UC+W+EV	3309829.401	1.97%

Table-6.32 illustrates comparison of 10-unit system (10% SR) for thermal-wind using hHHO-IGWO, CHHO and CSMA with other algorithms. In Table-6.33 cost comparison of 10-unit system (10% SR) for thermal-V2G with other algorithms is illustrated. From the comparative Tables (6.32 and 6.33), it is observed that proposed methods gives better performance compared to other methods.

Table-6.32: Cost comparison of 10-unit system (10% SR) for thermal-wind system with other algorithms

Method	Best cost	Mean	Worst cost	CPU time (in seconds)
Operational cycle based algorithm [272]	563,937.70	564,227	–	19.4
GA [137]	563,977	564,275	565,606	221
EACO [272]	563,938	564,831	565,869	–
DBDE [336]	563,977	564,028	564,241	3.6
PSO [137]	564,212	565,103	565,783	120
Clustering method [272]	563,938	563,945	563,976	39.6
QBGSA [272]	515,339.6	516,425.4	517,156.8	49
BPSO [272]	516,778.5	518,304.5	519,963.0	61
BGSA [272]	517,736.6	519,254.8	520,577.2	61
EP [310]	564,551	565,352	566,231	100
HPSO [272]	563,942	564,772	565,785	–
BF [337]	564,842	NA	565,872	110
SGA [137]	565,943	569,042	570,121	–
hGWO-RES [272]	511,680	511,683	511,687	80.3
hHHO-IGWO[Proposed Method]	**492400.2699**	494231.2616	495978.9707	0.05204
CHHO[Proposed Method]	**492466.6232**	493656.7593	494816.90	0.03168
CSMA[Proposed Method]	**492522.2178**	493701.8040	494987.2356	0.035625

Table-6.33: Comparison of 10-unit system (10% SR) for thermal-V2G with other algorithms

Method	Cost Without V2G in $	Cost With V2G in $
HSA[331]	573,879.34	554,134.59
CRO[172]	-	564,727.87
PM[338]	564,714	557,554.9
PSO[339]	563,741.83	559,0813.6
CS[340]	561,284.56	554,016.60
hHHO-IGWO[Proposed Method]	**563435.9964**	**489514.5979**
CHHO[Proposed Method]	**563387.6874**	**490174.8291**
CSMA[Proposed Method]	**563698.1582**	**490013.6840**

6.9 CONCLUSION

This chapter deals with solution to unit commitment Problem for 10, 20, 40 and 60 unit using three distinct methodologies. Three different scenarios have been considered for solving unit commitment problem. Firstly, the unit commitment problem has been resolved by hybrid Harris Hawk's optimizer for conventional UC, UC+W and UC+ W+ EV. Secondly, the unit commitment problem has been solved by Chaotic HHO method on similar platform. Finally, the problem by solved by using Chaotic SMA method. Comparative analysis has been performed for all three methods and it is observed that proposed methods gives better results as compared to other heuristic and meta-heuristic algorithms.

CHAPTER-7
CONCLUSION AND FUTURE SCOPE

7.1 INTRODUCTION

In this research work, an attempt has been made to develop a cost-effective solution strategy for solving the unit commitment problem incorporating V2G/G2V operation under uncertain renewable energy sources. Three different optimization strategies have been developed to examine the optimum solution strategy for the economic operation of a power system.

7.2 SIGNIFICANCE AND CONTRIBUTION

In this research, the details of various recent methodologies to solve complex design problems have been discussed. Unit commitment problems are one of the critical tasks of selecting an appropriate number of generating units to meet the required load demand. However, due to the possibility of the early existence of non-replaceable energy sources, tremendous efforts have been initiated to find new energy alternatives. Many small and medium microgrids are focusing on using renewable, sustainable energy sources. Solar and wind-based stations are evolving rapidly to cope with this crucial problem of increased power demand. But, as these energy sources cannot produce constant output power and depend totally on environmental conditions, it creates difficulties in supplying power with reliability. Moreover, due to advancements in power electronics and control engineering, renewable energy could be store in storage systems. These days, a new technology known as V2G is emerging rapidly to anticipate uncertainties associated with these intermittent energy sources, wherein the stored energy in electric vehicles is fed back to the grid. It seems that with sufficient charging/discharging facilities, an appreciable amount of power could be fed back to the grid during peak load and save a large quantity of energy. After acknowledging the efficiency of the proposed methods, a solution to the unit commitment problem has been determined for different IEEE systems consisting of 10, 20, 40, and 60 units.

In almost all the research work, conventional UC problems have been resolved, but research involving renewables and electric vehicles is still in an advanced stage. In the proposed research work, solutions to different unit commitment problems have been solved to develop a cost-effective solution strategy with substantial wind and EV penetration. In the proposed work, one hybrid algorithm and two chaotic algorithms are developed. The significant contributions from this research study are elaborated in the following section.

1. Initially, to check the effectiveness of the proposed methods, 23 standard test functions has been tested. The proposed algorithms are applied to seven unimodal benchmark functions from F1 to F7, six multi-modal benchmark functions from F8 to F13, and ten fixed-dimension benchmark functions from F14 to F23. The comparative analysis reveals that CHHO and CSMA yield improved feasible solutions compared to the hHHO-IGWO method. Further, it is inspected that CHHO gives better convergent results compared to hHHO-IGWO and CSMA due to better exploitation capability in the initial phase. This suggests that CHHO has better computational efficiency compared to other methods.
2. Furthermore, to validate the feasibility of the proposed research work, 10 real-world engineering design problems such as truss design problems, rolling element problems, welded beam designs, pressure vessel designs, etc. has been tested successfully, and validated by comparing with competitive algorithms.
3. Unit commitment is a non-convex, non-linear, mixed-integer optimization problem. A single-area, single-objective unit commitment problem has been analyzed to optimize the overall cost of generation while satisfying physical and technological constraints. To tackle the UC problem, two recently developed algorithms, Harris Hawk's optimizer (HHO) and Slime Mold Algorithm (SMA), are used. One hybrid algorithm has been developed by combing basic HHO with an improved grey wolf optimizer (IGWO). This new hybrid algorithm is abbreviated as hHHO-IGWO. Two chaotic variants of HHO and SMA have been developed. The Chaotic HHO method is developed by integrating the Tent Chaotic Map with the basic HHO method, while the Chaotic SMA method is developed by incorporating sinusoidal function with the basis SMA. These developed algorithms have been implemented to solve the UC problem to obtain the most cost-effective schedule for operating the generating units to meet the load demand. These methods are successfully implemented on standard test systems comprising 10, 20, 40, and 60 generating units.

4. Experimentally, it has been found that, for 10 unit generating system with wind penetration, hHHO-IGWO method gives 12.60 % cost saving, CHHO gives 12.58 % cost saving and CSMA gives 12.72% cost saving. Results revealed that CHHO is found to be more appropriate method to solve UC problem with thermal generating units.
5. On similar grounds for 10 unit generating system with wind and EV penetration, hHHO-IGWO method gives a 13.07 % cost saving, CHHO gives 12.85 % cost saving, while CSMA gives 13.16% cost saving. This suggests that CHHO is more efficient method compared to hHHO-IGWO and CSMA to tackle unit commitment problem for system with wind and EV.
6. The experimental results for 20 thermal units with wind penetration, hHHO-IGWO method demonstrate a cost saving of 6.39% while in case of CHHO and CSMA, 6.43% and 6.39% has been recorded.
7. Simulation results for 20 thermal units with wind and EV penetration, hHHO-IGWO method gives a 5.95% cost saving, CHHO gives 6.02% cost saving and CSMA gives 5.92% cost saving.
8. In case of 40 unit generating with wind penetration, hHHO-IGWO method gives a 3.16% cost saving, CHHO gives 3.75% cost saving and CSMA gives 3.29% cost saving.
9. In case of 40 unit generating system with wind and EV penetration, hHHO-IGWO method gives a 2.27% cost saving, CHHO gives 3.16% cost saving and CSMA gives a 2.87% cost saving.
10. For 60 unit generating system with wind penetration, hHHO-IGWO method gives 0.49% cost saving, CHHO gives 2.05% cost saving and CSMA gives 2.11% cost saving.
11. For 60 units generating system with wind and EV penetration, hHHO-IGWO method gives 1.34% cost saving, CHHO gives 1.71% cost saving and CSMA gives 1.97% cost saving. From the above summarized percentage cost saving analysis, it is concluded that proposed methodologies are effective in solving unit commitment problem with RES and EV penetration.

FUTURE SCOPE OF PROPOSED RESEARCH WORK

The possible area of research includes the following as future research directions for young researchers:

- The proposed method can be applied to solve multi-objective unit commitment problem, where emission cost can be included along with generation cost.
- Profit based unit commitment problem can be solved using proposed methodologies where the objective function of the problem is to maximize the profit instead of minimizing the generation cost.
- The Multi-area unit commitment problem can be solved with the help of proposed methodologies, where more number of areas can be included along with tie-line constraints.
- Combined cycle heat and power plants may be taken into consideration for futuristic research where the entire objective is to fulfill the heat demand along with the power demand.

Appendix-A

(i) Pseudo-code of CHHO

Pseudo-code for CHHO

INPUTS-: The population range is taken as N and maximum iteration number is taken as itn
OUTPUTS- : The target position and fitness
Initialization of stochastic population $X_i (i = 1, 2, 3......., N)$
While (iteration itn_{max})
For calculating the optimum robustness of Harris birds
Setting the parameter $X_{(prey)}$
for (each Harris birds X_i)
Do Update energy at primary condition E_0
$r^{0,1}$ =rand;
if $r^{0,1} < 0.7$
$r^{0,1}$ (t+1)= $r^{0,1}$ / 0.7 ;
end
if $r^{0,1} \geq 0.7$
$r^{0,1}$ (t+1)=(10/3)*(1- $r^{0,1}$);
end
$Uptate\ q = r^{0,1}(t+1);$
$Uptate\ r = r^{0,1}(t+1);$
if $|E| \geq 1$ **then** $\rightarrow$ **Phase of Exploration**
else if $q \geq 0.5$ **then**
$X(itn+1) = \{X_{randm}(itn) - r_1 \times abs(X_{randm}(itn) - 2 \times r_2 \times X(itn))$
else if $q < 0.5$ **then**
$X(itn+1) = \{(X_{prey}(itn) - X_m(itn)) - r_3 \times (Lb + r_4 \times (Ub - Lb))$
Position vector updated using $E = 2 \times E_0 \times \left(1 - \frac{itn}{itn_{\max}}\right)$
if $|E| < 1$ **then** $\rightarrow$ **Phase of Exploitation**
$X(itn+1) = \Delta X(itn) - E \times abs(JX_{prey}(itn) - X(itn))$
if $(r \geq 0.5)$ and $|E| \geq 0.5$ **then** $\rightarrow$ **placid bound**
Position vector updated using $\Delta X(itn) = \left(X_{prey}(itn) - X(itn)\right)$
else if $(r \geq 0.5)$ and $|E| < 0.5$ **then** $\rightarrow$ **Hard bound**
Position vector updated using $X(itn+1) = X_{prey}(itn) - E \times abs(\Delta X(itn))$
else if $(r < 0.5)$ and $|E| \geq 0.5$ **then** $\rightarrow$ **placid bound with fast dives**
Position vector updated using $Y = X_{prey}(itn) - E \times abs(JX_{prey}(itn) - X(itn))$
else if $(r < 0.5)$ and $|E| < 0.5$ **then** $\rightarrow$ **Hard bound with fast dives**
Position vector updated using $X(itn+1) = \Delta X(itn) - E \times abs(JX_{prey}(itn) - X(itn))$
end
end
end
end
Return X_{prey}

(ii) Pseudo code of CSMA

Pseudo-code of Chaotic Slime mould algorithm
Initialize the parameters *pop size*, $itn_{\max}$;
Initialize the positions of slime mould $X_i (i = 1, 2, ..., n)$;
While $(itn \leq itn_{\max})$
Calculate the fitness of all slime mould;
Update best fitness, X_b
Calculate the W by Eqn. (3.35);
For *each search portion*
$r_o = rand$;
$r_o(t+1) = 2.3 \times r_0^2 \times Sin(Pi.r_0)$
$r_1 = r_0(t+1)$;
Update p, vb, vc;
Update positions by **Eq.** (3.37);
End For
$itn = itn + 1$;
End While
Return *bestFitness*, X_b;

(iii) Minimum up-down Constraint

for h=1 to H

if h==1

Compute $T_h^{ON} = T_{h_0}^{ON}\ U_{i,h} + U_{i,h}'$

Compute $T_h^{OFF} = (T_{h_0}^{OFF})'\ \bar{T}_h^{ON} + \bar{T}_h^{ON}$

else

Compute $T_h^{ON} = T_{h-1}^{ON}\ U_{i,h}' + U_{i,h}'$

Compute $T_h^{OFF} = T_{h-1}^{OFF}\ \bar{T}_h^{ON} + \bar{T}_h^{ON}$

end

end

where,

$U_{i,h} = U_{i,(h-1)} F + U_{i,h} \bar{F}$ and $F = [T_{h-1}^{OFF} == 0 \ \& T_{h-1}^{ON} < MUT') | (T_{h-1}^{ON} == 0 \ \& T_{h-1}^{OFF} < MDT']^T$

(iv) Pseudo code for de-commitment of excessive generative units

```
for h=1: H
for i=1: N
do i = h(N+1-i) and calculate generating power P1 = P_{i(max)} × (U_{i,h})'
if u_{i,h} = 1 then
if P1 - P_{max(i)} ≥ D_h + SR_h then

if (T^{ON}_{i,h} > MUT_i) | (T^{ON}_{i,h} = 1) then
do u_{hi} = 0 and T^{ON}_{i,h} = 0
if h==1 then
do T^{OFF}_{i,h} = T^{OFF}_{i,h_0} + 1
else
do T^{OFF}_{i,h} = T^{OFF}_{i,h-1} + 1
end
else
continue;
end
else
break;
end
end
```

REFERENCES

[1] M. S. Shahriar, M. J. Rana, M. A. Asif, M. M. Hasan, and M. M. Hawlader, "Optimization of Unit Commitment Problem for wind-thermal generation using Fuzzy optimization technique," *Proc. 2015 3rd Int. Conf. Adv. Electr. Eng. ICAEE 2015*, pp. 88–92, 2016, doi: 10.1109/ICAEE.2015.7506803.

[2] P. K. Roy, "Solution of unit commitment problem using gravitational search algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 53, no. 1, pp. 85–94, 2013, doi: 10.1016/j.ijepes.2013.04.001.

[3] A. Y. Saber and G. K. Venayagamoorthy, "Resource scheduling under uncertainty in a smart grid with renewables and plug-in vehicles," *IEEE Syst. J.*, vol. 6, no. 1, pp. 103–109, 2012, doi: 10.1109/JSYST.2011.2163012.

[4] K. Hosseini, S. Araghi, M. B. Ahmadian, and V. Asadian, "Multi-objective optimal scheduling of a micro-grid consisted of renewable energies using multi-objective Ant Lion Optimizer," *IEEE Proc. 2017 Smart Grid Conf. SGC 2017*, vol. 2018-Janua, pp. 1–8, 2018, doi: 10.1109/SGC.2017.8308867.

[5] X. Chen, M. B. Mcelroy, Q. Wu, Y. Shu, and Y. Xue, "Transition towards higher penetration of renewables: an overview of interlinked technical, environmental and socio-economic challenges," *J. Mod. Power Syst. Clean Energy*, vol. 7, no. 1, 2019, doi: 10.1007/s40565-018-0438-9.

[6] Z. Yang *et al.*, "A binary symmetric based hybrid meta-heuristic method for solving mixed integer unit commitment problem integrating with significant plug-in electric vehicles," *Energy*, vol. 170, pp. 889–905, 2019, doi: 10.1016/j.energy.2018.12.165.

[7] Z. Yang *et al.*, "A binary symmetric based hybrid meta-heuristic method for solving mixed integer unit commitment problem integrating with significant plug-in electric vehicles," *Energy*, vol. 170, pp. 889–905, 2019, doi: 10.1016/j.energy.2018.12.165.

[8] S. Marrouchi, M. Ben Hessine, and S. Chebbi, "Unit commitment scheduling using hybrid metaheuristic and deterministic methods: Theoretical investigation and comparative study," *Proc. Int. Conf. Adv. Syst. Electr. Technol. IC_ASET 2017*, pp. 250–255, 2017, doi: 10.1109/ASET.2017.7983700.

[9] H. Pandzic, Y. Dvorkin, T. Qiu, Y. Wang, and D. S. Kirschen, “Toward Cost-Efficient and Reliable Unit Commitment under Uncertainty,” *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 970–982, 2016, doi: 10.1109/TPWRS.2015.2434848.

[10] F. H. Aghdam and M. T. Hagh, “Security Constrained Unit Commitment (SCUC)formulation and its solving with Modified Imperialist Competitive Algorithm (MICA),” *J. King Saud Univ. - Eng. Sci.*, vol. 31, no. 3, pp. 253–261, 2019, doi: 10.1016/j.jksues.2017.08.003.

[11] P. Adraktas and A. Dagoumas, “Integration of electric vehicles in the unit commitment problem with uncertain renewable electricity generation,” *Int. J. Energy Econ. Policy*, vol. 9, no. 2, pp. 315–333, 2019, doi: 10.32479/ijeep.7125.

[12] D. N. Simopoulos, S. D. Kavatza, and C. D. Vournas, “Unit Commitment by an Enhanced Simulated Annealing Algorithm,” *IEEE Trans. Power Syst.*, vol. 21, no. 1, pp. 68–76, 2006, doi: 10.1109/TPWRS.2005.860922.

[13] Z. Gaing, “Particle Swarm Optimization to Solving the Economic Dispatch Considering the Generator Constraints,” vol. 18, no. 3, pp. 1187–1195, 2003.

[14] M. D. W. Dobson, “The Automotive Industry Development Process for Major Radically New Technologies, Inception to Production: A Study of Electric and Hybrid Electric Vehicles.,” 2000.

[15] R. Adhikari and S. Mondal, “Power Generating Low Cost Green Electric Vehicle,” *Innov. Energy Res.*, vol. 07, no. 03, 2018, doi: 10.4172/2576-1463.1000217.

[16] F. E. Ahangar, F. R. Freedman, and A. Venkatram, “Using low-cost air quality sensor networks to improve the spatial and temporal resolution of concentration maps,” *Int. J. Environ. Res. Public Health*, vol. 16, no. 7, 2019, doi: 10.3390/ijerph16071252.

[17] C. Iclodean, B. Varga, N. Burnete, D. Cimerdean, and B. Jurchiş, “Comparison of Different Battery Types for Electric Vehicles,” *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 252, no. 1, 2017, doi: 10.1088/1757-899X/252/1/012058.

[18] D. G. Baur and N. Todorova, “Automobile manufacturers, electric vehicles and the price of oil,” *Energy Econ.*, vol. 74, pp. 252–262, 2018, doi: 10.1016/j.eneco.2018.05.034.

[19] K. S. Reddy, L. K. Panwar, R. Kumar, and B. K. Panigrahi, “Distributed resource scheduling in smart grid with electric vehicle deployment using fireworks

algorithm," *J. Mod. Power Syst. Clean Energy*, vol. 4, no. 2, pp. 188–199, 2016, doi: 10.1007/s40565-016-0195-6.

[20] L. Shi, T. Lv, and Y. Wang, "Vehicle-to-grid service development logic and management formulation," *J. Mod. Power Syst. Clean Energy*, vol. 7, no. 4, pp. 935–947, 2019, doi: 10.1007/s40565-018-0464-7.

[21] K. M. Tan, V. K. Ramachandaramurthy, and J. Y. Yong, "Integration of electric vehicles in smart grid: A review on vehicle to grid technologies and optimization techniques," *Renew. Sustain. Energy Rev.*, vol. 53, pp. 720–732, 2016, doi: 10.1016/j.rser.2015.09.012.

[22] C. Peng, J. Zou, L. Lian, and L. Li, "An optimal dispatching strategy for V2G aggregator participating in supplementary frequency regulation considering EV driving demand and aggregator's benefits," *Appl. Energy*, vol. 190, pp. 591–599, 2017, doi: 10.1016/j.apenergy.2016.12.065.

[23] L. Pieltain Fernández, T. Gómez San Román, R. Cossent, C. Mateo Domingo, and P. Frías, "Assessment of the impact of plug-in electric vehicles on distribution networks," *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 206–213, 2011, doi: 10.1109/TPWRS.2010.2049133.

[24] H. Min, F. Zhou, S. Jui, T. Wang, and X. Chen, "Vehicle-to-Grid(V2G) in India," *Distribution*, no. January, pp. 1–23, 2021, [Online]. Available: http://classtap.pbworks.com/f/SkillSoft+-+Blended+Elearning.pdf.

[25] S. Khan, A. Ahmad, F. Ahmad, M. Shafaati Shemami, M. Saad Alam, and S. Khateeb, "A Comprehensive Review on Solar Powered Electric Vehicle Charging System," *Smart Sci.*, vol. 6, no. 1, pp. 54–79, 2018, doi: 10.1080/23080477.2017.1419054.

[26] S. Pal and R. Kumar, "Electric Vehicle Scheduling Strategy in Residential Demand Response Programs with Neighbor Connection," *IEEE Trans. Ind. Informatics*, vol. 14, no. 3, pp. 980–988, 2018, doi: 10.1109/TII.2017.2787121.

[27] I. Pavić, T. Capuder, N. Holjevac, and I. Kuzle, "Role and impact of coordinated EV charging on flexibility in low carbon power systems," *2014 IEEE Int. Electr. Veh. Conf. IEVC 2014*, no. November 2015, 2015, doi: 10.1109/IEVC.2014.7056172.

[28] P. Sakthivel, K. A. Subramanian, and R. Mathai, "Indian scenario of ethanol fuel

and its utilization in automotive transportation sector," *Resour. Conserv. Recycl.*, vol. 132, no. December 2017, pp. 102–120, 2018, doi: 10.1016/j.resconrec.2018.01.012.

[29] J. Lee and F. Zhao, "Global Wind Report 2021," *Glob. Wind Energy Counc.*, p. 75, 2021, [Online]. Available: http://www.gwec.net/global-figures/wind-energy-global-status/.

[30] T. Senjyu, K. Shimabukuro, K. Uezato, and T. Funabashi, "A fast technique for unit commitment problem by extended priority list," *IEEE Trans. Power Syst.*, vol. 18, no. 2, pp. 882–888, 2003, doi: 10.1109/TPWRS.2003.811000.

[31] S. Chakraborty, T. Ito, T. Senjyu, and A. Yousuf, "Electrical Power and Energy Systems Unit commitment strategy of thermal generators by using advanced fuzzy controlled binary particle swarm optimization algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 43, no. 1, pp. 1072–1080, 2012, doi: 10.1016/j.ijepes.2012.06.014.

[32] S. Y. I. Abujarad, M. W. Mustafa, and J. J. Jamian, "Unit commitment problem solution in the presence of solar and wind power integration by an improved priority list method," *Int. Conf. Intell. Adv. Syst. ICIAS 2016*, 2017, doi: 10.1109/ICIAS.2016.7824076.

[33] C. L. TSENG, C. A. LI, "Solving the Unit Commitment Problem by a Unit Decommitment Method," vol. 105, no. 3, pp. 707–730, 2000.

[34] N. P. Padhy, "Unit commitment using hybrid models: a comparative study for dynamic programming, expert system, fuzzy system and genetic algorithms," *Int. J. Electr. Power Energy Syst.*, vol. 23, no. 8, pp. 827–836, 2001, doi: 10.1016/S0142-0615(00)00090-9.

[35] H. Daneshi, M. Shahidehpour, F. Member, S. Afshamia, A. Naderiam, and A. Rezaei, "Application Of Fuzzy Dynamic Programming And Neural Network In Generation Sc'heduling," 2003.

[36] S. Y. Chen and G. T. Fu, "Combining fuzzy iteration model with dynamic programming to solve multiobjective multistage decision making problems," *Fuzzy Sets Syst.*, vol. 152, no. 3, pp. 499–512, 2005, doi: 10.1016/j.fss.2004.10.006.

[37] S. S. Kumar and V. Palanisamy, "A dynamic programming based fast computation

Hopfield neural network for unit commitment and economic dispatch," *Electr. Power Syst. Res.*, vol. 77, no. 8, pp. 917–925, 2007, doi: 10.1016/j.epsr.2006.08.005.

[38] A. I. Cohen and M. Yoshimura, "A Branch-and-Bound Algorithm for Unit Commitment," *IEEE Trans. Power Appar. Syst.*, vol. 102, no. 2, pp. 444–451, 1983.

[39] X. Guan, Q. Zhai, and A. Papalexopoulos, "Optimization Based Methods for Unit Commitment: Lagrangian Relaxation versus General Mixed Integer Programming," *2003 IEEE Power Eng. Soc. Gen. Meet. Conf. Proc.*, vol. 2, pp. 1095–1100, 2003, doi: 10.1109/pes.2003.1270468.

[40] I. G. Damousis, A. G. Bakirtzis, and P. S. Dokopoulos, "A solution to the unit-commitment problem using integer-coded genetic algorithm," *IEEE Trans. Power Syst.*, vol. 19, no. 2, pp. 1165–1172, 2004, doi: 10.1109/TPWRS.2003.821625.

[41] S. Takriti and J. R. Birge, "Using integer programming to refine Lagrangian-based unit commitment solutions," *IEEE Trans. Power Syst.*, vol. 15, no. 1, pp. 151–156, 2000, doi: 10.1109/59.852114.

[42] R. Nieva, A. Inda, and I. Guillén, "Lagrangian Reduction of Search-Range for Large-Scale Unit Commitment," *IEEE Power Eng. Rev.*, vol. PER-7, no. 5, p. 52, 1987, doi: 10.1109/MPER.1987.5527261.

[43] F. Zhuang and F. D. Galiana, "Towards a more rigorous and practical unit commitment by lagrangian relaxation," *IEEE Trans. Power Syst.*, vol. 3, no. 2, pp. 763–773, 1988, doi: 10.1109/59.192933.

[44] S. Chusanapiputt, D. Nualhong, S. Jantarang, and S. Phoomvuthisarn, "A solution to unit commitment problem using hybrid ant system/priority list method," *PECon 2008 - 2008 IEEE 2nd Int. Power Energy Conf.*, no. PECon 08, pp. 1183–1188, 2008, doi: 10.1109/PECON.2008.4762655.

[45] W. Ongsakul and N. Petcharaks, "Unit Commitment by Enhanced Adaptive Lagrangian Relaxation," *IEEE Trans. Power Syst.*, vol. 19, no. 1, pp. 620–628, 2004, doi: 10.1109/TPWRS.2003.820707.

[46] F. Zhuang and F. D. Galiana, "Unit commitment by simulated annealing," *IEEE Trans. Power Syst.*, vol. 5, no. 1, pp. 311–318, 1990, doi: 10.1109/59.49122.

[47] S. Y. W. Wong, "An enhanced simulated annealing approach to unit

commitment," *Int. J. Electr. Power Energy Syst.*, vol. 20, no. 5, pp. 359–368, 1998, doi: 10.1016/s0142-0615(97)00062-8.

[48] K. Venkatesan and C. Christober Asir Rajan, "A simulated annealing method for solving multi-area unit commitment problem in deregulated environment," *2011 IEEE PES Int. Conf. Innov. Smart Grid Technol. ISGT India 2011*, no. 4, pp. 305–310, 2011, doi: 10.1109/ISET-India.2011.6145407.

[49] A. H. Mantawy, "A simulated annealing algorithm for unit commitment," *IEEE Trans. Power Syst.*, vol. 13, no. 1, pp. 197–204, 1998, doi: 10.1109/59.651636.

[50] A. H. Mantawy, "Integrating genetic algorithms, tabu search, and simulated annealing for the unit commitment problem," *IEEE Trans. Power Syst.*, vol. 14, no. 3, pp. 829–836, 1999, doi: 10.1109/59.780892.

[51] S. Mokhtari, B. Wollenberg, and J. Singh, "A unit commitment expert system," *IEEE Trans. Power Syst.*, vol. 3, no. 1, pp. 272–277, 1988, doi: 10.1109/59.43211.

[52] M. S. Salam, A. R. Hamdan, and K. M. Nor, "Integrating an expert system into a thermal unit-commitment algorithm," *IEE Proc. C Gener. Transm. Distrib.*, vol. 138, no. 6, pp. 553–559, 1991, doi: 10.1049/ip-c.1991.0069.

[53] S. Li, S. M. Shahidehpour, and C. Wang, "Promoting The Application of Expert Systems in Short-Term Unit Commitment," *IEEE Trans. Power Syst.*, vol. 8, no. 1, pp. 286–292, 1993, doi: 10.1109/59.221229.

[54] X. Ma, A. A. El-Keib, R. E. Smith, and H. Ma, "A genetic algorithm based approach to thermal unit commitment of electric power systems," *Electr. Power Syst. Res.*, vol. 34, no. 1, pp. 29–36, 1995, doi: 10.1016/0378-7796(95)00954-G.

[55] S. A. Kazarlis, "A genetic algorithm solution to the unit commitment problem, IEEE Transactions on Power Systems, pp. 83 -92," 1996.

[56] S. O. Orero and M. R. Irving, "A genetic algorithm for generator scheduling in power systems," *Int. J. Electr. Power Energy Syst.*, vol. 18, no. 1, pp. 19–26, 1996, doi: 10.1016/0142-0615(94)00017-4.

[57] A. H. Mantawy, Y. L. Abdel-Magid, and S. Z. Selim, "Unit commitment by tabu search," *IEE Proc. Gener. Transm. Distrib.*, vol. 145, no. 1, pp. 56–64, 1998, doi: 10.1049/ip-gtd:19981681.

[58] A. Borghetti, A. Frangioni, F. Lacalandra, A. Lodi, C. A. Nucci, and A. Trebbi, "Lagrangian Relaxation and Tabu Search Approaches for the Unit Commitment

Problem," 2001.

[59] H. Sasaki, M. Watanabe, J. Kubokawa, N. Yorino, and R. Yokoyama, "A Solution Method of Unit Commitment by Artificial Neural Networks," *IEEE Trans. Power Syst.*, vol. 7, no. 3, pp. 974–981, 1992, doi: 10.1109/59.207310.

[60] H. Sasaki, Y. Fujii, M. Watanabe, J. Kubokawa, and N. Yorino, "A solution method using neural networks for the generator commitment problem," *Electr. Eng. Japan*, vol. 112, no. 7, pp. 55–62, 1992, doi: 10.1002/eej.4391120706.

[61] N. P. Padhy, S. R. Paranjothi, and V. Ramachandran, "A hybrid fuzzy neural network-expert system for a short term unit commitment problem," *Microelectron. Reliab.*, vol. 37, no. 5, pp. 733–737, 1997, doi: 10.1016/S0026-2714(96)00095-9.

[62] K. Shanti Swarup and P. V. Simi, "Neural computation using discrete and continuous Hopfield networks for power system economic dispatch and unit commitment," *Neurocomputing*, vol. 70, no. 1–3, pp. 119–129, 2006, doi: 10.1016/j.neucom.2006.05.002.

[63] J. Valenzuela and A. E. Smith, "A seeded memetic algorithm for large unit commitment problems," *J. Heuristics*, vol. 8, no. 2, pp. 173–195, 2002, doi: 10.1023/A:1017960507177.

[64] H. A. Sanusi, A. Zubair, and R. Oladele, "Comparative Assessment of Genetic and Memetic Algorithms," *J. Emerg. Trends Comput. Inf. Sci.*, vol. 2, no. 10, pp. 498–508, 2011.

[65] L. OctavianMafteiu-Scai and E. Jana Mafteiu-Scai, "Solving Linear Systems of Equations using a Memetic Algorithm," *Int. J. Comput. Appl.*, vol. 58, no. 13, pp. 16–21, 2012, doi: 10.5120/9341-3658.

[66] L. OctavianMafteiu-Scai, "Improved the Convergence of Iterative Methods for Solving Systems of Equations by Memetics Techniques," *Int. J. Comput. Appl.*, vol. 64, no. 17, pp. 33–38, 2013, doi: 10.5120/10729-5733.

[67] Z. Guo, G. Liu, D. Li, and S. Wang, "Self-adaptive differential evolution with global neighborhood search," *Soft Comput.*, vol. 21, no. 13, pp. 3759–3768, 2017, doi: 10.1007/s00500-016-2029-x.

[68] S. Muelas, A. LaTorre, and J. M. Peña, "A memetic differential evolution algorithm for continuous optimization," *ISDA 2009 - 9th Int. Conf. Intell. Syst. Des. Appl.*, pp. 1080–1084, 2009, doi: 10.1109/ISDA.2009.47.

[69] R. Thomsen, “Multimodal optimization using crowding-based differential evolution,” *Proc. 2004 Congr. Evol. Comput. CEC2004*, vol. 2, pp. 1382–1389, 2004, doi: 10.1109/cec.2004.1331058.

[70] L. dos S. Coelho and V. C. Mariani, “An improved harmony search algorithm for power economic load dispatch,” *Energy Convers. Manag.*, vol. 50, no. 10, pp. 2522–2526, 2009, doi: 10.1016/j.enconman.2009.05.034.

[71] C. M. Wang and Y. F. Huang, “Self-adaptive harmony search algorithm for optimization,” *Expert Syst. Appl.*, vol. 37, no. 4, pp. 2826–2837, 2010, doi: 10.1016/j.eswa.2009.09.008.

[72] M. Afkousi-Paqaleh and M. Rashidinejad, “An implementation of harmony search algorithm to unit commitment problem,” *Electr Engg.*, vol. 10, no. 1007, pp. 10–202, 2010.

[73] R. Arul, G. Ravi, and S. Velusami, “Non-convex Economic Dispatch with Heuristic Load Patterns using Harmony Search Algorithm,” *Int. J. Comput. Appl.*, vol. 16, no. 1, pp. 26–33, 2011, doi: 10.5120/1976-2650.

[74] L. Yong, S. Liu, S. Tuo, and K. Gao, “Improved harmony search algorithm with chaos for absolute value equation,” *Telkomnika*, vol. 11, no. 4, pp. 835–844, 2013, doi: 10.12928/telkomnika.v11i4.1208.

[75] L. Xue-hui, Y. Ye, and L. Xia, “Solving TSP with Shuffled Frog-Leaping Algorithm,” *Proc. - 8th Int. Conf. Intell. Syst. Des. Appl. ISDA 2008*, vol. 3, pp. 228–232, 2008, doi: 10.1109/ISDA.2008.346.

[76] H. Quan, D. Srinivasan, A. M. Khambadkone, and A. Khosravi, “A computational framework for uncertainty integration in stochastic unit commitment with intermittent renewable energy sources,” *Appl. Energy*, vol. 152, pp. 71–82, 2015, doi: 10.1016/j.apenergy.2015.04.103.

[77] J. M. Anita and I. J. Raglend, “Shuffled Frog Leaping Algorithm,” *Int. Conf. Comput. Electron. Electr. Technol.*, pp. 109–115, 2012.

[78] D. Simon, “Biogeography-based optimization,” *IEEE Trans. Evol. Comput.*, vol. 12, no. 6, pp. 702–713, 2008, doi: 10.1109/TEVC.2008.919004.

[79] D. Du, D. Simon, and M. Ergezer, “Biogeography-based optimization combined with evolutionary strategy and immigration refusal,” *Conf. Proc. - IEEE Int. Conf. Syst. Man Cybern.*, no. October, pp. 997–1002, 2009, doi:

10.1109/ICSMC.2009.5346055.

[80] D. Simon, R. Rarick, M. Ergezer, and D. Du, “Analytical and numerical comparisons of biogeography-based optimization and genetic algorithms,” *Inf. Sci. (Ny).*, vol. 181, no. 7, pp. 1224–1248, 2011, doi: 10.1016/j.ins.2010.12.006.

[81] W. Gong, Z. Cai, and C. X. Ling, “DE/BBO: A hybrid differential evolution with biogeography-based optimization for global numerical optimization,” *Soft Comput.*, vol. 15, no. 4, pp. 645–665, 2011, doi: 10.1007/s00500-010-0591-1.

[82] B. Khokhar, K. P. Singh Parmar, and S. Dahiya, “Application of Biogeography-based Optimization for Economic Dispatch Problems,” *Int. J. Comput. Appl.*, vol. 47, no. 13, pp. 25–30, 2012, doi: 10.5120/7249-0309.

[83] Z. Mohammed and J. Talaq, “Unit commitment by biogeography based optimization method,” *Proc. Mediterr. Electrotech. Conf. - MELECON*, pp. 551–554, 2012, doi: 10.1109/MELCON.2012.6196494.

[84] Y. Zhang, S. Wang, and G. Ji, “A Comprehensive Survey on Particle Swarm Optimization Algorithm and Its Applications,” *Math. Probl. Eng.*, vol. 2015, 2015, doi: 10.1155/2015/931256.

[85] Y. Shi and R. C. Eberhart, “Parameter selection in particle swarm optimization,” *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 1447, pp. 591–600, 1998, doi: 10.1007/bfb0040810.

[86] S. C. Pandian and K. Duraiswamy, “Fuzzy logic implementation for solving the unit commitment problem,” *2004 Int. Conf. Power Syst. Technol. POWERCON 2004*, vol. 1, no. November, pp. 413–418, 2004, doi: 10.1109/icpst.2004.1460030.

[87] B. Wang, Y. Li, and J. Watada, “Re-Scheduling the Unit Commitment Problem in Fuzzy Environment,” in *2011 IEEE International Conference on Fuzzy Systems*, 2011.

[88] A. Y. Saber, T. Senjyu, T. Miyagi, N. Urasaki, and T. Funabashi, “Fuzzy unit commitment scheduling using absolutely stochastic simulated annealing,” *IEEE Trans. Power Syst.*, vol. 21, no. 2, pp. 955–964, 2006, doi: 10.1109/TPWRS.2006.873017.

[89] C. C. A. Rajan and M. R. Mohan, “An Evolutionary Programming-Based Tabu Search Method For Solving The Unit Commitment Problem,” *IEEE Trans. Power Syst.*, vol. 19, no. 1, pp. 577–585, 2004, doi: 10.1109/TPWRS.2003.821472.

[90] S. C. Selvi, R. P. K. Devi, and C. C. A. Rajan, "Hybrid Evolutionary Programming Approach to Multi-Area Unit Commitment with Import and Export Constraints," vol. 1, no. 3, pp. 223–228, 2009.

[91] M. Bavafa, H. Monsef, and N. Navidi, "A new hybrid approach for unit commitment using lagrangian relaxation combined with evolutionary and quadratic programming," *Asia-Pacific Power Energy Eng. Conf. APPEEC*, 2009, doi: 10.1109/APPEEC.2009.4918069.

[92] M. Dorigo and C. Blum, "Ant colony optimization theory: A survey," *Theor. Comput. Sci.*, vol. 344, no. 2–3, pp. 243–278, 2005, doi: 10.1016/j.tcs.2005.05.020.

[93] T. Sum-im and W. Ongsakul, "Ant colony search algorithm for unit commitment," *IEEE Int. Conf. Ind. Technol. 2003*, vol. 1, no. i, pp. 72–77, 2003, doi: 10.1109/ICIT.2003.1290244.

[94] N. S. Sisworahardjo and A. A. El-Keib, "Unit commitment using the ant colony search algorithm," *LESCOPE 2002 - 2002 Large Eng. Syst. Conf. Power Eng. Energy Futur. Conf. Proc.*, pp. 2–6, 2002, doi: 10.1109/LESCPE.2002.1020658.

[95] L. Shi, J. Hao, J. Zhou, and G. Xu, "Ant colony optimization algorithm with random perturbation behavior to the problem of optimal unit commitment with probabilistic spinning reserve determination," *Electr. Power Syst. Res.*, vol. 69, no. 2–3, pp. 295–303, 2004, doi: 10.1016/j.epsr.2003.10.008.

[96] D. Yu, Y. Wang, and R. Guo, "A hybrid ant colony optimization algorithm based Lambda-iteration method for unit commitment problem," *Proc. - 2010 2nd WRI Glob. Congr. Intell. Syst. GCIS 2010*, vol. 1, no. 1, pp. 19–22, 2010, doi: 10.1109/GCIS.2010.19.

[97] N. Chitra and J. Munda, "Ant Colony Optimization Adopting Control Strategies for Power Quality Enhancement in Autonomous Microgrid," vol. 63, no. 13, pp. 34–38, 2013.

[98] M. Xu, X. You, and S. Liu, "Dual Population Ant Colony Optimization Algorithm," vol. 5, 2017.

[99] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer," *Adv. Eng. Softw.*, vol. 69, pp. 46–61, 2014, doi: 10.1016/j.advengsoft.2013.12.007.

[100] A. Kaveh and P. Zakian, "Improved GWO algorithm for optimal design of truss

structures," *Eng. Comput.*, vol. 34, no. 4, pp. 685–707, 2018, doi: 10.1007/s00366-017-0567-1.

[101] S. Gupta and K. Deep, "A novel Random Walk Grey Wolf Optimizer," *Swarm Evol. Comput.*, vol. 44, pp. 101–112, 2019, doi: 10.1016/j.swevo.2018.01.001.

[102] E. Emary, H. M. Zawbaa, and A. E. Hassanien, "Binary grey wolf optimization approaches for feature selection," *Neurocomputing*, vol. 172, pp. 371–381, 2016, doi: 10.1016/j.neucom.2015.06.083.

[103] I. A. Hameed, R. T. Bye, and O. L. Osen, "Grey wolf optimizer (GWO) for automated offshore crane design," in *2016 IEEE Symposium Series on Computational Intelligence (SSCI)*, Dec. 2016, pp. 1–6, doi: 10.1109/SSCI.2016.7849998.

[104] S. Li, H. Chen, M. Wang, A. A. Heidari, and S. Mirjalili, "Slime mould algorithm: A new method for stochastic optimization," *Futur. Gener. Comput. Syst.*, no. April, 2020, doi: 10.1016/j.future.2020.03.055.

[105] A. Brabazon and S. McGarraghy, "Slime mould foraging: An inspiration for algorithmic design," *Int. J. Innov. Comput. Appl.*, vol. 11, no. 1, pp. 30–45, 2020, doi: 10.1504/IJICA.2020.105316.

[106] M. Mostafa, H. Rezk, M. Aly, and E. M. Ahmed, "A new strategy based on slime mould algorithm to extract the optimal model parameters of solar PV panel," *Sustain. Energy Technol. Assessments*, vol. 42, no. September, p. 100849, 2020, doi: 10.1016/j.seta.2020.100849.

[107] D. S. Sidhu, J. S. Dhillon, and D. Kaur, "Hybrid heuristic search method for design of digital IIR filter with conflicting objectives," *Soft Comput.*, vol. 21, no. 12, pp. 3461–3476, 2017, doi: 10.1007/s00500-015-2023-8.

[108] N. K. Yadav, "Hybridization of Particle Swarm Optimization with Differential Evolution for solving combined economic emission dispatch model for smart grid," *J. Eng. Res.*, vol. 7, no. 3, pp. 244–257, 2019.

[109] X. Fang, L. Bai, F. Li, and B. M. Hodge, "Hybrid component and configuration model for combined-cycle units in unit commitment problem," *J. Mod. Power Syst. Clean Energy*, vol. 6, no. 6, pp. 1332–1337, 2018, doi: 10.1007/s40565-018-0409-1.

[110] R. M. Rizk-Allah, "Hybridizing sine cosine algorithm with multi-orthogonal

search strategy for engineering design problems," *J. Comput. Des. Eng.*, vol. 5, no. 2, pp. 249–273, 2018.

[111] Z. M. Gao, J. Zhao, Y. Yang, and X. J. Tian, "The hybrid grey wolf optimization-slime mould algorithm," *J. Phys. Conf. Ser.*, vol. 1617, no. 1, 2020, doi: 10.1088/1742-6596/1617/1/012034.

[112] M. Abdel-basset, V. Chang, and R. Mohamed, "HSMA_WOA: A hybrid novel Slime mould algorithm with whale optimization algorithm for tackling the image segmentation problem of chest X-ray images," no. January, 2020.

[113] C. J. Baldwin, K. M. Dale, and R. F. Dittrich, "A Study of the Economic Shutdown of Generating Units in Daily Dispatch," *Trans. Am. Inst. Electr. Eng. Part III Power Appar. Syst.*, vol. 78, no. 4, pp. 1272–1282, 1959, doi: 10.1109/AIEEPAS.1959.4500539.

[114] G. B. Sheble and G. N. Fahd, "Unit commitment literature synopsis," *IEEE Trans. Power Syst.*, vol. 9, no. 1, pp. 128–135, 1994, doi: 10.1109/59.317549.

[115] P. G. Lowery, "Generating Unit Commitment by Dynamic Programming," *IEEE Trans. Power Appar. Syst.*, vol. PAS-85, no. 5, pp. 422–426, 1966, doi: 10.1109/TPAS.1966.291679.

[116] J. D. Guy, "Security constrained unit commitment," *IEEE Trans. Power Appar. Syst.*, vol. PAS-90, no. 3, pp. 1385–1390, 1971, doi: 10.1109/TPAS.1971.292942.

[117] D. Singh and J. S. Dhillon, "Ameliorated grey wolf optimization for economic load dispatch problem," *Energy*, pp. 398–419, 2019, doi: 10.1016/j.energy.2018.11.034.

[118] R. R. Shoults, S. K. Chang, S. Helmick, and W. M. Grady, "A practical approach to unit commitment, economic dispatch and savings allocation for multiple-area pool operation with import/export constraints," *IEEE Trans. Power Appar. Syst.*, vol. PAS-99, no. 2, pp. 625–635, 1980, doi: 10.1109/TPAS.1980.319654.

[119] C. L. Chen and S. C. Wang, "Branch-and-bound scheduling for thermal generating units," *IEEE Trans. Energy Convers.*, vol. 8, no. 2, pp. 184–189, 1993, doi: 10.1109/60.222703.

[120] T. Senjyu, T. Miyagi, A. Y. Saber, N. Urasaki, and T. Funabashi, "Emerging solution of large-scale unit commitment problem by Stochastic Priority List," *Electr. Power Syst. Res.*, vol. 76, no. 5, pp. 283–292, 2006, doi:

10.1016/j.epsr.2005.07.002.

[121] P. M. P. D.P.Kadam, S.S.Wagh, “Thermal Unit Commitment Problem by using Genetic Algorithm, Fuzzy Logic and Priority List Method,” *Proc. - Int. Conf. Comput. Intell. Multimed. Appl. ICCIMA 2007*, vol. 2, pp. 174–178, 2008, doi: 10.1109/ICCIMA.2007.338.

[122] T. Li and M. Shahidehpour, “Price-based unit commitment: A case of Lagrangian relaxation versus mixed integer programming,” *IEEE Trans. Power Syst.*, vol. 20, no. 4, pp. 2015–2025, 2005, doi: 10.1109/TPWRS.2005.857391.

[123] S. a. Kazarlis, a. G. Bakirtzis, and V. Petridis, “A genetic algorithm solution to the unit commitment problem,” *IEEE Trans. Power Syst.*, vol. 11, no. 1, pp. 83–92, 1996, doi: 10.1109/59.485989.

[124] S. J. Huang and C. L. Huang, “Application of genetic-based neural networks to thermal unit commitment,” *IEEE Trans. Power Syst.*, vol. 12, no. 2, pp. 654–660, 1997, doi: 10.1109/59.589634.

[125] K. Vaisakh and L. R. Srinivas, “Unit commitment by genetic evolving ant colony optimization,” *2009 World Congr. Nat. Biol. Inspired Comput. NABIC 2009 - Proc.*, pp. 1162–1167, 2009, doi: 10.1109/NABIC.2009.5393781.

[126] Y. F. Li, N. Pedroni, and E. Zio, “A memetic evolutionary multi-objective optimization method for environmental power unit commitment,” *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2660–2669, 2013, doi: 10.1109/TPWRS.2013.2241795.

[127] D. Karaboğa and O. Selcuk, “A Simple and Global Optimization Algorithm for Engineering Problems: Differential Evolution Algorithm,” *Turkish J. Electr. Eng.*, vol. 12, no. 1, pp. 53–60, 2004.

[128] A. Keles, A. S. Etaner-Uyar, and B. Turkay, “A Differential Evolution Approach for the Unit Commitment Problem,” *ELECO 2007 5th Int. Conf. Electr. Electron. Eng.*, pp. 132–136, 2007.

[129] M. G. H. Omran and M. Mahdavi, “Global-best harmony search,” *Appl. Math. Comput.*, vol. 198, no. 2, pp. 643–656, 2008, doi: 10.1016/j.amc.2007.09.004.

[130] M. Afkousi-Paqaleh, M. Rashidinejad, and M. Pourakbari-Kasmaei, “An implementation of harmony search algorithm to unit commitment problem,” *Electr. Eng.*, vol. 92, no. 6, pp. 215–225, 2010, doi: 10.1007/s00202-010-0177-z.

[131] A. S. Reddy and K. Vaisakh, “Economic Emission Load Dispatch by Modified Shuffled Frog Leaping Algorithm,” *Int. J. Comput. Appl. (0*, vol. 31, no. 11, pp. 58–65, 2011.

[132] R. Rarick, D. Simon, F. E. Villaseca, and B. Vyakaranam, “Biogeography-based optimization and the solution of the power flow problem,” *Conf. Proc. - IEEE Int. Conf. Syst. Man Cybern.*, no. October, pp. 1003–1008, 2009, doi: 10.1109/ICSMC.2009.5346046.

[133] R. Eberhart and J. Kennedy, “New optimizer using particle swarm theory,” *Proc. Int. Symp. Micro Mach. Hum. Sci.*, pp. 39–43, 1995, doi: 10.1109/mhs.1995.494215.

[134] J. Kennedy and R. Eberhart, “Particle swarm optimization,” 1995.

[135] T. O. Ting, M. V. C. Rao, C. K. Loo, and S. S. Ngu, “Solving Unit Commitment Problem Using Hybrid Particle Swarm Optimization,” *J. Heuristics*, vol. 9, pp. 507–520, 2003.

[136] W. Yao, J. Zhao, F. Wen, Y. Xue, and G. Ledwich, “A hierarchical decomposition approach for coordinated dispatch of plug-in electric vehicles,” *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2768–2778, 2013, doi: 10.1109/TPWRS.2013.2256937.

[137] B. Zhao, C. X. Guo, B. R. Bai, and Y. J. Cao, “An improved particle swarm optimization algorithm for unit commitment,” *Int. J. Electr. Power Energy Syst.*, vol. 28, no. 7, pp. 482–490, 2006, doi: 10.1016/j.ijepes.2006.02.011.

[138] A. Y. Saber and A. M. Alshareef, “Scalable unit commitment by memory-bounded ant colony optimization with A* local search,” *Int. J. Electr. Power Energy Syst.*, vol. 30, no. 6–7, pp. 403–414, 2008, doi: 10.1016/j.ijepes.2008.01.001.

[139] K. Venkatesan and (2012) Rajan C. C. A., “Ant Colony Search Algorithm For Solving Multi Area Unit Commitment Problem With Import And Export Constraints,” *Int. J. Eng. Res. Technol.*, vol. 1, no. 8, pp. 1–18, 2012.

[140] X. long Chen, P. hong Wang, Q. Wang, and Y. hua Dong, “A Two-Stage strategy to handle equality constraints in ABC-based power economic dispatch problems,” *Soft Comput.*, 2019, doi: 10.1007/s00500-018-03723-4.

[141] L. C. Kien, T. T. Nguyen, C. T. Hien, and M. Q. Duong, “A novel social spider optimization algorithm for large-scale economic load dispatch problem,”

Energies, vol. 12, no. 6, pp. 1–26, 2019, doi: 10.3390/en12061075.

[142] V. K. Kamboj, S. K. Bath, and J. S. Dhillon, “Implementation of hybrid harmony/random search algorithm considering ensemble and pitch violation for unit commitment problem,” *Int. J. Electr. Power Energy Syst.*, vol. 77, pp. 228–249, 2016, doi: 10.1016/j.ijepes.2015.11.045.

[143] V. K. Kamboj, S. K. Bath, and J. S. Dhillon, “A novel hybrid DE–random search approach for unit commitment problem,” *Neural Comput. Appl.*, vol. 28, no. 7, pp. 1559–1581, 2017, doi: 10.1007/s00521-015-2124-4.

[144] K. C. Chou, “Simulation of hourly wind speed and array wind power,” vol. 26, no. 4, pp. 199–212, 1981.

[145] R. Billinton and H. U. A. Chen, “Time-series models for reliabilty evaluations pf power systems including wind energy,” vol. 36, no. 9, pp. 1253–1261, 1996.

[146] V. S. Pappala, S. Member, I. Erlich, S. Member, K. Rohrig, and J. Dobschinski, “A Stochastic Model for the Optimal Operation of a Wind-Thermal Power System,” vol. 24, no. 2, pp. 940–950, 2009.

[147] K. Methaprayoon, C. Yingvivatanapong, W. Lee, and J. R. Liao, “An Integration of ANN Wind Power Estimation Into Unit Commitment Considering,” vol. 43, no. 6, pp. 1441–1448, 2007.

[148] S. S. Soman, H. Zareipour, S. Member, O. Malik, and L. Fellow, “A Review of Wind Power and Wind Speed Forecasting Methods With Different Time Horizons,” pp. 1–8, 2010, [Online]. Available: papers3://publication/uuid/01A9077B-50C8-47AB-9F17-B4E94F80DFDF.

[149] H. Siahkali and M. Vakilian, “Stochastic unit commitment of wind farms integrated in power system,” *Electr. Power Syst. Res.*, vol. 80, no. 9, pp. 1006–1017, 2010, doi: 10.1016/j.epsr.2010.01.003.

[150] S. K. M. Shahidehpour, “Generation expansion planning in wind-thermal power systems,” vol. 4, no. February, pp. 940–951, 2010, doi: 10.1049/iet-gtd.2009.0695.

[151] G. J. Osório, J. M. Lujano-rojas, J. C. O. Matias, and J. P. S. Catalão, “Electrical Power and Energy Systems A new scenario generation-based method to solve the unit commitment problem with high penetration of renewable energies,” vol. 64, pp. 1063–1072, 2015, doi: 10.1016/j.ijepes.2014.09.010.

[152] S. Umamaheswaran and S. Rajiv, “Financing large scale wind and solar projects -

A review of emerging experiences in the Indian context," *Renew. Sustain. Energy Rev.*, vol. 48, pp. 166–177, 2015, doi: 10.1016/j.rser.2015.02.054.

[153] A. M. Foley, P. G. Leahy, A. Marvuglia, and E. J. McKeogh, "Current methods and advances in forecasting of wind power generation," *Renew. Energy*, vol. 37, no. 1, pp. 1–8, 2012, doi: 10.1016/j.renene.2011.05.033.

[154] S. Singh and M. Fozdar, "Optimal bidding strategy with the inclusion of wind power supplier in an emerging power market," 2019, doi: 10.1049/iet-gtd.2019.0118.

[155] L. Zhao and B. Zeng, "Robust unit commitment problem with demand response and wind energy," *IEEE Power Energy Soc. Gen. Meet.*, pp. 1–8, 2012, doi: 10.1109/PESGM.2012.6344860.

[156] J. Li, J. Zhou, and B. Chen, "Review of wind power scenario generation methods for optimal operation of renewable energy systems," *Appl. Energy*, vol. 280, no. October, p. 115992, 2020, doi: 10.1016/j.apenergy.2020.115992.

[157] J. Hetzer, D. C. Yu, and K. Bhattarai, "An economic dispatch model incorporating wind power," *IEEE Trans. Energy Convers.*, vol. 23, no. 2, pp. 603–611, 2008, doi: 10.1109/TEC.2007.914171.

[158] A. Purwadi, M. Ikhsan, N. Hariyanto, N. Heryana, and Y. Haroen, "Wind speed calculation by using electrical output and wind turbine power curve," *Proc. - 2013 Int. Conf. Inf. Technol. Electr. Eng. "Intelligent Green Technol. Sustain. Dev. ICITEE 2013*, pp. 420–423, 2013, doi: 10.1109/ICITEED.2013.6676279.

[159] P. B. Luh *et al.*, "Grid Integration of Distributed Wind Generation: Hybrid Markovian and Interval Unit Commitment," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 732–741, 2014, doi: 10.1109/TSG.2013.2268462.

[160] A. Mahari and K. Zare, "A solution to the generation scheduling problem in power systems with large-scale wind farms using MICA," *Int. J. Electr. Power Energy Syst.*, vol. 54, pp. 1–9, 2014, doi: 10.1016/j.ijepes.2013.06.025.

[161] M. S. Shahriar, J. Rana, M. A. Asif, and M. Hasan, "Optimization of Unit Commitment Problem for Wind-Thermal Generation using Fuzzy Optimization Technique," pp. 88–92, 2015.

[162] M. Ban, J. Yu, M. Shahidehpour, and Y. Yao, "Integration of power-to-hydrogen in day-ahead security-constrained unit commitment with high wind penetration,"

J. Mod. Power Syst. Clean Energy, vol. 5, no. 3, pp. 337–349, 2017, doi: 10.1007/s40565-017-0277-0.

[163] C. Shao, X. Wang, M. Shahidehpour, X. Wang, and B. Wang, "Security-Constrained Unit Commitment With Flexible Uncertainty Set for Variable Wind Power," *IEEE Trans. Sustain. Energy*, vol. 8, no. 3, pp. 1237–1246, 2017, doi: 10.1109/TSTE.2017.2673120.

[164] R. Azizipanah-abarghooee, F. Golestaneh, H. Gooi, J. Lin, F. Bavafa, and V. Terzija, "Corrective economic dispatch and operational cycles for probabilistic unit commitment with demand response and high wind power," *Appl. Energy*, vol. 182, pp. 634–651, 2016, doi: 10.1016/j.apenergy.2016.07.117.

[165] R. Saravanan and S. S. Prabha, "Generation Scheduling With Renewable Energy Sources an Improved Fire fly Optimization Algorithm," vol. 7, no. 1, pp. 47–50, 2019.

[166] M. Esmaeeli, S. Golshannavaz, and P. Siano, "Determination of optimal reserve contribution of thermal units to afford the wind power uncertainty," *J. Ambient Intell. Humaniz. Comput.*, vol. 11, no. 4, pp. 1565–1576, 2020, doi: 10.1007/s12652-019-01231-3.

[167] A. Bhadoria, S. Marwaha, and V. K. Kamboj, *BMFO-SIG: A Novel Binary Moth Flame Optimizer Algorithm with Sigmoidal Transformation for Combinatorial Unit Commitment and Numerical Optimization Problems*. Springer Singapore, 2020.

[168] B. Ji, X. Yuan, Z. Chen, and H. Tian, "Improved gravitational search algorithm for unit commitment considering uncertainty of wind power," *Energy*, vol. 67, pp. 52–62, 2014, doi: 10.1016/j.energy.2014.02.014.

[169] C. Shilaja and T. Arunprasath, "Optimal power flow using Moth Swarm Algorithm with Gravitational Search Algorithm considering wind power," *Futur. Gener. Comput. Syst.*, vol. 98, pp. 708–715, 2019, doi: 10.1016/j.future.2018.12.046.

[170] K. Lakshmi and S. Vasantharathna, "Gencos wind – thermal scheduling problem using Artificial Immune System algorithm," *Int. J. Electr. POWER ENERGY Syst.*, vol. 54, pp. 112–122, 2014, doi: 10.1016/j.ijepes.2013.06.036.

[171] M. E. Khodayar, L. Wu, and M. Shahidehpour, "Hourly coordination of electric vehicle operation and volatile wind power generation in SCUC," *IEEE Trans.*

Smart Grid, vol. 3, no. 3, pp. 1271–1279, 2012, doi: 10.1109/TSG.2012.2186642.

[172] J. J. Q. Yu, V. O. K. Li, and A. Y. S. Lam, "Optimal V2G scheduling of electric vehicles and unit commitment using chemical reaction optimization," *2013 IEEE Congr. Evol. Comput. CEC 2013*, pp. 392–399, 2013, doi: 10.1109/CEC.2013.6557596.

[173] S. Chandrashekar, Y. Liu, and R. Sioshansi, "Wind-integration benefits of controlled plug-in electric vehicle charging," *J. Mod. Power Syst. Clean Energy*, vol. 5, no. 5, pp. 746–756, 2017, doi: 10.1007/s40565-017-0296-x.

[174] M. Ghofrani, A. Arabali, M. Etezadi-Amoli, and M. S. Fadali, "Smart scheduling and cost-benefit analysis of grid-enabled electric vehicles for wind power integration," *IEEE Trans. Smart Grid*, vol. 5, no. 5, pp. 2306–2313, 2014, doi: 10.1109/TSG.2014.2328976.

[175] S. Gao, K. T. Chau, C. Liu, D. Wu, and C. C. Chan, "Integrated energy management of plug-in electric vehicles in power grid with renewables," *IEEE Trans. Veh. Technol.*, vol. 63, no. 7, pp. 3019–3027, 2014, doi: 10.1109/TVT.2014.2316153.

[176] N. Zhang, Z. Hu, X. Han, J. Zhang, and Y. Zhou, "A fuzzy chance-constrained program for unit commitment problem considering demand response, electric vehicle and wind power," *Int. J. Electr. Power Energy Syst.*, vol. 65, pp. 201–209, 2015, doi: 10.1016/j.ijepes.2014.10.005.

[177] X. Zhang, K. W. Chan, H. Wang, B. Zhou, G. Wang, and J. Qiu, "Multiple group search optimization based on decomposition for multi-objective dispatch with electric vehicle and wind power uncertainties," *Appl. Energy*, vol. 262, no. May 2019, p. 114507, 2020, doi: 10.1016/j.apenergy.2020.114507.

[178] K. Clement-Nyns, E. Haesen, and J. Driesen, "The impact of Charging plug-in hybrid electric vehicles on a residential distribution grid," *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 371–380, 2010, doi: 10.1109/TPWRS.2009.2036481.

[179] W. Su, H. Rahimi-eichi, W. Zeng, and M. Chow, "A Survey on the Electrification of Transportation in a Smart Grid Environment," *IEEE Trans. Ind. Informatics*, vol. 8, no. 1, pp. 1–10, 2012.

[180] Y. Ma, T. Houghton, A. Cruden, and D. Infield, "Modeling the benefits of vehicle-to-grid technology to a power system," *IEEE Trans. Power Syst.*, vol. 27, no. 2,

pp. 1012–1020, 2012, doi: 10.1109/TPWRS.2011.2178043.

[181] Z. Darabi and M. Ferdowsi, "An event-based simulation framework to examine the response of power grid to the charging demand of plug-in hybrid electric vehicles," *IEEE Trans. Ind. Informatics*, vol. 10, no. 1, pp. 313–322, 2014, doi: 10.1109/TII.2013.2261305.

[182] G. Wang, J. Zhao, F. Wen, Y. Xue, and G. Ledwich, "Dispatch strategy of PHEVs to mitigate selected patterns of seasonally varying outputs from renewable generation," *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 627–639, 2015, doi: 10.1109/TSG.2014.2364235.

[183] M. Ansari, A. T. Al-Awami, E. Sortomme, and M. A. Abido, "Coordinated bidding of ancillary services for vehicle-to-grid using fuzzy optimization," *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 261–270, 2015, doi: 10.1109/TSG.2014.2341625.

[184] T. Shekari, S. Golshannavaz, and F. Aminifar, "Techno-Economic Collaboration of PEV Fleets in Energy Management of Microgrids," *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3833–3841, 2017, doi: 10.1109/TPWRS.2016.2644201.

[185] M. R. Andervazh and S. Javadi, "Emission-economic dispatch of thermal power generation units in the presence of hybrid electric vehicles and correlated wind power plants," *IET Gener. Transm. Distrib.*, vol. 11, no. 9, pp. 2232–2243, 2017, doi: 10.1049/iet-gtd.2016.1508.

[186] M. Clerc, "Particle Swarm Optimization," *Part. Swarm Optim.*, pp. 507–520, 2010, doi: 10.1002/9780470612163.

[187] R. J. Kuo and F. E. Zulvia, "The gradient evolution algorithm: A new metaheuristic," *Inf. Sci. (Ny).*, vol. 316, no. April, pp. 246–265, 2015, doi: 10.1016/j.ins.2015.04.031.

[188] R. Tang, S. Fong, X. S. Yang, and S. Deb, "Wolf search algorithm with ephemeral memory," *7th Int. Conf. Digit. Inf. Manag. ICDIM 2012*, pp. 165–172, 2012, doi: 10.1109/ICDIM.2012.6360147.

[189] A. H. Gandomi, "Interior search algorithm (ISA): A novel approach for global optimization," *ISA Trans.*, vol. 53, no. 4, pp. 1168–1183, 2014, doi: 10.1016/j.isatra.2014.03.018.

[190] Y. T. Hsiao and C. Y. Chien, "Enhancement of restoration service in distribution

systems using a combination fuzzy-ga method," *IEEE Trans. Power Syst.*, vol. 15, no. 4, pp. 1394–1400, 2000, doi: 10.1109/59.898118.

[191] W. S. Tan and M. Shaaban, "A Hybrid Stochastic/Deterministic Unit Commitment Based on Projected Disjunctive MILP Reformulation," *IEEE Trans. Power Syst.*, vol. 31, no. 6, pp. 5200–5201, 2016, doi: 10.1109/TPWRS.2016.2521326.

[192] H. Salimi, "Stochastic Fractal Search: A powerful metaheuristic algorithm," *Knowledge-Based Syst.*, vol. 75, pp. 1–18, 2015, doi: 10.1016/j.knosys.2014.07.025.

[193] A. Roy and J. Wallenius, "Nonlinear multiple objective optimization: An algorithm and some theory," *Math. Program.*, vol. 55, no. 1–3, pp. 235–249, 1992, doi: 10.1007/BF01581201.

[194] Z. X. Hua, Z. J. Quan, and C. X. Ying, "Unit commitment incorporating wind generators considering emission reduction," *Adv. Mater. Res.*, vol. 347–353, pp. 3973–3977, 2012, doi: 10.4028/www.scientific.net/AMR.347-353.3973.

[195] J. F. A. Tsai, "Global optimization of nonlinear fractional programming problems in engineering design," *Eng. Optim.*, vol. 37, no. 4, pp. 399–409, 2005, doi: 10.1080/03052150500066737.

[196] E. Mezura-Montes and C. A. Coello Coello, "A simple multimembered evolution strategy to solve constrained optimization problems," *IEEE Trans. Evol. Comput.*, vol. 9, no. 1, pp. 1–17, 2005, doi: 10.1109/TEVC.2004.836819.

[197] A. Husseinzadeh Kashan, "League Championship Algorithm (LCA): An algorithm for global optimization inspired by sport championships," *Appl. Soft Comput. J.*, vol. 16, pp. 171–200, 2014, doi: 10.1016/j.asoc.2013.12.005.

[198] G. Carpinelli, F. Mottola, D. Proto, and A. Russo, "A Multi-Objective Approach for Microgrid Scheduling," *IEEE Trans. Smart Grid*, vol. 8, no. 5, pp. 2109–2118, 2017, doi: 10.1109/TSG.2016.2516256.

[199] J. J. Grefenstette, "Genetic Algorithms," vol. 00, no. February, pp. 122–128, 1986.

[200] R. Storn and K. Price, "Differential evolution-a simple and efficient heuristic for global optimization over continuous spaces," *J. Glob. Optim.*, vol. 11, no. 4, pp. 341–359, 1997.

[201] A. I. Cohen and M. Yoshimura, "A branch-and-bound algorithm for unit commitment," *IEEE Trans. Power Appar. Syst.*, no. 2, pp. 444–451, 1983.

[202] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, “Optimization by simulated annealing.,” *Science*, vol. 220, no. 4598, pp. 671–80, May 1983, doi: 10.1126/science.220.4598.671.

[203] E. Rashedi, H. Nezamabadi-Pour, and S. Saryazdi, “GSA: a gravitational search algorithm,” *Inf Sci*, vol. 179, p. 2232, 2009.

[204] R. Moghdani and K. Salimifard, “Volleyball Premier League Algorithm,” *Appl. Soft Comput. J.*, vol. 64, pp. 161–185, 2018, doi: 10.1016/j.asoc.2017.11.043.

[205] F. Glover, “Tabu Search-Part I,” vol. 1, no. 3, pp. 190–206, 1989.

[206] S. C. Satapathy, A. Naik, and K. Parvathi, “A teaching learning based optimization based on orthogonal design for solving global optimization problems,” *Springerplus*, vol. 2, no. 1, pp. 1–12, 2013, doi: 10.1186/2193-1801-2-130.

[207] J. Kennedy and (1995) Eberhart R. C., “Particle Swarm Optimization,” in *Proceedings of the IEEE International Conference on Neural Networks*, pp. 1942–1948.

[208] M. Dorigo, M. Birattari, and T. Stutzle, “Ant colony optimization,” *IEEE Comput. Intell. Mag.*, vol. 1, no. 4, pp. 28–39, 2006, doi: 10.1109/MCI.2006.329691.

[209] I. Brajevic and M. Tuba, “An upgraded artificial bee colony (ABC) algorithm for constrained optimization problems,” *J. Intell. Manuf.*, vol. 24, no. 4, pp. 729–740, 2013, doi: 10.1007/s10845-011-0621-6.

[210] X. S. Yang, “Bat algorithm for multi-objective optimisation,” *Int. J. Bio-Inspired Comput.*, vol. 3, no. 5, pp. 267–274, 2011, doi: 10.1504/IJBIC.2011.042259.

[211] S. Mirjalili, “Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm,” *Knowledge-Based Syst.*, vol. 89, pp. 228–249, 2015, doi: 10.1016/j.knosys.2015.07.006.

[212] S. Mirjalili and A. Lewis, “The Whale Optimization Algorithm,” *Adv. Eng. Softw.*, vol. 95, pp. 51–67, 2016, doi: 10.1016/j.advengsoft.2016.01.008.

[213] A. A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja, and H. Chen, “Harris hawks optimization: Algorithm and applications,” *Futur. Gener. Comput. Syst.*, vol. 97, pp. 849–872, 2019, doi: 10.1016/j.future.2019.02.028.

[214] S. Li, H. Chen, M. Wang, A. A. Heidari, and S. Mirjalili, “Slime mould algorithm: A new method for stochastic optimization,” *Futur. Gener. Comput. Syst.*, 2020, doi: 10.1016/j.future.2020.03.055.

[215] J. C. Bednarz, "Cooperative hunting in Harris' hawks (Parabuteo unicinctus)," *Science (80-.).*, vol. 239, no. 4847, pp. 1525–1527, 1988, doi: 10.1126/science.239.4847.1525.

[216] T. Singh, "A chaotic sequence-guided Harris hawks optimizer for data clustering," *Neural Comput. Appl.*, vol. 32, no. 23, pp. 17789–17803, 2020, doi: 10.1007/s00521-020-04951-2.

[217] Z. Yu, X. Shi, J. Zhou, X. Chen, and X. Qiu, "Effective assessment of blast-induced ground vibration using an optimized random forest model based on a harris hawks optimization algorithm," *Appl. Sci.*, vol. 10, no. 4, 2020, doi: 10.3390/app10041403.

[218] E. H. Houssein, M. E. Hosney, D. Oliva, W. M. Mohamed, and M. Hassaballah, "A novel hybrid Harris hawks optimization and support vector machines for drug design and discovery," *Comput. Chem. Eng.*, vol. 133, p. 106656, 2020, doi: 10.1016/j.compchemeng.2019.106656.

[219] A. Abbasi, B. Firouzi, and P. Sendur, "On the application of Harris hawks optimization (HHO) algorithm to the design of microchannel heat sinks," *Eng. Comput.*, vol. 37, no. 2, pp. 1409–1428, 2021, doi: 10.1007/s00366-019-00892-0.

[220] X. Bao, H. Jia, and C. Lang, "A Novel Hybrid Harris Hawks Optimization for Color Image Multilevel Thresholding Segmentation," *IEEE Access*, vol. 7, no. 1, pp. 76529–76546, 2019, doi: 10.1109/ACCESS.2019.2921545.

[221] R. Devarapalli and B. Bhattacharyya, "Application of Modified Harris Hawks Optimization in Power System Oscillations Damping Controller Design," *2019 8th Int. Conf. Power Syst. Transit. Towar. Sustain. Smart Flex. Grids, ICPS 2019*, pp. 1–6, 2019, doi: 10.1109/ICPS48983.2019.9067679.

[222] F. A. Essa, M. Abd Elaziz, and A. H. Elsheikh, "An enhanced productivity prediction model of active solar still using artificial neural network and Harris Hawks optimizer," *Appl. Therm. Eng.*, vol. 170, no. January, p. 115020, 2020, doi: 10.1016/j.applthermaleng.2020.115020.

[223] M. Mafarja *et al.*, "Evolutionary Population Dynamics and Grasshopper Optimization approaches for feature selection problems," *Knowledge-Based Syst.*, vol. 145, pp. 25–45, 2018, doi: 10.1016/j.knosys.2017.12.037.

[224] H. M. Alabool, D. Alarabiat, L. Abualigah, and A. A. Heidari, *Harris hawks*

optimization: a comprehensive review of recent variants and applications, vol. 5. Springer London, 2021.

[225] A. R. Yıldız, B. S. Yıldız, S. M. Sait, and X. Li, "The Harris hawks, grasshopper and multi-verse optimization algorithms for the selection of optimal machining parameters in manufacturing operations," *Mater. Test.*, vol. 61, no. 8, pp. 725–733, 2019, doi: 10.3139/120.111377.

[226] H. Moayedi, A. Osouli, H. Nguyen, and A. S. A. Rashid, "A novel Harris hawks' optimization and k-fold cross-validation predicting slope stability," *Eng. Comput.*, vol. 37, no. 1, pp. 369–379, 2021, doi: 10.1007/s00366-019-00828-8.

[227] H. Chen, A. A. Heidari, H. Chen, M. Wang, Z. Pan, and A. H. Gandomi, "Multi-population differential evolution-assisted Harris hawks optimization: Framework and case studies," *Futur. Gener. Comput. Syst.*, vol. 111, pp. 175–198, 2020, doi: 10.1016/j.future.2020.04.008.

[228] B. Firouzi, A. Abbasi, and P. Sendur, "Improvement of the computational efficiency of metaheuristic algorithms for Improvement of the computational efficiency of metaheuristic algorithms for the crack detection of cantilever beams using hybrid methods," no. May, 2021, doi: 10.1080/0305215X.2021.1919887.

[229] C. Qu, W. He, X. Peng, and X. Peng, "Harris Hawks optimization with information exchange," *Appl. Math. Model.*, vol. 84, pp. 52–75, 2020, doi: 10.1016/j.apm.2020.03.024.

[230] M. R. Elkadeem, M. Abd Elaziz, Z. Ullah, S. Wang, and S. W. Sharshir, "Optimal Planning of Renewable Energy-Integrated Distribution System Considering Uncertainties," *IEEE Access*, vol. 7, pp. 164887–164907, 2019, doi: 10.1109/ACCESS.2019.2947308.

[231] R. Ebrahimzadeh and M. Jampour, "Chaotic Genetic Algorithm based on Lorenz Chaotic System for Optimization Problems," *Int. J. Intell. Syst. Appl.*, vol. 5, no. 5, pp. 19–24, 2013, doi: 10.5815/ijisa.2013.05.03.

[232] G. G. Wang, L. Guo, A. H. Gandomi, G. S. Hao, and H. Wang, "Chaotic Krill Herd algorithm," *Inf. Sci. (Ny).*, vol. 274, pp. 17–34, 2014, doi: 10.1016/j.ins.2014.02.123.

[233] Y. Ji *et al.*, "An Adaptive Chaotic Sine Cosine Algorithm for Constrained and Unconstrained Optimization," *Complexity*, vol. 2020, 2020, doi:

10.1155/2020/6084917.

[234] H. Afrabandpey, M. Ghaffari, A. Mirzaei, and M. Safayani, “A novel Bat Algorithm based on chaos for optimization tasks,” *2014 Iran. Conf. Intell. Syst. ICIS 2014*, pp. 2–7, 2014, doi: 10.1109/IranianCIS.2014.6802527.

[235] M. Kohli and S. Arora, “Chaotic grey wolf optimization algorithm for constrained optimization problems,” *J. Comput. Des. Eng.*, vol. 5, no. 4, pp. 458–472, 2018, doi: 10.1016/j.jcde.2017.02.005.

[236] L. Y. Chuang, C. J. Hsiao, and C. H. Yang, “Chaotic particle swarm optimization for data clustering,” *Expert Syst. Appl.*, vol. 38, no. 12, pp. 14555–14563, 2011, doi: 10.1016/j.eswa.2011.05.027.

[237] G. Kaur and S. Arora, “Chaotic whale optimization algorithm,” *J. Comput. Des. Eng.*, vol. 5, no. 3, pp. 275–284, 2018, doi: 10.1016/j.jcde.2017.12.006.

[238] A. A. Ewees and M. A. Elaziz, “Performance analysis of Chaotic Multi-Verse Harris Hawks Optimization: A case study on solving engineering problems,” *Eng. Appl. Artif. Intell.*, vol. 88, no. December 2018, p. 103370, 2020, doi: 10.1016/j.engappai.2019.103370.

[239] W. Fu, K. Shao, J. Tan, and K. Wang, “Fault Diagnosis for Rolling Bearings Based on Composite Multiscale Fine-Sorted Dispersion Entropy and SVM with Hybrid Mutation SCA-HHO Algorithm Optimization,” *IEEE Access*, vol. 8, pp. 13086–13104, 2020, doi: 10.1109/ACCESS.2020.2966582.

[240] H. M. Ridha, A. A. Heidari, M. Wang, and H. Chen, “Boosted mutation-based Harris hawks optimizer for parameters identification of single-diode solar cell models,” *Energy Convers. Manag.*, vol. 209, no. December 2019, p. 112660, 2020, doi: 10.1016/j.enconman.2020.112660.

[241] H. Hu, Y. Ao, Y. Bai, R. Cheng, and T. Xu, “An Improved Harris’s Hawks Optimization for SAR Target Recognition and Stock Market Index Prediction,” *IEEE Access*, vol. 8, pp. 65891–65910, 2020, doi: 10.1109/ACCESS.2020.2985596.

[242] S. Jiao *et al.*, “Orthogonally adapted Harris hawks optimization for parameter estimation of photovoltaic models,” *Energy*, vol. 203, p. 117804, 2020, doi: 10.1016/j.energy.2020.117804.

[243] Q. Fan, Z. Chen, and Z. Xia, “A novel quasi-reflected Harris hawks optimization

algorithm for global optimization problems," *Soft Comput.*, vol. 24, no. 19, pp. 14825–14843, 2020, doi: 10.1007/s00500-020-04834-7.

[244] A. S. Menesy, H. M. Sultan, A. Selim, M. G. Ashmawy, and S. Kamel, "Developing and Applying Chaotic Harris Hawks Optimization Technique for Extracting Parameters of Several Proton Exchange Membrane Fuel Cell Stacks," *IEEE Access*, vol. 8, p. 1, 2020, doi: 10.1109/ACCESS.2019.2961811.

[245] C. Li, J. Li, and H. Chen, "A Meta-Heuristic-Based Approach for Qos-Aware Service Composition," *IEEE Access*, vol. 8, pp. 69579–69592, 2020, doi: 10.1109/ACCESS.2020.2987078.

[246] T. A. Shehabeldeen, M. A. Elaziz, A. H. Elsheikh, and J. Zhou, "Modeling of friction stir welding process using adaptive neuro-fuzzy inference system integrated with harris hawks optimizer," *J. Mater. Res. Technol.*, vol. 8, no. 6, pp. 5882–5892, 2019, doi: 10.1016/j.jmrt.2019.09.060.

[247] H. Chen, S. Jiao, M. Wang, A. A. Heidari, and X. Zhao, "Parameters identification of photovoltaic cells and modules using diversification-enriched Harris hawks optimization with chaotic drifts," *J. Clean. Prod.*, vol. 244, p. 118778, 2020, doi: 10.1016/j.jclepro.2019.118778.

[248] Z. M. Gao, J. Zhao, Y. R. Hu, and H. F. Chen, "The improved harris hawk optimization algorithm with the tent map," *2019 IEEE 3rd Int. Conf. Electron. Inf. Technol. Comput. Eng. EITCE 2019*, no. June, pp. 336–339, 2019, doi: 10.1109/EITCE47263.2019.9095091.

[249] M. Kohli and S. Arora, "Chaotic grey wolf optimization algorithm for constrained optimization problems," *J. Comput. Des. Eng.*, vol. 5, no. 4, pp. 458–472, 2018, doi: 10.1016/j.jcde.2017.02.005.

[250] A. Adamatzky, "Slime mold solves maze in one pass, assisted by gradient of chemo-attractants," *IEEE Trans. Nanobioscience*, vol. 11, no. 2, pp. 131–134, 2012, doi: 10.1109/TNB.2011.2181978.

[251] A. Adamatzky and J. Jones, "Road planning with slime mould: If Physarum built motorways it would route M6/M74 through Newcastle," *Int. J. Bifurc. Chaos*, vol. 20, no. 10, pp. 3065–3084, 2010, doi: 10.1142/S0218127410027568.

[252] M. Beekman and T. Latty, "Brainless but Multi-Headed: Decision Making by the Acellular Slime Mould Physarum polycephalum," *J. Mol. Biol.*, vol. 427, no. 23,

pp. 3734–3743, 2015, doi: 10.1016/j.jmb.2015.07.007.

[253] M. Burgin and A. Adamatzky, “Structural machines and slime mould computation,” *Int. J. Gen. Syst.*, vol. 46, no. 3, pp. 201–224, 2017, doi: 10.1080/03081079.2017.1300585.

[254] M. Houbraken, S. Demeyer, D. Staessens, P. Audenaert, D. Colle, and M. Pickavet, “Fault tolerant network design inspired by Physarum polycephalum,” *Nat. Comput.*, vol. 12, no. 2, pp. 277–289, 2013, doi: 10.1007/s11047-012-9344-7.

[255] R. Kouadri, L. Slimani, and T. Bouktir, “Slime Mould Algorithm for Practical Optimal Power Flow Solutions Incorporating Stochastic Wind Power and Static Var Compensator Device,” *Electr. Eng. Electromechanics*, vol. 0, no. 6, pp. 45–54, 2020, doi: 10.20998/2074-272x.2020.6.07.

[256] E. Kropat and S. Meyer-Nieberg, “Slime mold inspired evolving networks under uncertainty (SLIMO),” *Proc. Annu. Hawaii Int. Conf. Syst. Sci.*, pp. 1153–1161, 2014, doi: 10.1109/HICSS.2014.149.

[257] D. İzci and S. Ekinci, “Comparative performance analysis of slime mould algorithm for efficient design of proportional–integral–derivative controller,” *Electrica*, vol. 21, no. 1, pp. 151–159, 2021, doi: 10.5152/ELECTRICA.2021.20077.

[258] X. -s. Yang, “A new metaheuristic bat-inspired algorithm, in: Nature Inspired Cooperative Strategies for Optimization (NICSO 2010),” *Springer pp*, vol. 65, 2010.

[259] S. Mirjalili, “Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems,” *Neural Comput. Appl.*, vol. 27, no. 4, pp. 1053–1073, 2016, doi: 10.1007/s00521-015-1920-1.

[260] J. Kennedy and R. C. Eberhart, “A discrete binary version of the particle swarm algorithm,” *1997 IEEE Int. Conf. Syst. Man, Cybern. Comput. Cybern. Simul.*, vol. 5, pp. 4104–4108, 1997, doi: 10.1109/ICSMC.1997.637339.

[261] X. Yao, Y. Liu, and G. Lin, “Evolutionary programming made faster,” *IEEE Trans Evol Comput*, vol. 3, p. 82, 1999.

[262] S. Saremi, S. Mirjalili, and A. Lewis, “Grasshopper Optimisation Algorithm:

Theory and application," *Adv. Eng. Softw.*, vol. 105, pp. 30–47, 2017, doi: 10.1016/j.advengsoft.2017.01.004.

[263] S. Mirjalili, "The ant lion optimizer," *Adv. Eng. Softw.*, vol. 83, pp. 80–98, 2015, doi: 10.1016/j.advengsoft.2015.01.010.

[264] X. Yang, S. Deb, and A. C. B. Behaviour, "Cuckoo Search via L ´ evy Flights," *Ieee*, pp. 210–214, 2009.

[265] H. John, *Holland, adaptation in natural and artificial systems*. Cambridge: MIT Press, 1992.

[266] S. Mirjalili, S. M. Mirjalili, and A. Hatamlou, "Multi-Verse Optimizer: a nature-inspired algorithm for global optimization," *Neural Comput. Appl.*, vol. 27, no. 2, pp. 495–513, 2016, doi: 10.1007/s00521-015-1870-7.

[267] E. Rashedi, H. Nezamabadi-Pour, and S. Saryazdi, "BGSA: Binary gravitational search algorithm," *Nat. Comput.*, vol. 9, no. 3, pp. 727–745, 2010, doi: 10.1007/s11047-009-9175-3.

[268] S. Mirjalili, "SCA: A Sine Cosine Algorithm for solving optimization problems," *Knowledge-Based Syst.*, vol. 96, pp. 120–133, 2016, doi: 10.1016/j.knosys.2015.12.022.

[269] S. Mirjalili, A. H. Gandomi, S. Z. Mirjalili, S. Saremi, H. Faris, and S. M. Mirjalili, "Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems," *Adv. Eng. Softw.*, vol. 114, pp. 163–191, 2017, doi: 10.1016/j.advengsoft.2017.07.002.

[270] V. K. Kamboj, A. Nandi, A. Bhadoria, and S. Sehgal, "An intensify Harris Hawks optimizer for numerical and engineering optimization problems," *Appl. Soft Comput. J.*, vol. 89, p. 106018, 2020, doi: 10.1016/j.asoc.2019.106018.

[271] A. Sadollah, A. Bahreininejad, H. Eskandar, and M. Hamdi, "Mine blast algorithm: A new population based algorithm for solving constrained engineering optimization problems," *Appl. Soft Comput. J.*, vol. 13, no. 5, pp. 2592–2612, 2013, doi: 10.1016/j.asoc.2012.11.026.

[272] A. Bhadoria and V. K. Kamboj, "Optimal generation scheduling and dispatch of thermal generating units considering impact of wind penetration using hGWO-RES algorithm," *Appl. Intell.*, 2018, doi: 10.1007/s10489-018-1325-9.

[273] H. Abderazek, D. Ferhat, and A. Ivana, "Adaptive mixed differential evolution

algorithm for bi-objective tooth profile spur gear optimization,” *Int. J. Adv. Manuf. Technol.*, 2016, doi: 10.1007/s00170-016-9523-2.

[274] V. K. Kamboj, “A novel hybrid PSO – GWO approach for unit commitment problem,” *Neural Comput. Appl.*, 2015, doi: 10.1007/s00521-015-1962-4.

[275] J. Wang and D. Wang, “Particle swarm optimization with a leader and followers,” *Prog. Nat. Sci.*, vol. 18, no. 11, pp. 1437–1443, 2008, doi: 10.1016/j.pnsc.2008.03.029.

[276] E. Rashedi, H. Nezamabadi-pour, and S. Saryazdi, “GSA: A Gravitational Search Algorithm,” *Inf. Sci. (Ny).*, vol. 179, no. 13, pp. 2232–2248, 2009, doi: 10.1016/j.ins.2009.03.004.

[277] J. Xie, Y. Q. Zhou, and H. Chen, “A bat algorithm based on Lévy flights trajectory,” *Moshi Shibie yu Rengong Zhineng/Pattern Recognit. Artif. Intell.*, vol. 26, no. 9, pp. 829–837, 2013.

[278] X. S. Yang, “Firefly algorithm,” *Eng. Optim. pp*, vol. 221, 2010.

[279] S. Mirjalili, “Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm,” *Knowledge-Based Syst.*, vol. 89, no. July, pp. 228–249, 2015, doi: 10.1016/j.knosys.2015.07.006.

[280] E. Cuevas, A. Echavarría, and M. A. Ramírez-Ortegón, “An optimization algorithm inspired by the States of Matter that improves the balance between exploration and exploitation,” *Appl. Intell.*, vol. 40, no. 2, pp. 256–272, 2014, doi: 10.1007/s10489-013-0458-0.

[281] D. Jagodzi, “A Differential Evolution Strategy,” vol. 1, no. 3, pp. 1872–1876, 2017.

[282] H. Nezamabadi-pour, M. Rostami-sharbabaki, and M. Maghfoori-Farsangi, “Binary Particle Swarm Optimization: challenges and New Solutions,” *J. Comput. Soc. Iran Comput. Sci. Eng.*, vol. 6, no. 1-A, pp. 21–32, 2008, [Online]. Available: https://www.researchgate.net/publication/258456389_Binary_Particle_Swarm_Optimization_challenges_and_New_Solutions.

[283] D. Dhawale, V. K. Kamboj, and P. Anand, *An effective solution to numerical and multi-disciplinary design optimization problems using chaotic slime mold algorithm*, no. Ml. Springer London, 2021.

[284] R. Y. M. Nakamura, L. A. M. Pereira, K. A. Costa, D. Rodrigues, J. P. Papa, and

X. S. Yang, "BBA: A binary bat algorithm for feature selection," *Brazilian Symp. Comput. Graph. Image Process.*, pp. 291–297, 2012, doi: 10.1109/SIBGRAPI.2012.47.

[285] R. Storn and K. Price, "Differential Evolution – A Simple and Efficient Heuristic for global Optimization over Continuous Spaces," *J. Glob. Optim.*, vol. 11, no. 4, pp. 341–359, 1997, doi: 10.1023/A:1008202821328.

[286] S. Jafari, O. Bozorg-Haddad, and X. Chu, "Cuckoo optimization algorithm (COA)," *Stud. Comput. Intell.*, vol. 720, no. 8, pp. 39–49, 2018, doi: 10.1007/978-981-10-5221-7_5.

[287] B. Chopard and M. Tomassini, "Particle swarm optimization," *Nat. Comput. Ser.*, pp. 97–102, 2018, doi: 10.1007/978-3-319-93073-2_6.

[288] A. H. Gandomi, X. S. Yang, and A. H. Alavi, "Cuckoo search algorithm: A metaheuristic approach to solve structural optimization problems," *Eng. Comput.*, vol. 29, no. 1, pp. 17–35, 2013, doi: 10.1007/s00366-011-0241-y.

[289] T. Ray and P. Saini, "Engineering design optimization using a swarm with an intelligent information sharing among individuals," *Eng. Optim.*, vol. 33, no. 6, pp. 735–748, 2001, doi: 10.1080/03052150108940941.

[290] W. Zhao, Z. Zhang, and L. Wang, "Manta ray foraging optimization: An effective bio-inspired optimizer for engineering applications," *Eng. Appl. Artif. Intell.*, vol. 87, no. September 2019, p. 103300, 2020, doi: 10.1016/j.engappai.2019.103300.

[291] B. Niu and L. Li, "A novel PSO-DE-Based hybrid algorithm for global optimization," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 5227 LNAI, pp. 156–163, 2008, doi: 10.1007/978-3-540-85984-0_20.

[292] K. Deb, "A Combined Genetic Adaptive Search (GeneAS) for Engineering Design," vol. 26, pp. 30–45, 1996.

[293] A. K. Qin, V. L. Huang, and P. N. Suganthan, "Differential evolution algorithm with strategy adaptation for global numerical optimization," *IEEE Trans. Evol. Comput.*, vol. 13, no. 2, pp. 398–417, 2009, doi: 10.1109/TEVC.2008.927706.

[294] M. Y. Cheng and D. Prayogo, "Symbiotic Organisms Search: A new metaheuristic optimization algorithm," *Comput. Struct.*, vol. 139, pp. 98–112, 2014, doi: 10.1016/j.compstruc.2014.03.007.

[295] H. CHICKERMANE and H. C. GEA, “Structural Optimization Using a New Local Approximation Method,” *Int. J. Numer. Methods Eng.*, vol. 39, no. 5, pp. 829–846, 2002, doi: 10.1002/(sici)1097-0207(19960315)39:5<829::aid-nme884>3.0.co;2-u.

[296] S. Mirjalili, S. M. Mirjalili, and A. Lewis, “Grey Wolf Optimizer,” *Adv. Eng. Softw.*, vol. 69, pp. 46–61, 2014, doi: 10.1016/j.advengsoft.2013.12.007.

[297] Q. He and L. Wang, “An effective co-evolutionary particle swarm optimization for constrained engineering design problems,” *Eng. Appl. Artif. Intell.*, vol. 20, no. 1, pp. 89–99, 2007, doi: 10.1016/j.engappai.2006.03.003.

[298] K. Deb, “Optimal design of a class of welded structures via genetic algorithms,” *Collect. Tech. Pap. - AIAA/ASME/ASCE/AHS/ASC Struct. Struct. Dyn. Mater. Conf.*, no. pt 1, pp. 444–453, 1990, doi: 10.2514/6.1990-1179.

[299] M. Mahdavi, M. Fesanghary, and E. Damangir, “An improved harmony search algorithm for solving optimization problems,” *Appl. Math. Comput.*, vol. 188, no. 2, pp. 1567–1579, 2007, doi: 10.1016/j.amc.2006.11.033.

[300] G. Wu, W. Pedrycz, P. N. Suganthan, and R. Mallipeddi, “A variable reduction strategy for evolutionary algorithms handling equality constraints,” *Appl. Soft Comput. J.*, vol. 37, pp. 774–786, 2015, doi: 10.1016/j.asoc.2015.09.007.

[301] A. Sadollah, H. Eskandar, A. Bahreininejad, and J. H. Kim, “Water cycle algorithm with evaporation rate for solving constrained and unconstrained optimization problems,” *Appl. Soft Comput. J.*, vol. 30, pp. 58–71, 2015, doi: 10.1016/j.asoc.2015.01.050.

[302] V. K. Kamboj, A. Bhadoria, and N. Gupta, “A Novel Hybrid GWO-PS Algorithm for Standard Benchmark Optimization Problems,” *Ina. Lett.*, vol. 3, no. 4, pp. 217–241, 2018, doi: 10.1007/s41403-018-0051-2.

[303] K. S. Lee and Z. W. Geem, “A new structural optimization method based on the harmony search algorithm,” *Comput. Struct.*, vol. 82, no. 9–10, pp. 781–798, 2004, doi: 10.1016/j.compstruc.2004.01.002.

[304] K. M. Ragsdell and D. T. Phillips, “Optimal design of a class of welded structures using geometric programming,” *J. Manuf. Sci. Eng. Trans. ASME*, vol. 98, no. 3, pp. 1021–1025, 1976, doi: 10.1115/1.3438995.

[305] H. Eskandar, A. Sadollah, A. Bahreininejad, and M. Hamdi, “Water cycle

algorithm - A novel metaheuristic optimization method for solving constrained engineering optimization problems," *Comput. Struct.*, vol. 110–111, pp. 151–166, 2012, doi: 10.1016/j.compstruc.2012.07.010.

[306] R. V. Rao, V. J. Savsani, and D. P. Vakharia, "Teaching-learning-based optimization: A novel method for constrained mechanical design optimization problems," *CAD Comput. Aided Des.*, vol. 43, no. 3, pp. 303–315, 2011, doi: 10.1016/j.cad.2010.12.015.

[307] P. Savsani and V. Savsani, "Passing vehicle search (PVS): A novel metaheuristic algorithm," *Appl. Math. Model.*, vol. 40, no. 5–6, pp. 3951–3978, 2016, doi: 10.1016/j.apm.2015.10.040.

[308] B. Saravanan, S. Das, S. Sikri, and D. P. Kothari, "A solution to the unit commitment problem-a review," *Front. Energy*, vol. 7, no. 2, pp. 223–236, 2013, doi: 10.1007/s11708-013-0240-3.

[309] S. Mirjalili and A. Lewis, "Adaptive gbest-guided gravitational search algorithm," *Neural Comput. Appl.*, vol. 25, no. 7–8, pp. 1569–1584, 2014, doi: 10.1007/s00521-014-1640-y.

[310] K. a. Juste, H. Kita, E. Tanaka, and J. Hasegawa, "An evolutionary programming solution to the unit commitment problem," *IEEE Trans. Power Syst.*, vol. 14, no. 4, pp. 1452–1459, 1999, doi: 10.1109/59.801925.

[311] W. L. Snyder, H. D. Powell, and J. C. Rayburn, "Dynamic Programming Approach to Unit Commitment," *IEEE Power Eng. Rev.*, vol. PER-7, no. 5, pp. 41–42, 1987, doi: 10.1109/MPER.1987.5527246.

[312] B. Y. Qu and P. N. Suganthan, "Novel multimodal problems and differential evolution with ensemble of restricted tournament selection," *2010 IEEE World Congr. Comput. Intell. WCCI 2010 - 2010 IEEE Congr. Evol. Comput. CEC 2010*, 2010, doi: 10.1109/CEC.2010.5586341.

[313] M. Reza Norouzi, A. Ahmadi, A. Esmaeel Nezhad, and A. Ghaedi, "Mixed integer programming of multi-objective security-constrained hydro/thermal unit commitment," *Renew. Sustain. Energy Rev.*, vol. 29, pp. 911–923, 2014, doi: 10.1016/j.rser.2013.09.020.

[314] C. C. Su and Y. Y. Hsu, "Fuzzy dynamic programming: An application to unit commitment," *IEEE Trans. Power Syst.*, vol. 6, no. 3, pp. 1231–1237, 1991, doi:

10.1109/59.119271.

[315] S. Mirjalili and A. Lewis, “Adaptive gbest-guided gravitational search algorithm,” *Neural Comput. Appl.*, vol. 25, no. 7–8, pp. 1569–1584, 2014, doi: 10.1007/s00521-014-1640-y.

[316] A. Merlin and P. Sandrin, “A New Method for Unit Commitment at Electricite de France,” *IEEE Power Eng. Rev.*, vol. PER-3, no. 5, pp. 38–39, 1983, doi: 10.1109/MPER.1983.5519156.

[317] L. Yang, J. Jian, Z. Dong, and C. Tang, “Multi-Cuts Outer Approximation Method for Unit Commitment,” *IEEE Trans. Power Syst.*, vol. 32, no. 2, pp. 1587–1588, 2017, doi: 10.1109/TPWRS.2016.2584862.

[318] H. Yapici and N. Cetinkaya, “A new meta-heuristic optimizer: Pathfinder algorithm,” *Appl. Soft Comput. J.*, vol. 78, pp. 545–568, 2019, doi: 10.1016/j.asoc.2019.03.012.

[319] S. Mirjalili, G. G. Wang, and L. dos S. Coelho, “Binary optimization using hybrid particle swarm optimization and gravitational search algorithm,” *Neural Comput. Appl.*, vol. 25, no. 6, pp. 1423–1435, 2014, doi: 10.1007/s00521-014-1629-6.

[320] M. A. Tawhid and A. F. Ali, “A Hybrid grey wolf optimizer and genetic algorithm for minimizing potential energy function,” *Memetic Comput.*, vol. 9, no. 4, pp. 347–359, 2017, doi: 10.1007/s12293-017-0234-5.

[321] C. Cheng, C. Liu, and C. Liu, “Unit commitment by Lagrangian relaxation and genetic algorithms,” *IEEE Trans. Power Syst.*, vol. 15, no. 2, pp. 707–714, 2000, doi: 10.1109/59.867163.

[322] Y. W. Jeong, W. N. Lee, H. H. Kim, J. B. Park, and J. R. Shin, “Thermal Unit Commitment Using Binary Differential Evolution,” *J. Electr. Eng. Technol.*, vol. 4, no. 3, pp. 323–329, 2009.

[323] N. Sadati, M. Hajian, and M. Zamani, “Unit commitment using particle swarm-based-simulated annealing optimization approach,” *Proc. 2007 IEEE Swarm Intell. Symp. SIS 2007*, no. Sis, pp. 297–302, 2007, doi: 10.1109/SIS.2007.367951.

[324] S. Khanmohammadi, M. Amiri, and M. T. Haque, “A new three-stage method for solving unit commitment problem,” *Energy*, vol. 35, no. 7, pp. 3072–3080, 2010, doi: 10.1016/j.energy.2010.03.049.

[325] Y. W. Jeong, J. B. Park, S. H. Jang, and K. Y. Lee, “A New Quantum-Inspired

Binary PSO for Thermal Unit Commitment Problems," in *Proc. 15th International Conference on Intelligent System Applications to Power Systems*, 2009, pp. 1–6.

[326] C. P. Cheng, C. W. Liu, and C. C. Liu, "Unit Commitment By Annealing-Genetic Algorithms," *Electr. Power Energy Syst.*, vol. 24, pp. 149–158, 2000.

[327] T. Senjyu, H. Yamashiro, K. Shimabukuro, and K. Uezato, "Unit Commitment Problem using Genetic Algorithm," pp. 1611–1616, 2002.

[328] C. Y. Chung, H. Yu, and K. P. Wong, "An advanced quantum-inspired evolutionary algorithm for unit commitment," *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 847–854, 2011, doi: 10.1109/TPWRS.2010.2059716.

[329] Z. Ouyang and S. M. Shahidehpour, "A multi-stage intelligent system for unit commitment," *IEEE Trans. Power Syst.*, vol. 7, no. 2, pp. 639–646, 1992, doi: 10.1109/59.141769.

[330] T. O. Ting, M. V. C. Rao, and C. K. Loo, "A Novel Approach for Unit Commitment Problem via an Effective Hybrid Particle Swarm Optimization," *IEEE Trans. Power Syst.*, vol. 21, no. 1, pp. 411–418, 2006, doi: 10.1109/TPWRS.2005.860907.

[331] R. P. Priya, "A Solution to Unit Commitment Problem with V2G Using Harmony Search Algorithm," *Int. J. Adv. Res. Electr. Electron. Instrum. Eng.*, vol. 04, no. 03, pp. 1208–1214, 2015, doi: 10.15662/ijareeie.2015.0403005.

[332] G. B. S. Tim T Maifeld, "GENETIC-BASED UNIT COMMITMENT ALGORITHM," vol. 6, no. 4, pp. 1359–1370, 1991.

[333] X. Yuan, H. Nie, A. Su, L. Wang, and Y. Yuan, "An improved binary particle swarm optimization for unit commitment problem," *Expert Syst. Appl.*, vol. 36, no. 4, pp. 8049–8055, 2009, doi: 10.1016/j.eswa.2008.10.047.

[334] S. Najafi and Y. (2011) Pourjamal, "A New Heuristic Algorithm for Unit Commitment Problem," *Energy Procedia*, vol. 14, 2011.

[335] J. H. Zhao, F. Wen, Z. Y. Dong, Y. Xue, and K. P. Wong, "Optimal dispatch of electric vehicles and wind power using enhanced particle swarm optimization," *IEEE Trans. Ind. Informatics*, vol. 8, no. 4, pp. 889–899, 2012, doi: 10.1109/TII.2012.2205398.

[336] Z. Bayraktar, M. Komurcu, J. A. Bossard, and D. H. Werner, "The wind driven optimization technique and its application in electromagnetics," *IEEE Trans.*

Antennas Propag., vol. 61, no. 5, pp. 2745–2757, 2013, doi: 10.1109/TAP.2013.2238654.

[337] M. Govardhan and R. Roy, "Economic analysis of unit commitment with distributed energy resources," *Int. J. Electr. Power Energy Syst.*, vol. 71, pp. 1–14, 2015, doi: 10.1016/j.ijepes.2015.01.028.

[338] M. M. H. Bioki, M. Z. Jahromi, and M. Rashidinejad, "A combinatorial artificial intelligence real-time solution to the unit commitment problem incorporating V2G," *Electr. Eng.*, vol. 95, no. 4, pp. 341–355, 2013, doi: 10.1007/s00202-012-0263-5.

[339] A. Y. Saber and G. K. Venayagamoorthy, "Unit commitment with vehicle-to-grid using particle swarm optimization," *2009 IEEE Bucharest PowerTech Innov. Ideas Towar. Electr. Grid Futur.*, pp. 1–8, 2009, doi: 10.1109/PTC.2009.5282201.

[340] S. M. A. Oussama Touaba and and A. Z. Mohamed El-Amine Slimani, Ahmed Bouraiou, *Proceedings of the 4th International Conference on Electrical Engineering and Control Applications*, no. December. 2019.